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The impact of heat electrification on the seasonal and interannual electricity demand of Great Britain

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HIGHLIGHTS

- Isolating the impact of heat pumps on national electricity under historic weather.
- Validations with measured data indicate the best heat demand generation method.
- 41 % heat pumps would increase Great Britain's winter electricity demand by 30 TWh.
- Year-to-year variability of electricity demand increases by 37 %.
- 25 % inaccuracy of future peak electricity demand estimates.

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ABSTRACT

Amongst all future developments it is the electrification of heat that is anticipated to have the largest impact on seasonal and interannual electricity demand. There is therefore a need to accurately quantify and assess this impact. This paper uses a combination of existing advanced techniques to modify the historic electricity demand to incorporate the impact of heat pumps alone for long-term historic weather data using Great Britain as an example. The methods for generating time series were compared and extensively validated. This includes comparisons with measured data that have not been used previously for this purpose. The research reveals that for predicted 2050 heat pump penetration levels the monthly demand for electricity doubles in winter. This leads to an increase of approximately 30 TWh for each winter month and a 37 % increase in year-to-year variability of electricity demand due to weather. Peak electricity demand is very sensitive to the method of generating heat demand and the assumptions on hourly heat pump operating profiles, suggesting inaccuracies of 25 % in estimates of future peak demand. This work, rather than just assessing the impact of projected changes provides a reference case for policy makers to guide the decision process and planning for future scenarios.

1. Introduction

30 % of primary energy demand in Europe is for the heat sector [1]. To reduce carbon emissions from fossil fuels such as natural gas it is likely that electricity generated from low carbon sources will be used to provide heating [2]. This migration to electric heating termed the electrification of heat has been shown to be one of the two most significant impacts on future electricity demand in cooler countries [3,4], the other being the electrification of transport. Most of the heat demand will be provided by electric heat pumps which are the most efficient way of providing electric heating [5]. Rather than converting electric energy to heat energy directly, heat pumps use electricity to pump heat from a colder location to a warmer one in a similar way to a domestic fridge.

National energy system models [6] to assess the future decarbonisation of heat, require electricity demand time series and renewable generation modelled from historic weather as inputs. At hourly time steps the models choose how to allocate the energy supply to different sources of demand according to a strategy such as minimization of CO_2, fuel use or cost. Using only a single year of weather is not enough to capture the variation in renewable power generation [7] to fully test an energy model. Therefore some studies are starting to use time series of several years of historic weather for example 10 years [8] or 30 years [9]. Most studies do not use historic electricity time series to generate future electricity demand but generate time series which are almost entirely synthetic. A typical example of this approach [10] generates

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Nomenclature

ASHP	Air Source Heat Pump
B_h	Hourly baseline electricity demand time series (TWh)
$COP_{h,g,s}$	Heat pump coefficient of performance for hour h, grid point g, heating configuration s
d	Day of the year
ΔT	Difference between heat pumps source and sink temperature (°C)
E_h	Hourly heating electricity time series (TWh)
F_h	Hourly historic electricity demand time series (TWh)
G	Weather grid point
GSHP	Ground Source Heat Pump
h	Hour of the year
$H_{d,g}$	Heat time series for day d and grid point g (Twh)
HD_{annual}	Annual heat demand
HDA_y	Annual heat demand for year y
HDD	Heating degree days (°C)
HDD_y	Heating degree days for year y
i	Hour of the day
J	Hourly heat profile (%)
K_s	Proportion of heating from configuration s
L	Proportion of heating which is electrified
nRMSE	Normalised Root Mean Square Error
P_g	Population at grid point g
R_d	Daily gas time series from linear regression (Twh)
RH	Resistive Heating
RHPP	Renewable Heat Premium Payment – trial of heat pumps
s	Heating configuration, eg ASHP with underfloor, resistance heating
S_h	Hourly electricity demand time series with heating provided by heat pumps (Twh)
$T^{amb}_{d,g}$	Mean daily ambient external temperature for day d and grid point g (°C)
$T^{Ref}_{d,g}$	Reference temperature for day d and grid point g (°C)

hourly electricity time series for the Danish electricity system. Separate time series for each sector are generated by splitting its annual demand into days and hours based on standard profiles, including historic weather time series or weather projections, seasonal and behavioural influences as appropriate. These separate time series are then aggregated. The DESSTINEE model and ELOAD [3] improve on this by incorporating residuals from the historic electricity demand time series to get a more realistic demand pattern.

The future impact of heating electrification on UK electricity demand has been assessed in several different ways. One study [11] used the historic gas series as a proxy for heat demand to predict the impact on electricity demand. A regression model with historic gas demand and weather was used in [4] to modify the historic electricity demand time series. In another study, heat pump simulations of 960 buildings [12] were used to predict net peak demand. Heat pump trial data was upscaled in [13] to represent the national housing stock. These studies focus mainly on the peak hourly demand with little attention given to the impact on the seasonal and interannual demand profiles. However, renewable energy sources also exhibit high seasonal variation. Therefore, when considering systems with high penetrations of renewable energy up to 100 % renewables and incorporating possibly storage, including long duration storage [14], it is also necessary, to account for both seasonal and interannual effects. A study that investigates such effects on electricity demand [15] incorporating long term weather effects too, is based on projections of demand into to the future achieved with the method of decomposition described earlier here and does not isolate the effect of heat electrification from other developments. Projections include anticipated changes in all sectors based on a scenario of possible future growth. Although there is some variation in electric vehicle efficiency with temperature [16] transport is not directly linked to temperature [17] whilst there is strong dependence of heating demand on weather. Therefore it is reasonable to anticipate that it is the electrification of heat that will have the largest impact on the seasonal and inter annual variation of electricity demand [15]. This will be particularly the case for countries with cold and long winters [17]. However, this effect has not yet been isolated from other factors. It is this impact of heat electrification alone on day to day, seasonal and interannual electricity demand that is the main focus of this work, and it is analysed and quantified for the case of Great Britain.

Rather than looking into all future scenarios for all sectors and all technological changes such as improvements in efficiency, insulation, and load shifting, and societal changes such as economic activity population, appliance mix and human behaviour in this work we isolate the impact of heat pumps from all other changes under long term realistic weather patterns. Based on current technological and socioeconomic conditions and accounting only for the anticipated implementation of electric heat pumps by 2050 this work introduces a method to isolate and study the impact of a specific change, which, in this case, is the electrification of heat. As such it provides a benchmark for planning and policy making towards sustainable developments and solutions. It improves on earlier studies by using a state of the art method for calculating heat demand [18] to generate heating electricity demand time series from 40 years of historic weather data. In contrast to other studies that use a constant heat pump coefficient of performance (COP) [8] or one population weighted temperature[3] we calculate a temperature dependent COP at each weather grid point and use this to calculate the electricity demand from that grid point's heat demand. The existing studies we are aware of generating heat demand time series top down use several different methods of splitting an annual heat demand into days. Previous work comparing these methods against each other [19] validates the heat demand only against gas. Here we perform in-depth validations using not only historic national electricity and gas time series, as typically done in previous works [18], but also measurements of heat, gas, and electricity usage from actual buildings, data sets that have not been used previously for this type of validation. Our research reveals firstly that introduction of heat pumps doubles the monthly demand for electricity in winter leading to an increase in about 30TWh for each winter month and secondly that the difference between the largest and smallest annual electricity demand for weather years 1980–2019 increases from 19 TWh to 26 TWh. It also reveals the sensitivity of generated peak electricity demand to the hourly profiles used in modelling leading to uncertainties in the estimations of peak electricity demand which vary over a range of 25 GW. This is quite significant compared to estimates of future peak demand of between 40 and 100 GW reported in research [17]. Such inaccuracies have not been quantified in previous research.

Similar to [15] our work does not capture effects due to future climate change and does not capture weather conditions that are outside of the near-term history.

Although our study is restricted to Great Britain, the methods can be applicable to any other country. The reason for using Great Britain as case study is because firstly, it has good availability of reliable historic long-term weather data and secondly, the demand for space and water heating is substantial [17].

The novel contributions of this work are:

- the method of modifying a long-term historic electricity demand time series to incorporate heating electricity for a given heat pump penetration.
- quantitative analysis, using long-term historic weather data, of seasonal and interannual variations of the impact of heat pumps alone, separated from all other factors, on the Great Britain electricity demand. This is in addition to quantification of peak demand that other studies do.
- the comparison of methods adapted from previous studies for generating national heat demand time series from long term historic weather.
- validations of methods for generating national heat and electricity demand time series against measured data

The rest of this paper is structured as follows. Section 2 lists the data used, section 3 describes the methods, and section 4 describes the validations. Section 5 discusses the results, there is a sensitivity analysis in section 6, and section 7 discusses the conclusions.

2. Input data

Weather data for Great Britain was taken from the ERA5 weather reanalysis [20] at spatial resolutions of 0.75° x 0.75° and 0.25° x 0.25°. Hourly 2 m ambient air temperature and soil temperature for the years 1980 to 2019 were used in the calculation of heat pump coefficient of performance (COP) and the generation and validation of heat demand time series. Monthly mean 10 m wind speeds for 1979 to 2018 were used to identify windy and non-windy locations in the generation of heat demand. The weather data was weighted by the Great Britain population taken from Eurostat [21] for 2011 so that the more populous weather grid points have a greater impact on the national demand.

Annual Fuel energy demand for space heating and hot water from table U2 in energy_2019_end_use_by_fuel.xlsx [22] were used to calculate annual space and water heating figures for input into the generation of heat demand time series. Since 2016 this data includes a more detailed breakdown including how much of space and water heating was provided by gas enabling a more detailed validation of the gas time series.

Amongst the various historic gas time series available from national grid gas data explorer [23], the Non-Daily Metered (NDM daily gas demand time series comes closest to including all heating and so we use it in this study to validate heat demand time series. Half hourly electricity time series for Great Britain for 2016–2019 from [24] were used (i) for validating the method of creating base line electricity demand and (ii) for assessing the impact of heat electrification on the electricity demand.

The methods of generating heat and electricity demand time series were validated using measurements from domestic houses in the Renewable Heat Premium Payment (RHPP) Scheme [25] and from public buildings in a smart meter trial [26] by The Carbon Trust.

3. Methods

Actual historic electricity demand time series include technological and economic changes over a long time period [27] that have led to an overall reduction in the UK electricity demand in the last decade and changes to the hourly pattern. An analysis of the impact of weather on the UK electricity demand from 1974 to 1990 [28] also found that the demand pattern has changed with correlation between demand and temperature weakening over time which might be explained by a move towards gas heating, or improved thermal insulation.

