OPTIMIZING BUILDING ENERGY SIMULATION MODELS IN THE FACE OF UNCERTAINTY

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ABSTRACT

Model-based optimizations usually neglect the fact that building parameters cannot be estimated with high accuracy. The highly nonlinear characteristics of building energy systems (e.g., on-off control and capacity limitations) makes it harder to quantify the impact of uncertainty of model parameters. In addition, buildings are not stationary as equipment ages and utilization changes over time, requiring adjustment of previously found optimal solutions. A methodology has been developed to overcome these shortcomings and is illustrated using a simple example: a building using a solar thermal collector for heating and domestic hot water. The approach entails Monte Carlo sampling from the uncertain domain, with an embedded optimization routine. Conditional probability density functions (e.g., energy consumption and demand) quantify the difference between base case and optimal scenarios in the presence of uncertainty.

INTRODUCTION

A model-based approach for designing, refining, and optimizing building energy systems is becoming the standard in modern building design, retrofits, and to support commissioning efforts. However, the influence of uncertainty in model parameters and disturbance variables is rarely considered when searching for optimal solutions. This will lead to a disparity (model mismatch) between the calculated optimal solution and measured results. The applicability of such model-based optimization is obviously limited by the accuracy of any assumption, and there are many of these in building simulations. This paper presents research toward the goal of optimizing building performance in the face of uncertainty in the model parameters defining a simulation to be optimized.

Focus here is placed on a methodology to alleviate concerns associated with the validity of a derived optimal solution when modeling uncertainties are present. The applicability of the methodology in buildings is potentially significant, given a growing concern for energy efficiency, utility costs, and indoor environmental quality. However, due to the complexity of modeling buildings, the relative impact of an uncertain parameter on the overall simulation outcome needs to be assessed and ranked, either by energy modeler or a sensitivity analysis.

A simple example building using a solar thermal collector for heating and domestic hot water illustrates the approach and how it can be used to estimate savings from model-based optimization. A Monte Carlo (MC) sampling routine is used to explore the uncertain domain, while an embedded optimization routine provides the energy or cost minimal solution conditional on the MC sample. The building used to demonstrate the methodology is occupant-driven, and therefore the uncertainty is associated with parameters dealing with infiltration air change rates and domestic hot water mass flow rates. In the example, the optimized parameter is the slope of the collector to achieve maximum annual energy savings.

LITERATURE REVIEW

Work on the combination of stochastic models with optimization is rare in the building sector. Many of the problems addressed in (Jiang, Reddy, and Gurian. 2007) are more general in nature. Although the optimization process itself is not treated in a stochastic manner, a formal decision analysis model is used to incorporate risk-management in decision making. Xu et al. (2005) combine the optimization with stochastic modeling via stochastic dynamic programming. However, their formulation of the stochastic model is very problem specific. Our aim here is to link well established techniques in the building sector to be easily available (e.g., modeling with general building simulation software, Monte Carlo methods and optimization). Henze (2003) also describes a combination of optimization in the face of uncertainty but the methods used there mainly deal with uncertainty in externally predicted (future expected) values and the distributions of the stochastic variables are not further incorporated into the optimization and no result distributions are reported on the results. The two techniques of stochastic models and optimization taken individually are well known in the building sector.

One of the first optimization studies applied to buildings (Bloomfield and Fisk 1977) examined intermittent heating (i.e., optimal start and stop times with consideration of thermal inertia) and compared the solutions to existing strategies. More recent studies have explored cooling season optimization and used the thermal inertia effect to reduce energy costs and peak demand, while maintaining adequate environmental comfort (Braun 1990). Focus has also been placed on the predictive optimal controller (Henze, Dodier, and Krarti 1996) used to manage a dedicated thermal energy system (e.g., ice storage) to optimally respond to dynamic changes in weather other forcing functions over some finite horizon. Optimization studies of building subsystems are more prevalent, with focus on primary equipment like chillers (Braun 1992), boilers (Taplin 1998), and air handling units (Seem, Park, and House 1999). On a larger scale, optimization of district energy systems has been investigated as well (Chen et al. 2007).

