# Community stochastic domestic electricity forecasting

Amin Amin *, Monjur Mourshed

*School of Engineering, Cardiff University, Cardiff, CF24 3AA, United Kingdom*

## ARTICLE INFO

## ABSTRACT

The domestic sector is a significant energy consumer – accounting for around 40% of global electricity demand – due to household demand diversity and complexity. An accurate and robust estimation of domestic electrical loads, environmental impacts, and energy-efficiency potential is crucial for optimal planning and management of energy systems and applications. However, uncertainties resulting from simplistic socio-technical attributes, microclimatic variations, and oversimplification of the effects of interdependent variables make domestic energy modelling challenging. In this research, a hybrid bottom-up community energy forecasting framework is developed to estimate sub-hourly domestic electricity demand using a combination of statistical and engineering modelling approaches by considering key factors influencing household consumption, including demographic characteristics, occupancy patterns, and the features, ownership, and utilisation patterns of electric appliances. The framework is tested on a community in Wales, UK and validated on an annual, daily, and sub-hourly basis with monitored electricity usage averages derived from the UK Energy Follow-Up Survey and the sub-national electricity consumption datasets. Results closely reflect annual and daily household demand at individual dwellings and aggregated levels, with an estimation accuracy of up to 90%. Moreover, the framework facilitates more reliable sub-hourly demand profiles compared to conventional simulation practices that overestimate daily electricity demand and sub-hourly peaks by up to 15% and 50%, respectively.

## 1. Introduction

Building energy modelling and forecasting, for both demand and generation, are crucial for decision support and formulation in many energy applications [1], including; determining energy supply requirements at local, regional, and national levels; planning, designing, operating, and managing utility network and smart grids; and predicting, evaluating and optimising energy-efficiency strategies, trading applications, and material and technology implementations [2–4].

Socio-economic developments, such as increasing living standards, lifestyle changes, income growth, and the ownership of household appliances, contribute to a rise in domestic energy demand along with rapid population growth, urbanisation, and weather variation [4], which add further burdens on the supply side that experience various cost, environmental, operational, and stability challenges, such as increasing energy prices, energy resource exhaustion, and negative environmental implications. These burdens have made energy-efficiency and saving strategies the primary objective for various research applications, technologies, and energy legislation policies [5–9]. For instance, the EU Commission has asserted that improving the energy performance of European buildings is crucial for reducing their global greenhouse gas (GHG) emissions by 20% in 2020 and the range of 80%–95% by 2050 for a long-term target [10].

In a similar vein, the increase of smart and decentralised energy systems with renewable energy sources (RES) provides a promising approach for energy-efficiency improvement and carbon emissions reduction, which require the integration of low-carbon strategies and advanced energy management technologies, such as demand-side management, that exploit generation and demand predictions to optimise system loads and enhance system stability [11–16].

The residential energy sector exhibits stochastic consuming behaviours, which fluctuate from dwelling-to-dwelling and day-to-day due to the diversity and complexity of household energy demand [17]. Dwelling and household types, together with socio-economic attributes and a wide variety of lifestyles, formulate the overall domestic electricity profiles in a certain community [18]. Therefore, investigating domestic energy modelling with high forecasting accuracy is crucial for (i) understanding primary drivers of electricity demand and energy-related behaviours; (ii) estimating/predicting future trends of domestic electricity consumption; and (iii) assessing energy-saving strategies and potentials for renewable energy sources [4,19,20].

This research developed and evaluated a hybrid model, called "domestic electricity load forecasting (DELF)", for stochastic estimation of UK daily household electrical loads from an individual device and

---

* Corresponding author.
  *E-mail addresses:* AminA8@cardiff.ac.uk (A. Amin), MourshedM@cardiff.ac.uk (M. Mourshed).

| ASHRAE | American Society of Heating, Refrigerating and Air-Conditioning Engineers |
| BEIS | Department for Business, Energy and Industrial Strategy |
| BESS | Battery energy storage system |
| BES | Building energy simulation |
| BRE | Building Research Establishment |
| BREDEM | Building Research Establishment's Domestic Energy Model |
| CIBSE | Chartered Institution of Building Services Engineers |
| $CO_2$ | Carbon dioxide |
| DELF | Domestic electricity load forecasting |
| DOE | The U.S. Department of Energy |
| DR | Demand response |
| DSM | Demand side management |
| E+ | EnergyPlus |
| EFUS | Energy Follow Up Survey |
| EPBD | Energy Performance Buildings Directive |
| EPW | EnergyPlus Weather |
| EU | European Union |
| GHG | Greenhouse gas |
| HES | Household Electricity Survey |
| HVAC | Heating, ventilation and air-conditioning |
| IDF | Input data file |
| IEA | International Energy Agency |
| IPMVP | International Performance Measurement and Verification Protocol |
| KPI | Key performance indicator |
| M&V | Measurement and Verification for Performance-Based Contracts Federal Energy Projects |
| MBE | Mean bias error |
| NOAA | National Oceanic and Atmospheric Administration |
| PV | Photovoltaic |
| $R^2$ | Coefficient of determination |
| RES | Renewable energy source |
| RMSE | Root mean square error |
| RU | Relative uncertainty |
| SEG | Smart Export Guarantee |
| TCR | Tariff comparison rate |
| ToU | Time of Use |
| UBEM | Urban building energy modelling |

**Units**

| % | Percentage |
| kW | Power in kilowatt |
| kWh | Energy in kilowatt hour |



**Fig. 1.** Global and regional residential energy consumption shares, 1990–2020. Data source: World Energy Balances online data service, IEA [25].

novelty of the proposed framework and significance resides in integrating statistical models – for robust and detailed forecasting of sub-hourly household occupancy patterns and electric device schedules – with building thermal and energy simulations to enhance forecasting accuracy. Besides, the capability for synthesising simulation scenarios and conditions allows (i) estimating a "baseline" electricity demand for the domestic sector; and (ii) scaling forecasting estimations to city, regional, or national levels.

An initial version of the DELF framework was a part of the "ToWArds Building rEady for Demand rEsponse (TABEDE)", a research and development project funded by the European Commission Horizon 2020, that aimed at allowing buildings to provide sufficient flexibility and participate in various demand response (DR) schemes [14,21, 22]. The version was used as the core of the "Real-time Energy and Environmental Forecasting and Simulation (REEFS)" component for forecasting day-ahead electricity demand and production profiles from an individual device to district levels [23]. In this research, further developments on the DELF framework were carried out by incorporating statistical models for estimating stochastic occupancy behaviours and internal loads to ensure high estimation accuracy of domestic electricity demand.

The article is organised as follows. The following section examines domestic electricity consumption trends in the UK. Section 3 analyses residential energy modelling approaches and related works. Section 4 then elaborates the key components and workflow of the DELF framework. Section 5 discusses the framework implementation in a case study. Results and validations are analysed in Section 7. Concluding remarks are summarised in Section 8.

## 2. UK domestic electricity

Residential energy consumption represents around 22% of worldwide energy consumption and is responsible for approximately 17% of GHG emissions in 2020, experiencing fluctuations over the last three decades, as illustrated in Fig. 1. Although a decrease in global residential energy consumption share has partaken over 1990–2010, an increase has been witnessed in European and UK residential consumption shares. In 2020, the share of residential energy faced an increase due to the COVID-19 restrictions that mandate everyone, except key workers, to work from home [24]. In Europe, dwellings account for 26% of total energy consumption [25]. Meanwhile, the UK residential sector commands a higher energy demand share of 32% and is responsible for 16% of total GHG emissions [26–29].

The UK domestic electricity demand amounts to 38% of the total electricity demand, as depicted in Fig. 2, which has experienced an increase of around 35% from 1990 to 2005 driven by an increase in electric appliance ownership and utilisation rates [30]. Legislation and enforcement of energy-efficiency labelling and standards have led to the development of a wide range of highly efficient appliances and equipment, especially for major household appliances, such as washing

dwelling to a community level. Our contribution lies in adequately reflecting the variability and fluctuations of individual household electricity demand by considering key factors influencing household power loads, including energy end-uses, demographic characteristics, occupancy behaviours, and the characteristics of domestic appliances in terms of diversity, features, ownership, and utilisation patterns. The
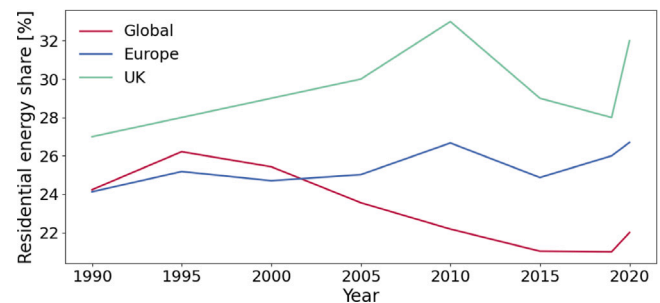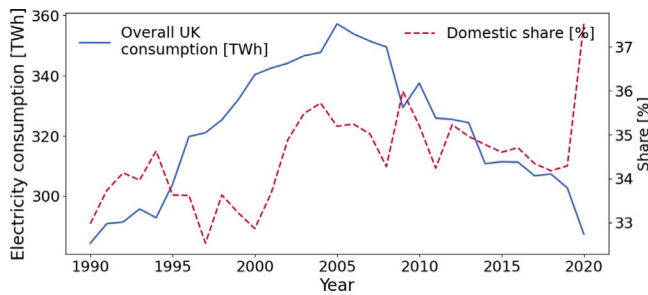
**Fig. 2.** Domestic electricity consumption share of total UK electricity consumption, 1990–2020.
Data source: Digest of United Kingdom Energy Statistics (DUKES) [28].

machines, refrigerators, and TVs [31], contributing to a significant electricity reduction in 2019 of 17% compared to 2005 [29]. Although overall UK electricity consumption decreased in 2020 by 4.8%, an increase in domestic electricity demand by 5.6% took place because of occupant behaviour changes and increased electrical appliance usage due to the COVID-19 lockdown [24].

Annual average electricity demand in UK dwellings widely ranges between 500 and 20,000 kWh, with around 60% of households consuming between 750 and 5,000 kWh and another 5% consuming over 10,000 kWh [24,29]. The annual mean and median demand of 2019 were 3,578 and 2,817 kWh, which decreased by around 5% and 10% compared to 2017 and 2012 [29], respectively. Recent daily household electricity demand is estimated between 1 and 68 kWh, with mean and median of 11.7 and 13.7 kWh, respectively. The daily household demand depends not only on dwelling and household types but also on internal electrical load characteristics. For instance, the daily mean and median electricity demand for households without electric heating are 8.2 and 9.5 kWh [32]. The daily household demand variances highlight the saving potential, especially for high consumers of up to 30%, through energy-efficient appliances, altering device schedule off-peaks, and occupancy behaviours [31,33,34].

## 3. Urban domestic electricity modelling

Urban building energy modelling (UBEM) has gained significant research attention to formulate a unified district model for determining energy consumption and generation, thermal loads, and $CO_2$ emissions at a zone/building, neighbourhood/district, or even city/region and national/country levels [1,35]. Two modelling approaches are broadly used; "top-down" and "bottom-up", with the terms referring to the data hierarchy utilised as model inputs [3]. A top-down approach is performed at an aggregated or national level that utilises historical energy consumption for long-term demand projection by investigating the inter-dependencies with demographic, economic, climate, and technological variables [36–38]. However, associated limitations are attributed to inadequately defined end-uses and coarse data [1].

On the other hand, bottom-up approaches extrapolate individual dwelling energy data from household survey samples or dwelling energy models to explicitly estimate energy consumption on a regional/national level, in addition to their capabilities for testing various scenarios, conditions, and technologies [3,38,39]. However, the limitations to this approach relate to the uncertainties regarding weather conditions, occupancy behaviour, techno-economic characteristics, and high computational demand [1].

Fig. 3 illustrates a general diagram for key factors, utilised data, and implementations of residential energy modelling broadly exploited in the existing literature. Residential energy consumption is highly dependent on five key aspects that can be grouped – from inside to outside – into: internal loads and energy systems, dwelling physical

characteristics, socio-economic characteristics, urban context and location, and local weather [3,33,34]. Generally, three modelling types are implemented for estimating and predicting household energy consumption on a daily (with hourly/sub-hourly resolution) or annual basis, as follows:

1. **Engineering** models, known as physical or white-box, apply building physics principles to calculate thermal and energy loads [20,35,40,41]. They require detailed data regarding building physical and thermal characteristics, outdoor conditions, occupancy, internal loads, and heating, ventilation, air-conditioning, and cooling (HVAC) systems [38]. Generally, engineering models are implemented on representative buildings/archetypes, samples, or distributions of detailed energy end-use patterns to estimate the overall energy consumption [42].

2. **Statistical** models, known as data-driven or black-box, exploit long-term historical energy data of individual buildings or aggregated/national levels, then employ statistical methods to predict consumption [3,4,13,17–19,30,33,34,37,39,43–48]. For instance, regression, time series (e.g. multiplicative auto-regressive models, auto-regressive moving average, auto-regressive integrated moving average, and auto-regressive moving average with exogenous input model), and artificial intelligence/ machine learning (e.g. artificial neural network, support vector machine, genetic algorithm, fuzzy logic, and particle swarm optimisation).

3. **Hybrid** models combine physical and statistical methods, especially at an aggregated building level, to reduce the modelling complexity and uncertainties to enhance estimation accuracy [38,49].

Increasing demand for energy-efficient buildings and improved software packages, including decreased computing requirements, the inclusion of further features, and enhancements of user interface and calculation accuracy, have highlighted the key role of building energy simulation (BES) tools in decision-making stages for building and energy applications, such as design and planning, operation optimisation, energy code analysis, and design compliance and performance verification for energy-efficiency schemes [50,51]. However, major challenges that may produce imprecise forecasting outcomes are due to the lack of a comprehensive tool covering all demand forecasting difficulties, excessive modelling workloads, and user complexity [12]. Many studies have reported discrepancies between simulation outcomes and actual building performance; hence, there is a need to better understand factors affecting forecasting accuracy and develop methods to ensure reliable results [52].

