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Probability density distributions for household air source heat pump electricity demand.

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Abstract

The Irish government is implementing policies to transition Ireland to a low carbon and environmentally sustainable economy by 2050. Ireland has sectoral targets of 600,000 installed heat pumps by 2030, currently roughly 28,000 are installed. Such a high target of heat pumps will not only have a significant effect on electricity demand but also on the management and operation of the grid. In this paper we explore the demand from homes heated by air source heat pumps using an innovative dataset from a field trial in Ireland. To assess the impact of large-scale adoption of heat pumps, this paper estimates the after diversity maximum demand per heat pump heated home. In particular we explore statistical distributions to best model coincident demand, and estimate after diversity maximum demand per home. We use the software package RStudio to model several different distributions. Based on goodness-of-fit statistics and criteria, a Gamma distribution is the best fit. We apply our methodology to data from a similar heat pump trial in the UK to complement our results.

Keywords: air source heat pump; probability density distributions; household electricity use; Ireland.

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1. Introduction

Energy efficiency and renewable energy is of paramount importance in the European Union's strategy for sustainable growth. Ambitions for low-carbon economies and competitive secure energy systems were endorsed and enhanced in 'Council directive 2018/2001' [1]. Heating must be substantially decarbonised if goals for the reduction of carbon dioxide and other greenhouse gas emissions are to be achieved.

Heat Pumps (HPs) are promoted as an attractive alternative for residential consumers to replace fossil fuel heating systems. HPs are energy recovery systems that use some electricity to transfer higher temperature heat from the external ground or air to the space heating and hot water systems of a building. They are advertised as low maintenance systems offering lower costs and contributing to lowering carbon emissions and improving local air quality. Additional benefits accrue when the electricity used to drive the HPs comes from renewable energy sources (RES) [2].

Nomenclature

ADMD	After Diversity Maximum Demand	DWH	Domestic Water Heating
ASHP	Air Source Heat Pumps	HP	Heat Pump
BER	Building Energy Rating	kW	kilowatt
CDF	Cumulative Distribution Function	SH	SuperHomes
DSO	Distribution System Operators	TSO	Transmissions System Operators

The Irish government is implementing policies to transition Ireland to a low carbon, climate resilient and environmentally sustainable economy by 2050. Ireland has sectoral targets of 70% for renewable electricity and 600,000 installed HPs of which 400,000 will be retrofitted by 2030 [3]. Ireland lies in the north Atlantic Ocean on the European continental shelf and has a temperate climate. Due to the temperate climate there is demand for space heating and domestic hot water (DWH) heating, but currently there is no demand for domestic cooling. Space Heating and DWH account for approximately 80% of energy use in the average Irish home.

Heat demand is low density because of the dispersal patterns of the population of 4.8 million people, the nature of the housing stock, and Ireland's temperate climate. Hence district heating has very limited potential, but HPs, particularly air sourced heat pumps (ASHPs), have significant potential to decarbonise heating. Currently domestic heating in Ireland relies heavily on conventional gas or oil boilers with hydronic radiators for space and water heating. Renewable heat accounts for just 6.9% [4]. An estimated 28,000 HPs are currently installed in Ireland [5].

Such a high target of HPs will not only have a significant effect on electricity demand but also on the management and operation of the grid. According to [6], there are four potential problems; at the Transmission System Operators (TSO) level, problems are peak demand and ramp rate increase and at the Distribution System Operators (DSO) level, excessive voltage drops and the reinforcement of low voltage feeder and transformers.

The metric after diversity max demand (ADMD) is used by DSOs in the design of distribution networks where coincident demand is aggregated over a sample of customers [7]. This metric allows the DSO to dimension the low voltage network in anticipation of the average concurrent maximum demand.

