Applied Energy 280 (2020) 115953

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

A combined GIS-archetype approach to model residential space heating energy: A case study for the Netherlands including validation

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HIGHLIGHTS

- A transferable residential space heating energy model is developed based on geo-referenced data and archetypes.
- Model results are spatially validated against measured energy consumption.
- Past refurbishment and occupant behavior significantly affect model results.
- The model is suited to identify spatial hotspots and assess energy-efficiency measures.

ARTICLE INFO

Keywords:
Building stock
Space heating
Spatially explicit model
Geographic Information System (GIS)
the Netherlands

ABSTRACT

High spatial resolution is critical for a building stock energy model to identify spatial hotspots and provide targeted recommendations for reducing regional energy consumption. However, input uncertainties due to lacking high-resolution spatial data (e.g. building information and occupant behavior) can cause great discrepancies between modeled and actual energy consumption. We present a modeling framework that can act as a blueprint model for most European countries based on geo- referenced data, building archetypes, and public algorithms. Further sophistication is added in a step-wise approach, including the shift from average to hourly weather data, refurbishment, and occupants' heating schedules. The model is demonstrated for the city of Leiden, the Netherlands, and the simulated results are spatially validated against the measured natural gas consumption reported at postcode level. Results show that when these factors are considered, the model can provide a good estimate of the energy consumption at the city scale (overestimated by 6%). At postcode level, nearly 83% of the absolute differences between modeled and measured natural gas consumption are within one standard deviation (±25 kWh/m^{2}a, about 30% of the mean measured natural gas consumption). Further research and data would be required to provide reliable results at the level of individual buildings, e.g. information on refurbishment and occupant behavior. The model is well suited to identify spatial hotspots of residential energy consumption and could thus provide a practical basis (e.g. maps) for targeted measures to mitigate climate change.

1. Introduction

The building sector is important for climate change mitigation [1], as it is responsible for approximately 40% of final energy consumption and 36% of the greenhouse gas (GHG) emissions in the European Union (EU) [2]. Spatially-explicit building stock energy models can be used to identify energy consumption hotspots, assess the energy-saving potential of various technologies, such as envelope insulation, efficient HVAC (heating, ventilation, and air conditioning) system, or optimize the integration of renewables [3], such as solar photovoltaic systems (PVS), and thus support building, neighborhood, or city-level decision making [4].

Many building stock energy models have been developed, which can be divided into top-down and bottom-up models [5]. The top-down models regard the building stock as a black box and estimate energy consumption by investigating the correlations between aggregated

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https://doi.org/10.1016/j.apenergy.2020.115953
Received 5 June 2020; Received in revised form 13 September 2020; Accepted 23 September 2020
Available online 6 October 2020

energy consumption and socioeconomic or sociotechnical drivers from a historical perspective, usually based on statistical data [6]. Due to lacking details of individual buildings, such models cannot capture the characteristics of the energy consumption of specific neighborhoods [7], especially those caused by discontinuous changes in techno-economic conditions, such as the wide application of new insulation materials, high-efficiency HVAC systems, and sustainable energy sources [8].

In contrast, bottom-up models use a hierarchy of disaggregated components as input data and account for the regional or national energy consumption by summation of the energy consumption of individual buildings or building groups [9]. Swan et al. [5] further classify the bottom-up models into statistical and engineering-based methods (also known as physical models or white box models [6]). The former performs statistical analysis (mostly regression techniques) on historical data and establishes the relationships between end uses and energy consumption [10] while the latter considers the building elements and HVAC of sample buildings representative of the building stock and simulates the energy demand with the balance of heat transfer in accordance with thermodynamic principles [11]. Kavgic et al. [8] add the hybrid models that estimate the energy consumption mainly influenced by occupant behavior, such as domestic hot water (DHW), cooking, lighting and appliances with statistical methods while calculate the energy consumption for space heating and cooling with engineering-based methods due to a lack of historic data and the application of new technologies.

According to the difference of aggregation process, Mastrucci et al. [9] divide the engineering-based bottom-up model into the archetype approach and building-by-building approach. The archetype approach employs a subset of archetype or sample buildings to represent a specific building cohort that has similar properties (e.g. building type and age), and extrapolates to total energy consumption (typically urban, regional, or national building stock) by factoring the results in proportion (by number or floor area per building type or age group) [12]. This method has been widely adopted by many studies [13]. However, the limited coverage and representativeness of archetypes for heterogeneous building stock may greatly influence the reliability of results for both individual buildings and the whole building stock [14]. Distinct from the archetype approach, the building-by-building method simulates building energy consumption one by one and then sums up the energy consumptions of individual buildings to the whole stock level. While this approach in principle has the capability to assess the different combinations of refurbishment measures applied to single buildings, expanding energy simulation tools from a single building to urban or national stock level makes data collection more challenging [15].

The input data for engineering-based building stock energy models mainly includes building geometries, physical properties (e.g. thermal transmittance, solar energy transmittance, and air exchange by infiltration), HVAC systems, occupant behavior (e.g. hours of occupancy, number of occupants, internal room temperature, internal heat gains and air exchange by use), and external weather conditions [16]. In the past decades, the method of Geographic Information Systems (GIS) has significantly increased the availability of large-scale geo-referenced building information, especially the building geometries, which makes such models more sophisticated and spatially-explicit [9]. GIS is mostly applied in result visualization or estimating the floor areas [4]. Only a few studies [4] use GIS data to quantify the areas of envelope elements and then simulate the energy consumption building by building. The main barrier is that the non-geometric building information such as properties, HVAC, and occupant characteristics [17], is typically not available at the city scale [4]. Therefore, archetypes complemented by assumptions are usually used to fill in the data gaps [18]. Besides, refurbishment records for existing buildings (i.e. the type and extent of insulation added or the upgrade of HVAC systems) are difficult to obtain and only a few studies [4] that take these into consideration. Therefore, simplified energy models are often used [8], while both model simplification and input data uncertainty may lead to notable discrepancies between simulated and measured energy consumptions, known as the 'energy-performance gap' [19].

