TRECO-Office: Towards Real Energy performance and COntrol by predicting, monitoring, comparing and controlling for Offices and Public Buildings

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'Research into factors influencing model choice'

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Rekenmodellen, simulaties en gebruikersgedrag

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Research into factors influencing model choice

Please note that this TRECO progress report reflects the results per January 2016. Later Sections 1, 2 and 3 of this report are published in the journal article: "Gaetani, I., Hoes, P., & Hensen, J. L.M. (2016). ***Occupant behavior in building energy simulation: Towards a fit-for-purpose modeling strategy****. Energy and Buildings, 121, 188-204". The fit-for-purpose framework (Section 3), the case study and the sensitivity analysis (Sections 4 and 5) are improved and updated since January 2016. The improved results are published in the journal article: "Gaetani, I., Hoes, P., & Hensen, J. L.M. (2016).* ***On the sensitivity to different aspects of occupant behavior for selecting the appropriate modeling complexity in building performance predictions****. Journal of Building Performance Simulation, Vol. 10, pp. 601-611".*

1. Definition of fit-for-purpose

A main issue with the introduction of occupant behavior models in building energy simulation (BES) is the choice of an appropriate modeling *complexity* for a specific case. The problem of selecting the right model complexity does not specifically concern building energy simulation, but rather simulation in general, which has led some researchers to state that "the choice of the best model is more of an art than a science" [1]. One of the pillars of modeling is the acknowledgement of the objectives of the model [2]: poorly understood modeling objectives can result in excessively complex models. This may cause errors in the simulation results, as well as unnecessary expenditure of time and money. Many studies (e.g. [3], [4]) advocate the use of parsimonious models, i.e., the simplest among competing models. Generally, as simple models introduce approximation errors and complex models introduce uncertainty due to estimation, the goal of the simulation user should be to minimize the overall potential error by finding a compromise solution [5]. The optimal predictive ability of a model is nevertheless very case specific. Underfitting and overfitting occur when the model selection moves from the optimum towards too simple or too complex models, respectively. It has to be noted that the resulting potential error from underfitting and overfitting could be comparable, depending on how far from the optimum a model is; however, in the case of overfitting additional time and cost efforts have to be taken into account.

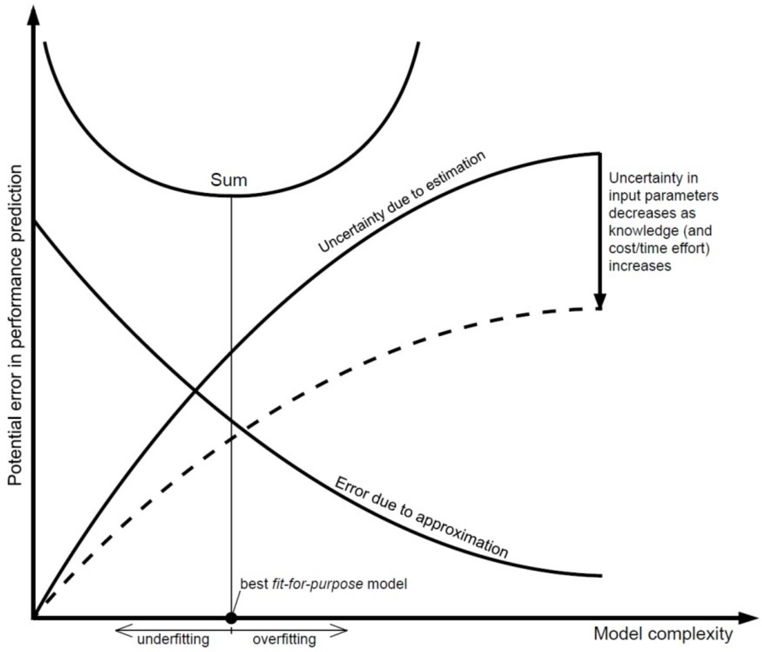


Fig. 2: Model uncertainty vs. complexity. Adapted from Trčka and Hensen [5]

In opposition to the principle of parsimony, a general increase in model complexity is observed. According to [6] this trend can be explained as a consequence of the following key factors: an "include-all syndrome" that leads modelers to include all available information; the progress of computing power that enables time-efficient, complex simulation; unclear simulation objectives.

