The Disaggregation of Whole-House Electric Load into the Major End-Uses Using a Rule-Based Pattern Recognition Algorithm

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ABSTRACT

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The focus of this thesis is the development of a residential end-use energy estimation model which is based on the disaggregation of the monitored whole-house electric load. The data used to develop the model involves a one-time intrusive monitoring period to collect rapid-sampling interval data of demand for each major appliance load and the whole-house for a period of one week for one dwelling. The data applied to test the model consists of only the whole-house demand for a period of two weeks. The model identified is a rule-based algorithm applying pattern recognition techniques. The model is developed to scan the whole-house electric demand profile and to detect a predefined appliance energy signature. The results are presented in terms of the appliance daily demand profile and energy use. The benefits of this approach are that the frequency and time of usage of an appliance can be estimated without regard to the energy-related habits of the household occupants, their social or demographic characteristics, or the thermal characteristics of the dwelling. Moreover, the model is conceptually simple and versatile because of its rule-base platform. Artificial neural networks are investigated as a possible alternative to some of the rules developed as part of the Pattern Recognition Algorithm. A neural network model is developed as a preprocessor to the Pattern Recognition Algorithm with the aim to detect the ON and OFF occurrences of an appliance from the whole-house demand profile based on one week's worth of training data. Commercially available neural network models with different architectures and training parameters are applied in this study. Both approaches show a promising potential for application in residential buildings. Both models developed are characterized by low cost, modest data collection needs, and no occupant-related information required.

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1. INTRODUCTION

Knowing the breakdown of actual energy use of residential customers by end-use has become an important issue for many entities involved in the energy market. This information is used in the development of many applications ranging from demand-side program development and delivery, and forecasting the impact of these programs on future energy scenarios by utilities to diagnostic tools to implement cost-effective energy conservation measures by homeowners. Although, there is an abundance of data regarding whole-house energy use, along with supporting audit information there is limited data regarding energy consumption by various end-uses.

Large-scale demand-side management programs are often sponsored by utility companies and/or government agencies as a means to meet consumer demand within their present energy generating capacity and to carry out regulated demand-side planning, forecasting, and program development. The information needed about residential customers' energy use patterns is often lacking in the planning stages of these programs. As a result, the potential effectiveness of the measures carried out as part of these programs can often fall short of their expected targets. Furthermore, large-scale programs will typically rely on monitoring of whole-house energy use to quantify the impact of these programs due to the high cost and level of customer intrusiveness that is associated with traditional submetering techniques. Again, this is a significant drawback for these programs because whole-house monitoring alone often fails to disaggregate or single-out the effect of individual energy conservation measures.

With the advent of deregulation of electric markets in North America, the average homeowner increasingly stands to benefit from better, clearer, and more usable information about their energy use patterns and costs. To date, revenue meter bills sent by their utility is their only source of information about the actual energy they use. The more information consumers have, the more incentives they may have to implement energy conservation measures. In some cases, energy usage will drop simply by increasing consumer awareness as to their energy use patterns.

The competitive energy market that is enfolding in the United States and eventually in Canada will spawn a new and much more technologically sophisticated energy industry where information will be key. One of the major issues in markets that have already been deregulated is metering and having access to customer usage patterns. This issue will directly impact the consumer in many ways. That is, the more information that is available to utilities, the better they will be able to target their customers and offer appropriate energy conservation measures and rate structures.

With these aspects in mind, research into new techniques for data collection, bill analysis, and visualization is evolving rapidly. The primary purpose of collecting and analyzing residential end-use data is to provide energy planners with useful information on how energy is actually consumed in homes, as well as, provide insights about factors that may affect energy consumption. Although, the findings of this research appear to offer greater benefits for utility companies, government agencies, and energy service companies; homeowners also stand to benefit from such research findings. The potential consumer market developments stemming from the availability of end-use energy consumption data include:

- A screening tool to identify customers with high potential for energy savings and offer to them rebate programs or energy saving incentives (increasing the cost-to-benefit ratio for these programs ensures their success, hence, continuation);
- A tool to build a detailed database that can be used for planning, forecasting, and marketing future residential energy efficiency programs;
- A method to screen candidates for time-of-use rate programs;
- A comparative assessment from which energy indices and performance targets for new and retrofitted houses can be determined; and
- An educational tool to help consumers understand their energy use patterns and increase their sensitivity to conserving energy.

In response to these needs, the research presented in this thesis has the objective of developing an end-use energy estimation model, based on the disaggregation of the monitored whole-house electric demand. Two possible model structures identified are (i) a rule-based algorithm using pattern recognition techniques, and (ii) an artificial neural network. The models present different strengths and weaknesses in their ability to disaggregate energy consumption.

The pattern recognition approach attempts to recognize the patterns of energy consumption of the various appliances in a dwelling. To do so, a rule-based algorithm is developed to scan the whole-house electric demand profile and to detect the expected signal response to the activation or disactivation of selected appliances. This approach requires extensive analysis of the training data in order to extract the features of appliance electric usage patterns. The benefits to using this approach are that the frequency and time of usage of an appliance can be estimated without regard to the energy-related habits of the household occupants, their social or demographic characteristics, or the thermal characteristics of the dwelling. Moreover, this approach is conceptually simple as an analytical tool, and versatile because of its rule-base platform.

The second approach, neural network processing, attempts to classify the various activations within the whole-house demand profile as the ON or OFF activation of a given appliance. To do so, the networks investigated are trained using one week's worth of energy use data for the appliance. Various pattern recognition and classification networks are considered for their applicability towards recognizing appliance energy usage patterns. Commercially available neural networks models with different architectures and training parameters are investigated to best process the data available in order to achieve acceptable network accuracy. What is interesting with this approach is not so much whether or not the network can provide accurate results, but rather to gain a better understanding of the energy signature features which drive the particular neural networks.

The training data used for both approaches consists of the electric demand profile for the whole-house and appliances of interest for one week. Whereas, the testing data used consists of only the electric demand profile for the whole-house. The two approaches presented are characterized by low cost, modest data collection needs during the application phases, and no occupant-related information required. The key to the approaches presented is a high sampling resolution of the monitoring data, which allows the detection of ON and OFF activations of individual appliances. The algorithms can be used for households from any geographic region or customer mix. Although the focus of this work is on the disaggregation of residential energy loads, the techniques developed can also be applied to the disaggregation of commercial and industrial energy loads.

2. LITERATURE REVIEW

This chapter presents the results of an extensive literature review on the application of residential end-use energy data, and the major contributions by researchers to obtain this data. To begin, the need for end-use load data for load-shape forecasting and analysis of various demand-side management options is discussed. Then existing methods for estimating residential end-use loads are presented and the strengths and weaknesses of each of these methods are discussed. This chapter also discusses neural network applications related to building energy use.

The main sources of information include published articles from energy and building-related scientific journals, publications posted on the Internet, and published reports from utility funded studies. It was observed that the bulk of the research performed was conducted by researchers at the Lawrence Berkeley National Laboratory of the University of California and the Electric Power Research Institute in the United States.

2.1 The Need for End-Use Load Data

End-use load data is an important factor in the planning efforts of many electric utilities. It provides detailed time-of-use information and a means of evaluating the impact of various types of utility demand-side programs. The types of programs range from information dissemination and weatherization audits to financial incentives, in the form of loans and rebates, for weatherizing or purchasing more efficient appliances. Energy professionals and policymakers need quantitative information on retrofits to make decisions, develop recommendations, and improve program planning. Audit tools to assist in selecting retrofit options and optimal sizing techniques for installing heating, ventilating, air-conditioning equipment based on theoretical considerations must eventually be based on or validated with measured performance data. An ultimate goal for the users of such tools is to be able to identify appropriate and cost-effective retrofits for individual homes.

In the absence of direct end-use metering (also referred to as submetering), whole-house load shapes are disaggregated into their various components by means of systematic comparisons [1]. For example, consider two customers who are identical in all aspects, except one has an electric water heater and the other does not. This pair of customers is used to infer, by subtraction, an end-use load shape for the water heater. By disaggregating several whole-house load shapes for each appliance in this manner, an average for the population of customers is obtained. Once this is done, the variation across customers due to factors such as appliance saturation or demographic and economic characteristics is utilized in a statistical model to deduce the effect of customer characteristics on the whole-house load shape. The result of which is a relationship between household characteristics and a set of parameters that can then be used to rebuild the load shapes. However, there is evidence that the seasonal variation in nearly all residential end-use load shapes precludes metering periods of less than one year from producing accurate end-use load shape results [2]. This can be a major concern when trying to reduce the duration and cost of metering projects.

Several utility funded conservation programs, designed to encourage customers to use electricity more efficiently, have been implemented in recent years and continue to be developed due to regulated energy efficiency activity [3]. However, utilities have considerable uncertainty in assessing the net impacts of their investments in these conservation programs [4]. The results from one study indicate that the average measured energy savings achieved by conservation retrofits installed in a large number of single-family homes in the United States was approximately two-thirds of the average predicted energy savings. On an individual house basis, the difference is even greater, and in some cases, post-retrofit energy savings were negative [5].

Whole-house metering fails to capture the savings for individual conservation savings if the interaction between measures in various subsystems is significant. For example, energy savings due to efficient lighting will increase the winter space heating loads, while decreasing the summer cooling loads. Thus, accurate estimates of the impacts of demand-side programs are required in order to evaluate their cost-effectiveness relative to supply-side options.

One approach to disseminate information to consumers about their energy use patterns is to provide them with a more informative energy bill. The goal of this strategy is to create a more energy-conscious consumer, who will be better equipped to make informed decisions about how to save energy in their home. One study reports energy savings of about 10 percent during a three-year study of homes in Oslo, Norway [6]. There are greater costs associated with more frequent and informative billing methods, but it is estimated that these costs are minimal in relation to the potential energy savings. The types of feedback information tested are: frequency, medium that attracts the consumer's attention, presentation of the information in the bill, and a comparative standard which gives the consumer a basis for benchmarking. A breakdown of the whole-house energy use into the major end-uses was not tested. However, researchers expect this type of information will lead consumers to have a better understanding of their energy use patterns.

Most weatherization programs assess energy savings by comparing the monitored data for the house in question against that of a reference house representing conventional energy use. This approach enables a controllable basis for comparisons, and by normalizing operational conditions and weather data, the energy savings of conservation measures, as a whole, can be evaluated. However, the impact of individual measures can not be evaluated using this approach. Furthermore, the issue of separating the naturally occurring energy savings and the program-induced conservation effects remains unresolved.

2.2 Existing Approaches of Estimating Residential End-Use Loads

Traditional approaches to estimating end-use loads in the absence of metered data fall into one of the following three categories: (i) engineering approaches, (ii) statistical approaches, including conditional demand analysis methods, multiple regression-based methods, and objective classification methods, and (iii) hybrids of basic modeling approaches. Each of these approaches is discussed in Sections 2.2.1 through 2.2.3.

Traditional load metered data is the most reliable source of end-use load data. However, the main drawback in using this approach to estimate end-use loads is that it presumes that energy usage will be similar to historical patterns. Thus, it does not allow for changes in economic, demographic, or appliance conditions over time. As a result, state-of-the-art load monitoring techniques have recently developed, referred to as non-intrusive load monitoring of appliance energy signatures. Three such techniques: (i) the Non-Intrusive Load Monitor, (ii) the Heuristic End-Use Load Profiler, and (iii) the Non-Intrusive Appliance Load Recognition Algorithm are presented in Section 2.3.2.

Another new, yet less proven technique than non-intrusive load monitoring involves the implementation of artificial neural networks. Energy-related applications of neural networks are presented in Section 2.4.

2.2.1 Engineering approach

Engineering models combine "*a priori*" knowledge or assumptions about frequency of appliance use and behavior such as thermostat settings, with models of the building envelope based on first principles of thermodynamics or appliance efficiency. The disadvantage of these models is that they often require extensive building audits, which can be time-consuming and not cost-effective.

Examples of engineering-based models are: (i) HOT2000 developed by Natural Resources Canada [7], and (ii) DOE2.1E developed by the United States Department of Energy [8]. HOT2000 is a simulation software that can be used for single-family buildings only. It is mostly well suited to estimating the heating and cooling requirements of houses. DOE2.1E is the software of choice in the industry for simulating the whole building energy consumption of multifamily or commercial buildings. The heat gains and losses through walls, roof, floors, windows, and doors are calculated separately and the heat transfer through the building envelope is computed using response factors which account for thermal mass, placement of insulation, sun angle, cloud cover, building location and orientation, and other architectural features.

2.2.2 *Statistical approach*

Statistical approaches are distinguished by their use of historical data and statistical techniques. They attempt to describe end-use loads as functions of economic, occupant, dwelling, and appliance characteristics, and weather variables. These methods do not require exhaustive data collection, hence, may reduce modeling costs. In using historical data, they are able to adjust to different geographic regions. Three common statistical methods are: (i) conditional demand analysis, (ii) multivariate regression analysis, and (iii) objective classification analysis.

Conditional demand analysis

Conditional demand analysis (CDA) is based on econometric models of residential building energy use which may be presented as a function of the demographic characteristics of the household and the economic system of the electric service market. This approach implies that energy consumption patterns are a complex technical and social phenomenon and, thus, to fully understand this phenomenon, they must be viewed from both engineering and social science perspectives. Most of the work done on CDA has been concerned with the aggregate demand for electricity rather than the end-use energy demand of individual households. CDA explains the cause and effect of energy use to the extent that the variables are all assumed independent, show variation across the modeled sample, and are statistically significant. This approach does not allow fundamental parameters, such as, appliance efficiency to be changed over time.

An example of CDA used at the household level is *Modèle d'estimation de la consommations d'électricité* developed by Hydro-Québec as part of the study *Étude sur le comportement énergétique des ménages québécois*. This study consisted of determining the residential electric consumption by end-use for approximately 3000 dwellings in the province. From the results of the study, researchers were able to develop simplified spreadsheet-type models for estimating the electric energy consumption and distribution within a dwelling, based on key socio-demographic characteristics of the dwellings, and building and equipment types.

Multivariate regression analysis

Multivariate regression analysis (MRA) is the most widely used approach to model whole house and end-use level energy use. This approach involves identifying a least-squares regression model between the energy consumption, for example, actual metering data and the predictor variables. The most common predictor variables are climatic parameters, such as, daily average outdoor temperature and solar radiation levels.

MRA is relatively simple, easy to implement, and has been used in numerous studies. Unfortunately, the results generated by these models in estimating end-use load shapes are poor. Due to the nature of regression methods, the peak demand observations tend to be flattened out, such that predicted values are less extreme than actual values [9]. Thus, regression-based models can not be accurately used to estimate an appliance's electric demand profile.

The most popular energy-related regression-based model is the Princeton Scorekeeping Method (PRISM) developed at Princeton University's Center for Energy and Environmental

Studies [10]. The PRISM software was initially developed with the purpose of normalizing energy consumption for the purpose of comparing pre- and post-retrofit energy use levels. It uses actual billing data for all fuel types of a minimum of one year, along with the actual degree-days (heating or cooling) for the billing period, and the long-term degree-days to determine a weather-adjusted index of energy use, referred to as Normalized Annual Consumption. The model generates three building-specific parameters: (i) base-level consumption, as a measure of the constant usage of lights and appliances in the house; (ii) reference temperature, as a measure of the average outside temperature at which the house's heating system begins to operate; and (iii) heating (or cooling) slope, as a measure of the effective heat-loss rate of the house and the efficiency of the HVAC system. An underlying assumption made by PRISM is that space heating (or cooling) is the only temperature-dependent end-use in a dwelling. In general, it has been found to give satisfactory results for long-term heating consumption but the three estimated building parameters could show large errors.

MRA models have often been faulted as a means of analyzing building energy use because of the potential for significant collinearity between the prediction variables. That is, simplified models that are based on only a few variables have been observed to have systematic bias even if they are associated with high coefficients of determination (R^2) [11]. For example, events affecting only one parameter are not likely to occur in isolation. Thus, if a regression variable that is correlated with another regression variable is omitted from the model then a strong bias may occur in the parameter estimates. This can lead to improper interpretation of the relative importance of the various physical regression parameters, which may result in a model with unstable regression coefficients (depicted by low t-statistics for individual regression coefficients). Researchers generally agree that multicollinearity effects are likely to yield misleading models when correlation among regression variables is extremely high. However, there is no consensus as to the extent of acceptable collinearity (e.g. $R^2 = 0.90$ or 0.95) among regression variables.

To address this issue some researchers have used principal component analysis (PCA) to preprocess multivariate data. Essentially, this statistical technique takes a group of *(n)* correlated variables and re-expresses them as another set of *(n*)* uncorrelated variables, each of which represents a linear combination of the original regression variables. The uncorrelated variables, known as principal components (PC), are ordered so that the first PC explains the largest factor of the variation of the original data, the second PC explains the second largest factor, and so on. If the original variables are highly correlated, then the PC of the first variable will be so significant that all other variables can be ignored in the MRA. As a result, the number of regression variables in the model can be reduced with little loss in the model's goodness-of-fit.

Principle Component Analysis is used extensively in such fields as social sciences, but it is seldom applied for building energy analysis. Examples of energy-related studies which have applied PCA techniques include: determining the relationship between daily residential space heating and meteorological variables for four dwellings [12], identifying and clustering residential customers based on their air-conditioner energy use profiles [13], and developing a tool to arrive at an overview representation of monitored hourly energy use in an office building over one year [14].

Objective classification analysis

Objective classification models use a combination of principal component analysis and cluster analysis to identify typical weather-day types, and then analyze patterns of energy consumption by weather-day type. These models are used by utilities to forecast energy load requirements. Also, since this approach provides a better understanding of the cause and effect relationship of energy use than most traditional models, it is used as a tool for weather normalization.

A study was reported which consisted of the analysis of commercial building data for patterns of energy consumption by weather-day types obtained using temporal synoptic index methodology [15]. In this study various weather-day types were used to define the load shape for a building type based on the HVAC system characteristics and the climatic conditions at the building site. Another study reported using a form of objective classification analysis to explore a weather normalization method for estimating the energy savings due to a building retrofit [16]. The results indicate that the normalized energy consumption can be calculated using the energy signature and the number of hours of occurrence for various outdoor temperature bins, provided that the annual energy signature of a building remains constant for all subsequent years. The latter implies that no major modifications to the building are performed during the subsequent years which could change the energy use patterns of a building.

An advantage to applying objective classification techniques is the ability to recreate hourly or yearly load profiles from the energy signature. This feature enables researchers to investigate the changes in patterns of energy consumption due to varying building conditions.

2.2.3 Hybrid of basic modeling approaches

In response to the deficiencies of the approaches aforementioned, researchers have recognized that the strengths of any of these models may be combined. For example, conditional demand models or regression-based models are used to establish baseline consumption to match utility billing data and determine a building's energy signature. Then engineering models are applied to predict the impact of various energy-efficiency measures. At least four distinct hybrid end-use load shape estimation models have been developed and tested, they include the:

(i) Statistically Adjusted Engineering Model (SAE) [17],
(ii) Residential Energy Consumption Analysis Program (RECAP) [18],
(iii) Residential End-Use Energy Planning System (REEPS) [19], and
(iv) End-Use Disaggregation Algorithm (EDA) [20].

With the exception of RECAP and EDA, both REEPS and SAE are utility-level models that do not address the end-use energy usage and load profiles at the whole-house level. RECAP can provide customers with estimated end-use energy savings. EDA can also provide this information, but detailed house simulations, in addition, to monitored hourly load profiles are required. The SAE model differs from the others, in that, statistical approaches are used to allocate the differences in loads. Whereas, in the last three models presented, deterministic approaches are applied which establish a direct physical link between loads and their causes. With the exception of RECAP, developed by the consulting group XENERGY in the United States, all the models were developed by researchers at the Lawrence Berkeley National Laboratory at the University of California.

Statistically Adjusted Engineering Model

The motivation for the Statistically Adjusted Engineering (SAE) model is that the loads for each end-use are used as explanatory variables in conditional demand models of observed customer-level loads. The estimated coefficients of these variables are then used to statistically adjust the initial engineering loads to reflect the customer's actual total loads. In other words, statistical approaches are used to allocate the differences in loads.

Field test results show that SAE can represent a substantial improvement over engineering loads for certain end-uses, whereas, for other end-uses, it seems to add error to the engineering loads. For instance, space heating estimates are improved, whereas, estimates for the stove, refrigerator, and clothes dryer are made worse. The reason for these findings is attributed to the methods used by engineering methods to estimate end-use loads. For example, engineering loads for air conditioners are based on principles of thermodynamics under certain behavioral assumptions. Whereas, the engineering loads for stoves, refrigerators, and clothes dryers are based primarily on previous end-use metering results, and domestic hot water heating loads are based partly on principles of thermodynamics and partly on previous metering studies.

Residential Energy Consumption Analysis Program

The Residential Energy Consumption Analysis Program (RECAP) combines both statistical and engineering analyses to estimate electricity and gas consumption by end-use for individual households. First, whole-house energy consumption is reconciled with actual bills for a specified period. Then, RECAP uses linear regression to determine initial heating/cooling and base load consumption. In parallel to this step, expected usage estimates for heating, cooling, and other major end-uses are developed using customer survey data, utility-level end-use load data, and engineering/behavioral models. Any error in the bill reconciliation is allocated to the individual end-use estimates based on a statistical algorithm that recognizes that some of the initial estimates are known with greater certainty than other non-metered estimates.

Due to the extensive database requirements, RECAP is mainly geared towards large-scale utility demand-side management programs. Whereby, it can provide customers with estimates of end-use energy and cost information, recommendations for the most efficient use of electric and gas appliances (in generic terms), and an evaluation of the alternative rate options offered by the utility. In Québec, RECAP was used by Hydro-Québec in their 1991 Éko-Kilo Program, in which 1.4 million questionnaires were completed.

Residential End-Use Energy Planning System

Similar to RECAP, the Residential End-Use Energy Planning System (REEPS) uses a micro-simulation approach for estimating utility-level energy use based on the simulated action of a sample of individual households. The model's output is used for strategic planning and marketing support, in addition to traditional electricity sales forecasting. The general REEPS forecasting framework consists of using a set of market drivers that describe forecast period appliance standards, demand-side management policy, customer characteristics, energy prices, and weather. These drivers, mainly, appliance size, appliance efficiency, and appliance usage are used in a set of behavioral and consumer choice models. Combined with consumer counts, REEPS generates estimated energy sales by end-use and customer segment.

End-Use Disaggregation Algorithm

The End-Use Disaggregation Algorithm (EDA) is an engineering method which primarily utilizes the statistical characteristics of measured short-interval (hourly) whole-building electrical load and its inferred dependence on temperature. Weather-sensitive end-uses, for example, space heating and cooling, are treated separately from non weather-sensitive end-uses. The disaggregation is done in two steps. First, preliminary end-use profiles are developed for the building of interest using on-site survey data and the DOE-2 energy analysis software. The initial end-use profiles are then reconciled with the measured whole-building hourly loads. The reconciliation is done on an hourly basis for two seasons (winter and summer) and for two-day types (weekday and weekend or holiday). EDA can assign higher confidence factors for any given end-use for any scheduled hour. For example, if lighting were metered, confidence in that end-use would be high, so EDA would not alter the initial lighting profiles estimated. The underlying motivation for EDA is that the correlation of monitored whole-building loads to monitored weather conditions is greater than with respect to simulations for weather-sensitive end-uses.

The Engineering Calibration Approach (ECA™) was developed by the engineering group RLW Analytics and the Electric Power Research Institute's Center for Electric End-Use Data in the United States [21]. Much like EDA, ECA integrates statistical sampling of hourly whole-building and end-use metering with site-specific DOE-2 modeling. The main difference between

EDA and ECA is that ECA also uses visual data analysis for the reconciliation of end-use loads. That is, once hourly load shapes for one year for a sample of buildings have been produced, data leveraging is then applied to extrapolate the load shapes to a target population using supporting audit and billing information.

The main advantage that ECA presents over traditional metered load data methods is its flexibility. Since the data is stored as models, it is easy to manipulate the data to perform 'What-If' scenarios. Unlike traditional load data, which is only a snapshot of a building's energy performance. On the down side, both the EDA and ECA approaches rely on submetered energy data to improve the results of their methods over traditional modeling approaches. For large-scale utility demand-side management programs this is not always feasible or cost-effective.

2.3 Energy Load Monitoring Approaches

Energy load monitoring studies generally fall into one of two categories: (i) utility load research and (ii) utility issues research. The first category, utility load research, is generally concerned with whole-house energy use. For example, the average energy use of a representative sample of houses is characterized by using a small number of metering points in each house. Applications of load research studies include cost-of-service studies, customer class load studies, and rate design research [22]. Whereas, utility issues research is generally oriented towards understanding the performance of specific types of houses, systems, and component technologies. The goal of these types of studies is to address building energy efficiency, energy conservation and demand-side management related issues. Applications of issues research monitoring include energy end-use monitoring, technology assessment, and diagnostic measurement.

Both categories of energy load monitoring apply some form of traditional load monitoring technique. Traditional monitoring techniques have been faulted for their intrusive nature due to the physical placement of sensors on individual appliances. This poses as an intrusion onto the occupant's property. As an alternative, researchers have developed non-intrusive techniques of load monitoring. Non-intrusive load monitoring techniques are based on the analysis of appliance energy signatures. Similar to building energy signatures, appliance energy signatures are developed to depict the pattern of electricity usage of an appliance based on high-resolution level electrical demand data. An appliance signature is defined as a measurable parameter of the whole-house demand profile that gives information about the operating state of an individual appliance in the whole-house load. Like building signatures, appliance signatures are assumed to remain constant for the life of the appliance given that no modifications are made or malfunctions occur. The main advantage of defining appliance signatures in terms of whole-house demand levels is that, afterwards, only a single monitoring point in the house is required to continue to gather the appliance load information.

2.3.1 Intrusive load monitoring techniques

Submetering is the most reliable source of data to validate engineering or statistical models used to estimate end-use load shapes. However, the capital cost of submetering, the expense of installation, its intrusive nature (as seen by the occupants), and the cost of retrieving the data combine to make this approach somewhat undesirable for gathering extensive end-use load data.

Also, as energy markets throughout North America become increasingly deregulated, the requirement for interval energy load data for all types of customers has created an emergence of sophisticated wireless data and customer communication solutions enabling access to real-time or quasi real-time customer energy usage patterns [23]. This transformation in the market has rendered traditional revenue metering techniques obsolete.

2.3.2 Non-intrusive load monitoring techniques

Compared to intrusive load monitoring techniques, non-intrusive load monitoring has a number of advantages. In particular, the non-intrusive nature of the equipment may increase consumer acceptance and decrease financial liability. Other advantages of this method include no restriction on the number of channels of data that can be recorded, and being less costly more sites can be monitored, reducing the potential for bias in small sample sizes. A disadvantage is that most small appliances operating at 100 Watts or less, continuously variable appliances (e.g. light dimmers), and appliances which operate constantly (e.g. clocks) are often not recognized using these techniques. However, with the exception of lighting, these appliances do not appear to be significant energy consuming appliances. More importantly, there is a greater potential for undetected error using non-intrusive techniques because the whole-house load is disaggregated analytically, rather than physically using separate sensors as in most traditional monitoring techniques.

All non-intrusive monitoring techniques are based on the analysis of some type of appliance energy signatures. The simplest appliance signature is defined as a two-dimensional vector representing step-changes in the measured power levels of an appliance over time. Most residential appliances can be appropriately modeled using steady-state signatures. Steady-state signatures have several advantages compared to transient signatures, mainly: (i) they provide a continuous indication of an appliance's operating state, thus, making it easier to detect a change in state, (ii) the sum of the power changes in any cycle of state transitions (ON to OFF / OFF to ON) is always zero for most residential appliances, and (iii) the energy signatures are additive when two occur coincidentally.

Power is one type of energy signature, but several other parameters can be used to define the appliance signature. For example, direct current, harmonic current, and alternating current can all be used to define the energy signature of a steady-state appliance [19]. The most appropriate signature basis for residential appliances is alternating current at the utility frequency of 60 Hertz. Three models of non-intrusive load monitoring are presented:

(i) Non-Intrusive Appliance Load Monitor developed by researchers at the Massachusetts Institute of Technology,

(ii) Heuristic End-Use Load Profiler developed by the group Quantum Consulting, Inc. in California, and

(iii) Non-Intrusive Appliance Load Recognition Algorithm developed by researchers at Concordia University.

The Rule-Based Pattern Recognition Algorithm presented in Chapter 4 is an original contribution toward the same goal as these three models.

Non-Intrusive Appliance Load Monitor

The Non-intrusive Appliance Load Monitor (NALM) is a micro-processor based device, initially developed in 1984, to sample the total electrical load of residential dwellings at a high speed to determine when appliances switch ON and OFF [24,25,26]. The prototypical NALM consists of five steps: (i) current and voltage measurements using a one second sampling interval, from which real and reactive power are calculated, (ii) detection of ON and OFF events, (iii) clustering of similar events, (iv) matching of ON and OFF events over time, and (v) equipment identification. When an appliance switches ON or OFF, power levels change and a new steady-state power level is established. The difference between two steady-state power levels defines an event. These events are then clustered, whereby, events within an established tolerance of real and reactive power are considered to be associated with one or more appliances with the same characteristics. ON and OFF events for similar types of appliances yield clusters of similar magnitude but opposite sign, from which pairs of clusters are used to construct a time-series of ON and OFF events. Appliance identification is done by comparing the power levels of typical appliances whose characteristics are known. To date, the NALM has a restricted set of target appliances, excluding small appliances, continuously variable appliances, and appliances that operate constantly.

Preliminary results indicate that estimated NALM energy consumption is usually within ±10 percent of the metered appliance loads. The stove typically yields higher error results due to many simultaneous events that go undetected. A possible source of error with this device may be due to incorrect installation of the device. The NALM must be mounted onto an existing meter socket and the secondary voltage and current sensors (those from the NALM) must be connected in phase with the primary voltage and current sensors (those supplying the house). The NALM attempts to increase its success over other traditional pattern recognition approaches by looking at both the real and reactive components of power.

Researchers in Japan have been able to apply the same technique of the NALM to residential gas appliances [27]. The method consists of a *Smart Gas Meter* equipped with a pulse meter, a data logger, and a software. The gas meter translates the movement of the diaphragm into a cyclic crank rotation and then transmits it to a digital indicator. One crank rotation is set equal to the minimum value of mechanically distinguishable unit of flow. A magnet attached to the gas meter emits an electronic pulse as the crank rotates. Another device detects the pulse and is connected to a microcomputer in the *Smart Gas Meter*. The gas use of individual appliances is then detected based on the volume of gas that flows between two pulses through a standard size meter, and a set of heuristic rules about the flow rate and duration of various gas appliances (based on house-specific audit information). This method is about 95 percent accurate.

The need for real-time energy scorekeeping has led the companies Borlänge Energi and Daltek in Sweden to develop the Kronometer™ [28]. It is being marketed as an "energy awareness device" that is plugged into any household power socket and communicates via the main supply line (using power-line data transfer technology) with a data-logger that is connected to the house's primary electric meter. The Kronometer is being tested in about 100 single-family dwellings. Early results indicate that in households in which the device is installed, average energy consumption has decreased by 15 to 20 percent just because users learn to recognize the cost of each appliance as it is turned ON and OFF.

Heuristic End-Use Load Profiler

The Heuristic End-Use Load Profiler (HELP) is a proprietary software consisting of a rule-based disaggregation algorithm [29,30,31]. The software, used by approximately 30 to 40 users, is mainly oriented towards electric utilities [32]. The algorithm uses premise-level data, such as, audit of appliance loads, customer appliance ownership data, and customer behavioral assumptions to construct estimated end-use load profiles. On a daily basis the algorithm scans the whole-house load profile and records the shape, timing of day, magnitude, and duration of all significant changes in the whole-house load. Next, the algorithm determines which of these changes correspond to the appliance considered based on general load profile knowledge. In cases where two or more major end-uses have similar demand levels, HELP distinguishes between them based on behavioral assumptions regarding the usage of these appliances (e.g. time of day, length of usage, and pattern of usage). The algorithm is implemented using a decision tree. A significant advantage of this method is that it can be used by utilities from any geographic region or customer mix, as long as there is existing load research data from which to extract the characteristics of the appliance connected loads.

HELP is used to produce load profiles for residential air-conditioning units, HVAC equipment, and water heaters. For instance, in an air-conditioning study for 40 households across four months, the average air conditioner energy consumption estimate differed from the actual energy consumption by less than 10 percent. The peak value of the disaggregated air-conditioning load profiles when averaged over all households for all 40 days differed from the actual peak by less than 5 percent.

Non-intrusive Appliance Load Recognition Algorithm

The Non-intrusive Appliance Load Recognition Algorithm (NALRA) developed by researchers at Concordia University [33,34] also consists of using premise-level data and previously defined operating characteristics of the appliance connected loads to detect ON and OFF appliance activations. The operating characteristics considered are one-dimensional, in that, they define the state of the appliance at a single point in the whole-house load profile. Thus, it is assumed that the appliance energy signature is depicted entirely as steady-state (ON or OFF). A key feature of the NALRA is the signal filtering techniques that are applied to "clean-up" the whole-house load profile, in order that the operating characteristics of the appliances may be detected. Results based on a one-week training period and a test period of up to 72 days for a single dwelling indicate that the NALRA yields acceptable estimations of end-use energy consumption.

2.4 Neural Network Approach

A more recent approach for modeling electric demand consists of using artificial neural networks (ANN). Neural networks have drawn significant attention for their ability to learn from training data and exhibit some capability for generalization beyond the data that is presented to the network. Instead of requiring explicit "*a prior*" rules or knowledge, the rules in an ANN are extracted, learned, and applied within the system. This enables the network to determine causal relationships amongst a large number of parameters apparent in the energy signature profiles of buildings and appliances.

The most common type of ANN is the Back Propagation Neural Network. This network is applied in a large number of applications in various fields, such as, signal processing, pattern recognition, and classification. It is also used for energy demand predictions. In fact, the need for accurate load forecasts has made the utility industry one of the major users of neural networks [35,36]. The results of one study show that the ANN used was able to interpolate among the load and temperature patterns of training data to perform acceptable short-term load forecasting. Another study demonstrated the applicability of neural networks to perform long-term load forecasting for a Middle Eastern electric utility [37]. Compared to other regression-based methods applied by researchers in this study, the ANN allowed for more flexible relationships between temperature and electric load patterns, thus, yielded improved results.

In a building energy prediction competition organized by the American Society for Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) in 1993, five of the six most successful models used varying neural network techniques [38]. The objective of the competition was to identify the most accurate method for making hourly energy use predictions based on two sets of measured energy and environmental data. No description of the building or other details about the data was made available to the participants. A key factor for the success of all of the models is that the training data sets included most of the variation in energy use to be predicted. This characteristic of ANN can sometimes be a significant drawback if appropriate historical data is not available. A second competition was held by ASHRAE in 1995 with the aim to evaluate the most effective empirical models for modeling hourly whole-building energy baselines for the purpose of measuring savings from energy conservation retrofits. Again, the results showed that neural networks can provide an accurate model of a building's energy use if the appropriate training data is available [39,40].

A Back Propagation Neural Network model was used to model occupant behavior in a single-family dwelling, in terms of a predicted domestic hot water load [41]. The neural network estimations were then integrated with building climate energy demand predictions generated by commercial dynamic energy simulation software. The study revealed that the annual energy predictions based on building-climate correlation were improved by 15 to 20 percent by including some knowledge of the occupant behavior for the domestic load.

Other building energy-related applications of neural networks include assessing HVAC system retrofits for commercial buildings [42], and building process control and energy management [43,44,45]. Most of the literature on the latter application describe how researchers use neural networks as process models that, in turn, are used to examine the behavior of the process and determine controller outputs that would produce the desired feedback signal. The main advantage of using neural networks in place of traditional energy prediction models is the neural network's ability to generalize in cases where the driving building parameters can not be clearly identified (e.g. no apparent correlation exists between variables), or when model input values are expected to extend beyond a model's boundary conditions.

The most common inputs for neural networks used to predict demand levels are climatic data, such as, radiation levels, wet- and dry-bulb temperatures, and wind-speeds. In some cases, characterizations of the function and operation of the building have also been used as neural network inputs. For example, occupancy schedules, production data, and room temperatures have all been investigated as acceptable neural network inputs [46]. Significant for all these applications are large data sets, which include most instances of variation of the model's input variables. In practice, however, it is difficult to first, identify, and secondly, to perform extensive measurements of all parameters that describe the energy demand patterns of occupants for each household.

An alternative approach to disaggregating whole-house electric load using neural network techniques is presented in Chapter 5. This method seeks to investigate whether common neural network techniques can be used to detect energy signature profiles for different appliances based solely on their inherent pattern characteristics apparent to the neural network. This approach eliminates the need for collecting extensive and costly external energy-use parameters.

2.5 Conclusion

The analysis of available publications related to the existing models for estimating end-use energy consumption has led to the following objectives for the research that is presented in this thesis.

