Computational Innovation Steering: Simulation-assisted performance improvement of of innovative buildings and systems

Computational Innovation Steering: Simulation-assisted performance improvement of innovative buildings and systems

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1. ABSTRACT

This paper presents a method for assisting the design innovation process, which is called 'Computational Innovation Steering' (CIS). CIS makes use of Building Performance Simulation and moreover focuses at the application of uncertainty analysis, sensitivity analysis and risk and opportunity analysis as promising tools for this purpose. Fundamental aspects of the presented procedure are the systematic definition of the required performance, generation of multiple design alternatives, use of utility functions to capture user preferences and application of Building Performance Simulation, supported with sensitivity and uncertainty analysis in order to predict the performance of each proposed design solution. The procedure offers building and HVAC specialists the opportunity to generate useful design information that can be put forward in the complex decision-making process usually present in design innovation. The paper not only describes the CIS procedure, it also presents a prototype implementation with the tools TRNSYS, Matlab and the freeware tool Simlab. A case study illustrates how the procedure works and gives an idea of the outcomes of a CIS analysis. The conclusion is that CIS can indeed provide the useful design information of both qualitative and quantitative nature.

Keywords: sensitivity analysis, uncertainty analysis, risk and opportunity, innovation, building performance simulation

2. INTRODUCTION

All over the world there is a need to develop a more sustainable built environment. The energy demand and corresponding greenhouse gas emissions keep on rising, especially in upcoming countries, such as China and India. Compared to 2005, the World Energy Council (2007) expects the total primary energy requirement to be almost doubled by the year of 2050. As a response, strict changes in regulations and design strategies have emerged in several countries. Moreover, building- and energy systems designers are challenged to come up with new, innovative and non-traditional design solutions, like concrete core conditioning systems, threefold glazing, ground source heat pumps, solar collectors and energy storage systems. However, the design of such innovative systems requires an integrated approach, concerning design methods and philosophy.

Over the last decades, a wide range of (integrated) design simulation tools has seen the light and is considered useful in the design of innovative buildings and systems. These tools are able to cope with a number of physical domains and can be used to study the simultaneous interaction of both building structure and Heating, Ventilation and Air Conditioning (HVAC) systems, which is considered important for innovative design.

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Another interesting development in the field of Building Performance Simulation (BPS), concerns that of sensitivity and uncertainty analysis. De Wit (2001) studied the uncertainties encountered in performance predictions of thermal comfort in buildings and concluded that explicit incorporation of uncertainties, influences the design decision to be made, compared to single valued performance outcomes. In addition, the application of uncertainty analysis (UA) and sensitivity analysis (SA) has been investigated by numerous other researchers (*e.g.* (Breesch, 2006; Hopfe, 2009; Lomas and Eppel, 1992; MacDonald, 2002)). All these investigators agree that both UA and SA can deliver valuable information to the design decision making process.

In the design innovation process, the design team is confronted with a number of decisions that have to be made regarding the performance of the considered innovation. In order to make effective decisions, the team has to be informed with the right type of information on the right moment. Particularly in the beginning stages of the design innovation process, where the level of uncertainty is the largest and major design changes can still be done useful design information must be generated. By quantifying the uncertainties or unknowns and their impact on the performance of the design, the complex decision making can be supported with information in the form of risks and opportunities. BPS, together with utility functions and UA and SA techniques are considered promising instruments for generation this type of performance information.

UA and SA have been under study for a number of years now, but risk and opportunity analysis has only been applied to a limited extent. The question now is, if risk and opportunities can be regarded as useful design information and also how risks and opportunities can be derived with help of BPS, UA and SA. This is illustrated in Figure 1.

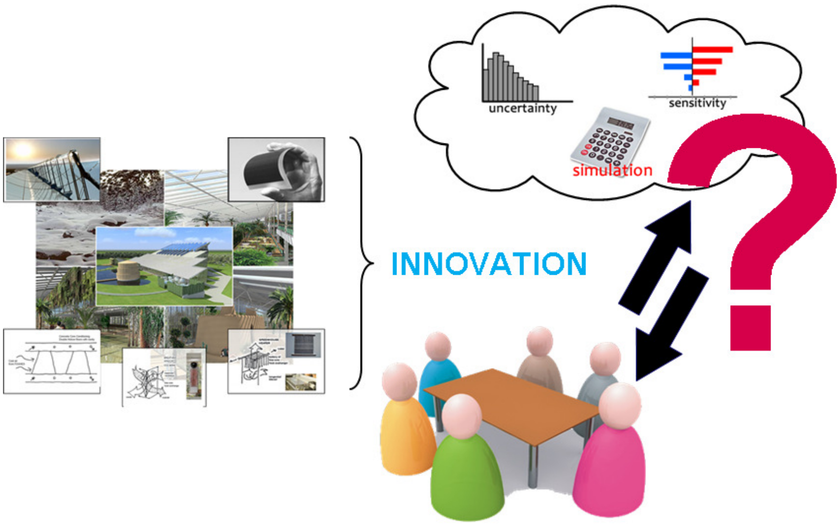

Figure 1: Conceptual representation of using UA, SA and risk analysis techniques for supporting design innovation (Houben, 2010)

The aim of the research presented in this article is to develop a part of a procedure which enables BPS experts to generate useful performance information by applying BPS, UA, SA and subjective information from utility functions. The results from this analysis are performance risks and opportunities, which should guide the design team into the design process of innovative building and/ or systems. The developed procedure is called 'Computational Innovation Steering' (CIS) and will be further explained in this paper. The paper is organized as follows. First, the results of literature research regarding the backbone of the developed CIS procedure will be presented. After that, the methodology of the research is elaborated on. The CIS procedure has been tested by means of a case study. Sections 5 and 6 present the description and an illustration of results of the case study. Moreover, a discussion regarding the obtained results and the CIS procedure is given. Finally, the main conclusions and directions for future work are described in section 7 of this paper.

3. PRINCIPLES OF THE CIS PROCEDURE

3.1 Performance-based design

In traditional building design, a prescriptive approach is applied. This means that building codes and regulations 'prescribe' how buildings should be constructed, instead of describing what the building or system is expected to do. This limits the designer in his/her creativity and usually leads to a standardized design solution that meets all regulatory criteria (Sexton and Barrett, 2005).

