Chapter 7
Review of Heat Demand Time Series Generation for Energy System Modelling

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Abstract National heat demand time series are important inputs into national energy system models. Although time series for primary fuel such as gas might be available, heat demand is not and measuring heat demand is only possible for individual buildings. Four different methods are used in this work to generate daily heat demand time series for Great Britain for 2016–2018 from temperature and windspeed and are validated against heat demand derived from national grid gas demand. All seem to model heat demand well.

Keywords Heat · Demand · Time series · Energy system · Modelling

7.1 Introduction

Energy system models [1, 2] used to investigate renewable electricity and heat at national level require knowledge of heat demand. Whilst estimating the heat demand of one building is possible by measuring internal and external temperatures and the input fuel energy, knowing the heat demand of an entire country is very difficult [3]. Bottom up statistical models using regression from measured data have been used to generate heat demand time series for periods up to 12 months [3–5] but tend to be limited to the year of the measurements. Bottom up aggregated thermal models have uncertainty over the many different parameters that need to be specified [6] and have difficulty capturing diversity on a national scale [7]. Multi-year daily national heat demand time series are typically generated top down [4] using methods which have few inputs apart from weather parameters and annual fuel demand. Gas energy time series are used for validation.

Top down methods use national heat demand from a reference year derived from fuel sales figures. Annual fuel sales are divided into end use based on a combination of consumer surveys, building measurements and modelling. The annual demand is split up into days using historic weather data [4]. Standard hourly heat demand profiles

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Table 7.1 2018 annual fuel use TWh

Fuel	Gas	Other	Total
Domestic space	191	68	259
Services space	56	36	92
Domestic water	56	12	82
Services water	7	6	15
Non heat use	98		
Total	408		

based on observations and modelling are then applied to each day to generate an hourly time series. This paper compares four typical top down methods of generating multi-year daily heat demand by generating time series for Great Britain.

7.2 Input Data Used in This Work

Monthly mean wind speeds for 1979 to 2018 and ambient air temperatures every 6 h for 2016–2018 were taken from the ERA 5 interim weather reanalysis [8] at a spatial resolution of 0.75° × 0.75° for Great Britain. The distribution of the Great Britain population on a 1 km grid is taken from Eurostat [9] for 2011.

UK annual fuel demand figures for space heating and hot water were obtained from [10] and multiplied by 0.99 to convert to values for Great Britain, the Northern Ireland gas usage [11] being only 1% of the UK. Northern Ireland has its own gas network, and therefore this study concentrates on Great Britain rather than the UK.

Table 7.1 shows these annual demand figures converted to heat demand assuming the following efficiencies: gas 80%, oil 85%, solid fuel 76%, electricity 100%, heat (e.g. combined heat and power) 100%, bioenergy and waste 87%.

The Non-Daily Metered (NDM) daily gas demand time series for 2016–2018 was taken from national grid gas data explorer [12] and excludes "most gas fired power stations and some large industrial units". It includes agriculture and some industrial space heating which may explain why the sum of this time series for 2018 of 435 TWh does not match the total gas energy from Table 7.1 of 408 TWh.

7.3 Top Down Methods

In top down methods annual space heating demand is usually split using a temperature dependent equation as in [13]. Water heating is either done in a similar way or sometimes just split equally between days [14]. Sometimes only a single daily temperature for the UK is used [14, 15], but a more sophisticated method is to use weather reanalysis data weighted by population density at weather grid points [13, 16]. To account for the thermal inertia of buildings an effective temperature including the temperature of previous days is often used [3, 13, 17].

Four typical top down methods were selected from a survey of UK energy system studies from the last 10 years. The selection was made to incorporate all the techniques used in multi-year UK studies.

- Regression equation based on building measurements from Watson et al. [3] (**Watson**)
- Gas demand methodology from German Association of Energy and Water Industries (BDEW) as used by Ruhnau [13] (**BDEW**)
- Heating degree days (HDD) with a base temperature of 15.5 as used by Barton et al. [15] and Staffell et al. [15, 16] (**HDD 15.5**)
- Heating degree days with a base temperature of 12.8 as used by Hooker-Stroud et al. [14] (**HDD 12.8**)

The python program used by Ruhnau [13] to generate heat demand time series using the BDEW method was modified so that it would generate heat demand time series for all four methods (modified code available at https://github.com/malcolmpeacock/heat).

