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Nonintrusive load disaggregation computer program to estimate the energy consumption of major end-uses in residential buildings

Medgar L. Marceau

A Thesis

in

The Department of Building, Civil, and Environmental Engineering

Presented in Partial Fulfillment of the Requirements
for the Degree of Master of Applied Science at
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ABSTRACT

Nonintrusive load disaggregation computer program to estimate the energy consumption of major end-uses in residential buildings

Medgar L. Marceau

The objective of this thesis is to develop a methodology and the related computer program for the nonintrusive load disaggregation of total-household electric load into its end-uses. The computer program estimates the energy consumption of individual electric appliances in a house based on the analysis of the current measured at the house-power-source interface using a minimum number of sensors. The program, written in the C programming language, is based on the analysis of total-household electric current data collected over a period of one year from a house in Montréal. The nonintrusive load disaggregation computer program can be incorporated into an Energy Monitoring and Management System (EMMS). An EMMS will (i) continuously monitor and quantify the real long-term energy impact of renovations, purchases, aging appliances, and changes in occupant behaviour, (ii) increase the home owner's awareness of actual energy performance, and (iii) provide helpful recommendations to the home owner for improving the energy performance of the house.

The program estimates the contribution of selected appliances to the total energy consumption of the house. The contribution of an appliance to the total energy consumption is called the appliance energy share. The results show that for most of the appliances the difference between measured and estimated energy shares is less than 5%.

ACKNOWLEDGEMENTS

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CHAPTER 1

INTRODUCTION

The need to conserve energy is universally recognized. The environmental consequences of energy production and use can no longer be ignored. Competition in the newly deregulated energy market is forcing energy utilities to offer their customers new services. For example, some electric utilities have already modified their residential rate-structure to reflect the time-of-day cost of producing electricity. However, the cost to the consumer will continue its inevitable increase until it actually reflects the true cost of energy production and use. To cope with these rising costs, home owners need to be aware of the actual energy performance of their homes, and they need access to appropriate advice for implementing energy conservation measures.

1.1 ENERGY CONSERVATION

Almost all houses today were built when energy was cheap and when the environmental consequences of energy production and use were usually overlooked. They were built before any regulations on energy efficiency were available or enforced. Consequently, today there are many opportunities for reducing energy consumption in the residential sector.

Renovations, aging appliances, newly installed appliances, and changes in occupant behaviour affect the energy performance of a house. But home owners are often unaware of *how* these changes will affect performance. For example, installing a more-efficient furnace will not necessarily reduce energy bills. If the occupants stop turning down the thermostat at night because the new furnace is cheaper to operate, their energy costs can actually increase [Zmeureanu and Marceau, 1998].

1.2 ENERGY AUDIT

To make informed decisions about energy conservation, home owners need a detailed picture of energy use. An energy audit is an accounting of all such uses. Although this kind of short-term monitoring is cost-effective, it can only provide energy auditors with information about energy performance at a specific time. Long-term monitoring, on the other hand, is more useful because it can provide feedback to the home owner, the utility company, and the energy auditor on energy use and *changes* in energy use. However, because it requires that all end-uses be monitored for a long time, it can be expensive, and it can inconvenience the occupants.

1.3 LOAD DISAGGREGATION

Over the past several years, researchers have developed methods of disaggregating the total energy consumption of a house into its end-uses. Analyzing the total-household energy consumption can provide as detailed a picture of energy use as does detailed long-term monitoring.

Load disaggregation is a method of extracting from the total load its constituent parts. It yields information about the energy consumption of end-uses without having to measure the end-uses directly for long periods of time; therefore, fewer sensors are needed, and less data is collected. Since there is less data, less analysis is required. Consequently, monitoring, storage, and transmission costs are lower.

Load disaggregation is intrinsically nonintrusive. Compare this to the conventional and intrusive practice of sub-metering. Using load disaggregation, building occupants are not inconvenienced by personnel installing devices on appliances throughout the building, and there are no visible devices that continually remind the occupants that their behaviour is somehow being monitored.

1.4 NONINTRUSIVE LOAD DISAGGREGATION COMPUTER PROGRAM

The objective of this thesis is to develop a methodology and the related computer program for the nonintrusive load disaggregation of total-household electric load into its end-uses. The computer program estimates the energy consumption of individual electric appliances in a house based on the analysis of the current measured at the house-power-source interface using a minimum number of sensors.

The development of the program was based on data collected from a house located in Montréal. The total electric demand of the house and of each major appliance was obtained from measurements of electric current over a period of one year. Figure 1 shows how variations in the demand of the individual appliances are reflected in the total-household demand. Rules that predict which appliance causes a particular change in the total demand were identified and organized into an algorithm. This algorithm, called the appliance-load recognition algorithm, forms the core of the computer program. The program is coded in the C programming language.

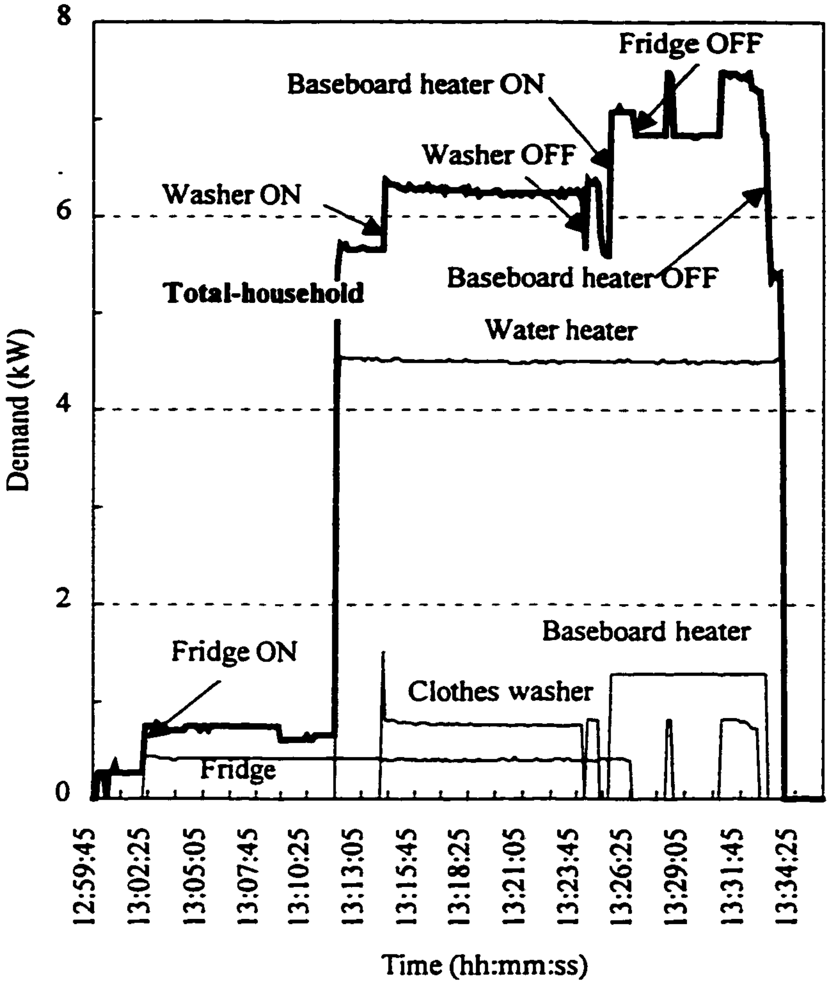


Figure 1. Variations in the demand of individual appliances are reflected in the total-household demand. From M. Marceau and R. Zmeureanu. 1998. A non-intrusive appliance load recognition algorithm to estimate the energy performance of major end-uses in residential buildings. Proceedings of Second European Conference on Energy Performance and Indoor Climate in Buildings, November 1998. Lyon, France.

The computer program has two major stages: (1) the sampling mode and (2) the evaluation mode. In the sampling mode, the operating characteristics of each appliance are defined using measurements collected over a sampling period of several days. At least one current sensor per appliance is required to collect the appliance current data during the sampling mode. In the evaluation mode, the appliance-load recognition algorithm analyzes the electric current measured from the main supply line using the previously identified statistics of each appliance. Two current sensors are required to collect the total current data in the evaluation mode, that is, one on each supply line. The computer program disaggregates the total-household electricity consumption into its constituent parts.

The nonintrusive load disaggregation computer program described in this thesis can be integrated into be the main component of an Energy Monitoring and Management System (EMMS). An EMMS will (i) continuously monitor and quantify the real long-term energy impact of renovations, purchases, aging appliances, and changes in occupant behaviour, (ii) increase the home owner's awareness of actual energy performance, and (iii) provide helpful recommendations to the home owner for improving the house's energy performance.

1.5 ORGANIZATION OF THESIS

Load disaggregation and the work done by other researches in this field is described in Chapter 2. The methods of disaggregating electric loads are emphasized.

The data used to develop the nonintrusive load disaggregation computer program is described in Chapter 3. The data was obtained from an energy audit of a house located in Montréal. The audit included detailed monitoring of electricity consumption of the entire house and of the major appliances.

The nonintrusive load disaggregation computer program is described in Chapter 4. The core of the program is the appliance-load recognition algorithm. The program estimates the energy consumption of the major household appliances based on short-term measurements of the appliances and on the long-term analysis of changes in the total-household electric demand.

The computer program is evaluated for 25 scenarios. These scenarios and the results of the evaluation are summarized in Chapter 5.

Finally, conclusions and recommendations for further work are presented in Chapters 6 and 7.

CHAPTER 2

LITERATURE REVIEW

The scope of the literature review encompasses the broad area of load disaggregation. Although this thesis is specifically about nonintrusive electric-load disaggregation, investigating a broader area will show how the thesis fits into the larger context.

There are two sections to this literature review. The first section contains a summary of the methods of load disaggregation developed by other researchers. The second section presents the conclusions from the literature review.

2.1 LOAD DISAGGREGATION

There are several ways of classifying load disaggregation research. For example, Figure 2 shows a classification scheme based on load type and appliance signatures. The three types are electric, gas, and hot water. The data for load research can be collected either intrusively or nonintrusively. Researchers usually focus on either the residential sector or the commercial sector, because each sector has load profiles that are characteristic to it. However, all methods essentially rely on the assumption that changes in the operation of an end-use produces recognizable and predictable changes in the total load. Sections 2.1.1 to 2.1.3 discuss each load type.

