Build Simul
https://doi.org/10.1007/s12273-023-1004-6

Research Article

Advances in Modeling and Simulation Tools

Advancing and demonstrating the Impact Indices method to screen the sensitivity of building energy use to occupant behaviour

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Abstract

A critical gap between the occupant behaviour research field and the building engineering practice limits the integration of occupant-centric strategies into simulation-aided building design and operation. Closing this gap would contribute to the implementation of strategies that improve the occupants' well-being while reducing the buildings' environmental footprint. In this view, it is urgent to develop guidelines, standardised methods, and supporting tools that facilitate the integration of advanced occupant behaviour models into the simulation studies. One important step that needs to be fully integrated into the simulation workflow is the identification of influential and non-influential occupant behaviour aspects for a given simulation problem. Accordingly, this article advances and demonstrates the application of the Impact Indices method, a fast and efficient method for screening the potential impact of occupant behaviour on the heating and cooling demand. Specifically, the method now allows the calculation of Impact Indices quantifying the sensitivity of building energy use to occupancy, lighting use, plug-load appliances use, and blind operation at any spatial and temporal resolution. Hence, users can apply it in more detailed heating and cooling scenarios without losing information. Furthermore, they can identify which components in building design and operation require more sophisticated occupant behaviour models. An office building is used as a real case study to illustrate the application of the method and asses its performance against a one-factor-at-a-time sensitivity analysis. The Impact Indices method indicates that occupancy, lighting use and plug-load appliances have the greatest impact on the annual cooling demand of the studied office building; blind operation is influential only in the west and south façades of the building. Finally, potential applications of the method in building design and operation practice are discussed.

Keywords

occupant behaviour;
building simulation;
occupant-centric building design;
building performance

Article History

Received: 04 November 2022
Revised: 09 February 2023
Accepted: 13 February 2023

1 Introduction

1.1 Motivation & background

The research community is promoting a paradigm shift in the occupants' role in the building design and operation practice. Instead of considering occupants as homogeneous and passive agents, an occupant-centric approach acknowledges diversity and active human-building interaction (Abuimara et al. 2019). As defined by Azar et al. (2020), an occupant-centric approach places occupants and their well-being as the main priority throughout the building life cycle. In parallel, international efforts have been deployed towards reducing the environmental footprint of the built environment. For example, in the European Union, the Energy Performance of Buildings Directive established a pathway for achieving a zero-emission building stock by 2050 (European Parliament Council of the European Union 2018).

Building performance simulation (BPS) is used to support the building's design decision-making process and achieve

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List of symbols

II	Impact Index	$Q_{L,Tot}$	total heat losses (J)
Q_G	heat gain (J)	Q_{NC}	sensible HVAC heat removal (J)
$Q_{G,Tot}$	total heat gains (J)	Q_{NH}	sensible HVAC heat addition (J)

increasingly pressing building performance targets (e.g., reducing non-renewable energy consumption and enhancing occupants' comfort and wellbeing) (Mahecha Zambrano et al. 2021). Because of the shift towards occupant-centric building design and operation, also occupant representation in BPS is changing. Occupants were traditionally represented as fixed profiles and constant occupant-related power densities. Conversely, the research community is actively promoting occupant representations that recognise the two-way interaction between occupants and the built environment (Azar et al. 2020). For example, research initiatives such as the IEA-EBC Annex 66 (Yan and Hong 2018) and its follow-up, Annex 79 (Wagner and O'Brien 2018) have motivated the investigation of occupant behaviour toward better understanding the human-building interaction, developing models that account for occupants' diversity and for the stochastic nature of the occupant behaviour, and integrating these advances through occupant-centric simulation, design, and operation of buildings. As a result, more than 300 models for representing occupants' presence and actions (OPA) have been published (Carlucci et al. 2020).

Nonetheless, a critical gap between the occupant behaviour research field and the building design and operation practice has been highlighted, which is limiting the application of detailed occupant behaviour models in practice (Mahecha Zambrano et al. 2021). While substantial progress has been achieved in the fundamental knowledge domain, attention needs to be placed on the integrated knowledge domain and supporting tools. The former includes data collection, model development and simulation strategies, while the latter comprises guidelines for choosing the most suitable occupant behaviour modelling approach and tools to facilitate its integration and application in BPS studies (Mahecha Zambrano et al. 2021).

It has been demonstrated that the impact of occupant behaviour on building performance is case and context-specific, i.e., the same behaviour could have more or less impact on a performance indicator depending on the specific building typology and climate context (Mahdavi and Tahmasebi 2016). Moreover, occupant behaviour is difficult to predict *a priori* as it is influenced by environmental, time-related, contextual, psychological, physiological, social, and economic factors (Stazi et al. 2017). As a result, general guidelines cannot be developed; instead, the integration of occupant behaviour modelling into simulation-aided building design and operation demands a (likely simulation-based) fit-for-purpose approach (Gaetani et al. 2020).

Ongoing research on this topic has acknowledged the need for identifying the occupant behaviour aspects to which the investigated building/performance indicator is more sensitive as an integral step of BPS (Gaetani et al. 2016, 2020; Mahecha Zambrano et al. 2021). This contributes to preserving a balance between model accuracy and model complexity. In other words, non-influential occupant behaviour aspects could be modelled using lower complexity representations (e.g., fixed schedules), whereas higher complexity models (e.g., probabilistic models, data-driven models, and agent-based models) might be required for influential aspects (Gaetani et al. 2016). This approach is not exclusive to occupant behaviour; on the contrary, sensitivity analysis is routinely used to identify influential parameters such as building systems, building materials, building design and weather (Hopfe and Hensen 2011). Sensitivity analysis is performed to understand how the input variations affect the building performance in applications such as building design, calibration of energy models, building retrofit, and the impact of climate change on buildings (Tian 2013). Sensitivity analysis methods can be classified into *local* and *global*. In the former, sensitivity measures are calculated against default values of a baseline case, often by changing one factor at a time leaving the other factors fixed; thus, it only explores a reduced space around a reference case. In the latter, input variables are tested simultaneously against different baselines, which enables assessing the impact on the model output of both individual parameters and interactions between parameters (Tian 2013; Pang et al. 2020; Carlucci et al. 2021). In general, local methods are less computationally expensive than global ones. Nevertheless, the number of simulations depends not only on the type of sensitivity analysis, but also on the number of factors and levels investigated, and on the occupant behaviour modelling complexity.

