Global sensitivity analysis for Building-Stock Energy Models: Application of three global approaches

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Abstract

Buildings-Stock Energy Models (BSEMs) recently gained vast momentum in battling the climate emergency. They allow for quick evaluation of competing policy solutions for determining effective energy reduction recommendations in the building sector. Yet, the output of these models hold a significant range of variation since it is impossible to precisely quantify all inputs and complex energy flows. Without understanding these limits of inference resulting policy advice is inherently defective. Uncertainty Analysis (UA) and Sensitivity Analysis (SA) enable to quantify these limits of inference and calculate each factor's share in the output's variation. This study presents a systematic comparison of three different global SA methods to an internally developed bottom-up BSEM (based on the regulatory model in ISO13790). Accuracy, calculation burden and complexity of application of each method is evaluated to provide guidance which can inform the application of these methods to other BSEMs.

Keywords

IEA EBC Annex 70

Building-Stock Energy Model

Uncertainty analysis

Sobol' sensitivity analysis

Morris method

Delta Moment-Independent Measure

Introduction

The International Energy Agency (IEA) forecasts an increase in primary energy demand of 3% every year between 2030 and 2050 (IEA, 2021). Meanwhile, a large group of countries have pledged to reach net-zero emissions by 2050 in order to try to limit the rise in global temperatures to 1.5 °C (IEA, 2021). With building energy use still accounting for 40% of the total primary energy demand and 36% of the CO_2-emissions (EU, 2020; IEA, 2019), the building sector is one of the most important areas to address. To boost decision-making, Building-Stock Energy Models (BSEMs) have become essential tools. These large scale building energy simulation models allow for quick evaluation of competing policy options, making them vital tools for determining sustainable energy reduction recommendations in the building sector (EC, 2020).

In recent years, the scale and complexity of these models has progressed rapidly with a trend away from bespoke standalone models to stock models "designed for wider applicability, allowing core modelling structures to be transferred to other cities, regions or countries by varying model input data" (Langevin *et al.*, 2020). When these models are used in critical policy decision-making settings and applied to new contexts, existing quality assurance approaches are increasingly inadequate since model validation is typically applied to the aggregate annual output of the whole model, giving little insight into the ability of the model to capture the changes in building energy demand and emissions resulting from changes in different parts of the building stock (Cerezo Davila, 2017).

Further, these approaches fail to identify the main drivers for building energy demand and emissions. Complex physical energy equations (typically modelled for bespoke single building energy models) are being simplified and generalised in stock models due to input parameter shortage and/or to allow for acceptable model computation times. As a results, the outputs of these models inevitably have a significant range of variation. Without understanding these limits of inference, resulting policy advice is inherently defective as there is a potential risk that assumptions, suitable for the original context, are erroneously carried through to the new context.

Uncertainty Analysis (UA) and Sensitivity Analysis (SA) enable to quantify these limits of inference and calculate each factor's share in the output's variation. This paper aims to broaden the knowledge on global sensitivity analysis application at BSEMs by application of the three different global SA methods (*i.e.*, Sobol' SA (Sobol', 1990), the Morris method (Morris, 1991) and DMIM (Borgonovo, 2007)) to an internally developed bottom-up BSEM (Delghust *et al.*, 2015/2015/2015) (based on the regulatory model in ISO13790 (ISO, 2007)). The study will evaluate the accuracy, calculation burden and complexity of application of each method which can inform practitioners of the application of these methods to other BSEMs.

Materials and methods

Definitions

BSEM	Building-Stock Energy Model
UA	Uncertainty analysis focuses on how uncertainty in the input parameters propagates through the model and affects the model output parameter(s).
SA	Sensitivity analysis is the study of how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input factors.
Y	The model output and $V(Y)$ the variance of the model output.
X_i	The i-th model input parameter and $X_{\sim i}$ denotes the matrix of all model input parameters but X_i.
S_i	The first order sensitivity index, which represents the expected amount of variance reduction that would be achieved for Y, if X_i was specified exactly. The first order index is a normalised index (*i.e.*, always between 0 and 1).
S_{Ti}	The total order sensitivity index, which represents the expected amount of variance that remains for Y, if all parameters were specified exactly, but X_i. It takes into account the first and higher order effects (interactions) of parameters X_i and can therefore be seen as the residual uncertainty.
*	Table 1: *Aleatory uncertainty:* Uncertainty due to inherent or natural variation of the system under investigation. *Epistemic uncertainty:* Uncertainty resulting from imperfect knowledge or modeller error; can be quantified and reduced.

