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Impact of Occupant Behaviour on Performance Optimized Building Retrofits

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Abstract

In the framework of the recent Directive 844/2018, practitioner often rely on Building Energy Simulation (BES) combined with Multi-Objective Optimization (MOO) to find optimal energy saving measures for building retrofits. However, occupant behaviour is usually oversimplified as a static schedule provided by technical standards mainly developed for energy certification. This can lead to a significant gap between the performance of the optimal designed solution and its actual performance. In this study, we investigate how detailed user-behaviour profiles – e.g. static, probabilistic, and adaptive models - for the operation of windows impact on the optimal retrofit strategy. While the standard and adaptive model use a base ventilation rate like a constraint for indoor air quality (IAQ), the probabilistic models rely solely on the occupant actions on windows. The results demonstrate that the behavioural models result in major differences in indoor comfort conditions. Optimal solutions defined through probabilistic models are likely to be not very robust to the ventilation rate showing the potential for performance gaps. The importance of realistic user behaviour representation is highlighted to raise awareness about its influence on the full potential of retrofitting a building, maybe excluding those solutions that could majorly improve comfort.

Key Innovations

- Direct comparison of different occupant behaviour models and their impact on the optimal energy efficiency measures.
- Evaluation of the impact of window opening models on the comfort performance of the optimal solutions focusing on thermal comfort (WDT_t), and IAQ (WDT_{CO2} & WDT_{RH}).

Practical Implications

Beware of the major impact behavioural models are having on the optimal solution for a building retrofit. Avoid solely relying on standardized schedules for occupant behaviour and evaluate suitable models and their predictors in your specific reference environment.

Introduction

The performance simulation of occupied buildings is always driven by assumptions made for occupant behaviour. If the models for e.g. windows, lighting, shading, heating set-points or the use of fans are not evaluated carefully or adjusted to the investigated reference, this can lead to a significant gap between the performance of the optimally designed solution and its actual performance, because people's interactions may severely affect energy consumption and comfort conditions. In international building codes, occupant-related approaches still vary considerably and need some further standardization (O'Brien et al., 2020), because they do not consider people as active. In recent years behavioural models relying on probabilities rather than schedules have gained more and more importance for modelling occupant behaviour (Roetzel et al. 2010; Fabi et al. 2012 and 2013). As a consensus in most research papers in the field, linear regression models are calibrated using previously obtain experimental data (Andersen et al. 2016; Fabi et al. 2013, 2015; Haldi et al. 2017; Page et al., 2008).

In the here presented study we investigate to which extend detailed user-behaviour models for the operation of windows impact on the retrofit strategy – comparing retrofit strategies as shown in the method section. Further, the energy, cost and comfort performance of the optimal retrofit design configurations are compared. The behavioural models used for optimization are a standard user-behaviour model following static schedules, two probabilistic models and a rule-based adaptive model. For probabilistic occupant behaviour an early minimalistic approach developed by Nicol (2001) is considered taking solely outdoor temperature into account. As a second model, a more complex approach by Andersen et al. (2013) is chosen to account for the variety of environmental conditions. Here, the probability of action is predicted by indoor and outdoor temperature, CO_2 concentration, solar radiation, and relative humidity. Both models are originally developed and fitted to residential apartments. The last model, the rule-based adaptive model, is an idealized behavioural model developed by Penna et al. (2016). It allows for user dynamic interactions with windows triggered by thresholds for indoor temperature. All models are explained in detail in the Method section. The optimization is carried out considering two optimization objectives (i.e. energy and cost). The evaluation of the results focusses on changes in energy demand, total cost, and weighted discomfort time (WDT) for thermal comfort and indoor air quality (IAQ) represented as discomfort for CO_2 and relative humidity (WDT_{CO2} & WDT_{RH}).

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Methods

As a case study, a simplified semi-detached residential apartment building in a shoebox-like configuration has been considered. The apartment specifications can be found in Penna et al. (2016). To quantify the influence of different climatic conditions, Milan and Messina are tested as representative Italian heating and cooling dominated climates belonging respectively to Cfa and Csa climatic groups according to Köppen classification. The national test reference years have been used (CTI 2016).

