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ORIGINAL RESEARCH PAPER

Morris method supporting building optimization

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ABSTRACT

As part of the energy design synthesis method, complex dynamic building simulation database was created with IDA ICE code for all family house building configurations for a considered problem. In this paper, the annual heat energy demand output parameter is considered to serve as basis of a building energy design investigation. The sensitivity analysis performed by Morris' elementary effect method was used. As the result of the sensitivity analysis of the output parameter, the most important input parameters can be identified, that influence the buildings' energy efficiency, that can support further building designs.

KEYWORDS

sensitivity analysis, elementary effect, Morris method, sampling strategy

1. FAMILY HOUSE

Design of buildings has a key role in the world's energy consumption and due to the negative environmental impacts caused by the building industry sustainable buildings frequently gain focus recently. In this relation, the process of building energy and climate responsive design represents a key factor. For energy issues see for example [1], and for nature-based solutions consider for example [2]. Unfortunately, conventional building design method in industry practice generates only one or a very limited number of concepts, based on previous experience. This is often supported by the fact, that architects consider the artistic side of design more important than complex building physics simulations and complicated mathematical models to be evaluated from the beginning of the design. Thus, when the architectural plan is ready, i.e., the building body shape together with the space organization or layout are ready as the most fundamental design features, and the technical apparatus is designed subsequently.

Energy design method [3] integrates some of these high-level engineering calculations to implement a sustainable architectural design. The method includes some heuristic building simulations, quantifying the chosen design concepts. As its extension, Energy Design Synthesis (EDS) method is a unique technique ensuring optimal buildings performing highest energy efficiency while offering best comfort. A family house geometry case was considered,

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where the house was constructed from 6 building blocks. First geometry generation rules were determined to generate all feasible and potentially optimal building configurations for a family house class. For these 167 configurations as accepted geometries, 5010 complex dynamic thermal simulations were performed, i.e., all the configurations were modeled and the family houses were fully generated within IDA ICE code. Please note that during the simulations two different structures including isolation as main building property were considered: one meeting the minimum standards of a family house, while the other is close to a passive house. Further, the simulations included 3 wall-window ratios and 5 orientations. From the simulation data, the annual heating energy demand as output parameter and some input parameters were selected for further investigations. Based on the results of the simulations, the most influential parameters and their dependencies were identified.

2. SENSITIVITY ANALYSIS

Generally, sensitivity analysis is used to identify the important parameters together with their relations, i.e., the individual importance of the selected design variables as well as their joint-effect is measured and evaluated. In other words, it is the study of how uncertainty in the output of a model can be apportioned to different sources of uncertainty in the model input. A sensitivity analysis determines the contribution of the individual design variable to the total performance of the design solution. As a result the dynamics of the variables can be investigated. Note that the effects may vary widely, therefore the order of importance is also significant. Further, individual, as well as aggregate influence occurs. For building design it is of importance, since architects will understand the underlying coherence between the input parameters of a building and its output annual energy demand. Therefore, already in the first building shape and layout design step expert decisions can be made that has direct significant influence on energy consumption sustainability.

Sensitivity Analysis (SA) methods can be classified for example in the following way:

(i) global sensitivity methods consider multiple design parameters;
(ii) local sensitivity methods evaluate the output variability based on the variation of a single design parameter; and
(iii) screening methods consider usually two extreme values on both sides of the standard value for selected design parameters to evaluate, which design parameters the building performance is significantly sensitive to.

Some local SA applications consider model parameters as varying inputs, and aim at assessing how their uncertainty impacts model performance [4]. Applications often apply One-At-a-Time (OAT) approach where the sample is constructed in a way that between two sampling points the influence of only one input variable is considered while all other variables remain constant; individual influences of the output variable are examined. In other words OAT design is called when only one parameter changes values between consecutive simulations, i.e., how the output value changes in case only one input variable changed and the other variables remained or considered to be constant. On the other hand, SA applications often consider interactions between the input variables also when examining the influence of the input variables on the output. In general, global SA sampling is more often performed by All-At-a-Time (AAT) approach, where all the input factors are varied simultaneously. As a consequence, the sensitivity to each input variable considers the direct influence of that factor as well as their joint influence.

It is one of the most important elements of the models to consider the distribution of the input variables. Frequently, well-known distributions describe the input variables, for example uniform, normal, lognormal, or Weibull distribution. However, in practice many variables describing the models are not continuous and their distribution cannot be described in this manner.

Here, Morris Elementary Effect (MEE) method is used [5], when the effect of the change along the adequately scale of OAT randomly selected variable is measured. This can be well applied with a larger number of variables also as a sampling based method.

