Contrasting the Capabilities of Three Different Sensitivity Analysis Methods for Building Energy Model-based Investigations

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Abstract

When using building energy models (BEM) for building design, it is often valuable to conduct a sensitivity analysis (SA) to help designers to focus their efforts on design variables that drive the majority of the building performance indicators such as energy use.

In this study, three different SA methods (Local, Morris and Sobol') were applied to two different BEMs (hourly dynamic and monthly quasi-steady-state) for SA analysis in two different stages of the building design process. The finding is that the choice of appropriate SA method depends on the purpose of the SA; whether it is a screening of equally probable design options, or a more thorough quantification and ranking of parameter uncertainty.

Introduction

Sensitivity analysis (SA) can be used to explore the behaviour of building energy models (BEM) and thereby identify which input parameters that drive the majority of the model output variation. Such an analysis is valuable as it enables building designers and contractors to focus their efforts on designing and obtaining the functional requirements of parameters most critical to the energy performance.

There are many examples in the literature on how to apply SA for BEM-based design, e.g. Heiselberg et al. (2009), Mechri et al. (2010) , Spitz et al. (2012), and Østergaard et al. (2015) to mention a few. However, a sound argumentation that vouches for the reliability, validity and necessary complexity of the chosen SA is rare. Kristensen and Petersen (2016) used a model of an existing residential building stock in a temperate climate (i.e. energy need was predominantly space heating) as case to demonstrate that the choice of SA method affects the identification and ranking of the input parameters most sensitive to the model output. The overall conclusion was that it is essential not to interpret the outcome of SA in a way that lies beyond the capabilities of the used SA method, as this may lead to suboptimal design decisions and wrong focus areas in the construction phase. Furthermore, the study also showed that the SA outcome – to some extend – is affected by the chosen BEM method; in this case, the simple hourly and monthly methods in ISO 13790:2008. Practitioners must therefore be careful to choose an appropriate combination of SA method and BEM that fits the purpose of the SA.

In practice, SA can be used for various purposes. In the early design stage, SA can help designer to identify which critical design variables to focus on. Prior to initiating the construction phase, SA can be used to identify which functional requirement to have special focus on obtaining during construction. The objective of this paper is to investigate the performance of three different SA methods combined with two different BEMs for the two above-mentioned SA purposes using an office building in a temperate climate as case. The intention is to provide an example to guide building designers in selecting the appropriate SA method depending on the purpose of the analysis and the type of BEM applied.

Method

An office case building was modelled using two different BEMs to calculate the annual energy need for space heating and cooling. Using three different SA methods of increasing capability and complexity, the sensitivity of the two BEMs was investigated and analysed for two different phases in the design of the case building;

1. the early design phase (Case 1) with uncertainty embedded in the free choice of model parameter values, and
2. the detailed design phase (Case 2) where uncertainty is embedded in the fixed parameter values chosen in the early design stage due to e.g. imperfections in building materials, construction errors, and stochastic occupant behaviour.

Description of case

The case consisted of a 24 m^2 (6x4 m) south-facing two-person office room in a single-story building (Figure 1); the window façade and roof faced the outdoor while the floor faced the ground. The remaining surfaces were assumed adiabatic.

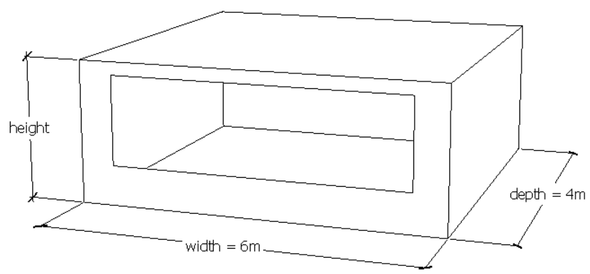

Figure 1: Case office room.

The room was assumed occupied weekdays between 8 am and 5 pm in which period a constant-air-volume system ventilated the room. Heating and cooling was supplied by separate systems. During the weekend, ventilation was turned off and no internal heat loads were assumed. The installed capacity of the heating and cooling systems was assumed able to always meet their respective set points. Internal heat loads, airflow rates and set points are given in Table 1.