In contrast, innovative design projects require more flexibility, which can be achieved with a performance-based approach. The performance-based design philosophy enables designers to investigate the feasibility of a multiple of design concepts at the same time, without too much governmental interference (Becker, 2008; Becker and Foliente, 2005; Sexton and Barrett, 2005). The differences between the traditional design approach and the performance-based perspective are further illustrated in Figure 2. Figure 3 shows the principle of the performance-based perspective: first the required performance has to be specified at several levels of granularity. Secondly, the design team can propose a number of design options, while taking the selected performance description into account. By matching the predicted performance of proposed design alternatives with the performance description, the best design option can be chosen.

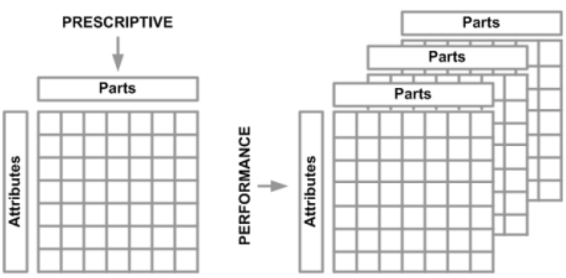

Figure 2: Traditional (left) versus the performance-based building approach (right) (Sexton and Barrett, 2005)

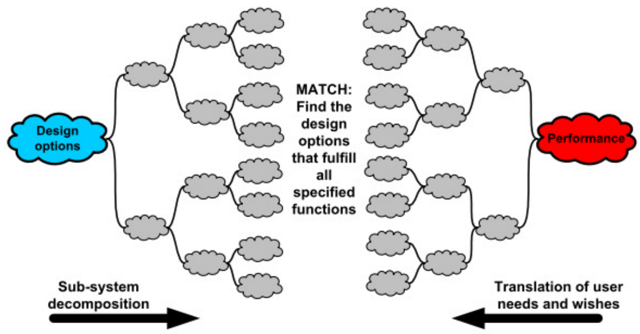

Figure 3: Principle of the performance-based perspective as considered for application of CIS (partially adapted from (de Wilde, 2004))

3.1.1 Assumptions for CIS application

De Wilde (2004) developed a method for the selection of energy-saving building components, which contains aspects similar to the CIS procedure. Based on (Becker and Foliente, 2005; Sexton and Barret, 2005; de Wilde, 2004) the following criteria are assumed, when applying CIS:

- Design decisions are based on a multiple of design alternatives or options.
- The decision between alternatives has to be made on basis of multiple criteria (*i.e.*, performance indicators or performance aspects).
- For each design option the same performance information must be available.

CIS differs from the approach of de Wilde (2004), due to application of UA and SA techniques, risk analysis, its scope and the use of utility elicitation for every performance indicator.

3.2 CIS procedure

An extended version of the developed CIS procedure is illustrated in Figure 4. In this research the optimization step in the simulation phase was considered for future work and therefore not implemented in the prototype environment. A short description of all features is indicated.

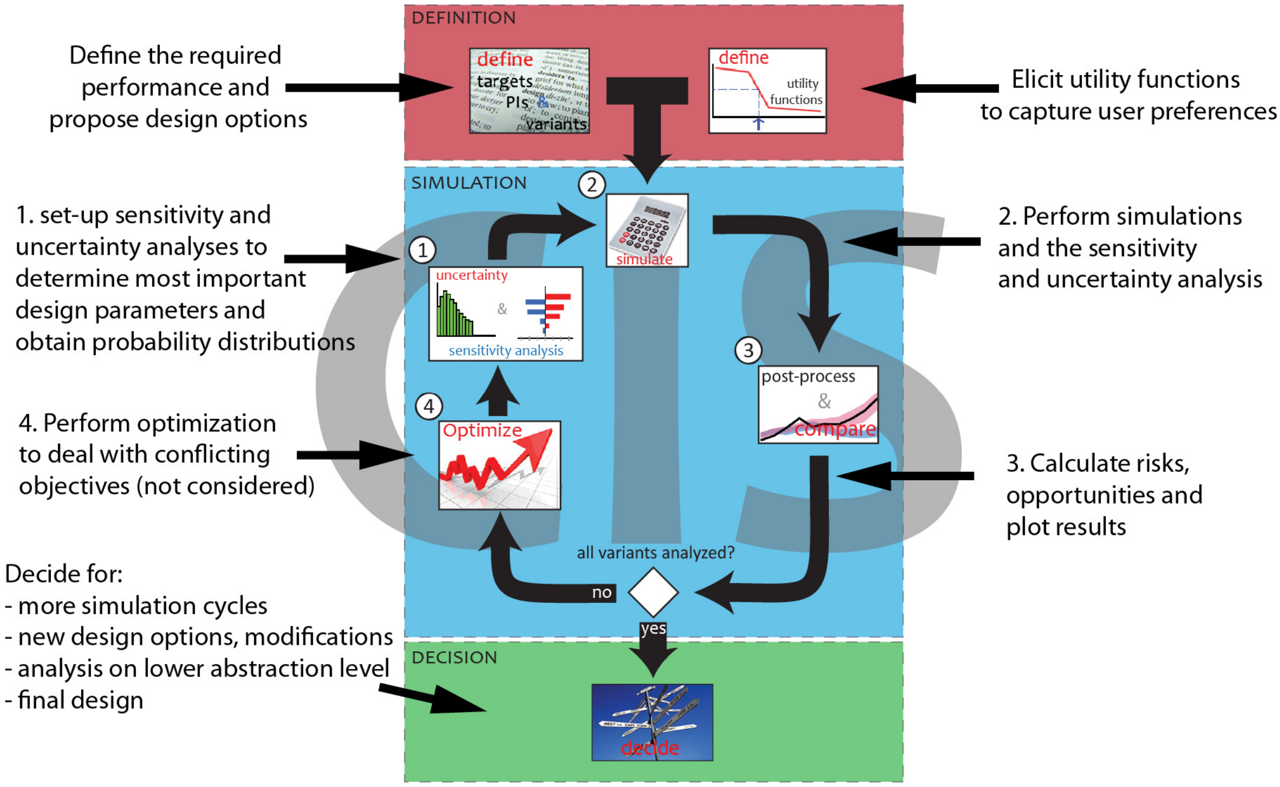

Figure 4: Overview of the developed CIS procedure (Houben, 2010)

3.3 Definition phase

3.3.1 Performance description

The first phase of CIS is concerned with (i) the definition of performance, (ii) the creation of an option space and (iii) the elicitation of utility functions. Performance is described by dividing it into objectives, performance indicators, acceptable ranges and requirements. An objective is the translation of a design task into specific goals to be achieved by the design team and a Performance Indicator (PI) is a quantified objective, having an acceptable range, definition, units and a direction of increasing or decreasing value (Augenbroe *et al.*, 2009). The requirement is the value of the PI that must be achieved in order to comply with the needs of the client. The performance description can be organized with the help of breakdown structure (de Wilde, 2004), of which an example is shown in the case study section of this paper. More in-depth information regarding PIs can be found in (Smaling and de Weck, 2007; Augenbroe *et al.*, 2009).

