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Monte-Carlo methods for the occupancy uncertainty issue in thermal building simulations

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Abstract

Thermal building simulations are widely used in R&D projects in civil engineering. It is common that as an input data for the simulation standard schedules of the occupants' presence, equipment usage, lightning and ventilation are used. However, generally unpredictable occupants' behavior can have an influence on each of the schedules listed above and, therefore, affect overall energy demand and most importantly - the heating and cooling peak loads during the day. Taking such impact on the thermal building models into consideration, the reliability and accuracy of the final simulation results can be improved and the value of their uncertainty can be assessed. The aim of the present research is to evaluate the impact of the occupants' behavior's uncertainty on the heating and cooling demand of a typical residential building. Furthermore, a method to account such an effect on thermal building simulations is presented. The results show that the variance of annual heating and cooling demand equals to 10 % of its absolute average value, although daily heating and cooling demands vary within the range up to 60 % of its average peak value.

Keywords: thermal building simulation, Monte-Carlo analysis, heating and cooling demand, uncertainty of simulation.

1. Introduction

Building thermal simulations are broadly applied for the evaluation of the building's heating and cooling demand, for the optimization of HVAC and building constructions, development of model predictive control strategies etc. Uncertainty issue in building thermal simulations is presented in a wide range of scientific papers. Basically uncertainty occurred due to: simplifications which take place in mathematical models, solver inaccuracy (discretization of differential equations etc.) and inaccuracy of the input data for the model [1]. Since the first two issues rely entirely on a model and can be reduced using more sophisticated mathematical approaches, the influence of input data should be considered more in-depth.

Inaccuracy of the input data can be generally divided in 3 groups: uncertainties in physical parameters, design and scenario variations [2].

Physical parameters' and design variations represent properties of building's constructions, building's system, building's topology and are usually constant, standardized or can be measured.

Scenario variations involve user's behavior and are in general unpredictable. Occupants can have both positive and negative influence on a heating demand of the building at the same time. Positive influence includes their presence (their heat losses), equipment usage and lightning – internal heat gain. Negative impact takes place with the ventilation. If the ventilation is mechanical, its parameters are usually known. However, natural ventilation strongly depends on a user and generally unknown internal heat gain. Several types of ventilation approaches can be used: constant, short-term or cross-ventilation [3]. Furthermore, level of CO_2 in practice is not measured in a building and it is also not clear, whether occupant feel comfortable during the ventilation and when it is decided to stop it. Hence, daily heating demand can vary in a wide range. Cooling demand in summer is more defined relatively to the user: air exchange and internal heat gain have the same negative influence.

Number of research papers [4,5,6] were aimed to define an empirical model for the occupant's driven natural ventilation (as one of the user's ways of influence) dependent on time, season of the year, ambient temperature etc. It is common that for this task real buildings are investigated and number of parameters is measured in real-time: number of people in a room/building, ambient and indoor temperatures, number of opened/closed windows etc. Some major trends in user's behavior were confirmed: for example, in winter the duration of an opening of the window is short and the percentage of opened windows is small. However, the results show that regression analysis cannot be successfully applied, because of the large distribution of the results: R^2 varies from 0.3-0.7 [4]. Furthermore, the estimated coefficients of the empirical model with its own accuracy in general will be valid only for the investigated building and, importantly, for the current building users.

Since experimental data shows that user's behavior cannot be accurately described with empirical models, it is point of interest to use probability analysis (such as Monte-Carlo analysis), which involves statistical randomization of the input parameters and simulations with these randomized values. Although it was successfully applied for the uncertainty assessment of the physical and design variations [2,7], its application for the scenarios variations is still topical.

2. Aim of the present research

The aim of the present research is to evaluate the impact of the occupants' behavior's uncertainty on the heating and cooling demand of a typical building using Monte-Carlo analysis. Furthermore a method to account such an effect on thermal building simulations is presented.

3. Methodology description

For this task a typical Swiss four-storied residential building with 8 flats is modeled and simulated for a 1 year period.

