Operational characterisation of neighbourhood heat energy after large-scale building retrofit

Paul Beagon[1,2], Fiona Boland[3] and James O'Donnell[1,2]

[1] School of Mechanical and Materials Engineering, University College Dublin, Belfield, Dublin 4, Ireland
[2] Energy Institute, University College Dublin, Belfield, Dublin 4, Ireland
[3] Royal College of Surgeons in Ireland, Lower Mercer Street, Dublin 2, Ireland
paul.beagon@ucdconnect.ie

Abstract. To achieve housing retrofit targets, traditional house-by-house approaches must scale. Neighbourhood retrofit also facilitates community participation. This paper aims to quantitatively characterise the heat energy demand of similar homes in a post-retrofit neighbourhood.

The method employs the Modelica AixLib library, dedicated to building performance simulation. A modern semi-detached house is modelled as thermal network. The passive thermal network is calibrated against an equivalent EnergyPlus model. The developed Modelica model then generates time series heat energy demand to meet occupant comfort. This model separates heating for internal space and domestic hot water. Simulation results are gathered for a range of house occupancy profiles, with varying heating schedules and occupant quantities.

The calibration results compare the time series of internal house temperature produced by the EnergyPlus and Modelica simulations. Modelica simulations of two heating schedules generate distinct annual demand curves against occupant quantity. As expected in a modern house, domestic hot water accounts for a relatively high proportion of heat energy. Over a year it ranges between 20% and 45% depending on occupant profile.

Overall conclusions are threefold. Firstly, occupant profiles of a post-retrofit semi-detached house increase annual heat energy demand by 77%, and the coincidence of daily peak demand persists across occupant profiles. Furthermore, percentages of domestic hot water demand start from 20% or 24% and plateau at 39% or 45% depending on space heating schedule. A statistical distribution of energy demand by neighbourhood homes is possible. Its curve plot is not perfectly normal, skewing to larger energy demands.

Keywords: Building retrofit, building simulation, Modelica, AixLib library, neighbourhood scale, statistical distribution.

1 Introduction

National and international policies aim to reduce greenhouse gas emissions and reduce reliance on fossil fuels. An enduring energy demand and cause of greenhouse gas

(GHG) is domestic heating, accounting for 57% of British heat use [1]. Domestic appliances and lighting form the remaining energy, but are excluded from this research.

Large-scale retrofit is a potential solution, albeit complex and challenging to deliver [2, 3]. In recent energy analysis of a semi-detached house in a oceanic climate, domestic superinsulation outperforms expansion of local renewable energy [4]. Policy documents concur that reducing energy demand of existing buildings by retrofit, precedes any integration of energy storage or local energy generation [5].

After an energy retrofit, the energy demand of the similar homes will reduce both on average and in variation. Improved statistical parameters facilitate the aggregation of homes as distributed energy resources. Such aggregation of a retrofitted neighbourhood into a distributed energy system is proposed by Koch [6].

The modelling and simulation of building archetypes is one method to estimate the statistical parameters of a retrofitted neighbourhood or national building stock [7]. Building archetypes already exist for European countries thanks to a large research effort [8]. In parallel Annex 60 of IEA-EBC (International Energy Agency Energy in Buildings and communities programme) delivered Modelica for building performance simulation [9]. One Modelica library is AixLib, that is capable of modelling heat demand of a city district [10].

The overall aim of this paper is to quantitatively characterise the heat energy demand of structurally similar housing in a post-retrofit neighbourhood. Responding to identified research gaps [6], statistical distributions of heat demand per home are calculated. The main objectives of this study are to employ time domain simulation that responds to standard weather files to (i) quantify annual heat demand per standard house, split by space and water heating, (ii) compute the annual heat demand per house as this varies with occupant schedule and occupant quantity, and (iii) illustrate the coincidence shared by heat energy time series caused by different occupancy profiles. It is this coincidence, or simultaneity, that drives energy demand peaks and sizing of energy supply infrastructure.

This research formulates and tests a semi-detached home as a thermal network or "RC" model. The RC name derives from the resistor and capacitance elements in the electrical analogy of a thermal model. RC models are proposed due to their aggregation potential into neighbourhood or city district scale [11]. The heat energy demand is split into space heating and domestic hot water (DHW) heating.