For this reason, rather than using actual long-term historic electricity demand time series, we generate a baseline electricity demand. First, we remove the existing heating electricity demand from a recent year's electricity demand time series, 2018. We do this to separate the weather dependent electricity demand from the weather independent electricity demand. The heating load correlates strongly with heating degree days [4,28] so heating electricity demand does depend on the weather. We call the remaining electricity demand baseline electricity demand, and we assume that this baseline electricity demand is independent of the weather. This concept of generating time series assuming the heating electricity demand to be the weather dependent demand has been used previously in research for characterising the response of the power system to weather [29] and for identifying events of simultaneous high demand and low renewable generation [30].

The method to generate the electricity demand time series consists of three steps:

1. Generation of heat demand time series. This will then be used in both subsequent steps.
2. Estimation of baseline electricity demand. We start with the historic electricity time series from a recent year which represents today's electricity system and remove the electricity for heating from it.
3. Estimation of electricity demand for future heating assumed here to be 41 % of heating supplied by heat pumps by 2050. This 41 % figure is taken from the net zero scenario from UK National Grid Future Energy Scenarios 2019 [2]. Future Energy Scenarios is a set of pathways towards a future decarbonized UK energy system. We add this electricity for heat pumps to the baseline demand based on the historic weather.

The detailed breakdown of fuel used for heating was available only for the years 2016–2018 [22]. Therefore, we select only amongst these years the one to use for the baseline electricity demand, and we have chosen to use the most recent one, 2018.

The following sections describe the steps used for the generation of electricity demand time series. The process is illustrated in Fig. 1 where brown backgrounds indicate processes unchanged from the when2heat dataset [18] and green backgrounds are added or changed as part of this study.

3.1. Generation of heat demand time series

Heat demand time series can be generated from historic gas demand time series [4]. However, we do not use the historic gas time series for generating heat demand here because the proportion of gas used for heating, efficiency of boilers and home insulation have changed over time, and we want to keep these factors constant.

Our method of generating heat demand time series is based on the method used to generate the when2heat dataset [18] which consists of time series of heat demand and heat pump coefficient of performance (COP) for each European country for the years 2008 to 2013. Daily temperatures on a grid with spatial resolutions of 0.75° × 0.75° from the ERA Interim weather reanalysis [31] were used to generate daily heat demand time series for each grid point by splitting the annual heat energy for each country derived from fuel use into days according to a temperature dependent equation. These were converted to hourly time series using an hourly profile derived from German gas usage which assigns a percentage of the daily value to each hour of the day, weighted by population, and summed to give an hourly heat demand time series for the whole country.

Heat pump hourly electricity profiles have lower peaks and a more even spread than gas usage profiles [13]. For this reason, we modified the when2heat method to use a heat demand profile that we derived from the RHPP heat pump trial [25], instead of the BDEW profile based on gas usage [18]. The BDEW profile and the RHPP profile for the temperatue bands −5 °C to 0 °C are shown in Fig. 2 and those for 10 °C to 15 °C are shown in Fig. 3. Both these profiles are a combination of space and water heating. It can be seen that the BDEW profile shows a higher peak in the first half of the day, and since there are other studies on German heat pumps showing a similar pattern [32] it would seem reasonable to assume that this is a difference in consumer behaviour

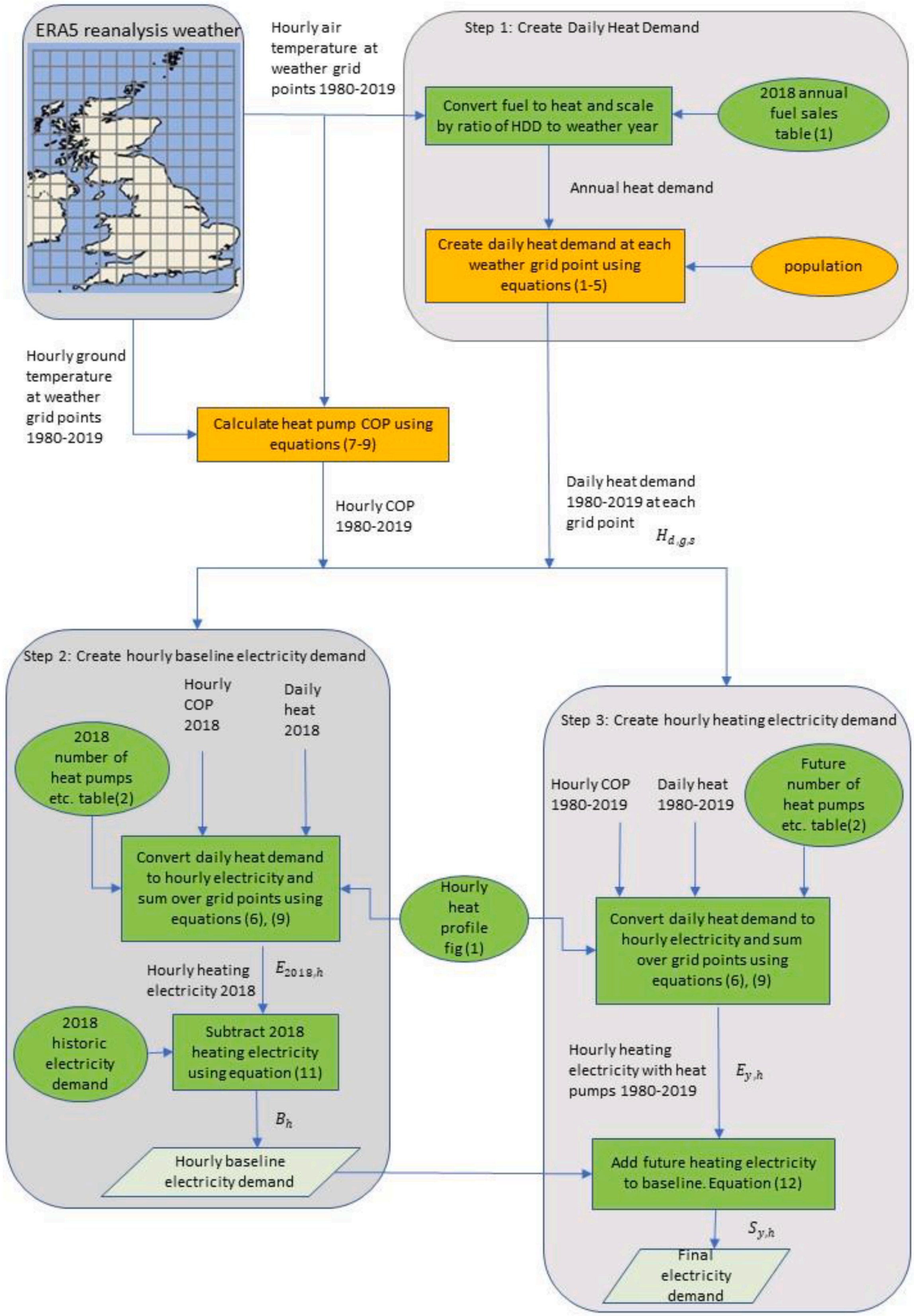

Fig. 1. The process of creating an electricity demand time series for a system kept constant at 2018 levels of demand apart from heating provided by heat pumps for 40 years of different weather.

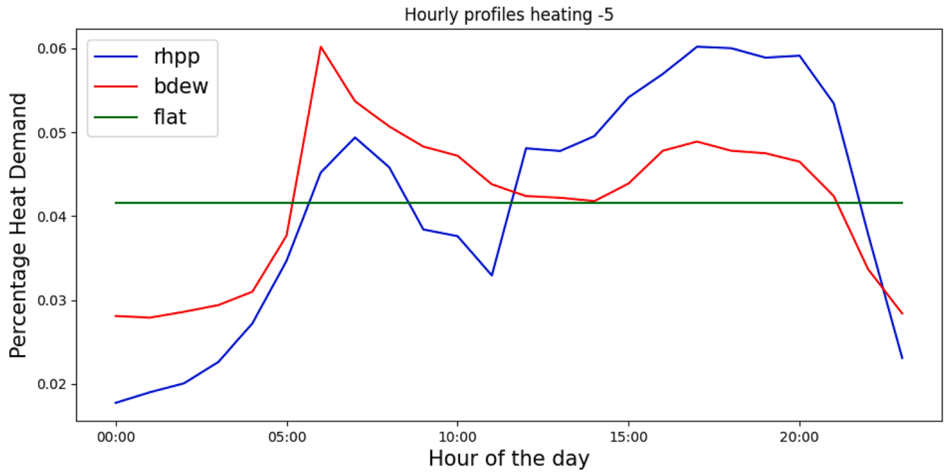

Fig. 2. Hourly heat demand profiles for external temperature bands −5°C to 0 °C.

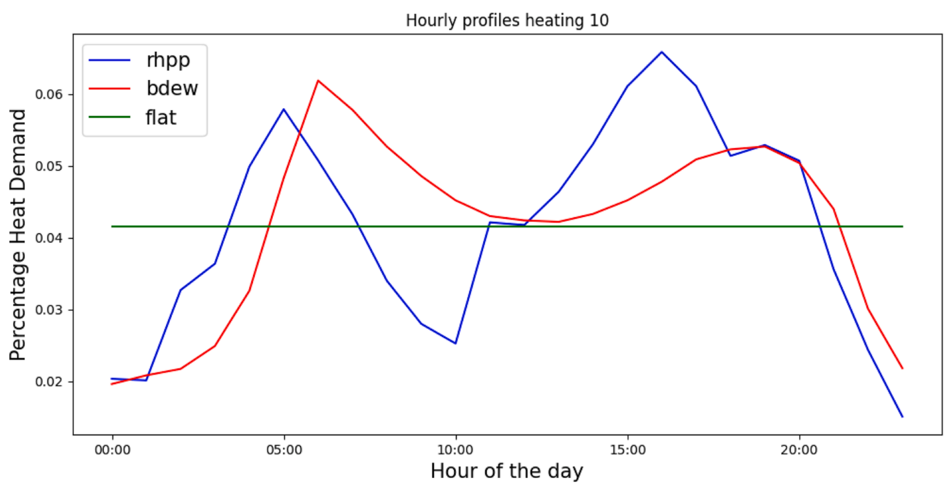

Fig. 3. Hourly heat demand profiles for external temperature bands 10 °C – 15 °C.

between the UK and Germany, rather than a difference between heat pumps and gas boilers.

We also improved on the when2heat method by using the ERA5 weather reanalysis [33] which is available on a finer grid.

A 40-year heat demand time series from 1980 to 2019 is generated for each weather grid point. This is done by splitting the population weighted annual demand for each year into days. First, the Great Britain annual heat demand for a particular year is calculated using the 2018 annual heat demand and heating degree days.

$$HDA_y = \frac{HDD_y}{HDD_{2018}} HDA_{2018} \tag{1}$$

Where HDD_y is the number of heating degree days for year y calculated from the UK population weighted temperature and HDA_y is the annual heat demand for year y. The annual heat demand for 2018 HDA_{2018} is calculated using government figures [22]. These are derived from fuel sales, monitoring and consumer surveys as shown in Table 1. The gas energy figures are used for validation later.

