Uncertainty and sensitivity analysis in building performance simulation for decision support and design optimization

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Christina Johanna Hopfe

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Dit proefschrift is goedgekeurd door de promotor:

prof.dr.ir. J.L.M. Hensen

Copromotor:
dr.rer.nat. M.T.M. Emmerich

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Samenstelling promotiecommissie:

Rector Magnificus, voorzitter
prof.dr.ir. J.L.M. Hensen, Technische Universiteit Eindhoven, promotor
dr.rer.nat. M.T.M. Emmerich, LIACS, University of Leiden, copromotor
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To my parents

Summary

Uncertainty and Sensitivity Analysis in Building Performance Simulation for Decision Support and Design Optimization

Building performance simulation (BPS) uses computer-based models that cover performance aspects such as energy consumption and thermal comfort in buildings.
The uptake of BPS in current building design projects is limited. Although there is a large number of building simulation tools available, the actual application of these tools is mostly restricted to code compliance checking or thermal load calculations for sizing of heating, ventilation and air-conditions systems in detailed design.
The aim of the presented work is to investigate opportunities in BPS during the later phases of the design process, and to research and enable innovative applications of BPS for design support. The research started from an existing and proven design stage specific simulation software tool.
The research methods applied comprise of literature review, interviews, rapid iterative prototyping, and usability testing. The result of this research is a prototype simulation based environment that provides add-ons like uncertainty and sensitivity analysis, multi-criteria and disciplinary decision making under uncertainty, and multi-objective optimization.
The first prototype addressing the uncertainties in physical, scenario, and design parameters provides additional information through figures and tables. This outcome helps the designer in understanding how parameters relate to each other and to comprehend how variations in the model input affect the output. It supports the design process by providing a basis to compare different design options and leads therefore to an improved guidance in the design process.
The second approach addresses the integration of a decision making protocol with the extension of uncertainty and sensitivity analysis. This prototype supports the design team in the design process by providing a base for communication. Furthermore, it supports the decision process by providing the possibility to compare different design options by minimizing the risk that is related to different concepts. It reduces the influence of preoccupation in common decision making and avoids pitfalls due to a lack of planning and focus.
The third and last approach shows the implementation of two multi-objective algorithms and the integration of uncertainty in optimization. The results show the optimization of parameters for the objectives energy consumption and weighted over- and underheating hours. It shows further how uncertainties impact the Pareto frontier achieved.
The applicability and necessity of the three implemented approaches has further been validated with the help of usability testing by conducting mock-up presentations and an online survey. The outcome has shown that the presented results enhance the capabilities of BPS and fulfil the requirements in detailed design by providing a better understanding of results, guidance through the design process, and supporting the decision process. All three approaches have been found important to be integrated in BPS.

Contents

1

1. Introduction

Energy efficiency and thermal comfort are of concern in building design. Due to the fact that one third of national total annual energy consumption is consumed in buildings, it is estimated that substantial energy savings can be achieved through careful planning for energy efficiency [Hong et al., 2000].

According to the World Business Council for Sustainable Development (WBCSD) the energy use in buildings can be reduced by up to 60 percent until 2050 when taking immediate action. Björn Stigson, president of the WBCSD formulates: “Energy efficiency is fast becoming one of the defining issues of our times, and buildings are that issue's ‘elephant in the room'. Buildings use more energy than any other sector and as such are a major contributor to climate change”.

In numerous countries already building regulations or directives exist to ensure that building energy performance improvement measures are considered by the building designer. However, buildings are still being commissioned every day that will use more energy than necessary, and millions of inefficient buildings will remain until 2050 [Sisson et al., 2009]. Therefore, it is important to improve also the existing building stock. The replacement rate of buildings is only around 0.2% a year. More than 60% of the building stock was built before 1975 [Sisson et al., 2009]. One challenge is therefore retrofitting existing buildings because “more than 80% of the current stock need retrofitting for high energy efficiency” [Sisson et al., 2009]. Many global projects are being developed to address these issues. The Energy Efficiency in Buildings (EEB) project for instance is a project that gives recommendations to transform the current building stock. It addresses six markets, Brazil, China, Europe, India, Japan and the US, altogether they cover almost two-third of the worlds energy use [Sisson et al., 2009].

It is necessary to establish building codes and regulations for new as well as existing buildings, that consider climate change, enforce energy savings, and reduction of CO_2 emissions. In either case design/retrofit decisions are taken that have a long lasting impact on the energy consumption of the building over its service life. Design decisions that typically impact the entire life cycle of the building need to consider the energy savings under different usage scenarios of buildings. The biggest challenge is to increase the comfort and to reduce the energy use at the same time. Traditional thinking is dominated by occupant satisfaction and sophisticated HVAC systems, often at the expense of energy use. The pressure of economic and ecologic considerations is mounting to invent new concepts to satisfy occupant requirements with substantial reductions in energy use. This requires new ways of evaluating systems and informing design teams to make optimal design decisions.

Typical decisions include the optimization of the façade of a building, supporting structure assisted thermal storage and optimization of heating, ventilation and air-conditioning (HVAC) systems.

Decisions are often suboptimal because not all consequences are studied. The reasons can be insufficient knowledge of the consequences but also insufficient knowledge of the use of the object. This has a large consequence over time as the variations due to different building occupants, climate change, etc. are significant.
As a consequence we face uncertainty in climate, occupant behavior, building operation, increasing the complexity of the necessary tools and methods to support design decisions.
It is therefore necessary to constantly face this complexity and improve our ability to predict the impact of changes, the consequences (e.g. risk) that may result. In doing so, the level of quality assurance of simulation results need to be increased.
This thesis' contribution is to increase our ability to better predict the impact of design variables, and therefore make better decisions and provide optimal solutions with the help of BPS.

1.1 The role of Building performance simulation in design

Building performance simulation (BPS) uses computer-based models that cover performance aspects such as energy consumption and thermal comfort in buildings. Crawly [2003] describes it as "a powerful tool which emulates the dynamic interaction of heat, light, mass (air and moisture) and sound within the building to predict its energy and environmental performance as it is exposed to climate, occupants, conditioning systems, and noise sources".
Although there are a large number of building simulation tools available, e.g., [DOE, 2003], most use the same modeling principles and are used in similar manner [Hopfe et al., 2005]. They are primarily used for code compliance checking and thermal load calculations for sizing of HVAC systems.
BPS is still not routinely applied in building design practice. Despite nearly 40 years of research and development, methods for the design assessment are costly to implement, time-consuming or not applicable [Preiser et al., 2005]. Design methods can help in improving the use of BPS by rapid prototyping and providing multiple design concepts for better design solutions.
For instance, the integration of design optimization is either not applied in simulation tools or it is not used because of expenditure of time and effort.

De Wilde [2004] states that simulation tools are neither used to support the generation of design alternatives, nor to make informed choices between different design options, and they are neither used for building and/or system optimization.
He furthermore suggests that building performance simulation could be used in a way of (i) indicating design solutions by for instance numbers and graphs, (ii) introducing an uncertainty and sensitivity analysis for guidance, (iii) supporting generation of design alternatives, (iv) providing informed decision making by choices between different design options and last but not least (v) building and/ or system optimization.

Building design is a process towards the planning of a building that needs multiple professions working interdisciplinary such as architects, building engineers and designers, amongst others. The building design process can even last over years, i.e., design decisions taken have a major impact.

In theory, the design process describes a series of actions and/or operations undertaken to solve a design problem. The process is typically structured forming a procedure with a start and finish to complete the design task. Its structured character enables to sequentially collect and produce design information as an aid for making design decisions [Lamb, 2004].
Typical design assessment criteria are cost, future flexibility, energy efficiency, environmental impact as well as productivity and creativity of occupants. The basic aim of the building design is to create a fully functional building that meets a set of pre-defined performance criteria. To achieve that goal, it is necessary for the design team members to interact closely throughout the design process [Harputlugil et al., 2006].
Within this building design process a number of design stages can be distinguished that are shown in Figure 1: decision, program of requirements, preliminary design, final or detailed design, and the contract document.
In the program of requirement or project brief the objectives and requirements are defined. In the conceptual or preliminary design stage the main systems are selected and a number of concepts is developed. In the detailed or final design stage the development and integration of design elements to operate design solutions takes place. In the contract document or the specification, the production of site drawings, product specification and construction resource documentation is finalized.
Followed by that and not shown in the figure are the construction and occupancy of the building. The design documentation is translated into a finished product, testing and commissioning, and product handover.

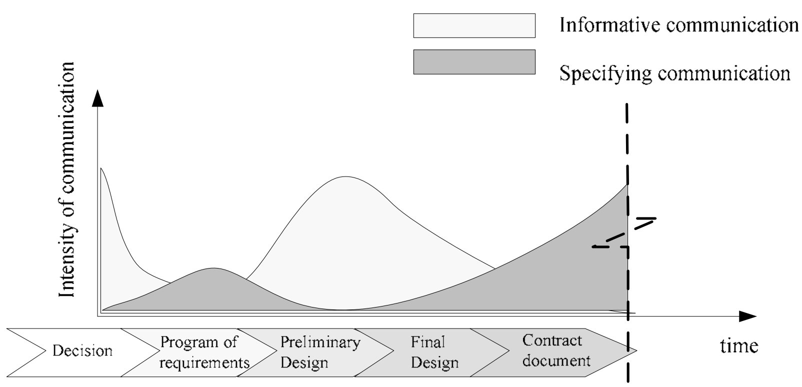


Figure 1 Illustration of the relationship between communication and simulation during the design process [Stoelinga, 2005].

The experience from experts concerning the design process is represented in Figure 1. Stoelinga [2005] divided the communication taking place during the design process into “informative” and “specifying” communication: informative communication meaning addressing the high amount of communication in the preliminary design stage. The information provided should answer questions such as “would it work” or “how does it perform" [Stoelinga, 2005]. There is a demand to use BPS for design support in particular for the generation and selection of alternative design concepts during early phases in the design process, where decisions have to be made with limited resources and on the basis of limited knowledge.

Opposed to this more qualitative character of communication in the beginning, the "specifying communication", as Stoelinga calls it, is more quantitatively as it is considered in the context of specifications in the later design phase. In the final design stage there is a peak of informative communication and another peak value of specifying communication which should be supported by the use of simulation or other tools. In current practice the connection between simulation tools as an evaluation procedure and the design analysis communication is poorly developed. The need for BPS is very strong in the final design stages in order to support the particularizing communication. One means of better connection should be provided by the simulation tools in providing a better insight into the role of uncertainties and unknowns on the evaluation results. BPS tools should therefore provide support to perform uncertainty and sensitivity analyses, and communicating them with other design partners leading to informed decision making, and optimization.

BPS should be an essential part in the building design process. Current applications do not fulfill the needs considering the support of design decision making or the seamless integration of optimization techniques.
The building design process needs to foresee how the detailed specific decisions relate to the resulting performance of the entire building or its functional components [Trinius et al., 2005]. In this respect, long term concerns such as life performance, durability, life cycle costs, etc. have a higher value than short term arguments such as direct costs, construction process for instance [Trinius et al., 2005].
Design meeting participants have to match the expected performance with the required one to be provided by the design solution [Trinius et al., 2005].

To sum up, a problem in current design assessment is the lack of ability to explicitly deal with the varying expectations, needs, and requirements throughout the design process. Tools and methods for different design stages should address this diversity of needs and enhance the communication required.
In the beginning of the design process less information is available caused by the fact that many issues are undecided. This leads to many unknowns when inspecting the potential impact of design alternatives. Under certain constraints these can be interpreted as uncertainties, which will diminish as design evolution proceeds.. However, even in the detailed design the building is not without uncertainty as there is imprecision in the construction process and natural variability in the properties of building components and materials [de Wit, 2001]. Besides, many external factors that influence the performance of the building are unpredictable.
Therefore, performance outcomes are the results of random processes and partly unpredictable because of uncontrollable unknowns. The combined assessment of the lack of knowledge and the external factors cause the uncertainty in the building performance [de Wit, 2001].

To consider these different sources of uncertainty, to include them into diverse approaches and therefore to improve the use of BPS during the later phases is the goal of this thesis.

1.2 Role of performance evaluation in late design

The information required in the final design stage is more detailed and needs to be treated more accurately. For example, similar options with slight changes in the layout might be compared. The exact specification of the options and the selection of all parameters used are therefore very important. Besides, selecting properties (e.g., glass properties) requires close coordination with the architect or the design engineer [Olsen and Iversen, 2006].

Possible applications in the final design are summarized by Olsen and Iversen [2006] as follows.

- Applying optimization as support also for decision aid in comparing different schemes, options, and systems.
- Improvement of envelope performance through energy studies determining and optimizing material properties such as insulation or glazing performance via uncertainty/ sensitivity analysis.
- Selection and observation of, e.g., different HVAC systems enabling the overview and comparison of energy use.

However, expected challenges according to Olsen and Iversen [2006] in the final design are due to as follows.

- Scheduling uncertainty (time requirement vs. mistakes).
- Consideration of design team cooperation and coordination. Design team members need to be aware of how decisions might affect each other. A model that is affected by several disciplines is going to enlarge this problem.
- Evaluating of different trade-offs through different options. If different performance aspects are considered, it might be that one scenario performs well in one aspect whilst another performs better in another one. Multiple choices with no clear-cut best solution can complicate the decision process.

1.3 Aim and objectives

The aim of the current work is to research and enable innovative applications of building performance simulation for design support during the later phases of the design process. Moreover, it’s objective is to broaden the current use of BPS by preparing the next generation of tools and methods with which the influences of uncertainty can be studied and incorporated in dialogues that lead to informed decision making.

For that reason, the emphasis of this thesis will not discuss the influence of uncertainties on outcomes, but it will show how the application of diverse prototypes could benefit and enhance building design methods, with the emphasis on discrete decision making and component optimization, under uncertainty.

The objectives are to find answers to the following research questions.

- How is software currently used in the final design?
- What are the requirements and needs during the final design?
- What should be improved in currently available simulation tools?
- What are appropriate performance assessment methodologies for the final design stage?
- How to satisfy simulation output requirements in view of an environmental engineer which enables him to communicate with other design team members?

The hypothesis that drives this thesis can be formulated as follows.
The conduction of an uncertainty and sensitivity analysis throughout the design process could be of great importance. It is hypothesized that uncertainty in performance predictions of competing options is not negligible and therefore should play a major factor in the decision.
It is hypothesized, that decision making between competing design options can be enhanced by including the effect of uncertainties in simulation outcomes that are presented to the decision makers. This would support a design team to reach an optimal decision by using a computational approach.
Furthermore, it is hypothesized that design optimization can be enhanced by the integration of the effect of uncertainties in simulation outcomes that are presented to the decision makers, or used in the optimization strategy.
The connected consequential hypothesis is that current simulation tools can be enhanced to deliver this new functionality in a way that is practical and acceptable to design practice.

1.4 Research methodology

The research starts from a set of existing and proven concepts and tools. All development is based on an existing, design stage specific simulation software.
The following steps are carried out.

1. A literature review is conducted to analyze the current state in building performance, design guidelines and rating systems. In order to start with ideas of how to improve the current use of BPS, an insight in BPS in practice, design simulation tools, optimization techniques, etc., is mandatory.
2. Interviews with world leading building performance professionals are carried out to get an idea of the current use of BPS, needs and wishes of practitioners.
3. Prototypes are iteratively implemented (development of prototypes, validation and testing). In total, three approaches are planned, implemented and improved based on the outcome of the literature review and the interviews. Three major hypotheses are addressed in these approaches: (i) the enhancement of performance prediction and quality assurance with uncertainty analysis; (ii) the enhancement of the decision process between two competing options by decision making under uncertainty; (iii) the enhancement of BPS with the integration of optimization under uncertainty.

4. Feedback of professionals (design development, design optimization, case studies) is necessary to prove the hypotheses by showing the prototypes to a number of professionals.

The first two steps result in a requirement specification in view of the intended role (function) of simulation tools. Specific scope of this research will be to support consultants in providing uncertainty and sensitivity analysis, support the decision process and optimizing façade, structure, etc., of building designs.
The requirement specification is then used to assess an existing tool and to identify the applicability of this tool to enhance the use of BPS and to eventually optimize the design. One important analysis tool in The Netherlands and also applied in this research is VA114. It is a building performance simulation tool developed by Vabi [2009] dedicated to the later phases of the design process.
Performance aspects considered of high importance will be thermal comfort, energy efficiency, indoor environmental quality, etc.
The backbone of the thesis is thereby uncertainty and sensitivity analysis that is expected to enhance the design process in several ways. Uncertainties do exist in multiple aspects, caused by insufficient knowledge of physical properties represented by input parameters of a model, or uncertainties in the way that the building is occupied, controlled and operated. UA can lead to identify uncertainties in the outcome of a model. SA is in integral part of the UA as it identifies what parameters are most sensitive and have the biggest impact on the uncertainty in the outcome. Furthermore, SA allows the analysis of the robustness of a model. It makes aware of unexpected sensitivities that might lead to wrong specifications.

The result of this research is a prototype simulation based environment which includes several multi level performance indicators for thermal comfort and energy use. The focus is to support the profession of an environmental engineer. This is accomplished by the following research methodology.

In Figure 2 the research methodology is shown graphically. A prototype simulation-based design environment covering uncertainty and sensitivity analysis for decision aid and for optimization of buildings and systems will be developed. Additional guidelines regarding the necessity and applicability of these prototypes for the final design stage are provided.
Figure 2 shows the task structure in general, the different prototypes and their validation through practice.

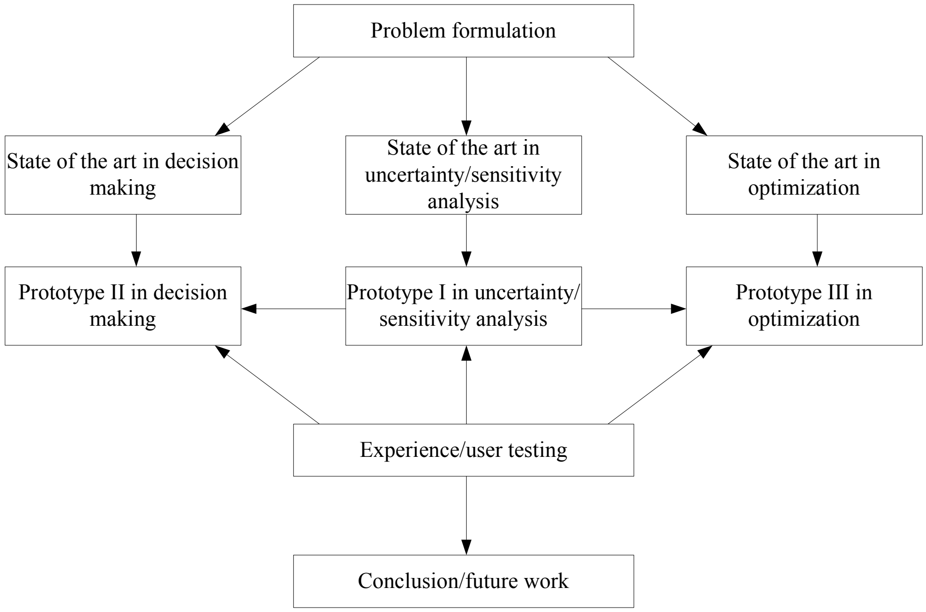


Figure 2 Illustration of the methodology used in the thesis showing the relation between the prototype development and feedback from practice.

1.5 Thesis outline

Chapter 2 starts by giving an introduction in background terminology and an overview of the current state of building performance simulation and design.
Chapter 3 introduces the issue of uncertainties. An insight is given in different types of uncertainties and techniques to measure uncertainties and sensitivities. Subsequently, results of a case study focusing on different groups of uncertainties in the use of BPS are presented.
Chapter 4 describes decision making approaches. The applicability in current building performance simulation is shown; followed by the demonstration of one technique applied considering uncertainty/ sensitivity analysis.
Chapter 5 evaluates optimization techniques, for single- and multi-objective problems. A case study is implemented showing the added value of optimization also considering decision aid for multiple building designs and the integration of uncertainty.
Chapter 6 summarizes the outcome of mock-up studies and an online survey that was achieved based on feedback from practice. Conferring with design professionals was crucial to fulfil the requirements in the detailed design stage and to verify the necessity and applicability of the developed prototypes.
Chapter 7 summarizes and concludes the work showing future challenges for research effort in this domain.
In Table 1 the outline of the thesis is illustrated.

Table 1 Illustration of the thesis outline.

Chapter	Title	Aim	(Research) question	(Research) Methodology
1	**Introduction/ problem statement**	Formulation problem statement; objectives; research questions	How is BPS used in the detailed design stage?	Literature review (LR)
2	**State of the art in BPS**		What are needs and requirements in the detailed design?	LR, interviews, software review, online survey
3.1-3.2	Uncertainty/ Sensitivity Analysis (UA/SA)	Analysis of the art in UA/SA, decision making, optimization applications	How can the use of BPS be enhanced in the detailed design stage?	LR
4.1-4.3	Decision making		How can UA/ SA support and furthermore be implemented into a tool?	
5.1-5.6	Optimization		How has decision making and optimization techniques previously being implemented in the design process?	
	Implementation and results			Iterative prototyping
3.3-3.8	Uncertainty/ Sensitivity Analysis	UA/SA in physical, scenario and design parameters.		
		Integration of UA in DM and in optimization.		
4.4-4.7	Decision making	Implementation of approaches with BPS tool VA114 by using the case study "het bouwhuis"		
5.7-5.10	Optimization			
6	**User Testing**	Analysis of applicability in practice	Do the developed prototypes support the designer? What can be improved?	Mock-up testing, online survey
7	**Conclusion**	Summary of different prototypes, findings, future work		

2

2. Building performance simulation and design

2.1 Introduction

As described in Chapter 1 there is a need for enhancing the use of BPS in detailed design. In this section a brief insight in building performance will be given by explaining basic concepts such as performance, performance aspects, indicators, etc. Other research efforts in building performance will be summarized and important insight in design guidelines, rating systems, etc., will be provided.
Followed by that, an insight is given into BPS explaining briefly the use of BPS in the design process and tool related integration efforts are pointed out.
This chapter ends by summarizing preliminary results of interviews and an online survey.

2.1.1 Definitions

Performance indicator
An indicator according to DOE [2009] is a "parameter or value derived from a set of parameters" used to provide information or to alert what to consider more and what has to be improved in order to communicate trends. A performance indicator is described further on as a "high-level performance metric" to simplify complex information and to point to general state. An example given is the average building energy use.
Pati et al. [2006] distinguish hard and soft indicators. Hard indicators or indicators based on hard objectives for assessing the performance in terms of energy, thermal comfort among others. Soft indicators for incorporating also the interaction between built environment and its users.

Performance metric
A performance metric like the building energy use intensity or the lighting power density is "a standard of measurement of a function or operation" [DOE, 2009]. That means, it is a measurable quantity that indicates a certain aspect of the performance. In Deru and Torcellini [2005] high-level performance metric is described as the means to simplify complex information and to point to the general state of a phenomenon.

Performance aspects
Performance aspects show the needs and requirements associated to a "value", e.g. in the economical or ecological domain. For instance, performance aspects such as visual, acoustic and thermal comfort belong to the value domain of "well-being". Other building performance aspects are for instance energy consumption and productivity.

Performance concept

A performance concept can be understood in several different ways. According to [Gross, 1996] it can be simply a concept without a systematic approach but it can also be understood as a concept that requires analysis and evaluation.

According to Mallory-Hill [2004] a performance concept is a framework for building design and construction in order to evaluate buildings. Human needs are translated into user requirements such as safety, comfort, functionality, etc. Furthermore, they are transformed into performance requirements and criteria and implemented to guarantee a satisfactory long term performance of the building.

2.1.2 Building performance and design

In this section an insight into non-simulation related information and research efforts in building performance will be provided.

Design guideline

According to DOE [2009] design guidelines are a "set of rules and strategies to help building designers meet certain performance criteria such as energy efficiency or sustainability". An example is the ASHRAE green guide. But also for instance LEED and BREEAM are often used as design guidelines [DOE, 2009] even though they are really only rating systems.

Building performance frameworks

Frameworks are for instance the building evaluation domain model (BEDM) shown in Figure 3 or the performance based building thematic network (Pebbu). The BEDM can be described as a 3-dimensional matrix with three axes referring to architectural, building, and human system level. It is a model for the incorporation of performance evaluation with requirement analysis [Mallory-Hill, 2004].

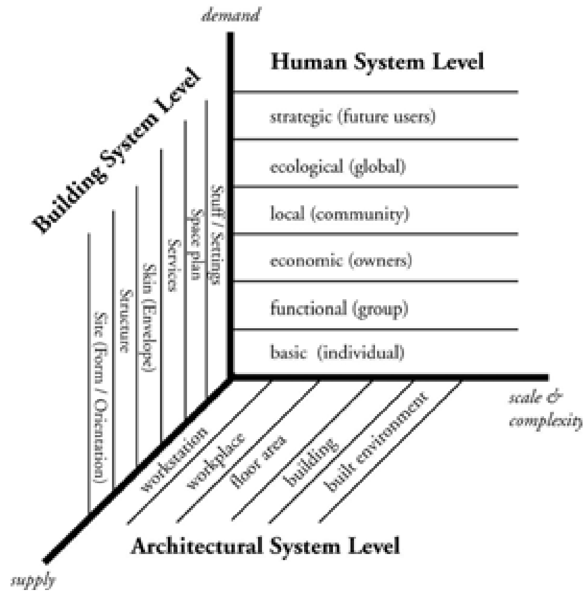


Figure 3 Illustration of the BDEM (building domain evaluation model) [Mallory-Hill, 2004].

The Performance Based Building (PeBBu) [PeBBu, 2009] is an international research cooperation project initiated by the international council for building (CIB). Aim is to counter difficulties that arise when using the building regulations and standards in an European context [Bakens, 2006].

Rating systems
Rating systems are described by DOE as "a system of rules for comparing the performance of a whole building or building system to benchmarks". Examples are LEED [2009], BREEAM [2009], and CASBEE [2009].

1. LEED (Leadership in Energy and Environmental Design – US)
LEED, developed by the US green building council, is designed to encourage the development of green buildings and to rate the expected performance during different design stages. In the Leeds rating procedure aspects considered cover water efficiency, energy, materials and resources, and indoor environmental quality.
LEED does not suggest the use of simulation as a measure to assess thermal comfort or control strategies.

2. BREEAM (Building Research Establishment Environmental Assessment Method - UK)
BREEAM is an environmental rating system to assess the performance of buildings in terms of energy use (operational energy and carbon dioxide (CO_2) issues), water

consumption and water efficiency, air and water pollution issues, indoor environmental quality among others.
Simulation is not an integral part of BREEAM. However, often is simulation used as an alternative to estimate the energy consumption and CO_2 emissions [DOE, 2009].

3. CASBEE (Comprehensive Assessment System for Building Environmental Efficiency - Japan)

CASBEE is a rating system for the evaluation of the building environmental performance and loadings in Japan.
Two categories are evaluated coded as Q for quality and L for loadings. They are further on divided into subcategories. Q covers aspects for the environmental improvement such as indoor and outdoor environment or quality of service. L considers the evaluation of negative environmental impacts such as resources and material, energy, etc.

Initiatives in building performance

Initiatives such as private public partnerships and the energy performance of buildings directive deal with the fact of how to achieve building performance in practice.

1. Private public partnerships (PPP)

Public-private partnerships (PPP) in building design are partnerships built in order to fund and develop public buildings without initial investment outlays by the government. They entail large investment sums for contractors and sponsors and therefore high risks [Bult-Spiering and Dewulf, 2006].
One aim of these partnerships is for instance the saving of energy in public buildings that leads to budgetary savings and contributes to climate protection (energy saving partnerships).

2. Energy performance of buildings directive (EPBD)

The EU directive for improvement of building consists of three main parts: energy performance requirements, energy performance certificates, and energy performance inspections.
Energy performance requirements are set by taking into account the type of building (e.g., new or refurbished), etc. Energy performance certificates (see Figure 4) show the energy performance of the building. Energy performance inspections of boilers, air condition systems, etc., further on aim to reduce the overall energy consumption, and also to ensure appropriate advice on improvements/replacements [Warren, 2003].

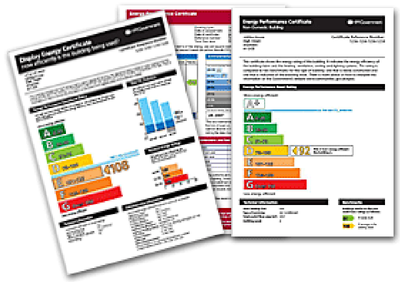


Figure 4 Illustration of energy performance certificates [DIAG, 2009].

US department of energy (DOE) high performance buildings metrics project
The U.S. Department of Energy initiated the performance metrics research project in order to standardize the measurement and characterization of a building with regards to the energy performance. First objective was to find out what performance metrics have the greatest influence on the energy consumption; second was the development of standard methods for measuring and reporting the performance metrics [Deru and Torcellini, 2005].

2.2 The role of information generated with BPS

A number of decisions has to be taken in the design process. Many decisions are outcomes of design explorations and brainstorming, and therefore hard to describe formally and hence difficult to support by evaluation tools. Some decisions however typically require the comparison of a set of well defined competing options. This type of "discrete" decision can be rationalized as choosing the best option, under the given set of constraints. The fitness of an option is usually expressed in terms of measures in different performance categories. The combination of all performance measures of a tested option quantifies the fitness of that option to meet or exceed the requirements as expressed in the design program. It is important to note that performance measures are related to outcomes rather than prescriptive features.

One first definition of a performance concept in building was given by Gibson [1982] as "first and foremost, the practice of thinking and working in terms of ends rather than means. It is concerned with what a building or building product is required to do, and not with prescribing how it is to be constructed".

The performance concept enhances design evaluation against objectively defined performance criteria and aims of the designer. In different performance evaluations, different performance indicators are relevant. In [Augenbroe, 2006] it is stated that performance indicators "are the associations between the design program and the design concept. As such, they help to establish a clear design objective and to organize the performance thinking around that objective. Thus, the designer can rationally establish efficient project goals by delimitating the aspects that influence the design decision."

Design aspects considered in different stages of the design process and difficulties are summarized by Morbitzer [2003] and shown in Figure 5.

design stages	design aspects	model creation	performance prediction analysis
program of requriements/ outline	orientation, heavy/ light buildings, space usage, heat recovery systems, etc.	typical users identified (architects) find it difficult to use advanced building simulation	performance prediction difficult for architects
preliminary/ scheme design	glazing area/ type, air change rate, lighting strategy	does not cause major difficulties to simulation expert but time consuming	important to have in-depth understanding of reasons behind building performance
final/ detailed design	different heating/ cooling systems; different heating/ cooling control strategies; different ventilation strategies	more challenging than scheme design, but possible for simulation expert	depending on simulation study ranges from easy to complex, tedious and time consuming

Figure 5 Overview of design stages, aspects and performance prediction [Morbitzer, 2003].

BPS in general is used to calculate, through predictive simulation, a variety of outcomes of the proposed design, such as energy consumption, performance of heating and cooling systems, visual and acoustic comfort, dynamic control scenarios for smart building technologies, smoke and fire safety, distribution of air borne contaminants, the growth of molds, and others [Augenbroe and Hensen, 2004].
The information needed to guide the decisions in the final design stage tends to become very detailed, and hence the use of BPS more demanding. An important issue in detailed design is how to quantify and qualify the information obtained from a simulation study and to translate it into aggregated performance measures that are easily understood by the design team and support rational decisions. It is fair to say that in current practice, simulation tools do not do this in an efficient manner. Not surprisingly, the best established use of simulation is after finalizing the design, i.e. for performance verification and commissioning [Morbitzer, 2003]. In essence, that means that current BPS is an accepted tool for design confirmation but not mainstream for true design support. The thesis is a contribution to many ongoing efforts to ameliorate this situation. This work's focus is on incorporating a transparent view on the effect of uncertainties, thus, increasing the resolution of information of the decision stakeholders and their need to make optimal decisions in the face of uncertain information.

2.3 A review of BPS tools

2.3.1 BPS in design

The aim of BPS is to predict real physical conditions in a building by using a computational model. Building simulation, according to Morbitzer [2003], expands the concept of performance prediction. With the help of BPS, the user can specify parameters that have an influence on the overall building performance. The simulation results achieved in the prediction are as close to reality as possible.
Until the 70s simplified calculations for energy use, e.g., based on simplified boundary conditions were used [Clarke, 2001]. Clarke [2001] summarizes the evolution from tools from traditional calculation to contemporary simulation in four generations from handbook oriented computer implementations to new developments considering program interoperability, more accessible user interfaces, quality control, air flow simulation, etc. (see Figure 6).

1^{st} Generation (1960's and early 1970's)	Handbook oriented Simplified Piecemeal	Indicative Applications limited Difficult to use
2^{nd} Generation (1970's)	Dynamics important Less simplified Still piecemeal	
3^{rd} Generation (1980's)	Field problem approach Numerical methods Integrated energy sub-systems Heat and mass transfer considered Better user interface Partial CABD integration	
4^{th} Generation (1990's)	CABD integration Advanced numerical methods Intelligent Knowledge based Advanced software engineering	Predictive Generalised Easy to use

Figure 6 Illustration of the evolution of building simulation [Clarke, 2001].

Due to the fact that nowadays buildings are appreciated with a low energy demand, it becomes essential to predict the building performance as realistic as possible. This is obviously not possible without the use of building performance simulation as tool in the design process.
However, despite the multiple ranges of tools available, there is still high potential in BPS due to the results provided, data exchange, and ease of use, among others.

2.3.2 Simulation tools

Different simulation tools such as design tools, analysis tools, modeling tools, etc., exist [De Wilde, 2004]. A brief summary of eight different simulation tools for dynamic thermal building simulation is described in this section. The tools have been selected to provide a brief overview, more or less randomly on the basis that they claim to be of use for different design stages. It was developed as part of a critical software review in cooperation with Struck and Harputlugil [Hopfe et al., 2005]. A more extended report on different energy performance simulation programs can be found in [Crawley et al., 2005]. Another overview is accessible on the building energy software tools directory from the U.S. Department of Energy [2007].

MIT Design Advisor

MIT Design Advisor is an on-line design tool for architects and building engineers. This tool has been developed to give preliminary estimates for the performance of building facades. Double skin facades may be compared to conventional facades, and location, occupancy and depth of the perimeter space may be adjusted and the effects viewed.

Building Design Advisor

The Building Design Advisor (BDA) is a stand alone integrated design tool. BDA claims to be most effectively used from the initial design to specific system definition. The software download and installation is free of charge and the package runs under windows. The tool is supposed to act as data manager and process controller for the three calculation modules DCM (day lighting computation module, ECM (electric lighting computation module), DOE2 (energy analysis module). It is planned to extend its capabilities to integrate Radiance and Athena.

Energy 10

Energy 10 is a conceptual design tool focused on whole-building tradeoffs during early design phases for buildings with less than 10,000 ft^2 floor area or buildings that can be treated as one or two-zone increments. It performs whole-building energy analysis for 8760 hours/year, including dynamic thermal and day lighting calculations. It is specifically designed to facilitate the evaluation of energy-efficient building features in the very early stages of the design process.

e-Quest

eQUEST is a sophisticated, yet easy to use, freeware building energy use analysis tool, which provides professional-level results with an affordable level of effort. eQUEST was designed to allow to perform detailed comparative analysis of building designs and technologies by applying sophisticated building energy use simulation techniques but without requiring extensive experience in the "art" of building performance modeling. This is accomplished by combining schematic and design development building model creation wizards, an energy efficiency measure (EEM) wizard and a graphical results display module with a complete up-to-date DOE-2 (version 2.2) building energy use simulation program.

SEMPER
SEMPER developed at Carnegie Mellon University, is a multi-aspect building performance simulation system [Mahdavi, 1999]. It has been developed as stand-alone design support tool. Based on it, SEMPER-II was developed which is an internet-based computational design environment handling multiple users and queuing multiple request of simulation runs [Lam et al., 2004].

VA114
VA114 forms part of the uniform environment. The uniform environment is a software tool box that allows shifting model files between several tools for different types of analysis, including heat loss and heat gain calculation. It is a simulation tool that is well-known and widely used in The Netherlands.
VA114 is a calculation engine dedicated to assess the annual heating and cooling demand and the thermal behavior of building, i.e., in particular, the over- and underheating risk in buildings. The simulation period can be defined and the set points from which the over- and underheating hours will be counted. The model itself is based on standard heat and mass transport equations.
Different climate files can be simulated. However, the most common one is the climate file for the reference year “De Bilt 64/65. Current research conducted [Hopfe et al., 2009; Evers et al., 2008] addresses the integration of climate change scenarios. Based on the existing traditional reference year “De Bilt 64/65”, NEN 5060:2008 released a new norm that introduces four new climate files for different types of climate adjustments. KNMI on the other hand assembled four different future scenarios for the expected climate change. The climate files from the NEN and the KNMI future scenarios have been combined in a future climate data analysis for usage within the simulation software VA114.

2.3.3 Tool related integration efforts

Because of to the growing importance of the building sector, the use of computers and simulation during the different design stages increases as well. New demands and requirements arise due to increased demands on energy and maintenance efficiency, maximum flexibility among others [Augenbroe, 1992].
As a matter of fact, research and standardization initiatives were started pursuing the development of common shared building representation. It began early 1990 with the initiation of Combine (a European community funded research program) or Ratas that arose from efforts from local industry.
Efforts that try to integrate the use of building simulation into the design process will be briefly summarized.

Combine (computer models for the building industry in Europe)
COMBINE tried to conquer the complexity of large model through subschema definitions. It is an interaction tool for actors participating in a design project [Augenbroe, 1995].
It was the first step towards future intelligent integrated building design systems (IIBS). The emphasis is on energy performance. The prototype consist of a set of design tool prototypes (DTP) that addresses tasks such as, e.g., HVAC design, construction design,

or the dimensioning and functional organization of inner spaces in the later design process [Augenbroe, 1995].
COMBINE 1 (1990-1992) was the first phase of the project resulting in a product model for building design information. COMBINE 2 (1992-1995) was the second phase of the project addressing the product model of the first phase in an operational context [deWilde, 2004].

Design analysis integration (DAI) – initiative
DAI was started in order to develop solutions for the integration of building performance analysis tools in the building design process. "Spearheads are an improved functional embedding of performance analysis tools in the design process, increased quality control for building analysis efforts, and exploitation of the opportunities provided by the internet" [de Wilde, 2004].
Aim is to have a more effective and efficient use of existing and emerging building performance analysis tool by building design and building engineering teams [de Wilde, 2004].

AEDOT (advanced energy design and operation technologies)
The objective of AEDOT is the development of advanced computer-based tools in order to promote the design and operation of energy-efficient commercial buildings [Shankle, 1993]. The energy assistance at the early design stage is emphasized.

BEMAC
BEMAC is a framework for the integration of existing software tools at different design stages such as design, construction and operation of the building. Addressed are aspects such as monitoring, analysis and control with regards to energy consumption [O'Sullivan et al., 2004].

2.4 BPS Challenges

Building simulation offers "unique expertise, methods and tools for building performance evaluation" [Augenbroe and Hensen, 2004]. The integration of physical interaction into BPS causes modeling as well as computational problems and challenges. In terms of decision making and robustness, the integration of design teams, etc., there is a demand of continuous improvement of BPS [Augenbroe and Hensen, 2004].
The use of building performance simulation in current building design projects is limited. Although there is a large number of building simulation tools available, the application of these tools is mostly restricted to the detailed design stage.
One capability, design optimization, was found to be important is missing from a large number of tools.
Many of the building performance tools that are currently in use are legacy software tools that have a monolithic software structure and are becoming increasingly hard to maintain.
The use of BPS tools requires expert skills to set up a model and run an analysis that the right output is generated from which the desired performance data can be extracted.

Design experience is essential for developing design concepts. The use of simulation tools enables an impact assessment of different parameters. However the use of BPS without experience in of building performance does not bring the benefit aimed for as users run the risk to produce results which do comply with the domain characteristics.

Furthermore, it is important that BPS should offer the possibility to consider more than one performance aspect, and to allow for their prioritization based on the project type and design discipline.
Another difficulty is the fact that the design stages are barely synchronized across disciplines as it is difficult for design disciplines to understand the impact of their design on the works of others.
Not including specific design disciplines early enough in the design process might cause the design team to make uneducated decisions, risking sub-optimal solutions or additional design iterations.
There is high theoretical challenge due to the complexity of scale and diversity of component interaction.

Augenbroe and Hensen [2004] summarize that "many aspirations remain to be achieved, such as the support for rapid evaluation of alternative designs, better adaptation of simulation tools to decision making processes, and team support of incremental design strategies. Quality assurance procedures and better management of the inherent uncertainties in the inputs and modeling assumptions in simulation are two other areas where more progress is needed".
The key challenge of this thesis, the consideration of uncertainty, the provision with quality assurance, the addressing of risk, will be targeted further on. It is conjectured that this challenge can be met in the way it is approached in this research. This will be shown in the following sections.

2.5 The role of uncertainties in building simulation

Building performance simulation is a multi-disciplinary, problem oriented, dynamic tool using numerical methods that approximate a solution of a realistic model.
The difference between traditional and simulation tools is in the complexity of the models. Present computer simulation, often including more than 10000 variables have therefore a bigger need for quality assurance [Olsen and Iversen, 2006].

Uncertainty and sensitivity analysis are part and parcel of many ongoing research activities. They find use in several approaches embedded for, e.g., parameter screening and reduction [Alam et al., 2004], or robustness analysis [Topcu et al., 2004; Perry et al., 2008].
The effective integration of issues related to risk and uncertainty in design has a great importance. That applies also to sensitivity analysis. Sensitivity analysis could assess the relevance of studying change options within the design and modeling process.
Uncertainty and sensitivity analysis for instance can provide information about reliability towards design parameters, respectively to the overall design.
At a certain level of resolution, design evolution can be viewed as a series of decisions under uncertainty. The reason is that the process of decision making is claimed to be

ill-defined, and decision problems human oriented. Uncertainties arise from "unquantifiable information, incomplete information, unobtainable information and partial ignorance" [Fenton et al., 2006]. The problem of imprecision and subjectivity [Fenton et al., 2006] requires that decision making considers uncertainty analysis, risk management and confidence. Especially in decision making with user judgment, one major aspect is uncertainty.

Uncertainty integrated in decision making is used within the decision process to explicitly support the outcome of BPS and make the user aware about the risk that one option is exceeding in a performance aspect. SA on the other hand supports the decision maker in identifying the most sensitive parameters.

2.6 Practitioners perspectives

As mentioned earlier, a number of BPS tools exist but the current design with simulation is not adequate. To deal with uncertainty and risk is one key challenge of this thesis.

One of the first steps of this work is to get an insight in professional experience with current BPS. Therefore, a number of interviews with international design professionals and an online survey are conducted.

Furthermore, this section will end showing how to close the gap between design and simulation and how based on the practitioners feedback, the hypotheses from Section 1.3 can be approached.

2.6.1 Interviews

The results of the interviews in this section were achieved in cooperation with Struck and Harputlugil [Hopfe et al., 2005].

Fifteen professionals were interviewed. Eight mechanical engineers, four building physicists, one civil engineer and two architects; three of them were academic, the other twelve were professionals.

The key issues of the interviews were:

A. Introduction of the interviewees and definition of their project involvement.
B. Problems repeatedly encountered during the design process.
C. Experiences using computational tools to support building design
D. List of issues in future design support tools should address.

The results were divided in four categories and can be found more detailed in [Hopfe et al., 2005; Hopfe et al., 2006]:

1 Classification of the interviewees
2 Perspective of the design process
3 Practice
4 Computational support

A short summary of the computational support category is given:

Asked if the use of computational support was common practice during the design process all interviewees responded positively. However, it depends on how the support is defined. Subsequently the interviewees were asked whether they use computational simulation support in general and if, in which phase of the design. The tools themselves were discussed, and the way of using (visualization/ simulation/ results presentation) them, ascertained. The interviewees were asked where they locate a lack in using computational support and how they expect the computational support to develop in the future.

It was stated that the use of simulation tools enables an impact assessment of different parameters. However the use of simulation tools without having an idea of building performance simulation does not bring the necessary benefit.

It was found that the interviewees have a different understanding when it comes to simulation. Whilst they agreed that simulation is the representation of physical processes, the techniques used to simulate differ significantly. And this was reflected while conducting the interviews. For some interviewees, simulation is drawing/ sketching concepts. For instance, one interviewee told the interviewers about simulating room conditions with actors in real world. Whilst for others, a simulation is conducted by using a computational tool.

The comments made on future expectations of computational support were contradictory. It was stated by the interviewees that tools should address a multitude of performance aspects, should be easy to use, be able to represent complex scientific phenomena, and that they should be tested and validated. A computer program should be an intuitive tool, offering 3D modelling capabilities, with an easy interface and a copy and paste opportunity - to facilitate the possibility to reuse parts of projects in compiling new projects. Such a tool should be able to produce initial results from a rough building representation and then allow for detailing parts of the building.

2.6.2 Online questionnaire

The presented results in this section come from on online survey conducted in the final year and are solely addressing the final design stage. Three main questions are summarized asking the current use of BPS, tool requirements, and improvement capabilities for BPS.

