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Indoor Climate Prediction Performance of Dynamic BES-Models in Dymola

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ABSTRACT

How accurately can reduced-order dynamic building energy simulation models (with Dymola simulation software) simulate the indoor climate (i.e., indoor air temperature, relative humidity and CO_2-concentration) in common inhabited residential buildings? In order to address this question, high resolution measurement data of a zero-energy case study dwelling were gathered through a measurement campaign. A dynamic multi-zone modelling approach has been applied to have room-level indoor climate results. Buoyancy driven airflow equations (validated with CONTAM) have been added to existing thermal heat balance components to allow for dynamic moisture and trace substance calculations as well as detailed air exchange and inter-zonal airflow calculations. The validation study reveals that dynamic multi-zone building energy simulation models (BES-models) can predict the indoor climate considerably well at room-level in inhabited dwellings (especially in the bedrooms).

INTRODUCTION

Accurate building energy consumption modelling and indoor air quality assessment continue to be prominent subjects in the fields of building physics, building energy prediction and indoor climate control. Buildings are still the largest energy consumer in the EU (European Commission Department of Energy 2019), despite energy reducing measures are mandatory for more than a decade and will continue to be for the time coming. Additionally, due to the fact that people spend more and more time indoors, the quality of the indoor environment becomes increasingly important. New software developments and improved computer capabilities have made it possible to develop more complex and detailed, multi-purpose modelling tools. These tools now enable to do both energy consumption, thermal comfort and indoor climate analyses simultaneously without suffering too much from computational costs, software boundaries and capabilities or methodological constraints. As a result,

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more accurate and detailed predictions can be made, which results in better underpinned conclusions, improved capabilities and enriched building energy modelling and indoor air quality research in general. This is the area in which Ghent University's R&D project '*Model-based Design of Ventilation Concepts*' is situated. One of the aims within the project has been to study the ability to accurately predict the indoor climate (*i.e.*, indoor air temperature, relative humidity and CO_2-concentration) in common inhabited, ventilated single-family houses and apartments, utilising dynamic multi-zone building energy simulation models (BES). The work reported in this paper aims to answer the above question by modelling, calibration and validation of a single-family case study building.

METHODS AND DATA

The case study dwelling, that has been selected for this study, is located in a suburb of Den Haag (The Netherlands). It is an inhabited, detached zero-energy single-family house that was completed in 2018. The dwelling is a detached house, is south-west oriented and has two stories. Three inhabitants (*i.e.*, single parent with two young children) are living there since completion and no pets are present. The dwelling has a pitched roof (completely covered with photovoltaic panels), is very well insulated, has underfloor-/ceiling- and wall-heating, a considerable number of windows, a two-story living area, a C+ demand-controlled ventilation system and an air-water heat pump.

A measurement campaign was carried out in this dwelling between September 2018 and July 2019, during which all required parameters (*i.e.*, indoor and outdoor climate, user behaviour and HVAC) were measured in detail (*i.e.*, 5-minute intervals) depending on necessity, feasibility and parameter usage in the physical background of the model. For the indoor and outdoor climate, Netatmo Weather Stations were used to measure the indoor temperature, relative humidity and CO2-cooncentration (accuracy: T ± 0.5°C, RH ± 5%, CO_2 ± 150ppm). A dynamic multi-zone building energy simulation model was developed in the Dymola simulation environment (*i.e.*, in the Modelica programming language), based on the architectural plans and additional dwelling and technical system information (*Figure 1 and 2*).