The review above demonstrates that lacking the data at individual building level is the main barrier for building stock models. Different models are developed for different countries or regions, depending on data availability and research purposes. Engineering-based bottom-up models are able to track the energy-efficiency measures while they differ significantly in the complexity of input data and energy simulation algorithms or tools. The previous models based on building-by-building approach require particularly large amounts of detailed data that are only available for certain countries [4]. In addition, the energy simulation methods are usually national standards or expensive software [20], some of which are incapable of processing largescale building stock. Therefore, these models have limited applicability in other countries, and typically lack high spatial resolution of energy consumption. There is a demand for a harmonized model that estimates the energy consumption of largescale building stock (city or national scale) with a high-level spatial resolution and can act as a benchmark method for policy makers and planners to effectively quantify the energy efficiency of the current building stock, identify energy consumption hotspots, and evaluate the energy-saving effects of measures or technologies aimed at mitigating climate change in the building sector. Recently, GIS data of building footprints, archetype buildings (notably the residential archetype buildings for 21 EU countries in TABULA [21]), and other data, such as high-resolution weather data, have become available for many countries, which provides the possibility of developing such a model framework for a larger number of countries.

The goal of this paper is to develop a transferable framework for modeling residential space heating energy consumption based on GIS data and archetypes. The model maps the typical geometry parameters, physical properties, and HVAC of archetypes to individual buildings in GIS data according to age and type, and then simulates the energy consumption building by building. As in most countries GIS data of buildings does not hold building types or simply differentiates between single-family houses and multi-family houses, we present an approach to identify them based on building size and morphology. A stepwise approach is presented to construct the model and thereby include key factors such as spatial building properties, building system, as well as temporally resolved weather data, refurbishment, and occupant schedule. The model is applied in Leiden, a city in the Netherlands and spatially validated against the measured energy consumption.

2. Materials and methods

2.1. Model overview

In order to develop a building stock energy model and simultaneously investigate the effects of various factors on the modeled energy

Table 1
Steps and factors increasing sophistication for the energy consumption for space heating.

Step	Main factors for energy consumption	Model implementation	Data type	Calculation method
S1	Basic input data	Derived from BAG [22] and TABULA [21]	Spatial and archetypal	Seasonal
S2	+ hourly weather data	Temperature and global solar radiation from KNMI [23]	Temporal and spatial	Hourly
S3	+ refurbishment	Random allocation by refurbishment rate [24]	Statistical	Hourly
S4	+ occupant schedule	Assumption: 18:00–08:00 (+1 day)	Temporal	Hourly

consumption for space heating, we stepwise simulate the energy consumption with increasing model sophistication. Step 1 (S1) uses the seasonal heat demand calculation method while S2-4 employ the hourly calculation approach (see Section 2.3). All steps use the same basic input data, including geometry, physical property, supply system, and occupant-behavior data other than occupant schedule. S1 uses seasonal average weather data, while hourly weather data is introduced in S2, refurbishment in S3, and occupant schedule in S4, as shown in Table 1.

Three principal data sources are used in this study:

(1) The GIS dataset from the Basic Registration of Addresses and Buildings (BAG) contains all official addresses and basic building information of the Netherlands [22]. The main information included in this dataset is the georeferenced building footprint as a polygon, function, year of construction, building height, and registered addresses per building.
(2) The TABULA database (Typology Approach for Building Stock Energy Assessment) contains residential building typologies for 21 European countries including the Netherlands [21]. It distinguishes six construction periods, i.e. before 1965, 1965-1974, 1975–1991, 1992–2005, 2006–2014 and after 2014, and five types of residential buildings, namely single-family house, mid-terraced house, end-terrace house, apartment building, and multi-family house (see Table S1 of supplementary material), and provides archetypical information on their surface areas, the thermal properties of envelope components, and supply systems.
(3) Weather data is from the Royal Dutch Meteorological Institute (KNMI) [23].

These data sources are combined in the four models as shown in Fig. 1. In order to characterize BAG buildings with TABULA archetypes, we first identify the types of BAG buildings, and then automatically map the parameters (typical geometries, physical properties, and supply system parameters) of archetypes to BAG buildings based on construction periods and building types. The following five criteria are employed to differentiate the types of BAG buildings: the number of shared walls, the number of registered addresses, building footprint area, gross floor area, and the number of stories (see details in Table S2 of supplementary material). These extracted parameters, together with the weather data, refurbishment statistics, and occupant-behavior data, constitute the input data for S1-4.

2.2. Input data

2.2.1. Building information

As proposed by Heeren and Hellweg [25], we use a number of strategies to correct and complete faulty and missing data. The implausible building heights (smaller than 2 m) are automatically replaced by the heights of the nearest buildings with the 'spatial join' tool of ArcGIS 10.6.1. Because floor heights vary significantly in reality and many buildings may have slanted roofs, the average floor height is assumed as 3 m [26]. The stories of buildings are estimated as follows:

$$stories = round(height \div 3m) \quad (1)$$

The gross floor area (A_{gross}) is calculated by multiplying the building footprint area ($A_{footprint}$) with the stories:

$$A_{gross} = A_{footprint} \times stories \quad (2)$$

The number and area of shared walls between adjoined buildings are critical for both identifying the building type and calculating the areas of façade components exposed to the outdoor air. ArcGIS 10.6.1 is employed to generate the shared line of two adjoined building footprints. The height of a shared wall is determined by the lower height of two adjoined buildings. It is formulated in Eq. (3):

$$A_{shared\_wall} = \sum_{i=1}^{n} length_{shared\_line_i} \times min(height_{building_0}, height_{building_i}) \quad (3)$$

where A_{shared_wall} is the area of shared walls of a given building. n is the number of walls that $building_0$ shares with its adjacent buildings. $length_{shared\_line_i}$ is the length of the shared wall between $building_0$ and its adjoined $building_i$.

