NEW EXTENSION OF MORRIS METHOD FOR SENSITIVITY ANALYSIS OF BUILDING ENERGY MODELS

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ABSTRACT

Sensitivity analysis is commonly used in numerical modelling to identify those inputs that have a large impact on model outcomes. We scrutinise the Morris method, known to be computationally efficient for parameter screening, through a case study. This paper demonstrates that the current Morris method with the absolute mean as measure of parameter ranking yields unstable results. We show that using the median value, which is less sensitive to outliers, yields more robust parameter rankings for evaluations with small sample sizes. The performance of the improved Morris method is validated against the variance-based sensitivity analysis. We also investigate correlations between elementary effects and parameter values and find that they can be efficiently used to identify higher-order parameter interactions from a single set of samples used in the Morris method.

INTRODUCTION

With various types of simulation software packages available, building energy models have become useful and easy-to-employ tools for a broad spectrum of applications, such as estimating potential reductions in the heating and cooling demand of buildings for retrofit options or system performance optimisation, and exploring options for energy supply systems at the design stage (Foucquier et al., 2013). Many input parameters of these models are associated with a certain degree of uncertainty due to simplifications and assumptions made in the models and lack of knowledge about the exact parameter values. Hence, sensitivity analysis of model parameters represents an important step in the modelling process in order to increase the confidence in the model results (Campolongo et al., 2007, Mara and Tarantola, 2008, Saltelli et al., 2008).

A comprehensive overview on different sensitivity analysis methods used in building energy analysis is presented by Tian (2013) including a detailed description of the theoretical framework of each method and of existing studies applying specific methods. A widely used method for parameter screening is the Morris method, which provides a qualitative measure to rank parameters according to their effect on the model outcome (Morris, 1991, Campolongo et al., 2007). In combination with the factorial sampling plan proposed by Morris (1991), it offers a good compromise between accuracy and efficiency and represents a suitable screening method for larger parameter sets in computationally intensive models (Tian, 2013, Garcia Sanchez et al., 2014). Variance-based sensitivity methods, on the other hand, use larger Monte Carlo or quasi-random Latin hypercube samples (LHS) of uncertain parameters and consequently require more computational time, but the results from these methods provide quantitative information.

Though some form of parameter screening or sensitivity analysis is usually applied to building energy models, there are few studies that investigate the performance of sensitivity analysis methods in relation to dynamic, high-order or non-linear behaviour and the high level of uncertainty in building energy models (Mara and Tarantola, 2008). Indeed, model inputs associated with the physical building characteristics and its operation often exhibit large ranges of uncertainty, which are likely to affect the sample size needed to obtain robust sensitivity results. In this study, we scrutinise the Morris method through a case study using the TRNSYS simulation model. The performance of Morris method is investigated with different numbers of trajectories to identify the number of trajectories needed for a robust ranking of the parameters. In addition, we propose an extension to the standard Morris method to improve the robustness of the parameter ranking without an increased number of trajectories. Results obtained from the Morris method are compared to a quantitative sensitivity measure, the Sobol's total effects sensitivity index, with regard to the parameter ranking and differentiation of important and non-influential parameters. In addition, we explore different ways for the characterisation of second-order effects, particularly by using correlation coefficients derived from the results by the Morris method and comparing them with second-order effects obtained with the Sobol method.

CASE STUDY

To test the performance and applicability of the methods we use the Architecture Studio building at the University of Cambridge as a case study, particularly the first floor area used for the undergraduate design studio (325 m^2). The energy model of the building is set up using the commercial software package TRNSYS (Version 17.02) and evaluated to estimate the annual heating demand of the Studio room, which is used as the quantity of interest in the sensitivity analysis. The annual heating demand for a given set point temperature is calculated by the building component (Type 56) in TRNSYS using actual weather data from 2013. Internal heat gains are defined in the building component by daily schedules for occupancy, lighting and appliances, such as computer and laptops.

