Development of a Python-based simplified hourly building model for non-domestic building stock operational energy simulations

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Abstract

Building stock (BS) energy simulation is an important tool for exploring a BS's greenhouse gas mitigation measures. Simulation presents the challenge of finding the trade-off between detail and computational requirements. This paper presents the development and validation of such a model based on the simplified hourly method of the ISO 13790, implemented in Python. The model was validated using 464 sample buildings from recently collected German non-domestic building stock data. The validation displayed an acceptable level of accuracy for the aggregated building stock with a bias of 19.3 % and 11.2 % for space heating and electricity use, respectively.

Introduction

The global climate crisis (IPCC, 2021) is pushing the global transition to a post-fossil fuel age. Buildings contribute significantly to energy use and greenhouse gas (GHG) emissions. The operation of residential and non-residential buildings cause 17 % and 10 % of all global energy-related GHG-emission respectively (International Energy Agency, 2021). Accounting for indirect embodied emissions, the global building stock (BS) is responsible for approximately 37 % of global energy-related GHG-emission (International Energy Agency, 2021). In Germany, the non-residential and residential building stocks accounted for 14.2 % and 27.4 % of total final energy consumption in 2010, respectively (IEA-BEEP, 2019). Therefore, the energy transition in the building sector must play an important role in climate protection policies.

Building stock models (BSMs) are important policymaking tools for exploring options to decarbonise building stocks, (Julian Bischof and Aidan Duffy, 2022; Röck et al., 2021; Mastrucci et al., 2017). The development of such models must satisfy several, often competing, objectives. Policymakers require these models to be representative, simple to use and easy to understand. Model developers require sufficient flexibility to amend and extend the model to adapt it to new requirements. Users also require acceptable execution time (Bischof and Duffy, 2021) and outputs which cover the main building energy end uses including space heating and cooling, and appliances. An hourly time step allows the model to capture transient behaviours such as embedded generation and grid balancing.

Several building energy models (BEMs) exist which could be used in the development of a BSM. These can be divided into either complex or simple models. Typically, complex models have been developed for the simulation of single buildings with comprehensive in- and outputs. They are detailed and accurate due to the very detailed physical representations employed which require many input parameters. For this reason, complex models are problematic to implement in BSMs since this level of input variable detail is often not available at a stock level (Malhotra et al., 2021; Julian Bischof and Aidan Duffy, 2022). Moreover, their complexity necessitates significant computational resources for multiple buildings resulting in long execution times. Common examples of such complex models are EnergyPlus and INSEL (Malhotra et al., 2021).

Simple BEMs have been developed to work with fewer model inputs to approximate energy demand (simulated energy use) based on the most dominant energy flows, thereby resulting in faster execution times (Lim and Zhai, 2017). A further advantage of such models is that they are easier to understand by non-experts such as policymakers, thus increasing the acceptance of the model (Bischof and Duffy, 2021). Examples include models based on the simplified hourly method of ISO 13790 or, more recently, ISO 52016 (Malhotra et al., 2021; Julian Bischof and Aidan Duffy, 2022).

Building stock energy and emissions models which use physical stock data are typically based on these relatively simple BEMs. However, the vast majority of these focus on domestic stocks, with only few examples for non-domestic stocks. The recently completed ENOB:DataNWG (see www.datanwg.de) project involved collecting statistically representative physical (e.g. energy, building fabric and systems) data on the German non-domestic building stock. However, for the reasons outlined above, no readily available model for its operational building energy simulation could be identified.

Aim and Methodology

A user requirements survey (Bischof and Duffy, 2021) and a state-of-the-art review (Julian Bischof and Aidan Duffy, 2022) have identified the need for a suitable and feasible energy computer simulation model for non-domestic building stocks which can be used to provide knowledge for policymaking. More specifically, the model should be physics-based, relatively simple, easy to understand, reliable and easy to adapt and based on best practice standards such as the ISO 13790. It should rely on the minimum required input variables, and these should be generally available for building stocks. To facilitate maximum user access, the software should be open source, and simulation times should be relatively short (less than one hour) for commonly-available desktop PCs. Finally, any simulation model developed must be tested and validated to ensure its reliability.

The development of the simulation tool involved the following steps:

1. identification of a model scope and most appropriate methodology;
2. screening suitable existing models as a basis for development;
3. identification of a suitable data-set for model simulation and validation;
4. extending the existing model to meet the required scope;
5. model simulation; and
6. model validation.

These steps are described in more detail below.