First, the model is tested with a weather profile for correlation with the popular building simulator EnergyPlus [12, 13]. Second, the space heating and domestic water heating (DHW) demand are computed for difference occupant quantities. The argument that DHW demand will persist or even grow are strong [14]. As a result, the proportion of DHW of total heat demand is quantified. Third, a distribution of housing gas demand is present of an example neighbourhood. Fourth, the coincidence of peak heat energy demand by different households is illustrated. This last point affects utilities and energy network operators. The retrofit of an entire neighbourhood affects home occupants and energy suppliers, especially where heating fuel switches from gas to electricity.

2 Methodology

The process to produce data and statistical distributions of household heat energy requires multiple steps (Fig. 1). Two initial steps develop and calibrate a thermal network model. Subsequently the process amends model parameters, executes simulations and analyses energy data. Electrical energy demand by plug loads and appliances is excluded.

The calibration step references a building model configured in the well-known EnergyPlus software. The model is available from other research planned for publication [15]. EnergyPlus was released in 2001 after five years of US federal funded development. It is accepted as a very popular and commonly used building energy simulator [16]. The reference EnergyPlus model resembles the archetype of a modern or retrofitted semi-detached house. Modelica can model and simulate the same house as a RC network. Iterative comparisons of simulation results guide the RC network design, shown as a feedback loop between the initial two steps (Fig. 1).

Subsequently, model parameters of heat generator type and storage tank size are configured. Simulations are now possible over different occupancy profiles, these combine occupant quantity and heating schedule.

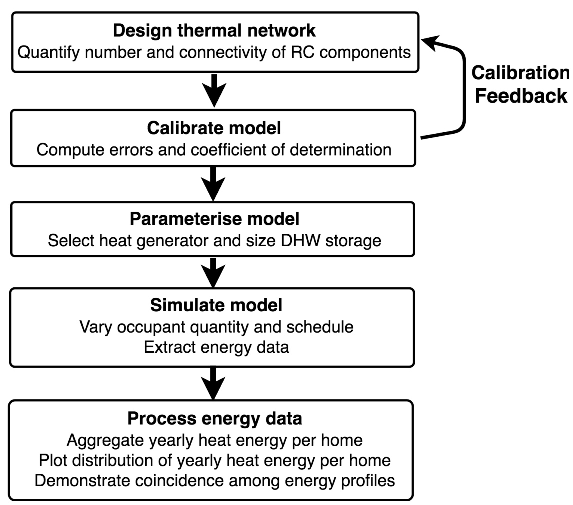

Fig. 1. Method process: develop and calibrate a thermal network model. Parameterise the network components and occupant quantities, before simulation and energy demand results.

2.1 RC model of the fabric

As mentioned in the Introduction, the model and simulation rely on components and examples from AixLib Modelica library. Buildings as thermal networks are configurable in AixLib [11]. The RC model is developed from existing low order thermal network model for dynamic simulation [11]. That model separates equivalent air temperatures of wall and windows for each building orientation. Thereby the effect of solar radiation is more accurately calculated. Radiated heat transfers across thermal network resistors, for example from windows to internal walls, impeded by resistor $R_{WinIntRad}$. Such resistor values are based on a heat transfer coefficient (α_{rad}); assumed constant in simulated temperature range at 5 W/(m^{2}K). The convective heat transfer coefficient (α_{conv}) is assumed at 2.7 W/(m^{2}K) and determines resistances such as to convective heat transfer at windows R_{WinCon}. Resistances and capacitances specific to the building construction, are external wall (ext), internal walls and objects (int), and the floor plate (floor). U-values and geometry of external, internal and floor structures, determine the building specific RC values. Retrofit of building improves (decreases) the U values with associated increase in resistances.

Due to over-responsiveness of simulated internal**,** lumped capacitances of the external walls and floor are split [17]. External wall capacitances are labelled C_{ext1} or C_{ext2}, and floor capacitances C_{floor1} and C_{floor2}; interconnected in Fig. 2. Internal capacitance C_{int1} and C_{int2} account for internal furnishings and the relatively small internal wall capacitance.