To achieve several competing retrofit goals, a multi-objective optimization analysis is performed to optimize the initial reference building. To minimize the target functions of energy demand and global cost equally, different energy efficiency measures (EEM's) are combined. The considered EEM's are:

- External wall insulation (WI) with incremental thicknesses increases of 1cm, from 1 to 20 cm
- Roof external insulation (RI) with incremental thicknesses increases of 1cm, from 1 to 20 cm
- Floor insulation (FI) with incremental thicknesses increases of 1cm, from 1 to 20 cm
- Improved choice of glazing systems (Wind): Double glass with high Solar Heat Gain Coefficient (SHGC) (DH); Double, low SHGC (DL); Triple, high SHGC (TH); Triple, low SHGC (TL). Further, a new aluminum window frame with thermal break is considered. Details are found in Penna et al. (2016).
- Replacement of old boiler (Boi) with modulating or condensing boilers with a climatic control system
- Installation of a mechanical ventilation system (MVS) with heat recovery

It is to mention that some of these measures result in energy performance increases without causing additional costs, which are further specified in Penna et al. (2016).

Multi-Objective Optimization

To find the best performing solutions, a genetic algorithm (GA) is used where different combinations of EEM's are treated as genes. The most suitable among the population of genes are selected and recombined as the next generation for the following optimization run. This is achieved through an NSGA II - a Non-dominated Sorting Genetic Algorithm (Deb et al., 2002). The initial population is composed of 128 individuals chosen by the Sobol's Method, which refers to a random process selecting compositions uniformly distributed through the range of the problem. According to Saltelli et al. (2004), this provides higher efficiency in gene development towards the optimal ones. The individuals are chosen in fractions of 0.5 tournament selection, 0.8 of arithmetic crossover, and a mutation rate of 0.1. The Optimization is run using the gamultiobj-function in Matlab and the Optimization Toolbox (Matlab, 2020).

Building Energy Simulation Modelling

The basic building model is set up in TRNSYS (Solar Energy Laboratory, 2017) and completed through the addition of an occupant behaviour subroutine using excel. By coupling excel and TRNSYS the direct effects of occupant's interactions on the mentioned performance indicators can be simulated dynamically. The simulation time step is 10 min to balance the level of detail and computational time. During the day the residential apartment is considered as not occupied.

Standard behavioural Model (SM)

The Standard Model assumes a static schedule provided by technical standards for window opening/closing and shading operations. The thermostat is set to an interval from 20 to 22°C to turn on and off the heating system. When replacing the boiler, the water supply temperature is assumed to be adjusted by an outdoor temperature reset control. The internal gains through the heating system are modelled half radiative and half convective according to UNI/TS 11300-1:2014 (UNI, 2014). The air change rate reaches 0.5 ACH during occupancy time (17-7 on weekdays; 15-10 on weekends). If mechanical ventilation is applied, a heat exchanger is used to recover exhaust heat. In summer the mechanical ventilation system is used to reduce overheating. Especially if indoor temperatures exceed comfort conditions and outside temperatures are cooler. The airflow rate of the mechanical ventilation system - if in use - is set to 0.5 ACH as recommended by EN 16798-7:2017 (CEN, 2017).

Probabilistic Model (PM)

The Probabilistic Models (PMs) focus on a linear regression predicting interactions with windows. The regression parameters β_k and predictors x_i are taken from two research advancements (Andersen et al., 2013; Nicol, 2001). These models interpolate behavioural data previously obtained by measurements in residential buildings. In the first examined regression model from Nicol (2001), surveyed data obtained in three different countries is interpolated using the mean values of all surveys throughout Europe. A best-fit line is obtained, showing the proportion of opened windows for a given outdoor temperature. The outdoor temperature is found as the most relevant predictor. Linking outdoor temperature to probability of opening/closing windows, is not creating a loop of action and considered as more robust and useful (Nicol, 2001). Nicol's work explicitly discusses the application of the model for building simulation and suggests considering other factors to complete the full analysis of stochastic processes involved and their effect on thermal comfort and IAQ. Therefore, a linear regression analysis developed by Andersen et al. (2013) has been chosen as a second probabilistic model. It uses measurements in 15 residential buildings in Denmark, clusters them into similar groups and provides a set of regression parameters for each group. For opening probabilities indoor temperature T_i, outdoor temperature T_O and indoor CO_2 concentration and solar radiation are considered. For closing probabilities indoor temperature