In Case 1 (early design phase), seven model parameters were open for design decisions: room height, U-values of external wall, roof and floor, %-window area of the external wall area, and the SHGC of the window. These seven unselected model parameters were all assigned a uniformly distributed probability range (Table 1) to reflect the uncertainty faced by building designers in the early design stage. The purpose of this analysis was to help building designers focus on the model parameters of most influence to the model output (energy need).

In Case 2 (uncertainty related to the realisation of values chosen in the early design stage), all parameter values were assumed fixed at satisfying levels by the building designers. However, due to e.g. imperfections in building materials, construction errors, and stochastic occupant behaviour, these selected values are subject to uncertainty. In Case 2, the sensitivity of the model output to this kind of uncertainty was investigated. This information can be regarded as advice on which parameters that demands special attention in the detailed design and construction phase to reduce the risk of not realising the design intentions.

Building energy modelling

The two BEMs used to calculate the annual energy need for space heating and cooling were 1) the quasi-steady-state calculation method with monthly time steps, and 2) the simple dynamic calculation method based on hourly time steps. Both model are described in ISO 13790:2008. Only energy need for space heating and cooling were considered; thus, COP coefficients of chillers etc. were not considered. Weather conditions were modelled using the Danish design reference year (DRY) dataset, containing hourly values of the necessary weather parameters (air temperature, normal solar radiation and diffuse solar radiation) (Jensen and Lund, 1995). Total solar radiation perpendicular to the building facades was calculated in both BEMs using the solar algorithm described by Bourges (1992).

Sensitivity analysis methods

Three SA methods were applied: a local partial derivative-based method (Lam and Hui, 1996), the global screening-based method of Morris (Morris, 1991), and the global variance-based method of Sobol' (Sobol', 1993). All three methods and how they were implemented for the analysis in this paper are described in detail in Kristensen and Petersen (2016). Information about the setup of the SA methods is given in Table 2.

Overall, the capabilities of the three SA methods can be contrasted in terms of their ability to take into account

1. the range and shape of input parameter distributions,
2. multi-dimensional parameter influence on the outcome when all input parameters are varied simultaneously, and
3. non-linear and non-additive effects when input parameter interactions are taken into account (model independency).

The only SA method featured in this paper that encompasses all three of the above-mentioned abilities is the global variance-based method of Sobol'. The Sobol' method makes a complete decomposition of the output variance by searching across the entire input space, simultaneously taking into account range and shape of parameter distributions and correlated effects.

Table 1: Probability density functions assigned to model input parameters for Case 1 and Case 2.

Input parameters	**Unit**	**Case 1**	**Case 2**
Room width	[m]	6.0	6.0
Room depth	[m]	4.0	4.0
Room height	[m]	Uniform (3.0;4.0)	3.5
U-value (ext. wall)	[W/m^{2}K]	Uniform (0.10;0.30)	Lognormal (-1.966;0.020^2)
U-value (roof)	[W/m^{2}K]	Uniform (0.08;0.20)	Lognormal (-2.303;0.039^2)
U-value (floor)	[W/m^{2}K]	Uniform (0.10;0.20)	Lognormal (-2.121;0.027^2)
Adjustment factor (ground)	[-]	0.7	Beta (15;3.75)
Window-%	[-]	Uniform (30%; 60%)	40%
Window frame fraction	[-]	20%	20%
U-value (window)	[W/m^{2}K]	0.8	0.8
SHGC	[-]	Uniform (0.3;0.6)	0.3
Ventilation rate (CAV)	[l/s/m^2]	0.83	Uniform (0.75;0.92)
Infiltration rate @ 50Pa	[l/s/m^2]	0.50	Lognormal (-0.240; 0.693^2)
Heat recovery efficiency	[-]	0.85	Beta (100;21.95)
Internal heat loads (people, light, appliances)	[W/m^2]	17	Lognormal (6.073; 0.269^2)
Internal heat capacity	[KJ/m^{2}K]	Uniform (110;260)	Lognormal (5.102; 0.088^2)
Heating set point	[˚C]	20	Normal (21.5;1^2)
Cooling set point	[˚C]	26	Normal (26;0.4^2)

Table 2: Input assumptions for the SA methods.