Uncertainty analysis in buildings is rare, but it has been examined both in terms of internal and external probabilistic approaches to quantifying the overall effect of parameter uncertainty in building simulations (Macdonald 2002). Attention has also been focused on how building-external stochastic processes (e.g., meteorological events) influence building thermal processes (Jiang and Hong 1993), or how building-internal process knowledge (e.g., occupancy patterns) can lead to improved building operation. A study of the general problem of inference in buildings (Dodier 1999) showed how prediction, diagnosis, and calculating the value of information could be applied and verified.

BUILDING CASE STUDY

The demonstration building shown in Figure 1 and located near Leipzig, Germany was modeled, simulated, and optimized according to the methodology. The building is an office that is heated by a gas boiler. A great deal of high-quality measurements were available for this building. Therefore, model calibration efforts, both in terms of measured heating energy and room temperature time series data, were shown to have good agreement with simulation data from a base case model (Burhenne and Jacob 2008). It is assumed that the building is occupied by 12 people and equipped with a 19 m^2 flat plate solar collector and 1000 L storage tank. This model provided a great testbed for a model-based study to evaluate the feasibility of a solar thermal collector and its optimization under uncertain conditions.

Building Modeling and Simulation

For reduced computation time, it is preferable to have an appropriately simple model for this numerically expensive simulation task. It is often the case that complex models with high parameter dimensionality do not perform any better than models with only a few parameters (Déqué, Ollivier, and Poblador 2000). The chosen model

Figure 1: Example office building located near Leipzig, Germany.

is described in more detail in (Burhenne and Jacob 2008) and (ISO 13790 2007). The object-oriented and equation-based modeling language Modelica (Elmqvist 1997) was used to describe the system.

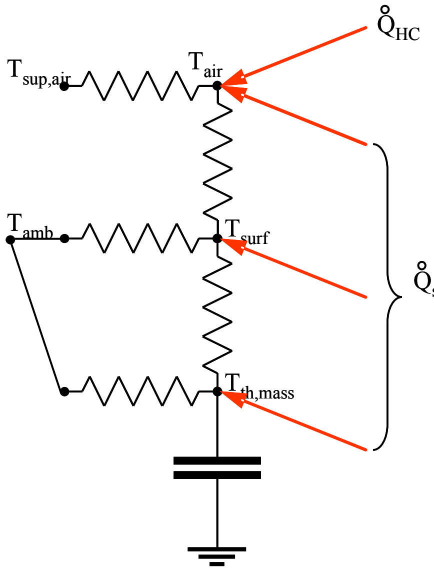

Figure 2: ISO 13790 zone model.

A simple zone model, called the "Simple Hourly Method" (SHM) according to standard ISO 13790 (2007), is implemented in the simulation model. The model is based on a network of five resistors and one capacitor, as shown in Figure 2. The solar collector model is based on Isakson and Eriksson (1993) designed to overcome some shortcomings of previous models with regard to the transition to stagnation (no flow) conditions. The model has a strictly continuous transition from flow to no-flow conditions which is crucial for numerical stability, especially in equation-based environments. For the tank, a very simple one resistor, one capacitor (1R1C) model is used. The boiler is modeled to keep the tank temperature at a minimum of 60°C as long as the maximum capacity of the boiler is sufficient. The collector circuit contains an on/off controller, which turns on the collector pump when the collector temperature is 8 K above the tank temperature and turns it off at 2 K above tank temperature. The domestic hot water flow rates were generated from IEA-SHC, Task 26: Solar Combisystems Jordan and Vajen (2003) in the Solar Heating and Cooling Program of the International Energy Agency, and are relayed to the simulation engine accordingly. Each simulation is executed for one year at fixed time steps of 60 seconds with a Runge-Kutta integration method. Weather data from a weather station 30 km from the building site was used.

METHODOLOGY

As a first step, the most relevant energy and/or cost influences need to be identified. Sensitivity analyses can be used to aid in selection of the pertinent parameters and/or variables (Saltelli, Chan, and Scott 2000). In the case study building, due to its relative simplicity and the copious amount of measured data indicating occupant-driven energy and cost concerns, the uncertainty in the infiltration air change rate and the domestic hot water consumption were selected for investigation; as the single optimization parameter, the slope of the solar collector was chosen. These specifications were used to develop the general methodology that can be applied to any model-based building optimization in the face of uncertainty.