In regard to building energy simulation, a similar problem existed in well-researched subdomains such as modeling of airflow [7], lighting [8], or systems [5]. For these subdomains, it is now widely acknowledged that different complexity levels should be used for different aims of simulation. In the area of occupant behavior modeling, possibly due to its relatively recent development, a similar common understanding has not yet been reached.

How is it possible to determine which model performs *best*? Goodness-of-fit is considered to be an unsuitable method to compare models. Instead, a good fit is necessary but not sufficient, as many models are able to fit a dataset reasonably well without necessarily bearing any interpretable correlation with the underlying process. Generalizability to other datasets is proposed as a good measure of comparison [4]. The plain definition of fit-for-purpose is *something good enough to do the job it was designed to do* [79]. It is hence to be expected that different models were identified as having the best predictive capability for different aims, buildings, etc. Indeed, the simulation user should choose the model complexity according to the specific case. Previous studies indicate the need for different occupant behavior modeling techniques according to the aim of simulation [16,80], to the phase of the building lifecycle [81], and to other building-related factors [80].

2. The influential factors

Table 4 shows a list of possible factors that could influence the choice of modeling technique. The intention should be to identify the simplest *fit-for-purpose* model, hence minimizing the potential prediction error. Typically, it will be possible to implement a simpler model in those cases where occupant behavior has a relatively lower impact on the performance indicator. Different building typologies have very different characteristic occupancy schedules that can be comparatively more or less predictable or constant throughout the day. For example, a school has a rather predictable occupancy schedule, while a dwelling is characterized by a much broader range of possibilities. When investigating the maximum heating load, a lower complexity than the one needed for the total heating energy consumption might be acceptable [80]. The selected performance indicator also influences the temporal granularity, or the choice of time-step during the energy simulation. In some phases of a building lifecycle e.g., design phase, it might not be possible to accurately predict the relevance of occupant behavior due to the lack of data or to the flexible design concept [81]. Finally, individual features of the building form, building envelope and building concept could also result in a variable influence of occupants. For example, in a museum users do not usually open windows, adjust blinds or the thermostat, while these are all basic requirements of acceptable comfort in households. The simple case study presented in Section 5 further demonstrates i) how different typologies of behavior have a different impact on a given performance indicator, and ii) how different performance indicators are differently influenced by occupant behavior. These results suggest that the most fit-for-purpose occupant behavior model might differ according to type of behavior as well as selected performance indicator. Our immediate future research will focus on identifying which of the factors or combination of factors presented in Table 4 and in Fig. 3 have most influence on the impact of occupant behavior on the predicted building energy and comfort performance.

