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Empirical variation in 24-h profiles of delivered power for a sample of UK dwellings: Implications for evaluating energy savings

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ABSTRACT

Improved methods for quantifying energy savings in buildings need to be supported by empirical measures rather than modeled estimates of future annual energy demand. This paper uses power temperature gradient (PTG, W/K), or the slope of power demand in response to changes in external air temperature; first, to categorise dwelling energy performance from daily energy data (when 0–15 °C outside); second, to investigate variations in 24-h profiles of delivered power. Estimates of PTG were obtained from 567 UK dwellings with 118,000 days of gas and electricity data. From a multivariable regression model, PTG was predicted by dwelling characteristics (number of bedrooms, number of floors, dwelling type, and dwelling age category (all $p < 0.001$)) but not by number of occupants. When dwellings were grouped into quintiles of PTG, mean PTG had threefold increase from the first to fifth quintile (188 to 563 W/K, respectively). This was reflected in 24-h profiles of delivered power (30 min intervals): at 0 °C, each 100 W/K decline in PTG corresponded to ~2.5 kW decline in mean morning and evening peak power. Using PTG to estimate reductions in peak power as equivalent 'negawatts' reframes potential benefits of energy efficiency retrofits and for grid resilience.

1. Introduction and background

The IEA has posited energy efficiency, conventionally defined as *using less energy to deliver the same or better levels of service or amenity*, as 'the first fuel' and in so doing has both underscored the priority placed on energy demand savings and their equivalence with generation from renewables or other zero-carbon energy sources [1]. This need to re-frame the concept of energy efficiency addresses the historical separation between energy supply and demand that has tended to distort the focus of energy research and policy development. With the evolving development of the 'smart grid', such a dichotomy appears untenable in the context of the integrated approach needed to manage and maintain a dynamic energy system with an increasing percentage of intermittent and distributed generation from renewables. Moreover, the building sector has been identified as not only making a key contribution to energy efficiency gains to meet carbon emission reductions, but as a central component in the development of smart grids, for instance with time sensitive tariffs and controls to manage demand peaks as well as on-site generation and storage. As a result there has been increasing research interest in understanding the 24-h profile of residential energy demand and the potential for shaving or shifting peak demand, such as with control systems [2] and time-varying tariffs [3]. Far less is understood about the variation in 24-h energy demand across the residential sector and the influence of energy efficiency on peak demand, with previous research mainly focussed on exemplar dwellings [4].

Quantifying the energy saved in a building that is specifically due to energy efficiency interventions, and hence to estimate equivalent 'negawatts' generated remains challenging [5,6]. First, while much of the policy on energy efficiency is focussed on the thermal performance of the building shell and heating system efficiency (for example, as mandated by building codes), categorising dwelling energy performance typically is based on annual consumption. Even if 'normalised' for floor space, annual consumption comprises a high degree of heterogeneity due to a range of factors, including diurnal patterns of dwelling operation, seasonal variations, and external factors such as changes in energy price from year to year. These factors can act to confound the impact of improvements in the building fabric or heating system efficiency.

Second, the use of normative models to predict annual energy demand in either absolute or relative terms remains problematic [7]. For instance, assumptions for thermal performance parameters are often used in energy demand models, such as for wall

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construction or heating system efficiency, whereas measured in situ values may be missing or inaccurate. These models also assume standard operational conditions within dwellings, for instance in the profile of daily heating and indoor temperature settings. Whereas, a range of social factors, such as occupancy heating practices or heating requirements are often not collected in energy surveys. Evidence suggests that models typically tend to overestimate the annual energy demand of older 'energy inefficient' dwellings and underestimate it for newer efficient dwellings [8].

These issues of estimating changes in energy demand before and after intervention are compounded in retrofit programmes, such as under the Green Deal in the UK, where the options and financing for retrofits are based on estimated savings in annual energy demand [9]. Policymakers have increasingly recognised the need to strengthen the evidence base and improve methods for quantifying reductions in energy demand. Unfortunately, limited empirical evidence has been available from large-scale field studies with sub-annual energy data. Moreover these datasets still pose considerable analytical issues, for instance establishing straightforward empirically based metrics on the relative energy performance of a dwelling, particularly with less than annual energy data and in the absence of detailed information available about the building or occupant characteristics.

1.1. Data driven approaches

Energy epidemiology provides an alternative way forward as it emphasises data-driven approaches for the analysis of large scale datasets, rather than applying *a priori* assumptions or normative models, to guide policy development [10]. In this paper we reprise the Princeton Scorekeeping method (PRISM) [11] for evaluating measured energy demand that, although adopted widely at the time, has received only occasional reference over subsequent decades from the research and professional community [12]. In part, this may be due to a misplaced emphasis on using PRISM to estimate annual energy demand via heating degree-days. Instead, this study focuses on one component of PRISM: the heating slope parameter obtained from monthly (or more frequent) metering [13]. Here, this concept is redefined as the power temperature gradient (PTG, W/K) using a slightly simplified methodology with daily data (and spanning only the heating season) to obtain the linear relationship between the delivered gas and electricity power and average daily external temperature (illustrated in Fig. 1 and described in more detail in Section 2).

From a steady-state perspective, PTG can be interpreted as a first order empirical metric for the effective rate of heat loss of the building in response to changing external conditions, including through the building shell, ventilation losses, and losses associated with the efficiency of the heating system. Similarly to the heating slope parameter of PRISM, a low PTG implies a low net dwelling heat loss and good energy performance; conversely high PTG indicates poor energy performance. As PTG comprises all metered energy input to the dwelling, it includes changes in incidental or indirect heat gains from other energy uses, such as lighting. PTG does not account, however, for any indirect heating from unmetered energy sources, such as varying solar gains as external temperatures decline. Moreover PTG should not be considered as just reflecting technical performance, but as a socio-technical parameter since it incorporates factors that influence power demand that change with external temperature, which may include the heating practices used by the dwelling occupants (e.g. their thermostat setting and heating system programme) and any energy conservation practices that are adopted to reduce heat losses, such as closing windows and curtains.

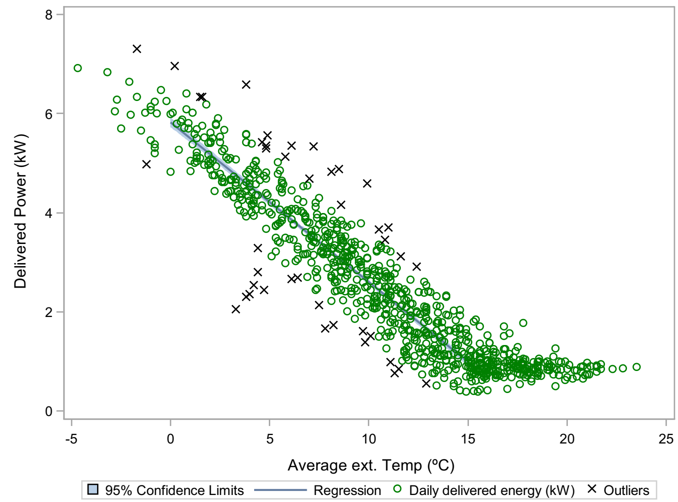

Fig. 1. Delivered power (gas and electricity) data from an example dwelling used to calculate PTG (W/K) from the slope of delivered power with respect to daily average external air temperature (0 °C to 15 °C).

