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CALIBRATION OF A SUMMER BUILDING SIMULATION MODEL BASED ON MONITORING OF USER BEHAVIOUR

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Abstract. Occupant behaviour is a field, that has always been of great interest to researchers. It could significantly modify the operation of the building and the user's energy needs, and it is also difficult to model it according to reality. Evaluation of measurements is a crucial step to calibrate dynamic simulations. Our goal was to analyse the indoor comfort conditions according to measurements, particularly in summertime, and find what solution closes the performance gap between the measured and simulated results. In this research, we investigated an apartment building that underwent an energy efficiency renovation. We have installed a weather station and monitoring sensors in selected apartments, with which we monitored the temperature, relative humidity, and CO_2 values of certain rooms, the presence of the inhabitants and the window opening and the operation of shading. In this paper, we focus on the monitoring and simulation results of the topmost apartment. The results can help us better understand how buildings work and how to implement user behaviour in dynamic simulations, how to calibrate the model according to measurements and make suggestions to increase the comfort of the residents.

Keywords: User behaviour, summer overheating, indoor comfort, in-situ measurement.

1. Introduction

The warming climate has an impact in many areas, not only in the way we design and develop our buildings but also in the way we operate them and adapt our habits to this changing climate. Measurements show that there is an increased risk of overheating in buildings [1, 2] and it can be predicted using external temperatures and characteristics of the housing and its surroundings [3]. These increased internal temperatures have an impact on human health, especially in the case of the elderly [4, 5] so we must use the right tools and building management [6–8] to reduce the internal temperature and adapt to the increased external temperature. Another qualitative factor is the CO_2 value, which mainly represents the indoor air quality, but it can also be used to predict and calculate the air change rates in the building [9–11].

Thermal behaviour and energy consumption of a building can be assessed with dynamic simulation. However, simulation without calibration can lead to substantial error in the calculated energy consumption. If properly calibrated, the building energy simulations can estimate the real energy consumption 90 % of the time [12]. In modelling, various uncertainties (specification, numerical, scenario, heuristic), inter-model variability, or even post-design changes can be important, increasing the performance gap. According to the literature, the most common causes are specification uncertainty in building modelling, occupant behaviour, and poor practice in operation, with substantial impacts (10–80 %) on energy use [13]. In the calibration process of a naturally ventilated building, the window openings are key factors, as well as the opening of the doors [14]. Calibration can be differently accurate for insulated and uninsulated buildings, which is why the two often need to be treated differently [15].

In this research, we examine a renovated, naturally ventilated apartment building located in Budapest and focus on the summer thermal comfort. Three apartments in the building were equipped with different sensors to determine the user habits and the indoor air conditions (temperature, relative humidity, and CO_2 concentration) inside the building. We monitored presence, window opening and shading operation in selected rooms. In addition to the measurements, dynamic whole-building simulations were carried out. The monitoring system and the measurements gave a better view about the user habits and also helped the evaluation of the overheating in the summer period. In this paper, we focus on the topmost apartment of the building, which is expected to have the highest risk of overheating. The monitoring measurement results were used to calibrate the model and evaluate the efficiency of using real-user behaviour data in simulation model.

2. Materials and methods

The analysed building is located in Budapest (Hungary) on the Gellért Hill (Figure 1). On the rectangular plot there are two two-storey high flat-roofed apartment buildings with basement (building “A” and “B”). In this study, we focus on Building B, which

