EVALUATION OF THE HOME POWER SAVINGS PROGRAM – PHASE 3
MODULE 2: LARGE APPLIANCE AND TARIFF ANALYSIS
FINAL REPORT

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Prepared by
THE INSTITUTE FOR SUSTAINABLE FUTURES, UTS
FOR
NSW OFFICE OF ENVIRONMENT AND HERITAGE
JANUARY 2015
Please cite this report as:

Rickwood, P., Mohr, S., Madden, B., 2015, *Evaluation of the home power savings program – Phase 3 Module 2: Large Appliance And Tariff Analysis*, prepared for the NSW Office of Environment and Heritage by the Institute for Sustainable Futures, UTS.

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Executive Summary

Traditionally, energy efficiency and demand management programs have been targeted at the general public, or else to particular groups (such as low-income households). It has not been common for specific households to be targeted, because determining which households have high energy saving potential is a difficult, expensive, and/or time consuming task.

In this report, ISF demonstrates that it is possible to accurately characterise the major appliance use of individual households by analyzing their interval data. Specifically, we describe algorithms which:

1. Detect household air-conditioner ownership and characterise its use, including:
   - (a) The temperature ‘comfort range’ of the individual household, within which the household typically does not engage in space heating or cooling.
   - (b) The strength of the household’s heating response (i.e. how many kWh the household consumes as temperature drops below the comfort range).
   - (c) The strength of the household’s cooling response (i.e. how many kWh the household consumes as temperature climbs above the comfort range).
   - (d) The probability that the household turns the heater on during a cold day.
   - (e) The probability that the household turns cooling on during a warm day.

2. Detect household pool ownership and pool-pump operation, including:
   - (a) Whether a household has a pool-pump (our algorithm correctly detects a pool-pump in ≈ 90% of households who have a pool).
   - (b) The approximate size of that pool-pump (in kW)
   - (c) The hours of operation in any given week

Note that these algorithms are completely automated, and so can be run on an arbitrarily large number of customers. For the results reported in here, the algorithms have been run for each of the approximately 3,000 HPSP households with interval data, and each of the ≈ 30,000 non-participant interval-data households provided by Ausgrid. However, it would be perfectly feasibly to run these same algorithms on a larger group. With Ausgrid’s permission, or another utility’s permission, the algorithms could be run on the entire customer database, to identify programs targeted at specific households. For instance, households who operate their pool-pumps during peak times could be targeted by an education campaign, using specific material informing them how much money they could save by shifting their pool-pump operation outside of peak times. Alternatively, the algorithms could identify households who had not changed their heating/cooling consumption behaviour in the past few years, and these households could be targeted by behaviour changes, education, insulation, and/or appliance upgrade programs.
Just as Google can target advertising at specific internet users based on their specific behaviour, we have demonstrated in this report that it is possible to target interventions at specific customers based on their behaviour (as determined by their interval data). This has potential to improve the targeting (and hence performance) of any future programs.

The final chapter in this report also contains some analysis of household tariff choices, and whether there are savings by switching between time of use (TOU) and including block (IBT) tariffs. We find that, in general, households are on the cheapest tariff for their consumption profile, or else will make only very modest gains of $0-15 per quarter by switching, but that there are a smaller number of households who could save upwards of $50 per quarter by switching tariff.

Note(1): Because we describe the methods used, as well as the results, much of the material in this report is somewhat technical in nature.

Note(2): All analysis in this report is based on interval-data households. As we discuss in Section 1.3, these households are a particular subset of households, and will differ from the general population. Thus, while results in this report are probably generally indicative of trends in the broader population, the exact numbers and results reported are specific to this subset.
Chapter 1

Introduction

1.1 Home Power Saver Program Overview

The Home Power Saving Program (HPSP) is an energy efficiency program ran by the NSW Office of Environment and Heritage between 2008 and March 2014. In total, over 220,000 households were engaged in the program. The program is no longer running, having reached its target of 220,000 participants.

Households who participate in the HPSP receive a visit by an energy advisor, who provides a Personal Power Savings Action Plan. In addition, eligible households could be provided with various items, such as showerheads and CFLs, from a Power Savings Kit (PSK) at no cost.

The program was intended to target low-income households in NSW, in both government and non-government accommodation. Eligible households had to possess some form of concession or pension card.

1.2 This Report

This report has been commissioned by OEH to use Ausgrid-supplied interval-meter data to look specifically at three things:

1. Air-conditioner use;
2. Pool pump ownership and operation;
3. Tariff analysis

Note that the aim here is not to look specifically at the impact of the HPSP on these behaviours, but to use interval data, combined with demographic data available from HPSP surveys, to delve more deeply into households behaviour. For example, from the OEH survey we have information about which households have a pool. It is an open question whether it is possible to analyze interval data and deduce pool-pump operation and use. Combining OEH and Ausgrid data, we will show in this report that it is possible to come up with an algorithm that automatically detects pool-pump operation, with high (≈ 90%) accuracy. This finding is important from the point-of-view of future program design, because it suggests that interval data alone, without an accompanying households survey, can be used to identify pool-pump operation. Based on our results, for example, it should be possible to identify households operating a pool-pump during peak times, and target those households for peak reduction and/or shifting.
1.3 Households Analyzed in this Report

As explained in the companion report, we analyze only Ausgrid households with an interval meter. Specifically, we analyze all Ausgrid households with an interval meter who enrolled in the HPSP, and who gave consent for their electricity consumption data to be used by OEH. We also analyze consumption data from a random selection of anonymized Ausgrid non-participant households, provided by Ausgrid so that we can compare HPSP participants with Ausgrid customers generally.

As explained in the companion report, households with interval-meters are a biased sub-sample of the population, for a number of reasons. For example, recently built households routinely have interval-meters installed, and so our sample is slanted towards recently built dwellings. See the companion report for a fuller discussion.

Data on the characteristics of participant households was provided by OEH, covering such aspects as dwelling type, occupancy, tenure, appliance ownership, hot water system, heating and cooling practices, HPSP Power Savings Kit items provided and other household and demographic information. Interval meter data for participants and non-participant households (to serve as a comparison) was provided by Ausgrid.

