A strategy for implementing demand side management for domestic electricity in New Zealand.[1]

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Abstract

This paper outlines a long term research strategy for investigating demand side management (DSM) options for improving domestic electricity usage in New Zealand. The first part of the investigation is explorative in that household electricity consumption is monitored at a number of different levels (appliance, total household and feeder station). A questionnaire is also administered to the households that are being monitored to gather data on their social and physical characteristics. Multiple regression analysis is then used to determine the key factors influencing electricity demand. Once these factors are understood a model of electricity demand can be developed and tested on new sets of data. The understanding of electricity consumption patterns from this work will be used to develop DSM options that reflect New Zealand's unique electricity consumption patterns. The proposed DSM options will be monitored to evaluate the effectiveness of the alternative proposals. The end results will be accurate information on the most effective methods for controlling domestic electricity demand in New Zealand.

1 Introduction

Demand side management (DSM) is defined as the intervention by the utility on the customer (demand) side of the meter to influence and change the characteristics of the customers' load. Specific DSM objectives include: peak clipping, valley filling, load shifting, energy efficiency, conservation and strategic load growth. The simple economic rationale behind DSM is that in many cases it may be cheaper to manage demand for electricity through improved efficiency and load control, rather than to upgrading generating capacity and supply infrastructure. Although DSM is often the least cost method of providing an energy service, it often does not happen for all sorts of reasons.

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A number of overseas projects to implement DSM in the domestic sector have been very successful and the role of this research project is to investigate the best way to implement DSM in New Zealand. In the domestic sector DSM is a largely an untapped resource. However it has the potential to reduce the cost of energy services. This paper outlines a strategy for developing and implementing DSM in New Zealand.

In the USA, DSM is a multi-billion dollar industry with utilities having some form of DSM program (Holman, 1994 p7). The DSM industry there had a massive burst of activity in the late eighties and early nineties when state and federal regulation offered incentives for DSM. However there has been some easing off as the true costs associated with some programs became apparent. With the move to deregulation there is a move back to DSM as a marketing tool and a means for understanding and controlling the market in which they operate. The importance of DSM has been emphasised by Hirst: "(DSM programs) will be important to utilities as powerful marketing tools, and they will be important to society because of their environmental and economic benefits (Hirst, 1994)"

2 Overview of a research strategy

The aim of Industrial Research Limited's domestic electricity investigation is to design an inexpensive data acquisition and modelling system that captures the key features of domestic energy use. This system can then be used to design and implement demand-side energy projects. An example of the type of question that we would like to answer is "what would happen if all new water heaters had certain specifications?" For this we need accurate data on water heater electricity consumption. This is not available in New Zealand at present. A further question would be "what are the main causes of hot water demand and how could this demand be influenced?" As well as being interested in DSM options we are also interested in the evolution of demand. For example, "what happens to electricity demand as incomes increase and the population ages?"

Overseas work shows that understanding and managing domestic electricity demand is very difficult because of the complex factors underlying demand. Unless the processes which give rise to demand are understood, attempts to control it can be expensive and even counter productive. Figure 1 illustrates IRL's strategy for investigating and managing electricity demand in the domestic sector. The five main sub-tasks within the project are data acquisition, finding significant relationships, refining data acquisition techniques, modelling demand and developing DSM programs or strategies. The interconnections between the different sub-tasks in the project are illustrated.