IEA EBC Annex 70: Building Energy Epidemiology

As part of the IEA EBC Annex 70 on Building Energy Epidemiology (IEA EBC, 2017), a group of research teams participated in a co-ordinated investigation to take existing global SA methods and apply them to their distinct stock models and datasets in a first attempt to quantify the added value of global SA for building stock modelling. Through this process the teams aimed to examine:

- The challenges of defining input parameter uncertainties for large-scale building energy models and collecting appropriate data.
- The applicability of different SA techniques in terms of robustness of results, quality assurance and computational cost.
- Key drivers of uncertainty in the models.

The chosen SA techniques that have been explored at scale by the authors and are further discussed in this paper is the Sobol‘ SA method, the Morris method and the DMIM. The dataset that is used contains data from the Flemish Energy Performance registry that the authors acquired through an earlier study in collaboration with the Flemish Energy and Climate Agency (VEKA) (Bracke *et al*., 2018; Defruyt *et al*., 2013). The subset of this data used here contains building characteristics of detached newly built houses with three bedrooms at aggregated level (*i.e*., total external volume, floor area, heat loss area, total window area, average U-value of the windows and the total building envelope *etc*.).

'The Tool'

The BSEM, used by the authors for the global SA study is an internally developed bottom-up quasi-steady state building stock model (Delghust *et al*., 2015/2015), internally appointed as 'The Tool', that uses multi-zone archetype buildings to simulate the building stock's total, heating, cooling, auxiliary and domestic hot water (DHW) energy demand on a monthly and yearly basis. It is a standalone application, with a calculation kernel inside, which is based on the official single-zone monthly quasi-steady state calculation method used in Flanders (VEA, 2017) and based on ISO 13790 (ISO, 2007). Additionally, a custom multi-zone quasi-steady state algorithm is implemented that allows for more detailed multi-zone energy demand calculations.

While the model is less detailed than dynamic simulation models, the multi-zone algorithm allows for different intermittent heating profiles to be taken into account in coupled zones (at room level) while keeping the calculation times very low in order to run simulations at scale. Furthermore it requires less data than dynamic models, thus making it more suited for situations with limited available data (Delghust *et al*., 2015).

Sobol' SA method

The Sobol' SA method (Sobol', 1990) is classified as a variance-based global SA, meaning that it is based on variance decomposition. It looks at the entire space of the input parameters' distributions using customary Monte Carlo methods of various sophistication (Sobol', 1990; Saltelli *et al*., 2010). One of the main advantages of variance-based methods (such as Sobol' SA) is that it is able to take into account interactions between input parameters (Saltelli *et al*., 2008; Santner *et al*., 2003).

Following common practice in global SA applications, two model-free normalised sensitivity indices for each input parameter are being used: the first order index (S_i) (or Main effect index) and the total order index (S_{Ti}) (or Total effect index), which includes the main effect and interactions.

For a model of the form $Y = f(X_1, X_2, \ldots, X_k)$, the two sensitivity indices are expressed as follows Saltelli *et al*., 2008):

$$S_i = \frac{V_{X_i}(E_{X_{\sim i}}(Y \mid X_i))}{V(Y)} \quad (1)$$

$$S_{Ti} = \frac{E_{x_{\sim i}}(Vx_i(Y \mid X_{\sim i}))}{V(Y)} = 1 - \frac{V_{x_{\sim i}}(E_{x_i}(Y \mid X_{\sim i}))}{V(Y)} \quad (2)$$

The guidelines for the Sobol' SA (Herman *et al.*, 2017) suggest that the Sobol' sequence is used to produce nested input parameter samples across stocks. Sobol' requires matrices of the form $(2p + 2)$ to calculate SA-indices with p the number of input parameters. The number of model evaluations is equal to $n \cdot (2p + 2)$ with n the number of input parameter samples/matrices. The number of required samples to reach convergence of SA results is not defined. Official guidelines for Sobol' suggest a number of 1000 but it will have to be examined in the result section if the suggested number is enough.