1.4 Report Structure

The structure of the remainder of this report is as follows:

- Chapter 2 provide estimates of the cost of space heating and cooling to HPSP participants.
- Chapter 3 has the development of an algorithm to identify households with a pool pump.
- Chapter 4 has information on whether HPSP participants are better off on time of use (TOU) or inclining block tariffs (IBT).
Chapter 2

AC detection

Air-conditioner and heater use is a major contributor to network peaks. Heater use in particular is also a significant component of total energy use for some households. Space heating and cooling is also one electricity end use amenable to behaviour change. Consequently, detecting air-conditioner/heater ownership and characterising its use is useful for understanding household behaviour, as well as for informing future programs and policies.

In the report for module 1, we characterise the overall (average) response of HPSP and non-HPSP households to temperature. In this section, we demonstrate that it is possible to detect air-conditioner ownership and characterise its use at the individual household level. This could be used to target particular households for future energy efficiency and/or demand management programs. For example, the technique described in this chapter could identify households who use a lot of energy for heating, based on their electricity consumption alone, and these households may be candidates for a program targeted at upgrading heating/cooling appliances, and/or educating households about efficient heating/cooling appliances and practices.

Consistent with the findings in the main report (for module 1), we find that overall, HPSP households heat and cool less than non-HPSP households. Specifically, for any given hot or cold day, HPSP electricity use for heating and cooling is on average $\approx 20\%$ lower than that used by non-HPSP households. This difference is over and above the $\approx 20\%$ difference observed in general (i.e. non heating & cooling).

2.1 Description of A/C Methodology

In the module 1 report, we know that electricity consumption increases markedly when the maximum temperature is outside of a temperature region of 21-26°C. We also know that the response to temperature has changed over time, with there being a noticeable decline in cooling-related consumption over the 2008-2014 period. Put another way, it is clear, even from aggregate data, that households are using less energy for cooling now than they did a few years ago. This observation is true after controlling for climate. From the aggregate data analyzed in the companion report, it also appeared that there was a reduction in heating, but this was more modest than the reduction in cooling.

In this section, we will delve more deeply into air-conditioner & heater use. A central assumption in this section is that changes to consumption related to temperature are primarily related to heater & air-conditioner use. That is, if consumption on a mild day is $x$ kWh, and consumption on a cold day is $y$ kWh (with $y > x$), we assume that the additional consumption (i.e. $y - x$) is due exclusively to heating. This assumption may not be strictly true, because it is
possible that use of appliances generally is somewhat correlated with temperature. For example, it is possible that households are more likely to stay home on cold winter days, and this would affect consumption. However, we do believe that space heating and cooling are responsible for the bulk of temperature-sensitive consumption.

In this section we will also further examine the effect time has had on heating and cooling behaviour, and explore the amount of energy and hence financial costs associated with space heating and cooling to HPSP participants. In order to achieve these aims, we fit a mathematical model to the daily consumption of each individual household in the dataset. This model estimates the effect temperature has on each individual household. The basic premise of the model is that outside some ‘comfort range’ (which is estimated separately for each household), then there is a probability that the household will turn on their heater/air-conditioner, and, if turned on, the conditioner consumes a certain number of kWh per degree above/below the comfort range. The description of the model is presented in full in appendix 5.1.1, but the following examples and application should be sufficient for readers to understand the approach taken.

The basics of the model can be described using three examples households, shown in Figure 2.1. Each graph shows household consumption (y-axis) plotted against maximum temperature (x-axis). Each dot represents a single day. We estimate, from these dots the comfort range of the household, heating and cooling slopes, and a probability of heating/cooling. Looking, for instance, at Figure 2.1b, we can see that the household has a ‘base’ (no heating/cooling) consumption of 10 kWh/day, and a comfort range of ≈ 20-23 degrees. Each degree below 20 degrees results in ≈ 2 kWh of additional consumption, if the household does switch on their A/C. We estimate the probability of the household switching on their A/C based on the consumption relative to the base level of consumption. In Figure 2.1b, for example, the red dots indicate days where we estimate there is no space heating or cooling, while the green dots indicate days where we estimate that space heating/cooling occurs. In other words, the model works by fitting three line segments: one for space heating, one for space cooling, and one for no heating or cooling. The heating and cooling slopes are determined based on the line of best fit through the green diamonds\(^1\), whereas the base consumption (no heating/cooling) is determined from days represented by the red circles. From this model, we can estimate both the extra consumption in energy due to heating and cooling and the probability that space heating or cooling will occur on the day (calculated from the proportion of days closer to the heating or cooling slope than the base consumption level).

Looking at the examples in Figure 2.1, we can see that the A/C detection algorithm has correctly identified that two of the three households engage in heating & cooling, but the first household (Figure 2.1a) does not appear to engage in heating or cooling. The algorithm has characterised the heating and cooling behaviour of the three households by fitting three separate lines which characterise their heating behaviour, cooling behaviour, and ‘comfort range’ (where no heating or cooling occurs).

\(^1\)Except for households such as 2.1a, which are identified as not engaging in any heating/cooling. In this case the green diamonds are ignored.
Figure 2.1: Examples between the model consumption and actual consumption versus temperature. Red dots indicate days where no space heating/cooling occurs. Green dots indicate days where electricity is used for heating/cooling, except for example 1, which the algorithm (correctly) determines does not operate heating/cooling appliances.
The model is applied multiple times, for different time periods, and energy consumption types. In particular, there are three data time periods examined, namely:

1. 2008–2010
2. 2012–2014

and four different consumption types fitted, namely:

1. Peak consumption (2-8pm workdays)
2. Shoulder workday (7am to 2pm and 8-10pm)
3. Shoulder weekend/public holiday (7am to 10pm)
4. Off Peak (10pm to 7am).

This means that there are 8 (2 date types × 4 consumption period) distinct fitted models generated for each Id.
Figure 2.2: Relationship between temperature and electricity consumption: the red line shows mean daily consumption of HPSP participants over the period Jan 2013 to June 2014; the blue line shows how much the maximum daily temperature deviated (either up or down) from 25 degrees.

2.2 Space heating and cooling

As already mentioned, we do not directly observe heating and cooling consumption. This would involve appliance sub-metering, which is expensive and time consuming. Because we do not directly observe heating and cooling behaviour, we need to make some simplifying assumptions in order to estimate space heating and cooling related electricity consumption. Our key assumption is that increases in consumption correlated to temperature are due to space heating and cooling. As already mentioned, this may not be strictly true: households may spend more time indoors on colder days, for example, and so general appliance use may be somewhat higher on those days, even ignoring any space heating-related consumption. Notwithstanding these complications, it is a reasonable simplification to make, because we believe that the large majority of temperature-related consumption is for space heating & cooling. For reference, see Figure 2.2, which shows how related consumption is to extremes in temperature. In winter in particular, we see that overall consumption is very closely related to deviations from a ‘comfortable’ temperature.
Table 2.1 shows the breakdown of participants in terms of electric heating/cooling devices, as determined by OEH survey data. Appendix 5.1.7 contains the definitions of the electric heating and cooling terms, and shows histograms for AC heating cooling versus no AC usage and the histograms for peak consumption (as opposed to total consumption).

