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# Time-Use Data Modelling of Domestic, Commercial and Industrial Electricity Demand for the Scottish Islands

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**Abstract:** Achieving emissions reduction targets requires improved energy efficiency to avoid an oversized and excessively expensive electricity network. This can be analysed using hourly demand modelling that captures behaviour profiles, technology types, weather factors and building typologies. Numerous domestic models exist, but whole systems energy modelling, including commercial and industrial demand, are limited by data availability. Time-use survey data has typically been used to model domestic demand- in this work is expanded to also model commercial and industrial electricity-heating for the Scottish islands at an hourly and individual building level. This method is widely applicable for modelling whole system energy demand wherever time-use survey data are available. Combinatorial optimisation has been applied to generate a synthetic population, match individuals to properties and apply construction types to building polygons. SimStock is used for heating and lighting modelling. Validation of the model with 2016 data shows that it reflects longer term trends, with a monthly mean absolute percentage error (MAPE) of 1.6% and an $R^2$ of 0.99. At the hourly level, the MAPE of 6.2% and $R^2$ of 0.87 show the model captures variability needed to combine it with a supply-side model. Dataset accuracy, variability in the date recorded, missing data and unknown data correlations are discussed as causes for error. The model can be adapted for other regions and used to analyse the costs and benefits of energy efficiency measures with a supply-side generation model.

**Keywords:** electricity demand modelling; Scottish Islands; hourly demand; time-use data; demand forecasting; domestic; commercial and industrial



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## 1. Introduction

Reducing emissions to meet the goal of net zero by 2045 in Scotland [1] will require significant change in all sectors. As demand is further electrified to displace fossil fuels, to avoid excessive costs from additional generation, storage or $CO_2$ extraction, reduction of energy demand across all sectors can play a key role. Without reduction from current demand levels, the potential 2050 net zero electricity system for the UK would need to be four times larger and prohibitively expensive [2]. Buildings can achieve zero carbon performance by improving efficiencies, eliminating fossil fuel use for heating, on-site and/or off-site renewable energy and implementation of low-carbon technologies. To compare potential costs and benefits of demand-side energy policies, quantitative, whole-systems energy models are needed. Considering demand-side policy implications alongside intermittent renewable generation and grid constraints requires a high-temporal and spatial-resolution model, but this can be limited by data availability.

Where data are available, models have increasingly considered both domestic and nondomestic sectors to cover whole system demand. At an annual scale, the Centre for Research into Energy Demand Solutions developed a scenarios-based demand reduction model for the whole UK energy system, combining bottom-up scenarios by sector with top-down cost optimisation using the UK TIMES model (codeveloped with the UK's energy ministry). Whilst this considered peak demand for energy system sizing, it noted that analysis could be improved with an hourly model, which would better capture interactions with short-term weather patterns [2]. Using building archetypes is commonly used to simplify higher-resolution demand models, with greater data availability and homogeneity of buildings [3]. This population sampling can, however, leave models prone to sampling bias, which can be minimised with 100% sample models [4]. The Dynamic Energy Agents Model (DEAM) does this by considering activity patterns and weather to account for hourly demand in services, residential, transportation and industrial sectors for the UK at a distribution network level. It uses standardised behaviour profiles but notes the limitations of nondomestic data availability [5]. Using the 3D Stock modelling framework, a database of the London building stock has been generated (particularly considering complex, mixed-used properties), with the "100% sample" eliminating sampling biases. Heating demand is modelled with standardised occupancy profiles using the SimStock framework, which generates an EnergyPlus (EP) [6] input file to calculate heating demand [7]. At higher temporal resolutions, however, using standardised, one-size-fits-all assumptions about occupant behaviour has been shown to match up poorly with recorded data [8,9]. An hourly bottom-up domestic and top-down nondomestic demand model for the 14 West African Power Pool countries highlighted the lack of country-specific occupancy profiles as challenging for developing countries [10]. For the models described that consider domestic and nondomestic demand, modelling at a higher temporal resolution would be improved with more specific behavioural data.

Time-use data provide a method of capturing both the demographic characteristics of a population and high temporal-resolution energy profiles without specific data collection. Recorded actions of a participant's day, usually at a resolution of 10 minutes [11], has been used to construct electricity demand and property occupancy profiles for modelling in Japan, Sweden, Italy, Ireland, France and Spain [12]. Combined with a synthetic population developed to match census distributions, the most relevant behaviour and energy profiles can be selected to match the demand of the actual population [13]. Despite this data capturing the actions and location of individuals throughout their day (not just at home but also at work, shopping, travelling, and so on), its application has focused on domestic energy modelling. No nondomestic or combined demand models using time-use data were identified in the literature.

Capturing the factors most influencing demand at the relevant spatial and temporal resolutions is crucial in energy modelling, particularly in sampling from a population of time-use profiles. Analysis of annual household energy demand has shown building factors can explain 39%, sociodemographic variables 24% and heating behaviour 14% of variability [14]. Household size and income are the demographic factors generally found to be most influential on annual demand [14–16], but at an hourly resolution, household composition and employment status have a more pronounced effect, influencing whether individuals are away from home at work or school [17]. These aspects and their influence on behaviour or energy demand are captured by time-use data with the UK survey containing 604 individual and 335 household demographic variables [11]. Heating behaviours recorded in UK households compared with the Building Research Establishment Domestic Energy Model heating model have shown that modelled assumptions tend to overestimate both heating hours and temperature, as well as poorly matching the temporal distribution [8]. Time-use data, demographic data and other recorded heating-demand profiles can therefore capture the factors driving demand and model domestic and commercial demand at an hourly, 100% sample resolution.

## 2. Methodology

This research focused on the development of an hourly electricity-demand model, considering 100% of the population, business and building stock. The contribution of the work is to demonstrate that nondomestic demand modelling can use time-use survey data, which are readily available in many jurisdictions, thereby improving data availability issues noted by other models.

The population and electricity modelling (Figure 1) used the demographic characteristics identified to generate a synthetic population of households from time-use survey energy profiles, combined to give domestic demand [13]. Business demographics, opening hours and the synthetic population occupancy profiles were combined with energy floor space factors to generate commercial electricity profiles. Building construction types, weather data, heating behaviour, and occupancy profiles from the synthetic population were used as inputs to SimStock [18], which generates and runs the heating and lighting demand using EP [6]. Heating and lighting combined with appliance electricity demand gives the demand for each property, which can then be combined at various spatial resolutions to validate the model. A complete summary of the databases used is given in Appendix A—all datasets are available freely under academic license unless stated otherwise.

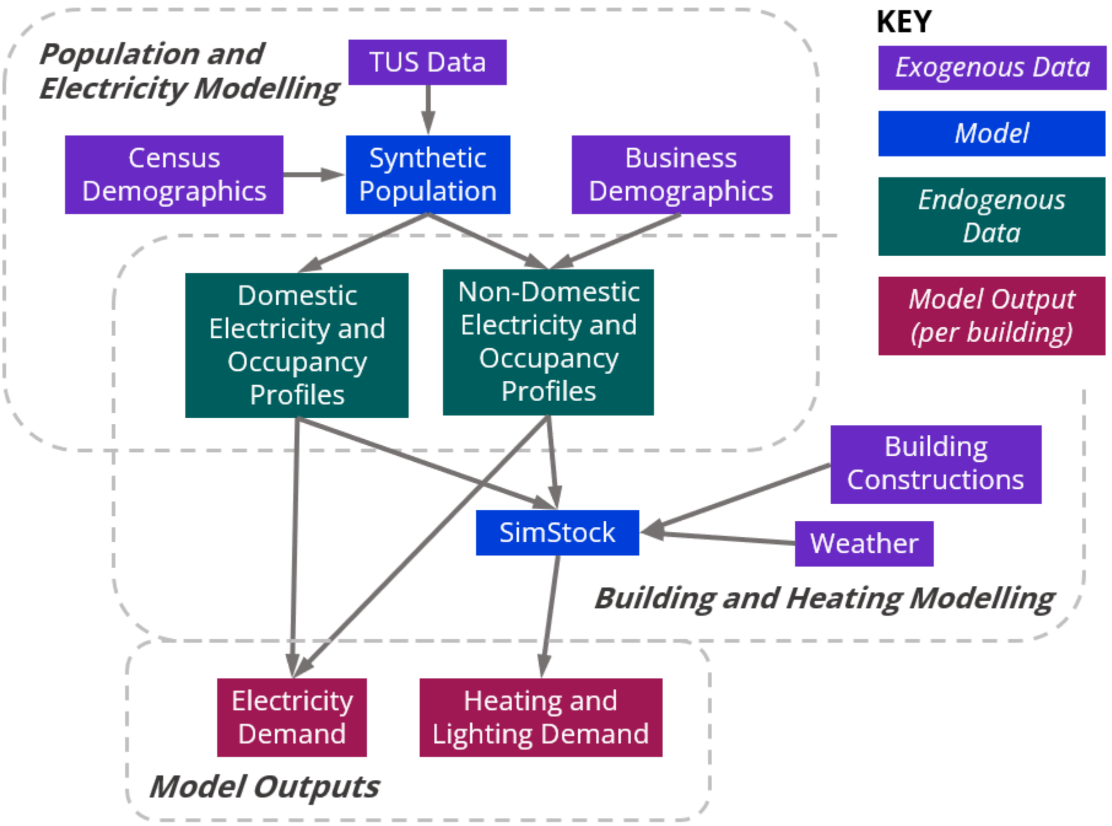


**Figure 1.** High-level flow chart of the modelling process.

Time-use survey data combined with census data were used for both sectors to model the behaviour and demographic factors, which have been shown to be a major driver of demand. The model captures these aspects to match the actual population, through including household size, age, employment status and deprivation indicators, as well as business types and opening hours. To model heating and lighting, building characteristics including building polygons, constructions, heating system types, weather data and occupancy profiles will be used. As standardised occupancy and activity profiles have been shown to match poorly with recorded data, profiles matched to the specific business or population demographic characteristics are used. Previously, time-use data has only been used for domestic demand models, but this study will use them to generate specific profiles for both domestic and commercial demand, with industrial considered separately. The model was validated with distribution network electricity demand data for the year

2016 [19], so it was crucial to capture every aspect of electricity demand to match the recorded system demand.

The model was developed for the Scottish islands. Currently, 76% of the domestic building stock is rated Energy Performance Certificate (EPC) D or lower [20] which, combined with high fuel prices due to lack of a gas network, drives islanders to experience some of the worst fuel poverty in the UK [21]. A secure, reliable and resilient energy system is important to enable Scotland's islands to preserve and develop economically, in which demand efficiency improvements can play an important role. Connecting additional generation to meet demand would require grid investment, which can be minimised by reducing demand.