- Achieve better statistical accuracy than most traditional disaggregation approaches.
- Level of homeowner intrusiveness must be minimal.
- Reduce training period of typical end-use load research projects.
- Allow for real-time applications to take advantage of current emerging remote data applications (e.g. Internet).
- Adoption of existing data logging equipment of low cost, and simple installation methods instead of custom hardware and experienced installers as with the NALM.
- Develop algorithms that are robust, yet flexible enough so as to allow researchers to cost-effectively improve the models, as well as, adapt the work to other appliances.

3. DESCRIPTION, COLLECTION, AND ANALYSIS OF MONITORED DATA

3.1 Description of the Case Study House

The data that is used to develop the algorithms was obtained by the detailed monitoring of a single-family home in Montreal. The house was built in 1947 and has a total heated floor area of 158.6 m^2 and four occupants. The house has two above-ground floors, a finished basement, and a ground-level garage. The primary heating source is an oil-fueled central hot water system. Two backup electric baseboard heaters are also available. The domestic hot water heater and all other appliances are operated by electricity.

3.2 Data Loggers

The monitored data consists of interval electrical current measurements for each selected appliance. The current measurements were obtained using a clamp-on current transducer (CT), models A60FL or A70FL from Amprobe Instruments, and recorded using a SmartReader 3 data logger from ACR Systems Inc. (Figure 3.1). In the case of appliances that are not connected to dedicated plugs, the clamp-on CT was installed on a line splitter. The CT is a split-core configuration allowing installation without disconnecting the load. The data was downloaded manually, every 6 days, using the TrendReader Software package from ACR Systems Inc. TrendReader automatically processes the logger data, and assigns a time and date to each sampling interval. The monitored data was then exported to Microsoft® Excel spreadsheets, in which the data was analyzed.

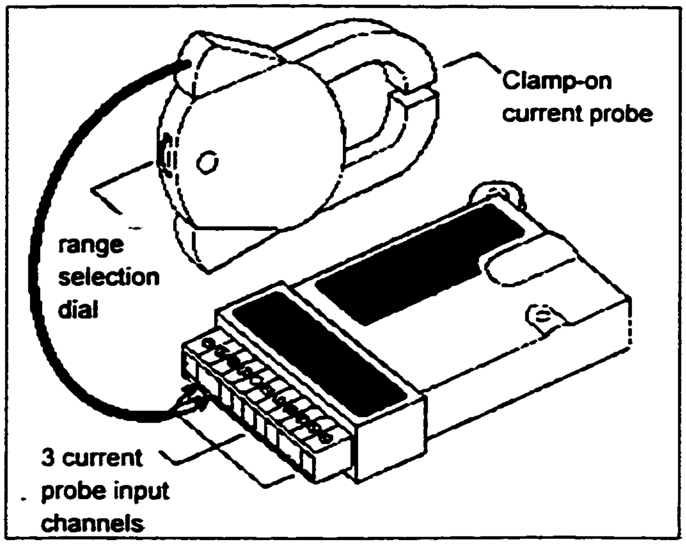


Figure 3.1 Schematic of monitoring equipment [47]

The manufacturer's specifications include a maximum working voltage of 660 Volts of alternating current (AC), and a measurement accuracy of either ±4% of the full-scale amperage plus 0.4 Amps if the maximum current is 100 Amps, or ±1% of the full-scale amperage plus 0.4 Amps if the maximum current is 25 Amps. Table 3.1 lists the amperage range selected for each monitored appliance.

Table 3.1 Current probe range selected for each monitored appliance

End-use	Number of lines	Range selected (Amperage)
Main electric line entering the house (called 'total')	2	100 each line
Refrigerator	1	25
Domestic hot water heater	2	100
Clothes dryer	2	25 each line
Clothes washer	1	25
Dishwasher	1	25
Stove	2	100 each line
Baseboard heater	2	25 each line

3.3 Description of the Monitored Data

The monitored data consists of measurements of alternating current (AC) at a 16-second interval. The real power for AC is the product of voltage, current, and power factor, whereby the power factor is calculated as the cosine of the phase shift angle (Φ) between the voltage and the current (Equation 3.1). Implicitly, power factor is the ratio of the real power (expressed in Watts) to the total or apparent power (expressed in Volt-Amperes). The Total power is comprised of a real power component (able to do work) and a reactive power component (produces no work). Real power is the basis upon which utilities bill customers.

$$\text{Real Power (Watts)} = \text{Voltage (Volts)} \times \text{Current (Amps)} \times \text{Power factor}, \quad \text{where Power factor} = \cos \Phi \qquad \textbf{(3.1)}$$

Assuming that the appliance receiving power from an AC power source behaves as an electric resistor, that is, the current passing through it is proportional to the voltage drop across it, both the current and voltage are in phase, thus, the phase shift angle (Φ) is 0 degrees, and cos(Φ) is 1. Hence, purely resistive loads have a power factor of one, indicating that real and apparent power are the same. In this case, the real power component is proportional to the voltage times the current, and the reactive power component is zero. Given that the sampling interval captures a full line cycle, then the demand at any given sampling interval is obtained from the measurements using Equation 3.2.

$$\text{Demand}_i \text{ (Watts)} = \text{Current}_i \text{ (Amps)} \times \text{Voltage (Volts)} \qquad \textbf{(3.2)}$$

Where, Current_i is the electrical current, expressed in Amperes, at time-step (i); and Voltage is the voltage drop across the appliance, and it is equal to 240Volts (2 x 120Volts) for the hot water heater, baseboard heater, stove and clothes dryer, and 120 Volts for other monitored appliances.

The utility voltage is generally known to vary between 105 Volts to 127 Volts at any given time for residential loads [48], however, Equation 3.2 assumes that the voltage remains constant.

Herein, the demand refers to the level at which electricity is drawn at each sampling interval, expressed in Watts. Whereas, the load refers to the amount of electric power that is drawn over an interval of time, expressed in Watt-hours.

As loads vary from purely inductive to resistive and to capacitive, the phase angle also varies from -90° to 0° to +90°, thus, the power factor varies from 0 to 1. The algorithms presented in this study are based on the assumption that the power factor of the monitored inductive appliances is very close to 1, indicating that these appliances behave as resistive loads. Resistive loads in a house include domestic hot water heaters, stoves, and baseboard heaters, whereas, inductive loads include refrigerators, clothes washers and dryers, and dishwashers.

The daily energy use for each monitored appliance is obtained by integrating the appliance demand across the sampling intervals for the selected day using Equation 3.3.

$$\text{Energy use}_{\text{MONITORED}} = \sum_{i=1}^{n} (\text{Demand}_i \times \Delta t) \qquad (\text{Watt-hours}) \tag{3.3}$$

Where, Demand_i is calculated using Equation 3.2; Δt is the time interval at which the electrical current is monitored (16 seconds); and (n) is the total number of sampling intervals for the day (Δt is 16 seconds thus (n) is 5400).

For the dwelling considered, measurements are made on the following electric circuits: (i) main supply line to the house (herein called 'Total'), (ii) domestic hot water heater, (iii) refrigerator, (iv) stove, (v) clothes washer, (vi) clothes dryer, (vii) dishwasher, and (viii) two backup baseboard heaters (Table 3.1).

Figure 3.2 illustrates a "snapshot" of the variation of the Total demand profile, as well as, the demand profiles of individual appliances in use for a period of one hour during a weekday evening (October 15, 1996). The Total demand is composed of each of the end-uses illustrated, that is, the domestic hot water (DHW) heater, stove, baseboard heaters, and refrigerator, as well as, miscellaneous plug and light loads that are not monitored individually.

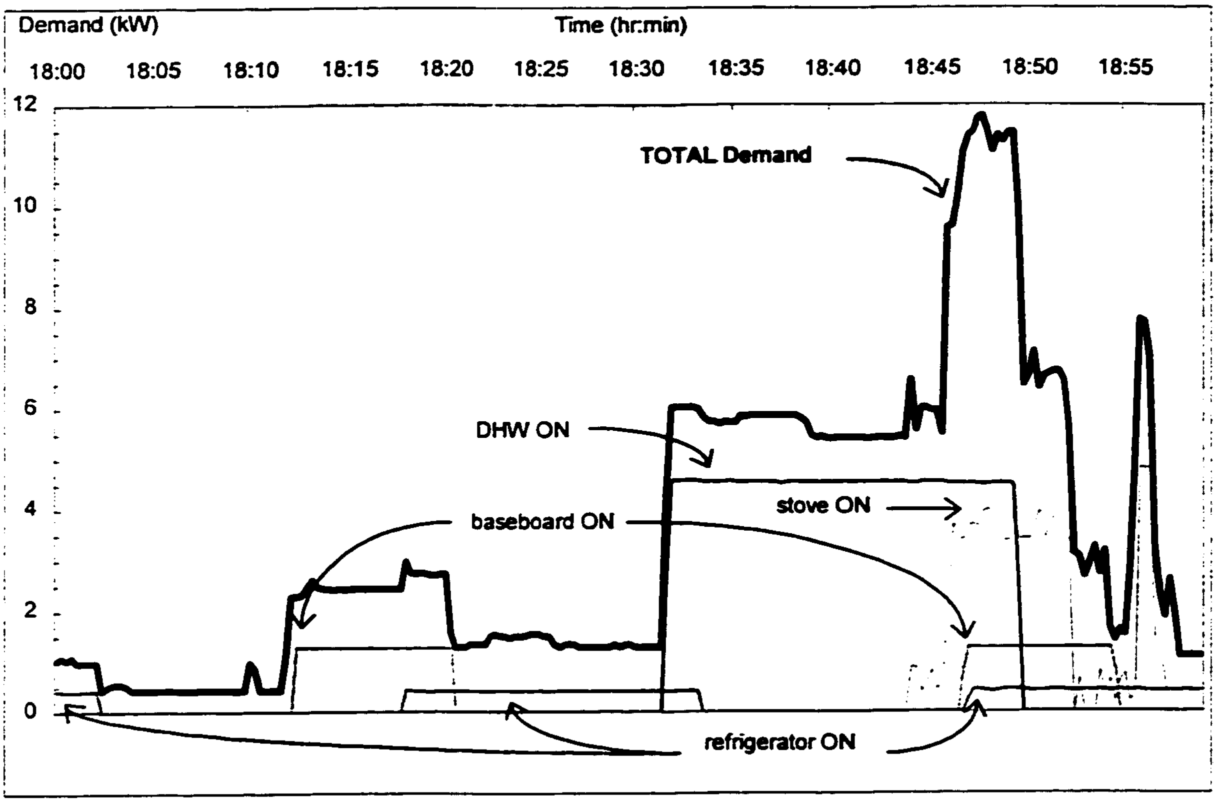


Figure 3.2 Monitored end-use demand profiles during a one-hour period on a weekday evening

From Figure 3.2, we can conclude that the peak in the Total demand profile at time 18:47 is caused by the almost simultaneous activation of the DHW heater, stove, baseboard heater, and refrigerator. Therefore, if the whole-house profile is considered and analyzed as a system of disaggregated components, the impact of each appliance on the Total demand profile becomes more evident. Moreover, it is seen that each appliance's demand profile is directly reflected on the Total demand profile. Whereby, any change in the profile of the Total demand indicates a status change (ON or OFF) of an appliance in the house.

The complete monitoring period extended from February 1996 to February 1997. The present study uses data collected during a six-day training period, from October 14th to the 19th, 1996 in order to develop the prototypes for the Pattern Recognition Algorithm and the neural network models. This period is referred to as the training period. In this case, a six-day period was selected because it includes each weekday and one weekend day type. The idea in determining the length of the training period is to observe sufficient appliance cycles over a short time period that is representative of long-term appliance energy signatures.

Both approaches are tested using two separate data periods. A six-day period, November 20th to the 25th, 1996 is selected to test the near-to-date applicability of the algorithms. Near-to-date refers to the period of time between the date of the training data and the testing data. A seven-day period, January 6th to the 12th, 1997 is selected to test the far-to-date applicability of the algorithms. The two periods together are referred to as the testing period.

3.3.1 Correction for measurement error in the monitored data

The monitored data was observed to have minor inconsistencies due to malfunctions in the data loggers. To minimize this measurement error, the Total load is corrected. Whereby, if the aggregate demand of the individual appliances is less than the Total demand, for time-step (*i*), then the Total demand is substituted by the value of the aggregate demand of the individual appliances at time-step (*i*). A comparison of the monitored and the corrected Total energy consumption for each day in the three data periods considered is presented in Table 3.2. On average, the correction factor is 9.3% for the training data, 5.6% for the November testing data, and 3.3% for the January testing data.

Table 3.2 Measured and corrected total energy use

Month	Day	Monitored Total energy use (kWh)	Corrected Total energy use (kWh)	Correction factor (%)
October	14	47.6	49.1	3.1
	15	27.4	29.1	6.1
	16	23.0	25.3	9.9
	17	23.1	25.1	8.9
	18	19.4	22.0	13.2
	19	29.6	31.8	7.4
Average				9.3
November	20	24.1	26.1	8.3
	21	33.0	34.6	5.0
	22	29.3	31.5	7.6
	23	38.1	39.6	3.9
	24	41.1	42.8	3.9
	25	58.7	61.6	4.8
Average				5.6
January	6	27.6	28.0	1.6
	7	37.5	38.8	3.4
	8	44.4	45.6	2.6
	9	31.3	32.9	5.3
	10	40.4	41.7	3.3
	11	86.0	86.7	0.8
	12	14.2	15.0	5.7
Average				3.3

3.4 Statistical and Graphical Analysis of the Monitored Data

This section presents a brief statistical and graphical analysis of the monitored data in the aim to demonstrate that the three data periods (one for training and two for testing) selected do not have similar energy consumption or demand patterns. It is important to validate this assumption because it precludes any possibility of predisposition of the models to accurately disaggregate the total load. To this end, the monitored data is assessed at four levels: (i) daily Total energy use, (ii) peak load duration, (iii) hourly Total energy use, and (iv) daily appliance energy use.

3.4.1 Daily Total energy use

For the first level of comparison, four indices are used to compare the monitored data from the training period and the two testing periods: (i) energy load, (ii) energy use share, defined as the percentage of the appliance load to the Total load, (iii) time-of-use share, defined as the ratio of appliance ON time to total time in a day, and (iv) the number of appliance activations or positive state changes. The results of this comparison are presented in Table 3.3 for the DHW heater and Table 3.4 for the refrigerator.

Table 3.3 Monitored data of the DHW heater for different data periods

Training day	Energy load [kWh]	Appliance energy use share	Appliance time-of-use share	Number of appliance activations
10/14 – Monday	23.9	0.49	0.26	13
10/15 – Tuesday	11.1	0.38	0.10	13
10/16 – Wednesday	12.2	0.48	0.11	10
10/17 – Thursday	10.2	0.41	0.09	10
10/18 – Friday	8.6	0.39	0.08	11
10/19 – Saturday	16.0	0.51	0.19	13
11/25 – Monday	10.0	0.38	0.10	13
11/26 – Tuesday	15.8	0.46	0.15	13
11/27 – Wednesday	20.1	0.64	0.19	10
11/28 – Thursday	10.7	0.27	0.10	12
11/29 – Friday	22.1	0.52	0.21	12
11/30 – Saturday	30.7	0.50	0.29	15
01/06 – Monday	16.2	0.32	0.15	7
01/07 – Tuesday	16.9	0.44	0.16	11
01/08 – Wednesday	22.4	0.49	0.21	14
01/09 – Thursday	11.2	0.34	0.11	11
01/10 – Friday	19.0	0.46	0.18	14
01/11 – Saturday	39.6	0.46	0.37	15
01/12 – Sunday	8.7	0.39	0.16	4

Table 3.4 Monitored data of the refrigerator for different data periods

Training day	Energy load [kWh]	Appliance energy use share	Appliance time-of-use share	Number of appliance activations
Oct 14 – Monday	5.2	0.11	0.62	36
Oct 15 – Tuesday	5.6	0.19	0.56	36
Oct 16 – Wednesday	5.6	0.22	0.56	36
Oct 17 – Thursday	5.5	0.22	0.55	39
Oct 18 – Friday	5.7	0.26	0.57	36
Oct 19 – Saturday	4.5	0.14	0.57	34
11/25 – Monday	5.8	0.22	0.59	34
11/26 – Tuesday	5.5	0.16	0.56	36
11/27 – Wednesday	5.2	0.17	0.54	38
11/28 – Thursday	5.4	0.14	0.56	37
11/29 – Friday	5.4	0.13	0.56	37
11/30 – Saturday	5.9	0.10	0.60	33
01/06 – Monday	5.5	0.11	0.56	25
01/07 – Tuesday	5.5	0.14	0.55	38
01/08 – Wednesday	5.5	0.12	0.55	40
01/09 – Thursday	5.9	0.18	0.60	37
01/10 – Friday	6.4	0.15	0.65	31
01/11 – Saturday	6.3	0.07	0.63	31
01/12 – Sunday	5.9	0.19	0.59	41

As expected the energy share is significantly higher for the DHW heater than for the refrigerator. For example, for October 18 the DHW heater energy share is 0.39 or 39% of the Total electric energy use for that day, whereas, the refrigerator energy share is only 26%. However, for the same day the refrigerator ON time is greater than the DHW heater ON time by over seven-fold, that is, 0.57 and 0.08, respectively. Also, the range of variation of the energy share for the refrigerator across all days, 0.19 (0.07 to 0.26), is half of that for the DHW heater, 0.37 (0.27 to 0.64). Whereas, the range of variation of the time-of-use share for the refrigerator, 0.11 (0.54 to 0.65), is less than half of that for the DHW heater, 0.29 (0.08 to 0.37). Lastly, the number of appliance activations for each day is an indication of the frequency of usage of the appliance. The difference in the values for the two appliances indicates that DHW heater usage is more sporadic than the refrigerator usage during these monitored days.

Based on these results there is no identifiable trend in the day-to-day energy use, in terms of load and time-of-use, for either the DHW heater or the refrigerator. However, as expected, the results suggest that the day-to-day energy use variation is more apparent for the DHW heater than the refrigerator. This is likely due to the fact that varying occupant activity and external factors have less of an impact on the refrigerator than the DHW heater energy use.

3.4.2 Peak load duration

For the second level of comparison, the peak load duration is assessed by comparing the Total electrical load factor (ELF) for each day for the three data periods (Figure 3.3). The load factor is defined as the ratio between the actual daily electricity consumption and the amount that would have been used if the usage had stayed at the occupants' peak demand level for the entire day (Equation 3.4).

$$\mathrm{ELF} = \frac{\sum_{i=1}^{n}(\mathrm{Demand}_i \times \Delta t)}{\mathrm{Demand}_{MAX} \times n \times \Delta t} = \frac{\mathrm{Demand}_{AVG}}{\mathrm{Demand}_{MAX}} \text{, and} \quad \mathrm{Demand}_{MAX} = \max_{i=1}^{n}\{\mathrm{Demand}_i\} \tag{3.4}$$

Where, Demand_i is calculated using Equation 3.2; Demand_{AVG} is the average Total demand for the day, expressed in Watts; (n) is the number of sampling intervals for the day; and Δt is the sampling interval (16 seconds).

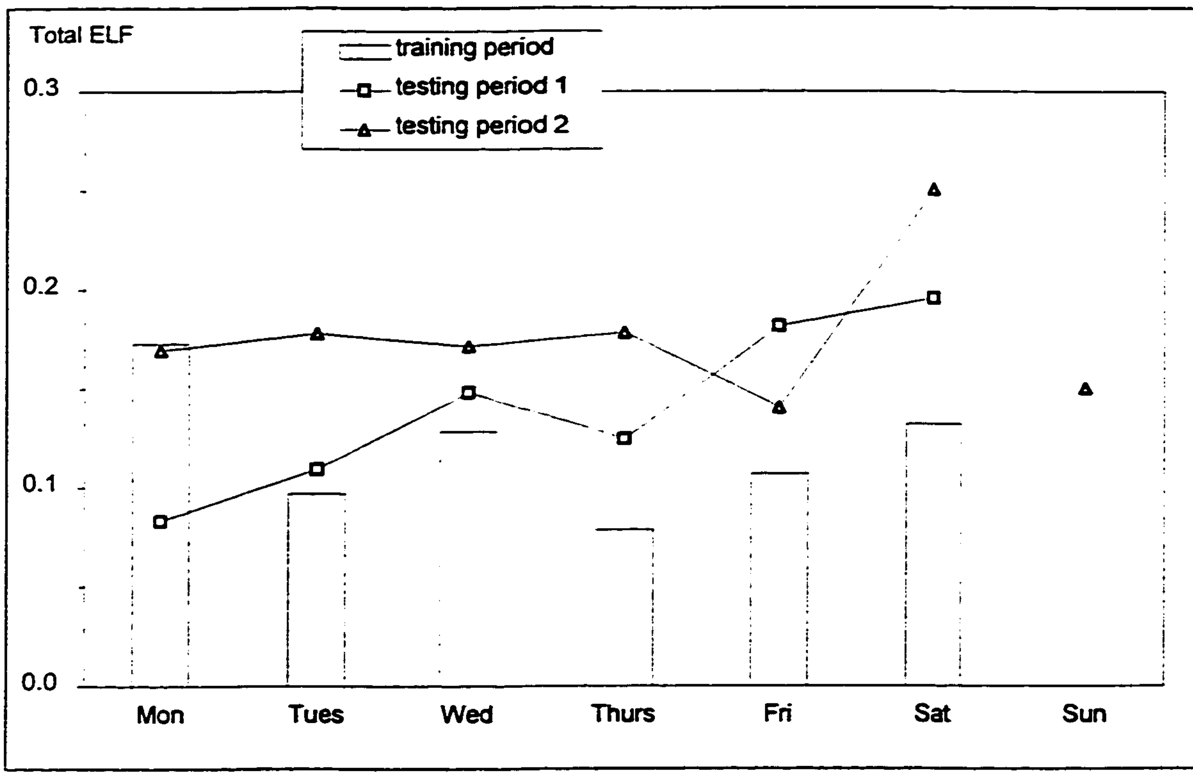


Figure 3.3 Daily electrical load factor for the Total load for all data periods

The results indicate that the load factor varies by data period, as well as, by day of the week. Thus, there is no underlying trend in the monitored data depicting the peak load duration of appliance usage.

3.4.3 Hourly Total energy use

To gain a better understanding of how whole-house electricity is consumed, both the daily and the hourly patterns are considered. The hourly energy use profile (expressed in kilowatt-hours or kWh) is presented in Figure 3.4 for the training period; Figure 3.5 for the near-to-date testing data; and Figure 3.6 for the far-to-date testing period to illustrate the varying energy demand patterns of the occupants throughout the day.

Although, the hourly profile exhibits an expected diurnal pattern of energy use, the magnitude of the peak loads varies somewhat. In addition, it is noticed that during the nighttime hours of 01:00 to 05:00 the energy use varies somewhat across the three data periods. This suggests that the hourly patterns of energy use in the house, across different days, are due to random rather than systematic occupant behavior.

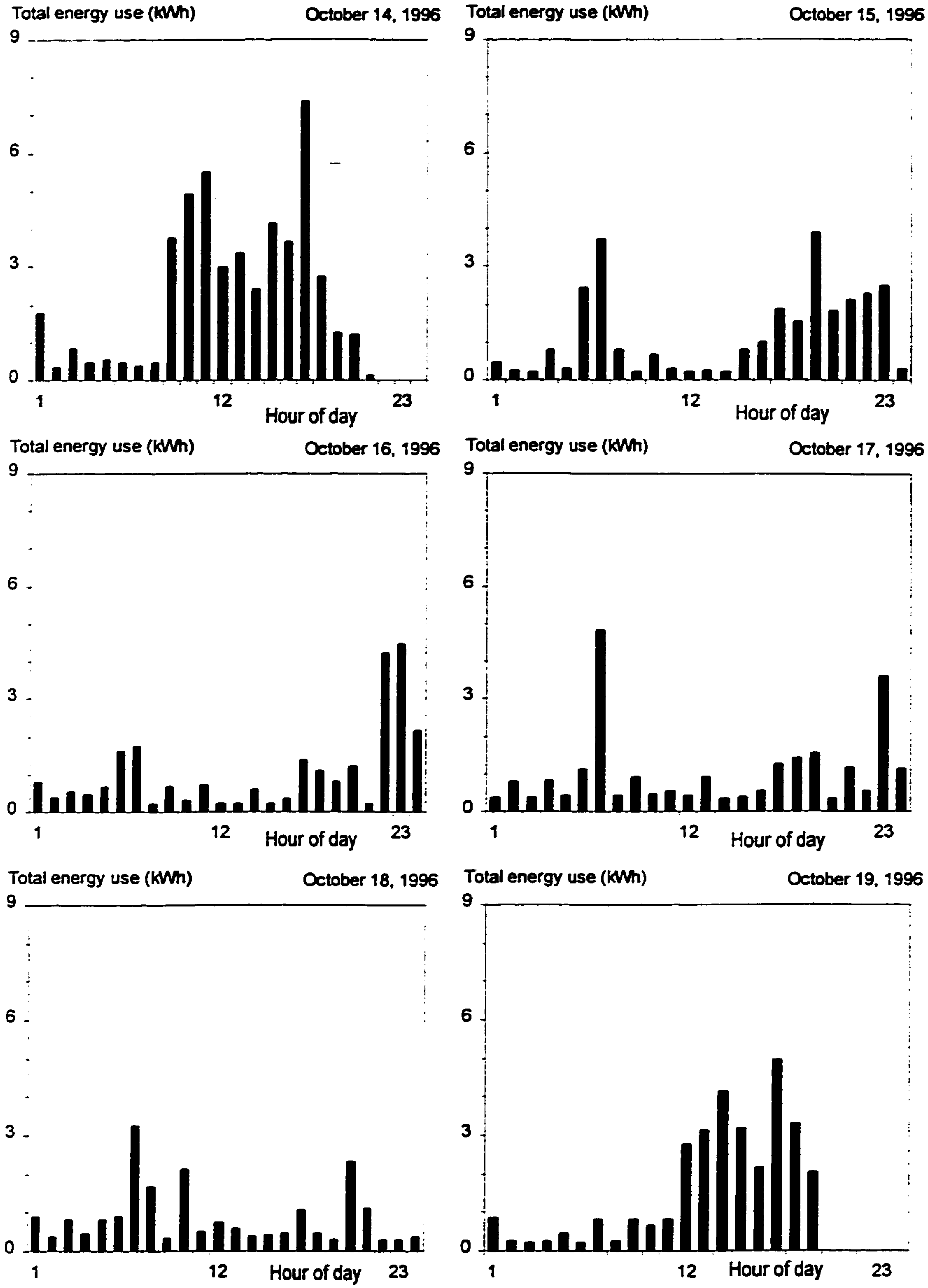


Figure 3.4 Hourly Total load profile for each day of the training period

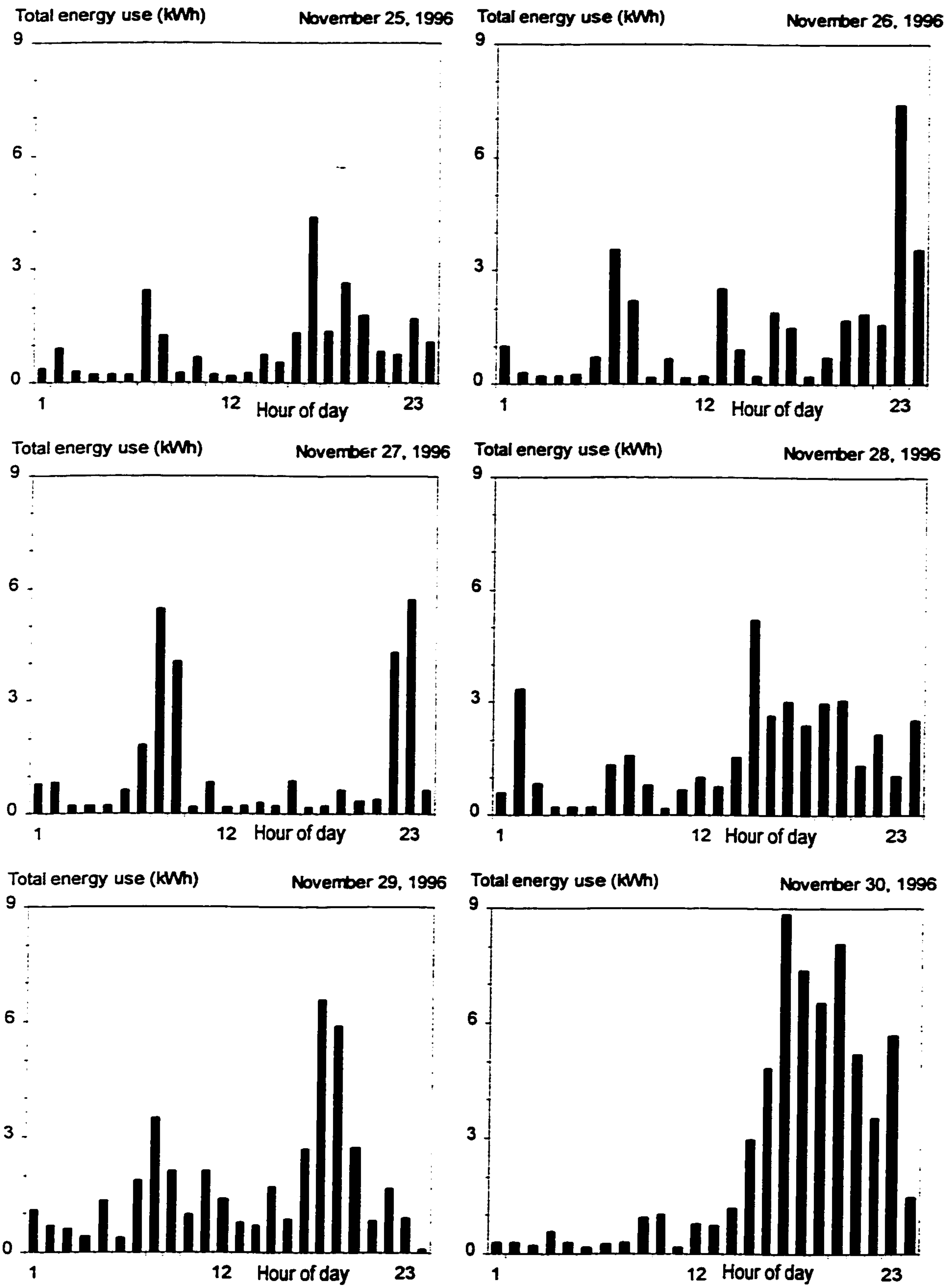


Figure 3.5 Hourly Total load profile for each day of the near-to-date testing period

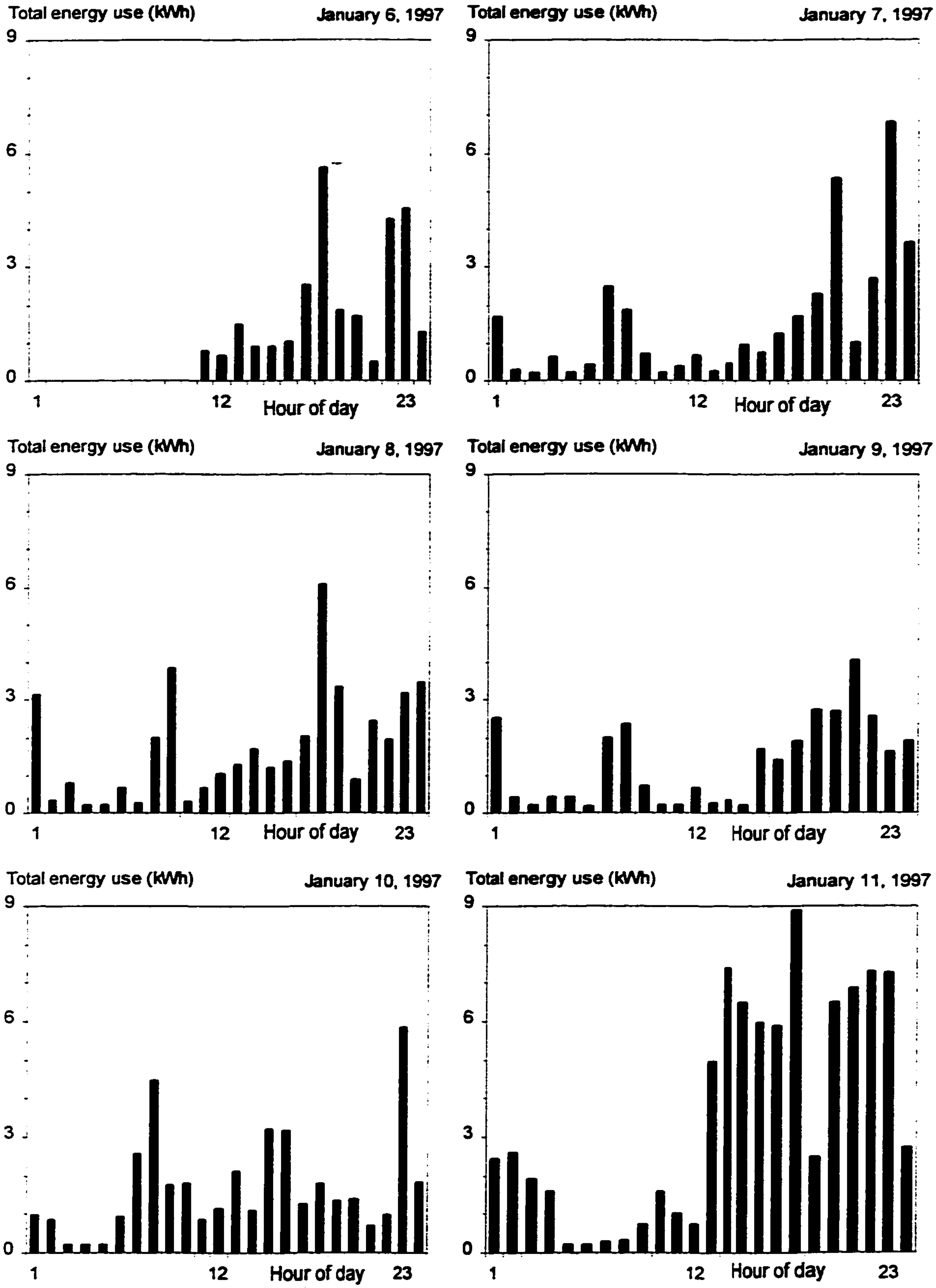


Figure 3.6 Hourly Total load profile for each day of the far-to-date testing period

3.4.4 Daily appliance energy use

From the results of the previous sections, preclusion of any tendency in the daily and hourly total energy use patterns can be made. The same assumption must also be justified for each end-use individually. Consider Figure 3.7, the range of daily energy use for each monitored appliance is illustrated for the three data periods.

The results show that the DHW heater's energy consumption varies the most among the monitored appliances, that is, from about 5 kWh/day to almost 40 kWh/day. This is likely due to varying household activity. The second highest variable appliance is the baseboard heater. This is likely due to varying heating requirements as the outside temperature changes considerably during the shoulder month of October, as well as, to people's thermal preferences. The values illustrated suggest that the aggregate sum of the two baseboard heaters can vary from 0 to 12 kWh for one day. The energy use of the remaining monitored appliances: refrigerator, dishwasher, clothes washer, and stove vary between 0 kWh/day and approximately 6 kWh/day. The OTHER end-use represents the residual load, that is, the total load minus all the monitored end-use loads. This category includes miscellaneous plug loads and lights. At the end-use level the monitored data does not have any inherent trends with regards to energy consumption or demand patterns across different days.