Figure 2.3: Modelled average total daily consumption by temperature for HPSP participants with (blue) and without (red) electric heaters and coolers (2012-14 fit).

We will use OEH survey data to assess the accuracy of our A/C detection method, but we should note that even when the survey data indicates no heater/cooler is used, the electricity consumption of the household sometimes indicates otherwise. Figure 2.3 shows the estimated consumption of those who indicated in the survey they did/did-not have heating/cooling appliances. Clearly those who have and use heaters/coolers consume considerably more electricity at temperature extremes than those who indicated they did not. However, there is a clear response to temperature even for those who indicate they do not own or engage in space heating/cooling. While some of this increase may be related to uses other than heating/cooling, much of it is probably related to unreported space heating and cooling.

Table 2.1: The number of participants with/without electric heaters and coolers

<table>
<thead>
<tr>
<th>Participant Cohort</th>
<th>Number of Participants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electric heater(s) and cooler(s)</td>
<td>1872</td>
</tr>
<tr>
<td>Electric heater(s) only</td>
<td>897</td>
</tr>
<tr>
<td>Electric cooler(s) only</td>
<td>474</td>
</tr>
<tr>
<td>No Electric heater or cooler</td>
<td>644</td>
</tr>
</tbody>
</table>
2.2.1 Changes in heating/cooling behaviour over time

We can examine changes in heating/cooling consumption patterns and how they have changed over time. To do this, we fit separate models for the 2008-2010 and 2012-2014 periods, and compare how these have changed over time. Table 2.2 has the summary of the average values of the fitted constants to total consumption. Note that these are average values, but the algorithm we use produces these on a per-household basis, so it would be possible to determine for each household whether the household has adjusted their heating behaviour by changing their ‘comfort’ temperature range, or have altered the slope of their heating/cooling response, or some combination. Clearly reporting results on a per-household basis is impractical in this report, so we just report means.

In Table 2.2, the parameters are as follows:

- $m_d$: The slope of the heating line. A value of -1 would indicate that each degree of temperature corresponded to 1 extra kWh of heating consumption.
- $m_u$: The slope of the cooling line. A value of 1 would indicate that each degree of temperature corresponded to 1 extra kWh of heating consumption.
- $T_d$: The lower end of the comfort range. A value of 20 would indicate that below 20 degrees, households engage in space heating.
- $T_u$: The upper end of the comfort range. A value of 30 degrees would indicate that above 30 degrees, households engage in space cooling.
- $P_d$: The probability of heating, for days with temperature below $T_d$. A value of 0.4 would indicate that on days with a temperature below $T_d$, there is a 40% chance that a household turns heating on.
- $P_u$: The probability of heating, for days with temperature above $T_u$. A value of 0.4 would indicate that on days with a temperature below $T_u$, there is a 40% chance that a household turns air-conditioning on.

Table 2.2 shows the results for total (daily) consumption, while Table 2.3 shows the average values for models of heating & cooling behaviour fitted to just peak-period (2-8pm) consumption. Note that in these Tables, households who do not heat/cool have been excluded, so the averages are only for those households that do heat or cool. This is because many of the parameters do not make sense if the households do not heat or cool. The concept of a ‘comfort range’, for instance, does not apply if there is not heating or cooling. The key findings from the analysis over time are:

- **More muted heating** There has been a 14% decline in heating slope between 2008-2010 and 2012-2014. So as temperature drops below the comfort range, consumption increases 14% less quickly than it used to.

- **Heaters still turned on** There has been no change in the heating comfort temperature (i.e. $T_h$), so households are still heating at the same temperature, but are using less energy. Households are also just as likely to heat on a cold day in 2008-2010 as on a cold day in 2012-2014. This suggests improvements in A/C efficiency or building thermal performance are responsible for decreased heating slope, and not behaviour, although we cannot say this definitively.

- **Much more muted cooling** There has been a 23% decline in cooling slope between 2008-2010 and 2012-2014. So as temperature rises above the comfort range, consumption increases 23% less quickly than it used to.
Delay in turning on cooling Unlike heating, HPSP households appear to have adjusted their comfort range, and are willing to live with an extra 0.7 °C before turning on an A/C.

Heating reduction in peak period is small (6%) The decline in peak-period heating slope is less than the overall decline: 6% compared to 14%.

Cooling reduction in peak period moderate (17%) The decline in peak-period cooling slope is less than the overall decline: 17% compared to 23%. There is a slightly more pronounced increase in the cooling comfort range.

Table 2.2: Mean parameter values for HPSP household total consumption, for different time periods

<table>
<thead>
<tr>
<th>Variable</th>
<th>fitting period</th>
<th>mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>$m_d$</td>
<td>2008-10</td>
<td>-2.95 ± 0.10</td>
</tr>
<tr>
<td>$m_d$</td>
<td>2012-14</td>
<td>-2.54 ± 0.06</td>
</tr>
<tr>
<td>$T_d$</td>
<td>2008-10</td>
<td>21.5 ± 0.1</td>
</tr>
<tr>
<td>$T_d$</td>
<td>2012-14</td>
<td>21.5 ± 0.1</td>
</tr>
<tr>
<td>$P_d$</td>
<td>2008-10</td>
<td>0.53 ± 0.01</td>
</tr>
<tr>
<td>$P_d$</td>
<td>2012-14</td>
<td>0.53 ± 0.00</td>
</tr>
<tr>
<td>$m_u$</td>
<td>2008-10</td>
<td>2.85 ± 0.17</td>
</tr>
<tr>
<td>$m_u$</td>
<td>2012-14</td>
<td>2.21 ± 0.07</td>
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<tr>
<td>$T_u$</td>
<td>2008-10</td>
<td>26.8 ± 0.1</td>
</tr>
<tr>
<td>$T_u$</td>
<td>2012-14</td>
<td>27.5 ± 0.1</td>
</tr>
<tr>
<td>$P_u$</td>
<td>2008-10</td>
<td>0.48 ± 0.01</td>
</tr>
<tr>
<td>$P_u$</td>
<td>2012-14</td>
<td>0.46 ± 0.00</td>
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</tbody>
</table>
Table 2.3: Mean parameter values for HPSP household peak period consumption, for different time periods