The model was developed for the 56 inhabited Scottish islands, over the six local authorities (Figure 2). Three-quarters of the islands have populations of less than a thousand—which is approximately the lower limit for lower super output areas in the census [22]. This greater spatial and demographic specificity makes them useful to test the applicability of using a synthetic population and time-use data to model energy demand. The islands also have a very low urban density, minimising urban heat island and shading effects identified as complicating factors in modelling energy demand in cities [23]. On several islands, there is already a high degree of heating electrification—60% of properties in Orkney and Shetland [20,24]. As only hourly electricity demand data were available, this improves validation of the heating model. Grid constraints were also an issue on several islands due to renewable capacity above the limits of the local network, which can be captured by the individual building resolution of the model.

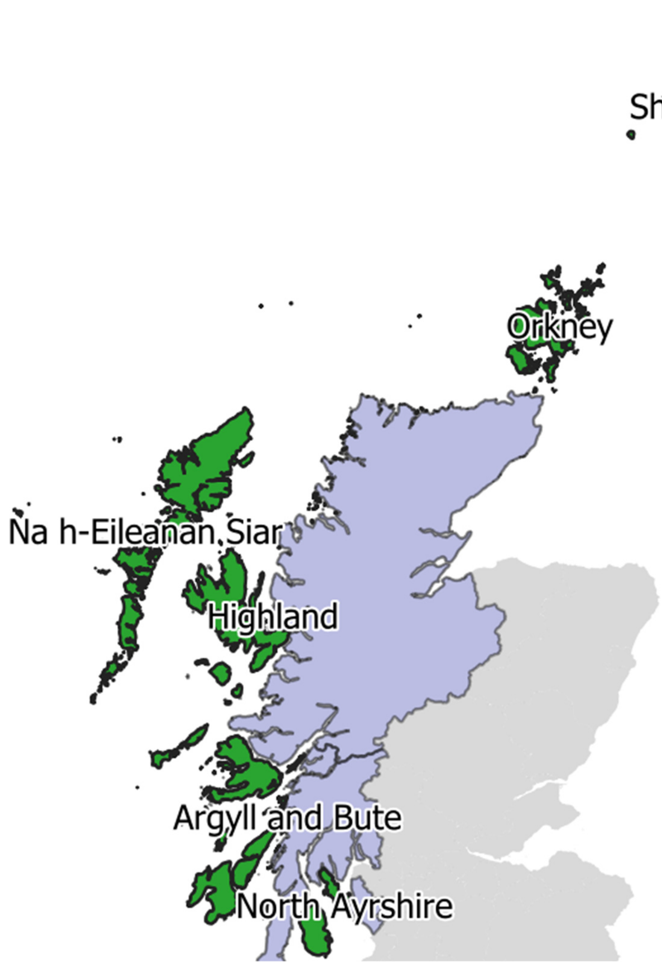


**Figure 2.** Modelled islands shown in green, with the six local authorities labelled and shown in blue where they are also on the mainland.

The model was run using a laptop (2.60 GHz Intel i7-9850H CPU and 16 GB RAM) and took approximately one day to run for the electricity and heating demand for 58,513 domestic and nondomestic buildings.

### 2.1. Domestic Demand Modelling

A detailed flow chart of the domestic model with reference to specific methods and datasets is shown in Figure 3. Combinatorial optimisation, a method used to generate small area microdata [25], was used to sample from populations and match known statistical distributions of data. The domestic method consists of five main steps:

1. Time-use data were combined with a survey of appliance electricity demand to generate a database of hourly, categorical household electricity demand profiles.
2. A synthetic population statistically representative of key census characteristics was generated (also used in the commercial model), which was used to select matching households from the household database. These first two steps are based on the method of [13].
3. The synthetic population was matched with relevant properties, to give household occupancy profiles.
4. Building constructions, heating behaviour, occupancy profiles, appliance electricity demand and weather were used as inputs to SimStock.
5. Appliance, lighting and heating demand were combined at various spatial resolutions to validate the model.

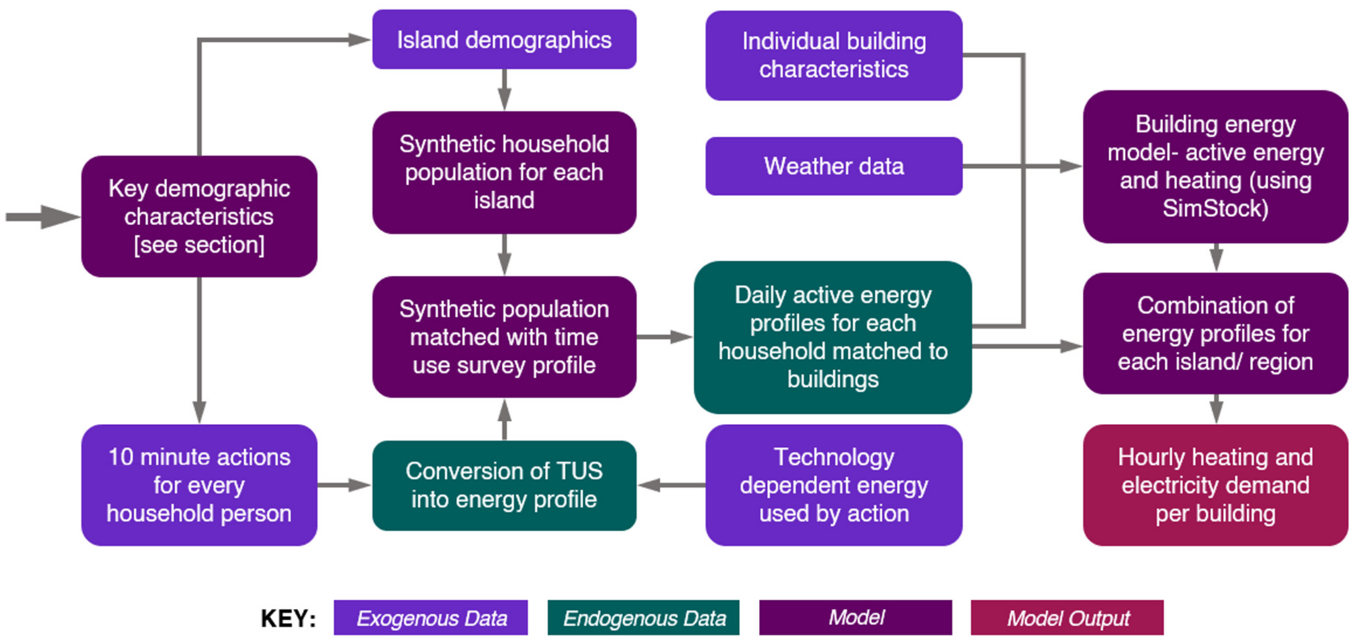


**Figure 3.** Flowchart of the domestic energy model.

#### 2.1.1. Household Electricity Profiles from Time-use Data

The time-use data detailed the daily actions and locations of 11,421 respondents at 10 min intervals [11]. Each individual action was then categorised by its electricity usage, with individual actions combined into household profiles using the algorithm described in [13] to ensure shared household appliances (washing machines, dishwashers, etc.) were only used in proportion to the household ownership detailed in the time-use demographic data. Household actions were combined with surveyed annual consumption of major household appliances [17] to give hourly electricity demand profiles categorised as per Table 1. Hot water demand was assigned to TUS actions using annual totals from a separate survey specifically measuring hot water demand [26].

**Table 1.** Domestic energy categories.

| Appliances | Laundry | Cold Appliances |
|---|---|---|
| **Electrical cooking** | Dishwashing | Lighting [1] |
| **Fuel-dependent cooking [2]** | Standby | Hot water [3] |

[1] Hourly lighting demand was calculated by EP (Section 2.3.4); [2] Inclusion with electricity demand is dependent on the main heating fuel used by the household (Section 2.3.2); [3] For households with immersion water heating, the demand was adjusted to occur overnight (00:00–07:00).

#### 2.1.2. Synthetic Population from Census Data

As household demographic data influence energy demand, census demographic data were used to select specific time-use electricity profiles. Combinatorial optimisation was used to create a synthetic population statistically representative of the islands demographics [25]. Households composed of individuals were sampled from the time-use data to make an initial population. Repeated replacement of households was then scored against statistics from census data [22]. If the new choice improved the score, the household was kept; if not, it was discarded. The process was repeated until a threshold score, resulting in a population of time-use households with categorical electricity demand profiles whose demographic characteristics matched the recorded census demographic data for each island. Household characteristics of the number of rooms per person and type of accommodation were used to match the population to relevant properties in the building database.

Demographic characteristics from the census which the population was sampled from are given in Table 2—references indicate research demonstrating the influence of the factor on energy demand. Each characteristic was mapped directly between the census and time-use demographic data apart from the deprivation indicators. Deprivation indicators of employment status, receiving benefits, crowdedness, long-term health conditions, and education status were considered according to published guidance [27]. Initially, households were selected based on a greater number of characteristics, such as industry of business, occupation and distance travelled to work. This, however, resulted in the population being overfitted to a smaller number of time-use individuals, leading to a much worse fit with the actual demand data.

**Table 2.** Census demographic characteristics sampled from.

| | Demographic Characteristic | Categories |
|---|---|---|
| **Individual** | Age [28,29] | <18; 19–64: >64 |
| | Hours worked per week [1] | <15; 16–30; 31–48; >48; N/A |
| **Household** | Size of household [28,29] | 1; 2; 3; 4; 5; 6; >7 |
| | Number of persons per room [28,30] | < 0.5; 0.5–1.0; 1.0–1.5; >1.5 |
| | Number of deprivation indicators [15,29,30] | 0; 1; 2; >3 |
| | Type of accommodation [14,31] | Detached; semidetached; terrace; flat/maisonette/other |

[1] Hours worked per week were chosen to assign individuals to places of work (see Section 2.2), not for influence on energy demand.

#### 2.1.3. Modelling Seasonal Tourism Population Changes

Seasonal changes in the population through tourism were anticipated to have an impact on domestic demand, particularly for islands with smaller populations. Monthly passenger statistics from the West coast ferry operator [32], Northern ferry operator [33], and Civil Aviation Authority for airports [34] were combined to estimate the total number of monthly visitors. This was combined with visitor surveys for the local authorities of Orkney [35], Shetland [36] and Na h-Eileanan Siar [37], which provided breakdowns of the proportion of passengers local to the islands and the proportion of tourists who would be staying in nonenergy-using accommodations such as camp sites. To account for this change in population, random households were duplicated in the synthetic population to match the population as it varied with visitor numbers.

### 2.2. Nondomestic Demand Modelling

The nondomestic sector model (Figure 4) was similarly structured around developing electricity demand profiles matched to properties for which heating and lighting demand was modelling using SimStock. The synthetic population developed for the domestic model could be reutilised for occupancy profiles, improving on the standardised occupancy profiles assumed in other models. Industrial demand was similarly modelled, but due to a lack of categorical demand data, the process was simplified as described in Section 2.2.3. The main steps of the commercial model consisted of:

1. Synthetic-population individuals were assigned to a database of commercial properties, matched by opening hours and time spent at work using combinatorial optimisation.
2. Business demographic data, the synthetic population and floor space energy factors were combined to generate electricity demand profiles for each business.
3. Heating and lighting demands were modelled using SimStock.
4. Profiles were combined at a range spatial resolutions to validate the model.

