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Understanding Energy Use in New Zealand Homes

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Understanding Energy Use in New Zealand Homes

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1. Abstract
BRANZ is conducting a long-term research project into residential energy use in New Zealand. This paper discusses some of the methods employed in obtaining energy use information, energy end-use and temperature data. It explores some results from the analysis of this data and discusses some ways to optimise information from monitoring programmes, which are typically budget and time constrained.

2. Introduction
Understanding how energy is used in homes is becoming an increasingly important issue as connections between the well being of people and their surrounding environment become evident. In addition, as the amount of energy we use increases, more pressure will be applied on depletable energy resources in the effort to match supply with demand. The last study of how energy is used in New Zealand homes was performed in 1971/72, which means there is a serious lack of in-depth knowledge[1,2].

The Household Energy End-use Project (HEEP) was established in 1995 as a long-term research activity to determine how energy is used in New Zealand houses. Its objectives are to create an up-to-date knowledge base of existing and developing patterns of energy use and end-uses, by bringing together the factors that influence how energy is used in houses. It is the first study of its kind in New Zealand to combine socio-demographic data with long-term energy and temperature monitoring data.

To maximise the information gathered specific sampling strategies have been developed. These include both measurement methods for the collection of data and analysis methods, including the use of neural networks for profile classification and disaggregation.

3. Data collection
Electricity is the largest single fuel type used in New Zealand homes. With its unique time of demand aspects it is also one of the most difficult fuel types to manage. Consequently much of the effort in monitoring houses for energy use is directed toward monitoring electricity and its diverse range of uses. HEEP currently consists of data sampling and analysis at two levels of detail: at end-use level where the energy is monitored at an appliance and circuit level; and at a total load (whole house) level where data is collected on total household energy and hot water usage. For both types of monitoring, temperature and social data is also collected.

3.1 End-use sampling
In monitoring electricity at an end-use level, the aim is to collect sufficient data to understand the way in which key appliances, hot water and lighting are used in a home.

The end-use monitoring equipment (EUM 2000[3]) currently being used in HEEP houses is capable of simultaneously monitoring 16 channels of energy data. This includes up to eight

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multi-function input channels (used to monitor household circuits using current transformers) and eight remote mains carrier channels. In addition, three mains voltage channels and four analogue input channels (AC or DC) are available. Each multi-function channel used with a current transformer is capable of monitoring either an individual circuit or a collection of circuits grouped together for a particular phase.

In nearly all houses, the total electrical load, the total hot water load and the total cooking load are monitored on individual channels. Collections of lighting circuits and power-point circuits are then grouped together to provide information about electricity use in different parts of the house.

Remote transponder units measure the power usage by major plug-in appliances, and use the local mains circuitry in the house as a carrier line to send data to the master unit where it is recorded. Because of the limited number of transponders, it is not feasible to monitor all appliances in a household continuously for a year. To overcome this, HEEP uses a strategy of rotating a set number of transponders around various appliances in the house, for a monitoring period of approximately 30 days. It is not necessary to monitor all appliances continuously as most have usage patterns that allow extrapolation. Some appliance patterns allow simple forward extrapolation, while others require more sophisticated techniques to take into account changing conditions, for example daylight hours. A random selection of appliances is made using weightings to ensure that those appliances that make the most important contribution to total energy use patterns and consumption have a greater likelihood of being monitored.

3.2 Total load monitoring

It is not possible to monitor all of the houses in the HEEP study at end-use level with the available equipment, timeframe and budget. Data is therefore also collected at a total load (whole house) level and through analysis, additional information is distilled. The collection is done through the use of a standard electric Watt-hour meter in conjunction with a custom-built pulse logger developed at BRANZ. The electric meter is capable of producing a pulsed output, of resolution 1 impulse per Watt-hour, while the pulse logger has four input channels and is able to measure a maximum of 255 pulses over a variety of intervals – 1, 2 or 10 minutes being the most common. With a storage capacity for 65000 one-byte readings, the logger can operate up to 42 days before requiring the data to be uploaded. The use of this system does however have limitations due to the maximum of 255 pulses. At logging intervals of two minutes, the maximum power that can be measured is 7650 Watts, while a logging interval of one minute translates to 15300 Watts.