How is software currently used in the final design stage?

- As a capacity calculation tool mostly for fire safety of parking garages (CFD), inner climate of large atria and special functions.
- For making calculations to help to take the right decisions.
- For production of energy performance certificates.
- As a communication and control system of human intuition.
- For code compliance checking.
- To check if design parameters, dimensions and capacities can fulfil the requirements and expectations.
- To check that design/ concept solutions lead to specified comfort level.
- To check the necessary cooling and heating demand and to realize the internal comfort, e.g., pmv for internal use.
- To permit application and capacity determination (building simulation tools such as VABI).

- For proof of concept (advanced building simulation tools, e.g., CFD).
- For dimensioning heating and cooling systems.
- To analyse possibilities for cost reductions (e.g., what are the consequences if shading devices are omitted); life cycle and/or investment.

What are tool requirements during the final design stage?

- To keep it to the subject and not integrate the 'design process' in it.
- To be a good analysis tool for results in graphs and a good reporting tool.
- To provide a good overview of input data.
- To give the possibility for directly editing input files and batch processing.
- To allow building regulation testing used with air leakage tests to, e.g., check that carbon dioxide emissions are not above minimum standards.
- To work like high level human decision makers do (top-down not bottom up). Informed decisions are usually made by digging down into the determining details not by solving every minor item, which by definition makes the result difficult to communicate and understand.
- To be easy to handle and to give good insight in comfort, sensitivity and alternatives.
- To provide good communication abilities.
- To determine the result in a predictable and repeatable way.
- To present bandwidth of reliability of results supporting communication with design team/principal at an appropriate level in accordance with technical state of the design.

What should/ could be improved in currently available simulation tools?

- User interface and speed of use and the re-use of data from former projects.
- Flexible control strategies for installations with simple rule and template based input.
- To learn from strong points of already existing tools. There are already too many too simple tools available (evolution and no revolution).
- To focus on inner climate/comfort; energy use is not the most important topic in building design.
- To show the effect that parameters have on each other.
- To be easier to use, to provide better and realistic models with integrated process control.
- To allow a better judgement of different installation concepts.
- To implement uncertainty and sensitivity analysis.
- To provide informed decision making.
- To include optimization techniques.

To summarize, Figure 7 shows the current satisfaction level of tools dedicated to the detailed design stage.

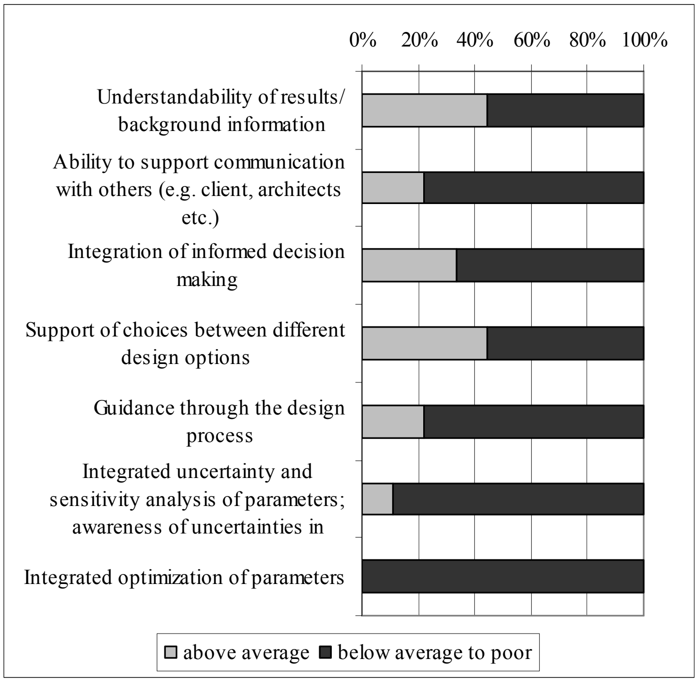


Figure 7 Summary of the current satisfaction level in BPS according to professionals' perception.

Research efforts in initiating new projects to enhance the use of BPS have been conducted widely. Nevertheless, this chapter also has shown that there is a need for the improvement of BPS in the final design stage.
The aim of the current research is therefore to start from existing and proven simulation programs. No new simulation tool will be developed. The research presented will be based on existing and proven according to professionals wishes (evolution and no revolution).
Design stage specific simulation software is considered and with aid of iterative prototyping, the existing design tool will be assessed.
That means, prototypes will be developed, validated and tested especially according to the feedback of professionals.

The hypothesis that drives this thesis is that decision making between competing design option and design optimization can be enhanced by including the effect of uncertainties in simulation outcomes that are presented to the decision makers, or used in the optimization strategy. Current simulation tools can be enhanced to deliver this new functionality in a way that it is practical and acceptable to design practice.

To close the gap between design and simulation and to approach the hypothesis of this work, three approaches will be developed according to professionals preferences. This is shown in Figure 8.

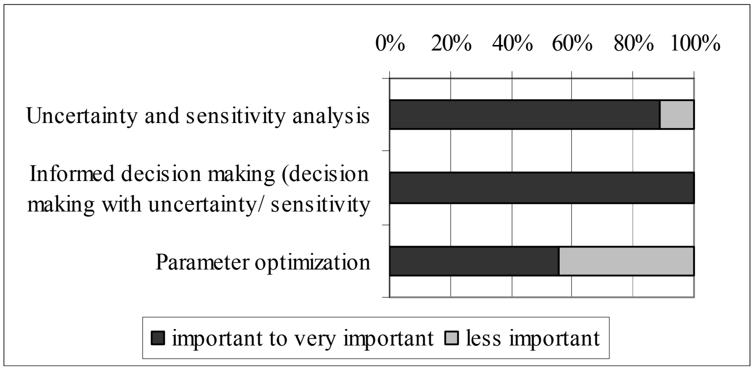


Figure 8 Wish list of techniques for the integration in BPS for detailed design use according to professionals.

The integration of uncertainty and sensitivity analysis is shown in Chapter 3. It is hypothesized that uncertainty in performance predictions is not negligible and therefore should play a major factor in the decision. The aim is to provide a better comprehension of standard BPS results and give background information of the parameters used.

In Chapter 4 the integration of informed decision making by providing additional information about the uncertainty and sensitivity of parameters is demonstrated. It is hypothesized, that decision making between competing design options can be enhanced by including the effect of uncertainties in simulation outcomes that are presented to the decision makers.

The integrated optimization of parameters is described in Chapter 5. It is hypothesized that design optimization can be enhanced by the integration of the effect of uncertainties in simulation outcomes that are presented to the decision makers, or used in the optimization strategy.

3

3. Uncertainty/sensitivity analysis for design support

3.1 Introduction

As shown in Chapter 2 the state of the application of BPS is still limited whilst it could provide relevant design information by, e.g., indicating directions for design solutions or uncertainty and sensitivity analysis. A major challenge in simulation tools is how to deal with difficulties through large variety of parameters and complexity of factors such as non-linearity, discreteness, and uncertainty. It is hypothesized that conducting an uncertainty and sensitivity analysis throughout the design process would be of great importance.

The purpose of uncertainty and sensitivity analysis can be described as identifying uncertainties in input and output of a system or simulation tool [Lomas, 1992; Fuerbringer, 1994; MacDonald, 2002].

In practice UA/SA have many additional benefits such as follows.

(1) With the help of parameter screening it enables the simplification of a model [de Wit, 1997].

(2) It allows the analysis of the robustness of a model [Litko, 2005].

(3) It makes aware of unexpected sensitivities that may lead to errors/ wrong specifications (quality assurance) [Lewandowska et al., 2004; Hopfe et al., 2006; Hopfe et al., 2007]

(4) By changing the input of the parameters and showing the effect on the outcome of a model, it provides a “what-if analysis”. It is for instance used in multiple decision support tools [Gokhale, 2009].

In the following section a summary of the terminology used in this chapter will be provided followed by a discussion of the techniques that exist for UA/SA.

Subsequently, a case study is performed based on an office building with respect to various building performance parameters. UA/SA are accomplished and results considering energy consumption (annual heating and cooling) and thermal comfort (weighted over- and underheating hours) are demonstrated and elaborated. The added value and usefulness of the integration of UA/SA in BPS is shown.

3.2 Overview methods in UA/SA

There are different techniques to conduct UA/SA and to analyze the provided output [Saltelli et al., 2005].

3.2.1 Local and global methods

Local methods (e.g., automated differentiation) can be only applied if the correlation between inputs and outputs is linear. A local method for instance is differential sensitivity analysis (DSA) or perturbation analysis that is applied in [Lomas et al., 1992]. It gives insight in the individual sensitivity meaning the influence on predictions of variations in each individual input parameter. The remaining parameters stay identical at their "base-case" values [Lomas et al., 1992]. However, by making changes in many inputs and therefore having suitable assumptions made, it can also provide insight in the total sensitivity that is due to uncertainties in the entire input file. Besides the ability of covering both, individual and total sensitivities, another advantage of the method is that its implementation is easy. In comparison to other techniques it is claimed to be computational faster [Lomas et al., 1992].
A drawback is that problems with non-linearity arise; input parameters need to be assumed behaving linearly and superposably in their effect to receive the total uncertainty.
In global methods the uncertainty in a specific input parameter is used to determine the uncertainty in the output. All variables are sampled simultaneously. The distribution assigned is typically a normal distribution. The main differences of global and local methods are summarized in Table 2.

Table 2 Comparison of local and global methods [Hoes and de Vaan, 2005]

		Local methods	Global methods
1	Aim	It is meant for the determination of the partial derivation of the output in relation to input.	It is meant for the determination of uncertainty of a specific input parameter in relation to the overall output.
2	Input parameters	The input parameters are sampled one by one.	The input parameters are sampled simultaneously.
3	Correlation between input and output	A linear correlation is assumed between input and output of a model.	A linear correlation is assumed between input and output of a model.
4	Choice of distribution	There is only one assigned distribution possible in the input.	In the input each variation/ distribution is possible.
5	Distribution of variables	The distribution is based on assumed boundaries that are usually valid for all variables.	The distribution of input is based on an assumed distribution of each parameter; that implies an insight in the behavior of the parameters.
6	Number of simulations	On average a high number of simulations is necessary (depends on the method).	In comparison to local methods not so many simulations are necessary.

3.2.2 Monte Carlo and linear regression

Monte Carlo filtering, regression, and correlation analyses are sampling based methods. Their objective is to identify regions in the input corresponding to the output.

The Monte Carlo analysis (MCA) is a simple analysis, where the expected value E and the variance V of the output Y are estimated by the following well-known expressions:

$$E(Y) = \frac{1}{N}\sum_{i=1}^{N} y_i \quad ; \qquad (2)$$

$$V(Y) = \frac{1}{N-1}\sum_{i=1}^{N}[y_i - E(Y)]^2 \quad ; \qquad (3)$$

where N = number of samples and i = number of input parameter.

MCA is an external global analysis method and it is one of the most commonly used methods to analyze the approximate distribution of possible results on the basis of probabilistic inputs. All uncertain inputs must be assigned a fully specified probability

distribution. All input parameters are varied simultaneously. This is important in order to consider the total sensitivity due to the uncertainties in the entire input.
One advantage of this method is that there is no problem with non- linearity in the input-output mapping. That means the correlation of the individual input parameter does not need to be linear to the output. In the context of BPS this is necessary, because the individual parameters are not behaving linearly in relation to the output considered.
The method itself is easy to implement (which will be shown in Section 3.3) and the post processing leads to comprehensible results.
Drawbacks are that only total uncertainties can be considered due to the fact that the input is varied simultaneously, i.e., sensitivities of the predictions to the individual input parameters are not presented.

The regression analysis is important for the analysis of the SA. Regression analysis shows more quantitative measures of sensitivity. A multivariate sample of the input is generated by some sampling strategy and the corresponding sequence of a number of output values is computed using the model under analysis [SIMLAB, 2009].

However, regression analysis often performs poorly when the relationships between the input variables are non-linear. By using rank transformations the problem with poorly linear fits to data can often be avoided. It is a simple procedure where the data in the output achieves a corresponding rank, i.e., the most sensitive gets rank 1 assigned down to the number of parameters varied.

3.2.3 Screening methods

Screening methods are a particular case of sampling based methods. Like other sampling based methods (e.g., Monte Carlo) they also consider the global sensitivity meaning the input parameter are varied over the whole range of their possible values. A well-established representative is the Morris analysis. The method of Morris varies one factor at a time and is thus referred to as OAT method. In Morris analysis, the uncertainty of the output is characterised by a value called “effect”. By varying the input parameter set, the “effect” is calculated several times [Zador et al., 2006]. It allows the selection of important input parameters, by evaluating the model with different inputs.
The results of the Morris analysis consist of one graph where the averaging coefficient for each parameter (μ) is compared against the dispersion (σ) from this coefficient per parameter. One high averaging means a higher tilt angle and consequently a big sensitivity; a small averaging one implies less sensitivity.
Another advantage is that it is possible in the method of Morris to distinguish parameters with linear effects from parameters with nonlinear effects.
A drawback of the Morris analysis is that it does not allow uncertainty analysis due to the fact that it does not take the shape of the probability density function of the parameters into account. [De Wit et al., 2002]

3.2.4 Variance based methods

Variance based methods are sampling-based methods but besides, they rely on the computation of conditional variances. They allow a global, quantitative and model independent sensitivity measure. Therefore, it is also understood as sort of subset of, e.g., Monte-Carlo based methods.

For non-correlated input factors (i.e., measures that do not need a linear or additive model behaviour) shortcuts are available, e.g., the FOURIER amplitude sensitivity test (FAST) that does not cover uncertainty.

FAST for instance is a variance based method to solve non-linear, non-monotonic problems (non-linear sensitivity analysis). It estimates the expected value and the variance of a model prediction by performing numerical calculations [Saltelli et al., 2008].

Variance based methods are of great importance if the model consists for unknown linearity or additivity [Saltelli et al., 2008]. An example of a variance based method for correlated input factors is the brute force method [Hwang et al., 1998]. The system is solved repeatedly while varying one or more input parameters at a time and holding others fixed.

Advantages are the appreciation of interaction effects among input factors, i.e., the analytic structure of the model to be analyzed can be unknown. Furthermore, the capacity to tackle groups of input factors as well as the capacity to capture influence of full range of variation of the input factors [Saltelli et al., 2008].

However, because of the advantages mentioned, to conduct a variance based method a high number of simulations need to be run compared to other sensitivity methods [Hoes, 2007]. Therefore, a disadvantage of this method is high computational costs as complexity and numbers of parameters increase.

The main arguments of all methods are summarized in Table 3.

Table 3 Comparison of four different methods to conduct global sensitivity analysis [European commission, 2009].

	I	II	III	IV
Local methods	no	no	no	yes
Monte Carlo analysis	yes	yes	yes	no
Screening methods	no/yes	yes	yes	yes
Variant based methods	yes	yes	yes	yes

I	Input The input should incorporate the effect of range of input variation and the probability density function (pdf). It is of importance if the pdf is normal or uniform distributed.
II	Variation of input factors Contrary to the computing of partial derivatives (local methods) the evaluation of a factor whilst the other input variables are changed as well.
III	Model independence The SA should perform well even if the model is not linear. Problems arise when effect of changing two factors is different from the sum of their individual effects.
IV	Treatment of group factors as if they were single ones This is important for agility of the interpretation of the results (no dense tables).

3.3 Overview UA/SA in BPS

The effective integration UA/SA in BPS for design information and quality assurance is of high importance and will be discussed further on. UA/SA for instance can provide information about reliability towards design parameters, with respect to the overall design.

In BPS, UA and SA are an important part of many ongoing research activities. They find use in several approaches applied for parameter screening/ reduction [Alam et al., 2004], meta-modelling [Leung et al., 2001], robustness analysis [Topcu et al., 2004; Perry et al., 2008], model validation [Pietrzyk et al., 2008] among others.

Other approaches in building performance are for instance shown in [Verbeeck et al., 2007] where a methodology is developed to optimize concepts for extremely low energy dwellings. A perturbation analysis supports in analyzing the sensitivity for errors and error propagation.

Pietrzyk et al. [2008] describe the reliability in building physics design in terms of the probability of exceeding the critical values by physical measures as result of changes in climatic, structural, or serviceability parameters. They provide an example for the air exchange showing the reliability in the design of ventilation.
Marques et al. [2005] for instance evaluate the reliability of passive systems by firstly identifying the sources of uncertainties and the determination of the important variables. Secondly, the uncertainties are propagated through a response surface. Finally, there is a quantitative reliability evaluation with the help of Monte-Carlo analysis.
The integration of UA and SA to Esp-r software is shown by Macdonald [2002]. He quantifies the effects of uncertainty in building simulation by considering the internal temperature, annual energy consumption and peak loads. In [MacDonald and Strachan, 2001] the partial application of uncertainty analysis is demonstrated by reviewing sources of uncertainties and incorporation of UA in Esp-r.
De Wit [2002] determines uncertainties in material properties and uncertainties stemming out of model simplification for design evaluation. In [Hopfe et al., 2009] uncertainties in physical properties and scenario conditions are used to support decision making due to differences in climate change.

The previous section provided important insight in the use, techniques and types of uncertainties. Furthermore, it has shown that UA/SA are part of reliability testing or parameter reduction in current BPS.
In the following section a case study will be presented showing the application of UA/SA in BPS. The intent is to show the effective integration of UA/SA in BPS for design information. The methodology will be described and it will be shown how UA/SA are conducted. Furthermore, different types of uncertainty are emphasized, such as uncertainties in physical, scenario, and design parameters. The impact, the different groups have, will be demonstrated. Finally, the added value of UA/SA in BPS is demonstrated.

3.4 Prototype description of applying UA/SA

By means of a case study it will be shown how to conduct UA/SA. The intent of the study, the methodology, and the procedure in detail will be described in the following section.

The process can be divided into:

(i) Pre-processing.
(ii) Simulation.
(iii) Post-processing.

In the pre-processing, all the considered input parameters are sampled with Latin hypercube sampling 200 times. This is done with the freeware tool Simlab [2009].

For the UA/SA, the MCA is selected. Further on, five different files for the BPS tool are generated out of the sampled input parameters. In these files all the necessary information for the simulation of the case study with VA114 is saved, e.g., the material properties of the construction, the internal heat gains, infiltration rate, amongst others. The generation of these files is done with Matlab.

The generated files are passed to VA114 and the simulation is started 200 times. This is done automatically via Matlab. The simulation output considered is energy consumption and thermal comfort.

In the post-processing, the output from the 200 VA114 simulations is compared to the sampled input files. The output analysis of the UA/SA is conducted with Matlab.

The flowchart is shown in Figure 9.

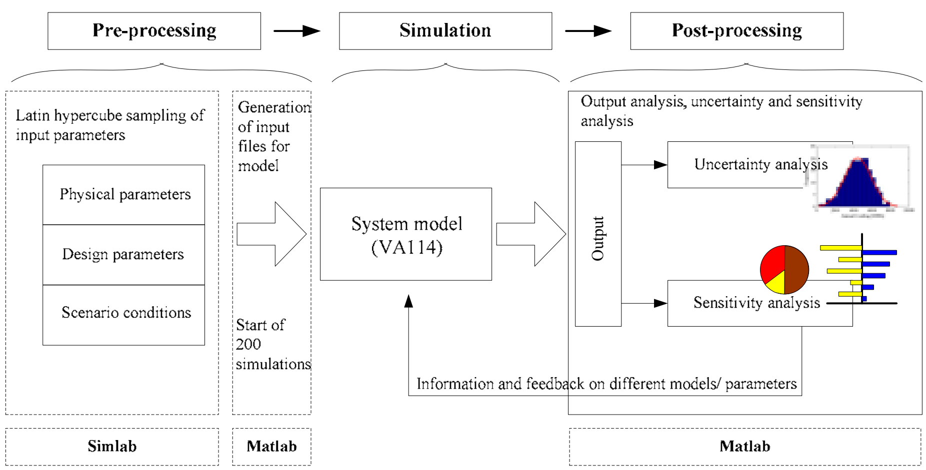


Figure 9 Illustration of the methodology of processing UA/SA divided into the three steps pre-processing, simulation, and post-processing.

As mentioned, focus of attention in the presented results is on energy consumption and thermal comfort. The results for energy demand are divided into annual heating and annual cooling in [MWh] for three different uncertainty cases.

The assessment of thermal comfort needs more explanation as a Dutch criterion is used. In VA114 there is one main criterion available which is called GTO-criterion. It is a criterion, published by the Rijksgebouwendienst [ISSO 2004]. The weighted under- or overheating hours (Dutch: gewogen temperatuur overschrijding (GTO)) criterion is based on theory of Fanger. The extent in which a predicted mean vote (PMV) of +0,5 is exceeded is expressed by a factor WF(Dutch: weegfactor).
Each hour during operation time this factor is determined. The sum of these hourly factors over the year results in the weighted overheating hours. A corresponding criterion exists for the weighted underheating hours where the predicted mean vote (PMV) is less than -0.5. In case the system is improperly sized, the number of weighted overheating hours can be rather high, even higher than the number of operation hours.
In case the number of weighted overheating hours stays below 150h per year the indoor conditions are in an acceptable range. The same is valid for the weighted underheating hours.
The GTO value of 150 hours per year is calculated with an operation time of 8 hours per day. The limit of 150h arises out the 2000h/y (8h/d* 5d/w*52w/y) *5% [percentage of below/ upper]*1.5 [averaged value].

3.5 Case study of applying UA/SA

The setup of the previous section will be described in more detail, starting with the intention of the UA/SA simulation, before describing the three steps of pre-processing, simulation, and post-processing.

3.5.1 Objective of the UA/SA

The aim of the UA/SA study is to support the design process by providing additional information of the parameters chosen. Different sources of UA/SA that play a role in the input of BPS have to be considered. It is hypothesized that uncertainties in the outcome due to physical, design or scenario uncertainties have a different impact on the outcome.

On the one hand, with the help of UA/SA it was aimed to show the effect of one group on the outcome in the uncertainty (normal distribution and range) and the sensitivity (order of most influential parameters). On the other hand, it was important to consider all three categories at the same time, as they all are supposed to play a role according to practitioners' experience in the final design process. This is shown in Table 4.

Table 4 Respondent results to the impact of three different uncertainty categories (physical, scenario, and design) in the conceptual, preliminary, and final design stage.

	physical uncertainties	scenario uncertainties	design uncertainties
Conceptual design stage	30%	30%	40%
Preliminary design stage	25%	41%	34%
Final design stage	36%	28%	36%

Table 4 shows the feedback from practice that was requested about the necessity of different uncertainty categories in different design stages. It summarizes the answer to the question of which group (physical, scenario, and design) they wanted to have considered in BPS tools in which phase of the design process.

It can be noticed that in the final design stage all categories of uncertainties are equally distributed. Thus, in order to identify all sensitive input parameters from the three different groups, four different cases are studied in this section.

The flowchart from Figure 9 is extended for the different cases developed in the pre-processing part and shown in Figure 10. The four different models for the generation of parameters are shown on the left hand side.

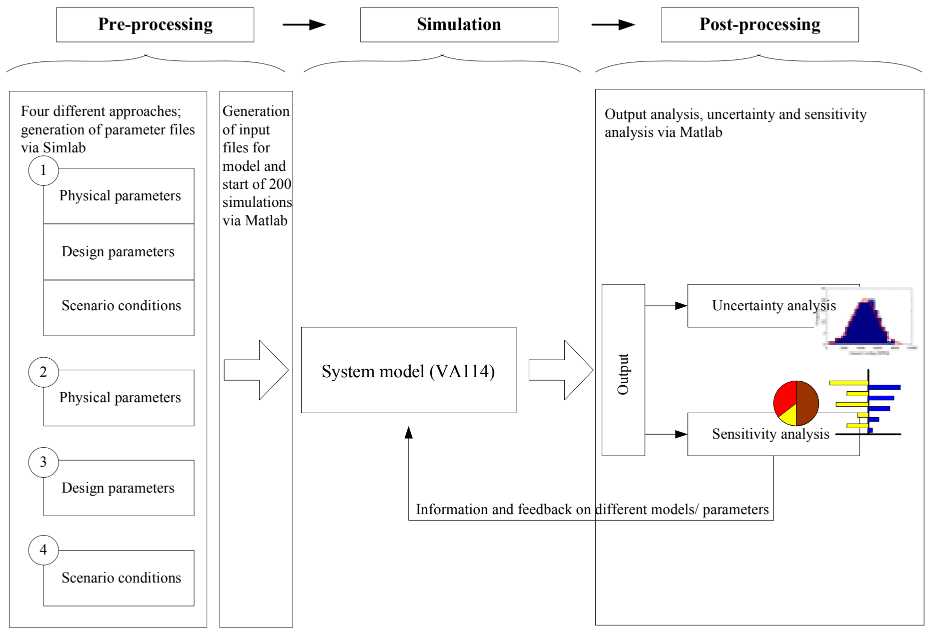


Figure 10 Illustration of the methodology of processing UA/SA divided into the three steps pre-processing, simulation, and post-processing and showing the four different input cases for physical, design, scenario, and combined uncertainties.

The procedure will be explained in more detail.

3.5.2 Pre-processing

The following steps were conducted in the pre-processing part of the UA/SA:

1. Selection case study.
In this research one case study was simulated. The simulation was conducted with an office building called “het bouwhuis” built in the Netherlands and shown in Appendix A.
Design option 1 is considered that uses conventional central heating and mechanical cooling. The building is conditioned by an all air conditioning system with constant air volume (CAV) consisting of an air handling unit, supply and return fans, ducts and control units. For more information see Appendix A.
Physical properties changed are listed in the Appendix B. They cover thickness (t), conduction (λ), density (ρ), specific heat capacity (c) for the wall, floor, and roof construction. Besides, the glazing properties, inside and

outside absorbtivity and solar absorptivity are changed. In Appendix B the mean (μ) and standard deviation (σ) are listed.

2. Description of a target function and consideration of the essential input.

The goal of the integration of UA/SA is to establish the impact uncertainties have on the predicted energy use and thermal comfort. The chosen case study consists of a number of parameters (more than 80 input parameters) dedicated to the different uncertainties groups.

3. Assignment of a normal distribution to the selected variables.

In order to analyze the approximate distribution of possible results on the basis of probabilistic inputs, all uncertain inputs are assigned a normal probability distribution.

The normal distribution maximizes the information entropy among all distributions with a known mean and standard deviation [Simlab, 2009]. That is why it is chosen as the underlying distribution for data summarized in terms of sample mean and standard deviation. In the normal distributions, no negative values are possible for the input parameters. For that reason, the normal distribution is truncated in some cases to avoid infeasible values.

The standard deviations are taken from literature. For instance, the infiltration rate and casual gains are comparable to a study reported in [Hopfe et al., 2007] and can be seen in the Appendix B. The standard deviation of the U-value and the solar transmittance (g-value) were fixed to 5 percent. Most of the deviations for physical properties can be found in literature, e.g., [Macdonald, 2002], whilst for design and scenario less information is available.

The calculated values in Appendix B are estimates reported in [Macdonald, 2002]. The standard deviation of the thickness of wall, roof, and floor layers however, is set to 10% -due to a lack of information. This percentage has been estimated and reported in [de Wit, 2001].

Furthermore, Macdonald [2002] derived for solar absorption an average value from [Clarke et al., 1990], which is based on a collection of data of thermo physical properties from standards and measurements [Breesch, 2006].

4. Generation of input matrix.

200 different samples have been generated with the help of Simlab. For the generation LHS was used.

In literature multiple suggestions about the number of simulations necessary can be found. For instance, in [MacDonald, 2002; Lomas, 1992] it seems that the reliability of results from the UA/SA does not increase after a number of 60-80 simulations – independent of the number of variables considered. Breesch [2002] mentions that the number of simulations should be 1.5 times the number of input variables taken into consideration in order to achieve reliable results.

In Figure 11 the relation of the total number of Monte Carlo simulations to a confidence interval of 95%/ standard deviation is shown published in [NEN 5128, 2001].

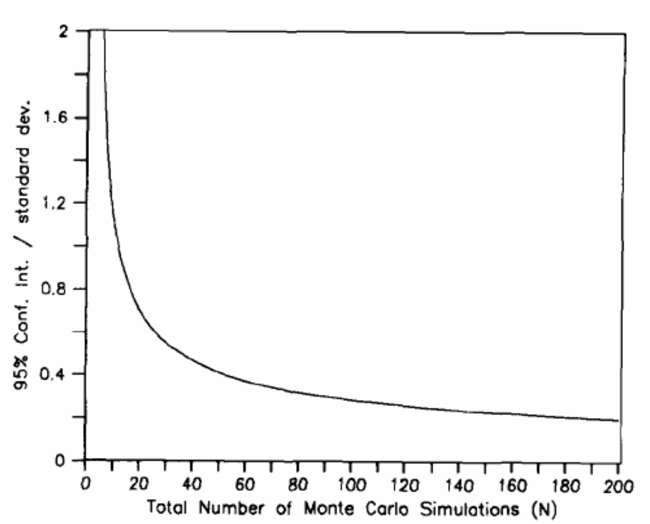


Figure 11 Reliability of the total number of MCA simulations [NEN 5128, 2001].

5. Selection of a method.

For assessing the influence or relative sensitivity of each input factor based on the target function a methods needs to be selected. The Monte Carlo analysis (MCA) is applied to analyze the approximate distribution of possible results on the basis of probabilistic inputs.

MCA is chosen because it is one of the most commonly used methods for UA/SA. MCA considers the total sensitivity due to the uncertainties in the entire input. That means, all input parameters are varied simultaneous.

3.5.3 Simulation

The simulation with VA114 was started with Matlab and conducted 200 times with different input files. VA114 is a commercially available, industry strength, and extensively used BPS tool in The Netherlands.

For the 200 simulations and the 80 variables five different input files were necessary for the BPS tool. In these files, the sampled parameters for material properties, geometry of the building, internal heat gains, infiltration rate, switch for single/ double glazing are saved.

3.5.4 Post-processing

The post-processing was done in Matlab after the 200 simulations. The histogram and the normality plots are chosen for demonstrating the results of the UA. The standardized rank regression coefficient is used for sensitivity analysis in this study. The values achieved in the end, are the indicator for the sensitivity of the parameter. The higher the value the more sensitive the parameter is.

The standardized rank regression coefficient (SRRC) is used for sensitivity analysis in this study. The usual least square regression analysis is then performed entirely on these ranks from the according regression analysis, which is the standardized regression coefficient (SRC) in this case. The values achieved in the end, are the indicator for the sensitivity of the parameter. The higher the value the more sensitive the parameter is.

3.6 Results crude uncertainty analysis

In literature it is distinguished between two types of uncertainty: aleatory and epistemic uncertainties.
Main focus of interest in the current research is the epistemic uncertainty that is reducible or even resolvable with the help of building performance simulation.
Uncertainties belonging to the epistemic group, and discussed in this work, do arise from many different sources and can be divided into three groups caused by different parameters: physical, design, and scenario uncertainties.

To cover uncertainties in physical parameters in the presented case study, all material properties have been varied. The mean and standard deviations of physical variables are summarized in Appendix B.

For the uncertainties in design parameters adjustments in the geometry as well as glass surface and glass properties have been made. The uncertainties in boundary conditions are covered by internal parameters such as infiltration rate and internal gains (loads people, equipment and lighting).

Table 5 List of the properties for uncertainties in scenario conditions and in design variations.

	μ	σ
Infiltration AC Rate [ACH]	0.5	0.17
Loads people [W/m²]	15	2.4
Loads lighting [W/m²]	15	2.4
Loads equipment [W/m²]	20	3.2
Glass surface [%]	75	22.5

Room size [m²]	[182, 325]
Switch between single/ double glazing	yes/ no

The results will be shown in the beginning for all categories combined that address physical, design and scenario uncertainties at the same time.

The UA in Figure 12 to Figure 15 show the distribution of the output caused by the uncertainties in the input which is demonstrated in a wide spread shown in the histogram on the left hand side.
The figures on the right demonstrate in how far the distribution matches the assumptions by means of a normality plot. Its purpose as described earlier is to graphically assess whether the data follows a normal distribution.

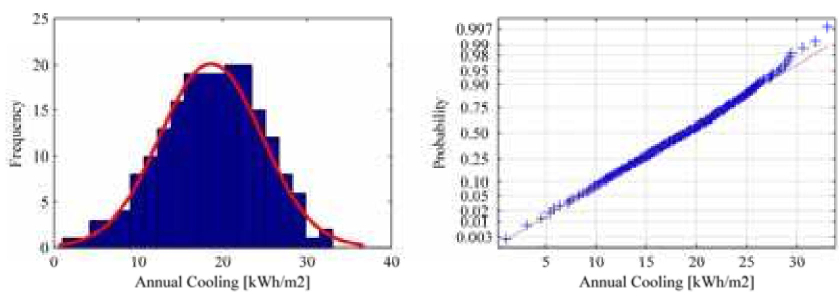


Figure 12 Frequency distribution and normality plot of annual cooling when considering uncertainty in all parameters.

The results for the annual cooling vary between 1 and 33 kWh/m². The normality plot on the right hand side follows a normal distribution.

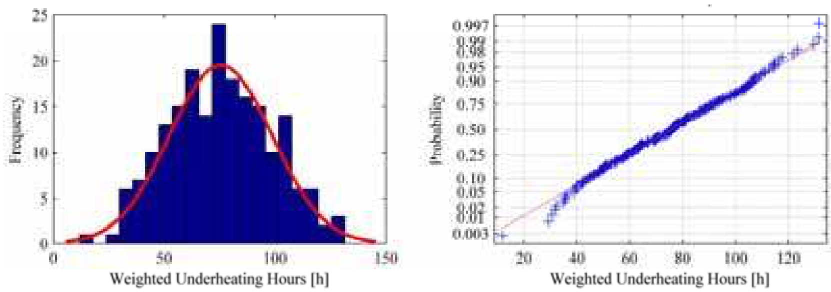


Figure 13 Frequency distribution and normality plot of weighted underheating hours when considering uncertainty in all parameters.

The results for the weighted underheating hours vary between 20 and 140h. The normality plot on the right hand follows a normal distribution.

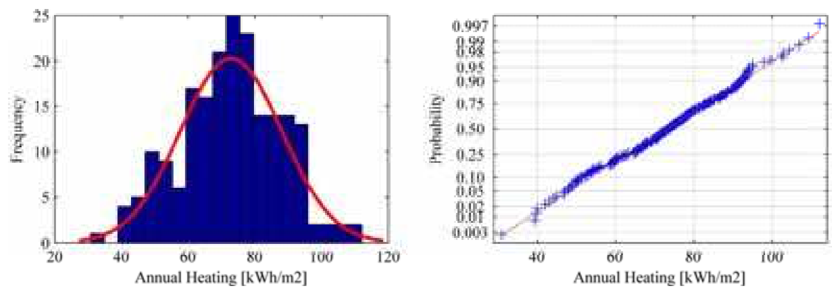


Figure 14 Frequency distribution and normality plot of annual heating when considering uncertainty in all parameters.

The results for the annual heating vary between 30 and 117 kWh/m². The normality plot on the right hand follows a normal distribution.

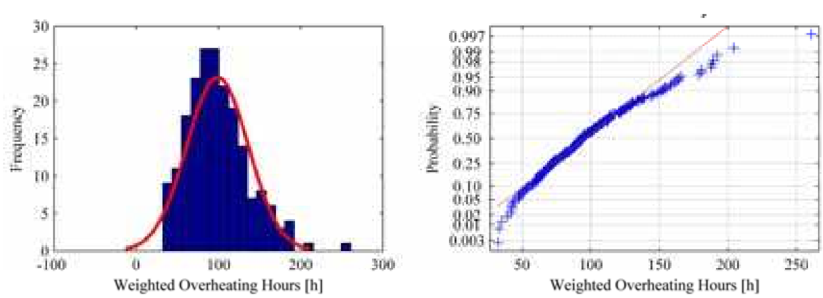
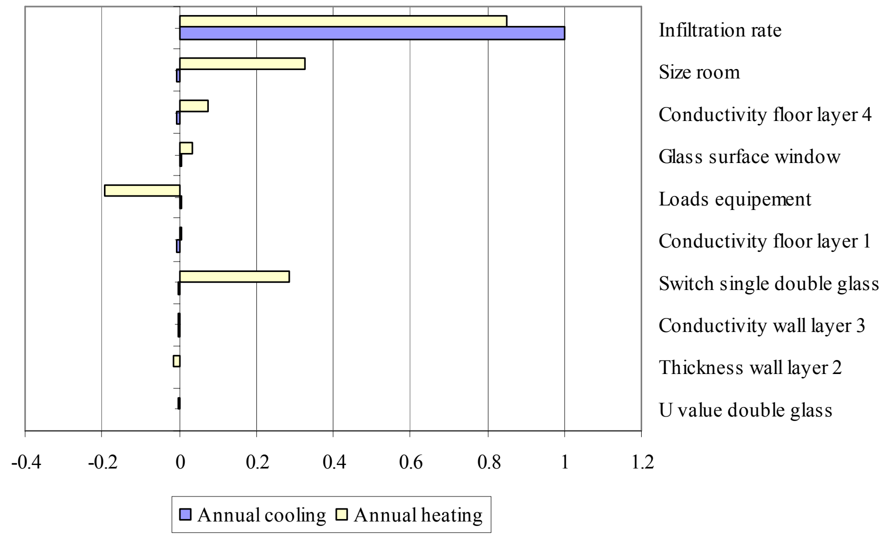


Figure 15 Frequency distribution and normality plot of weighted overheating hours when considering uncertainty in all parameters.

The results for the weighted overheating hours vary between 40 and 210h. The normality plot on the right hand does not follow a normal distribution.

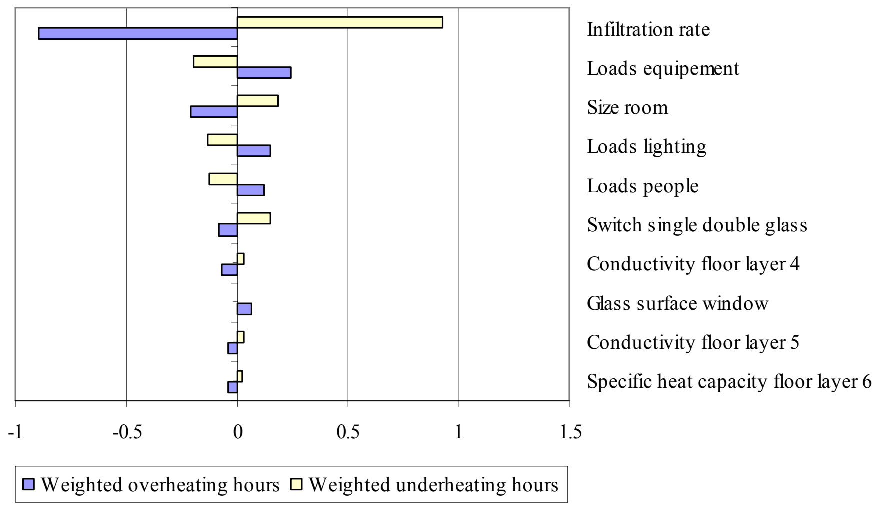
3.6.2 Results of the sensitivity analysis

The results for the SA will be shown for annual cooling/heating and weighted over- and underheating hours. The results are interpreted for the SRCC coefficient. The figures in the following section represent an extract of the ten most sensitive parameters relating to one performance aspect. For the energy, the ranking is based on the sensitivity of the annual cooling demand, and for the comfort criterion on the weighted overheating hours. Furthermore, it can be seen which effect a parameter has with the output, positive or negative.



rank	Annual cooling	Annual heating
1	Infiltration rate	Infiltration rate
2	Size room	Size room
3	Conductivity floor layer 4	Switch single double glass
4	Glass surface window	Loads equipement
5	Loads equipement	Loads lighting
6	Conductivity floor layer 1	Loads people
7	Switch single double glass	Conductivity floor layer 4
8	Conductivity wall layer 3	U value single glass
9	Thickness wall layer 2	Conductivity wall layer 1
10	U value double glass	Glass surface window

Figure 16 Sensitivity plot and table showing the 10 most sensitive parameters based on annual cooling and compared to annual heating when considering uncertainty in all parameters.



rank	Weighted overheating	Weighted underheating
1	Infiltration rate	Infiltration rate
2	Loads equipement	Loads equipement
3	Size room	Size room
4	Loads lighting	Switch single double glass
5	Loads people	Loads lighting
6	Switch single double glass	Loads people
7	Conductivity floor layer 4	U value single glass
8	Glass surface window	Conductivity floor layer 5
9	Conductivity floor layer 5	Conductivity floor layer 4
10	Specific heat capacity floor layer 6	Specific heat capacity floor layer 2

Figure 17 Sensitivity plot and table showing the 10 most sensitive parameters based on weighted overheating hours and compared to weighted underheating when considering uncertainty in all parameters.

3.6.3 Discussion

The previous section has shown a crude analysis covering all sorts of uncertainties arising in the design and decision process.
The observed results are based on a normal distribution on assessed 95% confidence interval for all the parameters. The parameters ranked highest, such as infiltration rate, size of the room, etc., need deeper consideration. Furthermore the uncertainties addressed will be separated as they deserve focus also considering their difference in assessment.
The data and knowledge on the various uncertainty types is limited. However, it is difficult and dangerous to combine them in the way it was done in the previous section. The three different categories of uncertainties differ in their sort of nature, and the significance they have on simulation, performance, and the building design.

That is why a distinction will be made in the following sections showing the separation between uncertainties in physical parameters, scenario conditions and design variations.

3.7 Uncertainty in physical parameters

As mentioned earlier it is dangerous to combine different sorts of uncertainties because their different source of nature, controllability, etc. Thus, a distinction will be made.

In this section only uncertainties in physical properties will be considered. Physical uncertainties are mostly identifiable as the standard input parameters in energy or thermal comfort simulation. Physical uncertainties refer to physical properties of materials such as thickness, density, thermal conductivity, etc., of wall, roof and floor layers. As a matter of fact, they are always there, and thus, inevitable.

Taking these uncertainties into account is related to quality assurance. The designer has no influence on this type of uncertainty.
The standard and mean deviations of the parameters are summarized in Appendix B. Besides, a change in the infiltration rate is considered that is varied between 0 and 0.2ACH. This change seems feasible as it can be caused through bad workmanship or cracks in the façade.

3.7.1 Building regulations

As mention in Chapter 2, in order to fulfill building requirements by the Dutch law, a brief check is provided to guarantee that the variations lie in specified boundaries and the results represent reliable variations of the output.

The thermal insulation according to article 5.2 and 5.3 Bb is limited as follows.
The thermal resistance Rc of the envelope, floor and roof construction should be equal or higher than 2.5m²K/W. The parameter variations are shown in Table 6 to Table 8.

Table 6 Limitation of thermal resistance according to building regulation for the roof construction.

Thickness [m]	Material	Conductivity [W/m·K]	Resistance = thickness / conductivity [m²K/W]
0.01	stone	0.96	0.01
0.005	bitumen	0.5	0.01
0.15	cast concrete	1.13	0.13
0.1345	glass fibre quilt	0.04	3.36
0.019	ceiling tiles	0.056	0.34
		Rc:	**3.85**
max. value			**4.70**
min. value			**2.45**

Table 7 Limitation of thermal resistance according to building regulation for the wall construction.

Thickness [m]	Material	Conductivity [W/m·K]	Resistance = thickness / conductivity [m²K/W]
0.005	steel	50	0.00
0.127	glass fibre quilt	0.04	3.18
0.2	concrete block	1.41	0.14
		Rc:	**3.32**
max. value			**4.50**
min. value			**3.10**

Table 8 Limitation of thermal resistance according to building regulation for the floor construction.

Thickness [m]	Material	Conductivity [W/m·K]	Resistance = thickness / conductivity [m²K/W]
0.8	london clay	1.41	0.57
0.28	brickwork	0.84	0.33
0.1	cast concrete	1.13	0.09
0.0635	dense eps slab ins	0.025	2.54
0.025	chipboard	0.15	0.17
0.015	synthetic carpet	0.06	0.25
		Rc:	**3.95**
max. value			**4.85**
min. value			**2.68**

The limitation of the air infiltration according to article 5.9 Bb varies between [0, 0.2] ACH.

3.7.2 Results of uncertainty and sensitivity analysis

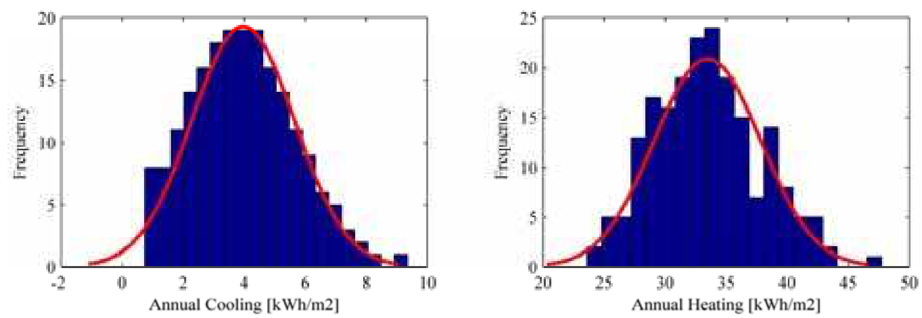


Figure 18 Frequency distribution of annual cooling and annual heating when considering uncertainty in physical parameters as shown in Appendix B.