<table>
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<tr>
<th>Variable</th>
<th>fitting period</th>
<th>mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>$m_d$</td>
<td>2008-10</td>
<td>-1.25 ± 0.04</td>
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<tr>
<td>$m_d$</td>
<td>2012-14</td>
<td>-1.17 ± 0.03</td>
</tr>
<tr>
<td>$T_d$</td>
<td>2008-10</td>
<td>21.2 ± 0.1</td>
</tr>
<tr>
<td>$T_d$</td>
<td>2012-14</td>
<td>21.0 ± 0.1</td>
</tr>
<tr>
<td>$P_d$</td>
<td>2008-10</td>
<td>0.50 ± 0.01</td>
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<tr>
<td>$P_d$</td>
<td>2012-14</td>
<td>0.49 ± 0.00</td>
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<tr>
<td>$m_u$</td>
<td>2008-10</td>
<td>1.63 ± 0.06</td>
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<tr>
<td>$m_u$</td>
<td>2012-14</td>
<td>1.35 ± 0.04</td>
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<tr>
<td>$T_u$</td>
<td>2008-10</td>
<td>26.6 ± 0.1</td>
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<tr>
<td>$T_u$</td>
<td>2012-14</td>
<td>27.6 ± 0.1</td>
</tr>
<tr>
<td>$P_u$</td>
<td>2008-10</td>
<td>0.44 ± 0.01</td>
</tr>
<tr>
<td>$P_u$</td>
<td>2012-14</td>
<td>0.42 ± 0.01</td>
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Table 2.4: Mean parameter values for non-participants, for different time periods

<table>
<thead>
<tr>
<th>Variable</th>
<th>fitting period</th>
<th>mean</th>
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</thead>
<tbody>
<tr>
<td>$m_d$</td>
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<td>-3.64 ± 0.04</td>
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<td>$m_d$</td>
<td>2012-14</td>
<td>-3.24 ± 0.03</td>
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<td>$T_d$</td>
<td>2008-10</td>
<td>21.7 ± 0.0</td>
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<td>$T_d$</td>
<td>2012-14</td>
<td>21.5 ± 0.0</td>
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<td>$m_u$</td>
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<td>$T_u$</td>
<td>2012-14</td>
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<tr>
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<tr>
<td>$P_u$</td>
<td>2012-14</td>
<td>0.45 ± 0.00</td>
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2.2.2 Comparison between participants and non participants

Since we have observed some changes in space cooling over time in the participants, it is prudent to examine how space heating and cooling has changed in the non participants. Table 2.4 has the summary of the mean values non participants. Figure 2.5 has the mean values for non-participants for the peak period only (2-8pm workdays). The main things of note are:

- Non-participant heating slope has declined 11% (compared to 14% for HPSP). For peak period, heating slope has not declined at all (compared to 6% decline for HPSP).
- Non-participants begin heating at approximately the same temperature as participants, and like participants, and have not altered this temperature. This applies to total and peak-period consumption.
- Non-participants are about as likely to heat on a cold day as participants, and this propensity to heat has not changed over time.
- Non-participant cooling slope has declined by 17%, somewhat less than HPSP participants. Unlike participants, their cooling slope is somewhat higher in the peak period (20%), but this could be due to sampling variation/noise rather than being a robust finding.
- Unlike participants, non-participants have not altered their comfort range for cooling much – in 20012-2014 they begin to cool at similar temperatures to what they did in 2008-2010.

As already mentioned, we fit a separate model to each household, and this model characterises that household’s electricity consumption with temperature. We can use these models to predict consumption for any household at any temperature. We do this, and show the average response of HPSP and non-HPSP households in Figure 2.4. We see that HPSP households in less heating and cooling than non-participants. We also see that between 2008-2010 and 2012-2014, there has been a slight decline in space heating for both participants and non participants over time. There has been a much more marked decline in space cooling.
Table 2.5: Mean parameter values non participant peak period consumptions, for different time periods

<table>
<thead>
<tr>
<th>Variable</th>
<th>fitting period</th>
<th>mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>$m_d$</td>
<td>2008-10</td>
<td>-1.48 ± 0.02</td>
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<td>$m_d$</td>
<td>2012-14</td>
<td>-1.47 ± 0.07</td>
</tr>
<tr>
<td>$T_d$</td>
<td>2008-10</td>
<td>21.4 ± 0.0</td>
</tr>
<tr>
<td>$T_d$</td>
<td>2012-14</td>
<td>21.3 ± 0.0</td>
</tr>
<tr>
<td>$P_d$</td>
<td>2008-10</td>
<td>0.49 ± 0.00</td>
</tr>
<tr>
<td>$P_d$</td>
<td>2012-14</td>
<td>0.48 ± 0.00</td>
</tr>
<tr>
<td>$m_u$</td>
<td>2008-10</td>
<td>2.00 ± 0.15</td>
</tr>
<tr>
<td>$m_u$</td>
<td>2012-14</td>
<td>1.60 ± 0.02</td>
</tr>
<tr>
<td>$T_u$</td>
<td>2008-10</td>
<td>26.0 ± 0.1</td>
</tr>
<tr>
<td>$T_u$</td>
<td>2012-14</td>
<td>26.7 ± 0.1</td>
</tr>
<tr>
<td>$P_u$</td>
<td>2008-10</td>
<td>0.43 ± 0.00</td>
</tr>
<tr>
<td>$P_u$</td>
<td>2012-14</td>
<td>0.42 ± 0.00</td>
</tr>
</tbody>
</table>

Figure 2.4: Modelled average total daily consumption by temperature for HPSP participants and non participants (2012-14 fit)
2.3 Cost of space heating/cooling

Table 2.6: Mean and median space heating/cooling costs for participants and non-participants calculated for three different time periods

<table>
<thead>
<tr>
<th>Group</th>
<th>fitting period used</th>
<th>mean</th>
<th>median</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$/d</td>
<td>% of bill</td>
</tr>
<tr>
<td>Participants</td>
<td>2012-14</td>
<td>0.40</td>
<td>7.9</td>
</tr>
<tr>
<td>Non-participants</td>
<td>2012-14</td>
<td>0.53</td>
<td>8.2</td>
</tr>
<tr>
<td>Participants</td>
<td>2008-10</td>
<td>0.51</td>
<td>8.4</td>
</tr>
<tr>
<td>Non-participants</td>
<td>2008-10</td>
<td>0.69</td>
<td>9.2</td>
</tr>
</tbody>
</table>