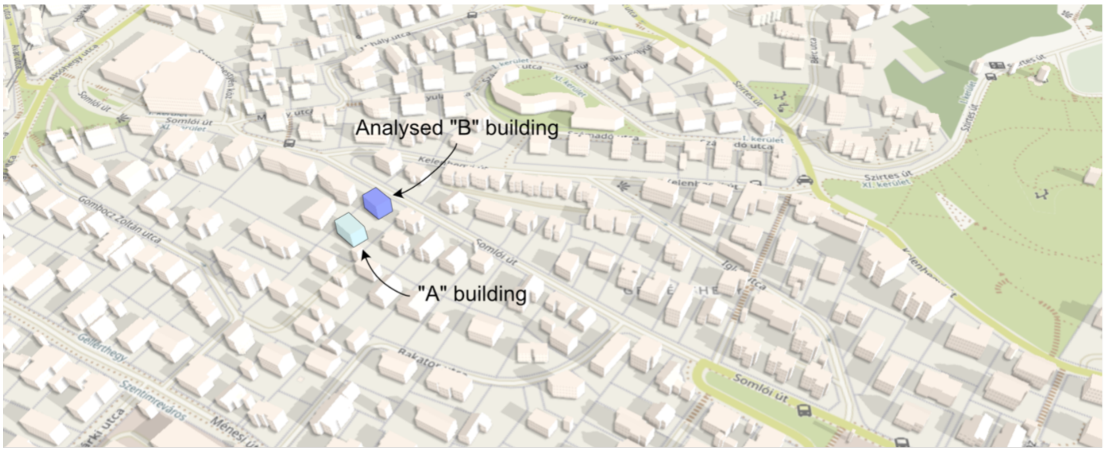


FIGURE 1. Monitored building's location (Building "B" is the subject of this study) [16].

FIGURE 2. Monitoring sensors in the apartment (window opening, shading, motion detection).

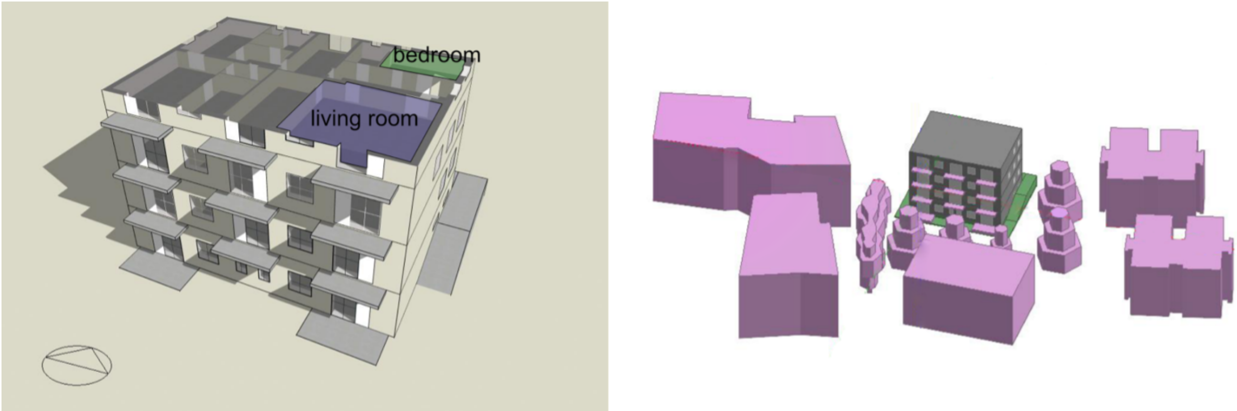
was awarded a grant to carry out the posterior thermal insulation and window replacement. During the renovation, 11 cm of external facade insulation (graphite EPS) and plaster was applied, 10 cm of plinth wall XPS thermal insulation were also installed. The flat roof was renovated with 20 cm of EPS 100 thermal insulation, and the waterproofing was made with EPDM membrane. The windows and doors were replaced with modern PVC windows and doors ($U_w = 1.15\,\mathrm{W/m^2K}$). The new windows and doors are insulated structures of the same size as the original. Shutters have been installed to increase summer heat protection. The building envelope improvements can result in significant reduction in energy consumption, so the renovation is partly about expected savings and partly about increasing the resident's comfort

2.1. In-situ measurements

The following parameters were measured in selected rooms of the apartments: temperature and relative humidity (Sensirion SHT85), CO_2 (Sensirion SCD30), presence detection (HC-SR501 PIR sensor), window opening and shading operation (FM-106 WH Reed relays). A custom wi-fi capable monitoring system and online user interface have been developed for the buildings by BCD Kft. (Figure 2). Temperature, relative humidity, CO_2 values were recorded at every minute for more than a year from 2020 summer until 2021 autumn. The temperature measurement tolerance was $\pm 0.1\,°\mathrm{C}$, the relative humidity tolerance was $\pm 1.5\,\%$, and the CO_2 tolerance was $\pm 30\,\mathrm{ppm} + 3\,\%$. During the processing of the data, the data series had to be cleaned and organised, and hourly averages were made for easier handling; this also helped its application in dynamic simulations. In addition to the internal measurements, a weather station installed on one of the balconies provided the external weather data. The weather station's real-time data, which can be monitored online, includes temperature, relative humidity, wind direction and speed, rainfall data and solar radiation. In this case, data cleaning and averaging was also done to be able to apply it in the simulation.