Thermal properties of the building's constructions correspond to the properties of the average existing building in Switzerland [8], ventilation is natural and is done manually by the occupants, weather conditions corresponds to the location of city Luzern, heating set-point equals to 21°C, cooling set-point – 26 °C. In each flat 3 types of rooms are considered: living room, kitchen and bathroom with respective floor areas (fig. 1a). Each type of the flat's room (living room, kitchen, WC and bath) was evaluated with a set of 4 schedules: occupancy, equipment usage, lightning and ventilation. Furthermore, ventilation, equipment usage and lightning are directly dependent on occupancy, although, lightning schedule is also dependent on solar irradiation which varies during the year (fig.1b).

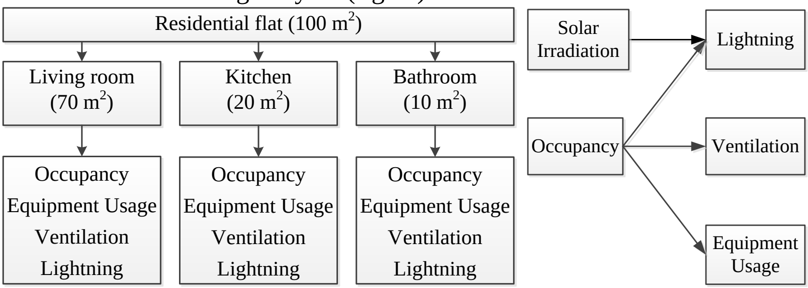

Fig. 1 Schedules' schematics for residential flat

The chain of the occupant's impact is briefly described on fig. 2. Influences of different weather conditions, installed systems of heating, cooling systems or control strategies in present research are not considered.

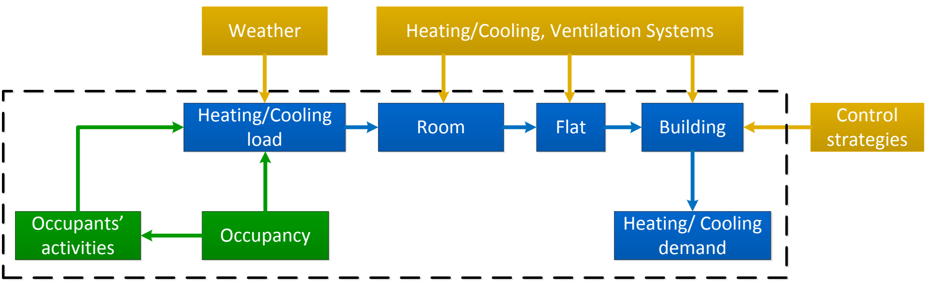

Fig. 2 Schedule of internal heat gain

Using Swiss standards for engineers and architects [9] mentioned schedules with their bandwidth were defined. Standard values of heat loads from [9] are presented in table 1.

Table 1 – Standard values of heat loads for 3 types of rooms [9]

	Living room	Kitchen	Bathroom
Occupancy, W/m^2	1.5±0.5	$14^{+3.5}_{-2.5}$	0
Equipment usage, W/m^2	2±1	40±10	0
Lightning, W/m^2	$9.4^{+0}_{-6.4}$	$17^{+0}_{-10.8}$	$11.1^{+0}_{-8.1}$
Ventilation, m^3/(h· m^2)	$0.6^{+0.2}_{-0.1}$	$20^{+5}_{-3.3}$	16 ± 3.2

Occupancy, equipment usage and lightning present themselves an internal heat gain relative to the floor area (W/m^2) in the room and, hence, can be combined in 1 common input for the whole flat. However, lightning load depends on the presence of global solar irradiation. On fig. 3 schedule of total internal heat gain is presented without consideration of sunlight presence. It can be seen that during the morning, afternoon and evening highest loads take place. Such effect concerns with the increasing use of the equipment and lightning in the kitchen during the day. Similar schedule can be obtained for the flat's ventilation. However, according to [4] it should be limited due to the comfort reasons.