BAG does not hold the types (flat or slanted) and inclination angle of roofs. According to the research by Froemelt and Hellweg [16], roof

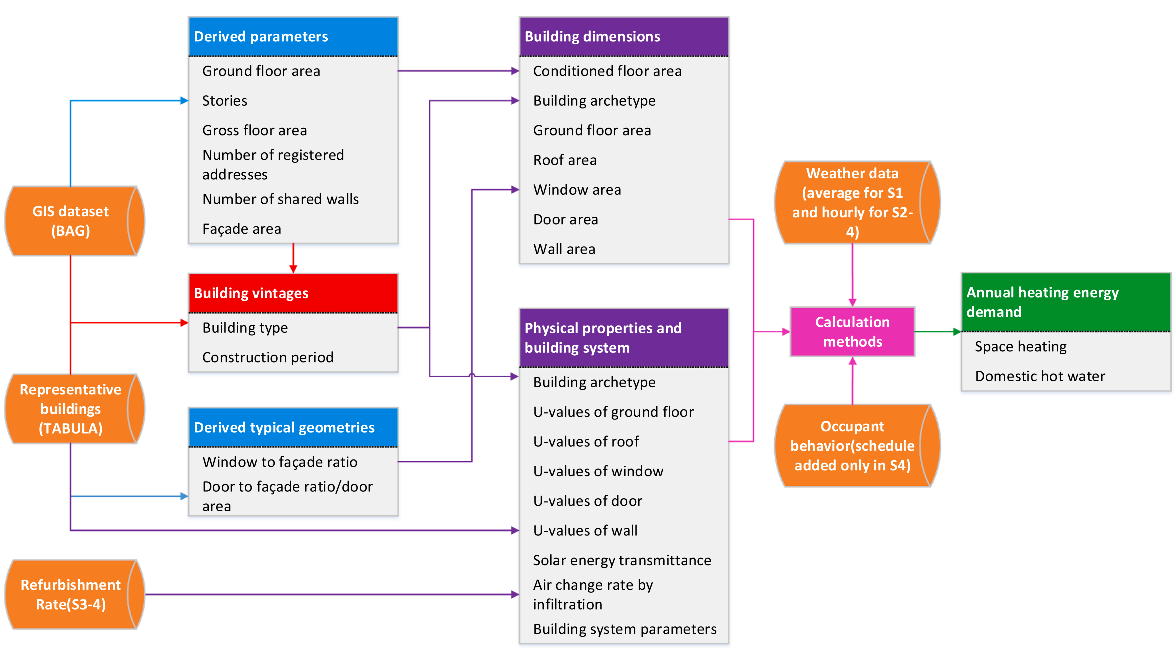

Fig. 1. Schematic overview of the relationships between different databases. The orange denotes data sources. The blue denotes the derived basic building parameters from BAG and TABULA. The red denotes the identified construction period and building type of each building. The purple denotes the derived input data for heating energy models. The pink denotes the calculation methods. The green denotes the outputs of different models. The colors of connection arrows are in line with the latter databases.

inclination has a very limited effect on overall energy consumption for space heating, so we do not consider the roof types and each building is simplified as a cube.

The area of roof and ground floor is assumed equal to the building footprint area. The façade consists of window, door and external wall (exposed to the outdoor air). Its area is calculated by multiplying the perimeter of each building footprint with the corresponding building height and subtracting the areas of shared walls:

$$A_{facade} = perimeter_{footprint} \times height - A_{shared\_wall} \tag{4}$$

In order to estimate the areas of windows, the window-to-façade ratio ($fraction_{window}$, see S2 of supplementary material) are derived from the envelope component areas of representative buildings in TABULA. Then the window area is calculated by multiplying the façade area with the window-to-façade ratio:

$$A_{window} = A_{facade} \times fraction_{window} \tag{5}$$

As the difference between the door areas of single-family house and terraced house is typically very small, the door areas of these buildings are obtained from the representative buildings in TABULA (A_{TABULA_door}, see S2 of supplementary material). The door areas of multi-family houses and apartment buildings are calculated by multiplying the façade area with the door-to-façade ratio ($fraction_{door}$, see S2 of supplementary material):

$$A_{door} = \begin{cases} A_{TABULA\_door} & for\ single-family\ house\ or\ terraced\ house \\ A_{facade} \times fraction_{door} & else \end{cases} \tag{6}$$

The area of external wall is calculated by subtracting the window area and door area from the façade area:

$$A_{external\_wall} = A_{facade} - A_{window} - A_{door} \tag{7}$$

According to the TABULA calculation method, the conditioned floor area (A_{con}) is determined by the internal dimensions [27]. In this study, the thickness of the external wall is assumed as 0.25 m [28,29] and the conditioned floor area is estimated by correcting the gross floor area:

$$A_{con} = A_{gross} - perimeter_{footprint} \times 0.25m \times stories \tag{8}$$

Based on the building classification and age determined above, the U-values (thermal transmittance coefficient) of envelope components, g-values (solar energy transmittance values) of windows, air change rate by infiltration, and supply system parameters from the archetypes in TABULA are allocated to BAG buildings.

2.2.2. Weather data

KNMI includes 50 weather stations distributed in the territory of the Netherlands and records the weather data per station per hour [23]. The typical heating season in the Netherlands is from October 1st to April 30th (212 days) [19]. S1 uses the average hourly outdoor temperature and global solar radiation, while S2-4 use the hourly weather data.

2.2.3. Refurbishment

TABULA includes refurbishment standards for representative buildings, including U-values of roof, window, wall and ground floor, and the g-values of windows. The U-values distinguish conventional refurbishment, i.e. to the current standard, and advanced refurbishment, i.e. to the nearly zero-energy level [21]. However, BAG does not hold the information on what refurbishment measures have been exactly implemented for which buildings. We allocate the refurbishment of archetypes to BAG buildings based on refurbishment rates. As the latest cumulative refurbishment rates for envelope components are only available for 2012 [24], we linearly extrapolate the annual refurbishment rates of 2013–2015 based on the average annual refurbishment rates of 2006–2012. Therefore, the cumulative refurbishment rates ($R_{component}$) of ground floors, external walls, roofs and windows are 63%, 77%, 81%, and 88%, respectively.

According to Milieu Centraal [30], the buildings constructed after 2000 are already well insulated and this is also shown by their U-values in TABULA database [21]. In addition, these recently constructed buildings are unlikely to have undergone significant thermal refurbishment. Therefore, we assume that only buildings constructed before 2000 might have been refurbished. The number of refurbished buildings for each type of envelope component ($N_{component}$) is determined as follows:

$$N_{component} = N_{building} \times R_{component} \tag{9}$$

where $N_{building}$ denotes the total number of buildings; $R_{component}$ is the cumulative refurbishment rate for a specific type of envelope component.

As the refurbishment rates are not differentiated by construction period and building type, we randomly choose $N_{component}$ BAG buildings constructed before 2000 and assume that the components of these buildings have experienced conventional refurbishment. Then the U-values of their envelope components are updated.