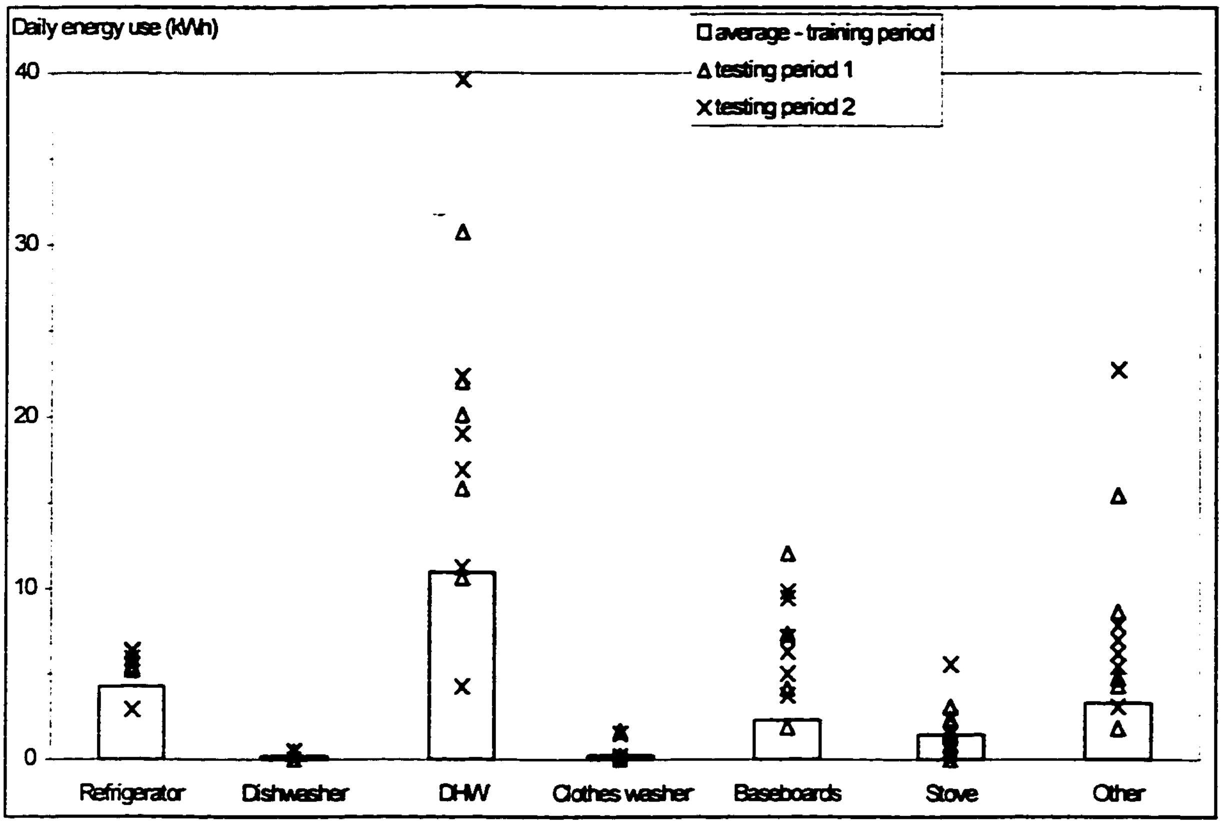


Figure 3.7 Ranges of end-use energy consumption for all days in the data periods

Figure 3.8 and Figure 3.9 present a sample of demand profiles plotted against time for the refrigerator and DHW heater, respectively, as monitored during the training day of October 15th, 1996. Note that the profiles for the two appliances are presented on different scales. Each profile depicts one appliance cycle. The tick marks on the horizontal axis of the figures represent the number of sampling intervals for each cycle. Typically, the refrigerator cycle duration is longer than the DHW heater cycle duration. The refrigerator profiles generally appear to be more discrete than the DHW profiles because the number of fluctuations appears to be less. The data markers (highlighted using gray boxes) at the start and end of each profile illustrate the number of intervals sampled before the appliance achieved its steady-state mode of operation. In the following chapter, this aspect is further discussed in the aim of recognizing the ON and OFF occurrence of an appliance. There are not two appliance cycles that depict identical patterns.

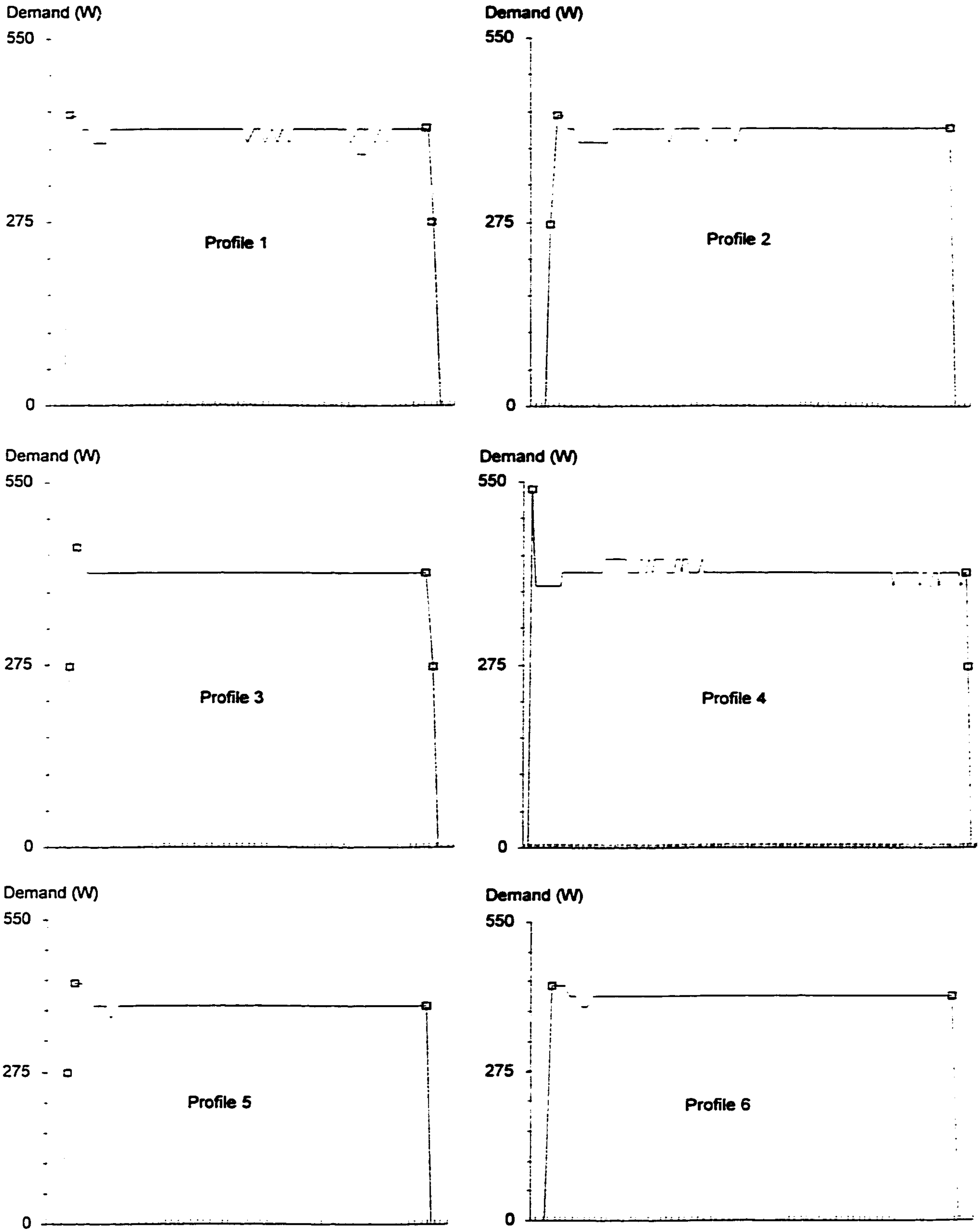


Figure 3.8 Sample of demand profiles of the refrigerator

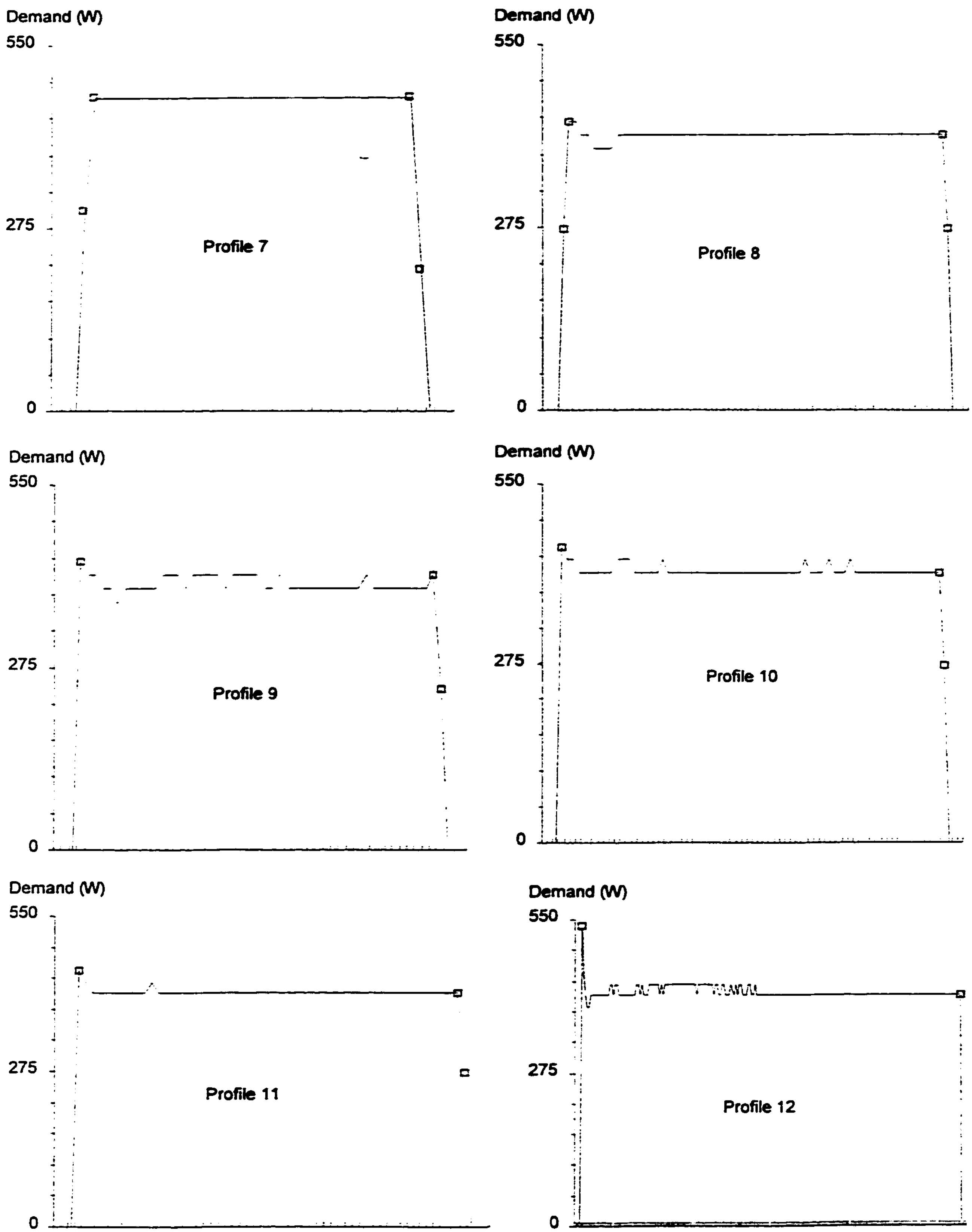


Figure 3.8 Sample of demand profiles of the refrigerator (cont'd)

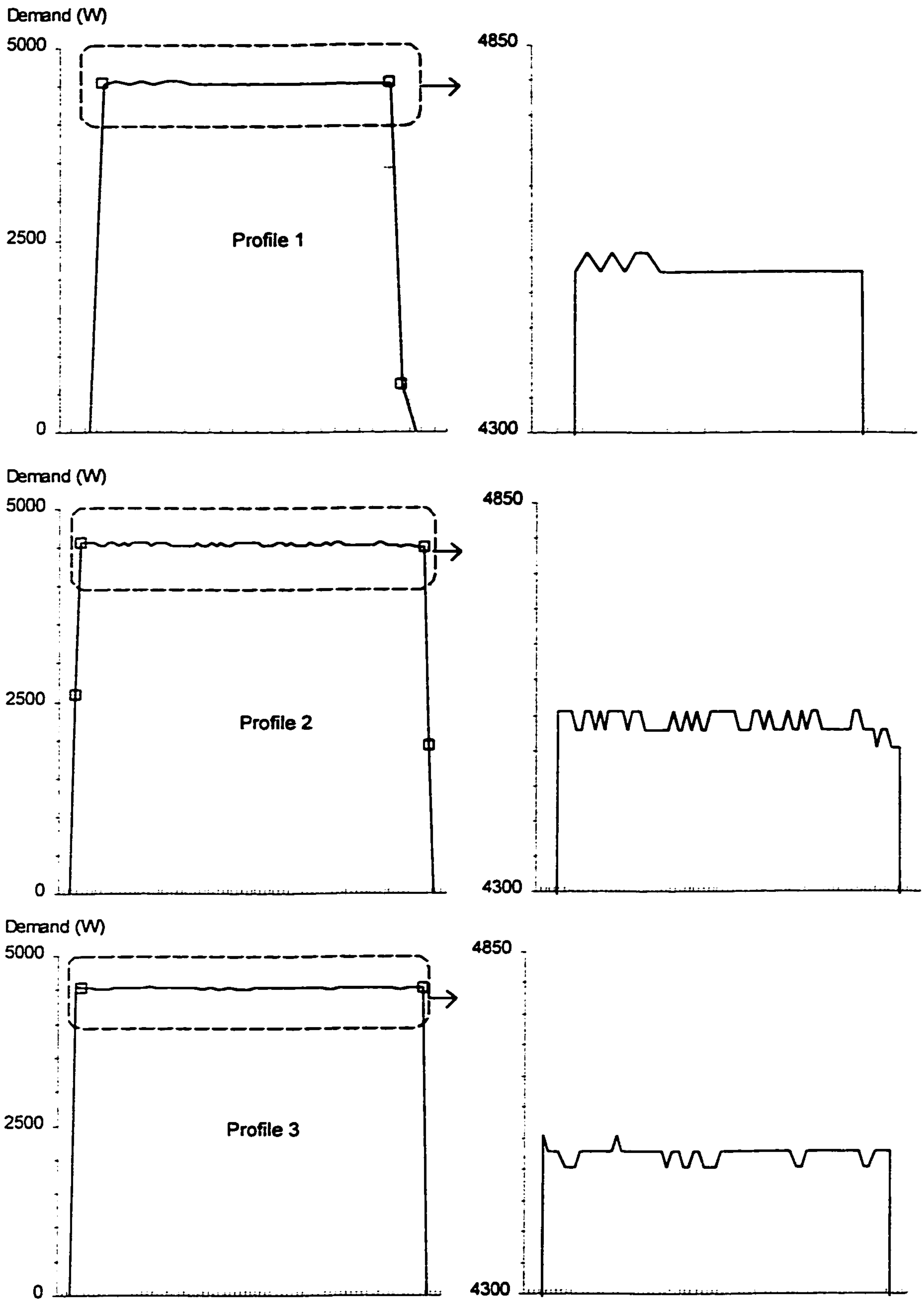


Figure 3.9 Sample of demand profiles of the DHW heater

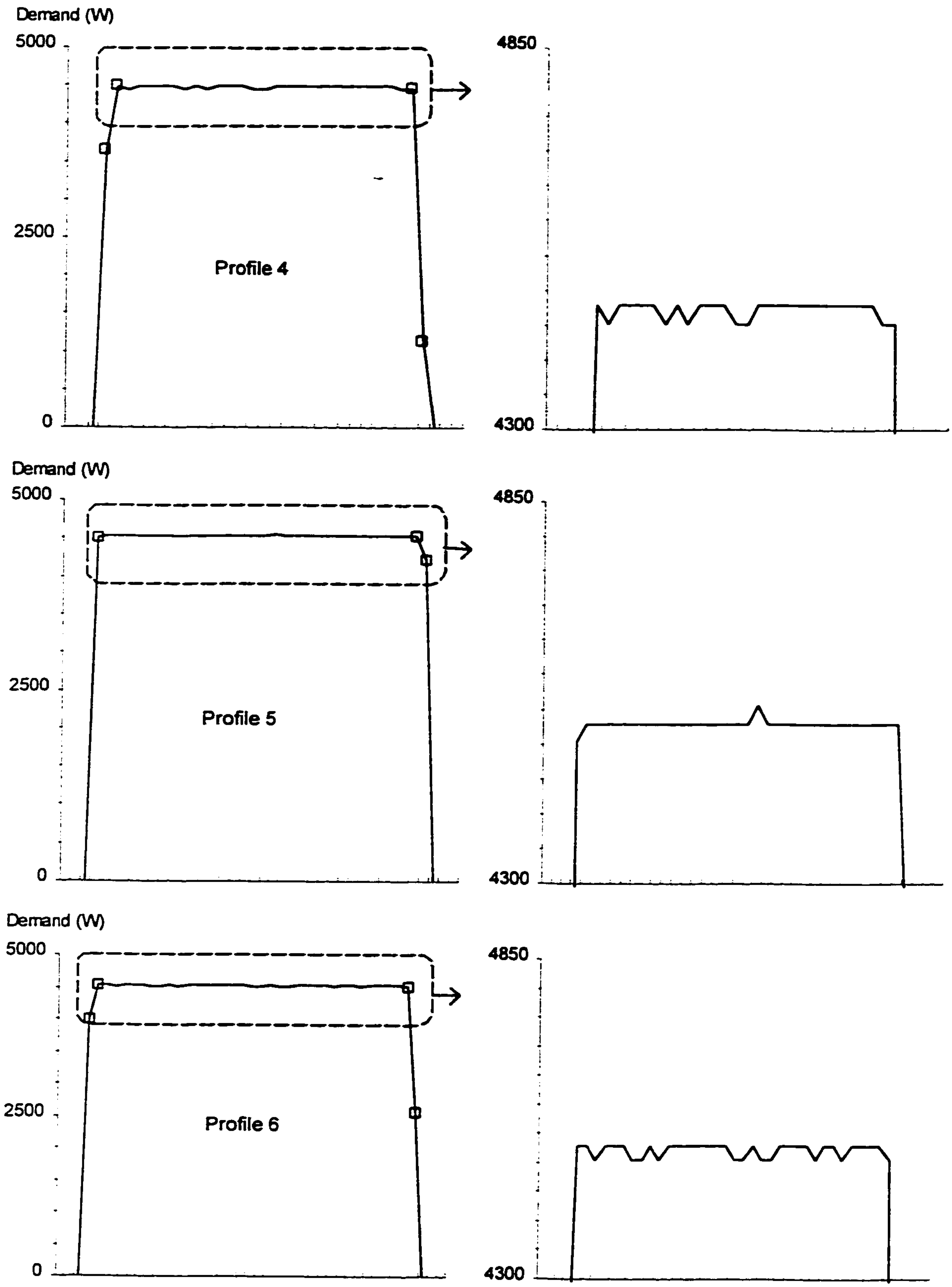


Figure 3.9 Sample of demand profiles of the DHW heater (cont'd)

3.5 Regression Analysis

This section presents the results of a regression analysis of the monitored data. The goal of this exercise is to assess the relationship between the energy consumption of any two appliances, and an appliance and the Total energy consumption of the house. If appropriate relationships are found based on the training data, then a function is defined, which is then used to estimate the energy consumption for the testing periods.

The correlation coefficient is used to assess the relationship between individual end-use loads and the total load. The analysis is done for two units of measurement, that is: (i) appliance energy share of the total load, and (ii) appliance energy consumption. The correlation coefficient (r) is calculated using Equation 3.5. If large values of daily energy use for one appliance are associated with large values of daily energy use for another appliance, then (r) is positive. Whereas, if small values of daily energy use for one appliance are associated with large values of daily energy use of another appliance, then (r) is negative. In the case that the two appliances are unrelated, then (r) is close to zero. The results for the training data are presented in Table 3.5 for the energy shares and Table 3.6 for the energy consumption.

$$(r)_{X,Y} = \frac{\sigma_{XY}}{\sigma_X \cdot \sigma_Y}$$

$$\text{where, } \sigma_{XY} = \frac{1}{n}\Sigma(X_i - \mu_X)(Y_i - \mu_Y), \quad \sigma_X^2 = \frac{1}{n}\Sigma(X_i - \mu_X)^2, \text{ and } \sigma_Y^2 = \frac{1}{n}\Sigma(Y_i - \mu_Y)^2 \tag{3.5}$$

Where, X_i is the energy use of appliance X for the day (i); Y_i is the energy use of appliance Y for the day (i); μ_x is the average daily energy use of appliance X for all days in the training period; and μ_y is the average daily energy use of appliance Y for all days in the training period.

The fact that the analysis yields different results based on the unit of measurement of the end-use, that is, as a function of the energy share or the unit energy consumption, indicates that the type of energy usage patterns of the appliances are different. For instance, the correlation between the refrigerator energy use share and the total energy use is very strong (r = -1.0). Whereas, the correlation between the refrigerator unit energy consumption and the total energy consumption is weak (r = -0.4). Therefore, it appears that the refrigerator energy use is somewhat constant, irrespective of the household activity.

In comparison, the correlation between the DHW heater energy use share and the total energy use share is weak (r = 0.3). Whereas, the correlation between the DHW heater unit energy consumption and the total energy consumption is strong (r = 0.9). In this case, it appears that the DHW heater energy share is somewhat constant indicating that the level of household activity, which influences the total energy use, also influences the DHW heater energy use. Since the DHW heater is the largest contributing appliance to the Total load, an increase in the DHW heater energy use is apparent on the Total load. Whereas, an increase in the refrigerator energy use may be overshadowed by increases in energy use of other appliances in the house.

Another significant relationship between end-uses is found for the clothes washer and the stove. For both bases of comparison, the interdependency is strong (r = 0.9 from Table 3.5 and Table 3.6). The clothes washer is also well related to the Total energy use based on energy share (r = 0.7 from Table 3.5) and energy use (r = 0.8 from Table 3.6), as is the stove based on energy shares (r = 0.7 from Table 3.5) and energy use (r = 0.9 from Table 3.6).

Table 3.5 Correlation coefficient (r) for appliances based on energy use shares

X ↓ Y →	Refrigerator	DHW heater	Dishwasher	Cloth. Washer	Baseboard	Stove
Refrigerator						
DHW heater	-0.3					
Dishwasher	-0.4	-0.5				
Cloth. washer	-0.7	0.5	0.2			
Baseboard	0.6	-0.4	-0.2	-0.8		
Stove	-0.8	0.4	0.1	0.9	-0.7	
Total	-1.0	0.3	0.4	0.7	-0.5	0.7

Table 3.6 Correlation coefficient (r) for appliances based on unit energy consumption

X ↓ Y →	Refrigerator	DHW heater	Dishwasher	Cloth. Washer	Baseboard	Stove
Refrigerator						
DHW heater	-0.5					
Dishwasher	0.4	0.1				
Cloth. Washer	0.0	0.8	0.2			
Baseboard	-0.7	0.0	0.0	-0.4		
Stove	-0.2	0.9	0.2	0.9	-0.2	
Total	-0.4	0.9	0.4	0.8	0.1	0.9

For appliances that yield a significant correlation to the Total load, a regression analysis is used to estimate the appliance energy use based solely on the Total energy use of the house. Various correlation functions are tested. The best-suited function is selected based on the highest goodness-of-fit, expressed by the coefficient of determination (R^2). For example, an R^2 of 0.9 indicates that 90 percent of the variation of the total energy consumption is directly related to the appliance energy consumption. The functions selected for the refrigerator and the DHW heater are illustrated in Figure 3.10. The results show that an exponential function best describes the energy share data of the refrigerator, whereas, a power function is best suited to the energy use data of the DHW heater.

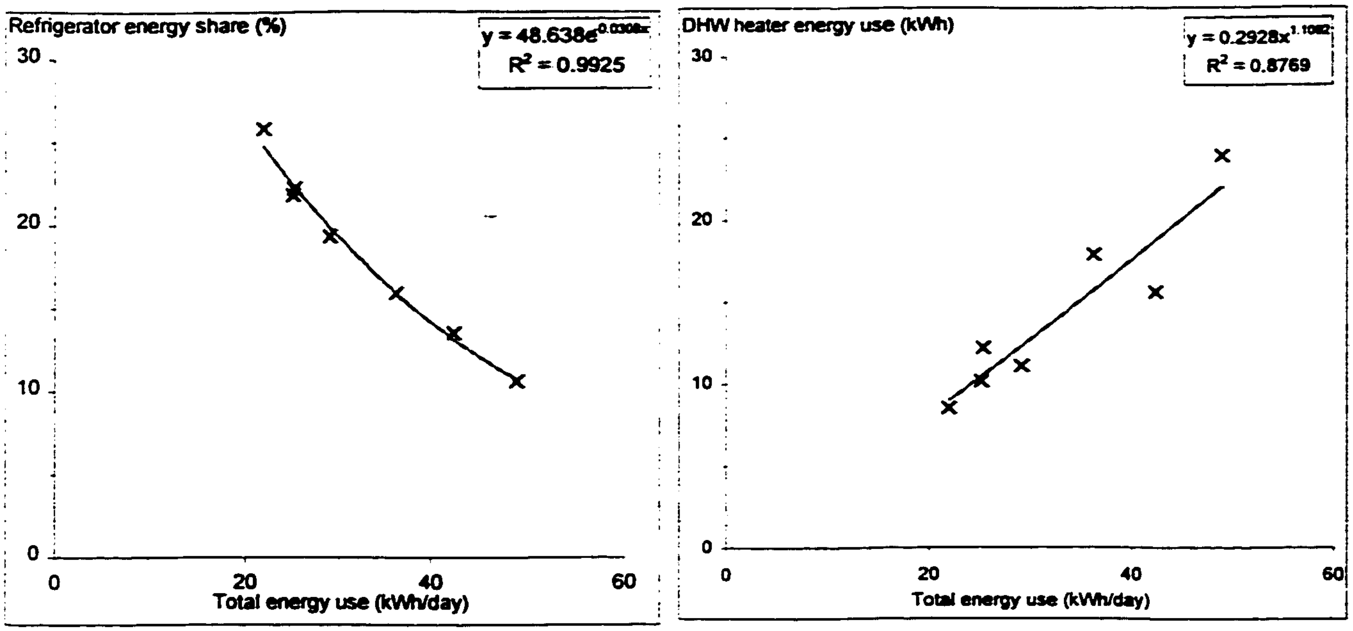


Figure 3.10 Correlation function of the refrigerator and the DHW heater energy use in terms of the Total load

These functions are then used to estimate each appliance's energy use for the two testing periods. The results are shown below in Figure 3.11.

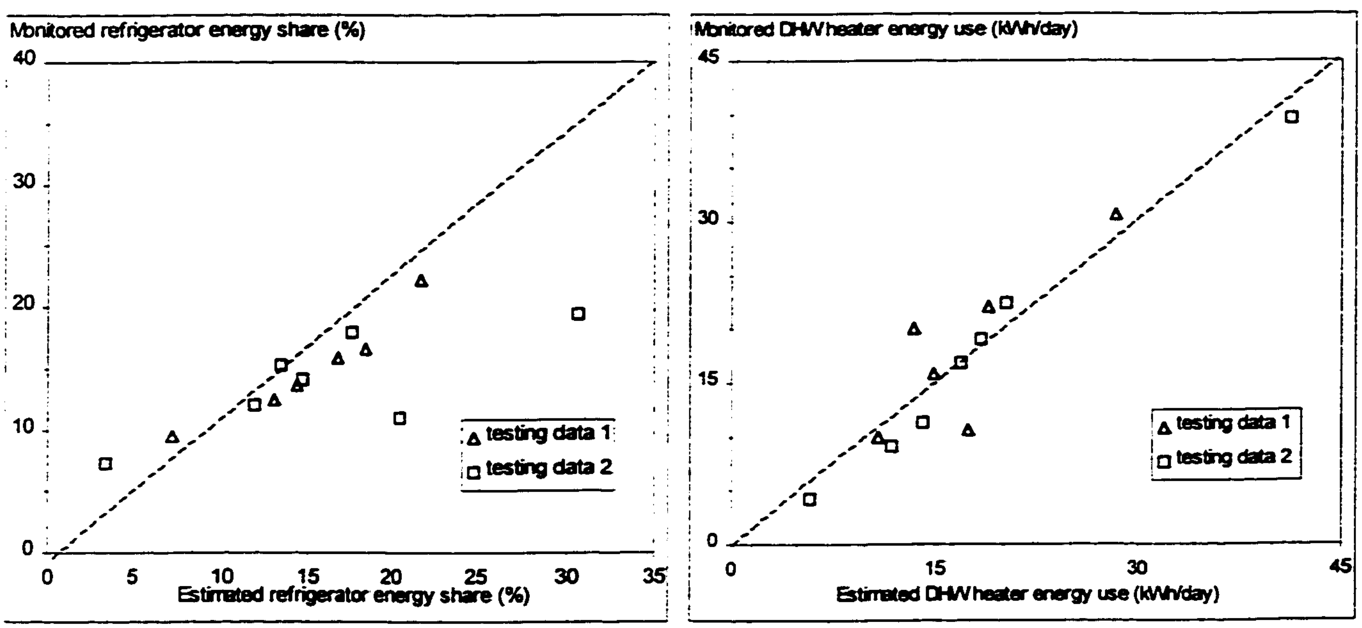


Figure 3.11 Comparison of the regression analysis results and the actual monitored data for the refrigerator and the DHW heater

For the refrigerator, the unit error in estimating the daily energy share varies from -11.2% to 3.8% from the actual energy share. For the DHW heater, the relative error in estimating the daily energy use varies from -6.7% to 3.2% of the actual energy consumption.

Acceptable estimates of the contribution of these two appliances (DHW heater and refrigerator) to the total energy consumption of the house can be obtained by using the relationships developed from the training data. However, this approach is based on the assumption that all factors that affected the energy use during the training period will remain constant throughout the testing periods. For example, if the number of occupants or their energy related habits should change, then the relationships derived from the training period are no longer valid. Moreover, a regression analysis approach can not provide additional information about the pattern of end-use energy consumption, such as, the number and the duration of appliance activations, and the corresponding energy consumption for different time intervals during the day (e.g. from 6:00 AM to 9:00 AM or from 6:00 PM to 10:00 PM).

Both approaches presented in the following chapters, pattern recognition and neural network techniques are developed with the aim to overcome this limitation. That is, an approach is presented that is not contingent on the behavior of household occupants, or any of their social or demographic characteristics provided that the major energy contributing appliances in a house are not replaced.

4. A RULE-BASED PATTERN RECOGNITION ALGORITHM TO DIS-AGGREGATE THE TOTAL ELECTRIC LOAD INTO THE MAJOR END-USES

The objective of the work presented herein is to demonstrate that end-use load data can be obtained by applying a pattern recognition approach to disaggregate the whole-house load data. Whereby, the whole-house electric load is disaggregated into its major end-uses by detecting individual appliance loads from rapid sampling of whole-house current levels. The results are presented in the form of daily load profiles and energy consumption for each major end-use. This chapter presents the development of the generic algorithms for both the DHW heater and the refrigerator. Subsequent to the initial development of the algorithms, a testing process is carried out to validate the algorithms by comparing their results with the results of the monitored appliance data.

The recognition of the various appliance energy signatures within the whole-house demand profile consists of two phases: (i) a one-time calibration (or training) process required to tune the generic algorithms, previously developed, to the characteristics of electric demand of the particular house under investigation; and (ii) an application (or testing) phase. During the training phase, the electric demand is monitored at the main electric entrance of the house and at selected appliances of interest. During the application phase, only the electric demand at the main electric entrance is monitored.

The generic algorithms are developed from the analysis of monitored data over a training period of one week on a test house. From the training data, a random sample of events corresponding to the selected appliances is selected. The response signal of the Total demand profile due to the activation and disactivation of selected appliances is assessed. This information is referred to as the appliance's energy signature (or demand profile), and is translated into pattern recognition rules. The generic algorithms can be applied to other houses given that the algorithm's parameters are modified, through a training process, to fit the electric characteristics of appliances for a house. The transferability of the generic algorithms to houses other than the test house has not been tested within the scope of the work presented herein.

The algorithms systematically apply a set of rules to recognize the operation of the selected appliance from the Total demand profile. Figure 4.1 illustrates a schematic representation of the overall process of development and testing of the algorithms.

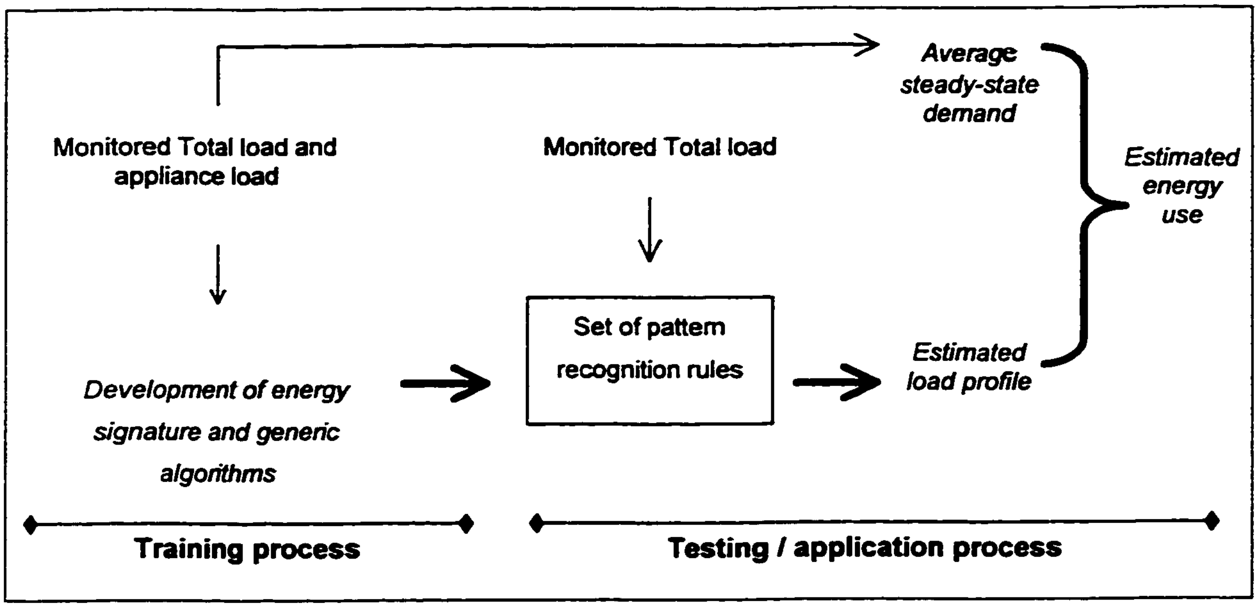


Figure 4.1 Flowchart of the algorithm development process for both appliances

The algorithms are based only on monitored data and do not require information to be provided by the occupants about the usage of the appliances. The training data consist of monitored data from a six-day period, from October 14th to the 19th, 1996. The testing data consists of monitored data from two separate data periods: (i) a six-day period in November (20th to the 25th) 1996 to test the near-to-date applicability of the algorithms, and (ii) a seven-day period in January (6th to the 12th) 1997 to test the far-to-date applicability of the algorithms. Near-to-date and far-to-date refers to the period of time between the date of the training data and the testing data. Results are also presented for the training period in order to determine the minimum error inherent in the algorithms.

The Total load for the case study house is disaggregated into the following categories: (i) domestic hot water heater, (ii) refrigerator, and (iii) other. Separate algorithms for the DHW heater and the refrigerator are developed. These two end-uses are selected for disaggregation because they appear to be the most important, in terms of their share of the Total load. Figure 4.2 shows the contribution of each individually monitored appliance to the Total load for the six-day training period in October.

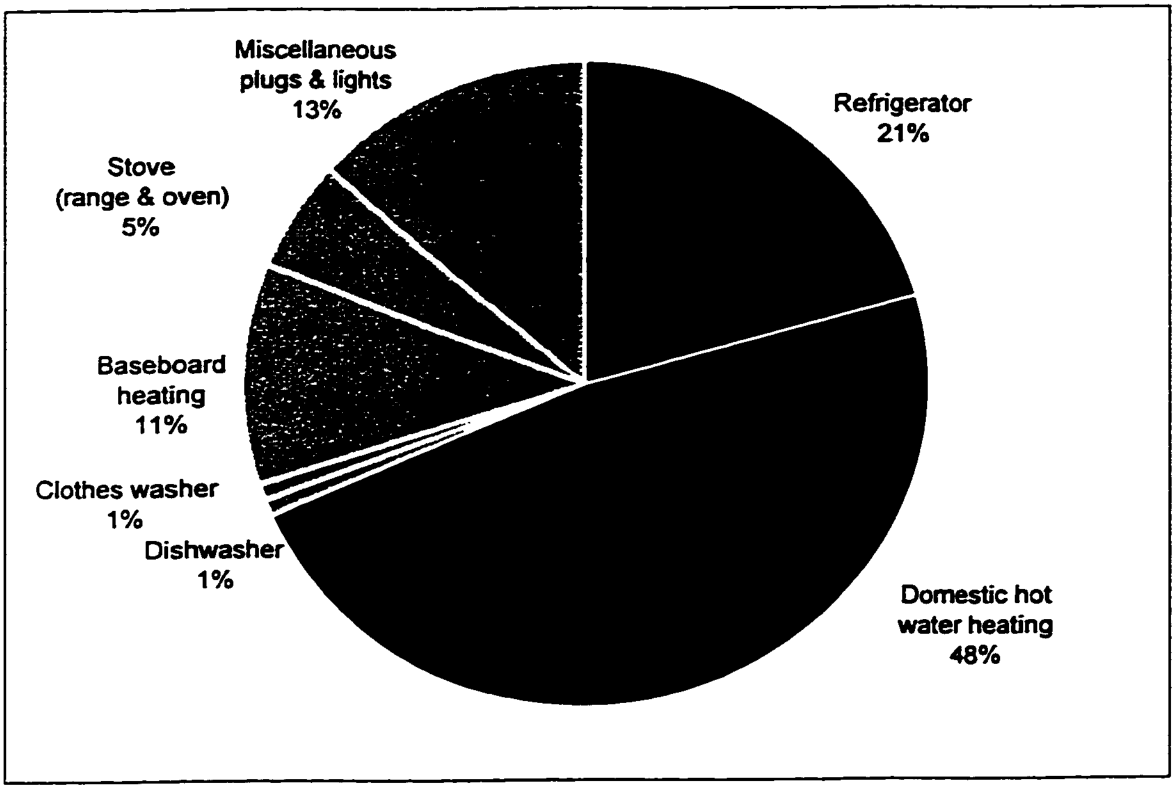


Figure 4.2 Average energy shares for each end-use monitored during the training period

Combined, the DHW heater and the refrigerator consume more than two-thirds (69%) of the electricity used in the whole house. The miscellaneous plugs and lights load is the residual load once the individual monitored loads are subtracted from the Total load. A clothes dryer was present in the house, however, it was not operated during the training period.