The Watt-hour meter is installed inline immediately following the power company’s total electricity and hot water meters. In a single-phase house, one meter is required for each of the hot water systems and the total electricity load. If a multi-phase supply is used, one meter must be used for each phase to capture the total and if the hot water has additional elements on separate phases, additional Watt-hour meters must be used to capture this. Two Watt-hour meters can be logged with a single pulse logger (on two-minute intervals) if the maximum power drawn is less than the 7.65 kW threshold. In houses with large power usage it is likely that the maximum power drawn will be greater than 7.65 kW and logging is carried out at one-minute intervals. It is unlikely that the power drawn will be greater than 15.3 kW as this equates to about 60 Amps.

3.3 Other data

Data is collected on all energy types used in homes. This currently includes reticulated natural gas, portable LPG and solid fuels. Temperatures are also monitored in order to provide some understanding of building performance and social patterns related to home heating.

Solid fuel

Solid fuel burners are used as a common method of heating in New Zealand homes. The types of burners vary from modern freestanding burners to open hearth fireplaces. It is possible to estimate heat output from a solid fuel burner by determining the relationship between the temperature of the fire, and hence the burner, and the combustibles used as fuel[4]. This is done by mounting a thermocouple onto the solid fuel burner or hearth grill in a position that will accurately measure the heat output of the fire and using a BRANZ microvolt logger to record the measurements over time. By comparing the temperature profile against the fuel burnt over a defined time period, the fuel consumed at each point on the profile can be estimated. Taking into account the efficiency of the burner and the calorific value of the fuel, an estimation of the energy output is calculated. While the method is coarse and relies on several assumptions (as well as the occupants keeping records of wood used), the method does provide considerable potential in understanding heat output from solid fuel burners.

Reticulated natural gas

The collection of gas usage information is achieved by installing standard tariff gas meters (similar to those used by New Zealand gas companies) on the pipelines that supply the different appliances. The meter presently used, a Gallus 2000 G2.5, is fitted with a pulsed output unit that pulses for each 0.01 m^3 of gas delivered. On average this equates to 0.11 kWh of energy. Detailed profiles of gas usage can be captured, when used in conjunction with the BRANZ pulse logger, set to log at one or two-minute intervals. The Gallus meter is a volume flow meter as opposed to a mass flow meter and correction must therefore be made for the difference in the volume calorific value at the point of measurement (the house) and at the point of calorific value measurement (standard point where the gas company makes their measurements). These corrections introduce an uncertainty of 2% in the measurable energy content of the gas[5].

Portable LPG heaters

Approximately 25% of houses in the HEEP study have an LPG heater, and it is estimated that there are in excess of 400,000 portable LPG heaters in New Zealand[6].

By monitoring the temperatures directly in front of the panels of an LPG heater it is possible to estimate the energy output of the heater. This is possible because most LPG heaters have only three discrete settings whereby on setting one, one panel is ‘on’, and on setting two, ‘two’ panels are on etc. By using three thermocouples and a logger to keep track of the temperatures in front of the heater, the number of heating panels (or the heater setting) being used can be inferred. The mass flow of gas for each combination of panel settings is determined through a calibration measuring the mass of gas burnt over a set time period, generally 1 – 1.5 hours. Some simple calculations allow for the estimation of the mass of gas consumed and, assuming heater efficiency, the power output of the heater. This method relies on a number of assumptions; firstly that the efficiency of the heater is constant with external temperature; secondly that the calorific value of the LPG is independent of the quantity of LPG in the cylinder; and finally that the mass flow of gas is independent of cylinder fullness. Trial measurements have indicated that the mass flow rate of gas changes by about 4.5% between a 100% full bottle and a 20% full bottle. It is expected that this change in flow rate is due in part to the change in the proportions of propane and butane as the volume of gas in the cylinder changes. Because of the different calorific values of propane and butane (46.3 and 45.7 MJ/kg respectively) this change cannot be directly related to a change in heat output.

Temperature
Temperatures are monitored in the main living area and the master bedroom in each house. Previous research has shown that measurements from these two zones are the most important factors in understanding temperature distribution within a house. Having two temperature sensors collecting data in the main living area also provides information on stratification. Outdoor temperatures are monitored in close proximity to a number of the houses and additional weather data (solar radiation) is obtained from the National Institute of Water and Atmospheric Research's (NIWA) national climate database[7].

4. Some analysis and results

4.1 Profiles
Determining the load profile of a particular house, based upon the socio-demographic characteristics of its occupants would be a powerful tool. It would, for example, allow the targeting of specific households groups for the purpose of demand-side management of peak energy deliveries with strategies such as load shifting[8].

