Computational building performance simulation for integrated design and product optimization

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COMPUTATIONAL BUILDING PERFORMANCE SIMULATION FOR INTEGRATED DESIGN AND PRODUCT OPTIMIZATION

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ABSTRACT

Integrated computational building performance simulation (CBPS) can help in reducing energy consumption and increasing occupant comfort. However, the deployment of CBPS in practice has not matured and its benefits have not been fully exploited yet. This paper explores the role of CBPS in product and integrated design development and optimization through two studies. The first study explores the use of CBPS for product development within the scope of climate adaptive building shells. The second study presents a method for assisting the design innovation process, which is called 'Computational Innovation Steering'.

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. Designers are challenged to come up with new, innovative and non-traditional components and integrated design solutions for building and its systems. Examples of innovative components are: climate adaptable building shells (CABS), concrete core conditioning systems, threefold glazing, ground source heat pumps, solar collectors, energy storage systems. However, the development of such innovative products and integrated system designs requires an integrated approach, concerning design methods and philosophy.

Over the last decades, a wide range of computational building performance simulation (CBPS) tools has seen the light and is considered useful in the integrated 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 product and integrated design development. However, the deployment of CBPS in practice has not matured and its benefits have not been fully exploited yet.

Besides for virtually analyzing and solving problems after completion of detailed product design, CBPS tools could also be used to facilitate product development by supporting decision making processes and assisting innovation processes in complex settings before detail product design.

In the innovative integrated design process, the design team is confronted with a number of decisions that have to be made regarding the performance of the innovation under consideration. 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. Thus, CBPS, together with utility functions and sensitivity and uncertainty analyses are considered promising instruments for generating this type of performance information.

In this paper, we present two case studies that use CBPS for innovative product development and innovative integrated design optimization.

CBPS FOR PRODUCT DEVELOPMENT

The first study explores the use of CBPS for product development within the scope of CABS. CABS have the ability to change their properties and behavior over time. Provided they are designed and operated effectively, CABS offer the potential for energy savings without the need for compromising comfort levels. This part of the paper explores the potential role that CBPS can play in product development by taking the innovative window technology Smart Energy Glass (SEG) as an illustrative case study.

Smart Energy Glass

SEG is based on a polymer coating that is placed between two layers of glass. These layers together form the external pane of an insulated glazing unit. By applying an external voltage to the coating, it is possible to control the optical properties of the window within less than a second. SEG can be switched into three different states: a bright state, a dark state and a translucent state. The polymer coating in SEG also acts as planar waveguide in the same way as a luminescent solar concentrator (LSC) (Goetzberger and Greube, 1977). The dye molecules absorb part of the incoming sunlight and re-emit photons in random direction at a longer wavelength. Via this mechanism, part of the incoming light is captured and redirected to the edges of the window where photovoltaic cells are situated to convert the collected radiation into electricity.

SEG is currently not a market-ready commercial product, and is still under development. Research and development activities currently focus on optimizing absorption and emission spectra, thermal performance of the window, optical losses, electrical circuits, etc. CBPS can help in the optimization process since it provides integrated view of the performance and facilitates identification of promising product solutions for specific applications.

Modeling SEG

The work presented in this paper complements and interacts with the development activities by providing computational support for assisting the innovation processes in product development. For this purpose, a model of SEG that integrates its electrical, thermal and optical properties is created.

In this study, electrical model is based on empirical knowledge obtained after conducting dedicated experiments, which were set-up with the emphasis on elucidating SEG's behavior under different light incident angles. The details of the experiment, model description and its validation can be found in Loonen et al. (2010).

The optical properties of SEG are altered by changing the global alignment of molecules in the dye. Characterization of these properties in bright and dark state was done for SEG samples in an experimental set-up (Loonen et al. 2010). Values for reflectance and transmittance were measured according to the protocols in ISO 9050 (2003). This data was then transformed into spectrally averaged properties with the aid of the software tool OPTICS (LBNL, 2010). Thermal window properties were established by using the complementary software tool WINDOW5 (LBNL, 2010).