Literature shows the application of sensitivity analysis to the occupant behaviour modelling field for multiple purposes such as: assessing the robustness of the building design to occupant's presence and actions (Rouleau et al. 2019); understanding the effect of the choice of occupant's presence and actions models on the building energy use (Carlucci et al. 2021); identifying influential building and occupant behaviour aspects that affect building performance e.g., CO_2 concentration in indoor spaces (Bouvier et al. 2019), thermal comfort (Ioannou and Itard 2015; Gaetani et al. 2017; Rouleau et al. 2019), heating and cooling energy use (Silva and Ghisi 2014; Ioannou and Itard 2015; Gaetani et al. 2016, 2017; Yousefi et al. 2017; Rouleau et al. 2019; Carlucci et al. 2021), and overall energy use (Azar and Menassa 2012; Kneifel et al. 2016; Yousefi et al. 2017; Rouleau et al. 2019; Carlucci et al. 2021) (see Table 1). While occupancy and window use are the most investigated occupant behaviour

Table 1 Reviewed literature on sensitivity analysis addressing OPA in BPS

Reference	Sensitivity analysis	OPA	KPI	Highlights
Carlucci et al. 2021	• Global • Mann-Whitney U Test • Generalized estimating equations	• Occupancy • Light switch-on • Light switch-off • Blinds use • Windows use • Clothing level	• Total electric energy use • Cooling energy use • Heating energy use	• Scope: OPA Model variability • Context: Small Office prototype ANSI/ASHRAE/IES Standard 90.1; Copenhagen, Denmark • Simulation period: 1 year • Stochastic OPA models • 7200 Simulations • Window operation has the highest effect on total energy use • Occupancy and light switch-off have a noticeable effect on output • Blind control and light switch-on are the least influential parameters
Bouvier et al. 2019	• Global • Monte Carlo method • Latin hypercube sampling • Standardised regression coefficients	• Occupancy • Generation of CO_2 per person • Windows use	• CO_2 concentration	• Scope: variability of indoor CO_2 concentration due to OPA and building physical aspects • Context: single-family house; Bordeaux, France • Simulation period: 1 week – winter • Deterministic OPA models • 500 simulations • Occupancy and CO_2 generation during the night have the highest effect on output
Rouleau et al. 2019	• Global • Monte Carlo method • Coefficients of variation • Standardised regression coefficients	• Occupancy • Hot water consumption • Appliance use • Heating setpoint • Windows use	• Heating demand • Total energy use • Number of hours of discomfort	• Scope: sensitivity of energy consumption and comfort due to OPA • Context: multi-residential building; Quebec, Canada • Simulation period: 1 year • Stochastic OPA models • 16000 simulations: 1000 samples × 16 dwellings • Heating demand is sensitive to the setpoint temperature, window operation and appliance use • Total energy use is sensitive to setpoint temperature, window operation and appliance use and DHW consumption • Thermal comfort is sensitive to the heating setpoint temperature, appliance use, window operation • Higher sensitivity when analysing single dwellings than the whole building
Gaetani et al. 2017	• Global • Diversity patterns • Mann-Whitney U Test	• Occupancy • HVAC use • Appliances use • Lighting use • Heating and cooling set point • Blind use • Windows	• Heating energy use • Cooling energy use • Weighted overheating hours	• Scope: sensitivity of energy use and comfort due to OPA • Context: 16 variants of a cubicle office Amsterdam, the Netherlands and Rome, Italy • Simulation period: 1 year • Deterministic OPA models • 3072 Simulations: 192 samples × 16 building configurations • All KPIs are sensitive to blind use in buildings with high solar heat gain coefficient • Light and equipment use had a greater effect on buildings characterized by higher power density • Building variants with bigger window areas are more sensitive to window use • Different climates and building variants lead to a diverse sensitivity of the KPIs to various occupant behaviour aspects

Table 1 Reviewed literature on sensitivity analysis addressing OPA in BPS (Continued)

Reference	Sensitivity analysis	OPA	KPI	Highlights
Yousefi et al. 2017	• Local • Relative percentage difference	• Occupancy • Appliance use • HVAC use • Lighting	• Cooling and Heating energy use • Total energy use	• Scope: sensitivity of energy use due to OPA and envelop configurations • Context: multi-residential building; Tehran, BandarAbbas, and Tabriz, Iran • Simulation period: 1 year • Deterministic OPA models • Cooling and heating energy use is highly sensitive to occupant behaviour • Different levels of sensitivity are observed depending on the building envelope characteristics and building location
Gaetani et al. 2016	• Local • Relative percentage difference	• Occupancy • HVAC use • Appliances use • Lighting use • Heating and cooling setpoints	• Heating energy use • Heating energy peak	• Sensitivity of heating energy use to OPA • Context: Medium-size office building (EnergyPlus reference building); Chicago, IL, USA • Simulation period: 1 year • Deterministic OPA Models • 48 Simulations • Heating energy consumption is sensitive to heating temperature set point, appliances power density, lighting power density, and occupancy rate • Heating peak energy is sensitive to heating temperature setpoint and appliances power density
Kneifel et al. 2016	• Local & global • Full factorial analysis • Relative difference	• Occupancy • Heating and cooling setpoints • Appliance use • Domestic hot water use	• Total energy use	• Scope: sensitivity of building performance to OPA and building characteristics • Context: single-family house (net-zero test facility); Gaithersburg, MD, USA • Simulation period: 1 year (monthly and yearly analysis) • Deterministic OPA models • 128 Simulations • Yearly and monthly analysis • Net-zero building design is more robust to thermostat setpoint • Appliance use has a greater impact than domestic hot water use
Ioannou and Itard 2015	• Global • Monte Carlo method	• Metabolic rate • Clothing level • Ventilation • Heating and cooling setpoints	• Heating energy use • PMV comfort index	• Scope: sensitivity of heating energy consumption and comfort to OPA and building physical characteristics • Context: 2 variations of a single-family house; Rotterdam, the Netherlands • Simulation period: 1 year (seasonal and yearly analysis) • When OPA aspects are included in the sensitivity analysis, it is reduced the influence of physical parameters on the heating energy use • Heating energy use is in average more sensitive to the thermostat setpoint and ventilation rate • The PMV comfort index is highly sensitive to the metabolic rate, followed by clothing level • The sensitivity level to different aspects depends on the building and heating systems characteristics
Silva and Ghisi 2014	• Global • Standardised regression coefficients • Latin hypercube sampling	• Occupancy • Lighting use • Window operation • Appliance use	• Heating and cooling degree-hours • Heating and cooling energy use	• Scope: sensitivity of thermal and energy building performance to OPA and building physical characteristics • Context: single-family house; Florianopolis, Brazil • Simulation period: 1 year • Stochastic OPA models • 2080 simulations • Occupancy schedules, the equipment power, and the number of occupants have the highest effect on building performance

Table 1 Reviewed literature on sensitivity analysis addressing OPA in BPS (Continued)

Reference	Sensitivity analysis	OPA	KPI	Highlights
Azar and Menassa 2012	• Local • Sensitivity index coefficients	• Occupancy • Plug-load equipment use • Lighting use • Cooling and heating temperature setpoints • Hot water consumption	• Total energy use	• Scope: sensitivity of building performance to OPA • Context: 3 office buildings (small, medium, large); 10 cities across USA • Simulation period: 1 year • Deterministic models • 990 Simulations • There is a changing influence of the considered parameters on energy use for different building size and weather conditions • Heating temperature setpoints more influential in small offices
Cuerda et al. 2019	• Local • Absolute difference	• Occupancy	• Heating and cooling demand	• Scope: variability of heating and cooling demand to occupancy patterns and occupancy densities • Context: apartment in multi-residential building; Madrid, Spain • Simulation period: winter and summer • Deterministic models • The variation between lowest and highest total heating demand is around 15% • Differences in occupancy patterns due to socio-economic and cultural factors are relevant
Barthelmes et al. 2017	• Local • Relative percentage difference	• HVAC use • Appliances use • Lighting use • Heating and cooling set point • Blind use • Domestic hot water	• Total energy use	• Scope: impact of occupant behaviour life-styles on the building energy performance, considering building characteristics • Context: 2 variations (i.e., nearly-zero vs traditional) of a single-family house; Turin, Italy • Simulation period: 1 year • Deterministic models • There is changing influence of the most relevant parameters depending on the building characteristics • In the nearly-zero energy building the most relevant aspect is appliance use followed by lighting use • In the standard building the most relevant aspects are temperature setpoints and appliance use
Buso et al. 2015	• Local • Relative percentage difference	• Appliance use • Lighting use • Temperature setpoints • HVAC use	• Total primary energy use	• Scope: impact of working occupant behaviour lifestyles on energy use • Context: 15 variations (i.e., envelop characteristics) of an office building – 1 floor – cellular offices; Stockholm, Sweden – Frankfurt, Germany – Athens, Greece • Simulated period: 1 year • 15 building variations × 11 simulations × 3 climates • Deterministic and probabilistic models • Austerity workstyle can save up to 50% of source energy, while the wasteful workstyle can increase energy use by 89% compared to the standard workstyle