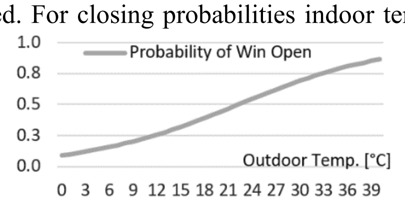

Figure 1: Opening/Closing Probability (Nicol, 2001)

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T_i, outdoor temperature T_O, indoor CO_2 Concentration, indoor relative humidity RH_i and outdoor relative humidity RH_O are considered. Both models depend on the current state of the window but use different environmental conditions as predictors. Probabilities p for occupant actions are calculated as a logistic model (1) that depends on a set of predictors x_i, e.g. the mentioned relevant environmental parameters, and regression parameters β_k obtained from the experimental data based on their statistical significance.

$$\text{logit}(p) = log\left(\frac{p}{1-p}\right) = \beta_0 + \sum_{k=1}^{n} \beta_k x_k \qquad (1)$$

With the obtained probability a new state for the windows and their corresponding opening angles are evaluated for each time interval of 10min. For the Andersen model, a continuous opening angle based on the probability p_O is calculated (2) whereas in the Nicol model opening angles are assumed to be 90°.

$$\gamma = p_O * 90° \qquad (2)$$

The linear regression models are implemented in EXCEL and outcomes are coupled with TRNSYS Type 62 to vary the ventilation rate used for the dynamic BES. It is worth mentioning that with PMs there is no guarantee that the required air change rate is provided.

During the summer period occupants are considered to actively operate shadings to adapt to irradiation.

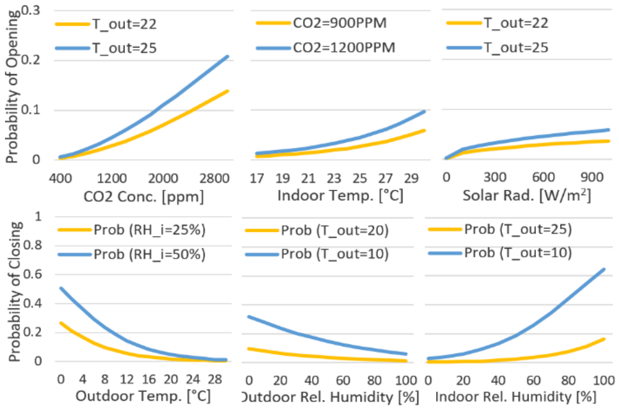

Figure 2: Opening/Closing Prob. Andersen et al. (2013)

Adaptive Model (AM)

The Adaptive Model is based on a research paper by Penna et al. (2016). Control actions regarding blind and window opening have been set as common-sense rational reactions to discomfort conditions. The AM correlates occupant reactions to the ambient conditions using temperature thresholds. These temperature bounds are set to represent the range of acceptable comfort conditions according to comfort category II of the Standard EN16798-1:2019 (CEN, 2019). In addition to the air change rate of 0.5 ACH during occupancy time (17-7 on weekdays; 15-10 on weekends), actions that reduce thermal discomfort are taken depending on the thermal sensation of the occupants: windows are opened or closed if the indoor temperature is outside or respectively inside of the defined boundaries, e.g. causing too cold or too hot sensations for the occupant. During the summer period occupants are considered to actively operate shadings. Windows are opened if the building is occupied, inside temperatures rise above the upper comfort threshold and outside temperatures are lower. Windows are closed if indoor temperatures fall below the lower comfort threshold. The corresponding ventilation rate has been modelled according to EN 16798-7 (CEN, 2017), which considers wind speed, temperature difference between inside and outside and window opening angle. The opening angle has been set to 90° (fully opened) during summer and 5° (partially opened) during winter.

Performance Indicators

The performance indicators should allow characterizing the behavioural models regarding the occupant's well-being, energy demand, and running costs. Therefore, indicators chosen are:

- Energy Performance for Heating (EP_h) as the primary energy used per heated area. Primary energy considers the boilers consumption of natural gas and electricity needed by pumps or mechanical ventilation systems.
- Net Present Value (NPV) represents the cash flow generated over the building's life span of 30 years. Referring to EU 244/2012 (European Commission, 2012) initial investment costs, Annual running costs, Replacement costs and Residual values are considered. More details can be found in Penna et al. (2016), Table 4 and EN 15459 (CEN, 2018).
- Temperature Weighted Discomfort Time (WDT_t) is measured in degree-hours of discomfort (CEN, 2005). This parameter indicates how long (τ in h) and to what extent (wf in K) the temperature is outside the comfort range. It is calculated using the Equations (5) and (6).