Morris SA method

The Morris method (Morris, 1991) is an efficient parameter screening method which uses a factorial sampling strategy to identify parameters that can be fixed at any value within their range without affecting the variance of the model outcome. For sampling, the parameter space is discretised by transforming the input parameters into dimensionless variables in the interval and dividing each parameter interval into a number of p levels, which form a regular grid in the unit-length hypercube H_k. The starting point for sampling on this grid is randomly chosen and each sample differs only in one coordinate from the preceding one, therefore it is also called a repeated One-At-a-Time approach. A sequence of $k + 1$ points, in which each parameter changes only once by a pre-defined value Δ_i, is called a trajectory. One point in this trajectory represents one evaluation run of the model. The magnitude of variation in the model output due to the pre-defined variation of one parameter X is called elementary effect (EE) (Morris, 1991):

$$EE_i = \frac{Y(X + e_i\Delta_i) - Y(X)}{\Delta_i} \quad (3)$$

where e_i is a vector of zeros, except for the i-th component that equals ± 1 and represents an incremental change in parameter *i* (Garcia *et al.*, 2014).

The guidelines for the Morris SA (Herman *et al.*, 2017) suggest that the Morris sampler is used to produce input parameter samples. Morris requires matrices of the form $(p + 1)$ to calculate SA-indices. The number of model evaluations is equal to $n \cdot (p + 1)$.

Delta Moment-Independent Measure

The DMIM approach (Borgonovo, 2007; Plischke *et al.*, 2013) is fairly recent and based upon computing the differences in mass density between the Probability Density Functions (PDFs) of prediction values computed *(i)* when all parameter values are varied simultaneously and *(ii)* when one parameter of interest is fixed at a constant value. Mathematically, this difference in mass density $[s_i(x)]$ is expressed as (Plischke *et al.*, 2013)

$$s_i(x) = \int_y \mid f_Y(y) - f_{Y|X_i=x}(y) \mid dy \quad (4)$$

where $f_Y(y)$ represents the PDF of predictions y and $\mid \cdot \mid$ represents the L1 norm (*i.e.*, the sum of absolute values). Essentially, this equation is used to compute the integral with respect to y of the absolute difference between the PDF of *(i)*, expressed as $f_Y(y)$, and the PDF of *(ii)*, expressed as $f_{Y|X_i=x}(y)$. The DMIM sensitivity of a given model prediction to a parameter of interest $[\delta_i]$ is then calculated as one half of the expected value of $s_i(x)$ (Plischke *et al.*, 2013):

$$\delta_i = \delta(Y, X_i) = \frac{1}{2}E[s_i(x)] = \frac{1}{2}E[\int_y \mid f_Y(y) - f_{Y|X_i=x}(y) \mid dy \quad (5)$$

where E is the expected value.

A large δ_i value indicates that the prediction of interest is highly sensitive to parameter X_i. In practice, the integrals in equations (4) and (5) are evaluated numerically using a kernel density estimator. The guidelines for the DMIM (Plischke *et al.*, 2013) suggest that a Latin Hypercube Sampling is used to produce input parameter samples. DMIM requires matrices of the form 1 to calculate SA-indices. The number of model evaluations is equal to $n \cdot 1$.

Global SA exercise set-up

In order to have a sufficiently meaningful and diverse global SA experiment, different types of input parameters (*i.e.*, parameters concerning the building envelope (U_{av} and v_{50}); the dwelling's orientation (*Orientation*); internal elements as doors, walls and floors (U_{int}); but also technical systems (Q_{nom} and Q_{DHW}) and the indoor setpoint temperature for space heating ($T_{set,heat}$)) were selected covering several essential characteristics that differentiate input parameters in the context of SA (*i.e.*, covering different sources of uncertainty; known or standard input values or assumptions; mean, mode and/or standard deviation of the input parameter distributions).

A general overview of the investigated parameters is listed in *Table 1*. In *Table 2*, an overview of the specified distributions for each parameter is provided (across stocks and within stocks). The physical parameters are average U-value (U_{av}), orientation of the facade (*Orientation*), measured air leakage per m^2 at 50Pa (v_{50}), U-value of internal doors/walls/floors (U_{int}), nominal percentage (*t%*) of the ventilation heat loss (Q_{nom}), fraction (*f*) of DHW energy use (Q_{DHW}) and internal heating setpoint ($T_{set,heat}$). Note that the investigated parameters (Prm.) in the analysis are considered the mean, mode or standard deviation of the distribution of the physical parameters (and so the aim of this global SA for stock models is to investigate what influence changes in the mean, mode or standard deviation of the distribution of the physical parameters have on the investigated model output (*i.e.*, Q_{tot})).