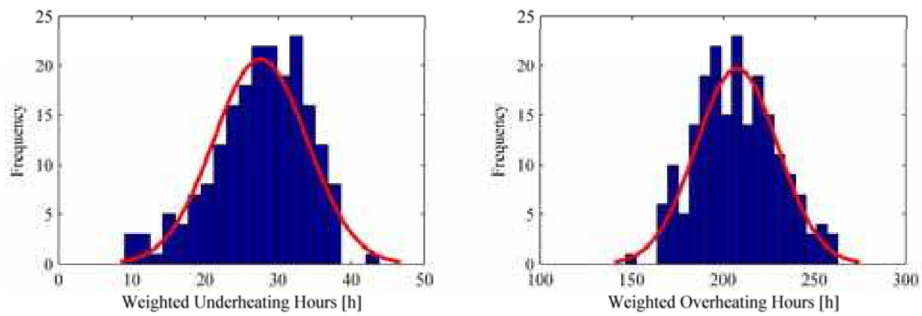


Figure 19 Frequency distribution of weighted over- and underheating hours when considering uncertainty in physical parameters as shown in Appendix B.

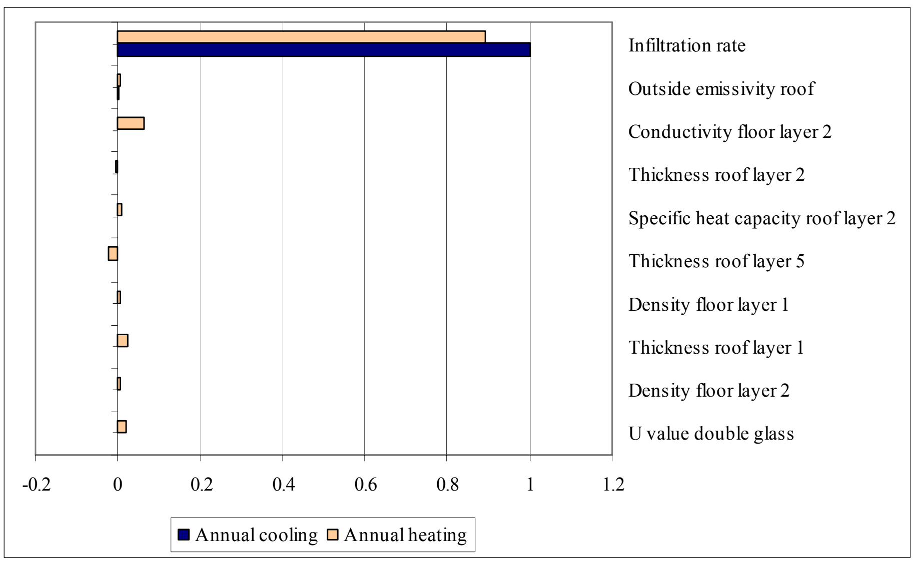


Figure 20 Sensitivity plot showing the 10 most sensitive parameters based on annual cooling and compared to annual heating when considering uncertainty in physical parameters as shown in Appendix B.

3.7.3 Robustness analysis

The model described is based as shown earlier on certain assumptions such as a normal distribution. If the distribution has outliers, the assumption and therefore also the parameters estimates, confidence intervals, etc., become unreliable. To provide the decision maker with the guarantee of reliable results, a robustness analysis is conducted.

In this section it will be shown a robust fitting compared to ordinary least squares.

A weight to each data point is assigned. This is done by iteratively re-weighting least squares.
This robustness analysis will be exemplified for the most sensitive parameter infiltration rate. The resulting figure shows a scatter plot with two fitted lines. There are two lines showing the robust regression and the ordinary least squares regression. Both lines match each other for the performance aspect annual cooling.

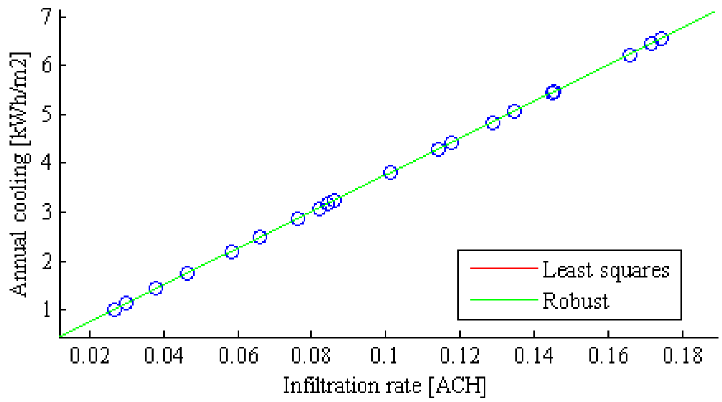


Figure 21 Robustness analysis comparing robust fit to least square when considering infiltration rate shown in relation to annual cooling.

The following figure shows the plot of least squares regression and robust regression for the performance aspect weighted underheating hours.

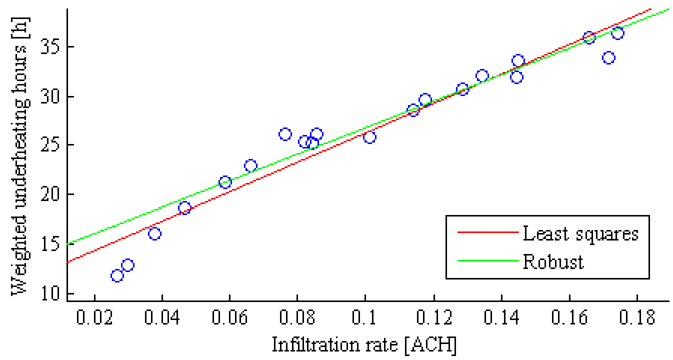


Figure 22 Robustness analysis comparing robust fit to least square when considering infiltration rate shown in relation to weighted underheating hours.

For the performance aspect weighted underheating hours as shown in Figure 22 a mismatch between both regressions is noticeable. This mismatch results in less robustness of the model. Bringing the right-most data point closer to the least squares line makes the two fitted lines nearly identical. The adjusted right-most data point has significant weight in the robust fit. For the infiltration rate considered in this study it leads to the conclusion that a variation above 0.05ACH should be assumed.

3.7.4 Stepwise regression and standardized rank regression coefficient

One possibility to conduct a sensitivity analysis is to construct regression models as mentioned earlier. The order of sensitive parameters is already demonstrated in Figure 20. It is one possibility of regression results provided by the standardized rank regression coefficient (SRRC).

Multiple methods such as linear or non-linear regression models or regression in a stepwise manner exist. Two of them will be exemplified showing sensitivity analysis: the non-linear regression model SRRC and a stepwise regression analysis.

In the construction of regression models in a stepwise manner, firstly the most influential variable needs to be determined based on the coefficient of determination R^2. The coefficient R^2 is the square of the correlation coefficient between the output of the model and the values used for prediction. It gives an impression of the goodness of fit of a model. R^2 varies between 0 and 1, i.e., if R^2 equals 1.0 the regression line fits perfectly the data.

The significance or sensitivity of a parameter is approached by a stepwise selection and the increase of the R^2 value, as additional variables are addressed in the stepwise regression. An example will be shown.
The regression model is shown for the weighted underheating hours. The most influential parameter infiltration rate is determined based on R^2 for the regression model. After, a regression model is done with infiltration rate and the second most sensitive parameter which is the conductivity of the floor layer 4. This parameter is determined based on R^2 containing the infiltration rate and the remaining variables.
The process continues until R^2 equals 1.0, i.e., the consideration of further parameters does not lead to an improved prediction, ergo, no other influential parameter can be identified.

Table 23 Comparison of stepwise regression analysis and the standardized rank regression coefficient for the 8 most affecting parameters on the weighted underheating hours.

Step	Parameter	R^2	SRRC
1	Infiltration rate	0.917705	0.989439
2	Conductivity floor layer 4	0.922615	0.0805242
3	U value single glass	0.927646	0.0617967
4	Thickness roof layer 4	0.932054	-0.0672
5	Conductivity roof layer 4	0.935914	0.0515716
6	Thickness roof layer 1	0.938452	0.000892
7	U value double glass	0.94057	-0.0153
8	Density roof layer 5	0.94273	0.0206818
:	:	:	:
:	:	:	:

The steps signify the movements taken in the stepwise regression. The steps determine all parameters in a stepwise manner that are most important. This procedure continues until the consideration of an additional parameter does not lead to an increase of R^2. However, it can be noticed that infiltration rate already causes a regression coefficient of more than 0.91. The further consideration of more parameters just increases the value slightly.
It shows that infiltration rate is the most dominant parameters even though it varies only between 0 and 0.2ACH. Other parameters considered affect the output as well although with lesser effect

3.8 Uncertainty in design parameters

Uncertainties in design parameters can be described as design variations that occur during the planning process. They are fully determined by the decision maker/ designer himself. They can be either caused due to a lack of knowledge of the designer or they arise due to changes or irregularities in planning phase of the building.

For instance, in the conceptual design, aspects such as building mass (heavy/lightweight) or orientation might be unknown. Opposed to this, in the detailed design the designer is more indecisive regarding the glazing area or type used, the type of system and so on.
The consideration of design uncertainties could improve and enable design decision support, in particular if it would be augmented by sensitivity analysis.
Design variations discussed in this section will cover changes in the room geometry and the window size as well as the switch between single and double glazing.
The range of parameters is summarized in Table 9.

Table 9 List of the properties for uncertainties in s design variations.

	μ	σ
Glass surface [%]	75	22.5

Room size[m²]	[183, 274]
Switch between single/ double glazing	yes/ no

Further on, it will be shown what impact these variations have, how sensitive the performance aspects are considering decisions by the designer or if some changes don't matter at all.

3.8.1 Results of uncertainty and sensitivity analysis

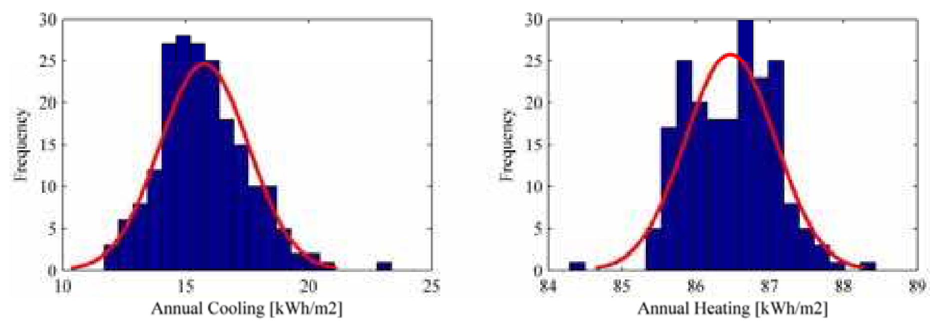


Figure 24 Frequency distribution of annual cooling and annual heating when considering uncertainty in design variations as shown in Table 9.

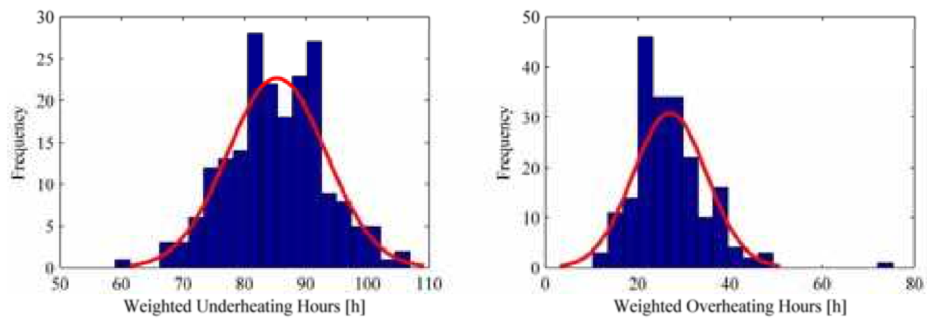


Figure 25 Frequency distribution of weighted over- and underheating hours when considering uncertainty in design variations as shown in Table 9.

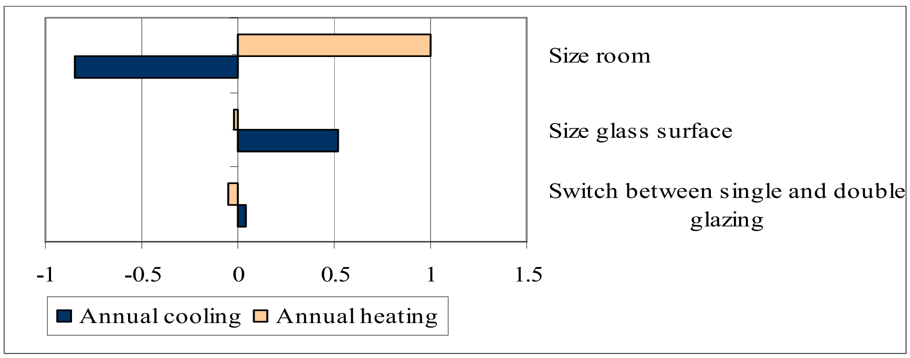


Figure 26 Sensitivity plot showing the sensitive parameters based on annual cooling and compared to annual heating.

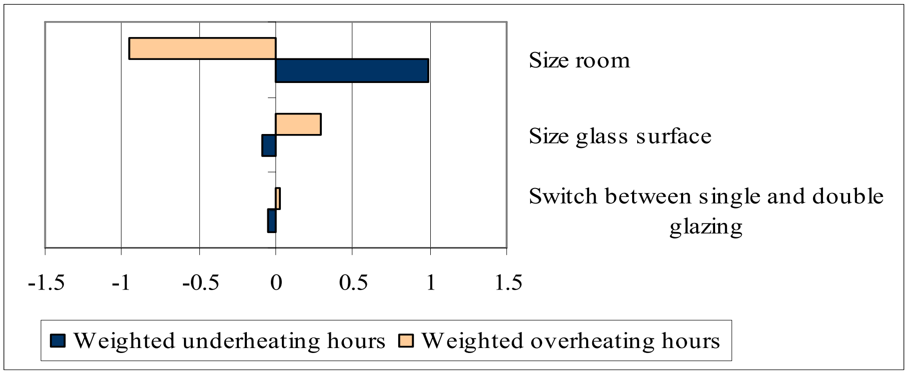


Figure 27 Sensitivity plot showing the sensitive parameters based on weighted underheating hours and compared to weighted overheating hours.

3.8.2 Robustness analysis

The following figure shows a scatter plot with two fitted lines. These two lines as explained earlier show the robust regression and the ordinary least squares regression. Both lines match each other for all performance aspect considered. The results are shown only for the weighted underheating hours compared to the room size.

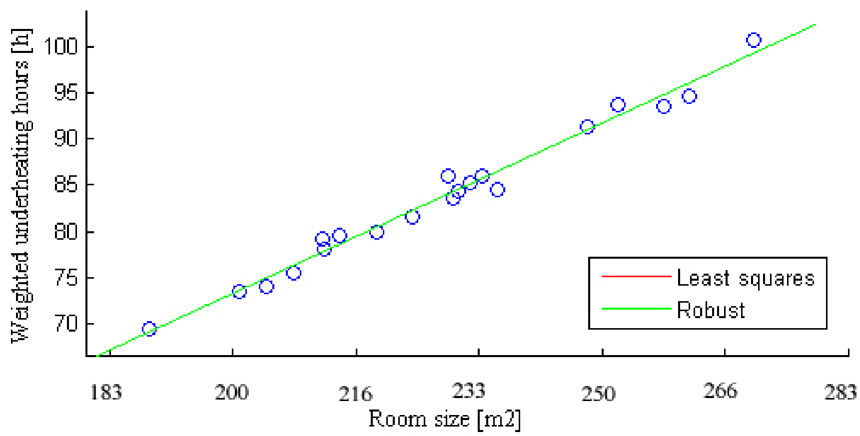


Figure 28 Robustness analysis comparing robust fit to least square when considering room size in relation to weighted underheating hours.

3.8.3 Stepwise regression and standardized rank regression coefficient

The regression model is shown for the annual heating and annual cooling.

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Table 29 Comparison of stepwise regression analysis and the standardized rank regression coefficient that affect the performance aspect annual heating.

Step	Parameter	R^2	SRRC
1	Size room	0.9955	0.99644
3	Switch single/double glazing	0.9989	-0.0479
2	Size glass surface	1	-0.0212

Table 30 Comparison of stepwise regression analysis and the standardized rank regression coefficient that affect the performance aspect annual cooling.

Step	Parameter	R^2	SRRC
1	Size room	0.730358	-0.873
2	Size glass surface	0.974628	0.491649
3	Switch single/double glazing	1	0.0425974

The most influential parameter for both performance aspects is the size of the room. In fact, for the annual heating it is very dominating. The second most sensitive parameter for annual heating is the switch between single and double glazing, whilst for the annual cooling the amount of the glass surface has a higher impact.
The process continues until R^2 equals 1.0, i.e., the consideration of all three varied parameters is taken into account.

3.9 Uncertainty in scenario parameters

Uncertainties in scenario conditions are very different compared to physical and design uncertainties in the sense that they can change during the building life time.
Taking scenario uncertainties into account is related to design decision support, in particular when considering design robustness and (future) flexibility of the building. They originate from considering the wide range in the possible usage of a building typically referred to as usage scenarios. Scenarios encompass the influence of infiltration rate (the operation of window openings), climate change (for instance due to global warming), lighting control schemes, and other occupant related unpredictable usage of the building.

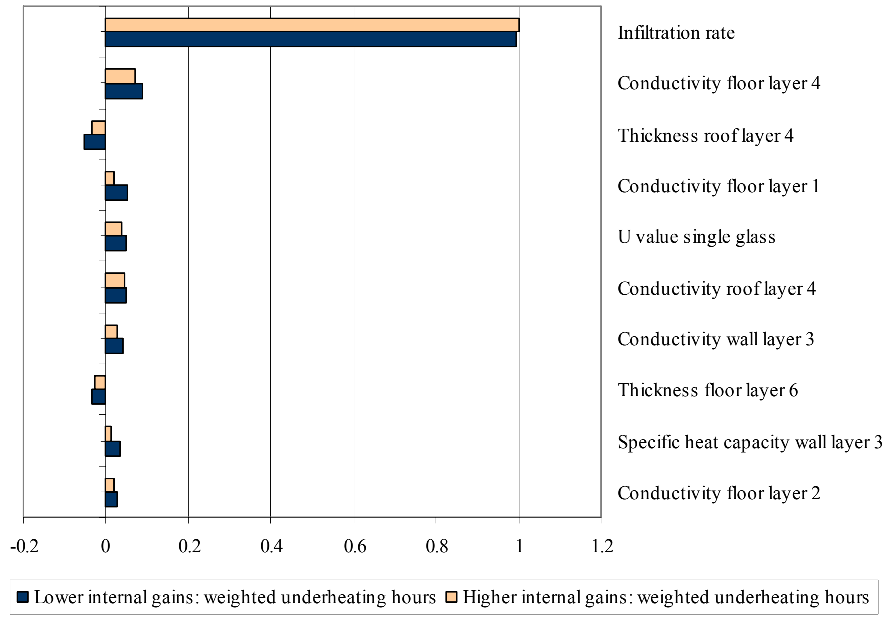
Scenario uncertainties or uncertainty in boundary conditions can be divided into internal or external scenario uncertainties. Internal uncertainties are related to the building operation such as internal heat gains from people, equipment, lighting, different set points, occupant behaviour due to control of shadings, windows, internal doors, etc. For instance, in natural ventilated buildings the airflow can be controlled by the occupants by, e.g., openable windows. External scenario uncertainties are caused by uncertainty in weather data or climate change.

Usually, uncertainty analysis is studied quantitatively by assuming a normal distribution. This becomes dangerous when scenario uncertainties are considered. Scenario uncertainties are based on a random process. The statistical assumption of Monte Carlo therefore is not verified. Thus, instead of sampling internal gains as well as the ventilation, a model needs to be created under a priori fixed scenarios.

An example is the consideration of different user behaviour related to operable windows. In [de Wit, 2001] for instance, a distinction between energy- friendly user and less energy friendly was conducted.
At present, models are created dealing with the user behaviour in buildings. Tabak [2009] developed a model that simulated the use of spaces by occupants in buildings. Hoes [2008] uses this model already and couples it with a BPS tool to predict realistic energy saving of occupants-sensing lighting control.
This approach is a first in dealing scenario uncertainties that would even make it possible to run different simulations assuming realistic internal heat gains.

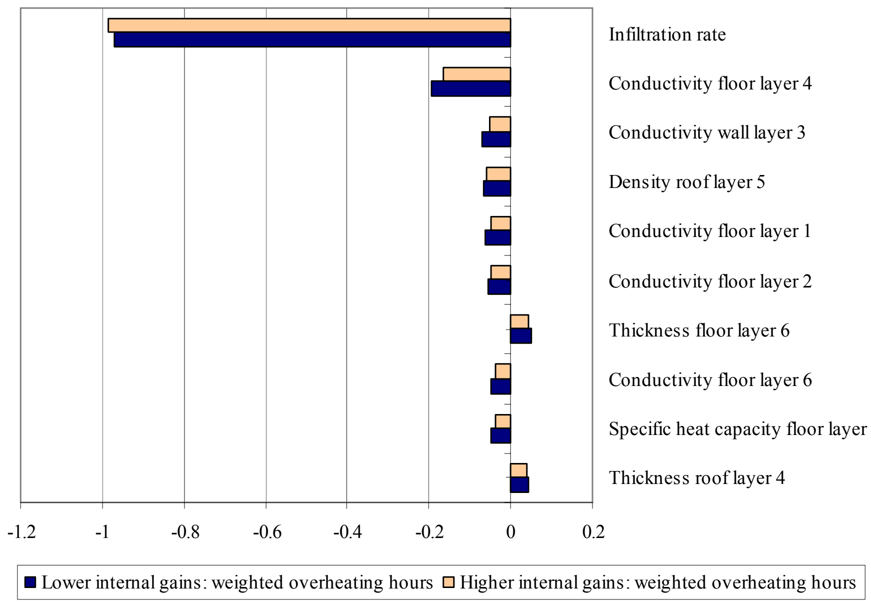
An example presented in this case study is the assumption of a new building owner that changes the building layout by considering a changed amount of employees in the building and a higher or lower amount of internal gains for equipment.
In this case, the uncertainty analysis considers two different scenarios and the uncertainty variation is solely over the physical parameters.
An example of the changed order of sensitivity for the weighted over- and underheating hours is shown in the next section. Two simulations have been run, one under the assumption of lower internal heat gains for people (9W/m²) and one under higher internal gains (16W/m²).

3.9.1 Results of sensitivity analysis



rank	Lower internal gains: weighted underheating hours	Higher internal gains: weighted underheating hours
1	Infiltration rate	Infiltration rate
2	Conductivity floor layer 4	Conductivity floor layer 4
3	Thickness roof layer 4	Conductivity roof layer 4
4	Conductivity floor layer 1	U value single glass
5	U value single glass	Thickness roof layer 4
6	Conductivity roof layer 4	Thickness wall layer 3
7	Conductivity wall layer 3	Conductivity wall layer 3
8	Thickness floor layer 6	Thickness floor layer 6
9	Specific heat capacity wall layer 3	Density roof layer 5
10	Conductivity floor layer 2	Conductivity floor layer 2

Figure 31 Sensitivity plot and table showing the 10 most sensitive parameters based on weighted underheating hours for lower internal gains and compared to weighted underheating hours for higher internal gains when considering uncertainty in physical parameters.



rank	Lower internal gains: weighted overheating hours	Higher internal gains: weighted overheating hours
1	Infiltration rate	Infiltration rate
2	Conductivity floor layer 4	Conductivity floor layer 4
3	Conductivity wall layer 3	Conductivity roof layer 4
4	Density roof layer 5	U value single glass
5	Conductivity floor layer 1	Thickness roof layer 4
6	Conductivity floor layer 2	Thickness wall layer 3
7	Thickness floor layer 6	Conductivity wall layer 3
8	Conductivity floor layer 6	Thickness floor layer 6
9	Specific heat capacity floor layer 6	Density roof layer 5
10	Thickness roof layer 4	Conductivity floor layer 2

Figure 32 Sensitivity plot and table showing the 10 most sensitive parameters based on weighted overheating hours for lower internal gains and compared to weighted overheating hours for higher internal gains when considering uncertainty in physical parameters.

3.10 Discussion

In the presented UA/SA the Monte-Carlo analysis and LHS for uncertainty and sensitivity analysis is used due to its ease of implementation. Other advantages are that different sensitivity analyses techniques such as standardized rank regression and stepwise regression are available. Furthermore, LHS is a stratified sampling, i.e., it

allows a dense range of the sampled parameters. It is a very sufficient method in analysing the verification of a model due to its robustness and correctness.
Uncertainties have been analyzed, identified and are propagated through the model to assess the resulting uncertainty; sensitive parameters are ranked. The SA allows the analysis of the robustness of a model. Furthermore, it makes aware of unexpected sensitivities that may lead to errors or wrong specifications (quality assurance). With the help of robust regression the robustness of the parameters compared to performance aspects are demonstrated.
Stepwise regression analysis is a method to identify most uncertain parameters that affect the uncertainty of performance aspects such as annual cooling/heating and weighted over-and underheating hours.
The parameter importance can be carried out with the rank regression coefficient and a stepwise regression by indicating the order of sensitive parameters being selected in a stepwise procedure.
This evaluation gives an idea of the significance and relevance of uncertainties for design decisions.

The focus of the analysis is a specific aspect of performance analysis in office buildings, meaning the energy consumption and the weighted over- and underheating hours in an office room.
The previous section showed different types of uncertainty analysis. Three different sets of parameters are considered: uncertainty in physical, design, and scenario parameters.
Physical uncertainties are due to uncertainties in physical properties. They are inevitable, however, they can be identified with measurements and tests. Taking physical uncertainty into account leads to quality assurance of the model. Their significance in the use of BPS is very high.
Considering design uncertainties could improve/enable design decision support, in particular if it would be augmented by sensitivity analysis. The input to a decision problem which system to use (option A and B) is very important in the meaning of the building design process.
Taking scenario uncertainties into account is related to design decision support, in particular when considering design robustness and (future) flexibility of the building.
All different types of uncertainties are essential with regard to simulation, performance, and building design. The integration of uncertainties in BPS can benefit design team meetings and dialogues with building partners.
In the case that several alternatives are provided to the decision maker, the designer can choose the design option that fits best his needs covering objectives such as best comfort, low energy demand as defined.
A designer might also leave the design as it (material properties) and consider different systems or change the building design, e.g., the glazing area and room geometry.
Many aspects take impact on this decision procedure. These aspects are difficult to judge, some of them are subjective, some objective. It is difficult to weight those, besides the weighting might differ in a decision making group.
To achieve the above, a special focus will lie on decision making approaches in BPS discussed in the following chapter.

3.11 Conclusion

A realistic case study has been simulated adapting UA/SA. Four different cases were shown considering three different groups of uncertainty: (i) physical, (ii) design and (iii) scenario uncertainties.
The results give a practical example of UA/SA for a specific case study identifying physical, design, and scenario uncertainties as being highly influential.

The integration of UA/SA could support the design process and provide additional information. The output of the UA/SA is presented in different figures and tables. These figures and tables would help the designer in several ways.

(i) Understanding of how parameters are related to each other.
(ii) Comprehension of how variations in the model input affect the output.
(iii) Support in the decision process by providing a basis to compare different design options.
(iv) Enhancement of the use of BPS by providing additional support, and therefore, leading to a better guidance in the design process.

In what manner the presented results will help in supporting the designer in designing building and systems and further in improving the planning process, will be evaluated with the help of mock-up studies and an online survey in Chapter 6.

4

4. Multi-criteria decision making

4.1 Introduction

Decision analysis (DA) describes theory and methodology to handle decision making in a formal manner. Multiple methods, procedures, algorithms and tools applying those approaches are available for structuring a problem into formal representation, guiding to a common consensus, addressing risk and uncertainty or experts experience.
DA according to Zhou [2006] can be structured as follows.
1. Decision making under uncertainty including decision tree, influence diagram, and multiple attribute utility theory (MAUT).
2. Multi-criteria decision making (MCDM) such as multi-objective decision making (MODM) or multi-attribute decision making (MADM).
3. Decision support systems (DSS) such as intelligent DSS based on intelligent agents or artificial intelligence (IDSS).

These techniques differ in complexity and set of strategies. E.g., MADM chooses from small, finite, or countable number of alternatives in the decision problem whilst MODM focuses on a large, infinite, or uncountable number of alternatives. Furthermore, MCDM is mostly classified based on the type of input data or on the calculation of the best solution. However, regardless which techniques are applied, in literature it was mostly referred to as MCDM.

Many reviews of MCDM have been conducted in the past. To mention some, Hobbs et al. [1994] describe methods for resource planning. DA in energy and environmental modelling under uncertainty is a review by Huang et al. [1995]. Salminen et al. [2006] present a review about multi-criteria methods for environmental planning. Pohekar et al. [2004] summarize application areas and trends in the context of sustainable energy planning, etc.

In the following section the theoretical background will be summarized. This chapter continues with state of the art of MCDM in building performance evaluation by providing a framework and categorizing the diverse approaches into three different schools of thoughts.
(1) Deterministic decision making, assuming one solution after weighting the criteria.
(2) Decision making with Pareto.
(3) “Smart” decision making - decision making through the help of expert judgment that implies a human process while less relying on a tool.
Furthermore, a case study is performed showing analytical hierarchy processing (AHP), one of the most famous deterministic decision techniques, extended with the use of BPS and the integration of UA/SA.

4.2 A framework for decision making approaches in building performance

Figure 33 describes a framework that is developed to show different approaches for decision making in the context of the design of building systems. This framework shows how decision makers could select the best design alternative for a particular performance problem.

Before the decision making process starts, the scope of the design decision problem must be completely defined in the format of the problem statement. This statement should describe specific design expectations for the building system of interest. On one hand, design expectations should be determined by a set of relevant design objectives that must be measurable by specific quantifiable outcomes. On the other hand, designers use their knowledge and expertise and combine them with creative thinking to generate as many as appropriate design solutions for the building system. Although a large number of alternatives for the building system extends the duration of the decision making process, it increases the possibility that the best design choice for the building system can be found. Design alternatives are characterized in terms of several attributes and can be either discrete or continuous. The objective of design decision making is to determine the most optimal values for these attributes that define the best design alternative for the building system. Thus, in building design decision making, specific design alternatives will be compared according to their contributions to particular design objectives.

Several decision making approaches have been applied in the design of building systems. These approaches can be divided into two broad categories. The first category contains decision making approaches that use building performance assessment models and simulations for comparing design alternatives. Approaches in this category can further be divided into deterministic and nondeterministic decision making approaches, depending on whether or not they consider uncertainty in the values of model parameters in design decision making. The second category contains decision making approaches that do not use any building performance simulation.

Building performance simulation has been developed and used to assess the future performance of building systems in multidimensional space of specific design objectives. Characteristics of design alternatives (A_1, A_2, …, A_n) are used as inputs for building performance assessment models and outcome values of design objectives (O_1, O_2, …, O_m) will be returned as outputs from building performance assessment simulation.

Building performance assessment models can be used as the backbone for the analysis procedure in a variety of deterministic decision making approaches for building system design. The value of model parameters are assumed to be fixed in deterministic design decision making approaches. The best design alternative will be selected under the certainty assumption. The selection phase that follows the analysis phase is based on one of the techniques in multi-criteria decision making theory under certainty. This approach will be presented in Section 4.4.1.

Many researchers suggest conducting uncertainty and sensitivity analysis on the chosen optimal design alternative(s) to overcome the limitation of fixed parameter values in deterministic decision making approaches. Uncertainty and sensitivity analysis helps design decision makers in assessing how changes in parameter values impact the performance of building systems. This way to study uncertainty in design decision making will be shown in Section 4.4.2 by combining the results from Chapter 3 with the classical Analytical Hierarchy Process (AHP).

However, most of the time it is not easy to pick a single design alternative as the best alternative for a building system since design alternatives compete with each other across multiple design objectives. Hence, designers perform Pareto optimality analysis to determine the frontier of design alternatives that are not dominated by other design alternatives with respect to their performance in the multidimensional space of design objectives. Several design alternatives will be removed from further consideration based on Pareto optimality analysis in deterministic decision making.

Building performance simulation can also be used as the analysis backbone in nondeterministic decision making approaches. The big difference is that the values of model parameters are not fixed in nondeterministic decision making approaches. Important sources of uncertainty that are identified by designers will be treated as nondeterministic parameters in building performance assessment models. The risk factors show uncertainty as indicated by (c_1, c_2, …, c_k) in Figure 33. Designers also provide the distributions of these uncertain parameters in building performance assessment models. Outcome values of design objectives will be computed by building performance assessment models for each design alternative. Probability distributions of multiple outcome values (or risk profiles of design objectives) will be calculated for each design alternative using building performance assessment models. Some researchers suggest using one of the multi-criteria decision making approaches under uncertainty to choose the best design alternative considering risk profiles of design objectives for the all design alternatives [Zhao et al., 2004; Cooke, 2008]. Other researchers have used MAUT as a standard decision analysis methodology for decision making under uncertainty [Blondeau et al., 2002; Nassar et al, 2003]. Designers express their preference for each possible set of outcome values of a design alternative. This preference is specified in terms of a single value, which is called the utility value. The utility values of design alternatives (A_1, A_2, …, A_n) are shown by ($U(A_1)$, $U(A_2)$, …, $U(A_n)$), respectively in Figure 33. Probability distributions (or risk profiles) of utility values will be summarized for each design alternative. MADM approaches will be used to choose the best design alternative considering risk profiles of utility values for the entire set of design alternatives.

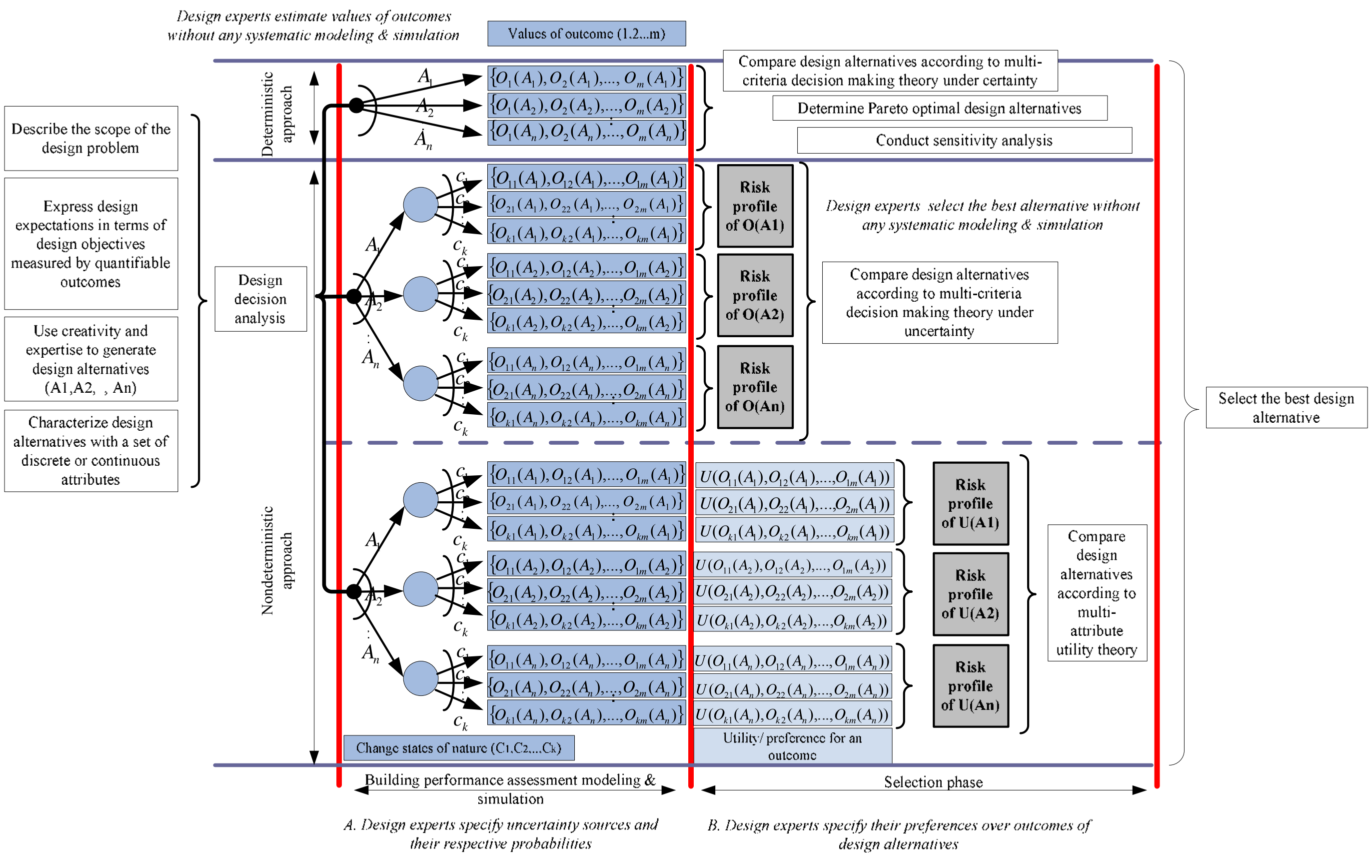


Figure 33 Visualization of a framework for different decision making approaches in the context of building design.

As mentioned earlier, there are also approaches that do not use formal models and simulations for design decision making. This can be as a result of limited resources (either financial or time wise) or the lack of sufficient knowledge about an underlying building system. Anyhow, inputs from outstanding designers are used for the decision making. Designers can help decision making in two ways as shown in Figure 33. Designers specify sources for uncertainty and evaluate probable errors in terms of a certain aspect [Hui et al., 2007]. This direct selection is primarily based on design expert opinions without using any formal modelling and analysis.
In addition, designers can estimate outcome values of design objectives for each design alternative [da Graca et al., 2007]. This estimation bridges the gap between design alternatives and values of design objective without any need for building performance assessment models and simulations.

4.3 Overview of techniques in DM

4.3.1 The deterministic weighted criteria approach

Most decision making is prescriptive or normative. It is aimed at making the best decision without taking uncertainties into consideration. Decision makers should have the perfect insight and knowledge to take the most rational decision/ solution in the end. In the normative theory, a model is provided that allows a rational decision maker to keep his preference over certain attributes consistent in his task [Moon et al., 2007]. It enables the ranking of available options by decision maker's preference [Moon et al., 2007]. The deterministic problem can be expressed in a matrix form that is shown in equation (1), where the criteria C indicate the performance to the alternatives A.

$$\begin{array}{cc} & \begin{array}{ccc} w_1 & w_2 & ..w_n \\ C_1 & C_2 & ..C_n \end{array} \\ \begin{array}{cc} x_1 & A_1 \\ x_2 & A_2 \\ \vdots & \vdots \\ x_m & A_m \end{array} & \begin{bmatrix} a_{11} & a_{12} & ..a_{1n} \\ a_{21} & a_{22} & ..a_{2n} \\ & & \\ a_{m1} & a_{m2} & ..a_{mn} \end{bmatrix} \end{array} \tag{1}$$

A set of m alternatives $A_1, A_2, A_3, ..., A_m$ is given, as well as a set of n decision criteria $C_1, C_2, C_3, ..., C_n$. Furthermore, it is assumed that the decision maker has determined the performance value a_{ij} (for the i^{th} alternative and the j^{th} decision criterion) of each alternative; w_j as the weight of the j^{th} criterion and x_i as the ranking value of the i^{th} alternative of each alternative.
The weighting w_j defines the importance of the criteria/alternatives. These weights are usually normalized. Several techniques have been developed and applied in the past. Some of them that have been implemented in BPS will be described briefly.

4.3.1.1 Simple multi-attribute rating technique (SMART)

SMART is based on the theory of multi-attribute utility. Its implementation is simple. There is a direct entry of relative score and weights. One example for the additive model to obtain the ranking value x_i (performance value) of alternatives A_j, taken from [Fülöp, 2005] reads

$$x_i = \sum_{j=1}^{n} a_{ij} w_j / \sum_{j=1}^{n} w_j , \qquad \text{for i= 1,2,…,m} \qquad (2)$$

In BPS only one application of SMART is found. In Salminen et al. [1998] it is used to compare it with three other multi-criteria methods. For that reason, they use four different real applications in the context of environmental problems.

An advantage of Smart is that all differences in criteria values are taken into account, i.e., differences such as preferences, indifferences, and incomparability are assigned a numerical value. It was stated that it is a very easy to implement method. However, it was also found out, that it only can be applied with a limited number of criteria; a maximum number of eight is advised.

In order to avoid problems in decision making with a higher number of criteria, Salminen et al. [1998] propose to rank the criteria first and then to drop those with a lower weighting.

The proposed formula for SMART is only one example. Different models for the utility values can be assumed, e.g., a variant named SMARTS (SMART using swings) considers the amplitude of utility values of the alternatives [Edwards et al., 1994]. That means the difference from worst to best utility value among the alternatives.

4.3.1.2 Analytical hierarchy process (AHP)

The AHP protocol (developed by Saaty in the 1970s) is one of the most widely applied and well-known techniques of MCDM. AHP lets stakeholders rank the criteria by their importance in relation to the decision problem and in relation to each alternative through a pair-wise comparison [Saaty et al., 1980]. The use of AHP applied for a case study is shown in Section 4.4.

AHP is based on the assumption that decision problems can be hierarchically structured with an one-directional relation between the decision levels.

The $A^*_{AHPscore}$ of the best alternative is calculated by

$$A^*_{AHPscore} = \max_i \sum_{j=1}^{n} a_{ij} w_j , \qquad \text{for i= 1,2,…,m} \qquad (3)$$

AHP is also the most commonly applied technique in decision making in BPS. More than 20 recent approaches are found in literature, e.g., such as follows.

Chiang et al. [2002] published a study on the comprehensive indicator of indoor environment assessment for occupants' health.

Wong et al. [2008] showed an application of the AHP in multi-criteria analysis for the selection of intelligent building systems.
Kim et al. [2005] developed a housing performance evaluation model for multi-family residential buildings considering criteria such as thermal comfort, indoor environmental quality, usability, and surroundings.
In general, it is stated that it is an easy to implement approach, applicable for multiple stakeholders and multi-criteria decision problems [Wong et al., 2008].

However, also many criticisms can be found. For instance, that it suffers from rank reversal if one of the criteria is deleted during the decision process [Hazelrigg, 2005]. Further, it lacks of firm theoretical basis and uncertainties are not considered in the conventional AHP.
Besides, the weighting scale of 1-9 can cause problems in the consistency of the ranking which has been shown in [Tam et al., 2006]. Tam et al. [2006] also propose an alternative method that limits the scaling to 1-3 and thus, automatically solves the issue of the consistency.

4.3.1.3 ANP (Analytical network process)

The ANP, also developed by Saaty [2004], can be described as the generic form of AHP. It provides a framework that enables the user to handle decision making considering dependencies of elements on different levels.
The ANP opposed to the AHP offers a control network that, instead of a linear hierarchy with a goal on the top down to the alternatives on the bottom (AHP), has a nonlinear structure. This is beneficial, if the decision problem does not consist of elements but groups of clusters. Within this control network, different criteria can be dealt with leading to the analysis of risks, opportunities, etc. [Saaty, 2004].
An example of the application of ANP in BPS is given in [Cheng et al., 2007]. They propose ANP in process models giving an example of strategic partnering. The problem is divided into partnering information (e.g., communication, team building), partnering application (partnering goals), and partnering reactivation (long-term commitment). The three top level aspects, information, application, and reactivation, are indirect or direct related to each other. To cover those relations, ANP is a good solution.
If the relationship between aspects and criteria is uni-directional and the elements of different decision levels along the hierarchy are uncorrelated, AHP is sufficient.

4.3.1.4 Weighted sum method (WSM)

The weighted sum method is according to the equation very similar to the AHP. The difference is that in the AHP the criteria are brought into relation and no actual values are used.

The WSM is the most commonly applied method in single dimensional problems [Triantaphyllou, 2000]. That means, problems, where two criteria exist that have the same unit in order to be comparable. As an example, if the criterion is cost related, the investment versus the running costs can be evaluated. However, the problem is not solvable with WSM, if thermal comfort should be compared to energy consumption.

The best alternative is based on the WSM score A^*_{WSM} :

$$A^*_{WSM} = Max\sum_{j=1}^{n} a_{ij} w_j \quad \text{for i= 1,2,3,..m} \tag{4}$$

WSM is based on the additive utility assumption which implies that the total value of each alternative equals the sum of products such as in equation (4) [Triantaphyllou, 2000].
Examples for the applications of WSM in BPS are in the design for sustainability shown in [Ugwu et al., 2007] or in the building environmental assessment by Soebarto et al. [2001]. They for instance describe theory and implementation of multi-criteria assessment of building performance. For this reason, they convert the multi-criteria problem into a two-criterion problem by forming a weighted sum of the benefits and costs for each solution.
However, if the problem is multi-dimensional (different units) the additivity assumption is violated [Solnes, 2003].
Another drawback of WSM is that the domination of one criterion may occur. This can be the case with a non-convex Pareto front. Only extreme solutions (solutions on the edges) can be found but no sufficient solutions in between [Emmerich, 2006].