If $y(x_1, x_2, \ldots, x_k)$ is an output parameter, depending on the $x_1, x_2, \ldots, x_k$ input parameters, then elementary effect corresponding to the i-th variable can be defined as Eq. (1). Note that Morris suggested $p = 6$ and $\Delta = p/(2\cdot(p-1))$ where the number of levels within the grid is denoted by p. However, this Δ is suitable, where the variables are continuous, and the sampling can be based on the discretization of the continuous variables. The sensitivity measure can be defined as Eq. (2), and further instead of mean μ_i, the mean of the absolute value of the elementary effects μ_i^*, introduced by [6], can be defined as given in Eq. (3). Note that r is the number of trajectories,

$$d_i(x) = \frac{y(x_1, x_2, \ldots, x_{i-1}, x_i + \Delta, x_{i+1}, \ldots, x_n) - y(x_1, x_2, \ldots, x_{i-1}, x_i, x_{i+1}, \ldots, x_n)}{\Delta}, \tag{1}$$

$$\mu_i = \frac{\sum_{s=1}^{r} d_s^{(i)}(x)}{r}, \tag{2}$$

$$\mu_i^* = \frac{\sum_{s=1}^{r} \left| d_s^{(i)}(x) \right|}{r}. \tag{3}$$

High result of the absolute expected value shows great influence of the input variable to the output. A low standard deviation means that effects are constant, namely the output is linear on this variable. High result of its standard deviation shows that there is a non-linear effect, or the interaction between the input variable and other input variables is significant. Therefore, significant parameters are depicted in the section of the $\mu^* - \sigma$ diagram, where both sensitivity measures are high. Further, if the distribution of elementary effects contains both positive and negative elements, some effects may cancel each other out, thus producing a low μ value even for an important variable. In this case the model is considered to be non-monotonic [7].

3. APPLIED METHOD

The selection of the right type of the input variables is crucial from the sampling point of view. Morris method requires uniform distribution on the [0,1] interval, nevertheless in practice this cannot be fulfilled. In many cases, the variables are discrete and their distribution cannot be known. To overcome this problem, some special sampling methods are applied, and the selected method serves as the heart of the sensitivity analysis afterwards.

For example, some processes are based on the Latin hypercube sampling techniques; other are based on distance measure and uniformity. A potential solution can be the following: the levels of the parameters are given by quantiles, then in the samples the even distribution of the variables is reached; for example [8]. There the sampling is not directly done, but based on the quantile values and thus the levels of the trajectories of the Morris method appear as equal distances.

There are other processes to reach uniformity also. For example [9], which is called sampling for uniformity method, or [10], which is known as the enhanced Sampling for Uniformity method, eSU in short. This latter is used hereinafter. Note that this is a key point, since here some variables cannot be considered as continuous and in case of eSU, the sampling method defines grids that correspond to the values of the variables.

4. MODEL INPUT PARAMETERS

The following total of 15 buildings' design variables was considered. As building design parameters structure, wall window ratio, and orientation were selected. Further, a set of input parameters related to the various building configurations was selected: roof surface (r), surface connected to the ground (g), balcony (b), external walls (w); together with specific edges and vertices. Further, a complex descriptor selected by the architects, namely envelope surface/Area/net floor Surface (A/S) ratio, was also considered as input variable.

5. RESULTS

The purpose of the sensitivity analysis here was to determine the contribution of the selected individual building design variables to the total energy performance. In other words, the order of the variables with the most influence on the annual energy demand is to be determined to support efficient or optimal building design.

Table 1. Order of the variables

#	Parameters	μ_i^* (kWh/a)	μ_i (kWh/a)	σ (kWh/a)
1	structure	3,982	−3,982	424
2	orientation	725	312	841
3	b	668	452	694
4	a_negative_edge	643	599	588
5	g	541	532	389
6	r	473	460	410
7	g_edge	460	457	313
8	window_rate	378	−69	475
9	r_positive_edge	374	366	312
10	a_positive_air_positive_vertex	334	318	261
11	r_negative_edge	254	33	344
12	g_positive_positive_vertex	220	203	251
13	a_positive_edge	200	4	269
14	a_per_s	107	103	131
15	w	98	12	146

Table 2. Order of the variables for structure 1

#	Parameters	μ_i^* (kWh/a)	μ_i (kWh/a)	σ (kWh/a)
1	orientation	834	322	1,005
2	b	715	515	715
3	a_negative_edge	663	609	622
4	g	558	556	391
5	r	462	454	395
6	g_edge	458	446	333
7	window_rate	412	−371	390
8	r_positive_edge	403	388	342
9	a_positive_air_positive_vertex	343	324	267
10	r_negative_edge	286	98	359
11	g_positive_positive_vertex	221	201	260
12	a_positive_edge	203	80	267
13	a_per_s	113	108	144
14	w	98	16	144