1.2. Study aims and objectives

This study investigates the use of PTG (W/K) as a simple metric of energy performance in relation to basic building characteristics and social factors, using data on a sub-annual level. It draws on a sub-sample of dwellings with metered 30-min gas and electricity data that were part of large-scale project on smart metering and energy demand by the UK Department of Energy and Climate Change (DECC). Specific objectives are to:

- establish the relationship of PTG to basic dwelling characteristics;
- categorise dwellings according to PTG as a metric of their energy performance;
- examine the difference between 24-h profiles of delivered power for dwellings with different PTG values under various external conditions and hence estimate potential dynamic diurnal energy savings as equivalent 'negawatts' generated.

2. Methods

2.1. Dwelling sample dataset

From 2007 to 2010 field trials were undertaken in the UK to investigate the effectiveness of various types of interventions that provided householders feedback on their energy use, such as from 'smart meters' that provided real-time display of energy data to comparisons of usage included in regular energy bills. The project was managed by OfGEM on behalf of DECC, with four energy suppliers conducting the studies on over 60,000 households who volunteered, including 18,000 with smart meters [14]. The data used in this study were drawn from one of these field trials conducted by the energy provider EDF and provided to the study. The dataset comprises 592 gas-heated dwellings with at least 80 days of both 30-min gas and electricity data as well as floor area and other basic dwelling and occupant characteristics. As little is known about the selection process of the original sample from EDF customers, or even the response rate, this volunteer sample should not be considered as representative of gas-heated dwellings in the UK residential sector. The final sample of dwellings in the analysis contains more than 300,000 days of gas and electricity consumption between 2008 and 2010, with a varying number of days and different monitoring periods for each dwelling.

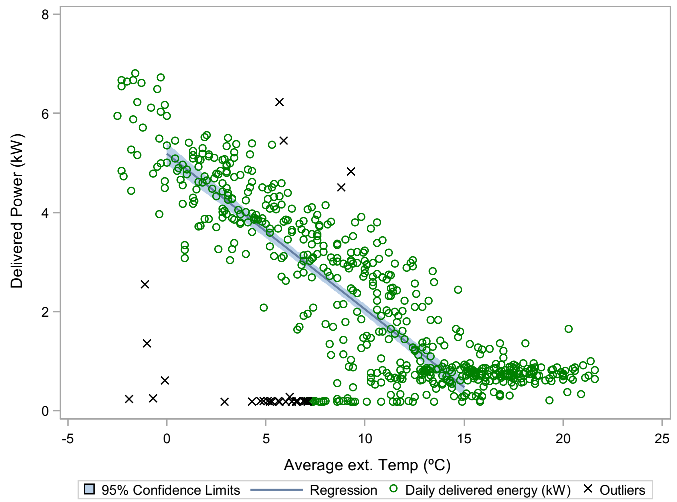

Fig. 2. Daily delivered power data for an example dwelling in relation to average 24-h external temperature, showing regression line for PTG (536 W/K and R^2 = 0.64) after outlier points were omitted (marked with an 'X'), note particularly the outliers identified with low values.

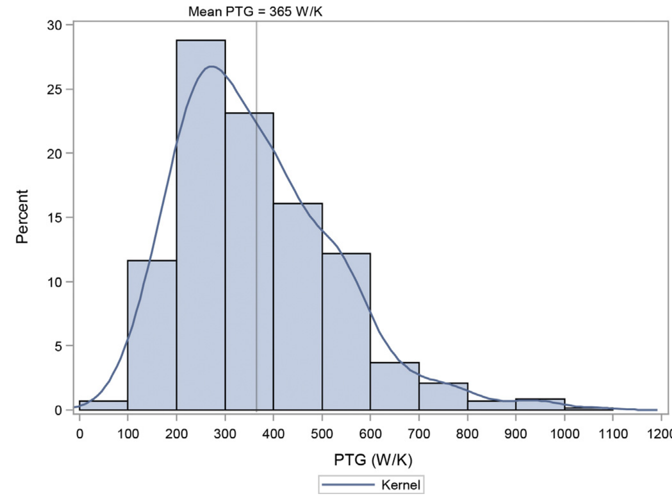

Fig. 3. Histogram of PGT (W/K) for 567 study dwellings.

2.2. Outcome variables

Delivered power (kW) over each 30-min period was obtained from the conversion and addition of electricity and gas energy (kW h) consumption.

Daily delivered power, used in the PTG estimation, was calculated as the average of the 30-min power over each 24-h period.

Annual energy consumption (gas and electricity) were obtained by taking the average daily consumption for each month (where there were at least 15 days of data and includes outlier days') and weighting appropriately to provide an estimate of annual consumption. These data were compared with 2008 annual energy consumption (gas and electricity) obtained from the publically available and anonymised form of the National Energy Efficiency Database (NEED) [15], using the 'small' dataset (sample size n = 49,815 dwellings) that had been selected as representative of the residential stock in terms of region, building type, age category, and size.

2.3. Covariates

Daily average external air temperature (°C) were drawn from data at 5 × 5 km grid points provided by the UK Meteorological office [16] with values matched according to the geographical location co-ordinates of the partial Postcode provided for each dwelling.

PTG (W/K) was calculated using linear regression analysis to estimate the rate of increase in delivered power for each 1 °C decline in average daily (24 h) external temperature between 0 °C and 15 °C. The lower boundary was identified both on the basis of having sufficient days in a heating season at 0 °C and to avoid an observed flattening of the power response at lower temperatures for some dwellings (that may reflect the limited capacity of the heating system). The upper boundary for the regression is slightly below that of the standard UK base temperature of 15.5 °C used in heating degree day calculations. Some 2% of daily values were identified as outliers (such as may result from when the dwelling is unoccupied) using Loess regression which is a piecewise smoothing regression process [17] and were subsequently omitted from the analysis. Fig. 2 shows an example dwelling where inclusion of outliers identified by the Loess regression would have affected the PTG estimate obtained from linear regression and substantially lowered the correlation coefficient (R^2). The estimate of PTG was defined as statistically acceptable if the beta co-efficient p-value $\leq$0.05 (that is the slop is non-zero) and the $R^2 \geq 0.6$. The equivalent slope estimates for the gas and electricity components of PTG are referred to as PTG-gas and PTG-elec, respectively.

These criteria for selection were reached after considerable investigation of alternatives and were adopted on the basis of being straightforward to understand while maximising the inclusion of dwellings in the subsequent analysis. The process adopted uses 118,000 days of data within the 0 to 15 °C temperature range to estimate PTG in 96% (567) dwellings from the 592 dwelling sample with sufficient energy and building data. Alternative methods included using robust regression techniques, which can deal with outliers, but require adjusting parameters to the scatter for each dwelling and with effectively different weightings for 'outliers' in each case. Another option is using a single low boundary value condition, but this is not sensitive to either low values being more acceptable under warmer conditions or for dwellings with low delivered power. Alternatively, simply using linear regression and ignoring the issue of unfeasibly low power demand on cold days (consistent with an unoccupied or minimally occupied dwelling) tends to lower the PTG values to some degree, but more importantly the increased scatter on the low side reduces the rate of inclusion of dwellings where PTG could be estimated. The analysis was repeated with some of these other estimation methods and apart from smaller samples sizes and some numerical changes in the values of PTG and PTG groups in the subsequent analysis, no substantive difference were evident in the main findings, such as on relative changes in peak power demand.

