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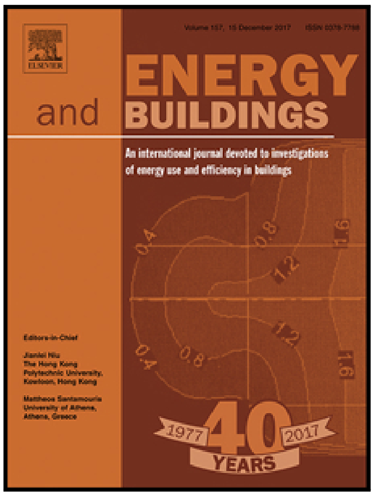

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Prerequisites for reliable sensitivity analysis of a high fidelity building energy model

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Abstract
Sensitivity analysis (SA) can be applied to building energy models (BEM) to identify which input parameters that drive the majority of the model output variation. The screening-based Morris method is often applied for this purpose; however, consideration regarding the effect of the user-defined number of levels (p) and trajectories (r) on the obtained results are rare. This paper investigates how the choice of p and r affects the outcome of a SA using the Morris method on a high fidelity BEM. The results indicates that the Morris method was not able to replicate the ranking from the variance-based Sobol' method no matter the choice of r and p. It was, however, able to identify groups of input parameters (parameter clusters) most sensitive to the model output variability, but it required significantly more r than usually applied in studies featuring the Morris method. The reason is that marginal differences in absolute values of elementary effects (the sensitivity indices of the Morris method) for some input parameters may lead to a change in ranking position several times as the number of r increases. Users of the Morris method must therefore not be predetermined on the size of the parameter cluster; instead, they must make a visual assessment of the convergence of the parameter ranking to qualitatively determine the appropriate size of parameter cluster. The final recommendation for future studies deploying the Morris method for SA applied to a high fidelity BEM is to choose $p \geq 4$ as it seems to lead the analysis towards a more truthful ranking, and then run simulations in steps of r=100 when making the visual assessment to determine convergence and the size of parameter cluster. The identified need for more r questions the general notion that the Morris method is a computationally efficient screening method in terms of absolute time use. However, the Morris method is still much more computational efficient than a Sobol'-based analysis if the purpose of the SA is to identify a cluster of input parameters most sensitive to the model output variability.

Keywords: Sensitivity analysis; Morris method; Sobol method; Building energy modelling

1. Introduction

Building designers may find it informative to employ a sensitivity analysis (SA) to a building energy model (BEM) to identify which design variables that drive the majority of the model output variation in terms of indoor climate and energy use. SA methods for this purpose can in general be categorised as either local sensitivity analysis (LSA) or global sensitivity analysis (GSA) [1].

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LSA methods rely on a one-parameter-at-a-time (OAT) technique where all parameter values have equal probability of occurrence. The OAT technique means that LSA methods do not account for any effects from correlated input parameters. However, LSA methods are easy to implement and fast to conduct as they require only few model evaluations.
The GSA category covers a range of methods applying different techniques. Common for the methods in the GSA category is that they evaluate the effect of an input parameter on the output by varying not only the parameter in question, but all other input parameters chosen for analysis as well. GSA methods are therefore able to include effects from correlated input parameters as well as non-linear and non-additive model behavior. The outcome of a GSA may therefore be more reliable than the outcome from a LSA but GSA methods are more complicated to implement and are significantly slower to conduct as they require many model evaluations.
A specific group of GSA methods are the so-called screening methods [2]. Screening-based SA methods are often considered useful for qualitative identification of design variables to which the model output variability is most sensitive, whereas more advanced GSA methods, such as a variance-based method, must be applied if a quantitative ranking of parameters is desirable. The screening method initially described by Morris [3], and since refined and expanded by different authors [4-5], seems to be widely used for BEM-based analysis; see Table 1 for an overview of BEM-based studies featuring the Morris method. A compelling argument for applying the Morris method, instead of a more comprehensive variance-based GSA method, is that it is a computational efficient alternative if only a rough ranking of the parameters is desired [6]. However, the analysis provided by Kristensen and Petersen [7] suggested that the Morris method is able to come up with an identical ranking of the input parameters most sensitive to the output of simplified BEMs, as the variance-based GSA method of Sobol' [8] using less computational time, but only when the probability density functions (PDF) of the input parameters are uniformly distributed. The Morris method could therefore be a computational efficient alternative to a global SA method e.g. in the early design stage. However, there are still issues to be investigated to fully understand the possibilities and limitations of the Morris method when used for SA of BEM. To explain these issues, the following sections provides a short description of the Morris method (section 1.1), a literature review on the use of the Morris method for BEM-based analysis (section 1.2), before finally outlining the specific contribution of this paper to the existing knowledge base (section 1.3).

1.1. The Morris method

This section provides a short description of the Morris method, which is intended to serve as background for the motivation of the investigation presented in this paper; see ref. [3-5] for more detailed descriptions of the method.
The user of the Morris method needs to define a model input space (Ω) of interest to be explored by the SA. This k-dimensional input space Ω is comprised by user-defined input parameters x_i for $i = 1,2, \ldots, k$, where k is the number of chosen input parameters to be investigated. For each parameter x_i, the user must define a range of possible values, i.e. a minimum value (x_i^-) and a maximum value (x_i^+), to be explored by the SA. The ranges are subdivided in a user-defined p number of points, denoted *levels*, with a distance Δ between them. Using uniform input distributions, Δ is obtained by dividing the interval in which each input parameter varies (i.e. from x_i^- to x_i^+) into equally large parts. However, the user can also let input parameters follow non-uniform distributions by manually selecting the levels e.g. as the quantiles of the distribution

[9]. Once the user has defined Ω, the Morris method employs a random one-at-a-time (OAT) sampling procedure to generate trajectories through Ω with each trajectory comprising $k+1$ random model realisations from Ω. This sampling procedure is repeated r times, each with randomly dispersed starting points for the trajectories, creating a global set of $r \cdot (k+1)$ building energy models to be simulated. The so-called elementary effect (EE_i) for each input parameter x_i is then calculated from the BEM output for every r set of k+1 models consequently providing r independent and identically distributed estimates of the EEs for each input parameter (Eq. 1).

$$EE_i(x) = \frac{y(x_1,\ldots,x_{i-1},x_i+\Delta,x_{i+1},\ldots,x_k)-y(x_1,\ldots,x_k)}{\Delta} \quad (1)$$

A central assumption in the Morris method is that the distribution of EEs is Gaussian for each input parameter independently, $EE_i \sim N(\mu_i, \sigma_i^2)$. The model output sensitivity to the input parameters can be assessed using the mean of the absolute value of the elementary effects, μ^*_i, for an r set of trajectories (indexed $t=1,2,\ldots,r$) is used for ranking the parameters in order of importance (Eq. 2)[2], while the standard deviation σ_i is used as a measure of the interactions with other parameters and any non-linear effects that the parameter takes part in (Eq. 3).

$$\mu_i^* = \frac{1}{r}\sum_{t=1}^{r}\left|EE_{i,t}\right| \quad (2)$$

$$\sigma_i = \sqrt{\frac{1}{(r-1)}\sum_{t=1}^{r}\left(EE_{i,t}-\mu_i\right)^2} \quad (3)$$

1.2. Literature review

As described in the previous section, the Morris method relies on the ranking of μ^* and σ as measures of input parameter sensitivity. This immediately raised the question: what is the sensitivity of the value of μ^* and σ to the user-defined number of levels (p) and trajectories (r)? A review of the literature where the Morris method has been applied for BEM-based analysis indicated that this concern seems to be rare in existing studies using the Morris method for BEM-based analysis. Table 1 indicates that only very few have arguments for choosing values for p and r; in fact, some authors do not even state the value for p and r used in their analysis. Especially information about p is absent. Heiselberg et al. [10] state that literature recommends a minimum value of r=4 to make sure that the region of variation is reasonably covered for all input parameters, while a value of r=10 is recommended to obtain very reliable results. No considerations regarding the choice of p are provided. More recent studies includes much larger values of r (>100) to a fixed value of p arguing that this is necessary to gain a consistent parameter ranking [7,11-12]. Nguyen and Reiter [13] was the only study found that investigated the sensitivity of their results to different values for p and r. They found that different sets of p and r could result in different parameter rankings, possibly because the random sampling sometimes led to an uneven distribution of input vectors on the designed levels of input parameters. A similar issue related to the random sampling was reported by Menberg et al. [11] who found that the parameter ranking can be biased by the occurrence (or absence) of outliers in individual Morris method runs as a consequence of the low number of r in combination with a comparably large parameter space (number of p is unknown). The findings of Nguyen and Reiter

[2] Eq. 2 is a revision of the original expressions by Morris [3], see Saltelli et al. [9] for details.

[13] and Menberg et al. [11] is aligned with Saltelli et al. [9] who from a general point of view note that the choice of *p* is strictly linked to the choice of *r*. More specifically, Saltelli et al. [9] state that an increase of *r* increases the probability that all levels are explored at least once, and that while a high value of *p* only appears to augment the accuracy of the sampling, it must be coupled with the choice of a high value of *r*; otherwise, many possible levels will remain unexplored. They indirectly suggests the use of *p*=4 and *r*=10 as it has produced good results in previous experiments involving chemical and environmental models [2,14-15]. BEM-based studies like Heiselberg et al. [10] and Kim et al. [16] refers to the experiences of such studies as argument for choosing *p* and *r* for BEM-based analysis. However, the study by Kristensen and Petersen [7] indicates that the ranking of input parameters using the Morris method can be influenced by the choice of BEM. This suggests that the appropriate choice of *p* and *r* may also depend on the model to which the Morris method is applied.