This section describes the analysis steps applied to determining examples of energy profile classes. The energy load profiles of most houses vary considerably during the year principally due to climatic factors. Space heating, which accounts for some 30-40% of household energy consumption, is used primarily over the winter season and almost not at all in summer. Because of this, the analysis was conducted on monthly average-day profiles. This provides one profile for each house for every month the house is monitored – in this analysis 239 profiles are used.

Two approaches may be considered in profile classification. The first focuses on the profile shape only and disregards the quantitative level of consumption. Each profile is normalised (rescaled to have a maximum value of 1). This places greater emphasis on the position of the peaks in the profile rather than their quantitative values. This method offers advantages in determining how to shift peaks. However, because of the disregard for actual consumption levels, categorisation which takes into account house size and occupant numbers, may be limited. The second approach attempts to classify profiles based on the actual demand. As such it will lead to focus on the grouping of profiles with similar actual power use (high power users or low power users) and the position of peaks or the shape of the profile will be less significant.

One method of classifying the large number of profiles available is to use artificial neural networks.

Artificial neural networks (ANN) are simplistic models based on the neural structure of the brain. Used for analysis the ANN will generally consist of three different layers – the input, the hidden or operational, and the output layer. Each layer contains nodes (neurons) that are interconnected in a network that allow interaction and feedback with other nodes. The intra nodal connections are weighted, either positively or negatively, and this allows modulation of the signals being passed between the nodes. Data is fed into the input neurons in the form of datasets and in the output layer the neurons return data back to the user. The hidden or operation area may contain many sub-levels. Figure 1 shows the relation between the layers in a neural network.

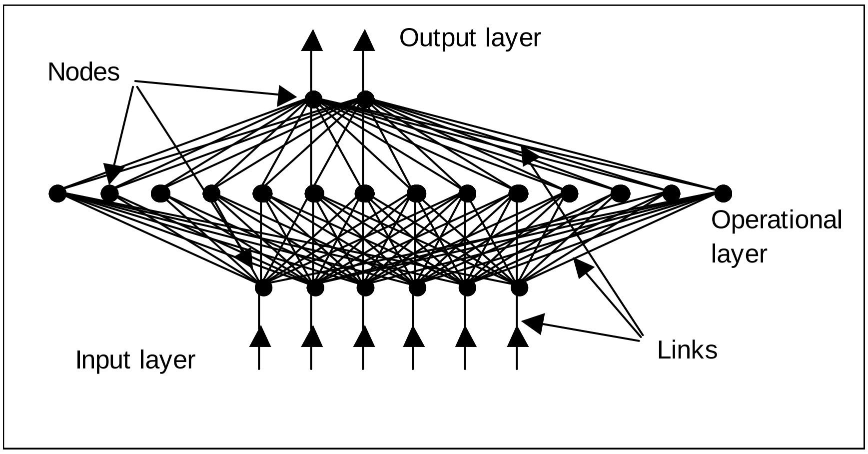

Figure 1. A diagram showing an example of an artificial neural network and the interactions between its three layers.

Probabilistic neural networks (PNN) are a type of ANNs that are particularly suited to pattern classification, and as such they provide a method to classify electricity load profiles obtained from monitoring houses in HEEP.

A total of 239 monthly average-day profiles from HEEP were analysed using a Kohonen probabilistic neural network[9]. This network is capable of classifying patterns without "supervision", i.e it defines its own criteria, yet still allows the user to set the number of categories and some of the learning parameters.

The inputs for the network are the data points that make up the profile to be analysed and in this case there are 24 – one for every hour of the day. The number of output nodes is the number of classes that the profiles will be separated into.

Six profile classes determined by ANN using the normalised approach are shown in Figure 2, with each line representing the daily electricity profile for one house averaged over one month.