For the 24-h profile analysis, a further 5% of dwellings with the most extreme PTG values were omitted to result in a restricted sample of 537 dwellings. This step reduces heterogeneity in the first quintile and especially the fifth quintile of PTG, which is evident in the histogram of PTG (Fig. 3). Inclusion of these extremes only adds to the differences in 24-h delivered power observed between these quintile groups.

2.4. Statistical analysis

SAS 9.3 software was used in the data preparation and analyses [18]. Further to the calculation for PTG described above (using PROC LOESS [19], and PROC REG [19]), PROC MEANS was used to compare the sample dataset with the NEED annual gas and electricity consumption for 2008.

Multivariable regression models for predictors of PTG were constructed using PROC GLM [19]. Variables such as 'number of bedrooms' were first included as categorical values in the model

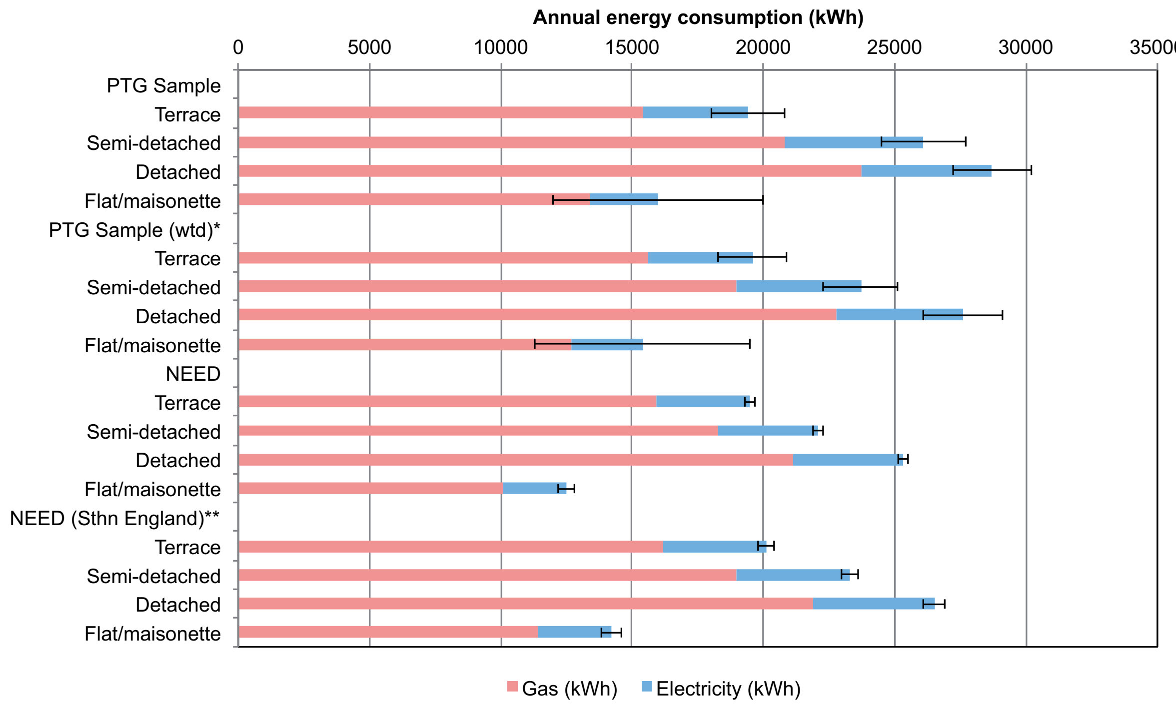

Fig. 4. Comparison of annual gas and electricity consumption (kW h) in the PTG sample with National Energy Efficiency Database (NEED) sample data for 2008 (with 95% CI); * PTG sample weighted by number of bedrooms within each dwelling type to match England and Wales residential stock; ** NEED sample for dwellings in the southern half of England.

and then as ordinal variables only if they appeared to have an approximately constant effect size for each unit increase. A second model was developed for predictors of estimated daily power demand at 15 °C (i.e. a weather normalised energy demand) in order to compare these with the predictors of PTG.

The 24-h profiles were formed from values at each 30-min interval, with the mean delivered power obtained for each dwelling. The data from each dwelling was obtained by binning external temperate measurements at intervals of 2 °C, e.g. the mean power at 14:00 and at 0 °C was based on all readings for that dwelling at 14:00 on days when average external temperature was between −1 °C and 1 °C. Thus for each temperature interval, a dwelling contributes only one value for delivered power at each time point through the 24 h period. (Otherwise the profiles for each quintile group would not reflect the number of dwellings but the amount of data collected, though it makes minimal difference to the profiles obtained.) PROC SPLINE was then used to calculate the smoothed curves for the 24-h profile for each quintile groups of 107 or 108 dwellings.

Table 1
Composition of the sample according to dwelling characteristics, with mean PTG (W/K).

Dwelling characteristics	*n* (%)	Mean PTG W/K (s.d.)
Number of bedrooms		
1 or 2	112 (20)	246 (92)
3	264 (47)	325 (119)
4	149 (26)	444 (134)
5	33 (6)	620 (163)
6 or more	9 (2)	763 (177)
Dwelling age		
Pre-1919	78 (14)	421 (211)
1919–1944	151 (27)	423 (162)
1945–1964	134 (24)	359 (131)
1965–1980	113 (20)	330 (138)
Post-1980	91 (16)	273 (130)
Dwelling type		
Terrace	148 (26)	281 (132)
Semi-detached	189 (33)	368 (161)
Detached	212 (37)	429 (157)
Flat/maisonette	18 (3)	260 (114)

3. Results

3.1. Dwelling characteristics, PTG, and annual energy demand

The study sample of 567 dwellings (Table 1) populates a range of building characteristics in terms of number of bedrooms (as a proxy for overall size), age category, and type. So although the study is not intended as a representative sample (for instance it is not geographically distributed across the UK but mainly from the southern half of England) and therefore is not directly generalisable. For instance, the sample composition appears to have a higher proportion of large dwellings, comprising 47% three and 26% four bedroom dwellings, which corresponds with 56% and 13%, respectively, for gas-heated dwellings of these sizes in the residential stock [20].

Consistent with the notion of acting as a metric for dwelling heat loss, the values for PTG in each category provide some initial indications that PTG increases with number of bedrooms (proxy for overall dwelling size), dwelling age category (corresponding to changes in construction type and building regulations), and dwelling type (related to external wall area). The overall mean of the PTG was 363 W/K, with the skewed distribution (Fig. 3) indicating that around half the dwellings fall in the range of 200 to 400 W/K, while less than 5% of the sample have a PTG over 700 W/K.