2.2.4. Occupant behavior

According to TABULA, the internal room temperature, air change rate related to the utilization of the building, and the internal heat gains from human metabolism and appliances, are 20 °C (T_{int}) and 0.4 1/h ($n_{ve,use}$) and 3 W/m^2 (q_{int}), respectively [21]. The above values are the same for S1-4 while the occupant schedule is only considered in S4. The average time that occupants stay at home differs across studies (e.g. 12 [31] or 16 [32] hours per day). Occupants are assumed present at home from 7:00 pm to 7:00 am (+1 day, 12 h) [31], and the heating supply systems are assumed only operating during this period.

2.3. Calculation of energy consumption

While the purpose of the study is to develop models for simulating the energy consumption for space heating, the validation data, apart from the energy consumption for space heating, also includes the energy for DHW. In order to ensure comparability, we thus additionally simulate the energy consumption for DHW generation. The energy demand for space heating and DHW is calculated based on EN ISO 13790 [31] and TABULA method [27]. S1 is a seasonal model (seasonal calculation timesteps), while S2-4 are hourly models. Then the energy demand is converted into energy consumption based on the TABULA supply system simulation method [27]. The detailed calculation process can be found in S3 of supplementary material and the simulation is performed with Python.

2.4. Case study

The residential building stock of Leiden, a city in the Netherlands is selected as a case study to demonstrate the developed model. Leiden is a typical Dutch city that has various kinds of residential buildings (totally 29,030 based on BAG). Its residential building stock characters can be found in S1 of supplementary material. Almost half of the buildings are built before 1964 while the 1975–1991 period seems a high tide of construction. Terraced houses account for approximately 52% of the total conditioned floor area in Leiden. As there is no weather station in Leiden, we use the weather data (2016) of Voorschoten, the closest weather station to Leiden.

2.5. Spatial validation

The Central Bureau of Statistics (CBS) holds the measured natural gas consumption data at the household level [33] but the data is only publicly available in an aggregated form at the postcode level. We use the natural gas consumption data in 2016 to validate the modeled

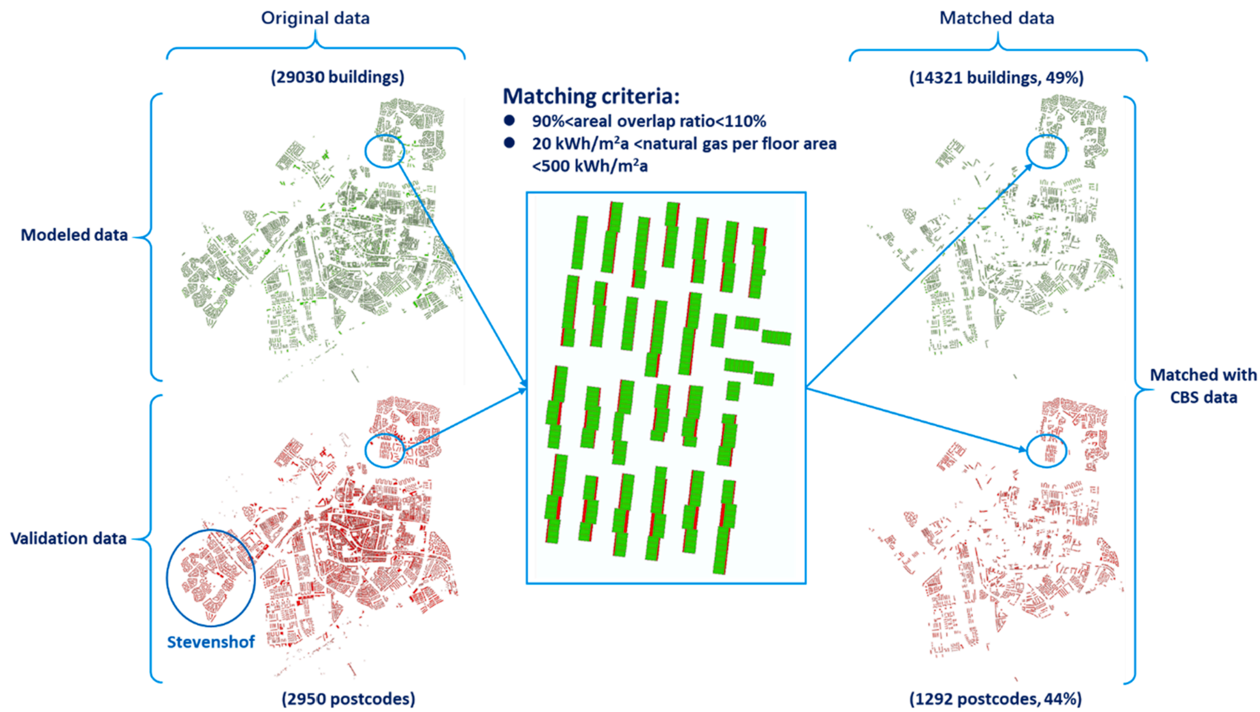

Fig. 2. Mapping the modeled results with measured data from CBS. The green polygons are BAG buildings and the red are the CBS buildings dissolved by postcode. The natural gas consumption is expressed in kWh/m^{2}a. In Stevenshof, the buildings are connected to district heating networks, so it is filtered.

natural gas consumption (aggregated to 2950 postcodes, see the distribution of buildings per postcode in S1 of supplementary material). In this study, the heating value of natural gas is used to convert the unit of measured natural gas (m^3) into kWh (1kWh = 3.6 MJ) and its value (35.2 MJ/m^3) is from the literature [34]. The physical properties of buildings' envelope elements vary with ages, so the 'age' of the postcode is regarded as the average building construction year weighted by conditioned floor area.

The measured natural gas does not distinguish between end-use energy purposes (mainly including space heating, DHW, and cooking), but the proportion of cooking is quite small (on average only 3.9% [34]). Therefore, we subtract 3.9% of the measured natural gas from each postcode and thus the remaining natural gas is mainly related to space heating and DHW.

Then the modeled natural gas consumption and conditioned floor area aggregated at postcode level are spatially linked to the measured natural gas consumption based on postcodes (see Fig. 2). The overlap ratio, defined as the ratio of the footprint area of dissolved buildings by postcode (BAG) to the footprint area of dissolved buildings by postcode (CBS) and vice versa, is used to guarantee that the same buildings are selected for validation. Only postcode pairs whose overlap ratios are within the 90–110% interval are selected (1241 postcodes excluded and 1709 postcodes left).