In *Table 1*, there is further specified whether the parameter input values were known from the Energy Performance registry, if they were standard values or if theoretical assumptions were made by the authors based on internal knowledge. Also, there is listed how the parameters are varied/implemented (*i.e.*, application) from a practical point of view. There is then specified how the parameters are varied across stocks (across stocks, the mean, mode or standard deviation of the distribution within stocks is sampled of every (to be simulated) stock, so for every model evaluation) and within stocks (values are sampled for every physical input parameter for every building in the stock). Lastly, the considered source of uncertainty is given (**Table 1*).

Physical parameter	Global SA exercise — General overview					
	Input values	**Application**	**Prm.**	**Across stocks** (seed = constant)	**Within stocks** (seed is varied)	**Uncertainty***
U_{av}	Known inputs for U_{av}	$X_i \cdot U_{av}$	P1	Mean (μ) of X_i is varied	Mean (μ) and stdev. (σ) of X_i are constant	epistemic
Orientation	Assumption	α	P2	Mean (μ) of α is varied	Mean (μ) of α is constant	epistemic
			P3	Stdev. (σ) of α is varied	Stdev. (σ) of α is constant	aleatory
v_{50}	Known and standard values	$v_{50,def}$	P4	Mode (μ) of $v_{50,def}$ is varied	Mode (μ) and stdev. (σ) of $v_{50,def}$ are constant	epistemic
U_{int}	Assumption	$1+Y_i \cdot 3$	P5	Mode (μ) of Y_i is varied	Mode (μ) of Y_i is constant	epistemic
Q_{nom}	Assumption	$t\% \cdot Q_{nom}$	P6	Mode (μ) of $t\%$ is varied	Mode (μ) of $t\%$ is constant	epistemic
			P7	Stdev. (σ) of $t\%$ is varied	Stdev. (σ) of $t\%$ is constant	aleatory
Q_{DHW}	Assumption	$f \cdot Q_{DHW}$	P8	Mode (μ) of f is varied	Mode (μ) of f is constant	epistemic
			P9	Stdev. (σ) of f is varied	Stdev. (σ) of f is constant	aleatory
$T_{set,heat}$	Assumption	$T_{set,heat} + T_{offset}$	P10	Mean (μ) of T_{offset} is varied	Mean (μ) of T_{offset} is constant	epistemic
			P11	Stdev. (σ) of T_{offset} is varied	Stdev. (σ) of T_{offset} is constant	aleatory

Table 1: Overview of investigated input parameters in the global SA exercise. The table also contains further info about the way the parameters are taken into account.

Physical parameter	Global SA exercise — Parameter distribution overview						
	Application	**Prm.** (across stocks)		**Across stocks distribution** (seed = constant)		**Within stocks distribution** (seed is varied)	
U_{av}	$X_i \cdot U_{av}$	P1	(μ of X_i)	uniform	(a = 1.0, b = 1.1)	normal	(μ = P1, σ = 0.05)
Orientation	α	P2	(μ of α)	normal	(μ = 45, σ = 10)	normal	(μ = P2, σ = P3)
		P3	(σ of α)	lognormal	(μ = 30, σ = 10)		
v_{50}	$v_{50,def}$	P4	(μ of $v_{50,def}$)	uniform	(a = 3.0, b = 6.0)	lognormal	(μ = P4, σ = 0.583)
U_{int}	$1+Y_i \cdot 3$	P5	(μ of Y_i)	uniform	(a = 0.1 b = 0.9)	inverse lognormal	(μ = f(P5), σ = f(P5)
Q_{nom}	$t\% \cdot Q_{nom}$	P6	(μ of $t\%$)	uniform	(a = 0.1, b = 0.5)	lognormal	(μ = P6, σ = P7)
		P7	(σ of $t\%$)	uniform	(a = 0.33, b = 0.66)		
Q_{DHW}	$f \cdot Q_{DHW}$	P8	(μ of f)	normal	(μ = 1.0, σ = 0.1)	lognormal	(μ = P8, σ = P9)
		P9	(σ of f)	uniform	(a = 0.0, b = 1.0)		
$T_{set,heat}$	$T_{set,heat} + T_{offset}$	P10	(μ of T_{offset})	uniform	(a = -2, b = 2)	normal	(μ = P10, σ = P11)
		P11	(σ of T_{offset})	uniform	(a = 0.0, b = 1.0)		

Table 2: Investigated input parameter distribution overview across stocks and within stocks. The parameters sampled across stocks link with the blue mean, modus or stdev-values within stocks.