Model scope, methodology identification and model screening (Steps 1 and 2)

A detailed model screening was undertaken considering 98 models identified in (Julian Bischof and Aidan Duffy, 2022), six in (Malhotra et al., 2021), one open-source non-domestic BEM available on GitHub (Jayathissa, 2020) and the VSA 2.0 model recently developed by (Bischof, 2021). In total 106 models were considered when selecting the most appropriate existing model to meet the requirements outlined above. The selection involved sifting the 106 models based on: suitability for non-domestic buildings; suitability for archetype/disaggregated building; the use of a building physics approach; appropriate output requirements (heating, cooling and electricity for appliances); confirmed validation or verification; open-source availability; model simplicity relative to other models; and free-to-use software.

Applying these criteria, the ISO 13790 based RC_BuildingSimulator (Jayathissa, 2020; Jayathissa et al., 2017) was identified as the most suitable model. This uses a widely accepted simplified hourly thermal network model with 5 resistances to the heat flow and one capacity for internal heat storage (5R1C). An open-source software version of the model – the Python-based RC_BuildingSimulator - was selected for the task of model development. The ISO 13790 model has two key advantages: it is simple, with few inputs required; and the method has been previously verified and validated (Maccarini et al., 2021). Its successor standard (ISO 52016) was not selected due to is its higher complexity (e.g. requiring highly disaggregated individual building elements) and more temperature nodes. While the additional detail improves model accuracy for individual buildings (assuming the necessary data are available), for building stocks, where detailed building element data are unavailable and must be inferred or interpolated, the additional model complexity only adds greater uncertainty, thus reducing simulation accuracy (van Dijk, 2020). This greater simplicity also means that the ISO 13790 model would have shorter execution times (Felsmann et al., 2020; van Dijk, 2020).

Validation data-set (Step 3)

Internationally, there are very limited data available for simulating non-domestic building stocks. One exception is the ENOB:DataNWG-Project which has made statistically representative data available on the energy-related characteristics and refurbishment rates of the German non-domestic building stock (further details available at: www.datanwg.de). While basic data were collected for larger samples of buildings, detailed data for 464 buildings were collected using on-site surveys. This involved measuring energy consumption, detailed physical building characteristics and the appliance usage parameters necessary for energy demand simulations, model calibration and validation (detailed documentation and variable descriptions are available at shorturl.at/bkIU7; building characteristics at shorturl.at/jtJSY; and measured energy use at shorturl.at/opGJN). Although the sample was biased (public bodies, for example, were overrepresented and transport buildings representing about 1 % of the German NDBS are not included), this did not affect its usefulness for model validation. However, for this reason, no extrapolations to the building stock level are undertaken here.

Model methodology (Step 4)

In the ISO 13790 5R1C model the internal air temperature node (θ_{air}) is influenced by internal gains (Φ_{int}), solar gains (Φ_{sol}) and heating and cooling power ($\Phi_{HC,nd}$) (see Figure 1). The latter ($\Phi_{HC,nd}$) provides the energy in- and outflow for conditioning the zone to stay within certain set temperature set points. The internal and solar gains act on the internal surface (θ_s) and the thermal mass (θ_m) temperature nodes. θ_{air} is connected to the supply air temperature node (θ_{sup}); this relationship is modelled using the ventilation heat transfer coefficient (H_{ve}). Heat transport between θ_s and θ_{air} is modelled by the heat transfer coefficient (HTC) ($H_{tr,is}$). θ_s is also influenced by the external air temperature (θ_e) via the HTC for transparent surfaces and doors ($H_{tr,w}$) and to the thermal mass temperature node (θ_m) via the HTC $H_{tr,ms}$ representing the internal heat transfer process for the opaque elements ($H_{tr,op}$). θ_m itself is coupled to θ_e through the external part of $H_{tr,op}$ the HTC $H_{tr,em}$. θ_m is further connected to the internal thermal storage capacity of the building (C_m). The details of the calculation of the resistances and storage capacity are described in the ISO 13790 as well as the available model documentation (see shorturl.at/cfsHS), and are therefore not repeated here.

In this paper, a new non-domestic stock model is proposed. The Dynamic ISO Building Simulator (DIBS), uses the 5R1C model described above and is adapted for simulating German non-domestic buildings. It includes occupancy schedules, appliance gains and lighting requirements according to the DIN V 18599-10 and the SIA 2024 for the calculation of the internal gains Φ_{int} through people's metabolism and their use of appliances and lighting. The natural lighting contribution to lighting demand and solar gains Φ_{sol} are estimated using window areas and directions. A location-based sun position model which considers direct and diffuse solar radiation is used based on (Quaschning and Hanitsch, 1995), coupled with assigned weather data of a typical meteorological year (TMY) for the nearest available weather station. A total of 93 weather station TMYs are available in the model. The choice of sun position and weather station is based on each building's postal code.