1.3. Scope of this paper

Based on the findings from the review of current literature, we found it necessary to conduct a study on how the choice of *p* and *r* affects the outcome of a SA using the Morris method on a high fidelity BEM[3]. The intention of the study is to provide a guideline for future studies to select the minimum values of *r* for a certain *p* needed for the Morris method to consistently rank input parameters according to their influence on the model output variability of a high fidelity BEM.

[3] The term 'high fidelity BEM' is used to differentiate tools that attempts to model physical behavior with a high level of detail (e.g. EnergyPlus and TRNSYS) from tools relying on more simplified representations of the physics (e.g. linearized hourly models and monthly quasi-steady state models).

Table 1. List of studies reported in literature using the Morris method for BEM-based analysis. Year: year of publication, Purpose: the purpose of using the Morris method, BEM: the building energy model(s) used, Levels and Trajectories: the reported settings used, Arguments: the arguments used for choosing p and r (respectively). N/A means "no argument".

Reference	Year	Purpose	Building Energy Model (BEM)	Levels (*p*)	Trajectories (*r*)	Arguments
de Wit and Augenbroe [17]	2002	Ranking input parameters	ESP-r and BFEP	N/A	5	*p*: N/A, *r*: A crude uncertainty analysis was desired.
Corrado and Mechri [18]	2009		ISO 13790 (quasi-steady state)	N/A	N/A	*p*: N/A, *r*: N/A
Heiselberg et al. [10]	2009		ISO 13790 (quasi-steady state)	4	4	*p*: N/A, *r*: Minimum according to literature [31].
Sanchez et al. [19]	2014		ESP-r	10	10	*p*: N/A, *r*: N/A
Hemsath and Bandhosseini [20]	2015		N/A	4	16	*p*: To enable building orientation in steps of 45° in the sampling, *r*: N/A
Østergaard et al. [21]	2015		ISO 13790 (quasi-steady state)	8	10 (100)*	*p*: N/A, *r*: N/A
Yang et al. [22]	2016		EnergyPlus	N/A	5	*p*: N/A, *r*: N/A
Faggianelli et al. [29]	2017		EnergyPlus	4	20 (200)*	Greater than the recommendations by Saltelli et al. [9]
de Wit [23]	1997	Identifying influential input parameters for more detailed analysis	BFEP	2	3	*p*: N/A, *r*: N/A
Brohus et al. [24]	2009		ISO 13790 (quasi-steady state)	N/A	N/A	*p*: N/A, *r*: N/A
Booth et al. [25]	2012		ISO 13790 (quasi-steady state)	N/A	N/A	*p*: N/A, *r*: N/A
Kim et al. [16]	2013		ISO 13790 (quasi-steady state) and EnergyPlus	4	4	*p* and *r*: Minimum values according to literature [14[16].
Le Drau and Heiselberg [26]	2014		Bottom-up heat balance	8	90	*p*: N/A, *r*: N/A
Yang and Becerik-Gerber [27]	2015		EnergyPlus	N/A	5	*p*: N/A, *r*: To make the analysis efficient.
Østergaard et al. [28]	2015		ISO 13790 (hourly, but simplified)	8	500	*p*: N/A, *r*: To obtain consistent ranking.
Nguyen and Reiter [13]	2015	How ranking of input parameters is affected by SA method	EnergyPlus	4/6/8	49/70	Investigates the effect of combinations of level and samples on BEM outcome.
Kristensen and Petersen [7]	2016		ISO 13790 (quasi-steady state) ISO 13790 (hourly)	5	250	*p*: N/A, *r*: To obtain consistent ranking
Menberg et al. [11]	2016		TRNSYS	N/A	150	*p*: N/A, *r*: To obtain consistent ranking
Kristensen and Petersen [30]	2018		ISO 13790 (quasi-steady state) ISO 13790 (hourly)	4	300	*p*: N/A, *r*: N/A

*This study used the modified sampling method proposed by Campolongo et al. [5] where an initial set of trajectories is reduced prior to simulation.

2. Method

A one-storey office building illustrated in Figure 1 was modelled as one thermal zone in EnergyPlus (EP) [32] using the inputs listed in Table 2. This model was then subject to a SA using the Sobol' method [8], the Morris method [3], and a One-At-the-Time (OAT) method [33], respectively. The quantities of interest for the SA was the energy use per year (kWh/year) for heating, cooling and mechanical ventilation, respectively. The annual simulations were performed using the Danish design reference year [37] and with a simulation time step of two minutes. Execution of the multiple model evaluations in EP needed for the SA analyses was handled using the 'multidirrun' file provided in the EP program folder. The following sections provides further details on these methods and why they are applied in the study.

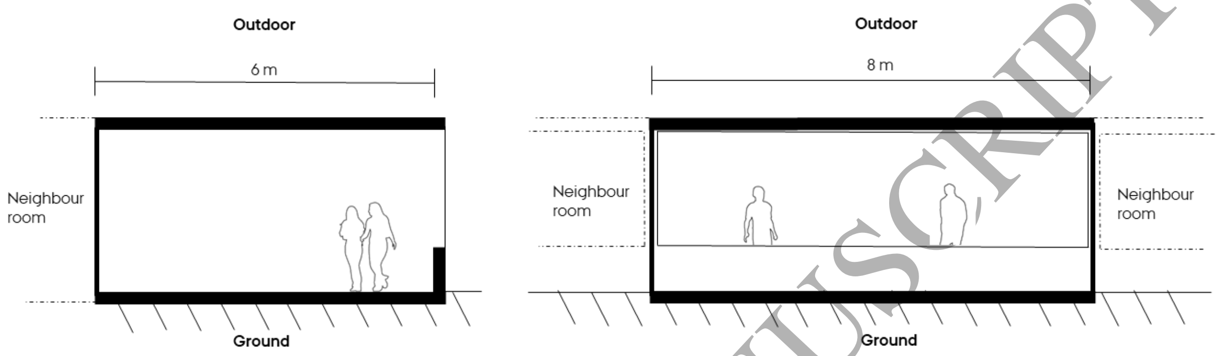

Figure 1. Internal dimensions and boundary conditions for the office building zone. Left: Vertical section of the zone. Right: Front elevation of the façade. The walls facing neighbour rooms are assumed adiabatic.

Table 2. Description of input data to the EP model. Model parameters are defined by fixed and/or variable inputs where variable inputs are subject to SA. The numeric values of the variable inputs are provided in Table 3. The far right column explains the EP modelling assumptions for the model parameter. The heat transfer algorithm used in all simulations is "conduction transfer functions" and a time step of 2 minutes.

	Model parameter	Fixed input	Variable input	Modelling assumptions
Building	North axis	-	Orientation	-
Windows	Area	-	Window-to-façade area ratio	-
	Frame	-	U-value; area fraction of window hole	"Simpleglazing" is used in favour of a more detailed option. It is noted that this method can lead to a minor error in absolute energy use compared to the full spectral method [34]. The total U-value of windows is calculated according to EN ISO 10077-1 [35].
	Glazing	LT is assumed to be a function of glazing SHGC; LT=0.5*SHGC+0.45	U-value; glazing SHGC; frame width; Ψ-value of spacer profile	
	Overhang	-	Length perpendicular out from the facade	The overhang always has the same width as the window, and is always flush with the top of the window.
Constructions	External façade	Bricks: 0.108 m; λ=0.034 W/(mK); ρ=1600 kg/m³; c=840 J/(kg K)	-	-
		Mineral wool: λ=0.037 W/(mK); ρ=200 kg/m³; c=700 J/(kg K)	Thickness of insulation layer	-
		Concrete: 0.1 m	Heat conduction (λ); density (ρ); specific heat capacity (c)	Density ρ is a variable; λ=0.0015ρ-1.5 and c=0.043ρ+830 (derived from DS 418 [36]).
	Floor construction	Mineral wool: λ=0.034 W/(m K); ρ=200 kg/m³; c=700 J/(kg K)	Thickness of insulation layer	Ground modelled as ground-coupled slab model (GroundDomain).
		Concrete: 0.1 m; λ=2.1 W/(m K); ρ=2400 kg/m³; c=1000 J/(kg K)	-	-

		Wood floor: 0.02 m; λ=0.12 W/(m K); ρ=850 kg/m³; c=800 J/(kg K)	-	-
	Roof	Mineral wool: λ=0.034 W/(m K); ρ=200 kg/m³; c=700 J/(kg K)	Thickness of insulation layer	-
		Concrete: 0.1 m; λ=2.1 W/(m K); ρ=2400 kg/m³; c=1000 J/(kg K)	-	-
		Air gap: R=0.17 (m² K)/K	-	-
		Gypsum: 0.013 m; λ=0.16 W/(m K); ρ=800 kg/m³; c=1090 J/(kg K)	-	-
	Internal walls	Concrete: 0.1 m	Heat conduction (λ); density (ρ); specific heat capacity (c)	Density ρ is a variable; λ=0.0015ρ-1.5 and c=0.043ρ+830 (derived from DS418 [36]).
Ventilation	Infiltration	Coefficients: A=0.606; B=0.03636; C=0.117; D=0	Infiltration rate	Infiltration rate is set to vary with air velocity in the meteorological data, and temperature difference between inside and outside.
	Ventilation rate, in-use	-	Ventilation rate (m³/s)	Constant air volume with a constant inlet air temperature of 18 °C.
	Ventilation rate, out-of-use	-	Ventilation rate (m³/s)	Only available in the months Jun-Aug (summer).
	Heat recovery rate	-	Sensible heat recovery effectiveness	-
	Heating set point, in-use	-	Set point	Added directly to the zone air (radiator).
	Cooling set point, in-use	-	Set point	Removed directly from the zone air (chilled beam).
	Heating set point, out-of-use	-	Set point	Added directly to the zone air (radiator).
	Cooling set point, out-of-use	-	-	Cooling not available in out-of-use periods.
	Specific fan power, ventilation	Motor efficiency=0.9; Motor in air stream fraction=0; Fan total efficiency=0.7	Pressure rise (Pa)	The pressure rise is varied to express how different SFP (kJ/m³) affects inlet temperature and thereby heating and cooling load. We derive the pressure rise from the sampled SFP (see Table 3); SFP is fan total efficiency (-) divided by pressure rise (Pa).
	COP, mechanical cooling	-	COP (-)	-
Schedule	In-use, out-of-use periods	In-use: 8:00-17:00, weekdays Out-of-use: remaining hours	-	-
Weather data		Danish Design reference year [37]	-	-
Internal loads	People load	Six persons	-	Auto-calculated sensible heat fraction
	Heat load from appliances, time-in-use	-	W/m²	-
	Standby heat load from appliances, out-of-use	-	W/m²	-
	Lighting (daylight controlled)	-	-	The heat load from daylight controlled lighting systems is omitted from the analysis. However, a fraction of the 'heat load from appliances' could be regarded as a simple representation of this heat load.