Simulation strategy for SEG

After reviewing capabilities of available state of the art CBPS tools, we have opted to use TRNSYS (TRNSYS, 2011) for performance prediction in the thermal and electrical domain, and to couple this model with the results of dynamic daylight simulations in DAYSIM (DAYSIM, 2011). Figure 1 shows a schematic representation of the simulation strategy that is used for performance predictions of SEG. Daylight simulations are first conducted in a preprocessing stage for all window states independently. Annual time-series of five minute luminance and illuminance values at specific sensor-points are then supplied to TRNSYS that 'selects' the right data during run-time corresponding to the controlled window state. Data is flowing across the three domains at every time-step and therefore data exchange is dynamic. The simulators in DAYSIM and TRNSYS are however invoked consecutively and therefore the workflow is sequential. This approach is justified by the short-term dynamics of daylight performance that does not suffer from 'history effects'.

The control component plays a central role in SEG's simulation model as indicated in Figure 1. Every time-step, output data from DAYSIM is accessed by the control component which decides upon the right adaptive actions on the basis of an imposed control strategy.

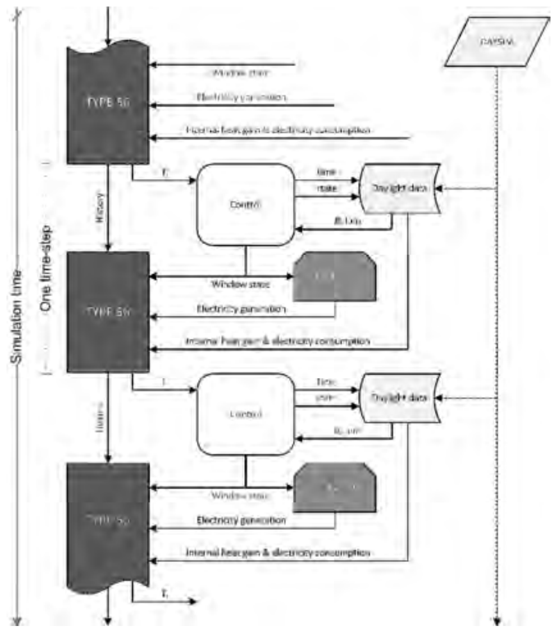

Figure 1: Simulation strategy for the SEG model.

This control logic is implemented via equation-types containing conditional statements that compare model output (e.g. temperature, window luminance, workplane illuminance) to target values and return window ID for the next timestep as output. This window ID is passed on to the thermal and electrical model and used in the respective calculations for the next time-step. The window state, together with incident radiation results in amount of collected radiation via the use of 'equation-types'. This energy flux is then converted into electricity via a photovoltaic array model (TYPE 180).

The influence that SEG exerts on thermal performance of a zone or building is evaluated by using the TRNSYS multi-zone building model (TYPE 56). In the simulations, window properties are changed during run-time with a function called variable window ID. Environmental conditions are ensured to be identical to those subject to the daylight model by selecting the same weather file. Internal heat gains of the building depend on the state of the window since the amount of artificial lighting changes with daylight availability. Together with occupants' presence, this data is imported from the data files pre-calculated by DAYSIM.

Analysing SEG performance for two-person office

The analysis in this study is restricted to a two-person south-facing perimeter office zone (3.6m x 5.4m x 2.7m), situated at an intermediate floor, and is assumed to be surrounded by identical office spaces. These adiabatic boundary conditions were selected to ascertain that observed performance differences are effectively attributable to SEG. Storage of thermal energy in internal partitions is taken into account, and typical office equipment amounts to a heat load of 10 W/m^2. The window-to-wall ratio of the south façade equals 35 %.

Occupancy in the office room follows DAYSIM's probability-based five day work-week schedule with intermediate and lunch breaks. Artificial lighting (15 W/m2 installed power) switches according to this same schedule and is continuously dimmable up to an indoor illuminance of 500 lx on the basis of the LIGHTSWITCH-2002 algorithms (Reinhart, 2004).

Lighting control is triggered by a work plane photosensor at a distance of 1.8 m from the envelope. Thermal conditions in the zone are controlled on the basis of indoor air temperature, with setpoints for heating (20^{o}C) and cooling (24^{o}C) between 8 a.m. and 17 p.m., and a heating setpoint of 16^{o}C outside working hours. Stochastically generated short time-step (five minute) solar irradiance data files (Walkenhorst et al., 2000) are created once for every case, and are used for predicting daylighting performance.