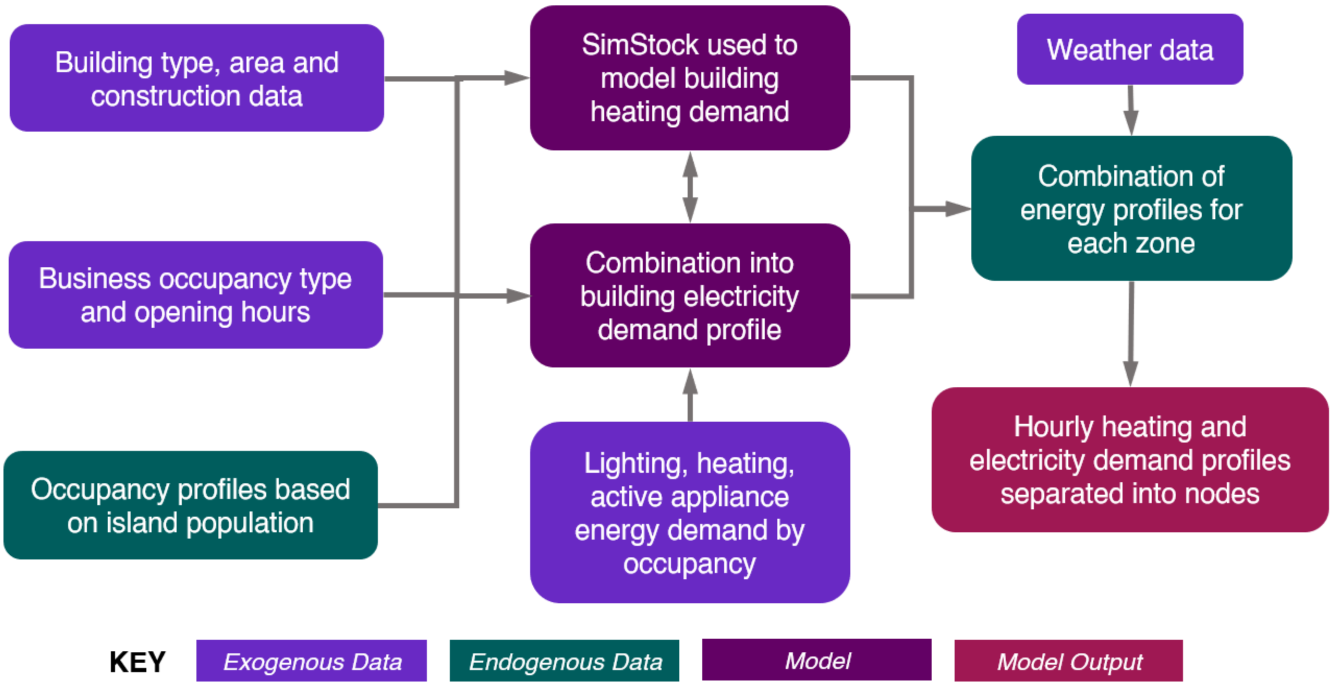


**Figure 4.** Flowchart of the commercial energy demand model.

#### 2.2.1. Business Occupancy Data

Open Street Map (OSM) [38] was used for business demographic data. To assign occupancy profiles to categories of the Building Energy Efficiency Survey (BEES), the 51 OSM were mapped to those in Appendix B. Occupancy-specific opening hours from the Google Places API [39] were sampled based on the occupancy type and assigned to the building database (see Section 2.3).

This database of businesses and sampled opening hours was then matched with individuals from the synthetic population. The time-use data include location, so the time synthetic-population individuals spent at work was scored against the opening hours of the property. Synthetic population individuals were randomly assigned to commercial occupancies, which, using employee density estimates [40], were given maximum occupancies to ensure employees were fairly distributed. Each person's working hours was then scored against the hours of the property. Employees were then randomly swapped and then scored; an improved score would keep the match, which was otherwise discarded. This process was repeated until a score of 1 was reached as per the synthetic-population methodology of [25]. Combining the synthetic-population occupancy profiles with business opening hours allows for accurate representation of commercial occupancy, profiles which are not readily available in the literature. Using the same synthetic population as the domestic model ensured that individuals and their actions were not duplicated between the domestic and commercial models, which could happen if unconnected or standardised profiles were used.

#### 2.2.2. Synthetic Population and Hourly Energy Profiles

To convert the opening hours and occupancy types into hourly energy profiles, floor space energy factors by occupancy type were used from BEES [41]. Annual energy per floor area (kWh/m$^2$) was grouped then categorised as baseload (refrigeration, HVAC or other—insufficient data on HVAC/other was available so it was considered baseload) or occupant related (appliances and catering) as per [42]. Floor areas were used from polygon in the UKBuildings and OSM databases (see Section 2.3.1).

Baseload categories were considered to occur throughout the year, given the power demand (W) in Equation (1), where $E_{annual}$ is the annual demand per area (kWh/m$^2$) from BEES and $A$ is the property area (m$^2$).

$$Baseload\ Power = \frac{E_{annual} \times A}{8760} \tag{1}$$

To model occupancy-based demand, the hourly business occupancy profile from Section 2.2.1 was used. The annual energy occurred over the total of these hours over the year. Over the hours (h) of a day, the occupancy profile ($f_{occ}(h)$) varied from 0 (empty) to 1 (full). The total number of synthetic-population individuals assigned to a property were used as a proportion of the maximum occupancy given by floor space factors [40], to give a fraction of the estimated BEES energy. The energy could then be described by Equation (2), which, solving for the peak energy, gave the occupancy-based energy profile for each occupancy. To consider variation through the week, this was performed for the seven days of the week for which opening hours were available.

$$E_{annual} = \int_0^{8760} \dot{E}_{peak} \times f_{occ}(h) \tag{2}$$

#### 2.2.3. Industrial Electricity Demand

Whisky distilling, fish processing and farming were known to have a significant energy demand in the Scottish islands [43] but specific annual energy density factors were not included in the BEES dataset. To account for these, annual demand was estimated based on production data summarised in Appendix B. Production values for the 27 island distilleries were used to apportion demand to the UKBuildings properties corresponding to each facility. Specific demand was not known for each farm or fish-processing facility, so the totals in Appendix B were used to create an annual energy density (kWh/m$^2$) value applied to each property. For fish processing, the energy was assumed to occur over the opening hours available for each property as per the BEES occupancy methodology. For distilling, detailed information of the temporal specificity of the demand was not available, so it was assumed that the electricity demand occurred continuously with a break over the summer months for facility downtime. Farming demand was modelled according to measured seasonal variability [44]. Historic demand for water treatment was included directly from Scottish Water through a freedom of information request [45].

2.2.4. Seasonality by Energy Type

Recorded energy demand showed the energy consumption varied throughout the year for heating/cooling appliances [17]. This was approximated to a linear relationship between the temperature and energy proportion (Figure 5). When combining the domestic and nondomestic profiles, appliance energy demand adjusted using this relationship and the local daily average temperature. The seasonality of heating and lighting was independently calculated by EP.

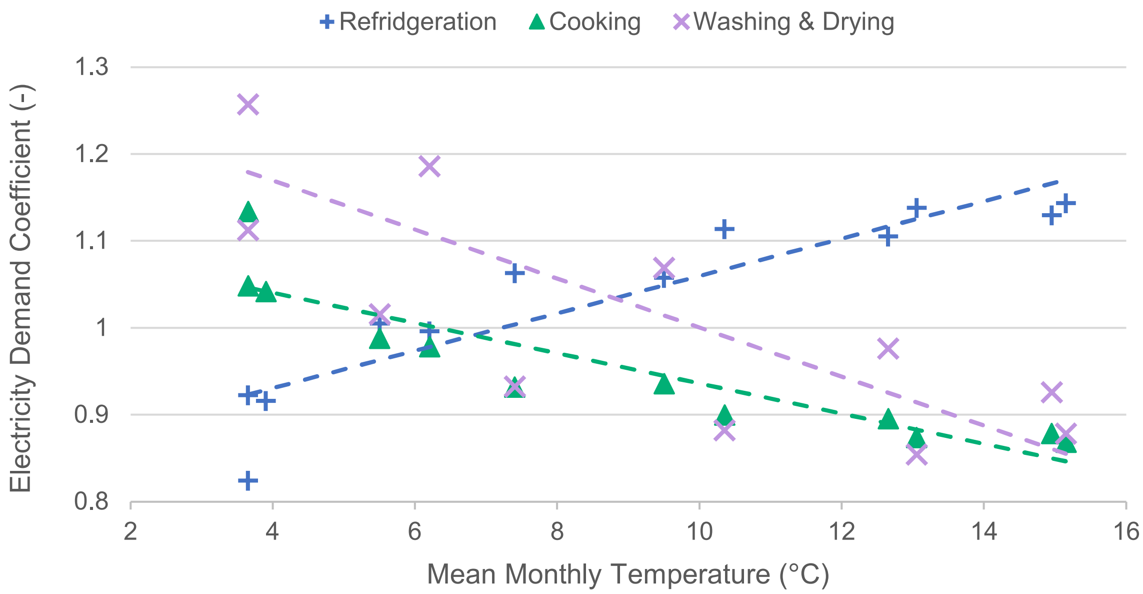


**Figure 5.** Extrapolated variation in energy demand extracted from the monthly curves.

### *2.3. Lighting and Heating Modelling*

Lighting and heating demand was calculated using SimStock [18] with inputs collated from a variety of sources. The basis of this was the UKBuildings [46] and OSM [38] for the Scottish islands, which contain building polygons and selected other building characteristics such as building type. Further data cleaning was needed to combine the two, separate polygon databases into unique property reference numbers (UPRNs) and identify building types. Known statistical distributions of building characteristics were then assigned to the buildings database using combinatorial optimisation. This included building construction databases, occupancy profiles (derived from the time-use data), heating behaviours and weather data. The SimStock framework [18], developed at UCL, takes this information in a tabular form and converts each building (divided into properties for semidetached or share properties) into a model for EP [6], which calculates the hourly heating and lighting demand. The process is shown in Figure 6. Calculating the hourly heating and lighting demand for the 21,775 electrically heated buildings in the Scottish islands took slightly less than a day to run.