4.3.1.5 Preference ranking organization method for enrichment evaluation (PROMETHEE)

PROMETHEE is a method that uses the outranking principle to rank alternatives. Like AHP, it provides pair-wise comparison of alternatives. In [Brans et al, 1986] six types of generalized criteria are presented: usual criterion, level criterion, Gaussian criterion, amongst others.
Further on, two ways were proposed: PROMETHEE I for obtaining a partial order of parameters and PROMETHEE II for obtaining a complete order.

PROMETHEE is compared to SMART in a BPS study by Salminen et al. [1998]. They apply the method in the context of environmental problems and present it as easy to implement and with comparable results to SMART.
Similar to the AHP approach, PROMETHEE suffers also from rank reversal.
Nevertheless, a disadvantage compared to AHP is that differences in criteria values, due to restrictions of the pair-wise comparison, are not taken into account totally. Other drawbacks of this method are summarized in [De Keyser et al., 1996].

4.3.1.6 Elimination and choice translating reality (ELECTRE)

ELECTRE is after the AHP approach the second most applied decision making protocol in BPS.
The ELECTRE method such as PROMETHEE was introduced to handle outranking relations by pair-wise comparison among alternatives [Triantaphyllou, 2000]. It can deal with discrete criteria of quantitative and qualitative nature [Pohekar et al., 2004]. ELECTRE uses the concordance/ discordance indices as well as threshold values.

The concordance index can be defined as the amount of evidence to conclude that alternative A_i dominates A_k; the discordance index defines the counterpart.

The presented index of global concordance C_{ik} shows the evidence to support the concordance among all criteria, assumed that A_i outranks A_k [Pohekar et al., 2004].

$$C_{ik} = \sum_{j=1}^{m} w_j C_j (A_i A_k) / \sum_{j=1}^{m} w_j \tag{5}$$

ELECTRE I is for constructing a partial ranking and choosing a set of promising alternatives. In [Blondeau et al., 2002] it is used for finding the most suitable ventilation strategy in a summer period considering indoor air quality, thermal comfort, and energy consumption.
ELECTRE II is applied for ranking the alternatives [Fülöp, 2005]. An application can be found in [Rutman et al., 2005] for analyzing the quality of an air-conditioned environment. Criteria used are thermal and acoustic comfort.
ELECTRE III is based on a global preference model, expressed by weights assigned to criteria [Beccali et al., 1998]. The measures for the ranking can be expressed by a degree of confidence. ELECTRE III is the recommended method among three techniques (SMART and PROMETHEE) by Salminen et al. [1998]. However, the application is also described of appearing rather complicated and time consuming. Therefore it is not advised choosing ELECTRE if fast results need to be obtained or the ranking of criteria can change during the decision process.

4.3.2 Decision making with Pareto optimization

Pareto was an Italian economist who, together with Edgeworth was the first to come with the concept of vector dominance or Pareto dominance, defining a partial order on the set of objective function vectors of a set of decision alternatives.
The maximum number of elements of this partial order are said to be Pareto optimal.
Pareto optimization identifies the set of non-dominated solutions and visualizes the projection of this set in the objective space. This projection, the so-called Pareto frontier, can be interpreted as a trade-off curve or surface on basis of which the decision maker can learn about the nature of the decision conflict and choose a compromise solution from the reduced set of alternatives.

Definition Pareto dominance

It can be said that y_1 dominates y_2 ($y_1 \succ y_2$), if it is better in at least one component and minimum equivalent in the remaining components. Dependent on the objective function it can be either < or >.
In case, two points do not dominate each other, they are both equivalent.

The amount of non-dominated solutions is called Pareto frontier.

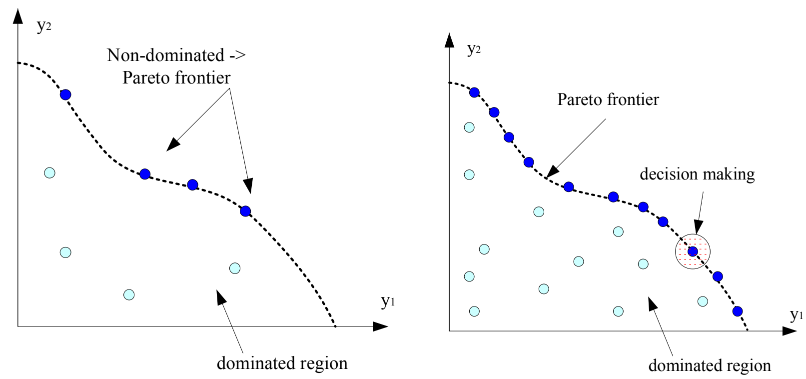


Figure 34 Visualization of the Pareto frontier as a set of all non-dominated points in the context of decision making.

In Figure 34 the Pareto frontier is shown as the set of all non- dominated points. In this example the maximisation problem is described of a two-order Pareto frontier, i.e., the decision problem induces two objectives. In high-order Pareto as in [Kollat et al., 2007] three or more objectives are applied.

Different methods enabling the user to generate the Pareto frontier can be found in literature [Wuppalapati et al., 2008] such as follows.

1. Genetic algorithms: a population of search points is moved gradually to the Pareto frontier, driven by mutation, recombination and selection operators. The non- dominated points are identified and adjustments are done in order to fitness the values (see Chapter 5).
2. Weighting approach: after defining the weighting, results are plotted in criterion space. It is applicable for problems with a non-convex Pareto frontier.
3. Constraint method: all except one objective are treated as constraints. By gradual relaxation of the constraints a complete picture of the Pareto frontier is obtained.

Three different approaches can be defined in Pareto optimization in the context of MCDM: a priori, a posteriori, and progressive.

4.3.2.1 A priori

The latin phrase "a priori" can be translated as "from cause to effect" or "from what comes before". It is a deductive method and implies that a decision regarding the preferred solution has to be made before the search of the solution space (decide → search). A priori methods are single objective approaches that require experience and knowledge from the decision maker when aggregating different objectives.

For the performance aspects weights have to be assigned. For the constraints boundary values have to be set. A classical a priori method is the normative decision making . An example shown in Figure 35 is the weighted sum of, for instance, two criteria yielding in a single objective function. Wright et al. [2002] show the cost function built out of the investment costs ($f_I(X)$) and the running costs ($f_R(X)$) with an assigned weighting.

$$f(X) = w_R f_R(X) + w_I f_I(X) \qquad (6)$$

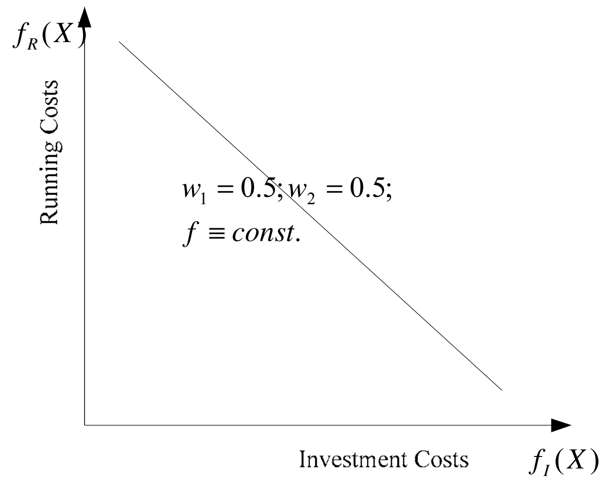


Figure 35 Illustration of the weighted sum of investment costs and running costs.

It needs to be added that a priori methods are very similar to weighted sum methods and have therefore been already discussed in 4.3.1.4. In contrast to Section 4.3.1.4, where a deterministic search space is considered, the search space in the context of Pareto optimization is much larger. Therefore it might be said that a multi-objective optimization problem is solved by recasting it as a single-objective optimization problem.

4.3.2.2 A posteriori

The latin phrase "a posteriori" stands for “from what comes after”. It is an inductive reasoning based on observation or observed facts. It means first search then decide. The Pareto optimal set has to be found first, before the decision is taken. The following example shows two objective functions $f_1(X)$ and $f_2(X)$. The non-dominated solutions are indicated in Figure 36 by the number "0". It means there is no other solution that has a lower value in any criterion; on the contrary the solution labelled "4" has four other solutions in the set that dominate it in both objectives.

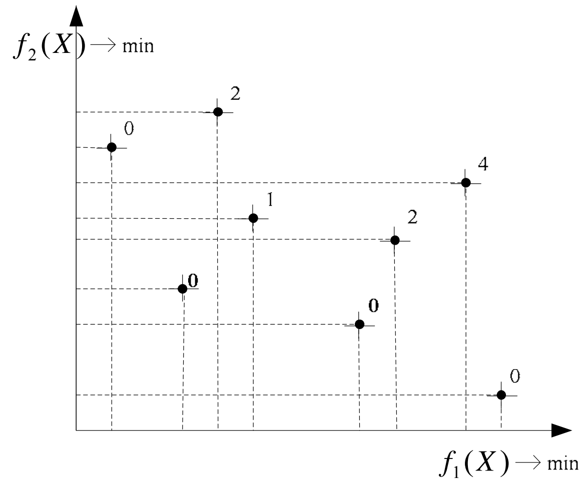


Figure 36 Illustration of a posteriori with two objectives to be minimized [Wright et al., 2002].

Multi-objective evolutionary algorithms (MOEA) support the multi-objective decision making; with help of the population-based search multi-objective evolutionary algorithms (MOEA) the entire Pareto front can be approximated in a single run of the algorithm [Deb, 2001]. Examples are shown in [Kollat et al., 2007] and [Emmerich et al., 2008].

4.3.2.3 Progressive

The progressive method stands for a decision making where deciding and searching is merged into each other (decide ↔ search). The process of guiding and searching is conducted interactively by assigning different weights throughout the decision process and repeating the optimization. It is obvious that this procedure is computationally intense and requires lots of time. This is the reason why it is less applied in building performance [Wright et al., 2002]. Examples can be found in [Miettinen, 1998].

4.3.3 "Smart" decision making

Smart decision making means that the decision process includes knowledge and experience from experts. It can be described as a snapshot of the experts’ knowledge that, based on information, experience, etc., can even change through time. Experts in building performance can be stakeholders participating in a design team meeting with equivalent or different background depending on the problem situation. Assuming that they are qualified, their specific expertise must be recognized. Decision making based on expert knowledge is a well-known method of decision analysis in engineering, risk assessment, and environmental research.

Formal processes can be applied starting by choosing the experts and stating their background and knowledge considering one problem area. Further on, the problem statement is defined, and methods are chosen to elicit and analyze the judgment.
Examples in literature, where user judgement is applied, include prediction of performance [Jensen et al., 2009], information about what data sets are of importance for an analysis [Wong et al., 2008], probability distributions in a problem situation [Hui et al., 2007], and importance/ necessity of variables in a statistical study [Chiang et al., 2002], among others.
The goal of expert judgement is usually to structure a problem, to find the necessary and relevant criteria, to provide estimates of failure, to determine factors for combining data sources, etc. The way to express the results/ estimates of expert judgment is either in a quantitative form (probabilities, uncertainty estimates, physical quantities, e.g., costs or weighted overheating hours) or in a qualitative form (written explanation of an experts assumption, physical quantities like "the system performs badly" or comments why certain data are relevant and others not) [Meyer et al., 2001]. It is a preferable method when information and data are expensive to achieve, or the problem is difficult or should involve different interpretation. Besides, it integrates heterogeneous information to determine the state of knowledge in a problem (for example, what is known and how well it is known) [Meyer et al., 2001].
For the analysis of the expert judgment statistics play a major role. Mathematical methods are provided for aggregating differing experts' responses, quantifying the accuracy of experts' predictions, combining different types and sources of data, and formulating models using the experts' responses [Cooke, 2008].
Expert judgement in BPS is often found in combination with Pareto [da Graca et al., 2007] and deterministic methods like AHP [Wong et al., 2008; Ugwu et al., 2007]. In some cases the expert judgment was further on used to achieve a prior estimation for distribution. Bayesian methods can be used after "real" data becomes available to update expert's reliability.

A Bayesian network (or Bayesian Belief Network (BBN) or causal probabilistic network) is a graphical model that provides support to experts dealing with incomplete or uncertain information. It consists of two parts: a probabilistic graphical model and its underlying probabilistic distribution [Naticchia et al., 2007].
It is a well-known method in the field of reasoning under uncertainty and therefore to deal with incomplete or uncertain information. Formally, a Bayesian network can be described as a directed graph, together with an associated set of probability tables [Pearl, 1988]. The graph consists of nodes that represent variables that are either discrete or continuous. The arcs encode conditional independencies between the variables.
There exist efficient algorithms that perform inference and learning in Bayesian networks, in order to support BBN for probability dissemination purposes and for elicitation of conditional probability tables [Naticchia et al., 2007].

4.4 Prototype description of applying AHP

In the previous sections, the state-of the art of several approaches for decision making in BPS were presented. None of the approaches that were demonstrated include the integration of results that are achieved from BPS and UA/SA of the simulation result. Due to the fact that UA/SA is an important subject, the implementation of a common decision making protocol coupled with BPS and UA/SA information will be shown in the next section.

The prototype description is divided into the conventional and the adapted AHP protocol. The setup will be described briefly before the more extensive description is shown in Section 4.5.

4.4.1 The classical AHP

The AHP protocol is a deterministic decision approach described in Section 4.3.1.2. AHP has been chosen as it is one of the most commonly applied techniques in decision making. The setup is easy to comprehend and sufficient for multi-criteria decision problems being solved by multiple stakeholders. Besides, it will be shown that it can be easily extended by the use of BPS and UA/SA.
First, the classical AHP will be described. Then the traditional decision protocol will be extended with uncertainty in performance prediction. The workflow of the classical AHP protocol is shown in Figure 37.

The decision making protocol starts with defining the objective of the decision making problem, stating number of stakeholders and the criteria relevant to conduct the decision.
The comparison matrix is built by a pairwise evaluation of each alternative and criterion. A priority ranking is developed in the end, indicating the best solution of the problem defined.

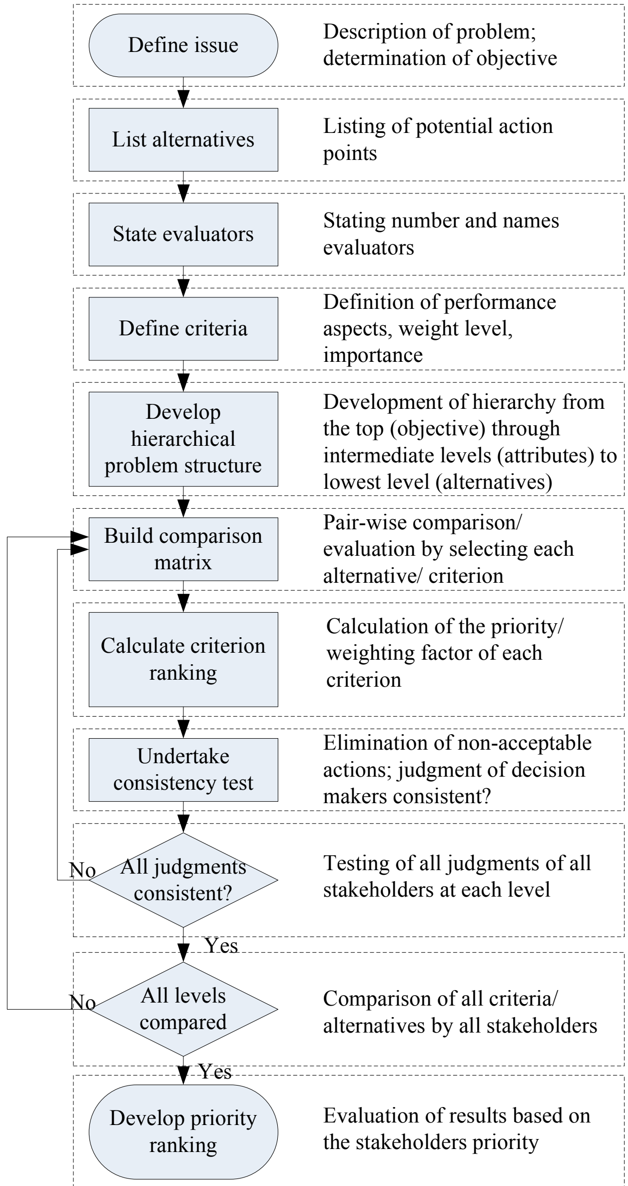


Figure 37 Illustration of the workflow showing the classical AHP protocol from defining the issue down to developing the priority ranking.

4.4.2 The adapted AHP

In Figure 38 the conventional AHP protocol is shown on the left hand side. On the right, the add-on to the classical approach is shown which will be described in Section 4.5.2 more detailed. The concept is to include UA/SA in the decision making process and to evaluate the performance aspects that are calculated with BPS under uncertainty.

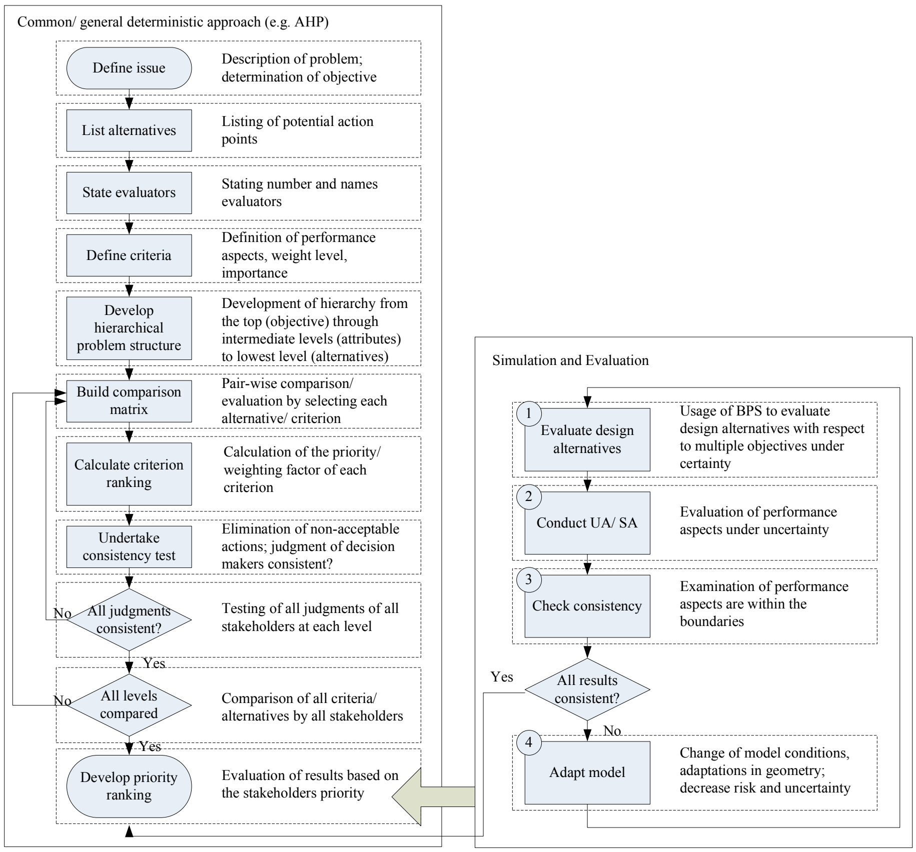


Figure 38 Illustration of the workflow of the adapted AHP protocol that includes the use of BPS and the conduction of UA/SA.

4.5 Case study of applying AHP

From evidence gathered from previous research, interviews with leading building and system designers [Hopfe et al, 2005], and design team observation [Hopfe et al, 2006] it can be concluded that decision making in the context of high performance buildings requires an integrated team approach.
Architects, engineers, building physicists, clients, and occupants should be involved from the early beginning. Over-restricted and/or unsynchronized design teams run the risk of limiting themselves too early in the design process.
However, even with well-coordinated partners, it can be difficult to find consensus on basic design concepts that lead to a design solution that all parties perceive as optimal.
The main reason for this is the multitude of perspectives, targets, and criteria on one hand. And on the other hand, the preferences that are present among each stakeholder. This begs for the adoption of rational decision making protocols by multi-stakeholder design teams. Most of the reported work found in literature (cf. Section 4.3) does not deal with an important aspect of decision making: the role of uncertainty and risk attitude of the stakeholders. It is hypothesized that uncertainty in performance predictions of competing options is not negligible and therefore should play a major factor in the decision.
At a certain level of abstraction, design evolution can be viewed as a series of decisions under uncertainty. A decision is taken based on the design options that produce the most desirable outcomes, while accepting the associated risk that this option may also produce less favourable outcomes in certain performance aspects. It is further hypothesized that in order to support a design team to reach an optimal decision a computational approach is needed. This informs the team about predicted building performance (also revealing the risk of under-performance) and may initiate a discussion aimed at identifying the most favourable concept given the risk attitude of the stakeholders.

In the following section a decision making protocol is described to achieve this. The case study from Appendix A is taken with an additional option. The building is an ideal case study because it combines flexibility and function. In addition the project's final stage confronted the design team with a choice between two options both of which were designed in great detail, i.e., both of them ready-to-be build. The first option represents a mainstream standard solution: a conventional heating/cooling system like the one chosen for the uncertainty/sensitivity study in Chapter 3. The second design option represents a novel, "risky" design, incorporating heating/cooling storage in combination with a double façade. Both systems are described in Appendix A and B.

The treatment of the case follows common rational decision theory and hence assumes that the decision process is purely rational. Furthermore it is assumed that stakeholders pursue no other agenda then choosing the best performing design option. In this decision process they are only influenced by the objective probabilistic predictions of the relevant performance measures, their subjective importance ranking and the risk attitude of each stakeholder. The decision problem thus falls in the standard category of multi-criteria decision making under uncertainty.

The design team of the project consisted of the following members, amongst others: the architect [Klunder architecten, 2009], the building physics consultant and systems/ building services engineer [Nelissen b.v., 2009].
Three members of the design team were asked separately to make a list with the most important performance aspects of the building. Performance aspects such as initial costs, architectural layout, image/symbolism, energy consumption and thermal comfort were mentioned by all participants although with varying levels of significance and importance.
The following table shows the (reduced set of) performance criteria that are the focus of the decision making process that is described in the next sections.

Table 10 Listing of the performance aspects that are relevant in the decision making process.

A	initial costs
B	indoor resultant temperature
C	overheating hours (weighted)
D	under-heating hours (weighted)
E	individual control
F	floor area per person
G	space height
H	energy consumption
I	architectural form
J	symbolism (image /status)
K	changeability (flexibility)

4.5.1 The classical AHP

In the classical AHP protocol the criteria have to be selected and ranked to each other by a pair-wise comparison and assigning numbers from 1 as ‘equally important’ up to 9 for ‘extremely more important’ (see Appendix D).
Table 11 shows the result of the ranking based on a consensus of three stakeholders. The result of the decision makers separately can be seen in the Appendix D. The column on the right side of Table 11 is the weighting factor based on normalizing all criteria after computing the eigenvalue. As Saaty [1985] has proven mathematically the eigenvalue is a good solution for obtaining a set of priorities out of a pair-wise comparison matrix. Therefore, the matrix is multiplied with itself, the sum of the rows is built and normalized.
It can be noticed that performance aspect A ‘initial costs’ is not included in Table 11. Even though it was stated that initial costs have an impact on the final decision, it was requested by the decision makers to exclude the costs in the beginning of the decision protocol as they become only relevant in the end of the decision process. The purpose is to show graphically the overall performance compared to a cost factor in the end.
It can be seen that symbolism has the highest impact followed by the weighted under- and overheating hours.

Table 11 Illustration of the decision matrix for the calculation of the weighting factors for the performance aspects B to K.

		B	C	D	E	F	G	H	I	J	K		
B	indoor resultant temperature	**1**	0.33	0.33	**1**	**5**	**7**	**1**	0.33	0.2	**1**	B	**0.061**
C	overheating hours (weighted)	**3**	**1**	**1**	**3**	**7**	**7**	**3**	**1**	0.33	**3**	C	**0.146**
D	Under heating hours (weighted)	**3**	**1**	**1**	**3**	**7**	**7**	**3**	**1**	0.33	**3**	D	**0.146**
E	individual control	**1**	0.33	0.33	**1**	**5**	**7**	**1**	0.33	0.2	**1**	E	**0.061**
F	floor area per person	0.2	0.14	0.14	0.2	**1**	**3**	0.2	0.14	0.14	0.2	F	**0.018**
G	space height	0.14	0.14	0.14	0.14	0.33	**1**	0.14	0.14	0.11	0.14	G	**0.013**
H	energy consumption	**1**	0.33	0.33	**1**	**5**	**7**	**1**	0.33	0.2	**1**	H	**0.061**
I	architectural form	**3**	**1**	**1**	**3**	**7**	**7**	**3**	**1**	0.33	**3**	I	**0.146**
J	symbolism (image /status)	**5**	**3**	**3**	**5**	**7**	**9**	**5**	**3**	**1**	**5**	J	**0.287**
K	changeability (flexibility)	**1**	0.33	0.33	**1**	**5**	**7**	**1**	0.33	0.2	**1**	K	**0.061**

As an example, the results of the weighting for performance aspect B = 0.061 is calculated as follows.
The sum of the products 1-10 from the first row (for B) with column 1 ((1*1)+(0.33*3)+ (0.33*3)+…) until column 10 ((1*1)+(0.33*3)+ (0.33*3)+…).

The result is normalized with all the other weightings, i.e., the total sum of the last column is 1.

The relative importance is shown graphically in Figure 39 in a Pareto plot. The criteria by means of their relative importance are shown in a block diagram and a cumulative graph.

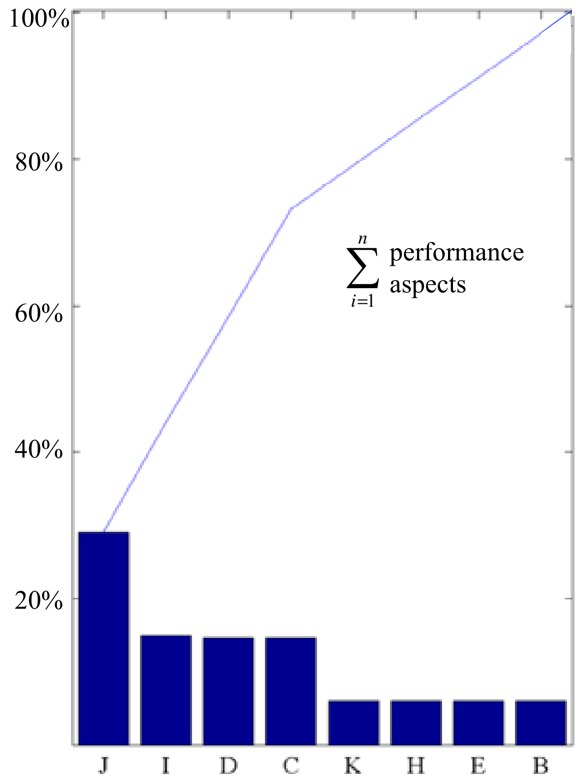


Figure 39 Illustration of the Pareto plot showing the percentage impact of the performance aspects considered to the total performance of 100%.

After calculating the weighting factor for the performance aspects B to K as shown in Table 11, the two options (Appendix A) have to be compared to each other. For that reason they have to be assessed for every performance aspect separately. This is shown in Table 12 and 13. The perception for each option considering criterion H 'architectural form' and I 'symbolism' is judged qualitatively by the stakeholders.

An example is shown for the aspect H (architectural form). Design option 2 is according to Appendix D “very strongly more important/ better” compared to design option 1. This relation is expressed with a ‘7’. The decision matrix is as follows.

$$\begin{array}{ll} & \begin{array}{cc} \textit{option } 1 & \textit{option } 2 \end{array} \\ \begin{array}{l} \textit{option } 1 \\ \textit{option } 2 \end{array} & \begin{bmatrix} 1 & 1/7 \\ 7 & 1 \end{bmatrix}^2 \end{array}$$

For the explanation of the calculation of the ranking for the criteria the following table is shown.

Table 12 Demonstration of the calculation of the weighting for the performance aspect architectural form.

H: architectural form						
	design option 1	**design option 2**				
design option 1	1	0.14	_(1*1)+ (0.14*7)+ (1*0.14)+ (0.14*1)_	2.28	_2.28/ 18.28_	**0.12**
design option 2	7	1	_(7*1)+(1*7)+ (7*0.14)+ (1*1)_	16	_16/ 18.28_	**0.88**
			∑	**18.28**		

The calculation of the final ranking of 0.12 and 0.88 is shown in the italic written parts. The weighting factor for design option 1 for architectural form is 0.12 and for design option 2 it is 0.88.

Comparable is the approach for the performance aspect symbolism. Design option 2 is according to Appendix D “strongly more important/ better” compared to design option 1 and is assigned with a ‘5’.

$$\begin{array}{ll} & \begin{array}{cc} \textit{option } 1 & \textit{option } 2 \end{array} \\ \begin{array}{l} \textit{option } 1 \\ \textit{option } 2 \end{array} & \begin{bmatrix} 1 & 1/5 \\ 5 & 1 \end{bmatrix}^2 \end{array}$$

For the explanation of the calculation of the ranking for the criteria the following table is shown.

Table 13 Demonstration of the calculation of the weighting for the performance symbolism.

I: symbolism						
	design option 1	**design option 2**				
design option 1	1	0.2	*(1*1)+ (0.2*5)+(1*0.2)+ (0.2*1)*	2.4	*2.4/ 14.4*	**0.17**
design option 2	5	1	*(5*1)+(1*5)+ (5*0.2)+(1*1)*	12	*12/ 14.4*	**0.83**
			∑	**14.4**		

The calculation of the final ranking of 0.17 and 0.83 is shown in italics. The weighting factor for design option 1 due to symbolism is 0.17 and for design option 2 it is 0.83.

Instead of weighting all performance aspects dependent on the stakeholders personal preference, the impact of subjective and thus, uncertain information is reduced. This is done by including the outcome of a building performance simulation tool. Results such as energy consumption and thermal comfort are calculated and inserted into the AHP protocol.
The approach is shown in Table 14. The amount of weighted overheating hours for both options is put into relation and gets normalized. Hence, the weighing factor is based on real data instead of users' preference.

Table 14 Demonstration of the calculation of the weighting for the performance aspect weighted overheating hours.

C: weighted overheating hours			
	[h]		
design option 1	17	*1-(17/21)*	**0.19**
design option 2	4	*1-(4/21)*	**0.81**
∑	**21**		

The amount of weighted overheating hours for design option 1 calculated by VA114 is 17h, for design option 2 it is 4h. The italic part shows the calculation of the final rank for both options regarding the weighted overheating hours.

Finally, the outcomes are summarized into one matrix. Table 15 shows a combination from data based on experts preference, experience, and personal judgement and on the simulation results provided by a tool.

Table 15 Ranking of both options for the performance aspects B to K.

	B	C	D	E	F	G	H	I	J	K
design option 1	0.50	0.19	0.19	0.50	0.25	0.50	0.42	0.13	0.17	0.25
design option 2	0.50	0.81	0.81	0.50	0.75	0.50	0.58	0.88	0.83	0.75

The values for performance aspects B, E, G, I, J, and K are achieved based on preferences and attitudes of decision makers according to Table 12. C, D and H are calculated by VA114 and normalized according to Table 14.

The final outcome based on the classical AHP protocol but with the help of BPS is for design option 1 0.23 and for design option 2 0.77. The final value is calculated by the sum of the products row 1 with columns B to K for design option 1 and the sum of the products row 2 with columns B to K for design option 2 from Table 10. It shows that design option 2 is clearly favourable to design option 1.

4.5.2 The adapted AHP

The traditional AHP protocol does not take into account that performance outcomes can be probabilistic variables. For the purpose of solving the application problem, the method is extended by adding uncertainty information that relates design options to all performance indicators.

The goal is to include risk assessment in the conventional AHP protocol. Uncertainty analysis (UA) is applied to enable the designer in getting an insight in parameters chosen for each option. As shown in Chapter 3, UA studies are conducted to show the variability in the output of a model that can be referred to different sources of variations in the input.

The workflow of the adapted AHP protocol is shown in Figure 38. This research considers 3 different categories of uncertainty: physical, scenario and design uncertainty (cf. Chapter 3). In this study the emphasis has been on physical parameters, mostly identifiable as the standard input parameters in energy or thermal comfort simulation, but also parameters from the other categories have been chosen. Approximately 80 parameters have been changed in total. Assessments were made under fixed scenarios, which is common in uncertainty analyses. An exception is the heat load of equipment, lighting and number of people in the space. The most important parameter in design uncertainties is the room geometry. As the decision had to be made at a stage where the floor plan in either option was undefined, room geometry was entered into the uncertainty analysis.

As an example, the outcome for annual heating is shown in Figure 40. The square shows the result of the first simulation – the result that is actually used in the conventional AHP protocol. The range gives an insight how much impact uncertainties have on the simulation outcome after conducting 200 simulations.

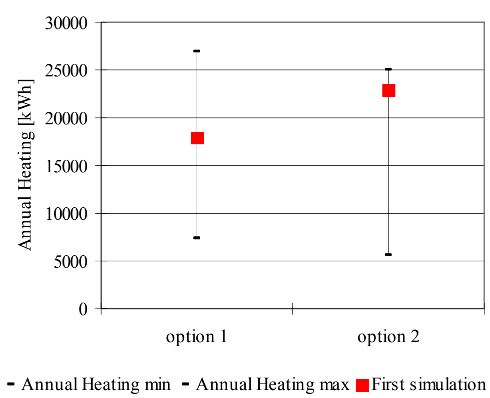


Figure 40 Range of the outcome for the annual heating obtained by 200 simulations considering physical, scenario and design uncertainties.

Due to the consideration of uncertainties in the parameters, the simulation results for energy and thermal comfort cover a range as shown in Figure 40. The boundaries of this range can be titled as worst and best performance due to the consideration of uncertainties. The worst and best performance also affects the weighting factor calculated in Table 10. How much both, the uncertainty and the weighting impact the result is demonstrated in Table 16. The table shows the typical AHP result (from the classical method), and additionally the best and worst performance for both options in relation to the entire design team and each design team member separately. The results are achieved comparable to the conventional method but with the difference that hereby the upper and lower confidence bound of the results are taken to show the best and worst performance for energy and thermal comfort apart.

Table 16 Demonstration of the relation of the outcome energy and thermal comfort compared to the both options dependent on the user.

		FS [%]	BP energy [%]	WP energy [%]	BP thermal comfort [%]	WP thermal comfort [%]
design option 1	**all**	23	23	23	25	21
design option 2	**all**	77	77	77	75	79
design option 1	**A**	25	25	25	26	24
design option 2	**A**	75	75	75	74	76
design option 1	**B**	36	35	35	37	34
design option 2	**B**	64	65	65	63	66
design option 1	**C**	24	24	24	26	23
design option 2	**C**	76	76	76	74	77

Legend		
	FS	*first simulation*
	WP	*worst performance*
	BP	*best performance*
	A,B,C	*Different users*

The percentage factor brings into relation the outcome of the simulation with the weighting calculated for energy and comfort. Due to the fact that the weighting differs for all three decision makers (A, B, and C) the percentage is also affected. The first columns ‘design option 1 and 2 all’ show the consensus of all three decision makers based on the weighting factor calculated in Table 11.

The differences in performance listed in Table 16 can be also shown graphically. In Figure 41 the performance value is compared to a cost factor. For this purpose, the performance in percentage includes the calculated comfort from the simulation and its confidence interval plus the other performance aspects listed in Table 10 except the energy consumption and initial costs.
The cost factor is composed out of the investment costs for each building plus the running costs due to the energy consumption for each option. Results are shown for all stakeholders separately in Figure 41. As it can be seen for all designers, design option 1 is the best performing alternative mainly because of its architectural form and thermal comfort. However, design option 1 is also the more expensive solution due to its higher investment costs.

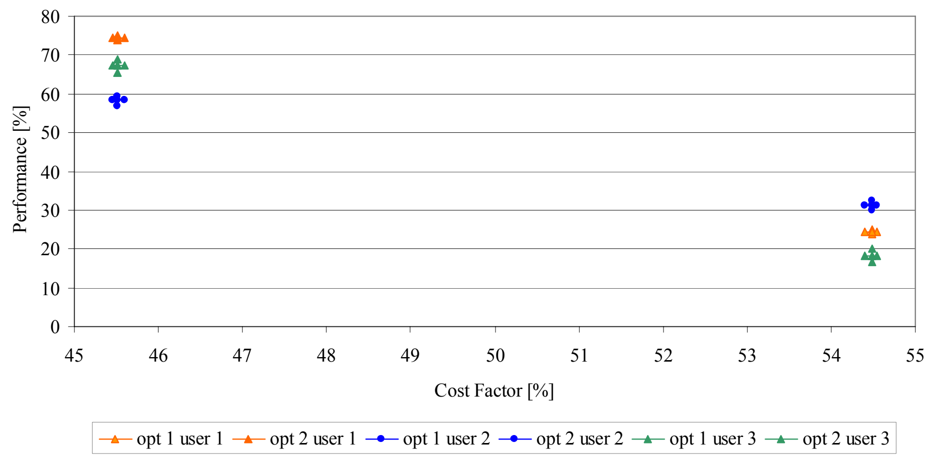


Figure 41 Illustration of the results for the decision makers separately (A, B, and C) comparing the cost factor to the performance.

Figure 41 shows the final output of the adapted AHP technique plus uncertainty protocol for comfort and energy. A performance value is compared to a cost factor. The performance value includes all performance aspects considered except energy and costs. The range in the performance is due to uncertainty and the weighting factor in the comfort prediction.
The cost factor contains the investment costs as well as the running costs based on the energy consumption. The range in the cost factor is a result of the uncertainty and the weighting in the energy consumption.

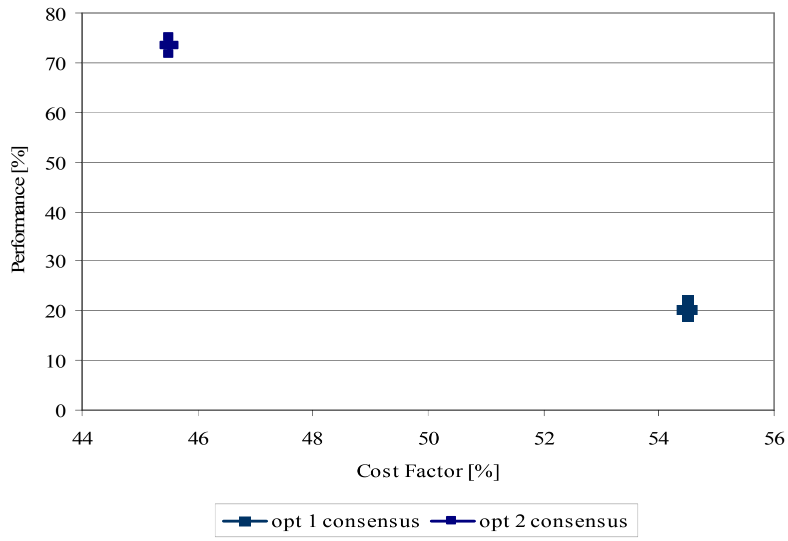


Figure 42 Illustration of the results for a consensus of the decision makers comparing the cost factor to the performance.

The result is comparable to Figure 41. The difference is that instead of separating the outcomes based on the weighting of each decision maker, a consensus based on the weighting from Table 10 is built.

The risk involved with each option, given by the uncertainty range is shown in Figure 43.

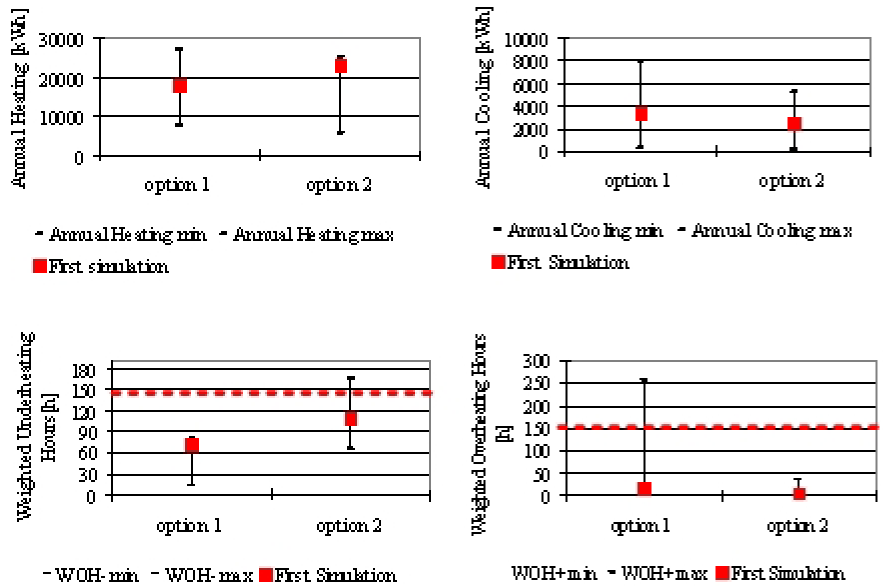


Figure 43 Illustration of the uncertainty range for annual heating, annual cooling and the weighted over- and underheating hours obtained by 200 simulations.

The square shows the results of the first simulation, the line with the barriers shows the results of the 200 simulations. The dashed line of the comfort criteria indicates if the compliance with a certain requirement is exceeded. These guarantees are stated as expressions of minimally required performance for the weighted over- and underheating hours.

The output shows that for the better performing design option 2 the amount of weighted underheating hours extends the upper confidence bound of 150h per year. In order to find out what parameters have the highest influence on the outcome, sensitivity analysis is used. Sensitivity analysis (SA) determines the contribution of individual input variable to the uncertainty in performance prediction. With the help of SA the most sensitive parameters for the weighted underheating hours can be outlined (see Figure 44).
Different techniques are available for the SA, for instance, PEAR, SPEA, PCC, SRCC, etc. [Saltelli et al., 2005] (cf. Chapter 3). They all rely on the same principle: the higher the coefficient, the more sensitive one variable is. The chosen one for demonstrating the results is the partial correlation coefficient (SRCC).

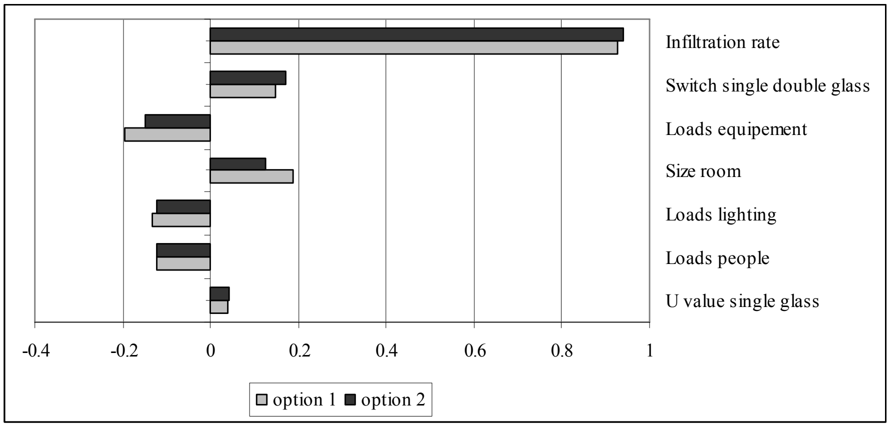


Figure 44 Results of the sensitivity analysis for weighted underheating hours for design option 1 and 2.

Figure 44 shows in an intuitive manner how sensitive the parameters of the two options are: the longer the bar, the higher the sensitivity.
The most sensitive parameter is infiltration rate, for both design options, followed by the single/double glazing, the internal gains for equipment, and the geometry of the room. It can be noticed that uncertainties in the so called scenarios have a major influence caused by varying boundary conditions in people/ equipment and lighting in addition to the uncertainty in infiltration rate. Infiltration in general becomes very important (as apparent from the uncertainty analysis); the infiltration rate in practice can easily exceed 5 times its as-designed value [Rooijakkers, 2008]. It is also noticeable that design design option 2 is more sensitive to infiltration than design option 1.

However, most crucial parameters are infiltration rate, the internal gains, and the room size. In order to diminish the uncertainty range, two alternatives will be pointed out taking the sensitivity into account: (1) Decreasing the risk of the scenario uncertainties, e.g., infiltration rate, and (2) adapting the design of the case study. The results will be shown for both approaches briefly:

1. Limiting the risk in the scenario uncertainties

One possibility is limiting the risk in the scenario uncertainties which means setting fixed limitations to boundary conditions. As an example, the risk limitation will be carried out for the infiltration rate. It is the most sensitive parameter and it is linear dependent on the weighed under- and overheating hours. This is shown with the help of scatter plots. Scatter plots are plots of values Y compared to corresponding values X .The creation of scatter plots is one of the simplest sensitivity analysis technique. This approach consists of generating plots of the points

$(x_{ij}, y_j), i = 1,...,m,$ for each independent variable xi [SIMLAB, 2009].