As discussed earlier, the various sampling methods are used to generate input parameter samples across stocks (depending on the global SA). A Latin Hypercube Sampling (LHS) is used to generate samples within the stock. The building stock size that is being used for analysis is a group of 1000 buildings. The model output parameter that is analysed is the average total yearly primary energy demand (*i.e.*, Q_{tot}) of the stock.

Robustness and quality control

In order to check the robustness of the global SA results, common practice (although very limited studies actually perform robustness checks) is to check for convergence of the global SA results. Convergence can be described as the fact that global SA results do not change (or change to a limited degree) when using a different number of model evaluations (of equal or larger size) (Sarrazin *et al*., 2016). The type of convergence that will be checked for is the convergence of the sensitivity indices. When the values of the indices remain stable with a reliable confidence interval, convergence is reached.

To assess convergence of the sensitivity indices, the width of the 95% confidence intervals were computed (5% significance level). A maximum width of the confidence intervals across all the model input parameters as a summary statistic is given by:

$$Stat_{indices} = \max_{i=1\ldots p} (S_i^{ub} - S_i^{lb}) \tag{3}$$

where S_i^{ub} and S_i^{lb} are the upper and lower bounds of the sensitivity index of the *i*-th input parameter and *p* the number of input parameters. Since the normalised sensitivity indices vary between 0 and 1, an absolute threshold value for $Stat_{indices}$ can be defined below which convergence is considered to be reached. In literature, a reasonable choice for this threshold was found to be 0.05 (Sarrazin *et al*., 2016).

Results

Uncertainty analysis

Figure 1 and *2* show the outcome of an uncertainty analysis for the three investigated global SA methods based on uncertainty in the eleven investigated input parameters of the stock of 1000 Flemish single-family houses. In *Figure 1*, the uncertainty of the stock's average total energy use is shown. The mean of the results from the Sobol' and DMIM approach is around 30,600 kWh/y with a 5-95% spread of approximately 5,000 kWh/y around the mean. The mean of the results for the Morris approach is slightly higher with 31,400 kWh/y with a 5-95% spread of approximately 7,200 kWh/y around the mean. This is the level of uncertainty in total building energy use that we can expect at stock level due to uncertainty in the eleven investigated input parameters. The results of the Morris method show a broader uncertainty range due to the used Morris sampling algorithm for the input parameters, which is based on a repeated One-At-a-Time approach and typically samples extreme values in the specified input parameter ranges while the Sobol' sequence and a LHS produce disperse input samples.

In *Figure 2*, the uncertainty of the stock's spread around the stock's average total energy use is shown. The mean of the results from the Sobol' and DMIM approach is around 6,300 kWh/y with a 5-95% spread of approximately 1,500 kWh/y around the mean. Similarly as for the stock's average total energy use, the mean of the results for the Morris approach is slightly higher with 6,500 kWh/y with a 5-95% spread of approximately 1,900 kWh/y around the mean.

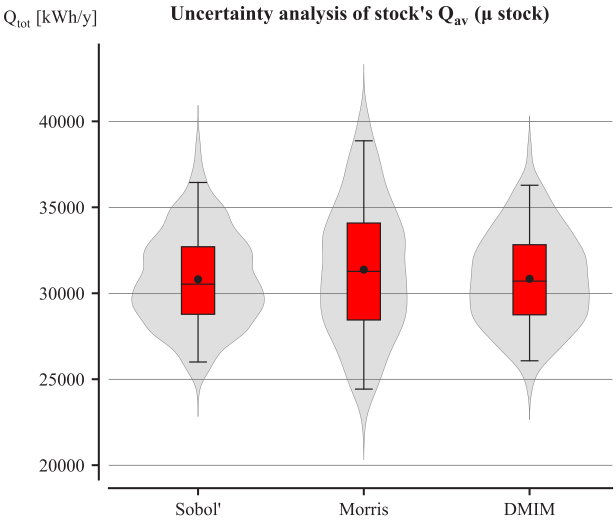

Figure 1: Uncertainty analysis of the stock's average total energy use for the three global SA methods. The boxplots show 5%, 25%, 50%, 75% and 95%-percentiles as well as a mean value (i.e., black dots).