The algorithms for the DHW heater and the refrigerator are presented separately in Sections 4.1 and 4.3, respectively, followed by a discussion of each algorithm's results in Sections 4.2 and 4.4.

4.1 Algorithm for the Estimation of the Energy Use for Domestic Hot Water Heating

Domestic hot water heating can be a large expense in a household's energy bill. With the increased use of convenience appliances such as dishwashers and washing machines, and with increased regard towards lifestyle, the costs of water heating have risen significantly over the last decade. A survey of household energy use in Québec indicates that the average DHW heater energy consumption for single-family detached dwellings is 5130 kWh/year [49]. This level of energy use corresponds to 88,220 litres/year or an average of 242 litres/day of hot water, assuming a constant inlet water temperature of 10°C and a supply water temperature of 60°C.

The amount of energy used to heat water is dependent upon several factors, including: (i) the number of persons in the household and their personal habits, (ii) the types of water-using appliances and their frequency of use, (iii) the thermostat setting on the storage tank, and (iv) heat losses from the storage tank, piping system, and leaky faucets. The nonlinear nature of these factors and their variation across houses poses a large obstacle to accurately estimate the contribution of the DHW heater load to the total load of a house based on traditional methods.

To circumvent this problem, the DHW heater load is obtained from the recognition of the DHW demand profile within the Total demand profile using a top-to-bottom rule-based algorithm. The application of the algorithm is outlined in Figure 4.3. The algorithm consists of three stages: (i) the detection of ON and OFF appliance events by their respective energy signatures, (ii) the estimation of the appliance's demand profile, and (iii) the calculation of the appliance's energy load. The notation (S) is used to indicate the status of the rules, whereby S is 1 if the rule passes and S is 0 is the rule fails or is nul.

The first stage of the algorithm involves the application of five rules. These rules are used to identify all possible start and end events from the Total demand profile. The first rule, or the *state change detection* rule (labeled HW1), is applied to determine a preliminary set of possible start and end events based solely on the detection of a given step-increase or decrease in the Total demand profile. The following three rules: the *profile vector norm* rule (labeled HW2), the *number of data points* rule (labeled HW3), and the *Total demand* rule (labeled HW4) are then applied to each possible event. An aggregate and weighted score of the performance for these three rules is then attributed to each possible event. This score is used to confirm or refute the occurrence of an event as recognized by the first rule (HW1). With the exception of the *number of data points* rule, the outcome of the scores of the *profile vector norm* rule and the *Total demand* rule can not directly refute an event. Next, the *minimum score* rule (labeled HW5) is used to filter out the weak events from the data set of possible events, that is, those events with low aggregate scores. The remaining set of selected start and end events proceed to the second stage of the algorithm, in which the daily demand profile of the DWH heater is constructed, and the daily load duration is estimated.

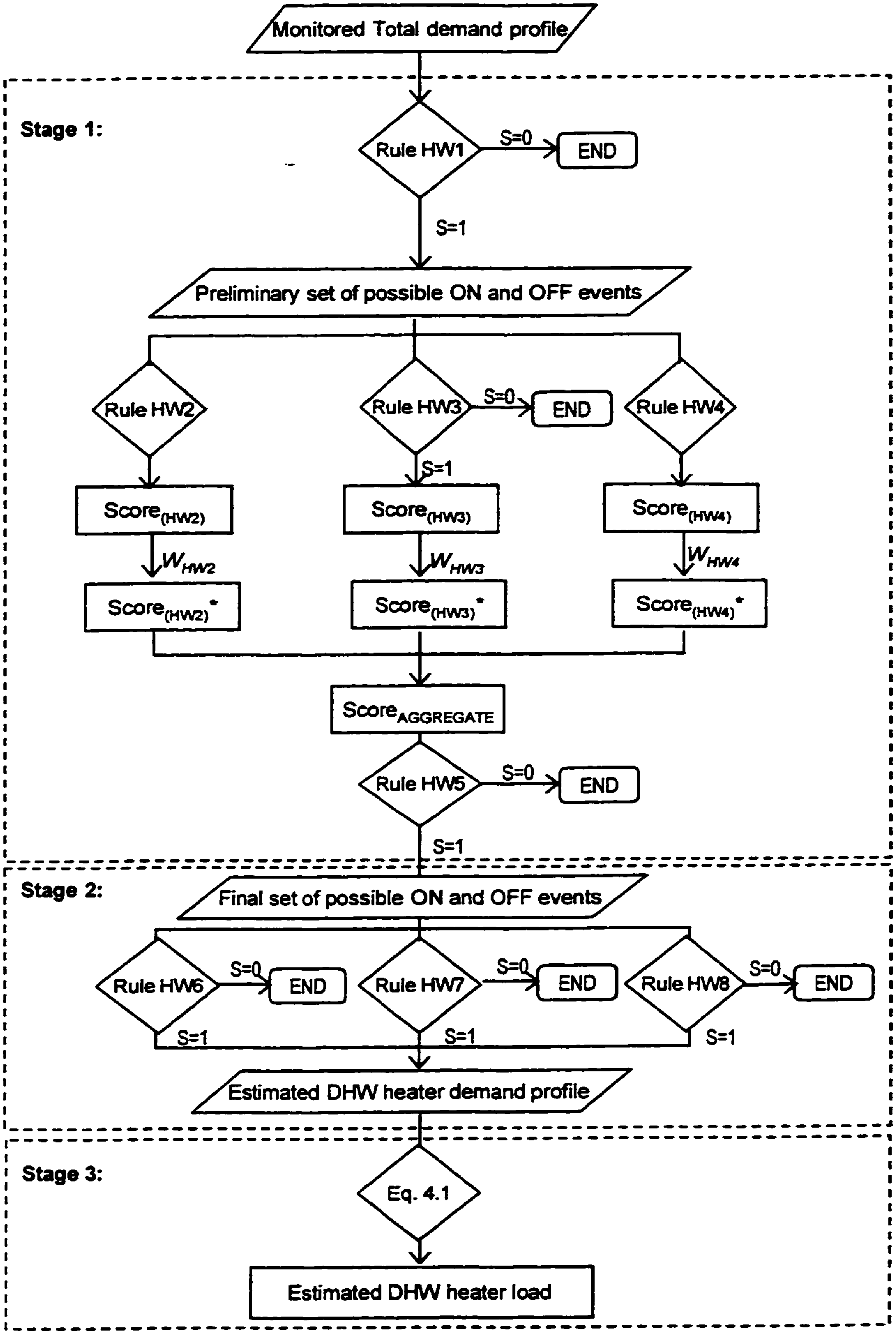


Figure 4.3 Flowchart of the Pattern Recognition Algorithm for the DHW heater

The second stage of the algorithm consists of three constraining rules: the ***highest scoring event*** rule (labeled HW6), the ***minimum ON and OFF interval*** rule (labeled HW7), and the ***minimum Total demand*** rule (labeled HW8). Unlike the first stage of the algorithm where the rules focus on the detection of the appliance energy signature, the aim of this set of rules is to verify that the DHW heater ON periods estimated in the first stage of the algorithm are consistent with the frequency of appliance usage observed from the training data. Similar to rule HW1 and HW3, these rules are applied on a pass or fail basis. That is, an event is either confirmed as a start event or it is recognized as a false start event. If it is recognized as a false event it is eliminated from the data set of possible events. Consecutive start and end events are then linked together to obtain the sequence of activation periods of the DHW heater. Once the ON and OFF periods of the appliance are determined, the DHW heater energy consumption for the duration of the day is calculated using Equation 4.1.

$$\text{Energy use} = \sum_{i=1}^{n} S_i \times \Delta t \times \text{Demand}_{\text{AVERAGE}} \qquad \left(\text{Watt}\cdot\text{hours}/_{\text{day}}\right) \tag{4.1}$$

Where, S_i is 1 indicating the appliance is estimated to be ON at time-step (i) else S_i is 0; Δt is the sampling rate, that is, the time interval at which the Total demand is monitored (16 seconds or 1/225 hour); and $\text{Demand}_{\text{AVERAGE}}$ is the average electric demand of the DHW heater observed from the training data, and is 4455 Watts.

The estimated DHW heater demand profile is obtained by plotting $\text{Demand}_{\text{AVERAGE}}$ for all estimated ON intervals of the appliance against time. Although the duration of the appliance load is obtained from the analysis of the ΔTotal profile, the appliance demand is assumed to be constant, equivalent to the average electric demand observed from the training data.

The algorithm processes the energy signature of an appliance cycle using three separate segments: the start, middle, and end of each cycle (Figure 4.4). The boundaries for each segment of the appliance energy signature are determined based on distinct changes in the demand profile during a cycle. For example, it is noticed that significant changes in the ΔTotal profile occur during the first six time-steps of a cycle in the case of a start event, and in the last six time-steps of a cycle in the case of an end event. The middle or steady-state segment remains approximately constant, therefore, this portion of the cycle is not distinguishable in the ΔTotal profile. Hence, the algorithm identifies the start and end events separately, and then joins the times of consecutive start and end events to obtain a sequence of load intervals when the DHW heater is estimated to be in use. An appliance cycle is described by the complete duration of a load from start to end. Whereas, an event is described by a change in status of an appliance, that is, either from OFF to ON or ON to OFF. Thus, by definition, a cycle consists of two events: an ON event (herein called 'start') and an OFF event (herein called 'end').

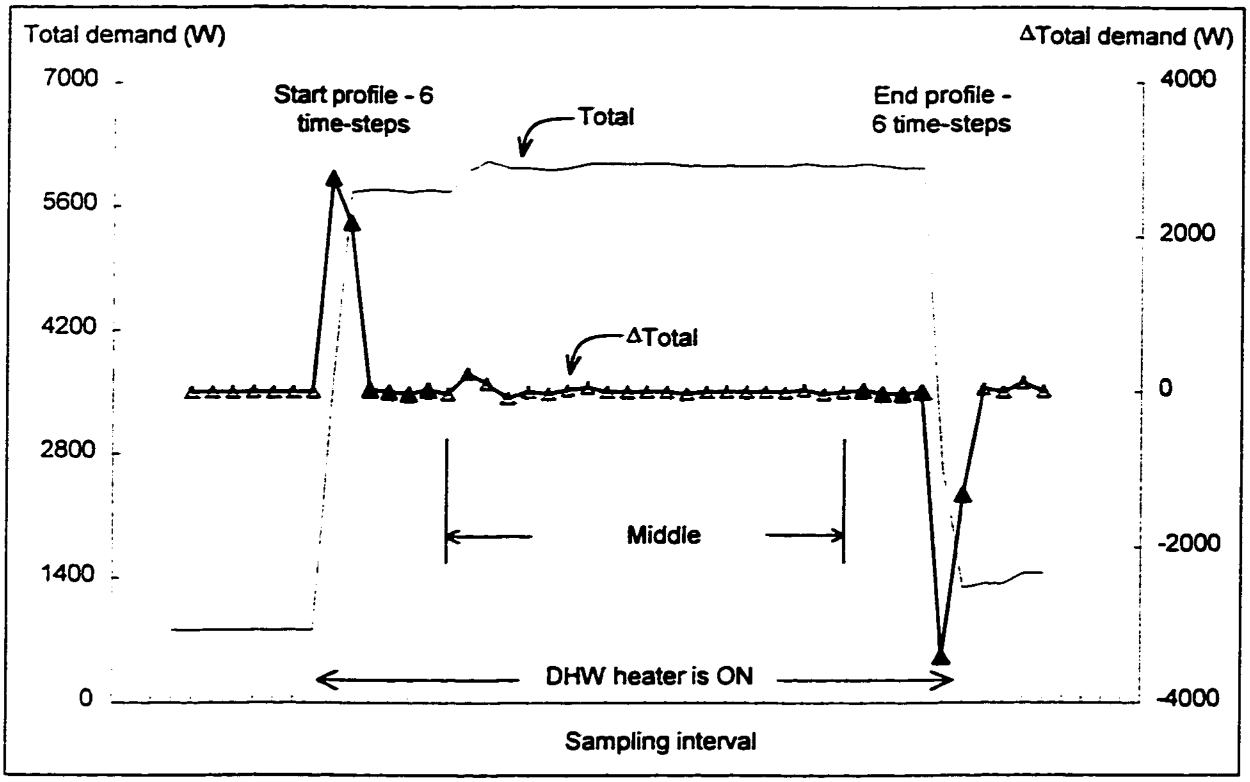


Figure 4.4 Decomposition of a DHW heater energy signature

The appliance energy signature is developed as a function of ΔTotal, whereby ΔTotal is the difference in Total demand levels, and is calculated as ($Total_i - Total_{i-1}$). This way the effects of other loads in the energy signature are expected to cancel out, except in the case of two simultaneous ON or OFF events. Thus, an assumption in the development of these algorithms is that there are no simultaneous events occurring (e.g. no more than one appliance is turned ON or OFF at any given time). This implies that an end or start event is not masked by the end or start event of another appliance. In Figure 4.4, the Total demand is read on the left axis, whereas, the difference in the Total demand (or ΔTotal) is read on the right axis.

Sections 4.1.1 to 4.1.8 describe the eight rules that compose the DHW heater algorithm.

4.1.1 Rule HW1: State change detection

The *state change detection* rule scans the ΔTotal profile for any step-increase or decrease that is within the range of variation monitored during the training period. This *"a priori"* information is determined by analyzing the ΔTotal demand levels at the start and end of a random sample of DHW heater cycles from the training data.

Explicitly, the *state change detection* rule states:

IF: ($X_{MIN\text{-}START} \leq (x_i + x_{i+1}) \leq X_{MAX\text{-}START}$) THEN: $S_i = 1$

ELSEIF: ($X_{MIN\text{-}END} \geq (x_n + x_{n-1}) \geq X_{MAX\text{-}END}$) THEN: S_n=1 ELSE: nul

HW1

Where, x_i is the step-increase observed in the Total demand profile at time-step (i) and is calculated as ($Total_i - Total_{i-1}$); x_n is the step-decrease observed in the Total demand profile at time-step (n) and is calculated as ($Total_n - Total_{n-1}$); $X_{MIN\text{-}START}$ is the minimum step-increase observed from the training data for ($x_i + x_{i-1}$) at the start of a cycle (2348 Watts); $X_{MIN\text{-}END}$ is the minimum step-decrease observed from the training data for ($x_n + x_{n-1}$) at the end of a cycle (-4200 Watts); and $X_{MAX\text{-}START}$ and $X_{MAX\text{-}END}$ are artificial upper and lower limits imposed by the algorithm

(9999 and -9999 Watts); S_i is 1 indicating a possible start event at time-step (i); and S_n is 1 indicating a possible end event at time-step (n). Since the DHW heater has the highest demand of the appliances monitored, imposing upper limits on the step-increase or decrease is not necessary. However, this is a generic algorithm that will be used to recognize other appliance energy signatures as well, thus, upper limits are included in the rule structure. In summary, if the first part of rule HW1 yields, a start event is recognized at time-step (i). Whereas, if the second part of rule HW1 yields an end event is recognized at time-step (n).

The step-increase considered by rule HW1 is the sum of two consecutive time-steps (x_i and x_{i+1}), rather than just one time-step (x_i). Similarly, the step-decrease is the sum of (x_n and x_{n-1}), rather than (x_n) alone. The reason being that although, electric water heaters are steady-state appliances which are depicted by discrete state-changes - due to the small sampling interval selected, start or end events are sometimes measured as continuously transient events composed of two consecutive step-increases or decreases. Figure 4.5 illustrates two examples of start profiles as measured for the DHW heater. One profile depicts one step-increase to the steady-state demand, whereas, the other profile depicts two consecutive step-increases to the steady-state demand. Also, a two step-increase may not necessarily be linear, as is the case shown in Figure 4.5. The likelihood of this behavior appearing in interval monitored data decreases as the sampling interval increases.

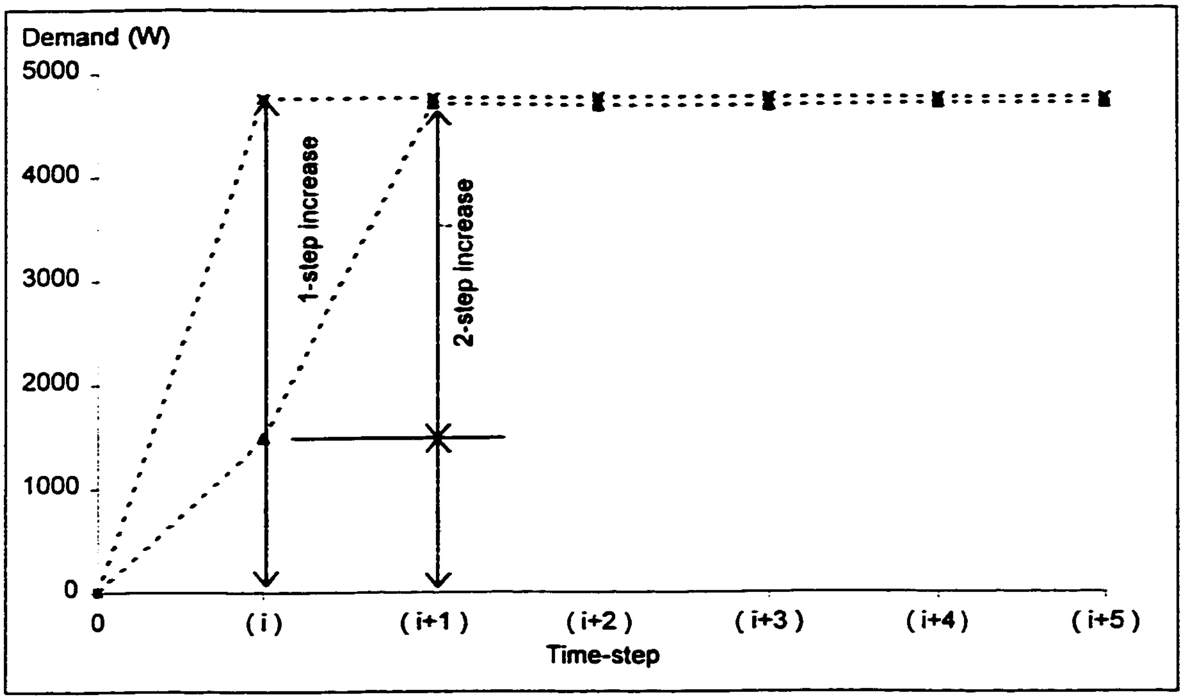


Figure 4.5 Comparison of two start profiles as measured for the DHW heater

The prototypical Pattern Recognition Algorithm is applied to the data on a daily basis with no regard to the transfer of results from one day to the next. Therefore, if an appliance is activated before 12:00 PM and operates into the following day, rule HW1 will not be able to detect the appliance within the ΔTotal demand profile on the second day because it did not detect an initial ON event. For the current prototype of the algorithm, if an appliance is in use during the first time-step of the day, the status of the appliance for rule HW1 is input manually, whereby, S_i is 1.

4.1.2 Rule HW2: Profile vector norm

The *profile vector norm* rule consists of calculating the vector norm of an appliance's energy signature (expressed as ΔTotal) with respect to the average start or end energy signature observed from the training data. This rule is based on the observation that the DHW heater start and end profiles are, in terms of pattern and demand level, distinguishable from those of other major appliances in the house. Figure 4.6 shows typical energy signatures for each of the six appliances

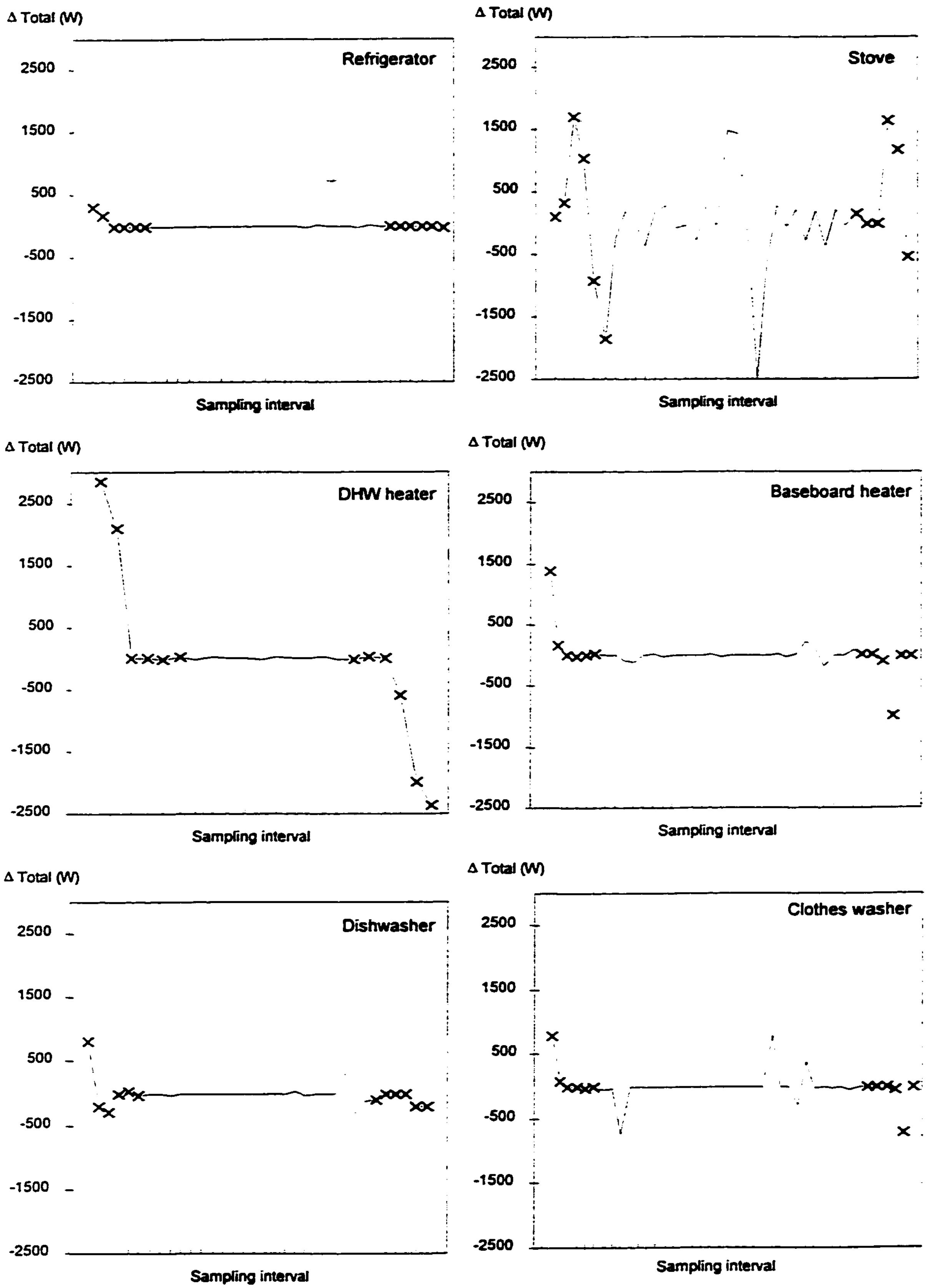


Figure 4.6 Typical appliance energy signatures for each monitored appliance

monitored, as a function of ΔTotal. The highlighted points on each profile illustrate the start and end boundaries considered by the algorithm.

The amplitude of the DHW heater signature distinguishes it from that of any other monitored appliance. The baseboard heater, dishwasher, and clothes washer all reveal intermediary step-decreases before the end of the cycle depicting multi-state operation. It is noticed that the stove's energy signature has the most fluctuations, which is likely due to the flickering heating elements.

The average start and end demand profiles of the DHW heater observed from the training data are listed in Tables 4.1 and 4.2. Negative values in the start profiles or positive values in the end profiles suggest that either another appliance turned OFF or ON during that sampling interval or that there are fluctuations in the load due to varying utility voltage.

Table 4.1 Start demand profiles for the DHW heater (expressed as ΔTotal – Watts)

Time-step	Pure profiles						Mixed profiles				Average Profile	Standard deviation
	1	2	3	4	5	6	1	2	3	4	C_i	
(i)	4757	4920	4704	1491	3910	3861	3678	2682	2620	2097	3472	
($i+1$)	0	-54	135	3212	847	870	0	2154	3621	0	1079	
($i+2$)	0	0	27	-27	0	0	-81	0	0	0	-8	
($i+3$)	0	0	0	0	0	-27	-27	0	0	-27	-8	
($i+4$)	0	0	0	27	0	27	0	-244	-766	27	-93	
($i+5$)	0	0	0	0	0	0	0	0	-807	-27	-83	
Norm-6	687	752	635	1190	209	190	452	549	1167	715	583	233
Norm-5	75	113	104	71	75	76	438	115	839	[illegible]	133	76

Table 4.2 End demand profiles for the DHW heater (expressed as ΔTotal – Watts)

Time-step	Pure profiles						Mixed profiles				Average Profile	Standard deviation
	1	2	3	4	5	6	1	2	3	4	C_n	
($n-5$)	27	54	-27	0	0	54	-27	0	-81	-27	-3	
($n-4$)	-27	0	0	0	0	54	27	27	27	-27	8	
($n-3$)	0	0	0	0	0	0	0	-27	-27	27	-3	
($n-2$)	27	0	27	27	0	0	-27	0	0	0	5	
($n-1$)	0	-2379	-1833	-874	-3266	-3370	27	0	-3169	-2748	-1761	
(n)	-4785	-2541	-3033	-3829	-1491	-1469	-4733	-4813	-1034	-2201	-2993	
Norm-6	719	254	32	362	614	658	730	719	576	403	507	195
Norm-5	788	286	60	398	673	721	[illegible]	788	676	450	564	212

The profiles are grouped as either pure or mixed based on whether the appliance start or end event occurred alone or concurrently with other appliances in the house. Both pure and mixed profiles are considered in the algorithm so as to determine probable ranges of performance criteria for the data which includes the effects of random noise in the Total demand profile.

As a result of the relatively small sample size selected, a robust average demand profile is required, that is, one that is unbiased to large variations in a small fraction of the data. For this reason, the sample profiles are examined visually and any unusual profiles are excluded. For example, in Table 4.1, mixed profiles (3) and (4) are not considered in the average start demand profile for the time-steps (i) and ($i+1$).

The vector norm, defined as the distance between the average start or end profile and a possible start or end profile, is calculated using two approaches. The first approach is to consider the first six time-steps from a start event at time-step (i) (labeled norm-6 in Tables 4.1 and 4.2), and the second approach is to consider the first two time-steps from a possible start at time-step (i) as one point and the next four time-steps as separate points (labeled norm-5 in Tables 4.1 and 4.2). Norm-6 is calculated using Equation 4.2 and norm-5 is calculated using Equation 4.3.

$$\text{Norm-6}_i = \sqrt{\left(\frac{(x_i - C_i)^2 + (x_{i+1} - C_{i+1})^2 + (x_{i+2} - C_{i+2})^2 + (x_{i+3} - C_{i+3})^2 + (x_{i+4} - C_{i+4})^2 + (x_{i+5} - C_{i+5})^2}{6}\right)} \tag{4.2}$$

$$\text{Norm-5}_i = \sqrt{\left(\frac{((x_i + x_{i+1}) - (C_i + C_{i-1}))^2 + (x_{i+2} - C_{i+2})^2 + (x_{i+3} - C_{i+3})^2 + (x_{i+4} - C_{i+4})^2 + (x_{i+5} - C_{i+5})^2}{5}\right)} \tag{4.3}$$

Where, x_i is the step-increase observed in the ΔTotal demand profile at the time-step (i); and C_i is the average start demand profile listed in Table 4.1. To apply Equations 4.2 and 4.3 to an end event, the sequence of time-steps {i, $i+1$, $i+2$, $i+3$, $i+4$, and $i+5$} is substituted by {n, $n-1$, $n-2$, n-

3, *n-4*, and *n-5*}, where, (*n*) is the time-step at which a possible end event is identified by rule HW1; and C_n is the average end profile listed in Table 4.2.

The results shown in Table 4.1 indicate that those profiles with a one step-increase pattern yield higher values for norm-6 (687 Watts) than for norm-5 (75 Watts) because the average demand profile characterizes a two step-increase pattern. Thus, to reduce the norm value for these profiles, time-steps (*i*) and (*i+1*) for start events, and time-steps (*n*) and (*n-1*) for end events are aggregated and evaluated as one point, rather than individually. As a result, the average standard deviation for the sampling group for norm-5 (76 Watts) is considerably lower than the average standard deviation for norm-6 (233 Watts). Since a vector norm with a small value is desired, norm-5 is selected as the basis of evaluation for the *profile vector norm* rule.

Explicitly, the *profile vector norm* rule states:

$$\text{IF: } \left(\text{norm}-5_i \leq \text{norm}-5_{\text{REFERENCE-START}}\right) \text{ THEN: } \text{Score}_{\text{rule HW2}} = 1$$

$$\text{ELSE: } \text{Score}_{\text{rule HW2}} = \left(\frac{\text{norm}-5_{\text{REFERENCE-START}}}{\text{norm}-5_i}\right)$$

HW2

Where, norm-5_i is calculated using Equation 4.3; and norm-$5_{\text{REFERENCE-START}}$ is 285 Watts, and is calculated as the average vector norm (133 Watts) plus two standard deviations (2 x 76 Watts) for a sample of start profiles observed from the training data (Table 4.1). To apply rule HW2 to an end event, norm-5_i is substituted by norm-5_n; and norm-$5_{\text{REFERENCE-START}}$ is substituted by norm-$5_{\text{REFERENCE-END}}$, where norm-$5_{\text{REFERENCE-END}}$ is 776 Watts, and is calculated as the average vector norm (564 Watts) plus one standard deviation (212 Watts) for a sample of end profiles observed from the training data (Table 4.2). A higher tolerance is accepted for the start profile than the end profile because the standard deviation of the sampling set is more restrictive for the DHW heater start profiles than for the end profiles.

4.1.3 Rule HW3: Number of data points

The *number of data points* rule evaluates the number of time-steps in a possible start and end demand profile whose demand level fall between the maximum and minimum demand levels established from the training data. This rule is developed to reinforce DHW heater events that do not score well in rule HW2 because their profiles deviate from the expected or average demand profile observed from the training data. This allows for some tolerance between the expected profile (verified by rule HW2) and the measured profile to account for noise, variability in the Total demand profile, or the concurrent start or end event of some other appliance. The maximum and minimum demand levels, summarized in Table 4.3, are determined using the same random sample of pure start and end profiles listed in Tables 4.1 and 4.2.

Table 4.3 Maximum and minimum demand profiles for the DHW heater (Watts)

Time-step	Start profile		Time-step	End profile	
	Maximum	Minimum		Maximum	Minimum
(i)	4920	1492	($n-2$)	28	0
($i+1$)	3213	-55	($n-1$)	0	-3371
($i+2$)	28	-28	(n)	-1470	-4785

Figure 4.7 illustrates these ranges for both the start and end profiles. Only the first three time-steps of the start and end profiles are considered in rule HW3 because the 4th, 5th, and 6th time-steps, generally, depict steady-state power draw. These time-steps are zero or near zero in the ΔTotal demand profile, hence, it is difficult to recognize them.

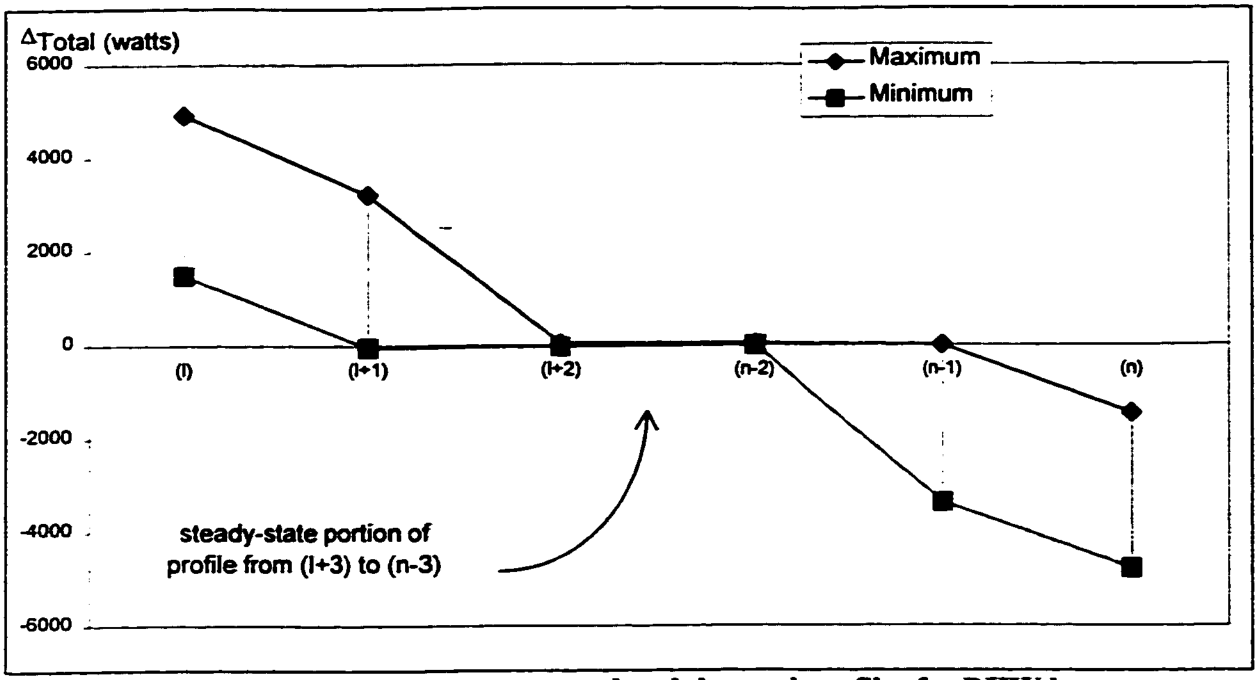


Figure 4.7 Maximum and minimum start and end demand profiles for DHW heater

Explicitly, the *number of data points* rule states:

IF: ($X_{MIN\text{-}START\text{-}1} \leq X_i \leq X_{MAX\text{-}START\text{-}1}$) and ($X_{MIN\text{-}START\text{-}2} \leq X_{i+1} \leq X_{MAX\text{-}START\text{-}2}$) and ($X_{MIN\text{-}START\text{-}3} \leq X_{i+2} \leq X_{MAX\text{-}START\text{-}3}$)

THEN: $Score_{HW3}$ = 1 and S_i = 1

ELSEIF: 2 out of the first 3 time-steps of a start profile fall between the maximum and minimum demand levels and

($\text{norm-}5_i \leq \text{norm-}5_{MAX\text{-}START}$)

THEN: $Score_{HW3}$ = 0.5 and S_i = 1 ELSE: $Score_{HW3}$ = 0 and S_i = 0

HW3

Where, $X_{MIN\text{-}START\text{-}1}$ is 1492 Watts; $X_{MIN\text{-}START\text{-}2}$ is –55 Watts; $X_{MIN\text{-}START\text{-}3}$ is –28 Watts; $X_{MAX\text{-}START\text{-}1}$ is 4920 Watts; $X_{MAX\text{-}START\text{-}2}$ is 3213 Watts; $X_{MAX\text{-}START\text{-}3}$ is 28 Watts; norm-5_i is calculated using Equation 4.3; and norm-$5_{MAX\text{-}START}$ is 1141 Watts, and it is selected as the maximum vector norm of pure and mixed start profiles observed from the training data (Table 4.1). To apply rule HW3 to an end event, the sequence of time-steps $\{i, i+1, i+2\}$ is substituted by $\{n, n-1, n-2\}$; $X_{MIN\text{-}START\text{-}1}$, $X_{MIN\text{-}START\text{-}2}$, $X_{MIN\text{-}START\text{-}3}$, $X_{MAX\text{-}START\text{-}1}$, $X_{MAX\text{-}START\text{-}2}$, and $X_{MAX\text{-}START\text{-}3}$ is substituted by $X_{MIN\text{-}END\text{-}1}$, $X_{MIN\text{-}END\text{-}2}$, $X_{MIN\text{-}END\text{-}3}$, $X_{MAX\text{-}END\text{-}1}$, $X_{MAX\text{-}END\text{-}2}$, and $X_{MAX\text{-}END\text{-}3}$; norm-$5_i$ is substituted by norm-5_n; and norm-$5_{MAX\text{-}START}$ is substituted by norm-

$5_{MAX-END}$, where, norm-$5_{MAX-END}$ is 800 Watts, and it is selected as the maximum vector norm of pure and mixed end profiles observed from the training data (Table 4.2).

4.1.4 *Rule HW4: Total demand*

The *Total demand* rule reinforces the recognition of a DHW heater event when the Total demand level is high. This rule is based on the assumption that the probability of recognizing a start or end event of the DHW heater increases as the Total demand increases. Figure 4.8 compares the demand levels, illustrated as one standard deviation above and below the mean, for each monitored appliance. The results indicate that the DHW heater has the highest demand level among the monitored appliances.