aspects in those papers, lighting and blinds operation, appliances and HVAC use, thermostat temperature setpoints adjustment, and occupants' clothing level and metabolic rate have also been explored. Further, most studies above implemented global sensitivity analysis using the Monte Carlo or Latin hypercube method to sample input variations. Finally, several papers highlighted that different climate, building variants, ventilation strategies, and spatial and temporal scales could lead to a diverse sensitivity of the KPIs to various occupant behaviour aspects (Azar and Menassa 2012; Ioannou and Itard 2015; Gaetani et al. 2017; Yousefi et al. 2017; Rouleau et al. 2019) stressing the need of including sensitivity analysis in the BPS workflow.

However, while the occupant behaviour research field has gained maturity, its application in practice is still in its early stages (Mahecha Zambrano et al. 2021). Consequently, different stakeholders are not well informed about the added value of integrating occupant behaviour modelling into the different stages of the building life cycle and building codes and standards do not require nor guide the application of advanced occupant behaviour models. Further, additional resources (i.e., time and budget) are not being added to the projects for considering occupant behaviour modelling and its implications in the building design and operation decision-making process as its added value is still not entirely perceived (Azar et al. 2020). As a result, methods and tools that facilitate the application of sensitivity methods for evaluating the influence of occupant behaviour on building performance need to be developed, integrated, and demonstrated. They need to be computationally efficient and produce and communicate readable and intuitive results to better inform the BPS process.

Considering that sensitivity analysis often requires a large number of simulations and practitioners often have limited resources to perform BPS analysis, Gaetani et al. (2018) developed a novel screening method, the Impact Index (II) method, to assess the potential impact of the occupants on the building's heating and cooling demand. With one BPS run, the II method quantifies the relative importance of heat gains to the cooling and heating demand, which can be associated with different occupant behaviour aspects. Thus, it could be used as a screening method to decide which specific aspects of occupant behaviour should be modelled more accurately in BPS or for providing preliminary information to perform more tailored subsequent sensitivity analysis.

While the II method emerges as a promising solution for supporting BPS users in identifying relevant occupant behaviour aspects, the formulation proposed in Gaetani et al. (2018) has been applied to simplistic building models and is limited by the assumption of having heating and cooling periods that are clearly defined i.e., distinct from each other. Depending on the building characteristics, building zones and uses, and weather, heating and cooling periods could be different among building zones, and single zones could require to be heated and cooled during the same period (e.g., day, month, etc.).

Moreover, a designer could be interested in understanding the potential impact of the occupants on the heating and cooling demand for specific periods or selected thermal zones. In this view, in order to be useful in practice, a general formulation of the II method is required to perform the analysis at any needed temporal or spatial resolution, and with realistic heating and cooling scenarios. Finally, an intuitive way of communicating the results will help to efficiently support BPS users in their decision-making process.

1.2 Objectives & structure

This article advances and applies to an office building a fast, efficient, and reliable method for quantifying the potential impact of various occupant behaviour aspects on the cooling and heating demand of an entire building or a thermal zone of a building. Building upon the II method first presented in Gaetani et al. (2018), its definition is advanced to address the following limitations: heating and cooling periods are distinct from each other, and they are the same for all the building zones; the II are defined for the whole building; the II are defined for the whole simulated period. Its application is then demonstrated by considering heating and cooling scenarios exhibited in real buildings. Specifically, this article contributes to the state-of-the-art of occupant behaviour research field by:

i. Proposing a general formulation for the II that allows their calculation at any temporal and spatial resolution;
ii. Addressing the limiting assumption that heating and cooling periods are distinct from each other to calculate the II;
ii. Providing an intuitive way of communicating the results to efficiently support BPS users in their decision-making process;
iv. Demonstrating the application of the II method using a real building that exhibits complex heating and cooling scenarios, such as cooling and heating of the same thermal zone within a day and cooling one thermal zone while simultaneously heating another thermal zone within the same day.

Consequently, it contributes to bridging the gap between the occupant behaviour research field and the building design and operation practice by advancing and demonstrating tools that guide and facilitate the integration of occupant behaviour into BPS studies.

The rest of the article is structured as follows: Section 2 reviews and advances the II method; Section 3 demonstrates its application including the description of the case study, the II results and their comparison to a one-factor-at-a-time (OFAT) sensitivity analysis to assess its reliability; Section 4 discusses potential applications of the method; Section 5 summarises the main results.

2 Impact Index method

2.1 Definition

For *distinct* heating or cooling periods i.e., periods during which only heating OR cooling occurs, the II for a given occupant behaviour aspect is estimated by subtracting the contribution of the related heat gain (e.g., the blind operation is related to heat gains through windows) from the heating (or cooling) demand (Gaetani et al. 2018). Table 2 presents the definition of the Impact Index (II) for each occupant behaviour aspect as reported in Gaetani et al. (2018).

Table 2 II definition

Impact Index	Heating period	Cooling period	
	(a)	(b)	
II_i	$\dfrac{Q_{\mathrm{L,Tot}}-(Q_{\mathrm{G,Tot}}-Q_{\mathrm{G},i})}{Q_{\mathrm{NH}}}-1$	$1-\dfrac{(Q_{\mathrm{G,Tot}}-Q_{\mathrm{G},i})-Q_{\mathrm{L,Tot}}}{Q_{\mathrm{NC}}}$	Eq. (1)

In Table 2, the subscript i denotes the given occupant behaviour aspect i.e., occupancy, lighting use, equipment use, and blinds operation which is associated with a heat gain component. These are $Q_{\mathrm{G,People}}$, $Q_{\mathrm{G,Lights}}$, $Q_{\mathrm{G,Eq}}$, $Q_{\mathrm{G,Win}}$, i.e., the heat addition due to people, lighting system, equipment, conduction and radiation through windows; $Q_{\mathrm{G,Tot}}$ and $Q_{\mathrm{L,Tot}}$ represent the total heat gains and losses, respectively; and Q_{NH} and Q_{NC} are the sensible heat addition and removal by the HVAC system. All the above quantities are defined as non-negative.

The heat balance for the heating period (see Eq. (2a)) and the cooling period (see Eq. (2b)), where $Q_{\mathrm{G,Tot}}$ represents the total heat gains, and $Q_{\mathrm{L,Tot}}$ the total heat losses, can be written as in Eq. (3a) and Eq. (3b), respectively. Replacing these expressions in the definition of the II indices (Eq. (4)) results in Eq. (5). Finally, this expression can be further simplified as in Eq. (6).