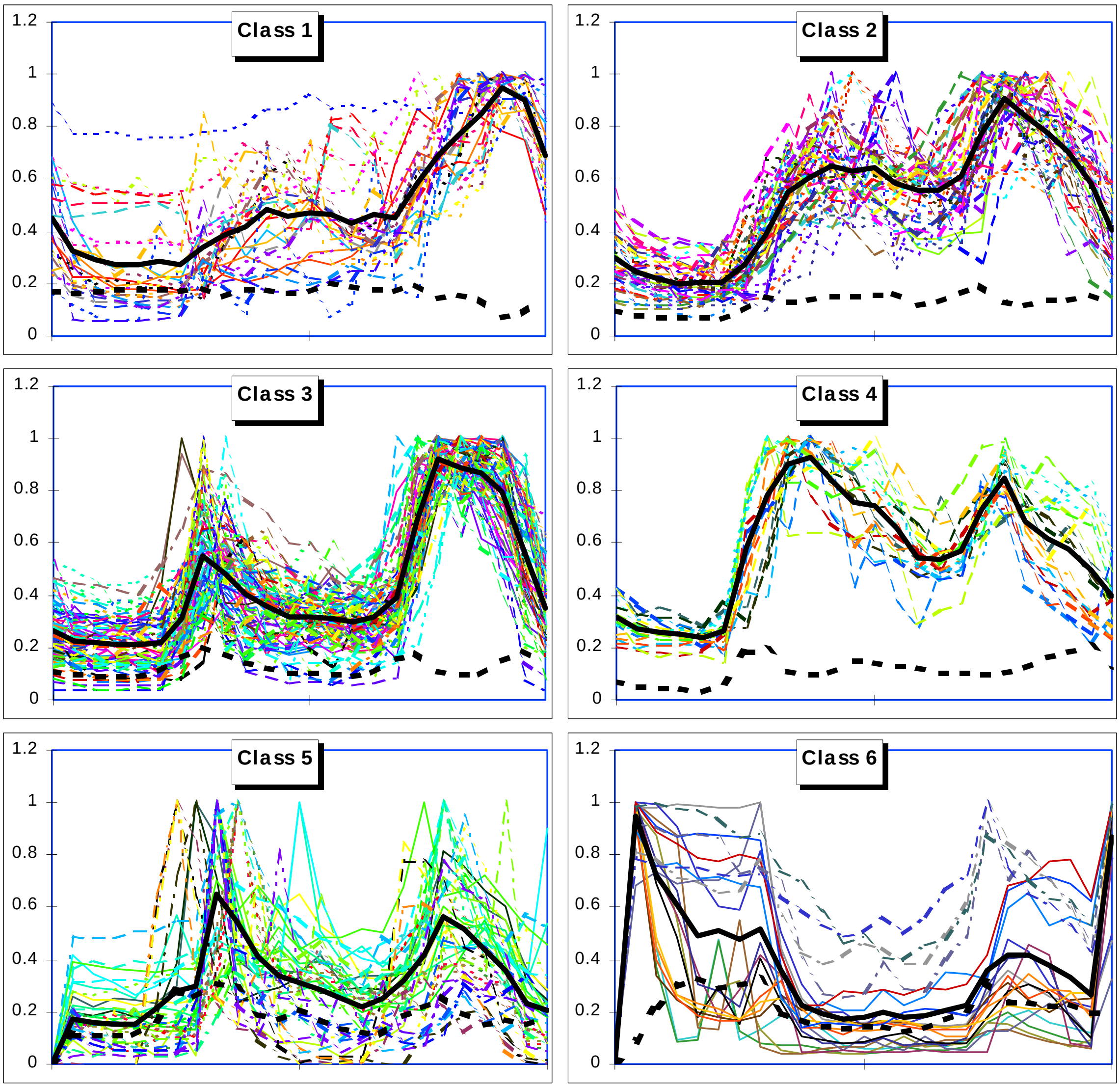

Figure 2. Daily electricity profiles as categorised using an ANN.

The thick dark line is the average profile of all the profiles in the class, while the dashed line gives the profiles standard deviation from the average. The horizontal axis is the time of day from 0:00 to 23:00, and the vertical axis is the relative consumption with respect to the maximum over the 24 hours.

Class 1: Low morning peak, high evening peak.
Class 2: Shallow morning, medium midday and high evening.
Class 3: Sharp mid morning, low midday, sharp high evening.
Class 4: High flat morning peak, high afternoon, small early evening peak.
Class 5: Sharp medium mid morning peak, medium afternoon and evening consumption.
Class 6: Night rate profile: High consumption over night period, flat low day consumption, medium evening.

Combined with additional socio-demographic information the load profile classes become a very powerful analysis tool.