In achieving national climate action plans, we need to estimate the impact of the adoption of low carbon technologies such as heat pumps on ADMD. Regulators and network operators, such as the DSO, require this information for planning purposes. In this paper we explore the electricity demand from homes heated by ASHPs using an innovative dataset from a field monitoring trial. In particular we address the following research questions:

1. Which statistical distributions best model electricity demand for ASHP heated homes?
2. What is the estimated ADMD arising from ASHP adoption?

High time resolution household electricity use is difficult to model due to seasonal and diurnal variations and as a result of appliance use, lighting and heating [8,9]. Bottom-up models can provide opportunities to investigate changes in technologies and usage patterns [10]. Munkhammar, et al. note that there are many studies on various levels of time resolution using different distributions for household load profiles such as Normal, Log-Normal, Gamma, Gumbel, Inverse Normal, Beta, Exponential, Rayleigh and Weibull [11-18]. There is generally no standard distribution type for modelling household electricity use [8]. McLoughlin et al. used a Weibull and log – logistic probability distribution function when characterising domestic electricity consumption in Ireland [9].

2. Methodology

We explore statistical distributions for the ADMD per ASHP heated home using a unique dataset of electricity usage for retrofitted typical Irish homes located in the countryside. We compliment the results for the Irish case study with analysis of heat pump data from the UK's Customer-Led Network Revolution (CLNR) project [19]. The CLNR data are time series measurements of the ASHP electricity usage only, and no other household appliances.

ADMD is used by DSO's in the design of distribution networks where coincident demand is averaged over a number of customers [7]. To estimate the ADMD we first smooth the electricity time series data by calculating the average usage per customer over the sample of *N* customers for each time step *t* in the sample time horizon *T*. Eq. 1. shows how we create the smoothed time series TS_t where d_{it} is the electricity demand for customer *i* in time step *t*.

$$TS_t = \frac{1}{N}\sum_{i=1}^{N} d_{it} \ \forall t = 1 \dots T \tag{1}$$

We used the software package RStudio for data analysis and modelling. The R package 'fittdistrplus' was used as it provides functions for fitting univariate distributions to different types of data and allowing different estimation methods. We fit and evaluate distributions for the data in TS_t.

We then calculate the ADMD, using Eq.2. to find the maximum average demand over the sample time horizon *T*:

$$ADMD = max_{t\in T}(TS_t) \tag{2}$$

We use a similar approach to calculate the additional maximum average heat pump demand $ADMD_{HP}$ over an averaged time series of heat pump electricity demand HP_t.

$$ADMD_{HP} = max_{t\in T}(HP_t) \tag{3}$$

2.1 The Superhomes Projects

Superhomes 1.0 was a concept developed by the Tipperary Energy Agency. It combined a range of deep retrofit measures along with the installation of ASHPs, Wood Stoves and Photovoltaic (PV) technologies. It helped homeowners upgrade their homes to a very high building energy rating (BER). In a follow on project, $Superhomes_{2.0}$ ($SH_{2.0}$), ASHP heat, flow, and electricity usage were monitored in 19 homes.

2.2 Data collection

The $SH_{2.0}$ dataset includes the average electricity use in kilowatts (kW) at 15 minutes resolution and several metrological readings. The electricity meter recorded total home including the ASHP and DWH hot water immersion heating. Due to privacy concerns, information about the size and make of the HP as well as socioeconomics and dwelling characteristics are not made available for this analysis. Recording of the houses began at different times in 2018 with the majority starting in January. To answer research question 1, we create a subset for the period 14th January 2019 to the 31st January 2019. This period was chosen for several reasons, it is the longest period of time of complete data for all 19 houses and it is during winter when the ASHP would be using the most electricity. The planned uptake of HPs could have a significant effective on electricity demand during the winter in temperate climates. Love et al. [6] also used a winter period when calculating the additional ADMD for HPs in the UK, $ADMD_{HP}$, because during these times heating energy demand is at its highest.