3.3.2 Generation of an option space

Step two of the definition phase is concerned with the generation of an option space. When the required performance is defined, the design team can start developing design alternatives. The option space comprises the collection or set of all possible design alternatives (Struck *et al.*, 2009). Creating an option space stimulates creativity and can be supported by a number of techniques, such as brainstorming, mindmapping, morphological charts (Roozenburg and Eekels, 1998; Struck *et al.*, 2009; de Wilde, 2004) or automated approaches, such as genetic algorithms for performing parameter variations (Gries, 2004; Parmee and Bonham, 1999).

3.3.3 Utility functions

The third part of the definition phase is the elicitation of utility functions. Utility functions make it possible to capture user preferences over the acceptable range of a PI. To enable decision making with the help of design information from UA, the preferences of the client need to be weighted over the probabilities of the outcomes (de Wit, 2001). This is also the case for the risk-/opportunity analysis that has to be performed: both utility values and probability values are needed to compute risks and opportunities.

For the case study in this research, utility functions were elicited with a software tool, called 'Assess', which uses the Lottery Equivalents method (Delquié, 2007, 2010). This method was chosen because it eliminates the effects of different forms of bias that are often encountered in the more 'classical' approaches, such as the Certainty Equivalents method (Farquhar, 1984; Law *et al.*, 1998; McCord and Neufville, 1986;). For the calculation of risks, only utility functions corresponding to a single PI, (Von-Neumann-Morgenstern utility functions) need to be derived over the selected validity range of the PI. The difference in utility (relative to the utility of the required PI value) is a measure of loss or gain of satisfaction, depending on the type of PI. As will be shown, this notion is useful for the determination of risks. For more information regarding utility functions, the reader is referred to (French, 1986, 2003; Keeney and Raiffa, 1993).

3.4 Simulation phase

In the second stage, BPS tools are used to predict the performance of the proposed design options. BPS is accompanied by the use of uncertainty and sensitivity analysis, aiming to generate more insight and therefore useful design information.

3.4.1 Sensitivity analysis

In CIS, the goal of SA is two-fold: (i) selecting the most important design parameters and (ii) reduction of the option space. Monte Carlo simulation with regression is the method of choice for the SA in the CIS procedure (Saltelli *et al.*, 2004). Uniform input distributions covering a relatively wide range are supplied to the simulation model. During each iteration cycle, all selected model parameters (*i.e.*, design variables) are varied. After the model executions, a regression analysis to between model in- and outputs is made for every design variable. The resulting set of regression coefficients is a measure for the influence of investigated design variables on the total uncertainty in the predicted performance outcome (Hopfe, 2009).

3.4.2 Uncertainty analysis

When dealing with design innovations, the design team is confronted with many new ideas and aspects, and a limited amount of information regarding the performance of the design innovation is available: the design innovation process is thus very uncertain. Consequently, the design team is deemed to make design decisions, based on an incomplete set of information. Therefore, it is useful to quantify the uncertainties. In this way, better-informed decisions can be made, leading to possibly better designs. Again Monte Carlo simulation is applied, but this time, probabilistic input distributions are fed through the models (Saltelli *et al.*, 2004). Typically, normal distributions are used, where the mean values of the model parameters are varied with over a small interval (in the order of five percent). Sampling is done by means of the Latin Hypercube method, because this delivers satisfactory results within a minimum number of sampling runs (Breesch, 2006; Hopfe, 2009). The result of the UA is a number of probability distributions for each of the considered PIs that can be used in the next step: determining performance risks and opportunities.

3.4.3 Risk and opportunity

Risk and opportunities are the actual forms of information that are to be generated with the help of CIS. In the light of CIS, the risks and opportunities refer to the (un)certainties that are associated with the (lack of) knowledge about the technical performance of the design innovation that is investigated. This concept of risk and opportunity has been inspired by the work of (Smaling, 2006; Smaling and de Weck, 2007). Risk can be defined as the likelihood that something happens times the corresponding consequence of it (Houben, 2010):

$$R_{PI} = p_{PI} \cdot I_{PI} = \sum_i p_{PI}(x_i) \cdot \left(U_{PI}(x_T) - U_{PI}(x_i)\right) \qquad (1)$$

, where

$p_{PI}(x_i)$ = the probability that a certain PI value occurs (-)

I_{PI} = the consequence (or impact) corresponding to the probability $p_{PI}(x_i)$ (-)

$U_{PI}(x_T)$ = the utility corresponding to the required PI value x_T (-)

$U_{PI}(x_i)$ = the utility corresponding to the actual PI value x_i (-)

It can be observed from the above definition that the impact is a function of the gap between the 'target' utility and the actual utility. Depending on the type of PI, the impact is defined between the required PI value and the maximum or minimum acceptable PI value that follows from the definition of the PI. Figure 5 shows a graphical representation of the risk definition for a smaller-is-better type PI (a smaller PI value is considered positive in this case). The impacts I_i, needed for the risk calculation are then defined in the range $x_T < x \le x_{\max}$. In a way similar to risk, opportunity can be defined (Houben, 2010):

$$O_{PI} = \sum_i p_{PI}(x_i) \cdot U_{PI}(x_i) \qquad (2)$$

, with

$p_{PI}(x_i)$ = the probability that a certain PI value occurs (-)

$U_{PI}(x_i)$ = the utility corresponding to the actual PI value x_i (-)

Opportunity is in fact the likelihood that a certain PI-value (performance) occurs and is therefore present over the entire acceptable PI range $x_{\min} < x \le x_{\max}$. Another definition of the opportunity as given in (Smaling and de Weck, 2007) was investigated in this research:

$$O_{PI} = U_{PI}(x_T) \sum_i p_{PI}(x_i) \cdot U_{PI}(x_i) \qquad (3)$$

, with

$p_{PI}(x_i)$ = the probability that a certain PI value occurs (-)

$U_{PI}(x_T)$ = the utility corresponding to the required PI value x_T (-)

$U_{PI}(x_i)$ = the utility corresponding to the actual PI value x_i (-)

Both implementations were used in order to investigate differences in the results. The overall risk and overall opportunity are obtained by means of a weighted sum approach:

$$R = \sum_i \alpha_i \cdot R_{PI\,i} \qquad (4)$$

, where

α_i = the weighting factor for PI i.