Given the differences in size composition of the PTG sample, comparison of the estimated annual energy consumption (Fig. 4 and Table A1) with the 2008 energy data from NEED by dwelling type shows that the PTG sample tended to be higher for semi-detached and detached dwellings. This difference narrowed substantially, however, when the PTG sample was weighted to the residential stock according to size (based on number of bedrooms) within each dwelling type and also when compared with NEED data for

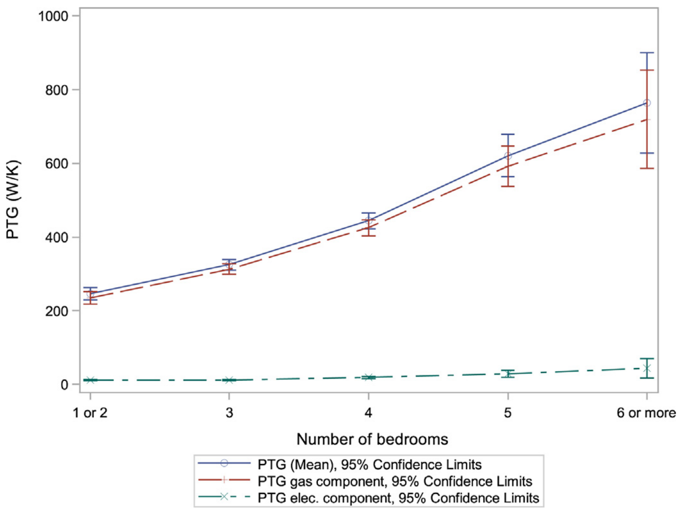

Fig. 5. Number of bedrooms versus mean PTG (W/K), PTG-gas, and PTG-elec (with 95% confidence interval).

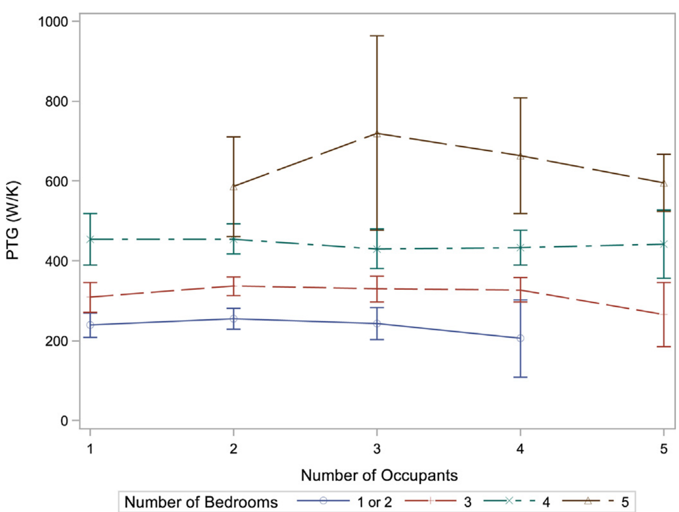

Fig. 6. Number of occupants versus mean PGT (W/K) for dwellings grouped by their number of bedrooms (with 95% confidence interval).

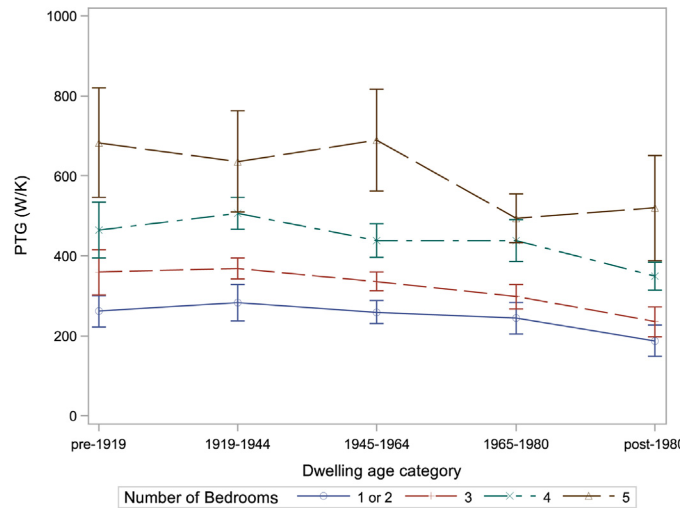

Fig. 7. Dwelling age category versus mean PGT (W/K) for dwellings grouped by their number of bedrooms (with 95% confidence interval).

the southern half of England (corresponding more closely to the geographical spread of the PTG sample).

3.2. Predictors of PTG

PTG has an approximately linear relationship with the number of bedroom (Fig. 5), with PTG-gas showing an almost identical relationship and PTG-elec increasing only slightly. In contrast, at each dwelling size (based on the number of bedrooms), PTG was essentially flat when plotted against the number of occupants (Fig. 6). Only the suggestion of a slight declining trend (Fig. 7) for PTG was apparent across dwelling age categories (again within each dwelling size band) and perhaps less than would be expected technically from improvements in the thermal performance of the building shell over time.

When examined using multivariable regression (to identify statistically significant predictors after mutual adjustment), strong evidence for the relationships between PTG and building characteristics emerged (Table 2). More than half the variation in PTG ($R^2 = 0.58$) was explained by just four factors. Increasing PTG was associated ($p < 0.001$) with the number of bedrooms, the number of floors, the dwelling type category, and dwelling age category. Each bedroom was estimated to add 79 W/K (95% CI 66, 92) and each floor 57 W/K (39, 75), while a detached dwelling tended to have 146 W/K (120, 173) higher PTG than an equivalent terrace. More recent dwellings had progressively lower PTG, with dwellings built since 1980 tending to have a lower PTG (−162 W/K) than equivalent pre-1919 dwellings. Similar results were evident for the predictors of the gas component of PTG, but not for the electricity component (PTG-elec) where weaker relationships were seen with respect to building characteristics. Furthermore, PTG-elec *was* statistically associated with the number of occupants (rising by 4 W/K per person; 95% CI 2, 6).

Multivariable regression analysis was also used to identify predictors of estimated delivered power at 15 °C external temperature (using the regression equation obtained for estimating the PTG) and when space heating is likely to be only a minimal component of energy consumption (Table 3). Strong predictors identified were number of bedrooms (137 W/K; 95% CI: 45, 229) the number of floors (an increase of 316 W/K; 190, 442) and number of occupants (an increase of 198 W/K; 119, 278) followed by dwelling type, but only weak evidence for dwelling age. For electricity, weak evidence identified that an increase in the number of adults was associated with a lower delivered power at 15 °C (−27 W/K; −53, −1).

3.3. Quintile groups of PTG

After omission of 5% of sample dwellings with extreme values for PTG, the remaining 537 dwellings had an overall mean PTG of 358 W/K and were grouped into quintiles. The mean PTG for each quintile groups (Table 4) has a three-fold increase from the first (188 W/K) to the fifth group (563 W/K). The omission of dwellings has greatly reduced heterogeneity in the fifth quintile to an acceptable level, and which otherwise would have ranged from ~500 to over 1000 W/K. Fig. 8 shows that PTG quintiles characterise the variation between groups in delivered power demand over a wide range of external temperature conditions.

The dwellings in the first and fifth quintiles of PTG tend to have distinct characteristics compared with the sample as a whole (Table 5). Specifically, the first quintile of PTG has a significantly lower percentage of dwellings with four and five bedrooms, detached dwellings, and dwellings built 1919–1944 than the sample as a whole; it has a higher proportion of two-bedroom dwellings, terraces, and post-1980 dwellings. In contrast, just over one in four (27%) of the dwellings in the fifth quintile have two or three-bedrooms, whereas such dwellings comprise two thirds of

Table 2
Predictors of PTG (total power, gas, electricity in W/K) from multivariable regression analysis, with the additional estimated effect size (and CI) of changing the covariate by one unit, or one category with respect to the reference category.

