Simulation-based Decision-making in Early Design Stages

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Abstract
The use of digital tools for building design has increased in the past few years with the introduction of building information modeling (BIM). However, the advantage of integrating decision support information into the early design stages has been little exploited. Such integration has the potential to enhance design solutions by providing knowledge of interactions and dependencies through explicit descriptions of the design space (DS), including dependence of energy performance on design parameters.

The design space exploration assistance method (DSEAM) proposed here allows designers to evaluate their design using project specific simulation results and the DS formed by the potential alternative solutions to ensure deeper understanding of the calculated results. The response surface methodology, a metamodeling method, provides rapid results. Moreover, the approach visualizes the impact of design changes. The proposed approach is integrated into a computer-aided design environment to guide designers through the DS to find a well-performing solution. An office design example illustrates the benefits of DSEAM for decision-making.

Keywords: Design Decision Support, visual programming, performance-driven design

1 Introduction
In recent years, the use of building information modeling (BIM) has been growing in the architecture, engineering, and construction (AEC) sector. However, the method is mainly used in the later phases of the planning process for very detailed models to generate blueprints or run detailed simulations when major decisions have already been made and most of the design process has been completed. The potential of BIM methods to gain and interconnect knowledge in very early phases, i.e., at the conceptual stage, is not well exploited. Typically, changes in the design concept in later phases are expensive as well as time-consuming. Therefore, an approach to gain insights into the consequences of design decisions is required as early as possible in the design process.

The design space exploration assistance method (DSEAM) utilizes available information and applies parametric modeling and simulation techniques including the response surface methodology (RSM) for metamodeling to render the DS, the parametric space of alternatives for a given design situation, interactively accessible for decision-making. This method focuses on the energy performance of the building under design. Typical design decisions in early phases concern the building shape and envelope as they exercise a major influence on future energy consumption and material and space usage.

1.1 Performance driven design
Owing to continuously enhanced energy standards and governmental certification programs, designers face the problem of focusing on performance-driven design instead of architectural design, which relies on space and form, their field of expertise. In addition, designers require new tools that are integrated into their design environment to maintain control of the design process and not hand

it over to green building specialist engineers (Shi & Yang 2013). Hence, substantial research has been conducted lately to integrate building performance simulation (BPS) into the design process in the early design stages. One present challenge in BPS is to ensure the development of adequate representation of the built environment and its performance, not a trivial task (Clarke & Hensen 2015).

There are three ways to integrate BPS into the design process: (a) a combined model, wherein all simulations can be performed within the modeling environment, (b) a central model, wherein the information is shared between different modeling and simulation tools using a data standard, and (c) a distributed model, wherein simulation tools are coupled to the modeling environment by middleware (Negendahl 2015). These systems often rely on either databases from which results from other projects are available, as in (Markova et al 2013), or generative approaches coupled to optimization algorithms that assist the designer in minimizing design iterations. The latter includes generative design support using parametric design as presented in (Lin & Gerber 2014) or grammars as in (Granadeiro et al 2013).

However, these approaches do not support the designer in decision-making for a specific design task that is different from previous ones, because even large databases often miss a well-fitting solution and optimization algorithms do not help find options other than the optimized one. Furthermore, all these methods lack an interface for designers that is easy to use and can be easily adapted to different design tasks in their common environment. Therefore, a new methodology integrated into a traditional environment must be developed to enable designers to define design problems and support the search for effective solutions.

1.2 Design Decision Support

To provide extensive supporting information on energy performance in early design phases, the conceptual building design, this study presents a new methodology (DSEAM) that interactively integrates computational model-driven design decision support (DDS) in a design process. The aim is to enable designers to define problems, automatically derive the performance characteristics within the DS and then present them in an easy to understand and interactive manner for further steps of decision-making. A key feature of this model-driven DDS is the rapid exploitation and visualization of DSs and alternatives that allow effective real-time support for design sessions.