Using the mathematical techniques already described, we have a concise mathematical model of each household’s electricity consumption, and how that changes with temperature. We can use this to look at the heating and cooling costs of households in different seasons. Specifically, we can calculate the energy used in each of the following periods, for a day of any given temperature:

1. Peak consumption (2-8pm on work days)
2. Shoulder consumption (7am to 2pm and 8-10pm on work days)
3. Shoulder consumption (7am to 10pm on week ends)
4. Off peak consumption (10pm to 7am all days)

The heating/cooling energy can be estimated by:

\[ C_{\text{space}}(T) = C(T) - b. \] (2.1)

Where \( C(T) \) is the estimated consumption for temperature \( T \), determined by the model. This consumption can then be converted into a cost, by applying the Ausgrid 2013-14 rates for the different consumption types as shown in Table 2.8. The cost can be calculated using the fitted constants from either the 2008-2010 period, or the 2012-14 period. Table 2.7 shows heating and cooling costs using 2013-14 electricity prices, 2013 calendar year consumption, and heating/cooling slopes fitted over different time periods. The 2008-2010 results, for example, indicate that if HPSP participants had continued to heat/cool like they did in 2008-2010, they would now be paying $0.51 per day in heating and cooling costs, whereas they are actually paying only $0.40, due to their altered heating/cooling behaviour. The costs are shown on a dollars per day basis in Figure 2.5 and in a percentage of total bill basis in Figure 2.6 and Table 2.7. Note that all households are included in these figures, including those that do not appear to heat/cool at all.
Figure 2.5: Histogram of the estimated space heating/cooling costs, by various fitting periods
Figure 2.6: Histogram of the percentage space heating/cooling costs relative to the full bill, by various typing periods
Table 2.7: Percentage of bill spent on heating/cooling costs for participants and non-participants calculated for three different time periods. Note: these averages are across all households (including those that do not heat/cool their dwellings).

<table>
<thead>
<tr>
<th>Group</th>
<th>fitting period used</th>
<th>mean %</th>
<th>median %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Heating</td>
<td>Cooling</td>
</tr>
<tr>
<td>Participants</td>
<td>2012-14</td>
<td>5.7</td>
<td>2.2</td>
</tr>
<tr>
<td>Non-participants</td>
<td>2012-14</td>
<td>5.8</td>
<td>2.4</td>
</tr>
<tr>
<td>Participants</td>
<td>2008-10</td>
<td>5.4</td>
<td>3.0</td>
</tr>
<tr>
<td>Non-participants</td>
<td>2008-10</td>
<td>5.9</td>
<td>3.3</td>
</tr>
<tr>
<td>Participants</td>
<td>2008-14</td>
<td>6.1</td>
<td>2.8</td>
</tr>
<tr>
<td>Non-participants</td>
<td>2008-14</td>
<td>6.4</td>
<td>3.2</td>
</tr>
</tbody>
</table>

Table 2.8: Energy Australia 2013-14 rates (Energy Australia, 2013)

<table>
<thead>
<tr>
<th>Time of day</th>
<th>rate (c/kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peak consumption</td>
<td>52.547</td>
</tr>
<tr>
<td>Shoulder week day</td>
<td>21.846</td>
</tr>
<tr>
<td>Shoulder weekend</td>
<td>21.846</td>
</tr>
<tr>
<td>Off Peak</td>
<td>13.167</td>
</tr>
</tbody>
</table>

Figure 2.7: Space heating/cooling costs by quarter for participants (blue) and non-participants (red).
Chapter 3

Pool Pump Identification

3.1 Introduction

Pool pumps are a major appliance: a household with a typical 1kW pool-pump, operating it at the recommended 6 hours a day, will consume 6 kWh of electricity, which is around a third of an average household’s daily consumption. Knowing pool pump ownership and operation is important for targeting energy efficiency and/or peak reduction programs:

**Peak demand management:** Pool-pumps can be operated on timers so that they are on outside of peak times. Being able to identify pool-pumps operating during peak times would allow programs targeted at those households shifting their consumption.

**Energy efficiency:** Households with pools may have high energy saving potential, as some of these households may be using an inefficient pump, may be operating their pump for longer than necessary. ISF’s evaluation of the Queensland Climate Smart Homes program identified the upgrade of inefficient pool pumps as a major source of savings: households with pools saved on average 1.4 kWh per day, with many claiming to have upgraded their pool-pump or altered the hours of operation.

As a consequence, being able to identify households with pool-pumps, and the hours of operation of those pool pumps, is valuable for targeting peak reduction or energy-efficiency programs. ISF has developed a technique for doing this, and by combining OEH survey data with Ausgrid interval data, we are able to test the accuracy of the technique, and find it to be around 90% accurate in detecting pools. The technique is completely automated, and so could be easily run to identify any households for which interval data is available. We describe the technique, and the results achievable by using it, in this section.

For completeness, we describe the development of the algorithm in some detail, but readers wishing to skip to the results can proceed directly to Section 3.5.

3.1.1 Data Used

OEH survey data contains information on pool ownership, and it is assumed that all households with a pool have a pool pump. Note that OEH data will not be 100% accurate: at the very least, some households without pools will have had pools installed since responding to the OEH survey, while some with pools may have drained them and they are in disuse. While we know the survey data is not 100% accurate, for the purposes of assessing the accuracy of our method,
we take the OEH survey data as definitive in determining whether a household does or does not have a pool. We have randomly split OEH participants into Groups A and B. Group A was used to calibrate our algorithm. The accuracy of the algorithm was tested on Group B.

3.2 Development of pool-pump detection method

For some households, it is possible to see a pool-pump in operation simply by examining the average summer load profile of the household. Figure 3.1 shows average summer load profiles for 10 randomly selected households. Off-peak hot water is evident in many of the households – operating in the hours either side of midnight. Even though all of the ten households identify as having a pool, a pool-pump-like signature is only evident in one of the households. Household 10 clearly has a pool pump, of about 2 kW, which operates regularly between about 10am and 4pm. Households 2 and 5 also seem to have clear pool-pumps (both also in operation between 10am and 4pm), but these are less clear.