2.3.1. Building Polygons

Building polygons were combined from the UKBuildings [46] and OSM [38] databases, which also needed to apply a cleaning process. Large buildings (>1000 m$^2$) labelled as domestic in the UKB database were checked and farming sheds were removed. It was found that while the OSM did not have as good a geographical coverage as the UKBuildings dataset, certain shared buildings (such as terraced houses or shopping streets) were divided more clearly into individual properties/UPRNs rather than whole building outlines. Where there were multiple OSM polygons for a single UKBuildings structure, the OSM superseded. This combined buildings database was then mapped with UPRNs for the islands [47]. Where building polygons contained UPRNs, they were assigned to that property, but in many cases, there were still multiple UPRNs assigned to a single polygon. Having the correct number and size of polygons was needed to assign each synthetic household and business to an appropriate property.

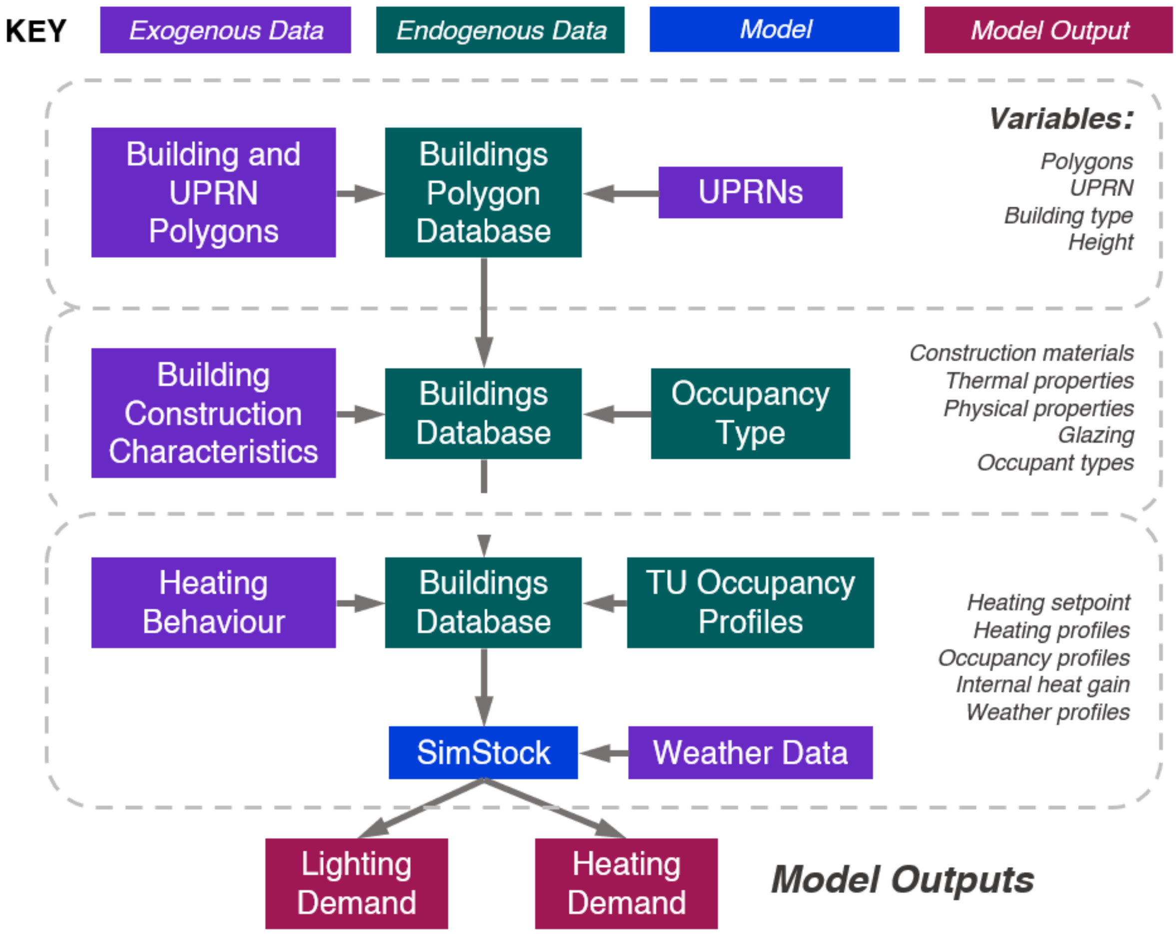


**Figure 6.** Workflow of the heating and lighting model using SimStock.

As there was no further polygon detail available for multi-UPRN buildings, a method based on a POSTGIS tool [48] was developed using Python to equally split complex, nonconvex building polygons. See Data Availability Section for the code. While the process shown in Figure 7 only approximates actual UPRNs, it is more representative of individual occupancies than using the original larger polygons. The method consisted of four steps:

1. Evenly spaced points were assigned to the surface of the polygon.
2. Spectral clustering was used to group points by the number of UPRNs for each polygon. The original method suggested k-means clustering [48] but for certain long, thin, nonconvex polygons, this resulted in some UPRNs being shared across empty space. Spectral clustering improved this performance for nonconvex shapes.
3. The centroid of these clusters was used to generate a Voronoi diagram.
4. Intersections of the Voronoi vertices with the polygon formed the shape of the new polygon for each UPRN.

Nondomestic property types were assigned to the building database, which allows for mixed-used buildings, identified as important in the literature [7], but only at the polygon extent due to more detailed floor-level information not being available. Manual checking showed other building types in the UKBuildings database were mislabelled, with agricultural buildings being identified as domestic (detached, terraced, semidetached, bungalow, block of flats), but not vice versa. As agricultural buildings formed clusters of remote, rural buildings, another clustering algorithm was used. A DBSCAN [49] model was trained on known farm locations and then used to predict which adjacent buildings would be part of the same cluster of farm buildings. This process was also repeated for distilleries, which, being a major industry in the Scottish islands, had significant complexes of buildings labelled incorrectly as domestic. Agricultural, distillery and buildings with UKBuildings type "domestic outbuilding" or "unknown" were then discarded from the heating model calculations.

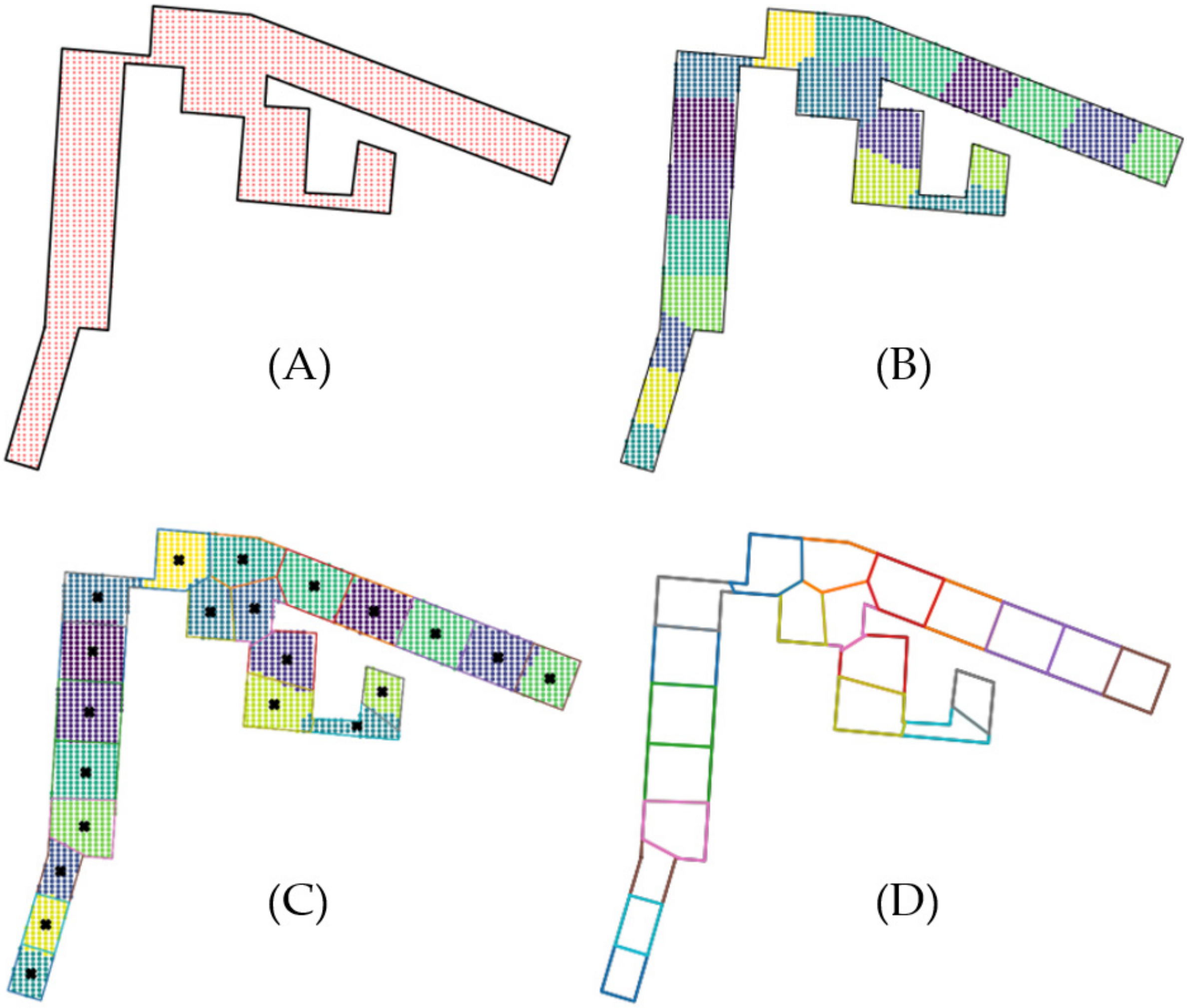


**Figure 7.** The polygon splitting process: (**A**) points assigned to a grid over the polygon; (**B**) spectral clustering groups for the number of building UPRNs; (**C**) centroids used to generate Voronoi diagrams; (**D**) intersection of Voronoi vertices generates new polygons for each UPRN.

2.3.2. Building Characteristics

Building characteristics (wall, roof, floor construction, window type, heating fuel, system, and improvements) were combined with the buildings database. Using the same combinatorial optimisation method described above, property EPCs for domestic [20] and commercial [24] buildings were sampled from to match surveyed building statistics for local authority areas [50]. Commercial EPCs did not, however, contain any building fabric data (only fuel and renewable energy types), so domestic EPCs had to be used for this. For the almost exclusively rural Scottish islands, where 54% of nondomestic buildings are single story [50], this is likely a reasonable approximation, but might be less appropriate in more urbanised areas. Constructions from the EPC database were converted into physical constructions to input to SimStock [18]. As there was no direct map between specific buildings in the UKBuildings database and de-identified buildings in the EPC database, buildings were randomly assigned according to local authority, banded floor area and type (flat, detached, semidetached and terraced).

A notably unavailable building construction aspect, for domestic and commercial, was glazing ratios. Data were not available in either the EPC or SHCS datasets, so an assumed value of 20% was used for domestic buildings. For commercial buildings, values recorded by a small-scale survey were used at the best approximation [51]. As a key factor influencing the modelled final energy demand [52], better data availability is needed.