In addition to its adaptation to a German environment, the model has been extended to incorporate aspects missing in the simplified ISO 13790 implementation of the RC_BuildingSimulator, but which are important for realistically simulating the demand for space heating, cooling and appliance electricity use.

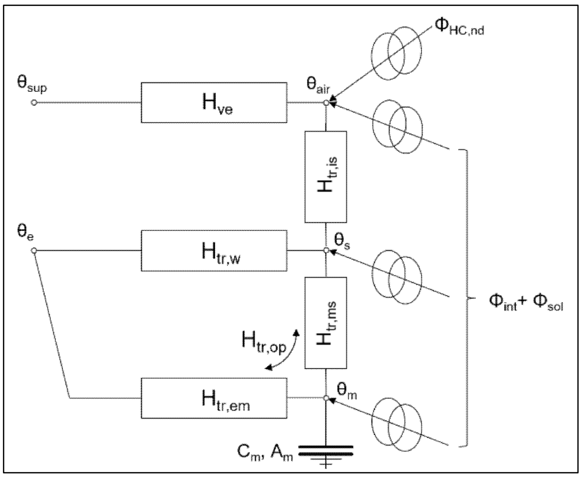


Figure 1: ISO 13790 5R1C simple hourly method network model for one building zone

For example, Φ_{sol} is adapted to include shading, and so reduce transparent surfaces' solar transmittance during summertime (1st of April to 1st of October); this applies in all cases where θ_e is above 24°C and thereby above the desired temperature in case of cooling ($\theta_{i,c,soll}$) for θ_{air}. This threshold applies to 86 % of the usage zones defined in the DIN V 18599-10 profiles. Where these conditions are met, the glass energy transmittance is reduced to a defined value depending on the type of window and shading available

The ventilation heat transfer coefficient (H_{ve}) was also adjusted to take account of occupancy periods so as to provide a estimate of ventilation heat losses. Here, occupancy schedules specify the periods of natural ventilation and mechanical ventilation to meet minimum air change rates. When unoccupied, infiltration only is considered. Appliance electricity use, although not part of the ISO 13790, is estimated based on the standard values of the DIN V 18599-10. Lighting demand is also considered during the occupancy periods. The final energy demand considers the efficiencies of all typical heating and cooling systems.

The DIBS model, including detailed documentation and a data preprocessor that directly translates survey coded variables and assigns them to DIBS input variables of on-site inspection data, is available under an open-source license on Github: https://github.com/IWUGERMANY/DIBS---Dynamic-ISO-Building-Simulator.

Inputs

The DIBS uses a total of 44 input variables providing information on the building's location, geometry, usage (including setpoints and gains), installed systems, their efficiencies and control, internal loads, physical attributes (e.g. lighting utilisation and transmittance) of the transparent surfaces, thermal properties of the building envelope, air change rates and the thermal capacity of the building. Many of these inputs are automatically generated in the data preprocessing module based on on-site inspection data. The assignment of default input variables is based on the building usage category (e.g. lighting load), window-type (e.g. glass light transmittance) and construction type (e.g. thermal capacity). A full list of all required input variables is available at shorturl.at/gmtBZ.

Outputs

The DIBS estimates the energy demand and the final energy use for space heating and cooling, differentiated by electricity and other energy carriers. The electricity demand for lighting and appliance use is also estimated. Because an engineering model methodology has been adopted, other intermediate results (e.g. the solar gains of transparent surfaces) of interest can also be outputted where desired.

Validation

Space heating and small power/lighting electricity demand were used to validate the DIBS, since measured data were available for both of these variables. Space cooling requirements are included with electricity since these data are aggregated in the dataset. To ensure a like-for-like comparison, measured data are climate- and vacancy-corrected by employing the approach used for calculating energy ratings for non-domestic buildings (Worm, 2015) (see shorturl.at/bkIU7).

Objects representing extreme outliers of over 600 kWh/m^2·a for the measured energy use or the simulated demand are excluded from the validation, as they are likely to be erroneous.

Results (Steps 5 and 6)

Before the ENOB:dataNWG survey data could be inputted into the model, it required preprocessing. For this reason, a data preprocessor was developed. The subsequent simulation takes about 5 seconds per building on an average Laptop (Lenovo ThinkPad L480, Win10 x64, Intel Core i7-8550U CPU @ 1.80 GHz 2.00 GHz (8 Cores), 31,9 GB RAM (see shorturl.at/kAQ57 for details)).

