MONTE CARLO-BASED SENSITIVITY ANALYSIS APPLIED TO BUILDING ENERGY ANALYSIS

PHÂN TÍCH ĐỘ NHẠY DỰA TRÊN PHƯƠNG PHÁP MONTE CARLO CHO PHÂN TÍCH NĂNG LƯỢNG CÔNG TRÌNH

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Abstract - This paper presents a technique used to examine the sensitivity of the output of a building energy model with respect to the variation of different design variables. The Monte Carlo-based sensitivity analysis was applied and a case-study house was used to demonstrate this technique. The paper carefully describes the process through which the Partial Correlation Coefficient of each design variable was calculated. Under the climate of Danang, the results of this analysis showed that in naturally ventilated dwellings, the building envelope and ventilation strategy are the most influential factors; meanwhile, the building envelope, the thermostat of HVAC systems and internal heat sources are significant in air-conditioned home. Sensitivity analysis can help designers to quickly choose appropriate solutions for their design problem and is useful for making choices in building renovation or retrofit.

Key words - sensitivity analysis; building simulation; Monte Carlo; thermal comfort; energy consumption.

Tóm tắt - Bài báo giới thiệu một kỹ thuật khảo sát độ nhạy của một mô hình năng lượng công trình xây dựng gây ra bởi sự thay đổi của các tham số thiết kế khác nhau. Phân tích độ nhạy dựa trên phương pháp Monte Carlo được áp dụng và một ngôi nhà điển hình được dùng để trình bày kỹ thuật này. Bài báo mô tả chi tiết quá trình mà qua đó Hệ số Tương quan Từng phần của từng tham số thiết kế được xác định. Trong điều kiện khí hậu ở Đà Nẵng, kết quả phân tích cho thấy trong nhà ở thông gió tự nhiên, vỏ bao che công trình và chiến lược thông gió là những yếu tố có ảnh hưởng lớn nhất; trong khi đó vỏ bao che công trình, nhiệt độ kích hoạt của hệ thống HVAC và các nguồn sinh nhiệt trong nhà là rất quan trọng trong nhà ở có điều hòa không khí. Phân tích độ nhạy cho phép người thiết kế chọn lựa nhanh chóng các giải pháp cho việc thiết kế và có ích trong việc đưa ra các quyết định khi cải tạo nâng cấp công trình.

Từ khóa - phân tích độ nhạy; mô phỏng công trình; Monte Carlo; tiện nghi nhiệt; năng lượng sử dụng.

1. A Brief Introduction of Sensitivity Analysis

Sensitivity is a generic concept. The term ‘sensitivity analysis’ (SA) has been variously defined by different communities. Until recently, SA has been conceived and defined as a local measure of the effect of a given input on the output [1]. If a change of an input parameter *X* produces a change in the output parameter *Y* and these changes can be measured, then we can determine the sensitivity of *Y* with respect to *X* [2]. This measure of sensitivity can be obtained by the calculation via a direct or an indirect approach, system derivatives such as $S_{X_j} = \partial Y / \partial X_j$, where *Y* is the output of interest and X_j is the input factor [1].

The philosophy of SA is that if we understand the relationships and the relative importance of design parameters on the building performance, we can easily improve the building performance by selecting appropriate design parameters. In building simulation, the SA is often quantified by the difference in simulated results caused by the changes of input parameters. A SA provides designers a robust tool to quantify the effect of various design parameters and to identify sources of uncertainties. In this study, the technique of SA was employed to assess the significance of various design parameters in the outputs of EnergyPlus program. The main objective of this study is to identify the most important design parameters with respect to the performance of a dwelling under the climate of Vietnam.

2. Methodologies of Sensitivity Analysis and the Choice of this Study

There are a number of approaches used in SA which can be distinguished by their methods, purposes, sensitivity indices... The choice of SA methods basically depends on the natures of the problem at hand. In this work we explored two EnergyPlus thermal models of a dwelling; hence the present problem is related to simulation outputs of these thermal models. Based upon this point, this work decided to perform global SAs which are based on the Monte Carlo method. A Monte Carlo-based SA provides statistical answers to problems by running multiple model evaluations with probabilistically generated model inputs, and then the results of these evaluations are used to determine the sensitivity indices [5]. The Monte Carlo-based SA used in this paper has 4 major steps as follows:

- Identifying which simulation inputs should be included in the SA and what are their probability distribution functions.