We apply our methodology to the CLNR ASHP data in [19] to complement our work and answer research question 2. We note this data were gathered in 2013/2014 for ASHPs in residential houses at SPF_{H2}, i.e. the electricity meter records just the ASHP space heating electricity and does not include any electricity used for DWH. A comprehensive guide to system boundaries appears in [20]. This allows us to estimate the additional electricity demand for just the ASHP.

3. Results

Fig. 1 shows a sample of three houses from the Irish $SH_{2.0}$ data to illustrate the highly variable nature of electricity use across households on 14th of January from the winter period. A peak in usage in one house does not correspond to a peak in another at the same point in time. House 'SH005' has little to no electricity use from 18:00 up until 23:00 while the other two houses exhibit higher demand. All the houses are located in the same county in Ireland so external temperatures do not vary greatly but heating patterns are may vary due to other factors like dwelling size, occupancy, thermal comfort preferences and the rated capacity of the ASHP.

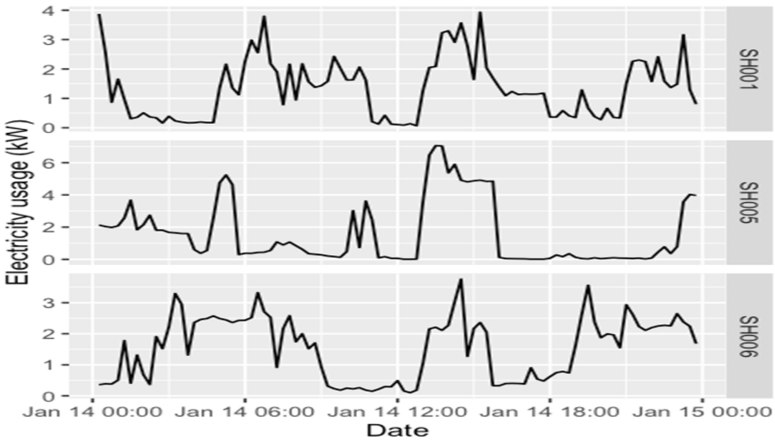

Fig. 1. electricity use for a sample three Irish ASHP heated homes on 14th January 2019.

Fig. 2. Shows the less volatile averaged use when compared to the individual data per home.

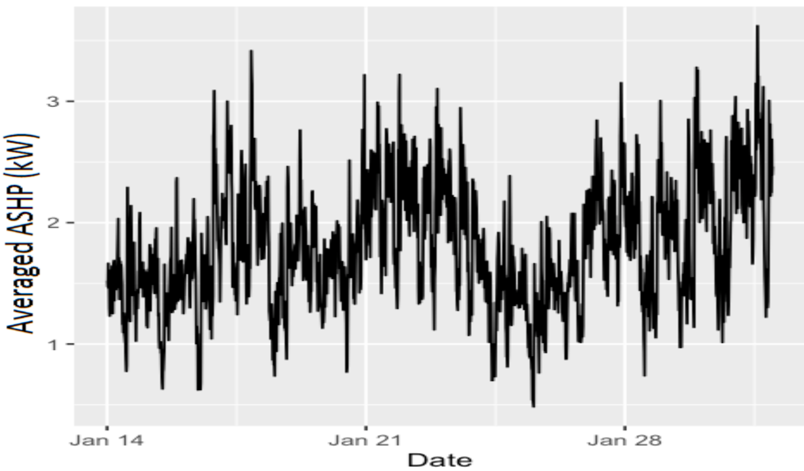

Fig. 2. The averaged electricity usage TS_t over the period 14th – 31st January 2019, n =19.

We then create a histogram of the averaged usage. Fig.3 shows the positive skewed pattern with a kurtosis close to 3, i.e., the histogram is slightly right skewed.