	Local	Morris	Sobol’
Points used from PDF	1% and 99% quantiles	1% and 99% quantiles, p = 4 (levels)	Entire PDF
Sample size	1	r = 300 (trajectories)	N = 10,000 (LHS)
No. model evaluations	2k+1	r(k+1)	N(k+2)
Convergence measure	N/A	$\Sigma(\mu) \approx$ constant	Σ (ST) $\approx$ constant

The resulting total-order sensitivity indices are bounded to sum to one which makes it physically meaningful to use them for identifying and ranking input parameters that drive the majority of the model output variation.

The method of Morris applies the absolute mean of a population of local elementary effects to quantify the global influence of a given input parameter. The method is to some extend able to take into account non-linear and non-additive effects (ability 3), but is not able to account for non-uniform distributions of model input parameters (ability 1) using the traditional Morris sampling technique (factorial sampling) applied in this study. Furthermore, the Morris method is potentially neglecting correlated effects (ability 2) because each parameter is varied locally one-at-a-time (OAT). Another disadvantage of the Morris method is the dubious interpretation of the mean elementary effect as a measure of global sensitivity. One should be careful with interpreting a large absolute value of the mean elementary effect from the Morris method as a sign of great parameter influence as such values vary from one model to another. Only the internal ranking of the means can be used to quantify the influence of the parameters and sort them in clusters of importance.

The Local method uses inputs and outputs from OAT parameter variations (one sample) to calculate a dimensionless sensitivity index expressing the elasticity of variation around the mean value as percentage change in output per percentage change in input. This SI-index is then used for identifying and ranking the input parameters most sensitive to the output. The Local method implies a strictly linear model (not fulfilling ability 3), it does not allow any quantification of correlated parameter effects (not fulfilling ability 2), and does not allow any utilisation of knowledge about the shape of the parameter distributions (not fulfilling ability 1). One should therefore be careful interpreting the identification and ranking if the model is not 100% linear, have interacting input parameters, and anything but uniformly distributed input parameters.

Model input parameters

In order to carry out the sensitivity analyses, input spaces had to be specified for the uncertain input parameters in both cases to reflect the a-priori uncertainty of their value. To do so, different continuous probability density functions (PDFs) were applied to set the probability of a given parameter value over a range of variation (Figure 2).

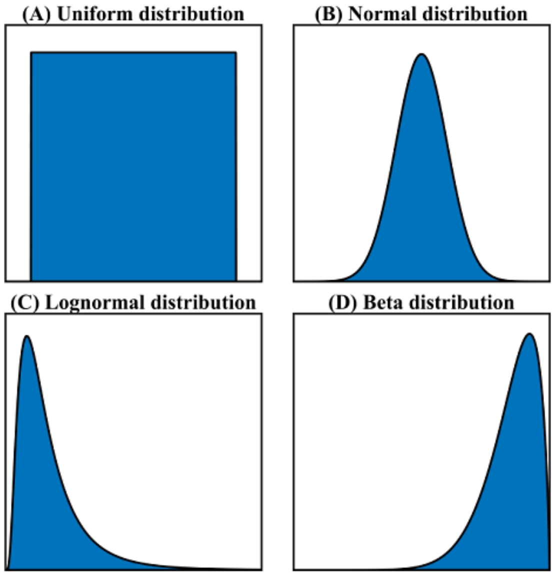

Figure 2: Probability density functions suitable for sensitivity analysis of building energy models.

The uncertainty of a parameter can be uniformly distributed across its defined range of variation *Uniform(A;B)*; doing so, the probability of all values within the parameter range are equal. This was appropriate for Case 1, as the purpose was to explore the effects of equally possible design options in the early design stage prior to any design decisions. The uniform PDF is often refered to as a non-informative PDF as no information can be extracted from it besides the range of variation.

