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# The Impact of Occupancy-Related Input Data Uncertainty on the Distribution of Building Simulation Results

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## Abstract

In building performance simulation, fixed input assumptions lead to fixed computed values for building performance indicators. This has been suggested to be misleading, as it does not express the uncertainty of simulation-based performance predictions. A counter-argument to this position suggests that the empirical basis for the determination of the statistical uncertainty distribution of occupancy-related input assumptions is rather scant. Arbitrary assignment of uncertainty functions (distribution ranges and shapes) to input variables can indeed generate corresponding performance result distributions. However, this could be even more misleading than fixed values, as the resulting uncertainty impression is empirically ungrounded. To address this objection, it has been suggested that the computed uncertainty ranges for performance indicators may be, to a certain extent, resistant to the ranges and shapes of associated input data distributions and hence still useful. In the present contribution, we examine the above suggestion, namely the resilience of performance simulation output distribution to the assumed model input uncertainties. To this end, parametric simulations were conducted and processed to explore the implications of different input data assumptions for the values of computed performance indicator values for a sample building model.

## 1. Introduction

A common argument against the use of such fixed input assumptions for building performance simulation is the uncertainty challenge. Hence, so goes the criticism, the input data uncertainty is not manifest in the results, which can be misleading (Mechri, 2009; Tian et al., 2018; Li et al., 2019).

It has been suggested that replacing single value input data assumptions with distributions of input data variables is preferable. However, there is a paucity of empirical information on the uncertainty distributions of occupancy-related simulation model input data assumptions. It is of course possible to select – more or less arbitrarily – some distribution ranges and shapes of certain input variables to generate corresponding performance result distributions instead of single values. However, this approach could be even more misleading as the resulting uncertainty ranges are not empirically grounded (Mahdavi, 2015; Mahdavi & Tahmasebi, 2019).

The present paper examines the suggestion that computed uncertainty ranges for performance indicators may be at least partially resistant to the ranges and shapes of associated input data distributions. We explore the validity of this suggestion via systematic simulation runs applied to a case study building in Italy. This case study model is subjected to variation (i.e. different distribution shapes and ranges) of input data assumptions for the values of computed performance indicators.

## 2. Method

In order to explore the implications of occupancy-related input data assumptions (i.e. different distribution shapes and ranges) for the values of key performance indicator values, an illustrative case, namely a typical apartment in a residential building in Italy, was selected (Fig. 1). This building is located in the Italian climatic zone E (Milano, 2404 HDD). General information on the building is given in Table 1 including geometry-related variables ($V_g$: gross volume; $A_{f,net}$: net floor area; $A_w$: window area) and construction-related variables (U-values of external wall $U_{ext,wall}$, wall adjacent to unheated space $U_{wall,unheated}$, floor $U_{floor}$, and window $U_{window}$). Within this case study, the aforementioned assumption, namely the resilience of performance simulation output distribution in view of input data variation, is tested via systematic simulation applied to this apartment.

The building is modelled in EnergyPlus (EnergyPlus, 2019) and parametric simulation runs are expressed in RStudio (RStudio, 2019). First, we obtained fix-value simulation results for the base case (BC), whose simulation model likewise involved only fix values of input variables. Subsequently, we considered different distribution shapes and ranges and examined the effect of input variable distributions on the corresponding distributions of computed performance indicator values. In the present contribution, a number of generic input data variations, namely three normal distributions with three different widths (labelled as N_N, N_S, and N_W) (Fig. 2) as well as one left-skewed distribution (S_L) and one right-skewed distribution (S_R) (Fig. 3) are considered.

The study considers the following input variables: Heating temperature set-point ($\theta_{sp\text{-}h}$ in °C), air change rates (ACH in $h^{-1}$), and internal gains ($q_{int}$ in $W.m^{-2}$). The simulated performance indicator is the annual heating demand ($q_{a,h}$ in $kWh.m^{-2}.a^{-1}$). The response of simulated performance indicator to input variable assumptions are captured in two distinct sets of simulation runs. Whereas in the first set only one input variable's value is parametrically varied, in the second set the values of multiple input variables are varied simultaneously.

In the following, the results of both groups of variation are discussed in detail.