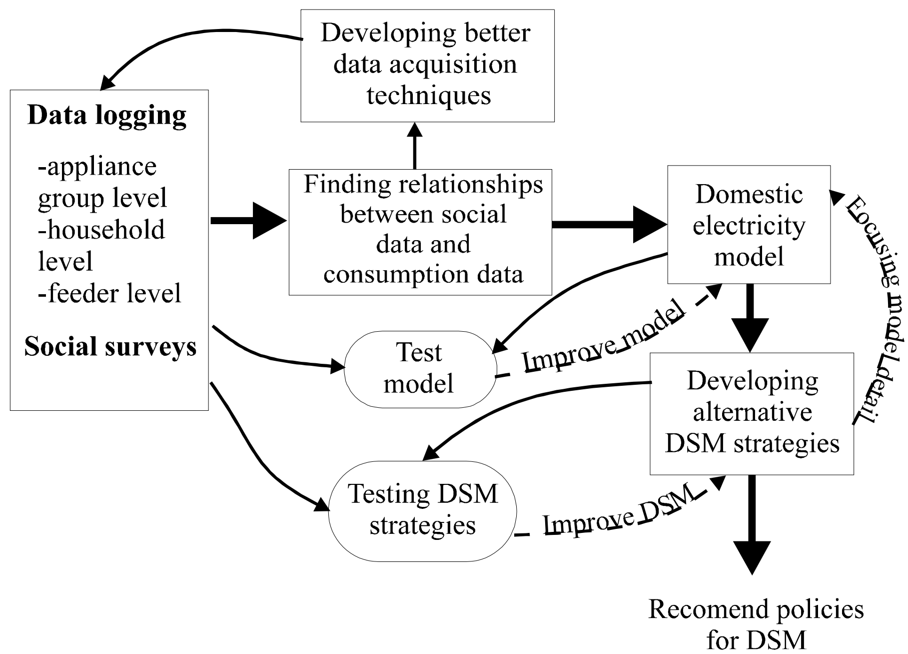

Figure 1 Overview of IRL's domestic electricity investigation

As can be seen in Figure 1 there is considerable interaction between the steps to improve the understanding and to reduce costs of data acquisition. Each step needs to be designed to fit into the overall scheme. For example, the model must be designed so that useful information can be gained about DSM and the data logging must be designed to fit into this model. The steps in the project are discussed below, along with the various interactions. The important steps of testing the models and the DSM options are also explained in detail below.

Rather than developing a comprehensive model of electricity demand a common method for implementing DSM projects is to use trial and error. This option is also discussed below.

3 Data acquisition

To explore socio-economic factors in domestic electricity demand at the household level, two sets of data are being collected: electricity consumption data, and social survey data.

3.1 Electricity consumption data

Logging electricity use is an essential part of a DSM strategy because it enables one to understand what is happening to electricity demand, and to test the effectiveness of DSM policies. The IRL project is gathering data on household electricity consumption from three sources:

a) Ten Christchurch households are being logged by IRL. This data is recorded at the appliance group level - i.e. separate data logging for water heating, cooking, heating, lighting, washing and "other" uses.
b) 100 Christchurch households are being logged by Southpower Ltd at the dwelling level only.
c) Electricity consumption of neighbourhoods is being collected as aggregations of 10-50 dwellings by loggers on feeder stations. This is matched with population and dwelling census mesh block data.

The choice of appliance groups was based on the assumption that these are the key factors in electricity demand and are easy to analyse. It would be preferable to split the "other" category to give more detail but this cannot be initially justified because of the high cost of data logging equipment required. However, in the long term we aim to examine the "other" category in detail. In addition to the electricity logging, the inside and outside temperatures have been recorded to assist understanding of heating demands.

3.2 Social survey data

Household social data, including social characteristic of the occupants, their electricity-using behaviours and the physical attributes and contents of the dwelling, are gathered in face to face interviews with the occupants in their own homes. Limited data on billed consumption for the previous 12 months and the product/billing regime for each household are also available. The questionnaire is comprehensive in that it attempts to cover as many of the likely relevant variables as possible. It is expected that the content of the questionnaire will be refined over time, since some of the questions may be shown to be unimportant and other results may point to the need for additional questions. Until the results of the links between electricity demand and social factors become more defined we have included as many questions as is realistically possible.

4 Determining relationships between social/physical data and electricity use

Multiple regression techniques are used to determine the key factors that influence electricity demand. Regression analysis allows us to identify the most significant factors influencing demand and to derive a linear equation linking the social and physical factors to electricity demand. As an example it may be that 80% of the variation in total household electricity consumption can be explained by income, household size and the method of heating the home. To date, such analysis has been done on three different levels of data:

- linking census data to feeder station electricity data
- linking social survey data to aggregate household data
- linking social survey data to individual appliance data

Analysis of links between census data and feeder station data is outlined in Fitzgerald *et al* (1995a). Links between social survey data and aggregate household demand are given in Fitzgerald *et al* (1995b). The analysis of links between appliance information and social surveys is in Fitzgerald and Ryan (1996). However the results of our initial investigations cannot be considered conclusive due to the small sample sizes in our studies to date. Further data logging to increase the sample size will remedy this.

An example of initial results of the regression analysis is that electricity used for lighting can be explained almost entirely by income level and the time people go to bed (ownership of high efficiency light bulbs is not high enough to be a significant factor). If this result can be shown to be statistically significant it will help formulate a DSM strategy for lighting. Initially we might conclude that since those consuming the most on lighting they are in a better position to afford light bulbs that are more efficient but initially expensive. It seems clear that it is not going to be possible to get people to go to bed earlier to save energy (nor should they). Lighting efficiency programs could also be targeted at those who stay up later.

4.1 Testing the regression models

The validity of the relationships found from the regression analysis can be tested in a number of ways. The simplest way is to try to estimate electricity consumption for a different set of households using the results of the regression analysis. If the model is able to estimate correctly the electricity consumption (as measured separately), then one can have confidence in the results. This of course requires additional data collection using loggers. Another test could be comparison of regression prediction of demand based on appliance logging with those based on aggregate household demand.