(a)	(b)	
$Q_{\mathrm{NH}}=Q_{\mathrm{L,Tot}}-Q_{\mathrm{G,Tot}}$	$Q_{\mathrm{NC}}=Q_{\mathrm{G,Tot}}-Q_{\mathrm{L,Tot}}$	Eq. (2)
$1=\dfrac{Q_{\mathrm{L,Tot}}-Q_{\mathrm{G,Tot}}}{Q_{\mathrm{NH}}}$	$1=\dfrac{Q_{\mathrm{G,Tot}}-Q_{\mathrm{L,Tot}}}{Q_{\mathrm{NC}}}$	Eq. (3)
$\mathrm{II}_{i,\mathrm{H}}=\dfrac{Q_{\mathrm{L,Tot}}-(Q_{\mathrm{G,Tot}}-Q_{\mathrm{G},i})}{Q_{\mathrm{NH}}}-1$	$\mathrm{II}_{i,\mathrm{C}}=1-\dfrac{(Q_{\mathrm{G,Tot}}-Q_{\mathrm{G},i})-Q_{\mathrm{L,Tot}}}{Q_{\mathrm{NC}}}$.	Eq. (4)
$\mathrm{II}_{i,\mathrm{H}}=\dfrac{Q_{\mathrm{L,Tot}}-(Q_{\mathrm{G,Tot}}-Q_{\mathrm{G},i})}{Q_{\mathrm{NH}}}-\dfrac{Q_{\mathrm{L,Tot}}-Q_{\mathrm{G,Tot}}}{Q_{\mathrm{NH}}}$	$\mathrm{II}_{i,\mathrm{C}}=\dfrac{Q_{\mathrm{G,Tot}}-Q_{\mathrm{L,Tot}}}{Q_{\mathrm{NC}}}-\dfrac{(Q_{\mathrm{G,Tot}}-Q_{\mathrm{G},i})-Q_{\mathrm{L,Tot}}}{Q_{\mathrm{NC}}}$	Eq. (5)
$\mathrm{II}_{i,\mathrm{H}}=\dfrac{Q_{\mathrm{G},i}}{Q_{\mathrm{NH}}}$	$\mathrm{II}_{i,\mathrm{C}}=\dfrac{Q_{\mathrm{G},i}}{Q_{\mathrm{NC}}}$	Eq. (6)

Ultimately, the II can be expressed as in Eq. (7), using a general notation where the subscript i denotes a given component (e.g., Lights), and x the cooling or heating period.

$$\mathrm{II}_{i,x}=\frac{Q_{\mathrm{G},i}}{Q_{\mathrm{N}x}} \qquad \text{Eq. (7)}$$

Equation (7) reveals that the formulation of each Impact Index is based on the impact of a single heat gain component on the sensible heat of the HVAC system. In other words, it makes the simplifying assumption that when varying a given heat component (e.g., $Q_{\mathrm{G,Lights}}$), mainly that component changes and is responsible for the change in the cooling or heating demand, while the other components do not change or change considerably less. Therefore, the II can be interpreted as follows.

- $\mathrm{II}_{i,x}\rightarrow 0$: The heat gains due to i represent close to 0% of the HVAC heating/cooling (H/C) energy demand. Hence, the potential impact of behaviour i on H/C is considered negligible.
- $\mathrm{II}_{i,x}\rightarrow 1$: The heat gains due to i represent close to 100% of the HVAC H/C energy demand. Hence, the potential impact of behaviour i on H/C is considered significant.
- $\mathrm{II}_{i,x}>1$: The heat gains due to i represent more than 100% of the HVAC H/C energy demand. Hence, the potential impact of behaviour i on H/C is considered larger than the HVAC H/C energy demand.

The last case can occur when very small cooling or heating is required; as a consequence, a specific occupant behaviour aspect can appear to be influential, but the resulting impact in absolute value might be irrelevant. To avoid large II that could be misinterpreted, the user of the method needs to define a threshold for the H/C energy demand depending on the simulation context. In other words, one could decide to neglect periods in which the H/C energy demand accounts for less than a predefined percentage (e.g., 10%) of total energy demand in that period.

2.2 Generalisation

Buildings can have a variety of spaces exhibiting different cooling and heating conditions depending on factors such as location within the building (e.g., internal room, perimetral room), use (e.g., personal office, open-floor office, conference room), and HVAC system design and control (e.g., single air-handling unit (AHU) for the whole building, multiple AHU serving different spaces, individual air conditioning systems, etc.). Accordingly, this could result in thermal zones with different heating and cooling periods thus, it is proposed to calculate the II at room level. Using a general notation, for a given zone j, considering an occupant behaviour aspect i, the impact index is defined as $\mathrm{II}_{i,x;j}$. The subscript x represents either cooling or heating. Cooling and heating periods might be not distinct e.g., an office space could be heated early in the morning when the occupancy is low but could be cooled when its occupancy is maximum. Therefore, the II need to be calculated considering the heat balance at each time step (see Eq. (8)).

$$Q_{\mathrm{HVAC};j,t}=Q_{\mathrm{G,Tot};j,t}-Q_{\mathrm{L,Tot};j,t} \qquad \text{Eq. (8)}$$

where the subscripts j and t refer to the zone and time step, respectively. This results in three possible scenarios:

- $Q_{\mathrm{G,Tot};j,t}=Q_{\mathrm{L,Tot};j,t}\rightarrow Q_{\mathrm{HVAC};j,t}=0$; i.e., no cooling or heating required

- $Q_{\mathrm{G,Tot};j,t} > Q_{\mathrm{L,Tot};j,t} \rightarrow Q_{\mathrm{HVAC};j,t} > 0$; i.e., cooling is required, $Q_{\mathrm{HVAC};j,t} = Q_{\mathrm{NC};j,t}$
- $Q_{\mathrm{G,Tot};j,t} < Q_{\mathrm{L,Tot};j,t} \rightarrow Q_{\mathrm{HVAC};j,t} < 0$; i.e., heating is required, $-Q_{\mathrm{HVAC};j,t} = Q_{\mathrm{NH};j,t}$

Then, for a specific period [t_1, t_2] (e.g., year, month, etc.), the heat balance for a given room during cooling (Eq. (9)) or heating (Eq. (10)) is given by:

$$\sum_{t_1}^{t_2} Q_{\mathrm{G,Tot};j,t} - \sum_{t_1}^{t_2} Q_{\mathrm{L,Tot};j,t} = \sum_{t_1}^{t_2} Q_{\mathrm{NC};j,t} \quad \text{Eq. (9)}$$

for t where $Q_{\mathrm{G,Tot};j,t} > Q_{\mathrm{L,Tot};j,t}$

$$\sum_{t_1}^{t_2} Q_{\mathrm{L,Tot};j,t} - \sum_{t_1}^{t_2} Q_{\mathrm{G,Tot};j,t} = \sum_{t_1}^{t_2} Q_{\mathrm{NH};j,t} \quad \text{Eq. (10)}$$

for t where $Q_{\mathrm{G,Tot};j,t} < Q_{\mathrm{L,Tot};j,t}$

Consequently, the Impact Index of a given zone j for a defined period [t_1, t_2] can be expressed as:

$$\mathrm{II}_{i,x;j t_1}^{\;t_2} = \frac{\sum_{t_1}^{t_2} Q_{\mathrm{G},i;j,t}}{\sum_{t_1}^{t_2} Q_{\mathrm{N}x;j,t}} \quad \text{Eq. (11)}$$