Dwelling/household characteristics[#]	PTG W/K (CI)	*p*-Value	PTG-gas (CI)	*p*-Value	PTG-elec (CI)	*p*-Value
n Bedrooms	79 (66, 92)	**<0.001**	76 (63, 89)	**<0.001**	3 (1, 5)	0.005
n Floors	57 (39, 75)	**<0.001**	57 (39, 75)	**<0.001**	0 (−3, 3)	0.97
Dwelling type		**<0.001**		**<0.001**		0.03
Terrace						
Semi-detached	71 (47, 95)		66 (43, 90)		5 (1, 8)	
Detached	146 (120, 173)		142 (116, 168)		5 (1, 8)	
Flat/maisonette	93 (40, 146)		89 (37, 140)		5 (−3, 12)	
Dwelling age		**<0.001**		**<0.001**		0.05
Pre-1919						
1919–1944	−21 (−52, 11)		−17 (−48, 13)		−4 (−8, 1)	
1945–1964	−63 (−95, −30)		−56 (−88, −25)		−6 (−11, −2)	
1965–1980	−100 (−132, −67)		−94 (−125, −62)		−6 (−11, −2)	
Post-1980	−162 (−196, −128)		−157 (−190, −124)		−5 (−9, 0)	
n Occupants	5 (−6, 17)	0.35	2 (−9, 13)	0.76	4 (2, 5)	<0.001
n Children (<16 yrs)	−11 (−26, 4)	0.16	−10 (−25, 5)	0.19	−1 (−3, 1)	0.29
n Older adults (65+ yrs)	−3 (−17, 10)	0.62	−4 (−18, 9)	0.53	1 (−1, 3)	0.42

[#] *n* = 'number of'.

Table 3
Predictors of delivered power (and gas and electricity components) when external temperature was 15 °C using multivariable regression analysis, showing the estimated effect size (and CI) of changing the covariate by one unit, or one category with respect to the reference category.

Dwelling/Household Characteristics[*]	Delivered power (W) at 15 °C (CI)	*p*-Value	Delivered gas (W) at 15 °C (CI)	*p*-Value	Delivered electricity (W) at 15 °C (CI)	*p*-Value
n Bedrooms	137 (45, 229)	**0.004**	75 (−7, 157)	0.07	62 (37, 87)	**<0.001**
n Floors	316 (190, 442)	**<0.001**	284 (171, 396)	**<0.001**	32 (−2, 67)	**0.07**
Dwelling type		**0.004**		**0.003**		**0.04**
Terrace						
Semi-detached	59 (−108, 227)		−6 (−155, 144)		65 (19, 111)	
Detached	258 (73, 444)		202 (36, 368)		56 (5, 107)	
Flat/maisonette	484 (119, 849)		426 (100, 752)		58 (−43, 158)	
Dwelling age		**0.04**		**0.02**		0.87
Pre-1919						
1919–1944	61 (−156, 278)		44 (−150, 238)		17 (−43, 76)	
1945–1964	−42 (−267, 183)		−70 (−271, 131)		28 (−34, 90)	
1965–1980	−203 (−427, 22)		−206 (−406, −6)		3 (−58, 65)	
Post-1980	−151 (−385, 83)		−167 (−376, 42)		16 (−49, 80)	
n Occupants	198 (119, 278)	**<0.001**	115 (44, 186)	**0.002**	83 (61, 105)	**<0.001**
n Children (<16 years)	−78 (−183, 27)	0.14	−56 (−150, 38)	0.24	−22 (−51, 7)	0.13
n Older adults (65+ years)	30 (−65, 124)	0.54	57 (−28, 141)	0.19	−27 (−53, −1)	**0.04**

[*] *n* = 'number of'.

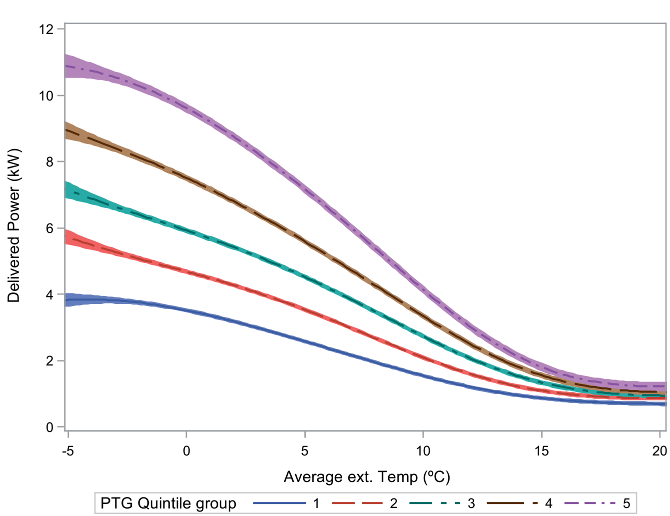

Fig. 8. Spline fit (with 95% CI) for delivered daily power (kW) PTG as a function of average daily external temperature by PTG quintile group.

the sample. The vast majority of dwellings (72%) in the fifth quintile have four or five bedrooms whereas they were only one third (33%) of the whole sample. Similarly, detached dwellings comprised 60% of the fifth quintile, compared with 39% of the sample.

3.4. PTG and the 24-h profile of delivered groups of PTG

The variation in 24-h profile of mean delivered power for each PTG quintile (Fig. 9) shows a progressive increase in the peaks, not only from quintile group 1 through group 5 but also as external temperatures decline. All, however, exhibited a characteristic morning and longer evening peak periods of power demand. At 0 °C

Table 4
Mean PTG for each PTG quintile group (*n* total = 537).

PTG Quintile group	*n*	PTG (W/K) Mean (min, max)
1	107	188 (120, 227)
2	108	264 (228, 297)
3	107	335 (298, 380)
4	108	424 (381, 486)
5	107	563 (487, 720)

Table 5
Dwelling characteristics of the first and fifth PTG W/K quintiles, compared with the sample.

Dwelling characteristic	Sample, n = 537, % (CI)	PTG Q1, n = 107, % (CI)	PTG Q5, n = 107, % (CI)
Number of bedrooms			
1 or 2	19.6 (16.2, 22.9)	43.9 (34.4, 53.4)**	1.9 (−0.7, 4.5)*
3	48 (43.8, 52.3)	52.3 (42.8, 61.9)	25.2 (16.9, 33.5)*
4	27.2 (23.4, 31)	3.7 (0.1, 7.4)*	50.5 (40.9, 60)
5	4.5 (2.7, 6.2)	0 (0, 0)	18.7 (11.2, 26.1)**
6 Or more	0.7 (0, 1.5)	0 (0, 0)	3.7 (−0.7, 4.4)
Dwelling type			
Terrace	25.3 (21.6, 29)	46.7 (37.2, 56.3)**	7.5 (2.4, 12.5)*
Semi-detached	33.5 (29.5, 37.6)	26.2 (17.8, 34.6)	31.8 (22.9, 40.7)
Detached	37.8 (33.7, 42)	18.7 (11.2, 26.1)*	59.8 (50.4, 69.2)**
Flat/maisonette	3.4 (1.8, 4.9)	8.4 (3.1, 13.7)	0.9 (−0.9, 2.8)
Dwelling age			
Pre-1919	13 (10.2, 15.9)	13.1 (6.6, 19.5)	19.6 (12, 27.2)
1919–1944	26.6 (22.8, 30.4)	14 (7.4, 20.7)*	40.2 (30.8, 49.6)**
1945–1964	24.6 (20.9, 28.3)	22.4 (14.5, 30.4)	17.8 (10.4, 25.1)
1965–1980	20.5 (17, 23.9)	21.5 (13.6, 29.4)	15 (8.1, 21.8)
Post-1980	15.3 (12.2, 18.3)	29 (20.3, 37.6)**	7.5 (2.4, 12.5)