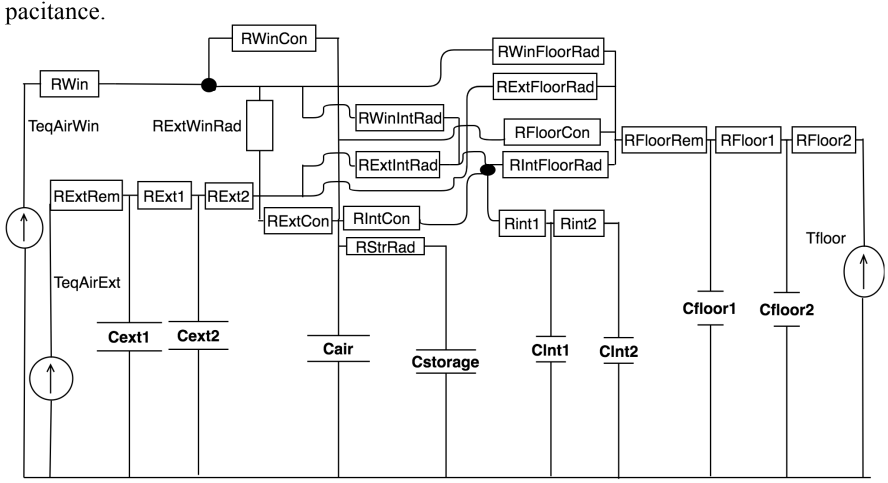

Fig. 2. Thermal network of semi-detached building extended from [11]. The external wall, building internals and floor are configured as 3R-2C sub-models.

2.2 Calibration of the fabric

Initially the modern semi-detached house is modelled in EnergyPlus which simulates building states variables such as inside temperature. EnergyPlus allows removal of all heating equipment and internal gains; reducing the model to a building fabric. Similarly, the Modelica RC is disconnected from heating and internal loads are zeroed.

Identical external loads of solar radiation and outside dry bulb temperature must be applied to each model of the building fabric. IWEC (International Weather for Energy Calculations) provides standardised weather data [18].

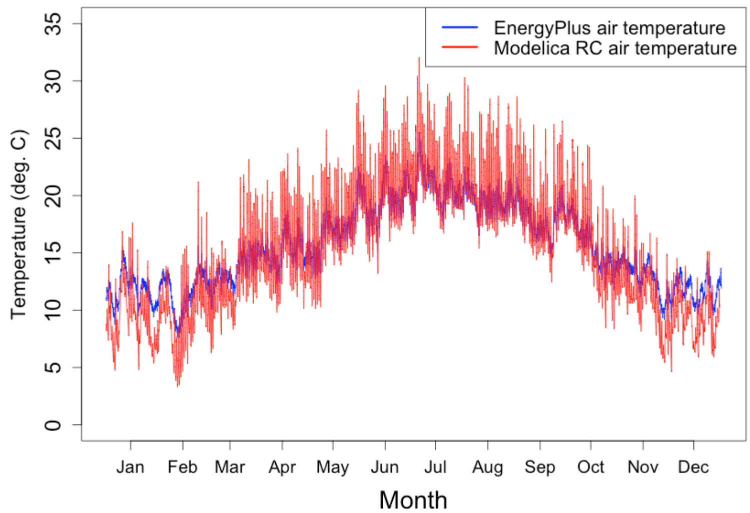

Fig. 3. Simulated heated space temperatures from EnergyPlus, and Modelica RC models.

An iterative process leads to the thermal network in Fig. 2. Every iteration compares the two time series of simulated internal temperatures. Standard error metrics of mean absolute error (MAE) and root mean square error (RMSE) are calculated, along with the coefficient of determination (R^2). Time series data points are available for almost every hour of the 12 months (Fig. 3**)**. The sample size is n = 8,736. As a trade-off between model simplicity and accuracy, the selected RC models computes inside temperature comparisons of MAE = 1.39, RMSE = 1.92 and R^2 = 0.9215.

2.3 Simulation of different schedules and occupancies

Realistic domestic energy evaluation comprises two demands; space heating and domestic hot water (DHW). Any future retrofit of a home will increase the proportion of energy demand by DHW. Therefore, the first simulated heat generator is a water based heat exchanger to meet both demands. This component can be considered as a 20 kW boiler of constant 85% efficiency. By its location outside the house thermal envelope, for example a garage, the remaining 15% of boiler energy is lost to outside air.

A water heater is connected to both radiators and a hot water storage tank. The storage tank is sized at 80 litres, with each occupant consuming 40 litres per day. Storage size influences the total heat transferred to a potentially empty home. Energy losses from unneeded air heating highlight the importance of accurate controls. Two heating schedules are applied: economical and comfort. The combination of heating schedule and occupant quantity is termed in the methodology as occupant profile.