There are two basic elements of the approach as illustrated in Figure 3. First, a Monte Carlo (MC) sampling routine is used to explore the domain of all uncertain parameters and/or variables under investigation (in the example case, the mass flow rate of the domestic hot water: $\dot{m}$ and the air change rate: ACH), indicated by the outer shaded region. Second, conditional on the MC sample, an optimization routine minimizes the objective function (e.g., energy or cost) for each MC sample. This is the iterative, embedded optimization and indicated by the inner shaded region of Figure 3. To calculate the objective function value (in the given case, the annual heating energy consumption), the building simulation is executed. At the end of the Monte Carlo process, a conditional probability density function of the result is obtained, for both the base case and the optimized case. The expected value from this posterior distribution of the optimization parameter is regarded as an overall reliable measure of the optimal value in the face of uncertainty. The determination of the posterior distribution for the base case is identical except for the fact that the design parameter is held at its default value and not optimized.

A variety of questions specific to the problem under consideration, can be answered by comparing MC results from the base case scenario for the design parameter and the optimal value found for this design parameter with the method outlined in Figure 3. This procedure is illustrated in Figure 4 for the calculation of the expected energy savings.

The methods shown in Figure 3 and 4 are implemented in a scripting language (R development core team 2008). It should be noted that prior distributions (probability density functions) for the uncertain parameters and/or variables must be specified. The whole procedure can easily be extended to include more uncertain parameters and/or various optimizations.

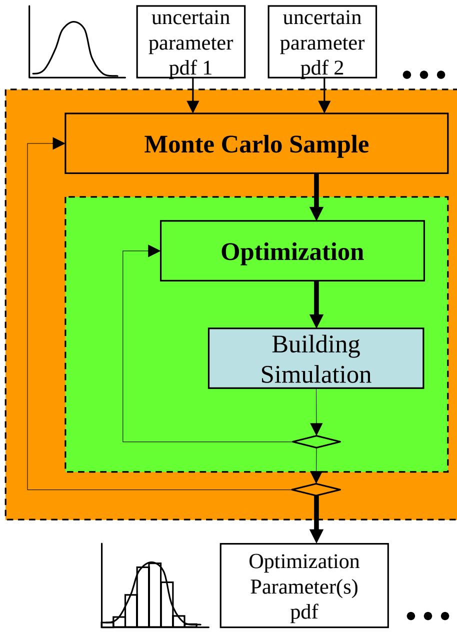

Figure 3: Flow chart of the optimization method.

The Monte Carlo Method

A Monte Carlo analysis consists of the following steps to randomly sample the modeling domain (Saltelli, Chan, and Scott 2000):

1. Selection of the probability density function (pdf) for each uncertain input (X_i).
2. Generation of a sample from each pdf.
3. Simulating the model for each element of the sample.
4. Analysis of the results.

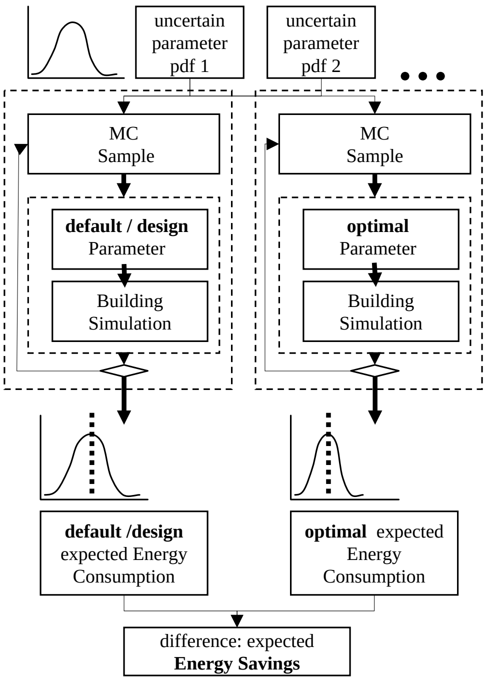

Figure 4: Flow chart for the determination of the expected energy savings from simultaneous optimization (right) and default design value MC simulations.