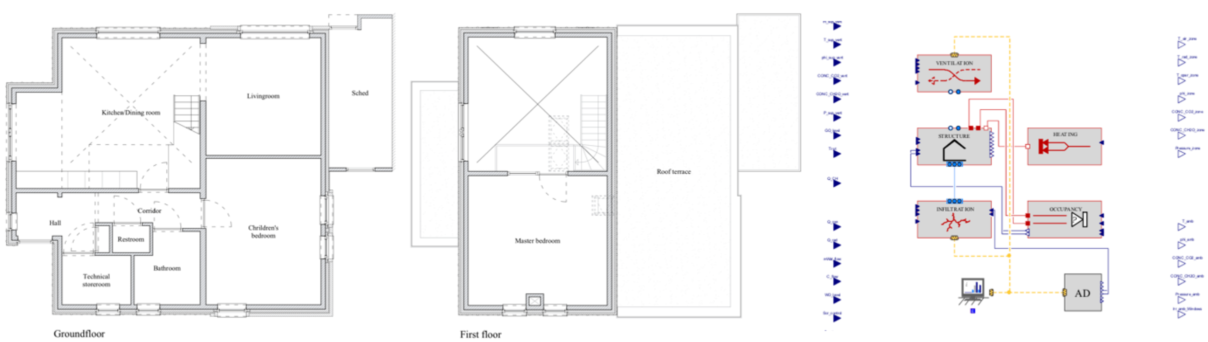

Figure 1. Architectural floor plans of the case study dwelling (left, middle) and a top-level model overview (right).

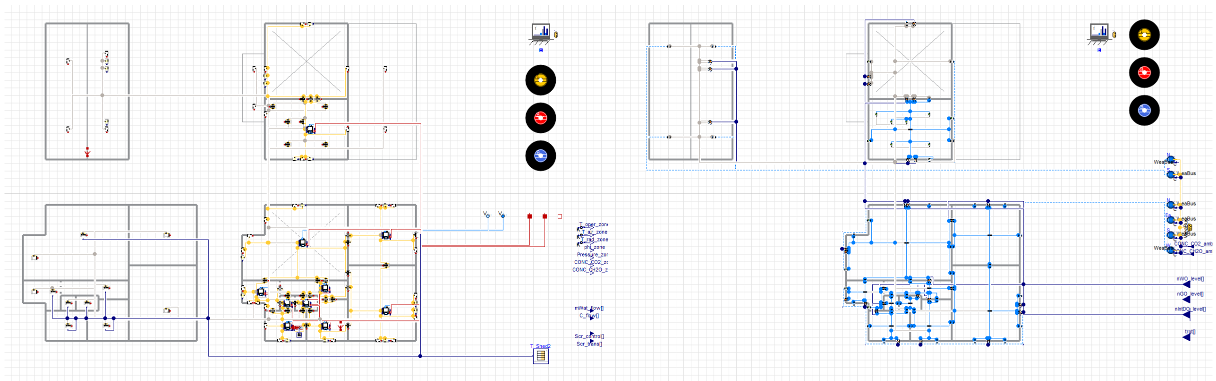

Figure 2. Overview of the model's thermal components (left). Overview of the model's buoyancy driven airflow components (right). The model components are structured on the dwelling's floor plans in the background.

Dassault Systèmes Dymola 2020 version was used to build the model with the built-in Modelica Standard Library-3.2.3. Also, the IDEAS 2.1.0 library (Jorissen *et al.* 2018) was used, which contains highly detailed and fast-calculating thermal building simulation components. Compared to other simulation environments (*e.g.*, TRNSYS, EnergyPlus, CONTAM), Dymola has the advantage that everything is open source such that developpers can build new components, adapt existing components to suit their project needs. Further, the modelling chain is straight-forward and fast (no co-simulation between programs or geometry inputs from sketch-up and the whole simulation process (once the model is finished) can be automated through Python (for scenario analysis, uncertainty and sensitivity analysis *etc.*).

So, before calibration, the model has been subject to a dynamic building energy modelling exercise in which the existing Dymola building energy components have been analysed, tested and expanded to suit the aim of this research. Practically, the existing components have been expanded with physical buoyancy-driven airflow equations (validated with CONTAM) from *Wetter (2006)*, which were then put together in a new Modelica library specifically built for this project.

