Sensitivity analysis of a simplified office building

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Abstract. The increase of thermal discomfort and the associated energy demand for the cooling of buildings further exacerbate the ongoing challenges for the design of new buildings and the adaptation measures of the current building stock to climate change. Dynamic, detailed and tailored building simulation methodologies are necessary to better understand and quantify the energy demand of buildings and consequences for supporting energy networks. The aim of this is to analyze the sensitivity of peak electricity demand for the provision of space cooling to different office building model parameters. In the research, two sensitivity methods, Morris Elementary Effect and Sobol, are used to evaluate the sensitivity of eight input model parameters. Relative to peak power consumption for cooling, the most important factor is the cooling set-point, followed by ventilation rate and internal heat gains, which are estimated to account for 38\%, 26\% and 25\% of the variation. Regarding the annual cooling demand for the HVAC systems, these factors account for 35\%, 33\% and 58\%, respectively.

1. Introduction

An increase in the frequency of buildings overheating and an increase in cooling demand of buildings have been identified over recent years in the UK. They occur more intensively during summer heatwaves, particularly in modern buildings which are highly insulated and air-tight [1]. In addition, thermal discomfort and the cooling demand of UK buildings for future climate projections are estimated to further increase [2]. This presents an ongoing challenge for the design of new buildings and adaptation measures of the current building stock. Similarly, building design and optimization present an important role in delivering energy efficiency improvement, the reduction of greenhouse gas emissions and potentially in balancing the supply-demand loads of the power network.

Dynamic building energy simulations are an important tool to support research into these topics; however, several challenges have to be acknowledged. For example, the energy performance gap; the difference between designed simulated performance and measured data [3]. The origins of this difference have been discussed and identified [3]; however, the energy performance gap has affected the credibility of the outputs of building energy simulations. In addition, the gap reveals the inherent complexity of whole dynamic building simulation systems, and the requirement for more holistic (detailed) simulation approaches, that consider the interaction effect over several different simulation outputs. Sensitivity analysis (SA) methods can support this endeavour, informing building developers of which parameters are important to better characterize and include in risks and scenario simulation analysis when making whole building systems design decisions [4].
Sensitivity analysis in whole building simulation research is becoming more popular and is considered essential for better evaluation of design choices [4,5]. The complexity of this analysis is multifold, and the potential number of statistical methods available is considerable. In building design, it has been used to analyze the implications of climate uncertainty, building envelope parameters, internal heat gains, occupancy schedules and densities [5]. Different types of simulation results have been analyzed, from overheating frequency, heating demand, and carbon emissions. However, only a few studies have analyzed the impacts of HVAC design operation parameters on the peak electricity demand for space cooling. Nevertheless, the peak cooling demand of buildings is a critical design choice for multiple systems, such as HVAC systems, the electricity distribution network and district cooling network.

This research comprises part of a PhD project examining cooling demand in office buildings under different levels of climate change and the effects of electricity demand for cooling on the power network. The research presented here will analyse the key parameters determining the cooling demand of office buildings, in order to contribute to the quantification of the effects of climate change on the cooling demand of the office building stock. This builds on previous analysis on the sensitivity of envelope and space operation parameters to the annual and peak space cooling demand of a simplified office building [6]. This study aims to analyze the sensitivity of peak electricity demand for space cooling due to office building model parameters. Here, two sensitivity methods, the Morris Elementary Effect and the Sobol, are used to evaluate the sensitivity of eight input model parameters, related to the building space operation, form and HVAC characteristics.

2. Methodology

The peak and annual demand of a simplified office building model are assessed using a set of model parameters covering a range of values. Firstly, a screening sensitivity method, the Morris Elementary Effect, is conducted in order to identify the input model parameters with higher predominance over the electricity requirements for space cooling, both peak and annual demand, from a large set of parameters. Secondly, a more complex global sensitivity method is applied to further analyze the implications of these parameters on the cooling demand of office buildings.

2.1. Office Model description

A generic simplified office building energy model is used for the analysis. A base one-floor building model was developed in EnergyPlus 8.9 [7], consisting of a single space zone, with a gross internal floor area of 1600 m², 40m width, 40m length, 3.5m height, with a glazing area of 40% on its external wall. A previous research study [6], analysed the space cooling sensitivity of 16 input parameters (focusing on the envelope, space operation, and form) of the same base model. In this case, a Fan coil HVAC system is coupled to the previous model, and the simulation output results covered are the electricity demand for HVAC systems. Further descriptions of the generic model characteristics are available in the previous research paper [6] and on the additional material provided in this paper.