2.2. Building energy modelling

The modelling and energy analysis of the building was carried out in Design Builder v6.1.5.002 [17] software, modelling the individual apartments and rooms, which are separated into thermal zones. During the assessment of overheating of dwellings, single-zone simulation can predict the overheating well, but it doesn't account for the thermal dynamics of the building or cross-ventilation. A multi-zone model was used, as this can give more realistic results [18]. The mod-



(a). Analysed apartment rooms.

(b). Whole building's model with surrounding buildings and trees.

Figure 3. 3D model of the analysed building.

Structure	Thermal transmittance (U-value) [W/m^{2}K]
External wall	0.24
Flat roof	0.16
Basement slab	0.79
Windows and doors	1.1; 1.4; 1.6; 1.8; 3
Internal walls 10 cm	2.24
Internal walls 38 cm	1.25
Load-bearing wall (basement)	0.96

Table 1. U-values of the analysed building.

elling also included balconies, surrounding buildings and trees, as these affect the building's exposure to environmental impacts (Figure 3); the transmissivity of the plants was adjusted according to their type, form and how much light they can transmit. There was no artificial cooling in the building and energy efficient lighting with controls was assumed.

The ventilation in the model (V1, V2) was set with the "calculated" method in DesignBuilder, where a control mode defines how the exterior openings are opened and closed. Wind and buoyancy pressure causes flow through the openings and cracks in the building and determines the rate of ventilation. Window opening is controlled by a timer and by ventilation setpoint temperatures. In our base case, this control mode was based on the monitoring data and windows were opened and closed according to the measured data. We assumed the crack template as "good" since the building underwent a renovation, improving the airtightness. In the more advanced method, the ventilation rate through each opening and crack is calculated based on the pressure difference:

$$q = C \cdot (DP) \cdot n, \tag{1}$$

where

q volumetric flow through the opening,

DP pressure difference across the opening/crack,

n flow exponent, varying between 0.5–1.0 depending on the flow type (turbulent or laminar flow),

C flow coefficient, related to the size of the opening/crack.

The thermal transmittances of the building are in Table 1; the U-values of the retrofitted structures meet the requirements of the Hungarian Regulation [19]. For the boundary conditions, the outdoor weather values were applied based on the measurement results. The estimated occupancy in the whole building was 0.04 people/m^2, with a built-in residential occupancy schedule [20], LED lighting with 2 W/m^2 power density and lighting control. In the selected apartment, the occupancy schedule from the monitoring was applied. During the period under study, the technical building system was not particularly important, as only natural ventilation was used. The external blinds were operated according to the monitored data in the selected apartment and with a setpoint of 250 W/m^2 in the rest of the building. The unknown parameters were determined iteratively during the runs.

The simulation was used to determine how much the measured user habits help the modelling and how they affect the overheating of the building during the summer week under study. In comparison, we tried different simulation alternatives. In the V1 model, we used the measured values for the analysed flat, and all the other parts of the building got default values, as described earlier. In comparison, two additional modelling approaches were considered: in the V2 model, the analysed flat was assigned with the same default