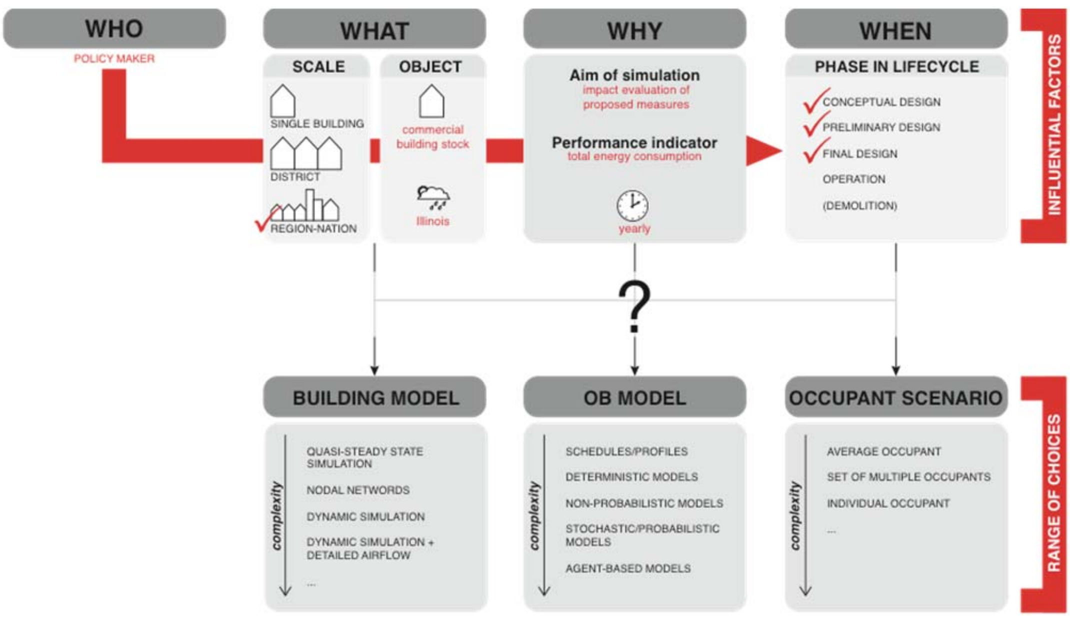
Object-related factors (a)	
Building(s) function [82]	Single family houses Apartment blocks/multi-family houses Offices Educational buildings Hospitals Hotels and restaurants Sports facilities Wholesale and retail trade services buildings Other types of energy-consuming buildings …
Building(s) characteristics	Conditioned/living area [m^2] Conditioned volume [m^3] HVAC system concept Ventilation strategy Main orientation …
Interaction building/outdoor	S/V [m^{-1}] Windows area North facade [%] Windows area South facade [%] Windows area West facade [%] Windows area East facade [%] Glass type (U [W/m^2K], SHGC [-], VT [-]) U value walls [W/m^2K] U value roof [W/m^2K] U value floor [W/m^2K] Solar shading Openable windows Dynamic facades Infiltration …
Interaction building/user	Lighting control Thermostat control Windows control Blinds control …
Climate characteristics	CDD HDD RH …
Aim of simulation (b)	
Policy making Design Retrofitting Initial commissioning On-going commissioning Fault detection Diagnostics Control …	
Performance indicators (c)	
Energy consumption	Heating energy demand [kWh/m^2y] Cooling energy demand [kWh/m^2y] Fans energy demand [kWh/m^2y] Electric lighting energy demand [kWh/m^2y] Total energy demand [kWh/m^2y] Total primary energy [MJ/m^2y]
Energy conservation	Avoided CO_2 emissions [kg/m^2y] Savings (from CO_2 and energy) [€/y] Operational costs [€/y]
Load	Max heating load [W] Max cooling load [W] Max lighting load [W] Max total load [W]
Lighting	Daylighting autonomy [% hours not requiring electric lighting]
Visual comfort	Daylighting glare avoidance [% hours in discomfort range (Daylighting Glare Index >= 24, just uncomfortable)]
Thermal comfort	Max T (a/op) in the zone [°C] Min T (a/op) in the zone [°C] PMV [-]

	PD (predicted % dissatisfied due to draft) [%]
…	

Table 4: First draft of possible factors that could influence the choice of modeling technique divided in: object-related factors (a); aim of simulation (b); performance indicators (c); phase of building lifecycle (d)

3. Fit-for-purpose framework

A graphical representation of the line of thought that was followed in the research problem definition follows below. Fig. 3 represents how two different stakeholders might use building performance simulation for different aims, which in turn have an impact on the influential factors. The listed *influential factors* should primarily determine the choice of software and modeling approach for the overall energy simulation. Typically, the energy simulation model for a large district will have a lower complexity level than the one performed on a single building. The building modeling approach will itself influence the selection of a behavioral model. The influential factors will also play a role in the choice of occupant scenario, i.e. if the simulation should include a unique average occupant or a set of multiple occupant scenarios. The decision to use an occupant behavior model at all, and which specific model is selected, has important consequences on the evaluation of a building's energy performance [83]. This decision can result in great differences in the comparison of design alternatives, both on the building level, such as the percentage of glazing or shading [84], and with respect to system control [16], system sizing and a range of other choices.