![Figure 1. Base model](image)

Table 1. Building Model Input Parameters

| Parameter                  | Range   | Base | Unit   |
|----------------------------|---------|------|--------|
| P1 – Int. Heat Gains (IHG) | 10-80   | 40   | W.m⁻²  |
| P2 – Ventilation Rate (ACH)| 0.5-10.3| 1.54 | ACH    |
| P3 – Cool. Set-Point (CSP) | 20 – 28 | 24   | °C     |
| P4 – Area Ratio            | 0.1-10  | 1    | -      |
| P5 – Chiller water SP      | 5.9     | 7.22 | °C     |
| P6 – Nominal Chiller COP   | 2.5-6   | 4    | -      |
| P7 – Chiller Sizing Factor | 1-1.4   | 1.2  | -      |
| P8 – Min. Unloading Factor | 0.1-0.4 | 0.25 | -      |

A parametric simulation was prepared using JEPPlus [10], providing multiple iterations of eight input parameters to be used in the SA. The assumptions used for the control settings and operational design
parameters are based on generic benchmark information for office buildings given by CIBSE [11] and BRE [8]. Korolija et al. [9] defined similar baseline assumptions for the base input parameters for the UK office buildings’ archetypal models used in their research. The base building model used in this research is presented in Figure 1, and the range of the input parameters iterated is described in Table 1. Simulations were executed using the whole annual hourly data in the test reference year weather file for the current climate in Manchester - UK, produced by the PROMETHEUS project [12]. The maximum dry bulb temperature registered in this weather file is 28°C and there are 103 annual cooling degree days based on a 15°C baseline temperature.

Previous SA of building energy models have assessed the sensitivity of the annual heating and cooling demand, annual CO₂ emissions in different simulation conditions. These simulations have tested input parameters such as envelope characteristics, and some control setting parameters. However, the sensitivity of peak power loads for cooling is not normally analysed. In addition, the iteration of HVAC system operation parameters is not generally explored in the literature analysed. Therefore, this research seeks to focus on addressing these challenges. Focusing on analysing the sensitivity of peak loads regarding HVAC and envelope parameters.

Regression methods are fast to compute, easy to comprehend and interpret, so they are the most widely used for SA in building energy analysis [5]. Several different studies by Tian et al. [2,13] and de Wilde et al. [14] have applied different techniques for SA in extensive building performance analysis. In most of these studies, SHGC is the parameter that presents the predominance over annual cooling demand, being followed in the parameters ranks by the chillers’ COP. The cooling set-point and internal heat gains (such as equipment, lighting or occupancy) follow consecutively [13]. The cooling demand is also considerably affected by climate conditions. Similarly, De Wilde [14] also concludes that weather conditions are the most important parameters of the cooling demand for office buildings.

2.2. Sensitivity Analysis

Two global sensitivity methods are applied in this study to analyse the effects of these input parameters in the peak and annual electricity demand for HVAC systems. Firstly, the Morris Elementary Effect method is applied, a screening method suited to rank the sensitivity of input parameters. This was applied to identify the parameters with the largest impact on HVAC electricity demand for cooling. The energy consumption considered for the HVAC system includes the energy demand for the ventilation systems (fans), and the electricity demand for the cooling plant, which includes pump, chiller and heat rejection sub-system.

The screening method evaluates the influence of the different parameterizations over a set of eight parameters. The Morris screening method is an efficient method to initially evaluate the relative influence of different parameters on an output. A detailed description of the method is given in [15]. The sensitivity measures, μ′ and α, are respectively the estimates of the mean and the standard deviation of the output distribution of random sampling to rank factors in order of importance. The sampling implemented for this analysis considered that the eight input parameters were discretised in 6 equidistant points (levels) over the parameters space range. 450 simulations were executed, as 50 trajectories are considered (starting from an initial state (1) and iterating for each parameter (8 times)).

The second stage of the research method, applied a more complex global sensitivity method, Sobol [15], for the same eight input parameters. Two random samples of 2500 iterations of the eight input parameters were executed and simulated using a random sampling technique, SOBOL. Thereafter, eight matrices for each parameter were generated, substituting in one sample (A) the column of the parameter (i) for the value in the second random sample (B). This enables, a full set of first-order and total-effect indices of model parameters to be computed. The Sobol indices are calculated for both peak and annual electricity demand for HVAC. Sᵢ is the measure of the main effect of the parameter, indicating how much the output variance could be reduced if the parameter i could be fixed. Sᵢ is the total-effect Sobol index, and is the addition of the parameter’s main effect and the interaction effect with other parameters. Analyzing both of the indices, it is possible to assess the combined effect of the parameter coupled with other parameters on peak and annual electricity demand for HVAC.
The SA performed as part of this research assesses the sensitivity of electricity consumption of HVAC systems over a whole year. The annual energy consumption for the whole HVAC system is considered as well as, the peak power demand of the system.

3. Results

An overview of the model simulation results is given in Table 2, presenting the range of results for the base model and for each SA method. The annual electricity demand for HVAC equipment in the base model is 38.9 kWh.m\(^{-2}\), and the peak power demand for cooling is 16.3 W.m\(^{-2}\). Benchmarks for the typical consumption for cooling in existing offices in the UK are in the range 31 to 41 kWh.m\(^{-2}\), and the values of peak electricity for cooling are in the range 20 to 30 W.m\(^{-2}\) [16].