1.3 Design Space Exploration

The DS is defined by all possible solutions to a given design problem. It contains all the parameters that stakeholders consider in their design subspaces (Figure 1). Hence, the design process can be described as DS construction, i.e., the definition of objectives, variables, and constraints, and DSE, which involves the examination and evaluation of different solutions (Maher 2000). Performed manually, this is a time-consuming process because all the solutions must be evaluated in their performance, e.g., costs, energy consumption, and carbon footprint. Therefore, computational support in DSE could provide a substantial benefit to this process for finding well-performing design solutions. However, computationally expensive performance evaluations provide a hurdle for DSE, because they

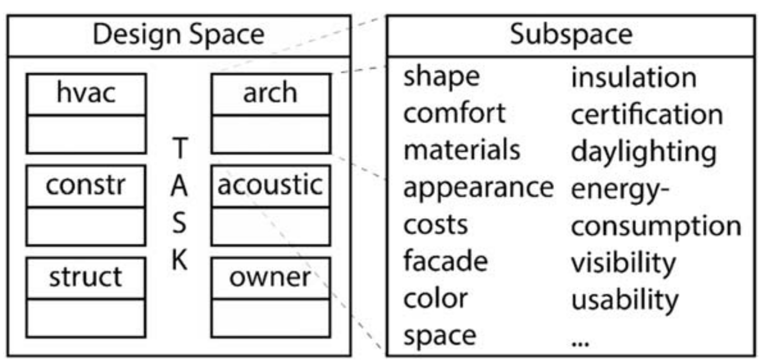

Figure 1 The DS contains all possible solutions for a given task. It can be divided into several subspaces, which are represented as the participants in building design. These can be subdivided among different experts within a group (e.g., a group of architects with different focuses).

hinder interactive design and are therefore often performed completely automatically without human–computer interaction.

Nonetheless, human–computer interaction must occur in computational DSE because of the aesthetic and emotional character of architectural design, which requires tacit knowledge and is therefore difficult to derive automatically. The designer needs to have the possibility of interfering with the DSE to drive the design in a direction that also fulfills the aesthetic aspects and brings in other tacit knowledge that cannot be computationally reproduced.

2 Design Space Exploration Assistance Method

DSEAM was developed to enable designers to perform a rapid DSE. Therefore, a representation of the DS, focusing on energy performance in the presented case, is integrated within a 3D computer-aided design (CAD)/BIM environment that visualizes the multidimensional DS interactively (Figure 2). The BIM environment is not intended to hold a detailed model but to use the results of DSEAM based on a conceptual model for further detailing.

Furthermore, DSEAM enables designers to gain knowledge of the DS. The rapid exploration of DS in terms of performance and representation allows exploration of the influence and impact of different solutions without actually modeling them. DSEAM utilizes a metamodel generated on the basis of a few initial variants that serve as supporting points. Hence, it is possible to explore the DS continuously and understand the sensitivity of the examined variables.

The modification of the complete DS (total modification) is insufficient in most cases owing to the complexity or irrelevance of a parameter in the entire setting, with the result that typically only a partial modification is deployed or only one subspace is explored (Maheri & Isikveren 2013). In the presented case, we focus on energy performance within the architectural subspace.

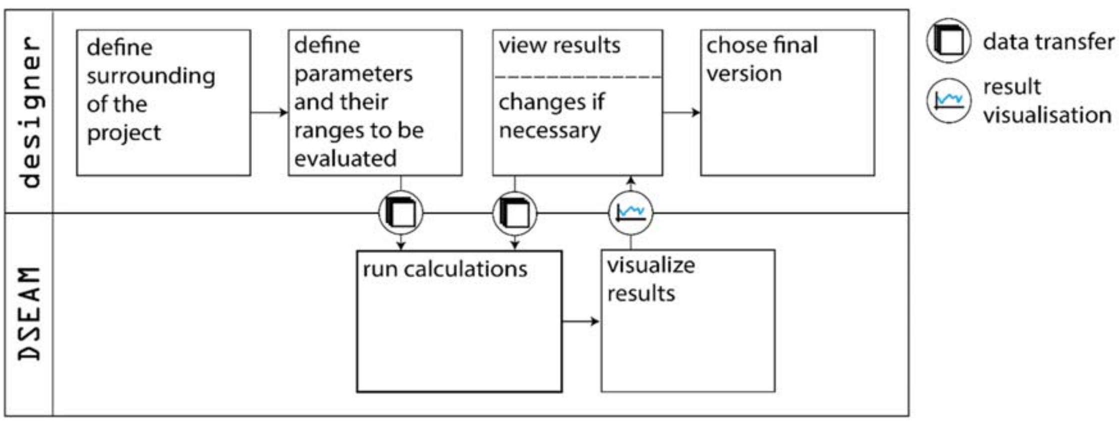

Figure 2 Integration of DSEAM into the design workflow.