### 2.3.3. Heating Demand Profiles

Recorded domestic temperatures profiles and demand hours were used. As EP calculates the energy required to heat a space to a given temperature, recorded temperatures in households were used rather than setpoint temperatures [53]. Commercial heating temperatures were available for seven occupancy types [54]. These were mapped onto the 34 modelled occupancies as a best estimate, but it is unclear how much variability between types there might be, especially given the small sample of 119, due to limited available data for the nondomestic model.

Boiler and heat pump operations have been shown to belong to three categories: daytime, bimodal and continuous [55] (Figure 8). The distribution of these varies by technology (with heat pumps three times as likely to operate in continuous mode) so these profiles were assigned to each property depending on the heating technology and distribution of profiles. However, 60% of electric heating on the islands is provided by electric storage heaters [20]. Given this majority of electrically heated households and much lower efficiency, their operational profiles had a large impact on the validation, but recorded operational data were not identified. Storage heater demand profiles had to be estimated using Equation (3) and data recorded for the islands. Subtracting the day-average hourly summer demand (i.e., average annual demand less heating) and non-storage heating from the recorded day-averaged total demand gives the remaining demand from storage heating. The normalised shape of this is shown in Figure 8, illustrating the main peak overnight followed by a second peak in the early afternoon for on-demand heating.

$$Storage\ heating = Annual\ mean - Summer\ mean - Nonstorage\ heating \tag{3}$$

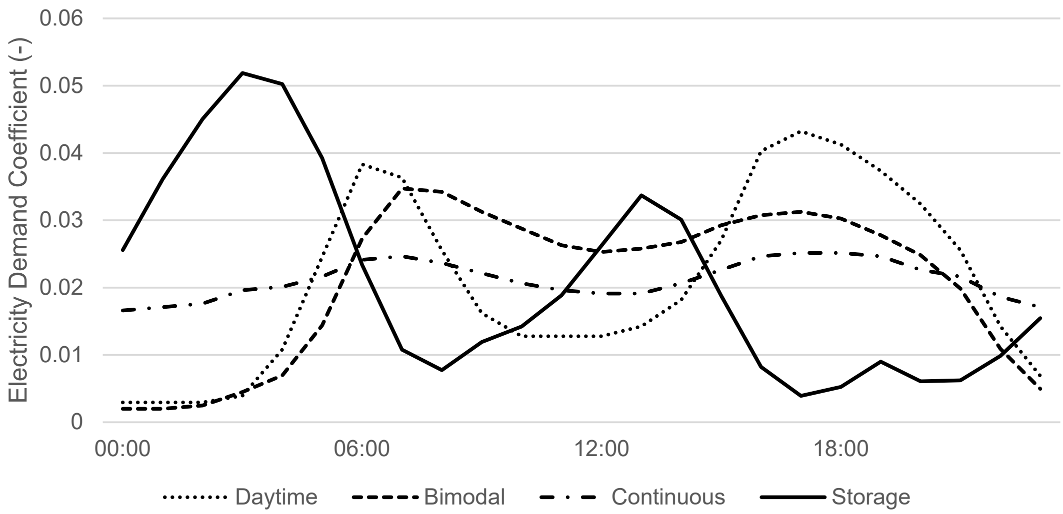


**Figure 8.** Modelled heating demand profiles, with daytime, bimodal and continuous from [55].

EP calculates the energy required to heat a property to the desired setpoint temperature without consideration of the capacity of the heating system. This was calibrated by capping the hourly heating demand at 0.92 of the maximum calculated by EP for each property.

#### 2.3.4. Lighting Calculations

SimStock (London, UK) was used to calculate lighting demand in EP. Time-use survey activity profiles, with a record of when individuals are awake and their location, was combined into an awake-occupancy profile for each property. The "DaylightingControls" EP object calculates the amount of illumination within a property then adjusts the lighting levels when building occupants are present and awake. The "Daylighting:ReferencePoint" objects used as points to calculate the illumination levels were evenly spaced throughout the property. This allowed EP to calculate the lighting demand for a reduced area of the property rather than the entire floor area. The $W/m^2$ for was assigned such that the annualised lighting demand matched recorded values for domestic [17] and commercial [41].

#### 2.3.5. Weather Data

Weather data was included using the OikoWeather API service [56], based on the reanalysis data published by the European Centre for Medium-Range Weather Forecasts. Weather data for a location and time-range were processed in Python 3.8 (Python Software Foundation, Fredericksburg, VA, USA) [57] into the EP ".epw" weather file. As described in Section 2.2.4, this temperature data were also used in the domestic and nondomestic energy models for the seasonality of heating/cooling appliance demand [17].

### 2.4. Model Calibration

The model was calibrated with a range of datasets and at a range of resolutions. Hourly electricity demand data recorded at a GSP level for the islands [19] were the main source of validation for the model. From 4 GSPs, 3.5% of the total data were unusable, therefore the data were approximated by using the average daily profile repeated along the exponential line of best fit at the monthly average resolution. Demand for the local authority area of Na h-Eileanan Siar was excluded from calibration—equivalent to 21% of the recorded demand [19]. This ensured that the model was not overfitted to the recorded data and could be validated separately for this region.

First, the domestic and commercial non-heating electricity demand aspect of the model has been calibrated to match the recorded values of the Intertek [17] and BEES [41] surveys. This was compared with the electricity demand data during the summer. This identified that the initial run of the domestic model using more detailed demographic characteristics (Section 2.1.2) was less representative due to overfitting and few demand profiles being chosen from too few households. Summer demand was also used to calibrate the timing of hot water demand, as many island households have electric immersion heaters that generate hot water overnight [20].

The heating demand could then be calibrated to the remainder of the year. At the seasonal level, this used the air change rate, which has been identified as the most significant factor influencing heating demand and used calibrate EP models [52]. SimStock was run to optimise the air change rate, so the seasonal heating demand matched the seasonal change in the recorded data. This revealed an inconsistency in results, as using consistent heating setpoints throughout the year resulted in the model significantly underheating in the springtime and overheating in the autumn. Domestic and commercial non-heating demand does not vary as significantly as heating demand throughout the year, except for farming energy, which peaks in the spring, which offsets this spring discrepancy. Changes in population through tourism were accounted for, which does not start to rise until the early summer. This leaves only the altered heating setpoint temperatures as the source of this seasonal error. This seasonality of heating demand has been observed elsewhere, indicating that individuals tend to turn the thermostat up after a colder winter than a warmer summer for equivalent thermal comfort [58,59]. Heating setpoint temperatures were adjusted +1°C in the spring, +0 °C in the winter and −1 °C in the autumn.

The model initially also overpredicted peak heating demand. This is due to EP calculating the energy required to heat an entire property to the specified temperature without consideration of heat distribution throughout the property or the heating system capacity. Temperatures will not be completely uniform, particularly on the coldest days, which, combined with the lack of an upper limit on the capacity of a heating system, could explain the overestimation of peak heating demand by the model. Peak heating demand for each property was capped at 92%, resulting in more representative peak heating demands.

## 3. Results

The hourly electricity demand models for domestic, commercial and industrial demand were combined at a variety of temporal and spatial resolutions to compare with recorded electricity demand data [19], i.e., hourly, daily, weekly and monthly averaged modelled and recorded electricity demand data (Figure 9). Note that all results have been normalised for data protection. At the highest hourly resolution, the model has a mean absolute percentage error (MAPE) of 6.4%, which improves up to 1.6% of the monthly resolution, demonstrating that the model captures the seasonal variability in demand driven by electric heating. The most significant improvement to the $R^2$ score between 0.87 hourly to the 0.94 daily indicates that the greatest improvements to the model could be made at the hourly level. At the hourly level, stochasticity of factors influencing demand is more pronounced, which averages out at the daily level.

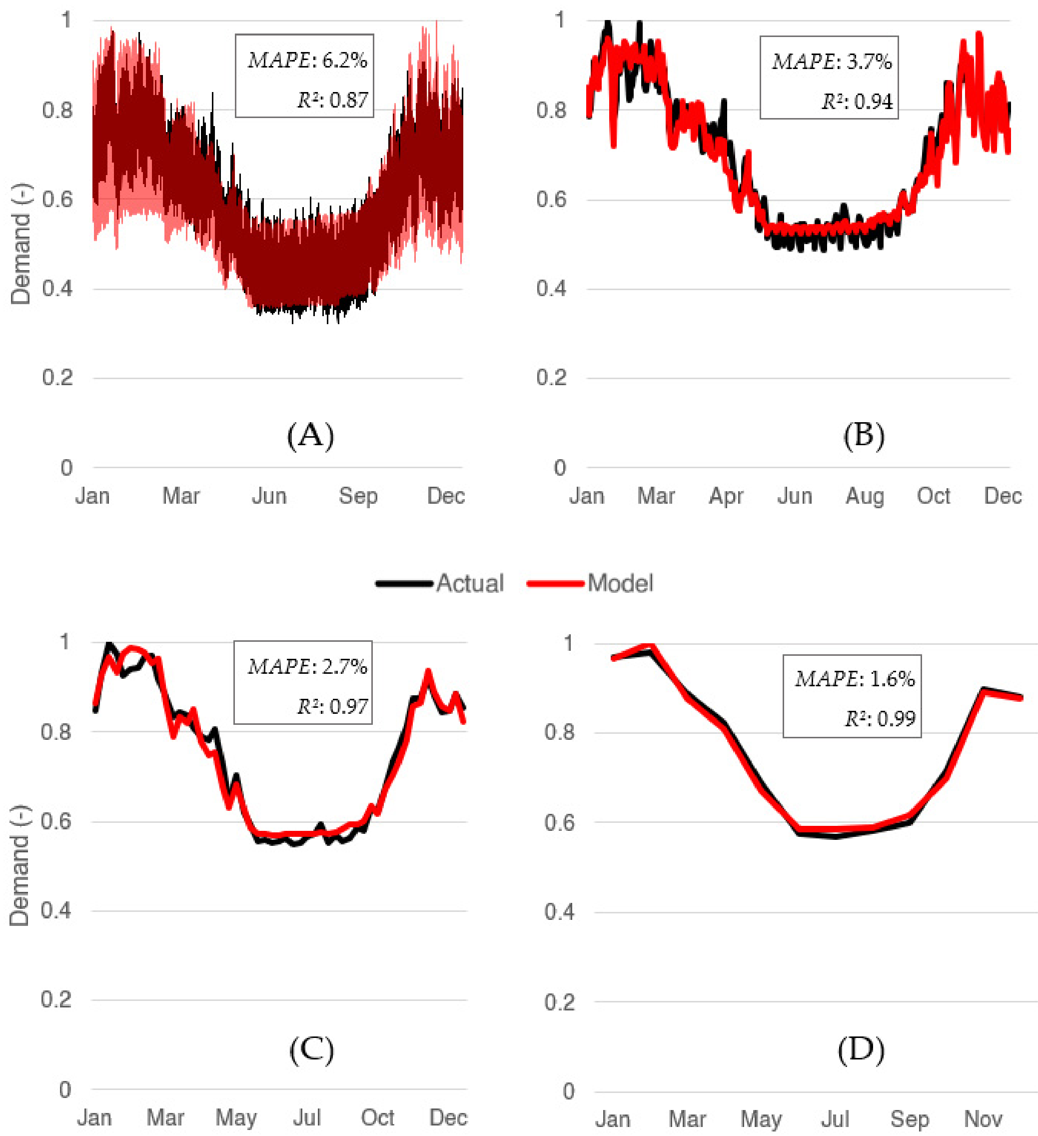


**Figure 9.** Averaged hourly (**A**), daily (**B**), weekly (**C**) and monthly (**D**) average modelled and actual electricity demand.