* Under-representation in the quintile compared with the sample as a whole at 95% CI.
** Over-representation in the quintile compared with the sample as a whole at 95% C.

the delivered power between peaks during the middle of the day has also increased, such that for the quintile group 5 it is ∼80% of the peak delivered power and suggests that for most dwellings in this group the heating remains on throughout the daytime period. Delivered power at night remains much lower than at other times, even during cold conditions. Delivered peak power for group 5 dwellings shows an increase of more than 10 kW in both as the temperature declined peaks (e.g. morning peak: rises from 2.5 W at 16 °C to 14 W at 0 °C), compared with ∼4.5 kW increase for dwellings in group 1.

Taking the difference between the delivered power for the first and fifth quintiles (Fig. 10) provides an estimate of the potential 24-h profile of power saved, for instance if group 5 dwellings were retrofitted with energy efficiency features such that their mean PTG reduced to that of group 1. The resultant profile of power difference gives the equivalent generation of 'negawatts' through the day of ∼8 kW under 0 °C external conditions, and ∼6 kW for the two peaks at 8 °C external temperature.

Based on a spline fit, the decline in morning and evening peak delivered power (Fig. 11) was found to have an essentially linear relation to PTG for various external temperature conditions, with the rate at 0 °C of ∼100 W/K reduction in PTG corresponding to ∼2.5 kW decline in peak morning power and similarly for the evening peak and at midday (Fig. A1). The rate of decline reduces under warmer conditions.

4. Discussion

This study has advanced the use of PTG, based on the PRISM heating slope parameter, as the linear response in delivered power with respect to external temperature (over the range 0 to 15 °C). The study of over 500 dwellings supports the notion that PTG provides a straightforward empirical metric of dwelling energy performance that only requires sufficient energy data and external weather data to perform linear regression rather than needing annual energy data. Moreover, findings from a multivariable regression model indicated that almost 60% (R^2 = 0.58) of the variation in PTG across dwellings was explained by basic building characteristics: number of bedrooms, number of floors, dwelling type, and dwelling age category. This is consistent with a metric that reflects thermal

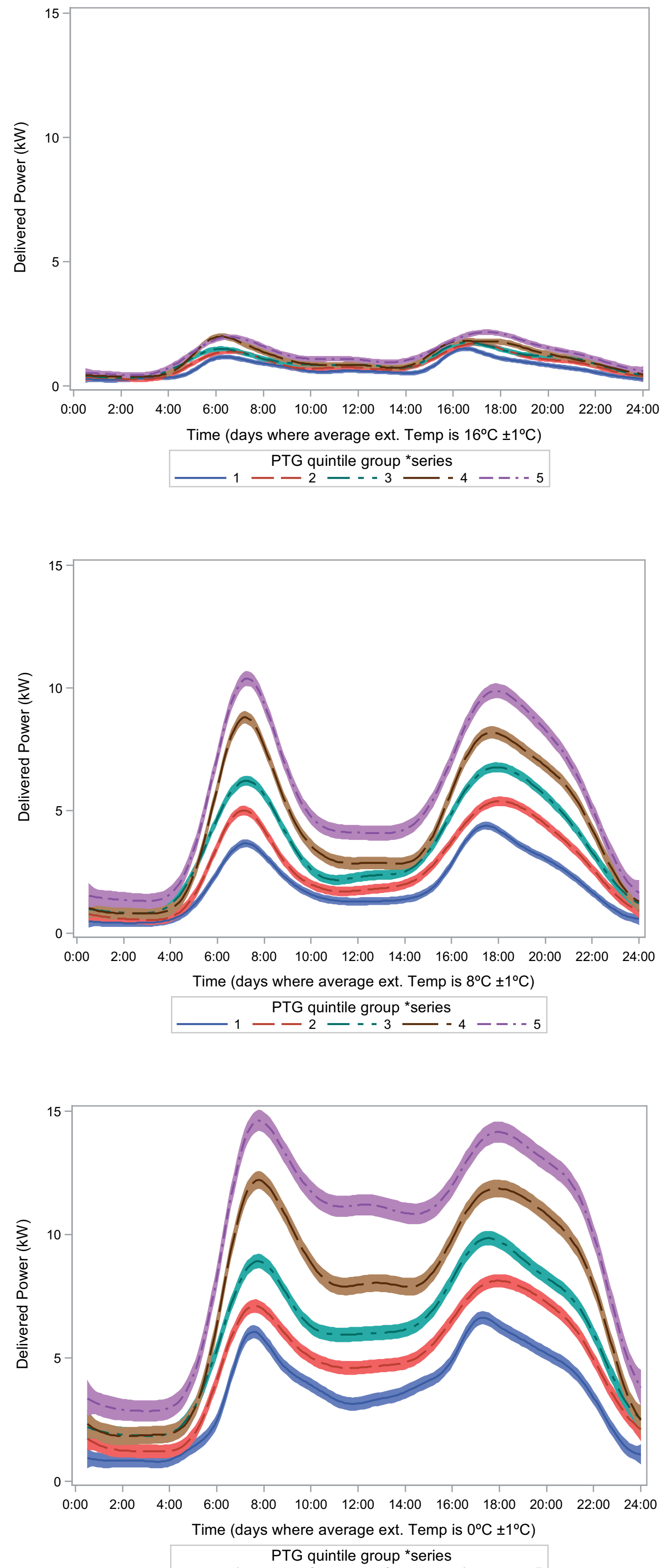

Fig. 9. Spline curves (with 95% CI) for 24 h delivered power (kW) profile by PTG groups 1 to 5, when external temperature is 16 °C, 8 °C, and 0 °C (±1 °C).

properties of the building shell and lies in contrast with the strong relationship identified between the number of occupants and the delivered power at 15 °C, when space heating is likely to contribute minimally to the total energy demand.

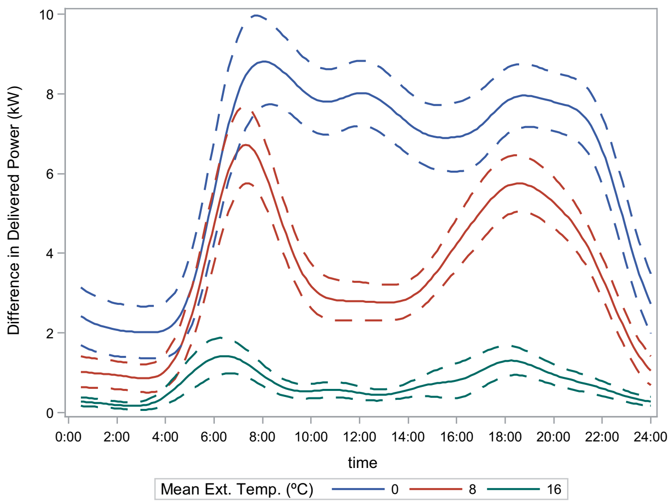

Fig. 10. Spline curves (with 95% CI) for the difference in delivered power (kW) profile between quintile group 1 and group 5, under external condition of 0 °C, 8 °C, and 16 °C.