2.1 Response Surface Methodology

RSM was first introduced by Box & Wilson (1951) as an important means of metamodeling and was then developed further (Box & Draper 2007, Forrester et al 2008). It assists in the construction of rapidly responding models based on supporting points. These points stem from an intelligent choice of experiments using the design of experiments (DoE) methodology. RSM has already been used for engineering problems, primarily in the field of mechanical engineering (Gholap & Khan 2007, Goel et al 2007, Ekren & Ekren 2008, Georgopoulou & Giannakoglou 2010, Zhang et al 2012, Cheng et al 2013). However, RSM has also been applied in an AEC context (Chlela et al 2009, Jaffal et al 2009, Geyer & Schlüter 2014).

DSEAM utilizes the approach of parametric simulation and metamodel construction for rapidly responding DSE. It enables the designer to describe the design task in a CAD modeling environment and obtain instant feedback regarding well-performing solutions and the impact of parameter changes (Figure 2). Hence, DSEAM enables the designer to implement informed decisions and gain knowledge of the explored DS and the impact of the various parameters.

2.1.1 Mathematical Model

In the traditional RSM approach, the structure of the equations is static since the DS is represented by second-order polynomials and either no or only first-order interactions. The typical form is

$$y = f(x_1, x_2), \tag{1}$$

where x_i are the design variables and y is the target value. The metamodel is represented as

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1^2 + \beta_4 x_2^2 + \beta_5 x_1 x_2 + \varepsilon = g(x), \tag{2}$$

where β_i are the fitting coefficients, ε is the modeling error, and $\hat{y}$ is the response.

In particular cases, manual extensions serve to improve accuracy. Chlela et al (2009) considered selected second-order interactions, and Forrester et al (2008) introduced the Vandermonde matrix, which allows higher-order polynomials. However, this requires mathematical and technical knowledge, discouraging typical designers. Consequently, rigid configurations, which lack a good fit to the real nature of the dependencies and interactions between factors, form the main application of RSM. They are inappropriate for providing general information on the behavior of an individual design case. Individual cases, especially in building design and retrofitting, are significantly different with respect to their component constitutions and thus their engineering dependency characteristics that lead to individual performance behavior requiring appropriate design strategies.

To enable metamodeling, a selected number of supporting points must be determined. There are three ways of achieving the responses for the supporting points: (1) calculation based, for example, on known physical behavior, (2) measurement through experiments, and (3) simulation. In this study, we focus on metamodeling using simulation owing to the lack or poor availability of measured data and the strong influence of the behavior of the people living in the examined area. Therefore, the required supporting points are evaluated using an energy analysis tool, EnergyPlus. These calculations also require some time, but the generated metamodel allows instant feedback for all further design changes.

2.2 Integration into the Design Process

To support the design process, DSEAM must be seamlessly implemented into the used environment. As an interface for the designer, visual programming language Dynamo (Keough 2015) is used.

The advantages of Dynamo are that it offers an easy to understand way of integrating additional functionalities into a common modeling environment, and it can be adapted easily to various scenarios. Dynamo can access and modify the parameters of a CAD model and can therefore apply to a defined design. This is important because design tasks have various requirements and constraints that differ for every new design task. Furthermore, designers have varying knowledge regarding specific points and need other feedback from the system.

Normally, DoE serves to determine a subset of supporting points that provide as much information with as few experiments as possible. However, in our case, to calculate the second-degree polynomial metamodel corresponding to equation (5), at least three variation steps (design points) of each factor are necessary. This leads to a minimum of 3^{n} simulations for the metamodel, which allows a full factorial exploration of the DS, where n is the number of variables. Then, each factor is normalized to a range of −1 to 1. To this end, the evaluation of the parametric simulation model is performed at steps −1, 0, and 1 to ensure the highest distribution of design points in the examined DS.

2.3 Implementation

The parametric CAD model is coupled to a simulation model via Dynamo to enable RSM for DDS in terms of energy performance. A framework was developed using MATLAB (Mathworks 2015) and EnergyPlus (U.S. Department of Energy 2013) to automate the generation of the metamodel.