Table 2. Overview of simulation results

|        | Peak [W.m\(^{-2}\)] | Annual [kWh.m\(^{-2}\)] |
|--------|---------------------|-------------------------|
| Base Model | 16.3                | 38.9                    |
| Morris EE Method | Mean 24.3 (49%)      | 43.2 (11%)              |
|        | Max. 72.3 (343%)     | 230.7 (493%)            |
|        | Min. 0.4 (-98%)      | 0.12 (-99.7%)           |
| Sobol Method | Mean 23.9 (+46%)     | 38.2 (-2%)              |
|        | Max. 92.5 (+467%)    | 312.9 (+704%)           |
|        | Min. 0.05 (-99.7%)   | 0.1 (-99.7%)            |

3.1. Morris Elementary Effect

The spread of the electricity consumption values over all simulation model iterations for the Morris EE method is significant as shown in Table 2. The variation of simulation results verified for peak power for cooling is between 0.4 W.m\(^{-2}\) to 72.3 W.m\(^{-2}\) (-98% to +343% of base model result), and the annual electricity demand is between 0.12 kWh.m\(^{-2}\) to 230.7 kW.m\(^{-2}\) (-99.7% to +493% of base model result).

The Morris elementary effect sensitivity metrics of the model input parameters analysed are shown in figures 2 and 3 above. Figure 2 presents the sensitivity metrics of input parameters relative to the peak power for cooling and Figure 3 presents these metrics relative to annual electricity demand. The sensitivity metrics relative to annual demand (Figure 2) are generally higher than for peak power demand (Figure 3). Considering peak power for cooling, the most important factors are the space cooling setpoint (P3) and the ventilation rate (P2). These are followed by the IHG (P1) and thus by the COP (P6). Considering the annual electricity demand for cooling, the IHG (P1) is the most important single factor, followed by ventilation rate (P2), and then by the cooling setpoint (P3).
3.2. Sobol

The main and total effects indices from the Sobol sensitivity method are presented in Figure 4 and Figure 5. Relative to peak power for cooling (Figure 4), the most important factor is the cooling set-point (P3), which is estimated to account for 38% of the variation in peak power for cooling. Ventilation rate (P2) and IHG (P1) follows, which can account for 26% and 25% of the variation in peak power, respectively. COP (P6) is the next most important factor, which can be responsible for 18% of the variation. The remaining factors account for low variations of these results.

Regarding the annual cooling demand for the HVAC systems (Figure 5), the IHG (P1) is the most important factor, which may account for 58% of the annual demand variation. The cooling set-point (P3) and the ventilation rate (P2) are the parameters that follow, which are estimated to contribute to 35% and 33% of the annual demand variation, respectively. Finally, the chiller’s COP is estimated to account for 6% of the annual demand variation and the remaining factors have low influence.

4. Discussion and conclusion

The SA of the simplified office building model with a fan coil HVAC system is conducted applying two different global SA methods: Morris elementary effect and Sobol. These SA are applied to examine the relative importance of parameters to two different results, peak and annual demand for cooling normalized to the building’s floorspace area. Each SA identified that for both peak and annual demand, four parameters stand out from the group of parameters analysed: the cooling set-point (P3), ventilation rate (P2) the IHG (P1) and to a lesser degree chiller’s COP (P6). In addition, both methods ranked the importance of parameters for both outputs in a similar pattern. The ventilation rate (P3) is the most important factor for the peak demand and the IHG (P1) are the most important factor for the annual demand.

The value of peak electricity for cooling demand of the base model, 16.3 W.m⁻², is slightly lower than the typical range for the UK offices (20-30 W.m⁻²). However, the chiller’s COP value considered in the base model is 4 instead of the value of 3 considered to be the UK benchmark. This difference could explain the difference on peak load value, and a lower COP would not increase as sharply the annual energy demand. The range of simulation output results registered for both SA methods is wide. The results range from -99% to more than +700% of the original base model annual demand per square meter. However, the variation range of the peak demand is smaller than for the annual demand, for example, the maximum value for peak demand identified is 450% of the base model result. Overall, the sensitivity metrics for annual demand for both SA methods are significantly higher for annual demand than for peak demand.

The SA methods executed are relevant to identify the parameters with the largest influence for the electricity requirements for cooling demand, both considering peak, and annual cases. However, it is important to acknowledge some of the limitations of the analysis. For example, in order to conduct SA methods, 450 iterations were executed for a Morris EE method and 25000 iterations for the Sobol method. The simplified characteristics of the building model reduced the simulation burden, thus the
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number of simulation iterations that were attainable. However, the methodology cannot be implemented or extrapolated as easily for more complex models or alternative modes of cooling provision and a larger number of parameters as would be required to understand the key influences in office building stock.

Other limitations of the methodology and their findings are for example the use of only a single office archetype and one HVAC system. Similarly, the analysis only considers the climate conditions for Manchester, using a single climate file, not exploring the results over wider climate assumptions. In addition, the effect of the different settings of input parameters ranges of the analysis is analysed. However, the scope of this research paper leads to such type of assumptions, in order to reduce the complexity and extension of the analysis. However, future research work should consider more detailed modelling methodologies and explore some of these limitations.

The necessary data and models to execute the analysis presented are available at: https://github.com/vascozeferina/CISBAT2019

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