The equations for generating heat and electricity demand time series are adapted from our previous work [19] using the when2heat dataset [18].

To generate the heat demand time series, a reference temperature (equation (2)) was calculated at each weather grid point (g) and day (d) based on the ambient temperatures of the N previous days to account for the thermal inertia of buildings (for $d < N$, $N = d$).

Table 1
2018 annual heat demand by fuel use converted to heat energy assuming efficiencies: gas 80%, oil 85%, solid fuel 76%, electricity 100%, heat (eg combined heat and power) 100%, bioenergy and waste 87%.

	Annual Heat Energy by Fuel (TWh)		
Sector	**Gas**	**Other**	**Total**
Domestic Space	191	68	**259**
Services Space	56	36	**92**
Domestic Water	56	11	**67**
Services Water	7	6	**13**
Total Heat	310	121	**431**

$$T^{Ref}_{d,g} = \frac{\sum_{n=0}^{N} 0.5^n T^{amb}_{d-n,g}}{\sum_{n=0}^{N} 0.5^n} \tag{2}$$

Where $T^{Ref}_{d,g}$ is the reference temperature for day d at grid point g and T^{amb} is the mean ambient air temperature for that grid point and day and N = 3. The daily heat demand at each grid point was calculated by weighting by population mapped onto the weather grid, equation (3).

$$H_{d,g} = \frac{HD_{annual} f_{d,g,\alpha(s)} . P_g}{P_{total} . f_{total}} \tag{3}$$

Where P_g is the population at grid point g, P_{total} is the total population, HD_{annual} is the annual heat demand derived from Table 1 and equation (1), f_{total} is the sum of all the demand factors and $f(d,g)_{\alpha(s)}$ is the daily demand factor for day d and grid point g. The parameter α(s) indicates which of the two equations below is used to calculate the demand factor $f_{d,g,\alpha(s)}$ for heating configuration $s \in \{1, 2, \cdots 9\}$ in Table 2.

$$f_{d,g,space} = \frac{A}{1 + \left\{\frac{B}{T_{d,g}^{Ref} - T_0}\right\}^C} + D + max\left(\frac{m_{space} - T_{d,g}^{Ref} + b_{space}}{m_{water} - T_{d,g}^{Ref} + b_{water}}\right) \tag{4}$$

$$f_{d,g,water} = \left(\frac{D + m_{water}.T_{d,g}^{ref} + b_{water}T_{d,g}^{ref} > 15^\circ C}{D + m_{water}.15 + b_{water}T_{d,g}^{ref} \leq 15^\circ C}\right) \tag{5}$$

Where T_0 is 40 °C and $A, B, C, D, m_{space}, m_{water}, b_{space}, b_{water}$ are factors taken from the code download for [18]. These factors depend on (i) UK 40 year mean wind speed and (ii) type of building (domestic: multi-family house 30 % / single family house 70 % or commercial building).

3.2. Generation of electricity demand time series

The daily heat demand time series at each weather grid point from equation (3) was converted to an hourly electricity time series and summed using equation (6) over the whole country to give the additional electricity that would need adding to the national grid to supply this heat demand with electric heat pumps.

$$E_{h,s} = \frac{K_s}{\eta}\sum_{g=0}^{NG}\frac{H_{d,g}.J_i}{COP_{h,g,\beta(s)}} \tag{6}$$

Where $E_{h,s}$ is the heating electricity demand for hour of the year h and heating configuration s (representing different type of heating as described below), η is a correction factor set to 1 for resistive heating or 0.85 for heat pumps to account for real world inefficiencies as per [18] and K_s is the proportion of heating configuration s in the country as shown in Table 2. The 9 different heating configurations (s) listed in Table 2 arise from the different combinations of space or water heating, source, and sink shown in that table. The heating is provided by ordinary resistive heating where the COP is assumed to be 1.0 and 2 types of heat pumps (ground source and air source). The heat is supplied to radiators, underfloor heating, or hot water with 3 different sink temperatures shown in Table 3. $H_{d,g}$ is the heat demand for day d at weather grid point g. $H_{d,g}$ is converted from daily to hourly demand by multiplying by J_i the hourly profile which determines the proportion of this daily heat applying to hour of the day i. $COP_{h,g,\beta(s)}$ is the heat pump COP for hour of the year h, grid point g and β(s). β(s) indicates which of the equations (7–9) is used to calculate COP for heating configuration s in Table 2. Summing up the contribution of all the NG weather grid points gives a final hourly time series for the whole country for each heating configuration (s).

In Table 2 the 2018 fraction represents 2018 proportions [2] and the simplifying assumption is that all existing heat energy not provided by heat pumps is provided by resistive heating with efficiency 100 %. The future fraction is based on the assumptions that all electric heating is provided by heat pumps (90 % ASHP, 10 % GSHP based on current proportions [2]) and that 90 % of heating is provided by radiators and 10 % by underfloor heating. Table 3 shows the 3 different sink temperatures.

Table 3
Source and sink assumptions [18].

Sink temperature (radiator)	40 °C – $T_{h,g}$ (or 15 °C if $T_{h,g} > 25$)
Sink temperature (floor)	30 °C – 0.5 $T_{h,g}$ (or 15 °C if $T_{h,g} > 3$)
Sink temperature (hot water)	50 °C

The COP is calculated at weather grid points using equations (7) or (8) as typical for the UK [5] or for ordinary resistive heating using equation (9).

$$COP_{h,g,ASHP} = 6.08 - 0.09\Delta T + 0.0005\Delta T^2 \tag{7}$$

$$COP_{h,g,GSHP} = 10.29 - 0.21\Delta T + 0.0012\Delta T^2 \tag{8}$$

$$COP_{h,g,RH} = 1.0 \tag{9}$$

Where $\Delta T = S - T_{h,g}$ and S is the sink temperature from Table 3 and $T_{h,g}$ is the hourly source temperature for that grid point. For ASHP this is ambient air temperature, for GSHP it is soil temperature.

All the heating configurations are then added together as per equation (10).

$$E_h = L\sum_s E_{h,s} \tag{10}$$

Where L is the proportion of heating electrified (taken from government figures [34] or future assumptions). This process described in equations (6–10) was repeated for each weather year y, giving $E_{y,h}$ as the electricity demand for year y and hour h.

Fig. 4 shows the COP curves of Staffell [5] equations (7) and (8) which we chose for out final model because they are representative of the UK compared those from other studies; Kelly [35], and Fischer [36] based on industry standard data (2011, 2014, 2016); Ruhnau [18] from industry standard data and RHPP derived from UK heat pump trial data [25].

In general, GSHP perform better than ASHP and since ground temperature tends to be higher and more constant than air temperature the ΔT tends to be lower. It should be noted that we are using COP to represent the whole system and not just the heat pumps. We do not consider the circulation pump electricity because it is similar to that used by a gas boiler which is already present in our baseline electricity demand.

3.3. Estimation of electricity demand

The 2018 hourly electricity demand time series B_h with heating

Table 2
Heating configurations, current and future.

Heating Configuration: heat use-heat source-heat sink				Equations Indices		Proportions of heating configuration s	
s	Use	Source	Sink	α(s)	β(s)	2018 Fraction (K_s)	Future Fraction (K_s)
1	Space Heating	Ground	Radiator	space	GSHP	0.0045	0.09
2	Space Heating	Ground	Floor	space	GSHP	0.0005	0.01
3	Space Heating	Air	Radiator	space	ASHP	0.0378	0.81
4	Space Heating	Air	Floor	space	ASHP	0.0042	0.09
5	Space Heating	Resistive	Radiator	space	RH	0.8577	0.0
6	Space Heating	Resistive	Floor	space	RH	0.0953	0.0
7	Hot Water	Ground	Water	water	GSHP	0.005	0.1
8	Hot Water	Air	Water	water	ASHP	0.042	0.9
9	Hot Water	Resistive	Water	water	RH	0.953	0.0

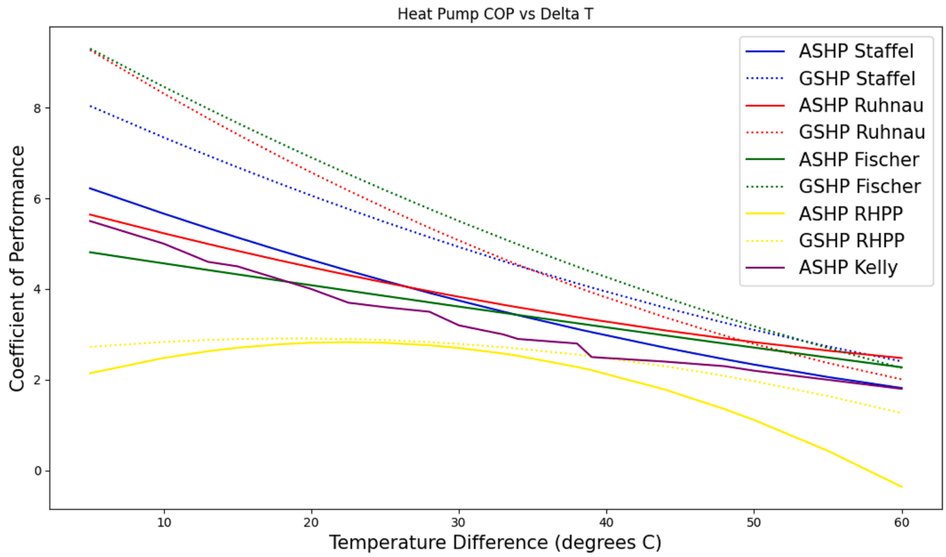

Fig. 4. Relationship between heat pump COP and difference between source and sink temperatures from different studies.

electricity removed is what we call the baseline electricity demand and was calculated as follows.

$$B_h = F_h - E_{2018,h} \tag{11}$$

Where F_h is the hourly historic 2018 electricity time series and $E_{2018,h}$ is the heating electricity time series for 2018 generated in section 3.2. This represents sources of demand other than heating, allowing us to study the impact of heating alone by adding in the electricity demand for each year of weather including future heating with heat pumps as follows.

$$S_{y,h} = B_h + E_{y,h} \tag{12}$$

Where $S_{y,h}$ is the electricity demand for hour of the year h and year of weather y, and $E_{y,h}$ is the heating electricity time series for hour h and weather year y generated in section 3.2.

4. Validations

The steps described in the methods in section 3 are shown in Table 4 along with the validations that are investigated in this section.

4.1. Validations of heat demand generation methods

Four methods of generating daily heat demand time series were compared in [19] using daily temperatures from the ERA5 weather reanalysis for the years 2016 to 2019. For convenience they were given the names **BDEW, Watson, HDD 15.5 and HDD 12.8**:

- **BDEW** (Bundersverbend der Engie und Wasserwirtschaft) The German gas company's equation to estimate consumers gas usage from [18] used in this study.
- **Watson**: a method based on a regression equation based on UK building measurements from Watson et. al. [37].
- **HDD 15.5**: Heating Degree Days (HDD) with a base temperature of 15.5°. [15,38]
- **HDD 12.8:** HDD with a base temperature of 12.8°.