### 3.1. Determinants of domestic electricity usage

Residential buildings are subjected to a variety of complex energy determinants, both internal and external, which can have a significant impact on their energy and thermal performance and influence the uncertainty and accuracy of energy models [53–55]. Key internal determinants include:

#### 3.1.1. Occupancy behaviour

Occupancy behaviour is defined as energy-related activities and actions of occupants in space in response to external or internal triggers, for instance, adjusting heating and cooling temperature set-points according to ambient temperatures or turning on/off artificial lighting according to daylight levels [56,57]. Demographic characteristics, such as the number of occupants, education level, and employment variations, have a key role in influencing household energy consumption patterns. Although household type is crucial for forecasting household demand profiles, occupancy patterns have considerable influences. Occupancy patterns are based on household personal characteristics
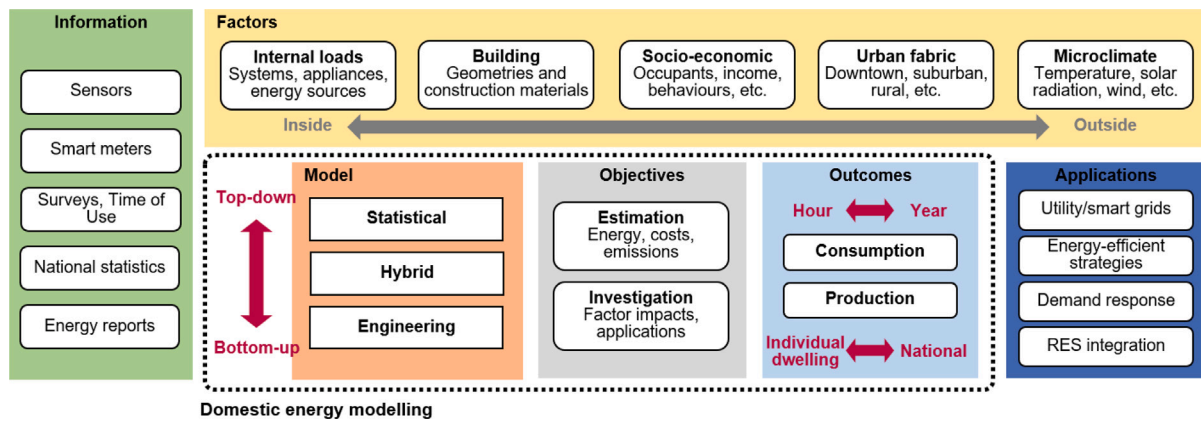
**Fig. 3.** Schematic diagram of district building energy modelling, including data sources, factors, methods, objectives, and applications.

and lifestyles that vary widely among households, even within the same social group. For instance, people tend to use less energy during bedtime and unoccupied periods when most appliances are switched off. Full-time working occupants may spend most of the day away and be back after 18:00. On the other hand, a single parent with dependent children may have a part-time job and a pensioner may spend more than 20 hours/day at home [18,38]. Additionally, around 35% of the UK working-age population works in service industries, namely retail, manufacturing, transport, food and beverages, and hospitality that have multiple daily working shifts and may operate for 24 h a day [58].

Three key factors that affect household occupancy patterns include (i) the number of occupants; (ii) the wake-up time and bedtime; and (iii) the unoccupied period. The number of occupants directly affects energy consumption levels, while wake-up and bedtime shape energy demand patterns during activities, such as cooking and lighting. Unoccupied periods also impact energy consumption as appliances and lights are mostly turned off [17,43,59].

At the urban level, occupancy patterns can be modelled using different approaches – static-deterministic, static-stochastic, dynamic-deterministic, and dynamic-stochastic – which consider the diversity of occupant presence and behaviours. Static models yield predefined profiles without considering interactions between occupants and their built environment, while dynamic models incorporate statistical approaches to account for the random nature of people's behaviours and their interactions with building components and energy systems [60]. On the other hand, diversity in occupancy patterns pertains to the variation and detail of factors considered in models using deterministic or stochastic modelling approaches. Deterministic approaches generate consistent occupancy profiles, while stochastic models vary in each simulation. Overall, dynamic stochastic-based modelling is more appropriate for representing occupants' impact on building energy performance at broader community levels [61].

### 3.1.2. Domestic appliances

83% of UK households use natural gas as a primary fuel for space and water heating, while air-conditioning is limited to 4% of households due to the UK's temperate climate. Around 90% of dwellings have central heating systems with radiators (91% of houses and 61% of flats). 59% of homes have combination boilers that supply hot water on demand, while 32% use additional hot water storage. Around 7% use electric space heating systems, such as electric storage and room heaters, and 8% depend on electric water heaters [62]. Recent statistics demonstrate that 75% of households use electricity as a cooking fuel, where 40% own electric hobs and 70% of households owning ovens have electric products [63,64]. Therefore, domestic appliances and lighting are the key electricity end-uses, contributing to around 75% and 15% of electricity demand, respectively [34,62,65,66].

The utilisation of electrical appliances significantly determines the overall electricity demand of a household based on their operation modes, power, usage frequency, and duration. Domestic electric appliances can be classified into: (i) continuous appliances, such as refrigerators and internet routers, that run continuously without being interrupted by residents; (ii) activity-dependent appliances, such as ovens and hobs for cooking, washing machines for laundry, and televisions for entertainment; and (iii) environment-dependent appliances, such as heating and lighting that are used in response to temperature and illuminance conditions [45].

### 3.2. Previous studies: information and applications

Many studies have investigated the development of urban residential energy modelling. Researchers have used information from such smart meters, energy sensors, questionnaires, Time of Use (ToU) surveys, national statistics, energy reports, or census for model developments aiming at: (i) accurately estimating domestic energy consumption [3,13,18,38,43,49]; (ii) analysing key factors influencing household energy consumption, including building characteristics [19,20,34, 37], occupancy behaviours [4,17,19,20,33,37,44], lighting [47], and household electric appliances [30,44–46]; and (iii) planning power systems and investigating the capabilities of energy-efficiency strategies for achieving zero/low carbon emissions or energy communities, such as integrating DR schemes [48], implementation of pre-paid meters [39], renewable energy penetration [35,40,41], electric vehicles charging behaviours [67], and assessing building retrofitting techniques (U-values) [37,41].

For instance, Yamaguchi et al. [45] used household ToU and monitored data to develop a statistical model for estimating the Japanese daily profiles of the washing machine with a 15-minute temporal resolution. On the other hand, Jones and Lomas [33] analysed one year of survey data to investigate factors affecting domestic electricity demand in the USA, including socio-economic characteristics, dwelling characteristics, and internal loads, where results have shown that higher incomes, big households and larger floor area homes are more likely to consume more electricity. Gao et al. [4] proposed a bottom-up data-driven framework to predict daily domestic load profiles in 10-minute intervals based on extracting data for similar days from historical data, such as outdoor conditions and internal influence factors, to train the forecasting model. Although the authors used one month of monitored energy data across 64 households, the method enhanced the prediction accuracy by up to 90%. On the other hand, Kavousian et al. [19] used eight months of smart meter data, with a 10-min resolution, and an online household characteristics survey for 1628 households in the USA to explore factors influencing residential electricity demand, such as weather and location, building physical characteristics, household appliance, and occupants. The results showed that 42% of the variability

in electricity demand may be determined by building characteristics, while occupant behaviours are responsible for 4.2%.

In the UK, Yao and Steemers [18] calculated daily domestic energy consumption profiles for electric appliances, hot water, lighting, and heating loads, with one-minute up to half-hour intervals, by clustering occupancy numbers and patterns extracted from pre-conducted electricity consumption surveys. Dunbabin et al. [46] analysed a household electricity survey for 250 households across the UK to provide a typical daily electricity demand profile by end-uses, in 10-min resolution, and the potential for peak load reduction and energy savings. Cheng and Steemers [37] developed bottom-up data-driven models for energy use and $CO_2$ emissions at both national and sub-national levels. The researchers used survey data to provide a perception of the impacts of various building physical, and non-physical (e.g. occupant behaviours) factors and the outdoor temperatures on energy consumption. Jones and Lomas [30] used one year of survey data for domestic appliances, to analyse the impacts of ownership rates and utilisation on the annual electricity consumption in UK homes. Ihbal et al. [17] utilised public reports and statistics to develop a statistical model for calculating daily electrical load profiles with 30-minute resolution based on eight occupancy scenarios and ownership rates of electrical appliances. Although the model was able to detect the utilisation patterns, it failed to adequately predict the total electricity demand and peaks. Similarly, Anderson [44] utilised the UK ToU data to analyse the difference in daily laundry profiles for 20 years in terms of day and time due to increasing female participation in the labour market and adaptation of energy tariffs. Tsagarakis et al. [43] converted occupancy activity patterns obtained from the UK ToU into individual daily electrical load profiles based on appliance ownership statistics. The results showed that there is a large variability within individual households with respect to aggregate electrical characteristics. Yohanis et al. [34] analysed almost two years of measured data from 27 dwellings with a 30-min resolution to estimate the monthly household electricity demand and investigate correlations with building (e.g. floor area, house type, location, and number of bedrooms) and socioeconomic characteristics (e.g. income levels, number of occupants, ages, and house ownership/rent).

Richardson et al. [13] exploited energy-related statistics and ToU survey to estimate daily electricity demand with one-minute intervals based on: (i) household appliance power load and ownership rates; and (ii) occupancy behaviours and appliance time of use. Although the model's capabilities in providing the temporal demand diversity, the results underestimated energy use during the night due to not considering the occupant's behaviour of leaving lights on at bedtime, as well as the power demand of small appliances, such as mobile chargers. Besides, the model was under-representing the seasonal variation as the used occupancy model did not consider that people are likely to stay home more on winter evenings and use more appliances, such as TV. Richardson et al. [47] estimated daily domestic lighting consumption profiles in 1-min resolution based on irradiance data and occupancy behaviours. However, the validation was through comparison at monthly and half-hourly levels with calibrated model results based on measured electrical energy consumption. Besides, the distribution of varied lighting power units within buildings needed to be considered.

### 3.3. Gaps and limitations

Data availability, modelling purpose, and assumption are key factors that influence the level of model input details, resulting in unreliable and imprecise outcomes. Although detailed information provides more comprehensive analysis and accurate estimations, the capability of existing UBEMs to accommodate the dynamic, stochastic, and non-linear inter-dependencies influencing the model accuracy is still limited [1,49,68], such as microclimate and socio-technical characteristics [1,12,49,68]. Most demand forecasting approaches lack transparency and the quantification of inherent uncertainty because of:

- Failure to adequately accommodate the stochastic demand fluctuations caused by socio-technical and economic aspects because of employing standard/categorised occupancy patterns [36]. As people behave in diverse and stochastic ways, occupancy behaviours are extremely complicated to predict. For instance, Ouyang and Hokao [69] investigated electricity demand differences between households with and without an energy-saving training scheme, where around 15% saving potential was highlighted when changing occupant behaviours. Although occupants within a social group may have similar characteristics, a certain behavioural pattern cannot fully represent a specific household type. However, integrating more social information could enhance prediction accuracy, but may result in redundant data and increased costs [38].
- Lack of high-resolution energy calibration standards and use of oversimplified methods result in imprecise demand profiles, particularly at peak loads [38]. As lower resolutions and simplified profiles fail to represent load details of high-demand appliances that are used for a short time (e.g. microwave, kettle and toaster) or major appliances whose power demand varies across their cycles (e.g. washing machine, dishwasher, and dryer) [45]. Besides, relying on representative days might not fully consider overall weekly/seasonal/annual demand variations [42].

Domestic electricity end-uses include heating and cooling systems, hot water, lighting, and household appliances that formulate the overall electricity demand profile based on their operation modes and power loads [1,45]. According to the literature, four essential factors influencing the performance of domestic energy modelling need to be considered [12,45]: (i) socio-economic aspects; (ii) intra/inter-household variance; (iii) temporal resolution differences between available information and quantifying calibration scale; and (iv) applicability to various circumstances, such as socio-technical attributes and climate change.

Without reliable energy demand data, it would be hard to ensure effective energy planning and strategies. Domestic energy forecasting approaches face excessive modelling workloads and high forecasting uncertainties. Although detailed engineering models have more adequate outcomes, they are compute-intensive, while oversimplified statistical models are less precise. Hybrid methods provide a promising approach for integrating various data patterns, enhancing forecasting accuracy, and developing more detailed investigations for specific cases.

### 4. Methodology

Aligned with essential challenges and features previously mentioned, a domestic electricity load forecasting (DELF) framework is developed for bottom-up estimation of daily household electrical loads at 15-minute intervals, for both demand and production, from an individual device and dwelling to community level, as shown in Fig. 4. The framework is built on top of a combination of different model types: (i) two statistical models that behave as key components for initially stochastically forecasting sub-hourly occupancy profiles and electric appliance schedules; and (ii) a physics-based model that handles energy simulations by integrating outcomes of statistical models and local weather data to estimate the thermal behaviours of electric appliances and their impacts on the overall thermal performance of dwellings and systems, then generates final electricity profiles.

Besides, the development of four comprehensive databases included (i) a dwelling information database dedicated to neighbourhood and dwelling characteristics; (ii) a household database that includes socio-demographic and employment characteristics; (iii) an electric load database that contains the features and ownership of common domestic electrical appliances in the UK; and (iv) historical meteorological information for key weather variables used in energy simulations for the community location.
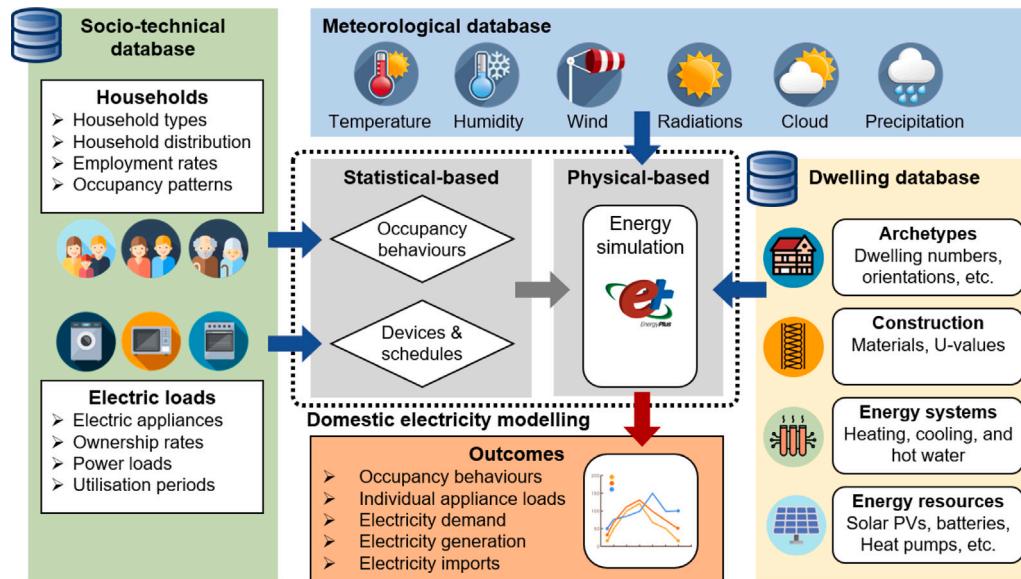
**Fig. 4.** A schematic of the domestic electricity load forecasting (DELF) framework. A physics-based model is the core engine that estimates the final electricity demand and production profiles from an individual device and dwelling to a community level.