- Generating a sample of *N* input vectors for the simulation model (EnergyPlus thermal models) by a probability *sampling method*.

- Run the simulation model N times on the input sample to produce *N* associated outputs.

- Calculating the *sensitivity indices* for each input, ranking them and drawing necessary conclusions.

At present, there are a number of *sampling methods*. The Latin Hypercube Sampling (LHS) method was selected for all sample generations. The LHS is a form of stratified sampling that can be used for multiple input factors. It is generally agreed that the LHS performs better than the random sampling method and is able to achieve a better coverage of the sample space of the input factors [5].

There are some highly reliable indices for measuring sensitivity of a non-linear and non-monotonic system, including those obtained by Sobol's method and the FAST method (see SimLab manual for details of their algorithms). However these methods require a very large number of model evaluations (960 simulations for 29 input variables) that tends to be inappropriate due to time-consuming EnergyPlus simulations. The Morris method, on the other hand, needs quite few numbers of simulations, but it can only give a qualitative estimation of variable sensitivity, and it cannot distinguish the non-linearity of an input variable from the interaction with other variables [8]. According to these obstacles, the author decided to use the *Partial Correlation Coefficient* (PCC) – a regression-based sensititvity index. The PCC reveals the strength of the correlation between an output Y and an associated input vector X_j which was cleaned off any effect due to the correlation between the vector X_j and other input vectors. In other words, the PCCs provide a measure of a variable importance that tends to exclude the effects of other variables [5]. The PCC performs fairly well even if there are strong correlations among input variables.

In this work, steps 2 (generating an input sample) and 4 (calculating sensitivity indices) of the Monte Carlo-based method were carried out with the support of SimLab – a software package for uncertainty and sensitivity analysis [11]. Step 3 was done using the parametric simulation function in EnergyPlus and the results were extracted and then passed to SimLab (for step 4) by an interface developed in Excel® by the author, allowing one to extract automatically the results from hundreds of EnergyPlus output files and to convert them into a predefined format readable by SimLab. This SA process is summarized and illustrated in Figure 1.

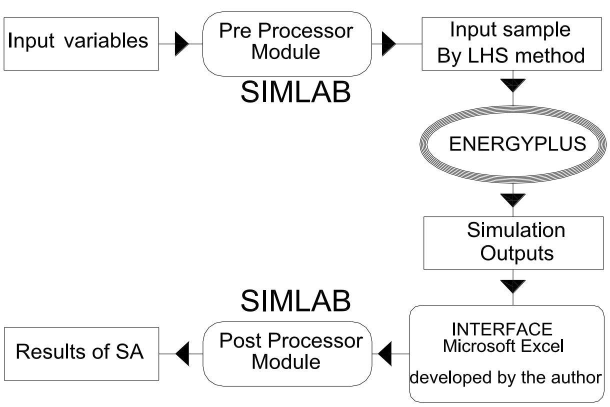

***Figure 1**. The full process of a SA using SimLab and EnergyPlus*

3. Sensitivity Analysis of EnergyPlus Thermal Model of an Actual Dwelling

The case-study dwelling is a typical row house in urban areas of Viet Nam (see Figure 2). It is located in a dense urban area of Danang city and was was occupied by a household. The house was supposedly operated in 2 operating modes: naturally- ventilated (NV) mode and air-conditioned (AC) mode.

An energy model of the house was established in EnergyPlus, allowing one to examine its performance through computer simulation. In the NV mode, external openings of the house were controlled by 10 common ventilation schemes in hot humid climates as shown in Table 1. The name of each ventilation scheme was codified by an integer number – from 400 to 409 – so that these ventilation schemes are readable by EnergyPlus. This trick was also applied for many other categorical design options, e.g. wall types, roof types, window types...