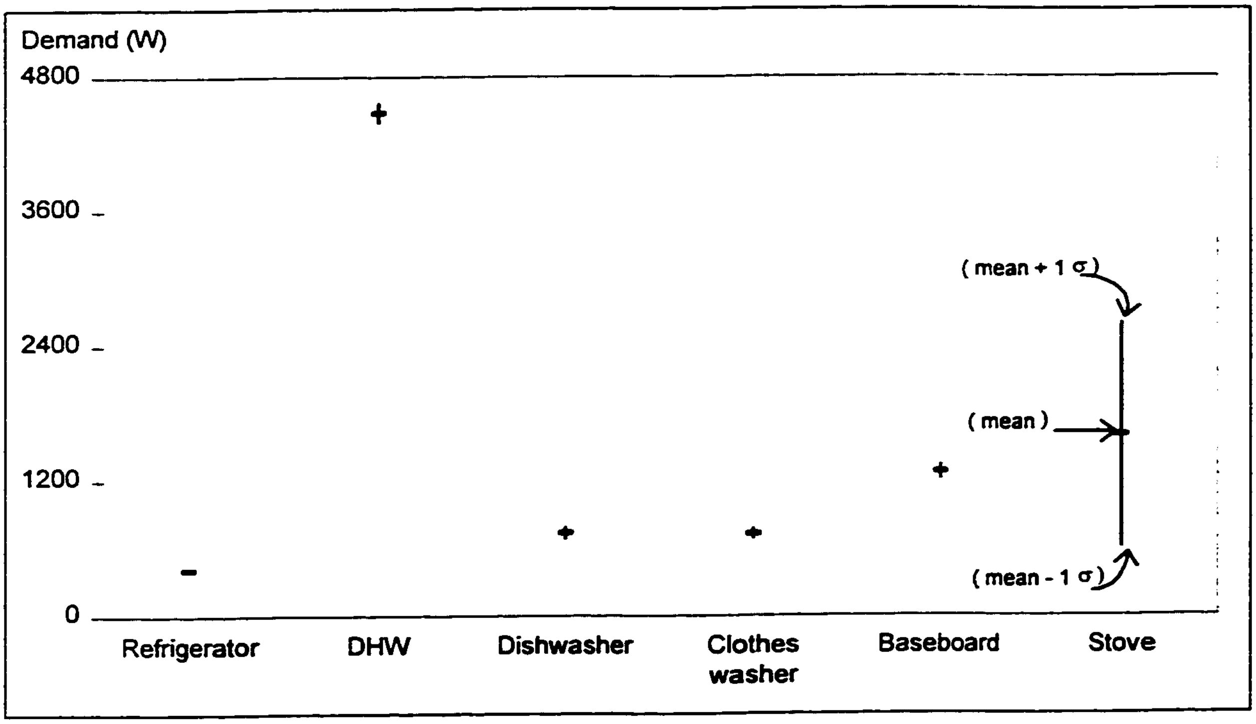


Figure 4.8 Demand levels for different end-uses observed from the training data

In some instances, the Total demand may be due to the concurrent operation of several end-uses, other than the DHW heater, whose demand levels add up to be equal to the demand level of the DHW heater alone. The results of an analysis of the Total demand during DHW heater ON and OFF periods from the training period is presented in Figure 4.9. The results show that there is a clear distinction between the two following scenarios: (i) a DHW heater in use alone (represented by the upper line), and (ii) the concurrent operation of several other appliances (represented by the lower line).

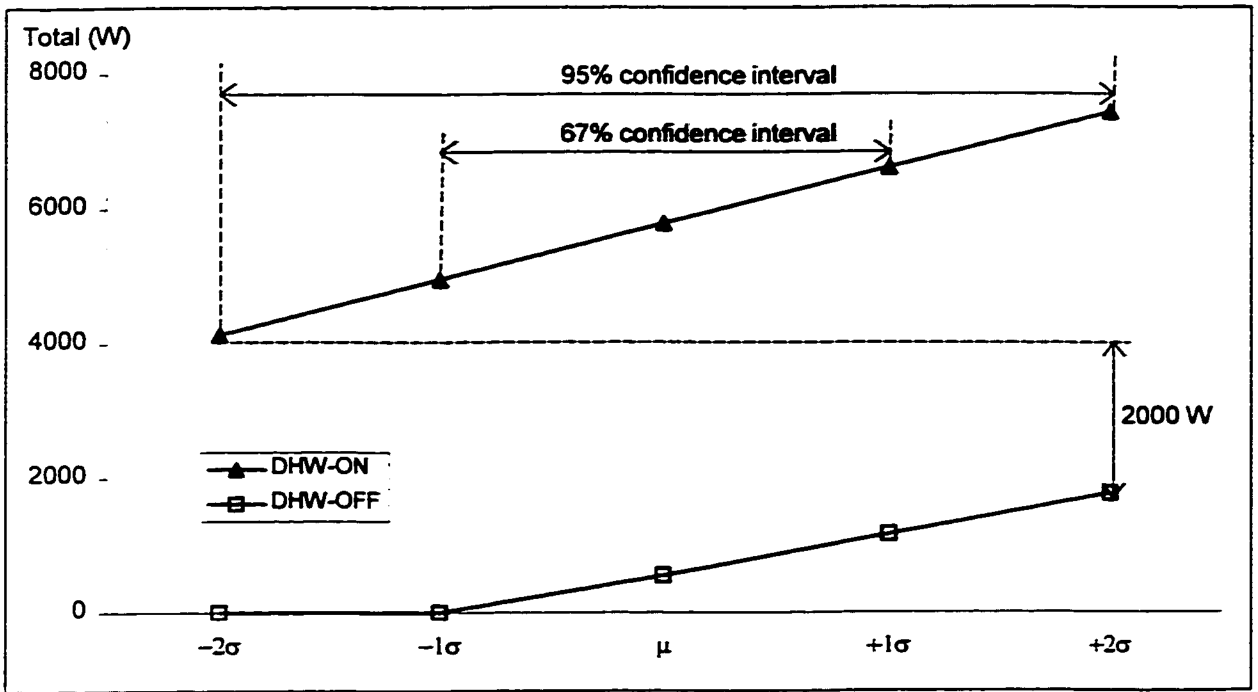


Figure 4.9 Comparison of the Total demand for DHW heater ON and OFF periods

The difference in the Total demand for the two inner extremes of the line profiles in Figure 4.9 is significant (approximately 2000 Watts). Thus, assuming that the monitored data is normally distributed, when the DHW heater is ON, the probability that the Total demand is less than the lower limit of the top line shown in Figure 4.9, corresponding to the mean minus two standard deviations (μ - 2σ), is very low (<2.5%).

The scoring scheme for rule HW4 is evaluated using a continuous unipolar function with an asymptotic variation when the Total demand approaches a very low or a very high level, defined by two standard deviations above or below the mean. This function is plotted in Figure 4.10.

Explicitly, the *Total demand* rule states:

$$\text{Score}_{\text{rule HW4}} = \left(\frac{1}{1+e^{\left(-\lambda \times \left(TL_{i,avg} - \mu\right)\right)}} \right) \qquad \textbf{HW4}$$

Where, λ is 0.0017845 and it is calculated by considering that 95% of all measurements of the Total demand are within the mean plus or minus two standard deviations; $TL_{i,avg}$ is the average Total demand for time-step (*i*) and it is calculated using Equation 4.4; and the constant μ is 5782 Watts and corresponds to the average Total demand observed during DHW heater ON periods from the training data.

The maximum Total demand observed is 7432 Watts, and it is assigned a score of 0.95 out of 1.0. This value is illustrated in Figure 4.10 by the point of coordinates x = 7432 and y = 0.95. The average Total demand (μ) observed is 5782 Watts, and it is assigned a score of 0.5 out of 1.0. This value is illustrated in Figure 4.10 by the point of coordinates x = 5782 and y = 0.50.

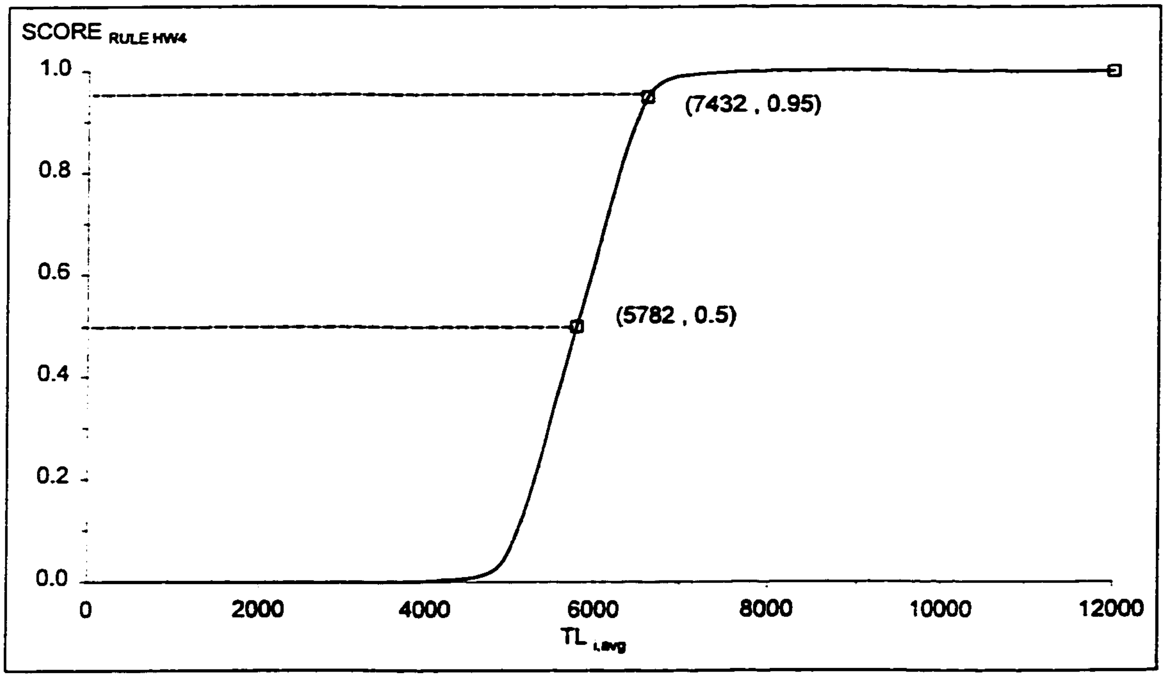


Figure 4.10 Continuous unipolar function used to evaluate rule HW4

$$TL_{i,avg} = \left(\frac{TL_{i+2} + TL_{i+3} + TL_{i+4} + TL_{i+5}}{4} \right) \quad \textbf{(4.4)}$$

Equation 4.4 does not consider the time-steps (i) and ($i+1$) to calculate $TL_{i,avg}$ because the demand monitored during the first two time-steps is not representative of the steady-state demand level.

4.1.5 Rule HW5: Minimum score

Before proceeding to the second stage of the algorithm, the data set of possible start and end events is evaluated using the ***minimum score*** rule and the aggregate score of rules HW2, HW3, and HW4. Rule HW5 consists of two parts – the first part calculates the aggregate score of each possible event, and the second part applies a filter to remove false events that typically are characterized by low scores.

The aggregate score for each start or end event is normalized to a value between 0 and 1, using rule-specific weight factors. These factors are selected so as to maximize the score of actual events and minimize the score of false events. This concept stems from the Generalized Delta Rule that is used in neural network applications to train a Back Propagation Network. Whereby, the neural network's connection weights are adjusted to reduce the output error based on the difference between the produced and target model outputs. Similar to the Generalized Delta Rule, the weight factors for rule HW5 are determined based on the performance of actual start and end events observed from the training data. Whereby, the average contribution of each rule's score to the aggregate score for actual events is determined (Table 4.4). For instance, for the training day of October 14, the average contribution to the aggregate score for actual start events is 0.35 for rule HW2, 0.38 for rule HW3, and 0.27 for rule HW4. The applied weight factors for start and end events are 0.40 for rule HW2, 0.40 for rule HW3, and 0.20 for HW4.

Table 4.4 Selection of weight factors for rule HW5

Training day (October 1996)	START events			END events		
	W_{HW2}: vector norm	W_{HW3}: # points	W_{HW4}: Total load	W_{HW2}: vector norm	W_{HW3}: # points	W_{HW4}: Total load
14	0.35	0.38	0.27	0.43	0.31	0.26
15	0.40	0.41	0.19	0.41	0.40	0.19
16	0.42	0.43	0.15	0.43	0.43	0.15
17	0.40	0.41	0.19	0.43	0.41	0.15
18	0.39	0.40	0.21	0.43	0.44	0.13
19	0.37	0.39	0.24	0.46	0.32	0.22
Average	0.39	0.40	0.21	0.43	0.39	0.18
Weight applied	0.40	0.40	0.20	0.40	0.40	0.20

Actual start or end events observed from the training data, typically, yield fairly high scores - on average 0.8 out of a maximum of 1.0 with an average standard deviation of about 0.1 for start events and end events. This indicates that, generally, the algorithms are able to recognize actual DHW heater events with a high certainty, repeatedly. However, transient appliances, such as, the stove or other miscellaneous plug loads, generally trigger false events because the demand of these appliances may cycle as high as the demand of the DHW heater. In this case, the first stage of the algorithm will signal the occurrence of a possible start or end event, which is in fact a false event. Typically, these events yield low aggregate scores. Therefore, once the aggregate score is normalized the second part of rule HW5 applies a minimum cut-off score to remove false events from the set of possible start and end events.

The cut-off score applied in the second part of rule HW5 is selected to be equal to the average aggregate score of actual events from the training period minus three standard deviations, that is, 95% of all events are included. This is equal to a score of 0.513 for start events and 0.531 for end events. Hence, the rounded value of 0.500 is applied for both start and end events.

Figure 4.11 illustrates the scores of actual start events observed from the training data, at three stages in the application of the Pattern Recognition Algorithm. The top figure illustrates the range of aggregate scores for rules HW2, HW3, and HW4 if these rules are applied to all time-steps in the training data. The second figure illustrates the range of aggregate scores for rules

HW2, HW3, and HW4 if these rules are applied to all time-steps in the training data that satisfy rule HW1. The bottom figure illustrates the range of aggregate scores for rules HW2, HW3, and HW4 is these rules are applied to only actual start events in the training data.

For rule HW5 to be effective, the aggregate scores of actual events should increase significantly as additional rules are applied, whereas, the aggregate score of false events should decrease as additional rules are applied. In fact, this pattern is shown in Figure 4.11 – there is an apparent trend of increasing average scores and decreasing maximum-to-minimum range of scores. In this case, if a cut-off score of 0.5 is applied to the events in the bottom figure, with the exception of the minimum score for October 14, 17 and 19, the score for all actual events exceeds the cut-off score.

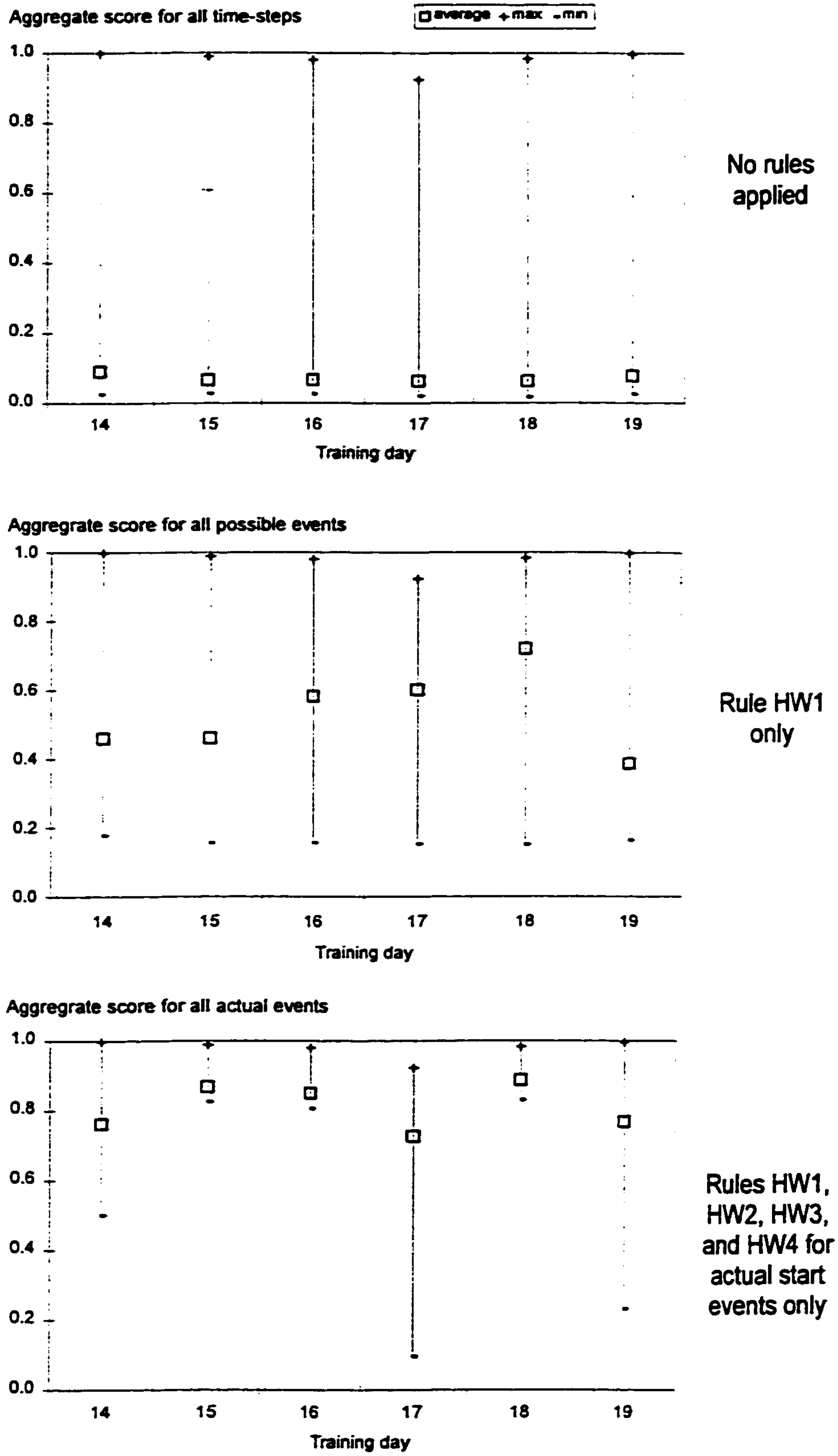


Figure 4.11 Scores for start events at 3 stages in the DHW heater algorithm

Explicitly, the *minimum score* rule states:

IF: ($Score_{AGGREGATE,i}$ > $Score_{CUTOFF\text{-}START}$) where, $Score_{AGGREGATE,i} = (Score_{HW2,i} \times W_{HW2}) + (Score_{HW3,i} \times W_{HW3}) + (Score_{HW4,i} \times W_{HW4})$ THEN: $S_i = 1$ ELSE: nul and $S_i = 0$ **HW5**

Where, $Score_{AGGREGATE,i}$ is the aggregate score for rules HW2, HW3, and HW4 for a possible start event at time-step (i); $Score_{CUTOFF\text{-}START}$ is 0.5; W_{HW2} is 0.4, W_{HW3} is 0.4, and W_{HW4} is 0.2; and S_i is 1 confirming a DHW heater start event or S_i is 0 refuting a DHW heater start event. To apply rule HW5 to an end event, $Score_{AGGREGATE,i}$ is substituted by $Score_{AGGREGATE,n}$; $Score_{CUTOFF\text{-}START}$ is substituted by $Score_{CUTOFF\text{-}END}$; and S_i is substituted for S_n, where, S_n is 1 confirming a DHW heater end event or S_n is 0 refuting a DHW heater end event.

4.1.6 Rule HW6: Highest scoring event

The *highest scoring event* rule verifies that the selected start event has the highest score among events within a range of 30 time-steps before and after the event (i). Similarly, the rule verifies that the end event selected has the highest score among events within a range of 30 time-steps before and after the event (n). The reason for imposing this constraint is again to remove false events that may have gone undetected so far.

Explicitly, the *highest scoring event* rule states:

IF: $S_i = 1$ and $Score_{AGGREGATE,i}$ > MAX $Score_{AGGREGATE}$ for the intervals $\{(i-30), \ldots, (i-1)$ and $(i+1), \ldots, (i+30)\}$ THEN: $S_i = 1$ ELSE: nul and $S_i = 0$ **HW6**

Where, S_i is 1 confirming an appliance start event or S_i is 0 refuting an appliance start event; and $Score_{AGGREGATE,i}$ is calculated using rule HW5. Similarly, to select the highest scoring end event the range $\{(i-30),\ldots,(i-1)$ and $(i+1),\ldots,(i+30)\}$ is substituted by the range $\{(n-30),\ldots,(n-1)$ and $(n+1),\ldots,(n+30)\}$; and S_i is substituted by S_n.

The range of 30 time-steps before and after event (*i*) is selected based on the observation that the minimum duration of activation of the DHW heater from the training period is 19 time-steps (304 seconds) and the minimum time interval between consecutive DHW heater cycles is 13 time-steps (208 seconds). Thus, the rounded value of 30 time-steps is selected as the minimum time interval between any two events of the same type (e.g. ON/ON or OFF/OFF). Table 4.5 lists the duration of ON and OFF periods for the DHW heater observed from the training data.

Table 4.5 Duration of ON/OFF periods for the DHW heater (time-steps)

Cycle	October 14		October 15		October 16		October 17		October 18	
	OFF	ON	OFF	ON	OFF	ON	OFF	ON	OFF	ON
1		26		53		297		62		24
	243		13		83		349		191	
2		71		57		19		27		29
	226		43		436		396		92	
3		271		31		21		42		40
	137		302		721		354		553	
4		44		34		20		26		21
	116		400		543		1000		1034	
5		40		69		20		27		26
	29		738		635		868		472	
6		49		29		22		27		72
	112		1104		550		344		488	
7		37		22		51		226		54
	98		565		401		427		48	
8		94		54		50		23		70
	128		34		84		591		85	
9		37		38		20		27		44
	146		27		1030		332		201	
10		61		67						31
	170		50						631	
11		176		76						21
	31		431							
12		270		25						
	27		790							
13		25		25						
	1346									
Sample size	13	13	12	13	9	9	9	9	10	11
Minimum duration	29	25	13	22	83	19	332	23	48	21

4.1.7 Rule HW7: Minimum ON and OFF interval

The ***minimum ON and OFF interval*** rule verifies that a proposed change in state of the appliance (OFF to ON or ON to OFF) is in accordance with the usual pattern of usage of the appliance, as seen during the training period. In essence, the rule verifies the previously estimated start and end events and confirms or refutes their occurrence based on the historical pattern of usage. The rule states that a positive change in state of the appliance, that is, from OFF to ON is likely to occur at time-step (i) if an end event occurs a minimum of 10 time-steps (160 seconds) prior to the time-step (i). The threshold of 10 time-steps is the rounded value of the minimum duration of inactivity (13 time-steps) of the DHW heater observed from the training data (Table 4.5). A negative change in state of the appliance, that is, from ON to OFF is likely to occur at time-step (n) if a start event occurs a minimum of 15 time-steps (240 seconds) prior to the time-step (n). The threshold of 15 time-steps is the rounded value of the minimum duration of activity (19 time-steps) of the DHW heater observed from the training data (Table 4.5).

Explicitly, the *minimum ON and OFF interval* rule states:

$$\text{IF: } S_i = 1 \text{ and } \sum_{i}^{j=MIN-OFF-TIME} S_{i-j} = 0 \quad \text{THEN: } S_i = 1 \quad \text{ELSE: } S_i = S_{i-1}$$

HW7

Where, S_i is 1 confirming an appliance start event; S_i is equal to S_{i-1} refuting an appliance start event; and MIN-OFF-TIME is the minimum duration of inactivity (10 time-steps) for the DHW heater. To apply rule HW7 to an end event, S_i is substituted by S_n; S_{i-1} is substituted by S_{n-1}; and MIN-OFF-TIME is substituted by MIN-ON-TIME, that is, the minimum duration of activity is 15 time-steps for the DHW heater.

4.1.8 Rule HW8: Minimum Total demand

The *minimum Total demand* rule verifies that if the DHW heater is estimated to be ON, the Total demand is at least as high as the minimum observed steady-state demand of the DHW heater, as measured on the Total demand profile, and observed from the training data. To illustrate the purpose of this rule, consider the case when an OFF event and the immediate ON event of an appliance go undetected or have low scores - the algorithm will connect the previous

ON event with the following OFF event. The resulting cycle could span hours if the appliance is not operated for a long period, and yield a significant error in the estimated energy use.

Explicitly, the *minimum Total demand* rule states:

$$\text{IF}: \sum_{i,j=1}^{j=4} S_{i-j} = 4 \quad \text{and} \quad TL_{i-2} < TL_{\text{MIN-TOTAL-DHW}} \quad \text{THEN}: S_i = 0 \quad \text{and} \quad S_n = 1 \quad \text{ELSE}: \text{nul}$$

HW8

Where, S_{i-j} is 1 indicating that the appliance is estimated to be ON for the time-step (*i-j*); TL_{i-2} is the Total demand at time-step (*i-2*); $TL_{\text{MIN-TOTAL-DHW}}$ is the minimum Total demand (2748 Watts) observed during DHW heater ON periods from the training data; and S_i is 0 indicating that an end event prior to time-step (*i*) has been missed by the algorithm and S_n is 1 indicating that an end event is assumed in order to minimize the algorithm error.

The minimum Total demand ($TL_{\text{MIN-TOTAL-DHW}}$) applied in this rule is higher than the minimum DHW heater demand (2748 Watts) observed during the same periods because the Total demand may include one or more appliances operating concurrently with the DHW heater. However, it is less than the average Total demand observed during DHW heater ON periods (5782 Watts) applied in rule HW4, and the average DHW heater demand (4455 Watts) applied in Equation 4.1. Rules HW8 and HW4 stem from the same basis, that is, that the Total demand is at least as high as the demand of the DHW heater. But, rule HW4 is applied to possible start and end events only, whereas, rule HW8 is applied to all time-steps between estimated start and end events.

4.2 Discussion of Results for the Domestic Hot Water Heater

The Pattern Recognition Algorithm is applied to data from three periods: (i) the training period of October 1996, (ii) the near-to-date testing period of November 1996, and (iii) the far-to-date testing period of January 1997. The ability of the algorithm to recognize and estimate the DHW heater energy use is assessed based on the following three estimated performance indices: (i) daily DHW heater energy use, (ii) daily DHW heater demand profile, and (iii) daily DHW heater share of the Total load [50].

In summary, the DHW heater events, typically, are well defined in the Total demand profile due their high demand level in comparison to other appliances in the house. The main source of error in the testing data is the simultaneous events with the stove.

4.2.1 Daily DHW energy consumption

The error in estimating the DHW energy consumption is calculated with respect to the monitored appliance energy consumption using Equation 4.5. The results are presented in Table 4.6, expressed as percent error and unit error of energy use. Negative percent errors indicate that the algorithm underestimated the actual appliance energy consumption, whereas, positive errors indicate an overestimation.

$$\text{Error} = \left(\frac{\text{Energy use}_{\text{ESTIMATED}} - \text{Energy use}_{\text{MONITORED}}}{\text{Energy use}_{\text{MONITORED}}} \right) \times 100 \quad (\%) \tag{4.5}$$

The average relative error in estimating the DHW heater energy consumption is calculated as the arithmetic average for the group of days in each data period. This value is under 5% for all periods, that is, -1.2%, 2.7%, and 4.7%. The average absolute error is defined as the average difference between the estimated and monitored appliance energy use, and is calculated using the absolute value of the daily relative error. This value is under 7% for all periods, that is, 3.2%, 3.3%, and 6.7%.

Table 4.6 Daily DHW heater energy consumption error

Day	Energy use % (kWh)	Average demand % (Watts)	Load duration % (time-steps)	Actual ON intervals missed % (time-steps)
Training period: October 1996				
14	-10.5 (2.51)	-0.7 (-28)	-9.8 (-118)	13.8 (166)
15	0.3 (0.03)	-0.3 (-11)	0.5 (3)	0.0 (0)
16	-1.4 (0.17)	-1.4 (-63)	0.0 (0)	0.0 (0)
17	-0.2 (0.02)	-0.8 (-36)	-0.6 (-3)	0.2 (1)
18	5.8 (0.50)	-0.2 (-8)	6.0 (26)	0.0 (0)
19	-0.7 (0.11)	-0.5 (-22)	-0.2 (-2)	6.8 (55)
Absolute average	3.2 (0.56)	0.7 (28)	2.9 (25)	3.5 (37)
Relative average	-1.2 (0.16)	-0.7 (-28)	-0.7 (-16)	3.5 (37)
Near-to-date testing period: November 1996				
25	12.6 (1.26)	2.1 (93)	10.3 (53)	0.0 (0)
26	2.4 (0.38)	1.8 (78)	0.6 (5)	0.1 (1)
27	1.8 (0.36)	1.6 (69)	0.2 (2)	0.6 (6)
28	-3.7 (0.39)	2.1 (92)	-5.6 (-31)	6.4 (35)
29	6.2 (1.38)	2.7 (116)	3.4 (39)	0.0 (0)
30	-3.0 (0.92)	1.1 (48)	-4.1 (-64)	13.7 (215)
Absolute average	3.3 (0.78)	1.9 (83)	4.0 (32)	3.5 (43)
Relative average	2.7 (0.49)	1.9 (83)	0.8 (1)	3.5 (43)
Far-to-date testing period: January 1997				
6	0.2 (0.02)	0.0 (1)	0.2 (1)	0.4 (2)
7	6.9 (1.17)	-0.1 (-16)	7.3 (62)	0.1 (1)
8	2.3 (0.51)	-0.4 (-4)	2.4 (27)	0.1 (1)
9	15.9 (1.79)	0.4 (-20)	15.4 (-88)	0.0 (0)
10	4.0 (0.76)	-0.3 (-15)	4.4 (42)	0.0 (0)
11	-7.1 (2.81)	-0.1 (-5)	-7.0 (-140)	9.3 (186)
12	10.6 (0.45)	-0.1 (-2)	10.6 (23)	0.0 (0)
Absolute average	6.7 (1.07)	0.2 (63)	6.8 (55)	1.4 (27)
Relative average	4.7 (0.82)	-0.1 (-3)	4.8 (15)	1.4 (27)

From Table 4.6, it would appear that there is a trend of higher error for the far-to-date testing period than the near-to-date testing period and the training period. This would indicate that there is a seasonal difference in the DHW heater's energy signature, which the algorithm does not capture. However, on an individual day basis, the errors are, in fact, fairly constant. For all testing days, only 3 out of 13 days (23%) yield errors greater than 10% of the monitored appliance energy use. Including training days, only 4 out 19 days (21%) yield errors greater than 10% of the monitored appliance energy use. Thus, the seasonal differences on a daily basis are not significant.

The estimated DHW heater demand ($Demand_{AVERAGE}$ = 4455 Watts) used in Equation 4.1 is based on the appliance's average monitored electric demand obtained from a sample of cycles from the training period. In Table 4.6, $Demand_{AVERAGE}$ is compared to the monitored average demand for each day in the analysis. The average absolute error for $Demand_{AVERAGE}$ is 0.7% for all periods, that is, 1.9% for both the training period and the first testing period, and 0.2% for the second testing period. On an individual day basis, the relative error for $Demand_{AVERAGE}$ is constant within each data period. For the first two data periods, $Demand_{AVERAGE}$ generally underestimates the actual average appliance demand. But, $Demand_{AVERAGE}$ overestimates the actual average demand for all days in the November testing period. Although, the difference is minimal - this indicates that the DHW heater does not always operate at a constant demand level throughout the year.

The accuracy of the estimated DHW heater load duration (obtained from the demand profile) is more significant than the accuracy of $Demand_{AVERAGE}$ to minimize the error of the daily DHW heater energy use. For instance, all days in the analysis in which the daily energy use error exceeds 10%, the load duration error also exceeds 10%, while the actual DHW heater ON intervals missed is 0% for all but one of these days. Therefore, the algorithm applied to the DHW heater is able to consistently recognize actual appliance events, but improvements should be made to further filter out false events which cause the appliance load duration to be overestimated.

4.2.2 Daily DHW demand profile

The accuracy in estimating the DWH heater demand profile with respect to the monitored demand profile, is assessed using four statistics. These statistics, summarized in Table 4.7, are the coefficient of determination (R-squared), average standard deviation, average absolute error, and average relative error.

Table 4.7 Daily DHW heater demand profile accuracy

Day	R-squared	Standard deviation (Watts)	Average absolute error (Watts)	Average relative error (Watts)
Training period: October 1996				
14	0.821	13	192	107
15	0.988	2	16	-1
16	0.996	1	15	7
17	0.989	2	13	1
18	0.935	4	30	-21
19	0.861	10	104	5
average	0.932	5	62	16
Near-to-date testing period: November 1996				
25	0.887	6	54	-53
26	0.988	3	18	-16
27	0.995	2	16	-15
28	0.929	5	38	16
29	0.962	5	57	-57
30	0.765	16	312	39
average	0.921	6	33	-14
Far-to-date testing period: January 1997				
6	0.985	4	11	-1
7	0.924	7	63	-49
8	0.972	5	39	-21
9	0.840	8	82	-75
10	0.953	6	49	-32
11	0.883	13	213	117
12	0.890	8	23	-38
Average	0.921	7	69	-14

The coefficient of determination of the estimated DHW heater demand profile, calculated using Equation 4.6, varies between 0.765 and 0.996 for any given day. This indicates that the estimated profile tracks the monitored profile fairly well, whereby, the closer R-squared is to one, the better is the fit between the estimated and monitored demand profiles.

$$\text{R-squared} = 1 - \left(\frac{\sum_{i=1}^{n} \left(\text{Demand}_{\text{MONITORED } i} - \text{Demand}_{\text{ESTIMATED } i} \right)^2}{\sum_{i=1}^{n} \left(\text{Demand}_{\text{MONITORED } i} \right)^2} \right) \tag{4.6}$$

Where, (n) is the total number of time-steps in one day based on a sampling interval of 16 seconds ($n = 5400$).

The average standard deviation of the estimated DWH heater demand profile, calculated using Equation 4.7, varies from 1 to 16 Watts of the monitored demand for all days.

$$\text{Standard deviation} = \frac{1}{n} \sqrt{\sum_{i=1}^{n} \left(\text{Demand}_{\text{MONITORED } i} - \text{Demand}_{\text{ESTIMATED } i} \right)^2} \quad \text{(Watts)} \tag{4.7}$$

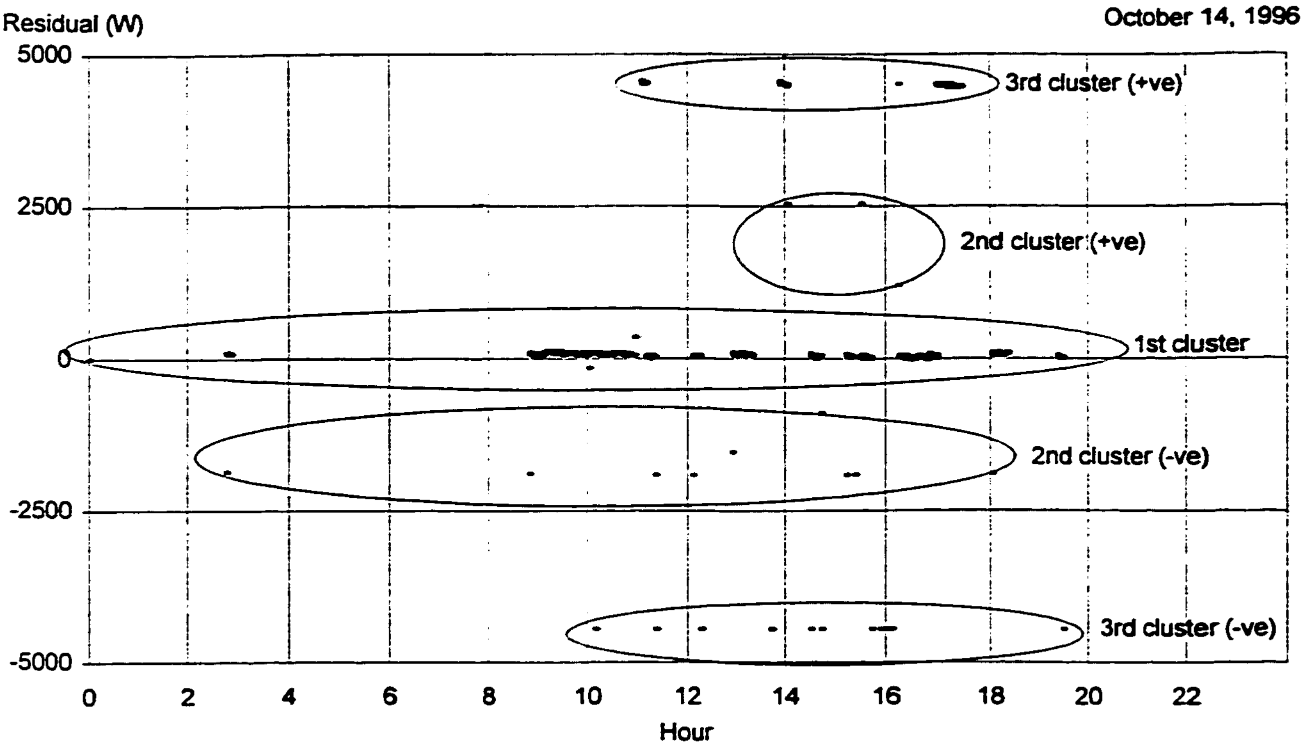
The average absolute error of the estimated DHW heater demand, calculated using Equation 4.8, varies from 11 to 312 Watts (0.2% to 7.0% of $\text{Demand}_{\text{AVERAGE}}$) of the monitored demand for all days.

$$\text{Average absolute error} = \frac{\sum_{i=1}^{n} \left| \text{Demand}_{\text{MONITORED } i} - \text{Demand}_{\text{ESTIMATED } i} \right|}{n} \quad \text{(Watts)} \tag{4.8}$$

The average relative error of the estimated DHW heater demand, calculated using Equation 4.9, varies from -75 to 117 Watts (1.7% to 2.6% of $\text{Demand}_{\text{AVERAGE}}$) of the monitored demand for all days.

$$\text{Average relative error} = \frac{\sum_{i=1}^{n} \left(\text{Demand}_{\text{MONITORED } i} - \text{Demand}_{\text{ESTIMATED } i} \right)}{n} \quad \text{(Watts)} \tag{4.9}$$

The residual demand profile for the DHW heater, that is, the difference between the monitored and estimated demand profiles for each time-step, is presented in Figure 4.12 for one training day (October 14) and one testing day (November 25). A positive residual indicates that the algorithm underestimated the appliance demand, whereas, a negative residual indicates that the algorithm overestimated the appliance demand. The residual profile for the training day shows about an even number of positive and negative residuals, whereas, the testing day shows only negative residuals. The largest cluster of residuals for both days is close to zero. These residuals correspond to events that the algorithm successfully recognized as being either ON or OFF. In this case, the residual is due to the difference between the estimated DWH heater demand and the monitored demand. The second largest cluster of residuals extends up to approximately ±2500 Watts. These residuals correspond to events that the algorithm successfully recognized as being either ON or OFF, but that the start or end demand profiles consist of a two step-increase or decrease (discussed in Section 4.2.1). In this case, the residual is due to the difference between the estimated DHW heater demand and the actual incremental demand. The third and smallest cluster of residuals extends up to ±4455 Watts. These residuals correspond to events that the algorithm incorrectly estimated to be either ON or OFF. The training day profile has 166 missed (positive) points and 48 false (negative) points; the testing day profile has no missed points and 53 false (negative) points. Note, that the scale of the Figure 4.12 is too small to distinguish each point separately.