## 4.1. Statistical modelling

### 4.1.1. Occupancy behaviour profiles (OBP)

A statistical occupancy behaviour profile (OBP) model is separately developed based on a combination of dynamic-stochastic and static-deterministic modelling approaches by generating stochastic daily sub-hourly occupancy profiles according to predefined UK occupancy scenarios and social features. After a thorough review of the literature, as an initial step, fifteen representative household working scenarios are conducted from literature [13,17–20,30,37,38,43,44,59,70,71] to properly reflect daily occupancy activity patterns in UK dwellings, as follows:

- **Morning-full-time:** Unoccupied period usually ranges between 09:00 and 18:00, as family members work full-time or away from home.
- **Morning-part-time:** Unoccupied period ranges between 09:00 and 13:00, as family members work part-time or away from home in the morning.
- **Afternoon-full-time:** Unoccupied period varies between 15:00 to midnight when occupants are away or work full-time in the afternoon, such as in service industries.
- **Afternoon-part-time:** Unoccupied period ranges between 13:00 and 18:00, where occupants work part-time or away from home in the afternoon.
- **Non-working:** Dwelling is occupied all day as family members are retired or not working. However, occupants may be away for a certain period. In this case, using the same part-time household scenarios is suggested.
- **Morning-full/morning-part:** Some occupants are away or working all day and others are away in the morning. The unoccupied period ranges between 09:00 and around 13:00, but higher loads would be after 18:00.
- **Morning-full/afternoon-full:** Some occupants are away or working all day and others are away at night. The unoccupied period ranges between 15:00 and around 18:00.
- **Morning-full/afternoon-part:** Similar to morning-full/morning-part households but unoccupied periods are between 13:00 and 18:00.
- **Morning-full/non-working:** Some occupants are away or working all day and others are not working. The dwelling is occupied all day, but higher loads would be after 18:00.

- **Morning-part/afternoon-part:** Some occupants are away or working in the morning and others are away in the afternoon. Unoccupied patterns are similar to morning-full/non-working households.
- **Morning-part/afternoon-full:** Some occupants are away or working in the morning and others are away at night. Unoccupied patterns are similar to morning-full/afternoon-full households.
- **Morning-part/non-working:** Dwelling is occupied all day, but some occupants are away or working in the morning. Higher loads would be after 13:00.
- **Afternoon-part/afternoon-full:** Similar to morning-part/afternoon-full households but lower loads would be after 13:00.
- **Afternoon-part/non-working:** Similar to morning-full/non-working households but lower loads would be between 13:00 and 18:00.
- **Afternoon-full/non-working:** Similar to afternoon-part/afternoon-full households but lower loads would be after 15:00.

A household database containing social characteristics of the required community is prepared that includes occupancy distributions, household types, and employment rates, as well as the predefined representative UK household working scenarios. The OBP model follows four steps to simulate sub-hourly occupancy activity patterns for a given household, as illustrated in Fig. 5:

1. Assign family type (e.g. a single adult or couple with/without kids) based on dwelling size (no. of rooms) and household type from the social information database. Then identify working patterns (e.g. full-time, part-time, non-working, and mixed) based on employment rate and profession (general or service industries).
2. Determine the occupancy behaviours for home and away activities based on the working pattern from the previous step. The model uses the predefined representative household working scenarios to simulate home and away activities. Two full-time working shifts (morning; 09:00–17:00 and afternoon; 15:00–23:00) are randomly distributed for households working in service industries, while the morning pattern is assigned for other full-time households.
3. Identify the sleep duration and time of the household according to get-up and sleep times for the key family member. The
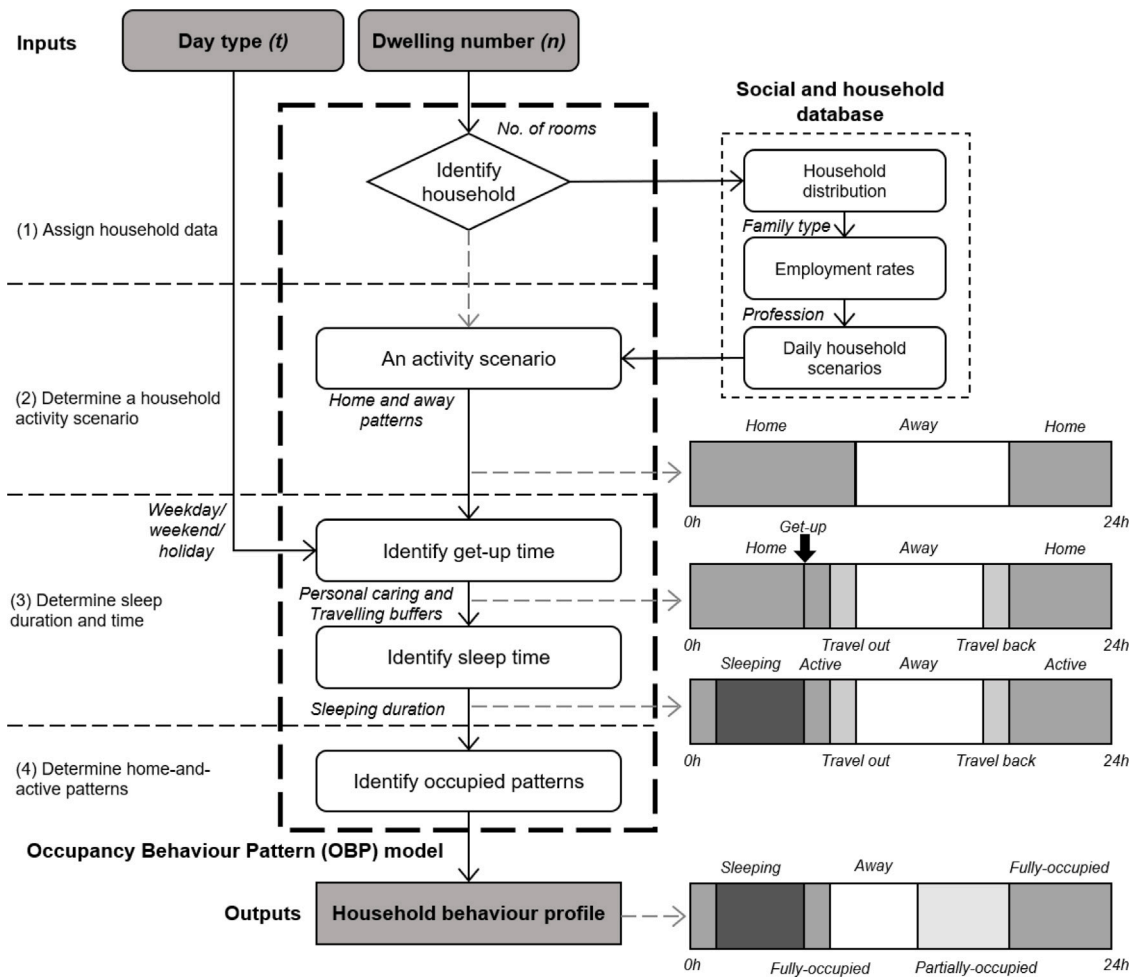
**Fig. 5.** The occupancy behaviour profile (OBP) model workflow for generating daily household behaviour scenarios and profiles.

model uses information for the day type (weekday or weekend/holiday), school (for families with kids) or work starting times (for families without kids), random time window (1.5–2.5 h) for personal care (showering/preparing food/dressing, ..etc.), and travelling duration to identify the wake-up time, then, uses a sleeping duration for the key occupant between 6–9 h [72].

4. Determine home-and-active and partially-/fully-unoccupied periods based on household working type (full-time, part-time, non-working, mixed), and the travelling duration.

The performance of the OBP model was validated by comparing its outcomes to the English household patterns derived from the UK ToU Survey 2014–15 [59,73]. The model was used to generate daily occupancy behaviour profiles for dwellings in the survey sample (1407 households) over a continuous year with considerations to the sample's household type distributions and employment rates, as illustrated in Figs. 6 and 7. Then, sub-hourly averages of which are used to create daily probability profiles. Notice that sleeping patterns are located between midnight to 6:00 on weekdays (Monday to Friday) with an hour shift at weekends (Saturday and Sunday) and holidays. Most of the occupants are away between 8:00–18:00 except for non-workers, part-time workers, and families with kids.

To evaluate the model's performance in terms of its ability to accurately predict the overall UK household occupancy patterns and peaks, the average profiles of weekday and weekend occupancy were then compared with the occupancy state probability of the UK ToU survey. The study focused on three types of patterns: sleeping, home-and-active, and away, as depicted in Fig. 8. The model was able to

capture the daily household behaviour patterns accurately. Sleeping pattern predictions are highly accurate – thanks to working and school time patterns – with accuracy estimations of 96% and 95% on both weekdays and weekends, respectively. Although the model can detect occupant activity patterns, home-and-active patterns are overestimated in morning and evening times, as well as unoccupied prediction limitations are due, especially during weekdays, to various unpredictable occupant behaviours and modelling factors (such as profession, away frequency and duration, traffic, sickness, absences). The model assumed that full-time employees follow a 9:00–17:00 schedule on weekdays. However, employees in the service industry often have diverse working patterns across weekdays and weekends, including day, afternoon, evening, or overnight shifts. Due to the limited availability of data and the complexity of the model, only two working shifts were assumed: a morning shift from 9:00 to 17:00 and an afternoon shift from 13:00 to 23:00.

*4.1.2. Electrical load schedules (ELS)*

A statistical electrical load schedule (ELS) model is also separately designed to accurately estimate daily sub-hourly electrical appliance power loads and schedules within households. The ELS model takes into account several features of each household, such as the diversity, ownership, and utilisation of electrical appliances, as well as considerations for occupancy behaviour patterns, as illustrated in Fig. 9.

Firstly, a comprehensive database was established for domestic electrical load end-uses conducted from the UK household electricity survey [65], BRE Energy follow-up survey report [74], and the
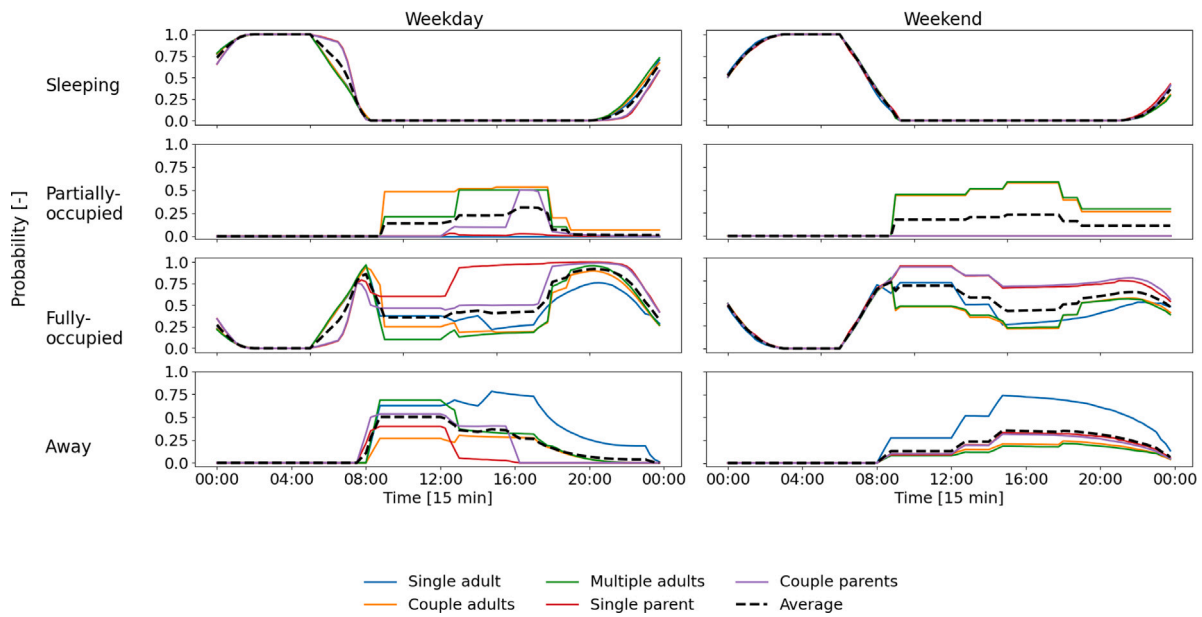
**Fig. 6.** Daily average occupancy probability profiles in UK dwellings based on household types.
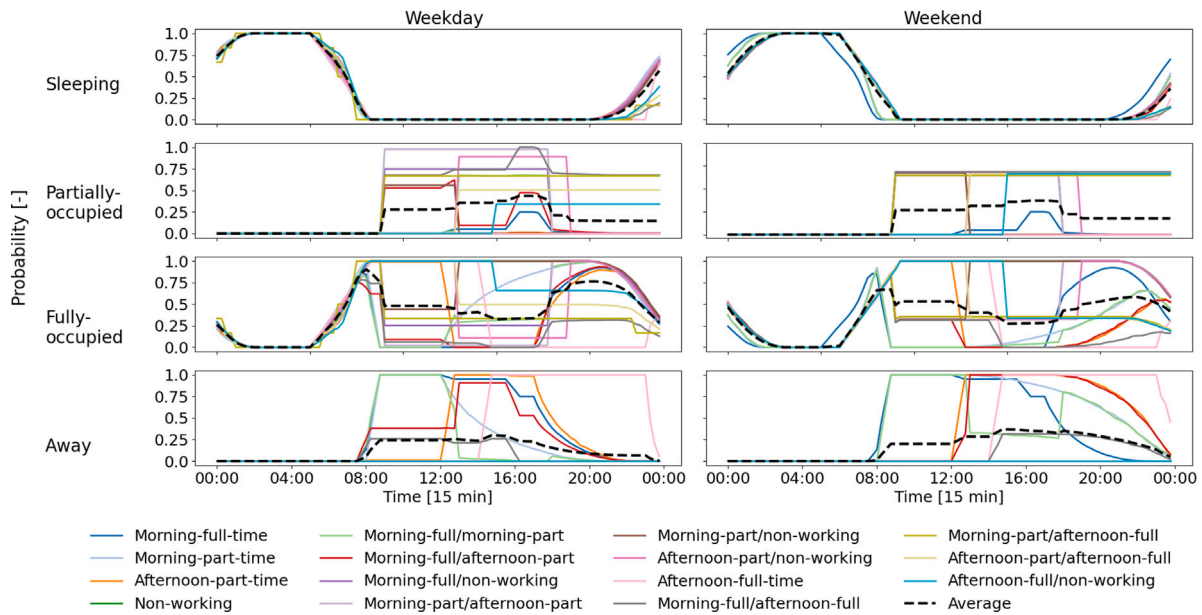


**Fig. 7.** Daily average occupancy probability profiles in UK dwellings based on working scenarios.

UK ToU Survey 2014–15 [73,75]. The database includes recent ownership rates, utilisation frequencies, and duration for common cold, wet, hot/cooking, brown/entertainment, and miscellaneous appliances. Moreover, the electricity consumption and rated power of leading household electronic products in the UK market are included for each appliance type [64], as summarised in Table 1.