A parameter can also be non-uniformly distributed if a-priori information allows it, e.g. expert judgements, historical data, or measurement error specifications. Such distributions were appropriate for Case 2, as the purpose was to explore the effects of uncertainty of the true value of an already decided parameter, i.e. error related to the practical implementation of the design. For this end, the normal distribution $Normal(\mu;\sigma^2)$ was applied to input parameters with an equally probable chance of variation around a most probable mean value (e.g. set point temperatures). The lognormal distribution $Lognormal(\mu;\sigma^2)$ was applied to positively defined parameters where higher values were more probable than lower values (e.g. U-values and infiltration rate). The beta distribution *Beta(a;b)* was applied to specify factors defined between 0 and 1 (e.g. heat recovery efficiency). The lognormal distribution is always skewed to the right (positive skew; right-tailed), but the shape will imitate the normal distribution for distributions with large variance. The beta distribution may assume almost any shape and skewness; thus, it is likewise possible to make it imitate the normal distribution if wanted (Figure 2).

Results

Partitioning heating and cooling need

A monthly partitioning of the energy need for space heating and cooling, calculated using the two BEMs respectively, is shown in Figure 3, applying the mean values of the inputs for Case 1 (Table 1).

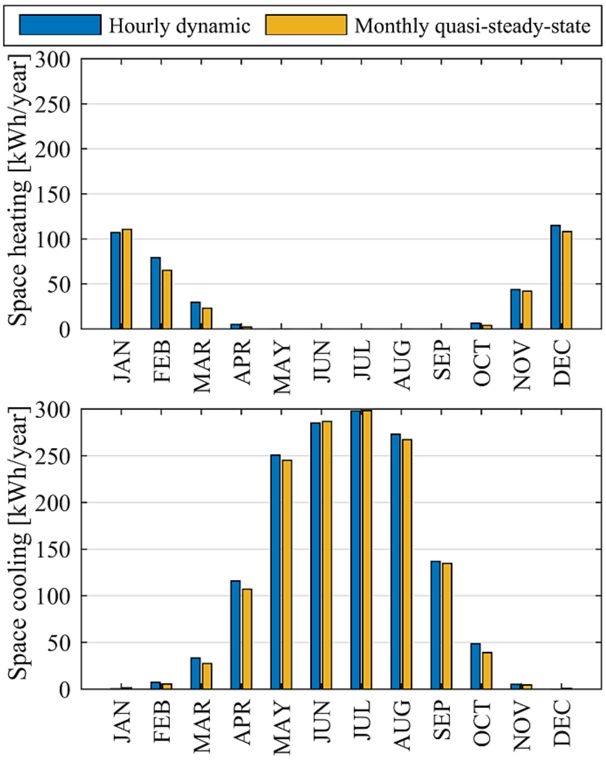

Figure 3: Monthly partitioning of energy need for space heating and cooling. Mean input values for Case 1 was applied.

The annually agregated energy need for space heating and cooling of the office room is dominated by the need for cooling (heating share of 20%; cooling share of 80%). The deviation between the annually agregated energy need for space heating and cooling of the hourly dynamic and the monthly quasi-steady-state BEMs is 4% (8% for heating; 2% for cooling). A larger internal deviation is present on the monthly scale.

Case 1: Early design decisions

Given the uniformly defined uncertainty specification for Case 1 (Table 1), the probable outcome of the annual energy need for space heating and cooling of the office room is shown in Figure 4A. Even though the BEMs were not calibrated prior to simulation, and thus were not expected to be consistent, their output distributions exhibit the same variation and shape. Their mean values are 1,890 kWh/year (hourly dynamic) and 1,810 kWh/year (monthly quasi-steady-state), respectively.

The amount of variation caused by each of the seven uncertain parameters is quantified by the three SA methods and depicted in Figure 5, and ranked in order of influence in Table 3.