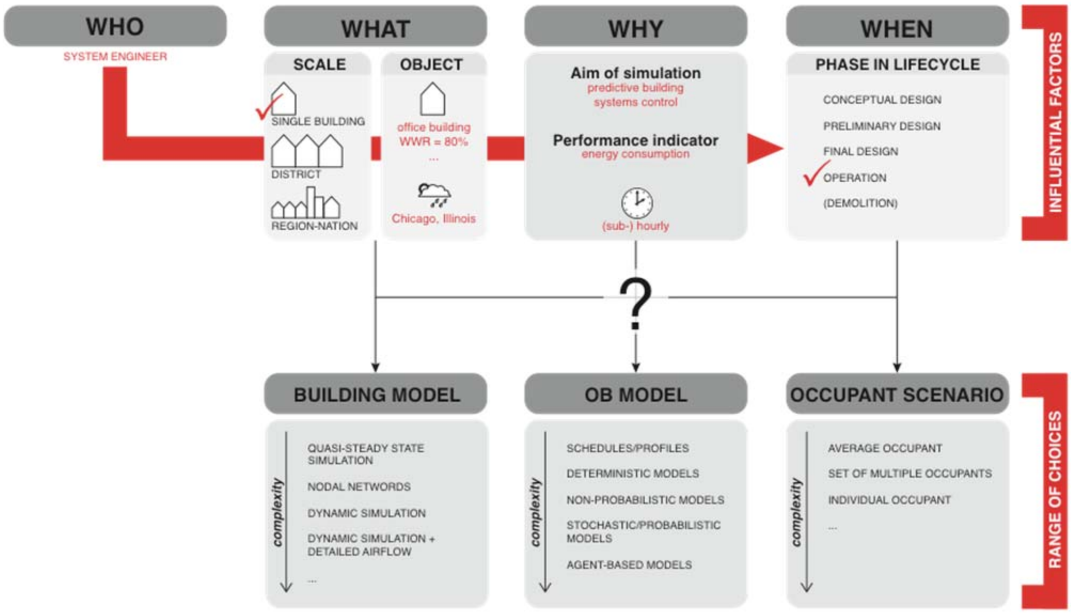


Fig. 3: Fit-for-purpose framework: policy maker vs. system engineer

4. Application to a case study

As can be seen in table 4, there are a large number of factors whose effects need to be determined. A small selection of these factors are investigated as a first demonstration of the fit-for-purpose approach in a simple case study. Future research by the current authors and others in the field will address these and other influential factors further. Fig. 4 represent the methodological flow which is at the basis of the fit-for-purpose occupant behavior modeling (FFP OBm) strategy. This sub-section explains each step until the definition of scenarios. The processing of results and consequent steps are in-progress and are outlined in sub-section 5.2.5. In this preliminary case study a dynamic simulation software (EnergyPlus) was chosen. The choice of a high building model complexity is due to the fact that the authors did not want the choice of the software to limit the development of the methodology in any sense.