To ensure the sufficiency of the appliance database, the penetration of electric appliances is identified across dwellings according to (i) family size to indicate the device presence (single-person families are found to have low ownership rates for dishwashers, clothes dryers, freezers, or even game consoles) and number (e.g. TVs, computers, laptops and ICT devices); (ii) the number of rooms to assign device numbers, such as TVs; and (iii) device ownership to identify the presence of other devices, such as washing machines for clothes dryers, fridges for separate freezers, and TVs for game consoles [33,63–65,73,74]. Finally, an electric appliances ownership scenario is generated by randomly

assigning product information from the appliance database for each device presented in dwellings, as shown in Fig. 10.

The ELS model follows four key steps to generate daily sub-hourly electrical appliance power loads and schedules for each dwelling, as illustrated in Fig. 9:

1. Identify the owned electric appliances in each dwelling by using the dwelling number and the electric appliance ownership scenario.
2. Determine the operation state (on/off) and duration of each device based on day type (weekday, weekend/holiday). This information is obtained from the developed electrical loads database, which includes the relevant device usage frequency and duration rates.
3. Integrate the daily occupancy behaviour profile from the OBP model. The model allocates the appliance operations based on
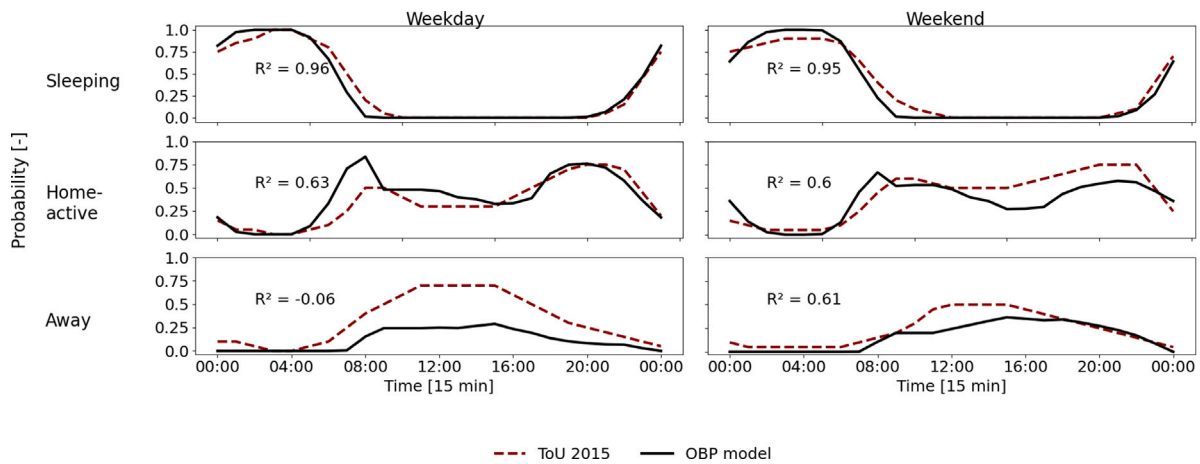
**Fig. 8.** Daily average occupancy probability profiles in UK dwellings generated by the OBP model compared to the UK ToU survey 2014–15.
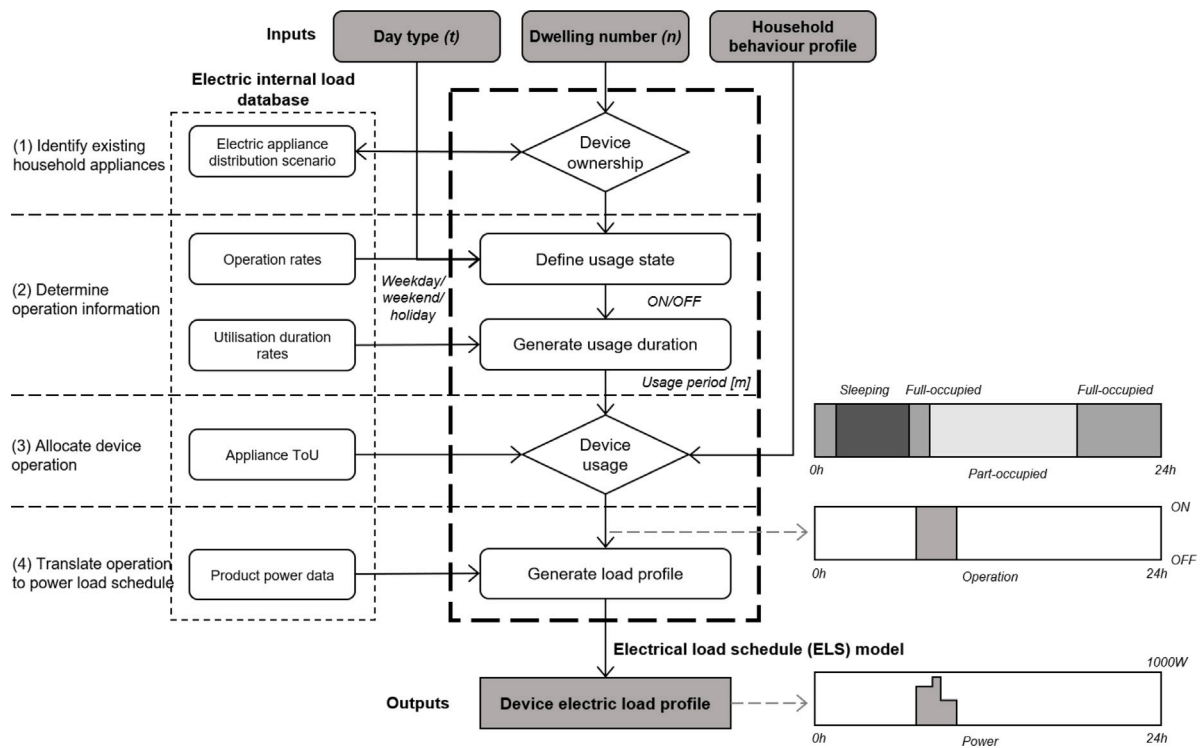


**Fig. 9.** The electrical load schedule (ELS) model workflow for forecasting daily power load profiles of domestic appliances.

the presence and activity of the occupants and the appliance Time-of-Use probabilities [73].

4. Finally, translate the switch-on periods of the electric appliances into electrical loads based on the rated power and profile of the assigned product in the dwelling from the relevant appliance database.

The reliability and accuracy of the ELS model are validated by comparing its outcomes with the appliance time-of-use probabilities of English households derived from the UK ToU Survey 2014–15 [73]. The comparison was performed by aggregating and grouping the ToU probability profiles generated by the ELS model and the probabilities obtained from the UK ToU survey according to the common domestic electricity end-uses, as illustrated in Fig. 11. Although the results highlight the model's capabilities in predicting usage periods when compared to ToU profiles, high usage probabilities of the appliances

are indicated during the morning (5:00–8:00) and evening (16:00–21:00), particularly during weekdays due to the overestimated home-and-active occupancy patterns generated by the OBP model which limit the usage of appliances in these periods and have a significant impact on the ELS model's performance. The ELS model's accuracy ranges from 0.5 to 0.9 for individual electricity end-user categories, with an overall accuracy of approximately 0.6.

### 4.2. Simulation-based modelling

Heat gains from electric appliances, such as cooking appliances, may reduce required heating loads in winter and increase summer cooling loads. Therefore, physics-based modelling is used to estimate the effects of electric appliance thermal behaviours on overall dwelling thermal performance and total electricity demand. Recently, several BES tools

**Table 1**

Common domestic electrical appliances in the UK dwellings: Ownership rates, utilisation and frequency, annual electricity consumption, and power load averages.

| Type | Appliance | Ownership[a] | Electric features | | Utilisation | | |
|---|---|---|---|---|---|---|---|
| | | [%] | Annual use | Power | Frequency | Duration [minute] | |
| | | | [kWh] | load [W] | [week] | Lower quartile | Upper quartile |
| Hot/ | Electric hob | 40 | 226 | 6600 | 5–10 | 30 | 180 |
| Cooking | Electric oven | 70 | 290 | 2600 | 3–8 | 30 | 120 |
| | Grill | 70 | 13 | 1550 | 1–4 | 10 | 30 |
| | Microwave | 93 | 56 | 850 | 3–8 | 2 | 10 |
| | Kettle | 95 | 167 | 2750 | 24 | 2 | 5 |
| | Toaster | 88 | 22 | 1600 | g* | 2 | 8 |
| | Coffee maker | 48 | 32 | 1260 | g* | 5 | 8 |
| Cold | Fridge | 90 | 162 | 110 | d | d | d |
| | Freezer | 53 | 330 | 131 | d | d | d |
| Wet | Washing machine | 98 | 166 | 2000 | 4.7[b] | 170[c] | 270[c] |
| | Dishwasher | 46 | 294 | 1950 | 3.3[b] | 180[c] | 230[c] |
| | Cloth dryer | 58 | 394 | 2400 | 5 winter[b] 1 summer[b] | 90[c] | 180[c] |
| Brown/ | TV_1 | 97 | 120 | 115 | 4-6h[e] | 180 | 420 |
| Entertainment | TV_2 | 63 | | 115 | 2h[e] | 60 | 180 |
| | TV_3 | 31 | | 115 | 1-2h[e] | 30 | 150 |
| | TV_4 | 13 | | 115 | 1-2h[e] | 30 | 150 |
| | Game console | 59 | 48 | 132 | 1–5h[e] | 30 | 330 |
| | Desktop PC | 24 | 166 | 192 | 2–4h[e] | 60 | 300 |
| | Laptop | 57 | 29 | 50 | 2–4h[e] | 60 | 300 |
| | Internet router | 87 | 58 | 8 | d | d | d |
| | Audiovisual[h] | 57 | 70 | 200 | 4–6h[e] | 180 | 420 |
| | ICT[i] | 73 | 60 | 60 | 2–3h[e] | 60 | 240 |
| Miscellaneous | Electric shower | 35 | 350 | 7000 | 4.4[bf] | 2 | 15 |
| | Care and beauty[j] | 63 | 30 | 1600 | 3–4 | 10 | 20 |
| | Vacuum cleaner | 89 | 18 | 260 | 1–2** | 10 | 30 |
| | Iron | 20 | 31 | 2600 | 1–2** | 15 | 60 |
| | Small kitchen appliance[k] | 75 | 10 | 800 | g*** | 4 | 10 |

[a] Ownership rates derived from [34,62–66,73–75].
[b] Data obtained from "At home with water" energy saving trust [76].
[c] Data derived from common appliance cycles in the UK market [64].
[d] Appliances that run all time.
[e] Daily utilisation time period.
[f] Weekly usage pattern per person.
[g] No available usage patterns and assigned similar to * electric hobs, ** care and beauty appliance; and *** grills.
[h] Devices used with TV sets (e.g. DVD, recorders, home cinema, amplifier, sound system, etc.)
[i] Information and communication technology (ICT) (e.g. printer, tablet, mobile, etc.)
[j] E.g. hairdryer, razor, etc.
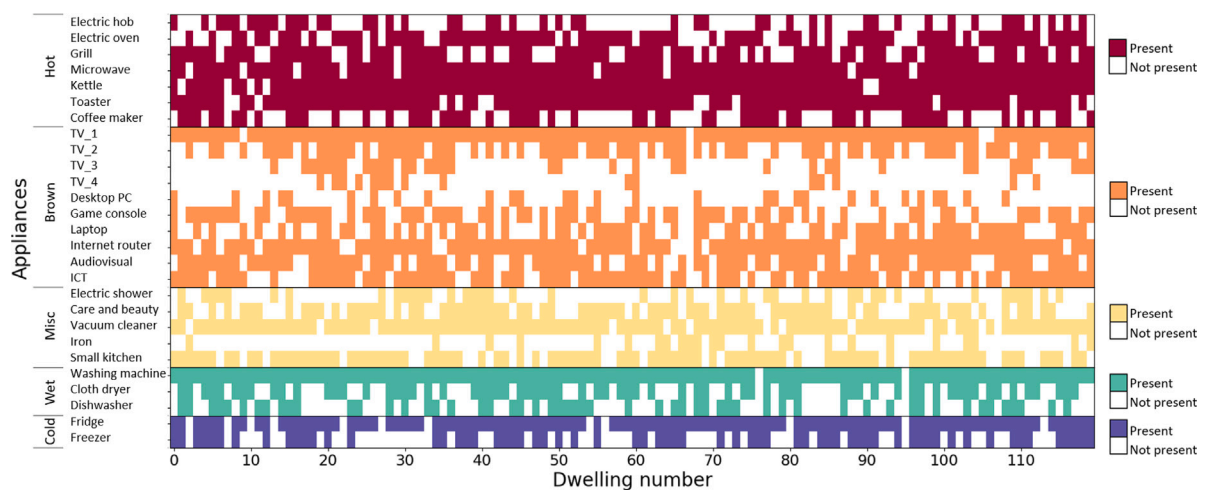[k] E.g. blender, food processor, juicer, etc.



**Fig. 10.** The distribution of household electric appliance ownership across modelled dwellings.

have been widely used in energy analysis at different scopes and resolutions, such as DOE-2, EnergyPlus, eQUEST, and TRNSYS. EnergyPlus (E+) is selected to perform as a core engine of the DELF framework for handling energy simulations due to its popularity, comprehensiveness, and high capabilities for calculating energy and thermal building performance [77–79] such as sub-hourly time steps, user-definable, and modular systems with heat balance model for zone simulation and renewable energy systems [80]. E+ requires two inputs to run the
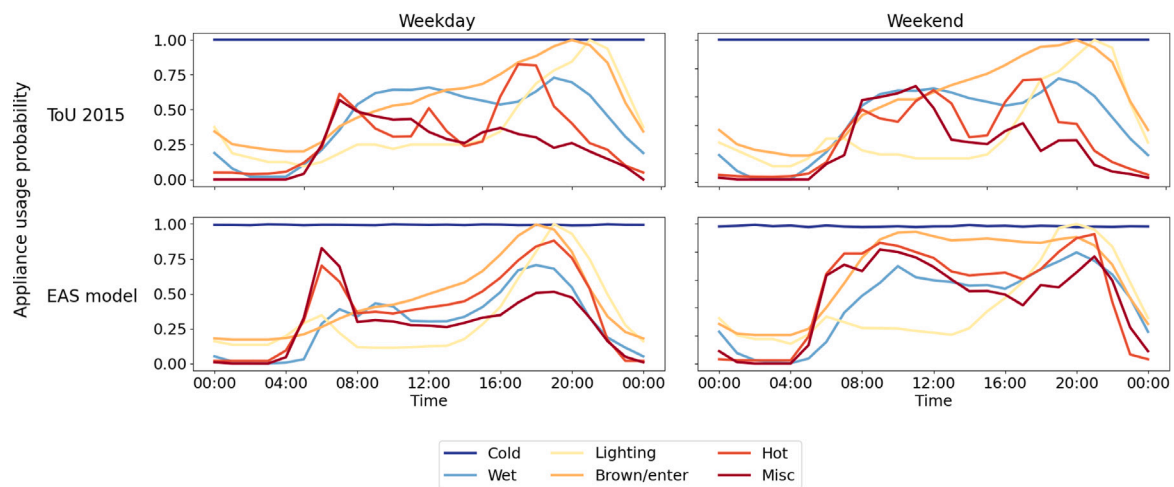
**Fig. 11.** Utilisation probability profiles of electrical appliances sorted in UK dwellings as per the UK ToU survey 2014–15 and by the ELS model.

simulation: (i) Input data file (IDF) that contains building information related to physical characteristics, materials, internal loads, schedules and occupancy; (ii) EnergyPlus weather (EPW) file representing typical/continuous weather information for the building location.