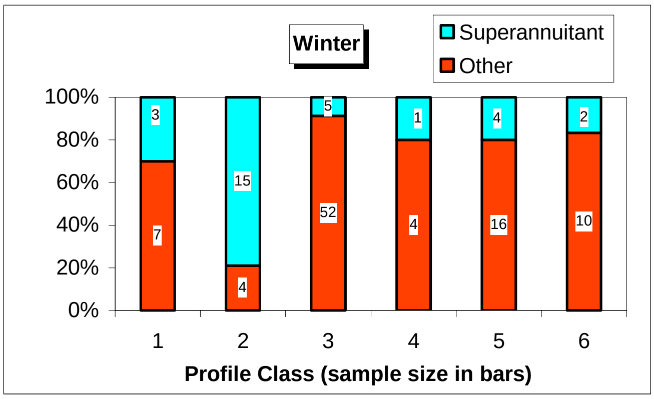

Figure 3. Profile classification based on householders receiving superannuation.

The chart in Figure 3 shows an example of the way in which socio-demographic data can be linked to a profile class. The chart shows the breakdown of each profile class, over the winter months, based on whether the occupants' main income is superannuation. Class two stands out because nearly 80% of its component profiles are those of superannuitants, while all other classes consist of mainly non-superannuitant profiles. Similar breakdowns can be done with many socio-demographic factors. Knowing the likely profiles of consumers in their supply areas could be valuable for power companies during planning for peak demands, load shifting or pricing strategies.

By using half-hourly wholesale electricity prices and linking these with the energy use for each profile class, it is possible to determine the cost of supplying electricity to a particular class. The chart in Figure 4 shows an example of the annual average hourly supply cost of electricity for six profile classes and indicates the cost of supplying electricity for an entire year. While this type of analysis is still fairly preliminary due to the small sample size, it does give some indications of how profile classes can be analysed and used in better understanding the markets.

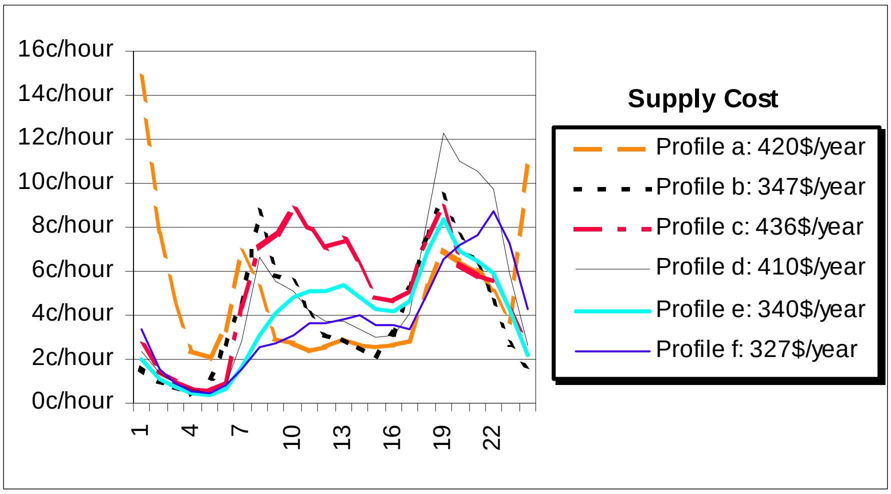

Figure 4. Supply costs of six profile classes.

The information gained from correlating socio-demographic data against profile classes shows its true benefits in the ability to look at socio-demographic data and work backwards to determine a probable profile class. The use of national census data (which collects household socio-demographic information on a four-yearly basis) in conjunction with known profile classes would therefore allow for better planning and management in the supply of energy to specific consumer groups.

4.2 Total load disaggregation

Monitoring only the total load circuits in a house provides only some of the information that can be obtained from an end-use monitored house. By examining the profile in detail, additional information about which appliances are ‘on’ can be inferred with a degree of confidence. Other researchers have tried a number of approaches[10,11,12].

Consider a function T(t) as the time-series of the sum of the energy consumption of all appliances except for the hot water, which is monitored separately. In addition to the total time-series T(t), the typical power rating of most of the large appliances (H for heater, F for fridge, etc.) is measured by connecting them individually to a power meter and switching them briefly ‘on’ and ‘off’. The total time-series function can be represented as $T(t) = H \times H_d(t) + F \times F_d(t) + \text{etc.}$ with $H_d(t)$, $F_d(t)$ etc. being dichotomous series indicating whether the individual appliance is ‘on’ or ‘off’.