This study evaluates the potential to use SEG as window replacement in a renovation case. The reference case assumes conventional double glazing and opaque construction elements with typical insulation standard for office buildings constructed around 1975 (Petersdorff et al., 2006). Solar shading and brightness control in the reference case is achieved via manually controlled internal venetian blinds. Operation of blinds in the simulations is 'ideally' controlled in DAYSIM on the basis of the Active users profile. This stochastic algorithm assumes that blind settings are rearranged on a regular basis with the aim of maximizing daylight availability while excluding glare (Reinhart, 2004).

The number of possible strategies for controlling SEG's adaptive behavior is virtually infinite. The aim of this paper is to explore their potential and provide some first insights in the cause and effect relationships of various options. Table 1 provides an overview of investigated control strategies.

The energy saving potential of SEG is assessed by considering overall annual energy demand, subdivided in terms of energy required for heating, cooling and artificial lighting.

Table 1: List of the investigated control strategies

A	Reference case
B	SEG always switched in the bright state
C	SEG always switched in the dark state
D	SEG switched to the dark state when indoor air temperature ≥ 21 $^\circ$ C
E	SEG switched to the dark state when daylight illuminance on work plane (*E*h) ≥ 700 lx
F	SEG switched to the dark state when window luminance (Lv) ≥ 1500 cd/m^2

A second performance indicator (PI) is peak heating and cooling demand. Saving energy is however only acceptable when this occurs in absence of discomfort. Consequently SEG's impacts on comfort are at least equally important. In this paper, thermal comfort is assessed on the basis of overheating risk. This is accomplished by counting the number of hours that indoor air temperature exceeds 25^{o}C. Allowing discomfort during maximum 5 % of working hours is usually seen as realistic and economic target value in the trade-off between energy and comfort. As a result, this amounts to an allowed number of 100 overheating hours.

Visual comfort is evaluated by considering the risk of glare, which is defined as "the sensation produced by luminance within the visual field that is sufficiently greater than the luminance to which the eyes are adapted to cause annoyance, discomfort or loss in visual performance and visibility" (IESNA, 2000). In this study, the risk of discomfort caused by glare is assessed by counting the number of times when the ratio between window luminance and paper task luminance is higher than 10:1 (IESNA, 2000).

Results

Figure 2 shows annual energy demand and comfort performance for each of the six cases as given in Table 1. The results suggest that cooling energy demand after window replacement with SEG is cut by more than a factor two. In addition, installed cooling power capacity was found to be safely reduced with more than 30 % (from 1.0kW to 0.67kW) when SEG is installed, while still achieving sufficient thermal comfort levels.

Figure 2 further shows that heating energy demand for the basecase (case A) compares well to that for SEG, even though the window U-value of SEG is lower as a result of the presence of a low-E coating. Closer inspection at the energy balance reveals that the transmission losses after renovation are indeed lower, but this difference is almost compensated by the decrease in valuable passive solar gains. The lower visible transmission values of SEG also give rise to a relatively large electricity demand for lighting. The results further show that occurrence of glare in the reference case is comparatively high. This is caused by the fact that (i) the window has a high visible transmittance, and (ii) blinds are operated manually.

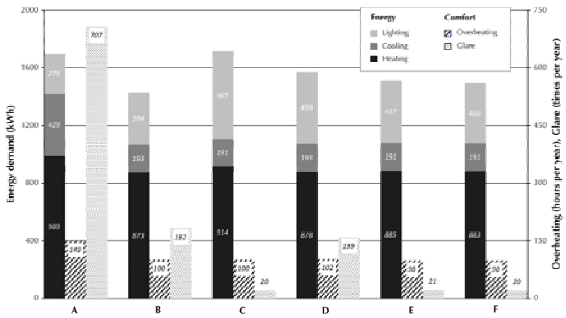

Figure 2: Comparison between energy and comfort performance of the reference (A) and SEG (case B to F) in an advanced renovation case. With on the left axis: heating, cooling and lighting energy consumption [kWh], and on the right axis: risk for overheating [h] and glare [times].