A database containing dwelling information for the required community is prepared regarding archetype, orientation, number of rooms, adjacent buildings, and solar PV and battery penetrations, as would be discussed in Section 5. Individual IDFs are constructed for each dwelling archetype and stored in the database to be used in the energy simulation process. On the other hand, occupancy behaviours, electric appliance penetration, and operation schedules within each dwelling are derived from the OBP and ELS models.

*4.3. Data- and work-flow*

The DELF framework follows nine steps to forecast sub-hourly electrical load profiles, as illustrated in Fig. 12. The framework performs on a daily basis to estimate day-by-day electricity demand and production using parallelisation algorithms for dwellings (*n*) in the community throughout loops (*d*) over the course of the simulation period. For each day d, statistical models and E+ simulations are parallel performed for n dwellings.

**The framework initiates preliminary data preparation:**

1. Simulation period included the start day and day numbers are identified.
2. Local weather data is accommodated from the meteorological database in an EPW format for the simulation period.
3. Dwelling information is recognised, including archetypes, orientation, adjacent buildings, and solar PVs and batteries (if available) from the dwelling database according to the dwelling number.

**For each day *d* in the simulation period loop, steps 4 to 8 are parallel performed for n dwellings:**

4. Occupancy profiles are generated for households in *n* dwellings based on the household and day types via the OBP model, as discussed in Section 4.1.1.
5. Electrical load schedules are identified for all devices in *n* dwellings by the ELS model according to occupancy profiles from the previous step, as discussed in Section 4.1.2.
6. Dwelling energy models are generated through the coupling with E+ to create unique IDFs for *n* dwellings from the archetypes using information from steps 3–5, as discussed in Section 4.2.
7. Energy simulations are dispatched in parallel for n dwelling IDFs using the updated EPW file.

8. Battery charging and discharging loads are mathematically estimated using predicted electricity demand and solar PV profiles if available in a dwelling.

**For the whole simulation period:**

9. Final results are generated by combining daily sub-hourly simulation outcomes for each dwelling (from steps 4–8) for (i) household activity patterns; (ii) electric appliance electricity demand; (iii) solar PV generation; (iv) battery charging/discharging loads; (vi) total household electricity demand; (vii) surplus/export electricity; and (viii) electricity import. Then, results are aggregated at the community level, including: (i) the aggregated electricity demand, (ii) community PV generation, (iii) RES self-consumption (PV-BESS), (iv) feed-in electricity, and (v) net electricity import.

High computational costs and modelling uncertainties are vital challenges confronting the DELF framework, where several mitigating strategies are followed;

- To reduce the computational cost, clustering techniques are followed to optimise the number of energy models by identifying dwelling archetypes based on building characteristics. Besides, parallelisation algorithms are applied to handle initial data pre-processing, call both statistical OBP and ELS models, run E+ energy simulations, and export final results for different dwellings in the community.
- Dealing with uncertainties depends on the nature of the underlying variables, such as occupancy patterns, internal load variation, and outdoor conditions, which may result from discrepancies in the parameter values used. Therefore, separate statistical OBP and ELS models are developed to generate reliable daily occupancy profiles and electrical load schedules and to integrate recent local weather information.

**5. Case study**

The DELF framework is tested on a part of a neighbourhood in the Vale of Glamorgan, around three miles south of Cardiff city centre, UK in order to evaluate the reliability and effectiveness of the DELF outcomes. The key information required for modelling is as follows.

*5.1. Dwelling characteristics*

A transformer substation with three feeding connections is responsible for distributing the electricity within the study neighbourhood. An
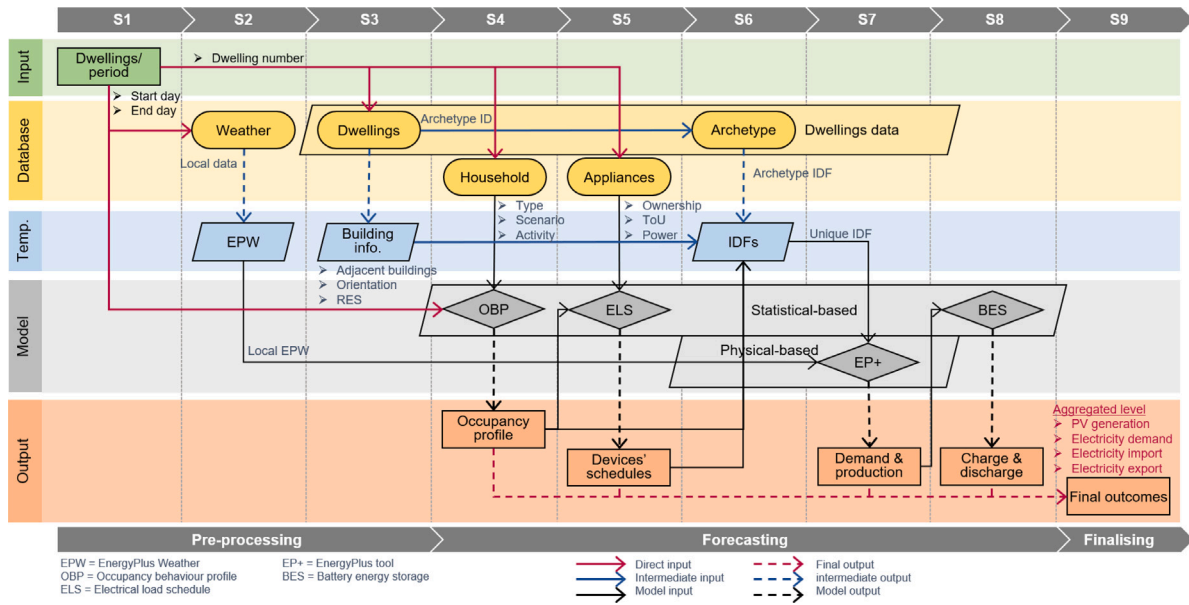
**Fig. 12.** A schematic of the data- and work-flow in the DELF framework to forecast sub-hourly domestic electrical load profiles.



**Fig. 13.** The power network layout for the case study area in the Vale of Glamorgan, UK.

**Table 2**
Dwelling archetypes in the study area.

| Dwelling | Archetype | Bedroom | Area [$m^2$] | No. | Share [%] |
|---|---|---|---|---|---|
| Flat 35% | Single aspect | 1 | 45 | 10 | 8.3 |
| | Triple aspect | 2 | 64 | 10 | 8.3 |
| | Dual aspect | 1 | 47 | 6 | 4.9 |
| | | 2 | 53 | 18 | 14.9 |
| House 65% | Detached | 2 | 62 | 1 | 0.8 |
| | Terraced | 2 | 62 | 23 | 19.0 |
| | | 3 | 76 | 19 | 15.7 |
| | | 4 | 126 | 7 | 5.8 |
| | | 3 | 62 | 6 | 4.9 |
| | | 3 | 88 | 7 | 5.8 |
| | | 4 | 126 | 14 | 11.6 |
| Total | | | | 121 | 100 |

area of 121 dwellings connected to a single feeder is selected for the DELF implementation, as marked in Fig. 13. Dwellings are distributed across terraced houses and blocks of flats. Eleven modelling archetypes are identified based on the dwelling type, position, room numbers, and floor area, enabling reliable insights into community-level electricity demand averages, as listed in Table 2. Dwelling geometries and material properties are obtained from construction documents and government building regulations [81].

### 5.2. Occupancy and schedules

Household types and occupant numbers recognised in the study area are summarised in Table 3 according to the authority census for the Vale of Glamorgan [82]. Meanwhile, the employment rate of people over 16 years is estimated at 75.6%, with around 73% of full-time and 27% of part-time employees [83]. The distribution of households is modelled as follows:

Firstly, household sizes are estimated based on dwelling floor area and room numbers following Eq. (1), developed by the Building Research Establishment's domestic energy model (BREDEM) [70], with consideration to census data, as detailed in Appendix A.1. Then, household and working types are stochastically distributed according to occupant numbers and dwelling features, which are added to the

household database to be used later by the OBP model for generating occupancy behaviour profiles.

$$if\ TFA <= 450,\ n = 0.0365TFA - 0.00004145TFA^2 \qquad (1)$$

where *TFA* is the total floor area of the dwelling and *n* is the number of occupants.

### 5.3. Internal electric loads

The penetration of domestic electric appliances is defined according to Table 1, while operation schedules are generated by the ELS model, as discussed in Section 4.1.2. Artificial lighting loads are obtained from "CIBSE: Lighting Guide LG09" [37,84], while lighting schedules are identified through energy simulations based on occupancy patterns and outdoor illuminance. Since gas-based boilers are used in the study neighbourhood for space and water heating, electric power loads ranging between 15–165 W are only considered for gas-boiler operation [85] according to occupancy-presence schedules from the OBP outcomes and the temperature set-points defined by "CIBSE Guide A: Environmental Design" [86].

### 5.4. Outdoor condition

Local historical weather data for key variables, namely dry-bulb and dew-point temperatures, humidity, pressure, wind speed and direction,

**Table 3**

The household size distribution within the study neighbourhood in terms of sizes and types according to the 2019 Census.

| Occupant | Adult | Child | Type[a] | Share by [%] | |
|---|---|---|---|---|---|
| | | | | Household | Occupant |
| 1 | 1 | | SA | 32.0 | 32.0 |
| 2 | 2 | | CA | 31.2 | 34.9 |
| 2 | 1 | 1 | SP | 3.7 | |
| 3 | 3 | | MA | 6.4 | 15.4 |
| 3 | 2 | 1 | CP | 7.1 | |
| 3 | 1 | 2 | SP | 1.9 | |
| 4 | 4 | | MA | 2.3 | 12.5 |
| 4 | 2 | 2 | CP | 9.5 | |
| 4 | 1 | 3 | SP | 0.7 | |
| 5+ | 5+ | | MA | 0.5 | 5.2 |
| 5+ | 2 | 2+ | CP | 4.5 | |
| 5+ | 1 | 3+ | SP | 0.2 | |
| Total | | | | 100 | 100 |

[a] Household types: Single adult (SA), Couple adults (CA), Multiple adults (MA), Single parent with children (SP), and Couple parent with children (CP).

and precipitation are obtained for one complete year (April 2019–March 2020) from an automatic weather station installed in the study area. Meanwhile, cloud cover and global solar radiation for the same year are retrieved from the Met Office Integrated Data Archive System (MIDAS) for the nearest meteorological station (Cardiff Airport) [87].

## 6. Validation and benchmark

Convergence analysis of DELF forecasts is accomplished on an annual, daily, and sub-hourly basis with electricity consumption estimates derived from (i) the Energy Follow-Up Survey (EFUS) report that contains monitored energy consumption for more than 400 English households in 2017 [32,63]; and (ii) the sub-national electricity consumption dataset by the Department for Business, Energy, and Industrial Strategy (BEIS) — providing electricity information for more than 16 million domestic metres broken down by postcodes across the UK [29]. At daily and sub-hourly levels, the median profiles of mean sub-hourly electrical load profiles for DELF and EFUS estimations are compared, while annual median forecasts are validated against EFUS and BEIS median estimations.

### 6.1. Quality and error metrics

Relative uncertainty (RU) is used for assessing the accuracy and capabilities of DELF in estimating the annual domestic electricity demand according to Eq. (2).

$$RU = \frac{|y_i - \hat{y}_i|}{y_i} \tag{2}$$

$y_i$ is the national average of annual electricity demand and $\hat{y}_i$ is the estimated annual electricity demand of the $i$th dwelling.

Meanwhile, three quality metrics are utilised for evaluating daily and sub-hourly electricity demand in terms of variability and fluctuations [88,89], as recommended by ASHRAE-Guideline 14 [90], the Measurement and Verification for Performance-Based Contracts Federal Energy Projects (M&V) [91], and the International Performance Measurement and Verification Protocol (IPMVP) [92], including the normalised mean bias error (NMBE), the coefficient of variation of the root mean square error (CV-RMSE), and the coefficient of determination ($R^2$). The acceptable tolerances for each matrix are listed in Table 4, which are estimated on a monthly, daily, or hourly basis according to Eqs. (3), (4), and (5), respectively [93,94]. The discrepancies

**Table 4**

Proposed thresholds of quality metrics for calibrating sub-hourly building energy models. Widely accepted thresholds and their sources for calibrating hourly, daily, and monthly models are also presented for context.

| Interval | Guide[a] | KPI | | |
|---|---|---|---|---|
| | | NMBE | CV(RMSE) | R-squared |
| Monthly | ASHRAE | 5 | 15 | >0.75 |
| | IPMVP | 20 | | >0.75 |
| | M&V | 5 | 15 | >0.75 |
| Daily | ASHRAE | 7 | 22 | |
| Hourly | ASHRAE | 10 | 30 | >0.75 |
| | IPMVP | | 10–20 | >0.75 |
| | M&V | 10 | 30 | >0.75 |
| Sub-hourly | | 15 | 25 | >0.75 |

[a] (ASHRAE) ASHRAE-Guideline 14 [90]; (IPMVP) International Performance Measurement and Verification Protocol [92]; (M&V) Measurement and Verification for Performance-Based Contracts Federal Energy Projects [91].

between these thresholds are used to propose further thresholds for the sub-hourly calibration of building energy models.

$$NMBE = \frac{1}{\bar{y}} \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n - p} \times 100\% \tag{3}$$

$$CV(RMSE) = \frac{1}{\bar{y}} \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n - p}} \times 100\% \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{5}$$

$y_i$ is the national average of daily/sub-hourly electricity demand and $\hat{y}_i$ is the estimated daily/sub-hourly electricity demand at time $i$, $n$ is the total number of data points, $\bar{y}$ represents the mean of national average data, and $p$ is the number of adjustable model parameters, where $p = 0$ for Eq. (3) and $p = 1$ for Eq. (4).