The economical schedule rations heating of air and water, especially during working hours (Table 1). It assumes the occupants minimise the heating of DHW during the morning. The comfort schedule assumes comfortable temperatures of 20 °C and 18 °C during waking hours and sleeping hours respectively.

Table 1. Air temperature setpoints for both economical and comfort schedules.

Time	Economical setpoint (°C)	Time	Comfort setpoint (°C)
00:00 - 07:00	10	00:00 - 08:00	10
07:00 - 08:00	20	08:00 - 23:00	20
08:00 - 17:30	10	23:00 - 24:00	10
17:30 – 19:00	20	-	-
19:00 – 21:00	10	-	-
21:00 – 23:00	20	-	-
23:00 – 24:00	10	-	-

3 Results

The results are calculated to primary energy. The popular metric of energy use intensity (EUI) expresses demand in kWh/m^2/year. The division by floor area (m^2) normalises the performance metric across different sized buildings. Many energy performance certificates (EPC) adopt the same metric. One EPC, the building energy rating (BER) for Irish homes, allocates calculated performance into discrete bands.

$$\textit{Total heating energy} = \textit{Total space heating energy} + \textit{Total DHW heating energy} \quad (1)$$

$$\textit{Total gas secondary EUI} = (\textit{Total heating energy} / 0.85) / \textit{floorspace} \quad (2)$$

$$\textit{Gas primary EUI} = \textit{Gas secondary EUI} \;*\; 1.1 \quad (3)$$

Computation of gas secondary EUI assumes a boiler efficiency of 85%. An 85% boiler efficiency is the EnergyPlus default and approximately average in [19]. Assuming gas heating fuel, multiplication by 1.1 converts secondary gas EUI to primary (or "source") EUI [20]. In future studies, electrical heating would incorporate a larger primary energy factor; calculated for Ireland in 2017 as 2.08 [21].

3.1 Gas consumption for heating under economical and comfort schedules

The total gas energy results, varied by occupant quantity, are presented for economical (Table 2) and comfort schedules (Table 3). A house archetype model in EnergyPlus corroborates the results; simulating approximately 8,000 kWh total energy per year [15]. Scaling down from total energy to heating energy, it lies between the gas used by three or four occupants in Table 2.

The aforementioned BER initially increments bands by 25 kWh/m^2/year to 225 kWh/m^2/year. Subsequent BER bands enlarge to cover the breadth of low performance buildings. Table 2 displays a range of gas primary EUI from 73.2 to 105.8 kWh/m^2/year. Range magnitude is 32.6 kWh/m^2/year. Table 3 displays a range of gas primary EUI from 86.4 to 117.2 kWh/m^2/year. Range magnitude is 30.8 kWh/m^2/year, slightly less than under the economic schedule. Under both heating schedules, increasing occupancy may re-allocate similar homes across at least two BER bands. In practice, BER bands are selected after accounting for pump and lighting energy

Table 2. EUI of reference home, under economical schedule and varying occupancy.

Number of Occupants	Total gas energy consumed (kWh)	DHW proportion of total gas energy	Gas secondary EUI (kWh/m^2/year)	Gas primary EUI (kWh/m^2/year)
1	5922	0.24	66.5	73.2
2	6609	0.33	74.3	81.7
3	7219	0.38	81.1	89.2
4	7756	0.40	87.1	95.8
5	8012	0.41	90.0	99.0
6	8194	0.42	92.1	101.3
7	8429	0.44	94.7	104.2
8	8566	0.45	96.2	105.8

Table 3. EUI of reference home, under comfort schedule and varying occupancy.

Number of Occupants	Total gas energy consumed (kWh)	DHW proportion of total gas energy	Gas secondary EUI (kWh/m^2/year)	Gas primary EUI (kWh/m^2/year)
1	7688	0.20	86.4	7398
2	8319	0.27	93.5	7992
3	8856	0.32	99.5	8489
4	9451	0.34	106.2	9046
5	9876	0.35	111.0	9445
6	10079	0.37	113.2	9634
7	10299	0.38	115.7	9841
8	10429	0.39	117.2	9964

The increases in total heating energy and its proportion to DHW are plotted in Fig. 4 and Fig. 5. The figures illustrate plateauing of both heat demand measurements.