Table 3: Ranking of input parameters for Case 1 (1 is most influential; 7 is least influential). L = local method; M = Morris method; S = Sobol' method.

Input	Hourly dynamic			Monthly quasi-steady-state		
	L	M	S	L	M	S
Window-%	3	1	1	2	1	1
SHGC	2	2	2	3	2	2
Room height	1	3	3	1	3	3
Internal heat capacity	4	4	4	4	4	4
U-value (roof)	5	5	5	5	5	5
U-value (ext. wall)	7	6	6	6	6	6
U-value (floor)	6	7	7	7	7	7

The parameter ranking based on the Morris and Sobol' analysis is identical for both BEMs, whereas the result of the Local method deviates a bit. The Morris and Sobol' methods identified the window-% as the single most influential parameter (approx. 45%-51% of the output variability in the two BEMs, respectively, can be ascribed the window-% cf. the Sobol' analysis), then SHGC as 2nd and room height as 3rd most influential. The Local method, on the other hand, identified room height to be most influential in both BEMs with the SHGC coming in as 2nd and the window-% as 3rd most influential.

In both BEMs, all three SA methods find the U-values (ext. wall, floor and roof) to be the least influential parameters given the input distributions of Case 1.

Case 2: Uncertainty of practical implementation

Given the mixed uncertainty specification for Case 2 (Table 1), the probable outcome of the annual energy need for space heating of the office room is shown in Figure 4B. The mean values are 1,410 kWh/year (hourly dynamic) and 1,300 kWh/year (monthly quasi-steady-state), respectively. In contrast to the output distribution of Case 1, the distribution of Case 2 has a lower variance (uncertainty).

The amount of variation caused by each of the 11 uncertain parameters is quantified by the three SA methods and shown in Figure 5, and ranked in order of influence in Table 4.

Table 4: Ranking of input parameters for Case 2 (1 is most influential; 11 is least influential). L = local method; M = Morris method; S = Sobol' method.

Input	Hourly dynamic			Monthly quasi-steady-state		
	L	M	S	L	M	S
Internal heat loads	3	2	1	4	2	1
Heating set point	2	1	2	2	1	3
Infiltration rate	5	4	3	6	3	2
Cooling set point	1	3	4	1	4	4
Internal heat capacity	4	5	5	3	5	5
Heat recovery efficiency	10	6	6	5	7	7
Adj. factor (ground)	8	7	7	9	6	6
U-value (roof)	6	8	8	7	8	8
Ventilation rate	11	9	9	11	10	9
U-value (floor)	7	10	10	8	9	10
U-value (ext. wall)	9	11	11	10	11	11