## 7. Results and discussions

Multiple daily simulations are executed for 121 individual dwellings in the study area over one complete year to estimate a baseline of domestic electricity demand profiles.

### 7.1. Daily and sub-hourly estimates

Fig. 14 illustrates the daily average profiles of individual dwellings for electricity demand generated by the DELF framework, as well as the overall daily average profile for the study area over one year. Daily domestic electricity demand estimates range between 3.6 and 13.78 kWh, with an average and median of 7.28 and 7.36 kWh, where the electricity demand varies by household and dwelling characteristics throughout the 24 h. The results demonstrate that household demand notably decreases after midnight to early morning (1:00–4:00) when most residents are sleeping. Most electricity demand is high in the morning (5:00–9:00) and high-intensive in the evening (17:00–21:00) when occupants are at home and active, while it settles from late morning to the afternoon (10:00–15:00) when part or all of the residents are away. The daily household electricity demand averages range from 17 to 150 Wh, with an average of 76 Wh and a daily minimum and maximum of 6 Wh and 380 Wh, respectively.

To validate the reliability and accuracy of the DELF approach in estimating domestic electricity demand, a comparison is conducted between the DELF results and EFUS sub-hourly electricity consumption profiles [32]. The comparison involved statistical analysis of the median profile of mean sub-hourly electricity demand profiles for DELF and EFUS estimations according to dwelling, household, day, and season types, as illustrated in Fig. 15.

Dwelling characteristics are a key driver of electricity demand variability among households. Small dwellings, such as flats, have
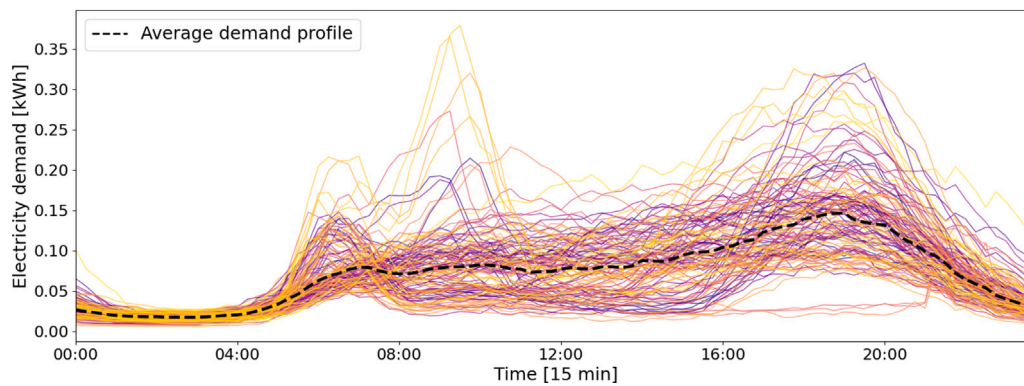
**Fig. 14.** Daily average electricity demand profiles resulted from the DELF framework for 121 dwellings over the course of a year. The dashed line represents the overall daily average profile in the study area in the UK.

lower daily consumption levels compared to houses. This is likely due to the limited liveable spaces and number of occupants in these dwellings, which reduces the demand for electrical appliances and lighting. Simultaneously, daily electricity demand increases with the number and type of occupants. The results indicate that single-person households have lower consumption levels than households with five or more occupants, highlighting the critical role of occupant behaviour in influencing household electricity demand.

Daily demand profiles slightly vary between weekdays and weekends. During weekends, the morning peak remains homogeneous during the day till the evening due to differences in occupancy patterns and activities between weekdays and weekends. On weekdays, households tend to have a more regular schedule, with occupants leaving for work or school during the day. In contrast, on weekends, households tend to have a more relaxed schedule, in which occupants may stay at home for a longer time during the day and are away on weekend nights, leading to increased electricity demand during the day. Meanwhile, outdoor temperatures and daylight hours are the main catalysts for gas boilers and artificial lighting usage, which is reflected in the seasonal electricity demand profiles. Winter months have the highest consumption levels due to increased heating and artificial lighting operations, while summer months have the lowest levels due to longer daylight hours and decreased heating demands.

Overall, DELF demand profiles, as expected, are slightly lower than EFUS profiles as UK household consumption decreased in 2019. The DELF framework overestimates evening demand peaks due to overestimated home-and-active patterns generated from the OBP model, especially for single-person families and flats, which limits most electric appliance usage in the evening, as mentioned previously in Section 4.1.1. However, underestimated demand profiles for multiple-occupant (four and more) families are predicted due to unidentified small and miscellaneous appliances associated with occupants. Besides, most of these families in the pilot community are couple parents with children, which have lower consumption shares per occupant compared to multiple adult families.

Table 5 summarises statistical indicators for daily DELF and EFUS electricity demand, as well as the quality metrics. Although daily DELF demand outcomes are lower than EFUS estimates, sufficient electricity demand estimations are calculated at both daily and sub-hourly levels, particularly on an overall basis during weekdays, weekends, and seasons. NMBE and CV-RMSE quality measurements highlight daily electricity demand estimation capabilities, which range between 68–94% at individual indicator levels and an overall between 84%–86%. Otherwise, at the sub-hourly level, quality measurements are satisfactory for both NMBE and CV-RMSE, while $R^2$ varies between 10–74% with an overall accuracy of 70%, which is due to underestimated demand profiles. These differences originate from:

- Demographic characteristic differences between the EFUS survey sample and the study area in terms of household type distribution, occupancy behaviours, and employment rates that formulate the usage of electricity.
- Time gap between the EFUS information and statistics implemented in the framework, namely electrical appliance ownership rates and power loads.

The findings are consistent with previous research, which demonstrates that occupancy behaviours and technical and dwelling characteristics all have a significant impact on household electricity consumption. Overall, results show the DELF's capability for representing the overall daily and sub-hourly variability and fluctuation of electricity demand in UK dwellings.

*7.2. Annual estimates*

At a higher level, the DELF framework facilitates adequate predictions for the annual household electricity demand, as listed in Table 6. Demand results have a normal distribution ranging between 1312–5029 kWh, where the average and median are sufficiently similar at 2684 kWh and 2657 kWh, respectively. Although annual demand predictions are lower than EFUS estimates, the prediction accuracy ranges between 67.6%–90% at individual dwelling and household levels. At an aggregated level, the accuracy is 88.6–90.5% and 94.3% compared with the recent BEIS statistics. However, discrepancies emerged when compared with the study area estimates (64.2%), which are due to:

- The implementation of national socio-techno information (occupancy behaviours, appliance ownership, and utilisation time-of-use) with local authority (household distributions) statistics.
- The study area was developed in 2013 with energy-efficient dwellings, where electric appliances and systems are more efficient than found in typical UK households.

*7.3. DELF effectiveness and challenges*

Further investigations are conducted to evaluate the effectiveness of the proposed DELF framework for domestic electricity forecasting compared to conventional practices in building energy simulations. A comparison is accomplished between the DELF outcomes and the results of using the typical meteorological year (TMY) for the nearest location at Cardiff Airport [95] and the standard domestic UK occupancy patterns from the BRE Domestic Energy Model (BREDEM) [70] that provides fixed sleeping patterns between midnight and 6:00 on weekdays and weekends, and occupants are only away between 9:00 and 16:00 on weekdays [70], as shown in Fig. 16.

The use of fixed occupancy patterns notably influences the overall daily electricity demand profiles, resulting in unreliable profiles
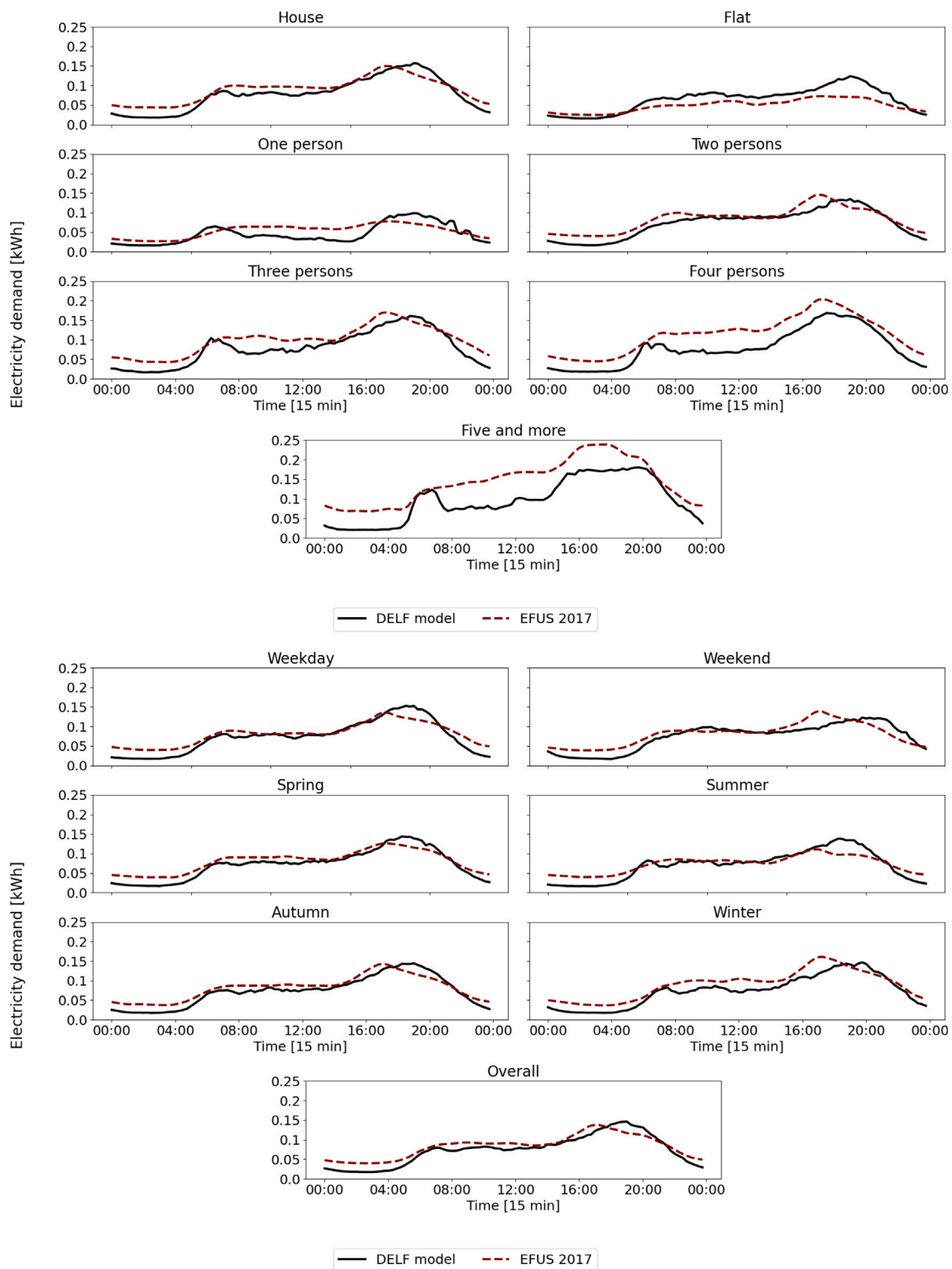
**Fig. 15.** A comparison between daily electricity demand profiles in UK dwellings as per the EFUS and by the DELF based on dwelling, household, day, and season types. The median of mean sub-hourly profiles is used to create daily demand profiles.

compared to the monitored EFUS consumption profiles, as shown in Fig. 17. Conventional simulation practices overestimate daily electricity demand compared to DELF forecasts by around 15%, with higher peaks during the morning (6:00–8:00) and evening (17:00–19:00) by around 49% and 28%, respectively. However, during the day, electricity demand is lower by 45%. On the other hand, conventional practices provide slightly higher annual electricity demand by around 10%, as illustrated in Fig. 18.

**Table 5**

Daily electricity demand in UK dwellings generated by DELF framework and from the EFUS report in terms of dwelling, household, day, and season types. Daily and sub-hourly error measurements for quality metrics are also listed.

| Indicator | Demand[a] [kWh] | | Quality metrics | | | | |
|---|---|---|---|---|---|---|---|
| | EFUS | DELF | Daily | | Sub-hourly | | |
| | | | NMBE | CV-RMSE | NMBE | CV-RMSE | $R^2$ |
| **Dwelling** | | | | | | | |
| Flat | 4.73 | 6.17 | −16.2 | 19.17 | −30.53 | 44.82 | −1.09 |
| House | 8.59 | 7.5 | 10.94 | 12.9 | 12.68 | 20.06 | 0.67 |
| **Household size** | | | | | | | |
| 1 | 5.15 | 4.39 | 14.33 | 17.53 | 14.84 | 36.5 | −0.46 |
| 2 | 8.04 | 6.99 | 19.78 | 21.28 | 13.02 | 19.73 | 0.69 |
| 3 | 9.46 | 7.58 | 15.7 | 17.64 | 19.85 | 24.68 | 0.53 |
| 4 | 10.89 | 7.61 | 30.3 | 30.84 | 30.43 | 32.49 | 0.36 |
| 5+ | 13.7 | 9.17 | 30.83 | 31.89 | 33.06 | 36.32 | 0.1 |
| **Day** | | | | | | | |
| Weekday | 7.72 | 7.03 | 11.27 | 12.1 | 8.96 | 20.92 | 0.62 |
| Weekend | 7.74 | 7.1 | 12.22 | 16.22 | 8.28 | 22.24 | 0.60 |
| **Season** | | | | | | | |
| Spring | 7.73 | 6.9 | 11.84 | 12.76 | 10.76 | 18.86 | 0.68 |
| Summer | 7.05 | 6.73 | 5.98 | 7.53 | 4.47 | 23.75 | 0.31 |
| Autumn | 7.85 | 7.0 | 12.0 | 12.84 | 10.83 | 18.5 | 0.74 |
| Winter | 8.64 | 7.1 | 18.31 | 18.78 | 17.78 | 22.66 | 0.67 |
| Overall | 7.94 | 7.3 | 13.98 | 15.47 | 11.45 | 18.97 | 0.70 |

