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Interactive urban building energy modelling with functional mockup interface of a local residential building stock

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ABSTRACT

The transformation towards a low carbon energy system requires municipalities to improve their local building stock. Urban building energy modelling (UBEM) is an emerging tool to support municipalities in shaping the necessary strategies by estimating energy demand with high spatial and temporal resolution. This study proposes a Functional Mockup Interface (FMI)-based UBEM that enables interactive capacities to simulate diverse environmental conditions without reinitialisation. The FMI-based approach allows to couple the building energy simulation EnergyPlus with external models. These capacities were tested on a real-world example in the German city of Wuppertal with urban microclimate data. The results are estimates of sub-hourly energy demand based on the adjacent environmental conditions of each building. In order to ameliorate the applicability, the FMI-based UBEM is further enriched by incorporating an automatic procedure to derive 3D building models, displaying high geometrical fidelity, from city-wide point clouds through the screened Poisson surface reconstruction algorithm. The study area contains 5736 residential buildings. A diverse residential building stock was modelled on the basis of the EU project TABULA. To demonstrate the functionality of the proposed UBEM, a demand response scenario was constructed with microclimate data and heat pumps instead of other heating and hot water systems. The capacity of UBE-FMI to dynamically change parameters (e.g. thermostat setpoint) in the building models can benefit the evaluation of demand response strategies and its potential to shed peak loads. In comparison with reference studies, UBE-FMI produced reasonable estimates of energy demand. The 3D building models and simulation results using "live" weather are visualized by a web-interface, which is implemented with the geospatial 3D framework NASA WorldWind.

1. Introduction

In response to climate change, the German Federal Government announced in 2010 a shift in the German energy policy: "Energiewende" (German for energy transition). This policy programme aims at replacing fossil fuels with renewable energy sources by 2050 (Scholz et al., 2014; Hake et al., 2015). In the aftermath of the Fukushima nuclear accident, the scope of the transition was broadened due to the abandonment of nuclear energy as bridging technology. The housing sector plays a key role because considerable significance is attributed to the improvement of energy efficiency and the housing sector still has potential in this regard (Ürge-Vorsatz et al., Butcher). Therefore, the German state-owned development bank KfW launched an energy-efficient urban redevelopment programme to support integrated municipal strategies for improving energy efficiency and expanding the utilization of distributed energy sources (Stein et al., 2014; KfW, 2011). The process of improving the sustainability of cities not only requires political will and financial resources, but also a profound understanding of the spatial and temporal patterns caused by energy demand and supply (Gils; Behboodi et al., 2016; Ferrari et al., 2019). The intermittent nature of renewable energy sources complicates the process. The misalignment between the varying supply of renewable energy (e.g. wind and solar) and energy demand poses a daunting challenge (Suberu et al., 2014). The research to understand the spatial and temporal patterns of weather and its impact on renewable energy supply continues to receive strong support. But the planning of a sustainable energy system also requires that

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the demand side receives more attention with the aim to improve the coverage of energy demand with renewable energy supply (Wang et al., 2015; Kwon et al., 2016). Additional efforts have to be invested in tools capable to comprehend the dynamics of energy demand of each building. Although statistical urban energy models (Huo et al., 2019a, 2019b) are robust and accurately estimate energy use on the basis of the demographic and economic developments of the entire area, i.e., top-down approach, or on the basis of vintage and function of the individual buildings in the area, i.e. bottom-up approach (Pasichnyi et al., 2019), these models depend on measured data. Their applications in the assessment of changing conditions, such as policies, occupant behaviours etc., are thus limited. Statistical bottom-up approaches have the additional constrain of depending on typically quarterly or annually collected data (Wilke et al., 2013; Abbasabadi and Ashayeri, 2019). This data basis restricts their applicability in the prediction of energy demand of individual buildings with a daily or hourly time step (Fabbri and Tarabusi, 2014). The relevance of this capacity lies in the evaluation of the outcome which individual or combined measures in the field of energy efficiency, storage and demand response have on the satisfaction of energy demand with distributed and renewable energy supply (Reinhart and Davila, 2016). Because data availability is a widespread concern, statistical models offer little recourse, in particular for higher spatial resolution. Urban building energy modelling (UBEM) contributes to address these challenges (Li et al., 2017). UBEM applies engineering methods in a bottom-up approach to perform building energy simulations for every building in the area of interest. The engineering methods refer to thermal models which are derived from mass and energy conservation laws. They form the underpinning of building energy models (BEM), which are used in the design and certification processes for high-efficiency buildings. The understanding of the energy demand patterns with an high spatial and temporal resolution under varying conditions (e.g. weather and behaviour of occupants) has the potential to quantify the impacts of new technologies and policies. In the short-term, a detailed demand assessment can inform demand response strategies and/or the need for energy storage in order to satisfy the demand with renewable supply. UBEM can furnish valuable insights about robust and long-term solutions in designing and sizing a distributed and renewable energy system (Schiefelbein et al., 2016), that must be able to satisfy peak loads. The uncertainties of climate change exacerbates the need to understand the consequences of different scenarios. The prolificacy of this field underlines the emerging importance of such modelling frameworks. A common implementation of UBEMs relies on the building energy simulation engine EnergyPlus (EPlus) (Crawley et al., 2001), which is developed by the US Department of Energy: Urban Modelling Interface (UMI) (Reinhart et al., 2013)/ Boston UBEM (Davila et al., 2016) and City Building Energy Saver (CityBES) (Hong et al., Piette). Other implementations apply simplified thermal models: CitySim (Robinson et al., 2009), SimStadt (Nouvel et al., 2015) and City Energy Analyst (CEA) (Fonseca et al., 2016). Furthermore, various literature reviews are available (Reinhart and Davila, 2016; Li et al., 2017; Sola et al., 2019; Hong et al., 2020) and emphasize the importance to overcome the still existing shortcomings before general adoption can be considered. Related to this field, but relying on an alternative, interesting approach, the load profile generator (Pflugradt, 2090; Pflugradt and Muntwyler, 2017) is derived from a psychological model to produce detailed load profiles for different household types, which can be aggregated to neighbourhoods and municipalities. This behaviour-based modelling would be a suitable extension for UBEMs to mitigate the uncertainty originating from occupant behaviour (O'Neill and Niu, 2017; Hong et al., 2016). Many existing implementations of UBEMs are theoretically capable to benefit from 3D city models with a Level-of-Detail 2 (LoD) (Gröger and Plümer, 2012) because they rely on CityGML (Gröger and Plümer, 2012), which is an open data model and XML-based format for the representation of virtual 3D city models. At LoD2, the buildings are three-dimensional, but their roofs are modelled with predefined shapes and not completely authentic. In practice, the 3D city models used in the corresponding studies, however, remain at LoD1 where the 3D model of a building is extruded from its footprint and its roof is consequently flat. Thus far, previous studies preferred simple 3D models or publicly available CityGML models. The reason is that the derivation of 3D city models is laborious. Further research efforts should focus to remedy this shortcoming with the intention to achieve higher fidelity to reality. This is important because roof sections are often completely or at least partially heated in Europe (Loga et al., 2016). Regarding simplified thermal models, they lack the sophistication and versatility of EPlus. On other hand, EPlus-based UBEMs are constrained by labour-intensive approaches in the modelling of buildings and rigid simulation requirements. For instance, simulating different scenarios involves the tedious process of altering text files which serve as input. The weather conditions also needs to be defined in an external text file for an entire year. The reliance on proprietary software and data in some UBEMs is another factor that hinders wide-spread adoption due to license fees, lower degree of interoperability and constraints in usage (Steiniger and Hunter, 2013). To support wide-spread adaptation of UBEMs and advance their development, the proposed approach extends UBEM with Functional Mockup Interface (FMI). FMI is an open-source standard coupling independent models and allowing the exchange of data. This extension yields interactive capacities because the model can be supplied during the simulation with "live" weather and occupancy data or other scenario data. Moreover, the parameters of every surface in a building model can be individually modified (e.g. temperature) as well as their states can be retrieved (e.g. heat loss). Such interactive capacities can particularly benefit urban microclimate analysis and help to merge UBEM with their climate models. To the knowledge of the authors, this is the first UBEM study to derive detailed 3D models of buildings from a point cloud. This study focuses on the detailed description of a FMI-based UBEM, which is referred as UBE-FMI, its comparison to reference studies and its potential application. The objectives are:

- To provide a FMI-based urban building energy model with the interactive capacity to change variables of individual model parts during the simulation. The impact of changing conditions (e.g. weather and occupancy) on the energy demand can be forecasted and peak loads can be identified with less effort.
- To derive and visualize a three-dimensional city model with LoD3 from a point cloud by exclusively utilizing public data and open-source software.
- To demonstrate that exemplary buildings with information on construction and building systems from the EU project TABULA (Typology Approach for Building Stock Energy Assessment) building typology (Loga et al., 2016) can be translated into building energy models, which simulate energy demand.