2.1. *Sobol' analysis*

The purpose of conducting an SA using Sobol' method was to establish a benchmark for assessing the minimum values of trajectories *r* for a certain level *p* needed for the Morris method to consistently rank input parameters according to their sensitivity to the model output variability. The SA method by Sobol' [8] is a global variance-based method which is able to attribute the total model variance to individual input parameters. The contribution of each parameter in explaining total model variance is often assessed using the so-called first-order effects (S_i) that describe the immediate effect of variations of the parameters independently, and so-called total-order effects (S_{Ti}) that take into account all possible interactions and non-linear effects that the parameters take part in. In this study, the Sobol' sensitivity indices S_i and S_{Ti} was obtained the same way as described by Kristensen and Petersen [7]. We used S_{Ti} to rank input parameters because SA methods which includes higher order interactions in complex models is known to alter parameter rankings based on S_i or μ^*_i [38]. It therefore also seems reasonable to use ranking according to S_{Ti} as benchmark for the performance of the Morris method.
A significant benefit from using Sobol' method for SA is its ability to take into account non-uniform distributions – a feature that the standard Morris method is incapable of by definition. We therefore make use of uniformly distributed PDFs in the Sobol' method to make a fair benchmark for the Morris method. The PDFs for the input parameters are listed in Table 3. A total of $N{\cdot}(k+2)$ model evaluations in EP needs to be calculated where N is the number of samples and k being the number of input parameters. The appropriate number of N relies on user-defined convergence criteria for S_i and S_{Ti}. We found it difficult to formulate a suitable convergence criteria for the quantities of interest in this study (energy use), which is why we decided to generate an immediate large quantity of models using N = 10,000 Latin hypercube samples from the PDFs of the k=24 input parameter listed in Table 3 resulting in 260,000 model evaluations, and then make a qualitative assessment of the convergence issue. The 95% confidence bounds of S_{Ti} were derived using 2,000 bootstrapping samples.

2.2. *Morris analysis*

The principle of the Morris method has been described in section 1.1; this section describes the assumptions used for the Morris analysis in this study. The model input space Ω for the Morris method was defined by the uniformly distributed PDFs of the 24 input parameters listed in Table 3. The original Morris sampling method [3] was applied using r=1,000 for six different values of p (2;4;6;8;10;12), resulting in 25,000 building zone models per level (150,000 simulations in total) for evaluation in EP. This way we are able to assess how an incrementally increasing number of r affects parameter ranking (i.e. μ^*_i listed in descending order) and, consequently, determine the minimum number of r needed for a consistent parameter ranking for different p. The reason repeating the Morris SA for various p is to investigate whether the choice of p affects the outcome of a Morris SA; the chosen p adds p=12 to the range of typical values of p applied in previous studies (see Table 1). It is noted that μ^*_i cannot be used for quantification of the magnitude of parameter influence as one can do based on the S_{Ti} obtained in the Sobol' method.

Table 3. The PDFs of the 24 variable input parameters in the EP model.

Input parameters	Unit	Uniform PDF [Min;Max]

Building orientation	degrees	[0;360]
Room height	m	[2.5;3.5]
Insulation thickness, external walls	m	[0.1;0.35]
Insulation thickness, roof	m	[0.1;0.45]
Insulation thickness, floor	m	[0.1;0.35]
Window-to-façade area ratio	-	[0.15;0.95]
Glazing U-value	W/(m² K)	[0.5;1.0]
Glazing SHGC	-	[0.15;0.6]
Glazing linear loss (Ψ)	W/(m K)	[0.03;0.2]
Window frame U-value	W/(m² K)	[0.8;2.0]
Window frame fraction	-	[0.05;0.25]
Overhang*	m	[0;1]
Ventilation rate, in-use	l/s/person	[4;10]
Infiltration rate	l/s/m² @50 Pa	[0.5;1.5]
Heat recovery rate	-	[0.65;0.9]
Heat load from appliances, in-use	W/m²	[2;10]
Standby heat load from appliances, out-of-use*	-	[0.05;1]
Thermal capacity, inner layer of walls	KJ/m² K	[1200;2400]
Heating set point, in-use	°C	[20;24]
Cooling set point, in-use	°C	[25;27]
Heating set point, out-of-use	°C	[16;20]
Night ventilation rate, summer	l/s m²	[0;2]
Specific fan power (ventilation)	kJ/m³	[0.5;2]
COP (mechanical cooling)	-	[1;5]

*Fraction of 'Heat load from appliances, in-use'.

2.3. *One-At-the-Time method*

The purpose of conducting an OAT analysis was to investigate whether this much less computationally demanding method compared to Sobol' and Morris is able to come up with the same ranking. If so, the use of OAT analysis for SA would be preferable as it is much more computationally efficient; only 49 simulations are required for the case used in this paper. The OAT method used for the analysis reported in this paper was based on partial derivatives where parameters are ranked according to a dimensionless sensitivity index SI_i; see e.g. ref. [7,32] for further details regarding this OAT method.

3. Results

For the Sobol' method, Figure 2-Figure 4 depicts the normalised S_{Ti} for the total energy use, heating only, and cooling only, respectively, as a function of model evaluations in steps of 13,000 (see Appendix A for further details). The figures shows no clear sign of convergence even after 260,000 model evaluations. The reason is that the absolute difference between normalised S_{Ti} of some parameters is marginal (e.g. between the input parameters "Insulation, roof" and "Appliances heat load, in-use" in Figure 2) leading to many shifts in relative ranking as a function of model evaluations.

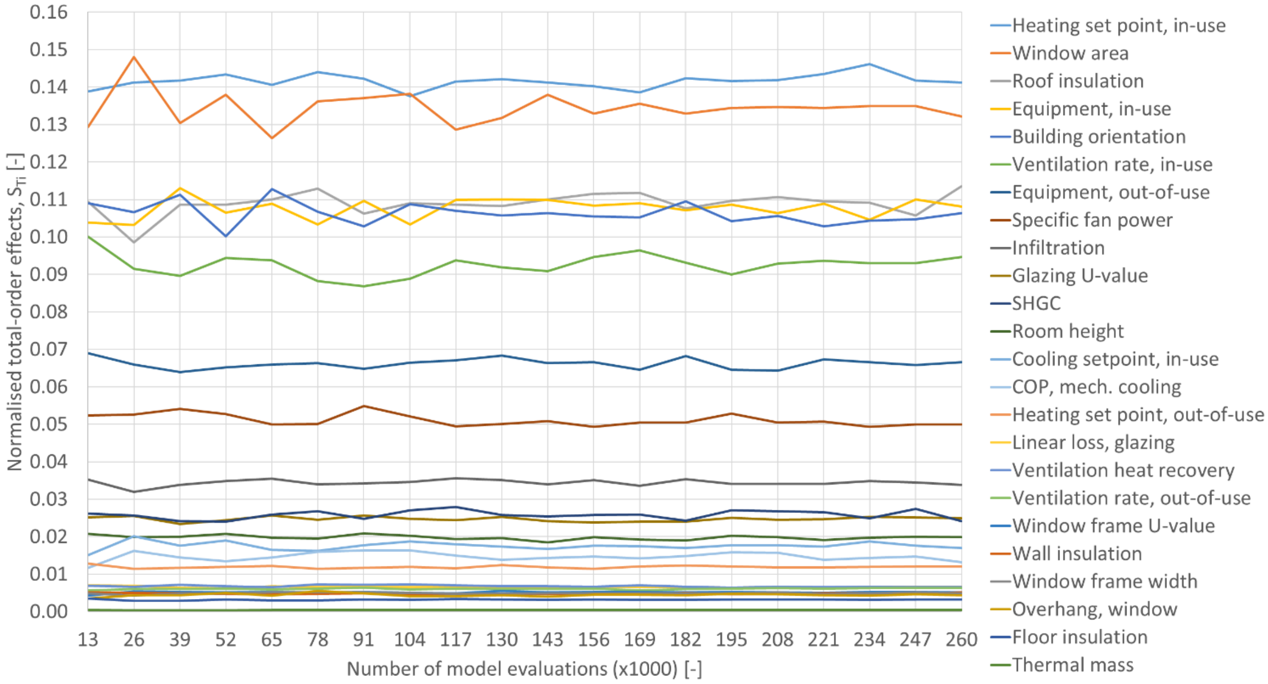

Figure 2. Normalised total-order effects (S_{Ti}) of the total energy use as a function of model evaluations in steps of 13,000. The order of the legend corresponds to the order of the lines in the graph.