R_{PI_i} = the risk corresponding to PI i.

$$O = \sum_i \alpha_i \cdot O_{PI\,i} \qquad (5)$$

, where

α_i = the weighting factor for PI i.

O_{PI_i} = the risk corresponding to PI i.

For more information regarding the definition of risk and opportunity the interested reader is referred to (Houben, 2010).

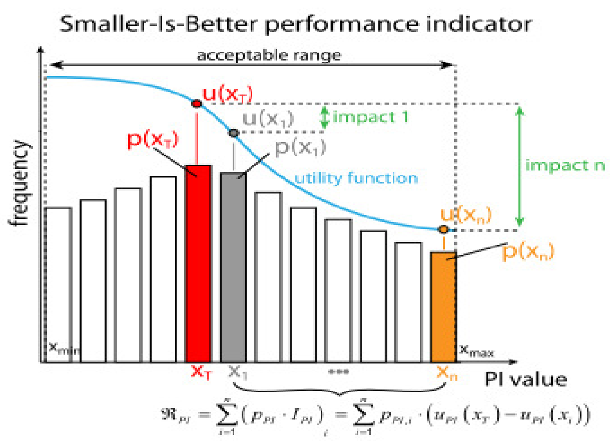

Figure 5: Definition of risk (Houben, 2010)

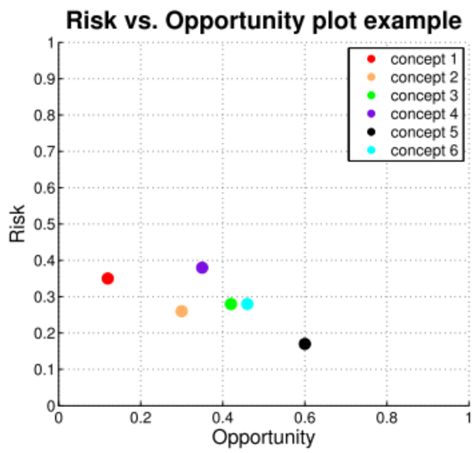

Figure 6: Example risk/opportunity plot (adopted from (Houben, 2010))

3.4.4 Optimization

Another step in the simulation phase is optimization. Design optimization is an interesting way to deal with conflicting objectives, which are often encountered in design innovation. Design optimization was, however, considered to be a research on its own and therefore not implemented in the CIS procedure for now. Nevertheless, optimization can be an interesting way to search for new design options, by applying genetic algorithms or similar methods (Gries, 2004; Hopfe, 2009; Parmee and Bonham, 1999). This enlarges the search space, which could lead to more creative, new design solutions.

3.5 Decision phase

When the risks and opportunities of all proposed design alternatives are calculated from the simulation results and utility functions, a decision can be made. By placing the results in a risk-opportunity plot (Smaling and de Weck, 2007), a direct comparison between all options is possible. Notice that all risks and opportunities are calculated for the same PIs, so the comparison is done in a rational way (based on one set of multiple criteria). Figure 6 illustrates an example of such a risk/opportunity plot.

4. CIS PROTOTYPE

The CIS procedure, illustrated in Figure 4, was implemented into a software prototype. The tools Matlab /Simulink 2008b (Mathworks, 2010), TRNSYS 16.1(TRNSYS 16, 2004) and Simlab (Simlab, 2010) were employed for the simulations, generating input samples, performing the SA, UA and post-processing of the results. Simlab is a statistical pre- and postprocessor useful for performing SA and UA and has been applied successfully in the past by a number of researchers (Breesch and Janssens, 2007; Hopfe *et al.*, 2007; Kotek *et al.*, 2007). In Figure 7 the workflow for the SA is illustrated. First preprocessing of the models is done with Matlab and Simlab, next sampling by means of the Latin Hypercube method takes place. After all models have been written out, they are successively simulated in TRNSYS. Finally, the Monte Carlo Analysis (MCA) results are post-processed in Simlab and regression coefficients are obtained.

A similar procedure for the risk opportunity analysis is followed as shown in Figure 8. The difference with the SA is that other input distribution types are supplied and that for post-processing of results, more steps are needed.

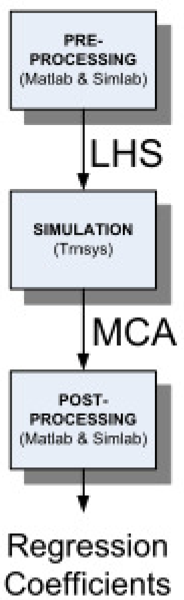

Figure 7: Overview of the prototype workflow for the SA.

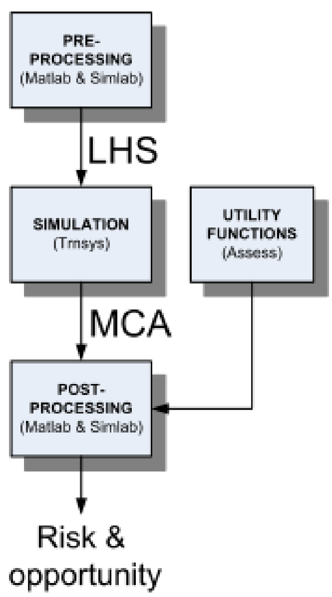

Figure 8: Overview of the prototype workflow for the risk and opportunity analysis.

5. CASE STUDY

To evaluate the developed CIS procedure, a case study was performed. The CIS prototype was run twice for the case study, with the goal to illustrate one full cycle of the procedure, how design changes arise out of the simulation analysis and to enable comparison of a number of studied design concepts.

5.1 Case study description

An innovative office building design, called 'Villa Flora', was selected for the case study. The dwelling is a design by architect and inventor prof. J. Kristinsson and is planned for construction at the 'Floriade' horticultural exhibition in 2012, in Venlo, the Netherlands (Kristinsson, 2007). The original sketch design concept was the point of departure for the case study.

Essentially, the Villa Flora design concept consists out of a combination of an office building and a greenhouse with a number of artificial climate zones (Sahara, Mediterranean, Amazone), which is considered beneficial for the heat balance in the building. A range of innovative HVAC and energy systems are part of the studied building design (Berghs *et al.*, 2007; Krisinsson, 2007):

- double-deck concrete floors with Concrete Core Conditioning (CCC),
- highly efficient heat exchangers for very low temperature heating and high temperature cooling,
- decentralized ventilation units with highly efficient heat recovery,
- parabolic pv/thermal collectors, for combined heat and electricity generation.