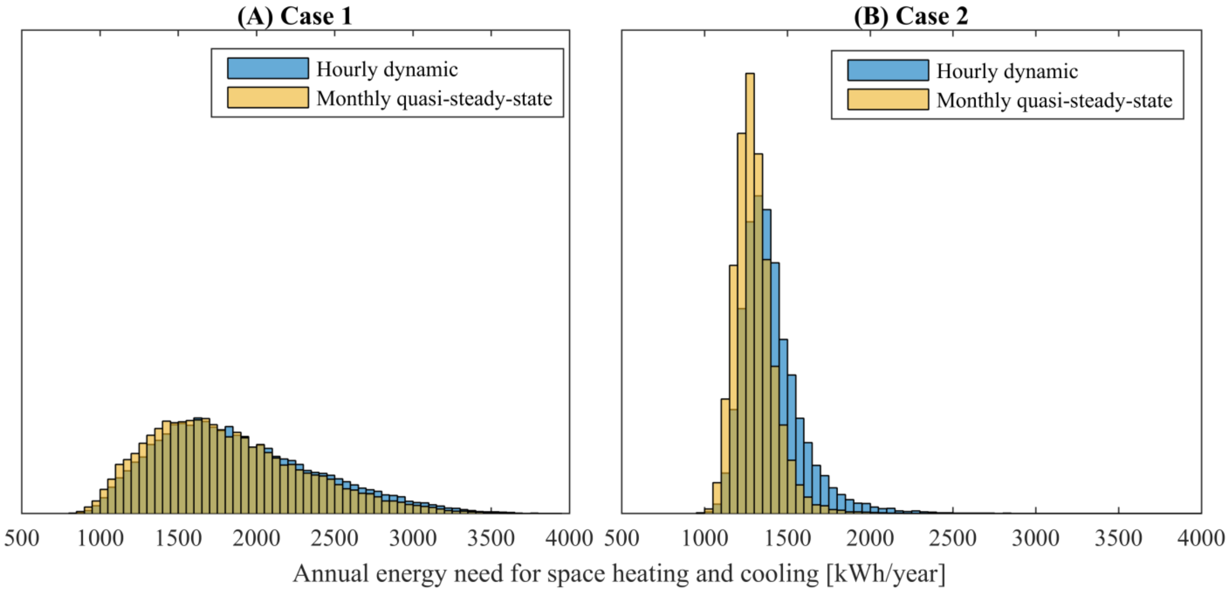

Figure 4: Probability distributions of annual energy need for space heating and cooling for Case 1 and Case 2. Latin Hypercube sampling was used to generate 10,000 simulation runs.

In general, the rankings are different for all three methods; however, the Morris and Sobol' methods tends to agree more with each other than with the Local method. Moreover, as opposed to the parameter ranking of Case 1, larger differences in the ranking are seen between the two BEMs for the same SA method.

According to the variance decomposition of the Sobol' method, the highest ranked parameter is the internal heat loads (people, lighting and appliances) in both BEMs, which accounts for 44%-47% of the output variability in the two BEMs, respectively. In total, the top-3 ranked parameters (internal heat loads, heating set point and infiltration rate) make up approx. 90%-92% of the output variability in both BEMs.

The Morris method identified the same top-3 for the quasi-steady-state BEM as the Sobol' method, but in different order. For the hourly dynamic BEM, the Morris method only identified top-2 from the Sobol' method, also in a different order. The 3rd most influential parameter was found to be the cooling set point instead of infiltration rate.

The Local method deviates from the Sobol' method by identifying the cooling set point as the most influential parameter in both BEMs. The heating set point is 2nd highest ranked in both BEMs while internal heat loads is only in top-3 for the hourly dynamic BEM; the quasi-steady-state BEM has instead the internal heat capacity in top-3. The infiltration rate (which was in top-3 for the Sobol' method in both BEMs) was on 5th and 6th place in the hourly and quasi-steady-state BEM, respectively.

Discussion

For Case 1, i.e. an early design phase with uniformly distributed probabilities, the differences in parameter ranking based on the different SA methods are very limited. The Morris and Sobol' methods tend to agree to a large extend. Assuming that the Sobol' method is correct, the Local method is in principle leading to a wrong identification of the most important input parameter; however, Figure 5 shows that this is only due to a marginal difference between the top-3 parameters. This is a good example of how the visual presentation of SA results might be more informative to building designers in an early design phase than discrete rankings, as the focus seems to be on parameter screening rather than precise uncertainty quantification.

For Case 2, i.e. the detailed design stage with the option of non-uniform PDFs to represent the modellers information about the parameter uncertainty, the Sobol' and Morris method by definition outperforms the Local method in terms of parameter ranking. The Local method does not respect the range and shape of the input distributions (ability 1); it assumes the same effect for all possible values of the parameters, which is why it identifies the cooling set point as very important. In reality, the plausible range of the cooling set point is very limited, and thus not that influential in the overall picture. The Morris method does respect the range of the distributions, but not the shape as in the Sobol' method, which makes the result of the Morris method approach the result from the Sobol' method somewhat better than the Local method. From a theoretical point of view, the Sobol' method would thus a-priori be regarded the most appropriate method for Case 2, as it has the ability to take into account the varying and somewhat skewed input distributions that were applied. Nonetheless, the Morris method showed to be appropriate for identifying the unranked cluster of the top-3 most important parameters, which together account for approx. 90% of the uncertainty in the energy need. Thus, if the purpose of the sensitivity analysis is to identify a group of most