The natural ventilation rate is calculated by taking into account air exchange through the windows due to an indoor-outdoor pressure difference induced by wind pressure Q_w (Rijal et al., 2007, ASHRAE, 2013) and due to thermal buoyancy effects Q_{th} (Larsen and Heiselberg, 2008), and applying superposition of Q_w und Q_{th} according to the ASHRAE Handbook (ASHRAE, 2013).

$$Q_w = C_v(f_{win} \cdot A)(U \cdot r_w) \quad (1)$$

$$Q_{th} = C_D\,(f_{win} \cdot A)\sqrt{2g\,dH_{NPL}\,(T_i - T_o)/T_i}\,, \quad for\; T_i > T_o \quad (2)$$

$$Q_{th} = C_D(f_{win} \cdot A)\sqrt{2g\,dH_{NPL}\,(T_o - T_i)/T_o}\,, \quad for\; T_o > T_i \quad (3),$$

With measured outdoor temperature T_0, measured wind speed U and indoor temperature T_i, which is equal to the set point temperature in TRNSYS Type 56. Window area A, fraction of window area for air inlet f_{win} and height of neutral pressure level dH_{NPL} are building characteristics. Qw and Qth are calculated in a MATLAB component in TRNSYS and the overall ventilation rate is an input to the building component.

For the sensitivity analysis, we select 11 uncertain parameters in our TRNSYS model (listed in Table 1) to enable detailed analyses with manageable computational effort. The uniformly distributed uncertainty ranges for these parameters are intentionally defined rather broad in order to examine the performance of the methods under unfavourable conditions that correspond to applications with limited information about the actual parameter values.

The definition of the ranges for set point temperature and infiltration rate is based on typical ranges obtained from the literature (Heo et al., 2012, Garcia Sanchez et al., 2014). The ranges for the radiative proportion of the heating system (which defines whether heat supply from the radiator to the room is dominated by radiative or convective heat transfer), thermal capacitance, and internal heat gains were set as ± 50% of the values suggested in the TRNSYS model based on the specific characteristics of the building. The ranges for uncertain parameters related to the calculation of the natural ventilation rate (see above) are derived from the literature used for setting up the ventilation model (Rijal et al., 2007, Larsen and Heiselberg, 2008, ASHRAE, 2013). In addition, we create a 'test parameter' to test the ability of the sensitivity methods to detect parameters with no influence on the model output when potentially strong parameter interactions are present in the model. We select dH_{NPL} as a 'test parameter', which is varied in the sample matrix, but intentionally fixed in the natural ventilation model (see equations 2 & 3) for computing model predictions for Morris and Sobol method.

Table 1: List of parameters and assigned uncertainty ranges used for the sensitivity analysis. Lower and upper outputs for the annual heating demand are calculated with the corresponding lower and upper bounds of each parameter and assigning average values to the remaining inputs. Output ranges were calculated as the difference between each lower and upper output, respectively.

Parameter	**Lower bound**	**Upper bound**	**Unit**	**Lower output (kJ/year)**	**Upper output (kJ/year)**	**output range (kJ/year)**
All parameters				1.29×10^8	2.32×10^9	2.19×10^9
Set point temperature	18	22	°C	2.32×10^8	1.43×10^9	1.20×10^9
Radiative proportion of heating system	0.2	0.6	-	6.25×10^8	1.27×10^9	6.48×10^8
Discharge coefficient	0.5	0.8	-	5.98×10^8	1.17×10^9	5.69×10^8
Infiltration rate	0.10	1.25	h^{-1}	1.18×10^9	7.29×10^8	4.49×10^8
Thermal capacitance	500	50000	kJ/K	1.24×10^9	7.93×10^8	4.44×10^8
dH_{NPL}	0.5	0.7	m	6.99×10^8	8.80×10^8	1.81×10^8
Wind reduction factor	0.2	0.6	-	7.40×10^8	9.08×10^8	1.67×10^8
C_v variation	-0.1	0.1	kJ/h	7.80×10^8	8.04×10^8	2.39×10^7
Occupant heat gain	0.5	52.9	kJ/h	7.93×10^8	7.92×10^8	3.10×10^5
Appliances heat gain	0.7	40.6	kJ/h	7.93×10^8	7.92×10^8	2.37×10^5
Artificial lighting heat gain	0.01	5	kJ/h	7.93×10^8	7.93×10^8	2.95×10^4

Table 1 includes a preliminary assessment of the influence of each parameter on the model output by calculating the annual heating demand using the lower and upper bounds for each parameter, respectively, while taking the mean values of the remaining parameters. This represents a basic form of differential sensitivity analyses in which one parameter value changes in the model with using the base values for the other parameters.