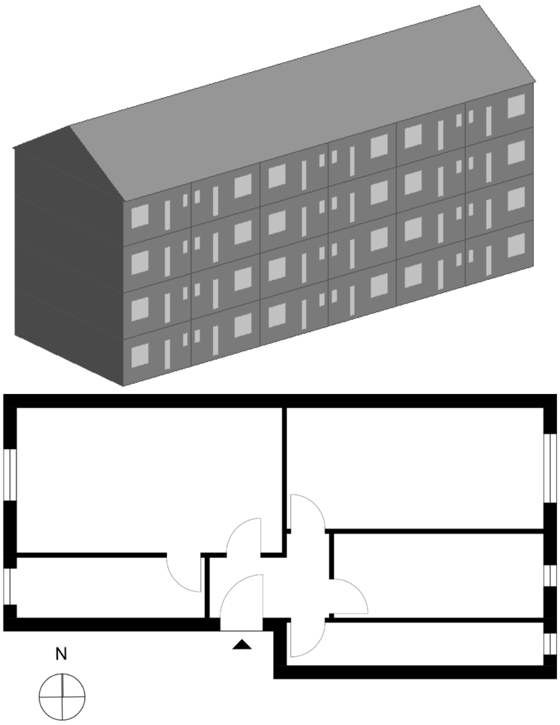


Fig. 1 – Case study building in Milan, Italy (Top: 3D model. Bottom: floor plan of the selected case study apartment)

Table 1 – Overview of case study apartment data

| | Variable | Unit | Value |
|---|---|---|---|
| Geometry | $V_g$ | $m^3$ | 259 |
| | $A_{f,net}$ | $m^2$ | 65 |
| | $A_w$ | $m^2$ | 7.96 |
| Construction | $U_{ext,wall}$ | $W.m^{-2}.K^{-1}$ | 0.26 |
| | $U_{wall,unheated}$ | | 0.56 |
| | $U_{floor}$ | | 1.34 |
| | $U_{window}$ | | 1.40 |

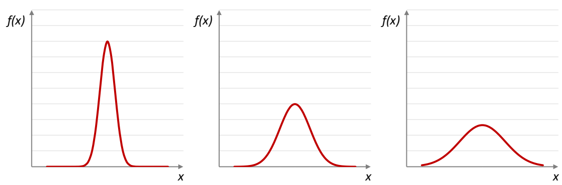


Fig. 2 – Narrow (N_N), standard (N_S), and wide (N_W) normal distribution

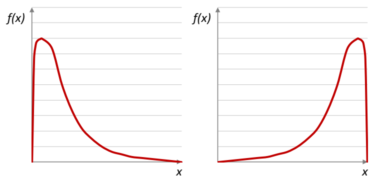


Fig. 3 – Right-skewed (S_R) and left-skewed (S_L) distribution

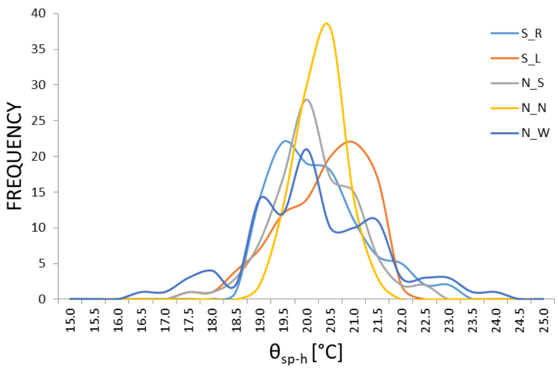


Fig. 4 – Assumed heating temperature set-point distributions toward computation of annual heating demand (see Fig. 5)

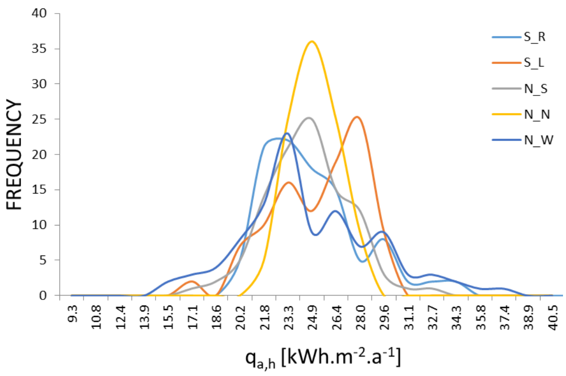


Fig. 5 – Computed annual heating demand distributions as a consequence of assumed input variable distributions (see Fig. 4)

# 3. Results and Discussion

## 3.1 One-at-a-Time Variation of Model Input Variables

The first set of results concerns the response of the simulated performance indicator (i.e. annual heating demand) to one-at-a-time variation of the model input variables. The distribution of the values of one input variable (heating temperature set-point) is shaped according to the aforementioned distributions. Fig. 4 shows the resulting five different heating temperature set-point distributions.

A total of 100 simulations are performed to generate each of the five resulting distribution functions of the annual heating demand. The corresponding simulation results are shown in Fig. 5. Table 2 includes a number of basic statistical markers for both the distributions of the input variable value (namely the heating temperature set-point $\theta_{sp\text{-}h}$) and the corresponding distributions of the computed building performance indicator values (heating demand $q_{a,h}$). These include the mean ($\mu$), standard deviation ($\sigma$), and coefficient of variation (CV) for the five aforementioned distribution functions.