They differ in the demand factor equation used to calculate $f_{d,g}$ in

Table 4
Summary of methods and validations.

Major Task	Sub Task	Validation
1) Generate heat demand time series using equations (1–5)	Split annual heat demand derived from fuel energy into days (using temperature (Section 3.1)	4.1.1 National gas: Find the heat in gas 4.1.2 Comparison of 4 models to gas heat 4.1.3 Heat pump measurements 4.1.4 Gas Meters
2) Remove heating electricity from 2018 electricity demand using equations (6,10,11)	Section 3.2 and 3.3	4.2 Linear regression
3) Add heat pump electricity for different years of weather using equations (6,10,12)	Estimate heating electricity demand time series from heat demand (Sections 3.1 and 3.2)	4.3.2 Previous studies 4.3.1 Heat Pump trial data

Table 5
temperature equations to factor annual heat demand.

Method	Demand factor equation	Reference Temperature
BDEW space [18]	$f_{d,g,space} = \frac{A}{1+\left\{\frac{B}{T^{Ref}_{d,g} - T_0}\right\}^C} + D + max\left(\frac{m_{space} - T^{Ref}_{d,g} + b_{space}}{m_{water} - T^{Ref}_{d,g} + b_{water}}\right)$	Current day and 3 previous days (N = 3)
BDEW water [18]	$f_{d,g,water} = \left(\frac{D + m_{water}.T^{ref}_{d,g} + b_{water} T^{ref}_{d,g} > 15^\circ C}{D + m_{water}.15 + b_{water} T^{ref}_{d,g} \leq 15^\circ C}\right)$	(N = 3)
Watson space [37]	$f_{d,g,space} = \begin{cases} -6.71 T^{Ref}_{d,g} + 111, for T^{Ref}_{d,g} < 14.1^\circ C \\ -1.21 T^{Ref}_{d,g} + 33, for T^{Ref}_{d,g} > 14.1^\circ C \end{cases}$	1 previous day (N = 1)
Watson water [37]	$f_{d,g,water} = -0.0458 T^{Ref}_{d,g} + 1.8248$	(N = 1)
HDD 15.5 space [15]	$f_{d,g,space} = \begin{cases} 15.5 - T^{Ref}_{d,g}, for T^{Ref}_{d,g} < 15.5^\circ C \\ 0, for T^{Ref}_{d,g} > 15.5^\circ C \end{cases}$	Current day only (N = 0)
HDD 15.5 water [15]	$f_{d,g,water} = 1.0$	
HDD 12.8 space[8]	$f_{d,g,space} = \begin{cases} 12.8 - T^{Ref}_{dgl}, for T^{Ref}_{d,g} < 12.8^\circ C \\ 0, for T^{Ref}_{d,g} > 12.8^\circ C \end{cases}$	Current day only (N = 0)
HDD 12.8 water[8]	$f_{d,g,water} = 1.0$	

equation (3) and in the number of previous days temperature (N) as shown in Table 5.

The BDEW method was found to be the best when validated against historic UK gas demand in the previous study [19]. However, a more rigorous investigation would quantify the amount of gas in the historic time series used for heating. That is what we do in this work. Additionally, we validate all heat demand methods using actual measurements from heat pumps and gas smart meters.

4.1.1. Proportion of the national gas time series used for heating

In countries such as the UK where natural gas provides a large proportion of heating, historic gas time series are often used in both generation and validation of heat demand time series. Some studies [4] have generated UK heat demand time series from natural gas time series, on the simplifying assumption that all gas is used for heating. We do not use the historic gas time series for generating heat demand here but instead use the method described in 3.1 to ensure that our heat demand time series are independent of technological developments such as efficiency and home insulation.

A previous study for validating heat demand time series against the 2013 UK gas demand [18] identified that there is some uncertainty about how much is actually used for heating because the time series also contains non heat uses [39], giving a discrepancy shown as unknown use in Table 6 for 2018. Using it as a ground truth for validation is potentially inaccurate Therefore, we investigate the gas time series to ascertain how much of it is heat.

Fig. 5 shows a strong correlation for 2018 between gas energy use and heating degree days. We assume that the part of the gas demand that is dependent on heating degree days is used for heating and that the remainder is not.

A standard method of estimating the proportion of the electricity demand time series used for heating is to use linear regression on heating degree days [29,40]. We use the same procedure separately on the 2016, 2017 and 2018 daily gas time series, the years for which we have detailed gas data, to find the constants a_0 and a_1 for each one of these years in equation (13).

$$R_d = a_0 + a_1 hdd_d \tag{13}$$

Where R_d is the daily (d) gas time series found by the regression, and hdd_d is the heating degree days for day d calculated using a population weighted base temperature of 15.5 °C. The time series of gas used for heating is therefore given by $a_1 hdd_d$ so the gas not used for heating can then be estimated as equation (14).

$$D_d = G_d - a_1 hdd_d \tag{14}$$

Where D_d is the daily gas time series without the gas used for heat and G_d is the historic daily gas time series, which are plotted in Fig. 6 showing that its use as a method of removing the heating energy looks plausible.

The sum of D_d from equation (14) is 162 TWh for 2018 and provides an estimation of the non-heat gas. To convert to heat demand we multiply by 0.8 (consistent with Table 1) for gas boiler efficiency giving 129.6 TWh. This is close to the unknown 125 TWh from Table 6 therefore, we conclude that this unknown use portion is not used for heating. A similar result was found for 2016 and 2017 with the percentage of heat in the gas time series varying by 2 % between the years 2016–2018 and the linear regression having a coefficient of determination R between 0.90 and 0.94.

Table 6
unknown portion of the gas time series.

Description	Energy
Sum of the 2018 gas time series converted to heat using an efficiency of 0.8	435 TWh
Gas heating energy for space and water heating derived from government surveys and sales figures [34], Table 1	310 TWh
Unknown use	125 TWh

4.1.2. Comparison of generated heat demand time series with that derived from gas.

Using the result from the previous section that the unknown use portion of the gas is not used for heating we generate a time series of heat for 2016–2018 from the gas time series using equation (15).

$$H_d = 0.8G_d - \frac{125}{365} \tag{15}$$

Where H_d is heat demand from gas for day d, G_d is the daily gas demand, 0.8 is the conversion efficiency of gas energy to heat, 125 is the amount of gas not used for heating which we deduced in section 4.1.1, and 365 splits this equally amongst days of the year. We then use this heat demand series to validate and compare the four methods described in section 4.1.

Fig. 7 shows all four methods of splitting the annual heating energy into days for 2018 along with a blue line for the gas time series. It can be seen that all of the heat demand methods over predict in summer and consequently under predict in winter. 2016 and 2017 show a similar pattern.

4.1.3. Validation of heat demand methods using heat demand measurements from a domestic heat pump trial

The Renewable Heat Premium Payment (RHPP) Scheme [25] monitored 418 UK houses in the period 2012 to 2015, including measurement of heat demand. We use the measured heat demand from this to validate the methods of splitting the annual heat demand into days (see section 4.1). Fig. 8 shows the heat demands of all the houses from the heat pump trial over the monitoring period compared to that predicted by the four methods of splitting the annual heat demand into days.

4.1.4. Validation of heat demand methods using gas smart meter readings from commercial and public buildings

The four methods of heat demand were also validated using gas meter readings for commercial and public UK buildings for the period 2004 to 2006 from a Smart Meter trial [26] by The Carbon Trust. The data consists of half hourly gas meter readings in KWh for the period 2004 to 2006 from 51 gas meters in public and industrial buildings. The purpose of the trial was to get customers to try out smart meters and to see if it prompted energy saving behaviour. It was noted in the study report that the participants in the trial were self-selected and had a greater than average gas demand, and so were not entirely representative of the whole country, and that some of the buildings were not used at weekends.

The gas demand time series from each building were combined and converted to heat demand assuming that all their gas boilers have the same efficiency (0.8) and that all the gas is used for space heating, which is mostly the case[26].

Fig. 9 shows the heat demand time series derived from the commercial buildings gas smart meters compared to that predicted by the four methods of splitting the annual heat demand into days. The 2nd winter shows a higher heat demand as more buildings were monitored during this period.

4.1.5. Heat demand validation results

The results of the heat demand validations from the previous 3 sections are summarised in Table 7. The BDEW method is shown to be better in all cases apart from the gas smart meter validation where the Watson method has the best R^2 and shows the least bias in the residuals plots (not shown here). Therefore, we concluded that the BDEW method should be used, confirming the result of our previous work [19]. This is an import result because the BDEW method has already been used to

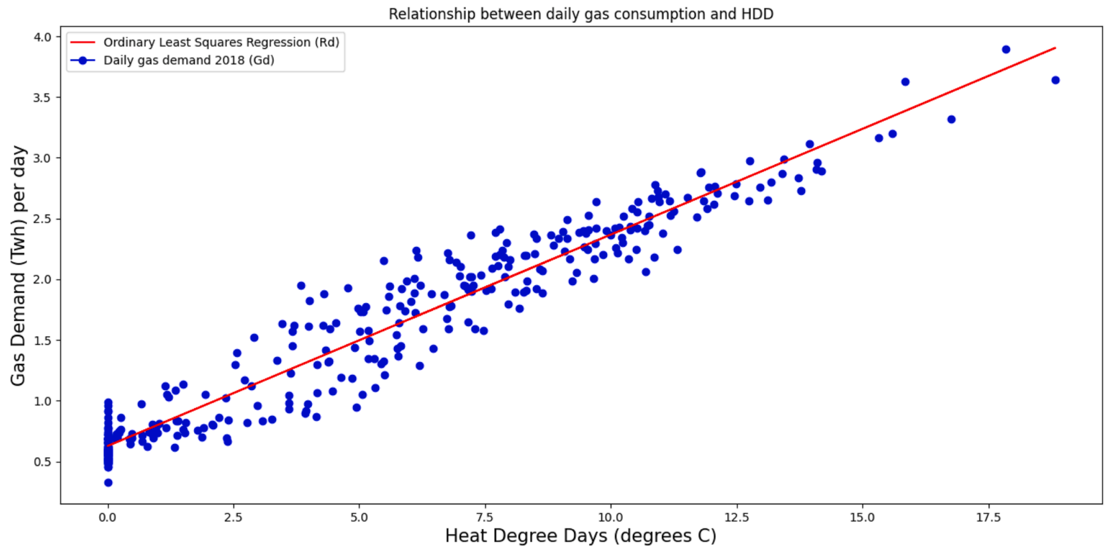

Fig. 5. Relationship between daily Great Britain gas consumption and heating degree days 2018.