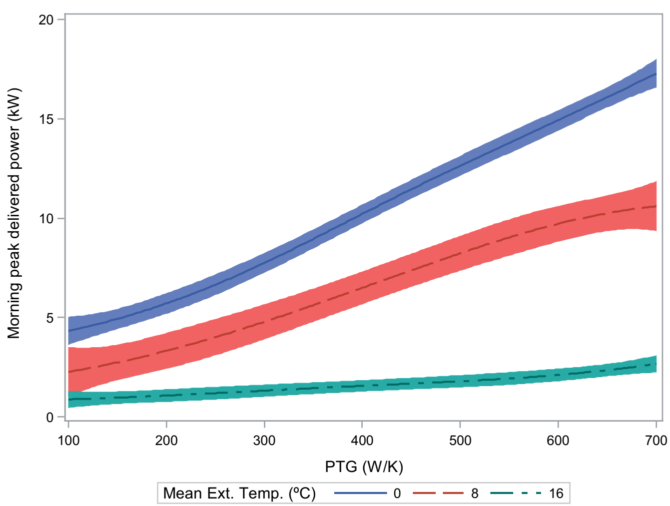

Fig. 11. Variation in mean peak delivered power at 0 °C, 8 °C, and 16 °C as a function of PTG for morning peak (07:00 to 08:00).

Using a restricted sample of 537 dwellings from the study to form quintiles of PTG that ranged from 120 to 720 W/K, with the first quintile (mean PTG) indicating the best energy performance and the fifth being the poorest. When the mean variation in the 24-h profile of delivered power was examined under a range of external condition for each quintile of dwellings, all groups exhibited a characteristic morning and longer evening peak of delivered power, with both peaks rising as the daily external temperature decreased, although at 0 °C delivered power for quintile group 5 was close to peak values throughout the daytime. Furthermore the absolute increase in peak delivered power for group 5 dwellings as the temperature declined from 16 °C to 0 °C was more than 12 kW, compared with less than half that amount (~5 kW) for dwellings in group 1. The difference in delivered power at 0 °C between these two groups, revealed a roughly constant ~8 kW gap throughout the daytime, with this reducing to ~6 kW at the morning and evening peaks when the external temperature was 8 °C. The findings also indicated a linear response to declining PTG such that at 0 °C, for every 100 W/K decline in PTG there was a corresponding decline of ~2.5 kW in the morning peak power and similarly for evening peaks.

The findings highlight that, contrary to conventional practice, consideration of energy efficiency only in terms of annual savings potentially can overlook or undervalue key benefits of an energy efficiency retrofit programme in delivering resilience to the grid by reducing peak delivered power. For instance, the evidence suggests that energy efficiency interventions that shifted a dwelling from the lowest energy performance quintile group (mean PTG of ~560 W/K) to the best energy performance group (mean PTG of ~190 W/K) would result in substantial energy savings during the winter and at peak times during the day. The cost of retrofit for individual dwellings would need to be evaluated, but in supply terms, these 'negawatts' generated from energy efficiency can be interpreted as equivalent to installing on site a zero-carbon heating system sized to deliver ~8–10 kW peak and operating at near full capacity from 7am to 10pm (for instance under winter conditions of 0 °C or lower). In the process of reducing fossil fuel use, the remaining energy demand for the retrofitted dwelling would be more amenable to being met via low carbon heating systems, such as heat pumps supplied by zero or low carbon electricity. Moreover the impact of peak energy savings further increase in size as their effect is progressively tracked back to the reduced energy generation needed at source (for instance, due to transmission losses).

Second, the results showed a progressive reduction as PTG reduced, so that each effective measure should have an impact on peak delivered power, with a substantial leverage: just reducing PTG by 100 W/K should lead to a drop at 0 °C of ~2.5 kW in the morning peak. If change in PTG directly relates to differences in thermal performance, then this may be considered as ~100 W/K reduction in heat losses through the building shell. For a three bedroom detached dwelling (which has an estimated 200 m^2 external wall area [21]), this equates to improvements in building shell that lowered the average *U*-value by ~0.5 W/m^2 K, while for a mid-terrace with 70 m^2 it would need to be around 1.4 W/m^2 K. By way of comparison, for a standard brick cavity wall, cavity insulation can reduce the *U*-value from say ~1.6 W/m^2 K down to ~0.3 W/m^2 K. Such considerations of lowering the peak demand should significantly impact the viability of energy efficiency measures available.

The study has both strengths and limitations. Although it relies on a volunteer sample rather than a stratified random sample of dwellings in the residential stock, the large-scale nature of the study with over 300,000 days of data and the heterogeneity obtained in most dwelling characteristics (size, type, and age) allows for extensive analysis of comparative differences. Comparison of a size weighted sample with NEED data for southern half of England showed that estimated annual energy consumption by dwelling type was in broad agreement. So while considerable caution is needed in drawing implications from some findings, such as absolute estimates for PTG in terms of generalisation to the UK residential stock, the PTG sample appears at least consistent with aspects of residential consumption. Moreover, the main findings and conclusions here concern relative differences and relationships between parameters, rather than absolute values.

External temperature data used are from modeled values (by the UK Meteorological Office) that correspond to 5 × 5 grid that is closest to the centre of the partial postcode provided, and therefore do not necessarily correspond to the location of the dwelling or to its micro-climate. Nor do they include exposure to wind or solar gains. This uncertainty, however, should not result in temperatures systematically biased in any particular direction.

PTG provides a first estimate of empirical energy performance, and here it does not distinguish between the amenity or service provided in different dwellings. For instance, the first quintile of PTG may comprise a mix of relatively large energy efficient dwellings at full occupancy and warm indoor temperatures as well as smaller and/or energy inefficient dwellings that are only partly occupied during the day and operated with highly constrained heating patterns and low average indoor temperatures. So the analysis assumes that after an appropriate energy efficiency retrofit (including socio-technical interventions), the 24-h delivered power profile of a fifth quintile PTG dwelling would be reduced to essentially the same as first quintile dwellings. There are not sufficient building details in the dataset to identify efficient dwellings based on the characteristics of walls and heating system, rather attributes can only be inferred from the size, typology, and age of the dwellings. It seems likely that if some more details were known, such as insulation or heating system efficiency, then the model for PTG would be improved. If indoor temperature were known, then this would provide a more direct estimate of dwelling heat loss, since currently PTG includes (or the inferred energy performance does not account for) any decline in indoor temperature as external conditions become colder. Although unusual, there are at least some relatively large (three or four bedroom detached) dwellings in PTG quintile group one that appear to respond to cold conditions like an energy efficient dwelling with a shallow and predictable linear rise in delivered power.