When the measured natural gas consumption is normalized by the conditioned floor area, outliers (the measured natural gas consumptions that are below 20 kWh/m^{2}a and above 500 kWh/m^{2}a [35]) are found,

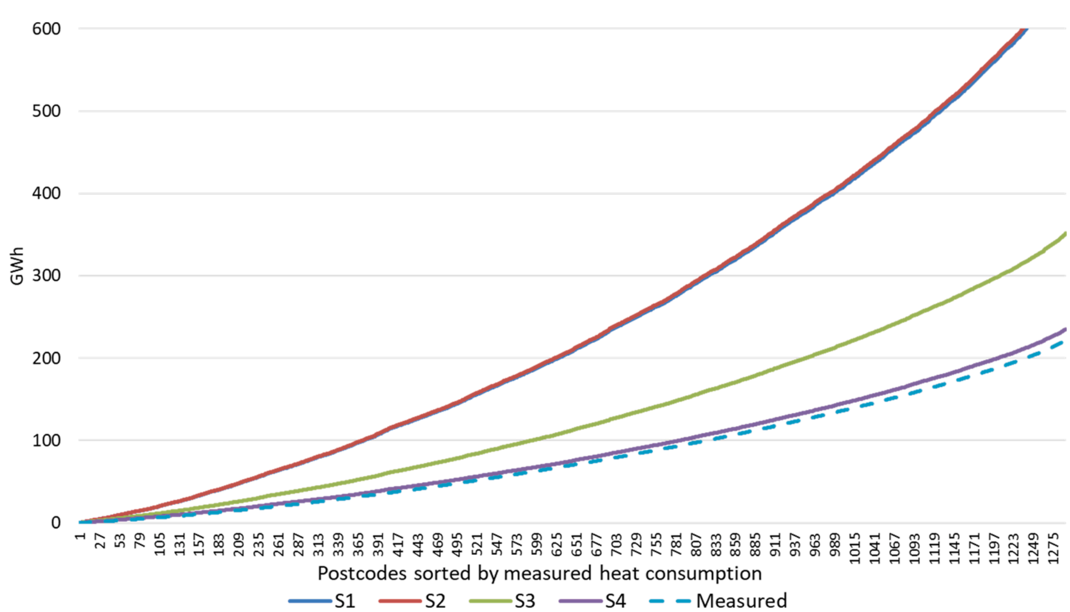

Fig. 3. Modeled and measured natural gas consumption cumulated for all 1292 postcodes. S is the abbreviations for step (both here and below).

which is mainly caused by the following reasons:

(1) There might be some data errors caused by limited data coverage or occupants' delayed registration.
(2) While the majority of buildings use natural gas for space heating and DHW in the Netherlands, some buildings are heated by other energy sources, such as electricity, CHP (combined heat and power), and geothermal heating [19]. In the heat transition atlas [36], we find that two CHP plants exist in Leiden and many buildings are connected with the heat distribution networks, for example, the buildings in Stevenshof (see Fig. 2).
(3) An extreme case is that the building's areas are only partly used by occupants and thus the natural gas consumption per conditioned floor area is very small.
(4) Some houses might have mix-use purposes. For example, ground floors are for business while the upper floors are for living.

Therefore, the postcodes with outliers are excluded from the comparison. Finally, 44% of postcodes and 49% of modeled buildings are left (see Fig. 2).

3. Results

3.1. Cumulative results

Fig. 3 shows the cumulative natural gas consumption for all the steps as well as validation data. S4 fits best with the measured data (overestimated by about 6% in total) and thus indicates that including all influencing factors yields the most realistic results. In contrast, S1-3 obviously overestimate the natural gas consumption. While there is hardly any difference between S1 and S2, suggesting that the additional weather model detail has little effect, the largest reduction arises from including refurbishment (S3) and then the second largest reduction from including occupant schedule (S4).

3.2. Influence of building age

From Fig. 4 we can see that both the simulated and measured natural gas consumptions decrease with the increasing construction periods (except for S3-4 in the 2006–2014 period). There is no great difference between the measured natural gas consumption of different periods, but the measured natural gas consumption of the 2006–2014 period declines significantly.

The natural gas consumption modeled by S2 is only slightly larger than S1. The modeled natural gas consumption plunges after refurbishment and occupant schedules are taken into account. S4 fits best with the measured natural gas consumption, but it slightly overestimates the natural gas consumption of buildings in the 1992–2005 period and obviously overestimates the energy consumption of buildings after 2006.

It is found that the measured natural gas consumption has a broader range than the modeled consumption. The reason is that the diversity of the real world is higher than what our models can capture. For example, the building geometries and thermal properties are derived from a limited number of representative buildings in TABULA, and occupant-related parameters are from TABULA and educated assumptions, which narrows the spectrum of modeled natural gas consumption.

3.3. Accuracy analysis

Fig. 5 maps the modeled and measured natural gas consumption of each postcode. Comparing Fig. 5a and Fig. 5b, we can find that the natural gas consumptions are quite large for certain spatially clustered postcodes, but the extreme natural gas consumption of validation data is more obvious than that of S4. It is also found in Fig. 5c that the deviations between S4 and validation data are in general very small, although the natural gas consumption modeled by S4 is not very consistent with the measured natural gas consumption for some postcodes. From Fig. 5d we can see that older buildings tend to consume more natural gas, but it is not always the case.

Fig. 6 shows the distribution of absolute deviations between S4 and validation data. The average absolute difference is −0.4 kWh/m^{2}a, which means that S4 slightly underestimates the natural gas consumption. Nearly 83% of the absolute deviations are in the $\pm\sigma$ interval while 98% are in the $\pm 2\sigma$ interval. The mean bias error (MBE) is −0.35 kWh/m^{2}a, and the coefficient of variation of root mean square error (CVRSME) is 31% [37]. Overestimations and underestimations almost symmetrically distribute on both sides of zero, which is one of the main reasons why underestimations and overestimations level off and the modeled natural gas consumption is in good agreement with the measured natural gas consumption on Leiden building stock scale.