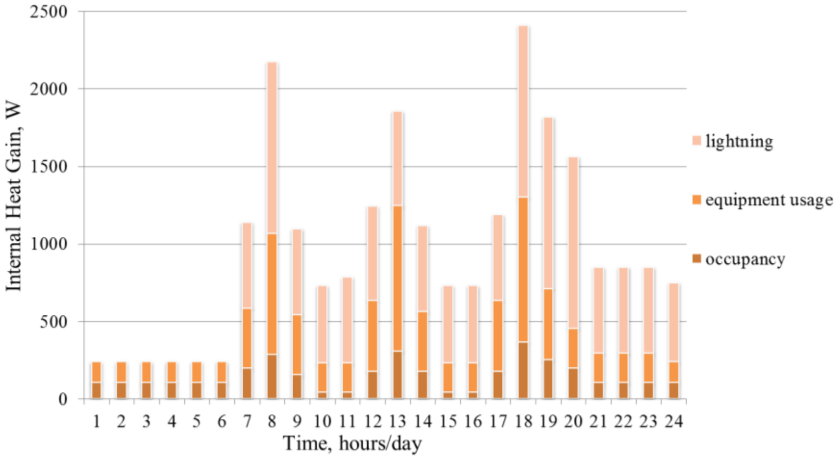

Fig. 3 Average schedule of internal heat gain

It is likely that the user's behavior should correspond more to the standard schedule than to its boundaries. Because of this reason for each constant part of the schedules of the internal heat gain Latin Hypercube Sampling algorithm [10] was applied, instead of simple randomization (fig. 4). Each part of the schedule was randomized independently without accounting adjacent parts. It can be seen from fig. 5. Since the optimal number of randomized values, which is enough for sensitivity analysis, was defined in paper [11] and equals 100, in present research 102 schedules were generated including 100 randomized profiles, lower and upper boundary schedules.

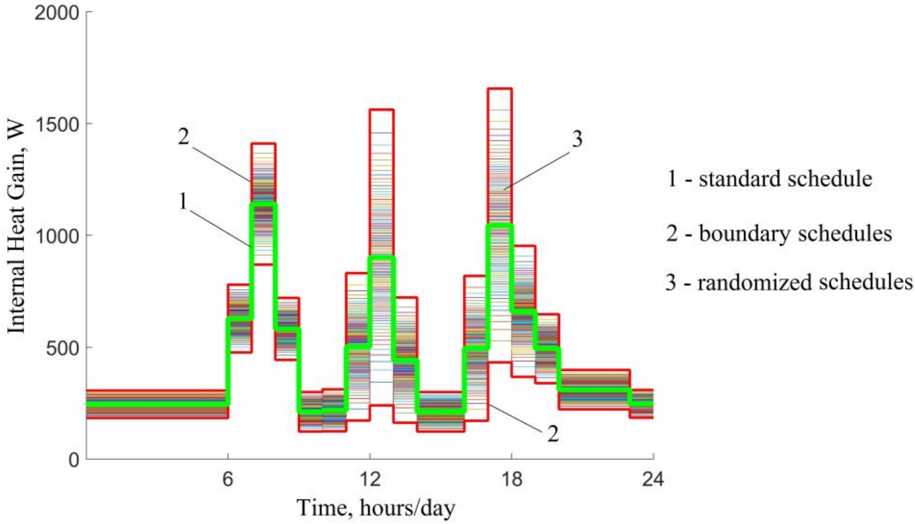

Fig. 4 Schedules' randomization using Latin Hypercube Sampling algorithm

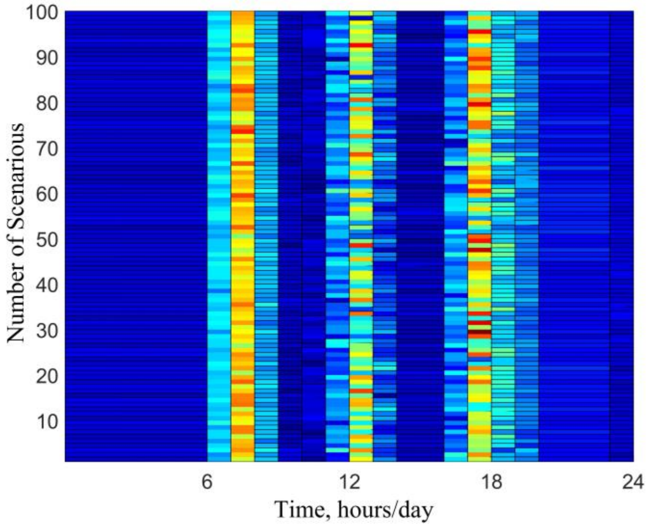

Fig. 5 Map of randomized schedules of internal heat gain

Annual thermal simulations were conducted using thermal simulation software IDA-ICE, although randomization of input parameters, management of simulations and results' handling were made using MATLAB software. General scheme of Monte-Carlo simulation procedure is present on fig. 6.