The EnergyPlus input files are generated within Dynamo, thereby allowing access to the model parameters. These files are then exported and used within MATLAB to evaluate the supporting points

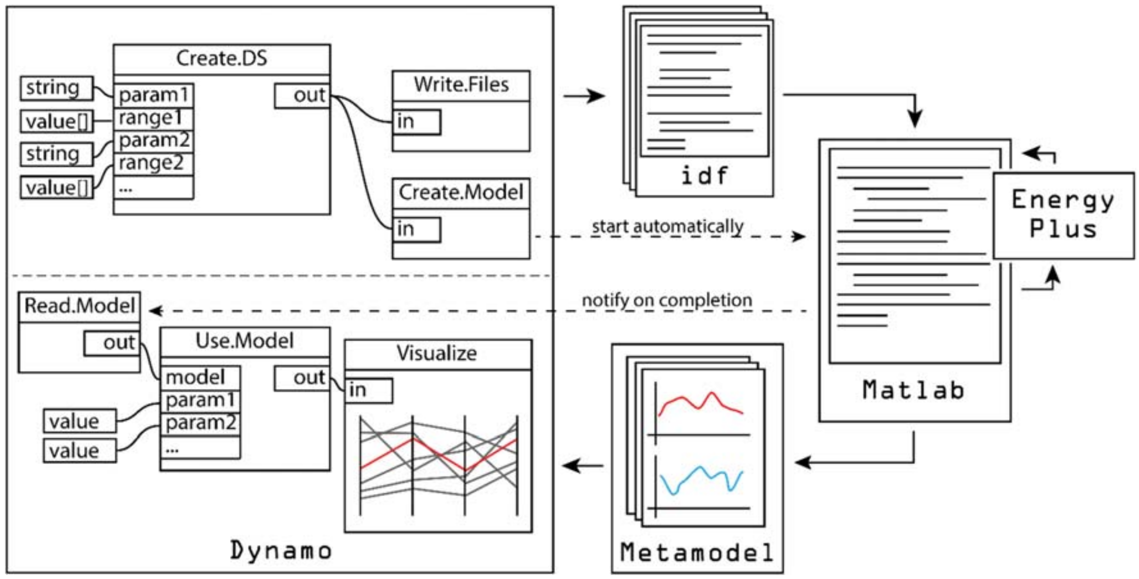

Figure 3 DSEAM workflow: The designer defines his or her first intention and the parameters desired for study in a given range. Next, DSEAM automatically creates the DS for the given problem and loads it into the CAD application. The designer receives instant feedback on the performance of the current design and the impact regarding parameter changes within the previously defined DS.

of the metamodel. The metamodel is then provided in Dynamo to visualize feedback and explore the DS (Figure 3).

2.4 Visualization and Exploration

The problem regarding visualization of the DSEAM results is their high-dimensional nature. As the response surfaces can be easily visualized in 3D (i.e., two parameters and the resulting impact, e.g., the glazing factor, the window U-value, and their impact on the heating energy consumption), more dimensions require specifications that are often not intuitively classifiable (Packham et al 2005).

One good solution for the visualization of high-dimensional problems is parallel coordinates. They display different options along scaled vertical axes for different parameters (Figure 4). They can be compared with a spider web graph but are more readable because they do not radially order the values.