The range of the heating demand for each parameter gives a rough estimate for parameter importance although it does not explore parameter interactions within the whole parameter space. The resulting ranges suggest heating related parameters (set point temperature and radiative proportion of the heating system) are the most influential parameters, followed by ventilation related parameters (discharge coefficient, dH_{NPL}, wind reduction factor, etc.), while internal heat gains (occupants, appliances, lighting) have a minor impact on the heating demand.

METHODS FOR SENSITIVITY ANALYSIS

Parameter screening with Morris method

Morris (1991) proposed an efficient parameter screening method in combination with a factorial sampling strategy in order to identify parameters that can be fixed at any value within their range without affecting the variance of the model outcome $V(Y(\boldsymbol{X}))$. For sampling, the parameter space is discretized by transforming the k input parameters into dimensionless variables in the interval (0;1) 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 (Morris, 1991). 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 trajectory is used to compute the magnitude of variation in the model output due to the pre-defined variation of one parameter X_i while keeping the other parameters constant. This output is called elementary effect (EE) (Morris, 1991):

$$EE_i = \frac{Y\left(X + e_i \Delta_i\right) - Y(X)}{\Delta_i} \quad (4)$$

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 Sanchez et al., 2014).

One trajectory yields one elementary effect for each parameter i, and a set of t trajectories forms the finite distribution of the elementary effects, which allows for a statistical summary of the overall importance of individual parameters. Statistical measures commonly used for the evaluation of the EEs include the absolute mean μ^* (Campolongo et al., 2007) and the standard deviation σ (Morris, 1991):

$$\mu^*_i = 0.5 \sum_{t=1}^{r} |EE_{it}| \quad (5)$$

$$\sigma = \sqrt{\frac{1}{(r-1)} \sum_{t=1}^{r} (EE_{it} - \mu_i)^2} \quad (6)$$

where the index t indicates a set of multiple trajectories. The criterion μ^* indicates the magnitude of influence of a parameter on the model outcome and is often used to rank the parameters according to their importance. The standard deviation σ is a measure for the spread in the model outcome, which is referred to as “interaction effect”. It indicates that the magnitude of influence of a parameter is dependent on the values of the other parameters, and can be interpreted as a measure for non-linearity and parameter interactions (Morris, 1991). This measure explains the overall effect of parameter interactions on the individual parameter importance but is not able to pinpoint parameters that have a high interaction effect with a certain parameter. Although the measure μ^* is often used in literature to identify influential parameters, it is technically a measure to identify ‘unimportant’ or not negligible parameters (Campolongo et al., 2007).

Variance-based sensitivity indices

Variance-based sensitivity methods offer quantitative measures for parameter sensitivity with regard to the overall model variance. A frequently used variance-based sensitivity measure is the total effect index (Homma and Saltelli, 1996, Saltelli and Tarantola, 2002):

$$S_{T_i} = \frac{E_{X_{\sim i}}\left(V_{X_i}(Y|\boldsymbol{X}_{\sim i})\right)}{V(Y)} \quad (7)$$

The total effects index S_{Ti} measures all effects involving the factor X_i, i.e. first-order effect and higher-order effects due to parameter interactions. As indicated by the inner conditional variance operator in eq. 7 the calculation of S_{Ti} is performed by varying the values for X_i over the entire parameter space and keeping all other parameters fixed. Accordingly, the total effects index is a measure to identify unimportant parameters, i.e. parameters that can be fixed at any value within their uncertainty ranges without affecting the variance of the output significantly (Saltelli and Tarantola, 2002).

Variance-based sensitivity analysis can also provide detailed measures that quantify the effect of parameter interaction within a certain parameter subset on the variance in the model output: for instance, the second-order effects S_{ij} for parameter pairs (Saltelli et al., 2008):

$$S_{ij} = \frac{V_{X_{ij}}\left(E_{X_{\sim ij}}\left(Y|X_i, X_j\right)\right)}{V(Y)} - S_i - S_j \quad (8)$$

The S_{ij} measure represents the fraction of variance in the model outcome caused by the interaction of parameter pair (X_i, X_j).