Considering SEG as an alternative can provide an adequate solution for fulfilling both thermal and visual comfort requirements. If continuously in the bright state (case B), total energy consumption gets reduced, but glare is still a problem. When always switched to the dark state (case C), the occurrence of glare drops drastically, but at the same time this also introduces an undesirable higher energy demand for artificial lighting. Implementation of an appropriate control strategy (e.g. case D to F) is the key that allows for profiting from the benefits of both the dark and the bright state. Apparently, best results are obtained when window state is controlled based on stimuli from the luminous environment (case E or F). In these cases, daylight is only allowed when desired and blocked when unwanted.

Discussion

The CBPS model is used to evaluate the potential of SEG subject to various control strategies and provides suggestions for future research and development of SEG. On the basis of the presented simulations it is not yet possible to give conclusive answers about SEG's energy saving potential. The concept however seems promising because energy savings can be achieved while at the same time comfort levels improve. On the other hand, the results do also suggest that there is still room for product improvements, such as:

- Switching the optical properties of SEG primarily takes place in the visible wavelength area. Blocking solar gains is therefore followed by a proportional increase in lighting energy use. The net result is that solar gains are exchanged for internal gains, and consequently part of the energy saving potential is counterbalanced. The luminescent dye technology however makes extension of the switching range to other parts of the spectrum viable. The ultimate solution would be a window that is capable of switching visible and infrared transmittance independently. Research efforts pursuing this aim are underway, but currently the luminescent materials active in the infrared wavelength area still suffer from low stability, low quantum efficiency, and a relatively small absorption spectrum (Goldschmidt, 2009).
- The bandwidth for switching SEG is relative narrow compared to other switchable windows. In addition, SEG only switches in either one of three states, without the possibility for gradual transitions in between.
- The produced amount of electricity is two orders of magnitude lower compared to the scale of hundreds of kWh in Figure 2. This has motivated further product development as self-sufficient SEG without consideration of further distribution of the generated electricity.

SEG is still in the prototype phase, and more work is required towards optimization of the final product. CBPS can help to identify the focus of attention for future product development in the laboratory as well as in the actual integration in the building shell. Currently, we are using the simulation model presented in this paper to investigate which optical and thermal properties and which control strategy yield the optimum performance of SEG for different applications.

CBPS FOR INTEGRATED DESIGN DEVELOPMENT

The second study presents a method for assisting the design innovation process, which is called 'Computational Innovation Steering' (CIS). CIS makes use of CBPS and moreover focuses at the application of uncertainty analysis, sensitivity analysis and risk and opportunity analysis as promising tools for this purpose.

Principles of CIS procedure

Based on de Wilde (2004) the following assumptions are made prior to developing CIS procedure:

- 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.

An extended version of the developed CIS procedure is illustrated in Figure 3. In this research the optimization step in the simulation phase was considered for future work and therefore not implemented in the prototype environment.

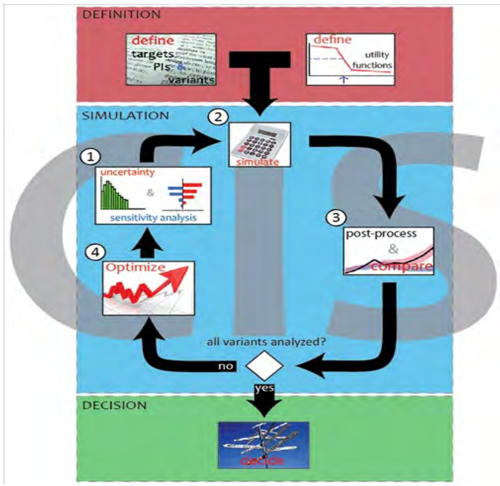

Figure 3: Overview of the developed CIS procedure

Definition phase

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.

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 options. The option space comprises the collection or set of all possible designs (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 or automated approaches, such as genetic algorithms for performing parameter variations (Gries, 2004).

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 (Keeney and Raiffa, 1993). Both utility values and probability values are needed to compute risks and opportunities.

Simulation phase

In the second phase, CBPS tools are used to predict the performance of the proposed design options. CBPS is accompanied by the use of SA and UA aiming to generate more insight and therefore useful design information.