Summarising, the II are calculated at zone level for any given temporal resolution over a chosen overall period, possibly adding up several periods within that overall period where only either heating or cooling was required. Regarding different spatial resolutions, we define a section as a group of thermal zones. A section can represent one level of the building, all the zones with similar uses, or the whole building. To this end, for a given section S, a weighting factor $w_{x,j}$ is defined for each zone within the section as the ratio between the zone total sensible cooling/heating demand and the section total sensible cooling/heating demand for a defined period [t_1, t_2] in which only heating or cooling was required. In this way the Impact Index of a section (with N zones) of the building for a defined period [t_1, t_2] can be expressed as:

$$\mathrm{II}_{i,x,S} = \sum_{j=1}^{N} w_{x,j} \mathrm{II}_{i,x;j} \quad \text{Eq. (12)}$$

3 Application and reliability assessment of the II method

3.1 Case study description

The case study selected to demonstrate and assess the reliability of the II method is based on the One Melbourne Quarter building, a 13 levels commercial building located in Melbourne, Australia (see Figure 1). The building is equipped with passive design features such as a high-performance façade with optimised shading (i.e., fixed overhangs in the north façade, vertical fins in the west and east façades), insulated curtain wall spandrels, thermally broken double glazing, motorized and manually operated internal blinds, air-tight building envelope, and 201 kW PV installed on the roof to cover approximately 10% of the base building's energy consumption. The windows are not operable. The HVAC system includes 7 AHU equipped with supply and extraction variable volume fans. Each unit serves different spaces of the building according to its location within the building i.e., interior, east, southeast, southwest, west, north, and northwest. Further, the HVAC plant has two gas boilers, two electric chillers, and three cooling towers.

Levels 1 to 3 were simulated for this study (see Figure 2). This space hosts the offices of an engineering consulting firm and includes meeting rooms, open offices, individual offices, a coffee bar, and laboratories. The three levels have a similar floor plan as in Figure 1. A conservative daily

Fig. 1 Left: One Melbourne Quarter (ARUP 2022); Right: schematic floor plan

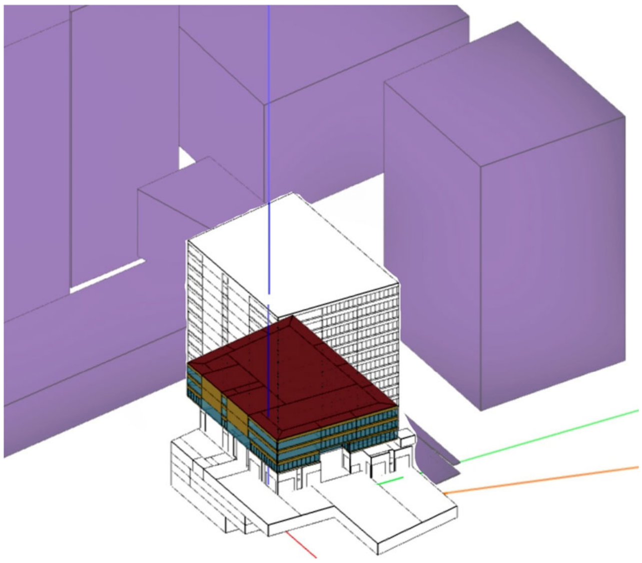

Fig. 2 Geometrical building model

average of 450 people work here using 450 laptops and 830 monitors. The BPS baseline model (identified as AUS_Code) implemented in EnergyPlus v9.2 was developed in compliance with the National Construction Code (NCC) of Australia (ABCB 2016) and the Australian/New Zealand Interior and workplace lighting (Standards Australia and Standards New Zealand 2016) and Use of Ventilation and Air-Conditioning in Buildings (Standards Australia and Standards New Zealand 2018) (see Table 3). External shading (i.e., fixed overhang and vertical fins), and surrounding buildings are included to estimate solar radiation in an accurate manner (Figure 2). The model includes 43 conditioned zones accounting for 5,818 m². The floor of level 1 and the ceiling of level 3 are assumed to be in thermal equilibrium with adjacent conditioned spaces (i.e., ground floor and level 4) thus, modelled as adiabatic surfaces. The HVAC system is modelled in detail according to the description given in the previous paragraph and its operation is allowed between 06:00 and 22:00 during weekdays. Further, the occupancy, lighting, and equipment (i.e., plug-load appliances such as laptops) schedules used are presented in Figure 3 (AUS_Code), and the related power densities are summarized in Table 3. Finally, the typical meteorological year for the Olympic Park is used (Melbourne, AU).

The building model distinguishes the conditioned zones according to their use as the main lobby, lift lobbies and offices. In this study, lobby spaces are considered transition spaces where the people have limited interaction with the building systems thus, only the office spaces are considered for the calculation of the II. Here, the thermostat cooling and heating setpoints correspond to 24 °C and 21°C, respectively. Finally, for the sake of this study, external blinds were implemented to understand their potential impact on the building's performance, and their operation is modelled considering they are off during the night and on when there is a cooling requirement and high solar radiation on window[1]. As highlighted in Gaetani et al. (2020), despite this strategy doesn't represent the actual occupant behaviour, it is accepted in practice since drivers motivating the operation of the blinds are often related to thermal and visual comfort.

Table 3 Building description

Building characteristics	Physical aspects	• 3 Levels • 43 Conditioned zones • Area: 5,818 m²
	Windows type	• Thermally broken double glazing • Not operable • *U*-value: 2.5 W/(m²·K) • *g*-value: 0.23 • Visible transmittance: 0.5
	Shading	• Fixed overhangs • External roller blinds*: ○ Visible transmittance: 0.1 ○ Visible reflectance: 0.8 ○ Manually operated
Occupant related aspects	Occupancy	• Density: 10 m²/person • Schedule: AUS_CODE (Figure 3)
	Lighting	• Power density: 7 W/m² • Schedule: AUS_CODE (Figure 3)
	Plug-Loads	• Power density: 5 W/m² • Schedule: AUS_CODE (Figure 3) • E.g., Laptops & monitors
	HVAC	• Cooling setpoint: 24 °C • Heating setpoint: 21 °C • Schedule: on during weekdays from 6:00 to 18:00

* Not present in the real building but implemented for the purpose of the study

The heat balance information is extracted from the baseline simulation to calculate the II defined in Section 2 and the results are presented in Section 3.3. In detail, annual and seasonal II are calculated for occupancy, lighting, equipment, and blinds. 5 different sections grouping the offices with similar use and the same location in the building are analysed i.e., interior, west, east, north, and south. Figure 4 shows a 3D model of levels 1 to 3 simulated in this study. Here, it is highlighted the extent of each section which is projected across the three levels. For example, the section north, highlighted in red, includes 4 offices on each level. Additionally, a section defined as Building includes all the offices located on levels 1 to 3. Finally, Table 4 summarises the number of zones, the percentage of floor area, and the window-to-wall ratios of each section.