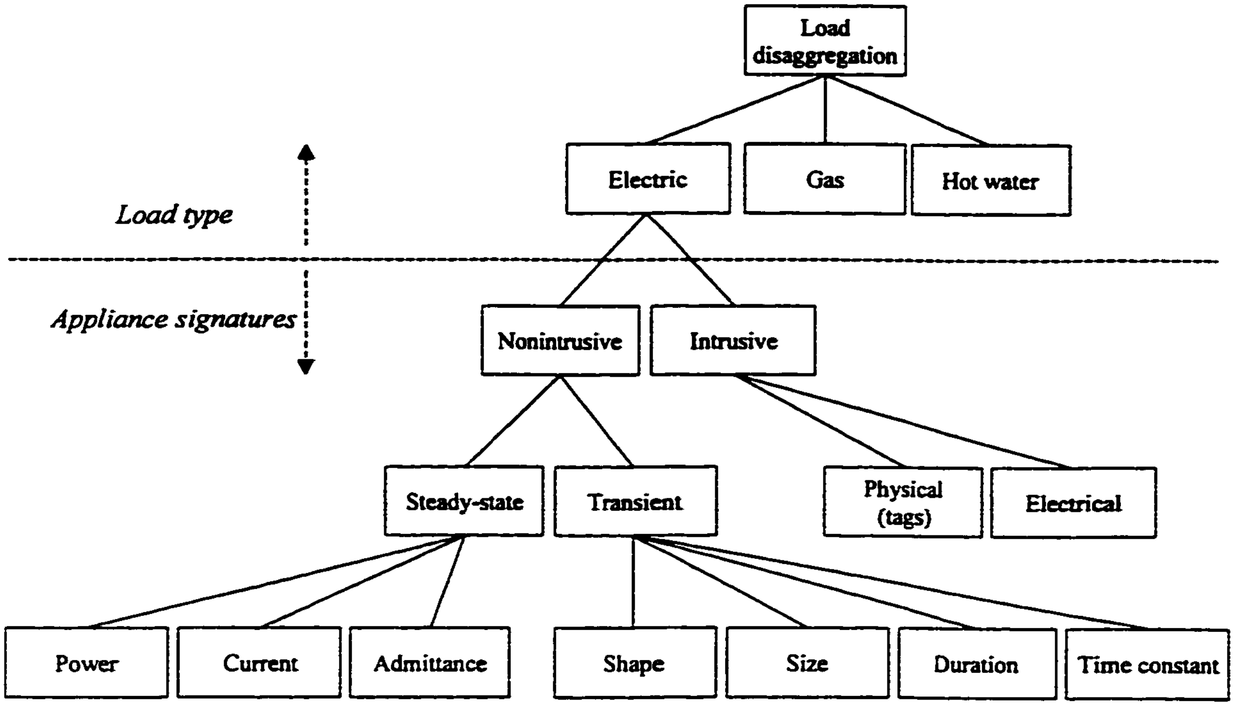


Figure 2. Load disaggregation research classified according to load type and appliance signature. Adapted from Hart, G.W. 1992. Nonintrusive appliance load monitoring. Proceedings of the IEEE. Vol. 80, No. 12, pp. 1870-1891.

2.1.1 Electric loads

Electric-load disaggregation means disaggregating the total electric load into its end-uses. The utility-building interface is the utility's electricity revenue meter. The paper by Hart [Hart, 1992] contains an exhaustive bibliography of research in the area of nonintrusive appliance-load monitoring up to 1992, and sections I to VI are an excellent introduction to the topic of electric-load disaggregation. In this paper, the author advances the concept of appliance signatures. He defines an appliance signature as a measurable parameter of the total load that gives information about the nature or operating state of an individual end-use in the load.

There are two classes of appliance signature: nonintrusive and intrusive. These classes also characterize two approaches to load disaggregation. It is unfortunate that the modifiers *intrusive* and *nonintrusive* mean different things depending on whether they refer to a procedure or to a signature. For example, a nonintrusive signature can be measured intrusively or nonintrusively; similarly, an intrusive signature can be measured intrusively or nonintrusively.

"*A nonintrusive signature is one that can be measured by passively observing the operation of a load*" [Hart, 1992], whereas nonintrusive monitoring means that physical intrusions onto the energy consumer's property are minimized or eliminated. Two types of nonintrusive signature are steady-state and transient.

Fundamental frequency signatures, such as power, current, and admittance, consist of the complex ordered pair of an in-phase and an out-of-phase component. However, either components alone could be used as a signature, although it would be less informative than using both [Hart, 1992].

Steady-state signatures are derived from the differences between the steady-state properties of an end-use's operating states. For example, the steady-state power signature of a baseboard heater is the power difference between its off state and its on state. Hart identifies three advantages to using steady-state signatures: (i) They are continuously present; therefore, high resolution data is not needed to detect their presence. (ii) They satisfy the constraint that the sum of power changes in any end-use's cycle of state transitions is zero. This implies that the act of an end-use turning off is also a signature.

(iii) They are additive when two or more happen coincidentally. This means it is possible to analyze simultaneous events when their sum is received by a processing algorithm.

Transient signatures, on the other hand, are more difficult to detect and provide less information than steady-state signatures. However, transient signatures are worthwhile investigating if they provide useful information to augment that from steady-state signatures [Hart, 1992]. For example, motors have a characteristic transient signature at start-up. Therefore, the presence of such a signature can be used to confirm that an appliance with a motor has turned on.

An intrusive signature requires some form of active interference at the energy consumer's property, while intrusive monitoring requires that each end-use be instrumented. Intrusive monitoring necessitates entering the energy consumer's premises and inconveniencing the occupants. There are two types of intrusive signature: physical and electrical. Both types must be generated.

Physically intrusive signatures can be generated by a small device attached to the power cord of an appliance. Whenever the appliance is activated, the device sends a signal to a data collector indicating the condition of the appliance's operating state. This kind of device could also be used to distinguish between two or more appliances with the same electrical signal.

Electrically intrusive signatures are generated at the electricity meter. It involves *"injecting a signal such as a voltage harmonic or transient at the utility interface. By analyzing the change in the current waveform, information can be gleaned concerning* *the types of devices active at that moment"* [Hart, 1992]. This procedure is analogous to sonar: a signal is sent out and the echo that comes back is analyzed. However, because of concerns about interference and power quality, utilities are reluctant to allow this form of active signature.

2.1.1.1 Four approaches to electric load disaggregation

This section summarizes four approaches to electric-load disaggregation. Each approach can be characterized by the input required and the output produced, the method of disaggregation, the accuracy of the results, and possible applications.

2.1.1.1.1 Nonintrusive Appliance Load Monitor

Hart [Hart, 1992] describes the development of a Nonintrusive Appliance Load Monitor (NALM). The NALM is a physical device that an electrician installs on the electricity meter. The outline of the NALM algorithm is shown in Figure 3.

The prototype performs steps 1 through 3 in the field and steps 4 through 8 are executed in the lab. The commercial unit performs steps 1 through 7 in the field and step 8 is performed in the lab.

The inputs are power and voltage. The electricity meter is the only point in the entire building that is instrumented. Sensors in the NALM measure average power and root mean square (RMS) voltage on each of the two legs over 1-second intervals. *"Each sensor is a digital alternating current monitor configured to calculate RMS voltage and real and reactive power digitally based on rapid samples of current and voltage waveforms for the two legs. The data measured is the ordered pair of real and reactive* *power"* [Hart, 1992]. Each set of data also has an associated time value that represents the time of the observed measurement. The inputs are used to calculate normalized power for each leg. Normalized power is equivalent to admittance. The power is normalized to remove the effects of varying line voltage.

The next step is to pass the data through the edge detection algorithm. It identifies the location of step-like changes. The location is defined by the time value. The algorithm segments the normalized power values into periods in which the power is steady and periods in which it is changing. A steady period is defined as three or more data sampling periods (that is, at least 3 seconds) in which the input does not vary by more than 15 W (or 15 VAR for reactive power). The remaining periods are defined as periods of change. The values within the steady periods are averaged, thereby minimizing the effect of electrical noise. The difference between steady periods is the step change in power. The time of the first value in the step change provides the time stamp. The sequence of time-stamped step-change vectors (they are called vectors because the process of an appliance turning on or off is analogous to a change in direction) is the output. All outputs below a certain size threshold are discarded. The magnitude of the size threshold depends on the power consumption of the appliances that the user wants the algorithm to identify.

Another algorithm groups the observed step changes into clusters. Ideally, each of these clusters represents one kind of state change for one appliance. Groups of clusters are paired to form the appliance models. Pairing clusters involves a number of tolerance criteria for matching the centroid of each cluster. Every time-stamped signature event corresponds to an appliance changing state. Each cluster represents an appliance. Now it is simply a matter of matching signatures. The statistics are tabulated given that each state change at every time is known. Finally, the appliances are named. The appliances are named based on operating power level, the 120-V versus 240-V nature, and the duration statistics.

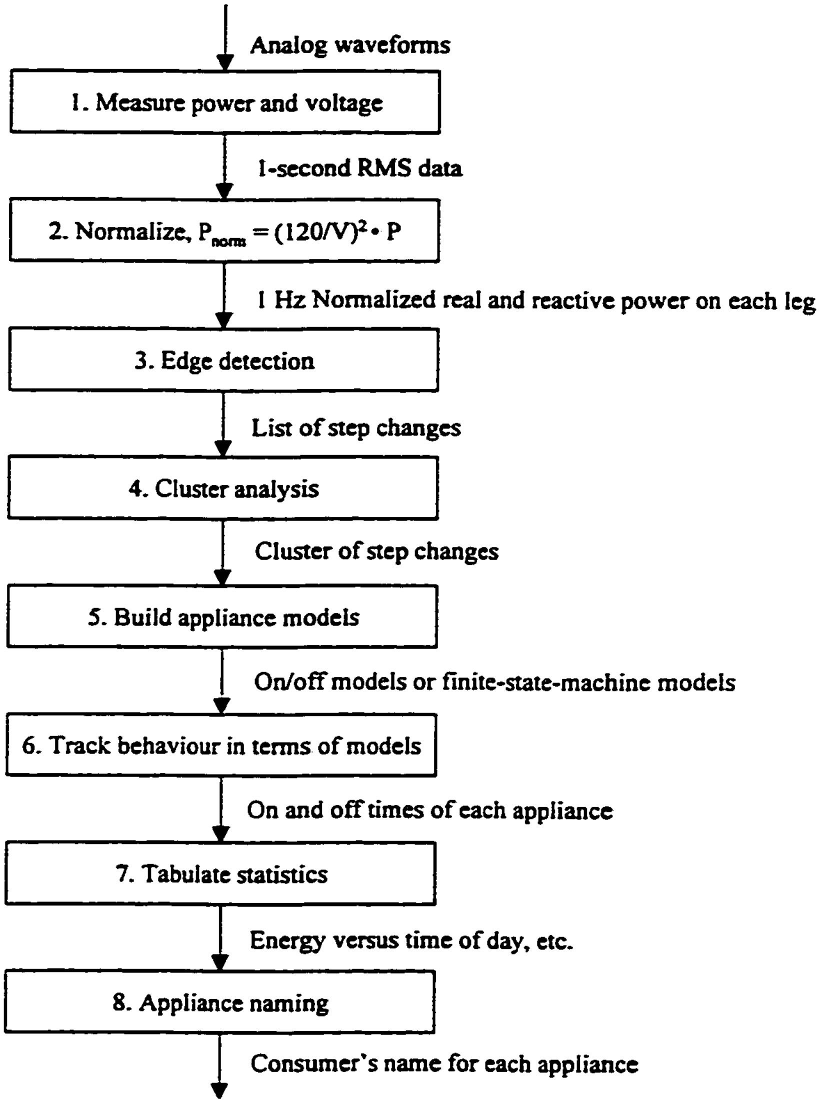


Figure 3. Nonintrusive appliance load monitor algorithm. From Hart, G.W. 1992. Nonintrusive appliance load monitoring. Proceedings of the IEEE. Vol. 80, No. 12, pp. 1870-1891.

Field-testing of the prototype NALM compared the performance of the NALM with data collected conventionally [Carmichael, 1990]. The NALM can recognize small kitchen appliances with a high degree of accuracy (-1.4% average error) but not lights (15.3% average error). For larger appliances the error ranged from -2.8% for washers to 46.7% for electric ranges. The average error for total household energy consumption was -6.5%. By 1996, seven utilities were field-testing NALMs at up to six customer sites each [Taylor, 1996]. In one evaluation period, the difference between the NALM estimates for monthly electricity consumption and data from direct measurement was less than 15% for all appliances; and less than 10% for pumps and refrigerators. In addition, the NALM also aided researchers in identifying about five faulty appliances. An important footnote says that nearly-simultaneous events, within 2 to 3 seconds, accounted for 4% of the events in one field test where they were carefully counted. But this will vary considerably, depending on the appliance inventory and usage [Hart, 1992].