[a] Daily electricity demand for the median of mean sub-hourly electricity demand profiles.
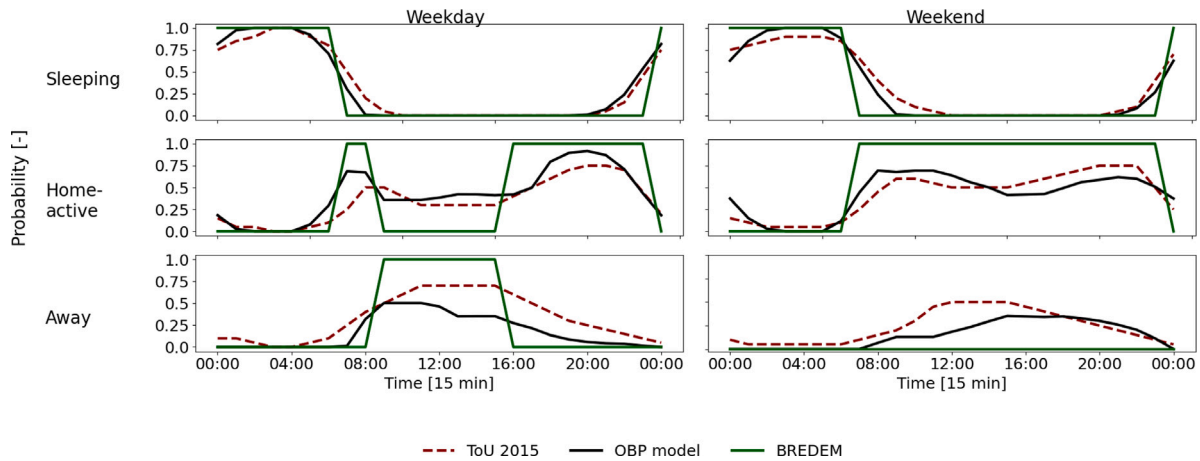


**Fig. 16.** A comparison between daily average occupancy probability profiles in UK dwellings by the DELF framework, the BRE Domestic Energy Model (BREDEM), and the UK ToU survey 2014–15.
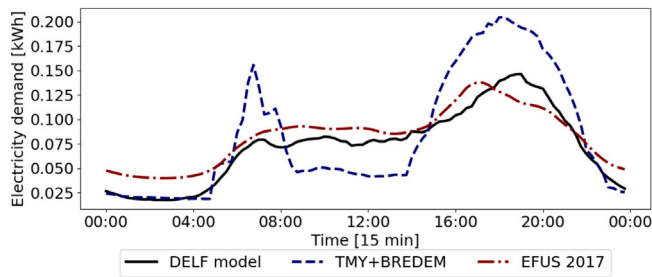


**Fig. 17.** Daily average electricity demand profiles in UK dwellings by the DELF framework compared to the use of conventional practices.
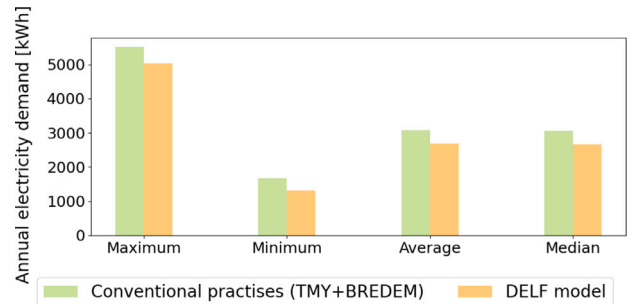


**Fig. 18.** Annual UK household electricity demand estimations by the DELF framework compared to the use of conventional practices.

The comparison highlights the importance of accurate modelling of occupancy patterns and the limitations of using fixed occupancy patterns. Overall, the outcomes underline the significant influences of demographic, economic, and technological attributes for each community on electricity demand at different aggregation levels. Besides, the DELF capability for synthesising simulation scenarios allows the

framework scalability in future implementations to a city, region, or national level through applying clustering techniques according to the five factors affecting urban energy modelling – from a broad to a detailed scale – in order to identify: (i) climate diversities and zones; (ii) urban characteristics for each climate zone; (iii) socio-economic

**Table 6**
Statistical analysis of annual electricity demand in UK dwellings generated by DELF framework compared to monitored usage estimates derived from the EFUS reports and BEIS datasets.

| Indicator | Annual electricity demand [kWh] | | | | | | RU[a] |
|---|---|---|---|---|---|---|---|
| | Estimates | | DELF result | | | | [%] |
| | Mean | Median | Minimum | Maximum | Mean | Median | |
| **Individual level (EFUS)** | | | | | | | |
| Dwelling type | | | | | | | |
| Flat | 2829 | 1726 | 1312 | 3664 | 2267 | 2105 | 22.0 |
| House | 4153 | 3135 | 1517 | 5029 | 2923 | 2820 | 10.0 |
| Household size | | | | | | | |
| 1 | | 1880 | 1312 | 2657 | 1757 | 1628 | 13.4 |
| 2 | | 2935 | 1553 | 4191 | 2644 | 2639 | 10.1 |
| 3 | | 3453 | 1517 | 4646 | 2935 | 2939 | 14.9 |
| 4 | | 3975 | 1816 | 5024 | 2948 | 2760 | 30.6 |
| 5+ | | 5000 | 1990 | 5029 | 3492 | 3379 | 32.4 |
| **Overall UK** | | | | | | | |
| EFUS 2017 | 3500 | 3000 | 1312 | 5029 | 2684 | 2657 | 11.4 |
| BEIS 2017 | 3729 | 2937 | 1312 | 5029 | 2684 | 2657 | 9.5 |
| BEIS 2019 | 3578 | 2817 | 1312 | 5029 | 2684 | 2657 | 5.7 |
| **Study area**[b] | | | | | | | |
| BEIS 2019 | 2182 | 1957 | 1312 | 5029 | 2684 | 2657 | 35.8 |

[a] According to annual median consumption values.

[b] For postcodes located in the study area.

and technological features of urban areas; and finally (iv) dwelling archetypes among each community.

## 8. Conclusion

This research presented the development of a hybrid bottom-up stochastic domestic electrical loads framework for estimating UK sub-hourly household electricity demand and production — from an individual dwelling to a community level. The framework combined detailed building simulation and statistical models for stochastically forecasting household electricity demand. The developed model appropriately reflected the daily demand variability and fluctuation in UK dwellings by considering key factors influencing household electricity consumption, including demographic characteristics, occupancy behaviours, and the diversity, features, ownership, and utilisation patterns of domestic electric appliances.

The study addressed existing challenges facing domestic energy modelling that result from unreliable and imprecise inputs related to socio-technical attributes and local outdoor conditions, or using over-simplified methods. To overcome modelling uncertainties from these challenges, integrated statistical models were developed to (i) stochastically generate daily occupancy behaviour patterns for common household types, and (ii) forecast various daily household electrical load schedules based on the national reports and statistics of the UK. In addition, the most recent annual local weather information was integrated. To address the lack of reliable energy calibration standards, the research examined and proposed additional permissible error thresholds for the calibration of the sub-hourly model.

The effectiveness of the framework was assessed using a community in Wales, UK, and validated on annual, daily, and sub-hourly timeframes with monitored electricity usage averages derived from the UK Energy Follow-Up Survey and the sub-national electricity consumption datasets. The framework exhibited a strong predictive capacity, achieving estimations as high as 94% for total annual electricity demand. Furthermore, the outcomes accurately captured the day-to-day variations and sub-hourly fluctuations in electricity consumption at both individual household and aggregated levels, achieving a level of accuracy ranging from 60% to more than 90%. In contrast to conventional simulation methods that rely on standard weather data and typical occupancy patterns, the newly developed framework facilitated the creation of reliable daily demand profiles. Conventional practices often overestimated annual and daily electricity demand by approximately 10% and 15%, and sub-hourly peaks by up to 50%.

Overall, the developed framework demonstrates an accurate, stochastic, comprehensive, and robust method for estimating and evaluating domestic electricity demand in the UK to support designers, engineers, and decision-makers at multiple levels of determining energy supply requirements, planning and managing utility grids, energy dispatching, trading applications, and demand response schemes.

## CRediT authorship contribution statement

**Amin Amin:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Monjur Mourshed:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Methodology, Investigation, Data curation, Conceptualization.

## 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.

## Data availability

Data will be made available on request.

## Acknowledgements

## Appendix

### A.1. Demographic and occupancy information

Table A.1 details occupancy number estimation within the study area based on dwelling characteristics according to the BREDEM model. It also shows household type distribution with regard to occupants, and dwelling characteristics.

**Table A.1**
Occupancy number estimations and family type distribution within the study area.

| Dwelling features | | | | Occupancy | DELF estimates | | | |
|---|---|---|---|---|---|---|---|---|
| Type | Room | Area [m²] | No. | BRE[a] | Occupancy | Share [%] Sub | Total | Family[b] |
| Flat | 1 | 45 | 10 | 1.6 | 1 | 8 | 31.4 | SA |
| | | 53 | 6 | 1.8 | 1 | 5 | | SA |
| | 2 | 47 | 6 | 1.6 | 1 | 5 | | SA |
| | | 53 | 16 | 1.8 | 1 | 13 | | SA |
| | | 53 | 2 | 1.8 | 2 | 2 | 36.4 | SP |
| | | 64 | 4 | 2.2 | 2 | 3 | | SP |
| House | 2 | 62 | 24 | 2.1 | 2 | 20 | | CA |
| | 3 | 62 | 6 | 2.1 | 2 | 5 | | CA |
| | | 76 | 8 | 2.5 | 2 | 7 | | CA |
| | | 76 | 8 | 2.5 | 3 | 7 | 14.6 | MA |
| | | 76 | 2 | 2.5 | 3 | 2 | | SP |
| | | 88 | 8 | 2.9 | 3 | 7 | | CP |
| | 4 | 126 | 3 | 3.9 | 4 | 2 | 12.4 | MA |
| | | 126 | 12 | 3.9 | 4 | 10 | | CP |
| | | 126 | 6 | 3.9 | 5+ | 5 | 5 | CP |
| Total | | | 121 | | | 100 | 100 | |

[a] Calculations are based on the occupancy estimation equation from Building Research Establishment's domestic energy model (BREDEM) [70].
[b] Family types: Single adult (SA), Couple adults (CA), Multiple adults (MA), Single parent with children (SP), and Couple parent with children (CP).

# References

[1] Swan Lukas G, Ugursal V Ismet. Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. Renew Sustain Energy Rev 2009;13(8):1819–35.

[2] Pallonetto Fabiano, De Rosa Mattia, D'Ettorre Francesco, Finn Donal P. On the assessment and control optimisation of demand response programs in residential buildings. Renew Sustain Energy Rev 2020;127:109861.

[3] Ghedamsi Rébha, Settou Noureddine, Gouareh Abderrahmane, Khamouli Adem, Saifi Nadia, Recioui Bakhta, et al. Modeling and forecasting energy consumption for residential buildings in Algeria using bottom-up approach. Energy Build 2016;121:309–17.

[4] Gao Bingtuan, Liu Xiaofeng, Zhu Zhenyu. A bottom-up model for household load profile based on the consumption behavior of residents. Energies 2018;11(8):2112.

[5] Pérez-Lombard Luis, Ortiz José, Pout Christine. A review on buildings energy consumption information. Energy Build 2008;40(3):394–8.

[6] Kelly Scott, Crawford-Brown Doug, Pollitt Michael G. Building performance evaluation and certification in the UK: Is SAP fit for purpose? Renew Sustain Energy Rev 2012;16(9):6861–78.

[7] Yang Liu, Yan Haiyan, Lam Joseph C. Thermal comfort and building energy consumption implications–A review. Appl Energy 2014;115:164–73.

[8] Hasanuzzaman M, Zubir Ummu Salamah, Ilham Nur Iqtiyani, Seng Che Hang. Global electricity demand, generation, grid system, and renewable energy polices: A review. Wiley Interdiscip Rev Energy Environ 2017;6(3):e222.

[9] Shewale Amit, Mokhade Anil, Funde Nitesh, Bokde Neeraj Dhanraj. An overview of demand response in smart grid and optimization techniques for efficient residential appliance scheduling problem. Energies 2020;13(16):4266.

[10] Capros Pantelis, Tasios Nikolaos, De Vita Alessia, Mantzos Leonidas, Paroussos Leonidas. Transformations of the energy system in the context of the decarbonisation of the EU economy in the time horizon to 2050. Energy Strategy Rev 2012;1(2):85–96.

[11] Zhou Kaile, Fu Chao, Yang Shanlin. Big data driven smart energy management: From big data to big insights. Renew Sustain Energy Rev 2016;56:215–25.

[12] Ma Weiwu, Fang Song, Liu Gang, Zhou Ruoyu. Modeling of district load forecasting for distributed energy system. Appl Energy 2017;204:181–205.

[13] Richardson Ian, Thomson Murray, Infield David, Clifford Conor. Domestic electricity use: A high-resolution energy demand model. Energy Build 2010;42(10):1878–87.

[14] Amin Amin, Kem Oudom, Gallegos Pablo, Chervet Philipp, Ksontini Feirouz, Mourshed Monjur. Demand response in buildings: Unlocking energy flexibility through district-level electro-thermal simulation. Appl Energy 2022;305:117836.

[15] Hassan Ahmed A, El-Rayes Khaled. Optimizing the integration of renewable energy in existing buildings. Appl Energy 2021;238:110851.

[16] Hassan Ahmed A, El-Rayes Khaled. Optimal use of renewable energy technologies during building schematic design phase. Appl Energy 2024;353:122006.

[17] Ihbal AM, Rajamani Haile S, Abd-Alhameed Raed A, Jalboub Mohamed K. Statistical predictions of electric load profiles in the UK domestic buildings. In: 2010 1st international conference on energy, power and control. IEEE; 2010, p. 345–50.

[18] Yao Runming, Steemers Koen. A method of formulating energy load profile for domestic buildings in the UK. Energy Build 2005;37(6):663–71.

[19] Kavousian Amir, Rajagopal Ram, Fischer Martin. Determinants of residential electricity consumption: Using smart meter data to examine the effect of climate, building characteristics, appliance stock, and occupants' behavior. Energy 2013;55:184–94.

[20] Wang Zhe, Zhao Zhen, Lin Borong, Zhu Yingxin, Ouyang Qin. Residential heating energy consumption modeling through a bottom-up approach for China's Hot Summer–Cold Winter climatic region. Energy Build 2015;109:65–74.

[21] De Fontaine Andre, Amin Amin, Gallegos Pablo, Kem Oudom, Ksontini Feirouz, Lennard Zia, et al. TABEDE: A new solution for demand response, clean energy & cost savings. In: CIRED 2021-the 26th international conference and exhibition on electricity distribution, vol. 2021. IET; 2021, p. 1889–93. http://dx.doi.org/10.1049/icp.2021.2037.

[22] Amin Amin, Kem Oudom, Gallegos Pablo, Chervet Philipp, Ksontini Feirouz, Mourshed Monjur. An intelligent infrastructure for enabling demand-response ready buildings. In: Proceedings of the 12th international conference on applied energy, vol. 11. 2020, http://dx.doi.org/10.46855/energy-proceedings-7291.