As stated by Li et al. (2017), the prevalence of using Typical Meteorological Year (TMY) in UBEM simulations underrates the potential benefits for operational applications in municipalities and their utilities. Because actual year-to-year weather data can considerably vary from one another and from TMY, UBE-FMI was conceived with the idea of facilitating scenario analysis of extreme and untypical climate conditions. UBE-FMI is also well suited for the analysis of urban heat islands for the reason that its FMI-based implementation can exchange data during the simulation between individual model parts like heat exchange between specific building surfaces and their immediate surrounding. This implementation remedies the rigidity of importing weather data from external text files (e.g. EPW file), which is a common feature in UBEM. UBE-FMI is a further step in overcoming the limitations mentioned in Davila et al. (2016): handling large amounts of data supplied by Light Detection and Ranging (LiDAR) to derive detailed building geometry; defining building parameters on construction, ventilation, heating and warm water systems. In this study, a scenario for a future low-carbon energy system in the German city of Wuppertal is constructed where the heating system is electrified, i.e., heat pumps, and a demand response strategy is introduced. The climate conditions are defined by building-specific microclimate data. The impact on energy demand and the potential energy savings are evaluated. The scenario highlights the functional enhancement of UBEM through dynamically alterable parameters in the building models due to the FMI-based implementation, and thus the potential extension of its application to operational planning in public utilities. An additional merit is the attempt to foster environmental awareness of stakeholders and the general public by having produced a web-interface (Issermann, 2019), which is called Wuppertal WorldWind Environmental Monitor (WupperWWEM), that indicates the impact of residential housing under “live” weather conditions. The long-term intention with the development of UBE-FMI is to address urban microclimate and the optimisation of energy saving measures.

2. Methodology

The section that follows describes the main steps of the UBE-FMI (Fig. 1): surface reconstruction of buildings from point clouds; building characterization with TABULA building typology; energy simulation with EPlus and visualization with NASA WorldWind.

2.1. 3D surface reconstruction

The surface reconstruction of buildings is the most crucial aspect in UBEM because a surface which is not airtight will lead the building energy simulation to fail. The reason is that EPlus cannot determine the volume of an open geometry and will stop with an error. In previous UBEM studies, the 3D model of a building was approximated by extruding its footprint. This approach leads to LoD1, where the roof is flat. In order to achieve an higher LoD with a fully formulated roof, the footprints are combined with a city-wide point cloud. The footprints of buildings can be retrieved from OpenStreetMap (OSM) (OpenStreetMap contributor). The point cloud of a city is generated by LiDAR, which is a set of points defined by geographic coordinates (x, y) and height information (z) in Fig. 2. It is normally used in the creation of Digital Elevation Maps. Fig. 2 demonstrates how the footprint of a building is applied as a filter to selected the points constituting the roof section of a building. After isolating the point cloud of the roof, it has to be cleaned from outliers, such as trees and reflections from windows. The next step detects the heights of the walls. This requires the identification of the roof outline by associating the heights of the closest points to the edges of the footprint. The resampling of a point cloud from the entire building envelope, including walls and floor, finalizes the point cloud processing. The screened Poisson surface reconstruction algorithm (Kazhdan and Hoppe, 2013) is subsequently employed to generate a triangle mesh of the building. This algorithm ensures an airtight mesh, which is a collection of faces, edges and vertices defining shapes of three-dimensional objects. An

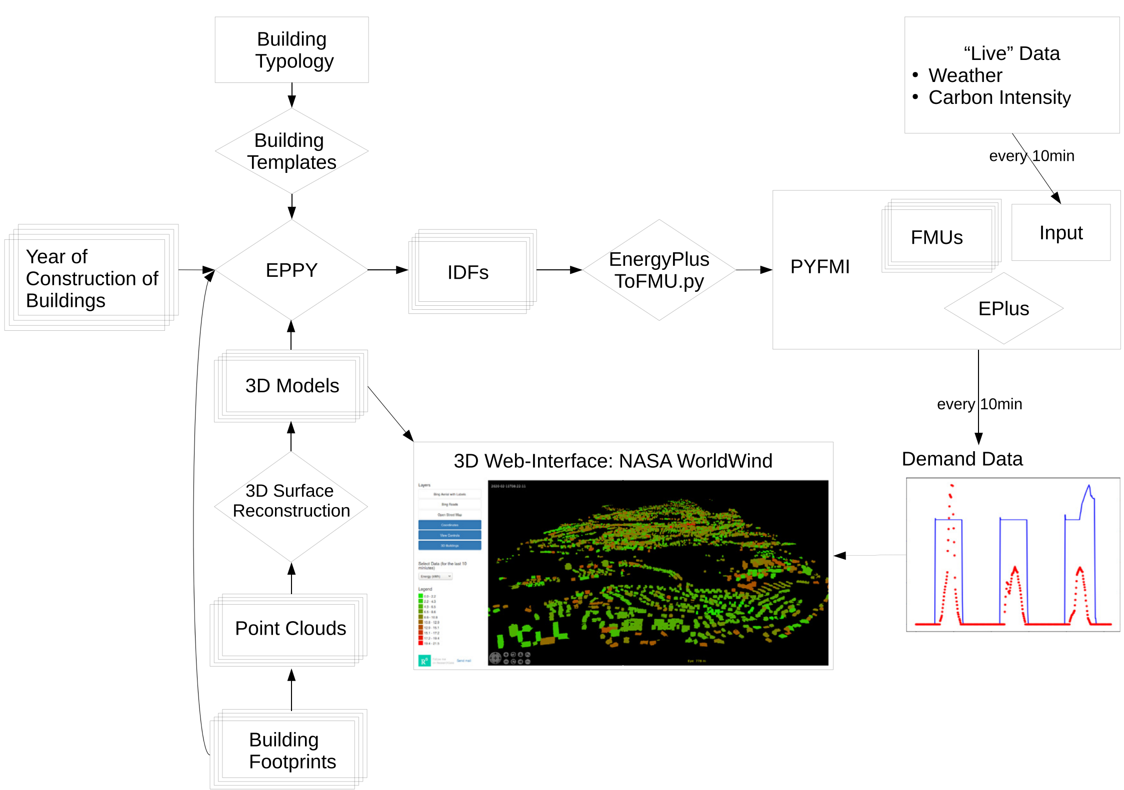


Fig. 1. Modelling flowchart of the UBE-FMI in “live” simulation mode.