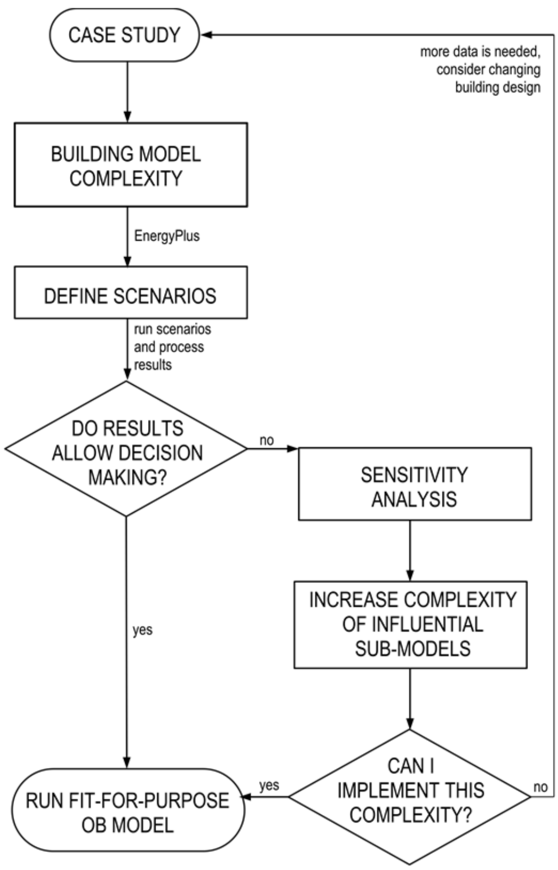


Fig. 4: Fit-for-purpose methodological flow

Reference building

The medium-size office building model developed for EnergyPlus by the U.S. Department of Energy in the framework of commercial reference buildings [16] was selected as a case-study. The reference building is a three-story office building located in Chicago, Illinois with a total floor area of 4982 m^2. The building has an aspect ratio of 1.5 and a glazing fraction of 0.33. The windows are non-operable and no sun screening system is present. Each floor of the building comprises one core zone and four perimeter zones. The roofs are flat and have insulation entirely above deck. The wall construction is steel frame. The wall construction, roof construction and window type of the reference buildings are location-dependent; Table 5 shows the construction of the considered reference building for Chicago, Illinois. The HVAC system consists of a furnace for heating, a packaged air-conditioning unit (PACU) for cooling and a multi-zone variable air volume (MZ VAV) for air distribution.

Building construction	
Window type	Double-pane window, low-e U-factor: 3.24 W/m^{2}K SHGC: 0.385 VT: 0.305
Wall construction	Steel-Frame Walls R-value: 1.95 m^{2}K/W
Roof construction	Built-up Roof: roof membrane + roof insulation + metal decking R-value: 2.66 m^{2}K/W

Table 5: Building construction parameters

Methodology

The impact of occupant behavior on the building energy performance is assessed by introducing simple variations to the building operation. The selected operation parameters and their respective variations are illustrated in Table 6; reference values correspond to the original EnergyPlus model while most variations are as in [17]. Such operation parameters do not claim to represent all possible interactions of the occupants with a building, but are nevertheless a starting point for this research. The operation parameters are varied one-at-a-time to evaluate their individual impact on the considered performance indicator. Then, the combinations of parameters are investigated to study possible operation scenarios. Only the combinations of high and low values are considered in order to limit the number of simulations. Moreover, schedules for equipment use, light use and occupancy vary according to their corresponding value (e.g., at high equipment power density corresponds high equipment use schedule only), which leads to 64 scenarios in total. 16 of these scenarios are discarded as $T_{sp,\ heating} > T_{sp,\ cooling}$; the remaining 48 scenarios are investigated.

The original building model uses the auto-sizing function of EnergyPlus to ensure that the system meets the peak loads. Thus, the size of the system would change for each scenario, as changing the operation parameters results in a modification of the DesignDay values. In order to avoid this inaccuracy, which renders results impossible to compare, the system was sized for the reference scenario and kept constant throughout the simulations, as it would occur in reality.