There are some disadvantages to this procedure. The first is the 1-second data sampling rate. Although a slower sampling rate would result in more simultaneous events, it would also mean lower storage, transmission, and analysis costs. Perhaps it is possible to decrease the sampling rate without losing critical event information. The second disadvantage concerns the data itself. Both the real and the reactive components of current and power are used as input. Perhaps only one of these measurements are needed to identify a significant number of events. Then there is the hardware: the NALM device itself requires a qualified electrician to install it. The complexity of the NALM is necessitated by the complexity of the data it has to collect. However, if only one parameter were needed, a simpler device would be sufficient to collect the data. Another draw back to this approach is the huge processing requirements. The algorithm must perform sophisticated analyses on all the data before it begins to attributing changes in the data to specific appliances. It would be more useful, say for a home automation system, if the data could be processed in real-time.

2.1.1.1.2 Heuristic End-Use Load Profiler

This rule-based algorithm has been developed by Quantum Consulting Inc. [Powers et al., 1991]. The approach can be classified as nonintrusive because it is unnecessary to enter the premises. The program disaggregates end-use load profiles from premise-level data. Premise-level means the total-household energy consumption as measured at the electricity meter. The algorithm rules are based on pattern recognition. The input to the program is the premise-level load data, appliance information for standard appliances, and customer behavioural assumptions obtained through surveys with the customer. For a given premise-day, the algorithm scans the premise-level load and records the occurrence, the timing, and the magnitude of all large changes. The algorithm then determines which changes correspond to the end-use being considered and adjusts them according to consistency checks. It also requires some information about previous and subsequent changes at the same premise. The algorithm disaggregates one end-use at a time for each day starting with the largest and working towards the smallest, that is, it removes the appliance with the largest operating load from the total load, then the next largest, etc. The output is heuristic load profiles and appliance energy consumption. A heuristic load profile is a disaggregated end-use load profile specific to the premise, appliance and day being analyzed. This procedure is useful to utility managers and demand-side program evaluators, and its advantage over sub-metering is low cost.

Results of the work are reported in [Margossian, 1994], [Powers et al., 1992], and [Powers et al., 1991]. Forty houses were evaluated during four summer months. For large end-uses, the procedure produces accurate results. The peak values of the disaggregated air conditioner load profiles when averaged over all households for all summer days differs from the peak of the average metered profile by less than 5%. The average air conditioner energy consumption estimate derived from the heuristic load profiles differs from the actual energy consumption by less than 10%. The timing of the average air conditioner peak is also predicted very accurately.

The procedure, however, is limited to end-uses with large operating levels, such as, air conditioners, HVAC equipment, and domestic water heaters. It is also limited to analyzing only one day at a time. Its greatest advantage is that it can use load research data that utilities may have already collected.

2.1.1.1.3 Individual and Automatic Diagnostics of Electrical Consumption

Another approach to monitor end-uses in houses is reported in [Lebot et. al., 1994]. The Individual and Automatic Diagnostics of Electrical Consumption (DIACE in French) procedure requires two visits by an electrician. During the first visit the electrician installs metering devices and data collectors and an assistant helps the customers fill out a questionnaire. During the second visit the electrician removes plugs and data collectors. The metering devices contain sensors called *Hall effect* sensors, and they are accurate to within two percent. The sensors measure voltage, current, and phase angle of the electrical energy. They store the energy (Wh), the instantaneous power (W, averaged on the last 10 ms) and the voltage measurement (V). The system can record data at 10-minute or 15-minute intervals or at an interval greater than 15 minutes. There is no need to use any wire to connect the system. Communication is through the electrical wiring in the house. The researchers claim that customer behaviour is unaffected during data collection, yet the procedure is both physically and electrically intrusive. But at least no user intervention is required on the part of the customer.

At the time the article was written, there was not enough data collected from a 100-household study to allow the authors to draw any significant conclusions about the performance of the system. The article reports that a second phase of the study will be a nonintrusive analysis of 1000 households. The data from the DIACE 100-household survey will feed the nonintrusive survey.

Accurate end-use information is important and desirable, but it can be expensive to collect. This system lacks the efficiency of NALMs and HELP. The data collected is sufficient for load forecasting, but the system is very intrusive and large amounts of data must be collected. However, because the plugs are so small, the researchers claim it is unobtrusive. It would be useful to have a benchmark with which to compare the performance of truly nonintrusive load disaggregation procedures.

2.1.1.1.4 Transient load detection in commercial loads

This procedure is an extension of the NALM described in Section 2.1.1.1.1 and the residential nonintrusive load monitor (res-NILM) described in [Norford et al., 1992]. The researchers extended the procedure of residential nonintrusive load monitoring to commercial loads and created the commercial non-intrusive load monitor (com-NILM) [Norford et al., 1992] and [Norford et al., 1996]. Load disaggregation in the commercial sector presents special challenges, because power quality is more important: especially in terms of the operating efficiency of mechanical systems. Furthermore, some equipment have embedded electronic components that make their steady-state power consumption appear to be nearly purely resistive. This creates a special problem for the com-NILM because it relies on reactive power as a component of the appliance signature: especially because it is common to find more motors, a source of reactive power, in commercial buildings. Classes of commercial equipment have characteristic start-up transient signatures. These signatures reflect the physical task the load is performing, for example, switching on a bank of fluorescent lights is different from turning on a motor. The com-NILM uses sampling rates significantly faster than 1 Hz to record the presence of start-up transients. Signal processing is used to analyze the transients and determine which load has been activated. The com-NILM has also been integrated with building automation systems to provide fault detection, such as loads that draw extremely distorted, non-sinusoidal, input current waveforms. Laboratory testing of the prototype has shown that it is capable of identifying electrical loads from space-conditioning equipment.

Field-testing needs to be done to further refine and validate this procedure. The concept of combining start-up transient identification with steady-state identification is interesting. Whereas either procedures alone may not be accurate enough, both together may complement each other.

2.1.2 Gas loads

Gas-load disaggregation means disaggregating the total gas load into its end-uses. In regions that have direct gas distribution systems, the volume of gas consumed is measured at the utility revenue meter. Sub-metering even a relatively small, statistically representative, sample of houses can be expensive. And unlike electric loads, there is no family of signatures for gas loads. So there are less possible methods of performing gas-load disaggregation. Gas utilities have tried to rely on conventional means of indirectly inferring end-use consumption based on monthly bills, the end-uses present at a particular site, and occupant profiles. However, these methods are not accurate enough to allow the utility to reliably forecast changes in demand due to changes in end-use or customer profiles. So research based on electric-load disaggregation has been tried for gas-load disaggregation.

In [Yamagami et. al., 1996], the authors present the results of research into the disaggregation of total household gas-demand in Japan. The flow rate (in ft^3 per elapsed time) of all gas appliances in an unspecified number of houses was monitored. Twenty pairs of gas-meters and data-loggers were installed. This represents about five to six houses, assuming three to four gas appliances per house. The authors created, tested and improved a disaggregation algorithm using this detailed data. Then they applied the procedure to 600 homes so that they could develop demand models where the gas demand for the various gas appliances is a function of occupant demographics and household configurations.

The authors used the disaggregated data of the 600 homes, obtained through conventional sub-metering, to validate the demand models. Furthermore, since some homes had been monitored for several years, the researchers were able to observe changes in demand due to changes in appliances, family demographics, and climate. The algorithm, however, can not consistently identify variable-rate gas appliances. The authors suggest that a look backward capability might be able to improve identification of variable-rate gas appliances. At the time the article was written, the authors were satisfied with the performance of the algorithm (95% accurate). They suggest that further development will be required to adapt their procedure to the American market place.

The authors' observation that a look backward capability might be able to improve identification of variable-rate gas appliances could also be applicable to electric-load disaggregation.

2.1.3 Hot water loads

Hot water-load disaggregation means disaggregating the total hot water load into its end-uses. Sub-metering all hot water end-uses in a home is too expensive: even to obtain a, relatively small, statistically representative sample. Unlike electric loads, there is no family of signatures for hot water usc. So, like gas load research, there are less possible methods for performing hot water load disaggregation.

In [Lowenstein et al., 1996], the authors present the results of research in which they disaggregate hot water use in a house and in the laundry room of an apartment building. It must be noted, however, that the data was originally collected to study the performance of heat-pump water heaters, not to perform load research. The data, from sixteen field test sites, represents the flow rate in gallons per 15-seconds on the cold water feed to the hot water tanks. By combining a pattern recognition approach and a bin analysis approach, they are able to disaggregate the total hot water load. However, their method cannot separate overlapping events. They conclude that it should be possible to develop a signal recognition algorithm to disaggregate overlapping events.

In conjunction with electric load disaggregation, this method could give building occupants a more detailed picture of their energy consumption.

2.2 CONCLUSIONS

All three areas of load disaggregation research present opportunities for further study. However, since most household appliances in North America are electric, there is greater potential for electric-load disaggregation in terms of load management, energy conservation, and new technologies like building automation and intelligent buildings. Furthermore, the volume of research devoted to electric-load disaggregation shows that there is more interest in this type of load research. Therefore, as a result of the literature review, the following issues have been identified as deserving of further study. They will be considered in developing the nonintrusive load disaggregation computer program.

1. Can a load disaggregation computer program be developed without using complex signal processing algorithms?

2. Is electric current alone a sufficient signature to identify the major appliances in a building?
3. Is there a simple and inexpensive way to measure and collect the data?
4. Can transient signatures in residential appliances be detected reliably enough to consider their signature in an appliance-load recognition algorithm?
5. What is the lowest data sampling rate before too many events are missed?
6. Is it possible to disaggregate a load in real-time?
7. Can a look-backward approach be used to increase the accuracy of a load recognition algorithm when an appliance event is missed?

CHAPTER 3

DATA AND DATA ACQUISITION

This chapter describes the data that was used to develop the load disaggregation computer program. The data was obtained from an energy audit of a house in Montréal. The audit included detailed monitoring of electricity consumption of the entire house and of the major appliances. Once the data was collected, it was manipulated so that it could be handled easily by the computer program described in this thesis.

3.1 THE MONITORED HOUSE

3.1.1 Main characteristics

The house was built in 1947. It has two floors above ground, a ground-level garage, and a finished basement, which contains an office, a laundry room, and a bathroom. The total heated floor area is 158.6 m^2. The house is heated by an oil-fueled central hot water system. There are also two electric baseboard heaters, and each one is installed in a separate room as a backup. All household appliances are electric. Four people, two adults and two teenagers, inhabit the house.

3.1.2 Appliances

The major appliances are the domestic water heater, the stove, the two baseboard heaters, the dishwasher, the clothes washer, and the refrigerator. These appliances consume about 85% of the total household electricity. Lights, small appliances, and the clothes drier consume the remaining 15%. The clothes drier was monitored, but, for unknown reasons, the data recovered was unusable. Note that there is no air-conditioning system.

3.1.3 Wiring

Figure 4 shows schematically how the appliances are connected to the utility power supply. The utility delivers electricity at a nominal 120 V in each of two legs. The 120-V appliances are connected to either one of the two legs, and the 240-V appliances are connected to both legs.