$$WDT_t = \sum wf * \tau \qquad (5)$$

With $wf = abs(\Theta_I - \Theta_{I,LowerLimit})$ if $\Theta_I < \Theta_{I,LowerLimit}$ or (6a)

$$wf = \Theta_I - \Theta_{I,UpperLimit} \;\; if \;\; \Theta_I > \Theta_{I,UpperLimit} \qquad (6b)$$

- CO_2 Weighted Discomfort Time (WDT_{CO2}) is measured in PPM-hours of discomfort. The parameter indicates the duration in hours weighted by the concentration above the specified threshold similar to WDT_t. Following EN 16798-1 (CEN, 2019) and assuming a normal level of expectation, (Category II according to ISO norms), discomfort occurs if the indoor CO_2 level raises 800ppm above outdoor air. Outdoor air is assumed to have 300ppm according to ASHRAE 62.1 p.38 (Hedrick et al., 2013).
- Relative Humidity Weighted Discomfort Time (WDTRH) is similarly defined considering discomfort outside of the foreseen comfort band between 25-65% as described in EN 16798:2019 (CEN, 2019).

Results

Description of Figures

To analyse the impact of the presented behavioural models on the retrofit strategy and its performance, the obtained optimal sets of solutions are presented as a parallel axis plot in figure 3. Each optimal retrofit solution

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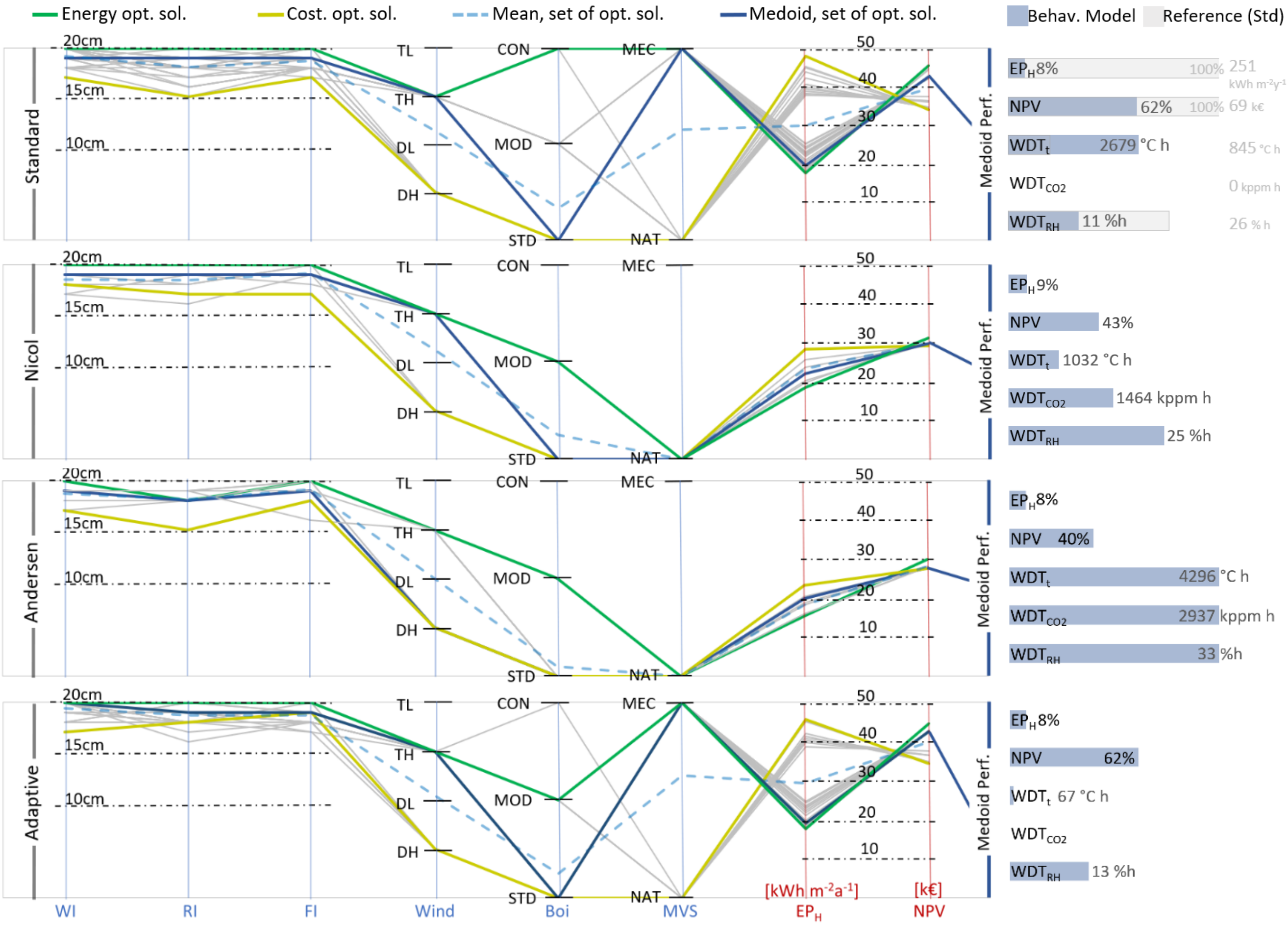