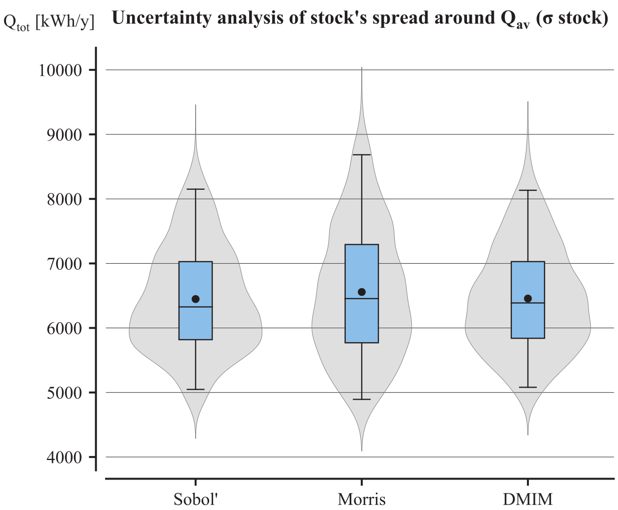

Figure 2: Uncertainty analysis of the stock's spread around the stock's average total energy use for the three global SA methods.

Global sensitivity analysis

The results for the Sobol' sensitivity analysis are shown in *Figure 3* as first-order indices S_i and total effects S_{Ti}. Four of the investigated parameters have a significant direct impact on the stock's average total primary energy use (*i.e.*, the mean of the distributions of the heating set point temperature and the average U-value and the modus of the distributions of the domestic hot water fraction and the default value for the building envelope's airtightness) and three have a significant direct impact on the stock's spread around the average total primary energy use (*i.e.*, the mean of the distributions of the heating set point temperature and the average U-value and the modus of the distribution of the default value for the building envelope's airtightness).

The results for the total order index S_{Ti}, as a measure of negligible model inputs, show that four parameters have a non-negligible impact on the stock's average energy use (*i.e.*, the mean of the distributions of the heating set point temperature and the average U-value and the modus of the distributions of the domestic hot water fraction and the default value for the building envelope's airtightness) and that three parameters have a non-negligible impact on the spread around the stock's average energy use (*i.e.*, the mean of the distributions of the heating set point temperature and the average U-value and the modus of the distribution of the default value for the building envelope's airtightness). Overall, the ranking in *Figure 3* (and *Table 3*) is in good agreement with rough sensitivity estimates from the literature, where often the set point temperature, infiltration, thermal properties, such as thermal conductivity of building components or internal thermal mass and domestic hot water parameters as influential for building energy models (Heo *et al.*, 2012; Yang *et al.*, 2015; Dominguez-Munoz *et al.*, 2010).

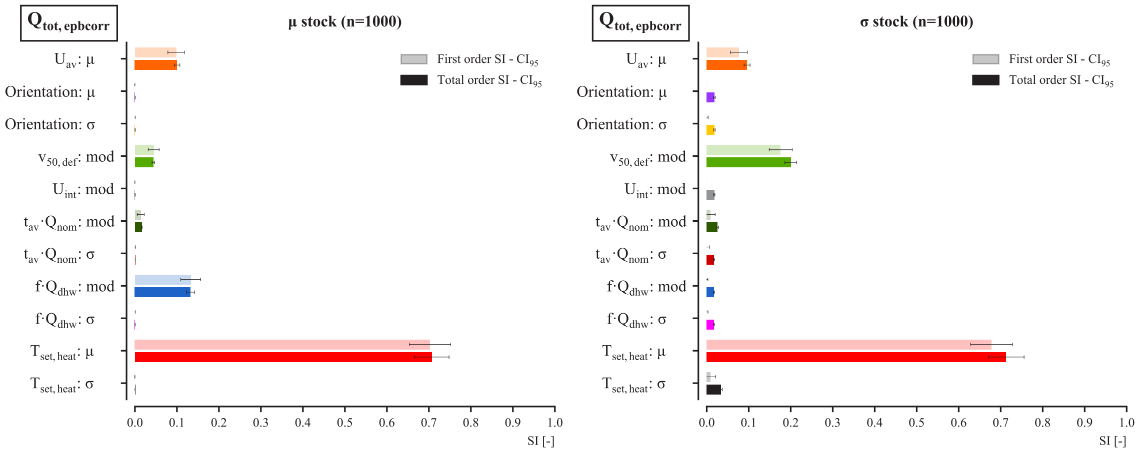

Figure 3: Results of the Sobol' SA first order and total order indices for the stock's average and spread around the stock's average total primary energy use. The 95% confidence interval of the indices is indicated by black error bars.