Step 1: In CIS, the goal of SA is twofold: (i) selecting the most important design parameters and (ii) reducing 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.

Step 2: 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.

This step starts with a defined set of design parameters[1] and given uncertainty of those recognized as influential in the step one of the second phase in CIS procedure. 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 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 (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.

Step 3: 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 and de Weck (2007). Risk can be defined as the likelihood that something happens times the corresponding consequence of it (Houben, 2010):

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

where p_{PI} is the probability that a certain PI value occurs (-); I_{PI} is the consequence (or impact) corresponding to the probability p_{PI} (-); $U_{PI}\left(x_T\right)$ is the utility corresponding to the required PI target-value x_T *(-)*; $U_{PI}\left(x_i\right)$ is the utility corresponding to the actual PI value x_i *(-)*.

[1] The definition of this set can be done using optimization. The identified PIs are used as objective functions and the set of the parameters recognized as influential in the step 1 of the second phase in CIS procedure are used as decision variables.

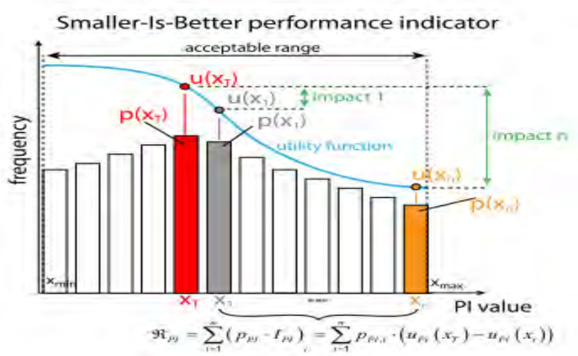

Figure 4: Definition of risk

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. Figure 4 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).

Opportunity is the likelihood that a certain PI-value (performance) occurs and is therefore present over the entire acceptable PI range. Opportunity can be defined using the following formulae (Houben, 2010):

$$O_{PI} = U_{PI}\left(x_T\right)\sum_i p_{PI}(x_i)\times U_{PI}\left(x_i\right) \quad , \qquad (2)$$

where $U_{PI}\left(x_T\right)$ is the utility corresponding to the required PI value x_T .

The overall risk and overall opportunity are obtained by means of a weighted sum approach:

$$R=\sum_i \alpha_i \cdot R_{PI_i} \quad , \quad \text{and } O=\sum_i \alpha_i \cdot O_{PI_i} \qquad (3)$$

where α_i is the relative weighting factor for PI *i* to be defined by the stakeholders, R_{PI_i} is the risk corresponding to PI *i* and the opportunity corresponding to PI *i*.

Step 4: 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 prototype procedure presented here. Nevertheless, optimization can be an interesting way to search for new design options (Hopfe, 2009).

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).

Decision phase

When the risks and opportunities of all proposed design options 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.

CIS prototype procedure

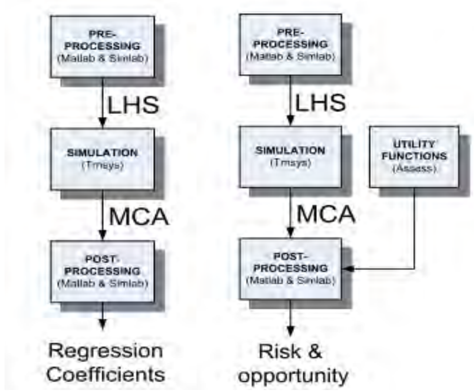

Figure 5: Overview of the prototype workflow for the SA, risk and opportunity analysis.

The CIS procedure, illustrated in Figure 3, was implemented into a software prototype. The tools Matlab /Simulink, TRNSYS (16.1) and Simlab 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 (e.g. Hopfe 2009). In Figure 5 the workflow for the SA, risk and opportunity analysis is illustrated.

Illustration of CIS procedure in building design

An innovative office building design, called 'Villa Flora', was selected for the case study. The high-ambitious project 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). Essentially, the Villa Flora design concept consists 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 (Kristinsson, 2007):

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

The details of the simulation model can be found in Houben et al. (2010). In this paper we identify overheating hours and HVAC electricity consumption as representative PIs. The 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. 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 Fiwihex systems.