Operation parameters	Low value	Reference	High value
HVAC Schedule	Weekdays: 7am-6pm Sat: 7am-6pm	Weekdays: 7am-10pm Sat: 7am-6pm	Weekdays: 5am-12pm Sat: 7am-6pm
$T_{sp,\ heating}$ [°C]	18	21	23
$T_{sp,\ cooling}$ [°C]	22	24	26
Equipment Schedule		See Fig. 4a	
Equipment Power Density (EPD) [W/m^2]	5.38	10.76	16.14
Lights Schedule		See Fig. 4b	
Lighting Power Density (LPD) [W/m^2]	5.38	10.76	16.14
Occupancy Schedule		See Fig. 4c	
Occupancy Rate [people/m^2]	0.027	0.054	0.107

Table 6: Operation parameters

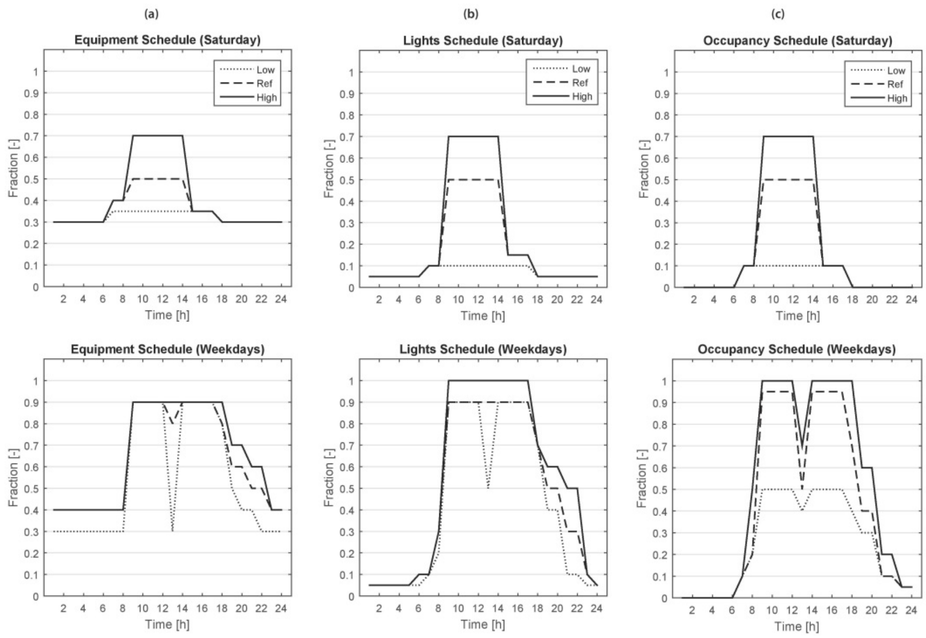


Fig. 5: Low, reference and high schedules for equipment use (a), lights use (b) and occupancy (c)

Results and discussion

Fig. 6 represents the percentage change of heating energy consumption and heating energy peak when varying each operation parameter, as well as worst and best case scenarios derived from the combination of all parameters. The results show how varying different operation parameters has a radically different effect on the selected performance indicator. For example, it is evident that equipment, lighting and occupancy schedules seem to play a negligible role in the variation of heating energy consumption for this specific case. On the other hand, the heating energy consumption is very much influenced by the $T_{sp,\ heating}$, the HVAC system schedule, EPD, LPD and occupancy rate. This suggests that a fit-for-purpose occupant behavior model should be composed of sub-models characterized by different levels of complexity. When looking at the heating energy peak, the only determining factors seem to be $T_{sp,\ heating}$ and EPD. These results imply that – for the considered building and performance indicators – occupancy, lights use and equipment use may be represented by simple schedules, as their effect on the energy performance is negligible. A higher level of complexity might be needed when representing other more influential operation parameters (e.g., $T_{sp, heating}$ when investigating heating peak loads).