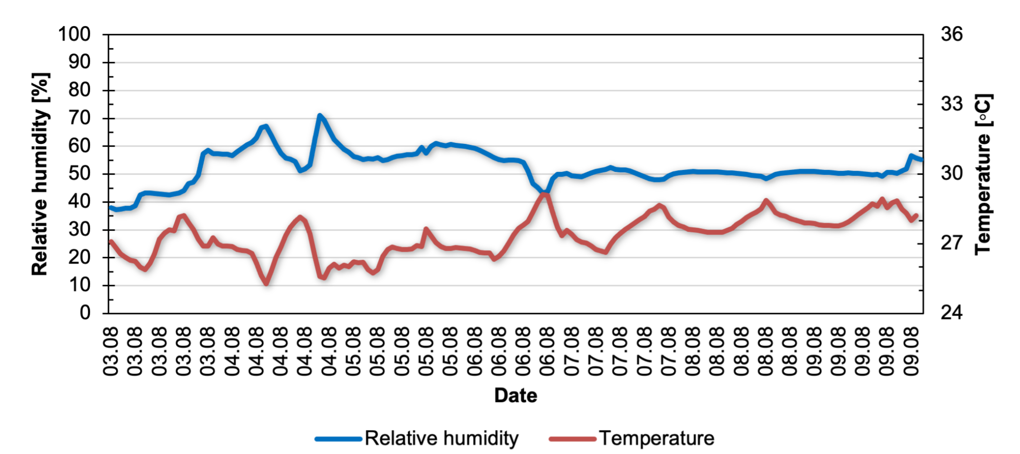


Figure 4. Measured values in the living room (temperature and relative humidity).

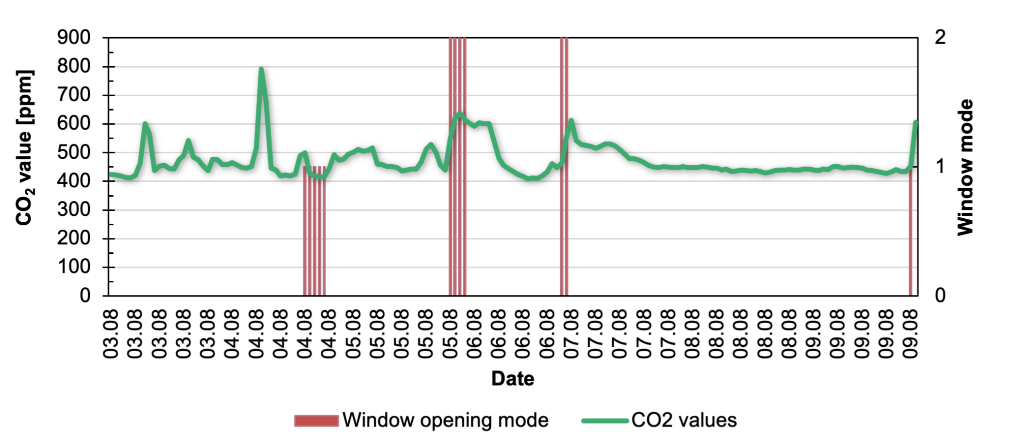


Figure 5. Measured values in the bedroom (CO2 and window opening).

values (occupancy, shading etc.) as the whole building, thus excluding the measured user habits. In the V3 modelling approach, we used simplified ventilation modelling (scheduled natural ventilation) with 3 ACH value in the building, with 2 °C "Delta T" limit to control it. The latter one means, that the ventilation stops if the external temperature can potentially heat the internal space; when the external air temperature is less than 2 °C cooler than the internal one, the ventilation turns off. The assumed ventilation rate is an arbitrary value, but is in line with the values found in the literature [21] and in the regulation [19, 22].

3. Results and discussion

3.1. Monitoring measurements

Due to the limited scope of the study, only a few values are highlighted. Figure 4 shows the temperature and relative humidity values in the living room in the analysed period (August 3 – August 8, 2020).

The temperature inside the room was 27.4 °C with a 29.1 °C maximum value. It can be seen that the indoor temperature in the living room was above 26 °C in more than 92 % of the time studied, which is not comfortable in summer. The temperature in the bedroom was also above 26 °C all the time. The relative humidity was 53 % in average in the living room and 51 % in the bedroom; CO_2 concentration inside the living room was not significant, 439 ppm in average and there was no major CO_2 enrichment during the week; so, in Figure 5 we have highlighted the bedroom's CO_2 values, which are a bit more interesting. In the bedroom the average CO_2 was 472 ppm, but during the nights, there are some enrichments (maximum: 791 ppm). Window positions were recorded in the monitoring system, when the residents changed their position, where "0" means a closed window, "1" is tilted and "2" is a fully open position. It can be observed that the measured CO_2 decreases after the night when residents opening the bedroom window.