[23] Amin Amin, Mourshed Monjur. A bottom-up approach for district-level domestic energy demand forecasting. In: CIRED 2021-the 26th international conference and exhibition on electricity distribution, vol. 2021. IET; 2021, p. 2700–4. http://dx.doi.org/10.1049/icp.2021.1556.

[24] Zhongming Zhu, Wei Liu, et al. Sub-national electricity and gas consumption summary report 2020. London, UK: Department for Business, Energy and Industrial Strategy; 2021.

[25] International Energy Agency (IEA). World energy statistics and balances. IEA; 2021, URL https://www.iea.org/data-and-statistics/data-product/world-energy-statistics-and-balances.

[26] Department for Business, Energy and Industrial Strategy. National statistics-energy consumption in the UK 2021. London, UK: Department for Business, Energy and Industrial Strategy; 2021, URL https://www.gov.uk/government/statistics/energy-consumption-in-the-uk-2021.

[27] Department for Business, Energy and Industrial Strategy. Final UK greenhouse gas emissions national statistics: 1990 to 2020. London, UK: Department for Business, Energy and Industrial Strategy; 2020, URL https://www.gov.uk/government/statistics/final-uk-greenhouse-gas-emissions-national-statistics-1990-to-2020.

[28] Department for Energy Security and Net Zero and Department for Business, Energy and Industrial Strategy. Historical electricity data: 1920 to 2020. London, UK: The Digest of United Kingdom Energy Statistics (DUKES); 2021, URL https://www.gov.uk/government/statistical-data-sets/historical-electricity-data.

[29] Zhongming Zhu, Wei Liu, et al. Sub-national electricity and gas consumption summary report 2019. London, UK: Department for Business, Energy and Industrial Strategy; 2020.

[30] Jones Rory V, Lomas Kevin J. Determinants of high electrical energy demand in UK homes: Appliance ownership and use. Energy Build 2016;117:71–82.

[31] Bansal Pradeep, Vineyard Edward, Abdelaziz Omar. Advances in household appliances-A review. Appl Therm Eng 2011;31(17–18):3748–60.

[32] Building Research Establishment (BRE). Energy follow up survey: Household energy consumption and affordability report. London, UK: Department for Business, Energy and Industrial Strategy; 2021.

[33] Jones Rory V, Lomas Kevin J. Determinants of high electrical energy demand in UK homes: Socio-economic and dwelling characteristics. Energy Build 2015;101:24–34.

[34] Yohanis Yigzaw G, Mondol Jayanta D, Wright Alan, Norton Brian. Real-life energy use in the UK: How occupancy and dwelling characteristics affect domestic electricity use. Energy Build 2008;40(6):1053–9.

[35] Polly Ben, Kutscher Chuck, Macumber Dan, Schott Marjorie, Pless Shanti, Livingood Bill, et al. From zero energy buildings to zero energy districts. In: Proceedings of the 2016 American council for an energy efficient economy summer study on energy efficiency in buildings. 2016, p. 21–6.

[36] Kavgic Miroslava, Mavrogianni Anna, Mumovic Dejan, Summerfield Alex, Stevanovic Zarko, Djurovic-Petrovic Maja. A review of bottom-up building stock models for energy consumption in the residential sector. Build Environ 2010;45(7):1683–97.

[37] Cheng Vicky, Steemers Koen. Modelling domestic energy consumption at district scale: A tool to support national and local energy policies. Environ Model Softw 2011;26(10):1186–98.

[38] Diao Longquan, Sun Yongjun, Chen Zejun, Chen Jiayu. Modeling energy consumption in residential buildings: A bottom-up analysis based on occupant behavior pattern clustering and stochastic simulation. Energy Build 2017;147:47–66.

[39] Ayodele TR, Ogunjuyigbe ASO, Atiba IA. Assessment of the impact of information feedback of prepaid meter on energy consumption of city residential buildings using bottom-up load modeling approach. Sustain Cities Soc 2017;30:171–83.

[40] Li Zhengwei, Quan Steven J, Yang Perry Pei-Ju. Energy performance simulation for planning a low carbon neighborhood urban district: A case study in the city of Macau. Habilit Int 2016;53:206–14.

[41] Caputo Paola, Costa Gaia, Ferrari Simone. A supporting method for defining energy strategies in the building sector at urban scale. Energy Policy 2013;55:261–70.

[42] Ferrari Simone, Zagarella Federica, Caputo Paola, D'Amico Antonino. Results of a literature review on methods for estimating buildings energy demand at district level. Energy 2019;175:1130–7.

[43] Tsagarakis George, Collin Adam J, Kiprakis Aristides E. Modelling the electrical loads of UK residential energy users. In: 2012 47th international universities power engineering conference. IEEE; 2012, p. 1–6.

[44] Anderson Ben. Laundry, energy and time: Insights from 20 years of time-use diary data in the United Kingdom. Energy Res Soc Sci 2016;22:125–36.

[45] Yamaguchi Y, Yilmaz Selin, Prakash N, Firth SK, Shimoda Y. A cross analysis of existing methods for modelling household appliance use. J Build Perform Simul 2019;12(2):160–79.

[46] Dunbabin Penny, Palmer Jason, Terry Nicola. Electricity use by domestic appliances in English households. In: ECEEE-2015 European council for an energy efficient economy. 2015, p. 1439–50.

[47] Richardson Ian, Thomson Murray, Infield David, Delahunty Alice. Domestic lighting: A high-resolution energy demand model. Energy Build 2009;41(7):781–9.

[48] Paatero Jukka V, Lund Peter D. A model for generating household electricity load profiles. Int J Energy Res 2006;30(5):273–90.

[49] Nutkiewicz Alex, Yang Zheng, Jain Rishee K. Data-driven urban energy simulation (DUE-S): A framework for integrating engineering simulation and machine learning methods in a multi-scale urban energy modeling workflow. Appl Energy 2018;225:1176–89.

[50] Yang L, Lam JC, Liu J, Tsang CL. Building energy simulation using multi-years and typical meteorological years in different climates. Energy Convers Manage 2008;49(1):113–24. http://dx.doi.org/10.1016/j.enconman.2007.05.004.

[51] Lindberg R, Binamu A, Teikari M. Five-year data of measured weather, energy consumption, and time-dependent temperature variations within different exterior wall structures. Energy Build 2004;36(6):495–501.

[52] Glasgo Brock, Hendrickson Chris, Azevedo Inês Lima. Assessing the value of information in residential building simulation: Comparing simulated and actual building loads at the circuit level. Appl Energy 2017;203:348–63.

[53] Oldewurtel Frauke, Parisio Alessandra, Jones Colin N, Gyalistras Dimitrios, Gwerder Markus, Stauch Vanessa, et al. Use of model predictive control and weather forecasts for energy efficient building climate control. Energy Build 2012;45:15–27.

[54] Oldewurtel Frauke, Sturzenegger David, Morari Manfred. Importance of occupancy information for building climate control. Appl Energy 2013;101:521–32.

[55] Serale Gianluca, Fiorentini Massimo, Capozzoli Alfonso, Bernardini Daniele, Bemporad Alberto. Model predictive control (MPC) for enhancing building and HVAC system energy efficiency: Problem formulation, applications and opportunities. Energies 2018;11(3):631.

[56] Uddin Mohammad Nyme, Wei Hsi-Hsien, Chi Hung Lin, Ni Meng. Influence of occupant behavior for building energy conservation: A systematic review study of diverse modeling and simulation approach. Buildings 2021;11(1):41.

[57] Chen Shuqin, Yang Weiwei, Yoshino Hiroshi, Levine Mark D, Newhouse Katy, Hinge Adam. Definition of occupant behavior in residential buildings and its application to behavior analysis in case studies. Energy Build 2015;104:1–13.

[58] Watson Bob. Employment in the UK: Estimates of employment, unemployment and economic inactivity for the UK. London, UK: Office for National Statistics (ONS); 2022, URL https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/bulletins/employmentintheuk/may2022.

[59] Aragon Victoria, Gauthier Stephanie, Warren Peter, James Patrick AB, Anderson Ben. Developing English domestic occupancy profiles. Build Res Inf 2019;47(4):375–93.

[60] Doma Aya, Ouf Mohamed. Modelling occupant behaviour for urban scale simulation: Review of available approaches and tools. In: Build Simul. Springer; 2022, p. 1–16.

[61] Gilani Sara, O'Brien William, Gunay H Burak. Simulating occupants' impact on building energy performance at different spatial scales. Build Environ 2018;132:327–37.

[62] Ministry of Housing, Communities & Local Government. English housing survey: Energy report 2019-20. Ministry of Housing, Communities and Local Government; 2019.

[63] Building Research Establishment (BRE). Energy follow up survey: Lights, appliances, and smart technologies. London, UK: Department for Business, Energy and Industrial Strategy; 2021.

[64] Statista GmbH. Household appliances ownership in the UK 2020. 2020, URL https://www.statista.com/forecasts/997843/household-appliances-ownership-in-the-uk.

[65] Zimmermann Jean-Paul, Evans Matt, Griggs Jonathan, King Nicola, Harding Les, Roberts Penelope, et al. Household Electricity Survey: A study of domestic electrical product usage. Intertek Testing & Certification Ltd; 2012, p. 213–4. http://dx.doi.org/10.5255/UKDA-SN-7874-1.

[66] Pothitou Mary, Hanna Richard F, Chalvatzis Konstantinos J. ICT entertainment appliances' impact on domestic electricity consumption. Renew Sustain Energy Rev 2017;69:843–53.

[67] Grahn Pia, Munkhammar Joakim, Widén Joakim, Alvehag Karin, Söder Lennart. PHEV home-charging model based on residential activity patterns. IEEE Trans Power Syst 2013;28(3):2507–15.

[68] Allegrini Jonas, Orehounig Kristina, Mavromatidis Georgios, Ruesch Florian, Dorer Viktor, Evins Ralph. A review of modelling approaches and tools for the simulation of district-scale energy systems. Renew Sustain Energy Rev 2015;52:1391–404.

[69] Ouyang Jinlong, Hokao Kazunori. Energy-saving potential by improving occupants' behavior in urban residential sector in Hangzhou City, China. Energy Build 2009;41(7):711–20.

[70] Henderson J, Hart J. BREDEM 2012 - A technical description of the BRE domestic energy model. UK: Building Research Establishment; 2012.

[71] Building Research Establishment (BRE). Energy follow up survey: Heating patterns and occupancy. London, UK: Department for Business, Energy and Industrial Strategy; 2021.

[72] Lamote de Grignon Pérez Juana, Gershuny Jonathan, Foster Russell, De Vos Maarten. Sleep differences in the UK between 1974 and 2015: Insights from detailed time diaries. J Sleep Res 2019;28(1):e12753.

[73] Gershuny Jonathan. United Kingdom time use survey, 2014-2015. University of Oxford; 2017.

[74] Hulme J, Beaumont A, Summers C. Energy follow-up survey 2011. Report 9: Domestic appliances, cooking & cooling equipment, vol. 13. UK: Watford; 2013.

[75] Buttitta Giuseppina, Turner William JN, Neu Olivier, Finn Donal P. Development of occupancy-integrated archetypes: Use of data mining clustering techniques to embed occupant behaviour profiles in archetypes. Energy Build 2019;198:84–99.

[76] Energy saving trust. At home with water. London, UK: Department for Environment, Food and Rural Affairs; 2015.

[77] Deru Michael, Field Kristin, Studer Daniel, Benne Kyle, Griffith Brent, Torcellini Paul, et al. US Department of Energy commercial reference building models of the national building stock. National Renewable Energy Laboratory; 2011.

[78] Bhandari Mahabir, Shrestha Som, New Joshua. Evaluation of weather datasets for building energy simulation. Energy Build 2012;49:109–18.

[79] Ciancio Virgilio, Falasca Serena, Golasi Iacopo, Curci Gabriele, Coppi Massimo, Salata Ferdinando. Influence of input climatic data on simulations of annual energy needs of a building: Energyplus and WRF modeling for a case study in Rome (Italy). Energies 2018;11(10):2835.

[80] Hong Tianzhen, Chang Wen-Kuei, Lin Hung-Wen. A fresh look at weather impact on peak electricity demand and energy use of buildings using 30-year actual weather data. Appl Energy 2013;111:333–50.

[81] Welsh Government. The building regulations 2010, Conservation of fuel and power: Approved document part L-2014 L1A-New Dwelling. Welsh Government Cardiff; 2016.

[82] StatsWales. Household estimates for Wales - Households by type by local authority. 2019, URL http://open.statswales.gov.wales/dataset/hous0206.

[83] StatsWales. Annual population survey / local labour force survey: Summary of economic activity - employment rate by Welsh local area and year. 2021, URL http://open.statswales.gov.wales/dataset/econ0006.

[84] The Society of Light and Lighting (part of CIBSE). Lighting Guide 09: Lighting for communal residential buildings. Norwich: Page Bros.; 2013.

[85] Gumarov Amir. How much electricity does a gas boiler consume? 2019, buildex.techinfus.

[86] The Chartered Institution of Building Services Engineers (CIBSE). CIBSE guide a: Environmental design. London, UK; 2018.

[87] Met Office. Met Office MIDAS open: UK land surface stations data (1853-Current). Centre for Environmental Data Analysis; 2019.

[88] Ruiz Germán Ramos, Bandera Carlos Fernández. Validation of calibrated energy models: Common errors. Energies 2017;10(10):1587.

[89] Chakraborty Debaditya, Elzarka Hazem. Performance testing of energy models: Are we using the right statistical metrics? J Build Perform Simul 2018;11(4):433–48.

[90] American Society of Heating, Refrigerating and Air Conditioning Engineers. ASHRAE guideline 14-2014: Measurement of energy, demand and water savings. ASHRAE guideline, American Society of Heating, Refrigerating, and Air-Conditioning Engineers; 2014.

[91] Webster L, Bradford J, Sartor D, Shonder J, Atkin E, Dunnivant S, et al. M&v guidelines: measurement and verification for performance-based contracts. US Department of Energy; 2015.

[92] Cowan John. International performance measurement and verification protocol: Concepts and Options for Determining Energy and Water Savings-Vol. I. Int Perform Meas Verif Protoc 2002;1.

[93] Robertson J, Polly B, Collis J. Evaluation of automated model calibration techniques for residential building energy simulation. United States: National Renewable Energy Lab (NREL); 2013, http://dx.doi.org/10.2172/1096687.

[94] Zhang Yuna, O'Neill Zheng, Dong Bing, Augenbroe Godfried. Comparisons of inverse modeling approaches for predicting building energy performance. Build Environ 2015;86:177–90.

[95] OneBuilding, Climate. Repository of free climate data for building performance simulation: from the creators of the EPW. 2022.