Figure 3: Parallel Axis Plot showing set of optimal retrofit strategies of each behavioural model for Milan, and their Energy & Cost Performance; Bar chart (right) showing Performance & Comfort of each models Medoid solution.

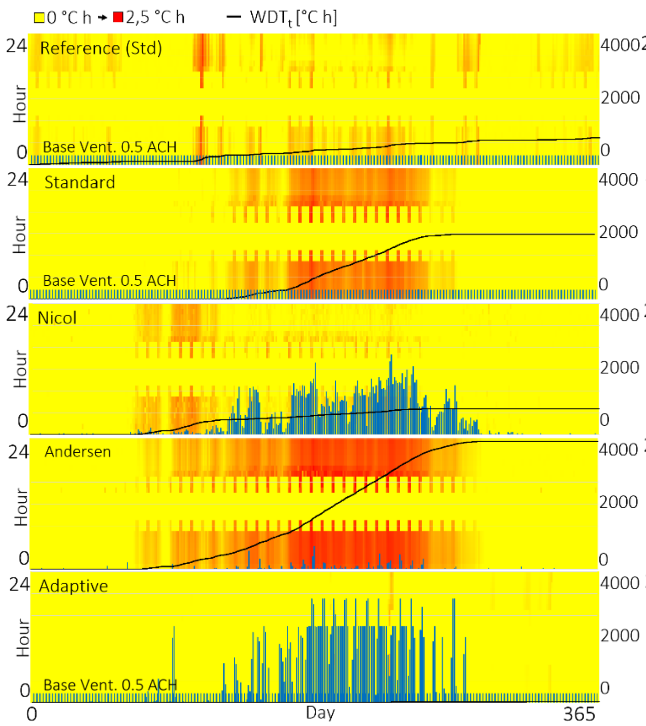

Figure 4: Heat Map hourly WDT_t & Plot for accumulated WDT_t , Cost-Optimal Solution, Milan

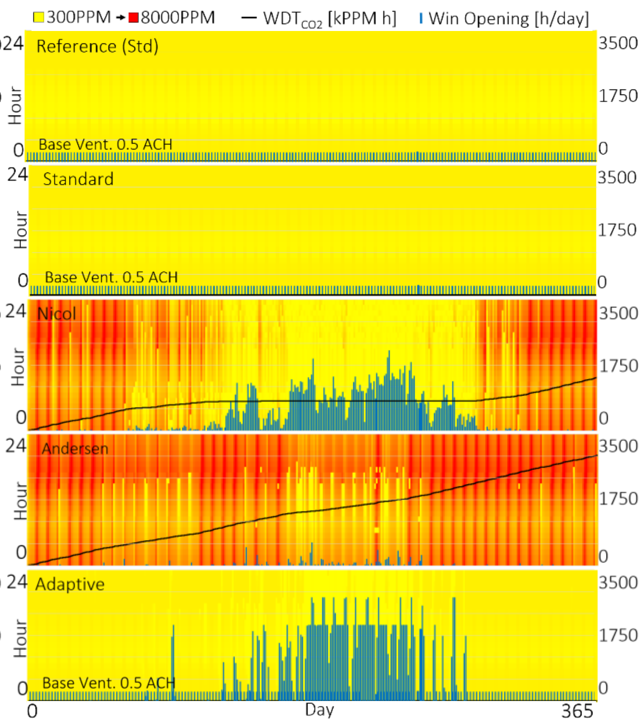

Figure 5: Heat Map indoor CO_2 Conc., Plot for WDT_{CO2} & Win. Opening times, Cost-Opt. Solution, Milan