In the first step of the study, the mass flow rate of the domestic hot water ($\dot{m}$) and the infiltration air change rate (ACH) are chosen for the uncertainty investigation. More parameters and variables could have been considered as uncertain. However, in the case under investigation the annual energy consumption of the gas boiler is very sensitive to the domestic hot water flow rate and the air change rate. Furthermore, both variables are driven by occupant behavior which is very uncertain and difficult to measure. In a second step, the generation functions for normal and lognormal distribution (R development core team 2008) produce the MC samples. The domestic hot water flow rate calculated according IEA-SHC, Task 26: Solar Combisystems Jordan and Vajen (2003) is scaled by a factor which represents the uncertainty. For this factor a normal distribution seemed adequate since the value can be lower or higher than the schedule value and both cases have the same probability. That is not the case for the air change rate because it is determined by the window openings. The value can never be less than zero and very high air flow rates may occur (e.g., when many windows are open and cross ventilation occurs). This fact makes the log-normal distribution appropriate which was also proposed by Macdonald (Macdonald 2002). The magnitudes of both distributions are assumptions and could be changed according to prior knowledge of the design question. The sampling functions use the default algorithm for generation of equidistributed uniform pseudo-random numbers from (Matsumoto and Nishimura 1998) with the inversion of the normal and log-normal distribution shown in Equations 1 and 2.

Table 1: Distribution parameters.

Uncertain Parameter	μ	σ	**Distribution**
$\dot{m}$	1.0	0.20	normal
ACH	1.0	0.19	log-normal

$$p(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right) \quad (1)$$

$$p(x) = \frac{1}{\sigma x\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{ln(x)-\mu}{\sigma}\right)^2\right) \quad (2)$$

In the third step, the optimization described in the next section and the building simulation model previously described were utilized. In the fourth step, the distribution of the optimization parameter, the slope of the collector, is the result of the Monte Carlo simulation. The expected value of this distribution is considered to be the optimal value, following the calculation of Equation 3. This equates to the mean of optimized values of the slope of the collector.

$$E(X) = \frac{\sum x_i}{N} = \bar{X} \quad (3)$$

Optimization Method

For this proof-of-concept study, a one-dimensional optimization problem was chosen since this is computationally inexpensive. The optimization parameter, the slope of the solar collector, is limited to [0°, 90°]. As the objective function the annual energy supplied by the boiler was chosen, it is expected to be convex. The standard one-dimensional line search optimization algorithm (R development core team 2008) was implemented into the method shown in Figure 3. The algorithm uses a combination of golden section search and successive parabolic interpolation; convergence is never much slower than that for a Fibonacci search (Brent 1973).

RESULTS

Monte Carlo Simulations

The MC routine continuously sampled from the prior distributions until the final results converged. The prior distribution of the MC sampled occupant behavior parameters are shown in Figures 5 and 6.

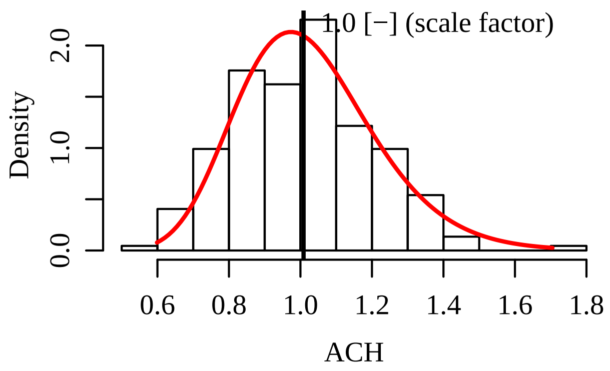

Figure 5: Distribution of the infiltration ACH scaling parameter. Log-normal distribution with μ=1.0 and σ=0.19

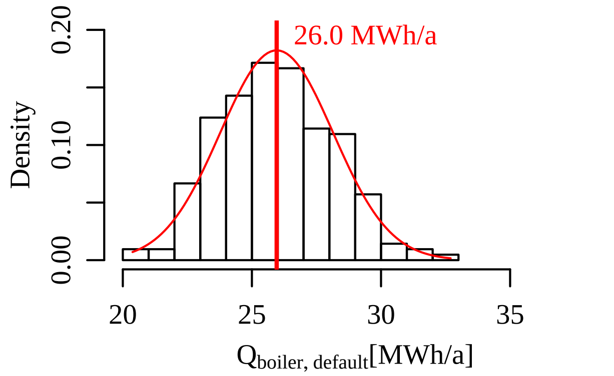

Figure 7: Distribution of the objective function: the annual energy consumption of the boiler.