Conceptually, the developed Dymola model (*Figure 1, right*) consists in its core of two connected layers: a thermal layer (*Figure 2, left*), in which the heat balance is dynamically calculated in the background, supplemented with an airflow layer (*Figure 2, right*) in which air (and by that also heat, moisture and trace substances) is exchanged between the indoor and outdoor environment and between different rooms based upon the present pressure differences (and where a mass balance is calculated in the background). For this reason, ventilation and infiltration air flow (and therefore also heat, moisture and CO_2-transport) throughout the single-family house is being calculated dynamically in much more detail. Additionally, several other components are incorporated that add demand controlled mechanical ventilation (*i.e.*, CO_2-controlled), space heating and user behaviour (*i.e.*, external and internal window and door operation, but also heat, moisture and CO_2-gains by inhabitants and appliances) to the indoor environment.

In order to add user behaviour of the inhabitants into the model, motion sensor data of the dwelling was used. As indicated earlier, the inhabitants do not have any pets that could influence the motion sensor data. This data was then converted to user profiles with assumptions for heat-, moisture- and CO_2-emission of an average person. Also, the household composition is taken into account when doing so (*i.e.*, maximum three persons in the livingroom) and some lifestyle assumptions are made (*i.e.*, the multi-sensor in the living area cannot pick up the amount of people in the room at any time, so assumptions on lifestyle are made based on knowledge of the family). Also, the window- and door-sensor data is used to include the opening of doors and windows.

After initial testing, the quality of the multi-zone BES-model was ensured in a calibration study. The model output results were tested against high resolution measurement data (*i.e.*, time series data from the measurement campaign). The model output evaluation metrics Mean Bias Error (MBE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and the Coefficient of Variation of the Root Mean Squared Error (CV RMSE) have been used to validate the model output, as described in *Coakley et al.* (2014). These metrics ensure the calibration performance and if they meet the criteria set out by the ASHRAE Guideline 14 (2002) (*Table 1*), the model can be considered as being 'calibrated'.

Table 1. Acceptance criteria and model evaluation metrics for calibration performance of BES-models.

Standard/ Guideline	Monthly criteria [%]		Hourly criteria [%]	
	MBE	CVRMSE	MBE	CVRMSE
ASHRAE (2002)	5	15	10	30
IPMVP (2007)	20	-	5	20
FEMP (2008)	5	15	10	30

$$MAE[X] = \frac{\sum_{i=1}^{N_p} |s_i - m_i|}{N_p} \qquad RMSE[X] = \sqrt{\frac{\sum_{i=1}^{N_p} (m_i - s_i)^2}{N_p}}$$

$$MBE[-] = \frac{\sum_{i=1}^{N_p} (m_i - s_i)}{\sum_{i=1}^{N_p} (m_i)} \qquad CV\ RMSE[-] = \frac{\sqrt{\frac{\sum_{i=1}^{N_p} (m_i - s_i)^2}{N_p}}}{\bar{m}}$$

RESULTS

In order to carry out the model calibration, the time series data of the measurement campaign was thoroughly inspected. Two time periods were chosen, a first period in February was selected as a training dataset and a second period in April was selected as check-up period to test whether the model can be considered calibrated. It is no secret that dynamic simulation models require a variety of input parameters (for model development, but also during simulation and validation). Therefore, the selection of both periods was influence by the available time series. The two most 'complete' sets of time series were chosen for the model calibration and validation (*i.e.*, time series without too many gaps for important parameters).

The BES-model has been validated on three indoor climate and air quality parameters, namely indoor air temperature [° C], relative humidity [%] and CO_2-concentration [ppm]. Because indoor air temperature and relative humidity are bound by a mathematical relationship (*i.e.*, if the water vapor content stays the same and the temperature drops/rises, the relative humidity increases/decreases), they had to be calibrated together. The indoor CO_2-concentration could be calibrated separately, as it has no significant link to the other two quantities. The outdoor CO_2-concentration was measured on site and set accordingly to a constant of 421 ppm in the model.

The length of the selected periods has been determined mainly by available measurement data in order to avoid gaps, but also by calibration feasibility. The model takes approximately 90 minutes of simulation time to calculate three weeks of results on a Dell T5820 Xeon W-2125 (4.0 GHz, 4C, 8.25 MB Cache, 64 GB RAM) which is quite slow for multi-zone reduced order BES models to perform manual calibration. Therefore, the length of the calibration and validation period was reduced to respectively four weeks and three weeks.