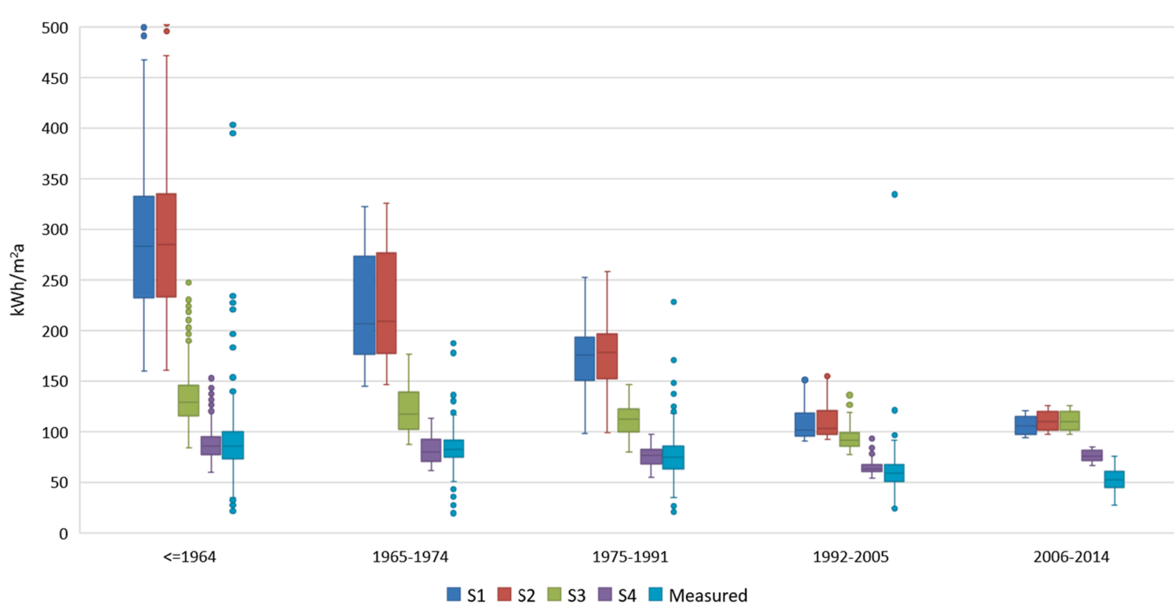

Fig. 4. The measured and modeled annual natural gas consumption of different construction periods. The solid line in the box is the median value.

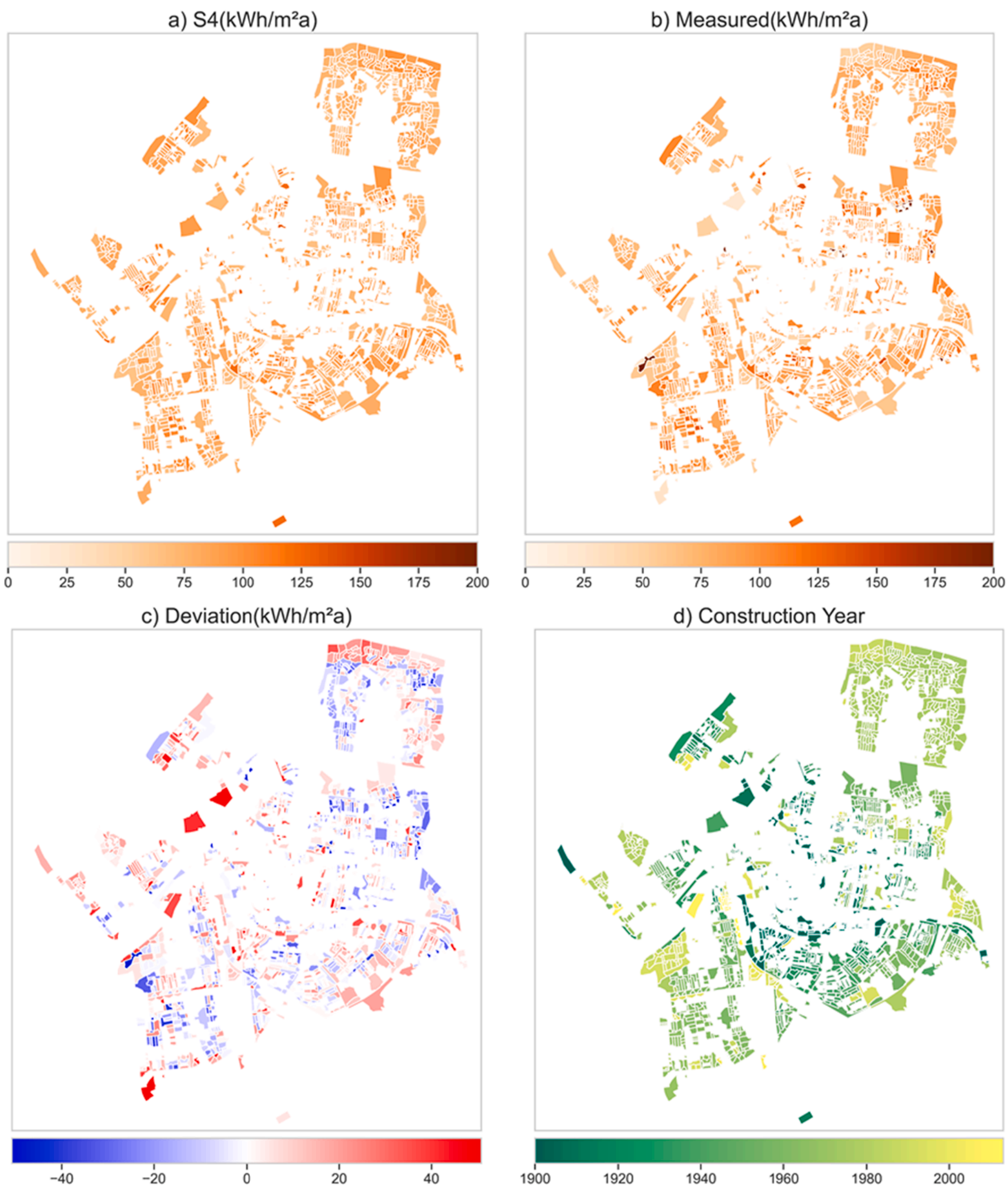

Fig. 5. Leiden maps of modeled and measured annual natural gas consumption of 44% postcodes for space heating. The subplot (a) shows the natural gas consumption modeled by S4. The measured natural gas consumption is shown in (b). The absolute deviations between S4 and the measured natural gas consumption are shown in (c, d) shows the age distribution.