Behaviour patterns could be influenced by seasonal weather patterns but using the same synthetic population households throughout the year could not capture this. To analyse this, the model error was compared with the weather data used in the model (including rainfall, cloud cover, irradiance and wind speed—only irradiance is used by EP in the heating calculations). No significant correlation was identified.

Average daily demand by category is shown in Figure 10, showing that the model accurately captures the infra-daily variation to within a MAPE of 2.5%. The largest gap occurs overnight, where peak heating demand from electric storage heaters is greatest and demand profiles were not available. The timing of the twin morning and evening peaks of demand is also slightly out. Given the latitudes of the islands at the extreme north of the UK compared with the time-use data mostly recorded in England, it is possible that daylight hours influence the electricity demand and, again, when people are indoors.

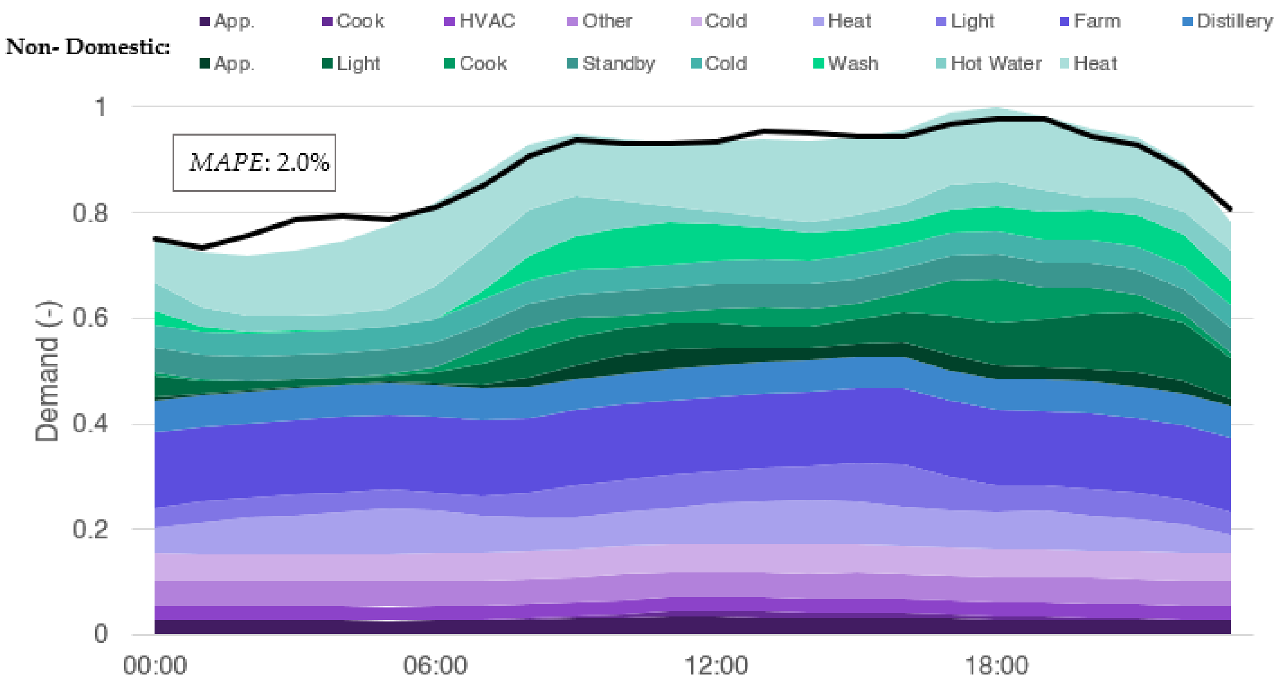


**Figure 10.** Average day of electricity demand by category for all islands, with actual demand in black.

### 3.1. Peak Demand

Modelled daily peak demand (Figure 11) matches the actual data with a MAPE of 4.6%. It can be seen that at times of the highest demand (i.e., the coldest time of year—December to February) the model still tends to overpredict despite the adjustment described in Section 2.3.3. The improved accuracy in the summer (when there is no heating demand) indicates that the problem is related to the heating model. Further work is needed to better understand how EP calculates heating demand and how it could be improved.

### 3.2. Seasonal Demand

For average hourly demand of a day in each season, the model agrees best during the summer (Figure 12- average demand from [19]). In the summer, there is a spike at 23:00 caused by lighting which diverges from the recorded data. The lighting model using the daylighting calculation feature of EP went through several iterations. Without detailed property room layouts, the allocation of lighting operations throughout the property were assigned evenly as daylighting reference points to prevent EP calculating the lighting demand for the entire floor area (i.e., the highest zonal resolution available). Whilst this provided a more representative lighting demand, which better matched household demand recorded by the household appliance survey [17], for much larger properties with an occupancy of greater than 10 (the highest number of reference points that could be added per property), it is likely the model would overestimate the lighting demand by lighting much greater areas of the property than required.

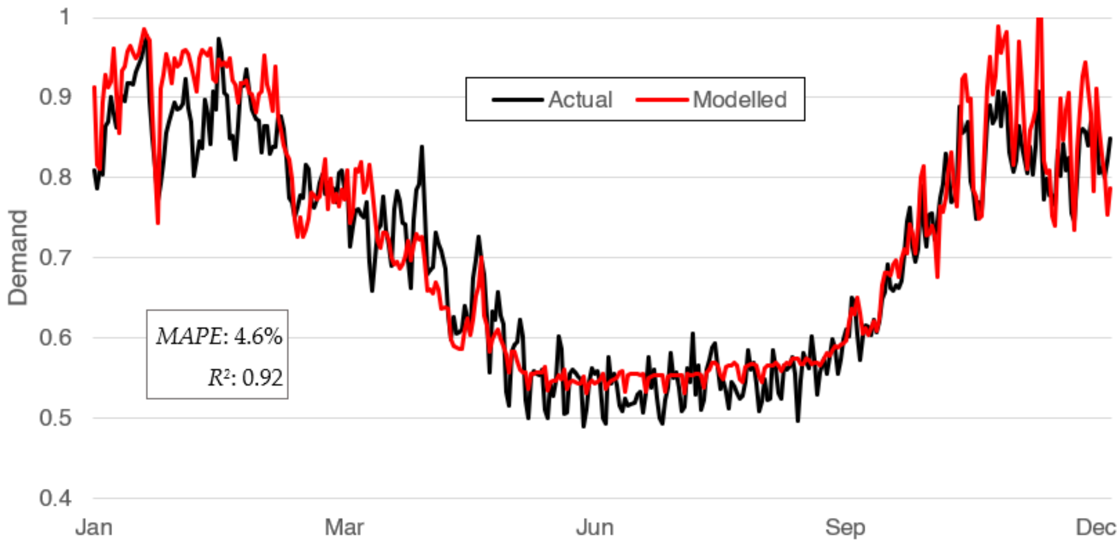


**Figure 11.** Modelled and actual daily maximum as a proportion of maximum annual demand.

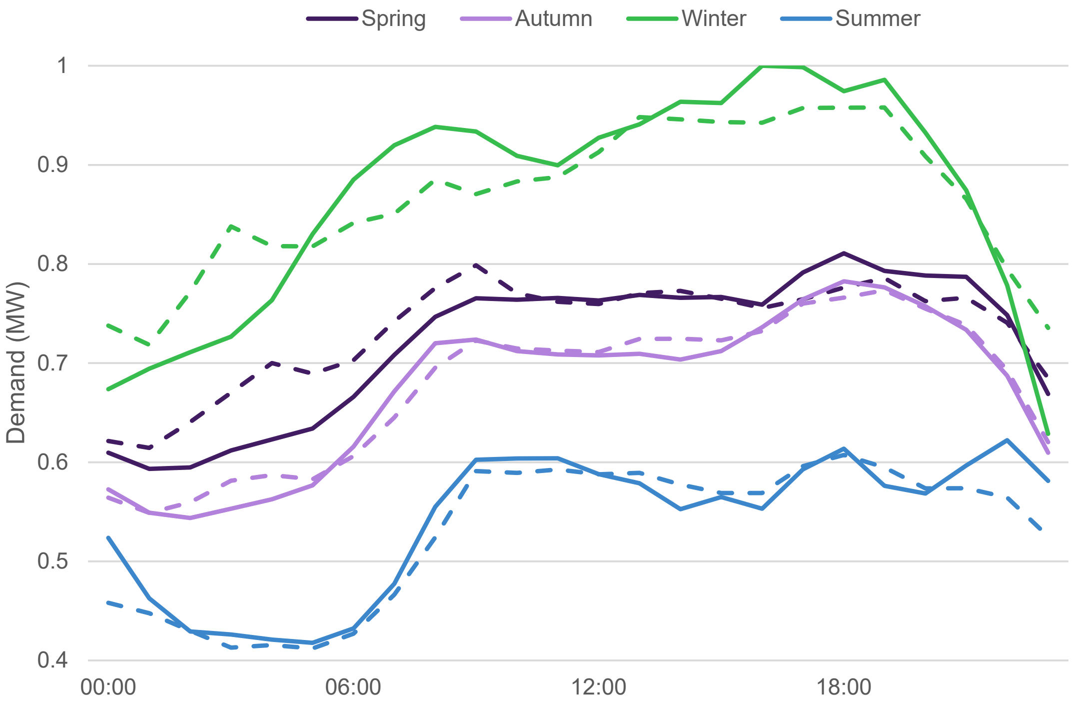


**Figure 12.** Average day of modelled (full line) and recorded (dashed line) demand by season.

### 3.3. Regional Demand

Geographically, at specific local authority level, the model captures the total annual demand, with the model error in the range of 8–20% (Figures 13 and 14—average demand form [19]). Na-h Eileanan Siar, the local authority excluded from calibration (see Section 2.4), has the smallest percentage error, indicating that the model captures the main factors driving local demand. However, the size of Na-h Eileanan Siar will influence this. Looking at the whole region modelled, errors in datasets average out to give a more representative overall demand profile. For four GSPs, 3.5% of the total demand data were unusable.