An artist-impression and overview of the HVAC and energy systems in Villa Flora are depicted in Figure 9 and Figure 10. The Villa Flora building design, including the CCC, heat exchangers and ventilation systems were considered for the case study.

Figure 9: Artist-impression of the Villa Flora building, used for the case study (Kristinsson, 2007)

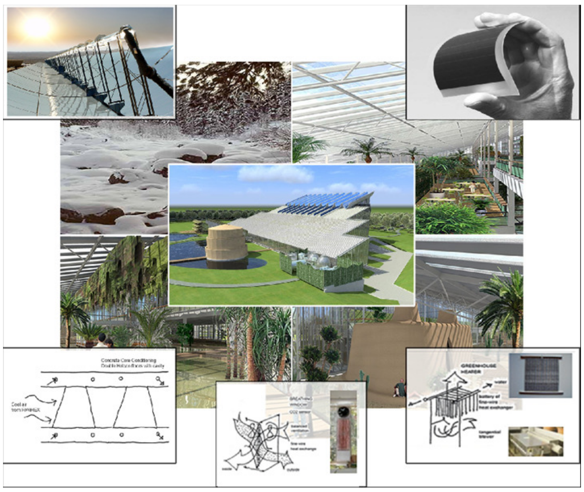

Figure 10: Overview of the HVAC- and energy systems incorporated in the Villa Flora design (Houben, 2009)

5.2 Simulation model

5.2.1 Building model

TRNSYS (TRNSYS 16, 2004) was applied for the case study simulations. With the help of TRNBUILD, a multi-zone building model of Villa Flora was created. For illustration purposes, the geometry of the building was modeled in a simplified way. The greenhouse area was split into three different zones and two vertical levels, in order to accurately model the CCC systems at in-between floors. The office areas were modeled in three levels: ground floor, first floor and the upper offices were modeled as one zone that is ideally controlled on the room temperature level of the ground floor area.

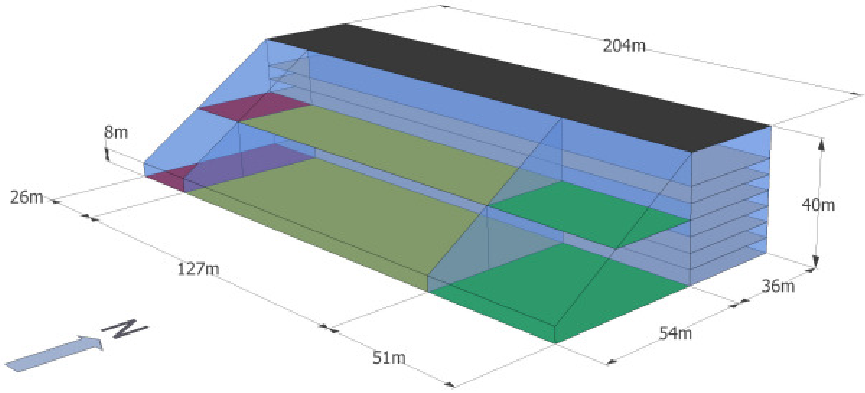

Figure 11: Overview of the zone abstraction for the simulation model (Houben, 2010)

5.2.2 Concrete core conditioning model

Two floor decks are used in the CCC system of the Villa Flora design. The one-dimensional 'active layer' approach, incorporated in the multi-zone building model in TRNSYS was selected for simulation of the CCC system (TRNSYS 16, 2004; Dorer & Koschenz, 1999). There is also a more sophisticated numerical simulation model for CCC systems (Fort, 2006), but this was considered too detailed/ time-consuming for the objectives of CIS. The 'active layer' approach calculates the one-dimensional heat transfer balance through a segment of pipe and concrete. The resulting thermal performance prediction consists out of a combination of mean water temperatures, average heat transfer coefficients and averaged floor and ceiling surface temperatures.

5.2.3 Heat exchanger models

The heat exchangers and ventilation units were modeled with the NTU-ε method as implemented in TRNSYS (TRNSYS 16, 2004). UA-values, mass flow rates and the water supply temperature were specified and based on this data and the energy balance from the building model, the effectiveness of the heat exchanger and temperatures of the outgoing heat flows were calculated.

5.2.4 Additional models

Besides the component models just described, electricity demand for pumps and fans and some other components were modeled. For details regarding these models, the reader is referred to (Houben, 2010).Three different types of utility functions were used for the risk opportunity calculations: utility functions of an inexperienced designer, utility functions of an experienced consultant and binary utility functions, such as applied in (Browning, 1998; Hu, 2009). Moreover, two different formulas for calculation of the opportunity were tested, in analogy with (Smaling and de Weck, 2007). These were already treated in section 3.4.3.

5.3 Performance definition

5.3.1 Performance breakdown structure

Table 1: The performance overview of the Villa Flora case study (Houben, 2010)

Objective	PI	Range	Symbol	Unit	Requirement
Thermal comfort	Overheating hours	0 – 200	OH	h	125
	Underheating hours	0 – 175	UH	h	100
Energy	Concurrence of heating energy	50 – 100	CON_{heat}	% of time	95
	Concurrence of cooling energy	50 – 100	CON_{cool}	% of time	95
	Heating energy supply	50 – 500	$E_{heat,s}$	$kWh/(m^2\ a)$	325
	Cooling energy supply	50 - 250	$E_{cool,s}$	$kWh/(m^2\ a)$	60
	HVAC electricity consumption	0 – 20	E_{el}	$kWh/(m^2\ a)$	15

5.3.2 Performance indicators

As results for the PIs overheating hours and HVAC electricity consumption will be shown in this paper, only their definition will be given here. All other PIs are defined in detail in (Houben, 2010).

Overheating hours

The PI overheating hours is defined as the number of hours in a year that the indoor air temperature is allowed to be higher than a specified threshold value. For the various climate zones of the Villa Flora building, different threshold values were chosen. For the office zones, for instance, an overheating hour was accounted for when the indoor air temperature of the zone got higher than 25 ºC. Overheating hours were specified to be acceptable between the ranges, as shown in Table 1.

HVAC electricity consumption

The HVAC electricity consumption is the amount of electricity needed to operate all auxiliary pumps, fans and valves, contained in the hydraulic circuits of the CCC and heat exchangers. The acceptable range of electricity consumption is given in Table 1.