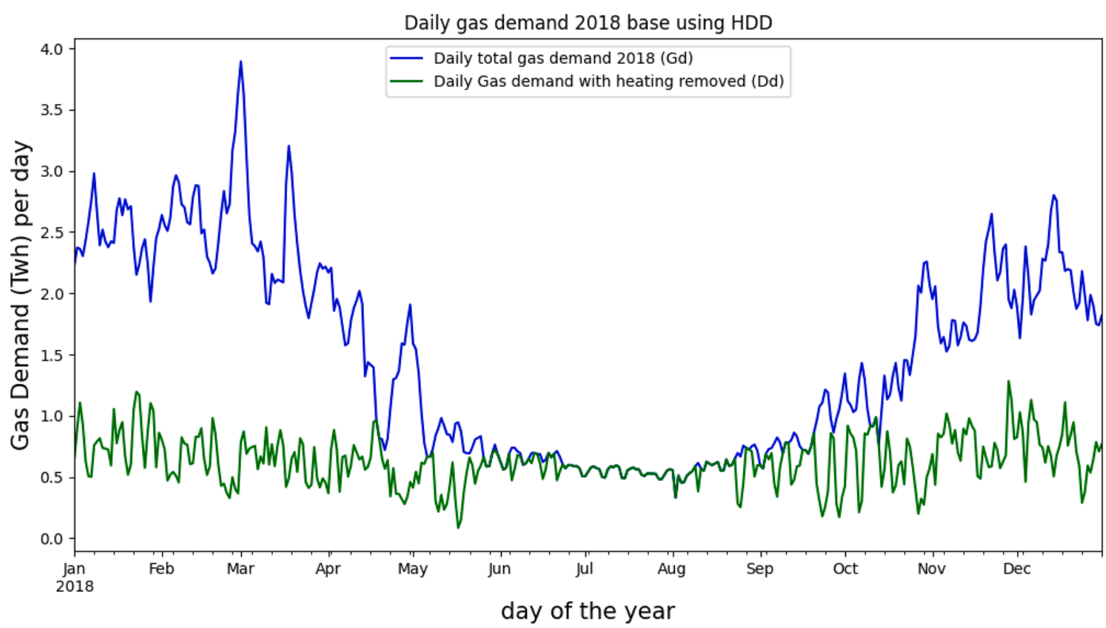

Fig. 6. Daily gas demand and daily gas demand with gas used for heating removed.

provide the UK heat demand input for several studies [41–44].

However, it should be noted that neither the group of houses in the heat pump trial nor the commercial buildings in the gas smart meter trial are fully representative of the national stock which may explain discrepancies between the modelled results and those from trials.

An experiment using the most accurate ERA5 weather grid of 0.25,0.25 rather than the 0.75,0.75 used for the results in 4.1.2 above found that in general the R^2 was unchanged, but that in some cases the nRMSE reduced by about 0.01, showing a small benefit in using a finer grid.

Simplifying the model by using no population weighting or by using no previous days temperature results in a decrease in accuracy (R^2 reducing from 0.982 to 0.970).

4.2. Validation of generated electricity demand time series

As described in section 1 we are generating a baseline electricity demand based on 2018′s electricity demand. We want this demand to be independent of the weather and for this reason we are removing the heating electricity as described in section 3.2.

We investigate if, using the resulting baseline electricity demand time series, and our method of generating heating electricity demand we can generate 2017 and 2019 electricity demand series similar to the historic ones. We restrict our investigation to just these two years to ensure similar technoeconomic conditions with 2018. We create a synthetic 2017 electricity demand time series by removing the 2018 heating electricity from the 2018 electricity time series and adding in the 2017 heating electricity. This approximates the historic 2017 electricity demand time series a per equation (16).

$$\widehat{E}_{2017} = E_{2018} - H_{2018} + H_{2017} \tag{16}$$

Where $\widehat{E}_{2017}$ is predicted 2017 historic electricity demand time series, E_{2018} is the actual 2018 historic electricity demand time series, H_{2018} is the generated time series of heating electricity for 2018 and H_{2017} is the generated time series of heating electricity for 2017. (E_{2018} - H_{2018} is the

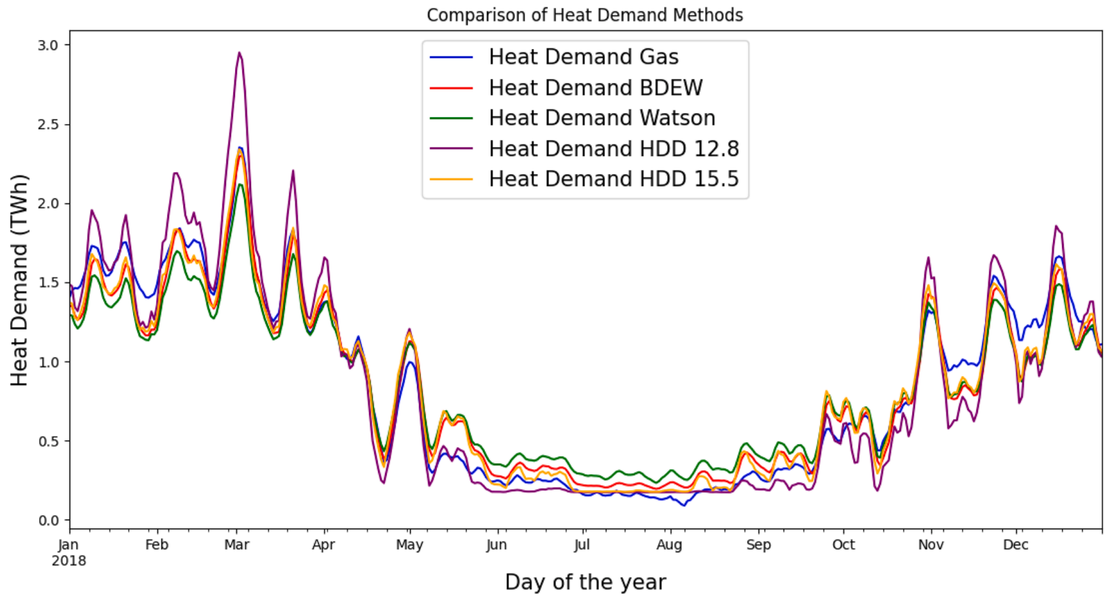

Fig. 7. comparison of methods of splitting annual heat demand into days with gas derived heat demand for 2018 (5 day rolling average).

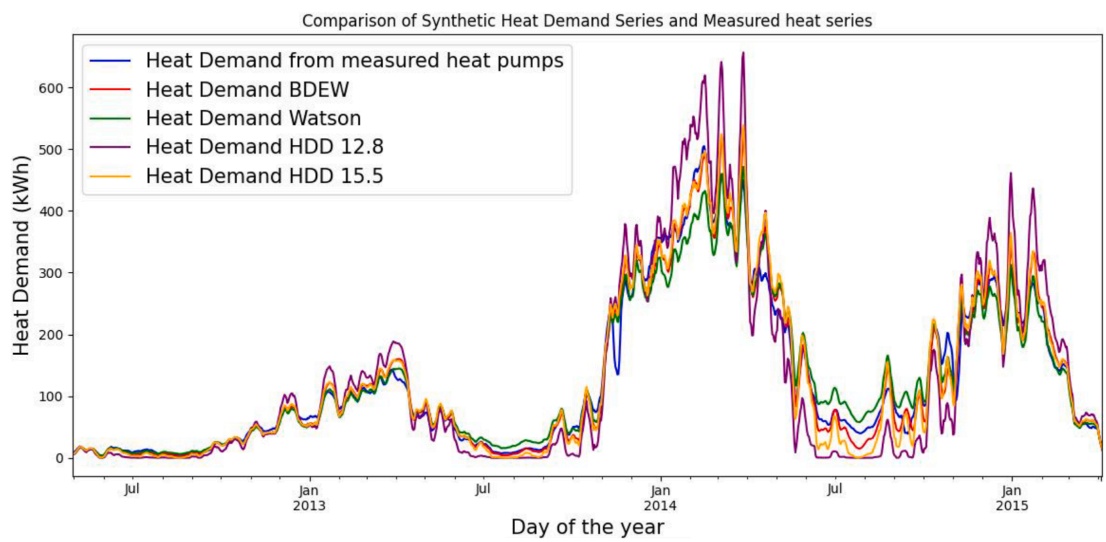

Fig. 8. Comparison of methods of splitting total heat demand over a period into days using measured heat pump data 7 day rolling average.

baseline electricity demand) This synthetic timeseries compares well with the actual 2017 electricity demand giving $R^2 = 0.994$ as shown in Table 8. For the 2019 time series it was $R^2 = 0.995$ and nRMSE = 0.08.

Previous studies [29] have used linear regression to find the heating electricity in a similar way to what we did with the gas demand in section 4.1.1, but including cooling degree days (CDD) as well as HDD. To compare the accuracy of this method with ours, linear regression was used to estimate the coefficients b, c, h in equation (17) to estimate the amount of heating and cooling in the electricity demand time series.

$$E_i = b + cC_i + hH_i \tag{17}$$

Where E_i is the electricity demand time series, C_i is a time series of Cooling Degree Hours (CDH) using a base temperature of 20 °C [45], H_i is a time series of Heating Degree Hours (HDH) using a base temperature of 14.8 °C. In line with the previous studies, we found that it is not necessary to include cooling electricity in the model. The heat demand from this standard linear regression was also used to validate the heating electricity demand using equation (16) and the result is shown as the 2nd row of Table 8. This linear regression also provides an important additional validation of the heat demand method itself using the electricity time series.

4.3. *Validation of heat pump electricity demand time series*

4.3.1. *Comparison of predicted heat pump electricity with trial data*

The heat demand measurements from the RHPP trial data were used to generate an electricity demand time series using the methods from section 3.3 to compare it with the actual measured electricity demand. Fig. 10 shows that the actual electricity demand measured from the heat pump trial data is higher than that predicted.

The modelled electricity demand time series to the measured one with $R^2 = 0.994$ reflecting the fact that both time series follow a similar pattern, but the high nRMSE of 0.70 reflects the under prediction in the model. There is also a large bias shown in the residuals plot (not shown here).