A reference temperature (Eq. (7.1)) was calculated at each weather grid point (l) and day (d) based on the ambient temperatures of the N previous days to account for the thermal inertia of buildings (for $d < N$, $N = d$).

$$T_{d,l}^{Ref} = \frac{\sum_{n=0}^{N} 0.5^n T_{d-n,l}^{amb}}{\sum_{n=0}^{N} 0.5^n} \tag{7.1}$$

where $T_{d,l}^{Ref}$ is the reference temperature for day d at location l and T^{amb} is the mean ambient air temperature for that location and day. The daily heat demand was calculated by summing up the demand values for all locations and weighting by population (mapped onto the weather grid), Eq. (7.2)

$$HDT_d = \frac{HD_{annual}}{P_{total} \cdot f_{total}} \sum_{l=0}^{NL} f_{d,l} . P_l \tag{7.2}$$

where $f_{d,l}$ the daily demand factor for day d and location l is derived differently for each method and for space and water heating as show in Table 7.2. HDT_d is the heat demand for day d, P_l is the population at location l, P_{total} is the total population, NL is the number of locations, HD_{annual} is the annual heat demand derived from Table 7.1, and f_{total} is the sum of all the demand factors.

In Table 7.2 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 [13]. 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).

Table 7.2 Temperature equations to factor annual heat demand

Method	Demand factor equation	Reference temperature
BDEW space [13]	$f_{d,l} = \frac{A}{1+\left\{\frac{B}{T_{d,l}^{Ref}-T_0}\right\}^C} + D + max\begin{pmatrix} m_{space} - T_{d,l}^{Ref} + b_{space} \\ m_{water} - T_{d,l}^{Ref} + b_{water} \end{pmatrix}$	Current day and 3 previous days (N = 3)
BDEW water [13]	$f_{d,l} = \begin{pmatrix} D + m_{water}.T_{d,l}^{ref} + b_{water} T_{d,l}^{ref} > 15°C \\ D + m_{water}.15 + b_{water} T_{d,l}^{ref} \leq 15°C \end{pmatrix}$	(N = 3)
Watson space [3]	$f_{d,l} = \begin{cases} -6.71T_{d,l}^{Ref} + 111,\ forT_{d,l}^{Ref} < 14.1°C \\ -1.21T_{d,l}^{Ref} + 33,\ forT_{d,l}^{Ref} > 14.1°C \end{cases}$	1 previous day (N = 1)
Watson water [3]	$f_{d,l} = -0.0458T_{d,l}^{Ref} + 1.8248$	(N = 1)
HDD 15.5 space [16]	$f_{d,l} = \begin{cases} 15.5 - T_{d,l}^{Ref},\ forT_{d,l}^{Ref} < 15.5°C \\ 0,\ forT_{d,l}^{Ref} > 15.5°C \end{cases}$	Current day only (N = 0)
HDD 15.5 water [16]	$f_{d,l} = 1.0$	
HDD 12.8 space [14]	$f_{d,l} = \begin{cases} 12.8 - T_{d,l}^{Ref},\ forT_{d,l}^{Ref} < 12.8°C \\ 0,\ forT_{d,l}^{Ref} > 12.8°C \end{cases}$	Current day only (N = 0)
HDD 12.8 water [14]	$f_{d,l} = 1.0$	

Space and water heating are then aggregated to give a final heat demand time series. In order to make a comparison with a heat demand time series generated from gas, space heat demand was scaled by 0.72 because only 72% of space heating comes from gas and water heating by 0.81 (derived from Table 7.1)

7.4 Validation Using Heat Demand from Gas

A heat demand time series was generated from NDM gas demand using Eq. (7.3)

$$HDG_d = \left\{0.8G_d - \left(\frac{0.8G_T - G_H}{365}\right)\right\} \tag{7.3}$$

where HDG_d is heat demand, G_d is the daily gas demand, 0.8 scales for boiler efficiency consistent with Table 7.1, G_T is the sum of the G_d values for the year, and G_H is the sum of the annual gas space and water heating from Table 7.1. This assumes that $0.8G_T - G_H$ is non-heat gas and is therefore not weather dependent and can be split equally between the 365 days of the year. The heat time series generated using the 4 methods were compared with this gas derived heat demand for 2016, 2017 and 2018

7.5 Results and Discussion

Heat demand time series generated from temperature are commonly validated by showing an $R^2 > 0.95$ correlation with time series derived from historic gas energy [3, 4, 13]. Table 7.3 shows R^2 calculated using the python statsmodels.OLS function [18] of 0.97 or greater for all 4 methods. This suggests for example, that 99% of the variation in gas energy is explained by the variation in heat demand for BDEW 2016.

The last two rows of Table 7.3 show experiments simplifying HDD 15.5. **HDD 15.5 1D** shows the results of using only the temperature of the current day ($N = 0$ in Eq. (7.1)). **HDD 15.5 1T** uses one mean temperature for the whole of Great Britain with no weighting by population ($NL = 1$ in Eq. (7.2)). This suggests that the additional effort of applying more complex methods may only give a small gain in accuracy.

The load duration curve, Fig. 7.1 plots the time series sorted by heat demand (instead of time) and suggests that the gas derived demand has lower troughs than the heat demand. The HDD 15.5 appears to match the gas series most closely and it also has the smallest RMSE for 2018.