In the next three paragraphs, first the model results of the training period are presented. Then, the model results of the validation period are presented and afterwards, the influence of user behaviour-uncertainty is discussed.

Model output results of the training period

In Figure 3, the time series results of the training period for indoor air temperature, relative humidity and CO_2-concentration are demonstrated for the livingroom, the open kitchen, a bedroom and a master bedroom. In Table 2, the MAE and RMSE-results for the four rooms are given. For the training period, the Netatmo-sensor in the children's bedroom was defect due to battery failure. No measurement data could therefore be produced for that room.

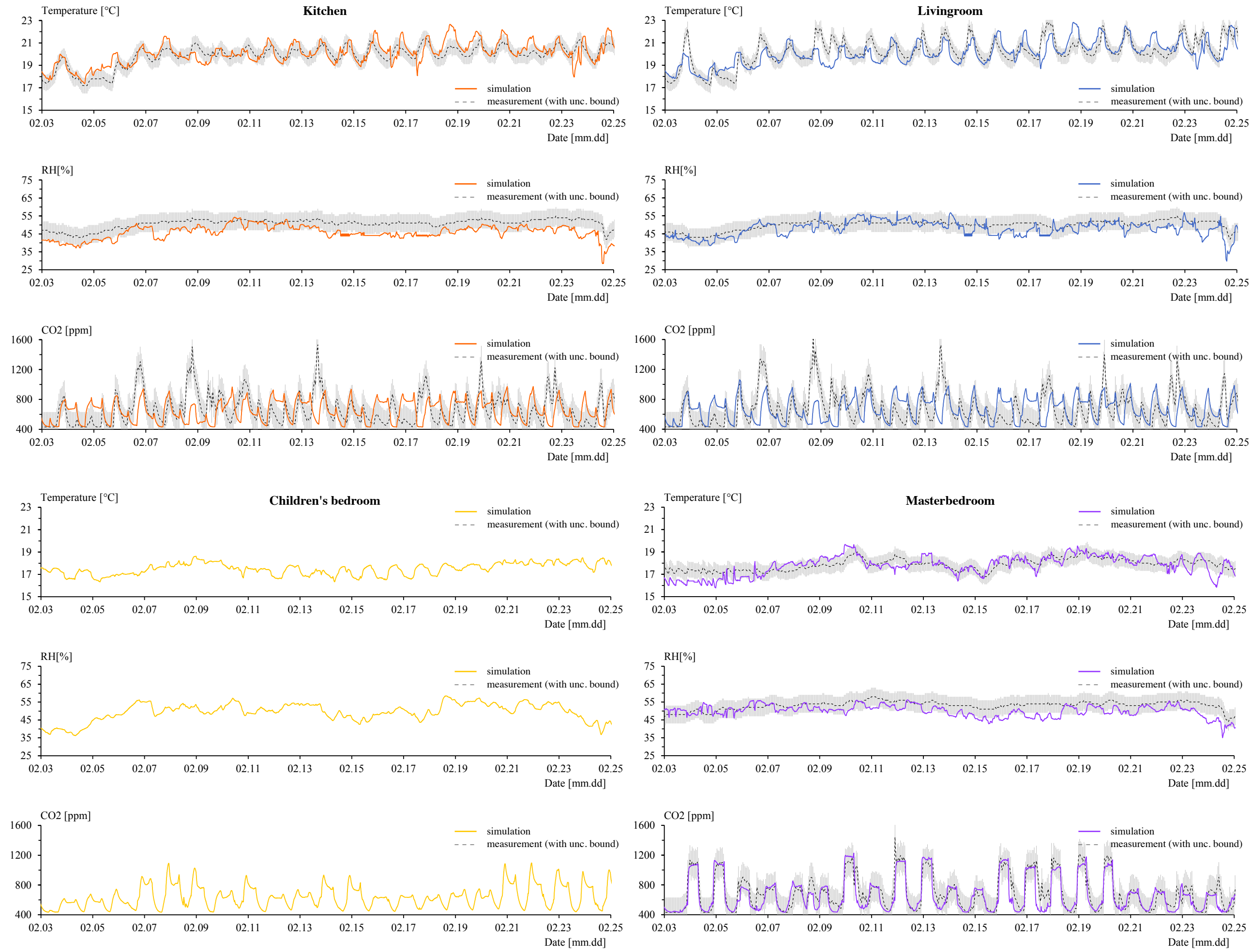

Figure 3. Graphical analysis of simulation results (colour) and measurement data (dotted dark grey) with corresponding uncertainty intervals (grey) (derived from measurement sensor accuracy and resolution) for the training period (February).