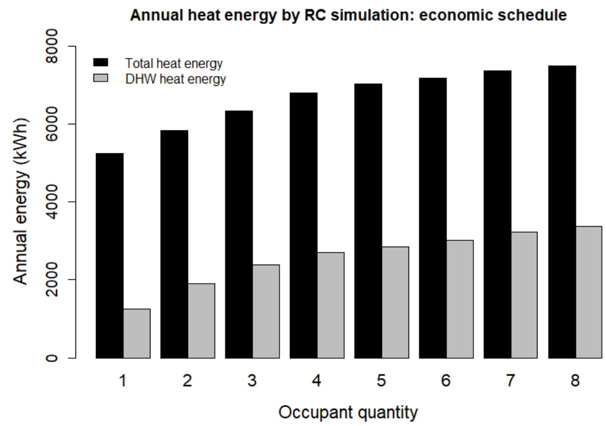

Fig. 4. Total and DHW heat energy against occupant quantity under economic heating schedule

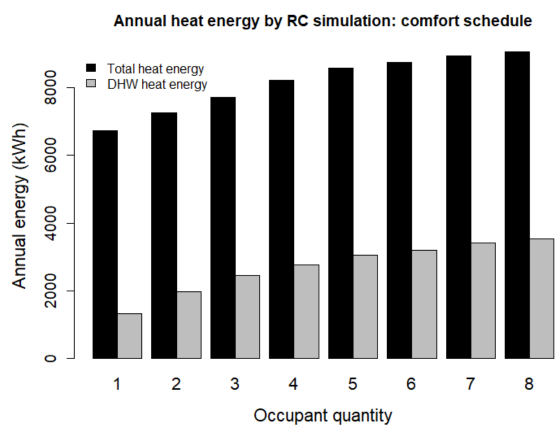

Fig. 5. Total and DHW heat energy against occupant quantity under comfort heating schedule

3.2 Combination of gas use and occupant quantity distributions

A social housing retrofit project took place in Ireland during 2014 of sample size n=188. Household interviews report occupant quantities ranging from one to eight persons. The median and mean averages equal 3.00 and 2.89 respectively.

The distribution of home gas demand by similar buildings in a neighbourhood can be considered as a combination of two distributions. The first is building demand distributed by occupant quantity; second a probability distribution of occupant quantity across the homes of a neighbourhood. The homes are of similar construction.

Two distributions of home gas demand across a neighbourhood appear in Fig. 6. They distinguish the home gas demands by aforementioned heating schedules. As expected in the literature of neighbourhood scale retrofit [6], the better performing schedule displays lower variance. The mean (μ) and standard deviation (σ) of each schedule are: economic μ=7,032 and σ=737, comfort μ=8,755 and σ=754.

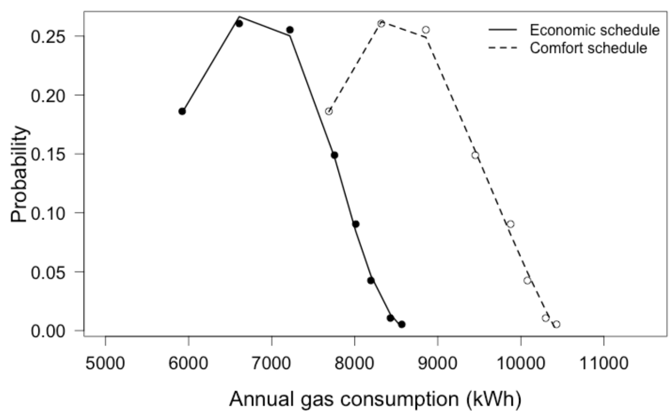

Fig. 6. Distributions of simulated house gas demand in a neighbourhood differ between economic and comfort occupancy schedules.

3.3 Peak gas demand on the utility network

Energy demands made by homes impact the energy distribution systems [1, 22]. To date, this research examines gas supply, but electrification of heat would affect the electricity grid. Peak gas energy demand and associated day of occurrence appear in Table 4. Strong coincidence of peak demand is displayed by the buildings. All but two households reach peak demand on two identical days: 4 and 42. The first day is dated in January and the other in February. The coincidence of time series gas demand of two different households is demonstrated in Fig. 7.

Table 4. Peak gas daily demand, simulated for occupant quantities under both economic and comfort schedules.