For the case study in this research, utility functions were elicited with a software tool, called 'Assess', which uses the Lottery Equivalents method (Delquié, 2010). The elicited utility functions for an experienced HVAC designer for the PIs overheating hours and HVAC electricity consumption are shown in Figure 6. 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).

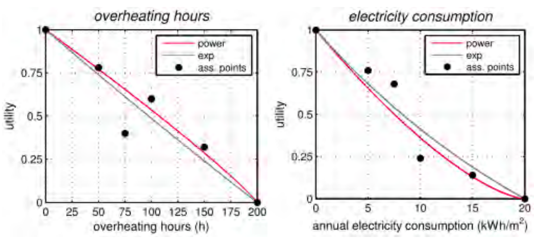

Figure 6: Example of derived utility functions of an inexperienced for PIs overheating hours and HVAC electricity consumption

SA results (Figure 7) revealed that the performance of both the CCC and Fiwihex systems 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).

In Figure 8 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). From the Risk/Opportunity plot (Figure 8) 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 option 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).

Discussion

CIS offers designers the opportunity to generate useful design information that can be put forward in the complex decision-making process usually present in design innovation. CIS procedure enables designers to:

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

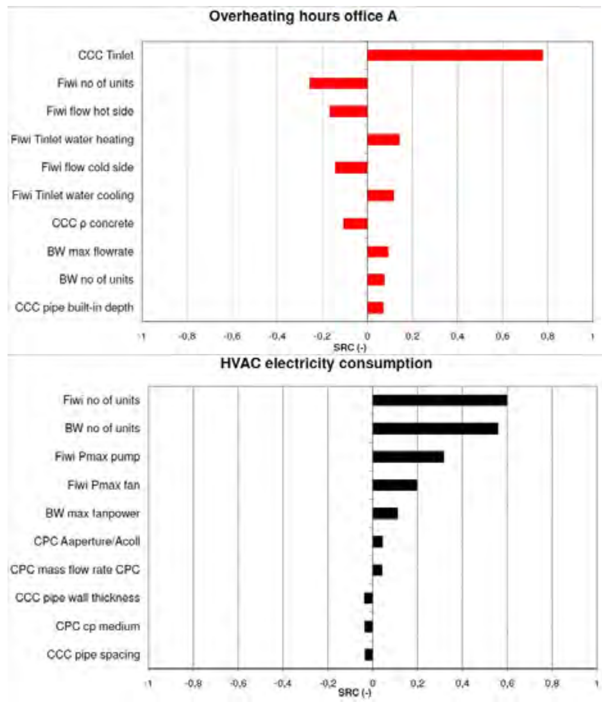

Figure 7: Tornado plots for base case - overheating hours and HVAC electricity consumption (SRC = Standard Regression Coefficient)

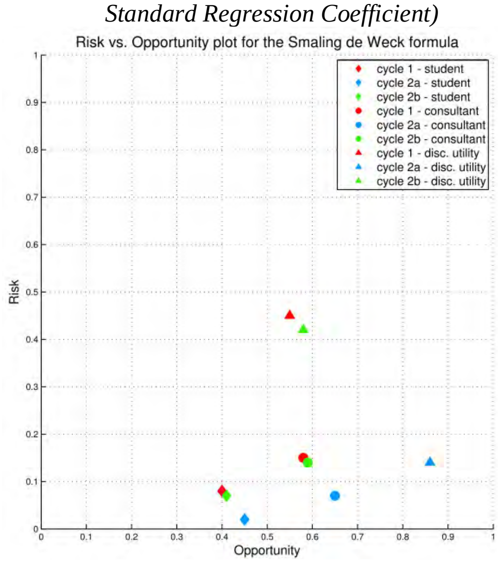

Figure 8: Risk/opportunity plots for two different formula

CONCLUSIONS

This paper presented two studies that make use of CBPS for both product development and design optimization. CBPS is able to facilitate increased insights in the integrated system's dynamics, ranging from short-term impacts to seasonal cycles. Thus, CBPS can be a valuable instrument in product design and development by supporting informed decisions in the product development process. In addition CBPS helps guiding the design innovation process. 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.

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