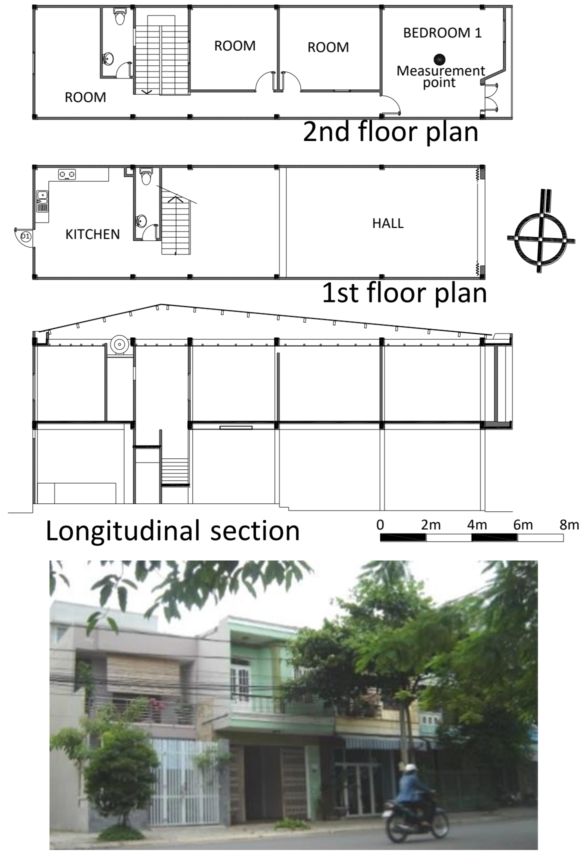

***Figure 2**. The selected row house for the SA study*

***Table 1**. Common ventilation schemes applied to the NV mode*

Names of ventilation schemes	Ventilation period	Ventilation	
		Day time	**Nighttime**
400	All year	Yes	No
401	All year	No	Yes
402	All year	Yes	Yes
403	All year	No	No
404	1 May - 30 Sep	Yes	No
405	1 Mar – 31 Oct	Yes	No
406	1 May - 30 Sep	No	Yes
407	1 Mar – 31 Oct	No	Yes
408	1 May - 30 Sep	Yes	Yes
409	1 Mar – 31 Oct	Yes	Yes

29 design variables were taken into consideration, including uncertainties in physical properties of materials, uncertainties in design and operation. The natures of these variables, probability distribution functions, and the assigned ranges were reported in Table 2.

***Table 2**. Design variables of the house in the SA*

NV/AC mode	Description of input variables	Range	Mean	Standard deviation
Both	Height of backward window level 1	0.4 – 0.8 m		
Both	Width of entrance door	2 – 3.7 m		
Both	Max equipment power – level 1		160 W	20
Both	Max equipment power – level 2		80 W	15
Both	Max equipment power – bedroom		160 W	20
Both	Insulation thickness-ground floor	0 – 0.03 m		
Both	External wall type	100 – 106, step = 1		
Both	Insulation thickness-roof	0 – 0.04 m		
Both	Insulation thickness-ceiling	0 – 0.04 m		
Both	Brick density (external wall)		1.6 T/m³	200
Both	Thickness - brick		0.07 m	0.008
Both	External wall color	0.25-0.85		
Both	Concrete slab thickness		0.09 m	0.01
Both	Concrete slab density		2.6 T/m³	200
Both	Roof color	0.25 - 0.85		
Both	EPS Insulation conductivity		0.035 W/m.K	0.003
Both	Window type	200; 201; 202; 203		
Both	Thickness of internal mass	0.1 -0.3 m, step = 0.05		
Both	Façade shading length	0.2 -0.4 m		
Both	Max number of occupant	2; 3; 4; 5; 6		
Both	Power of gas stove		400 W	200
Both	Width of front window level 2	1 - 2.0 m		
Both	Width of backward window level 2	1 – 2.5 m		
NV	Ventilation strategy (open or close the openings)	400 – 409, step = 1		
NV	Crack front window level 2	2 - 8 g/m.s		
NV	Discharge coefficient (DC) of front window level 2		0.45	0.1
NV	Crack backward window level 2	4 -12 g/m.s		
NV	DC of backward window level 2		0.5	0.1
NV	DC of the crack of the attic	0.18-0.35		
AC	Azimuth		- 7.5°	8
AC	Infiltration of level 1		15 l/s	0.003
AC	Infiltration of level 2		8 l/s	0.003
AC	Infiltration of Bedroom		10 l/s	0.003
AC	Infiltration of the attic		3 l/s	0.001
AC	HVAC Fan blades efficiency	0.6 – 0.7		
AC	HVAC Fan motor efficiency	0.8 – 0.9		
AC	HVAC Cooling coil COP		3	0.13
AC	HVAC Heating coil efficiency	0.95 - 1		
AC	HVAC Heating setpoint*	20° – 23°		
AC	HVAC Cooling setpoint*	26° - 27.5°		

*To ensure PPD does not exceed 20%, the HVAC setpoints are 20° - 26° in winter and 23° - 27.5° in summer