The results show that during the second half of the week, the occupants left the dwelling; no significant change in CO_2 is detectable, and the indoor temperature and relative humidity values are more uniform, showing no large variations, the effect of the ambient temperature is more significant. Although it is not the subject of this article, it is worth mentioning that the 2nd floor's living room in building "A" – which has not been renovated – had much higher values. During the week under review, the average temperature was more than 31.3 °C with a maximum

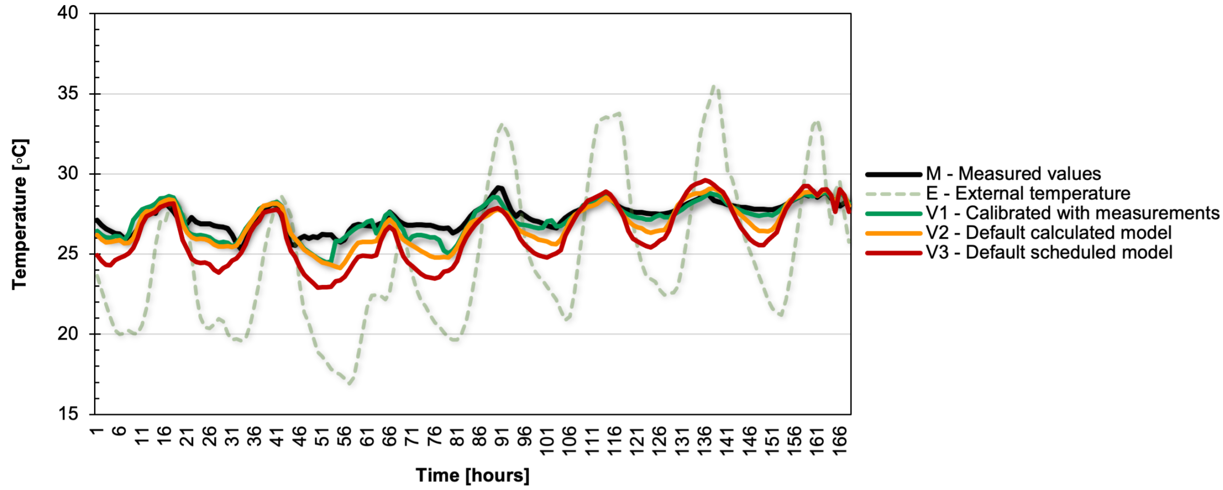
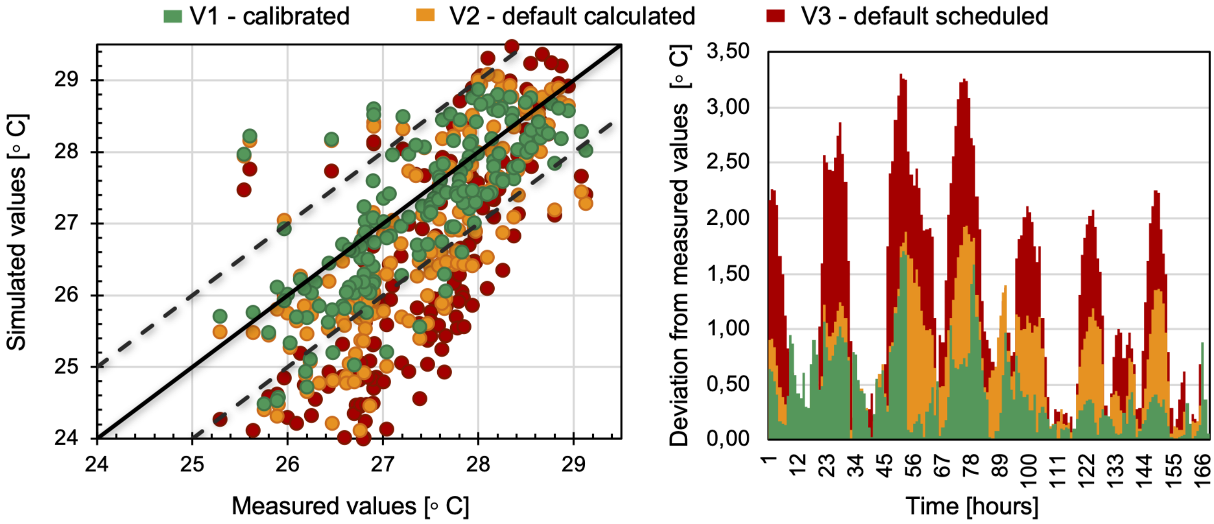


Figure 6. Measured and simulated temperature values in the living room.