4. Discussion

4.1. Key factors for modeling the energy consumption for space heating

The validation reveals that S1-2, which do not consider refurbishment and occupant schedule, fail in accurately simulating the natural gas consumption, while the modeled natural gas consumption becomes increasingly close to the measured natural gas consumption after refurbishment and occupant schedule are included in S3-4. Therefore, refurbishment and occupant schedule are important factors affecting the modeled natural gas consumption, which is in line with other studies [16].

In terms of the accuracy of weather data, the difference between the simple average weather data for the heating season (S1) and the hourly weather data (S2) does not make a significant difference to the modeled annual natural gas consumption (Fig. 4). However, the natural gas consumptions modeled by S1-2 are obviously higher than measured natural gas consumption. One of the main reasons is that S1-2 inherently oversimplify the heating process by assuming that the buildings are heated all the time during the heating season [38]. Therefore, the seasonal heat demand model (S1) is not suitable for accurately estimating the energy reduction effect of specific energy-efficiency measures, while the hourly model (S2) can take hourly weather differences into account and has more potential for accuracy improvement by including more detailed occupant schedule (e.g. S4).

In Fig. 4, we find that including refurbishment increases more accuracy for older buildings than including occupant schedule while the opposite seems to apply for newer buildings. The reason is that newer buildings have better thermal properties and refurbishment only has a limited impact on reducing the modeled natural gas consumption, which indirectly demonstrates that refurbishing the buildings constructed before 1964 can lead to the highest natural gas reduction potential. It is

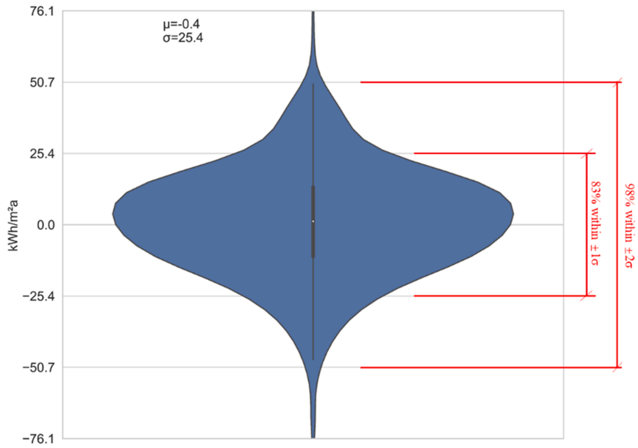

Fig. 6. Absolute deviations between S4 and measured natural gas consumption. μ is the mean absolute deviation and σ is the standard deviation of absolute deviation.

also found that for S3 and S4, the modeled natural gas consumption of the 1992–2005 period is even lower than the modeled natural gas consumption after 2006. The reason may be partially that the original thermal properties of the buildings of 1992–2005 period are only moderately worse than that of buildings after 2006, but refurbishment makes the envelope components of buildings in 1992–2005 period have even better thermal properties than the buildings after 2006 (for which no refurbishment is simulated).

S4 overestimates the natural gas consumption of almost all the buildings of the 2006–2014 period (Fig. 4). One of the main reasons may be that the U-values in TABULA only meet the national minimum requirement and these values cannot represent the thermal properties of these buildings [21]. In reality, more efficient heating or ventilation systems and renewable energy sources have been applied, but S4 does not account for such increasingly applied technologies. For example, in the Netherlands some heat boilers using natural gas are replaced by district heating or heating pumps, and their gas stoves are replaced by electric cooking stoves [30].

Fig. 5 suggests that the actual natural gas consumption is not only affected by the building age but also other factors such as refurbishment records and occupant schedule. Building age, as a key classification standard for TABULA archetypes applied in characterizing the Leiden residential building stock, can partially represent the energy efficiency of the current building stock, while the past refurbishment measures in reality have changed the energy performance of original buildings. Therefore, the refurbishment rate can be regarded as a supplementary for the limited representation of TABULA archetypes.

As increasing the sophistication from S1 to S4, some assumed data are introduced (e.g. refurbishment and occupant schedule), for which no spatial information is available. While S4 is the most complete among the four steps and produces the best results at a spatially aggregated scale (neighborhood or city level), it thus comes with the trade-off of decreased spatial accuracy, at least at a single-building level (see the schematic representation in S4 of supplementary material). This is a common dilemma in building stock modeling [5] and cannot be resolved unless spatially explicit data for factors such as refurbishment is available.

4.2. Limitations and research opportunities

The building information of TABULA archetypes is allocated to individual BAG buildings based on construction periods and the identified building types, which provides an opportunity to automatically characterize building information at large scales with limited data. However, the archetypes are unable to completely represent all the real buildings, such as geometries (e.g. window-to-façade ratio and door-to-façade ratio), physical properties, and supply systems, which is a systematical limit of the archetype-based method. In addition, sometimes the identified building types might be wrong. For example, the end-terraced houses and mid-terraced houses are assumed to respectively have one and two shared walls, but multi-family houses may also have one and two shared walls. This would cause some variations for the estimated envelope component areas (including windows, walls, and doors), while the differences between the U-values of different building types for the same period are almost negligible according to TABULA database [21]. Moreover, the buildings are simplified as cubes, which ignore the roof types and may cause some errors for the estimation of envelope component areas.

Due to a lack of supply system information and the corresponding energy sources for individual buildings, all the buildings are assumed to use gas-fired boilers from TABULA. Although most residential buildings are heated by natural gas in the Netherlands, there are increasing exceptions. For example, some more recent houses have been installed with gas-free heating systems (e.g. heat pumps or connecting to district heating networks).

The national refurbishment rates [24] of envelope components and the usual refurbishment from TABULA database are employed to reflect the physical properties of the current residential building stock. However, this can cause spatial uncertainty for the Leiden residential buildings stock, so more attention should be paid to reducing the uncertainties caused by unknown HVAC systems and refurbishment records (e.g. refurbishment year and insulation technologies) at postcode or even individual building level.