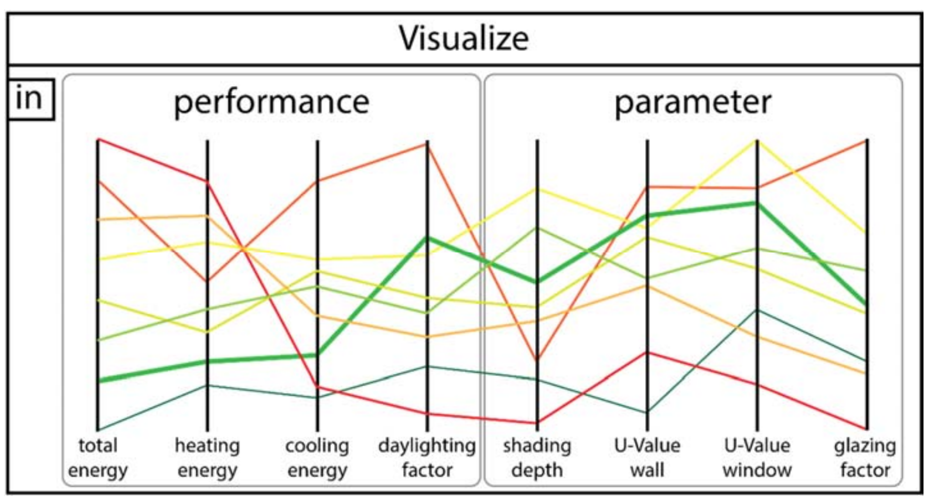

Figure 4 The different variants in parallel coordinates. They can be easily understood and compared. The selected variant (red) shows that the "optimal" result (least energy consumption) might not result in the intended design. The designer can evaluate the variants compared with his own intentions and decide accordingly.

3 Case study

In the following, the integration of DSEAM into the design process is explained using a conceptual design of an office building in an urban area.

3.1 Design Task

The task is to design an office building with a fixed usage area. Therefore, each space plan layout option uses the same amount of space on site. The designer begins by defining the initial geometries and constraints in the CAD environment and connects them to Dynamo. Owing to the urban environment, the design orientation is restricted to two main axes along the north and south sides of the site. Thus, a parametric conceptual mass is defined by the architect using a common CAD environment. The parametric layout is displayed in Figure 5. Moreover, the surrounding buildings are modeled as masses and integrated within the energy performance evaluation because they influence performance in terms of shading.

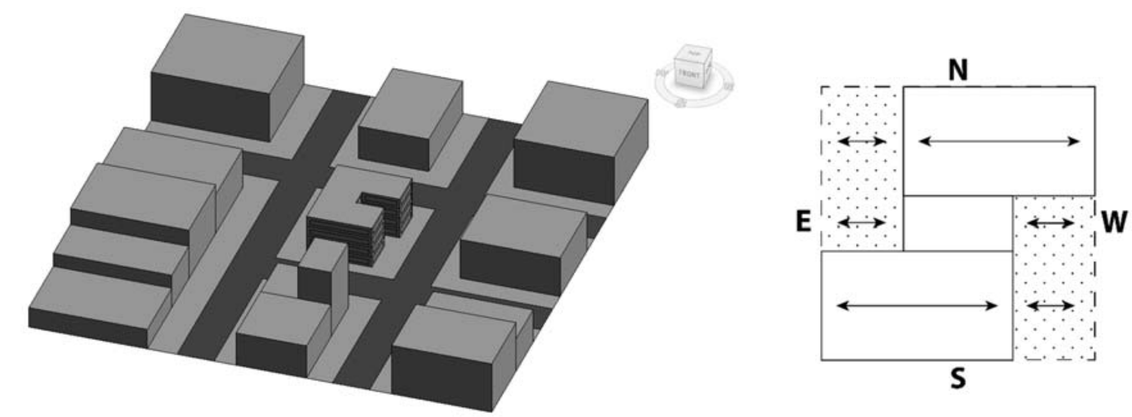

Figure 5 An office building in a city environment as modeled in Revit 2016 (Autodesk 2015). The geometry of the building is parametric and automatically steered by DSEAM via Dynamo. The parameters include the length of the north and south wings as well as the positions of the two wings and the connecting center part. The environment is also modeled with a high-rise building in the south of the office building to evaluate the influences of shading.

The ranges for design variables, representing the DS steps, are selected as shown in Table 1. The parameters are usually selected as continuous parameters and hence can form a response surface as the metamodel. This means that the wings can be placed along their sides between the west and east corners at any location. The length is also a continuous parameter, but owing to the restriction of the total space required, they are dependent on each other. Since the maximum length is restricted to 25 m, the minimum length is 10 m on order to satisfy the planned office space requirement. The two parameters' envelope quality and glazing factor are also continuous without affecting the space layout. Among the parameters, only the version is not continuously varied because the designer has decided to place the inner part at discrete positions. Therefore, each version will form a new metamodel, which can be explored individually or in parallel.