What is apparent in Figure 3.1 is that for some households pool pump is identifiable at this level, and others not. This may be because households vary the times at which they operate their pool pumps, or else they turn their pool pumps off while on holiday. For whatever reason, pool pump use is not consistent enough for many households to show up in their load profile. In short, looking at average profiles is not sufficient to identify pool-pump operation in general, and so we require a different method.

Next, we look at data for a specific week (1st - 7th of December 2013), and see if looking at specific days helps, rather than at seasonal averages.
Figure 3.1: Average mild summer day load profiles for 10 randomly selected pool-owning households. As a comparison, the average load profile of non-pool owning households with gas how water is also shown in blue.
3.3 Examining daily data

Examining daily consumption data across a week (shown in Figure 3.2), we can immediately see that pool-pumps are easier to spot on daily data. For all households other than households 1 & 8 we can see the pool pump operating. Based on these findings, we develop an algorithm who examines daily & weekly data to detect pool-pump operation.
Figure 3.2: Daily consumption profile for the week starting 1st December 2013 for random households with a pool.
3.4 Pool Pump Detection Algorithm

The method to determine pool pumps is a four step process:

1. Create estimated weekly base-load consumption
2. Identify all possible pool pumps
3. Find the most likely 1 cycle and 2 cycle pool pumps
4. Determine if a pool pump exists

3.4.1 Create estimated weekly standby consumption

The algorithm analyzes one week at a time. Interval data for each day in the week is used. The second lowest consumption value for all half hour intervals in the week is selected to represent a reasonable estimate of the weekly base-load consumption during the week. This base-load consumption data is then smoothed to make differences in the weekly base-load consumption more apparent. The estimated standby consumption for the 10 random households is shown in Figure 3.3.

3.4.2 Identify all possible pool pumps

The next step in the process is to identify possible pool pumps in the weekly standby consumption data. We assume that the consumption profile of a pool pump is rectangular (i.e. constant over time). This is true for many pool pumps (as is evident in Figure 3.2). The algorithm takes the weekly standby consumption and identifies all possible rectangles as follows:

1. The minimum of the weekly standby consumption is removed. That is, the standby graph is shifted down so that it touches zero at its minimum point.
2. All rectangles that fit under the adjusted standby graph are then found, subject to the following constraints:
   (a) Rectangles must be at least $\frac{1}{2}$ an hour in length;
   (b) No part of the rectangle can be above the adjusted standby graph;
   (c) The rectangle must touch the top of the standby graph at some point.

We identify these rectangles as an initial set of possible pool-pumps in operation. However, as you can imagine, there are a large number of these rectangles, and many of them will be too long (in time), or too short (in kW) to be actual pool pumps. The next stage of the algorithm identifies those rectangles that are the right size to be pool pumps.

3.4.3 Find the most likely 1 cycle and 2 cycle pool pumps

We restrict ourselves to detecting pool pumps that operate once or twice during the day. Some pool-pumps will operate for 3 or more cycles over the day, but detecting pool pumps becomes more difficult as they have many short cycles, and so at this stage we do not attempt to detect pool pumps with more than 2 daily cycles.

We have some prior knowledge about the likely power consumption of pool pumps, and how long they commonly run per day. We encode this prior knowledge by specifying probability distributions for power consumption and daily hours of operation. These are shown in Figure 3.4.
(a) Random household 1  
(b) Random household 2  
(c) Random household 3  
(d) Random household 4  
(e) Random household 5  
(f) Random household 6
Figure 3.3: Estimated standby consumption profiles for the week starting 1st December 2013 for random households with a pool.
3.6. Given the chance that the pump is running, which household is most likely to be present: standby consumption is (approximately) flat, with the addition of the most likely 1-cycle pool pump rectangle pair.

3.4.4 Determining if a Pool Pump Exists

There are now three possibilities to examine:

1. There is no pool pump: standby consumption is (approximately) flat.
2. 1 cycle pool pump is present: standby consumption is (approximately) flat, but with the addition of the most likely 1-cycle pool pump rectangle pair.
3. 2 cycle pool pump is present: standby consumption is (approximately) flat, but with the addition of the most likely 2-cycle pool pump rectangle pair.

These three competing standby profiles are shown graphically for a random week and household in Figure 3.5. Consumption at any half hour is assumed to be normally distributed with a mean and the underlying curve value and standard deviation of 0.2. The overall probability that is highest of the three possibilities is taken to be the case. So in the case of Figure 3.5, the most probable case is the 2 cycle pool pump (with a log-likelihood of -12.5), and so for that week and household the algorithm decides that that a 2 cycle pool pump was operating. The algorithm’s solution for ten random households with a pool pump (according to OEH survey data) is shown in Figure 3.6.

Note in Figure 3.5 the log-likelihood is shown, rather than the raw likelihood. Values closer to zero are more likely.
Figure 3.5: Underlying consumption curves compared to the weekly base-load consumption.
(a) Random household 1

(b) Random household 2

(c) Random household 3

(d) Random household 4

(e) Random household 5

(f) Random household 6
Figure 3.6: Weekly base-load consumption profile for the week starting 1st December 2013 for random households with a pool.
3.4.5 Determine pool-pump ownership

A household is determined to have a pool pump if the number of weeks the algorithm found either a 1 or 2 cycle pool pump is larger than the number of weeks no pool pump was found.

3.5 Results

3.5.1 Detection rates

We now examine how accurate the technique is in detecting pools, and, conversely, how often the technique incorrectly ‘finds’ a pool when no pool in present. As already discussed, we use OEH data as the authoritative indicator of pool ownership.

In order to prevent overfitting, all algorithm development was conducted using Group A only. To test the accuracy of the algorithm, we apply it to Group B. The results was that the algorithm was able to detect the presence of a pool pump in 83.1% of households that said they have a pool and had a false positive\(^2\) rate of 6.9%. It is important to note that these percentages are likely to be conservative as:

1. Some participants with a pool may have drained the pool or otherwise stopped using a pool-pump.
2. Some participants without a pool at the time of the OEH intervention date may have at a later date installed a pool.

The examination of Group B indicates that the algorithm is successful at identifying households with a pool pump.