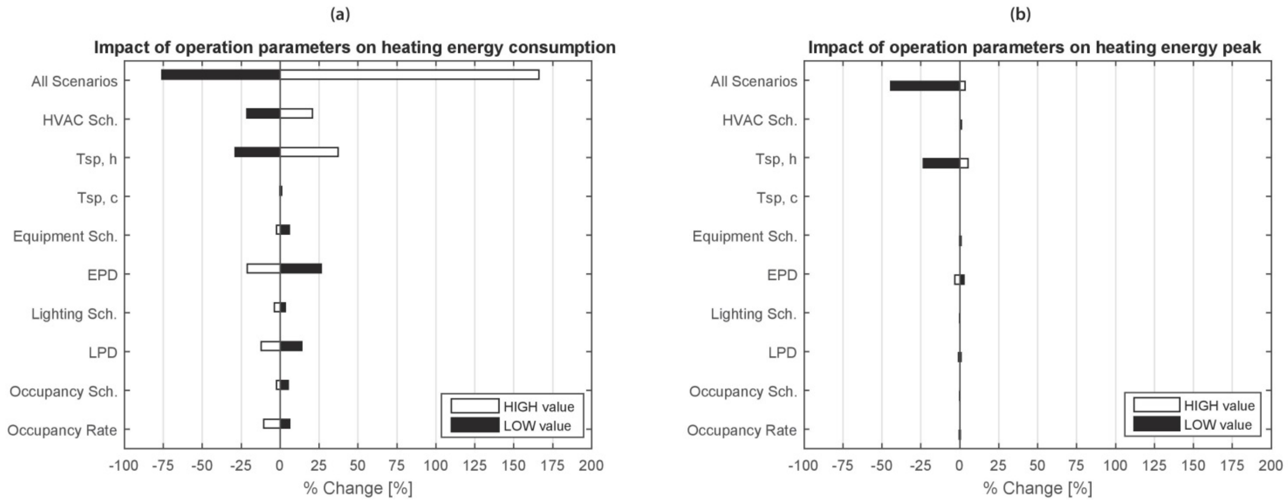


Fig. 6: Variations in heating energy consumption (a) and heating energy peak (b) due to operation scenarios

5. Sensitivity analysis and Mann-Whitney statistical test

A sensitivity analysis is needed in case the simulation user is not able to take a decision based on the distribution of values obtained by means of the use scenarios (e.g., a service company wishes to guarantee an energy consumption below a certain threshold, while the distribution with use scenarios exceeds this threshold). It is hence needed to further investigate the impact of each aspect of occupant behavior, and possibly increase the modeling complexity of those aspects that are particularly influential for the required performance indicator(s).

Fig. 6 highlights the need of taking all combinations of use scenarios into account, as not doing so would underestimate the possible concurring effects of use scenarios on building performance. For this reason, in order to evaluate the impact of each aspect of occupant behavior singularly, all scenarios characterized by a low value of one particular aspect are compared to those characterized by a high value of the same aspect, as shown in Fig. 7 for one performance indicator (total energy consumption) and two aspects of occupant behavior (lighting use and occupancy, or presence). By looking at the distributions of total energy consumption according to “high” or “low” behavior, it is evident how the distributions are independent on the level of occupancy, while there exists a significant dependency of the performance indicator on lighting power density and lighting use (here merged for the sake of simplicity).