The comparison of the on-site inspection stock (406 buildings with both measured and simulated space heating demand and 411 buildings for electricity) shows that on average the simulated space heating demand is 19.3 % above the measured, while the electricity demand is 11.2 % greater. Comparing the results based on the building usage category (listed in Table 1) a diverse picture unfolds (see Figure 2 and Table 2). While the OAGB, Trade and TU building

Table 1: Building usage categories included in the validation data set

- Buildings providing Boarding, Hotels, Restaurants or Catering (BHRC)
- Office, Administrative or Government Buildings (OAGB)
- Buildings for Research and University Teaching (RaUT)
- Buildings for Health and Care (HC)
- Buildings for Culture and Leisure (CuLe)
- Trade Buildings (Trade)
- Production, Workshop, Warehouse or Operations Buildings (PWWO)
- School, Day Nursery and other Care Buildings (Sch)
- Sports Facility Buildings (SF)
- Technical and Utility Buildings (supply and disposal) (TU)

categories show a good statistical agreement (< ±21 % PBias), the model overestimates space heating for the categories BHRC, CuLe, HC, RaUT and Sch, and, underestimates PWWO and SF. The RaUT buildings are overestimated by more than 280 % PBias. The scatterplot with linear trendlines for the individual usage categories and overall sample (ALL) is presented in Figure 3 and shows a general overestimation for higher values as well as underestimation for lower values, suggesting a systematic problem. Similar findings were made, for example, by (Hörner and Lichtmeß, 2017) regarding domestic buildings in Luxemburg.

With regard to electricity (see Figure 4), the simulated and measured electricity demands are similar (< 17 % |PBias|) for building usage categories CuLe, OAGB and RaUT, but BHRC, HC and PWWO are overestimated, while SF, Sch, TU and Trade are underestimated. Simular to space heating, an individual building comparison indicates a systematic overestimation of higher values while at the same time underestimation of lower energy use. The high values in the measurements are most likely caused by the inclusion of electric consumers not considered in the standard values used for demand simulation (e.g. more production-related consumers such as server units).

A full summary of validation figures and tables is available at shorturl.at/zBGV1.

Discussion and Conclusion

The simulation of space heating and electrical energy requirements using the DIBS model resulted in overall mean absolute errors of 99,77 and 45,11 kWh/(m^2·a) respectively, showing the potential for model improvement on an individual building level. These results were achieved using input variables which are commonly available in building stock databases. However, model accuracy was lower for certain building usage categories (see Table 2). This was likely the result of unrepresentative category-specific input zonal occupancy parameters such as temperature setpoints, lighting attributes (controls and load), air change rates, internal gains (occupancy and appliance), occupancy patterns and occupancy

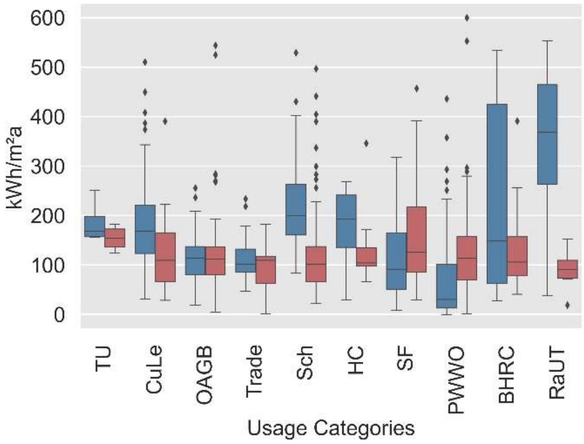
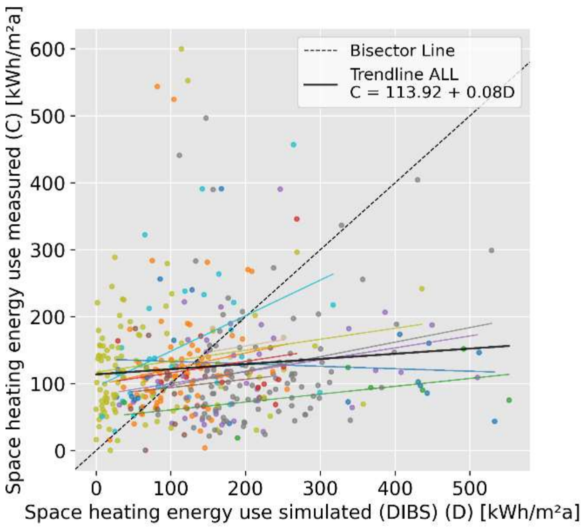