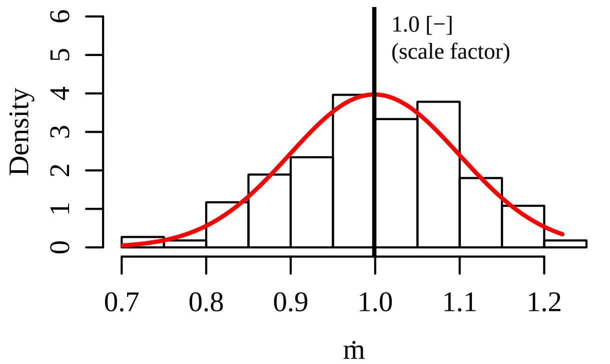

Figure 6: Distribution of the ṁ scaling parameter. Normal distribution with μ=1.0 and σ=0.20.

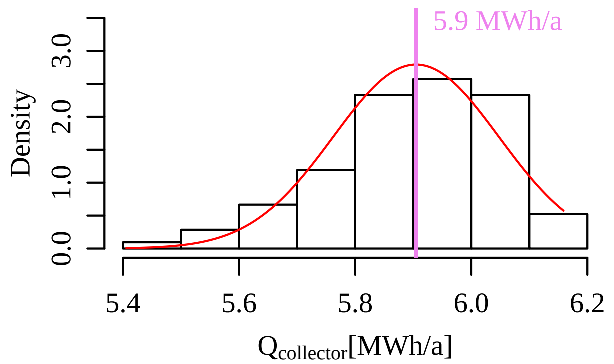

Figure 8: Distribution of the annual energy delivered by the collector system to the tank.

Simulations Results

Figure 7 illustrates the base case annual energy consumption of the boiler with the slope of the collector at its default value of 20°(slope of the roof); showing a mean consumption of 26.0 MWh/a ±8%.

The occupants' influence on the energy delivered by the collector system in the unoptimized base case is considerably smaller than on the boiler energy (see Figure 8). As expected, the annual intensity of 311 kWh/(m^{2}a) ±2.5% for the energy delivered by the collector system is rather small. This is due to the fact that a fully mixed tank model was employed, which is always kept at 60°C, so the (flat-plate) collector is running at unfavorable high temperature conditions.

Optimization Results

For each MC sample, the optimization algorithm searches the optimal slope (optimization parameter) for which the annual energy consumption of the boiler is minimized (Figure 9). According to Equation (3) the mean value of this distribution is the overall optimal slope setting. This distribution is rather narrow around the mean value of 42.8° ± 3%. This seems to be caused by the relatively small influence of the uncertain parameters on the delivered energy of the collector.

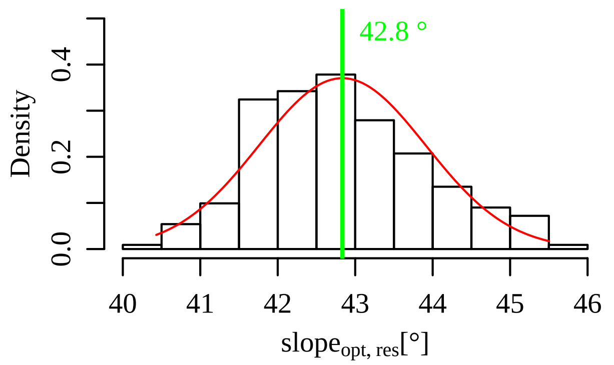

Figure 9: Distribution of optimal solar collector slope.

Figure 10 shows the objective function values (annual energy consumption of the boiler) for each element of the MC sample after the optimization. In this example, energy savings of approximately 1.6% could be realized.

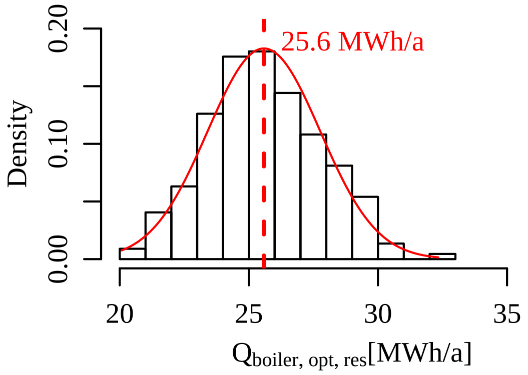

Figure 10: Distribution of the optimized annual energy consumption of the boiler.