These results suggest that the value of a computed building performance indicator strongly depends on the assumed distribution of the input variable value. This means that the usability of a simulation-based generation of output distributions would be very limited, if no basis or reasoning is provided concerning the underlying input variable distribution assumptions.

Table 2 – Statistical data regarding the first set of simulation runs (consequences of assumed heating temperature set-point assumptions for computed distributions of annual heating demand)

| | $\theta_{sp\text{-}h}$ [°C] | | | $q_{a,h}$ [kWh.m$^{-2}$.a$^{-1}$] | | |
|---|---|---|---|---|---|---|
| | μ | σ | cv | μ | σ | cv |
| BC | 20.00 | - | - | 24.15 | - | - |
| N_S | 19.89 | 0.89 | 4.46 | 23.86 | 2.74 | 11.48 |
| N_N | 20.02 | 0.50 | 2.52 | 24.24 | 1.57 | 6.50 |
| N_W | 19.91 | 1.40 | 7.05 | 24.00 | 4.39 | 18.29 |
| S_R | 19.99 | 0.98 | 4.88 | 24.19 | 3.10 | 12.81 |
| S_L | 20.12 | 0.94 | 4.66 | 24.59 | 2.89 | 11.75 |

## 3.2 Concurrent Manipulation of Multiple Input Variables

As mentioned previously, the second set of parametric simulations explore the response of simulation results to concurrent manipulation of multiple input variables in terms of distribution functions. To illustrate this point, Fig.s 6 and 7 show the concurrent parametric variation of two input variable values, namely heating temperature set-points [$\theta_{sp\text{-}h}$] and air change rates [ACH]. Thereby, three different combinations of distribution functions are considered (Fig. 6):

A. Right-skewed distribution of $\theta_{sp\text{-}h}$ and ACH
B. Standard normal distribution of $\theta_{sp\text{-}h}$ and ACH
C. Right-skewed distribution of ACH and left-skewed distribution of $\theta_{sp\text{-}h}$

The set of input values for the heating temperature set-points [$\theta_{sp\text{-}h}$] and air change rates [ACH] are generated according to the aforementioned three different combinations of distribution functions. A total of 100 simulations are performed to generate the resulting distribution functions for annual heating demand for each of the three combinations (see A, B, and C above).

Fig. 7 displays the resulting three different distributions of the computed heating demand of the aforementioned case study apartment.

According to the results of this second set of simulation runs, there is no evidence that arbitrary variations of input data distributions necessarily result in reproducible and consistent distributions of computed building performance indicator values.

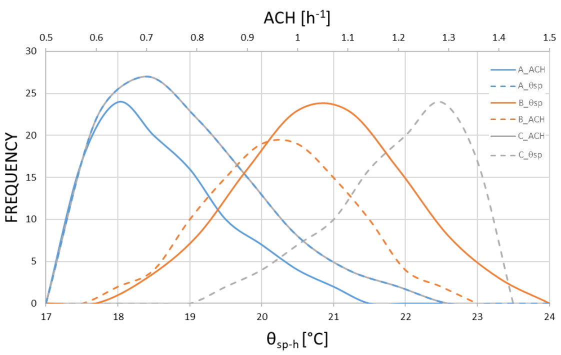


Fig. 6 – Selected distributions of input variables $\theta_{sp\text{-}h}$ and ACH toward computation of annual heating demand (see Fig. 7)

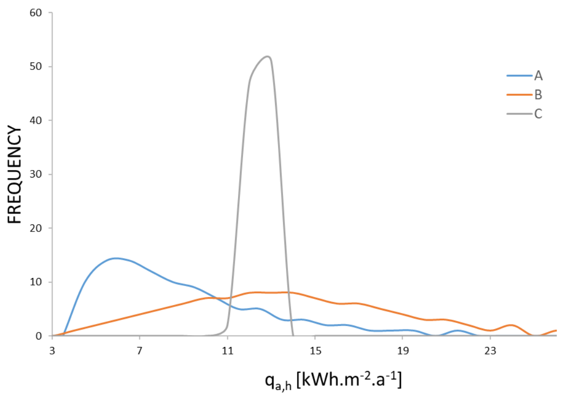


Fig. 7 – Computed distributions of annual heating demand as a consequence of assumed input variable distributions (see Fig.6)

To further pursue this point, we varied (concurrently and randomly) three different input data variables, namely the heating temperature set-point [$\theta_{sp\text{-}h}$], the air change rate [ACH], and the internal gain [$q_{int}$] (see Fig.s 8 to 10 for the corresponding distributions).

For each of the three input variables ($\theta_{sp\text{-}h}$, ACH, and $q_{int}$) the distribution functions are randomly selected. Subsequently, the values of each of the three input variables are randomly selected from a set of 100 values that constitute each of the distribution functions.