The purpose is to show the type of relationship or correlation that exists between two sets of data. On the vertical Y axis usually the response variable is covered whilst on the horizontal X axes some variable which is suspect to be related to the other. Sometimes scatter plots completely reveal the relationship between model input and model predictions; this is often the case when there is only one or two inputs that dominate the outcome of the analysis [SIMLAB, 2009]. This is the fact in case of the relationship thermal comfort and infiltration rate (see Figure 45).

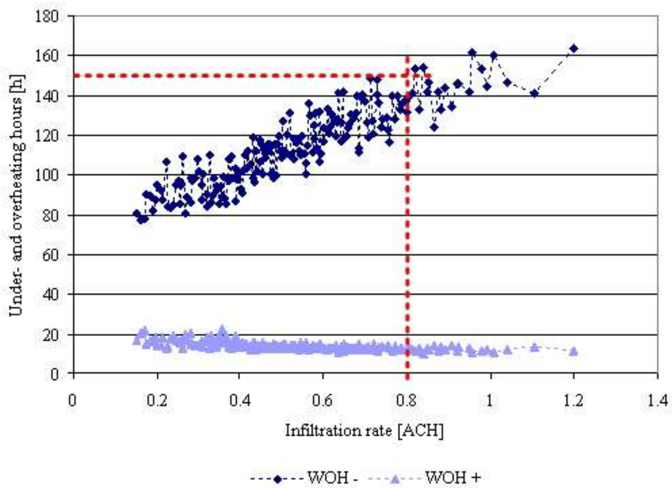


Figure 45 Scatter plot showing the relation between infiltration rate to weighted underheating (WOH-) and overheating hours (WOH+).

The dashed line in Figure 45 indicates that limiting the infiltration rate to 0.8 will guarantee not to exceed the minimally required performance of 150h per year. In this case, for erasing the risk, the limitation of 0.8 has to be fulfilled in order to avoid exceeding the confidence bound.

2. Adapting the room size

The geometry of the room is also very sensitive to the weighted overheating hours. Nevertheless, there is no linear correlation to the weighted under- and overheating hours recognizable.

For that reason, a new input file with different geometry data needs to be created and the uncertainty analysis needs to be conducted again. A new simulation with a slightly decreased room size is started. The results are shown in Figure 46.

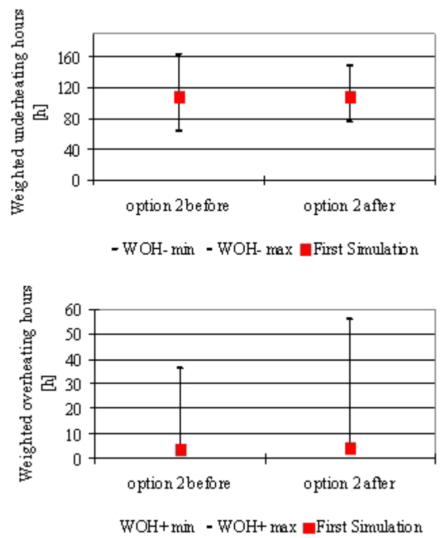


Figure 46 Illustration of the uncertainty range for weighted over- and underheating hours after the adaptation of the room size for design option 2.

The uncertainty range for design option 2 is shown for the original performance and the performance after the changed room size for weighted over- and underheating hours.

The number of exceeding weighted underheating hours is scaled down. However, it can also be concluded that improving the range of the design parameters in one direction can downgrade the uncertainty of another aspect, consequence of which is a slightly increased amount of overheating hours.

However, it can be inspected that by iteratively adding constraints on the parameter ranges of the options, the resulting conditional probabilities turn one option into the best option. Granted that, one option is optimal if it does not lead to unacceptable risk of under performance.

4.6 Discussion

In this chapter the conventional AHP protocol has been extended by the use of BPS and the integration of UA/SA.
Both, the conventional and the adapted AHP protocol fuse evaluations from multiple decision-makers with inconsistent viewpoints. The approaches average the evaluations to obtain a single consistent viewpoint (by having multiple decision makers).

For weighting criteria or performance aspects, the traditional AHP uses a qualitative ranking. The adapted AHP fuses subjective and objective information.

(i) Subjective or qualitative performance aspects such as the architectural layout.
(ii) Objective or quantitative performance aspects such as thermal comfort or energy consumption.

To handle performance aspects such as energy consumption, in the adapted AHP the output of BPS is used to include validated results into the decision process.
Furthermore, the adapted AHP supports uncertain information. The conventional AHP protocol that handles only deterministic information is enhanced by uncertain building performance data through the use of UA/SA. The sensitivity analysis in the adapted protocol is used to identify the most sensitive parameters that have the highest influence on the performance to eventually diminish the risk. The integration of UA/SA supports the risk identification as part of the decision process.

4.7 Conclusion

Current approaches in decision making for BPS do not integrate the combined use of simulation and uncertain information in the case study. The adapted AHP protocol is used to expand current BPS capabilities to support the design team in making decisions.
MCDM is herewith used to a lesser extent to indicate one solution as the best but to show the impact on user preferences to a discrete set of options facing uncertainty.
An advantage is that both subjective and objective evaluation measures are captured such as comfort, energy demand, and architectural layout.

The integration of a decision making protocol with the extension of UA/SA in BPS could support the design process and provide additional information. It would help the designer in several ways such as follows.

(i) Support of the design team in the design process by providing a base for communication.
(ii) Support in the decision process by providing a base to compare different design options.
(iii) Reduction of preoccupation in decision making and avoidance of pitfalls due to a lack of planning and focus.

(iv) Possibility to minimize risk related to different concepts with the help of UA/SA.
(v) Understanding of how parameters are related to each other.
(vi) Comprehension of how variations in the model input affect the output.
(vii) Enhancement of the use of BPS by providing additional support, and therefore, leading to a better guidance in the design process.

The developed approach is meant to enhance the information flow in the design process as it shows the impact of UA/SA embedded in a decision process. The appreciation of the extension of BPS with decision making under uncertainty will be tested with practitioners with the help of mock-up presentations and an online survey in Chapter 6.

5

5. Multi-objective optimization

5.1 Introduction

The building industry in contrast to other industries (e.g., car or ship industry) is very traditional. No prototypes are tried and tested before manufacturing. Each building is unique, thereby excluding large scale production. Nevertheless, during the design process a great number of decisions need to be taken. Typical design assessment criteria are spatial flexibility, energy efficiency, environmental impact as well as thermal comfort, productivity and creativity of occupants among others [Hopfe et al., 2005].

Design problems in building assessment often have the issue of conflicting objectives (energy consumption vs. thermal comfort). Nevertheless, it is aimed to find a well-balanced solution that takes into account all objectives.

Furthermore, it is hypothesized to be of great importance to autonomously optimize discipline specific designs continuously during the design process from the start to the completed example. The comments made on expectations for future developments in building performance simulation (see Chapter 2) apply equally to the design optimization which may be performed from conceptual to final design.

As computational power increases, the idea of using multi-objective optimization becomes more achievable.

Optimization techniques aim to solve problems in a systematic way by producing a set of solutions based on predefined objectives that are functions of design variables.

A number of publications are available reporting research that makes use of optimization techniques in architecture [Jagielski et al., 1997; Jo et al.; 1998; Michalek et al., 2002; Schwarz et al., 1994]. The focus thereby lays on automating the optimization process of the building topology and layout in terms of the architectural design. The research efforts in evolutionary design have also not gone unnoticed by researchers in the field of mechanical engineering. The concept generation and optimization using genetic algorithms has been applied to mechanical systems and their control mechanisms [Angelov et al., 2003; Wright et al., 2001, Wright et al., 2005]. Ongoing research also includes the feasibility of applying more than one assessment criterion simultaneously in the search for the optimum [Wright et al., 2002; Nassif et al., 2004].

This chapter gives an overview of optimization techniques that have been applied in building design optimization. It starts with some general definitions and explanations

before it describes single- and multi-objective optimization techniques in the context of building performance simulation.
Finally, the implementation of two multi-objective algorithms NSGA-II and SMS EMOA with and without the handling of uncertainties is demonstrated and evaluated by means of a case study.

5.2 Overview

Section 5.2 gives an introduction in terminology and definitions used in the context of optimization. Furthermore, an overview over different optimization procedures and different algorithm groups will be provided. However, examples for algorithms belonging to different algorithms groups will be already mentioned, before they will be described in more detail in Section 5.3.

5.2.1 Definitions

In this subsection some definitions are presented in order to understand better the descriptions of algorithms and simulation results.

Definition 1: optimization problem
The general problem formulation in optimization can be summarized as
maximize/ minimize $f(\vec{x})$ (function to be optimized) , subject to
$\vec{g}(\vec{x}) \leq 0$ (m inequality constraints),
$\vec{h}(\vec{x}) = 0$ (p equality constraints),
with $\vec{x} \in R^n$, $\vec{g}(\vec{x}) \in R^m$, $\vec{h}(\vec{x}) \in R^p$
The optimization problem is either constrained (with constraints) or unconstrained (without constraints). The solution set is reduced through the identification of feasible solutions subject to the constraints (linear/ non-linear).
In the domain of building performance for the design of HVAC systems [Wright et al., 2002] the optimization problem and its constraints are derived from restrictions on the design of coils or the performance envelope of the supply fan. It needs to be ensured that the system has sufficient capacity to meet supply air temperature and flow rate set points.

Definition 2: objective function
The objective function (also called cost function or optimization criterion) is the function $f(\vec{x})$ that is to be optimized, using an algorithm [Collette et al., 2004].
The objective function can be either linear or non-linear [Collette et al., 2004] with respect to the decision variables. For special classes of non-linear functions (e.g., quadratic functions) sometimes efficient optimization techniques are available.

Definition 3: decision variables
Decision variables are gathered in vector $\vec{x}$. The optimum of $f(\vec{x})$ is searched by gradually modifying the vector. When classifying optimization problems, one typically

distinguishes between problems with one decision variable (single variable) and several variables (multi variables) [Collette et al., 2004].
The variables can be continuous (real numbers), integer or discrete variables (integer numbers), or combinatorial (e.g., permutation on a set of numbers of finite size) [Collette et al., 2004].
Another differentiation is made by Anderson [2000]. He divides variables into independent design variables or parameters, and environmental or external variables that affect the design when used.
Decision/ problem variables, either discrete or continuous, should reflect the total set of alternatives measures that is available for improvement of the objective function (e.g., material properties such as insulation, production etc) [Diakakia et al., 2008].

Definition 4: global minimum
A vector $\vec{x}^*$ is a global minimum of an objective function f if $f(\vec{x}^*) \leq f(\vec{x})$ for any $\vec{x} \in F$ with $\vec{x}^* \neq \vec{x}$ and F is the feasible subspace of R^n (no constraint violations) (see M3 in Figure 47).

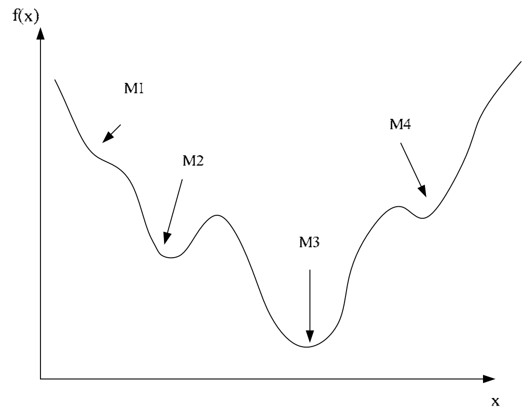


Figure 47 Illustration of the difference of global and local minima [Collette et al., 2004].

Definition 5: strong local minimum
A solution $\vec{x}^*$ is a strong local minimum of an objective function $f(\vec{x})$ if and only if $f(\vec{x}^*) < f(\vec{x})$ for any $\vec{x} \in V(\vec{x}^*)$ and $\vec{x}^* \neq \vec{x}$, where $V(\vec{x}^*)$ defines a neighborhood of $\vec{x}^*$ (see M2 and M4 in Figure 47).

Definition 6: weak local minimum
A solution $\vec{x}^*$ is a weak local minimum of an objective function $f(\vec{x})$ if and only if $f(\vec{x}^*) \leq f(\vec{x})$ for any $\vec{x} \in V(\vec{x}^*)$ and $\vec{x}^* \neq \vec{x}$, where $V(\vec{x}^*)$ defines a neighborhood of $\vec{x}^*$ (see M1 in Figure 47).

Definition 7: domination

A vector $\vec{x}_1$ dominates a vector $\vec{x}_2$ if $\vec{x}_1$ is as least as good as $\vec{x}_2$ for all objectives, and $\vec{x}_1$ is strictly better than $\vec{x}_2$ for at least one objective.

Definition 8: local pareto optimality

A vector $\vec{x}^* \in R^n$ is locally pareto optimal if there exists a real $\delta > 0$ such that there is no vector $\vec{x}$ which dominates $\vec{x}^*$ with $\vec{x} \in R^n \cap B(\vec{x}, \delta)$, where $B(\vec{x}, \delta)$ represents a bowl of centre $\vec{x}$ and of radius δ.

Definition 9: global pareto optimality

A vector $\vec{x}^*$ is globally pareto optimal, if there is no other vector $\vec{x}$ such that $\vec{x}$ dominates $\vec{x}^*$.

Definition 10: stationary point

A stationary point is either a saddle point or a local optimum. Stationary points are characterized by the condition $\nabla f(\vec{x}) = 0$.

Definition 11: trade-offs or Pareto frontier

The projection of the set of non-dominated solutions is called Pareto frontier or trade-off. A distinction is made between unbalanced and fair trade-offs. Figure 48 shows the meaning of unbalanced and fair trade-offs.

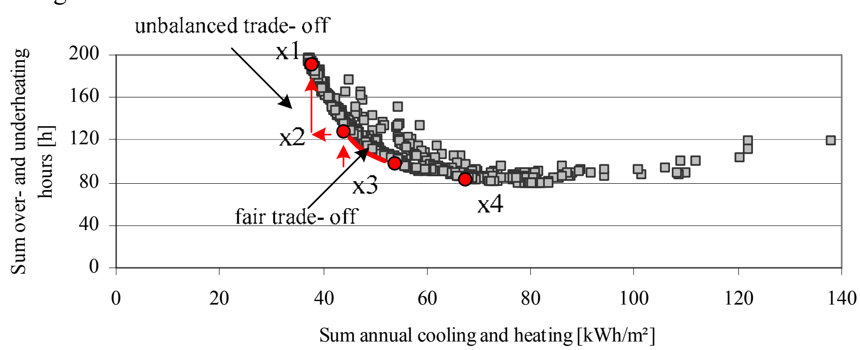


Figure 48 Exemplary illustration of the Pareto frontier for the two objectives energy consumption and thermal comfort.

The solutions x1 and x4 are ideal or extreme solutions considering one objective (over- and underheating hours or annual cooling and heating). Opposed to that, the solutions x2 and x3 lie in the area of good compromise solutions (knee points). The move from x2 to x3 has a balanced trade-off, whereas for the move from x2 to x1 the trade-off is very much in favor of the objective annual cooling and heating.

5.2.2 Deterministic and stochastic optimization

In the deterministic optimization the sequence of points that is evaluated is determined solely by the initial point (or starting point) and the geometry of each step of the algorithm is governed by a deterministic rule.

In contrast to deterministic optimization, in stochastic optimization some steps of the algorithm are governed by randomized decisions. Hence, the sequence of points generated by a stochastic optimization algorithm depends also on a set of random numbers used in the randomized steps.

As a rule of thumb, deterministic algorithms are considered to be more efficient and precise for local optimization than stochastic algorithms, while stochastic algorithms are considered to be more reliable in global optimization and robust to numerical noise. Moreover, for deterministic optimization algorithms convergence to a local or global optimum is usually guaranteed (under certain assumptions on the geometry of $f(\vec{x})$), whilst for stochastic optimization algorithms, if any, only probabilistic convergence can be guaranteed. An exception to this rule is given by some hybrid stochastic algorithms such as evolutionary pattern search [Williams et al., 2001].

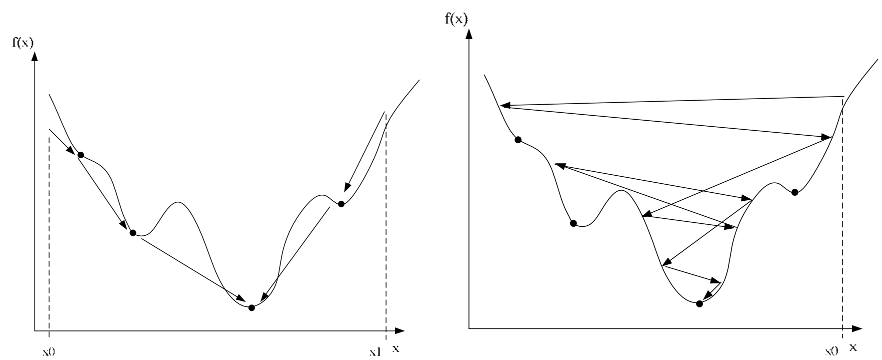


Figure 49 Illustration of the distinction between deterministic (left hand side) and stochastic optimization (right hand side) [Collette et al., 2004].

Deterministic algorithms such as coordinate search or Hooke-Jeeve algorithm find quickly a local optimum.
Stochastic optimization algorithms such as many population based optimization techniques for instance genetic algorithm, particle swarm, and genetic programming are based on a stochastic process to search the optimum. They are supposed to be less efficient than deterministic algorithms in terms of time but are able to find surprises, i.e., an optimum that is hard to find [Collette et al., 2004].
Besides, they are more robust with respect to numerical noise. However, in [Wetter and Wright, 2004] it was found that stochastic operators like in genetic algorithm and particle swarm optimization can cause a failure in the optimization especially if number of simulations is small.

5.2.3 Volume-based, path oriented and population based optimization

Volume based

Volume based optimization algorithms belong to the non-adaptive group of algorithms [Novak and Ritter, 1996]. Non-adaptive or non-iterative methods first determine all search points at which the function is to be evaluated. Then they evaluate the objective function at all these points and determine the approximation of the optimal solution based on the results. Design of experiments (DoE) and trial and error belong into this category.

Design of experiments is also a useful technique to analyze the effect of parameters and combinations of parameters (interaction) on the objective function value. Volume based algorithms converge very slowly to the optimum but given some restrictions they can often provide global convergence guarantees [Novak and Ritter, 1996].

Path oriented

Path oriented or adaptive (iterative) optimization [Novak and Ritter, 1996] such as Hooke-Jeeve [1961] and Nelder & Mead [1965] take the results of previous evaluations into account when determining a new search point. Search principles are, e.g., steepest descent, coordinate search, and conjugate directions. Path oriented methods have the advantage of a fast convergence to local optima. The local convergence is guaranteed, however they might not find the global optimum.

Population based

Population based optimization is strictly speaking adaptive techniques but as they maintain a whole set of intermediate solutions instead of a single point they can be viewed as a compromise between global, volume based and local, path oriented methods.

Population based approaches such as particle swarm optimization, genetic algorithms, evolutionary programming are of high importance in building performance. They are robust meta-heuristics that can balance between global and local search.

Search principles of population based methods are variation and selection of individual solutions from populations (solution sets). Advantages are moderate convergence speed for local optima and moderate to high chance to find the global optima.

However, they always have convergence problems, i.e., global convergence guarantees can only be provided for infinite running time.

Meta-models can be used to deal with time consuming simulations (Kriging) (see Section 5.5/ 5.8.3). They accelerate population based approaches.

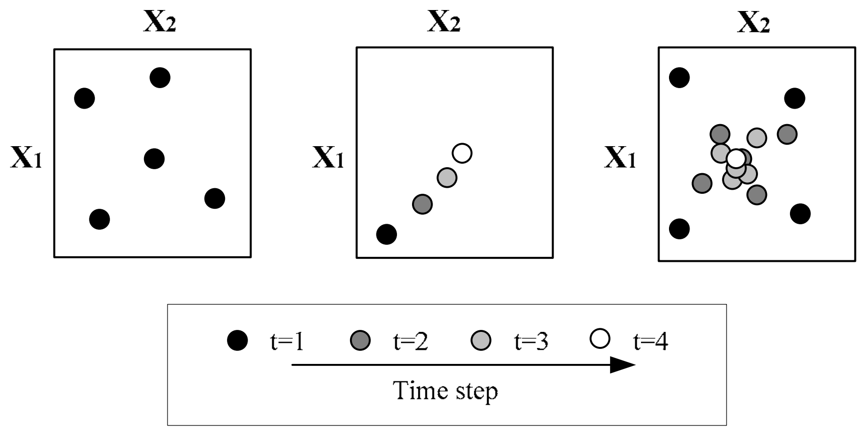


Figure 50 Illustration of the difference between volume based (left hand side), path oriented (middle), and population based (right hand side) optimization algorithms.

5.2.4 Gradient based and derivative free optimization

The gradient is a vector pointing into the direction of steepest ascent whilst its length or magnitude is indicator for the steepness.

The gradient of a scalar function $f(x)$ with respect to variables $x_1,..,x_n$ is denoted by

$$\nabla f(\vec{x}) = grad(f) = \frac{\partial f}{\partial x_1} e_1 + \frac{\partial f}{\partial x_2} e_2 + \ldots + \frac{\partial f}{\partial x_n} e_n = \left[\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \ldots, \frac{\partial f}{\partial x_n} \right]^T,$$

where ∇f is called Nabla operator.

The search of the new coordinate $\vec{x}_{new}$ can be described as $\vec{x}_{new} = \vec{x}_{old} + \nabla f * d$ with d being the step size and the steepness $\left\| \nabla f(\vec{x}) \right\|$.

An advantage of this method is a fast convergence to an optimum if a quadratic function of low condition number[1] is given (see Figure 51 left side). Furthermore, they guarantee high precision.

However, drawbacks are that gradient methods converge to a local optimum if there is a multimodal function or a saddle point. Besides, the optima on the interval borders are not found. Therefore, special adaptations are necessary, e.g., the projected gradient methods. Besides, numerical noise and discontinuity are harmful.

Examples of gradient based methods are steepest decent or Newton's method.

[1] The condition number is the quotient of the highest and lowest eigenvalue of the form matrix A in the quadratic objective function $f(\vec{x}) = a + b\vec{x} + \vec{x}^T A\vec{x}$.

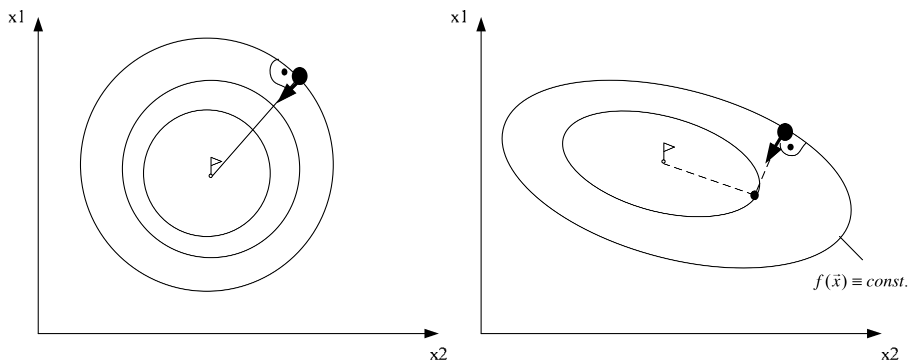


Figure 51 Illustration of the gradient based optimization method.

Derivative free optimization means that there are no derivatives of the objective function available. Typically these methods use interpolation, regression or other sample based methods. The model is nonlinear opposed to the derivative based (e.g., Taylor approximation) optimization that mostly provides methods for unconstrained optimization build on a linear or quadratic model. Examples are Hooke-Jeeve, Nelder-Mead simplex, and genetic algorithm.

5.3 Single-objective optimization

The conventional single-objective optimization produces a single result. Figure 52 shows a classification tree for single-objective optimization algorithms using the classification criteria from Section 5.2. It gives an insight in various commonly used optimization algorithms in design optimization.

Some optimization algorithms often applied in building performance simulation will be briefly explained.
The general description of the methods will start with some information about their processing, advantages and drawbacks of the algorithm, followed by examples from applications in building simulation.

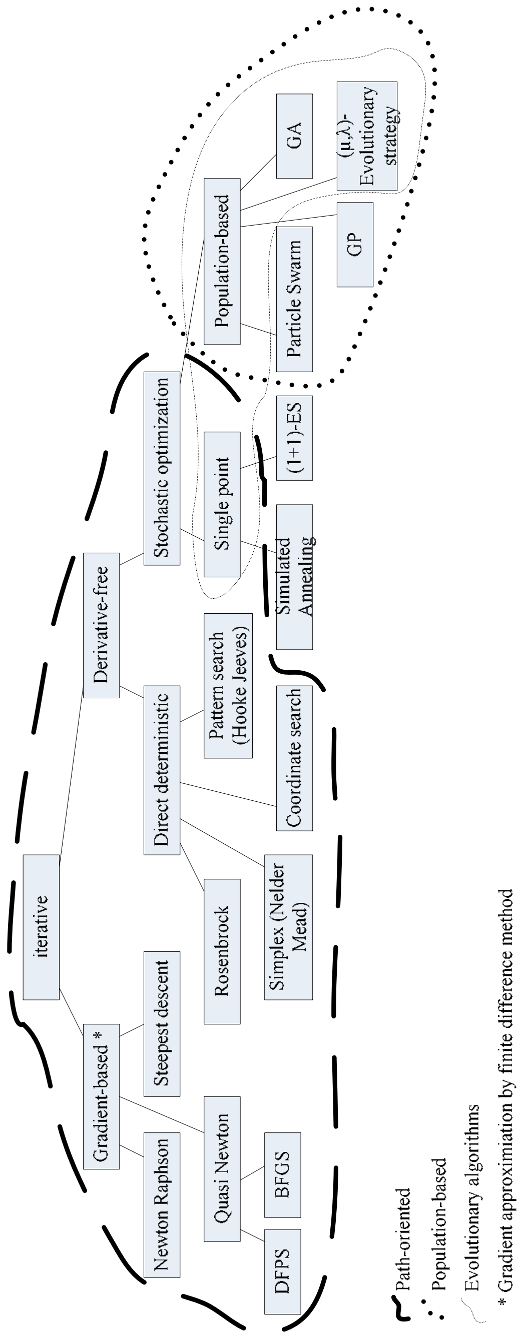


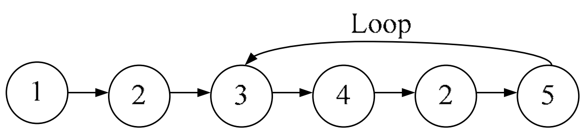
Figure 52 Overview of commonly used single-objective optimization algorithms.

5.3.1 Genetic algorithm

Genetic algorithms (GA) belong to the group of stochastic population based algorithms. GA have their roots in classical population genetics and were first studied as simulation models for adaptive populations in that field by Holland [1975]. When the GA is implemented it usually follows the cycle as shown below:

```
Initialization of population of individuals
Evaluation of fitness of all individuals of population
For i+ 1 to maxIt (increasing time counter determined by the time,
fitness, etc.)
       Random selection
       Selection of sub-population for offspring production
       Combining parts of 'parent chromosomes'/ crossover
       Mutation (perturbation of population stochastically)
       Evaluation its new fitness/ objective function computation
       Selection of the best from current fitness/ computation of
       efficiency
End for
```

Each optimization parameter is coded into a gene (real number or bit coded), the corresponding genes builds a chromosomes (e.g., binary string, array of real numbers) that actually describes the individual. Each individual represents a possible solution.



Legend:

1. Initialization population
 (set of individuals)
2. Efficiency computation
3. Crossover
4. Mutation
5. Selection

Figure 53 Schematic representation of the genetic algorithm [Collette et al., 2004].

An advantage of the GA is that it is very flexible, intuitive, and robust. They can handle continuous and discrete parameters. Both types of parameters are encoded as a binary string in the canonical GA. Recently, so called real coded GAs incorporate also floating point encodings. In that case GAs are very similar to evolution strategies discussed later in this section.

The use of GA is time consuming. Unfortunately, the convergence cannot be guaranteed whenever a high precision for the optimum approximation is required. GA incorporate inequality constraints by using a penalty function that is added to the objective function in case of constraint violation.
GA has been applied in building performance very successfully. For example, in HVAC design Wright and Zhang [2005] compare the energy performance with and

without an ageing operator by focusing on evaluation of the system performance, system operation and viability of system topology. Angelov et al. [2003] design a feasible and efficient system using GA. Dunn [1997] uses GA to optimize the performance of a variable air volume (VAV) system.
In [Wetter and Wright, 2003] pattern search (Hooke-Jeeve algorithm) is compared to genetic algorithm by considering a cost function based on the annual energy use.

5.3.2 Evolutionary programming

Evolutionary programming (EP) for discrete automata was invented by Fogel [1962] in the 60ties. It is comparable to GA but it does not use crossover as operator. The typical procedure is initialization of a population, mutation, evaluation of the fitness, and stochastically selecting the survivors from actual fitness in a tournament. However, due to the self adaptation of the step size opposed to the constant mutation rate of the GA, it is claimed to have a higher precision.
Fong et al. [2006] uses EP for an HVAC system, optimizing the set points of chilled water and supply air temperatures.

Opposed to EP the evolutionary strategies (ES) developed by Rechenberg [1973] and Schwefel [1975], has the advantage of a continuous step size adaptation. EP for continuous vectors also feature step size adaptation, but was much later introduced. In the beginning, ES also applies mutation as an operator but it is often combined with a recombination operator. An extensive study on the dynamic behavior of ES on different function geometries is performed by Rudolph [1997] and Beyer [2001].
However, state of the art is the Covariance Matrix Adaptation Evolution Strategy (CMA-ES), where recombination is used as supporting operator.

5.3.3 Hooke-Jeeve

The Hooke-Jeeve algorithm is a direct search method [Hooke-Jeeve, 1961]. This algorithm is a representative of a class of algorithms that today are classified under the framework of generalized pattern search (GPS).
The search is characterized by two types of move (see Figure 54) [Schwefel, 1995].
(i) Discrete steps in coordinate direction are taken by exploratory moves. Discrete steps in Figure 54 are, e.g., from the starting point to point 1, and from point 1 to point 2 and 3.
(ii) An exploration (pattern move) is made on the assumption that the move in diagonal direction (line joining) will lead to more favorable solution. In Figure 54 an exploration move is demonstrated in the move from point 3 to point 4.

After the each move the success is checked. The step size is either kept fixed or adapted. If there is no success the step size is decreased.

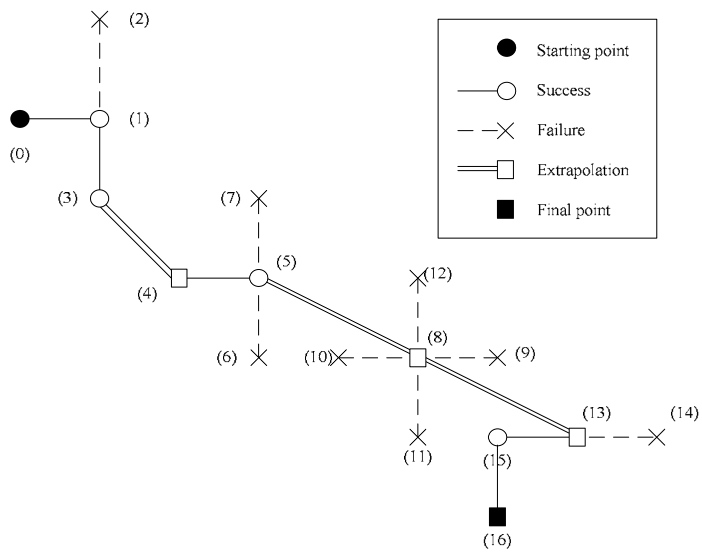


Figure 54 Illustration of the Hooke-Jeeve algorithm. [2]

An advantage of Hooke and Jeeve's algorithm is that it converges towards a stationary/ local optimum, slower than gradient based but faster than the GA algorithm.
In Hooke-Jeeve algorithm the computational operations are very simple and cannot lead to invalid manipulations; therefore it needs only small computer storage requirement.

However, it belongs to the path oriented group of algorithms that is typically less robust than population based algorithms. Another drawback is that it only looks in coordinate direction (arbitrary). The fixed coordinate system can cause problems. An improvement was suggested by Rosenbrock that is described in [Schwefel, 1995]. Hooke-Jeeve algorithm is only applicable in vector spaces, i.e., discrete variables are problematic.

As mentioned earlier it was applied in [Wetter and Wright, 2003] to compare the optimization based on the cost function for annual energy use with genetic algorithm.
In Wetter and Wright [2004] eight other algorithms are applied to evaluate stochastic and deterministic optimization for HVAC. In [Emmerich et al., 2008], Hooke-Jeeve algorithm is used to minimize the energy consumption considering different building scenarios and characteristics.
Another example is the minimization of life cycle costs by finding optimized values for design variables in building construction and HVAC system [Hasan et al., 2008].

[2] Simplified graphic of Schwefel [1995]

5.3.4 Nelder and Mead algorithm/ simplex

The Nelder and Mead algorithm or simplex search algorithm was originally published by Nelder and Mead [1965]. It is a frequently used optimization algorithm for unconstrained derivative free optimization.
It is suitable for non-smooth functions and widely used where function values are subject to noise. It requires only two function evaluations per iteration. However, it is also important how effectively the iteration improves the function value. The method is considered to be simple and has a moderate convergence speed. It starts with a big step size and gets more detailed in the end, but it might not converge to a global optimum. The method is only applicable for vector spaces. Moreover, it is difficult to find an optimum along the interval border.
The original method proposed by Nelder and Mead might even not converge to a stationary point but end up in a cyclic behavior. However, improvements were proposed by Torczon [1989] that guarantee convergence to a stationary point.

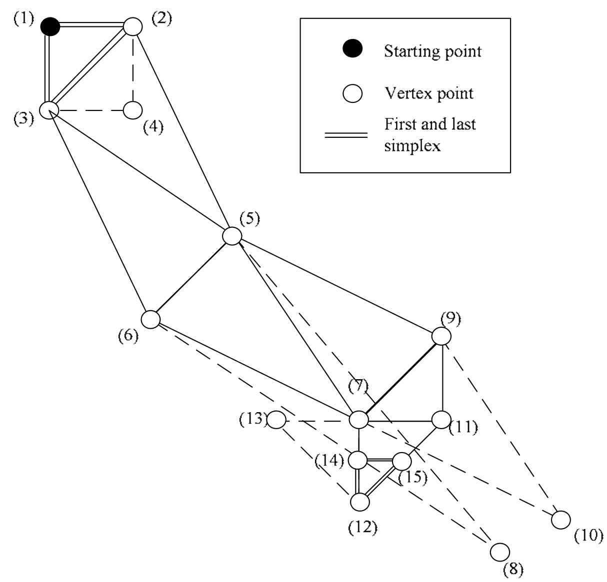


Figure 55 Illustration of the Nelder and Mead algorithm. [3]

The Nelder and Mead algorithm was applied by Al-Homoud [2005] for thermal design optimization of building envelopes for two objectives: minimization of the thermal discomfort and the energy budget. Both objectives were treated separately.

[3] Simplified graphic of Schwefel [1995]

Furthermore it is one of the nine different algorithms implemented in [Wetter and Wright, 2004]. However, it does not perform well. Despite a high number of simulations (more than 2000 compared to less than 1000 needed by others) it failed to find the minimum of the cost function.

5.3.5 Particle swarm optimization

Particle swarm optimization (PSO) is a population-based stochastic optimization algorithm, the design of which was inspired by the social behavior of animals. Individual particles represent potential solutions, which move through the search space looking for the optimal solution.
The position of each particle is adjusted according to its velocity (e.g., the rate of change). In its iteration the swarm goes more to the areas having the high-quality solutions.
The velocity of each particle is modified literately by its personal best position and the best position found by particles in the neighborhood.
Three main attributes exist in PSO algorithm [Blum and Merkle, 2008]:

1. Individual cells are updated in parallel.
2. The value of each cell depends on the old value and its neighbors.
3. All cells are updated using the same rules.

The new velocity $\vec{V}_{new,i}$ is calculated by

$$\vec{V}_{new,i} = \vec{V}_i + \alpha(\vec{p}_i - \vec{x}_i) + \beta(\vec{p}_g - \vec{x}_i)$$ with

$\vec{V}_i$ being the current velocity, $\vec{x}_i$ being the current position, $\vec{p}_i$ being the best position visited by individual i so far, and $\vec{p}_g$ being the best position visited by any individual so far.

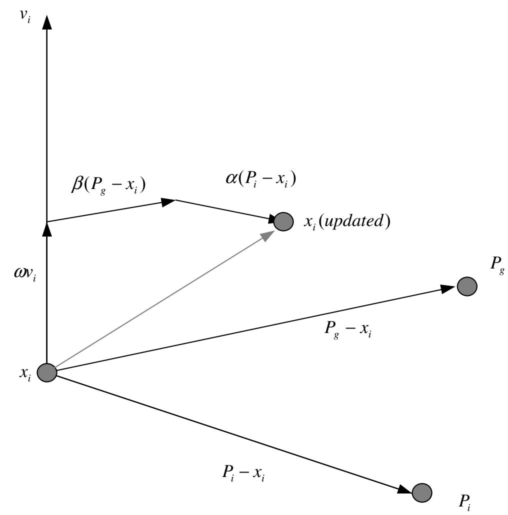


Figure 56 Illustration of the particle swarm optimization algorithm [Blum and Merkle, 2008].

PSO algorithm belongs to the group of population-based algorithms. Therefore, as in other population-based algorithms, global convergence gets more probable. Compared to the much earlier proposed genetic algorithms its convergence is very fast. It is a very robust and efficient algorithm for solving optimization problems.
The general problem of heuristic algorithms, that the convergence to local or global optimum is not guaranteed, applies also for PSO. Moreover, PSO is only applicable in vector spaces; categorical (discrete) variables are problematic.

It is also applied in [Wetter and Wright, 2004] where it comes close to the minimum with a low number of simulations. However, it performs worse in comparison to the hybrid approach which consisted of combining PSO with generalized pattern search.

5.3.6 Hybrid algorithms- combination of algorithms

Hybrid algorithms offer the possibility to combine favorable characteristics of different algorithms to achieve a certain objective.
Yen et al. [1995] classify hybrids into four categories:
1) Pipelining hybrids or staged hybrids: they allow sort of sequential solution. First they find possible regions, second they identify optimal points in these regions.
2) Asynchronous hybrids: for finding multiple solutions in multiple solution spaces. It uses a shared population to allow algorithms to proceed asynchronously. A method with a slower convergence can be for instance combined with a faster one.
3) Hierarchical hybrids: two different algorithms are used at two different levels of a problem. Example: GA and multivariate adaptive regression splines [Yen et al., 1995].

4) Additional operators: combining a reproduction operator with GA to perform local search. For instance, the simplex method is very much suited for this sort of hybrid.

In [Wetter and Wright, 2003] a hybrid pipelining optimization algorithm is proposed combining the global search of a genetic algorithm with coordinate search for local search. This minimizes the risk of finding a local minimum that is not global and the coordinate search enables clear convergence statements with a smooth cost function.
In [Wetter and Wright, 2004] a hybrid particle swarm and Hooke-Jeeve algorithm is introduced, that does a PSO on a mesh for a first iteration and starts afterwards the Hooke-Jeeve algorithm using for the initial start the mesh point that attained the best solution (first global then local search).
The same hybrid is used in [Hasan et al., 2008]. In both publications the algorithm achieves excellent results.
Furthermore in [Wetter and Wright, 2004] a simplex algorithm is used with the extension of O'Neill and a modification of the stopping criteria [O'Neill, 1971].

5.4 Multi-objective optimization

Contrary to single-objective optimization, multiple contradictory objectives can be optimized simultaneously by producing a set of solutions. This set of solution is mostly referred to as Pareto front (line of non-dominated solutions).
Two issues in multi-objective optimization are of higher relevance: to estimate the density in the population in the most appropriate way and to transform the partial order by Pareto dominance into a total order to achieve comparable solutions [Coello Coello, 2006].

Multi-objective optimization can be divided into 'a priori', 'a posteriori', and progressive methods (for explanation see Chapter 4).
Examples of 'a priori' optimization are linear weighted sum, goal programming, Tchebycheff aggregation (see Figure 57).

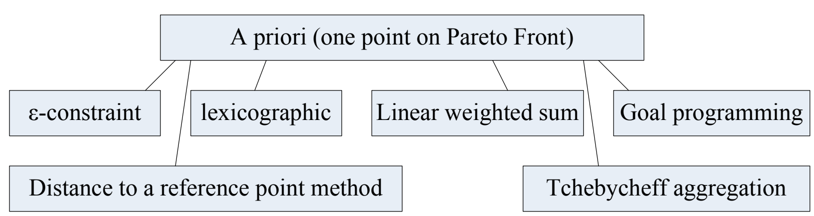


Figure 57 Illustration of the topology of 'a priori' algorithms.

Representatives of 'a posteriori' methods are, e.g., evolutionary multi-objective optimization algorithms.

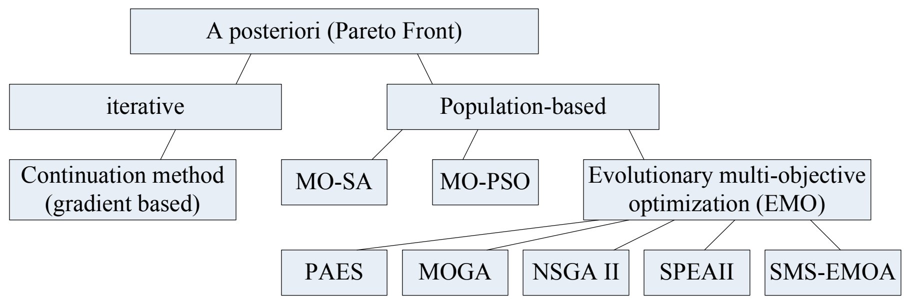
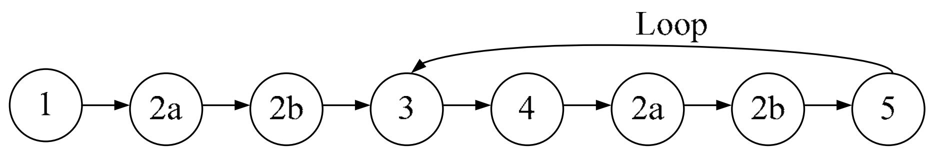


Figure 58 Illustration of the topology of ‘a posteriori‘ algorithms.

In the progressive approach user interventions are made during the optimization procedure to enable the reorientation of the search towards a direction of improving solutions. A drawback of the progressive way is that it requires lots of attention and time.

5.4.1 Multiple objective genetic algorithm

The multiple objective genetic algorithm (MOGA) proposed by Fonseca and Fleming [1995] belong to the first generation of multi-objective evolutionary algorithms (MOEAs) that “typically adopted Niching or fitness sharing” [Coello Coello, 2006].
There exist further non-Pareto based approaches such as vector evaluating genetic algorithm (VEGA) and Pareto-based approaches with non-dominated sorting to rank the search population.
The difference with the genetic algorithm is a vector/ efficiency transformation. After ranking the individuals, efficiency is assigned to each individual. By using a function for the ranking, the individuals are ranked from best to worst.
MOGA also uses restrictions for an individual to not arbitrarily recombine with any other individual (mating restrictions) [Coello Coello, 2006].
In multi-objective optimization many problems are constrained. MOGA includes an approach to handle constraint functions. Constraints are treated as criteria and “goal restraints” applied to force solution into desired feasible region (by penalizing Pareto rank of infeasible solutions) [Wright et al., 2002]



Legend:

1 Initialization population	3 Crossover
2a Efficiency computation	4 Mutation
2b Vector/ efficiency transformation	5 Selection

Figure 59 Schematic representation of the multi-objective GA [Collette et al., 2004].

In [Wright et al, 2002], the HVAC system for three different building types (low, medium and heavy case) is optimized using a simple MOGA. Two different objectives are considered: daily energy costs and the occupant thermal discomfort.
Manzan et al. [2006] optimize the thermal comfort and the energy use for HVAC systems with night ventilation cooling of a three level office building.
With the help of MOGA feasible solutions are found showing a fast progress towards the Pareto optimal solutions.
MOGA initiated according to Coello Coello [2006] the "second" generation of MOEAs like the non-dominated sorting genetic algorithm (NSGA-II) and SMS-EMOA.

5.4.2 Non-dominated sorting genetic algorithm

The non-dominated sorting genetic algorithm (NSGA-II) was introduced by Deb et al. [2002]. Although the name reminds to the earlier developed forerunner NSGA, it is significantly different. It addresses for instance drawbacks of the earlier version due to lack of elitism, sharing function and density estimation [Deb et al., 2002].

NSGA-II uses fast non-dominated sorting and crowding distance for ranking individuals. Moreover, it works with an elitist selection scheme that selects the best individuals from the union of the parents and offspring population [Coello Coello, 2006].

One essential difference to other multi-objective algorithms is the sharing function, σ_{share}, that works with crowding distance. In multi-objective optimization it has to be found out which solution is dominated by what set of solutions. With the help of σ_{share} or the crowded comparison approach, the density of the surrounding of one solution is calculated to maintain sustainable diversity in a population.