Table 2. RMSE/MAE results for the training period.

	RMSE			MAE		
	T_{air} [K]	RH [%]	CO_2 [ppm]	T_{air} [K]	RH [%]	CO_2 [ppm]
Kitchen	0.72	5.21	221	0.56	4.67	172
Livingroom	0.94	3.83	234	0.71	3.05	181
Children's bedroom	/	/	/	/	/	/
Masterbedroom	0.62	4.88	131	0.50	4.23	88

The RMSE-results for the indoor air temperature vary between 0.62 and 0.94 °C (MAE: 0.50-0.71 °C). For the relative humidity, the RMSE-results vary between 3.8 and 5.2% (MAE: 3.0-4.7%) and for the CO_2-concentration, the RMSE-results vary between 131 and 234 ppm (MAE: 88-181 ppm). These are normal and sufficient evaluation metric results for this type of dynamic multi-zone BES- models. Especially the indoor air temperature and relative humidity show good results.

Validation results of the validation period

In Figure 4, the time series results of the training period for indoor air temperature, relative humidity and CO_2-concentration are demonstrated for the livingroom, the open kitchen, a bedroom and a master bedroom. In Table 3 (next section), the MAE and RMSE-results for the four rooms are given.

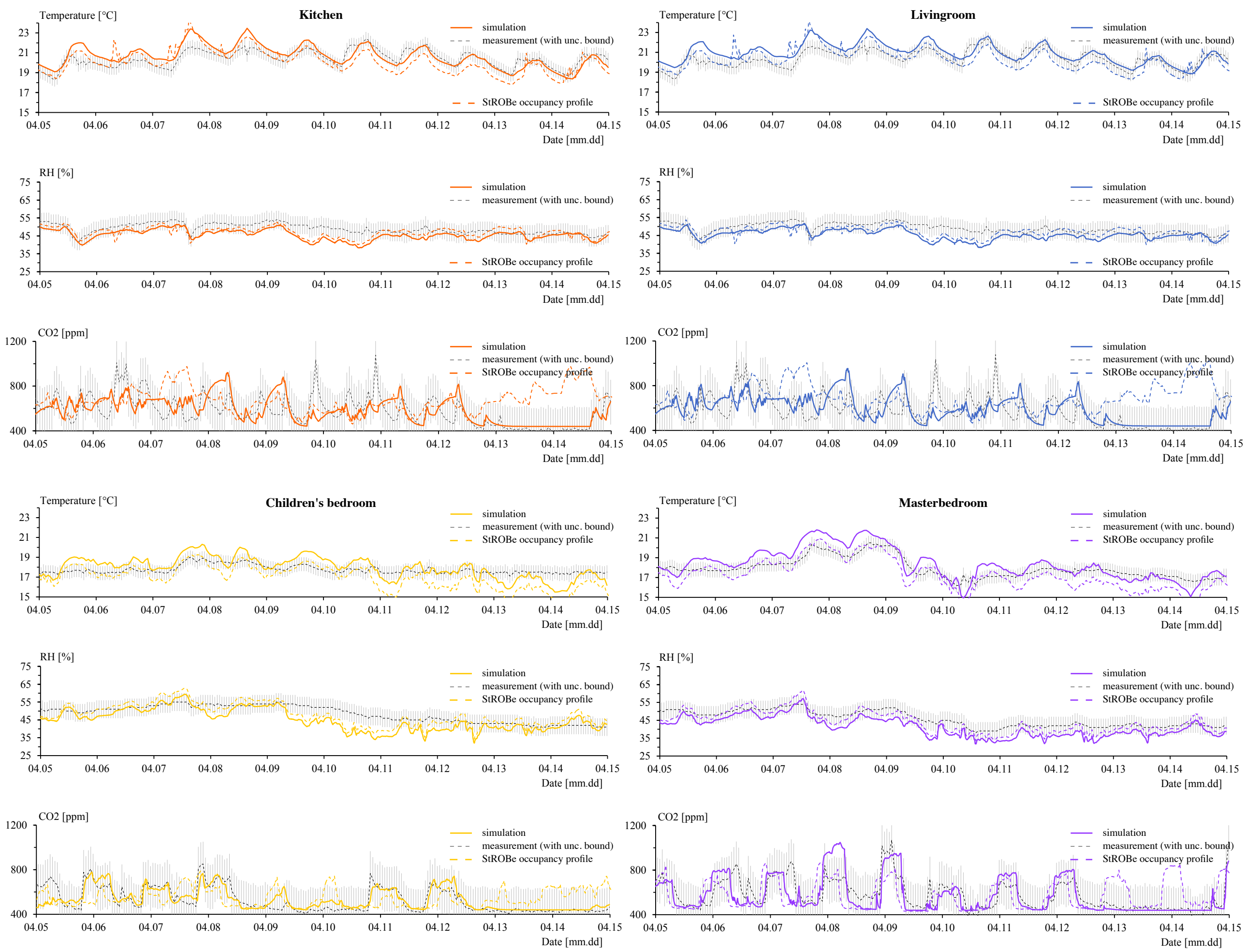

Figure 4. Graphical analysis of simulation results (colour) and measurement data (dotted dark grey) with corresponding uncertainty intervals (grey) (derived from measurement sensor accuracy and resolution) for the validation period (April).

For the validation period, the RMSE-results for the indoor air temperature vary between 0.76 and 0.94 °C (MAE: 0.60-0.78 °C). For the relative humidity, the RMSE-results vary between 4.2 and 5.4% (MAE: 3.5-4.6%) and for the CO_2-concentration, RMSE-results vary between 65 and 116 ppm (MAE: 45-87 ppm), which again ar d normal considere sufficient results for this type of dynamic simulation.

The RMSE/MAE-results for the CO_2-concentration seem rather large. Yet, given the uncertainties and assumptions in the inhabitant presence profiles and a measurement sensor uncertainty of 200 ppm, the obtained results are acceptable. Note that the difference in RMSE-results for CO_2-concentrations between the day and night zones is also remarkable (in the night zones, the error is only half the size compared to the day zones). The occupancy presence in the day areas is much more uncertain than in the night areas. Therefore, the model performance in the night areas is much higher for the CO_2-concentration results.