The sensitivity indices S_{Ti} and S_{ij} can be estimated by Sobol’s method (Sobol′, 2001), which is implemented in this study by Monte Carlo integration. The sample matrices are generated by applying Latin hypercube sampling to ensure a good coverage of the parameter space. With $(k+1)*N$ model evaluations needed for the measure S_{Ti}, a sample size of $N = 500$ and $k = 11$ parameter result in 6000 simulation runs required for the calculation of S_{Ti} (Saltelli et al., 2010). The additional estimation of the second-order indices S_{ij} for all 55 pairs of 11 parameters require $k*(k-1)/2*N$ model evaluations, which add up to additional 27,500 simulation runs.

RESULTS AND DISCUSSION

Parameter screening with Morris method

Figure 1 summarises 10 independent evaluations of Morris method with 10 trajectories per evaluation. The points in Figure 1 plot the average of the 10 absolute mean values $\mu*$ and standard deviations σ of the elementary effects for each parameter. The error bars indicate the overall range of $\mu*$ and σ values.

In this study, the highest $\mu*$ values are found for the set point temperature and thermal capacitance. Another group of parameters with slightly lower values includes radiative proportion of the heating system, discharge coefficient and infiltration rate, while the remaining parameters show a negligible effect on the heating demand. Regarding dH_{NPL} set up as a 'test parameter', the Morris method with the factorial sampling plan yields zero values for $\mu*$ and σ. This shows that Morris method is able to identify (un)important parameters in the presence of other parameters that have the similar effect on the model output. This feature makes the method usable to identify errors in the model or parameter settings. Overall, the ranking in Figure 1 is in good agreement with the differential sensitivity analysis estimates from Table 1, except thermal capacitance that plays a significant role in determining the effect of the other parameters. By accounting for parameter interactions, the Morris method identified thermal capacitance as the second dominant parameter in comparison to the differential sensitivity analysis method, which ranks it as the fifth. According to a classification scheme proposed by Garcia Sanchez et al. (2014) the ratio $\sigma/\mu*$ allows the characterisation of the model parameters in terms of (non-)linearity, (non-)monotony or possible parameter interactions (Figure 1). In our building simulation model almost all parameters exhibit a $\sigma/\mu*$ ratio > 1, which suggests that most parameters exhibit either non-linear behaviour, interaction effects with other parameters or both.

Another observation from Figure 1 is that the results from the Morris method regarding both $\mu*$ and σ vary significantly across the 10 individual evaluations as indicated by the large error bars. Small variations in the results of the $\mu*$ and σ values, especially for a low number of trajectories, are expected because they depend on the absolute values of the elementary effects, which vary with the randomly picked parameter combinations in each trajectory. The overlapping error bars in Figure 1 however indicate that parameter rankings are not consistent across the 10 independent evaluations.

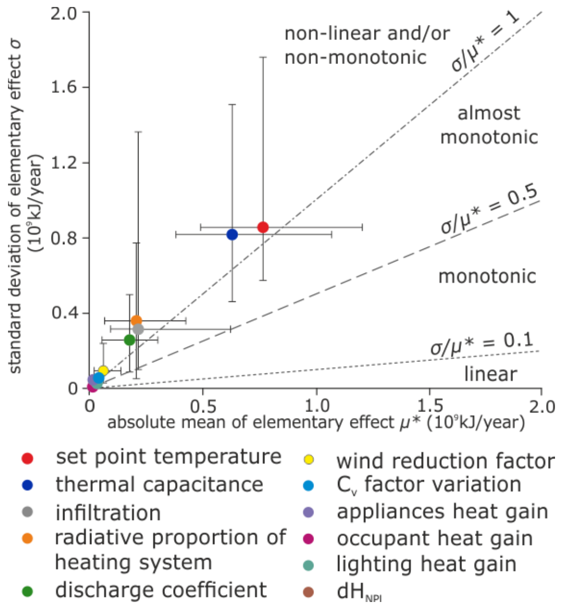

Figure 1: Results for parameter screening with Morris method from 10 screening runs with 10 trajectories each assigning the parameter ranges from Table 1.