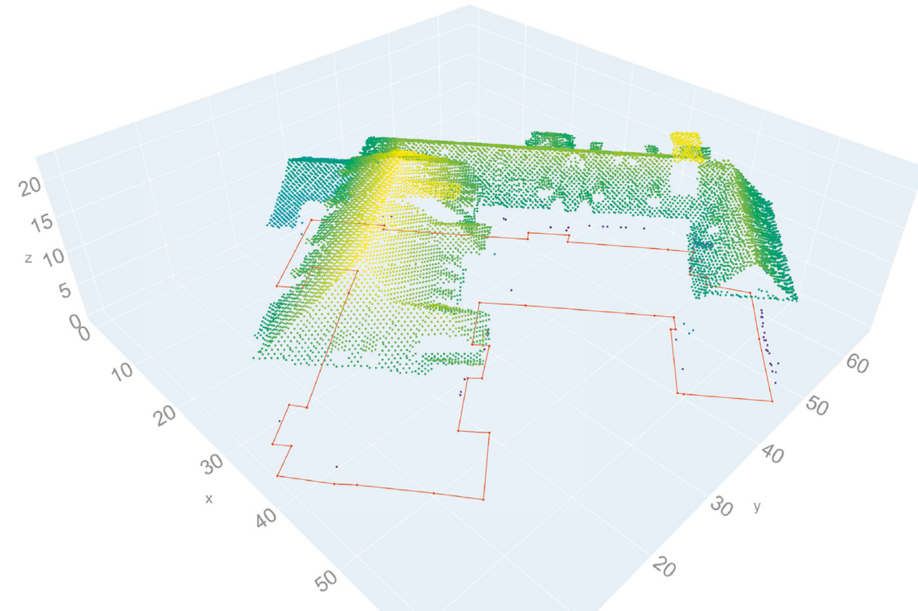


Fig. 2. Point cloud (point colors refer to elevation) and OSM footprint of a building. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

alternative would be to merge the easily determined floor and wall surfaces with the triangular roof surfaces, but this approach is not trivial in three-dimensional space. Screened Poisson surface reconstruction is implemented in the 3D modelling tool Meshlab (Cignoni et al., 2008). Besides mesh generation, Meshlab offers many other auxiliary algorithms and the convenience of a command-line interface to automate the process. The meshes are exported as Collada file type, which is a common file format for 3D applications. Fig. 3 shows the results of the mesh generation and surface classification.

2.2. Building characterization

This study relies on the TABULA building typology (Loga et al., 2016), which is a product of the EU projects TABULA and EPISCOPE. These projects analysed the European residential building stock with the purpose to define exemplary buildings with information on building envelopes, ventilation, heating and warm water systems. The building types are defined according to the period of construction and size class. The German residential building stock (Loga et al., Born) distinguishes 12 periods of construction and four main size classes, as well as a few subclasses which are specific in their construction or to a region. The four size classes are single-family houses (SFH), terraced houses (TH), multi-family houses (MFH) and apartment blocks (AB). The values utilized from TABULA are the U-values of the building surfaces and the energy expenditure coefficients of the heat generators for space heating and hot water. These values are available for all building types and the three states of refurbishment: existing state, usual refurbishment and advanced refurbishment. However, only the existing state and usual refurbishment are considered in this study because no information on the distribution of advanced refurbishment is available. The usual refurbishment differs from the existing state in terms of improved U-values of building surfaces (between 4 and 92 percent) and improved energy expenditure coefficients of heat generators (between 5 and 21 percent). The

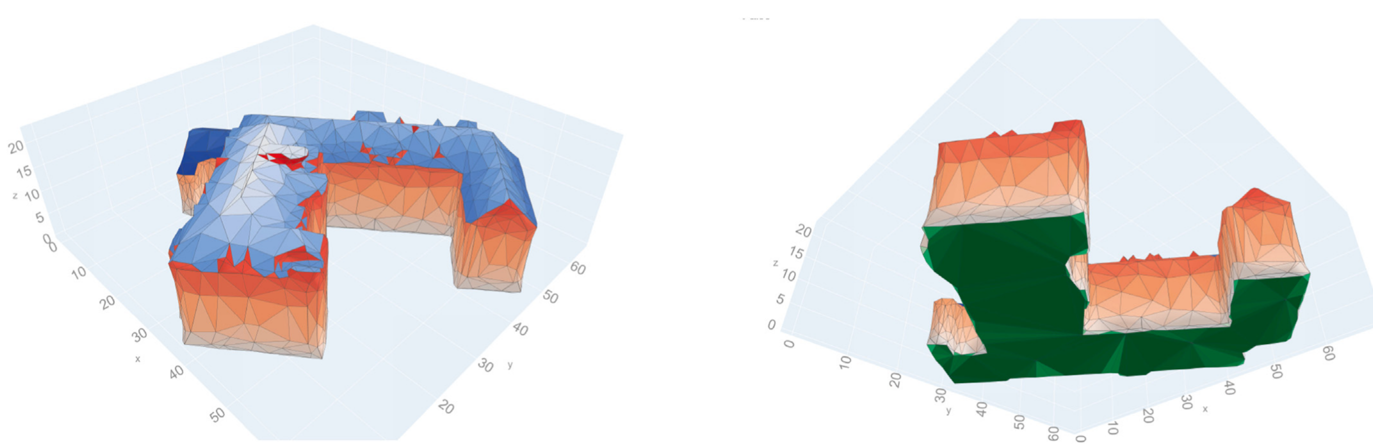


Fig. 3. Three-dimensional model of a building with surface classification (roof in blue, walls in orange and floor in green). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

information on each building type is translated by the mean of OpenStudio (Guglielmetti et al., 2011), which is a graphical interface to EPlus, into a model template for building energy simulation. Every template is designed as a single thermal zone with separated heating and warm water systems. The thermal zone is naturally ventilated and heated by baseboard heater. After defining the model templates, every building in the study area has to be classified. The year of construction and the number of floors are the main determinants. The distinction between single-family houses and terraced houses is more challenging. The distinguishable properties of a terraced house are shared edges with one or two other residential buildings and similarities in their building footprints. In fact, neighbouring terraced houses resemble each other in shape and appearance. Therefore, if a building with the size of single-family house shares walls with one or two other single-family houses and if the footprint of this house has a similar size and shape, then this building is considered a terraced house. Furthermore, the state of refurbishment can be assigned. However, the determination of whether an specific building was refurbished and to which extent is mostly not possible. To remedy this shortcoming, the progress of refurbishment (Loga et al., Born) can be randomly assigned to the buildings. The same random assignment is used for designating buildings with conditioned cellar and roof based on their empirical distribution. If a building has a conditioned cellar, the thermal zone is extended by one floor. In the case of an unconditioned roof, the roof section is excluded from the thermal zone by inserting a ceiling. If the cellar or roof are partly conditioned, then different thermal zones are introduced with an assumed temperature set point of 5°C to avoid frost. The next step is the generation of EPlus input files, i.e., IDF, for every residential building. In order to automate this process, the Python library Eppy (Santosh, 2019) merges the data of the building envelope, which contains the coordinates of every surface vertex, with the model template of the corresponding building type. Fig. 3 also indicates the surface classes, which are floor, wall and roof. Surface classification is important because the different classes are exposed to distinct simulation conditions.

2.3. Energy simulation

The underlying energy simulation engine is EPlus (Crawley et al., 2001). The interactive usage of UBEM is possible because of the integration of Functional Mockup Interface (FMI) into EPlus. FMI (Blochwitz et al., 2011) is a standardized interface that enables independent models to communicate and exchange data with each other. At first, the input and output variables need to be defined in the IDFs. For this purpose the external interface of EPlus is activated. The input variables (weather data, occupancy, internal electrical load and water use) are defined as “actuators” in this interface with name, name of component, component type, control type, FMU name and initial value. The output variables (gas, water and electricity meters) additionally require the Energy Management System (EMS) of EPlus, which is an internal programming interface to define custom control and modelling routines. In the EMS, every output variable is defined as a “sensor” with name and reference as well as “output variable” with name, EMS name, data type and update frequency. Besides, the output variables necessitate a specification as “variable” in the external interface with name, FMU name and an index key. Fig. 4 illustrates how to define an input and output variable in an IDF for the use in FMI.