The validation results in Table 3 correspond well to the results obtained in the calibration period (Table 2). Moreover, they are well below the acceptance criteria for calibrated models (*Coakley et al.* ,2014). Therefore, the model can be considered 'calibrated'. Results have also been calculated for the children's bedroom this time (*N.B.*, the Netatmo sensor in this room had failed in the calibration period) and clearly demonstrate similar findings to the results in the masterbedroom. CO_2-concentrations correspond well to the measured concentrations and the deviation from the measured data is also of the same order of magnitude for indoor air temperature and relative humidity.

Table 3. Comparison of RMSE/MAE results for the validation period with motion sensor-based occupancy profiles (white) and with StROBe occupancy profiles (grey).

Simulation-setup	RMSE			MAE		
	T_{air} [K]	RH [%]	CO_2 [ppm]	T_{air} [K]	RH [%]	CO_2 [ppm]
Kitchen (validation)	0.75	4.17	115	0.60	3.52	85
Kitchen (StROBe occ.)	0.97	3.31	202	0.78	2.70	152
Livingroom (validation)	0.80	4.21	114	0.66	3.60	85
Livingroom (StROBe occ.)	0.83	3.15	213	0.65	2.48	159
Children's bed. (validation)	0.86	5.38	65	0.73	4.18	43
Children's bed. (StROBe occ.)	1.18	4.24	133	0.93	3.38	104
Masterbedroom (validation)	0.94	5.05	107	0.78	4.61	75
Masterbedroom (StROBe occ.)	1.06	3.11	161	0.85	2.53	121

Model uncertainty due to user behaviour

The validation results, presented in the previous sections, were obtained with a model where the occupancy schedules have been constructed from motion sensor data in the dwelling and assumptions for common human heat, moisture and CO_2-emission rates. A second option to include user behaviour into the model could be to work with statistically generated occupancy profiles. As a good comparison for user behaviour uncertainty, a second model was simulated that uses statistical occupancy schedules.