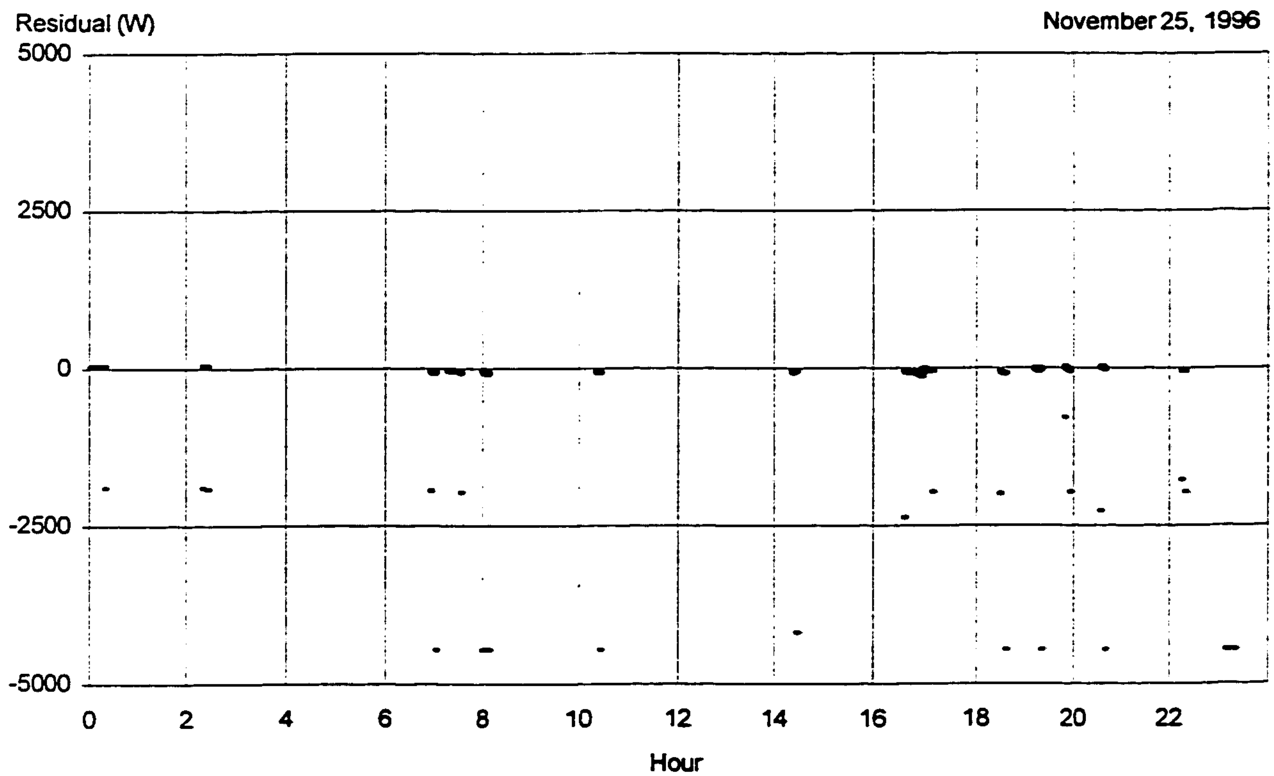


Figure 4.12 Residual profile for the DHW heater for a training and testing day

4.2.3 Daily DHW heater share of the Total load

The ratio of the DHW heater energy use to the Total energy use of the house is called the energy share of the appliance, and is calculated using Equation 4.10. The energy share is a more appropriate basis for the purpose of predicting end-use energy consumption than the unit energy consumption because the energy share may include nonlinear factors of energy use that can not be singled out and captured in the unit energy use, but that are necessary to estimate the appliance energy consumption (previously discussed in Section 3.5).

$$\text{Energy share} = \left(\frac{\text{Energy use}_{DHW}}{\text{Energy use}_{TOTAL}} \right) \times 100 \quad (\%) \tag{4.10}$$

The unit error of the DHW heater energy share is calculated using Equation 4.11, and the corresponding percent error is calculated using Equation 4.12 with respect to the monitored DHW heater energy use. The results are presented in Table 4.8. Negative errors indicate that the algorithm underestimated the actual energy share, whereas, positive errors indicate an overestimation of the energy share.

$$\text{Unit error} = \left(\text{Energy share}_{ESTIMATED} - \text{Energy share}_{MONITORED} \right) \quad (\%) \tag{4.11}$$

$$\text{Percent error} = \frac{\left(\text{Energy share}_{ESTIMATED} - \text{Energy share}_{MONITORED} \right)}{\text{Energy share}_{MONITORED}} \quad (\%) \tag{4.12}$$

For any given day, the unit error in estimating the DHW heater energy share is fairly low, varying from -5.1% to 5.5%. For each data period, both the average absolute unit error and average relative unit error of the appliance energy share is less than 2.5%.

Table 4.8 Daily DHW heater energy share of the Total load error

Day	Monitored energy share (%)	Estimated Energy share (%)	Percent error (%)	Unit error (%)
Training period: October 1996				
14	48.7	43.6	-10.5	-5.1
15	38.2	38.4	0.5	0.2
16	48.3	47.7	-1.2	-0.6
17	40.6	40.5	-0.2	-0.1
18	39.0	41.3	5.9	2.3
19	50.5	50.2	-0.6	-0.3
Absolute average	44.2	43.6	3.2	1.4
Relative average	44.2	43.6	-1.0	-0.6
Near-to-date testing period: November 1996				
25	38.4	43.2	12.5	4.8
26	45.8	46.8	2.2	1.0
27	63.9	65.1	1.9	1.2
28	26.9	25.9	-3.7	-1.0
29	51.6	54.8	6.2	3.2
30	49.9	48.4	-3.0	-1.5
Absolute average	46.1	47.4	4.9	2.1
Relative average	46.1	47.4	2.7	1.3
Far-to-date testing period: January 1997				
6	32.4	32.5	0.3	0.1
7	43.7	46.7	6.9	3.0
8	49.1	50.2	2.2	1.1
9	34.1	39.6	16.1	5.5
10	45.6	47.4	3.9	1.8
11	45.7	49.0	7.2	3.3
12	28.5	31.5	10.5	3.0
Absolute average	39.9	42.4	6.7	2.5
Relative average	39.9	42.4	6.7	2.5

4.2.4 Usefulness of the set of rules for the DHW heater

The results of a sensitivity analysis of the impact of each rule on the DHW heater algorithm's results are illustrated in Figure 4.13, 4.14, and 4.15 for each of the data periods. The sensitivity analysis focuses on the following three indices of accuracy: (i) daily DHW energy consumption (Section 4.2.1), (ii) daily DHW demand profile (Section 4.2.2), and (iii) daily DHW heater energy share (Section 4.2.3). The analysis starts by applying only rule HW1 to the data, that is, assuming that a start or end event occurs at each time-step whose step-increase or decrease is within the recognized limits for the DHW heater (labeled run 1). For the next runs, a new rule is added to the previous set of rules, consecutively. Rule HW6, the ***highest scoring event rule***, is applied in conjunction with rules HW2, HW3, and HW4 because these rules assigned score, therefore, the events need to be ranked using rule HW6. The order of rules applied in the analysis is as follows:

Run 1: Rule HW1 only.
Run 2: Rules HW1, HW2, and HW6.
Run 3: Rules HW1, HW2, HW3, and HW6.
Run 4: Rules HW1, HW2, HW3, HW4, and HW6.
Run 5a: Rules HW1, HW2, HW3, HW4, HW5a, and HW6.
Run 5b: Rules HW1, HW2, HW3, HW4, HW5a, HW5b, and HW6.
Run 7: Rules HW1, HW2, HW3, HW4, HW5a, HW5b, HW6, and HW7.
Run 8: Rules HW1, HW2, HW3, HW4, HW5a, HW5b, HW6, HW7, and HW8.

Rule HW5, the ***minimum score rule*** is represented as two rules, the first part (HW5a) consists of applying rule-specific weight factors and the second part (HW5b) consists of applying a minimum cut-off score.

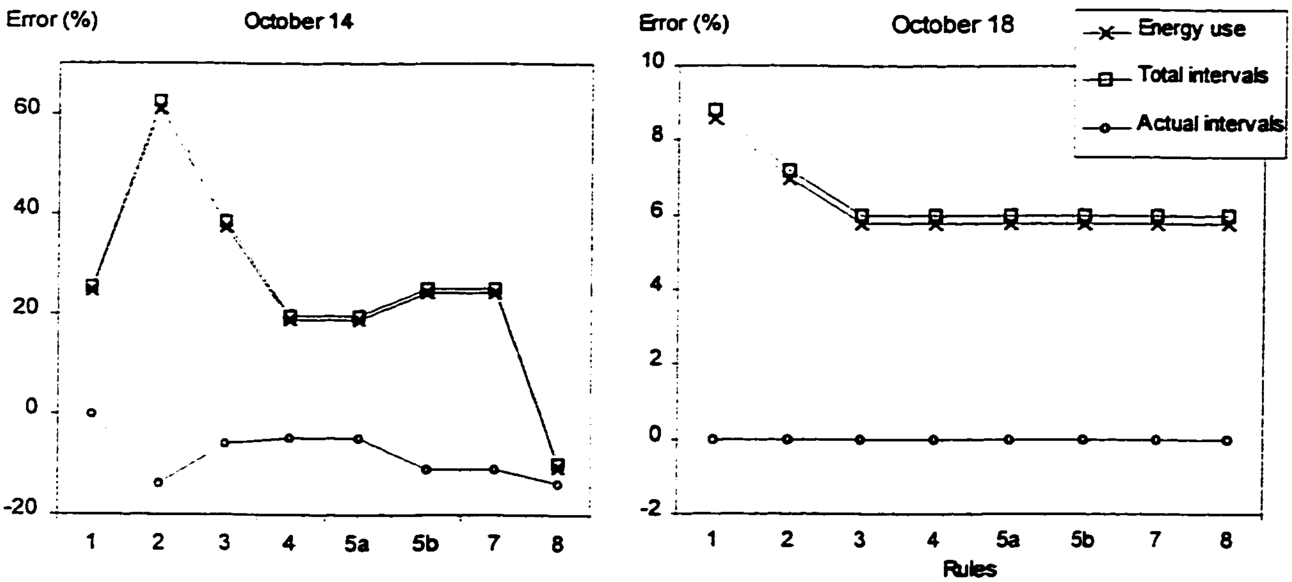


Figure 4.13 Sensitivity analysis results for the DHW heater for selected training days

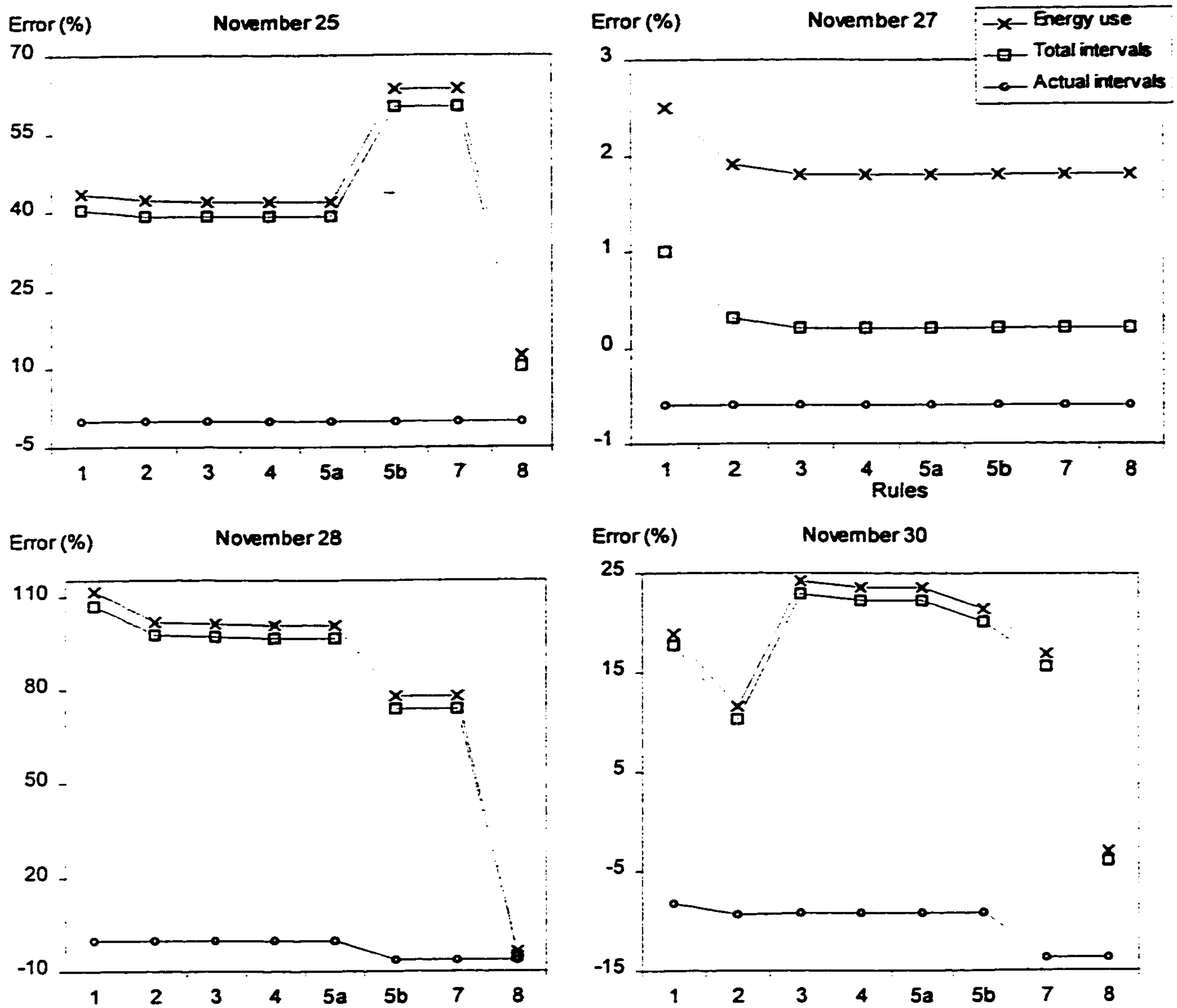


Figure 4.14 Sensitivity analysis results for the DHW heater for selected near-to-date testing days

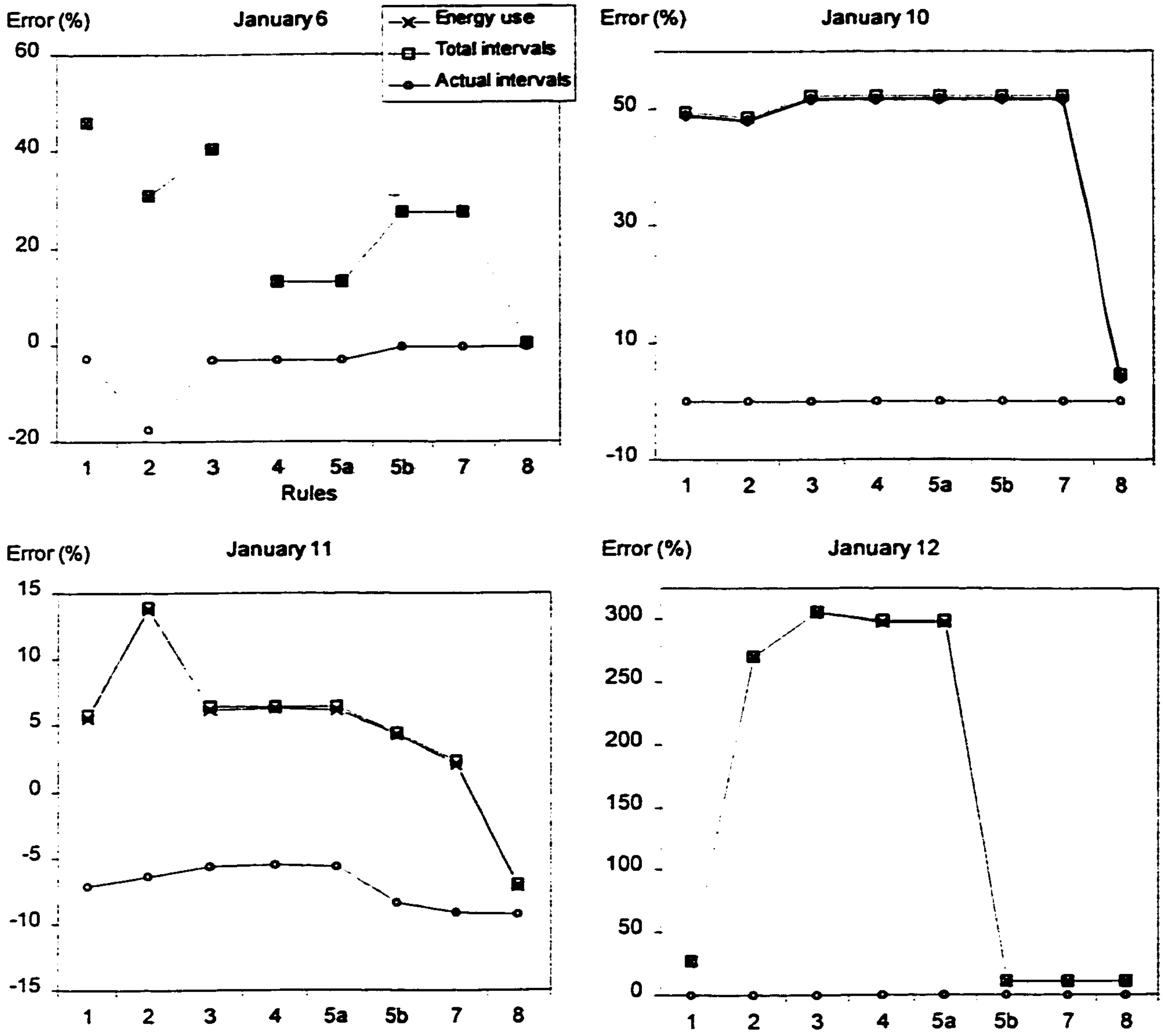


Figure 4.15 Sensitivity analysis results for the DHW heater for selected far-to-date testing days

Each rule has its own role in improving the accuracy of estimation. But, for individual rules there is no discernable pattern of impact on the algorithm's results, and not all rules influence the data in the same way. For instance, for November 25, the addition of rule HW5b results in an increase in the energy use error from 41.9% to 63.5%, by almost 22%. Whereas, for November 28 and 30, and January 11 and 12, the addition of rule HW5b results in a significant decrease in the energy use error. Another example, is rule HW8 – it has the largest impact of all of the rules for October 14, whereas, rules HW2 and HW4 have the largest impact of all the rules for October

18. Therefore, the combination of all eight rules proposed is required to effectively minimize the errors in the estimation of the DHW heater energy use.

4.3 Algorithm for the Estimation of the Energy Use for the Refrigerator

Excluding DHW heaters, residential refrigerators are the largest end-use of electricity in American houses and, altogether, consume about 7% of that country's electricity [51]. The same report estimated the 1993 energy consumption per refrigerator to be about 1100 kWh/year, based on field measurements within northern regions of the United States.

The refrigerator load is recognized from the Total demand profile using a top-to-bottom rule-based algorithm, similar to the DHW heater algorithm presented in Section 4.1. The application of the Pattern Recognition Algorithm to the refrigerator is outlined in Figure 4.16. The refrigerator algorithm consists of the same three stages applied in the DHW heater algorithm, that is: (i) the detection of ON and OFF events by their respective energy signatures, (ii) the estimation of the appliance's demand profile, and (iii) the calculation of the appliance's energy use.

The first stage of the refrigerator algorithm consists of five pattern recognition rules to identify possible start and end events as measured on the monitored Total demand profile. The first two rules are the *state change detection* rule (labeled R1) and the *baseboard false event* rule (labeled R2). The *baseboard false event* rule excludes those events that appear to be due to the start-up of the electric baseboard heater. It is observed that the first or second time-step of a baseboard event could yield similar characteristics as that of the refrigerator. Therefore, rule R2 is applied to minimize the number of false events. Based on the application of R1 and R2, a preliminary set of possible start and end events is established. The following two rules: the *profile vector norm* (labeled R3) and the *number of data points* (labeled R4) are then applied to each event in the preliminary data set. An aggregate score of the performance of these rules is attributed to each event using the *minimum score* rule (labeled R5) to confirm or refute the possible event as recognized by the first four rules.

The remaining set of selected start and end events proceed to the second stage of the algorithm, in which the daily demand profile of the refrigerator is estimated. To do so, the algorithm applies the following three constraining rules: the *highest scoring event* rule (labeled R6), the *minimum ON and OFF interval* rule (labeled R7), and the *minimum Total demand* rule (labeled R8).

Consecutive start and end events are then linked together to obtain the sequence of intervals during which the refrigerator is estimated to be operating. Once the ON and OFF periods of the appliance are estimated, the refrigerator energy consumption for the duration of the day is then calculated using Equation 4.1 presented in Section 4.1. Whereby, the average electric demand of the refrigerator observed from the training data, that is, $Demand_{AVERAGE}$. is 407 Watts.

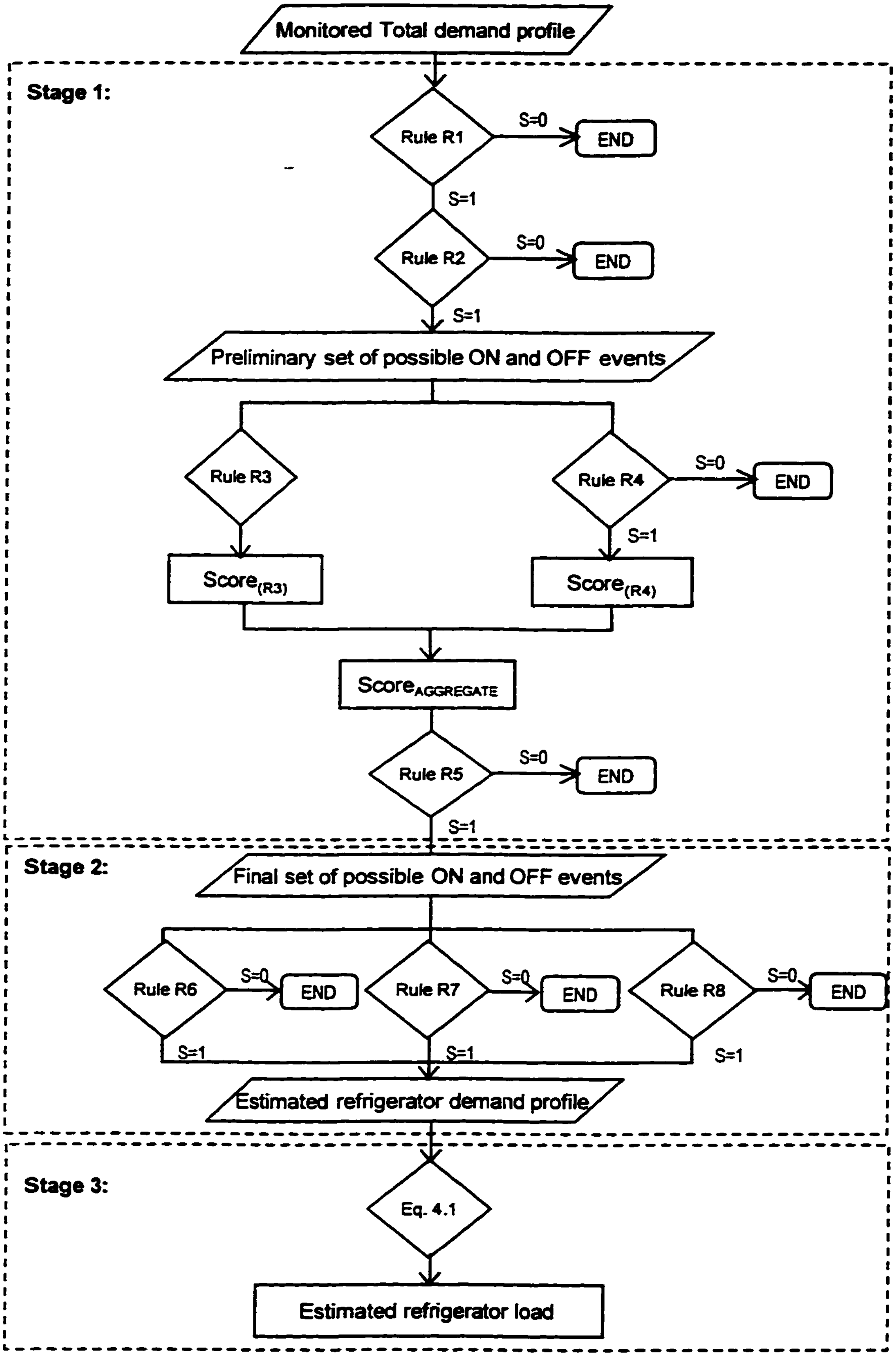


Figure 4.16 Flowchart of the PRA for the refrigerator

Similar to the DHW heater algorithm, the refrigerator algorithm processes the energy signature of an appliance using three separate segments: the start, middle, and end of each cycle. Figure 4.17 illustrates an appliance cycle of the refrigerator expressed as a function of ΔTotal.

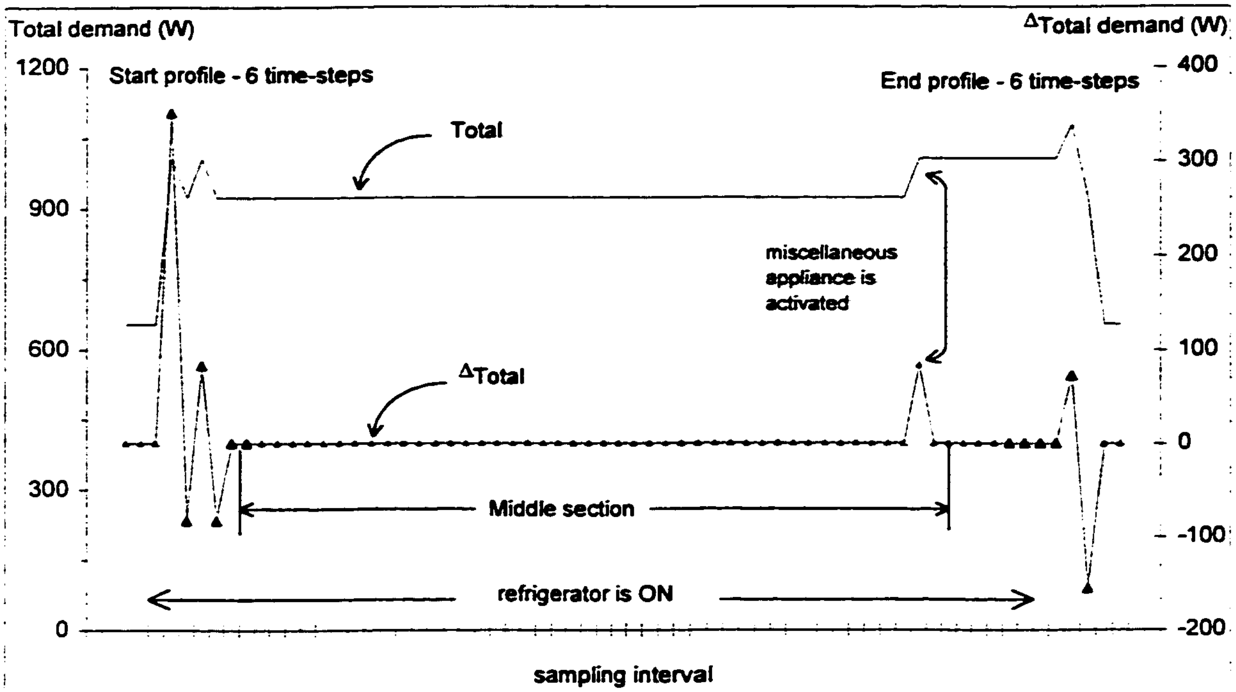


Figure 4.17 Decomposition of a refrigerator energy signature

Recall from Section 4.1 that the boundaries for each segment are determined based on distinct pattern changes in the Total demand profile during an appliance cycle. As seen in Figure 4.17, a spike at the beginning and end of each cycle distinguishes the refrigerator's energy signature (expressed as a function of ΔTotal) from that of other major appliances in the house. This spike depicts the start-up and shutdown of the refrigerator's compressor. Similar to the DHW heater, it is found that significant changes in the ΔTotal profile are captured within the first six time-steps of a cycle for a start event, and in the last six time-steps of a cycle for an end event. The middle or steady-state segment is indistinguishable in the ΔTotal profile.

Sections 4.3.1 to 4.3.8 present the eight rules that are specific to the refrigerator algorithm. Detailed descriptions of the generic development of these rules are presented in the previous sections, 4.1.1 through 4.1.8.

4.3.1 *Rule R1: State change detection*

The demand profile of the refrigerator, like the DHW heater, can occur as a one or a two step-increase profile due to the relatively small sampling interval selected, as seen in Figure 4.18.

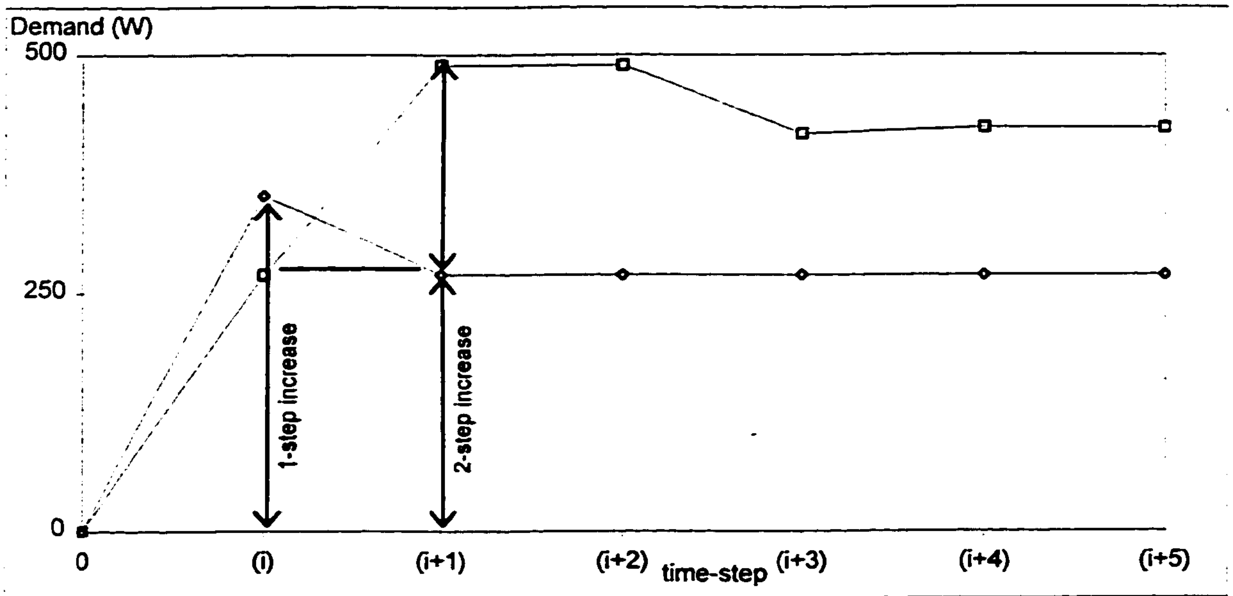


Figure 4.18 Comparison of two start profiles as measured for the refrigerator

The first rule (HW1) of the DWH heater applied to the refrigerator can not adequately distinguish a refrigerator's ON or OFF event based only on a two step-increase template because there are many appliances whose demand levels are within the same range as that of the refrigerator. Therefore, rule R1 which is similar to rule HW1 applied for the DHW heater (Section 4.1.1), is developed to recognize the ON and OFF events of a refrigerator based only on a one step-increase template.

Explicitly, the *state change detection* rule for the refrigerator states:

IF: ($X_{MIN\text{-}START} \leq x_i \leq X_{MAX\text{-}START}$) THEN: $S_i = 1$
ELSEIF: ($X_{MIN\text{-}END} \geq x_n \geq X_{MAX\text{-}END}$) THEN: $S_n = 1$ ELSE: nul
R1

Whereby, x_i is the step-increase observed in the Total demand profile at time-step (i) and is calculated as ($\text{Demand}_i - \text{Demand}_{i-1}$); x_n is the step-decrease observed in the Total demand profile at time-step (n) and is calculated as ($\text{Demand}_n - \text{Demand}_{n-1}$); $X_{MIN\text{-}START}$ is 80 Watts; $X_{MIN\text{-}END}$ is –179 Watts; $X_{MAX\text{-}START}$ is 753 Watts; and $X_{MAX\text{-}END}$ is -621 Watts; S_i is 1 indicating a possible start event; S_n is 1 indicating a possible end event at time-step (n).

4.3.2 Rule R2: Baseboard false event

Rule R2 is specifically developed to reduce the number of events falsely attributed to the refrigerator that are due to the activation of the electric baseboard heater. Since the refrigerator's demand level may be equal to that of the first or second step-increase in a two step-increase profile of the baseboard heater, rule R2 verifies that a possible start event for the refrigerator does not occur immediately after a large step-increase in the ΔTotal profile. Similarly, in the case of an end event, rule R2 verifies that a possible end event for the refrigerator does not occur immediately before a large step-decrease in the ΔTotal profile.

Explicitly, the *baseboard false event* rule states:

IF: $S_i = 1$ and ($\Delta\text{Total}_{i-1} < \text{Baseboard}_{MIN\text{-}START}$) THEN: $S_i = 1$ ELSE: nul and $S_i = 0$
R2

Whereby, ΔTotal_{i-1} is the difference in the Total demand profile at time-step (i-1), and is calculated as ($\text{Total}_{i-1} - \text{Total}_{i-2}$); $\text{Baseboard}_{MIN\text{-}START}$ is the rounded down value of the minimum step-increase of the baseboard heater at time-step (i) observed from a sample of events from the training data, and is 700 Watts. To apply rule R2 to a possible end event, $\text{Baseboard}_{MIN\text{-}END}$ is the rounded down value of the minimum step-decrease of the baseboard heater at time-step (*n*) observed from a sample of events from the training data, and is -700 Watts.

4.3.3 Rule R3: Profile vector norm

The *profile vector norm* rule for the refrigerator is similar to rule HW2 for the DHW heater, described in Section 4.1.2. The average start and end demand profile of the refrigerator observed from a sample of events from the training data is listed in Tables 4.9 and 4.10.