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is illustrated as a line connecting the corresponding renovation measure levels, which – from left to right - are insulation levels, window and boiler replacements and the presence of MVS. Additionally, the calculated EP_h and NPV for every strategy are shown. The key retrofit strategies are highlighted in different colors:

- Energy-optimal (green), providing the lowest EP_h.
- Cost-optimal (yellow), resulting in the lowest NPV.
- Medoid (blue) as the strategy closest to the average of all optimal solutions for a given behavioural model.

The clustered bar chart to the right of figure 3 shows the performance of the medoid solution. EP_h and NPV are shown as percentage of the calculated demand for the initial reference building. WDT_t, WDT_{CO2} and WDT_{RH} are presented as absolut values with bars adjusted to the maximum discomfort of all models (found for Andersen).

For an in-depth understanding of time-related discomfort in the cost optimal configuration, figure 4 shows a heat map for hourly WDT_t throughout the simulated reference year, colored from yellow to red, as well as a plot for the accumulated discomfort (black line). Figure 5 similarly represents IAQ as hourly CO_2-concentration and plots the accumulated WDT_{CO2}. For the readers convenience in both figures the window opening times per day are shown as bar chart (blue).

Results regarding retrofit strategies

From the presented figures, key findings emerge. Figure 3 shows that, independently from the behavioural model, only insulation thicknesses between 15-20cm are considered. For window replacements the cost-optimal solutions suggest double-glazed windows with high SHGC, whereas the energy-optimal solutions aim for triple-glazed high SHGC windows. This is probably related to the building system that only includes heating demand, which benefits from higher solar gains. Regarding the boiler, cost-optimal solutions suggest staying with the standard one, to save on investment costs, which cannot be balanced through energy savings. The energy-optimal solutions suggest investing in a modulating boiler if we assume probabilistic or adaptive occupant behaviour. Conversely, the standard approach opts for a condensing boiler combined with the highest insulation levels of 20 cm, as highly energy efficient retrofit measure. Major differences between the behavioural models occur regarding the presence of MVS. All optimal solutions for both probabilistic models rely solely on natural ventilation whereas for the standard and adaptive model, energy driven solutions rely on MVS. Investigating deeper into this difference, shows that the selection process is affected by the assumption that a fix 0.5 ACH for the Standard and Adaptive Model is the base ventilation rate due to their rational approach and compliance with the regulations. Contrarily, the probabilistic models rely solely on occupant actions for ventilation without setting any constraints regarding minimum ventilation. Therefore, air changes can be reduced to the mere infiltration which is again further reduced by improving windows. As we can see in figure 5, the Andersen model, has a very reduced ventilation throughout the entire year, whereas the Nicol model predicts increased ventilation in summer but not in winter. Thus, for probabilistic models, solutions with MVS are dominated by those without, because of the reduced overall ventilation of the latter ones, resulting in lower energy needs and costs, which are the primary optimization objectives.

As concerns performance, the generally lower ventilation rate predicted by the probabilistic models, results in a lower energy demand. Assuming standard and adaptive behaviour, a comparable energy demand as with the probabilistic models can only be achieved when a MVS with heat recovery is used, e.g. the energy-optimal solutions. In contrast, in cost-optimal solutions the predicted energy demand is nearly doubled, if a standard or adaptive behaviour is assumed. Regarding costs, the differences are less but still visible, ranging between 35-45 k€ for optimal solutions assuming standard or adaptive behaviour and slightly reduced costs (due to energy savings) of about 30 k€ for probabilistic behaviour. These findings are mainly confirmed in the climate of Messina, which is why we only show the visualizations for Milan. Differences in a warmer climate like Messina are that insulation thicknesses range slightly lower between 9-20 cm and most solutions aim for double glazing. Differences between the models regarding natural ventilation vs. MVS, replicate the findings of Milan for the same already mentioned reasons.

However, energy demand is drastically lower given the climatic context. This increases the relative difference between the probabilistic and standard/adaptive models to a 4-5 times higher energy demand for solutions without MVS. The absolute difference of about 10 kWh m^{-2} y^{-1} is comparable to what we found in Milan.