The occupancy schedules were calculated using an internally developed tool, based on the StROBe-model developed by Baetens *et al.* (2016), that outputs occupancy schedules for all kinds of household compositions, inhabitant lifestyles *etc.* So, the manually constructed occupancy profiles were replaced by profiles from the statistical occupancy tool for the same household composition and inhabitant lifestyle (but without relying on any motion sensor data from the dwelling or derivations from measured variables). In Table 3 and Figure 4, the results are shown together with the validation results from the model (*N.B.*, the model output with StROBe-occupancy schedules is given a dotted, coloured line).

CONCLUSION

The model validation results and accompanying time series figures prove that the dynamic multi-zone reduced-order simulation model predicts the indoor climate (*i.e.*, indoor air temperature, relative humidity and CO_2-concentration) realistically and sufficiently well. Surely, there is plentiful room for improvement. Yet, given the fact that a simulation model is always a simplification of the real world and thus with all possible uncertainties in mind (*e.g.*, user behaviour, outdoor climate, thermal and hygric capacity effects, doors and windows *etc.*), the validation results (*i.e.*, RMSE's between 0.76 and 0.94 °C (MAE: 0.60-0.78 °C) for the indoor temperature, RMSE's between 4.2 and 5.4% (MAE: 3.5-4.6%) for the relative humidity and RMSE's between 65 and 116 ppm (MAE: 45-87 ppm) for the CO_2-concentration) are sufficiently good to consider the model calibrated.

Hence, the overall modelling approach shows good ability to accurately predict the indoor climate in common inhabited single-family dwellings and even with quasi-random household occupancy profiles, but knowledge about the number of inhabitants and a rough understanding of the inhabitant's lifestyle, the model evaluation metrics and figures showed good results. In order to further improve the simulation results, the model's hygric building behaviour should be updated, since it appears to be underestimated by the current model (*i.e.*, the hygric capacitance of the air in the building is captured fairly OK by the model, however the hygric capacitance of the building envelope/internal walls and furniture should be modelled in more detail). Furthermore, the study also demonstrates that a good preparation is crucial to be able to perform a good validation for this type of dynamic simulation models. The measurement campaign has to be well thought out and continuous follow-up is necessary (*e.g.*, to avoid sensor failures for extended periods, missing data overall or biased data due to sensor misplacements).

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REFERENCES

Jorissen F., Reynders G., Baetens R., Picard D., Saelens D., Helsen L. 2018. Implementation and verification of the IDEAS building energy simulation library. *Journal of Building Performance Simulation*, 11.6, 669-688.

Wetter, M. 2006. Multizone Airflow Model in Modelica. *Proceedings of the 5th International Modelica Conference*, 2, 431-440.

Coakley D., Raftery P., Keane M. 2014. A review of methods to match building energy simulation models to measured data. *Renewable and Sustainable Energy Reviews,* 37, 123-141.

ASHRAE. 2002. ASHRAE Guideline 14: Measurement of energy and demand savings. *American Society of Heating, Refrigerating and Air-Conditioning Engineers*, Atlanta, 165 pages.

EVO. 2007. International performance measurement & verification protocol. *Efficiency Valuation Organisation*. 123 pages. US

DOE. 2008. M&V guidelines: measurement and verification for federal energy projects. *US Department Of Energy*, V3.0, 108 pages.

Baetens R., Saelens D. 2016. Modelling Uncertainty in District Energy Simulations by Stochastic Residential Occupant Behaviour. *Journal of Buildings Performance Simulation*, 9, 431–447.