The reason for the higher heat pump electricity demand from the heat pump trial data could be the fact that the sample of housing in the trial is mostly social housing [25] not representative of the UK housing

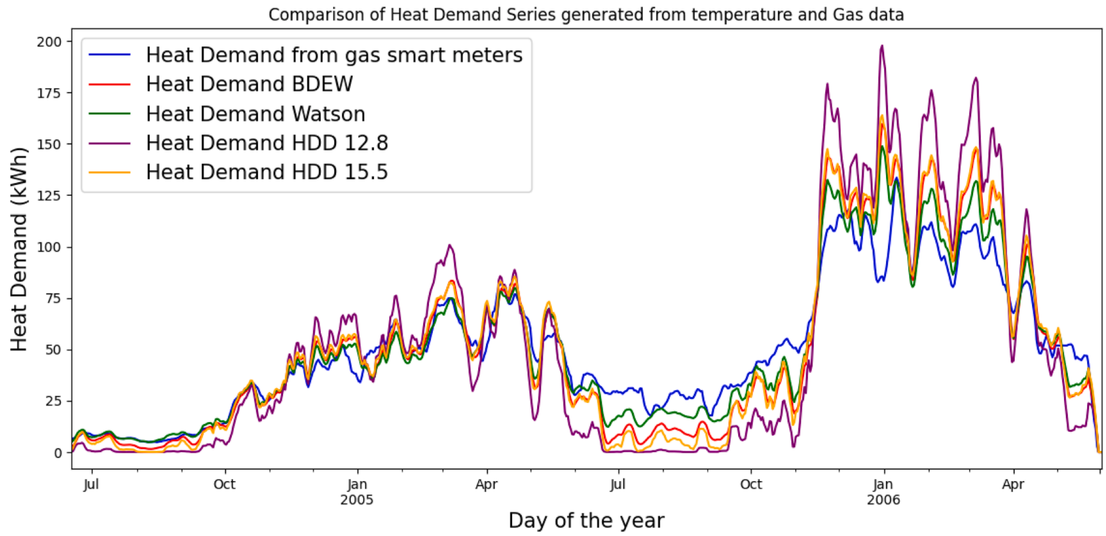

Fig. 9. Comparison of methods of splitting heat demand over a period into days using Gas smart meter data 7 day rolling average.

Table 7
Heat Demand Validation.

	National Gas Heat 2016–2018		RHPP Heat Pumps 2013–2015		Gas Smart Meters 2005–2006	
	nRMSE	R^2	nRMSE	R^2	nRMSE	R^2
BDEW	**0.12**	**0.989**	**0.25**	**0.977**	**0.57**	0.880
Watson	0.13	0.987	0.26	0.974	0.59	**0.896**
HDD15.5	0.16	0.982	0.33	0.964	0.63	0.859
HDD12.8	0.30	0.953	0.59	0.912	0.87	0.789

Table 8
Comparison of Electricity Time Series.

Comparison to the 2017 electricity demand time series	R^2	nRMSE
2017 synthetic time series from equation (12) using our heat demand method from section 3.1 to calculate H_{2018} and H_{2017}	0.994	0.08
2017 synthetic time series from equation (12) heat using linear regression model from equation (17) to calculate H_{2018} and H_{2017}	0.993	0.08

stock and containing heat pumps not representative of the typical heat pumps sold. Another reason could be that UK heat pumps perform less well than German installations [5] possibly due to lack of experience amongst installers. Another possible explanation is inaccuracy of the RHPP trial data, although a previous study [13] expressed doubts about the accuracy of the heat measurements rather than the electricity measurements. Finally, another cause could be that our model assumes that all the hot water is provided by heat pumps alone, but this may noy be the case.

It is clear from Fig. 4 that the temperature dependent COP we calculated from the RHPP heat pump trial data is very poor compared to those used in other studies. For ASHP, we calculated an average COP of 2.4 from the trial data, compared to the annual population weighted COP of 2.9 calculated using equations (7) and (8) based on the weather of 2010 to 2019. For comparison, a review of available heat pump data [46] notes a large variation in COP from 2 to 4, and that one trial of retrofitted homes in Northern Ireland reported a COP as low as 1.4. This variability in heat pump performance obtained from heat pump trials suggests that heat pump trial data should be used with caution in research. More trial data is required from heat pumps to accurately reflect the distribution of housing and heat pump types in the UK.

4.3.2. *Comparison of predicted heat pump electricity with other studies*

We compared the heating electricity time series from the DESTinEE model [3] which uses 2010 as its reference year and 50 % heat pumps with our model (equation (6)) using the same year and heat pump penetration.

The generated time series of heat pump electricity required to supply half the Great Britain heat demand using heat pumps from our model (blue line) is shown in Fig. 11 compared with that using the DESSTINEE model (orange line). Comparing these two time series we find R^2 = 0.962, nRMSE = 0.63 and that DESSTINEE finds a higher electricity demand.

Because the DESSTINEE model assumes a COP of 2.5 for 2010, whereas our model uses a temperature dependent COP at each weather grid point resulting in an average COP of 3.5 we also tried the DESSTINEE model with a COP of 3.5 which is shown in green on Fig. 11. This provides a closer match but there are still some differences in the pattern. These differences reflect variations in methods of calculating COP and heat demand. Although it is clear, that the change in the magnitude of the average COP from 2.5 to 3.5 has larger impact on the heat pump electricity demand profile overall, the variation of the COP due to temperature may have comparable impact during some periods.

5. Results

Although hourly time series have been generated, only the daily series are shown in the following plots for clarity.

5.1. *Baseline electricity demand*

Fig. 12 shows the daily historic electricity time series for 2018 (in blue) with the portion of that which was heating (in red) subtracted from it to give the baseline electricity demand without heating electricity (purple).

5.2. *Generated electricity demand time series*

By way of demonstration the results of our method applied to 10 arbitrary consecutive years from the total 40 are shown in Fig. 13. The purple line of Fig. 13 shows the baseline electricity demand. The orange line shows the effect of adding in the electricity demand for heat pumps assuming all heating was provided by heat pumps. As expected, this would have a very large impact as currently most UK heating is provided by gas.

Note that despite the removal of the weather dependence due to

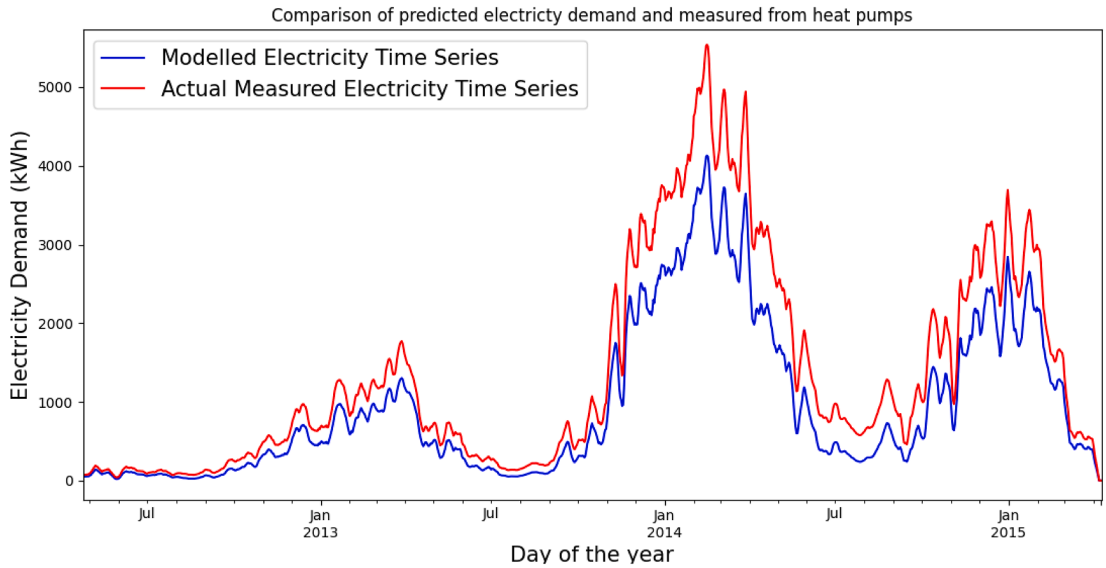

Fig. 10. Comparison of predicted electricity demand using our method with actual hourly electricity demand from measured heat pumps in the RHPP trial 7 day rolling average.

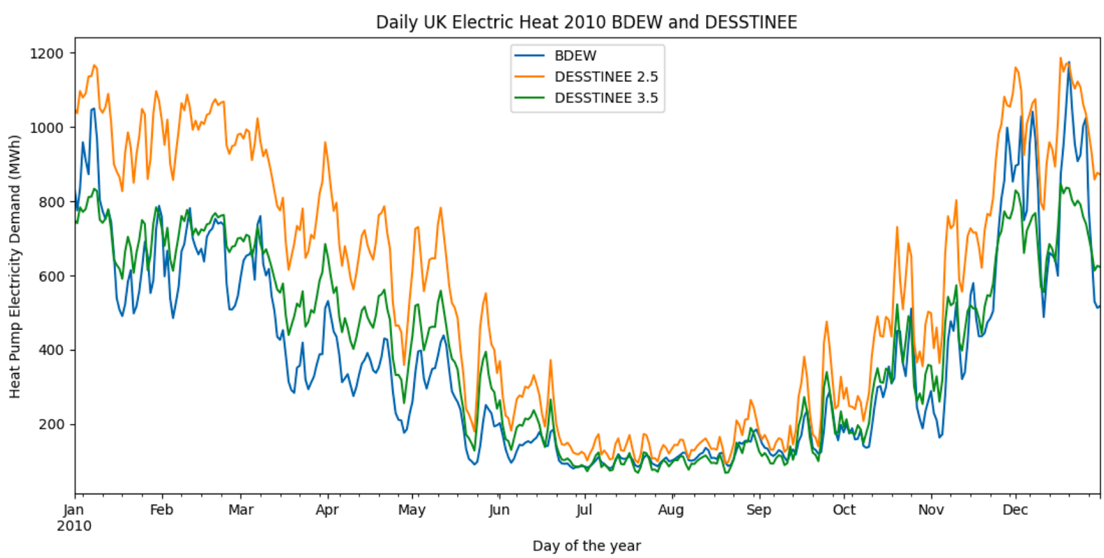

Fig. 11. comparison of BDEW heat pump electricity time series with DESSTINEE.

heating, the baseline electricity demand still shows some variation between months also visible in Fig. 12. December has a mean daily demand of 0.7 TWh where there is a noticeable dip in the holiday period at the end of month. The mean electricity demand of the other months varies between May with 0.67 TWh, July with 0.71 TWh and January with 0.75 TWh. A weekly cycle is also visible in Fig. 12, where demand varies within a week by 0.23 Twh compared to the variation between weeks of only 0.09 TWh. The baseline demand is very weakly correlated with heating degree days per hour ($R = 0.19$) and the correlation with temperature is also very weak. Therefore, it seems reasonable to conclude that most of the weather dependency has been removed, and that the pattern is due to time dependent consumer behaviour.

Fig. 14 shows the 2018 historic electricity demand (blue line) compared to what it would have been if all heating were provided by electric heat pumps (red line), where the annual electricity demand would increase from 299 TWh to 391 TWh. The green line represents a more realistic scenario of 41 % heat pumps from the 2050 prediction from [2] where the annual electricity demand would be 323 TWh. As expected, there is a noticeable increase in winter demand and the day-to-day variability of this demand.

However, it is also important to note the advantage of using heat pumps over traditional electric heating. The purple line in Fig. 14 shows the electricity demand for 2018 if the existing electric heating had been provided by heat pumps. This would result in a reduction in the annual demand of 16 TWh and a reduction in hourly peak demand from 54 GW to 48 GW.