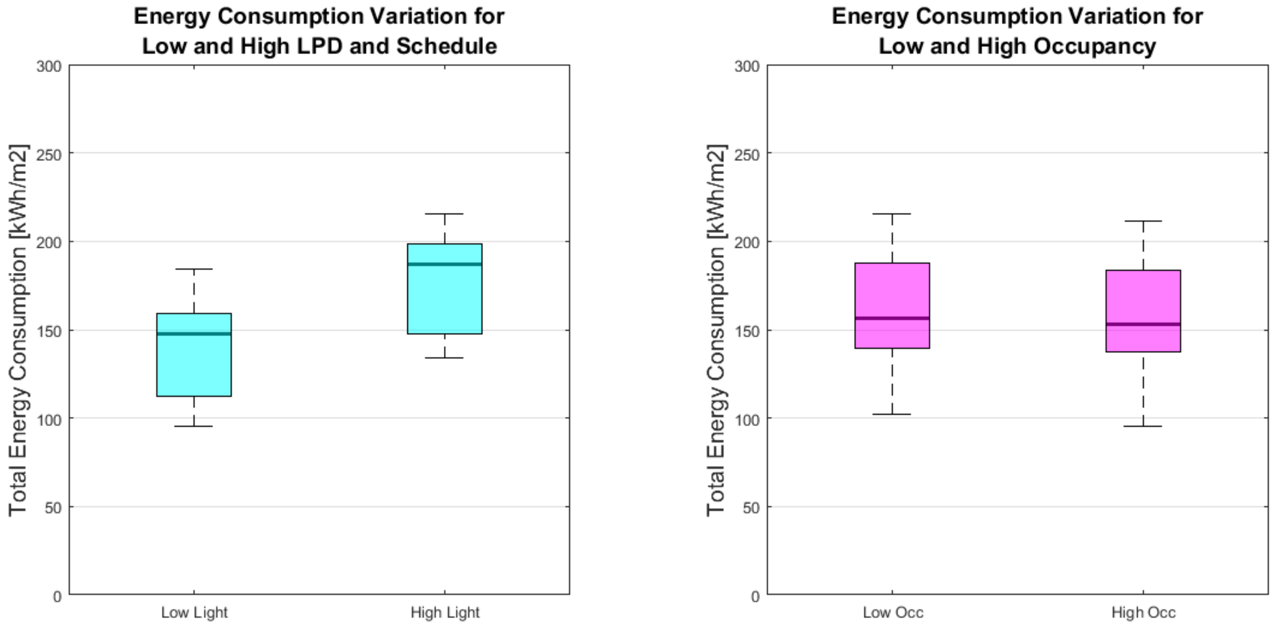


Fig. 7: Variations in total energy consumption due to high/low lighting power density and use behavior (left) and due to high/low occupancy (right)

The Mann–Whitney U test is a non-parametric statistical test used to establish whether the difference between the two distributions is significant or not. A significant value $p<0.05$ indicates a significant difference between the two sets of data. When applied to this case study, the results of the Mann-Whitney U test are visible in Fig. 8. In this case, it results that the total energy consumption of the case study building is strongly dependent on equipment and lighting power density and use (here merged), while all other aspects of occupant behavior are not relevant. This result is an indicator that more complex modeling of equipment and lighting might be needed. The next step of the research consists in applying higher complexity models to influential aspects of occupant behavior and verifying their impact on results.

The advantages of this methodology lay in the fact that it can be fully automated and applied to any sort of building. By doing so, insights on the influential factors can be gathered in an extremely time-efficient manner. Our preliminary runs already indicate that different aspects of occupant behavior indeed vary their influence according to performance indicator and building construction.

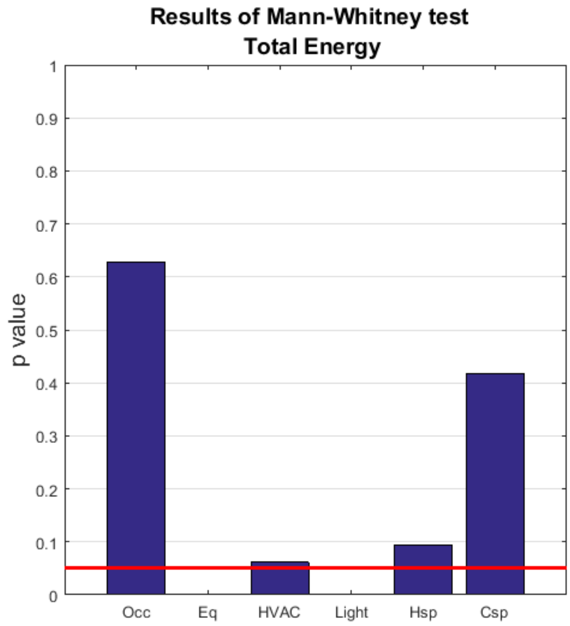


Fig. 8: Results of Mann-Whitney statistical test

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