Figure 2: Comparison of simulated space heating demand (blue boxes) to the measured space heating consumption (red boxes), by building usage category

Table 2: Statistical analysis of model results for space heating and their performance against measurements for the entire Stock (ALL) and individual usage categories (see Table 1)

Category	Space heating energy use measured - Mean [kWh/m²a]	Space heating energy use simulated - Mean [kWh/m²a]	Bias [kWh/m²a]	PBias [%]	MAE [kWh/m²a]	MAPE [%]
BHRC	128.92	218.69	89.77	69.63	170.62	184.27
OAGB	124.76	112.52	-12.24	-9.81	54.65	90.69
RaUT	89.54	344.70	255.15	284.94	264.85	378.28
HC	129.52	177.98	48.46	37.41	91.35	88.80
CuLe	117.21	195.86	78.66	67.11	102.23	128.92
Trade	96.01	114.73	18.72	19.50	53.36	827.84
PWWO	128.50	69.77	-58.73	-45.70	101.99	153.39
Sch	122.55	218.59	96.04	78.37	120.84	158.33
SF	157.14	116.62	-40.53	-25.79	80.68	53.37
TU	153.70	185.93	32.23	20.97	45.41	29.63
ALL	**125.43**	**149.65**	**24.23**	**19.32**	**99.77**	**165.58**

Figure 3: Scatterplot of simulated space heating demand to the measured space heating consumption, by building usage category



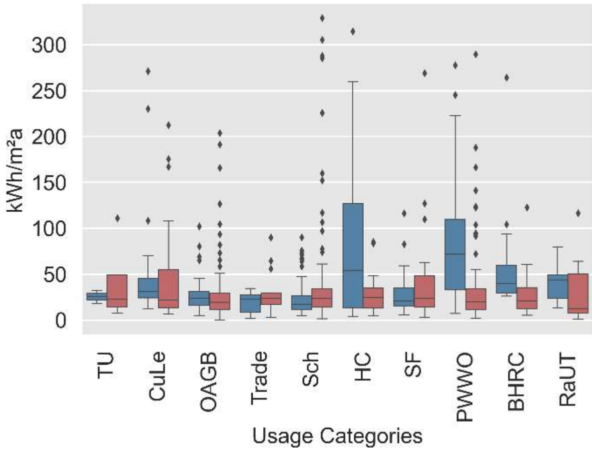


Figure 4: Comparison of simulated electricity demand (blue boxes) to the measured electricity consumption (red boxes), by building usage category

intensities. A sensitivity analysis found that the air change rate for natural ventilation (windows) had the greatest impact on the space heating demand.

One option to improve the accuracy of the DIBS building usage category outputs is to use building usage category average occupancy values, instead of the values of the most prominent usage zone in the building as it is done currently. For example in case of an OAGB building use the occupancy variables should be based on an area weighted average of: the usage zones of offices, kitchens, sanitary, storage, conference and traffic areas instead of applying the specific parameters for the office use on the entire building. Further, the default air change rates of building categories greatly overestimate the space heating demand and should be adjusted. Additionally, as there might be more hard-to-identify variables contributing to systematic errors (e.g. the assigned average u-values based on building age and construction type), a second improvement option is to apply statistical learning techniques to create calibration factors to “correct” the sum of the remaining systematic biases.

In addition to these possible improvements, it is planned to extend DIBS to simulate hot water use. Furthermore, DIBS will be used in conjunction with the statistically representative ENOB:dataNWG interview data-set to simulate the behaviour of the German non-domestic building stock under different input assumptions, allowing extrapolation on to the entrie stock.

Summary

This paper describes the development, implementation and validation of the DIBS model which builds on the ISO 13790 5R1C hourly simplified model. Compared to other stock simulation models, DIBS employs a relatively small number of input variables which are typically available in stock databases. Due to its simplicity, it results in a short computation time of 5 s per building on an average laptop. The model mean outputs were 19.3 % and 11.2 % above the measured space heating and electricity energy use respectively for a sample of the German non-domestic building stock. Significantly greater errors were observed for building-use sub-categories and for individual buildings which will be addressed in further work.

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CRediT authorship contribution

Julian Bischof: Conceptualization, Methodology, Investigation, Programming, Formal analysis, Visualization, Writing original draft, Writing – review & editing. **Simon Knoll:** Programming, Methodology, Visualisation, Writing – review & editing. **Aidan Duffy:** Supervision, Writing – review & editing.

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