As shown in Figure 5, in this building (i.e., levels 1 to 3)

1 EnergyPlus function: OffNightAndOnDayIfCoolingAndHighSolarOnWindow

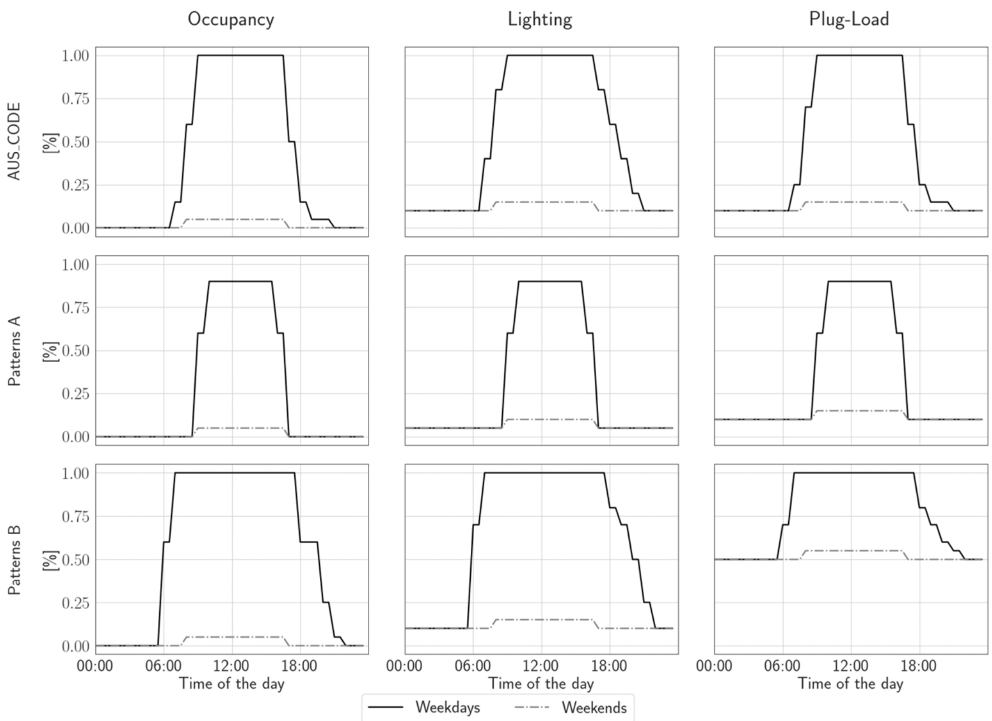

Fig. 3 Occupant-related schedules

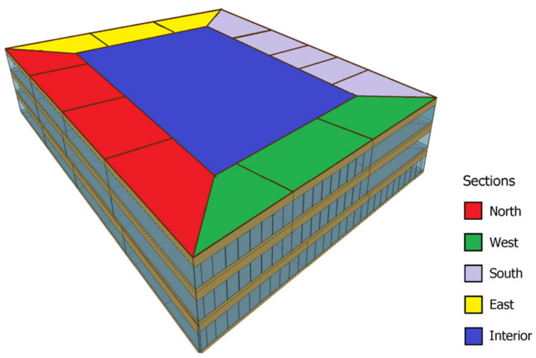

Fig. 4 Sections defined for the II calculation

Table 4 Summary – sections

Section	No. of zones	Floor area [%]	Window-wall ratio [%]
Interior	7	70.3%	—
North	12	11.8%	64.1%
West	9	7.7%	62.5%
South	8	4.1%	62.9%
East	7	6.1%	64.5%
Building	43	100%	

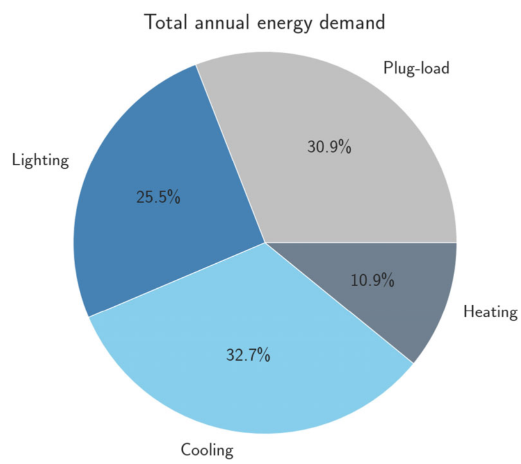

Fig. 5 Total annual energy demand by end-use

the simulated annual heating demand (10.9%) is rather small compared to the cooling demand (32.7%), the lighting system (25.4%) and equipment (30.9%) energy use. Occupants have a direct impact on the equipment and lighting energy use through manually controlled systems. However, the impact of the occupants on the HVAC energy use is not obvious. As the cooling demand covers 75% of the HVAC energy use, the subsequent analysis will focus on the cooling demand.

3.2 Reliability assessment of the II method

The II method is compared to an OFAT sensitivity analysis to investigate its reliability. The baseline simulation is modified by varying one occupant-related occupant behaviour aspect at a time from a low to a high level or vice versa. These levels represent pronounced, simplified changes in occupant behaviour to test the actual influence of these parameters on the results (adapted from (Azar and Menassa

2012; Gaetani et al. 2020)). Occupancy, lighting use and equipment (i.e., plug-load appliances) use are modified by changing the schedules. The low level (see Figure 3 – Patterns A) is characterised by a late start of the working day (i.e., 9:00 a.m.) and no after-work hours. Conversely, the high level (see Figure 3 – Patterns B) is characterized by an early start and extended working hours at the end of the day. The blind operation is modified from the baseline simulation where they are ON only when there is a cooling requirement and solar radiation on the window, by extreme behaviours where they are always ON (i.e., low level) and always OFF (i.e., high level). The HVAC on/off schedule is modelled as in the baseline simulation (see Section 3.1). Accordingly, eight additional simulations are performed (see Table 5). To this aim, the mean absolute values of the cooling variation between high-level and baseline simulations, and low-level and baseline simulations of each occupant-related aspect are compared to the corresponding calculated II using the baseline simulation (see Section 3.4).

3.3 Impact Indices

The II are calculated as defined in Section 2.2 using the baseline simulation (i.e., AUS_CODE schedules and parameters) considering different spatial and temporal resolutions for the people's presence, lighting use, equipment use, blinds operation, and thermostat set point adjustment. In each season (e.g., winter) the impact on the cooling demand is analysed when the total cooling demand during the period accounts for at least 10% of the energy demand in that period. Figure 6 presents an intuitive visualization of the annual II i.e., calculated using the whole simulation period (1 year). In the section *Building*, comprising all the offices on levels 1 to 3, results show that lighting use and

Table 5 Scenarios for the sensitivity analysis

Simulation ID	Occupancy	Lighting	Equipment	Blinds
Occupancy-Low	**Low level**	Baseline level	Baseline level	Baseline level
Occupancy-High	**High level**	Baseline level	Baseline level	Baseline level
Lighting-Low	Baseline level	**Low level**	Baseline level	Baseline level
Lighting-High	Baseline level	**High level**	Baseline level	Baseline level
Equipment-Low	Baseline level	Baseline level	**Low level**	Baseline level
Equipment-High	Baseline level	Baseline level	**High level**	Baseline level
Blinds-Low	Baseline level	Baseline level	Baseline level	**Low level**
Blinds-High	Baseline level	Baseline level	Baseline level	**High level**

Fig. 6 Annual II – sampled sections

occupant presence have the greatest impact, followed by plug-load use, and lastly blind operation. Further, while occupant presence, equipment use and lighting use have a similar impact across the building, it can be observed that blinds use has a high impact in the offices located on the south and west side of the building, and a medium impact on the north and east side. Additionally, while the heat balance in the interior section of the building is dominated by internal gains, the west section is dominated by solar radiation. Finally, the interior section covers 70.3% of the building floor area (see Table 4) and thus dominates the behaviour of the building. Accordingly, the large impact of the blinds in the south and west sections is reduced when focusing on the building II.