The study has broad implications for policymakers and energy service providers in highlighting the role of energy efficiency and helping re-frame potential savings in terms of negawatts generated at times of peak demand. Of the total 22.5 million gas-connected dwellings in the UK (and given the caveats of the representativeness of the sample but assuming that the results are broadly indicative of the distribution of PTG of the residential stock), then the fifth quintile of PTG is estimated to represents about 3.7 million dwellings (with an annual consumption between 30,000 and 50,000 kW h [15]). This study suggests such dwellings tend to be larger, older, detached and semi-detached dwellings, and for any retrofit programme an economic cost benefit analysis would be necessary to determine which combination of energy efficiency measures would be worthwhile. Nevertheless, the findings suggest that completing a retrofit program that shifted dwellings from the fifth quintile to the first quintile would result in an estimated mean reduction in peak power demand of about ~8 kW per dwelling for winter conditions of 0 °C or less, which equates to ~30 GW less delivered peak power required on site by the national energy supply system. This capacity is currently mainly provided by in-situ gas boilers (for the space and hot water heating), but with proposed electrification of the residential stock (alongside decarbonisation of the grid) it represents the equivalent to reducing the generation capacity needed by more than ~30 × 1 GW power stations, given additional transmission losses and back-up systems needed. In other words, the broad estimate from this approach *underscores the generation capacity that could be avoided* in the projected shift to electric heating as part of the development of a smart grid with a low-carbon residential buildings sector and the critical importance of energy efficiency programmes for enabling such a transition to occur [22].

5. Conclusion

Taking an energy epidemiology approach, this study advanced PTG as a practical way of evaluating energy performance of a dwelling and energy savings without needing annual data, instead needing only sufficient energy and external temperature data over the heating season to establish a linear relationship to estimate PTG. The analysis of 24-h profiles of delivered power for UK dwellings provides a way of quantifying energy savings from retrofit programmes in terms of a ‘first fuel’ on a dynamic diurnal basis. The resultant estimates for the reduction in the peak delivered power, suggests considerable added value of such measures for the energy system as a whole, such as equivalent ‘negawatts’ generated and improved resilience under extreme conditions, that are well beyond those obtained from a simple estimate of annual energy saving. Further research needs to explore the relationship of PTG with respect to socio-technical factors, such as indoor temperature settings and heating operation.

Acknowledgments

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Appendix A.

(Fig. A1)
(Table A1).

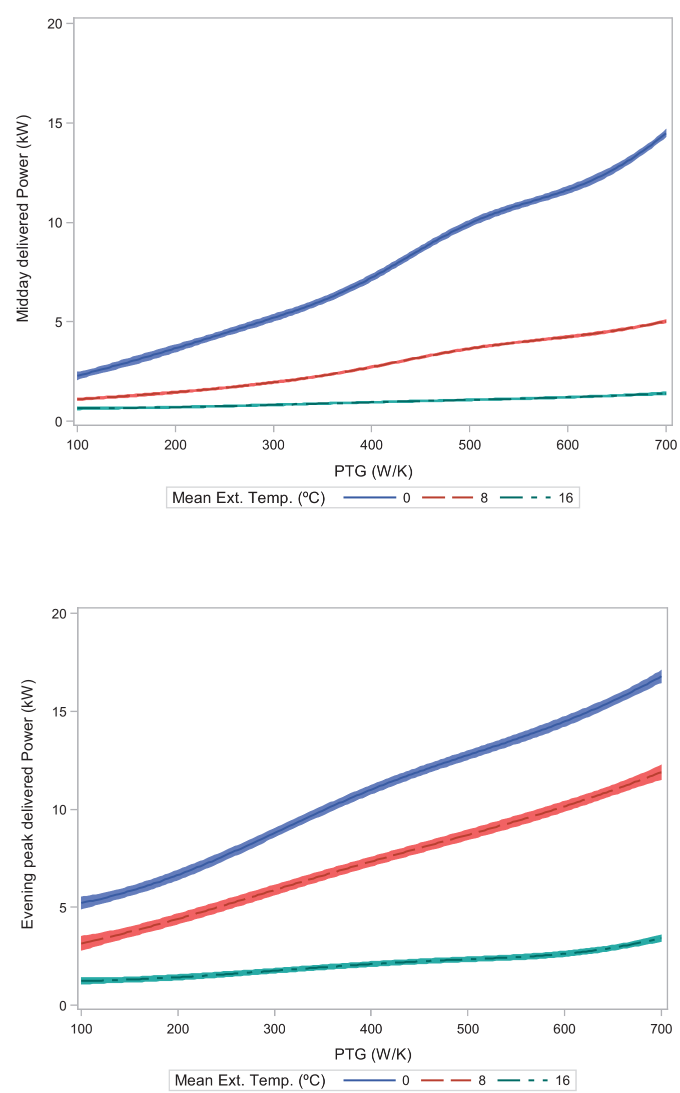

Fig. A1. Variation in mean peak delivered power at 0 °C, 8 °C, and 16 °C as a function of PTG for midday (12:00 to 13:00; top) and evening (17:00 to 19:00; bottom).

Table A1
Comparison of annual energy consumption of the PTG sample with NEED data for 2008 for gas heated dwellings (defined as gas consumption within the range of 2500 to 50,000 kW h).

Data source	*n*	Mean annual energy consumption (kW h)		
		Energy (95% CI)	Gas (95% CI)	Electricity (95% CI)
PTG sample				
Terrace	119	19,400 (18,000, 20,700)	15,400 (14,200, 16,600)	4000 (3600, 4300)
Semi-detached	155	26,100 (24,500, 27,700)	20,800 (19,400, 22,100)	5300 (4900, 5800)
Detached	172	28,700 (27,200, 30,300)	23,700 (22,300, 25,100)	5000 (4600, 5400)
Flat/maisonette	12	16,000 (12,000, 20,000)	13,400 (9600, 17,200)	2600 (2000, 3200)
PTG Sample (weighted)*				
Terrace	119	19,600 (18,300, 21,000)	15,600 (14,300, 16,900)	4000 (3700, 4400)
Semi-detached	155	23,700 (22,300, 25,000)	19,000 (17,800, 20,100)	4700 (4400, 5100)
Detached	172	27,600 (26,100, 29,100)	22,800 (21,500, 24,100)	4800 (4400, 5100)
Flat/maisonette	12	15,300 (11,200, 19,500)	12,700 (8800, 16,500)	2700 (2000, 3300)
NEED				
Terrace	7606	19,400 (19,200, 19,600)	15,900 (15,700, 16,000)	3600 (3500, 3700)
Semi-detached	7685	22,200 (22,000, 22,400)	18,300 (18,200, 18,500)	3800 (3800, 3900)
Detached	6307	25,300 (25,100, 25,600)	21,100 (20,900, 21,400)	4200 (4100, 4300)
Flat/maisonette	1835	12,400 (12,100, 12,800)	10,100 (9800, 10,400)	2400 (2300, 2500)
NEED (STH ENGLAND)**				
Terrace	4339	20,100 (19,800, 20,300)	16,200 (15,900, 16,400)	3900 (3800, 4000)
Semi-detached	3237	23,300 (23,000, 23,700)	19,000 (18,800, 19,300)	4300 (4200, 4400)
Detached	3254	26,500 (26,100, 26,900)	21,900 (21,500, 22,200)	4600 (4500, 4700)
Flat/maisonette	2480	14,200 (13,800, 14,500)	11,400 (11,100, 11,700)	2800 (2700, 2900)

* Weighted by bedroom within each dwelling type to match residential stock.
** Sub-sample of southern half of England to more closely reflect the PTG sample.

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