The IDF files for each building are then converted by the Python script EnergyPlusToFMU.py to Functional Mockup Units (FMU) (Nouidui et al., 2014). An FMU is built as a zip file, which essentially contains the shared libraries with C-functions defining the equations of the model and a XML file defining the variables used. The FMI establishes an hierarchy between the models. EPlus is a slave model, while the Python framework PyFMI (Andersson et al., 2016) is the master model. The master model sets the time step and controls the co-simulations. To run the simulations, PyFMI imports and initializes the FMUs as independent computer processes. In 10-min intervals, current weather data (temperature, relative humidity, wind speed and direction) are accessed via the Application Programming Interface (API) of OpenWeather (Openweather, 2020) and subsequently transferred to the individual EPlus process, which simulates one building. The values for occupancy, internal electrical load and water use are obtained from standard profiles used in the utility industry (Fünfgeld and Tiedemann, 2000) and then changed into schedules in OpenStudio. These schedules describe the normalized variations within one day. Depending on the floor space of the building, the schedule values are modified by the number of habitants. At each time step, the EPlus processes compute with the corresponding input values the heat balance of each building by taking into account the outside temperature, thermal conductivity of the surfaces, heat sinks and sources (heating, human bodies, etc.) in order to estimate the energy required to maintain the indoor target temperature. This demonstrates the capacity to interact with diverse parameters and receive an immediate feedback. After EPlus finishes the computation of gas, water and electricity demand for the time step, the data are imported back to PyFMI. Current carbon intensity of electricity generation, which is retrieved through the API of electricityMap (Tomorrow, 2020), is combined with carbon intensity of fossil fuel combustion to calculate the global warming potential. The data are finally exported as JSON file and uploaded to the web-interface of UBE-FMI (Issermann, 2019). The web-interface is implemented with the JavaScript library NASA WorldWind (Bell et al., 2007). NASA WorldWind is a virtual globe that allows to visualize three-dimensional data. The Collada files of the buildings are also visualized and indicate the global warming potential, energy and water demand of the last time step. Fig. 1 summaries the structure of UBE-FMI.

3. Case study

The study area is situated in the German city of Wuppertal. The web-interface of UBE-FMI is called Wuppertal WorldWind Environmental Monitor (WupperWWEM) (Issermann, 2019). The geodata portal of the German federal state North Rhine-Westphalia offers access to LiDAR data with a resolution of 4–10 points/m^2 (Geobasis, 2020) for every municipality. In addition to LiDAR data, a comprehensive data set on the year of construction for residential buildings is an essential requirement. According to the knowledge of the author, the City of Wuppertal is the sole provider in Germany of the year of construction for every residential and non-residential building (Wuppertal, 2020). The spatial distribution of buildings can be seen in Fig. 5. The year of construction of residential buildings is indicated according to color, while non-residential buildings are black.

In the study area, there are over 5700 residential buildings. Residential buildings with mixed usages (e.g. retail shops, doctor's surgery) were identified by the tags in OSM and excluded. Following the procedure described in Section 2.2, the segmentation of the building types according to the TABULA building typology is summarized in Fig. 6. The parameters characterising a building energy model are the U-values of the building surfaces and the energy expenditure coefficients of the heat generators for space heating and hot water. The 41 building types have each 8 versions, which depends on the state of refurbishment and heating system, and each version has 8 parameters. The authors kindly refer to the project website of TABULA building typology (WebTool, 2020) to find the exact parameter values because the corresponding number

```
ENERGYMANAGEMENTSYSTEM:SENSOR,
   meter_gas_ems,                  !- Name
   *,                              !- OutputVariable or OutputMeter Index Key Name
   Gas:Facility;                   !- OutputVariable or OutputMeter Name

ENERGYMANAGEMENTSYSTEM:OUTPUTVARIABLE,
   meter_gas,                      !- Name
   meter_gas_ems,                  !- EMS Variable Name
   Averaged,                       !- Type of Data in Variable
   ZoneTimestep;                   !- Update Frequency

EXTERNALINTERFACE,
   FunctionalMockupUnitExport;     !- Name of External Interface

EXTERNALINTERFACE:FUNCTIONALMOCKUPUNITEXPORT:FROM:VARIABLE,
   EMS,                            !- OutputVariable Index Key Name
   meter_gas,                      !- OutputVariable Name
   gas_fac;                        !- FMU Variable Name

EXTERNALINTERFACE:FUNCTIONALMOCKUPUNITEXPORT:TO:ACTUATOR,
   outdoor_wind_dir,               !- Name
   Environment,                    !- Actuated Component Unique Name
   Weather Data,                   !- Actuated Component Type
   Wind Direction,                 !- Actuated Component Control Type
   winddir,                        !- FMU Variable Name
   225;                            !- Initial Value
```

Fig. 4. IDF code defining an input (wind direction) and output variable (gas meter) for FMI.

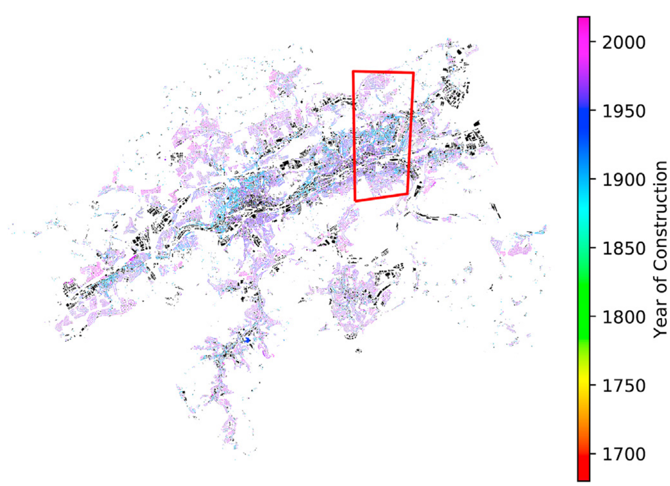


Fig. 5. Year of construction of residential buildings (non-residential buildings in black) in Wuppertal (study area framed in red). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

of parameter values are impractical to display. According to Fig. 6, Wuppertal features dense built-up areas and less urban sprawl. The housing sector mainly consists of multi-family buildings, but few buildings over 6 floors, i.e., apartment blocks. The majority of residential buildings was constructed before 1968. UBE-FMI requires additional assumptions to complete the modelling. The number of occupants in a building was inferred from the average living area per person in Wuppertal of 41 m^2 (Statistisches Bundesamt, 2011). The progress of refurbishment and whether the cellar and roof are conditioned were randomly assigned following the detailed statistics of the German housing stock (Loga et al., Born). The assignment of the energy carrier for each building followed the same procedure with values from the local distribution in 2010 (Reutter et al., 2050). The definition of the state of refurbishment refers to the description in TABULA building typology. In this study, only the existing state and usual refurbishment were considered. Table 1 summarizes the details of the simulation on which the web-interface rests.

Besides the simulation for the web-interface, another set of simulations was needed to indicate the appropriateness of the building modelling concept and to discover discrepancies. Unfortunately, the attempts to find time-series on energy consumption remained futile and poses a constant challenge in urban energy modelling. The reasons range from privacy issues for household data to competition regulation for district-wise measured data. Consequently, the results of the simulations are compared to reference studies. This approach was inspired by a previous study in UBEM (Davila et al., 2016). Simulated annual energy use intensities (EUI) were compared with reference studies (Fisch et al., 2012 (Fisch et al., 2012), Schröder et al., 2014 (Schröder et al., 2014) and Loga et al., 2017 (Loga et al., 2017)). Four simulation set-ups with different states of refurbishment and energy carriers were constructed and simulated: existing state with oil/gas heating; existing state with district heating; usual refurbishment with oil/gas heating; usual refurbishment with district heating. Table 2 gives an overview of the conditions for each set-up.