5.4 Design options

Three design options were considered in two CIS cycles. In the first run, the performance of the original Villa Flora design concept was predicted and risks and opportunities were calculated. Analysis of the UA / SA results revealed that the performance of both the CCC and heat exchangers is highly dependent on the water supply temperatures and medium flow rates. Therefore, two control strategies of the supply water temperature were proposed as new design options for the second CIS cycle:

(i) control of the supply water temperature as function of the indoor temperature (case2a),

(ii) control of the supply water temperature as function of the ambient temperature (case2b).

The results of the performance evaluations are described in the next section.

6. RESULTS

6.1 Utility curves

The elicited utility functions for an experienced HVAC designer for the PIs overheating hours and HVAC electricity consumption are shown in Figure 12. The assessment points given in the figures were obtained with the help of structured utility interviews. After assessment, the utility functions were fitted between the assessed points. In this research, also the influence of discontinuous (or binary) utility functions on the resulting risks and opportunities was investigated (Hu, 2009). In Figure 13 the principle of this type of utility functions is visualized.

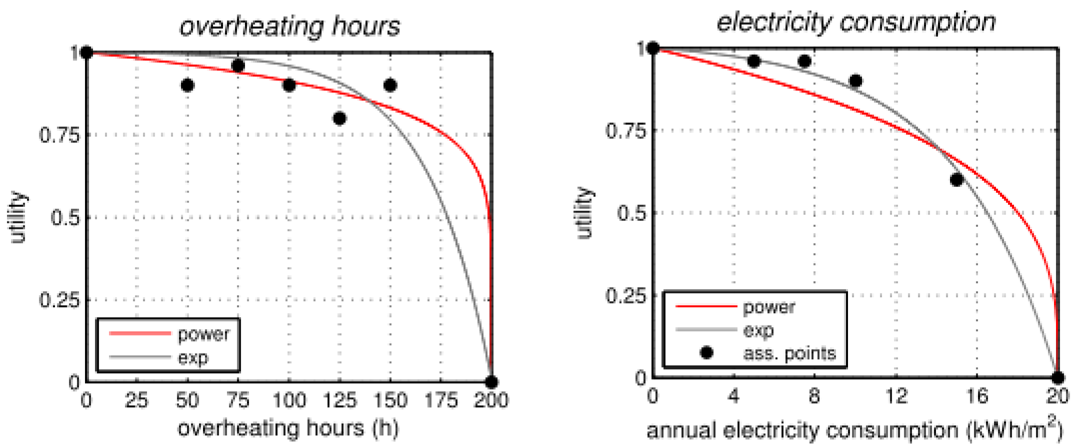

Figure 12: Example of derived utility functions of an experienced HVAC consultant for PIs overheating hours and HVAC electricity consumption (Houben, 2010)

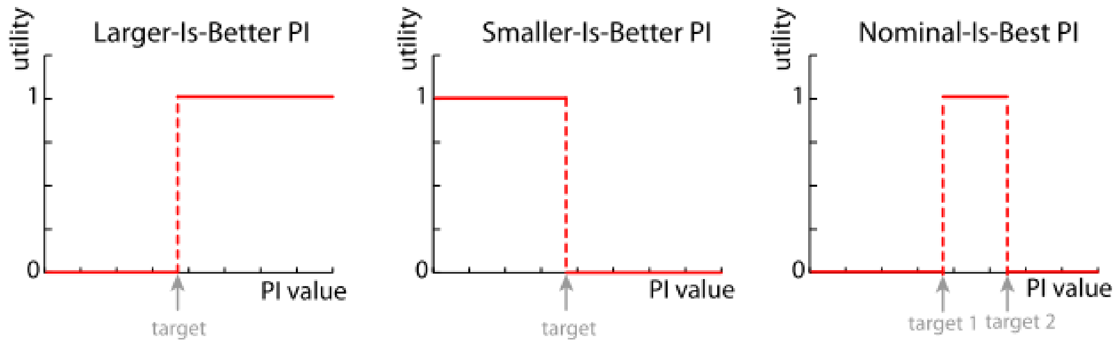

Figure 13: Discontinuous utility functions for three types of PIs (Houben, 2010).

6.2 Results for the base case

Results of the UA for the PIs overheating hours and electricity consumption are shown in Figure 14, the SA results in Figure 15.

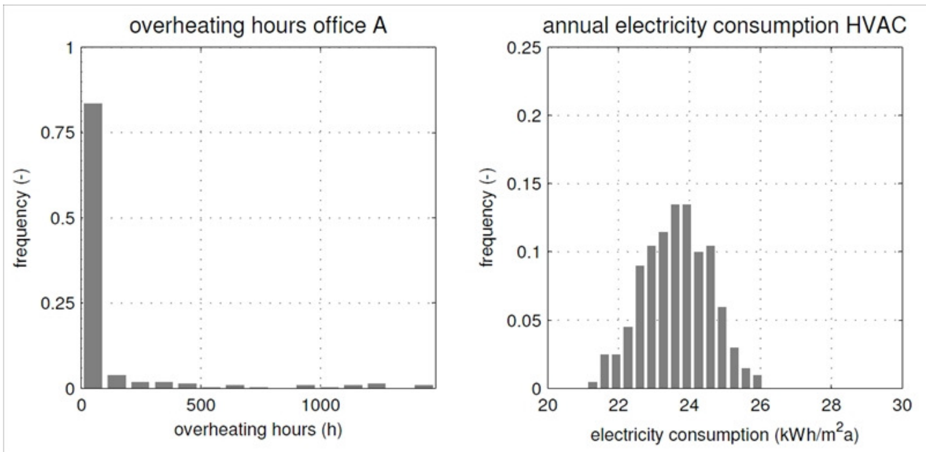

Figure 14: Obtained probability distributions for the base case, concerning overheating hours and HVAC electricity consumption (Houben, 2010)