Going into more detail, Figure 7 presents the seasonal II for each section of the building. This reveals important seasonal differences regarding the cooling requirements. In all seasons, the building cooling demand is significant due to the interior section. Expectedly, the impact of the occupancy, lighting use and plug-load use on the cooling demand of the interior section is higher in winter than in summer, because in summer the external solar heat gains become predominant. The cooling demand is negligible in the north, south and east sections during winter and spring, and in the west section during winter. As a result, for these sections and seasons, in Figure 7 the plot collapses to a single point equal to zero. Further, this intuitive way of presenting the II highlights differences between the sections. While in the north and east sections the impact of the blinds (i.e., solar gains) is rather low, it is medium in the south section and high in the west section. Finally, it is observed that the dominance of the interior section is maintained hence, the results from the other sections do not contribute significantly to the building II.

Finally, to illustrate the possible differences among offices located at the same level and side of the building, Figure 8 presents the annual II calculated for offices 3 and 4 located on the third level and north side of the building. Office 3 has adjacent offices on both sides while office 4 is in the northeast corner (see Figure 1). In office 3 occupancy, lighting use, and plug-load use have a medium impact while the blinds result more relevant. Office 4 has the same trend but shows a larger difference with an impact of the blinds higher by almost 50% than office 3. This is due to a higher direct solar radiation from north and east windows. Further, there are several buildings located in proximity to the building on the north and west side, while none are on the east side.

3.4 Comparison between the II method and OFAT sensitivity analysis

Figure 9 shows the relationship between the simulated cooling variation ΔC and the II for occupants' presence, lighting use, and equipment use. As explained in Section 3.2, the cooling variation is calculated as the absolute mean deviation of the annual HVAC cooling demand of the high and low-level simulations from that of the baseline simulation, i.e., 8 simulations (see Table 5). The demonstration

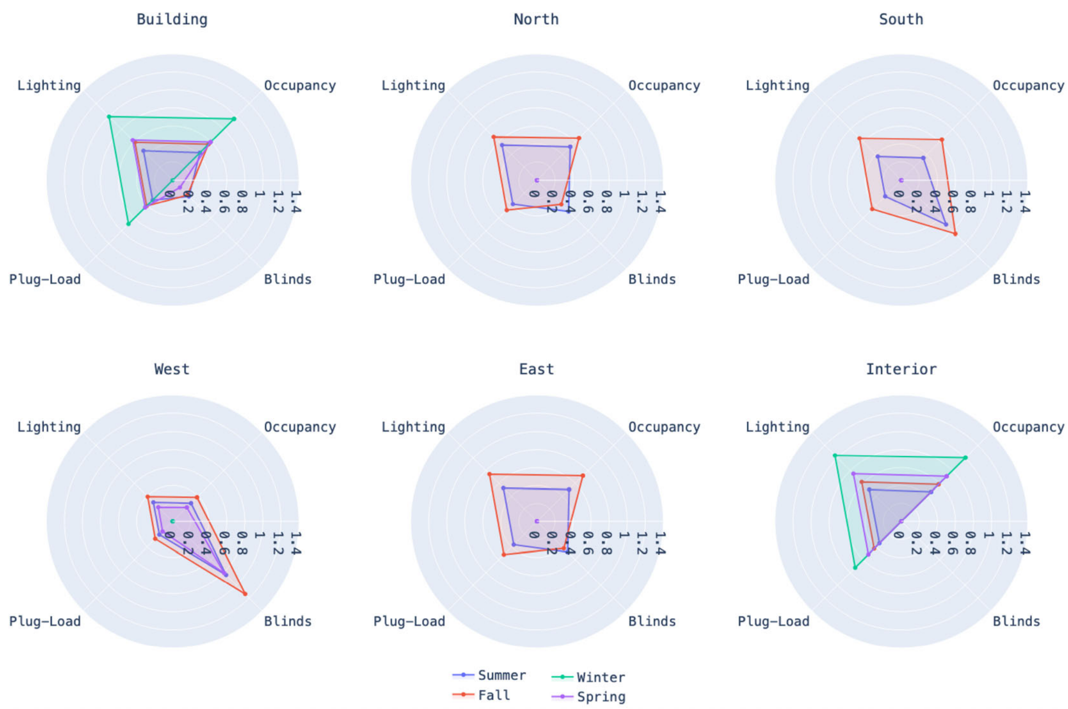

Fig. 7 Seasonal II – sampled sections

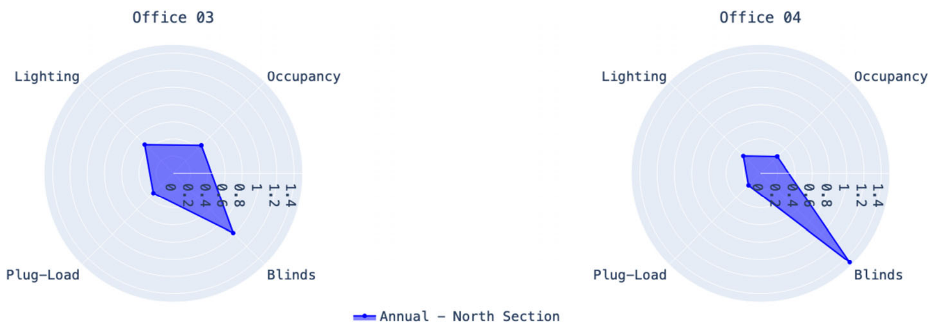

Fig. 8 Annual II – north section offices

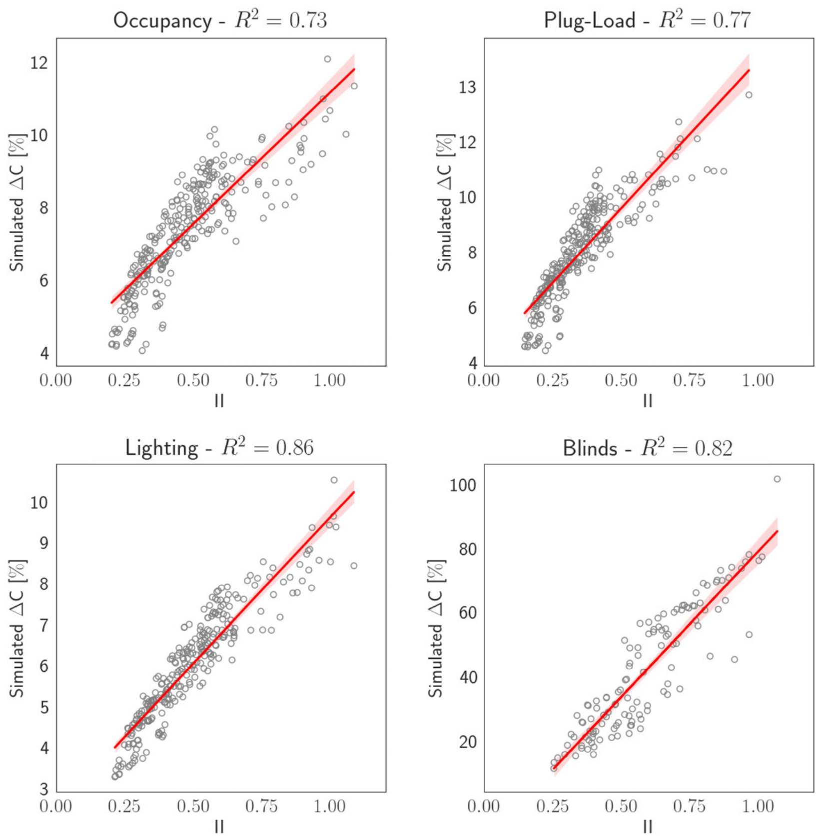

Fig. 9 Comparison of OAT sensitivity analysis vs. II method

is performed by combining a monthly, seasonal, and annual analysis (i.e., 12 + 4 + 1 = 17 periods considered) with single offices (i.e., 43 thermal zones), north, west, south, east, and interior sections of the building, and the section building (i.e., levels 1 to 3), for a total of 49 sections. As a result, the demonstration is performed with a theoretical maximum of 49 × 17 = 833 points for each occupant behaviour aspect. Nevertheless, for some sections and periods, the cooling requirement is negligible (i.e., less than 10% of the energy demand), thus resulting in a total of 275 points for each occupant behaviour aspect.