The set-ups in Table 2 were constructed with the intention to achieve comparable conditions with the reference studies. These studies gathered their data from companies issuing energy performance certificates (EPC). The certification procedure is stipulated in the German Energy Saving Ordinance (EnEV) (Bundesministerium für Verkehr, 2002). Both studies used a sizeable data set on buildings. Schröder et al., 2014 separated the results for space heating and hot water. Since Schröder et al., 2014 only distinguished between old and modern buildings in their existing state but not refurbished buildings, it was not considered in the comparison with the set-up concerning usual refurbishment. The study of (Fisch et al., 2012) differs in that it contains a class of refurbishment compromised of buildings built after 1995 and completely refurbished buildings. The authors saw it necessary to convert the values of their original data set from higher heating value (HHV) to lower heating value (HHV) by multiplying with 0.9. The results were hence back-converted to HHV for comparison. The study of (Loga et al., 2017) (Loga et al., 2017) provides an harmonized table for buildings in their existing state of both studies,

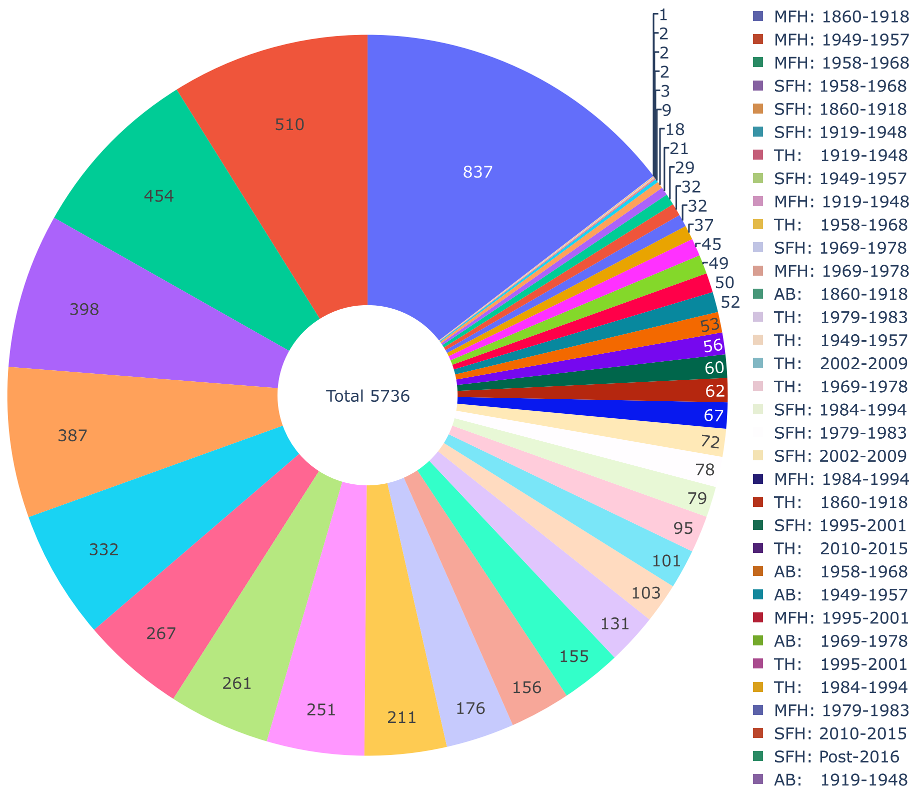


Fig. 6. Segmentation of building types in the study area (legend is sorted according to occurrence).

Table 1
Summary of simulation conditions for UBE-FMI in “live” mode.

Purpose	“live” simulation (web-interface)
State of refurbishment	existing state/usual refurbishment
Share of refurbishment	28% for SFH built until 1978, 11.5% for SFH built 1979–1994, 32.2% for MFH built until 1978, 17.2% for MFH built 1979–1994, Buildings built after 1995 are not refurbished
Energy carriers	gas (51%), oil (33.6%), district heat (10.2%), electricity (5.2%, without heat pump)
Number of buildings	5736
Year of construction	$\leq$ 2018
Building sizes	SFH, TH, MFH, AB
Building systems	heating/hot water
Heating value	higher heating value (HHV)
Conditioned roof	completely (33.6%), partly (17.9%), not (48.5%)
Conditioned cellar	completely (3.3%), partly (22.2%), not (61.9%), not existent (12.6%)
Simulation period	none (with 10min time step)
Weather data	“live” weather from OpenWeather (Openweather, 2020)
Weather harmonization	none
Reference area	EnEV reference area
Remarks	only MFH use district heat; Buildings constructed between 1995 and 2001 use gas boilers

thereby offering a broader data set to compare with. Details of the reference studies can be seen in Table 3. Unfortunately, none of the studies provided a detailed analysis of parameter values concerning refurbishment. For that reason, the state of refurbishment in this study refers to the definition of usual refurbishment in TABULA building typology.

4. Results

The web-interface of UBE-FMI for Wuppertal is presented in Fig. 7. It illustrates the capacity of the JavaScript library NASA WorldWind to visualize three-dimensional models. When the system is initialized, energy, water demand and global warming potential of every building of the last 10 min will be indicated, as described in Section 2.3. The web-interface demonstrates the capacity of UBE-FMI to response to changing conditions during the simulation without the need to re-initialize. Current or future weather data can be fed into the simulation to forecast energy demand. The web-interface might encourage to voluntarily shed loads.

The following two sections address the performance of the model in comparison to reference studies and test its application in the form of a scenario illustrating the possible benefits for municipalities and their public utilities.

4.1. Comparison to reference studies

The results of the set-up concerning buildings in their existing

Table 2
Summary of simulation conditions for comparison to reference studies.

Purpose	Comparison to reference studies (4 simulations)			
State of refurbishment	existing state	existing state	usual refurbishment until 1995, existing state for 1995 to 2002	
Energy carriers	gas (60%)/oil (40%)	district heat (100%)	gas (60%)/oil (40%)	district heat (100%)
Number of buildings	4835	4835	5414	5414
Year of construction	< 1979	< 1979	< 2002	< 2002
Building sizes	SFH, TH, MFH, AB			
Building systems	heating/hot water			
Heating value	HHV			
Conditioned roof	completely (33.6%), partly (17.9%), not (48.5%)			
Conditioned cellar	completely (3.3%), partly (22.2%), not (61.9%), not existent (12.6%)			
Simulation period	one year (with 10min time step)			
Weather data	long-term average of Wuppertal			
Weather harmonization	according to EnEV			
Reference area	EnEV reference area			
Reference to results	Fig. 8a	Fig. 8b	Fig. 9	Fig. 10
Remarks		SFH uses the same values of MFH for heating	Buildings constructed between 1995 and 2001 use gas boilers	SFH uses the same values of MFH for heating

state is illustrated in Fig. 8. Fig. 8a shows the results obtained by simulating the set-ups with the energy carriers gas and oil. The reference studies combine gas and oil because they only considered boiler systems and the results differ marginally. The simulations constantly underestimated the average values of energy demand presented in the reference studies. The reference studies likewise display great differences between each other. The reason for the underestimation might be the simplification in the modelling of occupant behaviour. Wasteful behaviour was neglected, and thus also contributed to the narrower spread. On the other hand, the simulations yielded extremer results because the surface reconstruction exaggerated the living area. For example, after visual inspection of few buildings it became evident that unconditioned balconies were often unnoticed. Unconditioned balconies became living area, thereby expanded the conditioned area. In this regard, the number of occupants increased. In addition, the results for SFH/TH suffer from misclassification of actual bigger buildings. The distinction of the size classes occasionally infringed the definition of building types by classifying MFH as SFH. The results for MFH/AB differ less from (Fisch et al., 2012), but more from Schröder et al., 2014). The lower medians and means of EUI comparing to the smaller class are associated with the additional thermal insulation provided by denser habitation. The conditioned volume of MFH is more limited than in SFH and their heating system might also benefit from some scale effect. Although the minimum EUI in SFH is lower, the narrower spread and lower average for MFH might be linked to less wasteful occupant behaviour and higher efficiencies.