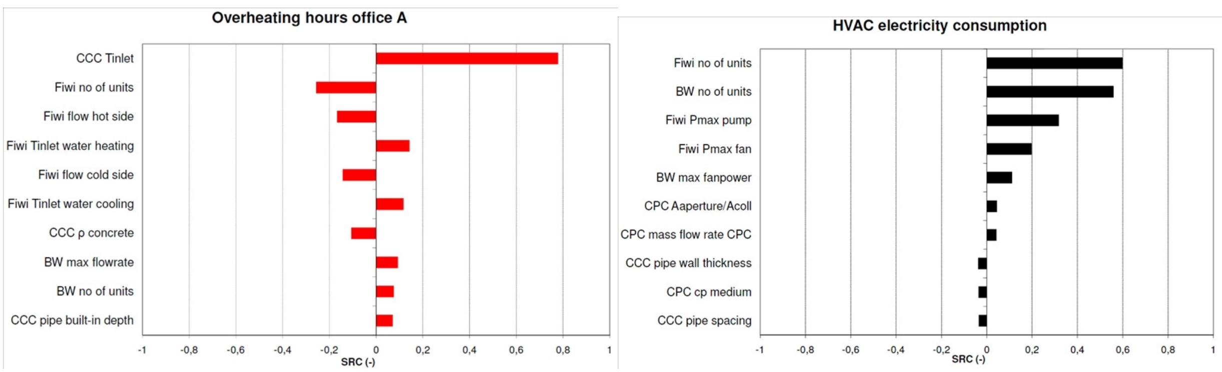

Figure 15: Obtained tornado plots for the base case, concerning overheating hours and HVAC electricity consumption (Houben, 2010)

6.3 Results of the second simulation run

6.3.1 Results case 2a

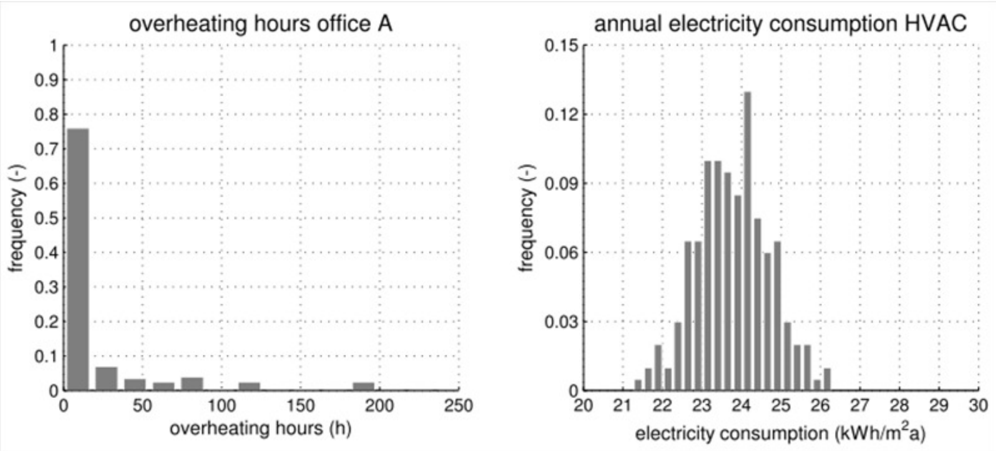

Figure 16: Obtained probability distributions for case 2a, concerning overheating hours and HVAC electricity consumption (Houben, 2010)

6.3.2 Results case 2b

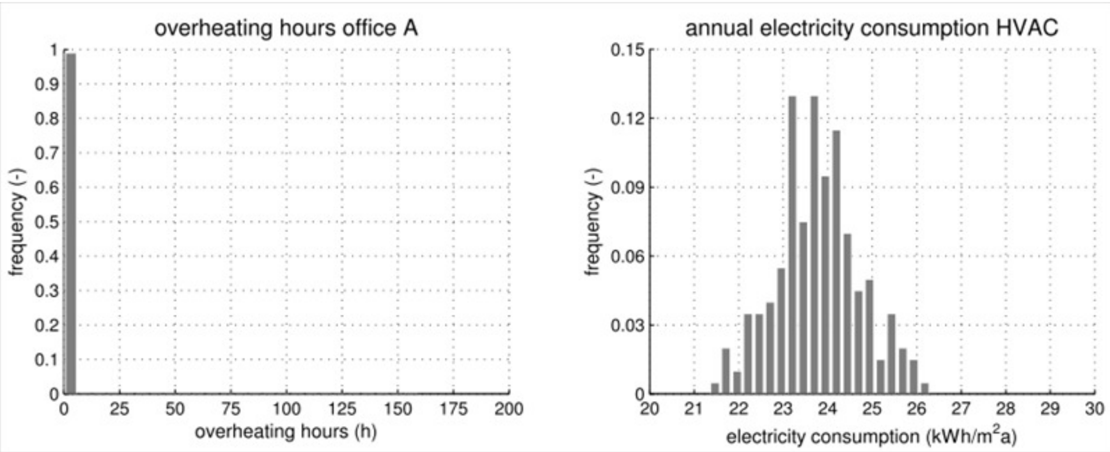

Figure 17: Obtained probability distributions for case 2b, concerning overheating hours and HVAC electricity consumption (Houben, 2010)

6.4 Risk/Opportunity results

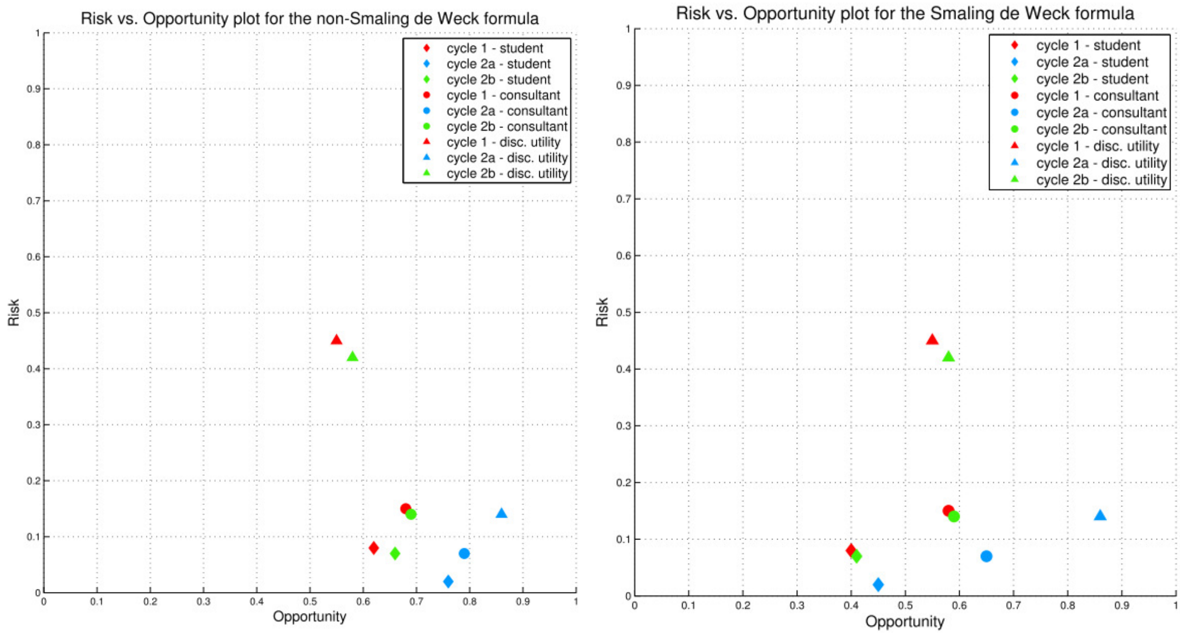

Figure 18: Risk/opportunity plots for two different formula (Houben, 2010)