Table 3.1: Summary of result of HPSP participants

<table>
<thead>
<tr>
<th>HPSP demographics</th>
<th>Group</th>
<th>Algorithm estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Has Pool</td>
</tr>
<tr>
<td>Has Pool</td>
<td>A</td>
<td>185</td>
</tr>
<tr>
<td>No Pool</td>
<td>A</td>
<td>128</td>
</tr>
<tr>
<td>Has Pool</td>
<td>B</td>
<td>192</td>
</tr>
<tr>
<td>No Pool</td>
<td>B</td>
<td>117</td>
</tr>
</tbody>
</table>

3.5.2 Pool-pump size/power ratings (kW)

Our algorithm detects not just the presence of pool pumps, but also their size (i.e. kW rating). We show the distribution of estimated pool-pump sizes in Figure 3.7. Note that the way the pool-pump algorithm works, we will tend to err on the side of estimating smaller-than-actual pool pumps. In other words, our estimates will be conservative, and this is clearly seen in Figure 3.7, where many pool pumps are quite small (below 1 kW). However, while we will tend to underestimate the size of pool pumps, and so may not be useful for estimating the actual power rating of pool pumps, it is useful in detecting the relative size (i.e. which households have large pool pumps, relative to other households).

\(^2\)False positives are where the algorithm identifies households as having a pool when they responded ‘No pool’ to the OEH survey.
5 **Households of operation**

Our algorithm detects not just the presence of pool pumps, but also their hours of operation. We calculate that:

- 14.3% of pool-pump use occurs in the peak period (2-8 pm)\(^3\).
- Between the 4-6pm period in summer, when absolute peak usage typically occurs, we find that pool pumps are on 12.9% of the time. This suggests that there is significant peak-demand reduction potential, and a program targeted at these particular households could reduce peak demand.

Note that the above numbers are for HPSP households only, and are calculated only for households that say they have a pool (in OEH survey data), and are ‘detected’ by our algorithm. We can thus be confident that very few of the households are mislabelled (i.e. are tagged as having a pool when they in fact do not). Consequently, we can have a reasonable degree of confidence in these numbers.

While we do not have any survey/demographic data for non-participant households, we can still apply the algorithm to them, and doing so, we obtain the following results:

- Of non participants with pools\(^4\) 25.2% of pool-pump use occurs in the peak period (2-8pm)\(^5\).
- Between the 4-6pm period in summer, when absolute peak usage typically occurs, we find that pool pumps are on 20.7% of the time for non-participants.

\(^3\)We exclude IBT-tariff households from this analysis, as they have no incentive to shift consumption.
\(^4\)as detected by our algorithm
\(^5\)Again, we exclude IBT-tariff households from this analysis.
Note that although the false-positive rate of our algorithm is low (6.9%), because the proportion of total households with pools is low, the numbers presented for non-participants will be somewhat less accurate than for participants. Based on these results however, it seems that pool-pump use during peak times occurs in a significant minority of pool owners amongst both HPSP households and non-HPSP households.

Figure 3.8: Estimated distribution of pool pump run time (hours)
Chapter 4

Tariffs

ISF has used the interval data available, as well as the tariff information supplied by Ausgrid for each household, to determine whether households are made better or worse off as a result of switching between time of use (TOU) and inclining block (IBT) tariffs. We can do this for each individual household simply by applying ‘typical’ residential tariff rates to the consumption data available for each household. Note that this will not be an exact method, because some households will have negotiated differed rates with their retail supplier. Retailers often, for instance, offer discounts to customers when they sign up or switch from another retailer, and we cannot include any of these. Hence the numbers in this section should be taken as indicative, and not exact.

The question of whether households are better off on a time of use (TOU) or inclining block tariff (IBT) can be examined by calculating the electricity bill for each household for the year 2013 using cost rates shown in Table 4.1. Figure 4.1 highlights the cost for the households if they switch to the different tariff type, and Table 4.2 highlights the number of households better off.

2013 was a reasonably mild year, so to examine the effect of extreme weather an alternative scenario was created where the 10 mildest winter and summer days were replaced by the 10 extreme (temperature wise) summer and winter days. The extreme weather costs are shown in Table 4.3 and Figure 4.2. The tables indicate that the more extreme the weather the better the outcome is likely for being on IBT over TOU.

Table 4.2 shows that for 2013 53% of households were financially better off staying on TOU tariff rather than switching to an IBT tariff, and 70% of households were better off remaining on IBT. An extreme year only changed these marginally: to 50% and 73% respectively.

Table 4.4 show that 53% in mild and 50% in extreme year are better off staying on TOU. However due to the asymmetry shown in Figure 4.1, if all household switch from TOU to IBT, then many of those households will be much worse off. This is why Table 4.4 shows that on average if the TOU tariff households switched to IBT there would be a net loss of $15.08 per quarter in a mild year and $13.04 per quarter in an extreme year. Table 4.2 highlights that most Ausgrid participants are slightly better off in a Time Of Use (TOU) tariff system then in an Inclining Block Tariff (IBT), and that general advice to households to switch to TOU tariffs is probably warranted, as even those households worse off after such a switch are rarely much worse off (see Figure 4.1).

Overall, the numbers indicate that households do a reasonable job of deciding which tariff is best for them, but there are still a significant number of households on the ‘wrong’ tariff, from a financial point of view. While no blanket rule can be applied (i.e. it is not the case that TOU is always cheaper than IBT), it is possible to identify many individual HPSP households
Table 4.1: Energy Australia 2013-14 rates (Energy Australia, 2013)

<table>
<thead>
<tr>
<th>Time of day</th>
<th>TOU</th>
<th>Block</th>
<th>IBT</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>rate (c/kWh)</td>
<td>Daily access</td>
<td>Daily access</td>
</tr>
<tr>
<td>Daily access</td>
<td>87.175</td>
<td>&lt;1,000 kWh per quarter</td>
<td>78.10</td>
</tr>
<tr>
<td>Peak consumption</td>
<td>52.547</td>
<td>1,000 - 2,000 kWh per quarter</td>
<td>27.39</td>
</tr>
<tr>
<td>Shoulder</td>
<td>21.846</td>
<td>&gt; 2,000 kWh per quarter</td>
<td>29.018</td>
</tr>
<tr>
<td>Off Peak</td>
<td>13.167</td>
<td></td>
<td>31.328</td>
</tr>
</tbody>
</table>

that could save over $20 per quarter by simply switching tariff. *Identifying these households and advising them to switch tariff is probably one of the simplest and easiest ways to assist low-income households.*

![Graph](image)

Figure 4.1: Savings achieved by switching to TOU or IBT tariffs, for participants and non-participants in 2013 ($ per quarter, negative values means it would cost more if the household switched)
Table 4.2: Analysis of tariffs for 2013