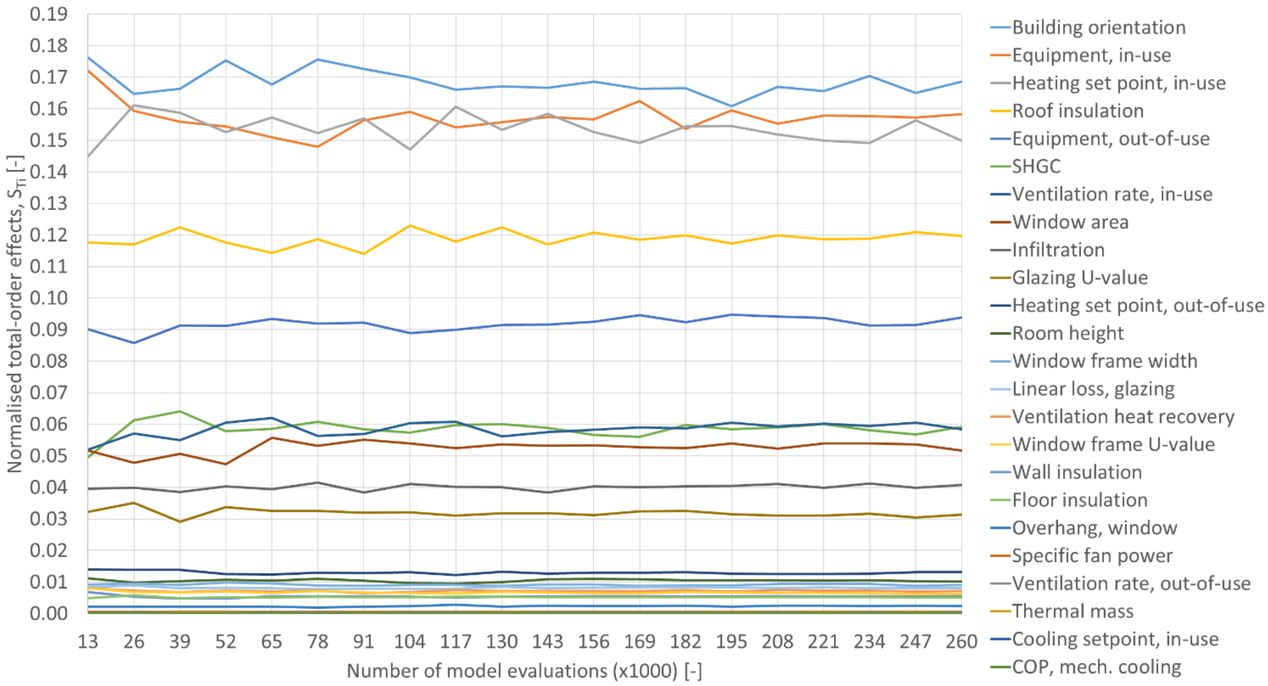

Figure 3. Normalised total-order effects (S_{Ti}) of the heating energy use only as a function of model evaluations in steps of 13,000. The order of the legend corresponds to the order of the lines in the graph.

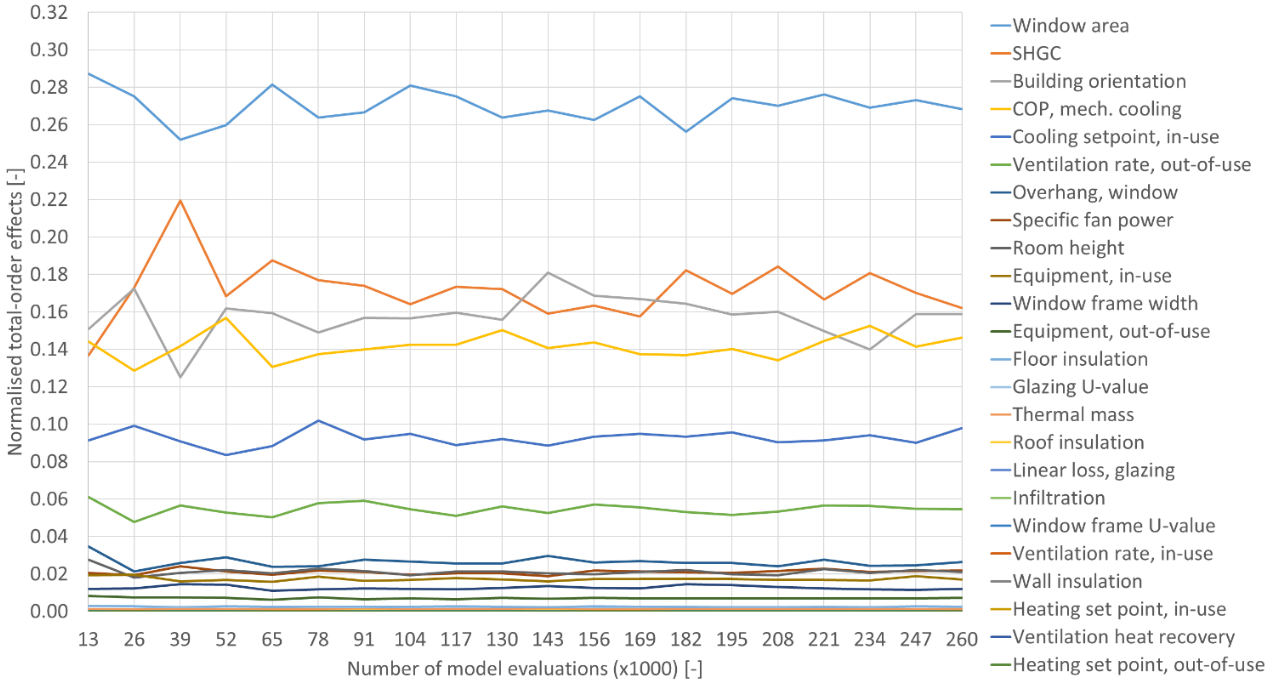

Figure 4. Normalised total-order effects (S_{Ti}) of the cooling energy use only as a function of model evaluations in steps of 13,000. The order of the legend corresponds to the order of the lines in the graph.

For the Morris method, Figure 5-Figure 7 shows the ranking of the 24 input parameters according to their μ^*_i after r=1,000 for all investigated p alongside the ranking obtained using the Sobol' method for the total energy use, heating only and cooling only, respectively (see Appendix B for further details). From these figures it is evident that no matter the value of p, the Morris method using r=1,000 was never able to rank the parameters according to the ranking based on S_{Ti} from the Sobol' method. However, it seems like the Morris method at some point during increasing r was able to consistently identify similar clusters of input parameters most influential to the variability of the model output as the Sobol' method. Our definition of such a 'cluster' is when the Morris method has identified the same group of input parameters as most influential to the variability of the model output as the Sobol' method but not ranked them in the same order. It is also noted that there seems to be a significant rearrangement of the parameter ranking when going from p=2 to p≥4.

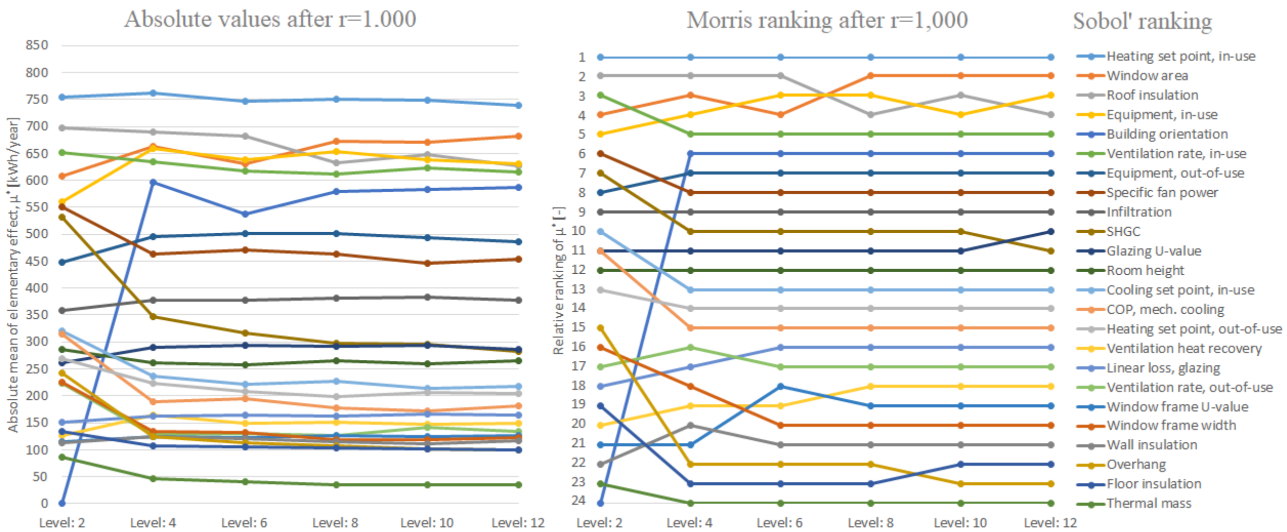

Figure 5. Values of μ^*_i and relative ranking of the 24 input parameters according to their μ^*_i with respect to the total energy use after r=1,000 for all investigated p alongside the ranking obtained using S_{Ti} from the Sobol' method after 260,000 model evaluations. The order of the legend corresponds to the order of the lines in the graph.