Results regarding comfort

In figure 4 and 5 the comfort aspects of thermal environment and IAQ respectively have been analysed. For increased comparability, the cost-optimal solution is chosen to be presented in the heat maps, given that all models consider a similar retrofit strategy as cost optimal, relying on double glazing low SHGC windows, no boiler replacement and natural ventilation. Consider that discomfort is not calculated during the day, if occupants are not at home (7-17 on weekdays, 10-15 on weekend). In figure 4, we observe that WDT_t is mainly occurring during the summer months. The Nicol and adaptive models predict low or negligible WDT_t, whereas the standard and Andersen models result in higher discomfort. As it can be seen, these findings are strongly related to window opening behaviour. Long opening times in summer, as the Nicol and the adaptive model are showing, efficiently remove excess heat and reduce thermal discomfort. In winter thermal discomfort is not a problem. The direct comparison of the reference building before and after the intervention (figure 4, top) shows, that an increase in insulation level, results in increased overheating during summer. This can lead us to the conclusion, that the higher the air tightness and thermal

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insulation gets, the more importance the ventilation of a building gains. If ventilation is not sufficient – as e.g. the Andersen model predicts - the building will constantly overheat during summertime and is prone to bad IAQ during the whole year.

This can be seen from the hourly CO_2-concentration shown in figure 5. From the heat map it is evident, that again the ventilation level is majorly affecting IAQ. Both probabilistic models show high CO_2 concentrations of up to 8000 ppm. For the Nicol model this is only valid for the wintertime. In summertime the predicted ventilation is sufficient to avoid high CO_2-concentrations. Andersen model shows year-round values outside of the foreseen comfort band which results in the double WDT_{CO2} compared to Nicol. Regarding the standard and adaptive approach, a good IAQ is ensured given the constrained minimum ventilation of 0.5 ACH. Similar qualitative comfort trends are found for Messina.

Discussion

The results obtained show that the optimal solutions depend strongly on the behavioural model used. Especially, regarding probabilistic occupant behaviour the solutions with MVS are too expensive and therefore dominated by natural ventilation ones, allowing a very low ventilation rate. This can be realistic in some real applications, even if not foreseen by the regulation and clearly not recommended. Regarding the comfort analysis, results are diverging showing an increase in discomfort, especially for naturally ventilated dwellings given by the Andersen model but quite significantly also for the standard approach, which is law compliant. Nicol and Adaptive models show this issue can be consistently improved in both reference climates.

Regarding CO_2 discomfort, it is evident that it mostly occurs in winter, contrarily resulting in energy savings. This means, choosing a cost- and energy optimal approach, solutions minimizing CO_2 discomfort are not being considered as retrofit strategy. This further highlights that a cost-optimal approach is not able to ensure sufficient ventilation if relying solely on occupant actions (probabilistic models without MVS). For solutions with MVS, window openings are adding ventilation to the already well-ventilated building. Contrarily, this results in a higher energy demand in winter, but a comfort increase compared to the standard model, mostly occurring in summer (figure 4). These diverse results are somehow consistent with previous studies on the performance gap by Shi et al. (2019), who reviewed papers on residential and office buildings, showing both positive and negative rebound effects. Turner & Frankel (2008) analysed 121 new LEED certified constructions showing that both performance gap and performance increase are commonly found.

It cannot clearly be said which occupant representation is the most suitable and realistic, rather the current study shows an effective way to compare them. To answer the question about what would happen if practitioners would choose one of the presented occupant representations, the following findings can be summarized:

- Every model predicts quite consistently that high insulation levels are needed. Double glazing are preferred for cost-optimal while triple glazing for energy optimal solutions. For the latter solutions, at least a modulating boiler is required, while MVS is necessary if the designer intend to guarantee the minumum required ventilation rate, even if that is not a solution chosen by all the models.
- Every model and retrofit strategy is able to drastically reduce the energy consumption EP_h to 8-9% of its original value (251 kWh m^{-2} y^{-1} considering the standard approach), provided the behavioral model assumed is consistent.
- NPV differences are more evident and depend on the presence of a MVS system. Nicol and Andersen models neglect solutions with MVS showing practitioners NPV savings of 20% compared to the other models.
- Predicted proportional differences between Energy and Cost Performance are more significant in warmer climates where energy demand and cost are generally lower, whereas the absolute differences are similar.