<table>
<thead>
<tr>
<th>Actual tariff</th>
<th>Cheapest Tariff TOU</th>
<th>IBT</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOU</td>
<td>1768</td>
<td>1557</td>
</tr>
<tr>
<td>IBT</td>
<td>82</td>
<td>188</td>
</tr>
</tbody>
</table>

Figure 4.2: Benefit of switching to TOU or IBT tariffs, for participants and non-participants in an extreme temperature year ($ per quarter, negative values means it would cost more if the household switched)

Table 4.3: Analysis of tariffs for extreme temperature year

<table>
<thead>
<tr>
<th>Actual tariff</th>
<th>Cheapest Tariff TOU</th>
<th>IBT</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOU</td>
<td>1648</td>
<td>1677</td>
</tr>
<tr>
<td>IBT</td>
<td>73</td>
<td>197</td>
</tr>
</tbody>
</table>
Table 4.4: Mean and median savings by switching ($ per quarter)

<table>
<thead>
<tr>
<th>Group</th>
<th>Year</th>
<th>From tariff</th>
<th>To tariff</th>
<th>mean</th>
<th>median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participants</td>
<td>2013</td>
<td>TOU</td>
<td>IBT</td>
<td>-15.08</td>
<td>-1.17</td>
</tr>
<tr>
<td>Participants</td>
<td>2013</td>
<td>IBT</td>
<td>TOU</td>
<td>-3.96</td>
<td>-6.95</td>
</tr>
<tr>
<td>Participants</td>
<td>Extreme Temp.</td>
<td>TOU</td>
<td>IBT</td>
<td>-13.04</td>
<td>-1.17</td>
</tr>
<tr>
<td>Participants</td>
<td>Extreme Temp.</td>
<td>IBT</td>
<td>TOU</td>
<td>-6.26</td>
<td>-8.56</td>
</tr>
<tr>
<td>Non Participants</td>
<td>2013</td>
<td>TOU</td>
<td>IBT</td>
<td>-37.42</td>
<td>-14.13</td>
</tr>
<tr>
<td>Non Participants</td>
<td>2013</td>
<td>IBT</td>
<td>TOU</td>
<td>6.54</td>
<td>0.13</td>
</tr>
<tr>
<td>Non Participants</td>
<td>Extreme Temp.</td>
<td>TOU</td>
<td>IBT</td>
<td>-35.67</td>
<td>-12.79</td>
</tr>
<tr>
<td>Non Participants</td>
<td>Extreme Temp.</td>
<td>IBT</td>
<td>TOU</td>
<td>4.86</td>
<td>-0.66</td>
</tr>
</tbody>
</table>
Chapter 5

Appendix

5.1 AC detection

5.1.1 AC model description

The model is an algorithm approach, with six key steps, namely:

1. Get initial fit
2. Check validity
3. Split heating/cooling data
4. Create final fit
5. Calculate slope probability

5.1.2 Get initial fit

In the first section of the algorithm, the model fits three linear functions to an individual household that has the following properties:

1. The combined function is continuous (that is, the modelled the consumption does not have any break points)
2. The slope of the middle linear function is 0 (that is, it is a horizontal line).

The function that has these properties is depicted in Figure 5.1 can be described mathematically as:

\[
C(T) = \begin{cases} 
  m_d T + b - m_d T_d & \text{if } T < T_d \\
  b & \text{if } T_d \leq T \leq T_u \\
  m_u T + b - m_u T_u & \text{if } T > T_u 
\end{cases}
\]  

(5.1)

This function is fitted to the consumption data using the Nelder-Mead algorithm, to determine the constants \( T_d, T_u, m_d, b, m_u \) that have the smallest sum of the square error.
5.1 Check validity

Note there are several ways in which a household can be excluded from the analysis, namely:

1. The number of days that have a temperature between $T_d$ and $T_u$ is at least 12
2. The number of days with consumption below $T_d$ and are closer to the slope estimate is at least 12
3. The number of days with consumption above $T_u$ and are closer to the slope estimate is at least 12
4. The slope constants, $m_d$ and $m_u$ (calculated only on the days that are closer to the first slope estimate) does not exceed 9 in magnitude.
5. The household has at least 90% of days in 2013 (329 days) of valid consumption data.

These conditions mean that a household which do not have a noticeable slope for either heating or cooling are typically excluded from the analysis.

5.1.4 Split heating/cooling data

In this component of the algorithm, the days that lie below $T_d$ or above $T_u$ are partitioned into two groups. The constant group contain days where consumption is closer to constant estimate ($b$) than the sloped line estimate (namely: $m_i.T + b - m_i.T_d$ where $i$ represents $d$ if $T < T_d$ and $u$ if $T > T_u$). Similarly, the slope groups contains days where consumption is closer to the sloped line estimates.

5.1.5 Create final fit

The slopes $m_d$ and $m_u$ are now recalculated using only the days whose consumption are in the slope groups.
5.1.6 Calculate slope probability

Finally, the probabilities $P_d, P_u$ that a given day will be closer to the slope estimate than the constant estimate based on the number of days that are closer to the final fit of the slope lines versus the total number of days either below or above $T_d$ and $T_u$ respectively. So e.g. if there are 10 days above $T_u$ that are closer to the slope line and 20 days closer to the constant estimate, then the probability $P_u$ is a third.
5.1.7 Electric heater/cooler definitions

The different heating and cooling are defined by the OEH meta data and specifically are:

- **ACHeat**, for this category a participant must own, and use one of:
  - Centrally ducted a/c (most of house)
  - Split system a/c (sized for larger room e.g. living room)
  - Split system a/c (sized for smaller room e.g. bedroom)
  - Small packaged a/c (e.g. mounted in window)

- **Electric Heater**, this category includes the ACHeat households and any household that own and use one of:
  - Large electric heater (greater than 2 kW)
  - Small electric heater (about 1kW)

- **ACCool**, for this category a participant must own and use one of:
  - Centrally ducted a/c (most of house)
  - Split system a/c (sized for larger room e.g. living room)
  - Split system a/c (sized for smaller room e.g. bedroom)
  - Small packaged a/c (e.g. mounted in window)

- **Coolers**, this category includes the ACCool households and any household that own and use one of:
  - Evaporative cooler (centrally ducted most of house)
  - Evaporative cooler (large room)
  - Evaporative cooler (small portable)
Figure 5.2: Histogram of the heating slope for various consumption types and appliance types
Bibliography