Fig. 15 shows the daily electricity demands assuming 41 % of heating provided by heat pumps for 40 consecutive years overlaid on top of each other. This is compared with the case when the electricity demand includes existing heating electricity. This shows a very large variation in the electricity demand in the winter months for different years and a much smaller variation in the summer for the case of 41 % heating from heat pumps. The monthly electricity demand has doubled leading to an increase in about 30TWh for each winter month (December, January, February).

Fig. 16 shows that for the 40 consecutive years of data we are

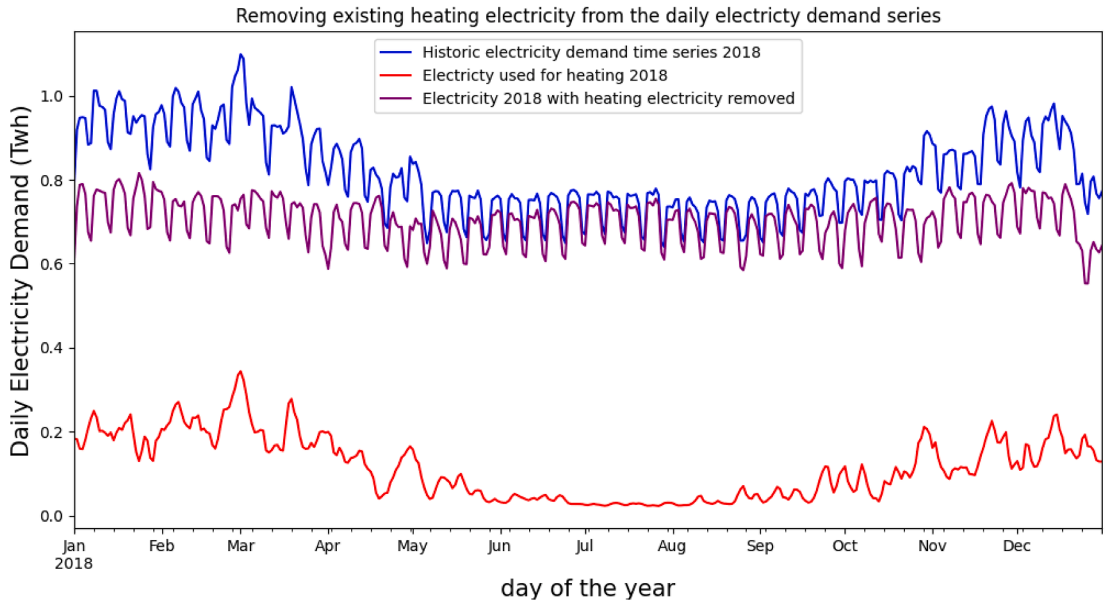

Fig. 12. Removing the electricity for heating from the historic electricity demand of 2018 to obtain the baseline electricity demand.

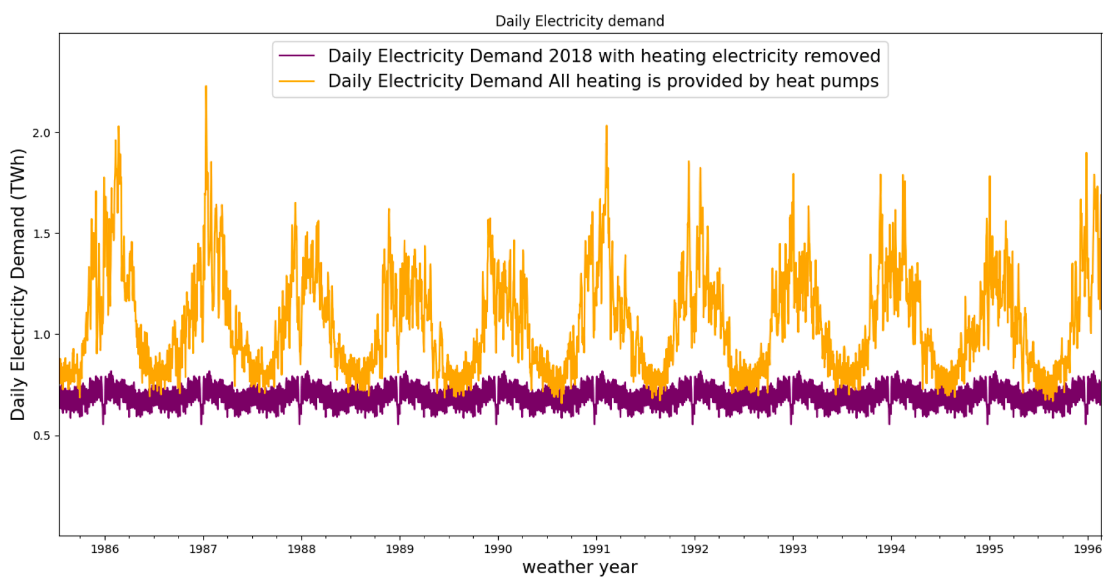

Fig. 13. Baseline electricity demand (2018 time series without the electricity used for heating) compared with generated electricity demand assuming all heating is provided by heat pumps.

considering in this study the annual electricity demand with the existing heating electricity would vary over a range of 19 TWh, whereas with 41 % of heating provided by heat pumps this variation increases by 37 % to a range of 26 TWh.

The decline in Great Britain's annual electricity demand with 41 % of heating provided by heat pumps visible in Fig. 16 is caused by a decline in annual heat demand of 70TWh over the 40-year period due to approximately 1 °C increase in the population weighted Great Britain temperature over the years 1980 – 2019.

Fig. 17 shows the variation in the day-to-day and seasonal patterns from one year to the next of the daily electricity demand incorporating 41 % of heating provided by heat pumps generated using our method (green) in comparison to the historic time series (blue). The increase in winter demand and its day-to-day variability both more noticeable in some years and less in others, impacts the required shares of weather dependent renewables and storage, and this must be addressed and quantified in further work.

Note that the 41 % heating by heat pumps figure was taken from the net zero scenario in the UK National Grid Future Energy Scenarios 2019 [2]. However, there is a large variation in future 2050 heat pump penetration projections. Seven plans for achieving a net zero UK in 2050 are reviewed in [47]. These plans have been developed by four different groups using different modelling methods and assumptions. The plan with lowest proportion has only 27 % of heating provided by heat pumps whereas the plan with most heating provided by heat pumps has 74 %.

Supplying the electricity for heat pumps in a sustainable way would require an increase in renewable energy, such as solar and wind energy, complemented with energy storage. Increases in transmission infrastructure would also be necessary [48] to cope with increased generation. Demand side management and use of thermal storage with heat pumps to reduce the variation in demand can also play an important role [15].

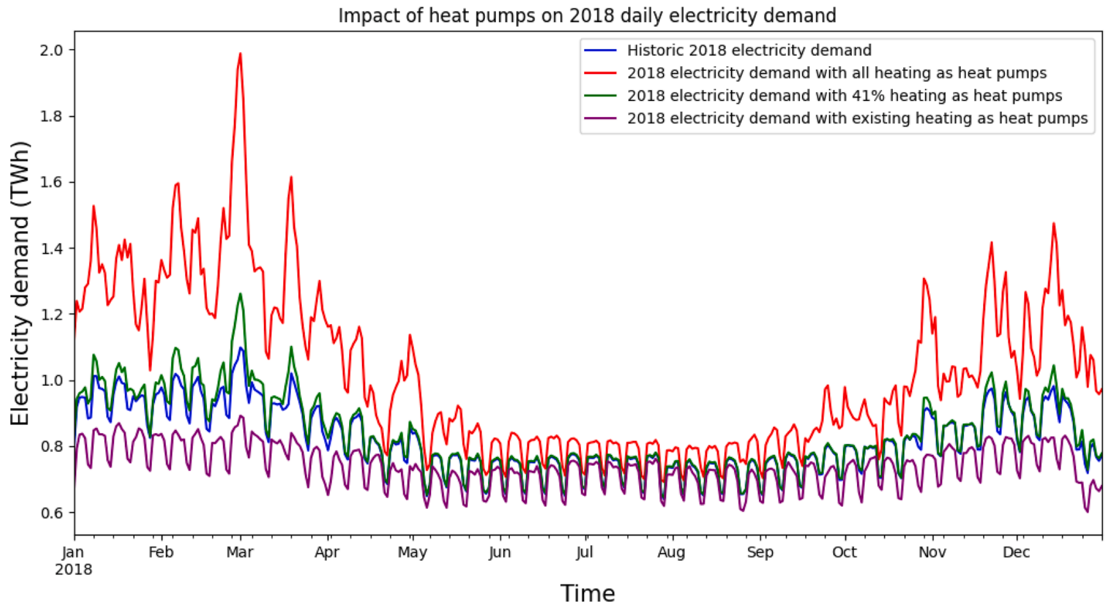

Fig. 14. The impact on the 2018 electricity demand if all heating were provided by electric heat pumps.

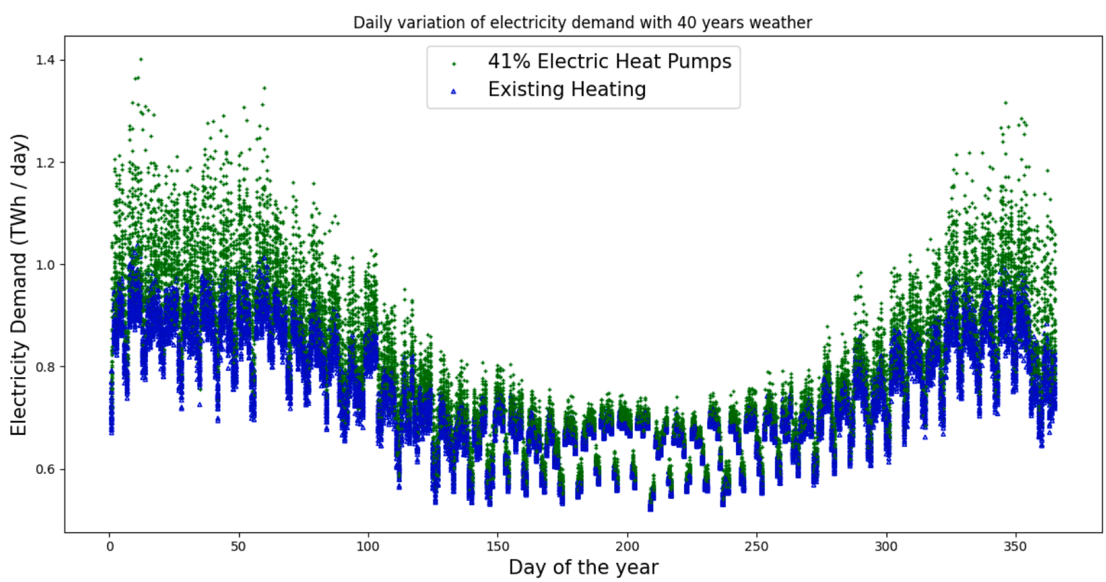

Fig. 15. 40 years generated daily electricity demand time series incorporating 41% of heating provided by heat pumps compared to existing heating.