In the AC mode, each thermal zone of the house was equipped with a Packed Terminal Air Conditioner (PTAC). Each PTAC consists of an electric heating coil, a single-speed cooling coil, a 'draw through' fan, an outdoor air mixer, a thermostat control and a temperature sensor. We assume that the heating coil efficiency is 1; the coefficient of performance (COP) of the cooling coil is 3; the efficiency of the fan blades and the fan motor are 0.7 and 0.8 respectively; heating and cooling supplied air temperatures of the PTAC are 50°C and 13°C. Other capacities (e.g. flow rates, power of the coils) of these components are automatically estimated by EnergyPlus to meet heating and cooling loads of the zone. In every house, each PTAC operates independently from the others. Energy consumption of a PTAC is the sum of heating electricity, total cooling electricity and fan electricity. Total energy consumption of the house is the sum of electricity consumed by the lighting system, equipments and the PTACs. Under this operating mode, 34 design variables were taken into consideration and their details were reported in Table 2.

The number of model evaluations (simulations) needed for a reliable Monte Carlo analysis is still subject to debate. This number must be large enough to guarantee convergence of the sensitivity indices, but should not be too large to delay the SA process. Yang [8] carried out a study on the convergence issue in SA using the HYMOD model (a model using in hydrology). He reported that the sample size of 500 was needed for the regression-based method. However, this value seems to be too high in building simulation. Although no explanation was mentioned, SimLab recommends the sample size of 1.5 up to 10 times the number of input factors. In [7; 12] the authors used the sample size of 200 for complex building systems.

4. Results

In the NV case, the input variables were randomly sampled 180 times by the LHS method, generating 180 input vectors for EnergyPlus. This number of input vectors is 6 times higher than the number of variables and it well exceeds 44 - the minimum value recommended by SimLab (1.5 times x 29 variables ≈ 44). Figure 3 presents the Cobwebs plot of 180 random input vectors for the NV house. Similarly, in the AC case, 200 input vectors were generated for EnergyPlus.