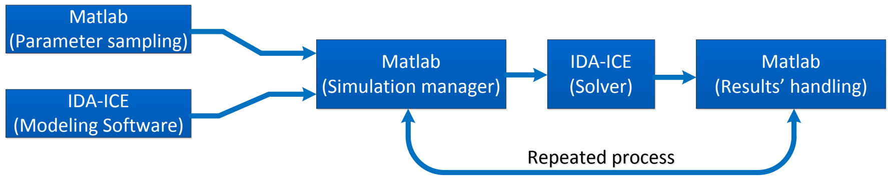

Fig. 6 Algorythm of the fullfilment of Monte-Carlo analysis

4. Results

Daily and annual heating demands obtained as a result of Monte-Carlo analysis are presented on fig. 7, 8 respectively; daily and annual cooling demand of the building are shown on fig. 9, 10. Red lines correspond to the lower and upper boundary schedules of the internal heat load and ventilation.

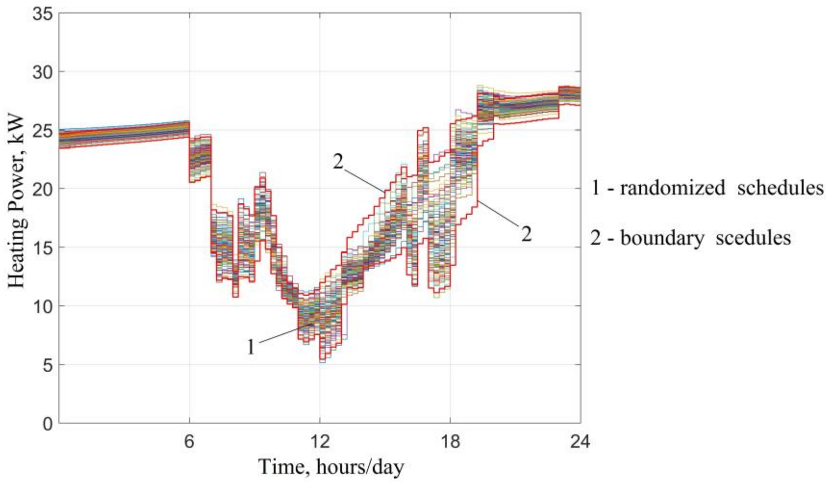

Fig. 7 Daily heating demand of the building during winter

The average annual consumption equals to 39 MWh, which corresponds to 50 kWh/m^2/year, which is equal to the heat demand of an average Swiss building with such dimensions [8]. The results show that the variance of annual heating and cooling demand equals to 10 % of its average value, although daily heating and cooling loads can vary within the range up to 60 % of its average value at certain time. In winter heating demand is decreasing during the day due to the internal heat gain. On the other hand, cooling demand is increased because of the same reason. Since internal heat gain and ventilation have an opposite influence on heating demand, some randomized cases lie out of the range of upper and lower boundary schedules (fig. 7).

On the other hand, since ventilation and internal demand have the same influence on a cooling demand, all randomized cases lie in the range of upper and lower boundary schedules (fig. 9).

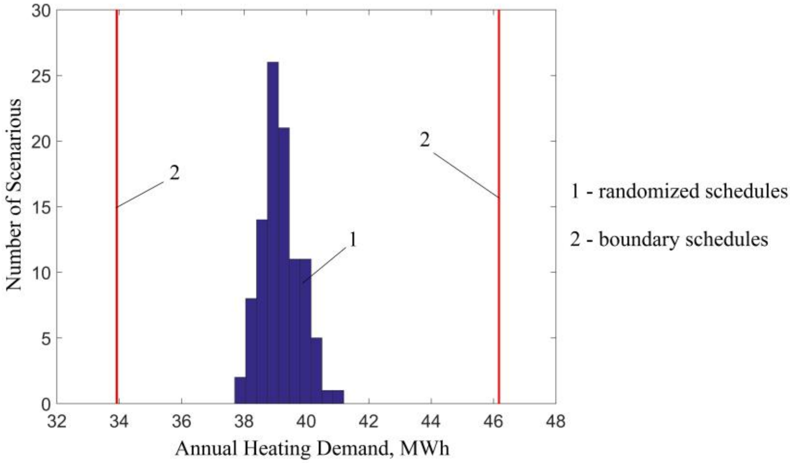

Figure 8 – Annual heating demand during winter

It also can be seen that because of independent partial randomization with LHS approach of the standard schedules range of the annual energy demand is narrower than a range obtained with boundary schedules (fig. 8, 10).