Table 1 Design variables for the office design

Design Variable	−1	0	+1
Version (Position of the inner part)	A (east)	B (mid)	C (west)
Wing Length Ratio (North/South)	10/25 m	17.5/17.5 m	25/10 m
Right Wing Position	east	mid	west
South Wing Position	east	mid	west
Envelope Quality [W/m²K]	$U_{wall} = 2.0$ $U_{window} = 1.85$	$U_{wall} = 1.1$ $U_{window} = 1.25$	$U_{wall} = 0.14$ $U_{window} = 0.65$
Glazing Factor	0.3	0.6	0.9

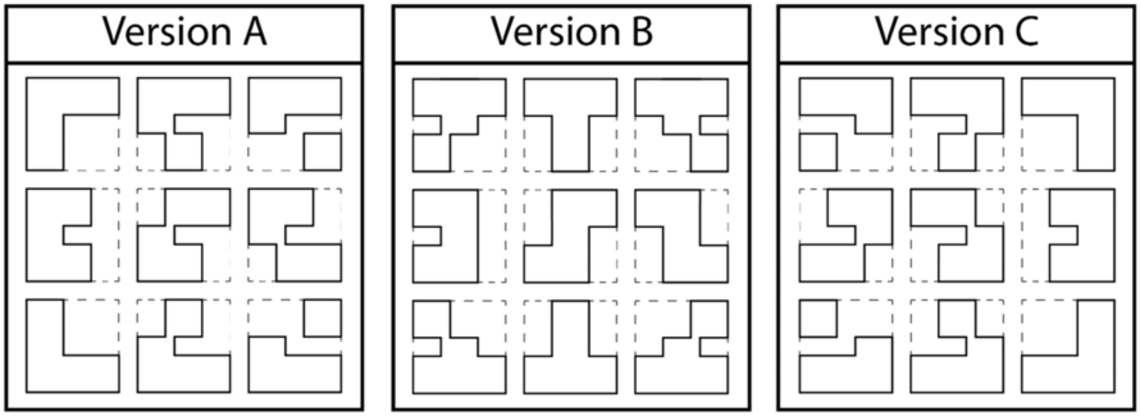

Figure 6 Space layouts that form the supporting points of the DS for the office building. All space layouts lead to the same amount of available office space within the buildings. The versions define the position of the connection between two areas (left, center, and right) and are explicit/discrete. The lengths and positions of the wings can be manipulated continuously and lead to space plan layouts where two buildings emerge.

The question now is how the different shapes affect the energy consumption of the building. Therefore, the designer uses DSEAM to generate the version metamodels for the given design task. In the first step, the variants that form the supporting points, i.e., the full factorial space of the values described in Table 1, are automatically generated and evaluated. The different geometric designs are displayed in Figure 6.

3.1.1 Results

The simulation results are the overall heating energy demand with a set point temperature of 20℃, the cooling demand with a set point of 24℃, and the maximal heating and cooling load that can be used by specialists to decide on the heating, ventilating, and air conditioning (HVAC) system. All values are related to the conditioned space for improved comparison.