Occupant quantity	Economic schedule peak day number	Economic schedule peak daily gas (kWh)	Comfort schedule peak day	Comfort schedule peak daily gas (kWh)
1	42	33.12	42	50.71
2	42	37.12	42	53.35
3	348	35.48	39	54.32
4	4	38.90	42	58.32
5	4	37.82	42	57.42
6	42	38.42	4	55.05
7	42	38.97	42	57.41
8	42	39.22	42	58.38

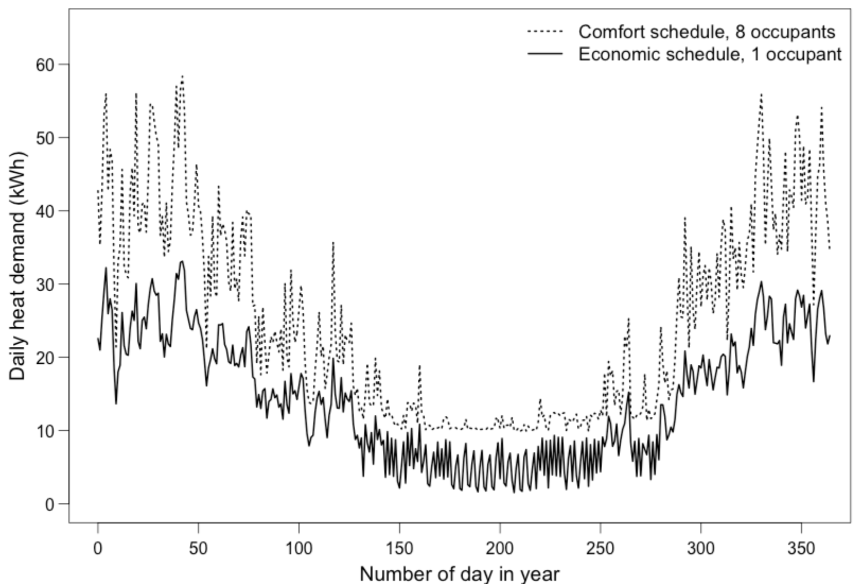

Fig. 7. Simulated daily heating gas demand over one year for two households: an economic schedule for one occupant and a comfort schedule for eight occupants.

Despite their mutual difference in annual demand, the daily demands caused by different occupancy profiles continue to coincide temporally. Most homes peak their heating demand on identical days (Fig. 7).

4 Conclusion and future work

A thermal network (RC) model of a semi-detached house was implemented in Modelica AixLib library. By reducing computational cost, RC models are better suited for neighbourhood scale simulations of heat energy demand. With the IWEC v1 sample days of Dublin weather, the Modelica simulated internal temperature responds faster than the equivalent EnergyPlus simulation. Nevertheless, an annual time series MAE (mean absolute error) of the passive fabric is relatively small at 1.39 °C. The slower thermal dynamics of EnergyPlus reduce annual heat demand by 12% when simulating the same house. Putting this difference in perspective, Waltz [23] views 10% simulation error as acceptable. Further corroboration if energy use results appears in Section 3.1. An archetype of a semi-detached house, modelled in EnergyPlus, locates annual heat energy in one of the distribution curves of annual heat energy from Modelica simulations.

As expected, domestic hot water increases its proportion of household heating demand with increasing building performance and occupant quantities. The proportion can exceed 40%, and care is needed to control DHW heat losses throughout the day.

A combination of per home heat demands (Table 2, Table 3), with a real distribution of occupant quantities produces two overlapping distributions of annual heat demand.

Each distribution curve represents one of two distinct heating schedules applied to similar houses of a neighbourhood (Fig. 6). By initial inspection of the distribution curves, asymmetry and skewness to higher heat demands prevent a classic “bell curve” associated with Normal distributions. Nevertheless, statistical distributions could be applied to retrofit planning at neighbourhood scale. Increasing the sample size would reduce variation and increase prediction accuracy of heat energy savings.

Future work includes increasing sample size and producing statistical distributions of heat energy demand for the most common housing archetypes. Other research [6] has already proposed that energy use of similar homes in a neighbourhood is best expressed as a statistical distribution function. The distribution function promises more accurate prediction of neighbourhood energy demand compared to individual homes. Ultimately, the prediction of energy savings by home retrofit at neighbourhood scale, will be more accurate.

Time series of home gas demands illustrate coincident peaks, regardless of occupant profile. This means that percentage reductions in annual energy demand due to retrofit may not repeat in reductions to peak demand. Energy utilities must size networks to fulfil aggregated peak demand. Such network sizing is very important if gas heating switches to electricity.

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