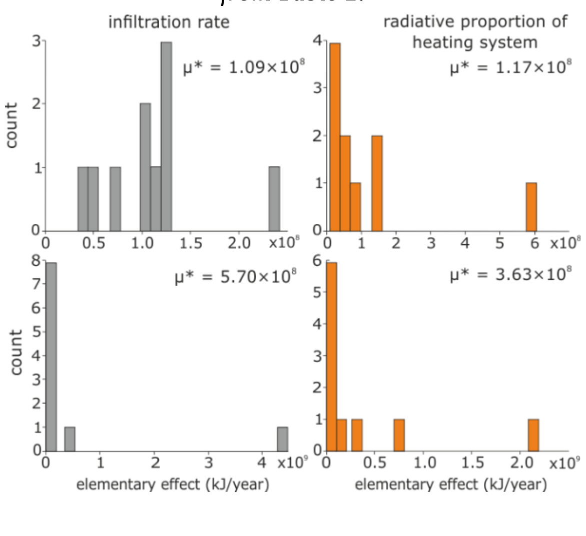

Figure 2: Four examples for histogram plots out of the 10 independent runs of Morris Method with 10 trajectories each, showing the distribution of absolute elementary effect values for the infiltration rate and the radiative proportion of the heating system, and the resulting values for the absolute mean value μ.*

To investigate the cause for this inconsistency in parameter rankings we analyse the elementary effects (EE) defined by the Morris Method (equation 4) in more detail. Figure 2 shows two sets of histograms of the EEs obtained from two runs of the Morris method. Each set shows the distribution of EEs for two parameters: infiltration rate and radiative proportion of the heating system. The corresponding value of μ^* per parameter (equation 7) is also listed in Figure 2.

If one were to use the μ^* value as the measure for overall parameter importance, the radiative proportion of the heating system would be identified as the more influential parameter from the results of one run of the Morris Method (shown in the top two histograms). However, results obtained from a second run would rank the infiltration rate as more influential (the two lower histograms in Figure 2). All the histograms show distributions that are discontinuous, with frequently occurring outliers. Figure 2 indeed demonstrates that parameter rankings obtained by the Morris method can be biased by the occurrence (or absence) of outliers and the resulting skewness in the EE distributions.

This varying occurrence of outliers in individual Morris method runs is a consequence of the low number of trajectories in combination with a comparably large parameter space (Table 1), which results in a low number of sampled EEs per parameter. The most intuitive solution to overcome this issue is to increase the number of trajectories so that the resulting EE distributions become more continuous and presumably more robust.

Figures 3(a)–(b) show results obtained from Morris method runs by incrementally increasing the number of trajectories from 10 to 150. Figures 3(a) plots the absolute mean values μ^* and figure 3(b) plots the relative ranking per parameter for each Morris Method run.