Table 4.9 Start demand profiles for the refrigerator (expressed as ΔTotal - Watts)

Time-step	Pure profiles								Mixed profiles				Average Profile	Standard deviation
	1	2	3	4	5	6	7	8	1	2	3	4	C_i	
(i)	479	424	179	269	390	489	352	654	220	352	424	538	399	99
$(i+1)$	41	269	0	220	158	-220	-83	352	214	-83	238	155	173	177
$(i+2)$	-46	0	-55	0	0	0	0	-83	0	0	-59	0	-20	
$(i+3)$	0	0	0	-72	38	0	0	83	0	0	0	-72	-3	
$(i+4)$	0	0	0	7	0	0	0	-83	-48	0	4	0	0	
$(i+5)$	-48	0	0	0	0	0	0	0	0	0	-59	0	-5	
$\{i+(i+1)\}$	521	693	179	489	548	269	269	1006	434	269	662	693	554	224
norm-6	66	41	115	64	20	165	107	139	78	107	39	65	98	48
norm-5	27	63	169	44	21	128	128	211	59	128	57	70	106	62

Table 4.10 End demand profiles for the refrigerator (expressed as ΔTotal - Watts)

Time-step	Pure profiles									Mixed profiles		Average Profile	Standard deviation
	1	2	3	4	5	6	7	8	9	1	2	C_n	
$(n-5)$	0	0	0	0	0	0	0	0	0	0	0	0	
$(n-4)$	0	0	0	-72	0	38	0	0	0	0	0	-4	
$(n-3)$	0	0	0	72	0	-38	0	0	0	0	0	4	
$(n-2)$	0	0	0	0	0	0	0	0	72	0	0	8	
$(n-1)$	0	0	0	-227	-196	0	0	0	-155	-189	0	-64	89
(n)	-461	-269	-548	-269	-352	-269	-269	-269	-269	-179	-196	-331	81
$\{n+(n-1)\}$	-461	-269	-548	-496	-548	-269	-269	-269	-424	-179	-196	-374	110
norm-6	27	27	27	77	54	39	27	27	45	51	27	39	13
norm-5	39	47	78	70	78	54	47	47	36	56	85	58	14

The standard deviation of the refrigerator start profile for the time-step (i) is 99 Watts. This value is less than the standard deviation for the time-steps $\{i + (i+1)\}$ (224 Watts) corresponding to a two step-increase. Similarly, the standard deviation of the refrigerator end profile for the time-step (n) is 81 Watts. This value is less than the standard deviation for the time-steps $\{n + (n-1)\}$ (110 Watts) corresponding to a two step-decrease. As a result, the standard deviation for the metric norm-6 is smaller than the standard deviation for the metric norm-5, for both the start and end profiles. Therefore, rule R3 is evaluated on the basis of norm-6.

Explicitly, the *profile vector norm* rule for the refrigerator states:

$$\text{IF}: \left(\text{norm}-6_i \le \text{norm}-6_{\text{REFERENCE-START}}\right)$$

$$\text{THEN}: \quad \text{Score}_{\text{rule R3}} = 1 \quad \text{ELSE}: \text{Score}_{\text{rule R3}} = \left(\frac{\text{norm}-6_{\text{REFERENCE-START}}}{\text{norm}-6_i}\right)$$

R3

Where, norm-6_i is the vector distance between the possible start profile and the average start profile listed in Table 4.9, and it is calculated using Equation 4.2; and norm-$6_{\text{REFERENCE-START}}$ is 194 Watts, and it is selected as the average vector norm (98 Watts) plus two standard deviations (2 x 48 Watts) for refrigerator start events observed from the training data. To apply rule R3 to an end event, norm-6_i is substituted by norm-6_n; and norm-$6_{\text{REFERENCE-START}}$ is substituted by norm-$6_{\text{REFERENCE-END}}$, where norm-$6_{\text{REFERENCE-END}}$ is 65 Watts, and it is calculated as the average vector norm (39 Watts) plus two standard deviations (2 x 13 Watts) for refrigerator end events observed from the training data (Table 4.10).

4.3.4 Rule R4: Number of data points

The *number of data points* rule for the refrigerator is similar to rule HW3 for the DHW heater, described in Section 4.1.3. The maximum and minimum demand levels used to evaluate rule R4 are summarized in Table 4.11 for both the start and end demand profiles of the refrigerator.

Table 4.11 Maximum and minimum demand profiles for the refrigerator (Watts)

Time-step	Start profile		Time-step	End profile	
	Minimum	Maximum		Minimum	Maximum
(i)	179	654	$(n-2)$	0	72
$(i+1)$	-220	820	$(n-1)$	-227	0
$(i+2)$	-83	0	(n)	-548	-269

Explicitly, the *number of data points* rule for the refrigerator states:

IF: $(X_{MIN\text{-}START\text{-}1} \le x_i \le X_{MAX\text{-}START\text{-}1})$ and $(X_{MIN\text{-}START\text{-}2} \le x_{i+1} \le X_{MAX\text{-}START\text{-}2})$ and $(X_{MIN\text{-}START\text{-}3} \le x_{i+2} \le X_{MAX\text{-}START\text{-}3})$

THEN: $\text{Score}_{R4} = 1$ and $S_i = 1$

ELSEIF: 2 out of the first 3 time-steps of a start profile fall between the maximum and minimum demand levels and
$(\text{norm-6}_i \le \text{norm-6}_{MAX\text{-}START})$

THEN: $\text{Score}_{R4} = 0.5$ and $S_i = 1$ ELSE: nul and $\text{Score}_{R4} = 0$ and $S_i = 0$

R4

Where, $X_{MIN\text{-}START\text{-}1}$ is 179 Watts; $X_{MIN\text{-}START\text{-}2}$ is –220 Watts; $X_{MIN\text{-}START\text{-}3}$ is –83 Watts; $X_{MAX\text{-}START\text{-}1}$ is 654 Watts; $X_{MAX\text{-}START\text{-}2}$ is 820 Watts; $X_{MAX\text{-}START\text{-}3}$ is 0 Watts; norm-6_i is calculated using Equation 4.2; and $\text{norm-6}_{MAX\text{-}START}$ is 400 Watts and it is selected as four times the standard deviation of the average vector norm for all pure and mixed start profiles observed from the training data (Table 4.9). To apply rule R4 to an end event, the sequence of time-steps $\{i, i+1, i+2\}$ is substituted by $\{n, n-1, n-2\}$; $X_{MIN\text{-}START\text{-}1}$, $X_{MIN\text{-}START\text{-}2}$, $X_{MIN\text{-}START\text{-}3}$, $X_{MAX\text{-}START\text{-}1}$, $X_{MAX\text{-}START\text{-}2}$, and $X_{MAX\text{-}START\text{-}3}$ are substituted by $X_{MIN\text{-}END\text{-}1}$, $X_{MIN\text{-}END\text{-}2}$, $X_{MIN\text{-}END\text{-}3}$, $X_{MAX\text{-}END\text{-}1}$, $X_{MAX\text{-}END\text{-}2}$, and $X_{MAX\text{-}END\text{-}3}$; and norm-6_i is substituted by norm-6_n, where, norm-6_n is calculated using Equation 4.2; and $\text{norm-6}_{MAX\text{-}START}$ is substituted by $\text{norm-6}_{MAX\text{-}END}$, where, $\text{norm-6}_{MAX\text{-}END}$ is 77 Watts and it is obtained as the maximum vector norm for all pure and mixed end profiles observed from the training data (Table 4.10).

4.3.5 Rule R5: Minimum score

The *minimum score* rule for the refrigerator is similar to rule HW5 for the DHW heater, described in Section 4.1.5. Rule R5 is applied to the preliminary set of possible start and end events established by rules R1 and R2 and evaluated by rules R3 and R4. The first part of this rule consists of normalizing the aggregate score of rules R3 and R4 to a value between 0 and 1 using weight factors in an effort to maximize the score of actual events and minimize the score of false events.

Rules R3 and R4 yield, on average, an equal contribution to the aggregate score (Table 4.12) for both start and end events of the refrigerator. Therefore, the weight factor applied for each rule is 0.5 for both rules R3 and R4 and for both start and end events.

Table 4.12 Selection of weight factors for rule R5

Training day (October)	START events		END events	
	W_{R3}: vector norm	W_{R4}: # points	W_{R3} : vector norm	W_{R4}: # points
14	0.49	0.51	0.56	0.45
15	0.49	0.51	0.56	0.44
16	0.48	0.52	0.54	0.46
17	0.47	0.53	0.54	0.46
18	0.48	0.52	0.55	0.45
19	0.45	0.55	0.57	0.43
Average	0.48	0.52	0.55	0.45
Rounded average	0.50	0.50	0.50	0.50

The second part of rule R5 involves applying a minimum cut-off score to remove false events from the set of possible start and end events. However, the confidence level of detecting only refrigerator ON and OFF events from the Total demand profile is somewhat low. This is mainly due to the proliferation of appliances within the same demand level as the refrigerator. Figure 4.19 illustrates the range of aggregate scores for actual start and end events from the training period.

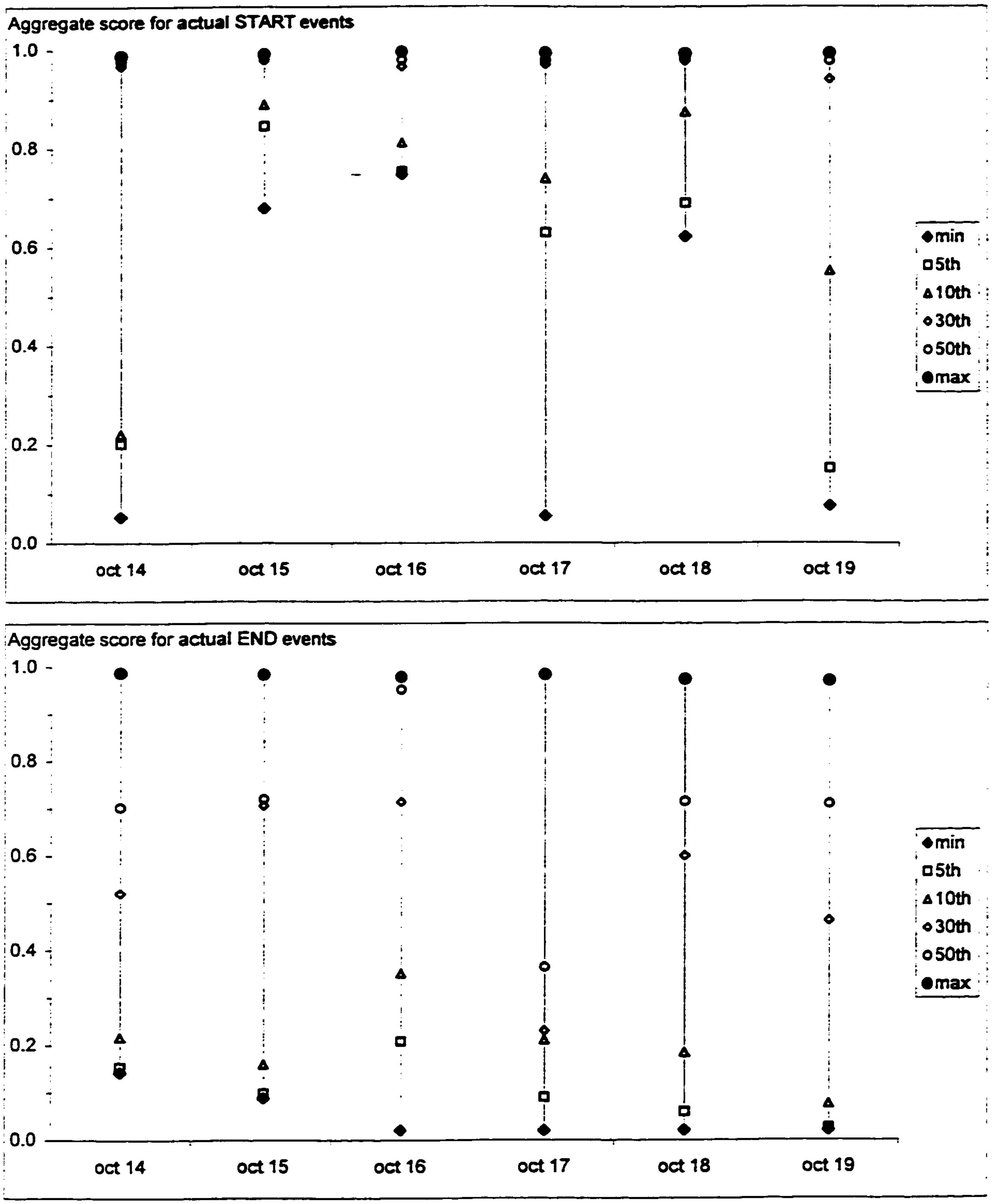


Figure 4.19 Scores for actual start and end events of the refrigerator

The same analysis for the DHW heater, illustrated in Figure 4.10, depicts an apparent trend of increasing average scores and decreasing maximum-to-minimum range of scores for both start and end events. In comparison, this trend is not present in the refrigerator results. For instance, if the same cut-off score that is applied to the DHW heater (0.5 out of 1.0) is applied to the refrigerator, only the 10th percentile of aggregate scores for actual end events pass. Although, the aggregate scores fair better for the start events than the end events, there are inconsistencies among the training days, such that, a constant cut-off score can not be applied across all days and yield good results. For this reason, a cut-off score of zero is applied for both start and end events of the refrigerator.

Explicitly, the *minimum score* rule for the refrigerator states:

IF: ($Score_{AGGREGATE,i}$ > $Score_{CUTOFF\text{-}START}$) whereby, $Score_{AGGREGATE,i}$ = ($Score_{R3,i}$ x W_{R3}) + ($Score_{R4,i}$ x W_{R4})	
THEN: $S_i = 1$ ELSE: nul and $S_i = 0$	**R5**

Where, $Score_{CUTOFF\text{-}START}$ is 0; W_{R3} and W_{R4} are 0.5; and S_i is 1 confirming a refrigerator start event or S_i is 0 refuting a refrigerator start event. To apply rule R5 to an end event, $Score_{AGGREGATE,i}$ is substituted by $Score_{AGGREGATE,n}$; $Score_{CUTOFF\text{-}START}$ is substituted by $Score_{CUTOFF\text{-}END}$; and S_i is substituted for S_n, where, S_n is 1 confirming a refrigerator appliance end event or S_n is 0 refuting a refrigerator end event.

4.3.6 *Rule R6: Highest scoring event*

The *highest scoring event* rule for the refrigerator is similar to rule HW6, described in Section 4.1.6. In the case of the refrigerator, rule R6 verifies that the selected start event at time-step (i) has the highest aggregate score among events within a range of 40 time-steps before and after the time-step (i). Similarly, the rule verifies that the selected end event at time-step (n) has the highest aggregate score among events within a range of 40 time-steps before and after the time-step (n).

Explicitly, the *highest scoring event* rule for the refrigerator states:

IF: S_i = 1 and $Score_{AGGREGATE,i}$ > MAX $Score_{AGGREGATE}$ for the intervals of {(i-40),...,(i-1) and (i+1),...,(i+40)}
THEN: S_i = 1 ELSE: nul and S_i = 0
R6

Where, S_i is 1 confirming a refrigerator start event or S_i is 0 refuting a refrigerator start event. To apply rule R6 to an end event, the range {(i-40),...,(i-1) and (i+1),...,(i+40)} is substituted by the range {(n-40),...,(n-1) and (n+1),...,(n+40)}; and S_i is substituted by S_n, where, S_n is 1 confirming a refrigerator end event or S_n is 0 refuting a refrigerator end event. The minimum thresholds are based on the observation that the minimum duration of activity of the refrigerator from the training period is 31 time-steps (or 496 seconds), and the minimum interval between consecutive refrigerator cycles is 13 time-steps (or 208 seconds). Thus, the rounded down value of 40 time-steps is selected as the minimum time interval between any two events of the same type, that is, ON/ON or OFF/OFF.

4.3.7 *Rule R7: Minimum ON and OFF interval*

The *minimum ON and OFF interval* rule for the refrigerator is similar to rule HW7, described in detail in Section 4.1.7. Rule R7 states that to accept a positive change in state of the appliance at time-step (i), that is, from OFF to ON, the appliance must have been estimated to be OFF for a minimum of 30 time-steps prior to the time-step (i). Whereas, for rule R7 to accept a negative change in state of the appliance at time-step (n), that is, from ON to OFF, the appliance must have been estimated to be ON for a minimum of 30 time-steps prior to the time-step (n). Table 4.13 lists the number of sampling intervals for ON and OFF periods of the refrigerator observed during the training period.

Table 4.13 Duration of ON/OFF periods of the refrigerator (time-steps)

Parameter	October 14	October 15	October 16	October 17	October 18
	OFF periods				
Average	59	58	58	57	58
Maximum	81	62	62	62	64
Minimum	29	39	15	13	31
Standard deviation	6	4	4	5	4
5th percentile	37	50	52	48	51
Sample size	30	39	40	42	20
	ON periods				
Average	102	74	75	69	80
Maximum	504	242	241	249	236
Minimum	35	34	33	31	35
Standard deviation	60	29	28	26	32
5th percentile	53	34	49	37	49
Sample size	31	41	40	43	20

For both ON and OFF periods of the refrigerator, the minimum value for the 5^{th} percentile of observed intervals is selected. The minimum OFF activity observed is 37 time-steps and the minimum ON activity observed is 34 time-steps - thus, the minimum of the two is selected. However, to allow some tolerance in the rule, the rounded down value of 30 intervals is applied.

4.3.8 Rule R8: Minimum Total demand

The *minimum Total demand* rule for the refrigerator is similar to rule HW8 for the DHW heater, described in Section 4.1.8.

Explicitly, the *minimum total demand* rule for the refrigerator states:

$$\text{IF:}\quad \sum_{i,j=1}^{j=4} S_{i-j} = 1 \quad \text{and} \quad TL_{i-2} < TL_{\text{MIN-TOTAL-REF}} \qquad \text{THEN:}\quad S_i = 0 \quad \text{and} \quad S_n = 1 \quad \text{ELSE:nul}$$

R8

Where, S_{i-j} is 1 indicating that the refrigerator is estimated to be ON for the time-step (*i-j*); TL_{i-2} is the Total demand at time-step (*i-2*); $TL_{\text{MIN-TOTAL-REF}}$ is the minimum Total demand (127 Watts) observed during refrigerator ON periods from the training data; and S_i is 0 indicating that an end event prior to time-step (i) has been missed by the algorithm and S_n is 1 indicating that an end event is assumed.

4.4 Discussion of Results for the Refrigerator

The refrigerator algorithm is evaluated on the same basis as the DHW heater algorithm, described in detail in Section 4.2.

4.4.1 Daily refrigerator energy consumption

The error in estimating the daily energy use of the refrigerator with respect to the monitored refrigerator energy use is calculated using Equation 4.5. The results are presented in Table 4.14, expressed as percent error and corresponding unit error of energy use. The average relative error for each data period is 1.9%, 6.0%, and -0.1%, whereas, the average absolute error for each data period is 3.4%, 6.0%, and 7.7%.

The error in estimating the refrigerator electric demand ($Demand_{AVERAGE}$ applied in Equation 4.1) with respect to the daily monitored electric demand is 1.6% (7 out of 407 Watts) for the training data, 0.7% (3 out of 407 Watts) for the November testing data, and 1.4% (6 out of 407 Watts) for the January testing data. On an individual day basis, $Demand_{AVERAGE}$ generally overestimates the actual refrigerator demand. For all testing days, the error in estimating the daily refrigerator load duration exceeds 10% for only 4 out of 13 (31%) days. Including the training period, the load duration error exceeds 10% for only 4 out of 19 days (21%) days.

The estimated refrigerator load duration and estimated demand both contribute equally to the error of the estimated energy use. For example, the days in which the energy use error exceeds 10%, the estimated load duration error exceeds 10%, and the number of actual refrigerator intervals missed also exceeds 10%. Whereas, the major source of error for the estimated DHW heater energy use is the estimated load duration in terms of number of false intervals.

Table 4.14 Daily refrigerator energy consumption error

Day	Energy use % (kWh)	Average demand % (W)	Load duration % (intervals)	Actual ON intervals missed % (intervals)
Training period: October 1996				
14	-1.2 (-0.07)	-0.7 (-4)	-0.5 (-14)	12.9 (368)
15	0.2 (0.01)	-1.6 (-7)	1.8 (55)	6.6 (201)
16	-3.2 (-0.18)	-2.3 (-10)	-1.0 (-29)	8.8 (268)
17	5.4 (0.29)	-1.4 (-6)	6.9 (205)	3.3 (99)
18	0.6 (0.03)	-1.4 (-6)	2.0 (63)	7.5 (231)
19	9.5 (0.54)	-2.2 (-9)	11.9 (370)	5.8 (182)
Absolute average	3.4 (0.10)	1.6 (-7)	4.0 (108)	7.5 (225)
Relative average	1.9 (0.19)	-1.6 (7)	3.5 (123)	7.5 (225)
Near-to-date testing period: November 1996				
25	3.9 (0.23)	-0.1 (-1)	4.0 (127)	7.6 (242)
26	3.0 (0.16)	0.4 (1)	2.6 (79)	10.7 (325)
27	4.3 (0.23)	1.1 (4)	3.2 (93)	9.6 (280)
28	8.9 (0.48)	1.2 (4)	7.6 (230)	13.0 (392)
29	13.9 (0.74)	1.5 (6)	12.1 (365)	10.5 (317)
30	1.9 (0.11)	-0.1 (-1)	2.0 (64)	10.7 (346)
Absolute average	6.0 (0.33)	0.7 (2)	5.3 (160)	10.4 (317)
Relative average	6.0 (0.33)	0.7 (3)	5.3 (160)	10.4 (317)
Far-to-date testing period: January 1997				
6	-10.4 (-0.32)	-1.2 (-5)	-9.3 (-157)	18.5 (313)
7	-6.5 (-0.35)	-1.3 (-6)	-5.2 (-155)	17.8 (529)
8	11.6 (0.64)	-1.3 (-6)	13.1 (391)	10.6 (315)
9	-2.1 (-0.12)	-1.6 (-7)	-0.5 (-17)	10.5 (336)
10	-2.2 (-0.15)	-0.9 (-4)	-1.3 (-46)	11.5 (400)
11	15.1 (0.95)	-1.6 (-7)	16.9 (578)	11.0 (374)
12	-6.2 (-0.18)	-2.0 (-9)	-4.4 (-69)	14.6 (231)
Absolute average	7.7 (0.07)	1.4 (6)	7.2 (75)	13.5 (357)
Relative average	-0.1 (0.39)	-1.4 (6)	1.3 (202)	13.5 (357)

4.4.2 *Daily refrigerator demand profile*

The statistics used to evaluate the accuracy of the estimated refrigerator demand profile are described in detail in Section 4.2.2. The results for the refrigerator are presented in Table 4.15.

Table 4.15 Daily refrigerator demand profile accuracy

Day	R-squared	Standard deviation (Watts)	Average absolute error (Watts)	Average relative error (Watts)
Training period: October 1996				
14	0.751	2.4	70	3
15	0.851	1.6	42	-1
16	0.832	1.7	46	8
17	0.862	1.6	38	-12
18	0.826	1.8	47	-1
19	0.771	2.1	63	-23
average	0.816	1.9	51	-4
Near-to-date testing period: November 1996				
25	0.802	1.9	54	-9
26	0.751	2.1	20	-18
27	0.765	2.0	18	-17
28	0.652	2.4	38	16
29	0.656	2.4	57	-57
30	0.764	2.1	64	39
average	0.732	2.2	42	-8
Far-to-date testing period: January 1997				
6	0.715	2.2	69	24
7	0.700	2.3	75	15
8	0.660	2.4	84	-26
9	0.797	2.0	57	5
10	0.781	2.1	64	6
11	0.613	2.8	108	-39
12	0.752	2.2	33	8
average	0.717	2.3	70	-1

For any given day, the R-squared of the estimated refrigerator demand profile varies from 0.613 to 0.862. For each data period, the average R-squared is 0.816, 0.732 and 0.717. The average standard deviation between the estimated and monitored demand profiles varies from 1.6 to 2.6 Watts for all days. The average absolute error of the estimated demand profile varies from 18 to 108 Watts for all days, that is, from 4% to 27% of the average refrigerator demand observed from the training data (407 Watts). Whereas, the average relative error of the estimated demand profile varies from -57 to 39 Watts for all days, that is, from 14% to 10% of the average refrigerator demand observed from the training data (407 Watts).

The residual demand profile for the refrigerator, that is, the difference between the monitored and estimated demand profiles for each time-step, is presented in Figure 4.20 for the training day of October 14. A positive residual indicates that the algorithm underestimated the demand level, whereas, a negative residual indicates that the algorithm overestimated the demand level. The residual profile shows about an even number of positive and negative residuals.

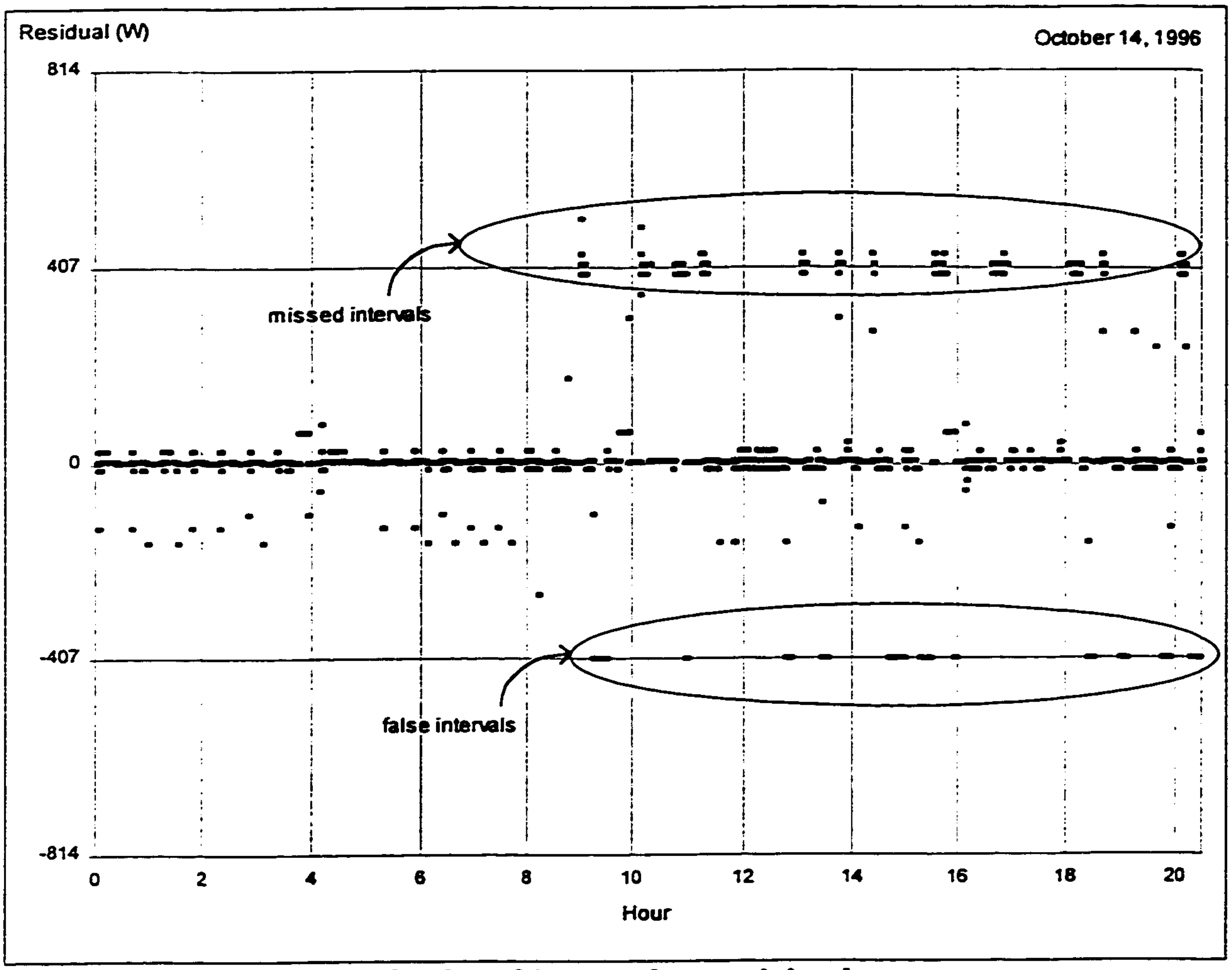


Figure 4.19 Residual profile for the refrigerator for a training day

The largest cluster of residuals is close to zero. They correspond to those time-steps at which the algorithm successfully recognized the events, but that the estimated demand differs slightly from the monitored demand. The next largest cluster of residuals is found at approximately ±407 Watts. These residuals correspond to those time-steps at which the algorithm did not recognize the events. The training day illustrated has 367 missed (positive) intervals and 353 false (negative) intervals. The final cluster of residuals occurs between the previous two clusters. These residuals correspond to those time-steps at which the algorithm successfully recognized the ON and OFF events, but at which there is a two step-increase or decrease (discussed in Section 4.3.1). Thus, the algorithm yields an error equal to the difference between the steady-state demand level estimated (407 Watts) and the monitored start-up or shutdown demand level.

4.4.3 Daily refrigerator share of the Total load

The actual and estimated refrigerator share of the Total load, and the corresponding percent error (calculated using Equation 4.12) and unit error (calculated using Equation 4.11) are listed in Table 4.16. Negative errors indicate that the algorithm underestimated the actual energy share, whereas, positive errors indicate an overestimation of the energy share.

For any given day, the unit errors are very low, varying from -1.2% to 1.7%. On a weekly basis, the average absolute unit error of the estimated energy share is 0.6%, 0.9%, and 0.8% for the training period, near-to-date testing period, and far-to-date testing period, respectively. The average relative unit error of the estimated energy share is 0.6%, 0.9%, and 0.6% for each period.

Table 4.16 Daily refrigerator share of the Total load error

Day	Monitored energy share (%)	Estimated energy share (%)	Percent Error (%)	Unit error (%)
Training period: October 1996				
14	10.6	10.5	-1.2	0.1
15	19.3	19.3	0.2	0.0
16	22.2	21.5	-3.2	0.7
17	21.8	23.0	5.4	1.2
18	25.8	25.9	0.6	0.2
19	15.9	17.4	9.5	1.5
Absolute average	19.3	19.6	3.4	0.6
Relative average	19.3	19.6	1.9	0.6
Near-to-date testing period: November 1996				
25	22.2	23.0	3.9	0.9
26	15.8	16.3	3.0	0.5
27	16.6	17.3	4.3	0.7
28	13.6	14.8	8.9	1.2
29	12.5	14.3	13.9	1.7
30	9.5	9.7	1.9	0.2
Absolute average	15.0	15.9	6.0	0.9
Relative average	15.0	15.9	6.0	0.9
Far-to-date testing period: January 1997				
6	11.0	9.9	-10.4	1.1
7	14.1	13.2	-6.5	0.9
8	12.0	13.4	11.6	1.4
9	17.9	17.6	-2.1	0.4
10	15.3	14.9	-2.2	0.3
11	7.2	8.3	15.1	1.1
12	19.4	18.2	-6.2	-1.2
Absolute average	13.8	13.6	7.7	0.8
Relative average	13.8	13.6	-0.1	0.6

4.4.4 Usefulness of the set of rules for the refrigerator

A sensitivity analysis of the impact of each rule on the results of the refrigerator algorithm is performed. The analysis focuses on the following three indices of accuracy: (i) daily refrigerator energy consumption (Table 4.14), (ii) daily refrigerator demand profile (Table 4.15), and (iii) daily refrigerator share of the Total load (Table 4.16).

The analysis starts by applying only rule R1 to the entire data set, that is, assuming that a start or end event could occur at each time-step where the step-increase or decrease is within the recognized limits for the refrigerator (labeled run 1). For the next runs, a new rule is added to the previous set of rules, consecutively. Rule R6, the *highest scoring event rule*, is applied in conjunction with rules R3 and R4 because these rules assign a score to the events, therefore, the events are ranked using rule R6. The order of rules applied in the analysis for the refrigerator is as follows:

Run 1:	Rule R1 only.
Run 2:	Rules R1 and R2.
Run 3:	Rules R1, R2, R3, and R6.
Run 4:	Rules R1, R2, R3, R4, and R6.
Run 5a:	Rules R1, R2, R3, R4, R5a, and R6.
Run 7:	Rules R1, R2, R3, R4, R5a, R6, and R7.
Run 8:	Rules R1, R2, R3, R4, R5a, R6, R7, and R8.

The results of the sensitivity analysis for selected days are illustrated in Figure 4.21. For the days illustrated, rule R4 always reduces the number of actual refrigerator intervals missed by the algorithm by an average of 16.5%. However, at the same time, R4 increases the error in estimating the refrigerator energy use for two out of these four days by an absolute average of 4.5%. Similarly, R4 increases the error in estimating the total number of intervals estimated for two out of four days by an absolute average of 6.3%.

Rules R7 and R8 significantly reduce the error in estimating the refrigerator energy use for the days shown in Figure 4.21, by a combined absolute average of 14.2%. It appears there is a trade-off between reducing the error in estimating the refrigerator energy use and the number of actual refrigerator intervals recognized. The deciding factor as to which parameter to improve upon depends on the intended use of the results. If obtaining the daily refrigerator load is of greatest interest then the combination of all eight rules proposed is effective to minimize the errors in the estimation of the refrigerator energy use.

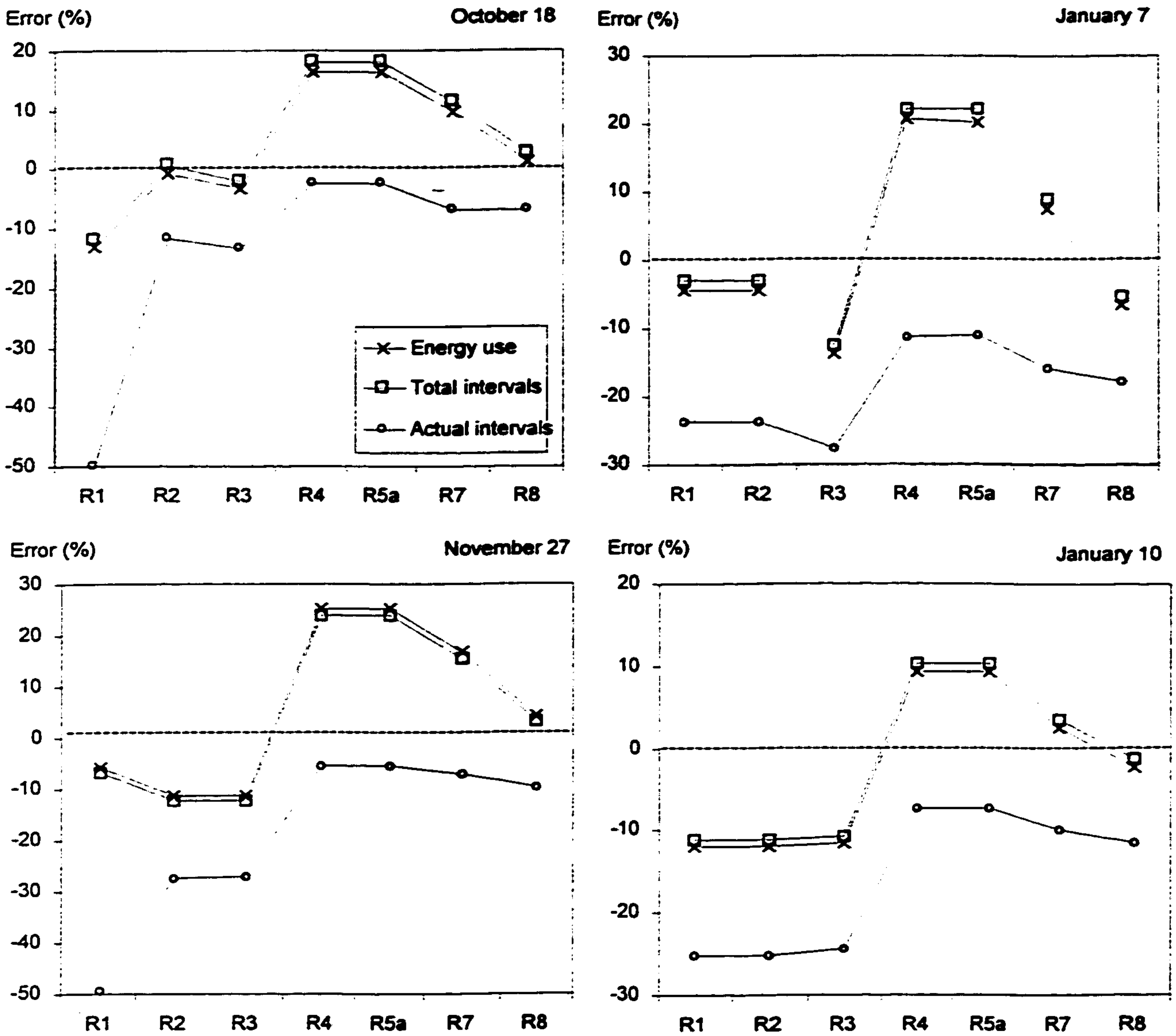


Figure 4.21 Sensitivity analysis results for the refrigerator for selected days

5. A NEURAL NETWORK APPROACH TO DETECT APPLIANCE EVENTS WITHIN THE TOTAL DEMAND PROFILE

The objective of this portion of the research is to identify: (i) the features of neural networks that enable them to successfully perform pattern classification which may be used to complement or make more robust the Rule-Based Pattern Recognition Algorithm presented in Chapter 4, and (ii) the differences in patterns of appliance energy signatures (in this case, for the DHW heater and the refrigerator) which impact the neural network results.