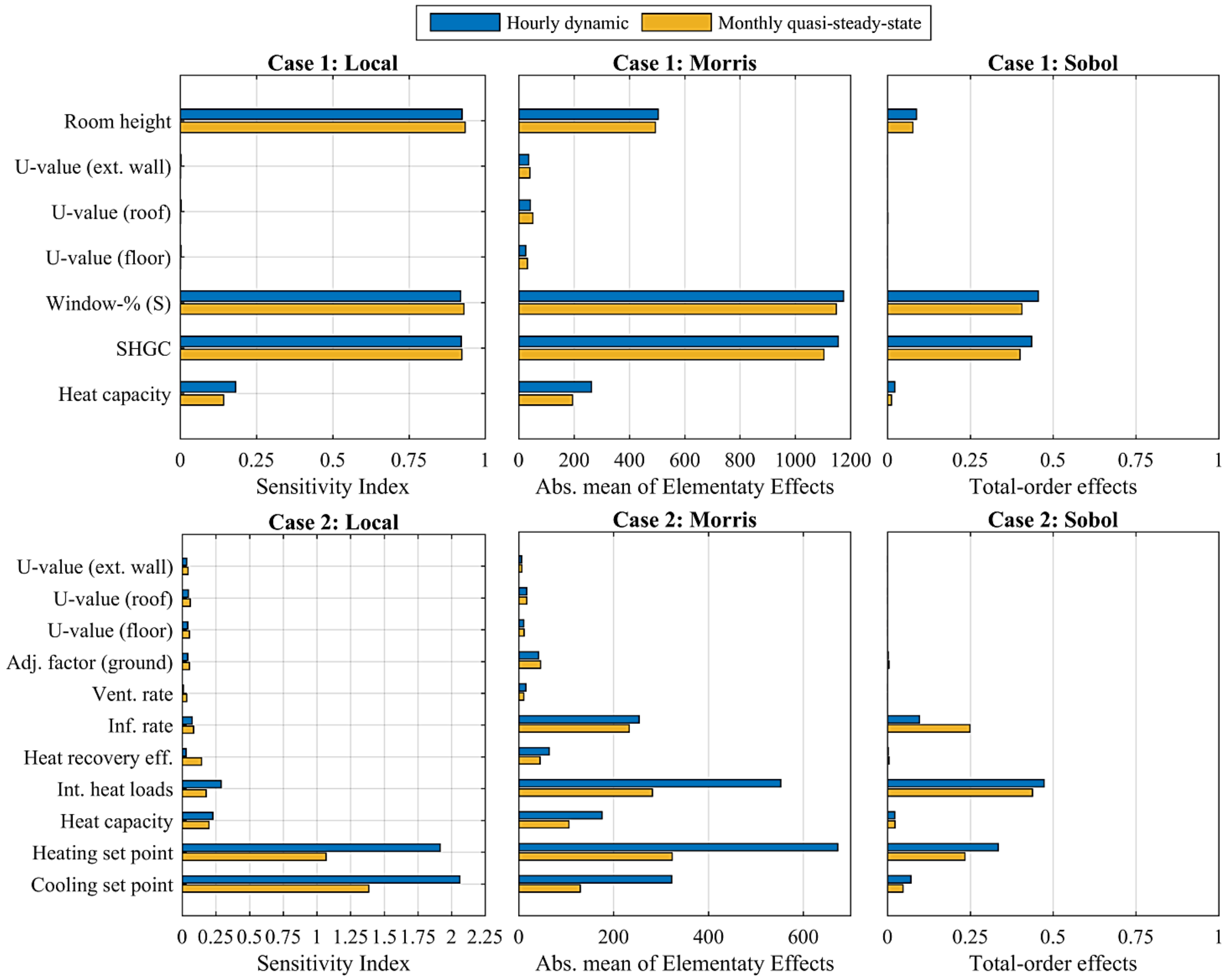

Figure 5: Result of sensitivity analysis of Case 1 and Case 2, using the Local, Morris and Sobol' method, respectively.