Exclusion of this data from the error calculation (rather than using the simply estimated replacement data described in Section 2.4) resulted in a decrease for three regions but an increase for Orkney. The completeness and accuracy of the buildings datasets is also uncertain—as stated in Section 2.3.1, 5% of buildings by overall area had to be manually removed due to being mislabelled as domestic. This was only conducted for buildings greater than 1000 m$^2$, so it is unclear how prevalent this was for smaller buildings. As one of the major drivers of the overall heating demand, this will have a significant impact on the modelled demand.

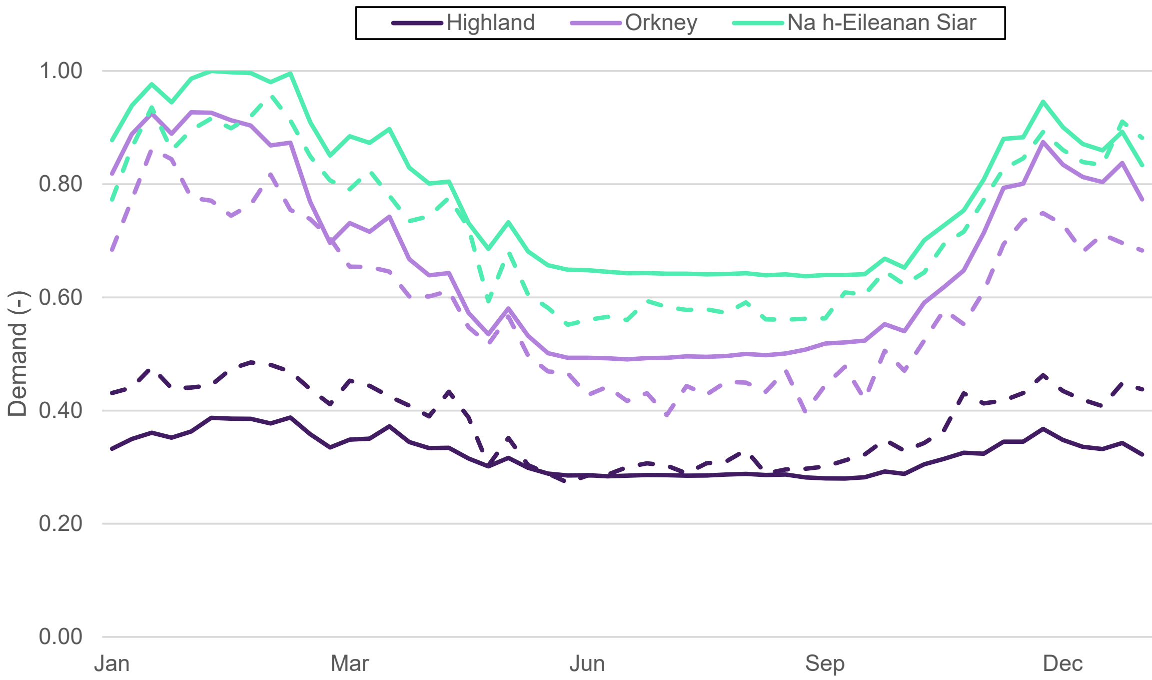


**Figure 13.** Weekly averaged demand aggregated for Highland, Orkney and Na h-Eileanan Siar, where the dashed line is actual demand and the solid line is modelled.

Whilst every care was taken to use datasets from the same time year as the recorded demand data, in some cases this was not possible. With smaller sample sizes for more geographically specific areas, this will make model error more pronounced, as shown in Figures 13 and 14. The year 2016 was modelled as a compromise, being in the middle of the range of time frames for the available datasets, but this introduces discrepancies between the data utilised and actual values. Particularly not available for 2016 was domestic and business demographic data as the basis of the domestic and nondomestic model, with the number of households or businesses directly driving demand. Domestic demographics had to be used from the 2011 Census [22] and nondomestic data were from 2021 [38] as there was no historic data available. For example, the population of the isle of Skye, the largest island in the Highland local authority area, has been estimated to have increased by 30% from 2011 to 2017 [60]. In the previous years of census surveys, more remote islands have followed a general trend of depopulation, with the reverse for larger towns.

The impact of the tourism model becomes clearer at the local authority level. For all local authorities, excluding the tourism model resulted in an increased local error, but it could still be improved with better data (Section 2.1.3). Geographic-specific tourism data were only available for the three local authorities entirely separated from the mainland (Na h-Eileanan Siar, Orkney and Shetland), where tourism is less significant proportionally to the local population. This had to be approximated for other areas where tourism is proportionally much greater. Being closer and more easily accessible from the mainland, these areas would have different tourism profiles, particularly for shorter (e.g., weekend) trips. This is particularly clear for North Ayrshire, shown in Figure 13, which has the smallest island population and greatest proximity to mainland population centres [22]. The model anticipated daily tourism numbers, which for Great Cumbrae peaked at 2.7 times the local population in the summer months. Over the peak tourist season, the model overestimates demand by ~50%, but as visitor numbers recede in the winter so does the discrepancy. More geographically specific seasonal visitor numbers would improve the model relative to the high-level surveys used, which assumed a constant proportion of local-to-tourist journeys throughout the year.

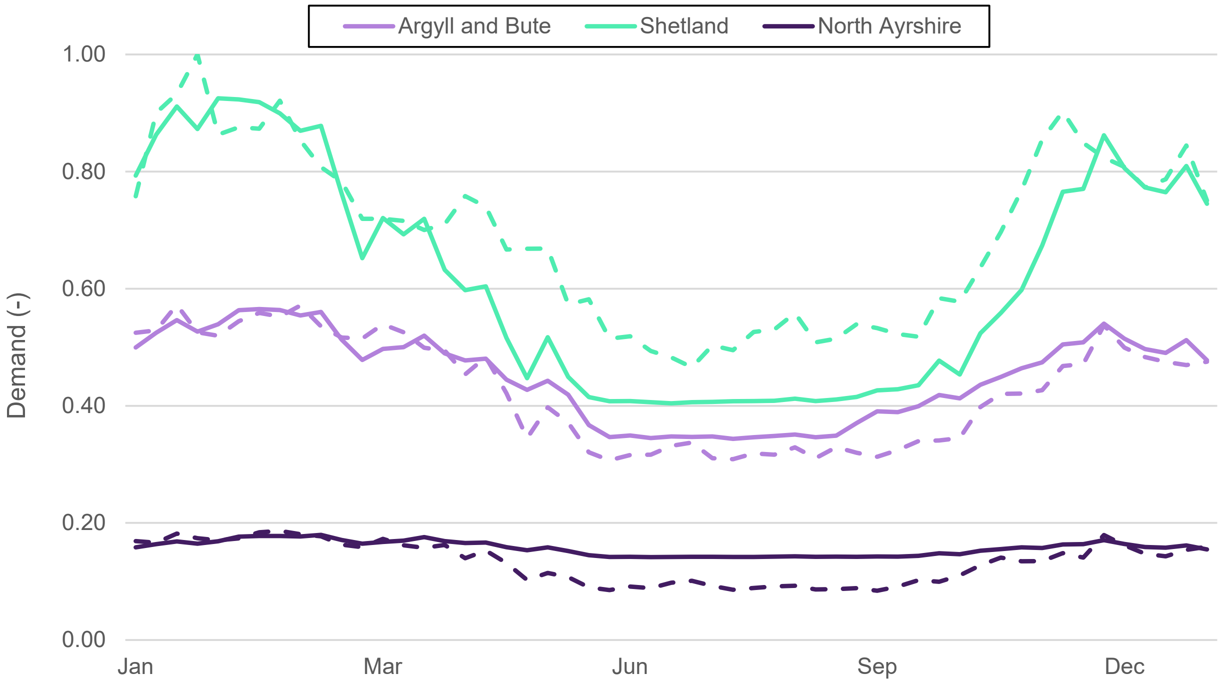


**Figure 14.** Weekly averaged demand aggregated Argyll and Bute, Shetland and North Ayrshire, where the dashed line is actual demand and the solid line is modelled.

### 3.4. Grid Supply Point Demand

Similar to the local authority-level data, error at the grid supply point (GSP) level (the highest geographic resolution available to validate the model) demonstrates that the model captures the variability of annual electricity demand for each region, error in demand tending to average out across the entire region (Figure 15). In addition to the errors discussed for the local-authority level, which apply here but for smaller levels of demand will be more pronounced, the geographic coverage of each GSP was not clear. Shapefiles or other coverage data were not available from the distribution network operator, so the coverage of each GSP had to be estimated by locating the distribution building in network shapefiles [61] and then assuming that the geographically closest region to each building covered the area of demand it served. The accuracy of this method is not clear—a more representative but complicated method could be to calculate the distance based on the distance along the distribution network lines rather than geographically, but there is no way to validate this based on the data in this study.

For the largest areas except Lerwick, the model agrees ±12%. For Lerwick, another significant uncertainty in the model is the CHP waste incineration plant, which provides heat to a large proportion of the town's properties [20]. Coverage data for the plant were not available due to privacy concerns, so the properties excluded from the heating model had to be estimated, introducing uncertainty, particularly for large nondomestic consumers of which there were numerous geographically close but not connected consumers. This is the cause of the most significant error for the largest annual GSP demand.

For GSPs with the smallest annual demand, the random assignment of households to building polygons would have a proportionally greater effect on the error. It is possible that for the islands, there is a correlation between the remoteness of a property with the likelihood of it being empty or a holiday home—in which case the model would overestimate the demand for that area.

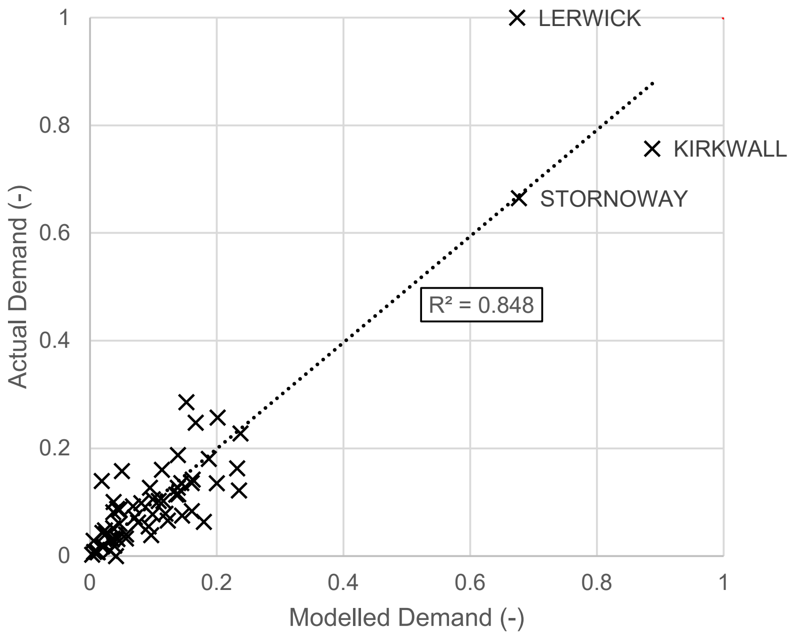


**Figure 15.** Comparison of modelled and actual annual GSP demand.

## 4. Discussions

Analysis of the results discusses how model error is likely been driven by inconsistencies in the data used. These can be summarised into four main categories: temporal accuracy, spatial accuracy, missing data and unknown correlations between datasets.