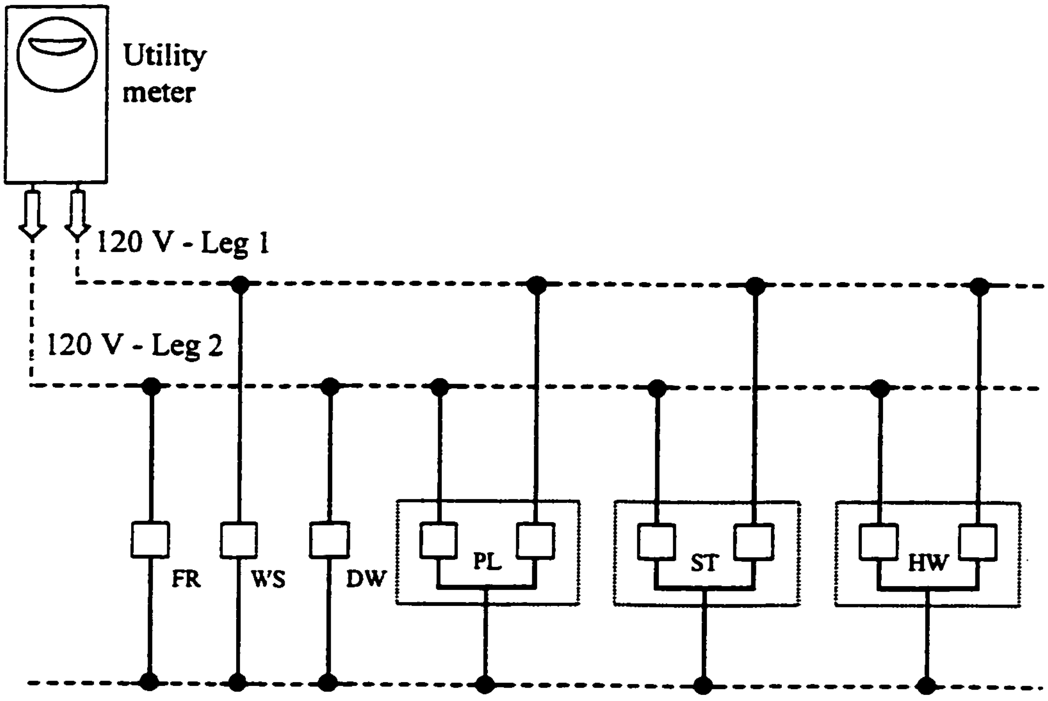


Figure 4. Appliance wiring schematic.

3.2 MONITORING

3.2.1 Current probes

Figure 5 shows the apparatus that is used to measure electric current. It consists of an ACR Systems SmartReader 3 electric-current and temperature logger connected to an

Amprobe current probe. Depending on the magnitude of the current expected, either the A60FL current probe or the A70FL current probe is used. The probe is clamped around one of the wires in the building-wire pair that deliver electricity to an end-use. If it is not possible to get access to the pair of wires, a line splitter is attached to the plug end of the appliance's power cord and the current probe is instead clamped around the line splitter. The data logger records the current at a user-specified rate. Each data logger, which has three channels, is capable of simultaneously recording current measured by three current probes. However, in order to use the maximum available memory of the data loggers and to minimize the data recovery frequency, only one current probe is connected to each data logger. According to the manufacturer's catalogue, the accuracy of the current probe is ± 4% F.S. + 0.4 A, where F.S. is the full scale that the user selects on the current probe (in this case either 25 or 100 A).

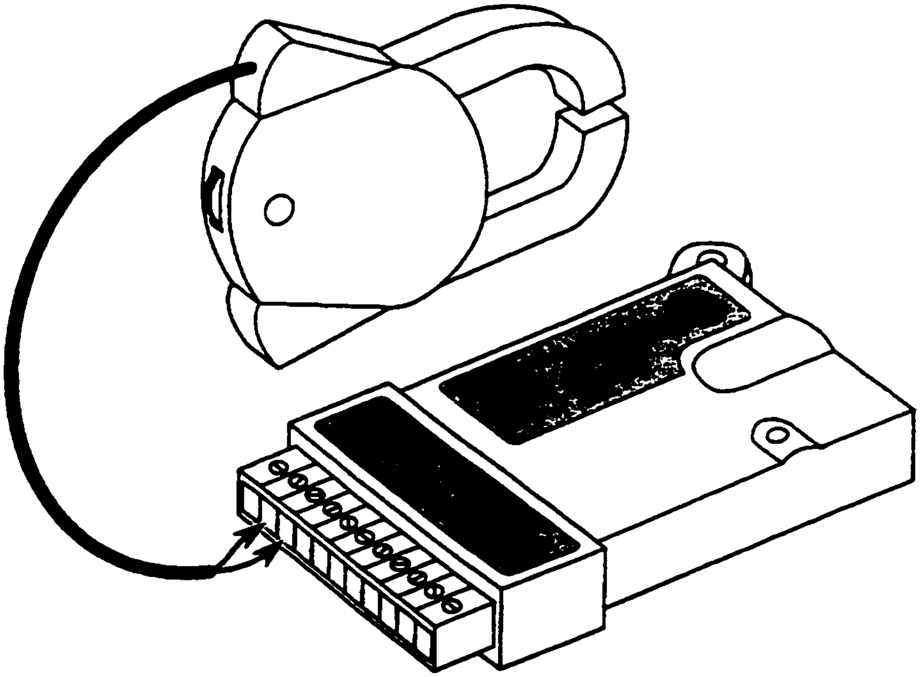


Figure 5. Clamp-on style current probe and data logger apparatus.

3.2.2 Location of sensors

Figure 6 shows the location of the current probes. Each of the two legs supplying the house with electricity was monitored individually. Each 120-V appliance was monitored with one probe and data logger apparatus. A line splitter was used on the refrigerator, the dishwasher, and the clothes washer, because it was not possible to monitor them directly from the electricity panel. The water heater is a balanced 240-V appliance. This means that each 120-V line draws an equal amount of current. Therefore only one probe is needed, and the measured current can be multiplied by two to obtain the total current. The stove and the two baseboard heaters, on the other hand, are unbalanced 240-V appliances. So each of their 120-V lines have to be monitored individually. In total, ten current probes and ten data loggers were used.

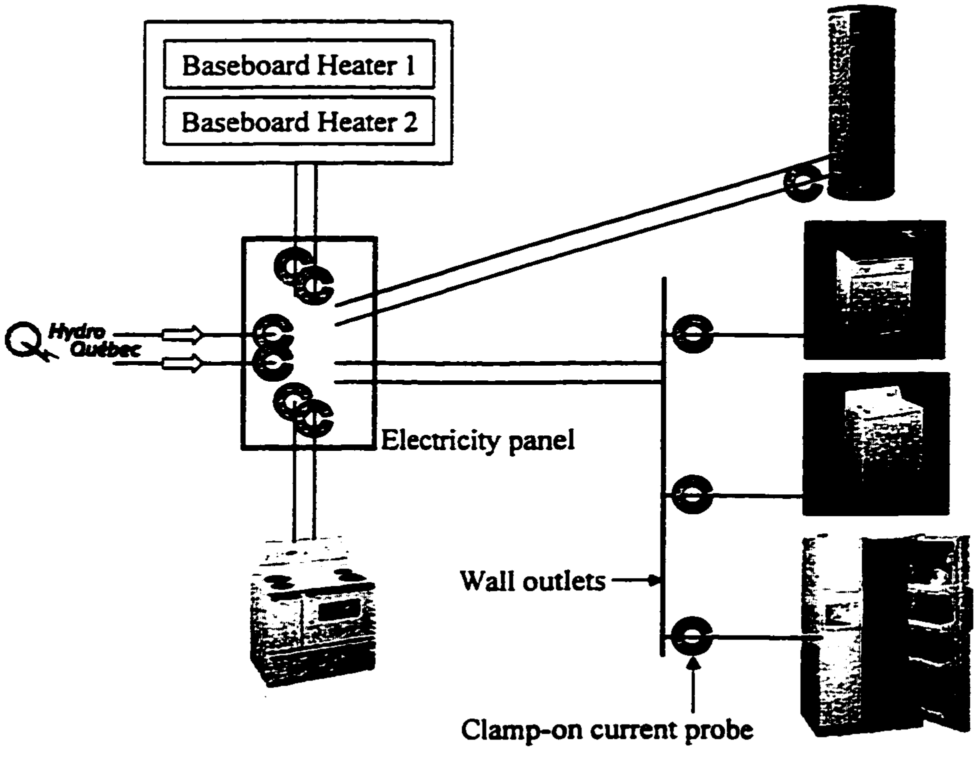


Figure 6. Location of current probes.

3.2.3 Duration and sampling rate

The appliances were monitored for 12 months. Four sampling rates were used, each for a different period. For example, the sampling rate from October 1996 to January 1997 was 16 seconds. The other sampling rates were 48, 32 and 8 seconds. The disaggregation algorithm was developed based on the data sampled at 8 and 16 second intervals.

3.2.4 Constant voltage assumption

It is assumed that the voltage supplied by the utility is constant. Nominally, the voltage is 120 V in each of the two legs. Although in reality, it can fluctuate within the range of 105 to 127 V, and the rate of these fluctuations can be as fast as 30 seconds [Brockman, 1998]. No description of how voltage varies over time was found in the literature. Utilities employ voltage taps inside transformers to provide as near-constant voltage as possible. So for the purpose of determining energy consumption, a constant voltage is assumed.

3.3 DATA

3.3.1 Data collection

One data logger can store 32,767 readings. So the frequency with which the data must be downloaded depends on the desired sampling rate. For example, when the sampling rate is set to 16 seconds, one data logger can store six days worth of data. Once the data logger is full, the data is downloaded to a portable computer. The software, TrendReader, that comes with the data loggers is used to save the data as an ASCII file. TrendReader automatically associates a date and time label to each current measurement. Spreadsheet software, MicroSoft Excel, is then used to manipulate and format the monitored data so that it can be used by the computer program described in this thesis.

3.3.2 Data manipulation

The individual data files are imported into a spreadsheet. The data from each appliance and the total-household data are aligned so that their date and time labels correspond as close as possible. The date and time labels from the total-household file that contains the data from leg 1 are used as the reference. The total-household, the stove and the two baseboard heaters were measured with two current probes each. So each pair of data files is added together. Then the demand for all data files is calculated using the relationship $P = (V \bullet I)/1000$, where P is demand in kilowatts, V is voltage in volts and I is current in amperes. Finally, appliance demand and total-household demand are saved as individual files. The energy consumption can be obtained by integrating the demand over time.

3.3.3 Data recovery

Three additional circumstances require that the data be manipulated before the computer program can use it. The first two are due to the time required to download and the second is due to synchronization.

The first two circumstances concern the time the data was downloaded. During the time it takes to download a data logger, the logger is not storing information. So that portion of the appliance's operation is not being recorded. However, since it takes less than two minutes to download a data logger, and downloading is done every six days (because the sampling rate is 16 seconds), less than one one-hundredths of a percent of the data is missed. In order to recover as much data as possible, the missing portion (that which can be reasonably judged as missing) is inserted between the available data. Table 1 shows an example of missing data in downloaded files. The boxed-in areas show where missing data was recovered.

The second circumstance has to do with larger gaps during downloading, for example, there were instances when the data was not downloaded for seven or eight days, and the earliest data was lost (first-in, first-out principle). So the input data is re-labeled consecutively because of the gaps in the collected data; otherwise, the program would make errors in calculating operating statistics. For example, if the refrigerator is on at the end of December 11 and the next two days' data is missing, and if the refrigerator is on again at the beginning of December 13, then it would appear as if the refrigerator is on continuously for more than two days. The first day of data, October 15, 1996, is re-labeled January 1, 1996. Appendix A shows the original dates with their corresponding new dates. Any future version of the program should be capable of handling non-consecutive data.