It is our hope that a model based on individual appliance logging will give enough information so that a community's electricity consumption can be estimated using readily available demographic data (household type, income etc). However it is likely that additional information would be required e.g. appliance ownership. We hope, in time, to be able to link appliance ownership with demographics such as household type and income. At present we find there is too much variation between individual houses for the model to predict any individual households consumption accurately but at the neighbourhood feeder level (10-50 homes) we feel the individual differences should average out.

An important part of the investigation is to perform the same regression analysis using only commonly available data. This data can be sourced from, for example, the Electricity Supply Association survey and census of population and dwellings. If it is shown that the same level of understanding can be gained from this data as from the detailed social survey, then it will be easy to build up a national picture of electricity demand. The analysis may also identify a number of key demand-influencing factors that are not available in commonly collected statistics. Once known a shorter questionnaire which collects the necessary additional data could be applied nationally.

5 Refining data acquisition techniques

In the first stage of data collection, the information will give a feel for the critical factor that effect long term electricity demand so that data logging can be targeted at specific areas in the future. Overseas projects on domestic energy modelling typically use large numbers of data loggers (400 households) on individual appliances However, collecting this quantity of data is extremely expensive.

Methods have been developed using inexpensive technologies to obtain appliance level data information which allows a significant quantity of data to be collected at a much reduced cost (Ryan and Willink, 1996, also see De Almeida, 1994). These methods use statistical tools to estimate how long dwellings need to be monitored for a statistically significant sample of data to be obtained. With this information data loggers can be rotated between dwellings to obtain the maximum information possible with a limited number of data loggers. The number of dwellings that need to be monitored to collect an adequate sample of data has been estimated from analysis of the variation of the data collected to date.

6 Modelling domestic electricity demand

Short term (1 minute to day) electricity load forecasting models are common in the electricity industry. The model developed for investigating DSM possibilities is quite different from the descriptive load forecasting models. To investigate DSM options the physical and social processes involved in the electricity demand need to be modelled. For a detailed discussion and survey of models developed for this purpose see Ryan (1996).

Information derived from the data logging can be used in a model such as EECA's Energy Efficiency Resource Assessment model. In this model the quantity of electricity used and the penetration of technologies are used as an input (for example, on average about 900 kWhr of electricity are used per year for lighting. Therefore if the old light bulbs are replaced with efficient bulbs the energy saving can be estimated). However, in our project we aim to go to the next level of understanding by investigating the underlying social and physical causes of electricity demand.

Relationships identified in the regression analysis can be used to build a simulation model of electricity demand. The particular form of the sub-model for each appliance is very much dependent on the results of the relevant regression analysis. The following equation is the basis for a general model of domestic electricity demand and can be applied to each group of appliances. This form of equation has been chosen because it identifies the different factors that influence electricity use patterns.

Total electricity demand = (Ave energy use per household)(No. households)*(Demand factor)*(Technology factor)*(Pattern of use)*

The average electricity used for each appliance or household can be estimated from the information found from the regression equations. The number of households has an obvious influence on the total electricity demand. The behavioural (demand factor) and appliance ownership (technology factor) have been separated and each are described in more detail below. The patterns of electricity use can be separated from the quantity of electricity consumed.

6.1 Average energy use per household

For each household and/or appliance the electricity use can be roughly estimated from the results of our current analyses. However, it may take some time before enough data is available to derive reliable regression equation for appliance groups. Data loggers will be targeted to the areas where the model is weakest; for example understanding different heating patterns.

6.2 Number of households

Models of household and population dynamics are relatively easy to develop (see Ryan and Schenk, 1996). Again, the level of detail in this part of the general model above depends on the results of the regression analysis. At a minimum, it will include the number of households of different sizes. If income and age and other factors, such as education, emerge as significant factors in demand, these will need to be included in the household simulation sub-model. By projecting population dynamics into the future, estimations of gross electricity demand can be made. For example, it is expected that as the population ages electricity demand will increase. This is because older people tend to live in homes with fewer occupants, and homes with fewer occupants tend to have a higher per capita electricity demand.

6.3 Demand factor

This "demand factor" reflects, among other things, the comfort level and the habits of household members which influence the quantity of electricity used. These behaviours may be associated with particular sections of the population who may hold different values and attitudes. However, changes in comfort level over time, for example, are very difficult to measure and estimate. Natural increase in comfort level may occur due to increased income and/or age (this could be determined through regression analysis). Time series data for individual dwellings will give insights into such changes.

It is possible that end-user education may help reduce demand while maintaining the same comfort level and technology. For example, not leaving appliances running unnecessarily can decrease demand without changing the technologies used.