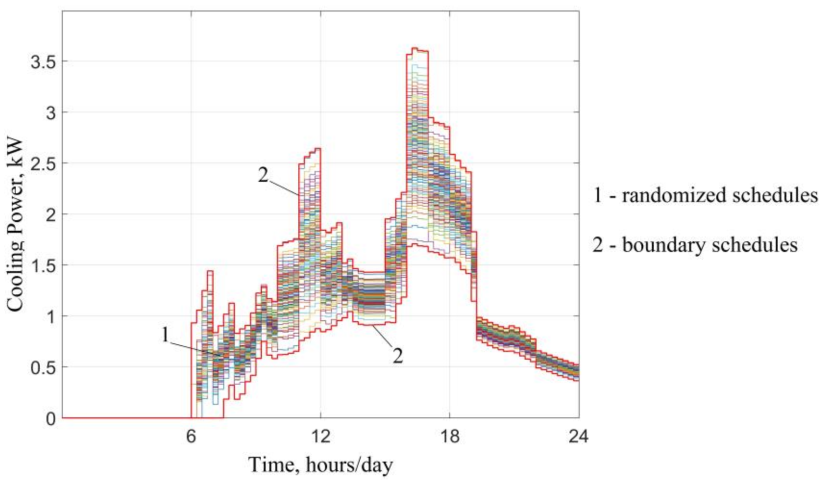

Figure 9 – Daily cooling demand of the building during summer

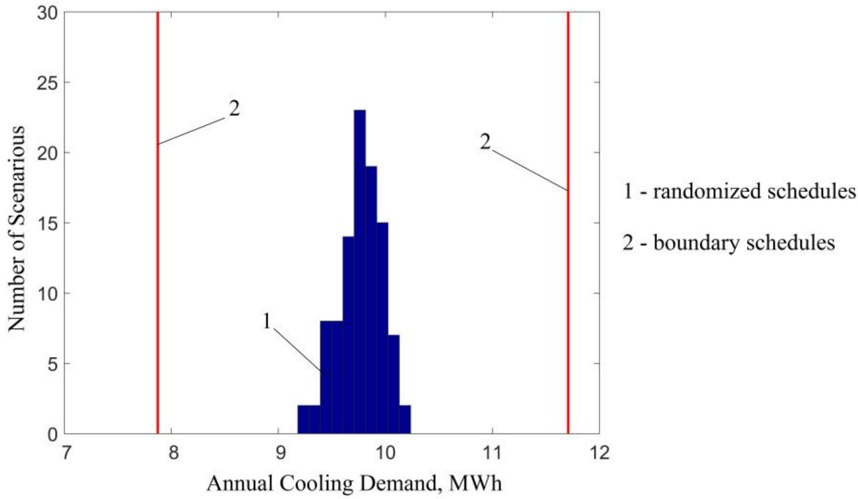

Fig. 10 Annual cooling demand of the building during summer

5. Discussion

Several points should be mentioned regarding obtained results of Monte-Carlo analysis:

- user’s behavior regarding ventilation during winter plays a huge role on a peak heat loads. In present research the investigation of the correct ventilation model was not a point of interest;
- with the standard sampling approach annual heating and cooling demand will have a wider range;
- influence of the user's behavior would be greater if investigated building is lightweight;

6. Conclusions

In present research users’ behavior as a driven uncertainty factor in building thermal simulations is considered and its impact is estimated. For this purpose special methodology based on Monte-Carlo analysis was proposed. The main concept of this methodology is concerned with the partial randomization of the normative schedules for further use for the thermal simulations. The results show that the variance of annual heating and cooling demand equals to 10 % of its average value, although daily heating and cooling loads can vary within the range up to 60 % of its average peak value. It also can be seen that the application of this methodology provides narrower variation range of annual energy demand than a range obtained with upper and lower boundary schedules. However, obtained quantitative values should be reconsidered for the case of interested ventilation model; however, qualitative result should be the same.

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