A brief introduction to artificial neural networks is presented, and the basic characteristics that define each of the three neural networks investigated in this study are discussed. Next, a description of the data preprocessing techniques applied is discussed along with the network parameters selected for this application. Lastly, the results of the three neural network models used to detect start and end events are presented for the domestic hot water heater and the refrigerator. These results are also comparatively assessed against similar results obtained using the Pattern Recognition Algorithm.

5.1 Background

Unlike the Pattern Recognition Algorithm, which consists of a set of explicit rules, neural networks draw upon knowledge or information that is inherent in the training data that is presented to the network. Inspired from neuroscience, artificial neural networks (ANN) are able to identify and learn patterns in data from examples, and thereafter generalize without prior process understanding. They can discern patterns and relationships that are beyond the capabilities of traditional methods like regression analysis. There are many types of ANN models. Each model is, primarily, characterized by the arrangement of neural processing units and their interconnections. A simple three-layer neural network is illustrated in Figure 5.1.

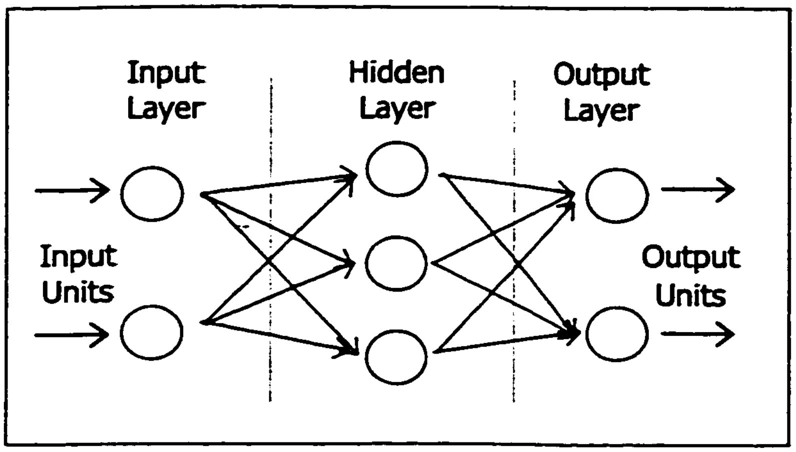


Figure 5.1 Simple three-layer neural network

A neural network model can be described using three parameters: (i) the topology or architecture, (ii) the learning paradigm, and (iii) the learning algorithm [52]. The topology of a neural network typically consists of an input layer that presents data to one or more layers of hidden processing units, which in turn present processed data to an output layer. The input processing units only receive external data from the user. The outputs received from a previous layer of units can be thought of as a vector of data, to which a transfer (or activation) function is applied, and the data is sent to the next layer of units. The direction in which the data is transferred across processing layers defines the network as either a feed-forward, limited recurrent, or fully recurrent network.

The learning paradigm defines the method that the network determines the appropriate connection weights for a given set of training data. The two learning paradigms investigated in this study are: (i) supervised, and (ii) unsupervised. Supervised learning is the most common training paradigm used to develop neural network classification and prediction applications, while unsupervised learning is often used for clustering and segmentation of data sets.

The third defining component of a neural network is the type of learning algorithm that is applied. Learning algorithms determine the contribution of error that is generated by each processing unit in the network for each training pattern. This information allows the connection weights for each unit to be modified in the direction that will reduce the error. This process is repeatedly applied for each training pattern until the desired error is achieved. Learning algorithms used by neural networks replace the programming required for conventional models.

In this study, the NeuroShell 2.0 environment [53] was used to test the application of ANN to detect the start and end events of appliances within the Total demand profile. The discussion that follows presents the differences between the three types of neural network models applied in this study. The three ANN models investigated are: (i) Back Propagation, (ii) Probabilistic, and (iii) Kohonen. These models are selected based on preliminary evaluations of the number of correctly classified events for a variety of models available in the NeuroShell 2.0 environment.

5.1.1 Back Propagation Neural Network

The Back Propagation Neural Network (BPN) is a feed-forward network with a supervised learning paradigm that applies the Generalized Delta Rule learning algorithm or more commonly referred to as the Back Propagation learning algorithm. The BPN is the most general-purpose and commonly used neural network mainly because it is suitable for almost all applications, particularly for classification, modeling, and time-series forecasting [54]. A BPN with supervised learning can be described as a nonlinear minimization problem in which the connection weights are the decision variables and the learning error (the difference between the estimated output and the actual output) is the objective function. While, a BPN with no hidden layers is essentially a linear multivariate regression model. Adding hidden layers to the network turns the linear regression model into a nonlinear multivariate regression model.

The basic BPN (which is applied in this study) consists of three components: (i) the input units, (ii) the hidden units, and (iii) the output units (Figure 5.2). The input units are presented to the input layer and are propagated across the hidden layers to the output layer. This forward pass yields an estimated output that is then compared to the actual output. The actual output is then subtracted from the estimated output and the difference is defined as the learning error or error signal. This error signal is then passed back through the neural network using the Generalized Delta Rule learning algorithm. Whereby, the contribution of each hidden unit to the total error signal and corresponding adjustment factors needed to produce the actual output are calculated. The connection weights are then adjusted accordingly and the process is repeated until the desired output accuracy is achieved.

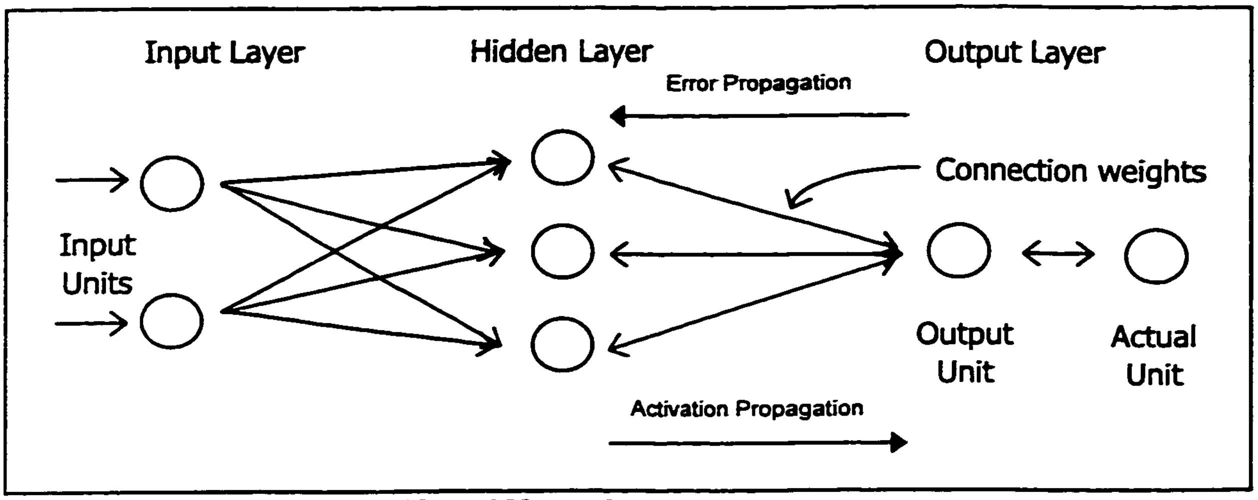


Figure 5.2 Back Propagation Neural Network

While the NeuroShell 2.0 software enables the user to define several parameters, the following two parameters appear to have the greatest impact on the BPN results: (i) the learning rate and (ii) the momentum. The learning rate determines the incremental magnitude of the connection weight adjustments. The momentum controls the incremental magnitude of oscillations in the connection weight adjustments. Whereby, its effect is to filter out any high-frequency changes in the connection weight values which are caused by altering signed error signals (positive vs. negative).

5.1.2 Probabilistic Neural Network

A Probabilistic Neural Network (PNN) is a feed-forward network with a supervised learning paradigm that applies a Probability Density Function (PDF) to determine the most probable output (Figure 5.3). Unlike the BPN, which maps the input attributes into the various classification categories, the PNN separates the input patterns into a user-specified number of output categories based on probabilistic reasoning. Whereby, a Gaussian activation function is applied on the hidden layers, and then the units for each possible output category are summed. The category in the summation layer with the highest probability is deemed the winner.

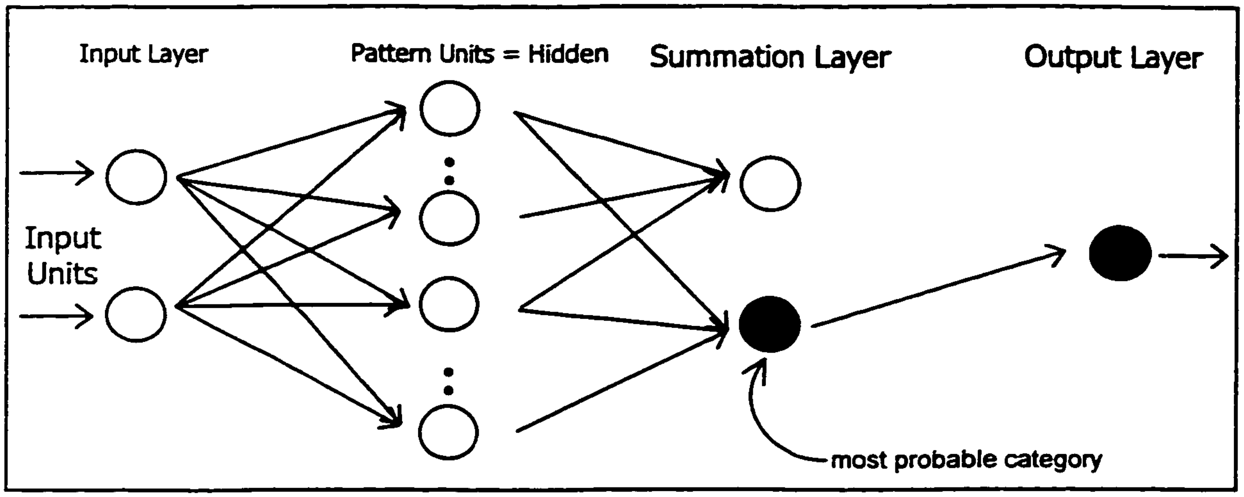


Figure 5.3 Probabilistic Neural Network

The main difference between a PNN and a BPN is that instead of adjusting the input layer connection weights using the Generalized Delta Rule, each input training pattern is used as the connection weight to a new hidden unit. Thus, PNN require that the number of units in the hidden layer be the same as the number of training patterns presented to the network. This enables the network to train more quickly on sparse data sets than more common iterative networks since there are no connection weight adjustments [55]. For the data used in this study, training is instantaneous. However, for large training sets, significantly more computational time and effort may be required.

The success of a PNN is highly dependent on the smoothing factor that is applied. Higher smoothing factors produce more relaxed surface fits through the data, reducing the difference between input and output patterns. For this study, NeuroShell's calibration feature is used to determine the optimum smoothing factor for the network. Whereby, the same smoothing factor is applied for all connection weights, and whole range of smoothing factors are automatically tested, and converge towards a value that maximizes the success of the network (Figure 5.4). The measure of success for classifier-type networks like PNN is the accuracy of the classifier, defined as the percentage of correct classifications made by the network.

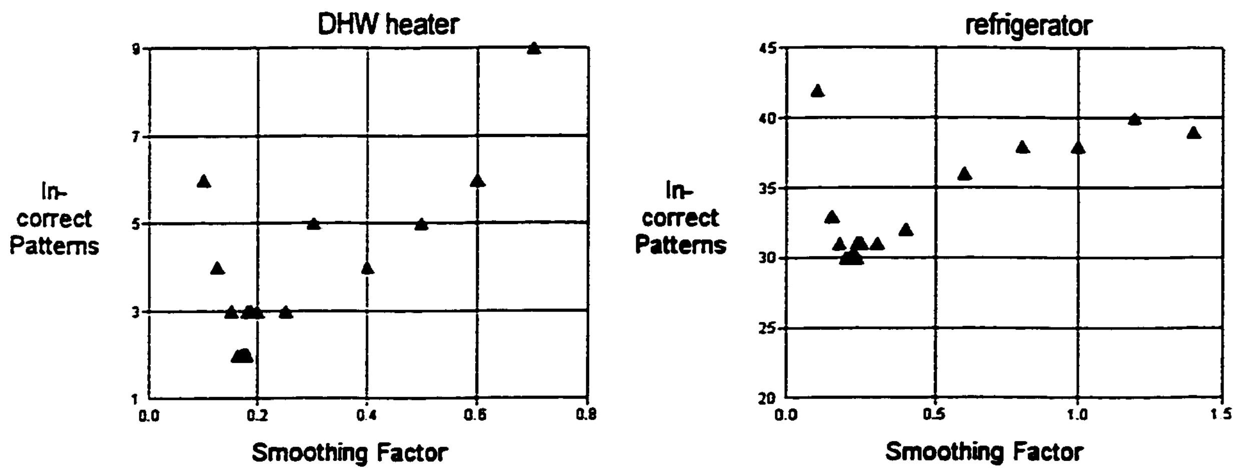


Figure 5.4 Convergence of smoothing factors for DHW heater and refrigerator start events

Advantages of applying a PNN over a standard BPN is that training is much faster, usually a single pass through the training patterns. Also, new training data can be added at any time without requiring retraining of the entire network. This feature of PNN is significant if the application is going to be used for real-time estimations with occasional calibration monitoring periods to ensure that the network is still valid. Lastly, because of the statistical basis of the PNN, the user can trace-back the basis for any decision made by the network. This reduces some of the "black-box" of neural networks discussed in Section 2.4.

5.1.3 Kohonen Self-Organizing Neural Network

The Kohonen Self-Organizing Map Network (KNN) is a feed-forward network with an unsupervised learning algorithm. An unsupervised neural network is called self-organizing because it does not receive any direction (or feedback) to move toward the correct output. Essentially, these networks look at the patterns of data and cluster them into a specified number of categories (or feature map) such that similar patterns are grouped into clusters. Unlike the two previous networks presented, the BPN and PNN, the KNN consists only of two layers of processing units; an input and an output layer - there is no hidden layer (see Figure 5.5). Similar to the PNN, the KNN requires a minimum of two output categories. Thus, the output of a possible start event is defined as either an "ON event" or "not an ON event". Similarly, the output of a possible end event is defined as either an "OFF event" or "not an OFF event".

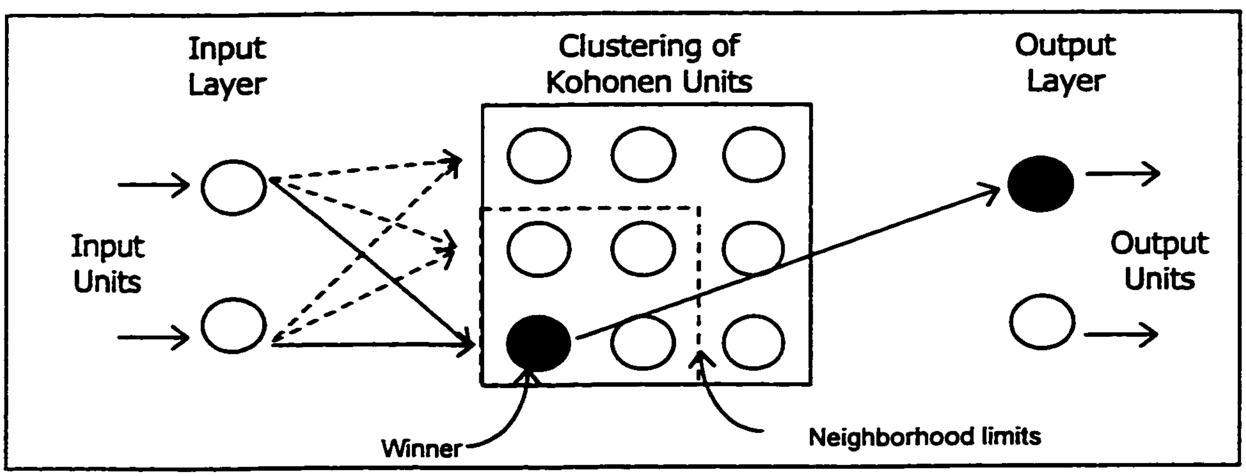


Figure 5.5 Kohonen Self-Organizing Neural Network

In the case of a KNN, the training process serves to determine an appropriate learning rate and neighborhood size for the data. Whereby, the activation for each clustered unit is calculated as the product of each input unit value by its corresponding connection weight, and then summing all inputs received by a Kohonen Unit. Mathematically, this process can be described as the dot product of the input vector and the connection weight vector. The Kohonen unit with the largest activation is declared the "winner"[2] and as such its connection weight is adjusted to more closely resemble the input vector just processed. The closeness of these two units is evaluated based on their distance from each other, calculated using the Euclidean Distance Metric. The Euclidean Distance Metric is calculated as the square of the distance (*d*) between the input pattern and the weight vector for a unit and is represented as $\Sigma(d)^2$. The basis for this comparison is the same as that applied by rules HW2 and R3, the *vector norm rule* in the Pattern Recognition Algorithm presented in Chapter 4. The winning unit is the Kohonen unit with the minimum distance from the input vector, and as such requires the minimum connection weight adjustment. The magnitude of the weight adjustment for the winning unit is determined by the learning rate applied. The learning rate is the most sensitive variable in a KNN. For instance, if the learning rate selected is too large then the network is not likely to stabilize.

In addition to the connection weights of the winning unit being adjusted, the weights of the adjacent units within a neighborhood of the winning unit are also adjusted. Hence, the network undergoes self-organization. The neighborhood size will slowly decrease as training progresses until it is zero, meaning that only the weight of the winning unit is changed and that the clusters of data have been defined. At this point, the connection weights represent a typical or prototypical input pattern for the subset of data that fall within that cluster. This prototypical input pattern is comparable to the average start or end demand profile (C_i or C_n) applied in rules HW2 and R3, the *vector norm rule*.

5.2 Data Preprocessing

The training data set is composed of 86,200 patterns assuming that all time-steps in one day are possible start or end events (e.g. 24 hours x 60 minutes x 60 seconds ÷ 16 seconds = 86,200 time-steps). To reduce the time and computational efforts required to train a network, a subset of the training and test data is presented to the network. Preprocessing the data also serves to reduce bias in the data due to the significantly higher ratio of non-events to actual start and end events. Rules HW1 (described in Section 4.1.1) and R1 (described in Section 4.3.1) of the Pattern Recognition Algorithm are used to preprocess the DHW heater and the refrigerator data, respectively.

The input data for all three networks is scaled into the data range that the ANN can process efficiently. Most ANN process data in the range of 0.0 to 1.0 or -1.0 to +1.0 depending on the activation functions used by the network. If the input patterns are not scaled, then patterns with very large magnitude swings would dominate or saturate the activation function. Since the activation of a unit is governed by the total simulation received by a pattern, once saturation is reached, changes in individual input units will yield little or no change in the result. A positive connection weight will enhance a unit's response to a signal while a negative connection weight will suppress a unit's response. Both the BPN and PNN require that the input data is scaled - the functions applied are listed in Table 5.1.

The input patterns consist of one or more input units. The relative differences among the individual input units can also be extracted and presented explicitly to a network. In this case, the data may be normalized or scaled as a group relative to one another. For the input data used in this study, it would be interesting to normalize the time-steps with respect to the first time-step. This may increase the effectiveness of the ANN for the DHW heater because it will amplify significant step-increases and step-decreases in the demand and minimize changes due to smaller appliances in the house. This option is available for further research.

Table 5.1 Summary of neural network parameters for the DHW heater and refrigerator data sets

Variable	BPN	KNN	PNN
TEST SET PERCENTAGE	20%		
NUMBER OF UNITS IN INPUT LAYER	6	6	6
SCALING FUNCTION	[-1,1]	n/a	= tanh(x), where x is the input unit
LEARNING RATE FOR ALL LINKS	0.9	0.5	n/a
MOMENTUM FOR ALL LINKS	0.6	n/a	n/a
NUMBER OF UNITS IN HIDDEN LAYER	= 0.5(number of inputs + number of outputs) + (number of training patterns)$^{0.5}$	n/a	= number of training patterns
ACTIVATION FUNCTION	Gaussian = exp(-x^2), where x is the Σ(weighted connection values) received from the previous layer	n/a	Gaussian = exp(-x^2)
NUMBER OF UNITS IN OUTPUT LAYER	1	2	2
ACTIVATION FUNCTION	Symmetric logistic = (2 / (1 + e$^{(-x)}$)) – 1, where x is the Σ(weighted connection values) received from the previous layer	n/a	Probability Density Function
SMOOTHING FACTOR	n/a	n/a	DHW heater: start - 0.179688 DHW heater: end - 0.600000 Refrigerator: start - 0.331250 Refrigerator: end - 0.233203
NUMBER OF TRAINING EPOCHS SPECIFIED	n/a	100	n/a
CALIBRATION METHOD	Momentum	n/a	Vanilla, iterative
STOPPING CRITERIA	Number of events since last minimum average error in test data >30,000		

For both of the supervised learning networks, that is, the BPN and the PNN, a subset of the training patterns are withheld from the training process and used as cross-validating data. This enables the network to gauge its incremental performance, and terminate the training process before the network is overtrained. Once a network is overtrained it functions as a lookup table rather than a prediction tool, which is then unable to generalize when presented with data that contains random variance.

5.3 Neural Network Architectures

The objective of this research is not to find the optimum configuration for each data set, but rather to observe the impact on the ANN results due to the differences in the patterns of energy signatures of the DHW heater and the refrigerator. Thus, the same network parameter values are used for the following four networks developed: i) DHW heater – start, ii) DHW heater – end, iii) refrigerator – start, and iv) refrigerator - end events. The proposed networks all contain six processing units in the input layer corresponding to the first six time-steps of a possible start or end event (as discussed in Section 4.1). The number of processing units contained in the output layer depends on the topology of the network. For instance, the BPN performs feature mapping, thus, one output unit is used. Figure 5.6 illustrates the layout of a BPN for one training pattern. The PNN and Kohonen Networks are classification and cluster-type networks that require a minimum of two categories. In this case, two output units, one denoting true positive (can be compared to $S_i = 1$ or $S_n = 1$ in Chapter 4) and the other false positive (can be compared to $S_i = 0$ or $S_n = 0$ in Chapter 4) are used.

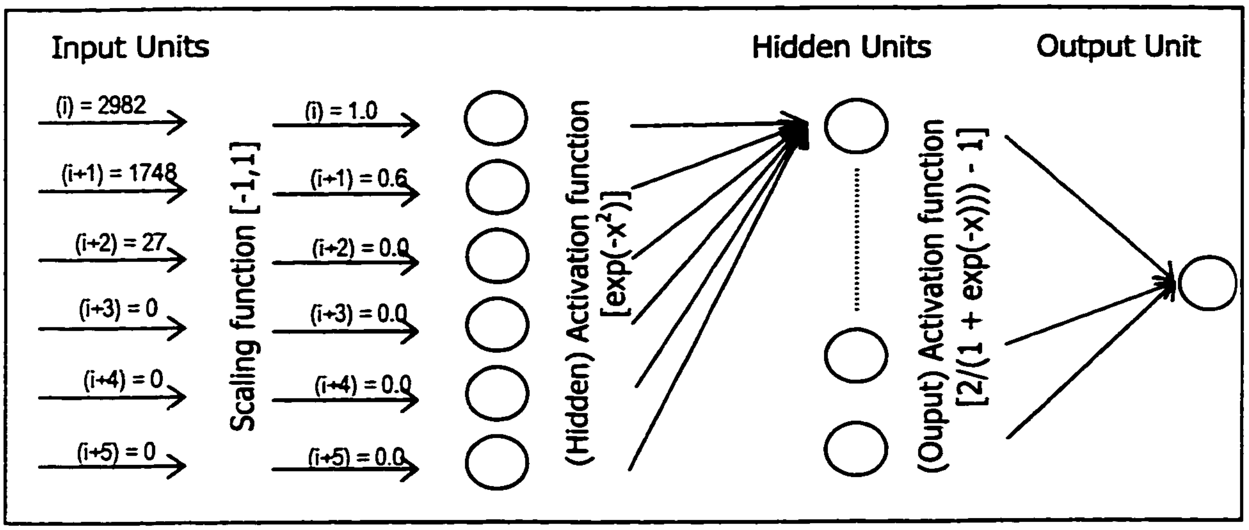


Figure 5.6 Example of a training pattern introduced to the BPN

When applicable, NeuroShell's calibration feature is used to test the neural network's performance. This involves retaining a subset of patterns during training and processing them at various iterations (or epochs) of the network's training phase. This ensures that the ANN is able to generalize the output unit for any given input unit, rather than memorize the input-output relationship of each training pattern.

Building neural networks is an iterative process that demands a reasonable understanding of the parameters of a particular network, as well as, lots of patience. The network parameters presented in Table 5.1 are selected from several iterations of the networks and parameter combinations. It is difficult to apply a systematic approach to building neural networks. In fact, a common criticism of neural networks is the "black-box" approach often used for building them. It is deemed more of an "art-form" than a scientific process [56]. Nonetheless, an attempt is made to characterize the developmental approach of arriving to the final three network architectures. This approach is illustrated in Figure 5.7.

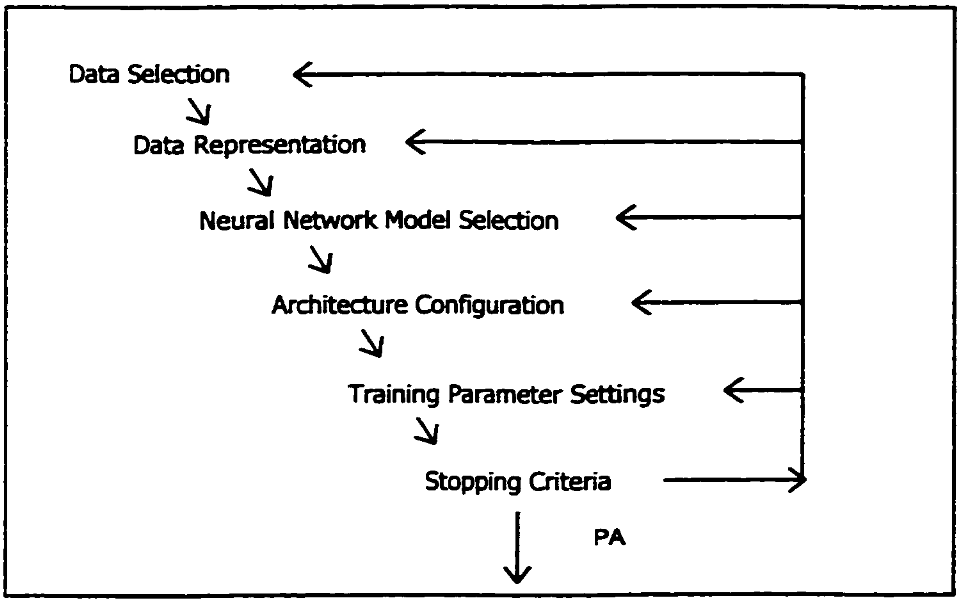


Figure 5.7 Iterative process for building neural networks

Due to the significant noise in the data, achieving discrete output unit values of zero or one is not always possible. For this reason, the BPN output unit values, computed as any number within the range of [0,1], are rounded off so as to obtain discrete values of either zero or one. The PNN automatically computes the number of correctly classified output units based on the higher probability of each possible output value. The KNN does not provide accuracy statistics because it is not presented with the actual outputs. In this case, the estimated output values are exported to a spreadsheet, where they are then compared against the actual outputs.

5.4 Neural Network Accuracy Results

The performance of the neural networks is assessed using two criteria: (i) the percentage of actual events classified and (ii) the overall network accuracy. The percentage of actual events classified is defined as the percentage of actual start or end events correctly classified by the network. Whereas, the overall network accuracy is defined as the percentage of all events (actual events and non-events) correctly classified by the network. The results for both performance metrics are presented in Tables 5.2, 5.3, and 5.4 for the DHW heater, and Tables 5.5, 5.6, and 5.7 for the refrigerator for each of the three neural network models.

Table 5.2 BPN results for the DHW heater

Criteria	Training period: October		Near-to-date testing period: November		Far-to-date testing period: January		Average
	Start	End	Start	End	Start	End	
Actual events classified	98.5 %	100 %	79.5 %	100 %	92.6 %	95.8 %	94.4 %
NN accuracy	97.1 %	98.7 %	82.8 %	78.9 %	84.2 %	87.9 %	88.3 %

Table 5.3 PNN results for the DHW heater

Criteria	Training period: October		Near-to-date testing period: November		Far-to-date testing period: January		Average
	Start	End	Start	End	Start	End	
Actual events classified	98.5 %	100 %	81.9 %	96.8 %	88.2 %	94.4 %	93.3 %
NN accuracy	96.6 %	98.7 %	81.3 %	77.8 %	81.0 %	73.8 %	84.9 %

Table 5.4 KNN results for the DHW heater

Criteria	Training period: October		Near-to-date testing period: November		Far-to-date testing period: January		Average
	Start	End	Start	End	Start	End	
Actual events classified	95.6 %	69.6 %	84.9 %	55.6 %	89.7 %	47.9 %	73.9 %
NN accuracy	72.5 %	71.1 %	62.6 %	42.2 %	72.3 %	35.5 %	59.4 %

Table 5.5 BPN results for the refrigerator

Criteria	Training period: October		Near-to-date testing period: November		Far-to-date testing period: January		Average
	Start	End	Start	End	Start	End	
Actual events classified	70.3 %	16.2 %	72.7 %	0 %	41.9 %	0 %	33.5 %
NN accuracy	82.6 %	51.3 %	83.2 %	0 %	78.3 %	0 %	49.2 %

Table 5.6 PNN results for the refrigerator

Criteria	Training period: October		Near-to-date testing period: November		Far-to-date testing period: January		Average
	Start	End	Start	End	Start	End	
Actual events classified	97.4 %	98.3 %	98.3 %	95.6 %	84.6 %	86.5 %	93.5 %
NN accuracy	78.2 %	79.6 %	78.1 %	73.6 %	63.5 %	70.3 %	78.9 %

Table 5.7 KNN results for the refrigerator

Criteria	Training period: October		Near-to-date testing period: November		Far-to-date testing period: January		Average
	Start	End	Start	End	Start	End	
Actual events classified	50.5 %	60.7 %	45.9 %	0.0 %	67.5 %	0.0 %	37.4 %
NN accuracy	46.7 %	42.8 %	31.1 %	0.0 %	34.8 %	0.0 %	25.9 %

The results indicate that, generally, the best results are obtained using a Probabilistic Neural Network, whereby, the average model accuracy is 84.9% and 78.9% for all data sets for the DHW heater and the refrigerator, respectively. The BPN accuracy fairs better for the DHW heater results, but is unable to process any of the refrigerator test data for end event. In general, the three network types yield higher accuracy results for the DHW heater data than the refrigerator data. This is likely due to the greater variability observed in the refrigerator data than the DHW heater data, thus, reducing the effectiveness of the network to learn the inherent patterns in the data.

The percentage of actual start or end events correctly classified is highest for the PNN for both appliances, that is, 93.3% for the DHW heater and 93.5% for the refrigerator. In fact, the PNN is the only network that is able to satisfactorily classify actual events for both appliances. The two supervised networks, that is, the BPN and the PNN, are more suitable to classifying energy signatures than the unsupervised KNN.

5.5 Comparison of the Neural Network and Pattern Recognition Algorithm

The comparison of the rule-based pattern recognition and neural network approaches is based on the ability of each model to detect actual start and end events within the whole-house demand profile, while minimizing the number of false events. To do so, both approaches are applied to same input data, that is, a sliding template of six time-steps in the Total demand profile (defined in Section 4.1).

Tables 5.8 and 5.9 compare the actual events correctly classified by the "best" performing neural network (in this case, the PNN) and the Pattern Recognition Algorithm (PRA) for the DHW heater and the refrigerator, respectively. The percentages listed are calculated with respect to the total number of actual start or end events within the period considered.

Table 5.8 Comparison of actual events correctly classified by the PNN and PRA for the DHW heater

Data set	Training period: October		Near-to-date testing period: November		Far-to-date testing period: January	
	Start	End	Start	End	Start	End
PNN	98.5%	100%	81.9%	96.8%	88.2%	94.4%
PRA	94.5%	92.3%	98.6%	93.1%	98.1%	95.2%
Difference	4.0%	7.7%	-16.7%	3.7%	-9.9%	-0.8%

Table 5.9 Comparison of actual events correctly classified by the PNN and PRA for the refrigerator

Data set	Training period: October		Near-to-date testing period: November		Far-to-date testing period: January	
	Start	End	Start	End	Start	End
PNN	97.4%	98.3%	98.3%	95.6%	84.6%	86.5%
PRA	92.8%	63.4%	92.0%	48.1%	91.4%	59.6%
Difference	4.6%	34.9%	6.3%	47.5%	-6.8%	26.9%

The results indicate that on average the PNN is less effective in detecting DHW heater events than the PRA. Whereas, on average the PNN is more effective in detecting refrigerator events than the PRA. The reason for this is that although the PRA can effectively isolate the energy signature of an appliance, it's ability to filter through noise in the data is not as effective as that of the neural network. The results in Table 5.10 support this statement. Table 5.10 lists the percentage of non-events of the refrigerator that are classified as actual events by each of the models, with respect to the total number of actual events within the period considered.

Table 5.10 Comparison of false events incorrectly classified by the PNN and PRA for the refrigerator

Data set	Training period: October		Near-to-date testing period: November		Far-to-date testing period: January	
	Start	End	Start	End	Start	End
PNN	54%	31%	55%	91%	109%	66%
PRA	200%	60%	23%	110%	248%	96%
Difference	-146%	29%	-32%	-19%	-138%	-30%

The comparison of these results for both the neural network and PRA indicate that the PRA yields a higher start and end event detection rate than the PNN for the DHW heater only. The refrigerator - whose energy signature is often masked by noise from other appliances with similar operating characteristics in the house - is more effectively detected using the neural network than the PRA. In this case, further research should be carried out to investigate possibly integrating a neural network, such as the PNN into the rules of the PRA.

6.0 RESEARCH CONTRIBUTIONS

Both the Pattern Recognition Algorithm and the Probabilistic Neural Network approaches show a promising potential for the disaggregation of the whole-house electric load into the major end-uses in residential buildings. The models developed are characterized by low cost, modest data collection needs, and no occupant-related information required. Moreover, the Pattern Recognition Algorithm is conceptually simple and versatile because of its rule-base platform. Additional rules can be easily and intuitively added to the Algorithm, and existing rules can be modified for its application for other appliances not investigated in this study.

The domestic hot water (DHW) heater energy signature for both start and end events is, typically, well defined in the Total demand profile due the appliance's high demand level in comparison to other appliances in the house. Thus, the DHW heater algorithm's rules can be allowed to be more constraining with less effort than the rules for other appliances that typically have lower demand levels, such as the refrigerator. The main cause of error in the testing data for the Pattern Recognition Algorithm is the simultaneous events with the stove in the case of the DHW heater, and the electric baseboard heater in the case of the refrigerator.

Whether the refrigerator algorithm should be improved to bring the accuracy parameters of the estimated demand profile within the same range as that of the DHW heater depends on the intended use of the results. There is a trade-off between reducing this error and the complexity of the algorithm. Given that the energy share errors are consistently low, it is determined that the refrigerator algorithm is acceptable as presented herein.

6.1 Recommendations for Future Work

The transferability of the Pattern Recognition Algorithm among a variety of dwelling types needs to be assessed. While most dwellings have a refrigerator, and there is a certain electrical similarity among them owing to the economics of manufacturing and marketing, there is still a wide range of variability. The extent and cause of this variability needs to be determined for a representative share of the Canadian housing stock. In addition, a survey of most commonly found large connected loads in a house is required. With this information, it may result that the energy signatures of two or more major appliances, not present in the case study house, are not distinguishable using the prototypical Pattern Recognition Algorithm. In this case, additional rules should be integrated in the Algorithm. For instance, rules to verify the systematic load behavior of an appliance, such as, the time-of-use, frequency of use within a day, and weather dependence are possible variables to consider.

The preliminary results of the Probabilistic Neural Network indicate that the approach should be further investigated with the aim of possibly combining or substituting some of the rules in the Pattern Recognition Algorithm for the Probabilistic Neural Model in an effort to increase the algorithm's overall accuracy. The function of the neural network as part of the Pattern Recognition Algorithm may be thought of as a subroutine or function. Whereby, the input data is presented and processed by the neural network, and a data set of possible start and end events are returned to the Pattern Recognition Algorithm for validation and estimation of the appliance demand profile and aggregate load. Like the Pattern Recognition Algorithm, the transferability of the Probabilistic Neural Network across a variety of dwellings must be tested.

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