The presented model uses standard occupant parameters from other literature and reasonable assumptions (e.g. occupant's schedule) to fill in the data gaps and calculates the energy consumption from a demand perspective (quantify the energy required to maintain a given room temperature), while it omits the diversity of individual occupant behavior. Previous studies [39] have revealed that occupants can impose a critical impact on building energy consumption and sometimes even reach the same extent of technical interventions. For example, internal room temperature setting, ventilation (time of leaving windows and doors open), schedules, and DHW consumption highly depends on the specific occupants (e.g. living habits, number, age, income, and job) [40]. However, it is difficult to collect so much detailed occupant information on building scale especially for a city-scale energy model, and future research should pay more attention to this.

The internal room temperature of a given building varies in space and time (named as 'non-uniform heating' [27]). The use status of various rooms (e.g. living rooms, bedrooms, and kitchens) can be quite different. The areas like staircase, attics, and garages are typically unheated. Additionally, intermittent heating or reduced setting-point temperature may occur during different periods (e.g. night and weekend). However, in this study the internal room temperature is set as a fixed value (20 °C [31]) in the whole space of buildings.

For validation, due to lacking measured energy consumption data for individual buildings, the weighted average ages rather than the pure age of individual buildings are employed to represent the construction periods of postcodes, although the buildings with the same postcode are likely to have similar ages.

4.3. Model applicability and transferability

Due to a lack of refurbishment records at the level of individual buildings, its accuracy for individual buildings is limited. However, the presented model qualifies to offer a good overview of the energy consumption characteristics at the neighborhood and city scales, for which validation is possible. It can also reflect the energy efficiency of buildings belonging to different age groups.

The presented model makes a compromise between sophistication and accuracy through making full use of public data sources (geometries in GIS data and TABULA archetype building information). It gathers the input data as matrices (building information) or time series (weather data and occupant behavior) and calculates energy consumption based on public energy simulation algorithm, which allows for analyzing largescale building stock (neighborhood, city, or nation) and realizing transferability to other countries.

Due to a lack of spatial data on individual buildings as well as the diverse occupant behavior, building stock energy models previously developed applied diverse input data [41]. Especially the model proposed by Buffat et al. [4] applied high-resolution spatial data available in Switzerland that is not available for many other countries. In contrast, the data required for the presented model mainly involves the GIS data (including building registration), archetype buildings, weather data, refurbishment records, and occupants, which are available and public in many countries. Below is a summary of the availability of input data:

(1) The GIS data of buildings is available in many EU members and the OpenStreetMap can be an alternative data source [4]. The availability and detail level of individual building attributes (e.g. construction year, building types, heating systems, energy sources, refurbishment records, occupant characteristics) differ significantly in each country, such as the Danish BBR [42] and the Swiss FRBD [25]. However, the building type identification method developed in this study based on building morphologies in GIS data provides the opportunities for filling in these data gaps with archetypes or sample buildings.
(2) The archetype buildings are available for many countries [43] and it is also worth mentioning that TABULA project currently contains the representative buildings of 21 European countries [21]. However, for larger countries the archetype system might be quite complex due to various climate regions and construction technologies.
(3) The weather data is almost available for every country while its spatial and temporal resolution might be quite diverse.
(4) The detailed refurbishment records for individual buildings are very rare in most countries but can be managed by the local authorities. In some EU countries, the EPC (Energy Performance Certificate) databases contain buildings' past refurbishment or suggested energy efficiency measures as well as energy labels (A–G), actual energy use, physical properties, and HVAC systems, but the building information types in these databases differ from country to country and not every building has an energy label at present [44]. Alternatively, the refurbishment rates of building elements can be collected from the published reports (local or from other countries/regions).
(5) The occupant data (e.g. household age structure, the number of occupants, income and education level) that is quite related to human behavior is available in some developed countries, such as the SHAERE database of the Netherlands [45] and the property register of Sweden [46], but it is usually not public and spatialized for privacy protection reasons. However, reasonable assumptions can be made to fill in the data gaps in the absence of better data (e.g. room temperature, internal heat gains, and occupant schedule).

5. Conclusion

This study presents a GIS-archetype based bottom-up building stock model for energy consumption for space heating. In order to allocate the typical geometries, thermal properties, and heating systems of archetype buildings to the individual buildings, this paper develops a method to identify the types of individual buildings according to building size and the number of shared walls. Then different input data (e.g. average weather data, hourly weather data, refurbishment, and occupant behavior data) and calculation methods are gradually included to explore the key factors affecting the model accuracy. The main conclusions are:

(1) The spatial validation shows that the most sophisticated step can well reflect the energy consumption at the city scale while other steps are completely off reality. However, due to lacking heating systems, refurbishment records, and occupant behavior for individual buildings, the modeled energy consumption is moderately acceptable at postcode level but likely inaccurate for individual buildings. This demonstrates that including more factors can increase the model accuracy at city scale, but simultaneously increases the uncertainty for single buildings. Additionally, as more than half of the postcodes are filtered (only 44% postcodes left), the validation data of higher quality would be valuable to assess the developed model.
(2) The comparison between steps demonstrates that the seasonal model fails in accurately simulating the energy consumption for space heating. It is found that including past refurbishment in building stock energy models are necessary for achieving reliable results. Taking the assumed occupant schedule into account can narrow the gap between the modeled and measured energy consumption though the occupant behavior data in this study is quite rough.
(3) The model is valuable for city planners to understand the current energy efficiency status in space, determine the priority of implementing retrofit measures, and assess the energy-saving potentials of refurbishment technologies. Local authorities need to spatialize detailed information for individual buildings if more specific energy-efficiency suggestions are required. Furthermore, the presented model probably is transferable for other countries as long as the input data such as GIS building datasets and archetype buildings, is available.

CRediT authorship contribution statement

Xining Yang: Conceptualization, Methodology, Software, Validation, Investigation, Writing - original draft, Writing - review & editing. **Mingming Hu:** Conceptualization, Methodology, Supervision, Writing - review & editing. **Niko Heeren:** Methodology, Writing - review & editing. **Chunbo Zhang:** Resources, Writing - review & editing. **Teun Verhagen:** Resources, Software, Validation. **Arnold Tukker:** Writing - review & editing. **Bernhard Steubing:** Conceptualization, Methodology, Supervision, 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.

Acknowledgements

The authors would like to thank the China Scholarship Council (CSC) for funding the research project (project No. 201806050100).

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2020.115953.

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