The results for the Morris method are shown in *Figure 4* and for our model, the highest $\mu^{\star}$ values for the stock's average total primary energy use are found for the mean of the distributions of the heating set point temperature and the average U-value and the modus of the distributions of the domestic hot water fraction and the default value for the building envelope's airtightness. The highest $\mu^{\star}$ values for the stock's spread around the average total primary energy use are he mean of the distributions of the heating set point temperature and the average U-value and the modus of the distribution of the default value for the building envelope's airtightness. The remaining parameters are identified as negligible parameters. The input parameter ranking is summarised in *Table 3*.

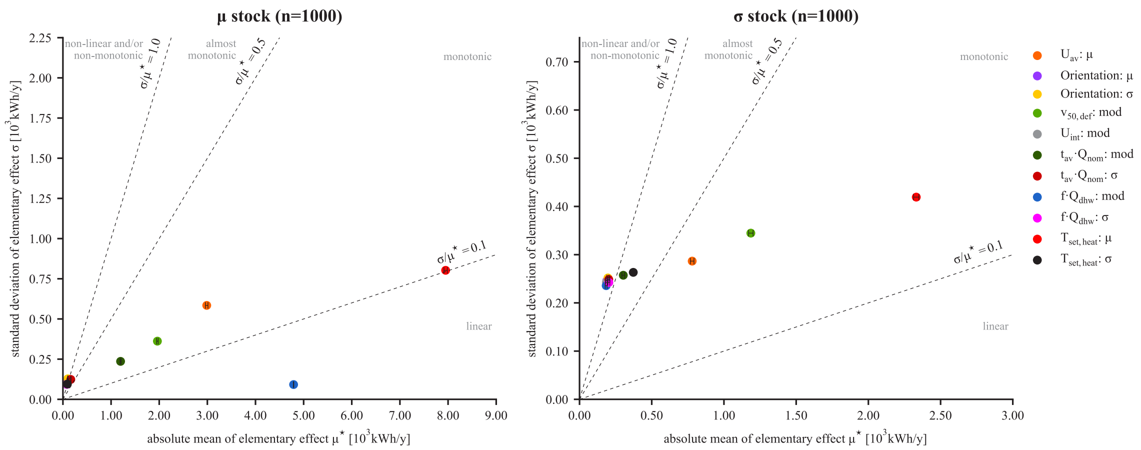

Figure 4: Results of the Morris method for the stock's average and spread around the stock's average total primary energy use.

The results of the DMIM SA are shown in *Figure 5* as first-order indices S_i. Four of the investigated parameters have a significant direct impact on the stock's average total primary energy use (*i.e.*, the mean of the distributions of the heating set point temperature and the average U-value and the modus of the distributions of the domestic hot water fraction and the default value for the building envelope's airtightness) and three have a significant direct impact on the stock's spread around the average total primary energy use (*i.e.*, the mean of the distributions of the heating set point temperature and the average U-value and the modus of the distribution of the default value for the building envelope's airtightness). The input parameter ranking is summarised in *Table 3*. The rankings of Sobol' S_i, Morris $\mu^\star$ and DMIM S_i show good correspondence.