A function of this form can have more than one solution at any point in time (for example $H \times H_d(t_1) = M \times M_d(t_1) + S \times S_d(t_1)$: one appliance using 100 W has the same effect as one with 30 W and one with 70 W running at the same time) and so it is necessary to use other indicators to find the most likely solution.

One indicator is the switching of the appliance, as this can generally be seen as a step in the function. It is unlikely that two appliances would switch on or off at the same time step (i.e. 2 minute logging interval), however, a contributing difficulty is, that some of the appliances have continuous load levels.

Additional indicators can be used to increase the probability of selecting the right combination of appliances in use. One indicator looks at the likelihood of an appliance being used at a certain time. While people are not entirely predictable, it is unlikely – although not impossible – that cooking occurs at 3 pm, heating most commonly occurs in the evening etc. Other indicators are the appliance run-time characteristics – refrigerators tend to have a 15 min ‘on’ cycle followed by an ‘off’ cycle, microwaves tend to be used in short bursts of 2 – 5 minutes.

By using visual inspection to detect the characteristics of each profile automatic disaggregation procedures can be set up.

Two analysis methods have been examined, both using two-minute profiles.

1. Rule-based separation of end uses.
2. Pattern recognition algorithms using Artificial Neural Networks (ANN).

The rule-based algorithm uses features such as: the absolute value of the demand; the demand before and after the investigated time step; and a number of smoothing functions.

ANNs have been applied for the use of energy disaggregation by Yoshimoto et al[13] and Farinaccio et al[14]. The ANN investigated in this study was based on the Probabilistic Neural Network (PNN) paradigm. A set of the measured data is presented to the network together with the desired network output. In this instance, a modified time series of two-minute averages of the total load profiles over approximately half an hour was used as input values. The output value was a switch whether the hot water heating element was on or off.

The following example from the HEEP investigation shows the extraction of the hot water consumption from the total load profile.

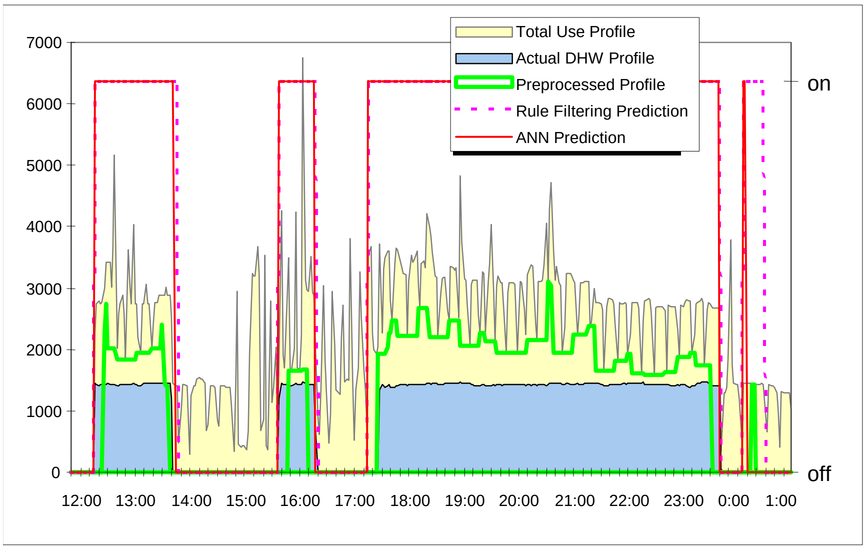

Figure 5. End-use disaggregation using a rule based algorithm and ANN.

In this case we know the hot water power consumption, however in the future we may train the network on synthetic data. The figure contrasts the results from a rule-based algorithm with the ones from the neural network approach. It shows that for most of the time the predictions of both methods are identical.

Initial results seem to suggest that both methods have similar performance. Future investigation will follow a combined approach that will include the initial definition of some indicators – time of day; last switching amplitude; total current power; length of power plateau at the current level; etc, – and then feed these and the time series itself into a neural network classifier.

5. Conclusion

The household energy end use project has now monitored over 100 houses. The methods used to obtain data from households have proven robust and workable. The analyses performed have proven interesting although the results are statistically limited due to sample size.

The use of neural networks for the classification of profiles combined with social data can provide information on the typical profiles expected from segments of the community. The example in this paper shows how one profile is matched to occupants who are receiving superannuation. There is potential to explore this area further in order that it is used in planning and demand side management as well as costing.

The disaggregation of total electricity loads as a method to optimise information regarding appliance use is a way of maximising returns from monitoring at a total load level.

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