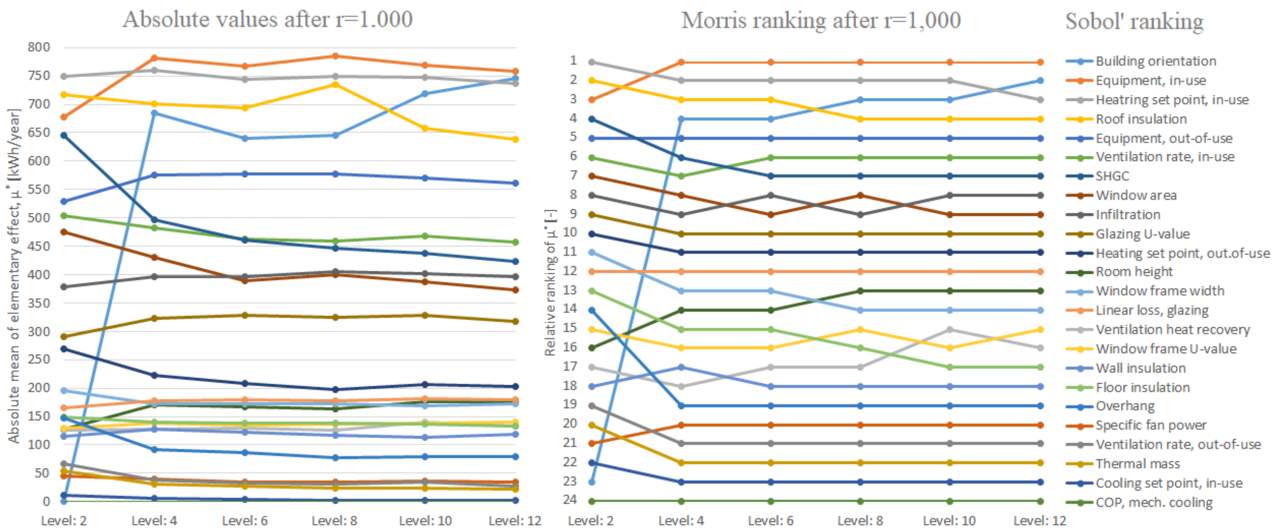

Figure 6. Values of μ^*_i and relative ranking of the 24 input parameters according to their μ^*_i with respect to the heating energy use only after r=1,000 for all investigated p alongside the ranking obtained using S_{Ti} from the Sobol' method after 260,000 model evaluations. The order of the legend corresponds to the order of the lines in the graph.

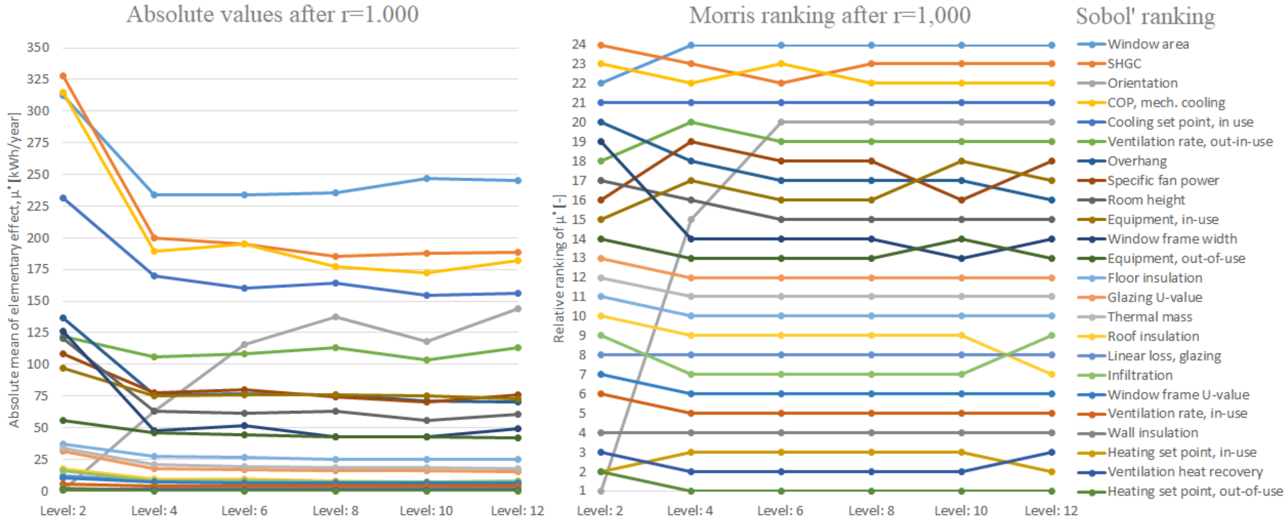

Figure 7. Values of μ^*_i and relative ranking of the 24 input parameters according to their μ^*_i with respect to the cooling energy use only after r=1,000 for all investigated p alongside the ranking obtained using S_{Ti} from the Sobol' method after 260,000 model evaluations. The order of the legend corresponds to the order of the lines in the graph.

Table 4 shows the minimum values of trajectories *r* for all levels *p* needed for the Morris method to identify the same cluster of x_i that the Sobol' method identified as most influential to the variability of the model output. The influence of *p* on the number of *r* needed for a consistent identification varies depending on the type of energy consumption (total, heating, or cooling), and the number parameters included in the cluster of parameters most influential to the variability of the model output (top 1-11). Special for p=2 is that μ^*_i of the parameter 'orientation' was always zero, and consequently never appeared in the top 11 parameters. The reason is that p=2 leads to no actual variation of the orientation as the two levels are the minimum and maximum parameter values, 0° or 360°, respectively, which is both due south by definition. All calculations with p=2 are therefore ignored in further interpretations of the results in Table 4. There is no clear tendency that the number of *p* has any effect on the needed number of *r* for a consistent identification of clusters of parameters most sensitive to the output variability in terms of the total energy use. For heating energy only, there is a tendency that the identification of top 3 input parameters became better with increasing number of *p*. For cooling energy only, there seems to be a slight benefit from choosing p>4. This is probably because the cooling system has non-linear behavior. For all three energy consumptions, the number of *r* needed to consistently identify top 1-11 input parameters for each *p* depends on the absolute difference between μ^*_i for all x_i. For example, the reason that the number of *r* for p=4 for total energy use (see Table 4) increases from nine to 476 when screening for top 6 and top 7, respectively, is that the value of μ^*_i of the seventh and eighth parameter in top 8 are only marginally different up until approx. r=476. Prior to r=476, the two parameters changes ranking position several times, and thereby the content of the top 7 cluster (see appendix B).

Table 4. The number of trajectories needed for the Morris method to consistently identify the same top 1-11 of x_i that the Sobol' method identified as most influential to the variability of the model output. The term 'never' means that the Morris method was not able to identify the parameters after r=1,000 trajectories. The number in brackets in the heading of the columns is the cumulative sum of normalised S_{Ti} according to the Sobol' method. The OAT rows indicate whether the OAT method was able to identify the same top 1-11 as the Sobol' method (Yes/No).

Total energy use	Top 1 (14.1 %)	Top 2 (27.5 %)	Top 3 (38.4 %)	Top 4 (49.2 %)	Top 5 (59.8 %)	Top 6 (69.0 %)	Top 7 (75.7 %)	Top 8 (80.8 %)	Top 9 (84.2 %)	Top 10 (86.9 %)	Top 11 (89.4 %)
p=2	21	never	never	never	never	never	never	never	never	never	never
p=4	108	never	283	137	never	9	476	5	44	15	46
p=6	22	never	never	301	never	27	155	33	97	24	26
p=8	27	286	never	379	never	20	29	44	72	11	11
p=10	29	46	373	634	never	39	113	16	13	572	68
p=12	70	458	never	71	never	56	14	13	9	907	226
OAT	No	No	Yes	No	No	No	No	No	Yes	No	No

Heating energy use	Top 1 (16.9 %)	Top 2 (32.6 %)	Top 3 (47.8 %)	Top 4 (59.7 %)	Top 5 (68.9 %)	Top 6 (74.8 %)	Top 7 (80.6 %)	Top 8 (86.0 %)	Top 9 (90.0 %)	Top 10 (93.1 %)	Top 11 (94.4 %)
p=2	Never	Never	Never	Never	Never	Never	Never	Never	Never	Never	Never
p=4	Never	Never	Never	11	60	Never	8	5	4	6	69
p=6	Never	Never	Never	12	25	881	25	Never	48	5	11
p=8	Never	Never	12	91	43	538	6	334	91	10	6
p=10	Never	Never	113	28	5	31	76	Never	86	6	29
p=12	Never	417	128	19	17	13	307	Never	3	4	46
OAT	No	No	No	No	No	No	No	No	Yes	No	No

Cooling energy use	Top 1 (26.9%)	Top 2 (43.9 %)	Top 3 (59.5 %)	Top 4 (74.0 %)	Top 5 (83.4 %)	Top 6 (88.9 %)	Top 7 (91.5 %)	Top 8 (93.6 %)	Top 9 (95.7 %)	Top 10 (97.4 %)	Top 11 (98.7 %)
p=2	Never	Never	Never	Never	Never	Never	Never	Never	Never	Never	Never
p=4	1	726	Never	Never	Never	Never	Never	Never	Never	100	21
p=6	42	Never	Never	Never	11	34	Never	33	Never	57	12
p=8	30	25	Never	Never	18	Never	308	Never	Never	30	64
p=10	12	101	Never	Never	5	32	Never	Never	Never	Never	Never
p=12	21	93	Never	Never	24	5	Never	Never	Never	Never	Never
OAT	Yes	No	No	No	No	No	No	No	No	No	No

The result of the OAT analysis is also listed in Table 4 and shows that the OAT method was rarely able to identify the same cluster of input parameters to which the model output variability was most sensitive as the Sobol' method (the full outcome of the OAT method is shown in appendix C).