6. Sensitivity analysis

Both the method used to generate daily heat demand time series from section 4.1 and the selection of the hourly profile of heat pump operation from Figs. 2 and 3 will impact the final electricity demand time series. We study here the effect on peak demand, annual demand, and ramp rates.

Previous work on generating hourly heat pump electricity demand time series [3] has used hourly profiles derived from gas boilers. Flat profiles [49] have also been suggested assuming that heat pumps would be configured this way as the best way of reducing peak demand whilst ensuring thermal comfort. Whilst it is clear that using an hourly profile derived from actual heat pump data would be an option, different trials have shown heat pump profiles with different shapes [50] due to the way the heat pumps are configured.

We therefore investigate the sensitivity of the generated hourly electricity demand both to the hourly profile and the method of generating the daily heat demand time series. The result of using different hourly profiles to generate an hourly time series from the daily series generated using the BDEW heat demand method are shown in Table 9. Peak demand is important for estimating the required generation capacity and ramp rates are important for the stability of the electricity system as it has to react to the sudden addition or loss of load. The higher peak demands for the RHPP profile will have been caused by its higher afternoon peak shown on Fig. 2 because the time of peak demand in the historic series also occurs in the later afternoon.

The results of varying the daily heat demand method but keeping the same hourly profile are shown in Table 10.

The choice of method (splitting the annual heat demand into days) and hourly profile only have a small impact on the annual electricity demand. However, the hourly peak demand values vary over a range of 25 GW (25 %) which is quite significant compared to estimates of what the future peak demand might be. For example a study into electricity demand and weather variability [17] predicts that electrification of heat

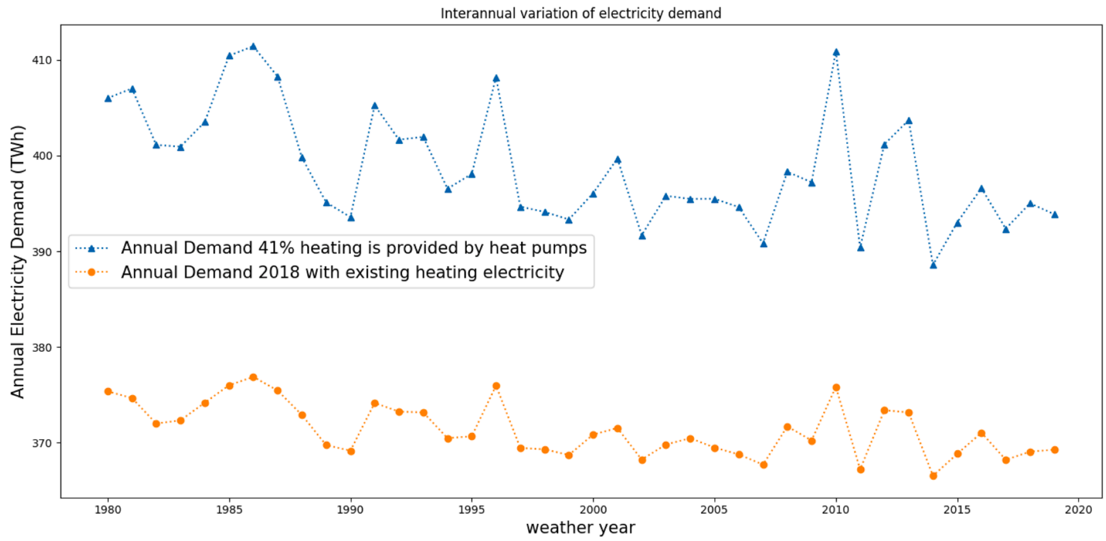

Fig. 16. annual demand with 41% heat pumps compared with heating electricity at 2018 levels.

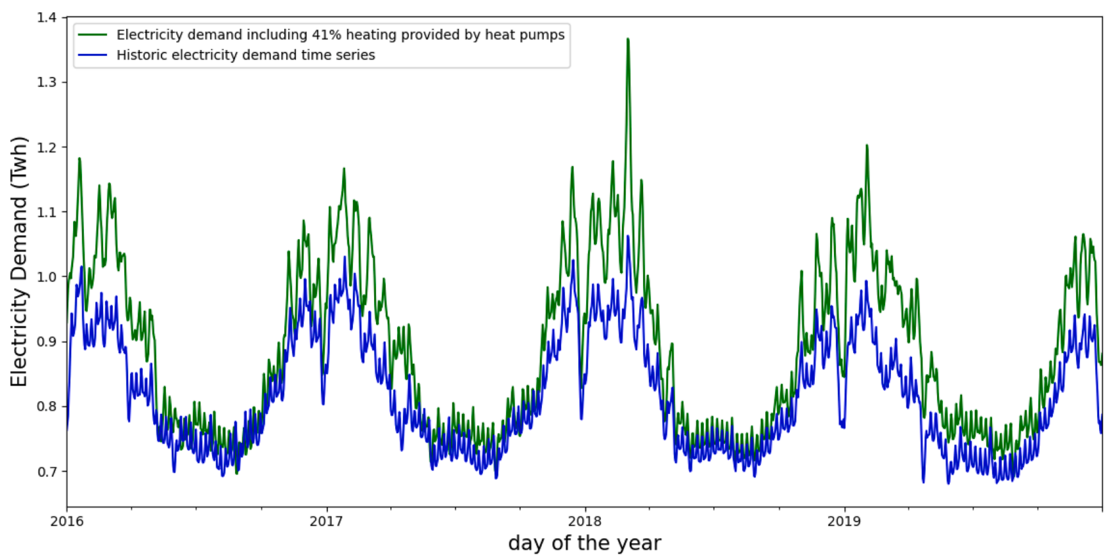

Fig. 17. Impact of 41% heating provided by pumps 5 day rolling average.

Table 9
hourly electricity time series comparisons if 2018 had heat electrification.

Electricity Time Series	Hourly Profile	Hourly Peak Demand	Hourly Ramp up	Hourly Ramp down	Annual Demand
Historic (existing heating)		54 GW	7 GW	6 GW	266 TWh
BDEW method (heat pumps)	BGW	94 GW	12 GW	11 GW	397 TWh
BDEW method (heat pumps)	Flat	89 GW	7 GW	5 GW	380 TWh
BDEW method (heat pumps)	RHPP	100 GW	20 GW	15 GW	379 TWh

will double peak demand from about 50 GW to 100 GW and in a study including other sectors as well as heat [15] hourly ramp rates of ± 15 GW are predicted by 2030. This suggests that estimates of peak demand are very inaccurate if they can vary so much depending on the method of generating the heat demand time series.

Despite being based on the same annual heat demand, the annual electricity demands estimated from the different methods and shown in Table 10, differ, because the methods assume both different hourly heat pump operation profiles and daily total heat demand. The intraday temperature variations mean different COP for each hourly profile of heat pump operation and hence the total amount of electricity required to generate the same heat varies accordingly.

7. Conclusions

The paper describes a method to generate long-term electricity demand time series accounting for the expected electrification of heat using heat pumps. In contrast to previous reported research, the generation of this synthetic time series is based on modifications of the actual historic data series which enables the method to capture the

Table 10
Sensitivity of the hourly electricity demand to heat demand method.

Electricity Time Series	Hourly Profile	Hourly Peak Demand	Hourly Ramp up	Hourly Ramp down	Annual Demand
Historic (existing heating)		54 GW	7 GW	6 GW	266 TWh
BDEW method (heat pumps)	RHPP	100 GW	20 GW	15 GW	379 TWh
Watson method (heat pumps)	RHPP	95	16 GW	13 GW	378 TWh
HDD 12.8 method (heat pumps)	RHPP	120 GW	24 GW	18 GW	381 TWh
HDD 15.5 method (heat pumps)	RHPP	102 GW	19 GW	15 GW	380 TWh

variation due to 40 years historic weather whilst keeping current technological and socio-economic conditions.This resulting time series allows us to study the impact of heat pump penetration alone on electricity demand.

Four methods of generating heat demand time series were compared to measured data. All these methods compared well. However, the methods based on gas demand (BDEW and Watson) do slightly better than those based on HDD. One way that these better performing methods differ from the other two is that they assume that hot water demand is dependent on temperature rather than being constant throughout the year, so this could partly explain why they perform better. More specifically, from analysis of the gas time series, and trial data validations we concluded that the BDEW method used for the when2heat dataset performed the best. This is an important result because the when2heat dataset has already been used by several studies to provide the UK heat demand. Validation revealed that population weighting and using previous days temperatures improved accuracy sufficiently to be worth including in the method.

Our model under predicts the heat pump electricity demand in comparison with actual electricity measurements from UK heat pump trial data. Variation in heat pump COP from UK trials suggests that the performance of heat pumps depends so much on their specific implementation that electricity demand measured from existing heat pump trial data is not representative of the whole country. This restricts the usefulness of the existing data in nationwide models of energy systems. More data is needed to accurately reflect the distribution of housing and heat pump types in the UK.

It was found that the peak electricity demand is very sensitive to both the choice of hourly heat profile used to convert daily to hourly series and to the method of splitting the heat demand into days. Specifically, the hourly peak demand values vary over a range of 25 GW which is quite significant compared to some estimates of future peak demand of 100 GW. This suggests that estimates of peak demand may be very inaccurate and that more research is required in this area.

The advantage of using heat pumps over traditional electric heating was quantified in our work. As an example, we have shown that if the existing electric heating in 2018 had all been provided by heat pumps it would have resulted in a reduction in the annual demand of 16 TWh and a reduction in the hourly peak demand from 54 GW to 48 GW.

Our model shows that annual electricity demand with existing heating electricity varies over a range of 19 TWh between different years due to differences in the weather. However, with 41 % of heating provided by heat pumps this variation in electricity demand increases by 37 % to a range of 26 TWh. Finally, it was found that the electrification of heat expected by 2050 with the introduction of heat pumps, modifies the seasonal profile of electricity demand doubling the monthly demand for electricity leading to an increase in about 30TWh for each winter month. Given that the main renewable energy sources wind and solar exhibit high seasonal variation further research should investigate how this change in the seasonal profile of electricity demand due to heat electrification will impact the role of wind and solar contribution and storage requirement in a future highly renewable electricity system.

8. Code Availability

The python program used for generating heat and electricity demand time series is available at https://github.com/malcolmpeacock/heat.

CRediT authorship contribution statement

Malcolm Peacock: Conceptualization, Methodology, Software, Writing – original draft, Validation, Visualization. **Aikaterini Fragaki:** Supervision, Writing – review & editing. **Bogdan J Matuszewski:** Writing – review & editing.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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