important parameters, one might apply the computationally efficient Morris method in favour of the by far more complex and computationally heavy Sobol' method. However, if the purpose is a detailed quantification of the uncertainty contribution of each parameter, and how these interact and affect each other, there is no way around a variance-based method like the one by Sobol'. For practical reasons though, the application of the Sobol' method seems infeasible in ordinary building design. The Local method fell short by only identifying one and two out of top-3 most important parameters, for the monthly quasi-steady-state and hourly dynamic BEMs, respectively; hence, it is most suitable for the simple screening-based analyses in the earliest stages of a building design process.

In general, uncertainty in the inputs was propagated similarly through the two BEMs resulting in approx. equal output distributions. However, some differences in the influence of the inputs were found due differences in model behaviour and dynamics. Thus, one should be careful interpreting the outcome of a sensitivity analysis of one BEM as generally applicable for all BEMs; besides the applied SA method itself, the outcome of a sensitivity analysis is influenced by model behaviour, the exact selection of input parameters, and their investigated distributions (range and shape).

Conclusion

From the results of this study, it is evident that the applicability of the different SA methods used depends on the purpose of the SA. If the purpose is to identify which parameters – all with uniformly distributed probability – affects the model output, then a simple Local method seems to suffice from a practical point of view. This is especially true if an exact ranking of parameters is of minor importance, and if the building physics is represented using linear equations. However, the Local method can only be used to identify an unranked cluster of maybe the upper half most important parameters if the probability distributions of the input parameters for some reason are non-uniformly distributed. In such cases, the Morris method is preferred as long as the probability distributions are well defined without any long tails; if the majority of the parameters are normal or lognormal distributed with large variance and/or beta distributed, then the Sobol' method is preferred.

In addition to the choice of SA method itself, the results indicate that the ranking of important input parameters – and thus the proper selection of SA method – is influenced by the applied BEM. This aspect of SA performance is relatively unexplored and ought to be further investigated in future work.

References

Bourges, B. (1992). Climatic Data Handbook for Europe: Climatic Data for the Design of Solar Energy Systems, 1st Edition, Springer Netherlands, ISBN 978-0-7923-1716-6.

Heiselberg, P., H. Brohus, A. Hesselholt, H. Rasmussen, E. Seinre, and S. Thomas (2009). Application of sensitivity analysis in design of sustainable buildings. *Renewable Energy* 34, 2030–2036.

ISO 13790:2008 (2008). Energy performance of buildings – Calculation of energy use for space heating and cooling, 2nd Edition.

Jensen, J.M. and H. Lund (1995). Design Reference Year, DRY - Et nyt dansk referencer (in Danish), Technical University of Denmark, announcement number 281.

Kristensen, M.H. and S. Petersen (2016). Choosing the appropriate sensitivity analysis method for building energy model-based investigations. *Energy and Buildings* 130, 166–176.

Lam, J.C. and S.C.M. Hui (1996). Sensitivity analysis of energy performance of office buildings. *Building and Environment* 31(1), 27–39.

Mechri, H. E., A. Capozzoli and V. Corrado (2010). Use of the anova approach for sensitive building energy design, *Applied Energy 87,* 3073–3083.

Morris, M.D. (1991). Factorial sampling plans for preliminary computational experiments, *Technometrics* 33(2) 161–174.

Sobol, I.M. (1993). Sensitivity estimates for nonlinear mathematical models. *Mathematical Modeling and Computational Experiment* 1(4), 407–414.

Spitz, C., L. Mora, E. Wurtz and A. Jay (2012). Practical application of uncertainty analysis and sensitivity analysis on an experimental house, *Energy and Buildings 55,* 459–470.

Østergaard, T., S.E. Maagaard and R.L. Jensen (2015). A stochastic and holistic method to support decision-making in early building design, in: *Procs. of BS 2015, the 14th International Conference of the IBPSA*, Hyderabad, India.