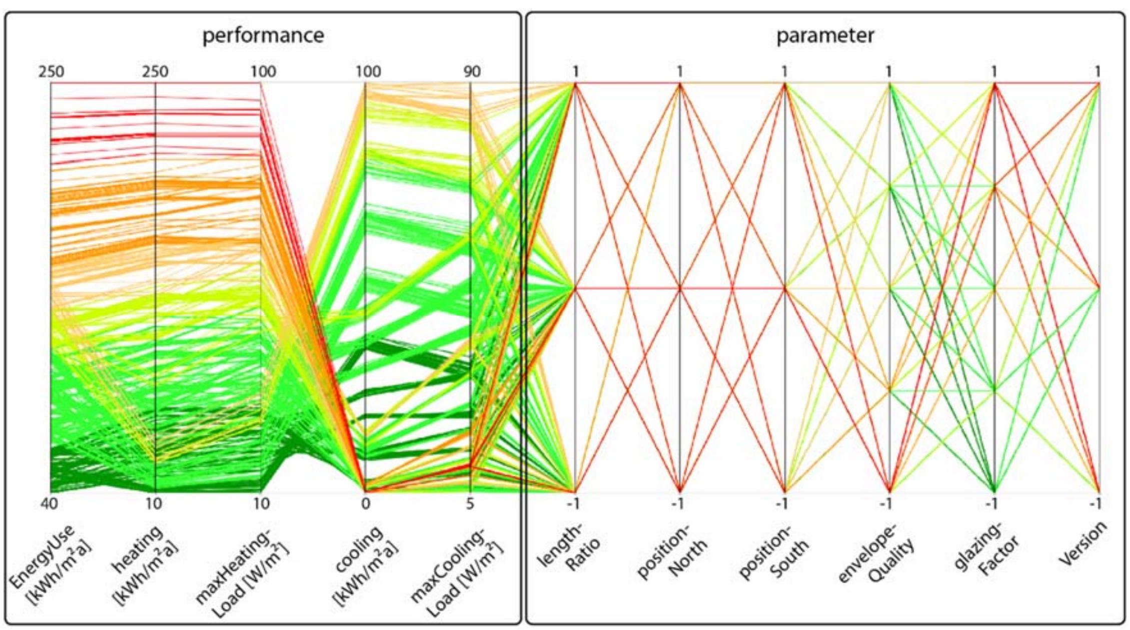

Figure 7 The results of the different office building variants that form the supporting points for the metamodel in parallel coordinates. Each line represents a dedicated design variant that can be visualized within the CAD environment according to the selected performance.

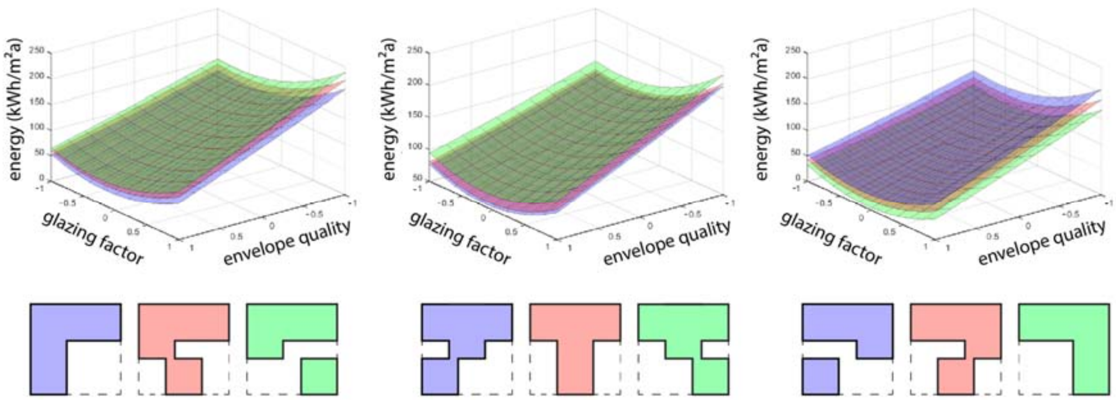

Figure 8 Visualization of the metamodel for Versions A (left), B (middle), and C (right). The response surfaces are displayed for three specific cases of each version. More cases can be added or removed for detailed exploration. The differences between Versions A and C are related to the defined environment (surrounding buildings).

The resulting performance is shown in parallel coordinates in Figure 7. Results show a total energy demand (heating and cooling) ranging from 40 to 250 kWh/m²a. This is a very wide range owing to the chosen range of the envelope quality, 2.0–0.14 W/m²K.

The metamodel is then obtained by regression (minimizing the quadratic mean error), whereby the absolute error is calculated using the following equation:

$$\varepsilon = \hat{y} - y, \tag{3}$$

where $\hat{y}$ is the result of the metamodel and y is the simulation results. The calculated errors are shown in Table 2.

Table 2 Error of the metamodel for the three versions

Version	Max Error [%]	>10%	>15%
Version A	38	136 out of 675	57 out of 675
Version B	50	160 out of 675	84 out of 675
Version C	40	140 out of 675	59 out of 675

The metamodel can then be explored again in parallel coordinates or by displaying the response surfaces. The response surfaces cannot be explored in higher dimensions but offer the opportunity to understand the influences in more detail.