6.4 Technology factor

It is commonly assumed that the technologies used influence the pattern and level of household electricity use (as evidenced in current energy saving programs). A number of appliances are of particular interest: water heating system, space heating system, clothes dryer ownership etc. Surveys on appliance ownership provide information on the penetration of different technologies. Our social survey collects such information. Determining the penetration rates of different technologies and how they may be accelerated is obviously an important DSM strategy.

6.5 Pattern factor

The importance of splitting the aggregate electricity use and the pattern of use has been emphasised by many authors (see Broehl, 1981). Initial results indicate that although there is a large variation in the quantity of electricity consumed in different households, there is a relatively small number of distinct use patterns (load profiles) for households. A cluster analysis technique developed by Ryan and Willink (1996) can be used to group households by their load profiles. These households can then be identified for DSM strategies which seek to achieve more desirable load profiles. While understanding and controlling the pattern of electricity will not necessarily reduce electricity demand, it can identify methods for shifting appliance loads which will allow supply authorities to provide electricity at a lower cost.

6.6 Examples of some factors that may affect electricity demand

Table 1 shows some of the different factors which influence electricity demand for different appliance types. It is not possible to know which factors will have the most influence in New Zealand until the electricity logging and regression analyses have been completed. Note that factors influencing the demand, technology and pattern of use can be quite different though there will be links between the factors that influence each of these.

Table 1 Examples of some factors that may influence electricity demand

Appliance group	*Demand factor (behaviour and attitude)*	*Technology factor (appliance ownership)*	*Pattern of electricity use*
Cooking	% using microwaves	% with microwaves	Time at home
Lighting	Unnecessary use of lighting	% with efficient lighting, sensors	Time at home, time awake
Washing, drying	% using dryers	% with efficient appliances % with dryers	Time of year, temperature, technology (timers)
Water heating	Temperature setting, washing habits	% with efficient water heaters, insulation wraps etc.	Time of year, temperature, technology (night rate)
Heating	Comfort level, knowledge of heating losses	% with central heating, physical envelope	Time of year, temperature, technology

7 Developing demand side management strategies.

Demand side management strategies can be split into education, incentives or regulation. The DSM strategy will vary depending on whether there is the need to control the use of electricity compared to other fuels, control the demand factor, the technologies used, or the pattern of electricity use. Some examples of DSM strategies are outlined in Table 2.

Table 2 Examples of different types of DSM strategies

	Education	*Incentive*	*Regulation*
Demand factor (behaviour)	Education campaigns on efficient energy behaviours	Different pricing tariffs and policies.	Maximum electricity quotas
Technology factor (appliance ownership)	Promote technologies that reduce use e.g.. product labelling systems etc.	Subsidise energy efficiency technologies.	Building codes, minimum appliance standards.
Pattern factor	Promote pattern changing technologies e.g. timers on appliances, night store, etc.	More variation in time of day price difference - warning lights	Load control measures like ripple control.

The preferable options for DSM are education and incentives. Regulation is commonly seen as a last resort to be used in the event of market failure. It is important that the difference between education, incentive and regulation is recognised when designing a DSM policy and it must be clear whether the objective is to change behaviour (demand factor), technology or pattern of use.

7.1 Testing DSM strategies

The data loggers already installed in New Zealand dwellings offer an excellent opportunity to test a DSM strategy before implementing an extensive and expensive campaign. Experience overseas stresses the importance of having some means to evaluate the effectiveness of DSM, and in the US, nearly 70% of the states require electric utility-sponsored DSM programs to be evaluated.

Analysis to date suggests that different strategies may be required for different communities. Because loggers are installed in many different areas, the effectiveness of different policies can be tested on specific communities and the results of the policy can be monitored. One of the better opportunities to test DSM options is to monitor the projects associated with the "energy saver fund". The "energy saver fund" is a pool of public money that can be competitively bid for projects designed to reduce domestic electricity consumption. Project proposals are ranked according to the anticipated. Ideally each of these dwellings should be monitored to test the effectiveness of the DSM project. This information should be used as the basis for selection the next round of "energy saver" funded projects.

Experimenting with DSM options, rather than developing them from a formal model of demand, is considered valid but the DSM projects have to be monitored to measure the effectiveness of different options. If this is done, performance using indicators such as "take back" can be calculated. For example, the "take back" figure used in the energy saver fund calculation for improved insulation is 0.7. (meaning that only 70% of the savings are realised and 30% of the possible savings are taken back in increased comfort). However, actual "take back" levels have never been measured in New Zealand.

8 Concluding comments

The overall goal of the IRL project is will take some time to be fully realised. The expense of acquiring a sufficiently large body of data and the complexity of behaviours and attitudes (as they are manifested in "comfort level") mean that the initial models will be tentative. However the process collecting data, modelling and testing as described above will provide a basis for formulating DSM policies for the domestic electricity sector in New Zealand.

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