Table 3. Order of the variables for structure 2

#	Parameters	μ_i^* (kWh/a)	μ_i (kWh/a)	σ (kWh/a)
1	orientation	708	290	844
2	a_negative_edge	639	603	557
3	b	638	410	655
4	g	583	582	435
5	r	491	483	422
6	g_edge	445	445	326
7	r_positive_edge	352	345	286
8	window_rate	319	258	293
9	a_positive_air_positive_vertex	298	274	230
10	r_negative_edge	272	26	361
11	g_positive_positive_vertex	207	197	212
12	a_positive_edge	190	−39	257
13	a_per_s	93	90	113
14	w	84	−26	120

Here, Morris method was considered with a level of 6, i.e., for the variable models the trajectories were moved on six levels. Note that in the literature the minimum level is 4. The calculations were based on 30 trajectories.

Table 1 demonstrates the sensitivity analysis results of the full input data; i.e., the order of the considered input variables is given according to Eq. (3). Note that the table shows clearly the difference in the interpretation of the

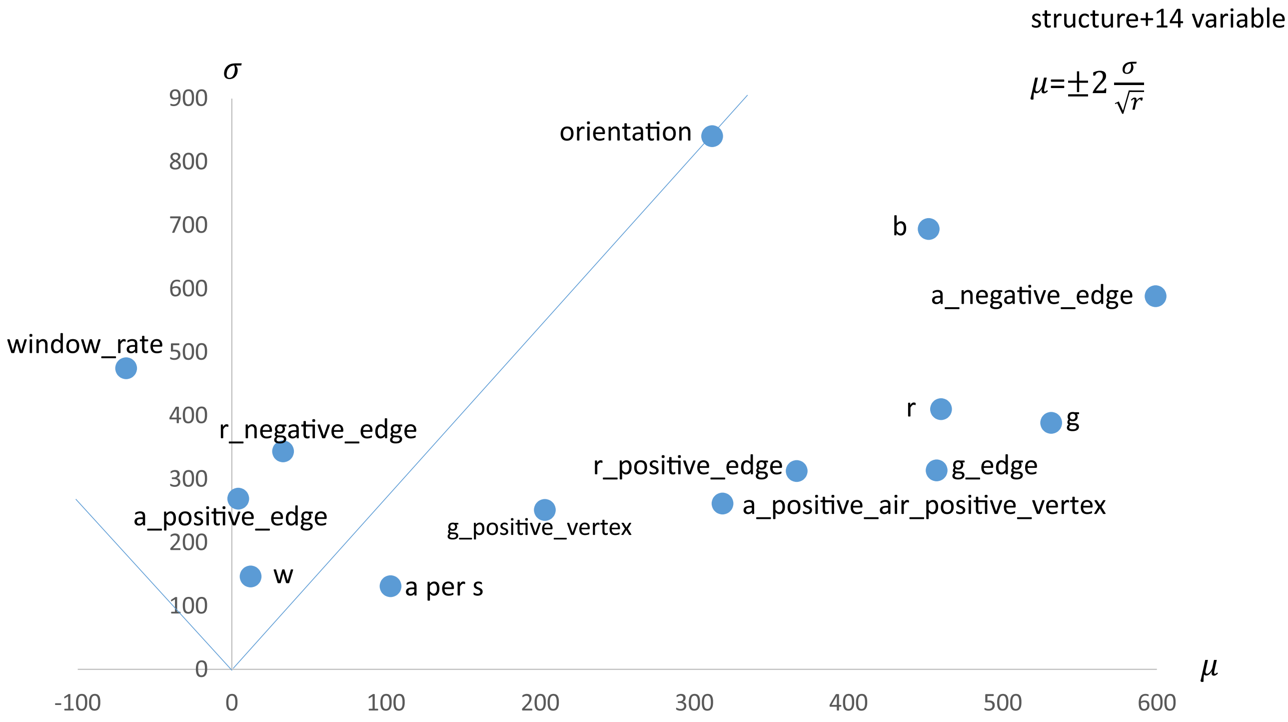

Fig. 1. Dominant variables

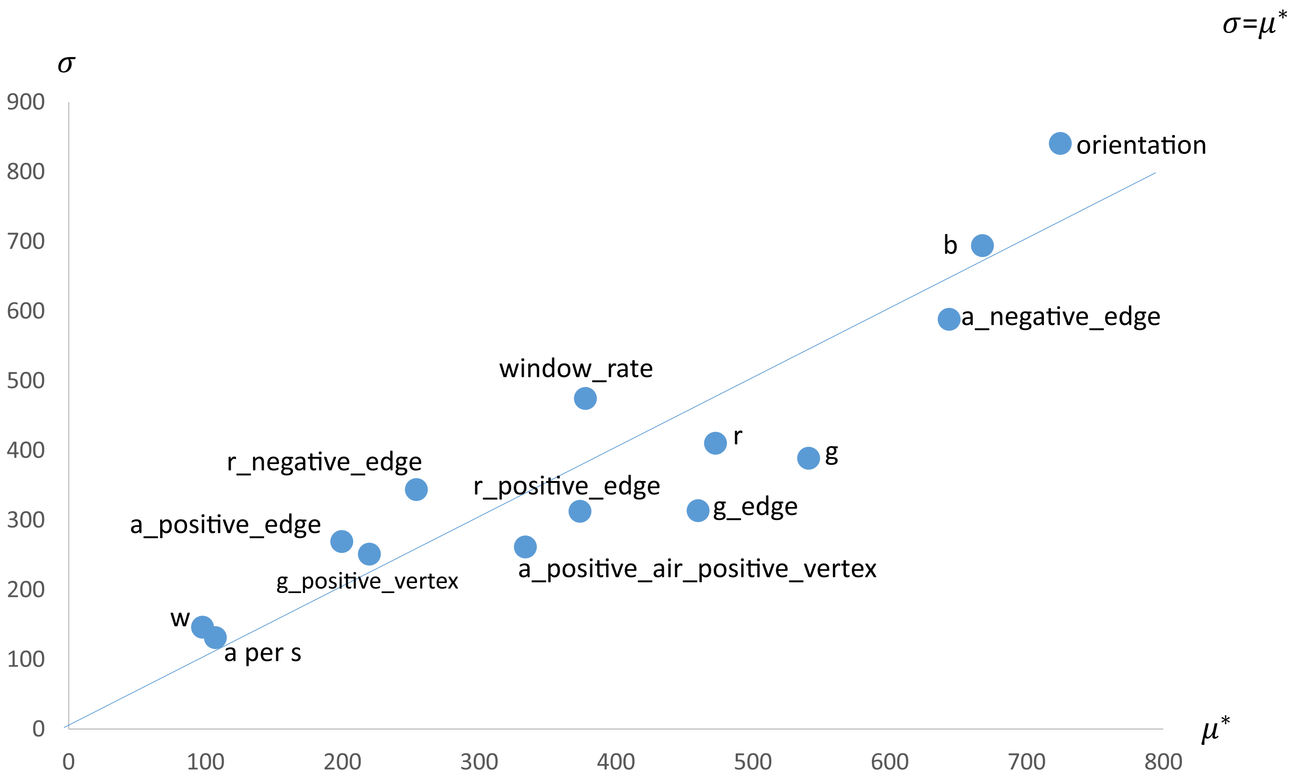

Fig. 2. $\mu^* - \sigma$ relation of the variables

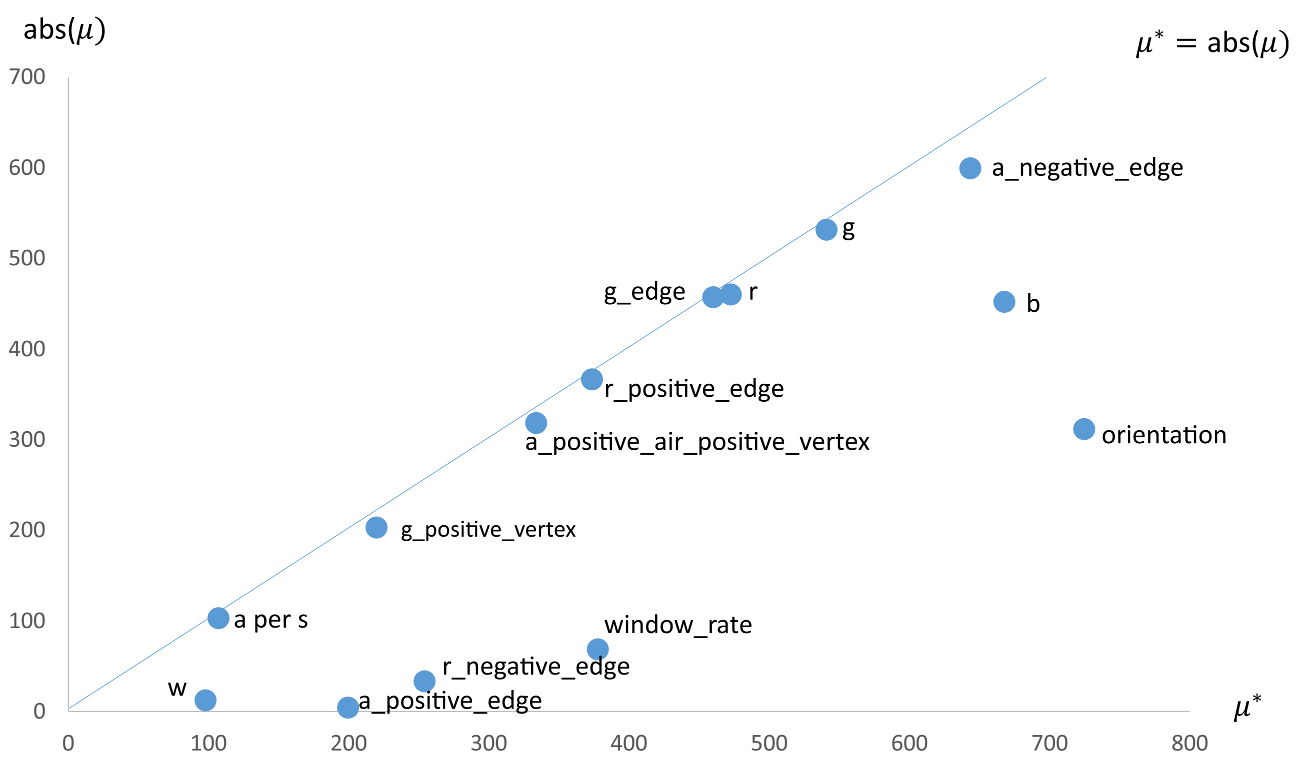

Fig. 3. Monotonicity of the variables

sensitivity measures discussed earlier. The corresponding unit of the investigated annual heating energy demand is kWh/a, and therefore the unit of the sensitivity measures μ and μ^* as well as the standard deviation σ have the same unit within the tables detailed below, i.e., kWh/a.