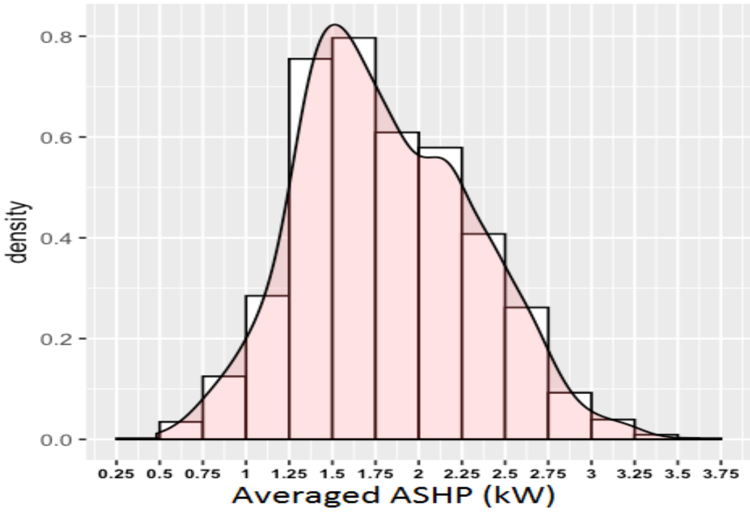

Fig. 3. Coincident averaged electricity Histogram and Empirical Density, 14th – 31st January 2019.

Table 1 shows descriptive statistics for the electricity data such as mean and median. We can read the *ADMD* value from Table 1, i.e. the maximum value is 3.263 kW. This is the maximum coincident demand the DSO can expect per ASHP heated home. We note that the min, mean and max temperature during this period were -2.5, 4.5 and 10.5 °C.

Table 1: Descriptive Statistics for averaged electricity demand per customer

Number of observations = 1,727: 19 homes, 15 minute resolution averaged over 18 January days	
Min Consumption (kW)	0.482
Max Consumption (kW)	3.623
Mean (SD) Consumption (kW)	1.809 +/- 0.51
Median (kW)	1.752
Skewness	0.295
Kurtosis	2.737

Next we use curve fitting to model the ADMD. We use the function ‘descdist’ of the ‘fittdistrplus’ package in RStudio to produce a Cullen and Frey graph to reduce the set of possible candidate distributions. Based on this information, we consider; Gamma, log-normal, normal and Weibull distributions, but not logistic or exponential distributions. The parameters of the distributions are estimated using maximum likelihood estimates (MLE).

Goodness of fit plots for the four probability distributions are presented in Fig. 4. From the histogram and cumulative distribution function (CDF) plots we see the Gamma distribution function is a good fit. However, viewing the Q-Q and P-P plots indicates limitations and alternative probability distributions. The Q-Q plot highlights the lack-of-fit at the tails, the Weibull and normal probability distributions are preferred here for their better description of the right tail distribution of the empirical distribution. The P-P plot highlights the lack-of-fit at the distribution centre, all probability distributions fit the distribution centre to different degrees with Gamma being the best fit and Weibull the least good fit.

Table 2 presents the results of the ‘gofstat’ function which computes the goodness-of-fit statistics for parametric distributions. The three goodness-of-fit statistics produced by this function are; Kolmogorov-Smirnov, Cramer-von Mises and Anderson-Darling. All goodness-of-fit statistics are in favour of the Gamma distribution over the other distributions. The Gamma fit measures are highlighted in bold font.

The MLE estimates for the Gamma distribution shape and rate parameters are shape ≈ 12.264, rate ≈ 6.778. We use these estimates to explore the tails of the distribution. The 99, 95 and 90 % cut off points are 3.223kW, 2.735 kW and 2.495kW per customer respectively. This allows the DSO to estimate the probability of electricity demand for homes heated by ASHPs being above these cut off points.