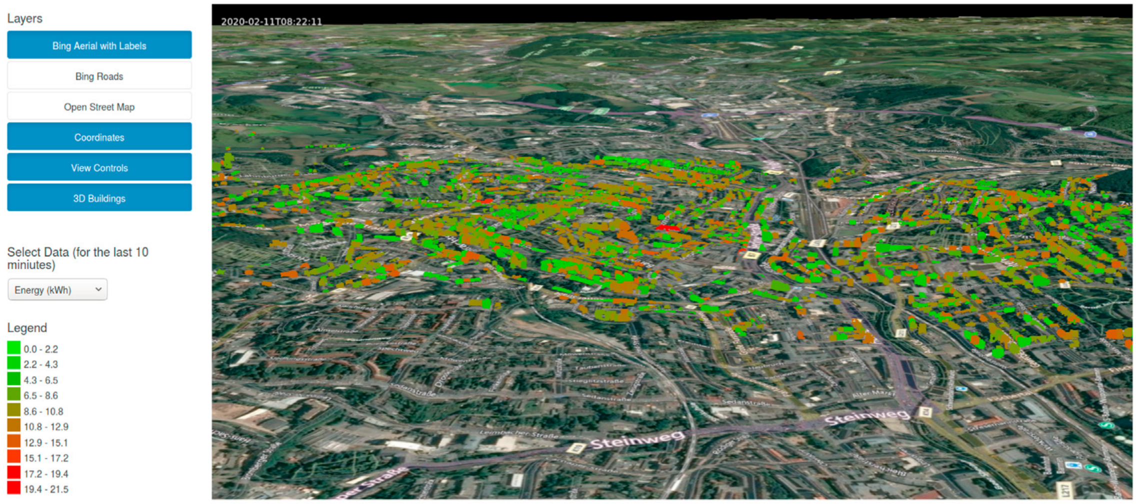
The simulated results for the district heating in Fig. 8b are proportional to those of gas and oil heating because there are only slight differences in their models. In general, the results follow the downwards tendency in the reference studies because district heating is more efficient. Less heat losses can partially explain this, but also the fact that more MFH are connected to district heating than SFH. The modelling of district heating in EPlus is also simple, and thus might contribute to the better results. However, the number of SFH with district heating in (Fisch et al., 2012) is just 12.

Fig. 9 only presents Fisch et al., 2012 because Schröder et al., 2014 does not include refurbished buildings. In the study of (Fisch et al., 2012), there is no distinction between SFH and TH. The energy performance of refurbished buildings, both simulated and measured, is better than of buildings in their existing state. The averages of simulated EUI tends to become lower with building size but still remain below the reference values. The standard deviations also become narrower. Although similar behaviour is displayed by the reference values, the spread of simulated values is still narrower. The simulations with refurbished buildings represent better the reference values than the simulations with buildings in their existing state. The greatest difference in averages and standard deviations between simulated and reference values can be observed in MFH because MFH might also include some luxurious SFH.

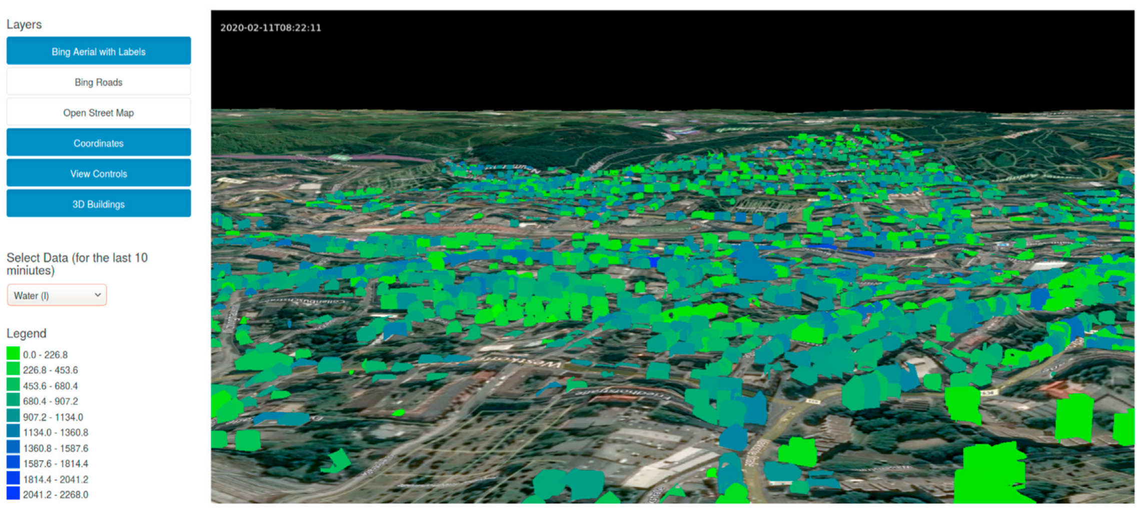
The higher efficiency of district heating is supported by Fig. 10 showing refurbished buildings with district heating. According to the results from the simulations and reference studies, district

Table 3
Description of reference studies.

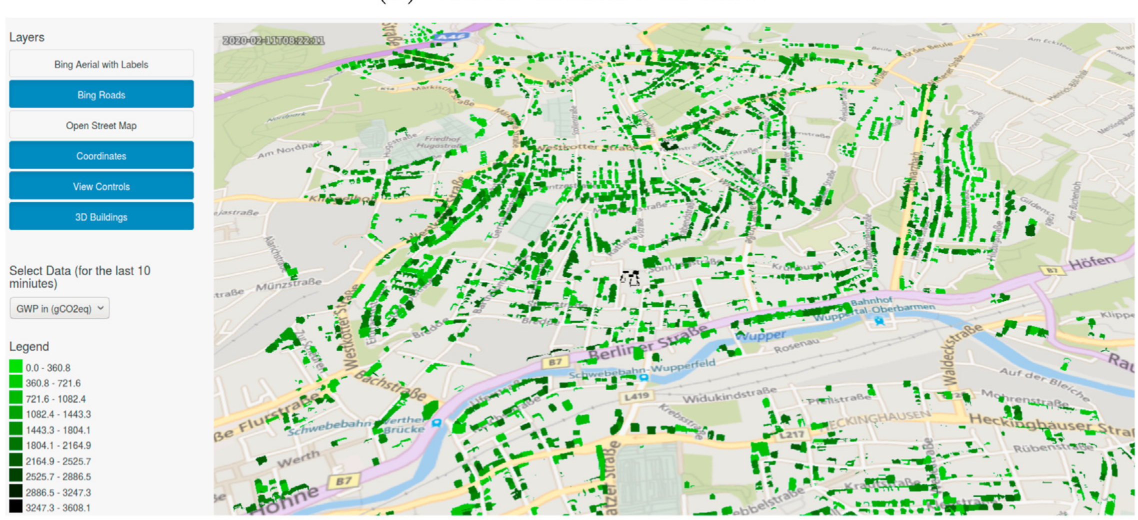
Studies	Fisch et al., 2012 (Fisch et al., 2012)	Schröder et al., 2014 (Schröder et al., 2014)	Loga et al., 2017 (Loga et al., 2017)
Data source	Empirical data from the issuance of EPCs	Empirical data from the issuance of EPCs	harmonized table of (Fisch et al., 2012) and (Schröder et al., 2014)
State of refurbishment (used here)	4 classes (built after 1995/completely refurbished)	existing state	existing state
Number of buildings (used here)	57,562 (13,607)	138,550 (none)	153,267 (98,747)
Periods of construction (used here)	none	4 classes (none)	4 classes (< 1979)
Building sizes (used here)	4 classes (all while 2 classes were merged)	5 classes (none)	2 classes (all)
Building systems	heating/hot water	heating and hot water (separately)	heating/hot water
Heating value	LHV = 0.9 HHV	HHV	HHV
Energy carriers	gas/oil and district heat		
Weather harmonization	according to EnEV		
Reference area	EnEV reference area		
Data collection area	national		
Results	annual energy use intensities (EUI in kWh/m2a)		
Reference to results	Figs. 9 and 10	none	Fig. 8



(a) Energy demand in kilowatt hour.