Optimal parameter value energy savings

The distribution of the optimal collector slope values is narrow, lending good faith in the robustness of the expectation of the optimal collector (Equation (3)) slope of 42.8°. The mean difference in the objective function is only 896 Wh/a higher which is a relative deviation of the order of 10^{-5}. Also the distribution of the objective function is almost identical as shown in Figure 11.

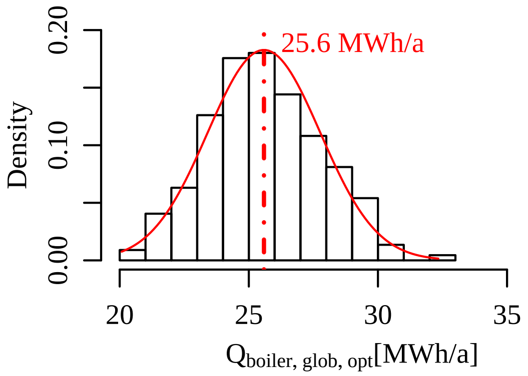

Figure 11: Distribution of the annual energy consumption of the boiler for the expectation of 42.8° of the optimal collector slope.

From Figure 12, a savings potential of 0.31 MWh/a ±3% by optimizing the slope of the collector can be expected.

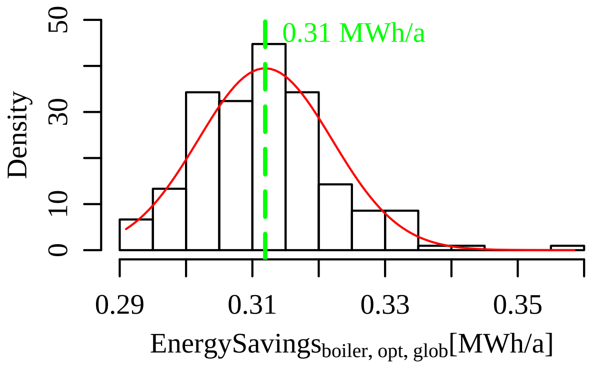

Figure 12: Distribution of the energy savings potential for the expectation of 42.8° of the optimal collector slope.

CONCLUSION

This study presents a methodology for optimizing building energy simulation models in the face of uncertainty. It is applied to a simple example of a building with a solar thermal collector system. This simple case was selected because it is well behaved and doesn't show strong signs of non-linearity. In this situation there should be no differences between the classical approach (non-stochastic, always calculating with the mean values) and the stochastic approach. And this is true for the example. Future applications in the building sector with greater complexity might be less well behaved and these cases explicit stochastic methods are much more appropriate then classical approaches. The methods developed here are intended for this situation and it is planned to apply them as soon as possible to more challenging situations. However, the presented analysis is meant to serve as a validation of the overall approach. The coupled application of Monte Carlo analysis and optimization is new to the building sciences field and merits further investigation. Examples with a higher impact of the uncertain parameters on the optimization parameters and less well behaved need to be investigated.

Due to legislative changes and social awareness, the design and construction of low-energy buildings is increasing. In low-energy buildings, uncertain parameters (e.g. occupant behavior, internal loads, climate) have a much higher influence on energy, costs and comfort than in traditional buildings. As the technical and building automation system complexity in new buildings increases, the prediction of the influence of uncertain parameters also tends to become more complex. Therefore it it will become increasingly important to consider uncertainty when simulating and optimizing low-energy buildings. For many practical problems, a larger number of uncertain parameters and, correspondingly, larger sample sizes are expected. The outlined procedure is applicable to parallel computing techniques to cope with this issue. For more complicated cases (e.g., multiple optimization parameters), probably additional numerical issues will have to be addressed including the avoidance of local minima.

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NOMENCLATURE

ACH	air change rate
$\mathrm{E}(x)$	expected value of a variable x
MC	Monte Carlo
$\dot{m}$	mass flow rate for domestic hot water
n	number of samples
$p(x)$	probability density function of x
pdf	probability density function
$\dot{Q}_{sol}$	solar power to zone
$\dot{Q}_{int}$	internal load to zone
$\dot{Q}_{HC}$	heating and cooling power to zone
T_{air}	zone air temperature
$T_{sup,air}$	air supply temperature
T_{amb}	ambient temperature
T_{surf}	effective surface temperature
$T_{th,mass}$	thermal mass temperature