The third circumstance concerns the current data for the 240-V appliances. Each 120-V half was stored on a separate data logger. It was not foreseen that the two should be synchronized to start recording at the same instant. The result is that when the two halves are added together, one-off errors are sometimes created. Figure 7 shows the results of one-off errors. The file that contains the total-household data from leg 1 is used as the reference, and all the other files are aligned so that their time labels match as closely as possible those of the household leg 1. The two halves of the baseboard heater file, shown in Figures 7d and 7e, are aligned according to the best matching times with the reference file in Figure 7a. However this makes it appear as if the ON signal consist of two distinct changes in demand (Figure 7f) when in fact it is only one. A similar situation occurs at the OFF signal. In the total-household file, this kind of error may result in an event that shows apparently two ON signals instead of just one. The solution to preventing one-off errors in the final appliance files is to align each pair of appliance files so that the start and end of each event lines up as close as possible (Figures 7g to 7i). The same solution is not practical with the total-household files: There is just too much data to go through, and it is not obvious what is causing a change in demand in the total. Sections 4.3.4 and 4.3.5 describe two preprocessing algorithms that are used to minimize this kind of error.

In order to avoid downloading time and syncronization-related problems in the future, downloading time, both in duration and frequency, should be minimized, and all data loggers should be synchronized so that they start recording at the same time.

3.3.4 Input data-files

After the monitoring period is over, and the data is collected and compiled, there are seven files: one file for each appliance and one file for the total-household. The values in each file consists of demand, in kilowatts, with an associate date and time label.

Table 1. Sample of missing data due to downloading time.

Total - Leg 1			Total - Leg 2		Water Heater		Stove - Line 1		Stove - Line 2		Baseboard - Line 1		Baseboard - Line 2	
Time	Date	Current (A	Time	Current (A	Time	Current (A	Time	Current (A	Time	Current (A	Time	Current (A	Time	Current (A)
23:20:13	11/24/96	24.224	23:20:08	35.783	23:20:20	18.657	23:20:15	0.000	23:20:06	0.000	23:20:06	0.000	23:20:15	0.000
23:20:29	11/24/96	23.999	23:20:24	34.033	23:20:36	18.118	23:20:31	0.000	23:20:22	0.000	23:20:22	0.000	23:20:31	0.000
23:20:45	11/24/96	21.967	23:20:40	22.871	23:20:52	17.793	23:20:47	0.000	23:20:38	0.000	23:20:38	0.000	23:20:47	0.000
23:21:01	11/24/96	21.967	23:20:56	22.645	23:21:08	17.793	23:21:03	0.000	23:20:54	0.000	23:20:54	0.000	23:21:03	0.000
23:21:17	11/24/96	21.967	23:21:12	22.645	23:21:24	17.793	23:21:19	0.000	23:21:10	0.000	23:21:10	0.000	23:21:19	0.000
23:21:33	11/24/96	21.967	23:21:28	22.645	23:21:40	17.793	23:21:35	0.000	23:21:26	0.000	23:21:26	0.000	23:21:35	0.000
23:21:49	11/24/96	21.967	23:21:44	22.645	23:21:56	17.793	23:21:51	0.000	23:21:42	0.000	23:21:42	0.000	23:21:51	0.000
23:22:05	11/24/96	21.967	23:22:00	22.645	23:22:12	17.901	23:22:07	0.000	23:21:58	0.000	23:21:58	0.000	23:22:07	0.000
23:22:21	11/24/96	21.967	23:22:16	22.645	23:22:28	17.793	23:22:23	0.000	23:22:14	0.000	23:22:14	0.000	23:22:23	0.000
23:22:37	11/24/96	21.741	23:22:32	22.871	23:22:44	17.793	23:22:39	0.000	23:22:30	0.000	23:22:30	0.000	23:22:39	0.000
23:22:53	11/24/96	21.741		22.645	23:23:00	17.793	23:22:55	0.000	23:22:46	0.000	23:22:46	0.000	23:22:55	0.000
23:23:09	11/24/96	21.516		22.645	23:23:16	17.793	23:23:11	0.000	23:23:02	0.000	23:23:02	0.000	23:23:11	0.000
23:23:25	11/24/96	21.741		22.645	23:23:32	17.793	23:23:27	0.000	23:23:18	0.000	23:23:18	0.000	23:23:27	0.000
23:23:41	11/24/96	21.741		22.645	23:23:48	17.793	23:23:43	0.000	23:23:34	0.000	23:23:34	0.000	23:23:43	0.000
23:23:57	11/24/96	21.741		22.645	23:24:04	17.793	23:23:59	0.000	23:23:50	0.000	23:23:50	0.000	23:23:59	0.000
23:24:13	11/24/96	21.741		22.645	23:24:20	17.793	23:24:15	0.000	23:24:06	0.000	23:24:06	0.000	23:24:15	0.000
23:24:29	11/24/96	21.741	23:24:27	22.645	23:24:36	17.793	23:24:31	0.000	23:24:22	0.000	23:24:22	0.000	23:24:31	0.000
23:24:45	11/24/96	21.741	23:24:43	22.645	23:24:52	17.793		0.000	23:24:38	0.000	23:24:38	0.000	23:24:47	0.000
23:25:01	11/24/96	22.871	23:24:59	22.645	23:25:08	17.793		0.000	23:24:54	0.000	23:24:54	0.000	23:25:03	0.000
23:25:17	11/24/96	22.871	23:25:15	22.645	23:25:24	17.793		0.000	23:25:10	0.000	23:25:10	0.000	23:25:19	0.000
23:25:33	11/24/96	22.871	23:25:31	22.645	23:25:40	17.793		0.000	23:25:26	0.000	23:25:26	0.000	23:25:35	0.000
23:25:49	11/24/96	22.871	23:25:47	22.645	23:25:56	17.901		0.000	23:25:42	0.000	23:25:42	0.000	23:25:51	0.000
23:26:05	11/24/96	22.871	23:26:03	22.645	23:26:12	17.793	23:26:06	0.000	23:25:58	0.000	23:25:58	0.000	23:26:07	0.000
23:26:21	11/24/96	22.871	23:26:19	22.645	23:26:28	17.793	23:26:22	0.000	23:26:14	0.000	23:26:14	0.000	23:26:23	0.000
23:26:37	11/24/96	22.645	23:26:35	22.645	23:26:44	17.793	23:26:38	0.000	23:26:30	0.000	23:26:30	0.000	23:26:39	0.000
23:26:53	11/24/96	22.645	23:26:51	22.645	23:27:00	17.793	23:26:54	0.000		0.000	23:26:46	0.000	23:26:55	0.000
23:27:09	11/24/96	22.645	23:27:07	22.645	23:27:16	17.793	23:27:10	0.000		0.000	23:27:02	0.000	23:27:11	0.000
23:27:25	11/24/96	22.871	23:27:23	22.645	23:27:32	17.793	23:27:26	0.000		0.000	23:27:18	0.000	23:27:27	0.000
23:27:41	11/24/96	22.871	23:27:39	22.645	23:27:48	17.793	23:27:42	0.000		0.000	23:27:34	0.000	23:27:43	0.000
23:27:57	11/24/96	22.871	23:27:55	22.645	23:28:04	17.793	23:27:58	0.000	23:27:51	0.000	23:27:50	0.000	23:27:59	0.000
23:28:13	11/24/96	22.871	23:28:11	22.645	23:28:20	17.793	23:28:14	0.000	23:28:07	0.000	23:28:06	0.000	23:28:15	0.000
23:28:29	11/24/96	22.871	23:28:27	22.645	23:28:36	17.793	23:28:30	0.000	23:28:23	0.000		0.000	23:28:31	0.000
23:28:45	11/24/96	22.871	23:28:43	22.645	23:28:52	17.793	23:28:46	0.000	23:28:39	0.000		0.000	23:28:47	0.000
23:29:01	11/24/96	22.871	23:28:59	22.645	23:29:08	17.793	23:29:02	0.000	23:28:55	0.000		0.000	23:29:03	0.000
23:29:17	11/24/96	22.871	23:29:15	22.645	23:29:24	17.793	23:29:18	0.000	23:29:11	0.000		0.000	23:29:19	0.000
23:29:33	11/24/96	22.871	23:29:31	22.645	23:29:40	17.793	23:29:34	0.000	23:29:27	0.000	23:29:32	0.000	23:29:35	0.000
23:29:49	11/24/96	22.871	23:29:47	22.645	23:29:56	17.793	23:29:50	0.000	23:29:43	0.000	23:29:48	0.000		0.000
23:30:05	11/24/96	22.871	23:30:03	22.645	23:30:12	17.793	23:30:06	0.000	23:29:59	0.000	23:30:04	0.000		0.000
23:30:21	11/24/96	22.871	23:30:19	22.645	23:30:28	17.793	23:30:22	0.000	23:30:15	0.000	23:30:20	0.000		0.000
23:30:37	11/24/96	22.645	23:30:35	22.645	23:30:44	17.793	23:30:38	0.000	23:30:31	0.000	23:30:36	0.000		0.000
23:30:53	11/24/96	22.645	23:30:51	22.645	23:31:00	17.793	23:30:54	0.000	23:30:47	0.000	23:30:52	0.000		0.000
23:31:09	11/24/96	22.645	23:31:07	22.645	23:31:16	17.685	23:31:10	0.000	23:31:03	0.000	23:31:08	0.000		0.000
23:31:25	11/24/96	22.645	23:31:23	22.645	23:31:32	17.685	23:31:26	0.000	23:31:19	0.000	23:31:24	0.000	23:31:24	0.000
23:31:41	11/24/96	22.645	23:31:39	22.419	23:31:48	17.685	23:31:42	0.000	23:31:35	0.000	23:31:40	0.000	23:31:40	0.000

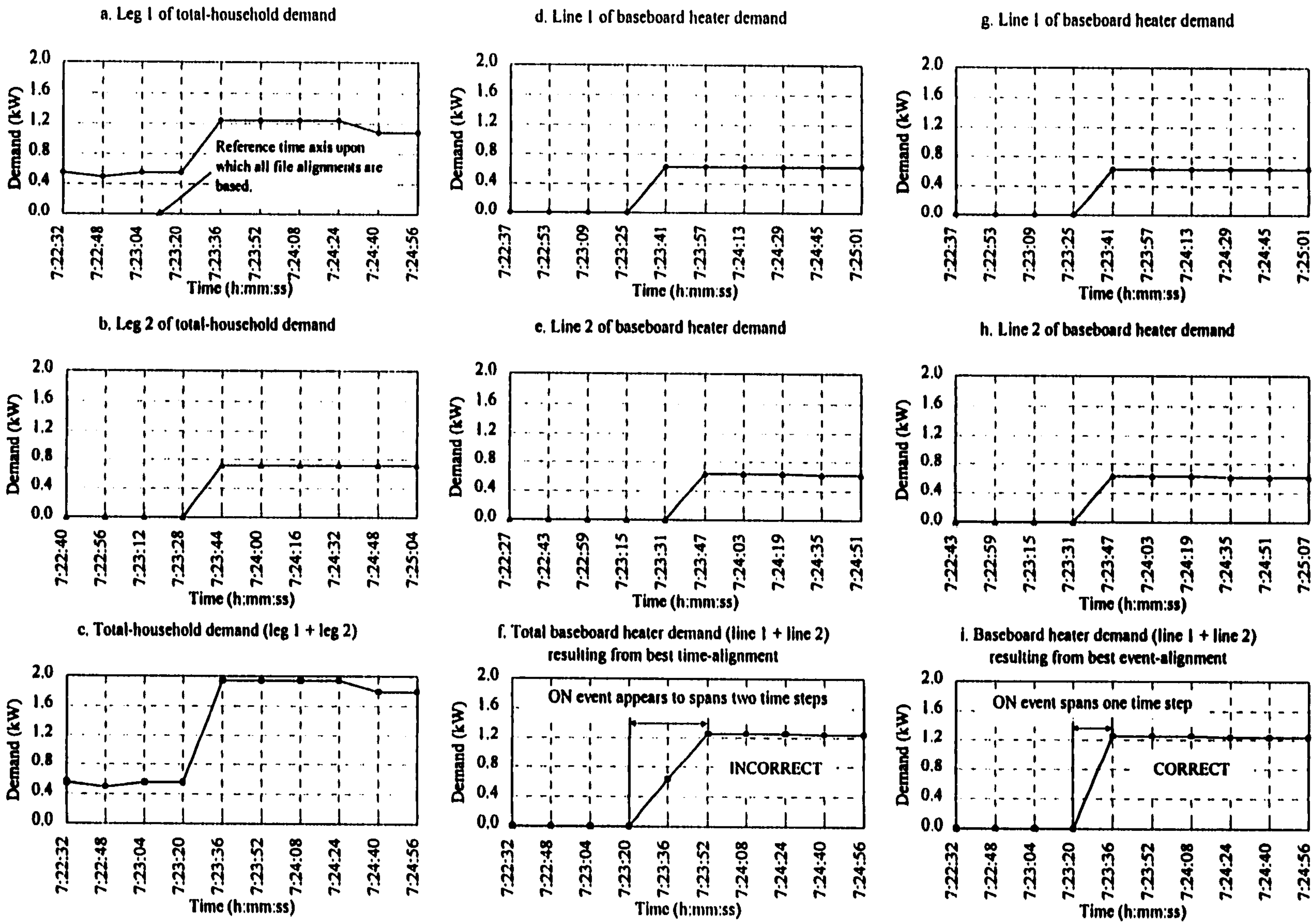


Figure 7. Combining appliance files so as to avoid one-off errors.