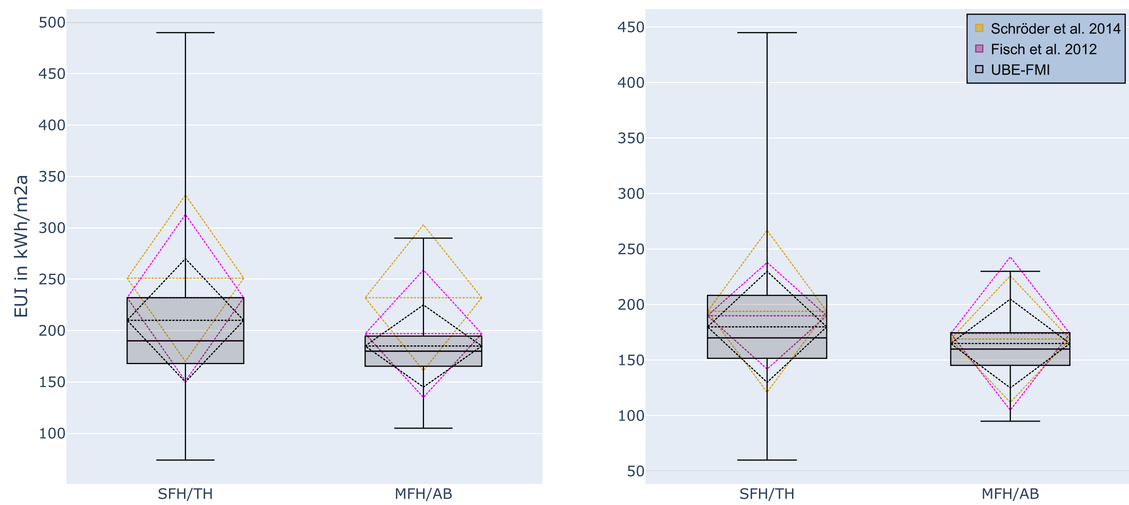


(b) Water demand in litre.



(c) Global warming potential in gram of CO_2 equivalent.

Fig. 7. The web-interface for 3D visualization (https://wupperwwem.github.io/) of "live" environmental impact of an urban area in Wuppertal (Issermann, 2019).



(a) Gas and Oil. (b) District heating.

Fig. 8. Summary of annual energy use intensities for buildings in their existing states in comparison with Loga et al., 2017, which harmonizes the results of (Fisch et al., 2012) and Schröder et al., 2014. Arithmetic means and standard deviations are symbolised by dashed lines, while medians and quartiles are symbolised by solid lines.

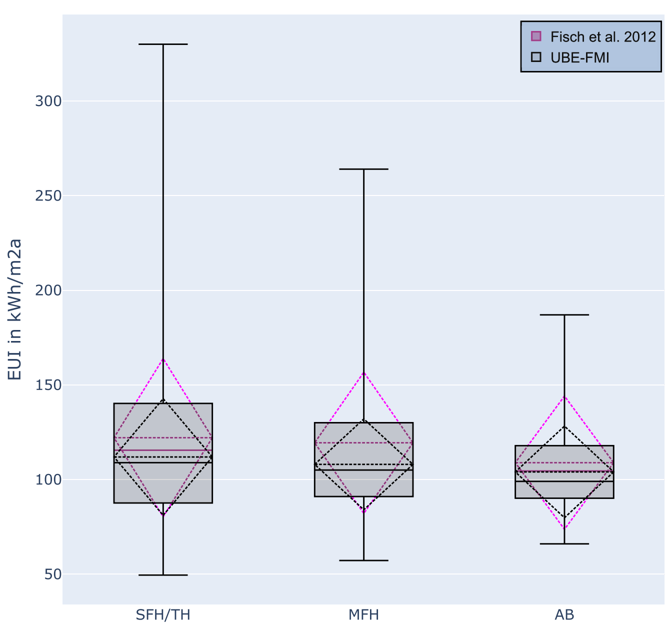


Fig. 9. Summary of annual energy use intensities for buildings with usual refurbishment and gas/oil heating in comparison with Fisch et al., 2012. Arithmetic means and standard deviations are symbolised by dashed lines, while medians and quartiles are symbolised by solid lines.

heating in refurbished buildings is unsurprisingly the least energy intensive way to provide viable conditions. The exception in (Fisch et al., 2012) is SFH with higher average EUI and wider spread of values than the same class with gas and oil heating. The cause is a much lower number of buildings in this class with only 25. The performance in simulating MFH and AB improved comparing to gas and oil heating. However, the averages of simulated EUI is still below the reference values, while the spread of values is narrower.

4.2. Scenario: demand response

The transition of the German energy supply to a low carbon system will not be possible without the decarbonisation of heat production (Connolly et al., 2014), which represents almost two-third of Germany's energy consumption. Electrification by the means of heat pumps is suggested to play a considerable role (Leibowicz et al., 2018). Heat pumps use electricity to transfer heat from colder sources (e.g. outside air or underground) to heat sinks

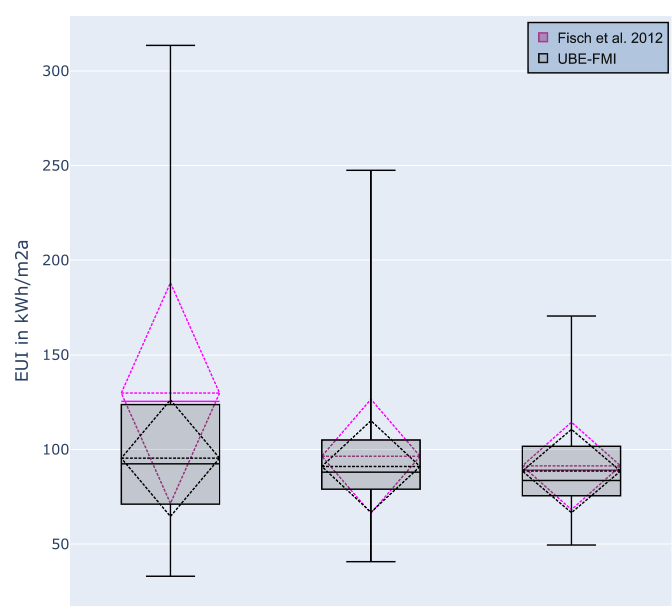


Fig. 10. Summary of annual energy use intensities for buildings with usual refurbishment and district heating in comparison with Fisch et al., 2012. Arithmetic means and standard deviations are symbolised by dashed lines, while medians and quartiles are symbolised by solid lines.

through the compression of a medium called refrigerant. To demonstrate one possible application of UBE-FMI and which role it can play for the future management of energy systems, a scenario with the simulation conditions for "live" simulation in Table 1 was constructed. But the heating and hot water system in every building were replaced with heat pumps. The spatial variations (two-dimensional) of climate conditions were estimated with the Urban Multi-scale Environmental Predictor (UMEP) (Lindberg et al., 2018) to approximate urban microclimate. The outcome for air temperature of one time step can be seen in Fig. 11. The spatially varying climate conditions could directly be applied to the closest building surface of every individual building due to the FMI implementation of UBE-FMI. Energy simulations for every building with their own specific and heterogeneous climate conditions were conducted for the period of one week-day. The results of electricity demand for all buildings in the area are aggregated in Fig. 12. It shows a week-day demand for electricity with an high temporal resolution (10min). The demand peaks in the evening hours when the occupants return home and require heating and hot water. Another peak is in the morning hours. The demand is low during working hours as residential buildings are less occupied. The ENTSO-E Transparency Platform of the European transmission system operators (ENTSO-EENTSO-E, 2020) provides data of the European electricity composition by source. Fig. 12 illustrates that the largest gap in the satisfaction of electricity demand from renewable sources is during the peak hours in the evening. Even with continuing efforts in the expansion of renewable energy supply, the satisfaction of peak demand will pose a challenge. Therefore, demand response strategies are an appropriate mean to reduce peak demand (Sæle and Grande, 2011; Gils, 2014). In Fig. 12, the peak load can be reduced by 25 MWh if the thermostat setpoint is lowered by 3 $^{\circ}C$ during the peak hours. UBE-FMI can predict this impact when supplied with weather forecasts. In the light of climate change and the possibility to run heat pumps in cooling mode, demand response strategies and the ability to estimate their impact on demand will also become more relevant in the summer season. UBE-FMI could contribute to better align demand with the supply of renewable energy.