The parameter σ_{share} defines areas for the efficiency computation of an individual by comparing the distance of two points on one sight (see Figure 60). Therefore non-dominated solutions are preferred over dominated, but the one in a less crowded region is also preferred compared to the one in a crowded.
The value of the solutions x_i in Figure 60 depends on its neighbors. The crowding criterion is herewith used for ranking. For instance, x_5 (rank 3) outperforms x_4 (rank 4).

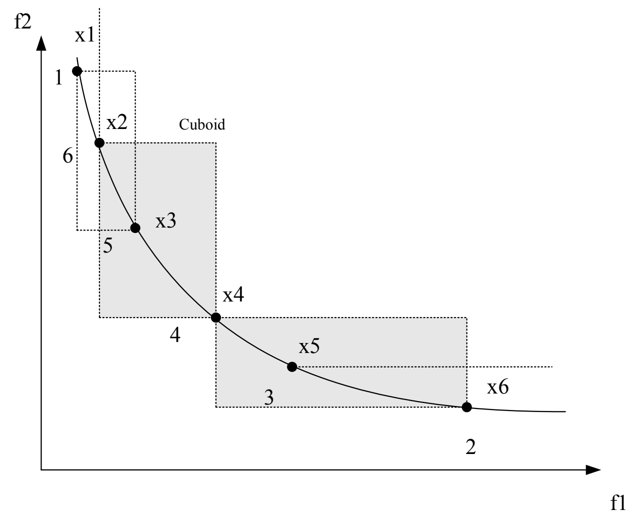


Figure 60: Illustration of the NSGA-II and its crowding distance calculation.

The implementation of NSGA-II in building assessment is dedicated to the optimization of thermal comfort and energy consumption in the domain of HVAC systems [Nassif et al., 2004, 2005] and building scenarios/ design [Emmerich et al., 2008].

5.4.3 SMS EMOA

One of the recent MOEAS has a selection mechanism based on performance indicators for the Pareto fronts. It combines the non-dominated sorting with a selection operator based on the hypervolume measure [Emmerich et al., 2005; Beume et al., 2007]. It is very similar to NSGA-II which can be seen in Figure 60. The main two differences are the selection (steady-state of SMS EMOA and (μ+μ) selection in NSGA-II) and a different ranking of solutions on the Pareto front.
As mentioned earlier, in NSGA-II solutions converge to a uniformly distributed set on the Pareto front with help of crowding distance. In SMS EMOA, the hypervolume distributes them in a way to maximize the covered hypervolume. The hypervolume is the "size of space covered or size of dominated space" [Emmerich et al., 2005].

In the SMS EMOA, points are selected based on their contribution to the dominated hypervolume. The value of the solutions x_i in Figure 61 depends on the position of the point itself. For instance, x_4 (rank 3) outperforms x_5 (rank 4) [Emmerich et al., 2005].

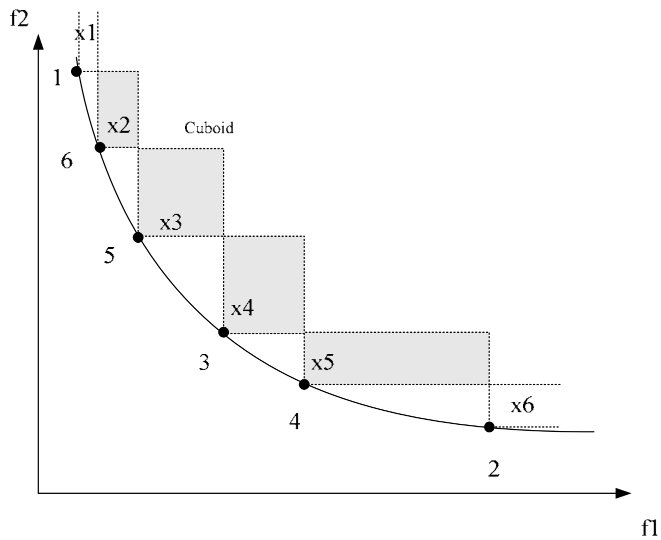


Figure 61: Illustration of the SMS EMOA- sorting by Δs [Emmerich et al., 2005].

An advantage of the SMS EMOA is that good compromise solutions can be found. Compared to the NSGA-II, solutions close to knee-points of the convex parts of Pareto frontier are ranked higher.
An example of SMS EMOA applied in building performance is shown in [Emmerich et al., 2008]. In a case study the energy consumption and comfort are optimized by varying the building geometry and internal loads.

5.5 Robust design optimization or optimization under uncertainty

As stated in Chapter 3, multiple sources of uncertainties can be defined. It is of major importance to achieve solutions that are not only fulfilling the requirements with respect to performance (i.e., energy and comfort) but that also perform well under variations due to uncertainties (e.g., decision making with uncertainty in Chapter 4). Solutions embedding those variations caused by uncertainty are defined as robust optimum solutions leading to a robust design.

Maystre et al. [1994] define robustness analysis as a method that "tries to determine the variation domain of some parameters in which the sorting of solutions or the choice of a solution remains stable."
Early attempts in looking for robust design solutions trace back to Taguchi who was using design of experiments to evaluate different designs [1989]. However, as stated in Schueller and Jensen [2008] the method lacks of optimization efficiency.
Sources of uncertainty in optimization can be divided into four main groups [Kruisselbrink, 2008]:

1. Uncertainties in design variables.
2. Uncertainties in environmental parameters.
3. Uncertainties due to noise in the output.
4. Uncertainties due to vagueness of constraints.

Kruisselbrink furthermore splits the determination for stating/ predicting the robustness of a solution in three categories:

1. Using sampling methods as Monte Carlo or Latin- hypercube sampling (see Chapter 3).
2. Using gradients to achieve an approximation for the optimization function by, e.g., Taylor-series.
3. Using previous evaluations by using meta-models and estimating the robustness.

The meta-model or surrogate is a function of the design variables that approximates the objective function, thus, helping in fast assessing the robustness. Meta-models are built from the information gathered in previous evaluations of the objective functions. Meta-models are beneficial, because whenever applied they are much faster to evaluate than the original function.
Some examples of techniques are, e.g., Kriging models [Kleijnen and Beers, 2004], neural networks [Badiru and Sieger, 1998], and response surface methodology [Ng et al., 2008].

Kriging models in this research are used in conjunction with a sampler to generate an initial response surface.
One issue of building performance simulation is the simulation time that increases whilst the amount of parameters gets higher and the results become more detailed. A single simulation of a nine-storey office building easily takes 3-9 minutes on a Pentium IV quad-core processor. As a consequence the use of techniques like uncertainty/ sensitivity analysis, what- if analysis, and design optimization become infeasible as the conduction of minimum 100 up to 1000 simulation evaluation becomes too time consuming.
The motivation of using Kriging meta-models is to allow optimization under uncertainty in a lower/ reduced time demand.
Without meta-models the number of simulation runs in an optimization is the number of optimizer iterations, the number of evaluations per iteration multiplied with the number of Latin hypercube samplings. With the use of Kriging meta-models the number of runs is reduced to the seeding runs and extra runs for online adaptation of the meta-model. In total, the number is reduced to a fraction of 5% to 20% of runs needed of the original algorithm.

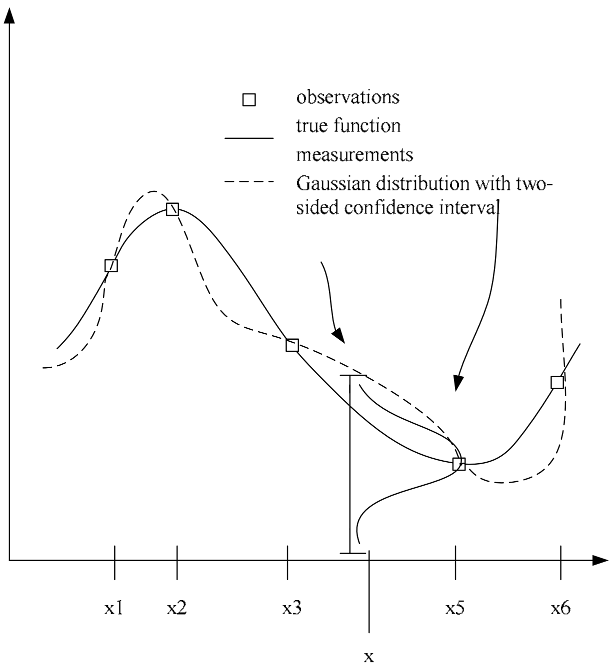


Figure 62 Illustration of a Kriging meta-model of a one-dimensional objective function.

5.6 Optimization tools

Optimization techniques are not a standard feature in building performance software so far. However, there exist several optimization tools that can be easily integrated with standard BPS.

5.6.1 Genopt

Genopt is an optimization program for the one –objective function to be coupled to an external simulation program such as EnergyPlus, TRNSYS, etc. It is developed for a cost function where "the cost function is computationally expensive, and its derivatives are not available or may not exist "[GenOpt, 2009].
It can be coupled to any BPS. It reads the input from text files and writes the output to text files. The independent variables can be discrete and/ or continuous (box constraints).
The cost function can cover almost everything, from minimization to maximization of any objectives (energy, indoor air quality, thermal comfort, etc.).
GenOpt provides local and global multi-dimensional and one-dimensional optimization algorithms such as follows.

- Generalized pattern search algorithms (the Hooke-Jeeves algorithm and the coordinate search algorithms), which can be run using multiple starting points.
- Particle swarm optimization algorithms (for continuous and/or discrete independent variables), with inertia weight or constriction coefficient and velocity clamping, and with a modification that constricts the continuous independent variables to a mesh to reduce computation time.
- Nelder and Mead's simplex algorithm.

Genopt has for instance been applied in optimization procedures in building assessment in [Wetter et al., 2002; Wetter et al., 2003].

5.6.2 Topgui

Topgui is a toolbox for parameter optimization. It provides a number of optimization methods as Genopt but consists of a Java graphical user interface (Gui) and provides also algorithms for multi-objective optimization problems.
In addition, batch commands (that can be controlled by the Gui) can be inserted to start the optimization passing the optimization algorithm, number of evaluations, design variables, etc. Additional, extra strategy parameters can be provided for some algorithms, e.g., for the evolution strategy by editing the population size parameters.
There are multiple algorithms available and the list can be easily extended by inserting new algorithms. To mention some the following optimization strategies are implemented into Topgui [Emmerich et al., 2003].

- HOOKE-JEEVES: Hooke Jeeves algorithm
- (μ,κ,λ)-Evolution Strategy
- ES1P1: (1+1)-Evolution Strategy with $1/5^{th}$ success rule
- EXPERIMENT: DoE- Scheduler
- NSGA-II
- SMS- EMOA

Topgui has also already been applied in [Emmerich et al., 2008] for the optimization in BPS.

5.6.3 Others

Besides Genopt and Topgui, there exist also some other approaches. For instance Wetter [2005] presents an automated multivariate optimization tool called BuildOpt which is an energy simulation program that is built on models that are defined by differential algebraic equations (DAE).

Ellis et al. [2006] demonstrate an optimization tool that employs multiple modules, including a graphical user interface, a database, a preprocessor, the EnergyPlus simulation engine, an optimization engine, and a simulation run manager.
Another application shows the use of Lingo [Lindo, 2009]. It is used in [Diakakia et al., 2008] as optimization software that offers, e.g., linear/ non-linear programming and global optimization. It is meant to maximize the profit whilst minimizing the costs.

The state of the art in MOO in BPS is the application of the NSGA-II algorithm. SMS EMOA shows promising results in [Emmerich et al., 2008], however, besides this publication it is not applied in the context of building simulation so far.
The comparison of both algorithms in the domain of BPS, the different Pareto frontiers achieved, the optimization results, the number of simulations, etc., is the intent of the following section.
Furthermore, the use of Kriging meta-models for the integration of UA/SA in optimization has not been applied in BPS so far. It is aimed to show the impact of UA/SA in a typical optimization procedure and to compare the outcomes of a conventional Pareto frontier and the one covering uncertainty.

5.7 Prototype description of applying MOO

After reviewing algorithms in single- and multi-objective optimization, providing examples of applied optimization in BPS, the following section will present the implementation of two multi-objective algorithms NSGA-II and SMS EMOA. NSGA-II algorithm was chosen as it is a state-of-the-art algorithm in MOO and has already been successfully applied in other applications in BPS [Nassif et al., 2004; Emmerich et al., 2008]. SMS EMOA is part of the recent MOEAs generation and belongs to the up-to-date trends in MOO [Coello Coello, 2006]. These two have been selected for the optimization of the energy use and thermal comfort of an office building. As a case study, design option 1 from the Appendix A, is chosen. Both optimization procedures are conducted with the help of the optimization platform Topgui.

The aim is to simulate both algorithms, to compare the results, the time demand, and eventually the Pareto front achieved.
In Figure 63 the flowchart of the optimization is shown.

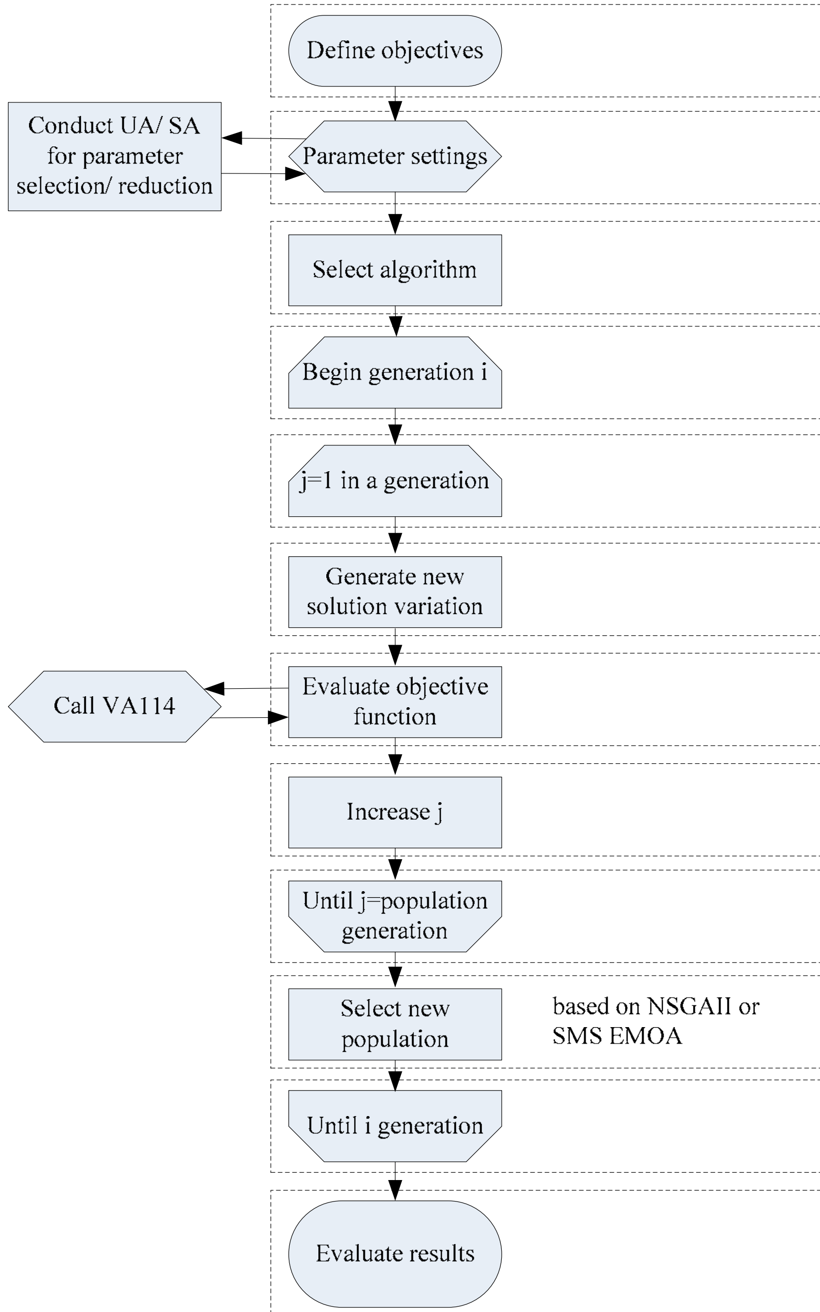


Figure 63 Illustration of the workflow for conducting MOO in BPS.

After having defined the two objectives (reduction of energy consumption and the improvement of thermal comfort) the parameter settings are defined. The six selected parameters for the optimization with NSGA-II and SMS EMOA are chosen because of the results from Chapter 3. After the selection of the algorithm, the number of evaluation is set to 2000 and the population size is limited to 20. The high number of evaluations is chosen to avoid the early breakdown of the optimization. The population size of 20 seems to be sufficient as it was found in literature [Wetter, 2006]. The objective function is the sum of the energy demand (annual cooling and annual heating) and the comfort criterion (weighted over- and underheating hours). During the evaluation of the objective function, the BPS tool VA114 is started with new parameters achieved for the optimization. The iteration is increased until the optimum is found.

5.8 Case study description of applying MOO

The application of the two algorithms and the results obtained are discussed in the following sections.

5.8.1 The application of NSGA-II algorithm

The NSGA-II is a MOO algorithm that is implemented in Topgui. In order to start the optimization with NSGA-II only one file needs to be created that imports the parameters changed, generates the different input files for the BPS tool VA114, defines the objective function, and includes the command line to start VA114. After that, the optimization procedure is easily started in batch mode.

In the command line the following parameters are passed for the optimization as shown in Appendix E.

Table 17 Demonstration of the input parameters (maximum and minimum boundary conditions) for the optimization with NSGA-II algorithm.

			Internal gains			
	Glass area on two sides [m²]	Size room [m²]	People [W/m²]	Lighting [W/m²]	Equipment [W/m²]	Infiltration rate [ACH]
Min	10	160	6	6	6	0.2
Max	20	260	25	35	30	1

After 1000 simulations the optimization stops having generated 1000 solutions shown in Figure 64. The dots in the graphic symbolize the 1000 different solutions resulting in a well distributed Pareto front.

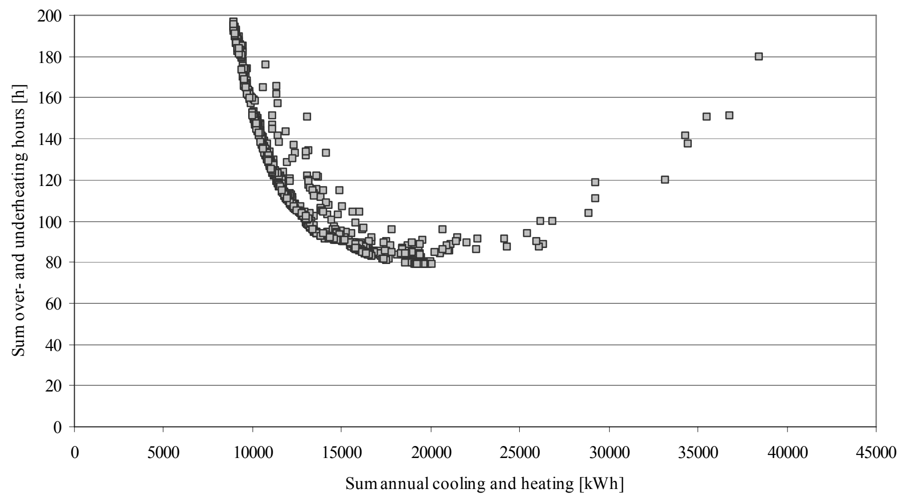


Figure 64 Results of MOO using NSGA-II algorithm for the two objectives energy consumption and thermal comfort using the parameter settings from Table 17.

The final values of the problem variables are summarized in Table 18, the final outcome of the two objectives energy consumption and thermal comfort in Table 19.

Table 18 Results of MOO using NSGA-II algorithm after 1000 simulations for the input parameters using the parameter settings from Table 17.

			Internal gains			
	Side length window [m]	Side length room [m]	People [W/m²]	Lighting [W/m²]	Equipment [W/m²]	Infiltration rate [ACH]
Result	1.34	23	15	10.4	7.8	0.2

Table 19 Final outcome of MOO using NSGA-II algorithm for the two objectives energy consumption and thermal comfort.

Energy consumption	14338	kWh
Weighted over- and underheating hours	92	h

All dots on the Pareto frontier are possible solutions. However, the solution, where the optimization program stops shows one good compromise between the two objectives energy consumption and thermal comfort. It is shown in the figure below.

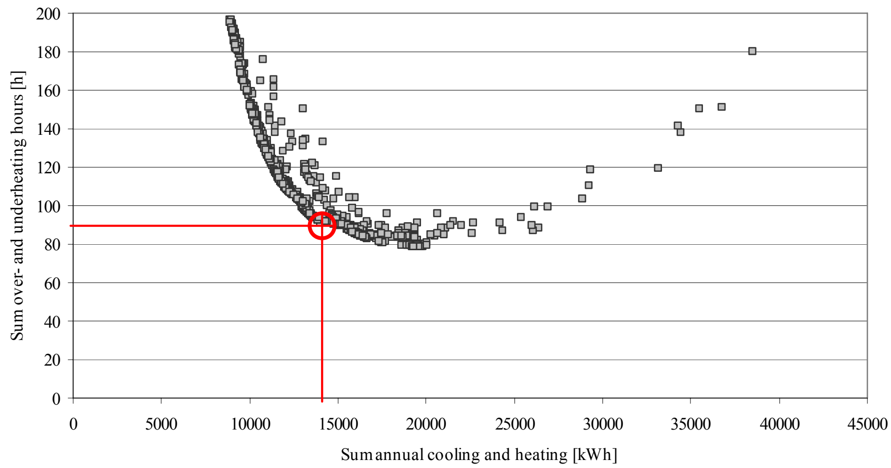


Figure 65 Results of MOO using NSGA-II algorithm for the two objectives energy consumption and thermal comfort using the parameter settings from Table 17 and showing the result of the optimization outcome.

Another possibility of using optimization techniques is to compare different design options. For that reason, the NSGA-II algorithm is used to contrast different designs such as in the decision making process of Chapter 4. Therefore design option 2 (see Appendix A and B) was simulated using the same input parameters as in the first case. Unfortunately, the results are not sufficient because of the circumstances that the second option consists of two models, one for the summer and one for the winter simulation. Therefore, not the entire year can be simulated as it has been done for design option 1. Two different simulations need to be run- for the summer and the winter separately resulting in two different parts of a Pareto front. Results are presented in Figure 66.

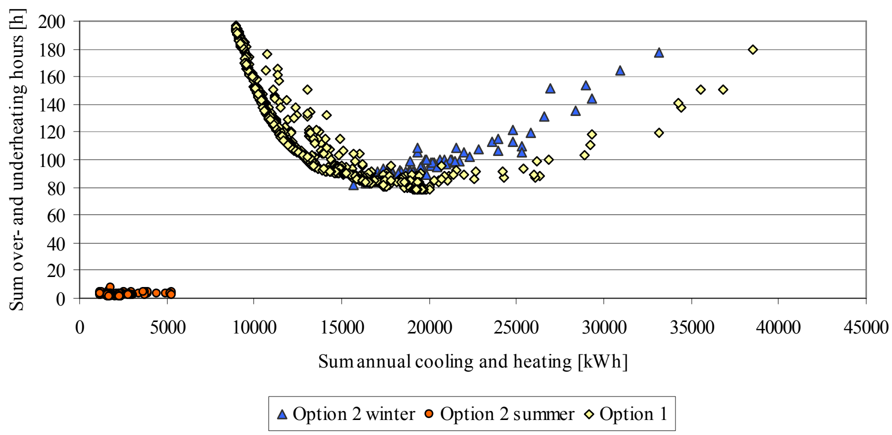


Figure 66 Results of MOO using NSGA-II algorithm for the two objectives energy consumption and thermal comfort using the parameter settings from Table 17 and showing the Pareto frontiers for design option 1 and design option 2.

The well distributed Pareto front for the first option is already shown in the Figure 64. The triangles show the results after the optimization for the winter season. The dots in the left hand corner are the optimized results for the summer scenario. Due to the fact that two different simulations had to be conducted, the Pareto front consists of two parts for design option 2 that are not connected.

A possibility to solve this problem and thus, to consider decision making with both options, would be to separate the objectives into a summer and winter case, i.e. an optimization of the annual cooling versus weighted overheating hours and the annual heating versus weighted underheating hours.

The summer case of Figure 66 is shown in more detail in Figure 68.

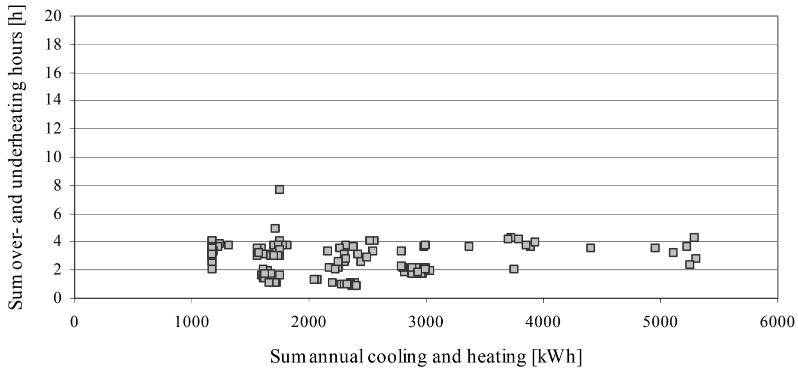


Figure 67 Results of MOO using NSGA-II algorithm for the two objectives energy consumption and thermal comfort using the parameter settings from Table 17 and showing the Pareto frontiers for summer case of design option 2.

5.8.2 The application of SMS-EMOA algorithm

In this section the optimization is conducted with SMS EMOA. The case study and the input parameters are identical to the approach with the NSGA-II. The SMS EMOA is also easily started in batch mode.

The optimization procedure with the SMS EMOA needs a higher number of simulations. Opposed to the 1000 simulations of the NSGA-II, the optimization with the SMS EMOA stops after 2140 simulations. It generates 2140 solutions shown in Figure 64. The dots in the graphic symbolize the 2140 different solutions performing a well distributed Pareto front comparable to the NSGA-II.

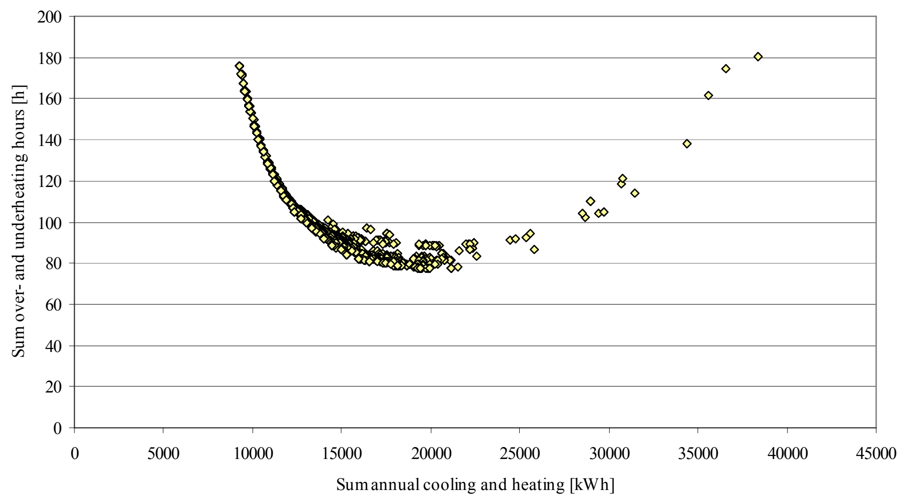


Figure 68 Results of MOO using SMS EMOA algorithm for the two objectives energy consumption and thermal comfort using the parameter settings from Table 17.

The final values for the problem variables are summarized in Table 20, the corresponding result in Table 21.

Table 20 Results of MOO using SMS EMOA algorithm for the two objectives energy consumption and thermal comfort.

			Internal gains			
	Side length window [m]	Side length room [m]	People [W/m²]	Lighting [W/m²]	Equipment [W/m²]	Infiltration rate [ACH]
Result	1.45	23	6	17	24	0.2

One possible result provided by the algorithms is shown in Table 19 for the two objectives. For the energy consumption it is 10832kWh and for the sum of the weighted over- and underheating hours it is 128h.

Table 21 Results of MOO using SMS EMOA algorithm for the two objectives energy consumption and thermal comfort.

Energy consumption	10832	kWh
Weighted over and under heating hours	128	h

The solution of the optimization where the simulation stops is marked in the figure below.

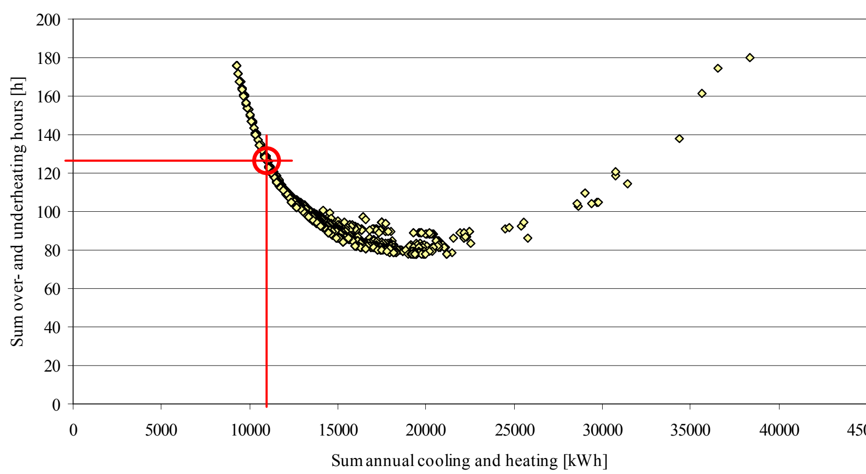


Figure 69 Results of MOO using SMS EMOA algorithm for the two objectives energy consumption and thermal comfort using the parameter settings from Table 17 and showing the results of the optimization outcome.

For the second design option, the case study with heating/cooling storage, the summer case is further optimized with the SMS EMOA. It is shown in Figure 70.

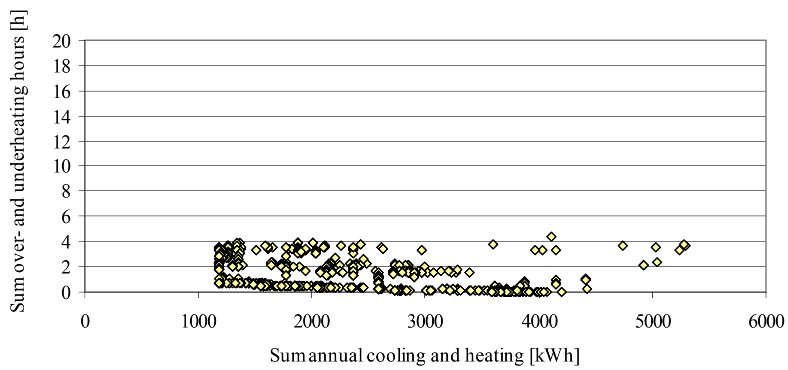


Figure 70 Results of MOO using SMS EMOA algorithm for the two objectives energy consumption and thermal comfort using the parameter settings from Table 17 and showing the Pareto frontiers for summer case of design option 2.

5.8.3 The application of Kriging (plus uncertainty)

To allow the optimization under uncertainty, Kriging meta-models are used. They have already been introduced in Section 5.5.
Besides the parameters varied for the optimization, uncertain parameters have to be defined. In a first trial of the Kriging meta-modeling five variables for the optimization and 72 for uncertainty analysis have been considered. Unfortunately no feasible results have been achieved as the number of parameters being used for Kriging meta-modeling is limited to around 20 [Paredis, 2008].

The second trial focused on the optimization of 5 variables and the uncertainty analysis of 5 variables. In Table 22 the in total ten parameters for optimization and uncertainty are listed; the other parameters are kept constant.

Uncertainty	Thickness wall layer 3	Conductivity floor layer 4	Conductivity floor layer 2	Infiltration rate	switch single/ double
Optimization	Size room	Size windows	Internal gains: people	Internal gains: equipment	Internal gains: lighting

Table 22 Overview of Kriging meta-model input parameters for the optimization and uncertainty analysis.

The parameters varied for the optimization are identical to the approach with NSGA-II and SMS EMOA algorithms in Table 17. The selection of the parameters considered for the uncertainty analysis is based on findings of the UA/SA in Chapter 3. The infiltration rate, the conductivity of two floor layers, the thickness of a wall layer, and the switch of double and single glazing are considered. Detailed information about the mean and standard deviation can be seen in Appendix B.

For the calculation of the correlation parameters a maximum likelihood heuristics is used. For the maximization of this likelihood term in Kriging meta-models a Covariance Matrix Adaptation Evolution Strategy (CMA-ES) is applied [Hansen et al., 2003]. CMA-ES is a stochastic, population-based, iterative optimization method belonging to the class of evolutionary algorithms.

In Figure 71 the results of the Kriging are summarized. The figure includes the worst, the mean, and the best case, each 200 rounds (simulation calls) in length. For each optimization the model is called 200x201 = 40200 times. The number of calls to the model that are required for the initialization of the parent set is ‘number of parents’ multiplied with 201.

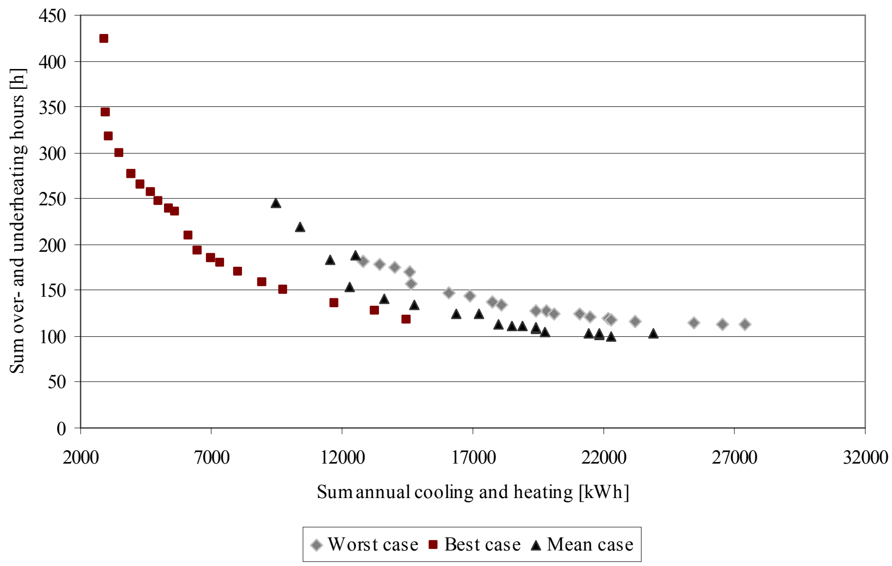


Figure 71 Results of Kriging meta-modeling for the two objectives energy consumption and thermal comfort using the parameter settings from Table 17.

In Figure 71 the Pareto front after 200 iterations of the algorithm is shown. Three different cases are distinguished: the worst case, the mean case and the best case. Compared to the optimization in Section 5.8.1 and 5.8.2 less results need to be evaluated to achieve a well distributed Pareto front. The three cases show the best, mean, and worst prediction of the conducted case study with regards to the optimization of thermal comfort and energy consumption including uncertainty.

The model comes up with less quality predictions for the best case, although the best case Pareto front looks well distributed (see Figure 71). The quality prediction is a result of the y-y' plots in Figure 72 and Figure 73.

A reason for this could be that for the best case solutions are found on the boundaries of the parameter ranges. As a consequence of this, new points that lie on the boundary lack for quality neighborhood points to support the prediction. This problem does not hold for the mean and worst case because here the points lie further from the boundaries.

It is obvious that the worst and the mean case are more interesting for the performance under uncertainty as they provide more insight in worse scenarios and therefore are better for making less risky predictions. However, the best case is used as a reference to check the functioning of the system regarding the quality of the output and to compare it with the NSGA-II later on.

Figure 72 and Figure 73 demonstrate for both objectives the y'-y diagrams which show the predicted points relatively to the real points. The preferred outcome is that all points lie on the separatrix between the y- and the y'-axis.

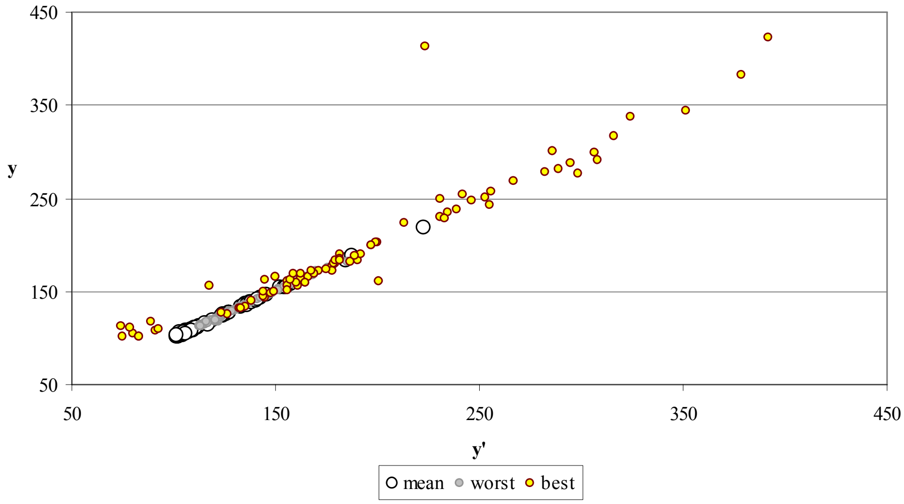


Figure 72 Results of Kriging meta-modeling showing the relation of predicted points relatively (y') to the real points (y) for the objective weighted over- and underheating hours.

The comparison of the predicted points relatively (y') to the real points (y) for thermal comfort is shown in Figure 72. For the mean and the worst case the results form a straight line whilst for the best case the results are slightly spread. This consequences a worse quality prediction for the best case.

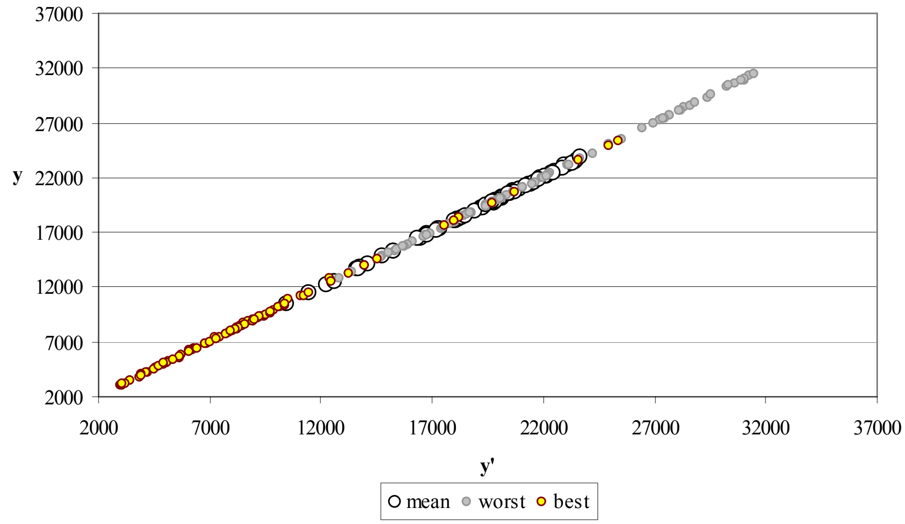


Figure 73 Results of Kriging meta-modeling showing the relation of predicted points relatively (y') to the real points (y) for the objective energy consumption.

The comparison of the predicted points relatively (y') to the real points (y) for energy consumption is shown in Figure 73. All outcomes presented follow a line. That means that the predicted points match the real points for the best, mean, and worst case. Therefore, the quality prediction for all cases is sufficient.

5.9 Discussion

The trade off curve (Pareto front) is shown for the NSGA-II and SMS EMOA.

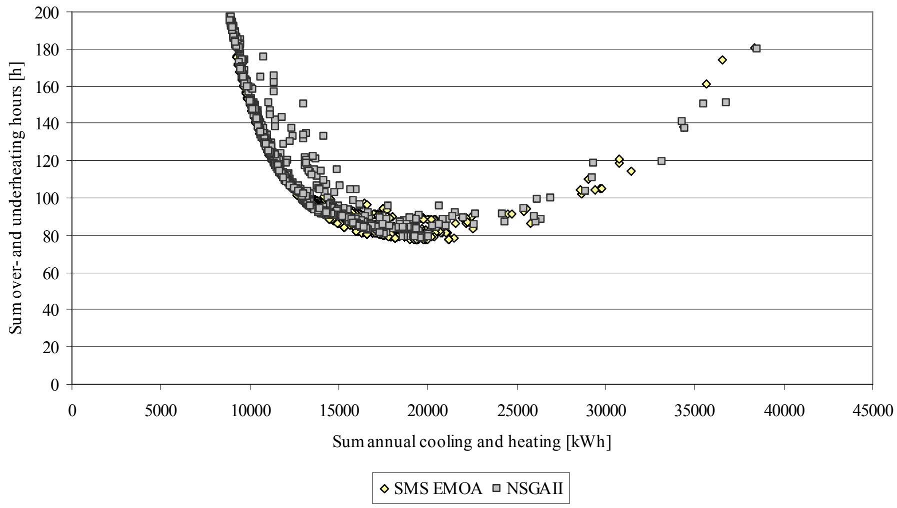


Figure 74 Results of MOO comparing NSGA-II and SMS EMOA algorithms for the two objectives energy consumption and thermal comfort using the parameter settings from Table 17.

In Figure 74 the comparison of NSGA-II and SMS-EMOA algorithms for design option 1 is shown. It can be seen that the Pareto-front is well distributed and that both Pareto fronts match each other.

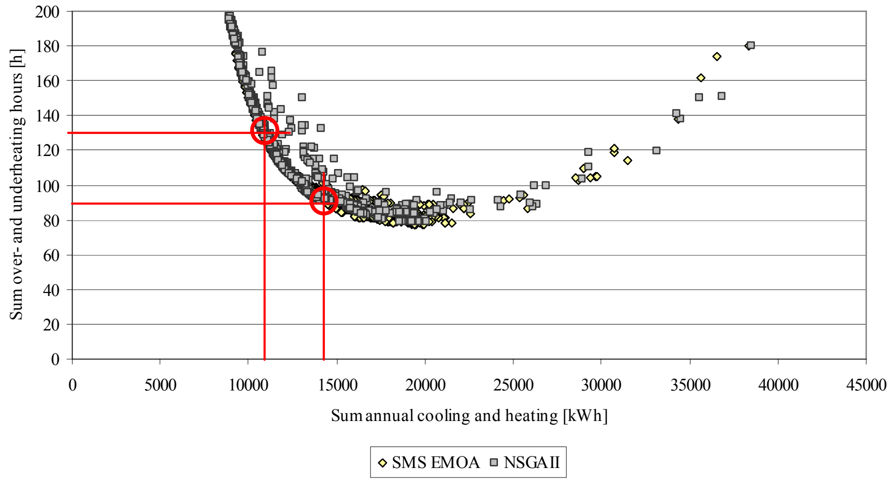


Figure 75 Results of MOO comparing NSGA-II and SMS EMOA algorithms for the two objectives energy consumption and thermal comfort and indicating the two good solutions from the algorithms.

Figure 75 shows the results of both algorithms indicating the good solutions. It can be seen that both algorithms achieve a well-distributed Pareto front. This is a valid proof that the global optimum was found. The solutions provided by the algorithms are shown in the figure above. Both solutions surround the area of a fair- tradeoff. Solutions in between those two are all possible, well optimized solutions.

Table 23 Comparison of the results (output and number of evaluations necessary) of NSGA-II and SMS EMOA algorithms for design option 1.

		NSGA-II	Number simulations	SMS EMOA	Number simulations
Energy consumption	[kWh]	14338	1000	10832	2140
Weighted over- and underheating hours	[h]	92	1000	128	2140

The Pareto frontiers are comparable. However, the time difference is significantly higher for the SMS EMOA. To conduct 100 simulations it takes around 20 minutes. In total, the optimization with the NSGA-II takes slightly more than 3 hours whilst the optimization with the SMS EMOA needs more than 7 hours on the same machine.

In Figure 76 and Table 24 the results are compared for design option 2 of Appendix A (summer case).
Figure 76 shows, that the results provided by SMS EMOA build a better Pareto front approximation compared to the NSGA-II.

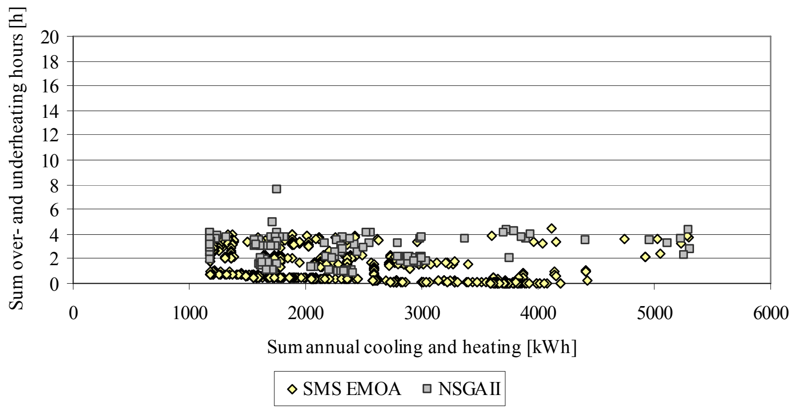


Figure 76 Results of MOO comparing NSGA-II and SMS EMOA algorithms for the two objectives energy consumption and thermal comfort for design option 2.