In total, 10000 simulations are performed to generate the distribution function of the annual heating demand. The resulting distribution of the computed overall annual heating demand is shown in Fig. 11. An overview of the statistical markers pertaining to distributions of the input variables and the distribution of the results is given in Table 3.

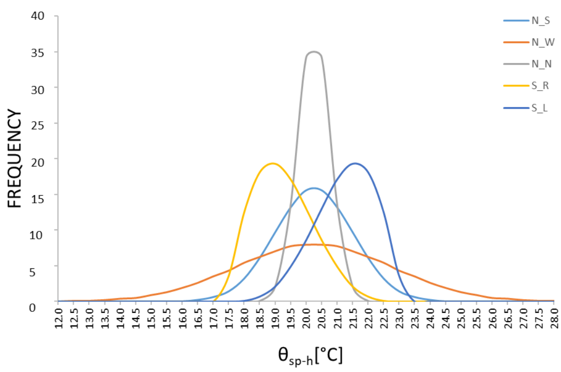


Fig. 8 – Selected distributions for heating temperature set-point [$\theta_{sp\text{-}h}$] toward computation of annual heating demand (see Fig. 11)

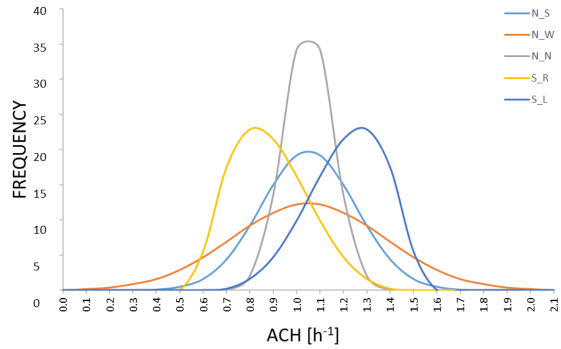


Fig. 9 – Selected distributions for air change rate [ACH] toward computation of annual heating demand (see Fig. 11)

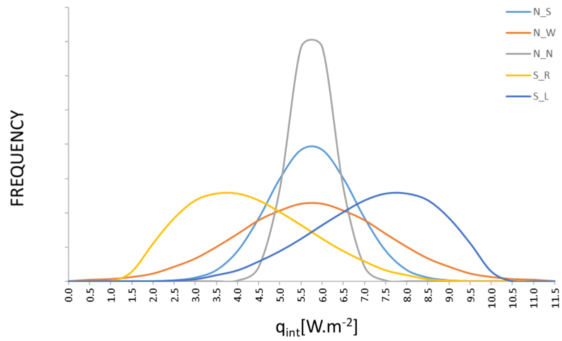


Fig. 10 – Selected distributions for internal gains [qint] toward computation of annual heating demand (see Fig. 11)

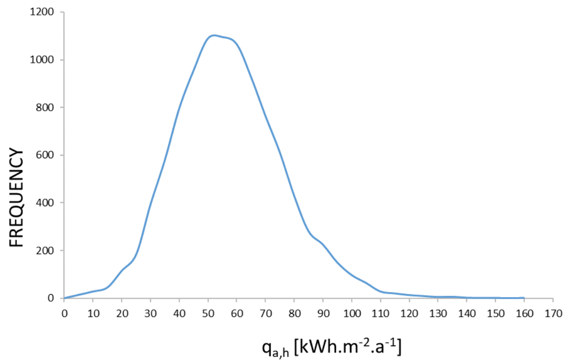


Fig. 11 – Computed distribution of annual heating demand as a consequence of assumed input variable distributions (see Fig.s 8 to 10)

Table 3 – Statistical data regarding the assumed distributions of concurrently varied input variables (θsp-h, ACH, and qint) as well as the resulting distribution of the output variable (qa,h)

| | μ | σ | cv |
|---|---|---|---|
| $\theta_{sp\text{-}h}$ | 20.00 | 1.50 | 0.08 |
| ACH | 1.00 | 0.24 | 0.24 |
| $q_{int}$ | 5.55 | 1.86 | 0.34 |
| $q_{a,h}$ | 54.84 | 18.58 | 0.34 |

These last results imply that a fairly stable distribution of the simulated values of a performance indicator may emerge, if we conduct extensive Monte Carlo simulations involving both multiple input variables and multiple distribution shapes of those variables. For a given group of such variable sets and distributions sets, we may even be able to propose default uncertainty ranges. However, this approach would not resolve the problem stated at the outset. As long as the combination of input variable sets and corresponding distribution shapes involve arbitrary choices, the resulting output distributions and corresponding uncertainty ranges remain likewise arbitrary. Provision of standardized uncertainty ranges (for instance, standard deviations) for simulation results may be a possible option, assuming the availability of predefined input variable distribution shape catalogues. The question is, however, whether conducting an extensive set of parametric simulation runs is not a rather prohibitive expenditure of time and effort, given the fairly limited meaning and utility of the provided uncertainty information.

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