CHAPTER 4

NONINTRUSIVE LOAD DISAGGREGATION COMPUTER PROGRAM

The purpose of this chapter is to describe the load disaggregation computer program. The program estimates the energy consumption of the major household appliances based on short-term measurements of the appliances and on long-term analysis of the total-household electric demand. It is written in the C programming language, and has four principal components, or blocks. The blocks are described in Sections 4.2 to 4.5.

4.1 PROTOTYPE NONINTRUSIVE LOAD DISAGGREGATION COMPUTER PROGRAM

This section gives an overview of the computer program in general terms. Figure 8 shows the outline of the computer program divided into four blocks.

The input data for the computer program was described in detail in Chapter 3: Data and data acquisition. The input is a set of data files, which contain a series of electricity demand values in kilowatts and their date and time labels. There is one data file for each major household appliance and one data file for the total-household demand. The series of demand values obtained from the total-household demand is called the *total demand signal*. The series of demand values obtained from each appliance are called the *appliance demand signals*.

The final output from the computer program is the estimated energy consumption of each appliance. This output is summarized and presented as the estimated percentage contribution of each appliance to the total electricity consumption of the house. These percentage contributions are simply referred to as energy shares. The output will be discussed in more detail in Section 4.5.

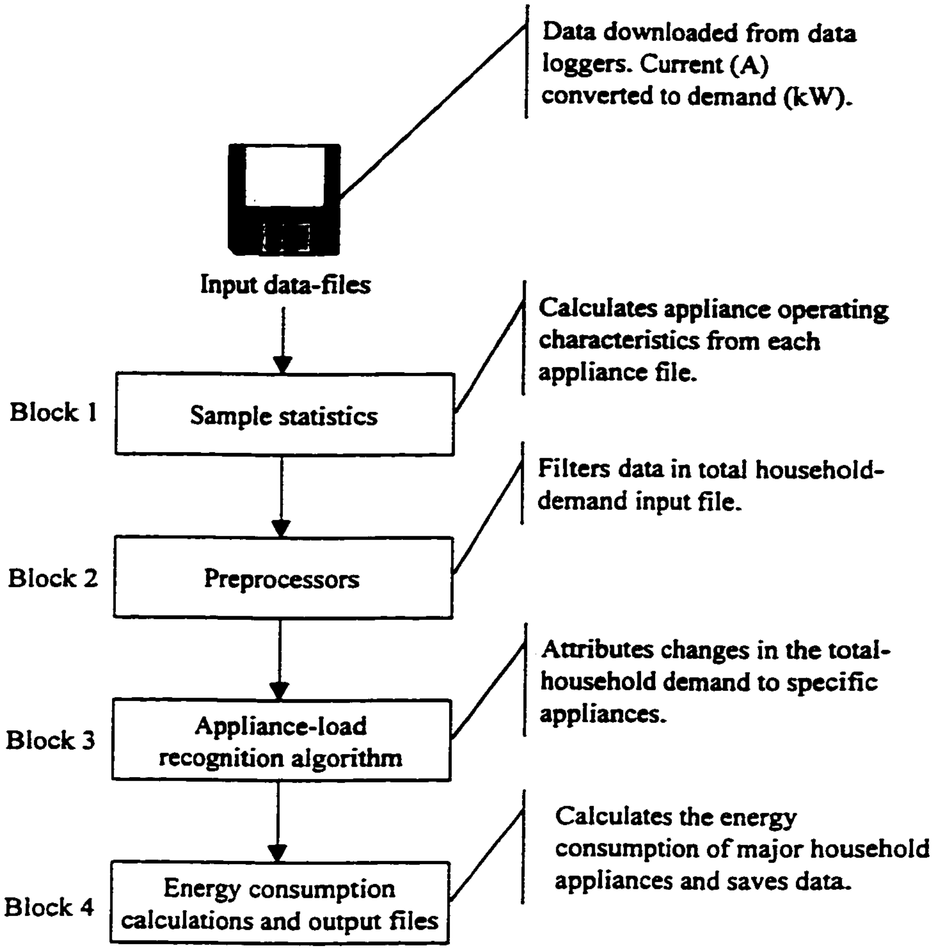


Figure 8. Four main components of load disaggregation computer program.

Each block of the computer program contains several functions. These functions perform specific operations, such as, calculating the standard deviation of a series of values, preprocessing the input data, or formatting data so it can be viewed easily on the screen. But in the descriptions that follow, only the most significant functions will be described.

In the first block the user enters the starting and ending dates of the sampling period; then, the program calculates the sample statistics for each appliance. In the second block, the user enters the starting and ending dates of the total demand file for which the program is to disaggregate. This portion of the original total-household electric demand data is first treated by a series of signal processing algorithms. These algorithms are called preprocessors because they filter the total demand signal before appliance-load recognition begins. The third block is the appliance-load recognition algorithm. In the fourth block the program calculates the energy consumption of each appliance by integrating the estimated electric demand over time. Finally, it calculates the percentage contribution of each appliance to the total electricity consumption of the house. The details of each of these blocks are described in the following sections.

4.2 BLOCK 1: SAMPLE STATISTICS

This block contains all the operations required in the *sampling mode*. The appliance-load recognition algorithm and some of the preprocessors require the appliances' operating characteristic parameters in order to detect an appliance's ON or OFF signal. These parameters are called sample statistics. They are calculated from the appliance demand signals. First the user chooses the period of time for which the program is to calculate sample statistics. Then the program reads each appliance file in turn and performs the relevant calculations. The sample statistics will be used by the preprocessors and by the appliance load recognition algorithm.

4.2.1 Choose sampling period start and end ranges

The program displays the date and time of the first and last reading in the total demand file. It then prompts the user to enter the starting and ending dates for which sample statistics are to be calculated from the appliance files. For example, the user could enter 1996-01-01 00:00:01 and 1996-01-07 23:59:59 to instruct the program to create temporary appliance files containing only the measurements that fall within these starting and ending dates. Then the program reads each temporary file in turn and calculates the appliance event operating statistics. An event in the appliance files is defined as a consecutive sequence of non-zero measurements. In other words, an event is the set of data between an appliance's ON signal and OFF signal. The mean and standard deviation of all the demand values during an event are calculated along with the events' average, maximum and minimum duration.

4.2.2 Standard deviation coefficient

The user is prompted to enter a standard deviation coefficient. Then, the program estimates the upper and lower operating range limits for each appliance using the formula $\mu \pm \alpha \bullet \sigma$, where μ is the mean, α is the standard deviation coefficient, and σ is the standard deviation. The implications of this procedure are discussed below in Section 4.4.1, which declares all the assumptions necessary to run the program.

4.3 BLOCK 2: PREPROCESSORS

The second block contains the seven signal processing algorithms. These algorithms are called signal preprocessors because they filter the total demand signal before appliance-load recognition begins. All seven preprocessors smooth out small or erratic variation in the total demand signal. The first preprocessor adjusts the total signal so that it is never less than the sum of the demands of all the monitored appliances. The second preprocessor smooths the signal while variations are within the range of a predetermined limit. The third preprocessor removes the effect of the data sampling rate while an appliance is turning on. The fourth preprocessor removes the effect of the data sampling rate while an appliance is turning off. The fifth preprocessor might well be called the stove-load recognition algorithm because this is essentially what it does. It is placed here because early testing of the appliance-load recognition algorithm showed that the presence of the stove signal in the total demand resulted in a large number of events being falsely attributed to other appliances. The sixth preprocessor removes individual asymmetrical spikes. The seventh preprocessor removes individual symmetrical spikes. The final filtered signal consists of distinct rectangular shapes where each increase or decrease in demand is more likely to represent a significant ON or OFF signal. Figure 9 shows an example of the total demand signal before and after preprocessing.

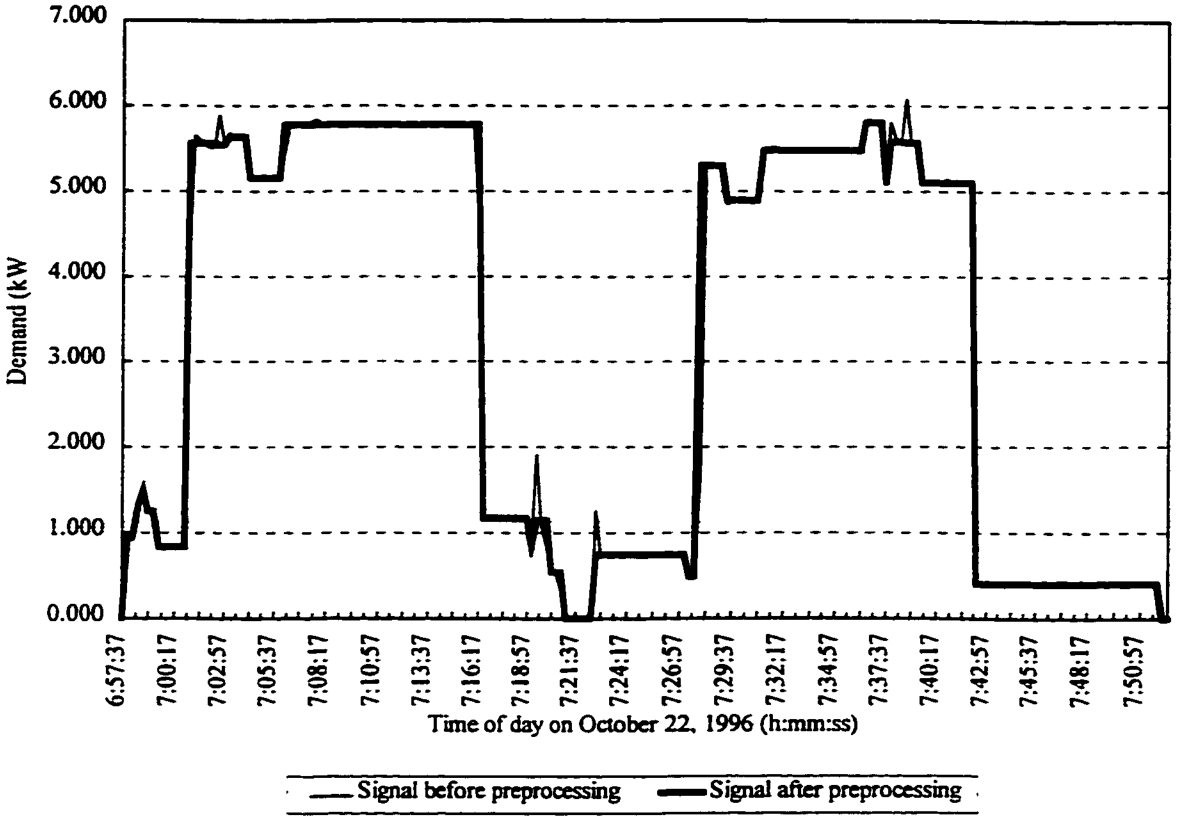


Figure 9. Total demand signal before and after preprocessing

4.3.1 Choose evaluation start and end

The first step in the program is the selection of the period of time for which the user wants the total demand signal disaggregated. The program displays the date, time and value of the first and last measurement in the total demand file. The user is asked to enter the period of time for which the signal will be disaggregated. For example, if the input file contains measurements from January 1 to June 30, the user can enter 1996-01-01 0:00:01 and 1996-01-31 23:59:59 to get the energy consumption of each appliance in January. The program will only consider the data in this portion of the file.