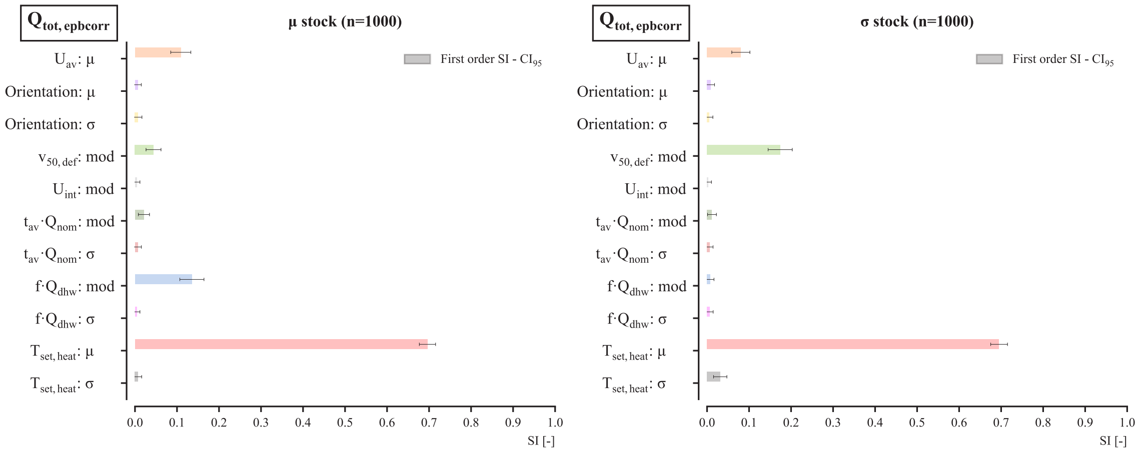

Figure 5: Results of the DMIM first order index for the stock's average and spread around the stock's average total primary energy use. The 95% confidence interval of the indices is indicated by black error bars.

Table 3: Overview on the paramater rankings, obtained by the investigated sensitivity analysis methods, for the stock's average total primary energy use.

	Sobol' S_i	Sobol' S_{Ti}	Morris $\mu^\star$	DMIM S_i
1	$T_{set, heat}$: μ	$T_{set, heat}$: μ	$T_{set, heat}$: μ	$T_{set, heat}$: μ
2	$f \cdot Q_{dhw}$: mod	$f \cdot Q_{dhw}$: mod	$f \cdot Q_{dhw}$: mod	$f \cdot Q_{dhw}$: mod
3	U_{av}: μ	U_{av}: μ	U_{av}: μ	U_{av}: μ
4	$v_{50,def}$: mod	$v_{50,def}$: mod	$v_{50,def}$: mod	$v_{50,def}$: mod
5	$t_{av} \cdot Q_{nom}$: mod	$t_{av} \cdot Q_{nom}$: mod	$t_{av} \cdot Q_{nom}$: mod	$t_{av} \cdot Q_{nom}$: mod
6	$T_{set, heat}$: σ	$t_{av} \cdot Q_{nom}$: σ	$T_{set, heat}$: σ	$T_{set, heat}$: σ
7	Orientation: μ	$T_{set, heat}$: σ	Orientation: μ	Orientation: μ
8	U_{int}: mod	Orientation: σ	U_{int}: mod	U_{int}: mod
9	$t_{av} \cdot Q_{nom}$: σ	Orientation: μ	$t_{av} \cdot Q_{nom}$: σ	$t_{av} \cdot Q_{nom}$: σ
10	Orientation: σ	$f \cdot Q_{dhw}$: σ	Orientation: σ	Orientation: σ
11	$f \cdot Q_{dhw}$: σ	U_{int}: mod	$f \cdot Q_{dhw}$: σ	$f \cdot Q_{dhw}$: σ

Conclusion

This study investigated the applicability of three global SA methods (*i.e.*, Sobol' SA, the Morris method and the DMIM) for large-scale BSEMs. The uncertainty analysis proved how important reporting uncertainty is for BSEMs and showed that applying the Morris method, which is a repeated One-At-a-Time approach, results in broader uncertainty ranges in the output as compared to Sobol' SA and DMIM. Sobol' SA and DMIM showed that 95% of the variation in the stock's average total primary energy use (due to uncertainty in eleven considered input parameter) is caused by only four input parameters (*i.e.*, the mean of the distributions of the heating set point temperature and the average U-value and the modus of the distributions of the domestic hot water fraction and the default value for the building envelope's airtightness) and 95% of the variation in the stock's spread around the average total primary energy use is caused by only three input parameters (*i.e.*, the mean of the distributions of the heating set point temperature and the average U-value and the modus of the distribution of the default value for the building envelope's airtightness). Note that changes in the standard deviation of the distribution for each of the physical model input parameters does not have any influence on the stock's average total primary energy use or the stock's spread around the stock's average total primary energy use as the effects average out at stock level (even for non-normally distributed parameters). The S_i-indices of Sobol' SA and DMIM show good correspondence and fall within each other (bootstrapped) confidence interval. When comparing the three global SA methods in terms of ranking, they also show perfect correspondence. Convergence of the indices for Sobol' SA occurred after 35784 model evaluations, for the Morris method after 10848 model evaluations and for the DMIM after 607 model evaluations. While Sobol' SA results in the most qualitative and elaborate results, the method clearly requires the most computation time.

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