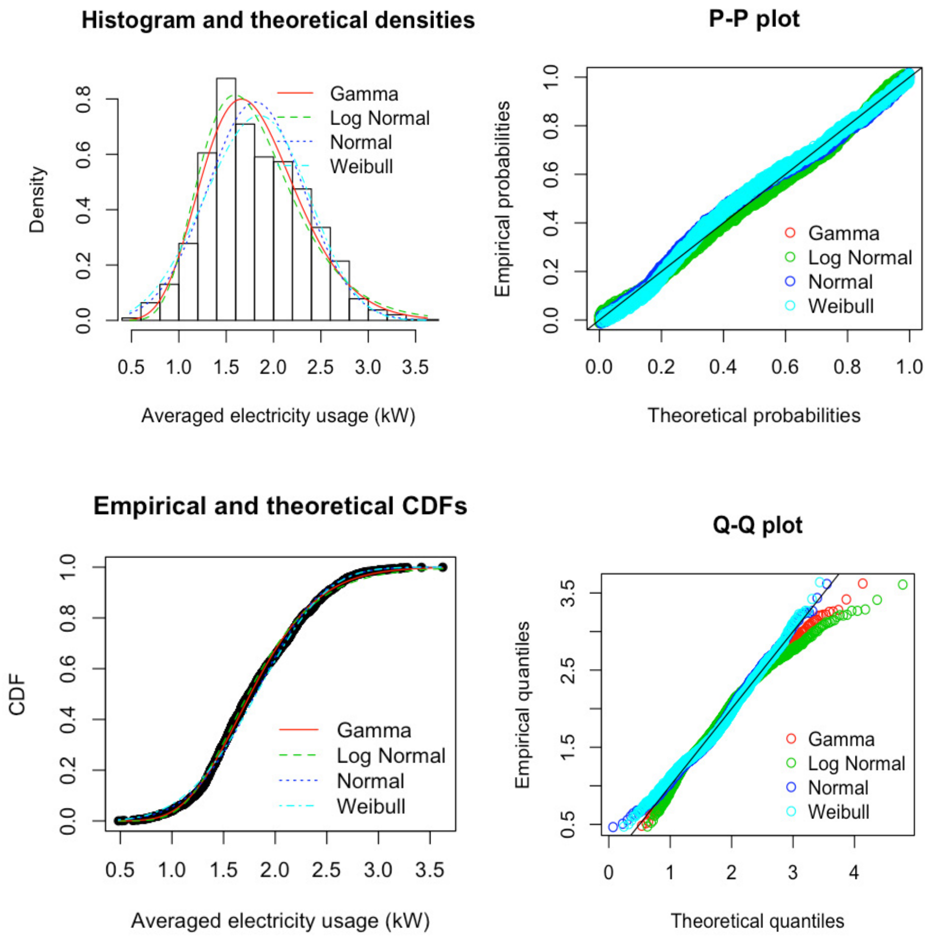

Fig. 4. (Top Right) density function of the fitted distribution along with the histogram of the empirical distribution. (Top Left) Q-Q plot representing the empirical quantiles (y-axis) against the theoretical quantiles (x-axis). (Bottom Left) CDF plot of both the empirical distribution and the fitted distribution. (Bottom Right) P-P plot representing the empirical distribution function evaluated at each data point (y-axis) against the fitted distribution function (x-axis).

Table 2: Good-of-fit statistics & criteria

		Gamma	Log Normal	Normal	Weibull
Goodness-of-fit statistics	Kolmogorov-Smirnov statistic	**0.03**	0.04	0.06	0.05
	Cramer-von Mises statistic	**0.34**	0.54	1.26	1.39
	Anderson-Darling statistic	**2.43**	4.75	6.57	7.89
Goodness-of-fit criteria	Akaike's Information Criterion	**2528.85**	2589.98	2549.83	2569.10
	Bayesian Information Criterion	**2539.76**	2600.89	2560.74	2580.01

In order to complement our method and results, we applied the same procedure to the CLNR ASHP dataset [19] which profiles UK domestic customers' ASHPs from 1st May 2013 to the 30th April 2014. We took ASHP usage for a sample of 22 houses for 18 days in January to compare with the Irish whole home electricity dataset. Fig. 5. shows the histogram of the coincident averaged CLNR ASHP usage. The lower values compared to the $SH_{2.0}$ data help explain the difference in ADMD due to the ASHPs. Additional differences may be due to weather conditions, system boundaries and ASHP design and installation, building types, occupancy behaviours as well as other factors.