4.3.2 Preprocessor 1: adjust total with refrigerator

In Chapter 3, the issue of data recovery was discussed. In some situations, the total signal is less than the sum of all the measured appliances. This discrepancy is noticed when the refrigerator is the only measured appliance that is on. So this preprocessor *fixes* the total signal. The program reads the refrigerator appliance file (*fr_dat.prn*) and the total demand file (*preinput.prn*). It compares the two files with each other, and whenever the value of the total signal is less than the value of the refrigerator signal, the difference is added to the value of the total signal. The program then creates a new file called (*input.prn*) which becomes the new input signal.

4.3.3 Preprocessor 2: averaging

The second preprocessor removes fluctuations in the total signal while they are within ± 0.1 kW. Figure 10 illustrates how fluctuations are removed for a small segment of data. The minimum value for any significant ON or OFF signal is set at 0.2 kW because this is just slightly less than the smallest observed demand of any of the measured appliances in this house. Variations below this level are assumed to be due to small household appliances, lights and random variations in voltage and current. This assumption is also supported by data assembled by Hart [Hart, 1992]. The algorithm for this preprocessor compares every two successive demand values. If the difference is within ± 0.1 kW, it writes the first value to a temporary file. When it encounters a pair of successive values whose difference is outside these limits, the program calculates the average of the values in the temporary file and writes this average value for all the date and time labels of the values in the temporary file to new file (*procssd1.prn*). The process of checking for differences in the signal outside the range of ± 0.1 kW and writing the average values to the file is repeated until the end of the file is reached. Figure 11 shows an example of the total signal before and after averaging. The thin line is the original total demand and the thick line is the demand after averaging with preprocessor 2.

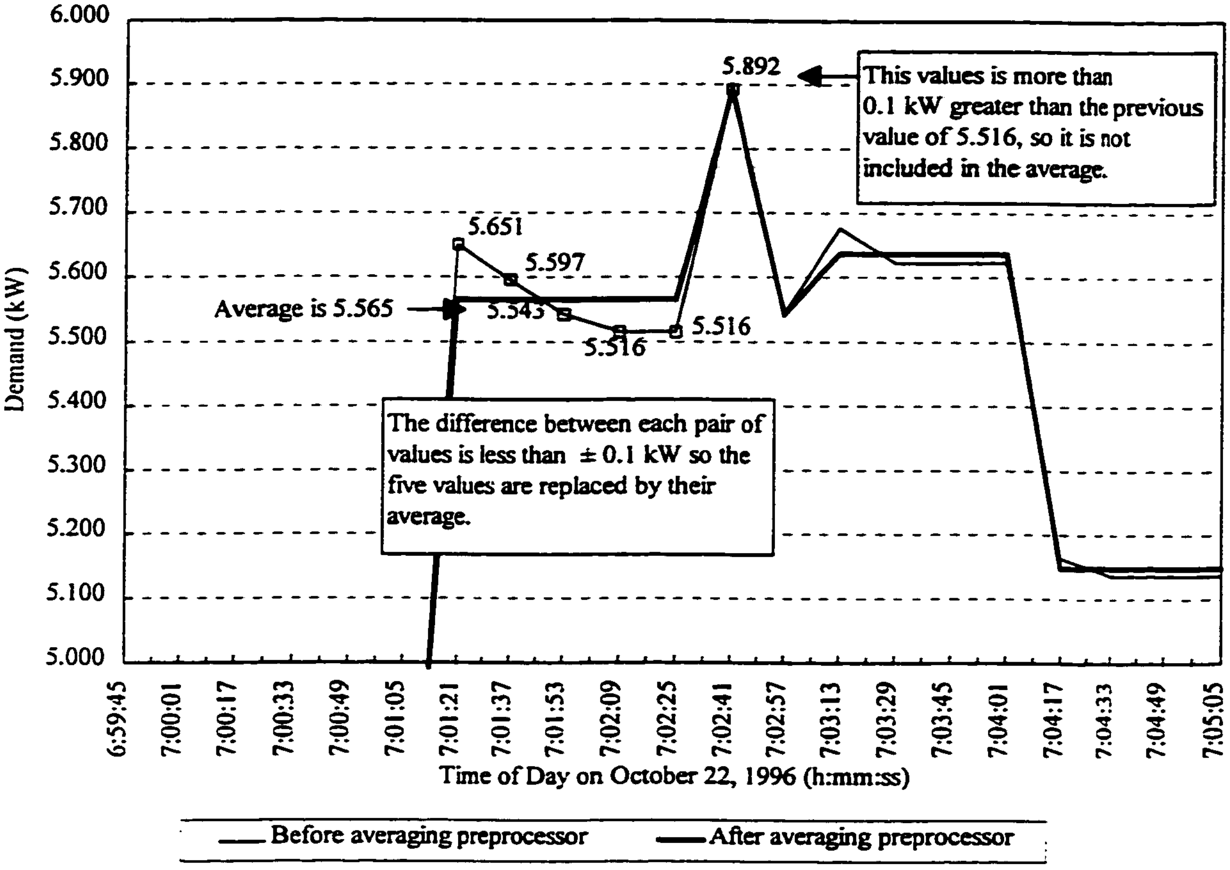


Figure 10. Detail of averaging preprocessor.

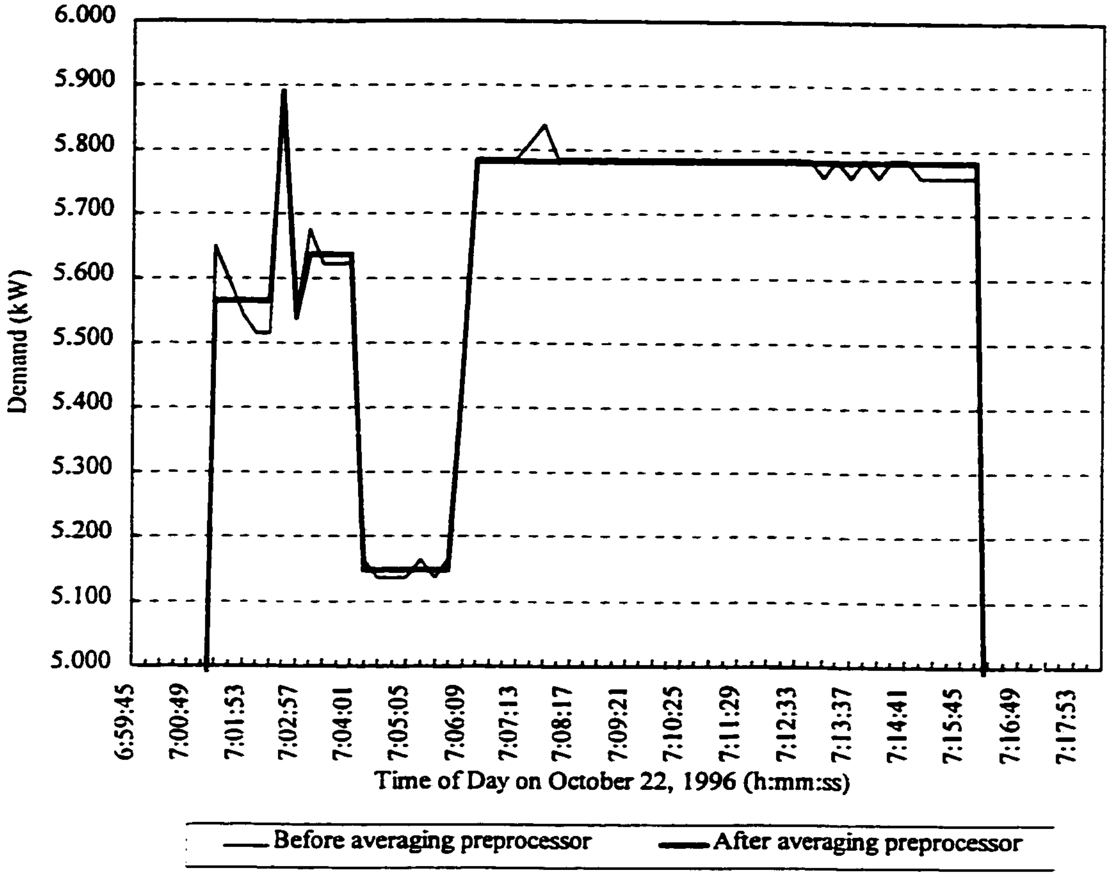


Figure 11. Averaging preprocessor

4.3.4 Preprocessor 3: stepped ON signal

The third preprocessor fills in the gap left by an initial stepped increase if it is followed by a constant demand. Because the data sampling rate is 16 seconds, an appliance's ON signal does not necessarily appear to occur instantaneously. For example, an appliance may come on just before a reading is made. When the reading is made, the appliance may be at 50% of its average operating level. At the next instant a reading is made, it may be 100% of its average operating level. The magnitude of the difference between two demand values is the indicator for an appliance coming on. But if it is only at 50% of its average value, it may not be detectable by the appliance-load recognition algorithm. During early testing of the algorithm, it was found that in some situations the third preprocessor tended to filter out the baseboard heater's ON signal. Therefore, a checking subroutine was added to the preprocessor. It does not allow the third preprocessor to filter the signal if either of the pair of step increases is within the range of the baseboard heater operating limits unless the sum of the pair is within the hot water operating limits. Figure 12 shows two instances where each of these conditions apply.