Figure 8 shows the metamodels as an example of visualization of the response surfaces. The parameters for the glazing factor and envelope quality are selected for visualization. Each model shows three specific geometrical layouts with the north wing length at a maximum. It can be easily seen that the highest influence on the energy consumption of the building is the envelope quality (y axis of the response surface in Figure 8). High envelope qualities can halve the energy consumption of the building. The second important parameter is the glazing factor (x axis of the response surface in Figure 8), which has an optimum glazing of approximately 60%. With this factor, the building has sufficient solar heat gain to maintain low heating energy consumption in winter but less than sufficient to avoid overheating, with consequent high cooling energy consumption in summer. Owing to the shading of the high-rise building in the south, version C's performance is somewhat better than those of the other two versions.

To get a better understanding of the sensibility of each variable, the influences can be displayed in bar charts as well (Figure 9). The influence of the envelope quality has at least an influence of 70% up to about 85%. This is also related to the wide range in which this variable is modeled. The glazing factor also has a high influence, which will be reduced if also shading elements are considered. But

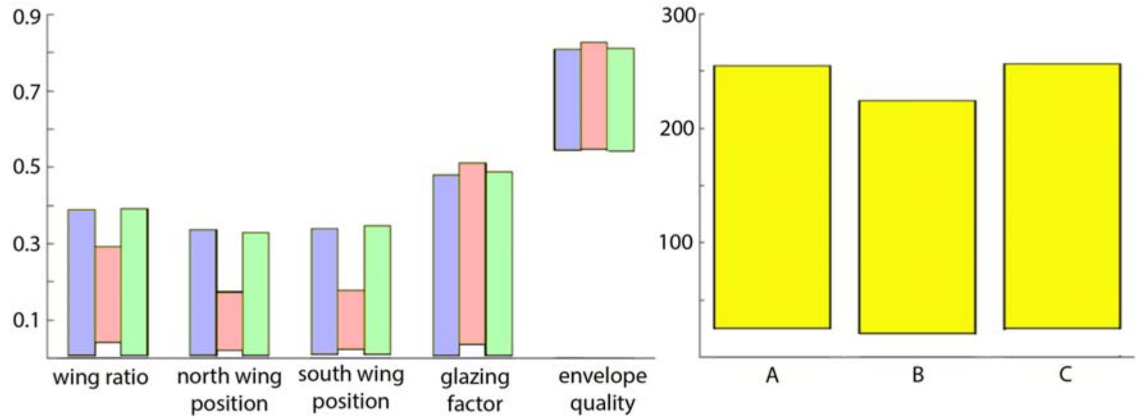

Figure 9 Left: Visualization of the influence of the five variables for the three, Versions A (blue), B (red), and C (green). Right: The best performance can be achieved with Version B.

also the influence of the space layout cannot be neglected with impacts up to 40%. Only the Version B has a very low influence due to its compactness. On the right side of Figure 9, the energetic performance ranges of the three versions are shown. Also here it can be seen, that the compact version B performs better than the other two. But with a range from 250 kWh/m²a down to 25 kWh/m²a the examined parameters have to be chosen reasonably.

Finally, the designer now has the possibility of making informed decisions based on the metamodel. The designer can decide on design changes in combination with his or her aesthetic and emotional design intent, architectural knowledge, and other requirements that cannot be computationally evaluated well. Also if some general perceptions may be clear (like that the most compact and insulated design grants the best performance) it enables designers to see how much worse or better their design is compared to the "optimized" solution and hence find the best performing solution for the design task including their tacit perception of architectural and spatial design.

4 Conclusion

This study presented DSEAM, an approach that allows rapid DS evaluation in terms of energy performance within a common design interface. It interactively visualizes the performance indicators of the multidimensional DS.

Parametric modeling, energy simulation, and metamodeling were applied to enable rapid DSE and additional DS knowledge. The method enables DDS in conceptual design without limiting the solutions to automatically optimized ones. The designer can explore the DS, gain knowledge of the influence of parameters, and decide on the basis of the performance indicators visualized in parallel coordinates and response surfaces and on his or her design intentions and architectural knowledge.

The presented case study of an urban office building showed the advantages of DSEAM for evaluating energy performance. It was clearly seen that the envelope quality is the most important factor and must be considered.

In further steps, predefined generic parametric components that directly integrate DSEAM will be developed. Furthermore, additional analysis tools for evaluating the daylighting factor, material use, and costs, for example, will be implemented.

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