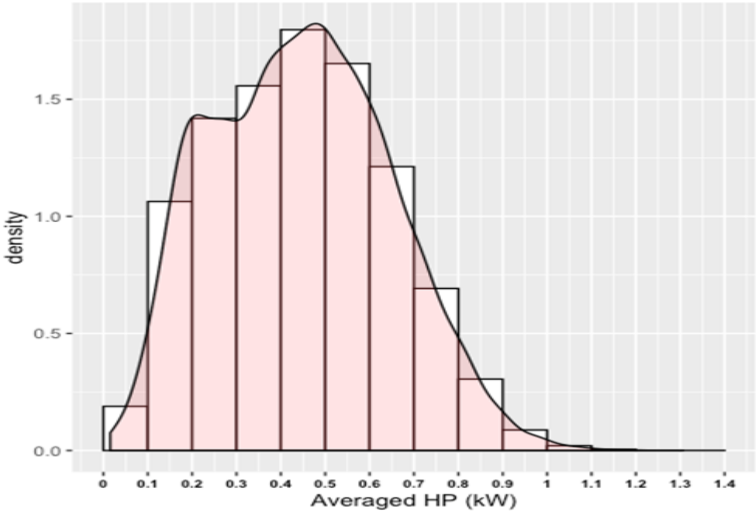

Fig. 5. Coincident averaged CLNR ASHP Histogram and Empirical Density, 14th – 31st January 2014.

Table 3 shows descriptive statistics for the CLNR data. We read the $ADMD_{HP}$ value is 1.306 kW. We note that the min, mean and max temperature during this period were 3.1, 5.8 and 8.4 °C which was warmer on average than in Ireland with no dips below zero.

Table 3: Descriptive Statistics for CLNR averaged ASHP demand per customer

Number of observations = 22,816: 22 homes, 1 minute resolution averaged over 18 January days	
Min Consumption (kW)	0.015
Max Consumption (kW)	1.306
Mean (SD) Consumption (kW)	0.446 +/- 0.199
Median (kW)	0.445
Skewness	0.218
Kurtosis	2.498

Similar distributions to our study were considered, based on the good-of-fit statistics and criteria, preference was given to a Weibull distribution with parameter estimates of shape ≈ 2.397, and scale ≈ 0.504. In this case the 99, 95 and 90 % cut off points are 0.952 kW, 0.795 kW, and 0.713 kW per ASHP customer respectively.

4. Discussion & Conclusion

Ireland has set an ambitious target to grow from a base of less than 30,000 to 600,000 HP installations by 2030 in an effort to electrify and decarbonise the residential heating sector. This will have significant effect on electricity demand and on the management and operation of the grid. Examining the electricity use in the $SH_{2.0}$ data set, total demand between houses is highly variable with peaks in some houses met with troughs in others at similar time points. The coincident average demand per customer allows for network planning. Using the $SH_{2.0}$ data we calculated the ADMD per home as 3.623 kW. We note the CLNR value of 1.306 kW per ASHP is captured in the $SH_{2.0}$ data as the metering is at the boundary of the homes rather than the heat pump system. We find that a Gamma distribution is useful to model the $SH_{2.0}$ averaged electricity demand probability distribution, and analysis of the tails of the distribution provides useful information for network planning purposes.

Our modelling approach is transferable to other ASHP data sets. The size of the $SH_{2.0}$ dataset limits the generalisation of our results and further research is warranted. Additional data and analysis will allow us to explore models for the demand at different measurement boundaries. We plan to extract further interesting insights by modelling the variation caused by weather conditions, differences in system boundaries and ASHP design and other factors. We also plan to explore mixed models to better understand the tails of the distributions.

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