The comparison of the NSGA-II and the SMS EMOA algorithms are shown in Figure 76 for design option 2 the summer case. The results of the NSGA-II are more spread and do not build a well distributed Pareto front whilst for the SMS EMOA better solutions are found.

Table 24 Comparison of results (output and number of evaluations necessary) of NSGA-II and SMS EMOA algorithm for the summer case of design option 2.

		NSGA-II	Number simulations	SMS EMOA	Number simulations
AC	[kWh]	1662	120	2049	2137
WOH+	[h]	1	120	0	2137

Table 24 shows the comparison of the outcome for the summer case with NSGA-II and SMS EMOA algorithms. The results show the demand of annual cooling opposed the weighted overheating. The SMS EMOA finds the solution after 2137 simulations whilst the NSGA-II stops automatically after 120 simulations.

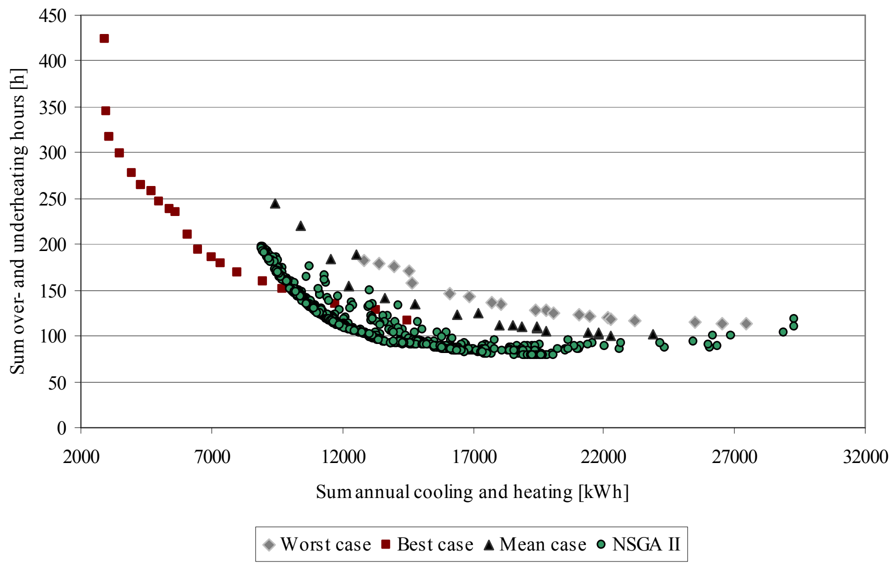


Figure 77 Results of MOO comparing NSGA-II algorithm and Kriging meta-modeling for the two objectives energy consumption and thermal comfort.

In Figure 77 the results of the Kriging are compared with the outcome of the NSGA-II. The best, the mean, and the worst case of the Kriging meta-modeling are compared to the NSGA-II. The Pareto front of the NSGA-II lies in between the best and mean case; however without considering any uncertainty in the parameters.

5.10 Conclusion

In this chapter multi-objective algorithms have been applied in the context of building performance. The results of two algorithms NSGA-II and SMS EMOA have been presented and compared to each other. Besides, the implementation of Kriging meta-models shows the affect uncertainties have on the Pareto frontier.

The NSGA-II algorithm provides sufficient results especially for design option 1. However, the results achieved with SMS EMOA for design option 2 are significantly better even though the number of simulations is much higher. This is due to focusing on knee-points without loosing extreme points in finding solutions (cf. Section 5.4.3). The reason why the optimization with the NSGA-II breaks up already after only 120 simulations however is not clear. This requires further evaluations of the differences among both algorithms, the convergence and the influence of the different options applied.

At first sight, looking at design option 1 the use of NSGA-II seems more convenient. Considering the fact that the time for 1000 simulations averages three hours, i.e., the SMS EMOA runs for almost seven hours. However, as computational power increases, the limitation of the simulation with SMS EMOA will be elevated, and appears therefore more promising. In order proof the above, it is advised to run both algorithms with another case study.
Nevertheless, both algorithms were successful in finding Pareto front for design option 1.

Kriging meta-modeling is an approach to reduce the number of objective function evaluations which becomes indispensable when the robustness of solutions needs to be tested in order to compare their performance. The results for the best, the mean, and the worst case give good insights to the behavior of the objective function under consideration of only five variables for uncertainty.
A disadvantage of Kriging meta-modeling is that it is limited to objective functions with only a low number (ca. 1-20) of design variables.
However, this problem was circumvented with the help of parameter reduction as a result of using uncertainty/sensitivity analysis in the first step to identify the five most sensitive parameters (results from Chapter 2).

The results of the MOO presented would help the BPS designer in several ways such as follows.

(i) Integrated optimization of parameters leading to an optimized result.
(ii) Comprehension of how uncertainty can affect the Pareto frontier.
(iii) Support in the decision process by providing a base to compare different design options.
(iv) Enhancement of the use of BPS by providing additional support, and therefore, leading to a better guidance in the design process.

For evaluating the added value of optimization for design support in BPS, the results of the first case will be presented to a number of professionals in an online survey. Due to the fact that both algorithms do not differ significantly for design option 1, only one algorithm (NSGA-II) is used for demonstrating the results of the optimization to practitioners.

6

6. Usability Testing

6.1 Introduction

Preceding chapters presented three different approaches embedding UA/SA and/or optimization. The overall aim was to improve the use of building performance simulation in the final stage. Therefore, it is essential to test the usability of the three prototypes developed in practice with a number of design professionals.

1. Prototype: the application of UA/SA (cf. Chapter 3).
2. Prototype: the application of decision making with UA/SA (cf. Chapter 4).
3. Prototype: the application of MOO (cf. Chapter 5).

Usability testing involves one or more users to use a prototype whilst possibly an observer follows the work-through. Mills et al. [1986] for instance define the usability of a tool as the ease with which an application can be used.
Nielsen [1995] separates four basic ways of evaluating user interfaces.

1. Automatic approach by running a user interface through some program.
2. Empirical testing of the interface with real users.
3. Formal calculation of usability measure through formulas.
4. Informal approach based on experience of evaluator and rules of thumb.

The empirical testing seems advantageous because feedback from many users can be collected. By running through the program feedback from practise can be achieved by the intended user group. Drawback is that the rapidly developed prototypes do not provide an applicable user interface so far that would it make possible to let users test it self-contained.
Therefore one emphasis of the usability testing focussed on observation (methods). D'Hertefelt [1999] describes observation methods and gives advices for usability testing. He divides observation methods into two variants: (i) unobtrusive observation and (ii) obtrusive observation. Unobtrusive observation lets the users do, and helps in finding out if the system is easy to use, i.e. understandable. On the other hand, obtrusive observation allows the interaction with questions from the observer. This type is better to learn about the usefulness and acceptance of prototype.
For achieving an insight in the individual attitude of a user, the distinction between the linguistic, the motor-expressive and the physiological level is made [Horeni, 2007]. The two latter ones work with facial expression, gestures during observations, measurements of neurological changes, etc., and are inappropriate. The linguistic level on the contrary implies methods/ techniques such as interviews or questionnaires.
Preston [2009] summarizes a range of methods for usability testing on the linguistic level. Three of them, appearing relevant for this research, are as follows.

- Interviews and observations. These are one-on one session with designers, asking questions like what they do, want, prefer in building assessment. This method was chosen to start the research project and assess the state of the art in the use of building performance (cf. Chapter 2).
- Focus groups. Focus groups are meetings with multiple attendees from the specific target group. Even so it is a promising method especially for initiating discussions it was not possible to apply due to the difficulty of bringing professional together at the same time and location.
- Questionnaires. A formal questionnaire is an instrument for gathering information from a group of people. Advantage is that it is not influenced by the interviewer. It is easy to conduct if online spread, and implies therefore less effort than interviews. Besides, a bigger number of respondents can be covered. The answers can be gathered standardized which makes the data analysis easy as well.

The research started with a series of interviews with design professionals interrogating the satisfaction with present simulation tools, problems, and future wishes amongst others.
Consequently and continuously feedback from practice was achieved, developing concepts in terms of ongoing research activities and in direction to expectations and requirements and claims of practitioners. Two series of interviews have been conducted, and two extensive mock-up studies with a selected group of designers have been carried out. The results are summarized in Section 6.2. Finally, after the development of three prototypes, a survey was published on internet to achieve a better coverage and objective feedback without interrogation.

6.2 Usability testing with mock-up presentations

Two mock-up presentations have been carried out during the development of the different prototypes to achieve feedback from practitioners before the finalization of the project. These mock-up studies consisted of a number of PowerPoint slides showing possible inputs and outputs for the three prototypes that have not been implemented at that point.
The results of the two mock-up studies are summarized in the following section.

6.2.1 Feedback to uncertainty/sensitivity analysis

Uncertainty/ sensitivity analysis was a very much appreciated approach by the user group. However, some issues or add-ons for the current prototype and the output presentations have been recognized.

- Demonstration of the techniques and provision of practical conclusions with analysis results surprise and give answers to questions such as, e.g., “What is the added value when increasing the Rc value from 2.5 as required by standard to 3.0 relative to varying the infiltration rate.”
- It is an important question with what amount of money something can be achieved in order to see which parameters has the biggest impact on the performance. This consequences, that one can focus more on that specific

issue. It shows where the higher investment should be spent in order to achieve a certain goal (decision making under uncertainty).
- Consideration of uncertainties in systems (part load performance, conflicting component operation, etc.) is interesting as long as the tool is able to model the system components detailed enough.
- Infiltration in general becomes very important (this can also be noticed in the uncertainty analysis). The infiltration rate in practice can easily exceed 5 times the factor that is assumed. It was stated that one design concept is more sensitive to infiltration than another.

Output visualization
- Graphs of UA/SA appear very abstract and are consequently very hard to understand for simulation user.
- Suggestion of a normal graph of energy consumption and comfort to see the influence and variation in between the different simulations (the effect of energy consumption/ percentage of change).
- Explanation of results is important. Appreciation of the chosen form of presenting sensitivities, e.g., bar charts indicating regression coefficients as being intuitive ("the longer the beam the bigger the influence") but at the same time it admits the need for basic knowledge in statistics to understand the presented data. It is nice to get answers to following questions: "What is changing?" "Why are parameters changing or have a different influence?" "What is the expectation?" "What could happen?"

6.2.2 Feedback to decision making under uncertainty

Decision making with the help of UA/SA was perceived as a very good approach for having (i) the evaluation and analysis of performance of varieties, and (ii) the illustration of the costs including the risk of the underperformance of an option. The chosen decision protocol analytical hierarchy processing (AHP) is comprehensible. The outcome is easy to use and very nice to demonstrate in presentations. Certain comments are summarized about the issue of communication, the weighting of the criteria and the robustness analysis.

Communication
- Communication is of major interest in the entire design process- also in the detailed design stage. Communication and flexibility are important because "if people do not understand they do not make a decision. It is important to know what the consequences are of each option or decision are and why something is better!" [P. Stoelinga, 2008].
- The application of a decision support technique as AHP was encouraged as it supports the communication in the design process.

Weights & aspects
- Change of weights associated with performance metrics might change over the building process (e.g., costs are not important as long the budget is not

exceeded; fluctuation in daylight availability is accepted as long it is not dark). It is beneficial to be able to change the weighting factor from time to time.

- It is difficult to define right performance aspects and to find the right weighting factor.
- Fear of a predisposition of engineers that might influence the decision when using weights. Decisions will be taken on subjective rather than objective arguments.

Robustness

- The use of parameters contributes to robustness. In the beginning other performance aspects are important (such as energy consumption, comfort); but costs is something that everybody understands. Therefore costs become very important in the end. That includes comparison of different options to the cost factor.
- The danger of "goal thinking" was noticed: "this is what I want the answer to be! The more complex the problem is - the bigger the danger of goal thinking." [Wiedenhoff, 2008] It should be aimed to identify the weakness of design options rather than forcefully seeking for a solution to the design problem.
- Exposure of decisions purely based on logical reasoning to the risk of garbage in and garbage out.
- Inclusion of the productivity into the cost function. An extra annual income due to enhanced indoor air quality equals annual depreciation of building and components. Temperature and fresh air rate have a direct relation to the productivity. Therefore, a quantitative assessment is possible. Control strategies and possible manual adjustments of environment have also a qualitative relationship to productivity.

6.2.3 Feedback to optimization

The implementation of optimization techniques is perceived as very complex but promising. Some feedback is outlined.

- Optimization techniques might support the decision process in design. The black box approach requires confidence in a technique and the results can not be communicated traditionally using cause and impact. An analogy "client – designer" was used for explanation. A client requests a design trusting the designer that the design delivered will meet his expectations.
- Statements were given as "not sure about it" but also like "feeling" best about optimization prototype. The integration into a design tool seems easy.
- Questions that need to be answered in the future:
    - How does it fit into the design process?
    - How can it be integrated into the decision making?
    - Who will be the user group?

6.2.4 Summarized results of mock-up presentations

- AHP seems to be process oriented because it assists the decision finding process. Optimization seems to be tool oriented because it enhances tool capabilities.
- Both approaches are applicable for the final design stage. The idea of MCDM under uncertainty for instance is very helpful and not recognizable in standard simulation tools; “that is something that could make it worth doing a simulation even in the case of where it is not necessary” [E. Rooijakkers, 2008].
- The role of the consultant is to analyze consequences of choices and to make design team members and the principle aware of those consequences. The project manager should steer and the principle should make the decisions accordingly. MCDM has potential in supporting this procedure and to explain consequences of decisions to design team members and the principal.
- The user group for decision making and parameter optimization differs.
- Communication is a very important factor.
- If the user wants to have more insight in the calculation, the optimization is of higher interest. It is a very detailed approach and therefore especially beneficial in the final design stage.
- People only use tools with confidence when the results meet their expectations. Ideally the data presentation should indicate relationships for easy conclusions.
- There is a weakness in optimization as implicit knowledge is not being considered. For that reason the use of multi- criteria decision making on top of it might be beneficial.
- A systematic-mathematical approach was suggested: “Use optimization techniques first to get an objective picture of the situation; nail it down to two choices, which are more closely related and expose their weakness (“weakness- analysis”) and eventually use AHP to steer the team towards the preferred design option” [Wiedenhoff, 2008].
- To sum up, the prototypes are perceived as a coherent story. The prototypes are expected to support the design process in a very effective manner.

6.3 Online survey

6.3.1 Introduction

After the development of all three approaches, the aim is to receive a final feedback of the practitioners.
Instead of conducting another mock-up study, the final part of the usability testing comprises an online survey that was filled in at the end of the research.
The key questions during the two mock-up sessions were: ”how much interaction is too much?”; “how much influenced/ affected is the provided answer by the question?”
However, intending to avoid the risk of interpreting behaviour and thus, influencing the interviewee, an online survey was developed. The online survey itself can be found in Appendix F.

The setup needs to be explained as the survey questionnaire comprises of several modules: an introduction page followed by three scenarios dedicated to the prototypes from Chapters 3-5.

Structure online survey

1. Introduction with general questions about state of the art in building performance, user satisfaction, etc.
2. Representation of prototype 1: the application of UA/SA (cf. Chapter 3).
3. Representation of prototype 2: the application of decision making with UA/SA (cf. Chapter 4).
4. Representation of prototype 3: the application of MOO (cf. Chapter 5).
5. Summary and conclusion part.

Participants

The online survey was conducted by seven world leading building services professionals: four mechanical engineers and three building physicists: all of them holding positions in industry, having high to very high experience in the use of building performance simulation. Further on, they frequently participate in design team meetings, are due to that experienced in the communication with other design team members.

Directions to be addressed

Different categories have been addressed in the survey:

1. the requirements fulfilments for BPS in the final design stage.
2. the appreciation and traceability (comprehension) of the results.
3. the support of the design process in terms of communication and guidance.
4. the usefulness of the integration in BPS.

There are two different question types that have been included in this questionnaire.

(i) Closed-ended questions where the respondent can easily select the preferred answer in selection of possibilities with radio buttons or check boxes.

(ii) Open-ended question asked at the end of each prototype for further suggestions or comments.

Typical response scales for closed-ended questions are as follows [Trochim, 2006].

(i) Thurstone or equal appearing scaling.

(ii) Likert or summative scaling.

(iii) Guttman or cumulative scaling.

Thurstone scale provides statements. The user has to decide which complies best with his attitude. A mean score is computed out of the chosen statement that indicates ones attitude [Fishbein et al.,1975].

Likert scale is the mostly applied scale in questionnaires. Respondents, e.g., specify the level of agreement or importance to a statement. Very often five level scales are used,

but it also varies from 3 to 7 level answers. If the intention is to force the respondent to give an answer and to avoid "neither nor" replies, no middle number is provided (4,6,8, etc.)
In Guttman or cumulative scaling items are arranged that a respondent who agrees with an answer also agrees with items falling into the same category, e.g., being of a lower rank-order. It can be described as sort of achievement test.
The Likert terms selected in this questionnaire are mostly forced choice scales stating the importance (very important to unimportant), agreement (strongly agree to strongly disagree), standard (very high to very low), or quality (excellent to poor) of a question/ graphic.

6.3.2 Results online survey

The online survey itself is shown in Appendix F. In this chapter merely the results are summarized.

Prototype 1: uncertainty/ sensitivity analysis
Three different outputs for the analysis of uncertainties are shown to the use group. 'UA1 frequency'- this figure is used in Chapter 3. It shows the frequency plot of an outcome. 'UA2 probability'- this figure is used in Chapter 3. The normality plot is shown and gives insight if the output follows a normal distribution. 'UA3 range'-this figure is used in Chapter 4. The range shows simplified in what range the output will perform.

The participants are asked to rate the added value of the three different outputs for uncertainty.

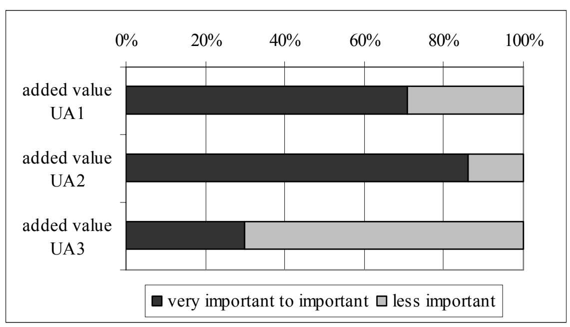


Figure 78 Illustration of the percentage of the added value of three different graphics showing the uncertainty based on practitioners feedback.

The added value of the figures for frequency information (UA1), probability distribution (UA2), and the range of the output (UA3) is shown in Figure 78. Especially the second graphic that shows the probability is appreciated. Less important is the output that shows the range.

Two possibilities to demonstrate sensitivity are presented. In 'SA1 table' the 10 most sensitive parameters for different aspects are ranked. 'SA2 graphic' shows graphically the impact of uncertain parameters. Both results are shown in Chapter 3.

The participants are asked to rate the comprehension of the sensitivity results presented in a table (SA1) and a figure (SA2).

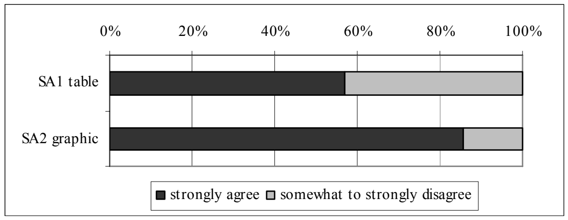


Figure 79 Illustration of the percentage of the comprehension of a table and figure showing the sensitivity based on practitioners feedback.

The comprehension of the results for sensitivity is shown Figure 79. The graphic is perceived to show the sensitivity information in an intuitive manner. Besides the ranking that is indicated in SA1, the user gets more information, e.g., about the impact of sensitivity and if it is positively or negatively affecting the output.

The participants are asked if they agree that the results of UA/SA can be taken as a basis for communication with others.

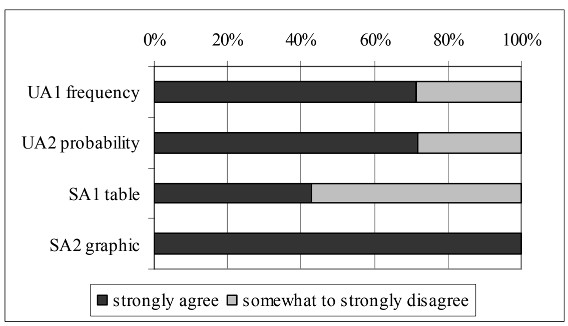


Figure 80 Illustration of the percentage of the agreement of practitioners that the results for UA/SA can be taken as a basis for communication.

The appreciation as a basis for communication with others is shown in Figure 80. In this question all outputs for UA/SA are presented. The bar chart for the sensitivity is the most appreciated graphic as base for communication.

Further the participants are asked if they agree that the results of UA/SA are intuitively understandable.

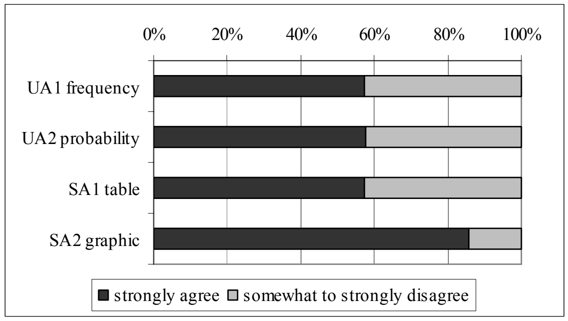


Figure 81 Illustration of the percentage of the practitioners' perception of being intuitively understandable for different UA/SA figures.

The participants have on average more problems with the outcome of the uncertainty information. However, the graphic showing the sensitivity of the parameters is perceived as very understandable.

The participants are requested if the results of UA/SA have potential in supporting the design process.

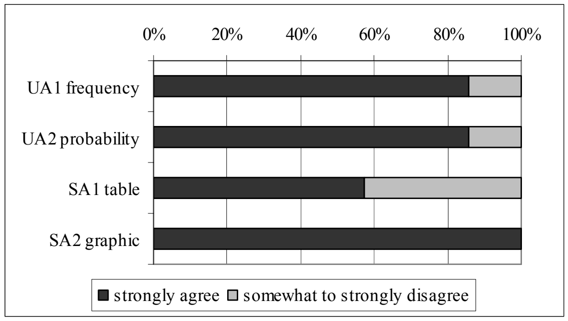


Figure 82 Illustration of the percentage of the practitioners' perception of supporting the design process for different UA/SA figures.

The appreciation to support the design process is shown in Figure 82. No outcome of the UA/SA was perceived as not having an added value of supporting the design process. The 'SA2 graphic' has the highest potential - all the users strongly agreed that it gives support.

The final question in the UA/SA approach was dedicated to the need of the integration of UA/SA in building performance simulation.

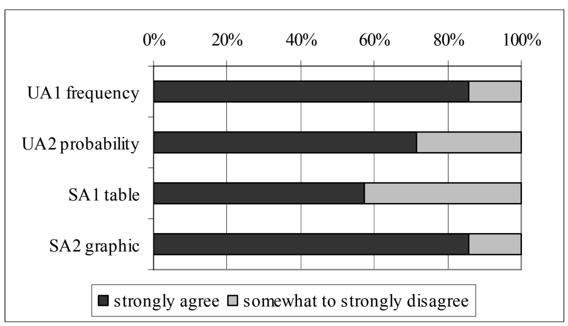


Figure 83 Illustration of the percentage of the practitioners' perception of the need to be integrated in BPS for different UA/SA figures.

The wish for the integration in BPS is shown in Figure 83. None of the participants was contra the information achieved with UA/SA. However, having the simple results of UA1 and SA2 almost 90% of the users agreed on being very important to integrate in BPS.

Prototype 2: decision making under uncertainty

The decision making protocol with the extension of BPS and UA/SA information is presented as it is demonstrated in Chapter 4. The participants are asked six questions.

1. How important do you rate communication in the design process?

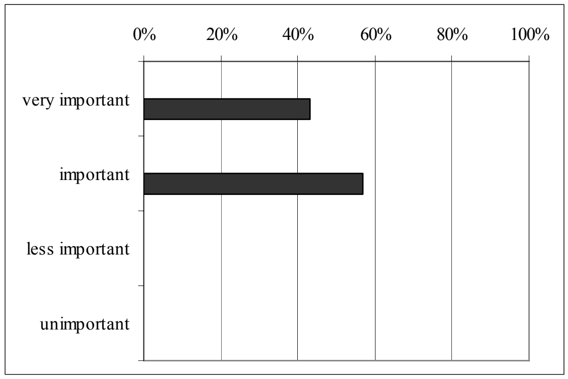


Figure 84 Illustration of the percentage of how important communication is rated in the design process based on practitioners' perception.

The perception of the importance of communication in the design process is shown in Figure 84. All participants agree that communication is a very important factor in the design process.

2. Do you think that BPS in general should provide the possibility to communicate results with other design team members?

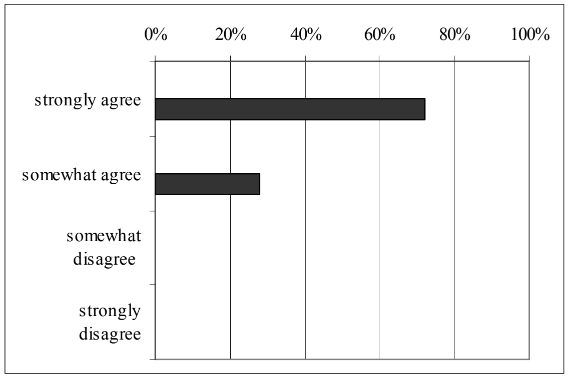


Figure 85 Illustration of the percentage of practitioners' perception if BPS should provide the possibility to communicate results.

The importance for BPS to provide the possibility to support communication with other design team members is shown in Figure 82. 70% of the participants strongly agree that BPS should provide the possibility to support communication. 30% somewhat agree to this.

3. How important is it that the preferred option is the option with the minimum risk?

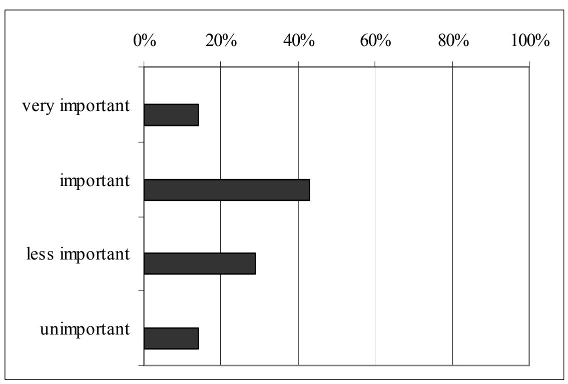


Figure 86 Illustration of the percentage of practitioners' perception of how important it is that the preferred option is without risk.

The importance that the preferred option is without risk is shown in Figure 86. The answer to this question varies significantly. In total the amount of participants on perceiving, that the preferred option should be without risk, is higher. Nevertheless it can be noticed that the perception of ‘very important’ and ‘unimportant’ is the same.

4. Do you see an added value in integrating uncertainty/ sensitivity analysis in BPS due to future climate scenarios?

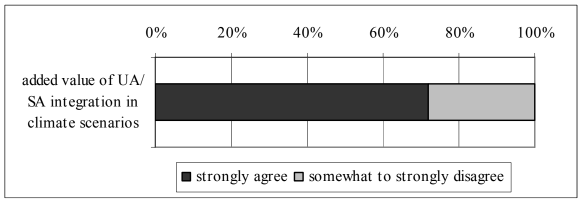


Figure 87 Illustration of the percentage of the added value of UA/SA integrated in BPS for climate change based on practitioners’ perception.

Figure 87 shows the perception of practitioners if UA/SA in climate scenarios should be integrated in decision making. Results on a study considering climate change in scenario conditions have been presented. 70% strongly agreed that is has an added value.

5. Do you see a potential of UA/SA in supporting the decision process?

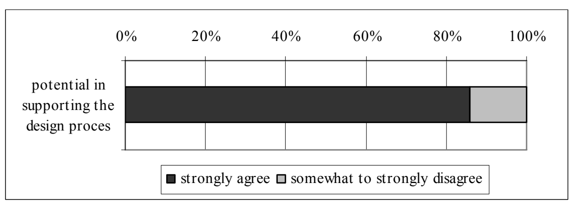


Figure 88 Illustration of the percentage of the potential of UA/SA to support the design process based on practitioners’ perception.

Figure 88 shows the support UA/SA can provide in the design process. Almost 90% agreed that adding UA/SA into a decision making protocol has a high potential. None of the users disagreed on this question

6. Do you agree that the prototype decision making with uncertainty and sensitivity:

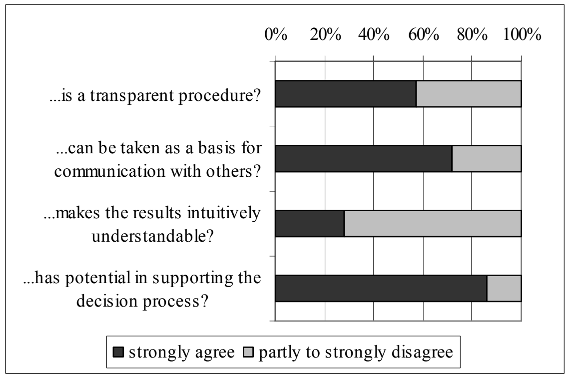


Figure 89 Illustration of the percentage of the summarized appreciation of the second prototype based on practitioners opinion.

The second prototype addressing decision making with uncertainty and sensitivity is a transparent procedure, can be taken as basis for communication and has high potential in supporting the design process. However, more than half of the users had problems in intuitively understanding the results.

Prototype 3: parameter optimization
In the third approach, the outcome of the optimization with the NSGA-II is presented showing the Pareto front for the optimization of energy and thermal comfort.
The participants are asked of they think that the provided results:

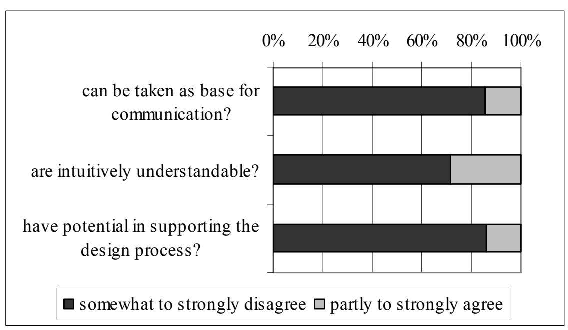


Figure 90 Illustration of the percentage of the summarized appreciation of the third prototype based on practitioners opinion.

The results of the third prototype addressing parameter optimization are perceived of being valid as basis for communication. They are intuitively understandable and they have potential in supporting the design process.

Comparison of the three prototypes

In the final part of the online questionnaire, the three approaches are compared to each other in the following categories.

1. Reliability of results.
2. Supporting the decision process.
3. Guidance through the design process.
4. Fulfilling the requirements of BPS in the final design.
5. Usefulness/ importance of integration in BPS software.

1. Reliability of results

In the first part 'reliability of the results' it is checked how much trust the participants have in the results presented.

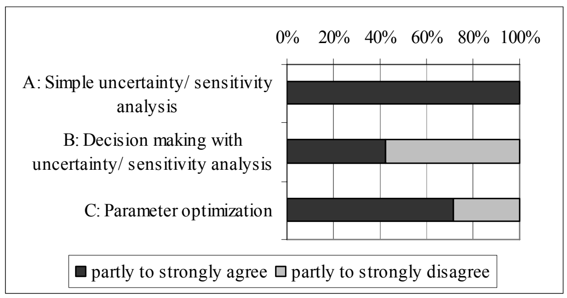


Figure 91 Illustration of the percentage of the reliability of the three different prototypes based on practitioners' feedback.

It can be seen that prototype 1 UA/SA is comprehended by all of the participants. This is because of the results are perceived as easy to understand in an intuitive manner.
The second prototype is not as accepted as the first prototype. The feedback was that the process was not entirely clear. Immediately, the perception decreased noticeable.
The third prototype received very good feedback by around 70% of the participants. Part of the users appreciated optimization techniques as there is trust in mathematical techniques. However, it was also stated that the third prototype is a black box approach, and a lack of insight in the optimization procedure was stated.

2. Supporting the decision process

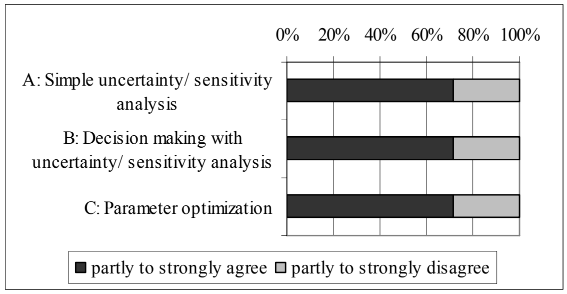


Figure 92 Illustration of the percentage of the support of the decision process of the three different prototypes based on practitioners' feedback.

Having asked about the support of the design process, the appreciation is constantly high for all prototypes. All approaches have an added value by providing additional information, even though the results presented differ.

3. Guidance through the design process

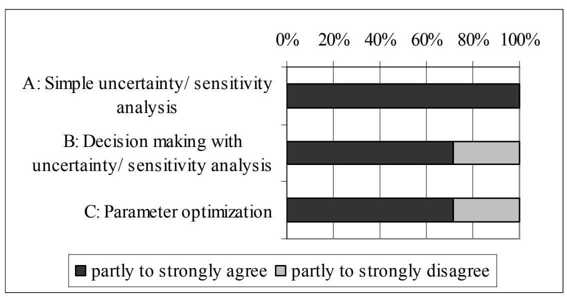


Figure 93 Illustration of the percentage of the guidance through the design process of the three different prototypes based on practitioners' feedback.

All three approaches provide guidance through the design process. The UA/SA approach is highly appreciated by all users. 100% feel leaded by the extra information in bar charts/ scatter plots or distribution curves.
But also the second and third approach help in guiding through the design process by the information provided.

4. Fulfilling the requirements of BPS in the final design

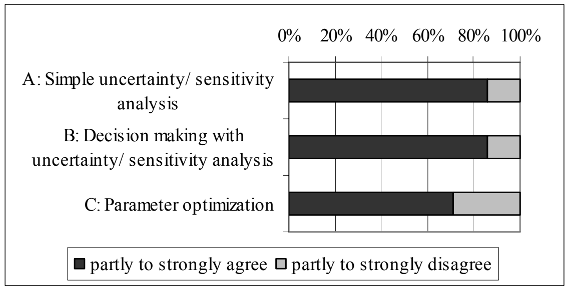


Figure 94 Illustration of the percentage for the requirements fulfillment of BPS in the final design of the three different prototypes based on practitioners' feedback.

The appreciation of all approaches as shown earlier in guidance through the final design and supporting the decision process is very high. Therefore it is self-explanatory that all three approaches fulfil the requirements for the final design.

5. Usefulness/ importance of integration in BPS software

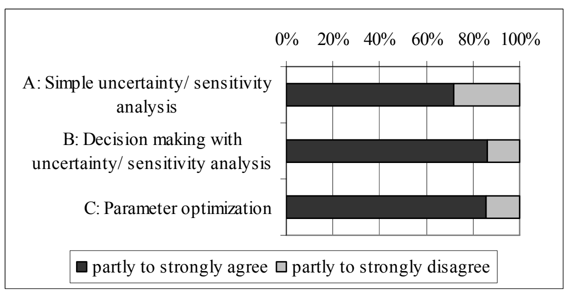


Figure 95 Illustration of the percentage of the usefulness and importance of integration in BPS of the three different prototypes based on practitioners' feedback.

In Chapter 2 it was already indicated, what should be improved in BPS during final design. It was shown that there is a need of the three techniques. After the implementation and the results representation, the feedback was very positive. Asked about the usefulness and importance of the integration in BPS software, all three approaches are appreciated.

6.4 Conclusion

In the mock-up presentations and the online survey, the feedback of practitioners was collected to the three different prototypes.

- (i) Prototype applying of UA/SA.
- (ii) Prototype applying decision making with UA/SA.
- (iii) Prototype applying MOO.

The prototype applying UA/SA is very well comprehended by all the participants. The support of the decision process with the UA/SA output is perceived also very high with around 70%. In guiding through the design process -a very important factor in the use of BPS- the appreciation of UA/SA is 100%.
Also the fulfilment of the requirements of BPS in the final design and the importance of the integration in BPS is around 80%.

The prototype addressing decision making under uncertainty is very much appreciated in the context of guiding through the design process. But it can also be noticed that the feedback about the comprehension of the results is very low. Remarks given by the practitioners were due to difficulties in following the work-through with the online survey. It is hypothesized that with a better guidance through the AHP protocol under uncertainty, the appreciation would be much higher.

The final prototype considering the optimization of two objectives in BPS received also very high appreciation of all practitioners. Especially the reliability of the results and the support of the decision process are very high.

In general it can be concluded that all three prototypes fulfil the requirements of BPS in the final design and there are all perceived as useful and important to be integrated in BPS.

7

7. Closure

The final chapter of this thesis will give a brief summarize, provide some concluding remarks and directions for future research.

7.1 Summary

As summarized in Chapter 2, it was aimed to improve current available simulation tools such as follows:

- to implement uncertainty and sensitivity analysis.
- to allow a better judgement of different concepts.
- to provide informed decision making.
- to include optimization techniques.

The research indicated problems and limitations due to BPS in the final design. These problems were tackled from three different sides, considering different user level and varying influence on the simulation tool (black box approach to actively taking impact).

The work presented has summarized the state of the art and the application of three techniques:

1. uncertainty/sensitivity analysis.
2. decision making techniques.
3. optimization methods.

Approach 1: integration of uncertainty/ sensitivity analysis

In Chapter 3 the integration of UA/SA in BPS is described. Results are shown for UA and SA separately and conclusions are drawn regarding the impact of different categories of uncertainties. For that reason, it was distinguished between three different kinds of uncertainties: uncertainties due to physical properties, design adaptations and scenario conditions.

Approach 2: multi-criteria decision making with UA/SA

Chapter 4 presents the second approach, the enhancement of a well-known decision making protocol with UA/SA information.

This approach gives the opportunity to see, how the impact of performance aspects can vary if they have different priority. Further, with the help of UA/SA, it is shown how much this can influence the final result. Finally, it is demonstrated, how risk that comes with an option, can be diminished.

Approach 3: multi-objective optimization
The third approach considers the application of MOO applying two different algorithms (NSGA-II and SMS EMOA). Further, the implementation of Kriging meta-models also provides promising results with consideration of UA.

Usability testing
It was aimed to improve the use of BPS in the final design stage. Three approaches have been shown that were developed, validated and tested according to the feedback of professionals.
The capabilities in current building performance simulation have been shown also in demonstration of the usability on the addressed target group.
A number of design professionals were asked after the presentation of the three approaches about the following key issues.

- Comprehension of results.
- Fulfillment of requirements for the final design.
- Guidance through the design process.
- Importance to be integration in BPS.
- Supporting the decision process.

7.2 Concluding remarks

Approach 1: integration of uncertainty/ sensitivity analysis
The graphical output of the UA/SA is perceived as intuitively understandable and very valid for the integration in BPS. A disadvantage is, that it depends on the user to understand and use the information gained.
The presented results are applicable only for the case study chosen. A different case study will imply a different sort of sensitivity ranking and also a different uncertainty. Therefore no general guidelines for UA/SA can be provided to explain users how to deal with the information gained. Another drawback is that the results achieved show the impact uncertainties have on current simulation output based on a distribution taken from literature. Nevertheless, the variations assumed are not proven and still burrow plenty of space for research.

Approach 2: multi-criteria decision making with UA/SA
The advantage is that it is a very easy approach. The decision process is multi-disciplinary and made transparent for the participants. Even non-simulation experts can get an insight in the performance of different design options. The approach considers multiple aspects (such as energy use, comfort, architectural form) that can be calculable by a tool or simply depend on users' judgement.
A disadvantage is that there is no integration of parameter optimization. Besides, the weighting depends on the participants; therefore, the risk of a local (subjective) optimum arises.

Approach 3: multi-objective optimization
Advantages are that the approach is easy to conduct and in a very simple way already feasible results can be received.

A disadvantage is that it is a black box approach. From the definition of the parameters considered, the limitation of the boundary values to the achievement of the Pareto front, no insight in the simulation process is given. It might be possible that after a very long calculation time, results can be wrong, because not the right optimum was found.

Usability testing
All three approaches facilitate the comparison of different outputs, results and comprehension. This has been shown with a realistic case study.
The feedback was very positive. According to the participants, the results are easy to comprehend, have potential in supporting the decision process, and therefore enhance the guidance through the design process. They fulfill the requirements for the final design and are perceived of being very important to be integrated in BPS.

7.3 Future challenges

Enhancing the use of BPS in the conceptual design stage
As mentioned in the introduction this research project started in complementary work with another project dedicated to enable innovative application of building performance simulation for design support in the conceptual design stage [Struck, 2009]. However, in contrast to that study, the approach of this research focused more on addressing details and bringing the information gained into the decision process.
Two steps for the integration of the two approaches can be carried out further such as follows.

1. Analysis of potential synergy between the initial prototypes of both projects.
2. Analysis of inter/intra phase of model generation, expansion or reduction.

Coupling with other extensions
In the use of BPS the building designers have to rely on several predictions taken by computer models. The reliability of these predictions is obviously of high importance. One issue, e.g., is the influence of the occupant behaviour that is still very simplified in current building simulation and was proven to be one of the most sensitive parameters in the uncertainty study.
Attempts in this direction are provided by Tabak [2009] and Hoes [2007].
Tabak [2009] developed the USSU-model (User Simulation of Space Utilisation). USSU simulates the movement of occupants and the use of spaces by occupants in a building.
Hoes [2007] couples the USSU model with the SHOCC-model (Sub-Hourly Occupancy Control) that combines and improves different behaviour models and integrates these models in the one building energy simulation program (ESP-r).
With the combination of SHOCC and USSU it is for instance possible to give a prediction of the realizable energy savings of occupant-sensing lighting control.

Consideration of climate change
In the case studies considering scenario uncertainties the impact of future climate scenarios would be beneficial. Preliminary studies have been carried out showing the impact of future climate scenarios in decision-making techniques [Hopfe et al., 2009].

However, this impact could also enhance and improve the information flow in the optimization procedure.

Dealing with uncertainties

The research only showed the need of including uncertainties in tools but didn't put any research effort in generating concepts models for the verification of the amount of uncertainty necessary. More effort in the amount of deviations of parameters, also in new materials is a major challenge in future integration of uncertainty.

Another issue noticed in the UA/SA is the skewness of the probability plot of the weighted overheating hours (see Section 3.4.3). This problem needs to be evaluated and reasons need to be found for further reliability of data analysis.

Prototype based approach

The research presented and the three prototypes developed are not an end product yet. They are only for testing feasibility of different design process enhancing techniques.

However, the implementation is limited to very rough data input. There exists no user interface, no direct integration in a simulation tool yet. This development is challenge for future research.

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Abbreviations and Acronyms

AC	Annual cooling
AEDOT	Advanced energy design and operation technologies
AH	Annual heating
AHP	Analytical hierarchy process
ANP	Analytical network process
BDEM	Building domain evaluation model
BPS	Building performance simulation
BREEAM	Building Research Establishment Environmental Assessment Method
CASBEE	Comprehensive Assessment System for Building Environmental Efficiency
CFD	Computational fluid dynamics
CMA-ES	Covariance Matrix Adaptation Evolution Strategy
Combine	Computer models for the building industry in Europe
DA	Decision analysis
DAI	Design analysis integration
DM	Decision making
DSS	Decision support systems
DOE	Department of energy (US)
ELECTRE	Elimination and choice translating reality
EP	Evolutionary programming
ES	Evolutionary strategies
GA	Genetic algorithm
GPS	Generalized pattern search
GTO	Gewogen temperatuur overschrijding
HVAC	Heating, ventilation and air-conditioning
LEED	Leadership in Energy and Environmental Design
MADM	Multi-attribute decision making
MAUT	Multiple attributes utility theory
MCDM	Multi-criteria decision making
MODM	Multi-objective decision making
MOGA	Multiple objective genetic algorithm
MOO	Multi- objective optimization

NSGA-II	Non-dominated sorting genetic algorithm
Pebbu	Performance based building thematic network
pdf	Probability density function
PMV	Predicted mean vote
PROMETHEE	Preference ranking organization method for enrichment evaluation
PSO	Particle swarm optimization
SA	Sensitivity analysis
SMART	Simple multi-attribute rating technique
SMS EMOA	S-metric selection multi-objective evolutionary algorithm
SRCC	Standardized rank regression coefficients
UA	Uncertainty analysis
VEGA	Vector evaluating genetic algorithm
WSM	Weighted sum method ()
WF	Weegfactor
WHO+	Weighted overheating hours
WHO-	Weighted underheating hours

Glossary

Additivity

The function f is said to be additive for any two parameters a and b if $f(a+b) = f(a) + f(b)$. The function is additive, if the effect of applying a function to parameters individually and adding the results is identical, to summing the parameters up first and applying the function afterwards.