4. Discussion

As stated in the introduction, the aim of this study was to provide a guideline for future studies to select the minimum values of *r* for a certain *p* needed for the Morris method to consistently rank input parameters that has most influence on the model output variability. This aim was partly based on the findings by Kristensen and Petersen [7], which suggested that the Morris method is able to identify the same ranking of the input parameters most sensitive to the output of simplified BEMs as the Sobol' method provided that the PDFs of the input parameters are uniformly distributed. However, results of this study suggests that this is not true for high fidelity BEMs, but it seems to be able to identify clusters of input parameters to which the model output variability is most sensitive. Some overall guidelines for applying the Morris method to identify clusters of input parameters are provided in the following[4].

First of all, choosing $p \geq 4$ seems to lead the analysis towards a more truthful ranking and, consequently, a more reliable identification of most important parameter clusters – especially if orientation of window areas is included in the same way as in this paper. Note that an even higher value of p (closer to p=12) seems to be beneficial if only cooling energy is of interest.
It is difficult to provide an exact recommendation of the number of r needed for an outcome of the Morris analysis similar to the Sobol' method. The reason is that any marginal differences in values of μ^*_i between two parameters means that an excessive number of r is needed for the ranking to converge (see result section). This reason also makes it difficult to predetermine the appropriate size of the cluster of most influential parameters. For example, for total energy use (Table 4) no matter the choice of p>2, it would make sense to have top 6, 8 or 9 in the cluster containing the most important parameters – but e.g. not top 5 as μ^*_i of the sixth parameter is always close to the fifth, and not top 7 as it is difficult to determine which parameters are actually belonging to this cluster. It is noted that this is not only an issue for the Morris method; the ranking according to the Sobol' method is also sensitive to the absolute difference between indices (S_{Ti}). The value of the individual S_{Ti} should therefore also be listed to enable a qualitative assessment on how many of the ranked input parameters that would be appropriate to highlight as most sensitive to the model output variability according to the Sobol' method.
The uncertainty of parameter ranking from the Sobol' method seem to defeat the whole purpose of using the Sobol' method to benchmark the ranking from Morris method. This is why it seems more reasonable to use the Morris method – and even the Sobol' method – to identify a certain clusters of most influential input parameters rather than attempting to obtain a true ranking of the input parameters. Based on the results of this study, the recommended approach for the identification of a cluster of most influential input parameters using the Morris method is to1) generate models for r=1,000 (or more) but start by simulating only a fraction of the models, e.g. for the first r=100 models, 2) calculate and plot μ^*_i for the quantity of interest for all x_i as a function of r like in appendix B, and 3) make a qualitative (visual) assessment of whether the values of μ^*_i have converged to a degree where it seems possible to determine a cluster for the most influential parameters. It is noted that one should not have a predetermined cluster size for the most influential parameters prior to this qualitative assessment but decide how many parameters to include during the qualitative assessment. If μ^*_i seems not to be converged, then simulate the performance of the next e.g. r=100 models, update the plot of μ^*_i for the quantity of interest for all x_i as a function of r, and make a new qualitative assessment. Repeat this process until μ^*_i seems converged. A similar approach could also be used for the Sobol' method to investigate convergence of S_{Ti} and appropriate cluster size.

[4] The guidelines are only considered valid for a Morris analysis using uniform PDFs and sophisticated BEMs.

The above recommendation for the Morris method suggests a step of r=100 in the attempt to obtain convergence of μ^*_i. This is far from what is commonly used for similar analyses using high fidelity BEMs (see Table 1); here r between five and ten is often used, which corresponds to the recommendations provided in the fundamental literature describing the Morris method [2,14-15]. This may change the notion of Morris being a computationally efficient method for parameter screening. One model evaluation of the EP model used in this study takes approx. 1 minute, which leads to a total calculation time of approx. 42 hours for a model with 24 variable input parameters and r=100 (2,500 model evaluations). It is therefore of practical interest to reduce the number of r needed for a reliable Morris SA as this also would reduce computational time. One option that could be investigated in future studies is to rank the input parameters according to the median value of *EE*s, as findings by Menberg et al. [11] indicated that ranking based on median values converges after fewer numbers of r compared to ranking based on mean values. Another option could be to use the modified sampling method suggested by Campolongo et al. [5] who claims that this method is always to be preferred over the original Morris sampling method as it reduces the number of model executions needed for a reliable analysis.

We acknowledge that the use of different weather data, a different set of input parameters and/or different PDF ranges may lead to different rankings than the ones observed in this study, but the above recommendations is in this regard considered to be on the safe side. Furthermore, this study made use of EnergyPlus for model evaluations but it seems like many prefer to use more simplified BEMs (Table 1). A future study could be to repeat the study of this paper using simplified BEMs for model evaluations. In this relation, it would also be relevant to analyse the consequence of different BEM approaches on input parameter ranking as the study by Kristensen and Petersen [7] indicates that it can be influenced by the choice of BEM.

5. Conclusion

The intention of this study was to provide a guideline for future studies to select the minimum values of trajectories (r) for a certain level (p) needed for the Morris method to consistently rank input parameters according to their influence on the model output variability of a high fidelity BEM when compared to parameter ranking using the Sobol' method. Results indicates that the Morris method is not able to replicate the ranking from Sobol' method no matter the choice of r and p. The reason is that ranking according to the Morris method as well as the Sobol' method is quite sensitive to marginal absolute differences in the metric used for ranking. Consequently, it is not possible to provide guidelines for future studies with precise values for r and p as intended. However, the study enables us to provide some guidance on how to produce a reliable SA using the Morris method.

The Morris method may not be able to generate a reliable ranking of input parameters but it is able to identify the same cluster of input parameters – i.e. groups of unranked input parameters – most sensitive to the model output variability as the Sobol' method. However, reliable identification of such clusters seems to require significantly more r than usually applied in studies featuring the Morris method. Furthermore, users must not be predetermined on the size of the parameter cluster prior to the analysis; instead, one must make a visual assessment of the convergence of the parameter ranking to qualitatively determine the size of parameter cluster.

The need for more *r* may question the general notion that the Morris method is a computationally efficient screening method in terms of absolute time use, but it is still much more computational efficient than a Sobol'-based analysis. A simple one-at-the-time method, which can be regarded the best sensitivity analysis method in terms of computational efficiency, was also tested; however, it did not produce clusters comparable to the outcome of the Sobol' or Morris method.

6. Acknowledgement

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Appendix A. Sobol' method

The figures A.1-A.3 below depicts the outcome of the Sobol' analysis, i.e. the total-order effects (S_{Ti}) for each input parameter for the total energy need (heating+cooling+ventilation), heating energy only, and cooling energy only, respectively. S_{Ti} for energy for ventilation only is not displayed because it only is linearly affected by the input parameter 'Ventilation, in-use', 'Ventilation, out-of-use', and 'Specific fan power'.

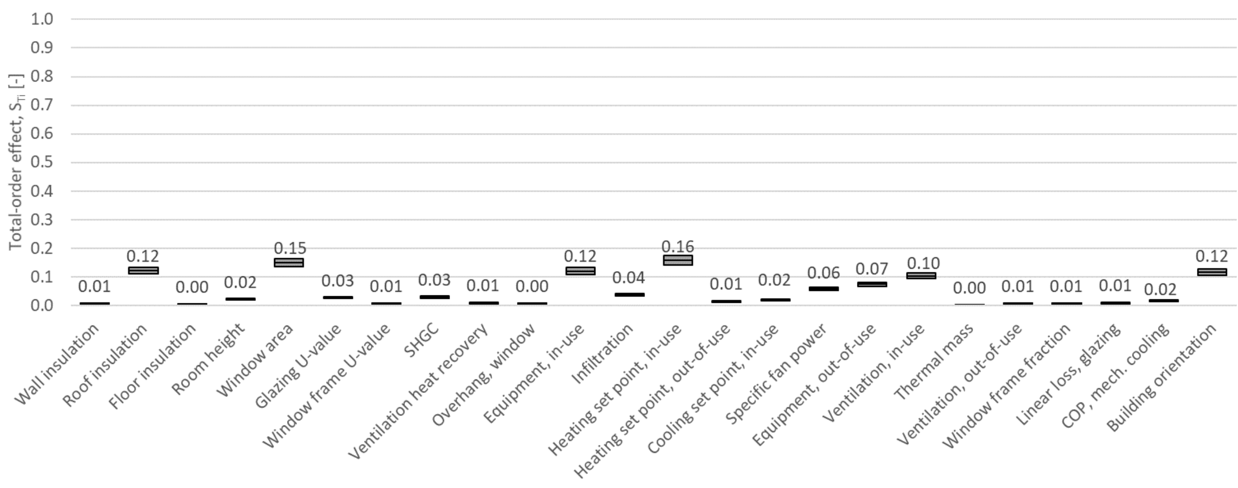

Figure A.1. Total-order effects (S_{Ti}) for each input parameter for the total energy need (heating+cooling+ventilation) after 260,000 model evaluations. Boxes indicate the 95% confidence intervals around the mean value (black line).