Figure 7.2 shows all 4 methods compared against the expected heat demand derived from gas energy for 2018. There tends to be over prediction in summer and

Table 7.3 Comparison of methods

Method	Year	RMSE	R^2
BDEW	2016	0.18	0.99
Watson	2016	0.22	0.98
HDD 15.5	2016	0.17	0.99
HDD 12.8	2016	0.17	0.99
BDEW	2017	0.18	0.98
Watson	2017	0.22	0.97
HDD 15.5	2017	0.17	0.98
HDD 12.8	2017	0.17	0.97
BDEW	2018	0.16	0.98
Watson	2018	0.20	0.97
HDD 15.5	2018	0.16	0.98
HDD 12.8	2018	0.21	0.97
HDD 15.5 1D	2018	0.20	0.97
HDD 15.5 1T	2018	0.20	0.97

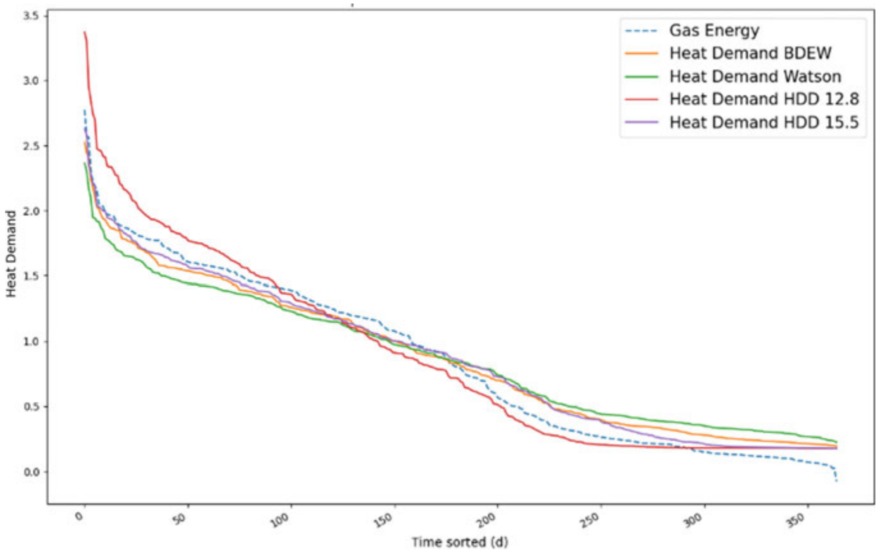

Fig. 7.1 Load duration curve heat demand 2018

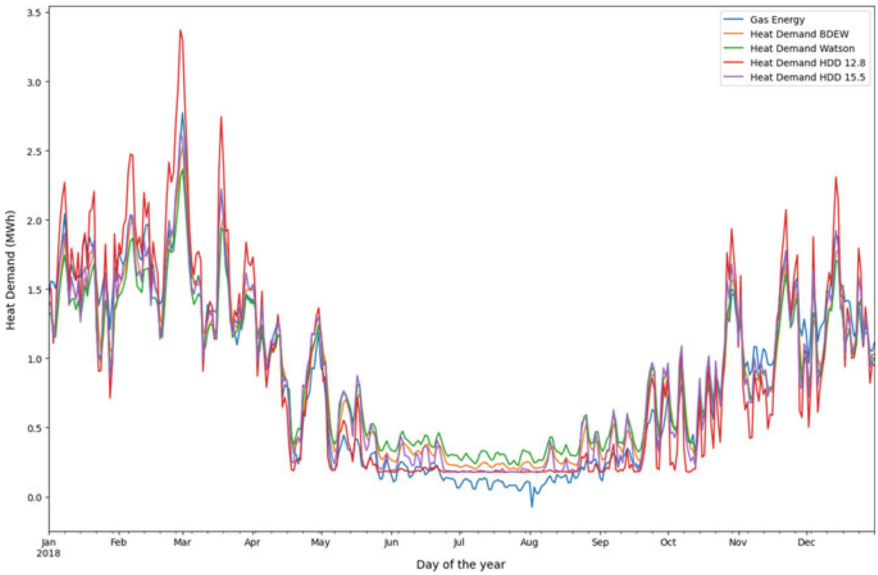

Fig. 7.2 Heat demand (HDT_d) and gas heat demand (HDG_d) daily time series for 2018

under prediction in winter. The low values between 2nd and 5th August suggest underestimation of the weather dependent part of the gas time series in Eq. (7.3).

7.6 Conclusions

Heat demand time series were generated from three years temperature and windspeed time series using four existing top down methods. All four methods seem to represent the observed data equally well. This suggests heat demand time series from any of these methods could be used as input to a national energy model. It was shown that simpler methods using a mean Great Britain temperature without thermal inertia also produce good results. However, considering the wider context of the present work, it will be the implementation of these generated heat demand time series in the national energy system model that will determine the required level of accuracy. Possible future work might be investigation of how the choice of heat demand method impacts the electricity demand time series generated from them and the resultant impacts on models of projected future peak loads and energy storage.

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