On the left side of Figure 18 the Risk/Opportunity plot for all design options and concerning three types of utility functions, is given. The opportunity is calculated according to Equation (2) in that case. On the right side of Figure 18 the same Risk/Opportunity graph is given, but now, the opportunities have been determined according to Equation (3).

In order to obtain accurate probability distributions and therefore calculations of the risks and opportunities, the number of bins is an important parameter to consider. To investigate the influence of the number of bins on the calculated risks and opportunities, a sensitivity study was carried out. Figure 19 shows the results of this analysis.

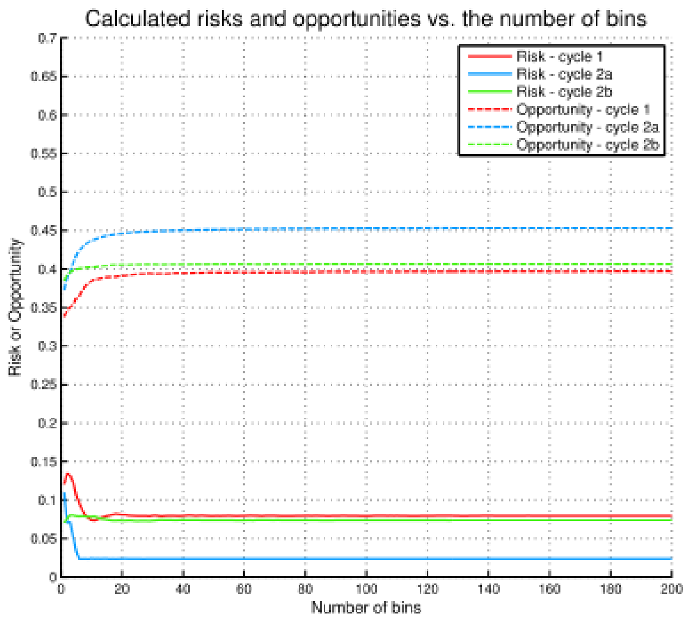

Figure 19: Accuracy analysis results for the student (Houben, 2010)

6.5 Case study results discussion

The results from the SA in Figure 15 indicate that an increase of the supply water temperature of the CCC system results in a large growth of the number of overheating hours. The right side of Figure 15 visualizes that the number of heat exchangers and ventilation units has a large influence on the HVAC electricity consumption as well as the maximum fan and pump capacities. Based on these results the designer could make the decision to investigate the influence control strategies of the supply water temperature on the thermal comfort and other PIs. In the case study, two control strategies had been investigated (case 2a and case 2b).

From the Risk/opportunity plots it can be noticed that an active control strategy of the supply water temperature as function of the ambient temperature seems to be the most promising design alternative for the HVAC system design (*i.e.*, it indicates the lowest risks and highest opportunities for all three types of utility functions and each of the considered equations for the opportunity calculation).

Figure 19 visualizes that the outcome of the CIS analysis is also dependent on the number of bins. After about thirty bins or more, steady risk and opportunity values for all cycles can be observed. The accuracy analysis shows that sensitivity analysis regarding the number of bins is an invaluable tool for quality assurance of the results. Moreover it enables the designer to make design decisions based on well calculated risks. If not enough bins would have been used or an unsteady influence of the number of bins on the risks and opportunities would be observed, probably other decisions would be made, because of different risks and opportunities.

7. CONCLUSIONS

This paper has shown the backgrounds and application of a part of the CIS procedure, which is meant to ‘guide’ the innovation process with simulation, SA, UA and risk- and opportunity analysis. It can be concluded that the presented CIS implementation enables designers to:

1. reduce the parameter space,
2. indicate and focus on the most important design parameters,
3. steer the innovation process by providing useful design information, in the form of R/O plots, tornado diagrams, probability distributions and utility curves.

The current structure of the CIS procedure can still change due to the introduction of optimization techniques or additional steps. In order to successfully apply CIS, a performance-based design philosophy and team organization is recommended, because this motivates the application of simulation tools in the design process. Besides, the design team can explore multiple design options next to each other and is offered the opportunity to make rational decision based on a multiple of aspects. This leads to an increased creativity and therefore enlarged chance to arrive at innovative design solutions.

Another important conclusion is that quality checks must always be performed to ensure consistency of results. Especially the influence of the number of bins on the results and the effect of the number of elicited points on the utility curve are recommended to be evaluated.

Concerning the case study, active control of the supply water temperature of both the CCC system and heat exchangers was found to be an improvement, compared to the simulation results of the original design concept.

Future research to CIS can focus on practical application of the prototype, extension of the method with optimization techniques and further incorporation of other types of uncertainties (*e.g.*, uncertainties concerning the simulation models, uncertainty in weather data, occupancy profiles etc.). The CIS procedure can also be improved by incorporating expert knowledge, especially for the steps in the definition phase, because the definition of the principal's needs and the assignment of probability distributions require a lot of design experience. The same is truth for the elicitation of utility functions. Finally, further research can focus on the application of CIS during various stages of the design process and at differing levels of detail. Only practical application of CIS can reveal its benefits as supporting tool for the design innovation process.

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10. NOMENCLATURE

Table 2: nomenclature of symbols, variables and corresponding units, used in the paper

variable	***unit***	***description***
OH	h	Overheating hours
UH	h	Underheating hours
CON	% of time	Concurrence of energy supply and demand
E	kWh/m^2 or kWh	Energy
R	-	Risk
O	-	Opportunity
Greek		
α	-	Weighting factor for a performance indicator
Indices		
heat	-	Heating
cool	-	Cooling
heat,s	-	Heating supply
cool,s	-	Cooling supply
el	-	Electricity
PI	varies	Performance Indicator