Regarding comfort criteria, practioners would notice the greatest difference between the studied behavioral models:

- The standard model is able to remove most WDT_t and all WDT_{CO2} assuming the base ventilation rate of 0.5ACH. However, higher costs need to be accepted.
- The Nicol model predicts similar ventilation rates in summer like the adaptive model. Therefore, solely taking T_{OUT} as predictor for window opening behavior already represents one possibility to restore thermal and CO_2 Comfort. However, in winter windows are not opened enough to ensure an adequate IAQ.
- The Andersen model takes CO_2 as additional predictor, but results - contrarily to expectations – not in an improved IAQ. However, this confirms the observations in real applications where uncomfortable CO_2 levels are often not noticed by occupants. For the here presented reference building and climates, the model is not sensitive enough to indoor temperature and CO_2 concentrations, resulting in a year-round poor IAQ and increased overheating in the summer time.
- The idealized adaptive approach strongly improves all WDT_t while maintaining a suitable IAQ and acceptable EPh and NPV in both tested climates
- The robustness of the optimal solutions to an inconsistent assumption of behavioral model, i.e. the case the actual behavior pattern is different from the one assumed in the optimization, is not investigated here, but in a previous research investigation by Donges et al. (2021).

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Conclusion

This work is intended to analyse the impact of the initial choice for window opening models in BES on the definition of the optimal retrofit strategies and their performance in terms of energy demand, total cost and indoor comfort.

Two probabilistic models have been compared with a standard approach based on the prescribed ventilation rates from technical standards and regulations (0.5 ACH in occupied period). In addition, a rational approach based on the standard ventilation rate and a discomfort driven opening strategy (adaptive approach) has been analysed in order to overcome overheating issues and insufficient ventilation rates.

The results have highlighted some main findings regarding the characteristics and relevance of the analyzed occupant models and the resulting impact on retrofit analysis. It is important to say that the obtained results and conclusions can be at least applied to all the cases located in the same climatic group as Milan and Messina.

Regarding the occupant model comparison, the main findings are:

- Probabilistic models show that energy and cost savings are paid for with major drawbacks on IAQ (increase in WDT_{CO2}) and overheating in the case of Andersen's model.
- On the other hand, the adaptive model can eliminate discomfort, given the assumed idealized behaviour not based on probabilities, but on fixed thresholds.

Regarding the impact of the occupant models on the retrofit design the study has shown the following conclusions:

- In a cost-optimal analysis the choice of the occupant model does not influence much the energy saving measures applied to the cost-optimal solution, nor its EP_h, or NPV.
- Regarding the energy-optimal retrofit solutions, it has been demonstrated that the values of EP_h are not affected much by the behavioural model used in the simulation. However the probabilistic models tend to exclude the MVS as retrofit measures for the energy optimal leading to an estimated NPV lower than the other analyzed models.

Regarding the impact of the occupant models on the indoor environmental conditions of the optimal solutions the main conclusions are:

- Optimal solutions obtained with different behavioural models are characterized by different indoor comfort, both regarding thermal environment and air quality.
- Optimal solutions defined through probabilistic models are likely to be not very robust to the ventilation rate. If ventilation rates were compliant with the regulations, these configurations would be prone to worsen their performance with potential for performance gaps.

The main take-aways are therefore to consider the value of comfort while choosing retrofit strategies. In doing, occupant actions for restoring comfort are often strongly connected to the ventilation rate. Practically this aspect cannot be neglected, so it is recommended that a minimum ventilation of 0.5 ACH is used as a constraint during optimization, to account for this and promote solutions making use of a MVS if necessary. Alternatively, comfort objectives should be added to the purely cost and energy centered optimization process, to directly account for it from the beginning.
Using probabilistic models, practitioners might miss to ensure the full retrofitting potential, maybe excluding solutions that could majorly improve comfort.

This concern is broadly consistent with recent research trends investigating the reliability and veridicity of behavioural models (O'Brien et al., 2020).

As a future development, a sensitivity analysis for each retrofit measure can be implemented showing its relevance in the analysis. Possible indicators could be the retrofit measures spread (range of solutions found; less spread highlights relevance of measure) and its differing representation for each behavioural model.

In a similar way the robustness of each optimal solution towards changing occupant behaviour can be assessed.

Finally, to overcome drawbacks on thermal comfort and IAQ, additional optimization objectives (WDT_t & WDT_{CO2}) or even a constraint for a minimum ventilation rate should be considered.

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