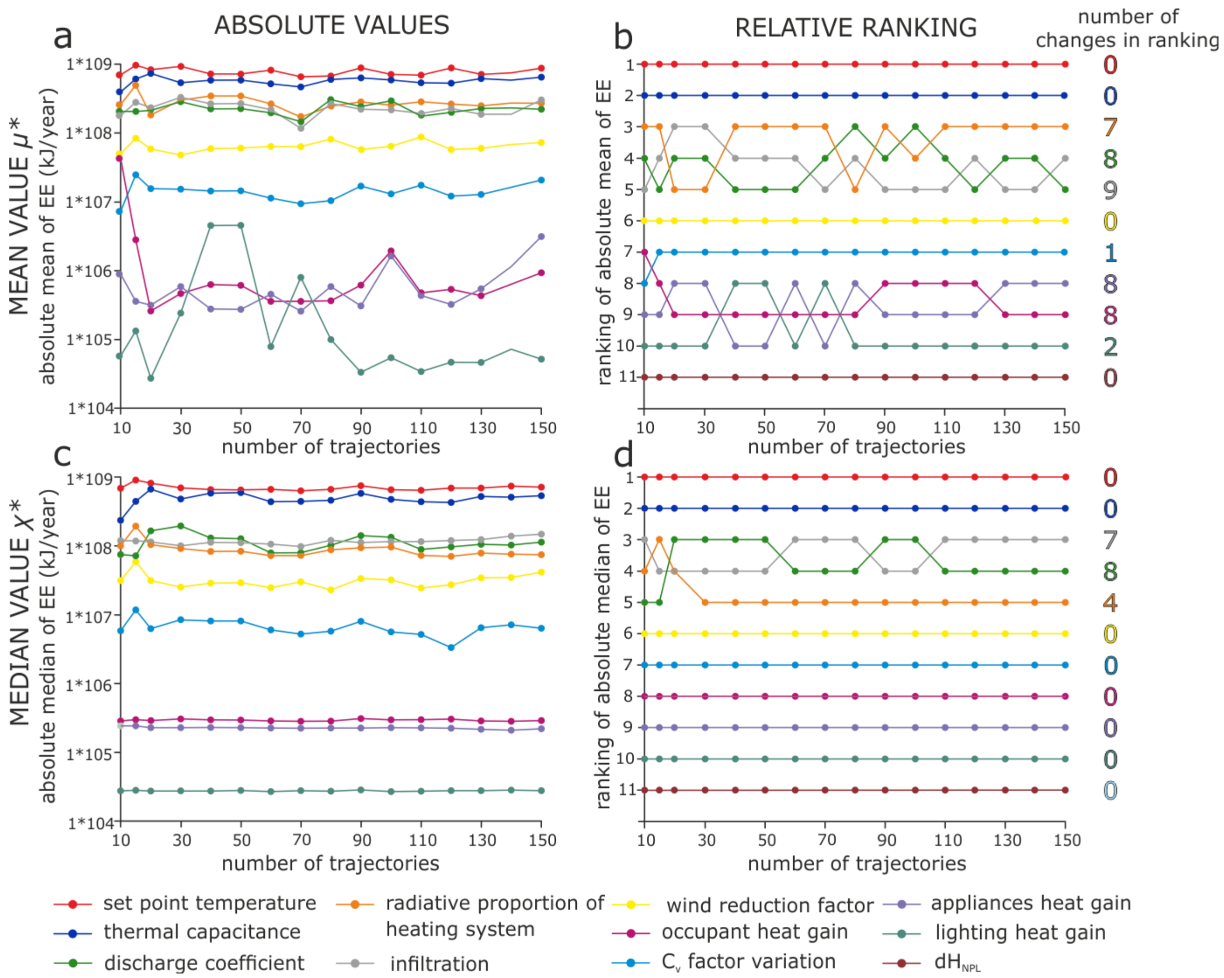

Figure 3: Comparison of Morris method results for an increasing number of trajectories, showing absolute values (a, d) and the resulting ranking of parameters (b, d) using the mean value of the elementary effects (a, b) and the median value (c, d). The numbers on the right-hand side indicate the number of changes in the ranking, taking the most often occurring rank as base rank.

Note in figures 3(a) and 3(b) that variations in μ^* result in different parameter rankings also for evaluations with large numbers of trajectories, though it seems that the changes become less frequent for runs with more than 120 trajectories. Changes in parameter ranking are particularly frequent for the following three parameters: radiative proportion of the heating system, discharge coefficient, and infiltration rate. This might be due to the fact that increasing the number of trajectories results in less discontinuous EE distributions, but does not tackle the problem of their skewedness. Moreover, increasing the number of trajectories by large amounts would undermine the advantage of the Morris method, which is designed to allow for parameter screening with low computational costs.

Another alternative solution to this problem is to explore a more robust measure for the evaluation of the elementary effects: one that is less influenced by the type of distribution of the EE and by outliers. Instead of using the absolute arithmetic mean we suggest the use of the absolute median χ^* to characterise the EE distribution. The median of a certain number of data samples is defined as the number dividing the total number of ordered observations in half, which is recognised as a robust measure of location for skewed distributions with much reduced influence of outliers on the final results (Dunn and Clark, 2009). The median values for the four EE distributions in Figure 2 are 1.12×10^8 and 1.09×10^8 kJ/year for the infiltration rate and 5.11×10^7 and 5.46×10^7 kJ/year for the radiative proportion of the heating system for the two runs of Morris method shown in Figure 2. Indeed, using the absolute median χ^* as a measure of elementary effect results in the same ranking of the two parameters in both Morris method runs, with the infiltration rate being rated more influential than the radiative proportion of the heating system.