Table 2 demonstrates the sensitivity analysis results of the input data related to structure 1, where the minimum standards were considered as the necessary building properties, while in Table 3 is demonstrated the sensitivity analysis results of the input data related to structure 2, close to a passive house' properties. The order of the considered input variables is given according to Eq. (3) in both cases. It is important to mention that there is only a slight difference in the order as well as in the data of the results, which can be considered as not significant and may be a result of the random generation steps. Obviously, the structure and orientation are the most important parameters. Then, variables describing the various building configurations follow for every separate study.

The $\mu = \pm 2\sigma/\sqrt{r}$ lines were proposed originally by Morris to identify factors with dominant non-additive and/or non-linear effects; these lines are also depicted in Fig. 1. Factors, i.e., variables, above the lines in both plots are considered to have dominant interactions, while the factors under the line are almost monotonic. Similarly, the $\mu^* - \sigma$ relation is depicted in Fig. 2. Note that the small standard deviation (see the corresponding tables) indicates monotonicity in a way that the elementary effect values are almost constants. High standard deviation indicates that the relationship of the output variable, namely the annual energy demand, and the factor, namely the considered input variable, is not linear. In other words, the value of the elementary effect can be smaller or greater depending on the value of the input variable and/or the change is greatly influenced by other input variables' changes, i.e. there is an interaction between the input variables. Reference [7] suggested the following boundaries of the standard deviation per mean: 0.1, 0.5 and 1; note that 1 is depicted in Fig. 2.

Figure 3 corresponds to monotonicity, the variables on the $\mu^* = |\mu|$ line are monotone, and the variables close to the line can be considered to be almost monotone. It is also worth mentioning that in both cases the indicators define the same monotonicity and non-linearity as well as interaction between the variables.

6. CONCLUSIONS

The sensitivity measures μ and μ^* of the study presented show that the structure is inevitable the most influential parameter, when considering the energy performance. When considering this parameter the $\mu^* = |\mu|$ equality holds, this means that its relationship to the output variable is monotone. Moreover, due to its minimal standard deviation this relationship can be considered as linear. Note that the method discussed in the paper applies a technique where in general the samples are randomly selected. Therefore, those input parameters that have the most influence on the output are identified; moreover, these parameters remain with multiple runs. In other words, the model is robust. The model screens the most important and the negligible variables in the considered building annual heating energy model. For more than half of the variables, the model showed a monotonic or close to monotonic effect on the annual heating energy demand input variable, which may be important information during design.

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