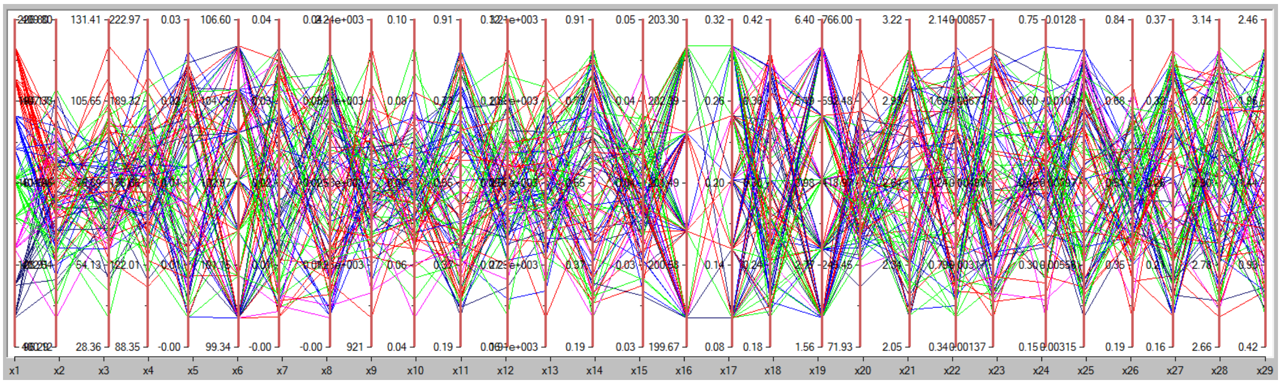

Figure 3. *Cobwebs plot of 180 input vectors generated by the LHS method*

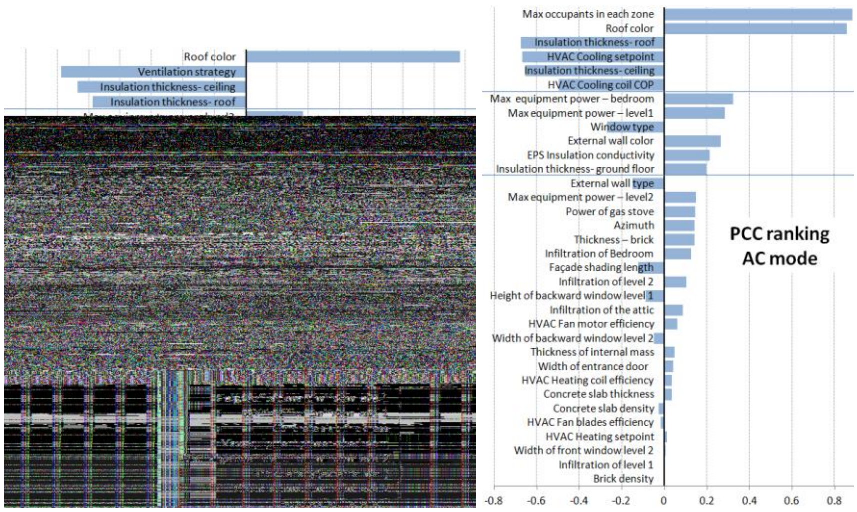

Figure 4. *Sensitivity rankings via the PCC of the NV and AC houses*

The 180 (or 200) input vectors were implemented into EnergyPlus for 180 (or 200) corresponding simulation runs. The simulated results of these 180 (or 200) runs were extracted and embedded into SimLab where the PCC of the input variables were calculated. The EnergyPlus outputs were the Total Discomfort Hours (TDH) in the NV house and Total Energy Consumption (TEC) in the AC house.

The calculated PCCs of the input parameters of the NV and AC houses were sorted from the largest to the smallest as shown in Figure 4. The higher the absolute PCC is, the more influential the parameter is. The positive / negative sign of the PCC indicates the proportional / inverse relationship between a variable and the TDH.

It is clear that the predictions of the most sensitive variables by the PCC were quite consistent in both NV and AC houses. In the NV house, it can be stated that *the roof color*, *the roof thermal insulation* and *ventilation schemes* are the most influential factors of the TDH. Their PCCs were much higher than those of the remaining, indicating that their influences on simulated results were significant. They should therefore be chosen with care during the design process. In the AC house, the *roof color* and the *number of occupant* is as important as the roof parameters. The *HVAC cooling setpoint*, *the roof insulation*, and *the cooling coil COP* were among this first group. The *HVAC heating setpoint*, in contrast, was completely not influential possibly due to the warm climate of Danang; but it may become much influential in cold climates. The most important things obtained from this result were that the heat flow through the metal roof of the row house must be strictly controlled for better indoor environment and energy saving.

In the remaining group, the input parameters were much less influential than those of the first group. These variables have rather uniform PCCs, their ranking are thus not strictly accurate. They can be considered moderately influential factors. The less sensitive parameters were rather similar in the PCC ranking. Notably, the *building orientation* and the remaining variables of the HVAC setting were among this group. Surprisingly, the *infiltration rates* of all AC thermal zones were dropped into the less influential group.

5. Conclusion

This series of SA provides a very clear insight of the influence of building parameters on the design objectives. In NV buildings, the building envelope and ventilation strategy are the most influential factors. Meanwhile, the building envelope, the thermostat of HVAC systems and internal heat sources are significant in AC buildings. The results of SA may help designers to quickly choose appropriate solutions for their design problem. It might also be useful for making choices in building renovation and retrofit.

REFERENCES

[1] Saltelli, A., et al., *Sensitivity analysis in practice*, John Willey & Sons, Chichester, 2004.

[2] Lam, J. C. and Hui, S. C. M., "Sensitivity analysis of energy performance of office buildings", *Building and Environment*, Vol. 31, Elsevier, 1996, pp. 27-39.

[3] Joint Research Centre - European Commission. Simlab 2.2 Reference Manual. Brussels: JRC, 2008.

[4] Kotek, P., et al., "Technique for uncertainty and sensitivity analysis for sustainable building energy systems performance calculation", in *Proceedings: Building Simulation 2007*, IBPSA. Beijing, 2007. pp. 629-636.

[5] Yang, J., "Convergence and uncertainty analyses in Monte-Carlo based sensitivity analysis", *Environmental Modelling & Software*, Vol. 26, Elsevier, 2011, pp. 444-457.

[6] Simlab - Software package for uncertainty and sensitivity analysis. Downloadable for free at: http://simlab.jrc.ec.europa.eu [Last accessed 10 Dec 2012]. Joint Research Centre - European Commission. 2011.

Hopfe, C. J. and Hensen, J. L. M., "Uncertainty analysis in building performance simulation for design support", *Energy and Buildings*, vol. 43, Elsevier, 2011, pp. 2798–2805.

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