In order to assess the performance of the absolute median χ^* in comparison to μ^* Figures 3(c) and (d) show the χ^* values and the resulting parameter rankings derived from the same trajectories used for calculating the mean values (Figure 3a and b). The rather straight lines for each parameter in Figure 3c indicate that the χ^* values across the individual evaluations are quite similar in contrast to the varying μ^* values in Figure 3a. This is particularly obvious for the less important parameters, such as heat gains from appliances, occupants and electric lighting. As the result, the rankings of the parameters based on the median value (Figure 3d) are much more consistent regardless the number of trajectories than those with the μ^* values (Figure 3c). As suggested by the number of changes in ranking on the right side of the figure, use of the median value provides a robust ranking of most parameters with a reduced number of trajectories. Differences in the ranking of discharge coefficient, radiative part and infiltration rate are observed because their absolute values of χ^* are so similar that ever minor variations in the χ^* values can cause a change in the ranking (Figure 3c); which indicates that these three parameters have a very similar influence on the model outcome.

Variance-based sensitivity indices

Figure 4 shows the results for variance-based sensitivity analysis with the Sobol's method. The total effects index S_{Ti} identifies five parameters as clearly non-negligible (set point temperature, thermal capacitance, radiative proportion of the heating system, infiltration rate and discharge coefficient). Wind reduction factor is almost negligible and the other parameters are clearly negligible. The test parameter dH_{NPL} is assigned a very low S_{Ti} value with no impact on the model output. Hence, it is correctly identified as an unimportant input parameter. Overall, the Morris method and the Sobol's method with total effects yield quite similar parameter rankings regarding the non-negligible parameters. In addition, clusters of model parameters distinctly grouped by the S_{Ti} values are also consistent with the results from the Morris method using the median value (shown in Figure 3c).

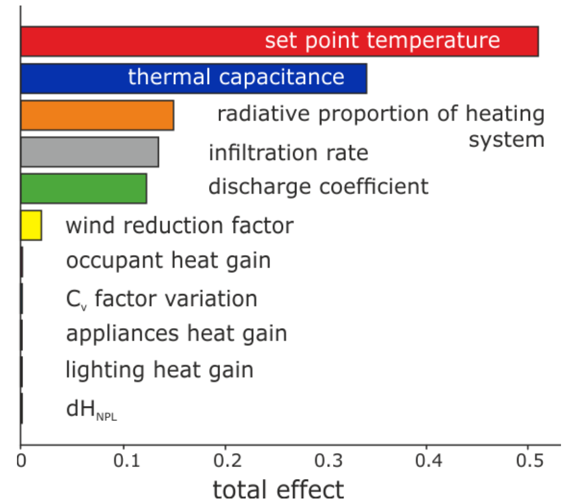

Figure 4: *Results for total effects with Sobol's method showing the values for* $S_{Ti.}$

Second-order effects

Sobol second-order effects provide a measure to evaluate the interaction effect of parameter pairs on model output. However, as the calculation of Sobol second-order effects requires large number of model runs. Thus, the approach may not be feasible to investigate parameter interactions for computationally expensive models with a large number of parameters. Alternatively, we explore a more efficient way to investigate the interaction effect between two parameters by utilising the results generated from the Morris method. For a given pair of two parameters, Morris (1991) suggests evaluating the correlation coefficient of the first parameter (its value) with the elementary effect (EE) of the other parameter as an indication of second-order effects. The correlation coefficient of each parameter pair is calculated twice: (a) the elementary effect of the first parameter with value of the second parameter, and (b) vice versa.

Although the calculation of the correlation coefficients for a pair of two parameters is computationally trivial, one needs a rather large number of trajectories to interpret the correlations meaningfully. Therefore, we use the input parameter matrices and their corresponding EEs obtained from sensitivity analysis runs ranging from 50 to 150 trajectories to compute the corresponding Pearson's correlation coefficients. As a result, we now have matrices of correlation coefficient per sensitivity run. We then select from these results the coefficients with a p-value < 0.005 to calculate the average of the absolute correlation coefficients for each parameter pair. Table 2 lists the average correlation coefficients of the top six parameter pairs obtained from this process and the corresponding Sobol second order indices, ordered by the highest S_{ij} values.