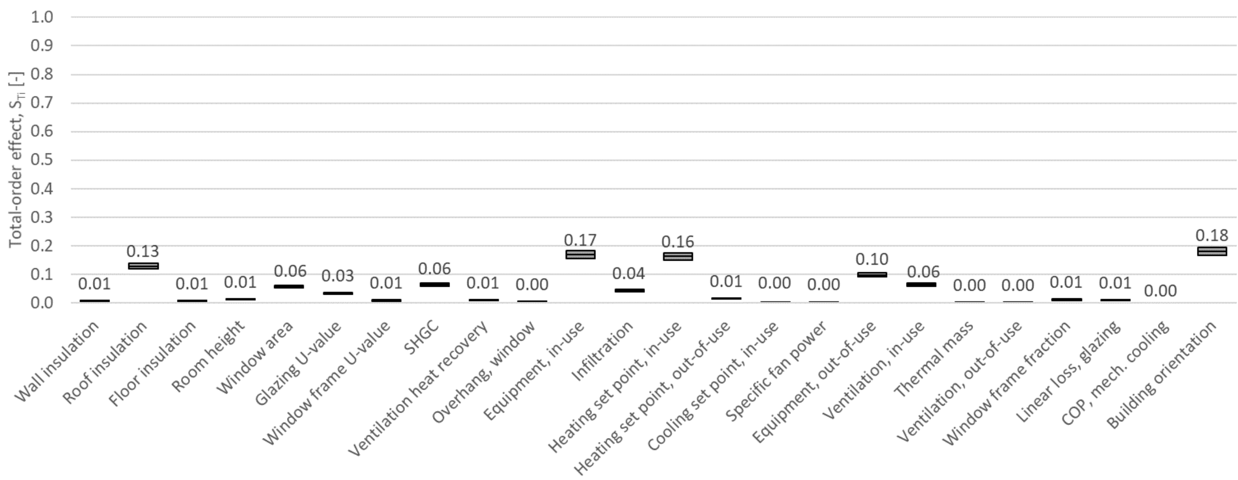

Figure A.2. Total-order effects (S_{Ti}) for each input parameter for the heating energy only after 260,000 model evaluations. Boxes indicate the 95% confidence intervals around the mean value (black line).

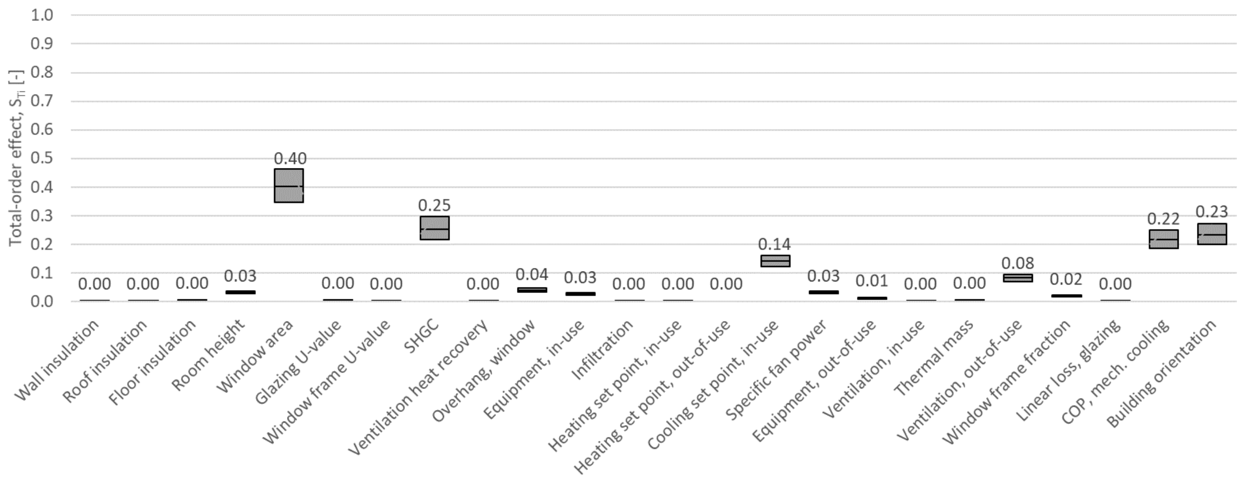

Figure A.3. Total-order effects (S_{Ti}) for each input parameter for the cooling energy only after 260,000 model evaluations. Boxes indicate the 95% confidence intervals around the mean value (black line).

Appendix B. Morris method

Figure B.1-B.3 illustrates for every p the evolution of μ_i on the total energy need (heating+cooling+ventilation), heating only, and cooling only, respectively, for all x_i as a function of r. The evolution of μ^*_i on ventilation is not displayed because the value of μ^*_i for all of the 24 input parameters is not affected by r>1.

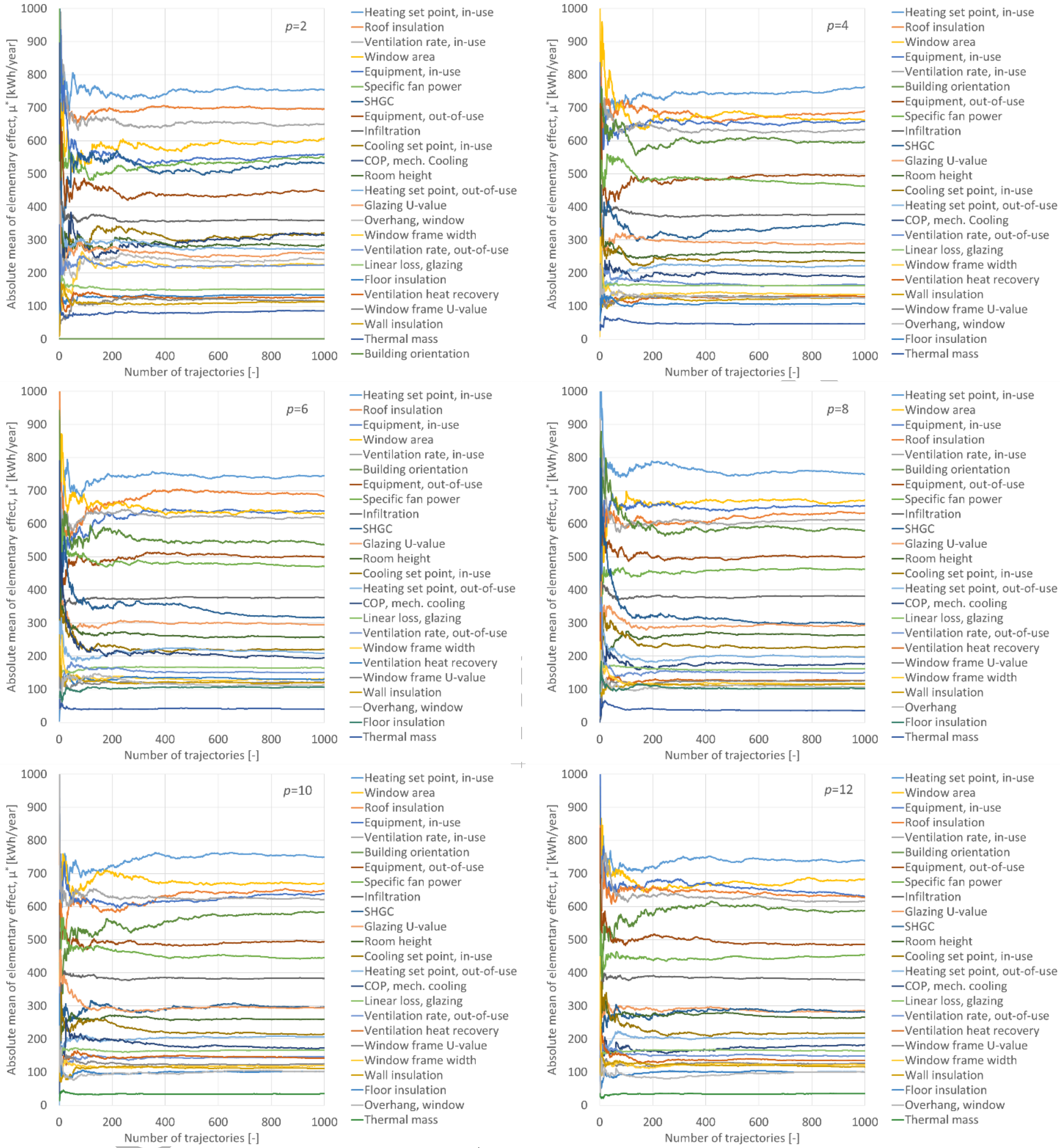

Figure B.1. The evolution of mean elementary effect (μ^*_i) on the total energy need (heating+cooling+ventilation) for all measures (x_i) as a function of the number of trajectories (r) for six different levels (p). The order of the legend corresponds to the order of the lines in the graph.