Aleatory uncertainties

Aleatory or stochastic uncertainty arises through the random behavior/ variation associated with a physical system. It is unpredictable and as a matter of fact irreducible. In literature it is mentioned that aleatory uncertainty reflects expert's direct experience because knowledge might be a useful method to quantify it. [Daneshkhah, 2004]. Examples are for instance variation due to technological life of an HVAC system or variations due to non-considered change in climate conditions.

Alternative

Alternative is a word regularly used to specify one of two options. In the context of decision making however, it is used more freely to specify a higher number of options. The number of alternatives can be finite or infinite, from single to multiple alternatives that can be either discrete or continuous.

A posteriori

It is an inductive reasoning based on observation or observed facts. It means first to search and then to decide (search →decide).

A priori

It is a deductive method and implies that a decision regarding the preferred solution has to be made before the search of the solution space (decide → search).

Changeability

Changeability describes the ability to adapt to the changing needs of buildings.

Confidence interval

It is a statistical term that shows the mean for a particular variable and its upper and lower confidence boundaries.

Criteria

Criteria are described as a composition of feature, target and an assigned weighting. In decision making they are also often referred to as goals, decision criteria, attributes, or performance indicators.

Epistemic uncertainties

Epistemic uncertainty is due to a lack of knowledge, i.e., it is related to incomplete or inadequate information. It is also referred to as subjective or reducible uncertainty or even conceptually resolvable uncertainty. Examples are lack of experimental data, incomplete knowledge about new materials used, poor understanding of cause and effect.

Expert

As an expert in the context of BPS a person is considered with extensive knowledge due to expertise and intuition in building design.

Feature

A feature in the context of decision making is a performance metric such as weighted over- and underheating hours.

Flexibility

Flexibility refers to low costs and rapid change.

Global methods

In global methods the uncertainty in a specific input parameter is used to determine the uncertainty in the output. All variables are sampled simultaneously.

Histogram

The histogram compares the frequency of the results with the outcome itself. It gives an insight in the range that the output varies.

Individual sensitivities

The individual sensitivity describes the sensitivity in each individual input parameter that is due to the influence on predictions of variations. In order to study the individual sensitivity, the remaining parameters are not changed.

Latin hypercube sampling (LHS)

The LHS is a particular case of stratified sampling which is meant to achieve a better coverage of the sample space of the selected input parameters [Saltelli et al., 2005].

Least squares

Least squares are often applied in regression analysis. It can be described as method of fitting data where the best fitting is the parameter for that the squared residuals are the smallest.

Lilliefors method

The Lilliefors method tests the null hypothesis that the sample comes from a normal distribution [Matlab, 2009]. If the test returns the value x=1 it rejects the hypothesis, i.e., it does not come from a normal distribution. However, the value x=0 indicates that the deviation from a normal distribution of the sample is not significant.

Linearity of parameters

Parameters behave linear if there is a linear relation between the variations of the input parameter in comparison to the output considered.

Local methods

Local methods give an insight in the individual uncertainty, i.e., the influence on predictions of variations in each individual input parameter. They can be only applied if the correlation between inputs and outputs is linear.

Mean deviation μ

In statistics, the mean deviation is the expected value of a random variable. The mean deviations that are used in the demonstration refer to the values of the variables considered.

Meta-modeling

A meta-model is an approximation of the input/output (I/O) function that is implied by the underlying simulation model [Kleijnen, 2007]. Its final aim can be described as validation and verification (V&V) of the simulation model, a what-if analysis or a sensitivity analysis.

Normal distribution

A normal distribution or Gaussian distribution is a statistic distribution with probability density function defined by the two parameters, the mean deviation, μ and the standard deviation squared, σ^2.

Normality plots

The purpose of a normality plot is to graphically assess whether the data follows a normal distribution. If the data is normal distributed, the plot appears linear.

One factor at a time (OAT) method

OAT is the description of the sampling procedure that varies only one factor at a time.

Parameter screening/ reduction

Parameter screening describes the use of UA/SA to reduce the parameter set in order to enable the simplification of a model.

Pareto dominance
Pareto dominance defines a partial order on the set of objective function vectors of a set of decision alternatives.

Pareto frontier
The projection of the set of non-dominated solutions is called Pareto frontier.

Pareto optimality
The maximum number of elements of this partial order of Pareto dominance are said to be Pareto optimal.

Pareto optimization
Pareto optimization identifies the set of non-dominated solutions and visualizes the projection of this set in the objective space.

Problem space
Insight the problem space the type and number of objectives, the alternatives and the impact of uncertainties play a role.

Progressive
The progressive method stands for a decision making where deciding and searching is merged into each other (decide ↔ search).

Prototype
A prototype is an Initial version of a module developed to test the effectiveness of the implementation to solve a particular problem.

Regression analysis

The regression analysis is important for the analysis of the SA. Regression analysis shows more quantitative measures of sensitivity. A multivariate sample of the input is generated by some sampling strategy and the corresponding sequence of a number of output values is computed using the model under analysis [SIMLAB, 2009].

Risk attitude
The attitude the designer is willing to deal and accept risk that a preferred solution might have compared to alternatives.

Robust regression
Robust regression belongs to regression analyses and offers an alternative to least squares estimated that are non-robust to outliers.

Robustness analysis

Robustness analysis makes aware of unexpected sensitivities that may lead to errors/ wrong specifications (e.g., quality assurance).

Sampling based methods

In sampling based methods the model is conducted repeatedly with input values that are sampled with a known distribution (typically a normal distribution). Very often in sampling based methods, UA/SA are conducted simultaneously.

Sensitivity analysis

The sensitivity analysis (SA) determines the contribution of individual input variable to the uncertainty in the model prediction. SA determines factors that are responsible for the variation in the outcome.

Solution space

The solution space covers the range of the results that can be either discrete or continuous.

Stepwise regression

Stepwise regression includes regression models in which the choice of predictive variables is carried out by an automatic procedure. Usually, this takes the form of a adjusted R-square.

Standard deviation σ

In statistics, the standard deviation is a measure of the variability of a data set. If the standard deviation is rather small, it indicates that the data set behave closely to the mean deviation. If the standard deviation is high, the range of the data set is more spread.

Symbolism

Symbolism as it is used in the context of decision making refers to the image or status that is represented by the design concept.

Target

The target specifies how alternatives relative to criterions will be evaluated.

Total sensitivities

The total sensitivity describes the sensitivity that is due to uncertainties in the entire input file. In order to study the total sensitivity, all input parameters need to be changed simultaneously.

Uncertainty analysis

Uncertainty analysis (UA) specifies the uncertainty in model prediction due to the imprecise knowledge of input variables. I.e., it intends the range of the output the model output will obtain.

Appendix

Appendix A: Case study description

“Het bouwhuis” is a building located in Zoetermeer, the Netherlands between The Hague and Gouda, shown in Figure 96. It is the headquarters of Bouwend Nederland, the Dutch organisation of construction companies. The building is an ideal case study because it combines flexibility and function. In addition the project’s early stage confronted the design team with a choice between two options both of which were developed in great detail.
The building has characteristics as follows.

- Office building with 11 floors in a T-shaped plan.
- Two levels/ stories underground parking (7000m²).
- Flexible office concepts/ dispositions dividable from separate rooms up to open floor plan office solutions.
- Conference facilities including meeting rooms on the two top floors, which protrude over the office floors below.
- Conference room equipped with individual air- conditioning, presentation screen and discussion systems.
- Restaurant with roof garden.
- Auditorium equipped with sound and projection screen

Figure 96 Illustration of ”Het Bouwhuis”

The building process (from conceptual stage through realisation of the building) took from 2002 -2006.
Two options were designed in great detail, i.e., both of them ready-to-build. The first option represents a mainstream standard solution: a conventional heating/ cooling system. The second design option represents a novel, “risky” design, incorporating heating/cooling storage in combination with a double façade. Both systems are described briefly below.

Design option 1: Conventional heating/ cooling system

Design option 1 uses conventional central heating and mechanical cooling; the building is conditioned by an all air conditioning system with constant air volume (CAV) consisting of an air handling unit, supply and return fans, ducts and control units.

Heating is provided by electricity driven radiators inside the room and an electric heater in the air-handling unit (AHU). The system is regulated on the air temperature; during the office hours (8-20, 5 days per week) and on standby the rest of the time (0-24h, 7 days per week). The AHU keeps the supply air temperature at 20°C when the incoming outside air temperature is 16°C up to 28°C when the outside air temperature goes up to 40°C.

The ventilation system provides fresh air with a supply fan (1000m³/h) and exhausts the air by an exhaust fan (1000m³/h). Air change rate is 0.5 per hour. There is no night cooling.

Design option 2: Heating/ cooling storage

The second option is based to design a building with a high percentage of glazing in the transparent facades: from the second floor up to the eleventh floor the building is on its "crosscut" sides provided with a double façade (see Figure 96 and Figure 98).

The double skin is built one meter distance from the façade of the building; hence a magnifying cavity is created.

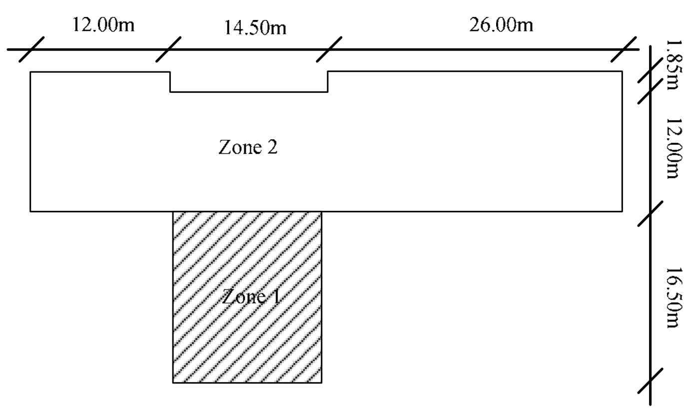


Figure 97 Illustration of the footprint for design option 1 of "Het Bouwhuis".

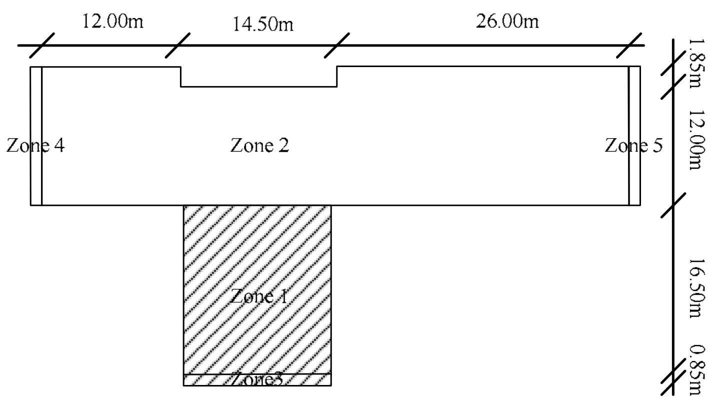


Figure 98 Illustration of the footprint for design option 2 of ”Het Bouwhuis”.

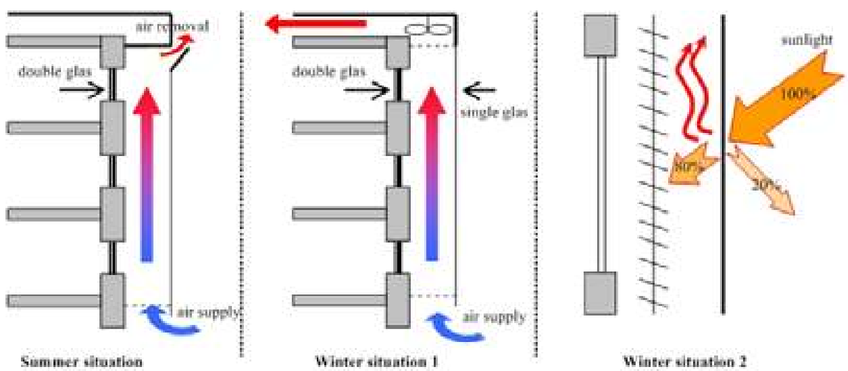


Figure 99 Illustration of the summer and winter case for design option 2 of ”Het Bouwhuis” [Nelissen, 2008].

In winter the ventilation air is drawn via the double skin façade where it is naturally pre-heated, then supplied as external air to the air handling unit. This method can be regarded as a heat-recovery system.

In summer the double façade forms an extra barrier for solar radiation to enter the spaces as heat is removed from the façade air cavity through natural buoyancy driven ventilation to the outside. Another advantage is the increased noise barrier performance of the façade. The building is provided with a heat pump in combination with a heating-cooling storage. Both systems (summer and winter) are demonstrated in figure 2.

The double glass façade is designed to have a positive influence on energy savings and to provide superior comfort.

Material properties are identical for both options and are summarized in the Appendix B.

For the assessment of both alternatives, the following characteristics are constituted:

- Internal heat gains: equipments (20W/m²); people (10 W/m²) and lighting (15 W/m²).
- Zoning: the assessment is conducted for the standard floor level comprising two zones for design option 1 and 5 zones for design option 2 (see Figure 97 and Figure 98).
- The assessment is based on the simulation of one room. All presented results relate to the smaller office room. The cavity space is located at the south-facing surface of the building (see Figure 97 and Figure 98).
- Set Points: The indoor set point in the office is 27°C for cooling and 21°C for heating.

Appendix B: Case study material properties

Table 25 Description of the material properties and deviations for the outside wall of "Het Bouwhuis".

Outside wall		t (m)	λ (W/mK)	ρ (kg/m³)	c (J/kgK)
steel	μ	0.005	50	7800	480
	σ	0.0005	0.75	25.74	19.2
glass fibre quilt	μ	0.127	0.04	12	840
	σ	0.0127	0.0032	1.08	56.28
concrete block	μ	0.2	1.41	1900	1000
	σ	0.02	0.1269	28.5	106

Table 26 Description of the material properties and deviations for the floor construction of "Het Bouwhuis".

Floor construction		t (m)	λ (W/mK)	ρ (kg/m³)	c (J/kgK)
london clay	μ	0.8	1.41	1900	1000
	σ	0.08	0.4653	332.5	107.5
brickwork	μ	0.28	0.84	1700	800
	σ	0.028	0.2772	297.5	86
cast concrete	μ	0.1	1.13	2000	1000
	σ	0.01	0.1017	30	106
dense eps slab ins	μ	0.0635	0.025	30	1400
	σ	0.00635	0.00875	21	378
chipboard	μ	0.025	0.15	800	2093
	σ	0.0025	0.025	25	134
sythetic carpet	μ	0.015	0.06	160	2500
	σ	0.0015	0.0078	18.4	945

Table 27 Description of the material properties and deviations for the roof construction of "Het Bouwhuis".

Roof construction		t (m)	λ (W/mK)	ρ (kg/m³)	c (J/kgK)
stone chippings	μ	0.01	0.96	1800	1000
	σ	0.001	0.288	228.6	195
felt/bitumen layer	μ	0.005	0.5	1700	1000
	σ	0.0005	0.25	493	330
cast concrete	μ	0.15	1.13	2000	1000
	σ	0.015	0.1017	30	106
glass-fibre quilt	μ	0.1345	0.04	12	840
	σ	0.01345	0.0032	1.08	56.28
ceiling tiles	μ	0.019	0.056	380	1000
	σ	0.0019	0.02436	102.6	108

Table 28 Description of the properties and deviations for the glass properties of "Het Bouwhuis".

Double glazing		t (m)	λ (W/mK)	U (W/m2K)
pilkington 6MM	μ	0.01	1.7	1.21
	σ	0.001	0.85	0.0605
clear float 6MM	μ	0.01	1.7	
	σ	0.001	0.85	

Single glazing		t (m)	λ (W/mK)	U (W/m2K)
clear float 12MM	μ	0.02	1.06	5.1034
	σ	0.002	0.53	0.25517

Table 29 Description of the properties and deviations for the solar absorptivity, the inside and outside emissivity of "Het Bouwhuis".

SPECIFICATION		μ	σ	%
Solar Absorptivity	ROOF	0.6	0.006	1
	FLOOR	0.6	0.006	1
	WALL	0.6	0.006	1
	GLASS	0.6	0.006	1
Inside Emissivity	ROOF	0.9	0.0198	2.2
	FLOOR	0.9	0.0198	2.2
	WALL	0.9	0.0198	2.2
	GLASS	0.9	0.0198	2.2
Outside Emissivity	ROOF	0.9	0.0198	2.2
	FLOOR	0.9	0.0198	2.2
	WALL	0.9	0.0198	2.2
	GLASS	0.9	0.0198	2.2

Appendix C: Workflows for multi-criteria decision making (MCDM)

Figure 100 Illustration of the workflow showing decision making approaches in BPS

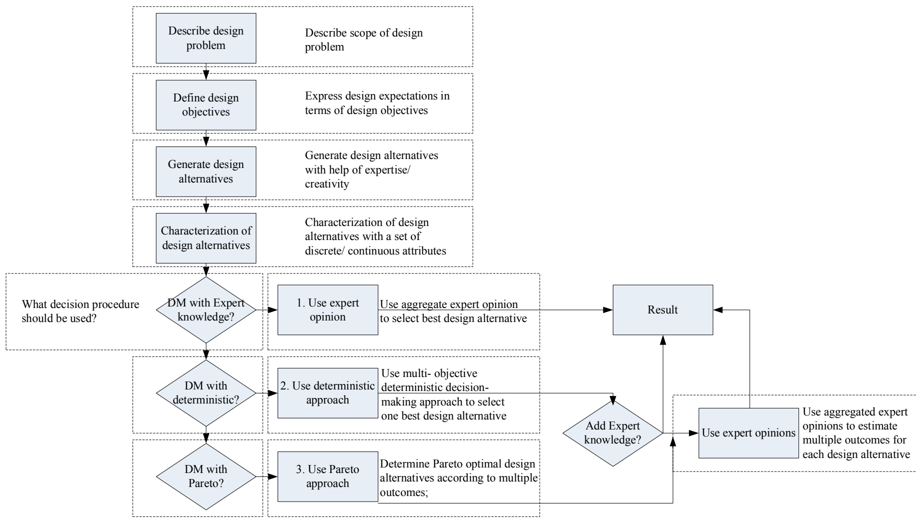


Figure 101 Illustration of the workflow showing the deterministic approach in MCDM decision making (e.g., AHP).

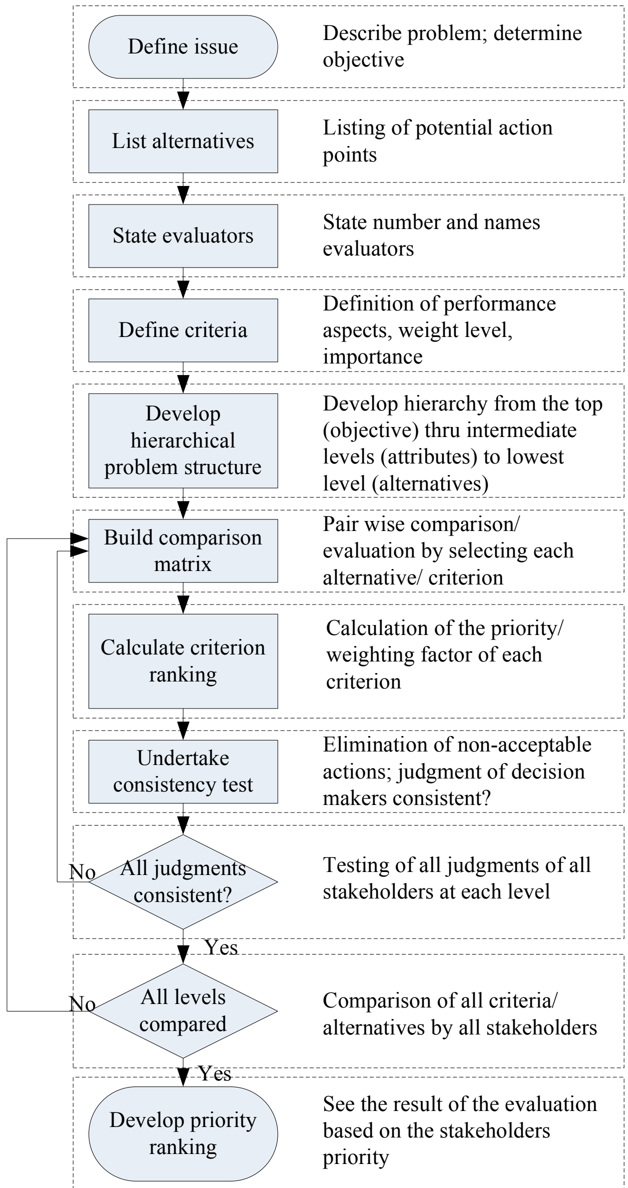


Figure 102 Illustration of the workflow showing decision making with Pareto optimality.

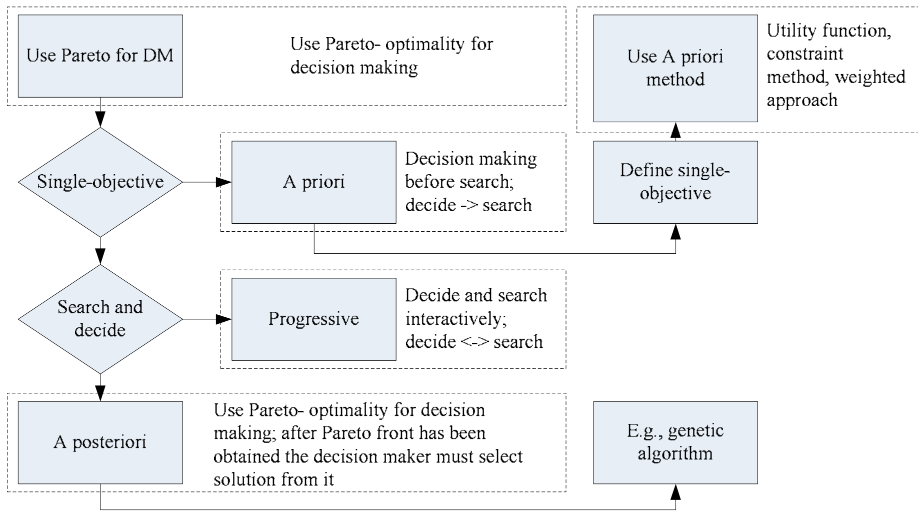
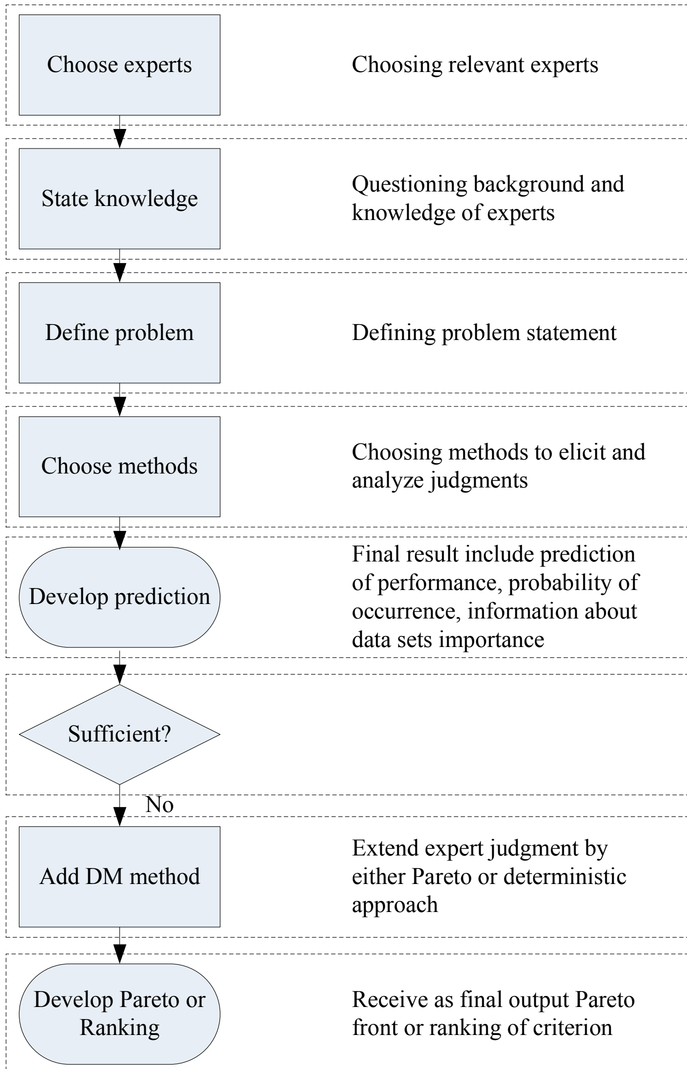


Figure 103 Illustration of the workflow showing decision making with the help of experts knowledge.



Appendix D: Tables for the AHP protocol

Table 30 Illustration of the weighting in AHP.

1	equally important	two elements have equal importance
3	moderately more important	experience or judgment slightly favors one element
5	strongly more important	experience or judgment strongly favors one element
7	very strongly more important	dominance of one element proved in practice
9	extremely more important	the highest order dominance of one element over another

Table 31 Listing of the performance aspects and their ranking based on three practitioners.

	Team Member		A		B		C	
	Needs & Requirements associated to value domain	Performance Aspect	y/n	AHP	y/n	AHP	y/n	AHP
1	Money/Investment cons	initial costs	y	0.094	y	0.126	y	0.097
2		operational costs	y				n	
3	Thermal comfort	indoor resultant temperature	y	0.213	y	0.046	y	0.046
4		relative humidity	y				n	
5		air velocity	y				y	
6		overheating hours (weighted)	y	0.094	y	0.135	y	0.046
7		underheating hours (weighted)	y	0.094	y	0.135	y	0.046
8		individual control	y	0.213	n	0.009	y	0.166
9	Visual comfort	daylight factor; transparency	y				y	
10		view to outside	y				y	
11	Acoustic comfort	reverberation time	y				y	
12	Spatial comfort	floor area per person	y	0.010	n	0.021	y	0.025
13		space height	y	0.010	n	0.021	y	0.009
14	Energy conservation	energy consumption	y	0.094	y	0.126	n	0.011
15	Aesthetics	architectural form	y	0.040	y	0.126	y	0.254
16		symbolism (image /status)	y	0.094	y	0.126	y	0.254
17	Labour conservation	operation & maintenance	y				y	
18	Space conservation	changeability (flexibility)	y	0.040	y	0.126	y	0.046
19		brutto/ netto area ratio	y				y	

Table 32 Overview of performance aspects and their results for both design options.

	Performance Aspect	Criterion	Range	Predicitable using nodal BP simulation
1	initial costs	less is better	<3.000.000.00 €	no
2	indoor resultant temperature	specific target best	~25 °C	yes
3	overheating hours (weighted)	less is better	<150h	yes
4	underheating hours (weighted)	less is better	<150h	yes
5	individual control	qualitative	/	no
6	floor area per person	more is better	4-10 m2	no
7	space height	specific target best	2,70m	no
8	energy consumption	less is better	790.000-1.100.000 kWh/year	yes
9	architectural form	qualitative	/	no
10	symbolism (image /status)	qualitative	/	no
11	changeability (flexibility)	qualitative	/	no

Appendix E: Command lines for the optimization

Figure 104 Illustration of the command lines for the algorithms NSGA-II and SMS EMOA.

Command line to start the optimization with NSGA-II:

```
CRNSGA2.exe -t c:\MSphere.exe -d 6 -e 2000 –b 0.9 1.5
23.0 30.0 6.0 25.0 6.0 35.0 6.0 30.0 0.2 1.0 -nf 2
```

`CRNSGA2.exe -t c:\MSphere.exe` // name of *.exe where files for simulation are generated and objective function is defined
`-d 6` // number of design variables being changed in the optimization
`-e 2000` // number of objective function evaluations
`–b 0.9 1.5 23.0 30.0 6.0 25.0 6.0 35.0 6.0 30.0 0.2 1.0`
// boundary values for the six different design variables
// b1: size window
// b2: size room
// b3: internal gains: people
// b4: internal gains: light
// b5: internal gains: equipment
// b6: infiltration rate

Command line to start the optimization with SMS EMOA:

```
SMS.exe c:\MSphere.exe p.in p.res 2000 20 1 2 2 0 0 41 0
```

Appendix F: Summary of the online survey for the usability testing

1. Introduction:

Dear participant!
This questionnaire is the final step of my thesis. It is intended to help me in finding out the feasibility and applicability of three different developed prototypes. Building performance simulation (BPS) is a powerful tool which emulates the dynamic interaction of heat, light, mass (air and moisture) and sound within the building to predict its energy and environmental performance as it is exposed to climate, occupants, conditioning systems, and noise sources. (source: Dru Crawley presentation, ASHRAE Meeting, Chicago, 2003).Despite nearly forty years of development, building performance assessment is still not routinely applied to mainstream building design practice [Preiser W and Vischer J. (eds), Assessing Building Performance Practical advice on assessing and monitoring building performance, Butterworth-Heinemann, 2004].

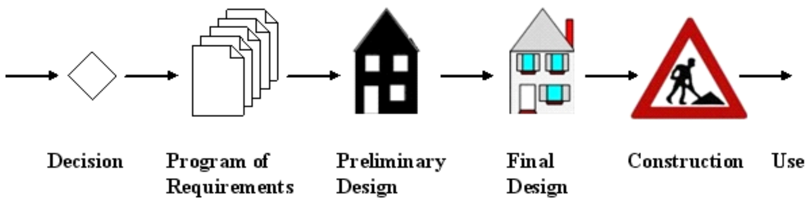


Figure: Design process

The aim of my PhD project is to encourage the use of BPS in the final design stage where building simulation is still mainly used for code compliance checking.In the following questionnaire 3 prototypes will be presented and their plausibility, feasibility and applicability in the final design stage has to be assessed. The questionnaire comprises in total 5 pages (introduction, 3 different scenarios, and conclusion) and won't take longer than 15 minutes.

Thank you very much in advance for the time and effort spent!

Christina Hopfe

Please note: answers marked with a * are required!

2. Background/ opinion page Please enter your name (last name, initials) *

Please scale your level of experience in *

	Very high	high	medium	low	very low
Usage of Building Performance Simulation (BPS)	○	○	○	○	○
Participating in design team meetings/ communication with other design team members	○	○	○	○	○

Have you been personally involved in design/ project consultancy in the last years?

always	frequently	occasionally	rarely	never
○	○	○	○	○

Do you see a need of the integration of the following techniques in standard BPS software: *

	very important	important	less important	unimportant
Uncertainty and sensitivity analysis Informed decision making (decision making with uncertainty/ sensitivity analysis) Parameter optimization	○	○	○	○

What is your satisfaction level of current BPS tools in terms of: *

	excellent	above average	below average	poor
Understandability of results/ background information	○	○	○	○
Ability to support communication with others (e.g. client, architects etc.)	○	○	○	○
Integration of informed decision making	○	○	○	○
Support of choices between different design options/ Guidance through the design process	○	○	○	○
Integrated uncertainty and sensitivity analysis of parameters; awareness of uncertainties in building design	○	○	○	○
Integrated optimization of parameters	○	○	○	○

How is software currently used in the final design stage?
What are tool requirements during the final design stage?
What should/ could be improved in currently available simulation tools?

3. First scenario: The integration of uncertainty/ sensitivity analysis (UA/SA) in BPS

This paragraph is to find out about the necessity of the integration of uncertainty analysis (UA) and sensitivity analysis (SA) in building performance simulation. A distinction will be made between three different sources of uncertainties: physical, scenario and design uncertainties:
1. Physical uncertainties: uncertainty in physical properties as conductivity, thickness, density of the different material layers etc..
2. Scenario uncertainties: influence of infiltration rate (the operation of window openings), climate change (for instance due to global warming), lighting control schemes, and other occupant related unpredictable use of the building.
3. Design uncertainties influenced by the designer in type of glazing, glass surface, geometry.

Which group (physical, scenario, and design) do you want to have considered in BPS tools in which design phase? *

	physical uncertainties	scenario uncertainties	design uncertainties
Conceptual design stage	☐	☐	☐
Preliminary design stage	☐	☐	☐
Final design stage	☐	☐	☐

Following graphics are provided:

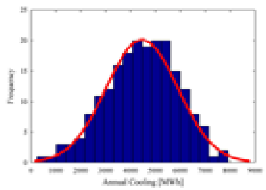


Figure: UA1 (frequency)

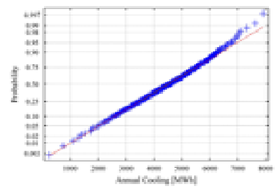


Figure: UA2 (probability)

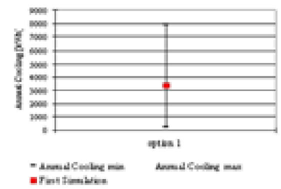


Figure: UA3 (range)

Please rate the added value of the three following demonstrations of uncertainty analysis in BPS:

	very important	important	less important	unimportant
Please rate the added value of UA1 (frequency) *	◯	◯	◯	◯
Please rate the added value of UA2 (probability) *	◯	◯	◯	◯
Please rate the added value of UA3 (range) *	◯	◯	◯	◯

A case study is given with a conventional heating/ cooling system. For the result analyses one room on the ground level will be considered:

The following graphic shows the 10 most sensitive parameters out of 80 for different energy and comfort parameters:

	ENERGY		THERMAL COMFORT	
nr	Annual cooling	Annual heating	Weighted overheating	Weighted under-heating
1	Infiltration rate	Infiltration rate	Infiltration rate	Infiltration rate
2	Size room	Size room	Loads equipement	Loads equipement
3	Conductivity floor layer 4	Switch single double glass	Size room	Size room
4	Switch single double glass	Loads equipement	Loads lighting	Switch single double glass

physical uncertainties
scenario uncertainties
design uncertainties

Figure: SA1 (table)

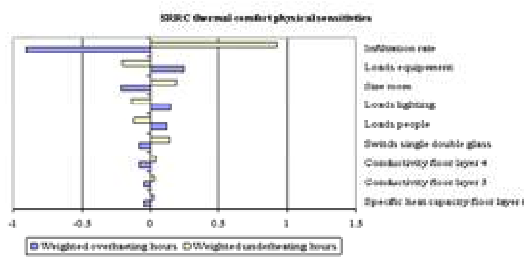


Figure: SA2 (graphic)

Rate the plausibility of the results *	strongly agree	somewhat agree	somewhat disagree	strongly disagree
SA1 table	○	○	○	○
SA2 graphic	○	○	○	○

Do you agree that the results of UA/ SA can be taken as a basis for communication with others? *

	strongly agree	somewhat agree	somewhat disagree	strongly disagree
UA1 frequency	○	○	○	○
UA2 probability	○	○	○	○
UA3 range	○	○	○	○
SA1 table	○	○	○	○
SA2 graphic	○	○	○	○

Do you agree that the results of UA/ SA are intuitively understandable? *

	strongly agree	somewhat agree	somewhat disagree	strongly disagree
UA1 frequency	○	○	○	○
UA2 probability	○	○	○	○
UA3 range	○	○	○	○
SA1 table	○	○	○	○
SA2 graphic	○	○	○	○

Do you agree that the results of UA/ SA have potential in supporting the design process? *

	strongly agree	somewhat agree	somewhat disagree	strongly disagree
UA1 frequency	○	○	○	○
UA2 probability	○	○	○	○
UA3 range	○	○	○	○
SA1 table	○	○	○	○
SA2 graphic	○	○	○	○

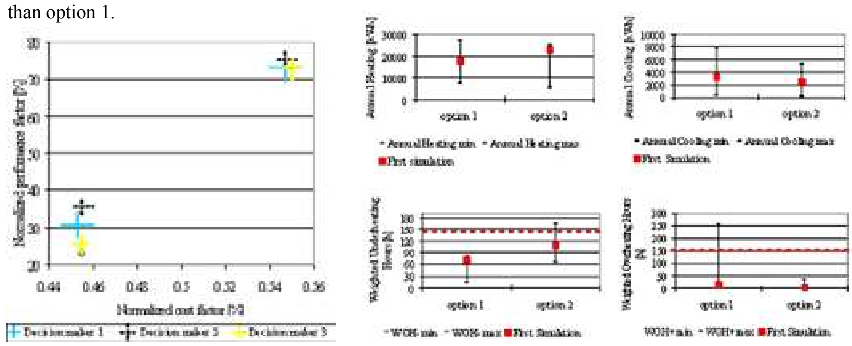
Do you agree that the results of UA/ SA should be integrated in building performance simulation? *

	strongly agree	somewhat agree	somewhat disagree	strongly disagree
UA1 frequency	○	○	○	○
UA2 probability	○	○	○	○
UA3 range	○	○	○	○
SA1 table	○	○	○	○
SA2 graphic	○	○	○	○

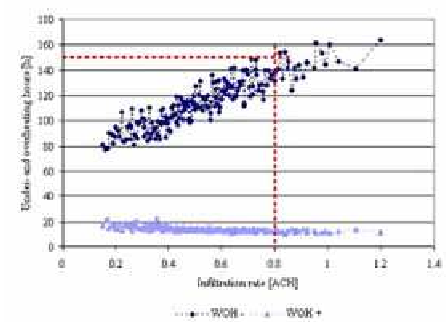
Do you have further suggestions to the integration of optimization? Comments etc.

4. Second scenario:

Decision making with the help of uncertainty/ sensitivity analysis Imagine the following procedure: For an office building, two different options are given:
Option 1: conventional heating/ cooling system
Option 2: heating/ cooling storage
A design team (owner, structural engineer, architect, environmental engineer, etc.) has to decide which option is the better one in relation to performance aspects such as costs (investment and running costs), thermal comfort, architectural form, symbolism, and flexibility, among others.
First step:
Every design team member assigns a weighting to each performance aspect, from most important to least important.
Second step:
Performance aspects that cannot be simulated/ calculated by a tool (like symbolism, aesthetics) depend on the user. These aspects have to be evaluated by each design team member compared to each option (e.g. how much better is the architectural form of option 1 compared to option 2). The result will be a number (assumed the total performance is 1) for example architectural form option 1 is 0.8 and option 2 0.2.
Third step:
Aspects like comfort and energy consumption can be simulated with a BPS tool. The results are brought into relation for both options; i.e. in the end the outcome will be comparable to the second step: e.g. option 1 is 0.6; option 2 is 0.4.
Final step:
The outcome of the second and third step for each option to every aspect is multiplied by the weighting from step 1. In the end there will be one number for each option showing in relation which one is better (due to performance, weighting, and user). A consensus of all design team members is built by combining all separate results.
Following graphic shows the normalized performance (sum of aspects such as comfort, aesthetic) of both options compared to a normalized cost factor (energy costs, investment costs) for all design team members.
The graphic shows that the higher the performance, the better the option. The higher the cost factor the worse (more expensive) the option. The graphic shows that option 2 (right) is better performing but also more expensive than option 1.



The uncertainty analysis shows that for the most preferable option 2 the weighted underheating hours are exceeding. The sensitivity analysis (as shown earlier) identifies the infiltration rate as most sensitive parameter. Looking deeper into the correlation of the infiltration rate to the weighted underheating hours, it can be seen that it is almost linear. Limiting the risk, e.g., setting limitations to the infiltration rate, minimizes the risk of exceeding the underheating hours. This turns option 2 indeed into the better option by eliminating the risk.



Do you think that BPS in general should provide the possibility to communicate results with other design team members? *

strongly agree	somewhat agree	somewhat disagree	strongly disagree
○	○	○	○

Do you agree that the prototype "decision making with uncertainty and sensitivity"... *

	strongly agree	somewhat agree	somewhat disagree	strongly disagree
...is a transparent procedure?	○	○	○	○
...can be taken as a basis for communication with others?	○	○	○	○
...makes the results intuitively understandable?	○	○	○	○
...has potential in supporting the decision process?	○	○	○	○

How important is it that the preferred option is the option with the minimum risk? *

very important	important	less important	unimportant
○	○	○	○

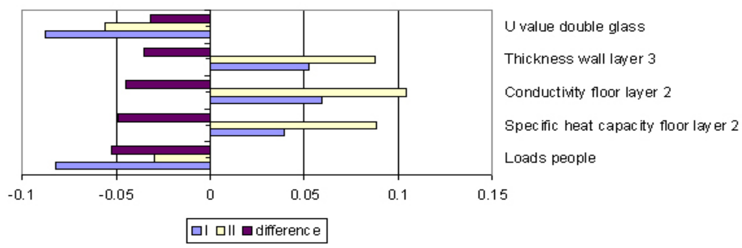
How important do you rate communication in the design process? *

very important	important	less important	unimportant
○	○	○	○

Do you have further suggestions to the integration of optimization? Comments etc.

Decision making with the help of future climate scenarios

In a climate scenario the simulation was conducted with another weather file showing the situation in 30 years (I: current/ present climate; II: climate in 30 years). The order of sensitivity is based on the difference; i.e. the difference in sensitivity due to climate change is the highest for the casual gains (loads people).



Do you see an added value in integrating uncertainty/ sensitivity analysis in BPS due to future climate scenarios? *

strongly agree somewhat agree somewhat disagree strongly disagree

○ ○ ○ ○

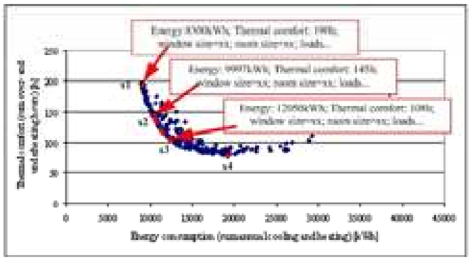
Do you see a potential in supporting the decision process? *

strongly agree somewhat agree somewhat disagree strongly disagree

○ ○ ○ ○

5. Third scenario:

Optimization in building performance simulation An office building is given. The objective is to optimize parameters such as geometry, window size, and loads. This will result in a better comfort and energy demand. In the graphic below the outcome ("Pareto front") is shown for one floor with two objectives to be optimized: thermal comfort (the sum of weighted over and underheating hours) and energy consumption (annual cooling plus annual heating).



Do you think that the provided results... *

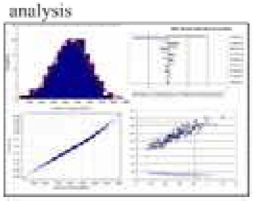
	strongly agree	somewhat agree	somewhat disagree	strongly disagree
can be taken as base for communication?	○	○	○	○
are intuitively understandable?	○	○	○	○
have potential in supporting the design process?	○	○	○	○

Do you have further suggestions to the integration of optimization? Comments etc.

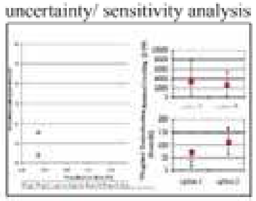
6. Summary

Please rank your impression about the three presented scenarios (see above A, B, and C) in terms of...

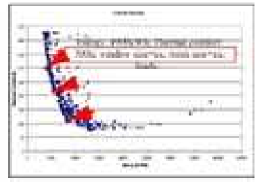
A: Uncertainty/ sensitivity analysis



B: Decision making with uncertainty/ sensitivity analysis



C: Optimization



...reliability of results *	excellent	above average	below average	poor
A: Simple uncertainty/ sensitivity analysis	◯	◯	◯	◯
B: Decision making with uncertainty/ sensitivity analysis	◯	◯	◯	◯
C: Parameter optimization	◯	◯	◯	◯

...supporting the decision process *	excellent	above average	below average	poor
A: Simple uncertainty/ sensitivity analysis	◯	◯	◯	◯
B: Decision making with uncertainty/ sensitivity analysis	◯	◯	◯	◯
C: Parameter optimization	◯	◯	◯	◯

...guidance through the design process *	excellent	above average	below average	poor
A: Simple uncertainty/ sensitivity analysis	◯	◯	◯	◯
B: Decision making with uncertainty/ sensitivity analysis	◯	◯	◯	◯
C: Parameter optimization	◯	◯	◯	◯

...fulfilling the requirements of BPS in the final design *	excellent	above average	below average	poor
A: Simple uncertainty/ sensitivity analysis	◯	◯	◯	◯
B: Decision making with uncertainty/ sensitivity analysis	◯	◯	◯	◯
C: Parameter optimization	◯	◯	◯	◯

...usefulness/ importance of integration in BPS software *	strongly agree	somewhat agree	somewhat disagree	strongly disagree
A: Simple uncertainty/ sensitivity analysis	◯	◯	◯	◯
B: Decision making with uncertainty/ sensitivity analysis	◯	◯	◯	◯
C: Parameter optimization	◯	◯	◯	◯

Acknowledgement

This Ph.D. thesis is the result of four years researching, developing and improving approaches dedicated to the enhancement of BPS in the detailed design.
It started in April 2004 and ended in June 2009. It was embedded in the Building Physics and Systems group of the faculty of Architecture, Building and Planning of the Eindhoven University of Technology.

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Curriculum vitae

Christina Hopfe was born on 6th of July 1976 in Seeheim-Jugenheim, Germany. She studied civil engineering at the Technical University in Darmstadt, Germany with major in finite elements theory and object oriented programming.

During her studies she gained already working experience whilst conducting diverse projects in consulting agencies and software development companies, among others.

After graduating, Christina started her Ph.D. research in the Building Physics and Systems group, at the Department of Architecture, Building, and Planning, Eindhoven University of Technology, The Netherlands.

During her Ph.D. studies, Christina was fortunate to spend four months at the Georgia Institute of Technology in Atlanta, Georgia (2007).