Both the Sobol second-order S_{ij} and the correlation coefficients identify the parameter interaction between the set point temperature and the thermal capacitance as the most significant. In addition, results indicate that infiltration rate and discharge coefficient have significant interactions with both set point temperature and thermal capacitance.

Table 2: Second-order sensitivity indices S_{ij} from Sobol method for parameter couples with S_{ij} > 0.20 and average absolute correlation coefficients between elementary effects and parameter input values from Morris method.

Parameter couple	**second-order sensitivity index S_{ij}**	**average of correlation coefficient**
set point temperature – thermal capacitance	0.54	0.41
set point temperature – discharge coefficient	0.34	0.39
thermal capacitance – radiative proportion of heating system	0.33	0.38
thermal capacitance – infiltration rate	0.29	0.33
set point temperature – infiltration rate	0.26	0.32
thermal capacitance – discharge coefficient	0.24	0.17

It should be noted that the two measures need to be interpreted differently as per the method used. High S_{ij} values indicate larger effect of simultaneous variation of two parameters on changes in the model outcome than the sum of changes caused by equivalent variations of the parameters. A high positive correlation coefficient, on the other hand, indicates that, e.g. by increasing thermal capacitance values, the change in the heating demand due to an incremental change in the set point temperature also increases, and vice versa. While higher S_{ij} values were observed for 6 parameter couples (Table 2), not all of them exhibit a significant correlation coefficient. This difference may be due to outliers in the elementary effects that may cause correlations to be cancelled out. The latter can be easily resolved by inspecting the data used for the calculation and applying a rule to sort out outliers, but more work may be needed to ensure robust results. Nevertheless, given the number of trajectories used in this exercise, all parameter pairs showing a statistically significant correlation also exhibit a significant S_{ij} value.

CONCLUSION

An in-depth assessment of the Morris method in the context of analysing a building energy model revealed that parameter rankings, obtained by using the absolute mean value μ^* of the elementary effects as a criterion, are potentially unstable. This is especially the case when parameter ranges are large and non-linear parameter behaviour or high parameter interactions occur (these features are common in building energy models). We show that, for a low number of trajectories, the use of the median value χ^* increases the robustness of parameter ranking. When two or more parameters exhibit very similar χ^* values, the ranking of the parameters still varies across the independent evaluations. However, slightly different rankings within a cluster of parameters with very similar χ^* values would not bias the ranking process. In our case study, 10 trajectories are sufficient to get a robust ranking when the median value is used, which was confirmed by the rankings obtained by the Sobol Method (variance based sensitivity analysis). Furthermore, the distribution of the relative differences between individual χ^* values is very similar to the differences in the quantitative sensitivity indices obtained from Sobol total effects. Another advantage of Morris method is that parameters with absolutely no influence on the model outcome are clearly identified (with zero value of the elementary effect).

In summary, by using median values to quantify the elementary effect of parameters, the computationally more efficient Morris Method is able to provide consistent parameter rankings in comparison to the more intensive Sobol method. An additional advantage attributed to Sobol method is that it also quantifies higher-order effects associated with model parameters, albeit at high computational costs. We show that it is possible to also estimate some higher-order effects from the outputs of the Morris method. We do so by correlation analysis of parameter values against their elementary effect, although the results need to be further tested for robustness and stability. As such, the correlation analysis represents a useful technique to identify parameter interactions in a model at no additional computational costs.

NOMENCLATURE

A,	area of window openings (m^2);
f_{win},	fraction of window area for air inlet (-);
C_D,	discharge coefficient (-);
C_v,	effectiveness of window openings (-);
dH_{NPL},	height neutral pressure level (m);
g,	gravitational acceleration (m/s^2);
r,	wind reduction factor (-);
T_i,	indoor air temperature (°C);
T_o,	outdoor air temperature (°C);
Q_{th},	air flow rate due to wind pressure (m^3/s);
Q_w,	air flow rate due to thermal buoyancy effect (m^3/s);
U,	measured wind speed (m/s);

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