### *4.1. Dataset Temporal Accuracy*

The most significant of these is the temporal discrepancy between the validation year of 2016 and the major datasets used—demographic data (2011) [22], building data (2021) [52] and business demographic data (2021) [38]. This will increase errors in the model by sampling the incorrect number and type of households or businesses from the generated energy profiles. When the overdue census for Scotland is updated [22], repeating this analysis with up-to-date data for these three main datasets could improve results, particularly at the more geographically specific level.

The main dataset of the model, time-use data, has also been shown to vary over time as people's behaviour patterns change with demographic, social and economic factors [62]. Whilst this is less specifically a problem for this version of the model (with the time-use data from 2014 to 2015), in future versions of the model used to forecast demand based on demographic and technology changes, this will introduce further uncertainty. This will be particularly relevant for changes in behaviour influencing heating, which will be particularly important in estimating future peak demand in the UK as heating is further electrified.

### *4.2. Dataset Spatial Accuracy*

Improving the geographic specificity of several datasets would improve the model. While building construction data were available from domestic EPCs [20], this was not the case for commercial data. Data for a range of nondomestic aspects had to be approximated from other, much less-specific sources. These included building constructions (assumed to match domestic), heating demand temperatures (mapped from a studied seven to the modelled 34 occupancies), heating profiles (assumed to follow opening hours exactly), HVAC equipment operation (as above), air change rates (calibrated so heating demand would match BEES) and glazing ratios (mapped from a smaller study carried out in England). To take the next step in understanding demand of the whole electricity system including nondomestic stock, more specific and detailed datasets will be needed.

Tourism demand was approximated for Orkney, Shetland and Na-h Eileanan Siar from route-specific island ferry passenger numbers and the proportions of trips by visitors/locals on wider local authority-level surveys (Section 2.1.3). This could be improved with more specific data for the other local authorities, which being closer and more accessible to the mainland, experience much different tourist visitor numbers than the more remote islands.

### 4.3. Missing Data

Some data were known to be missing specific aspects or were inaccurate to an unknown degree. The electricity demand data [19] used to validate the model were missing 3.5% of total demand, the exclusion of which resulted in reduced errors compared to a simply approximated substitution for some regions but not others. The impacts of this are, therefore, uncertain. The building polygon dataset, as the main input of the heating model, contained several errors, such as mislabelling large agricultural buildings as domestic. Care was taken to clean this data, but this could only be validated manually; thus, cleaning was limited to the largest buildings only. Further influence on the model is uncertain, but it is likely that for more-populated and better-documented areas, the error would be reduced. Both these cases introduce significant errors which could be improved.

Running the model with identical heating setpoint temperatures year-round identified an underprediction of heating demand in the spring and overprediction in the autumn. In this case, seasonality of demand is not being described by the model. Electricity demand for domestic and services industries should not vary significantly throughout the year, other than for lighting (calculated using EP and validated with the household appliance survey). Seasonality of industrial demands, particularly farming and whisky distilling (making up 41% of nondomestic demand) was included. Therefore, the only factor remaining to explain the discrepancy is heating demand. The only survey of electric storage heaters (the main electric heating technology on the islands [20]) identified in the literature demonstrated a seasonal aspect of overheating after colder winter months and underheating during the autumn [58], making this the likely cause of the discrepancy. Altering heating setpoint temperatures to account for this improved the accuracy of the model, but it is not clear how representative the modelled timing or extent of heating demand change is and how much it could be improved.

As the largest electric heating demand on the islands, daily hourly electric storage heater profiles were absent from the reviewed literature. They were approximated from the heating demand missing from the model, which matched an expected profile of an overnight peak and subsequent smaller on-demand peak later in the day. Access to recorded storage heater demand profiles would improve the accuracy of the model, but as heating should be provided by heat pumps in the future, this omission will become less important.

### 4.4. Unknown Data Correlations

Several correlations between datasets had to be estimated or randomised due to a lack of available data. Building constructions, households and heating profiles had to be matched to suitable polygons. Construction types were matched with the building type, island and banded floor area, but it is possible there are other correlations not captured. Generating a more specific building construction database, which matches the specific building, would be very problematic or even impossible due to privacy concerns. EPC data could be assigned more specifically at the geographic postcode area, but this would be less representative as the EPC database contains mainly households that have been sold in the last decade. Sampling to match the SHCS statistics allowed the data to represent a wider cross-section of the building stock. It is not therefore clear how the housing database could be improved to account for these correlations.

Without any available matched demographic and heating data, time-use households, heating profiles and EPC/UKBuildings properties were randomly assigned. This aspect could be improved with more detailed household construction and heating data in the time-use data, but it would have to be excluded from being matched directly with the census data. Earlier iterations of the census population matching with more detailed individual and household characteristics resulted in the model overfitting to too few households, so added details such as household construction (not identified in literature as a significant factor influencing electricity demand—although it would have a much greater impact on heating demand) would likely do the same. An option would be to include the EPC rating in the time-use data, which could then be used to match with actual properties.

EP was set to run with the main weather factors of temperature, wind and irradiance. The time-use demand profiles had no correlation with the weather, but it is possible that weather could have an impact on people's behaviour (e.g., people spend less time outdoors when it rains). Overall errors in the results could not be correlated with a range of weather conditions, such as wind, rainfall, cloud cover, temperature and irradiance, but this does not mean that no relationship exists. Further analysis of results could reveal patterns in the error, but it is currently unclear if this has any significant impact on the model.

## 5. Conclusions

An electricity and heating demand model has been presented and validated using a combination of domestic, commercial, industrial and other datasets identified as influencing energy demand. A synthetic population based on time-use profiles matched to demographic data using combinatorial optimisation was used to connect behavioural patterns influencing energy between home and work use. Combinatorial optimisation was used to combine datasets and develop statistically representative commercial occupancy profiles and the building database. Other data science techniques, such as spectral and DBSCAN clustering, were used to clean and combine data in the structure presented. Although developed for the case study of the Scottish islands and validated using recorded data for 2016, this modelling framework of using time-use data for both domestic and commercial demand could be widely applicable wherever time-use data and other data are available (subject to available computing power). The categorical representation of 100% of the households and businesses demand allows the model to consider future changes to energy demand, particularly from changes in behaviour and technology driven by the push to net zero. This validation of the model has been the initial stage—next it will be combined with nonelectrical demand and scenarios of technology deployment to predict future electricity demand. A combination of this with a supply-side model will allow understanding of the dynamics of potential net zero energy systems to make informed policy recommendations towards net zero.

**Author Contributions:** C.M.; conceptualization, methodology, data curation, analysis, validation, writing (original draft) and project administration. C.S.; conceptualization, methodology, supervision, writing (review & editing) and funding acquisition. All authors have read and agreed to the published version of the manuscript.

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**Data Availability Statement:** Code for the polygon splitting methodology described in Section 2.3.1 is available at: https://github.com/IslandsLab/Scottish-Islands-Energy-Model (accessed on 6 April 2023). Other data availability is detailed in Appendix A.

**Conflicts of Interest:** The authors declare no conflict of interest.

## Acronyms

| | |
|---|---|
| BEES | Building Energy Efficiency Survey |
| CHP | Combined heat and power |
| DEAM | Dynamic Energy Agents Model |
| EP | EnergyPlus |
| EPC | Energy performance certificate |
| GSP | Grid supply point |
| MAPE | Mean absolute percentage error |
| OSM | Open Street Map |
| UPRN | Unique property reference number |

## Appendix A Description and Availability of Data Sources

**Table A1.** Description of data sources.

| Description | Name | Author/Owner | Availability | Link |
|---|---|---|---|---|
| 10-minutely actions for a day and demographic data of 11,421 people | Time Use Survey 2014–15 [11] | UK Data Service | Freely available under UKDS End User License | |
| Demographic data for Scotland's 56 occupied islands | Census Data 2011 [22] | National Records of Scotland | Freely available | |
| National survey recording annual electricity demand by each appliance for 251 households | Intertek Household Electricity Survey 2012 [17] | Intertek | Freely available | |
| EPCs for domestic and nondomestic properties | Energy Performance Certificates [20,24] | Scottish Government | Freely available | |
| Polygons and building type data | UKBuildings [46] | Geomni | Available at cost | |
| Polygons and building occupancy types | Open Street Map [38] | Open Street Map | Freely available | |
| Local authority statistics of surveyed building characteristics | Scottish Housing Condition Survey 2014–2019 [50] | Scottish Government | Available under academic license | |
| Unique property reference number's locations | UPRN [47] | Ordnance Survey | Freely available | |
| Phone surveyed kWh/m$^2$/year and potential energy efficiency measures for nondomestic building types | Building Energy Efficiency Survey (BEES) [41] | Department for Business, Energy and Industrial Strategy | Freely available | |
| Nondomestic building occupancy types and opening hours | Google Places [39] | Google | Freely available within monthly API limits | |
| EP weather files based on NASA MERRA database | OikoLab [56] | OikoLab | Freely available within monthly API limits | |
| Grid supply point electricity demand data for Scottish islands | Islands demand data [19] | Scottish Southern Electricity Network | Available at cost | |

## Appendix B Additional Data

**Table A2.** Modelled nondomestic occupancies.

| | | | | |
|---|---|---|---|---|
| Office | Theatre | Health centre | Museum | Hospital |
| School | Farm | Water treatment | Hairdresser | Fish farm |
| Pub | Airport | Showroom | Large food shop | Brewery |
| Hotel | Workshop | Emergency Services | Leisure centre | Distillery |
| Factory | Store | Club & community centre | Large nonfood | Ferry terminal |
| Pub | Restaurant | Small shop | Fish processing | Law court |
| | Place of worship | | Cafe | |

**Table A3.** Summary of data and source used to calculate annual energy demand of major industries.

| Aspect | Annual Production | Electrical Energy Factor | Annual Demand |
|---|---|---|---|
| Whisky Distilling | 37.25 MLPA [63] | 1.28 kWh/MLPA [64] | 47.7 GWh |
| Fish Processing | 55,365 t [65] | 20 kWh/t [66] | 1.1 GWh |
| Farming | 10,626 HA [67] | 108 kWh/HA [68] | 59.5 GWh |

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