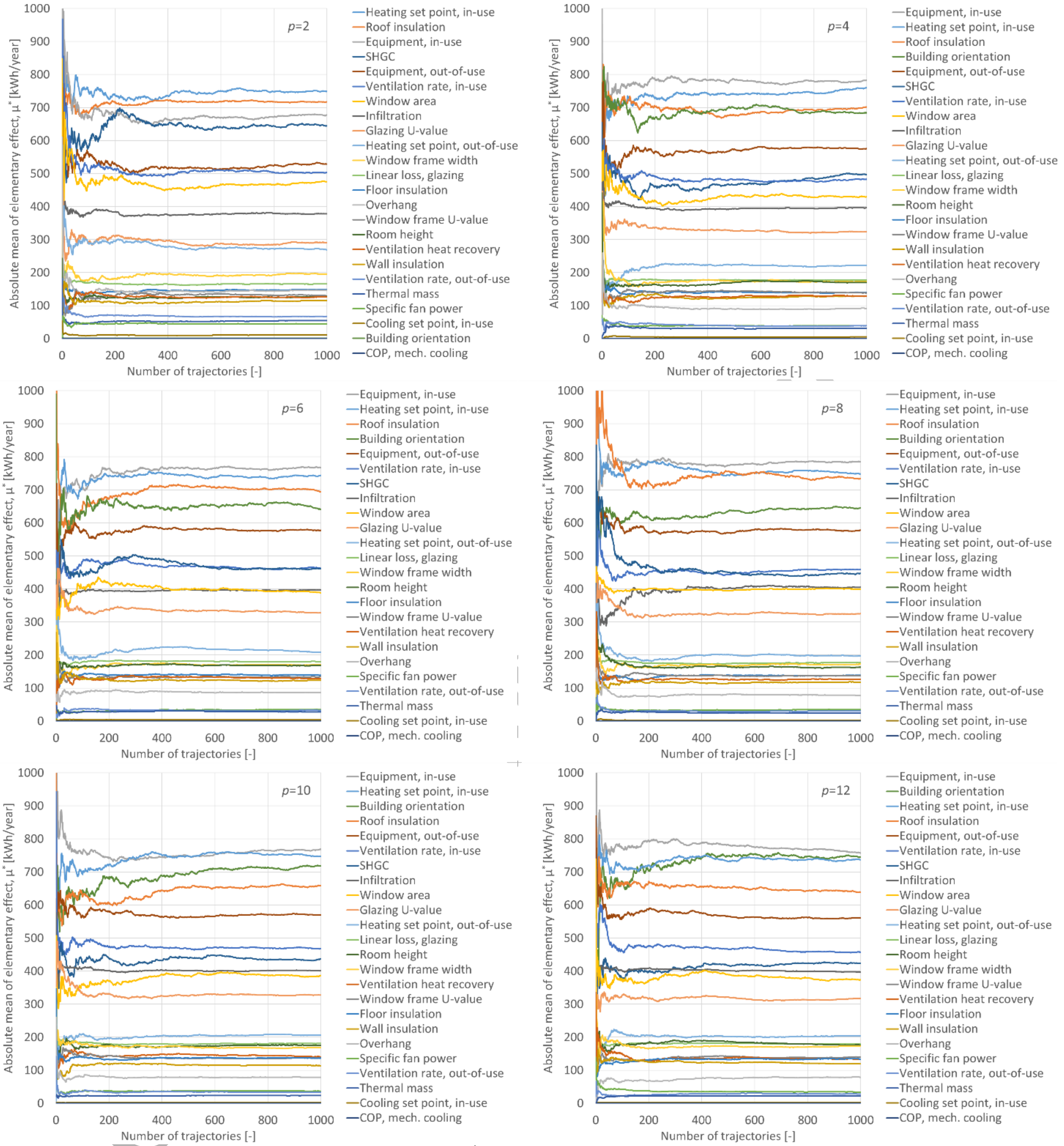

Figure B.2. The evolution of mean elementary effect (μ^*_i) on the heating energy need for all measures (x_i) as a function of the number of trajectories (r) for six different levels (p). The order of the legend corresponds to the order of the lines in the graph.

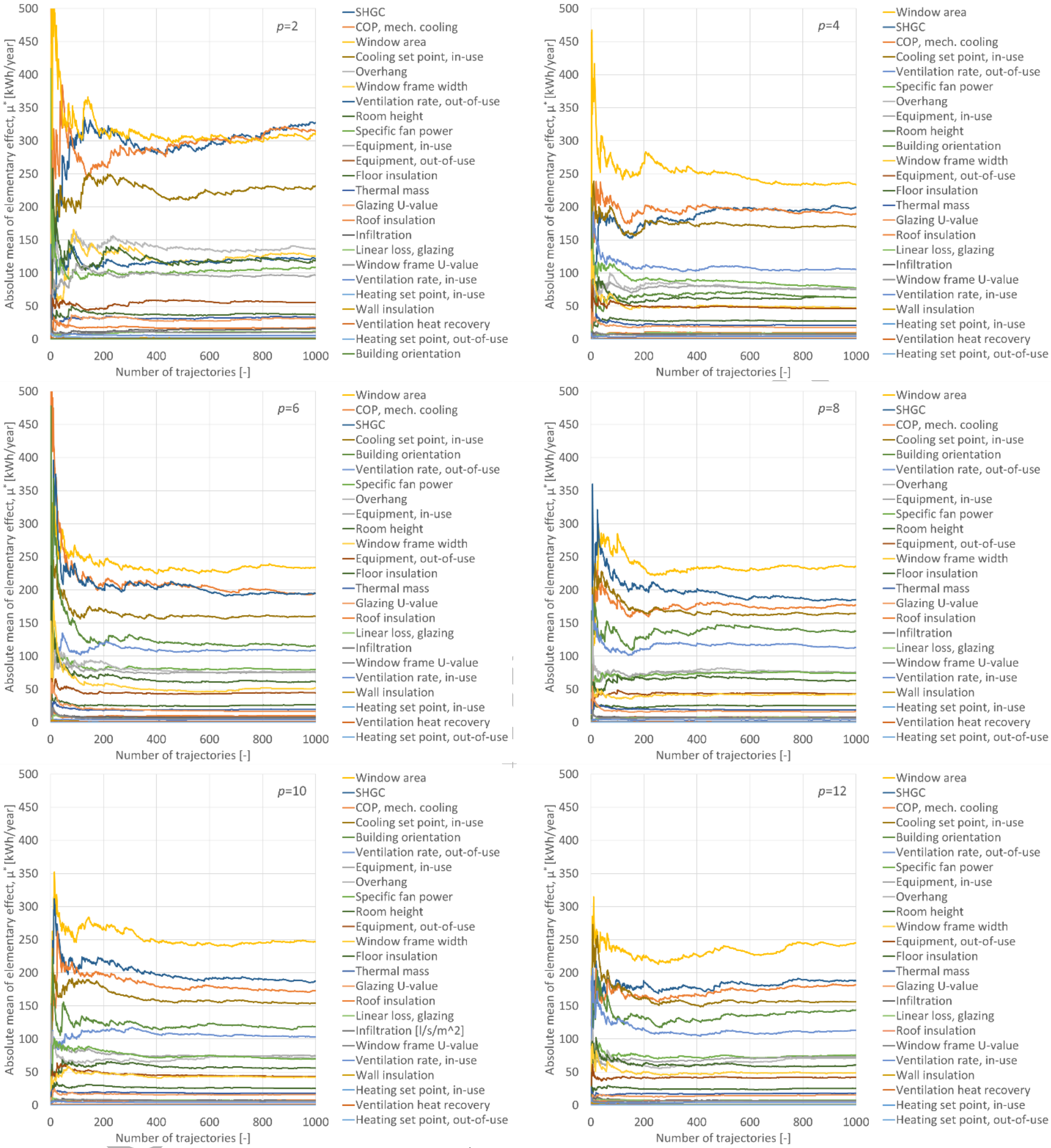

Figure B.3. The evolution of mean elementary effect (μ^*_i) on the cooling energy need for all measures (x_i) as a function of the number of trajectories (r) for six different levels (p). The order of the legend corresponds to the order of the lines in the graph.

Appendix C. Local method

Table C.1 lists all input parameters ranked according to the sensitivity index, SI_i, calculated OAT based on the partial derivative of the model output for total energy use (heating+cooling+ventilation), heating only, and cooling only.

Table C.1. Ranked sensitivity indexes (SI_i) for all input parameters calculated OAT based on the partial derivative of the model output.

Total energy		Heating energy only		Cooling energy only	
Input Parameter	SI_i	Input Parameter	SI_i	Input Parameter	SI_i
Window area	1.064	Window area	0.932	Window area	4.127
Roof insulation	0.622	Roof insulation	0.858	Cooling set point, in-use	1.607
Heating set point, in-use	0.553	Heating set point, in-use	0.765	SHGC	1.364
Equipment, out-of-use	0.388	Equipment, out-of-use	0.614	COP, mech. cooling	1.333
Infiltration	0.300	Infiltration	0.428	Ventilation rate, out-of-use	1.333
Specific fan power	0.290	Building orientation	0.413	Overhang	0.628
Building orientation	0.262	Equipment, in-use	0.375	Specific fan power	0.597
Ventilation rate, in-use	0.244	Ventilation rate, in-use	0.238	Equipment, in-use	0.488
Equipment, in-use	0.216	SHGC	0.238	Equipment, out-of-use	0.483
Wall insulation	0.160	Linear loss, glazing	0.226	Building orientation	0.324
Linear loss, glazing	0.152	Wall insulation	0.224	Window frame width	0.315
Cooling set point, in-use	0.136	Glazing U-value	0.191	Floor insulation	0.299
Glazing U-value	0.128	Floor insulation	0.180	Thermal mass	0.228
Floor insulation	0.096	Ventilation heat recovery	0.127	Roof insulation	0.129
Ventilation heat recovery	0.092	Room height	0.119	Linear loss, glazing	0.080
COP, mech. cooling	0.085	Heating set point, out-of-use	0.116	Glazing U-value	0.071
Heating set point, out-of-use	0.084	Window frame width	0.096	Infiltration	0.059
Room height	0.079	Window frame U-value	0.080	Ventilation rate, in-use	0.048
Window frame U-value	0.054	Overhang	0.045	Room height	0.046
Ventilation rate, out-of-use	0.036	Thermal mass	0.026	Window frame U-value	0.030
Window frame width	0.035	Specific fan power	0.020	Wall insulation	0.019
Overhang	0.031	Ventilation rate, out-of-use	0.009	Ventilation heat recovery	0.006
SHGC	0.028	Cooling set point, in-use	0.000	Heating set point, in-use	0.003
Thermal mass	0.002	COP, mech. cooling	0.000	Heating set point, out-of-use	0.000

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