(a). Comparison of the living room's temperature (measured versus simulated values).

(b). Simulation's deviation from the measured values.

Figure 7. Results of the dynamic simulation.

value of 33.5 °C. In addition, the variability of the curves is much higher, with less damping of the effect of the outside temperature since that building is not thermally insulated.

3.2. Dynamic simulations

In the modelling, the number of occupants in the rooms was adjusted to reflect reality. Furthermore, the presence, shading and window use of the occupants formed the basis for the simulation input data. Figure 6 shows the measured and simulated temperature values in the living room. In the analysed period, the temperature varied between 25.3 °C and 29.1 °C in the living room. The chart shows all three versions tested. It can be seen that the average deviation from the real-life data is 0.91 °C for the model calibrated with measurement, 1.13 °C for the model with default values, and 1.70 °C for the simplified ventilation case. The V2 version appears to follow the measured calibrated values quite well, but in many cases, it underestimates the internal temperature; the simplified model (V3) shows more significant differences. One reason for the differences in the second half of the week is presumably that the residents were not in the apartment during this period, which the V1 model was able to take into account, while in the other two cases this was not possible with the predefined schedules.

The two charts below (Figure 7) illustrate the differences within the models more clearly. Figure 7a shows the relation of the simulated temperature values in the living room compared to the monitoring data. In the graph, parallelly to the ideal line (where the measured and simulated values are equal), two additional dashed lines show ±1 °C difference from that. It is almost impossible to achieve a perfect match during calibration compared to the measured temperatures due to the several unknown factors and effects, but our goal for the simulation is to be able to reach a match within ±1 °C difference in most cases. A dynamic simulation that returns the monitoring measurement results within a degree difference can be considered sufficiently accurate. The model calibrated with monitoring data (V1) appears to fall much closer to these theoretical limits than the other two approaches (V2 and V3). If we observe the results, 57.1 % of the V1 model is within the ±1 °C limit, 45.2 % for the V2 model and only 29.2 % of the simulated values for the V3.

Figure 7b shows the deviation from the measured values over time for the different models. The difference between the versions is even more apparent here, with the version calibrated with measurements (V1) showing an average deviation of only 0.91 °C among the different modelling options. The outlier for all models was on measurement day 2, where the calibrated model also underestimated the monitoring measurement values by about 1.5 °C. However, in the rest of the measurement, the calibrated model has visibly lower differences than the default calculated (V2), or default scheduled (V3) dynamic simulations. Latter performed the worst against the monitoring measurement, achieving up to 3 °C difference even on those days, where the calibrated model's difference was just half of that. From these figures, it is also visible that the calibrated model usually performed on average up to around 1.5 times better than the default calculated V2 model and up to about 2.5 times more precision than the default scheduled V3 model. Figure 7 shows that using the proposed calibration procedure, the dynamic simulations can achieve better accuracy compared to default simulation techniques.

4. Conclusion

Measurements provided accurate and real data on the operation and behaviour of the buildings. Furthermore, this study also offered the opportunity to analyse the period without occupants in a renovated and thermally insulated building. With the measured user habits, the thermal comfort within the apartment was not achieved; further studies are needed to see if this can be improved by other ventilation and shading strategies or if mechanical cooling is necessary.

One of the lessons of the research is, when creating and calibrating models, it is important to take into account user habits and also the software's limitations. Based on the results of the study, it is worthwhile to assess and record user habits and implement them in the simulation, as this will provide more accurate results than other simplified modelling options. Schedules based on the monitoring measurement helped to calibrate the model and led to smaller deviations from the measured temperatures. Although the use of simplified ventilation may seem simpler and more efficient (faster run time), calculated ventilation rates lead to more accurate results.

In the further part of the research, the user habits of the other apartments will be implemented, and a detailed comparison of the insulated and uninsulated buildings will be carried out. Another interesting aspect of the question is how the inclusion of coupled heat and moisture transport would affect the results, and the calculation time in this case, how much more accurate the values would be compared to the measurement.

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