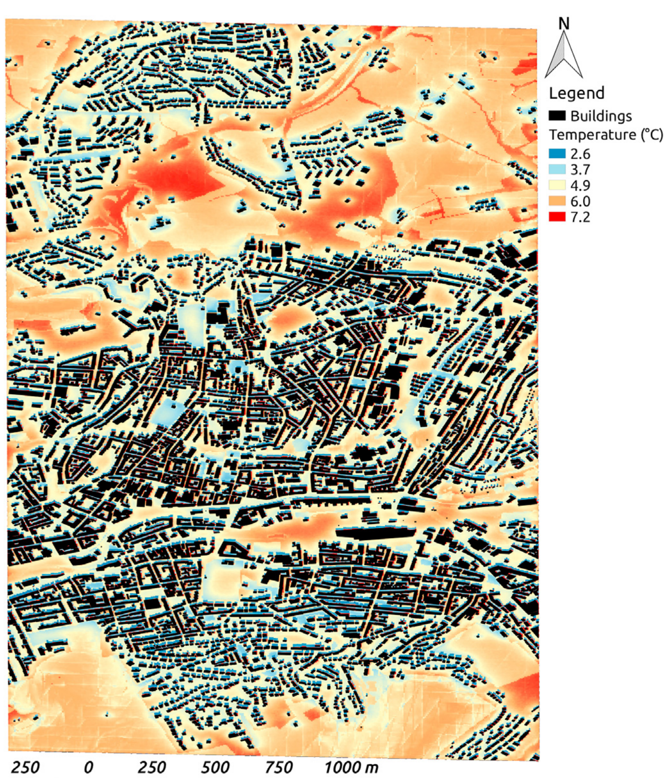


Fig. 11. Spatial variation (two-dimensional) of air temperature in the study area at 12.30pm on February 3, 2020.

5. Discussion

A principal limitation of UBEM on the basis of building typologies is that the descriptions and parameters of exemplary buildings originate from a statistical analysis of real-world buildings. The derived informations only represent a simplification of reality and might deviate from the actually constructed buildings. On the other hand, even though there are initiatives to capture a virtual representation of cities, such as CityGML (Gröger and Plümer, 2012), the generated models lack detailed information on construction and building systems for every individual building. The main obstacle is that data are simply not available in a digital format. The application process for construction permits is still mostly paper-based. As a result, gathered informations are not transferred to a digital repository. Data protection laws contribute to this situation. There are two possible remedies. One is used in this study: building typologies. The other possibility requires the full commitment of the local municipality with the purpose to digitalise their archives and conduct building surveys. Although the emerging trend towards building information models (BIM) will facilitate this process, the costs of such undertaking are currently prohibitive. Regarding the definition of refurbishment, the reference studies lack statistical analysis about the extent and effectiveness of refurbishment which limits the comparability of results with refurbished buildings. They were nevertheless included to describe in a more comprehensive way the building stock. The inclusion of residential buildings with mixed usages (e.g. offices, eateries) is a priority for the future project development. However, overcoming this limitation requires changes in the building modelling approach because multiple thermal zones, at least one for each floor, would be necessary. Another problem is to gather data for validation of mixed usages. The incorporation of mixed usages and non-residential buildings (e.g. schools, retail shops, public buildings) would render UBEM more realistic. The lack of building typologies for non-residential buildings will pose an obstacle. On the other hand, energy saving ordinances and other standards might serve as starting point. Another worthwhile extension would be the incorporation of behaviour-based load profiles (Pflugradt and Muntwyler, 2017). More heterogeneous occupant behaviour could be simulated and might affect the differences between the simulation results and reference studies for smaller buildings. The simulation results of smaller buildings suffer from the lack of more extreme occupant behaviour, like wealthy residents, and underestimate their energy demand comparing to the reference studies. The reference studies might also be biased towards an over-representation of wealthier residents because their data originate from the issuance of EPCs. The different behaviour profiles would be derived and distributed on the basis of local subgroups with their distinct socio-economic features. Stochastic load profiles proved to be better than standard load profiles (Fischer et al., 2015). The shading of buildings should also receive attention. Previous studies on UBEM neglected the heat exchange between adjacent buildings. The proposed FMI-based model has the potential to consider these factors in future versions. Furthermore, the lack of more localized information on the progress of refurbishment, conditioned cellars and roofs affects the capability to assess the environmental impact of the local building stock. More engagement from the local authorities would ameliorate the situation. Although time-series of energy demand of

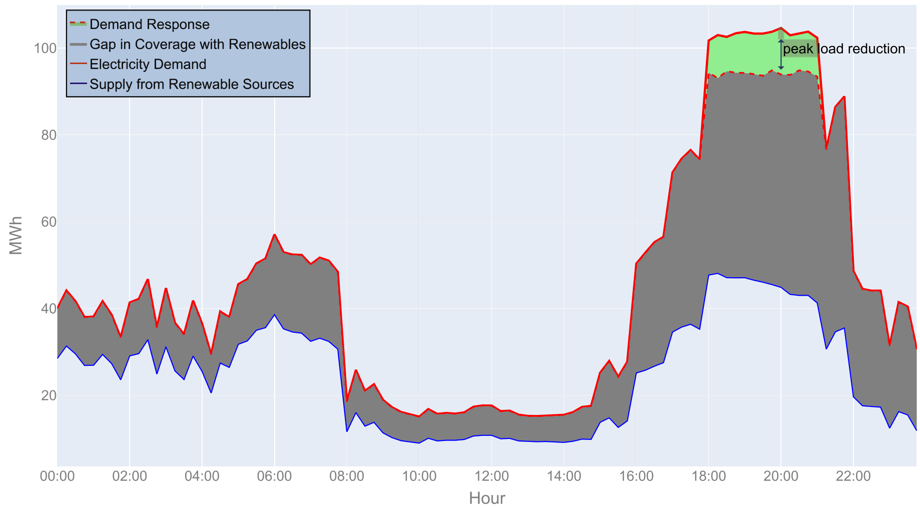


Fig. 12. Week-day (February 3, 2020) demand of electricity based on the scenario with heat pumps and demand response.

individual buildings are not gathered by public utilities, except in the rare cases of smart-metering projects, they could release district-wise measured data from their supervisory control and data acquisition (SCADA) systems. Such data would help to better understand the temporal distribution of energy demand and offer a better approach for validation. One reason that this has not yet happened might be that public utilities often combine local distribution and generation of energy. Because of European competition law, the release of such data needs to benefit all competitors and not just another subsidiary.

6. Conclusions

This study described how to successfully create a detailed urban building energy model (UBEM) which is implemented with Functional Mockup Interface (FMI). UBE-FMI demonstrated that its FMI implementation enables extensive control over model components during simulation with the possibility to manipulate and exchange data at each time step. The result is the sub-hourly estimation of energy demand for every building on the basis of spatially and temporally varying climate conditions. The functionality of UBEM is enhanced through the incorporation of dynamically alterable parameters in the building models due to FMI. This novelty is highlighted in the scenario and can extend the applicability of UBEM to the operational management in public utilities, for instance, by informing about the impact of demand response strategies. Moreover, the dynamic modification of parameters in the building models, down to individual surfaces and components, can contribute to urban microclimate and heat island analysis by allowing detailed surveillance and control of heat exchange between the immediate environment and the building envelope. The scenario results suggest that slight changes in the indoor target temperatures of buildings, which were triggered by demand responses during peak hours, result in considerable energy savings. The long-term prospects of UBE-FMI lies in the planning and optimisation of energy saving and generation measures. In the development of UBE-FMI, it is shown how to automate the generation of three-dimensional building geometries from large-scale LiDAR data and achieve building models with higher Level-of-Detail than previous UBEMs. The comparison with reference studies suggests that the exemplary buildings in TABULA building typology are appropriate as templates for construction and building systems in an UBEM. The accompanying 3D visualization of the environmental impact of urban areas could foster a better environmental awareness of the wider public, as Google's Environmental Insight Explorer (Google and Google Environmen, 2020) or electricityMap (Tomorrow, 2020) already demonstrate. UBE-FMI has the potential to import data from behaviour-based load profiles (Pflugradt and Muntwyler, 2017) of occupants via FMI to better approximate their influence on energy demand. The involvement of municipalities and their public utilities could considerably further the development of UBEM by the provision of more localized data on buildings and actually metered energy data for validation.

CRediT authorship contribution statement

Maikel Issermann: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing - original draft, Writing - review & editing. **Fi-John Chang:** Funding acquisition, Project administration, Supervision. **Pu-Yun Kow:** Resources, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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