High linear correlations between the II and the ΔC from the sensitivity analysis with coefficients of determination (R^2) above 0.73 can be observed for all considered occupant behaviour aspects, thereby demonstrating the suitability of the proposed method to fast screen the influence of occupant behaviour aspects on cooling demand. Specifically, the variations defined for occupancy, lighting use, and plug-load use have a similar effect on the cooling demand (in the range of 4%–13%). Instead, the variations in the operation of the blinds have a larger impact in the range of 15%–100%. In this case study, the high and low levels defined for the blind operation are more extreme than for the other occupant behaviour aspects.

3.5 Case study remarks

In the shown case study, the II method provided a fast screening of which occupant behaviour aspects are expected to have an important impact on cooling demand and thus require more detailed modelling. For example, to reduce the uncertainty in the prediction of the building cooling demand, there is no need for integrating high complexity models for blind use since its impact is low i.e., annual II of 0.2 (see Figure 6 – Section: Building) and seasonal II lower than 0.2 (see Figure 7 – Section: Building). Instead, stochastic models might better represent occupancy, lighting and plug-load use, where the annual II of these aspects on the building cooling demand are closer to 0.6 (see Figure 6 – Section: Building). Furthermore, during summer they have a mild impact with an II of 0.4, which increases during spring and fall to an II of 0.6, and becomes highly important during winter with an II close to 1. When comparing the shapes of the II plots of each section (i.e., annual and seasonal analysis), it can be observed that the cooling demand of the building is mainly driven by the interior section. Indeed, during winter there is a cooling demand due to the high impact of the internal gains in this section. Thereby, occupants' engagement and education programs as well as occupant-centric control strategies could be deployed to reduce the lighting and plug-load appliances' energy use in the interior section, particularly during winter.

As mentioned before, blind use has a low impact on the cooling demand when it is analysed at the building level. However, it is relevant if the study is focused on the west and south sections of the building, especially during fall. As shown in Figure 9, the cooling demand can vary up to 107% when comparing the baseline simulation with the simulations for blind operation at high and low levels. This can be explained by the extreme high/low scenarios tested where the blinds are assumed on/off during the whole simulated period. While this result highlights the importance of an appropriate modelling of occupant behaviour and the possible impact of failing to do so, in this study these variations were defined with the sole purpose of assessing the reliability of the II method. Accordingly, rather than quantifying the change in the cooling demand, the II method is developed as a fast-screening method to identify the potential occupant behaviour aspects that could have a significant impact and hence need to be carefully considered in practice when taking modelling, design and operation decisions.

4 Discussion on applications

The II method identifies which occupant behaviour aspects are expected to have an important impact on cooling demand. This information can be used in the building design practice to support a variety of decisions. The method becomes part of a fit-for-purpose approach for selecting the most suitable occupant behaviour modelling approach. Non-influential aspects, i.e., occupant behaviour aspects characterised by low II, can be modelled with low-complexity models such as fixed schedules while influential aspects, i.e., occupant behaviour aspects with II close to 1, should be modelled with higher complexity models such as stochastic or agent-based models (Gaetani et al. 2020). The advances in the method presented in Section 2.2 allow identifying the influence of occupant behaviour aspects at different spatial scales. Accordingly, low-complexity models can be implemented for zones where the influence of occupant behaviour aspects is low, and more advanced models can be set for those with high influence.

Being a screening method, it can be used to filter the most influential occupant behaviour aspects prior to an in-depth sensitivity analysis, thus reducing the computational cost of exploring all possible occupant behaviour aspects within the latter. This is important because building engineering practice has few available resources (i.e., time and budget), if any, to explore the impact of human-building interaction on building performance. The proposed method may further be applied to improve the building's performance robustness (i.e., its resilience against variations in occupant behaviour) by assisting the definition and selection of design alternatives, control strategies, or retrofit options that minimize the II. Similarly, it may be used to assist the definition of occupant engagement and education programs by focusing on the most important occupant behaviour aspects during the relevant periods. In smart building applications, the II method may assist the selection and location of sensors and more in general occupant behaviour-related data gathering, tailoring solutions to the relevant occupant behaviour aspects. Likewise, the II method could be used to support the risk assessment related to occupant influences when setting up performance contracts.

5 Concluding remarks

This article improves and extends the impact indices method, which is a fast and computationally efficient screening method for assessing the potential impact of occupant behaviour on the heating and cooling demand. By simplifying the definition and advancing the method, complex heating and cooling behaviours in real buildings can be assessed at different temporal and spatial resolutions to decide which occupant behaviour aspects need to be modelled in more detail depending on the thermal zone and period of the year.

The II method was illustrated on a model of a real commercial building and its reliability was tested against an OFAT sensitivity analysis. While it proved to be effective as a screening method, important limitations can be observed in this study. First, the Impact Indices studied included occupancy, lighting use, plug-load use and blind operation. Other relevant occupant behaviour aspects such as thermostat adjustment and window operation should be included in future studies. Second, the II method cannot unveil possible interactions between occupant behaviour aspects. Nevertheless, it doesn't intend to replace detailed analysis but aims to simplify the process when resources are limited. Third, to perform the OFAT sensitivity analysis low and high-level variations were defined for the occupancy, lighting use, plug-load use, and blind operation. The choices made in this study are based on the literature review and possible yet extreme variations. These choices have an influence on the sensitivity of a performance indicator, in this case, the cooling demand. Nevertheless, the correlation between the variation in the cooling demand and the correspondent Impact Index is not expected to change significatively. While under these conditions the II method proved to be reliable, future work should explore the results using different high/low levels and control strategies.

Future work should also include testing the method in contexts where the heating demand is significant, or for buildings with different uses (e.g., residential buildings). In addition, future research should focus on evaluating the potential application of the II method to support a variety of design and operation decisions tailored to specific spaces. Some examples could include the ranking design or retrofit alternatives towards robust solutions that minimise the variability of the building performance due to occupant behaviour; optimising resources regarding sensor placement for smart buildings applications; directing the development of occupants' engagement and education programs to optimise the information, suggestions, and goals included.

Acknowledgements

The authors benefited from participating in the IEA EBC Annex 79 meetings. Furthermore, the authors want to thank the Sustainable Buildings team of Arup (Australia) who facilitated the building model used in this work, in particular Iona Norton, Shaw Kudo, Richard Stokes, Mitchell Harvey, and Wayne Lobo. Finally, the authors want to thank Prof. Pieter-Jan Hans for his review and feedback.

Funding note: Open Access funding provided by ZHAW Zurich University of Applied Sciences.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

Author contribution statement

All authors contributed to the study conception and design. Material preparation and data collection were performed by Juan Mahecha Zambrano. Analysis was performed by Juan Mahecha Zambrano, Isabella Gaetani and Ulrich Filippi Oberegger. The first draft of the manuscript was written by Juan Mahecha Zambrano and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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