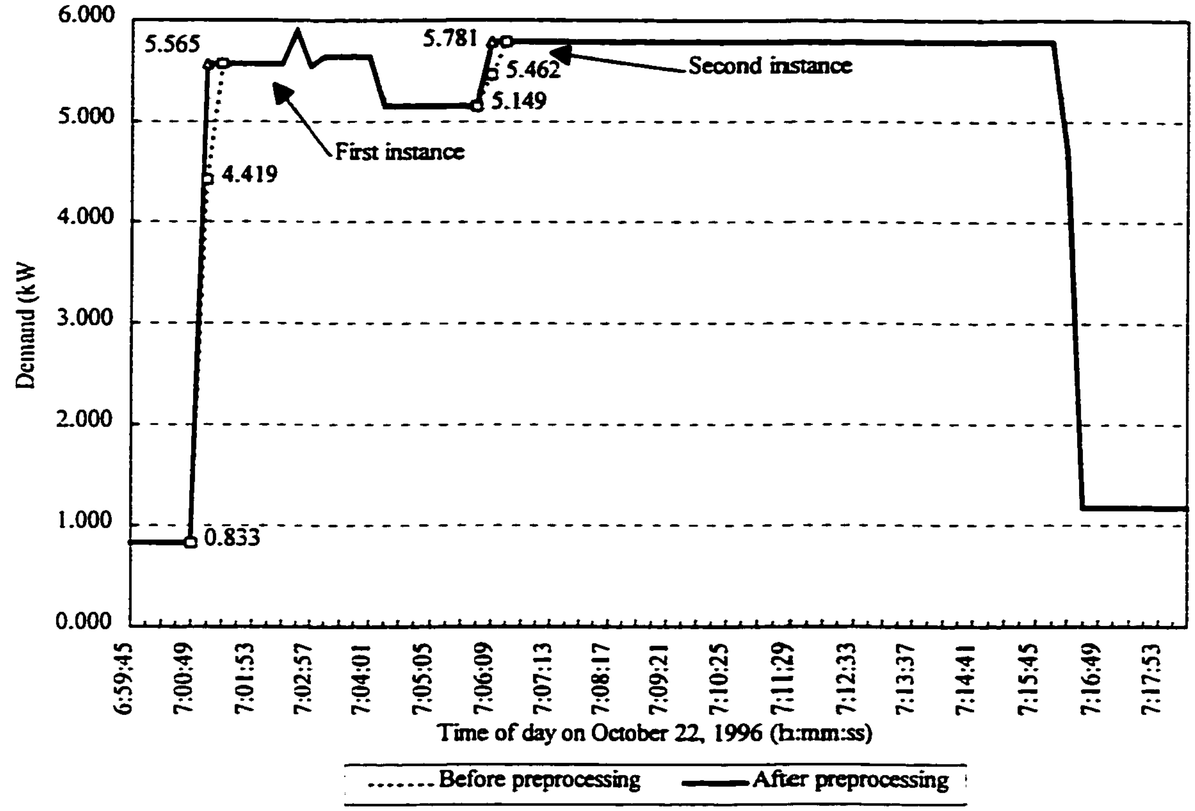


Figure 12. Stepped ON signal preprocessor

4.3.5 Preprocessor 4: stepped OFF signal

Sometimes an appliance's OFF signal spans several time-steps and shows a gradual decrease in demand. Since this kind of signal is more difficult for the appliance-load recognition algorithm to detect than a sudden decrease, the fourth preprocessor fills in the gap left by a terminal stepped decrease if it is preceded by a constant demand.

4.3.6 Preprocessor 5: characteristic stove profile

Early testing of the appliance-load recognition algorithm indicated that the presence of the stove signal in the total-household signal resulted in a large number of falsely identified events. One of the characteristics of the stove signal is that it has a large amplitude and a short period. In other words, the magnitude of both the amplitude and the period varies greatly. Although this behavior is characteristic of only the stove, the stove operating range also overlaps that of all the other appliances. Therefore, if the stove signal is left in the total-household signal, some of the fluctuations due to the stove may be falsely attributed to other appliances during appliance-load recognition. Therefore, preprocessor 5 identifies, isolates and removes the estimated stove signal component of the total-household signal. Figure 13 shows the result of this procedure. The top curve (thin line) shows the measured total-household signal, and the middle curve (thick line) shows the total-household signal after the estimated stove component has been removed. The portions removed are stored in a temporary file, which will be used later in block 4 to estimate the stove energy consumption. In order to show how accurate this preprocessor is, Figure 13 also shows the measured stove signal (dashed line). In this case, preprocessor 5 overestimates the actual energy consumption of the stove.

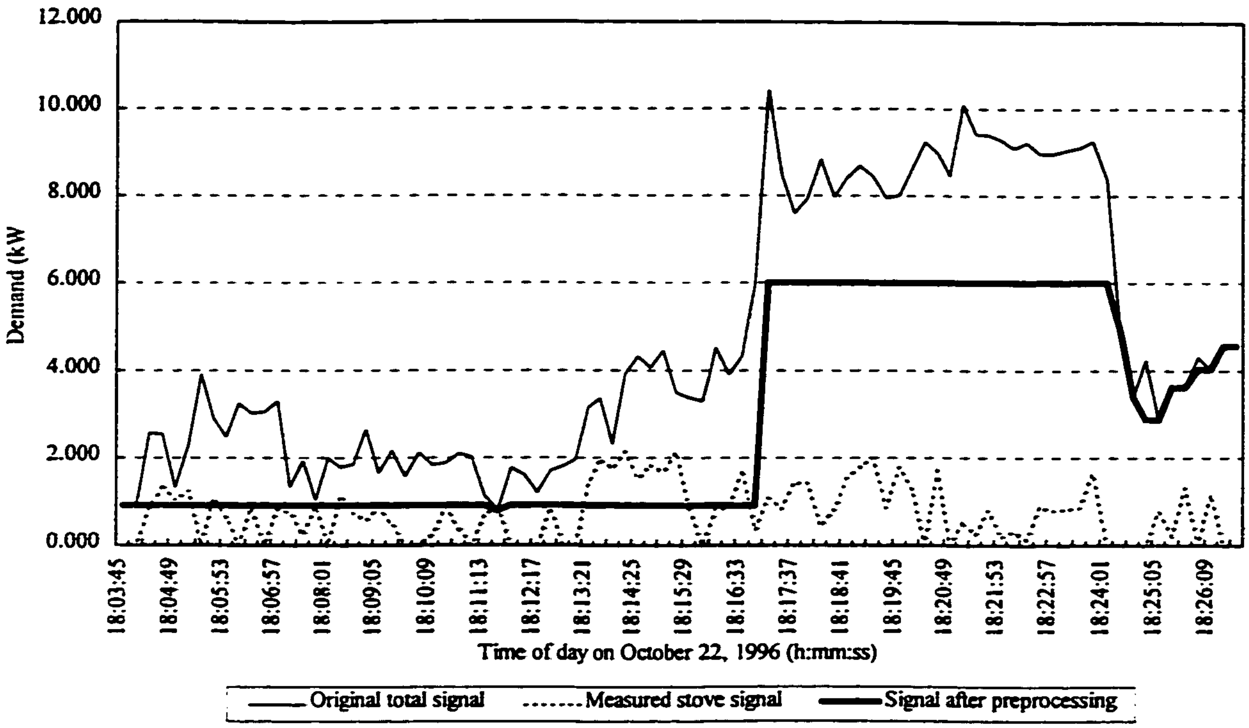
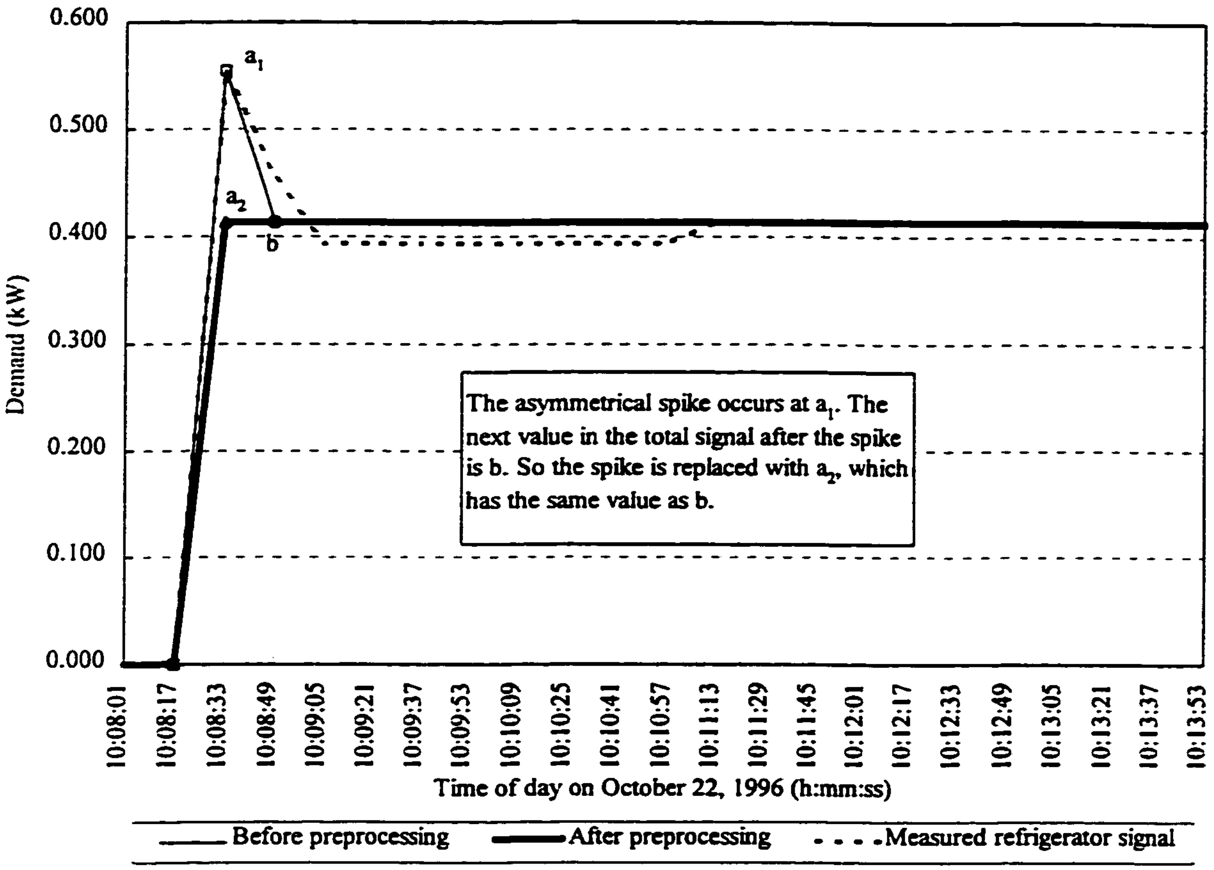


Figure 13. Stove signal preprocessor.

4.3.7 Preprocessor 6: asymmetrical spikes

This preprocessor removes asymmetrical spikes from the total signal. Spikes in the total demand are occasionally observed when appliances that have a reactive component to their voltage come on. The refrigerator and the washers have reactive components to their voltage. The asymmetry indicates the beginning of an event. These spikes may be characteristic of these appliances. However, it is not known whether or not these spikes always occur when the appliance comes on, because the 16-second data sampling rate is sometimes greater than the duration of these spikes. So if the spike occurs during the instant the data is sampled, it will be recorded. However, consider the following two cases: In case 1, if the spike occurs between two instances when the current is sampled, the spike will not be recorded. In case 2, if no spike occurs between two instances when the current is sampled, again, no spike is recorded. There is no way to discern case 1 from case 2. Therefore, the program cannot rely on the presence of these spikes as appliance event indicators. So, preprocessor 6 removes asymmetrical spikes by replacing the spike value with the next value in the data stream. Figure 14 shows an example of a refrigerator ON signal embedded in the total demand signal where the initial spike is identified and filtered out by preprocessor 6.



The asymmetrical spike occurs at a_1. The next value in the total signal after the spike is b. So the spike is replaced with a_2, which has the same value as b.

Figure 14. Asymmetrical spikes.

4.3.8 Preprocessor 7: symmetrical spikes

This preprocessor removes symmetrical spikes from the total signal. Short duration spikes can also occur for reasons not related to the measured appliances. There are a few reasons why these spikes exist. They may be caused by appliances that were not measured, random surges in the current, occupant behaviour, or some unknown reason. Their characteristic profile consists of a relatively symmetrical spike in a relatively constant period of demand. For example, Figure 15 shows an example of a symmetrical spike. Unlike an asymmetrical spike, it does not occurs at the beginning or the end of an event.

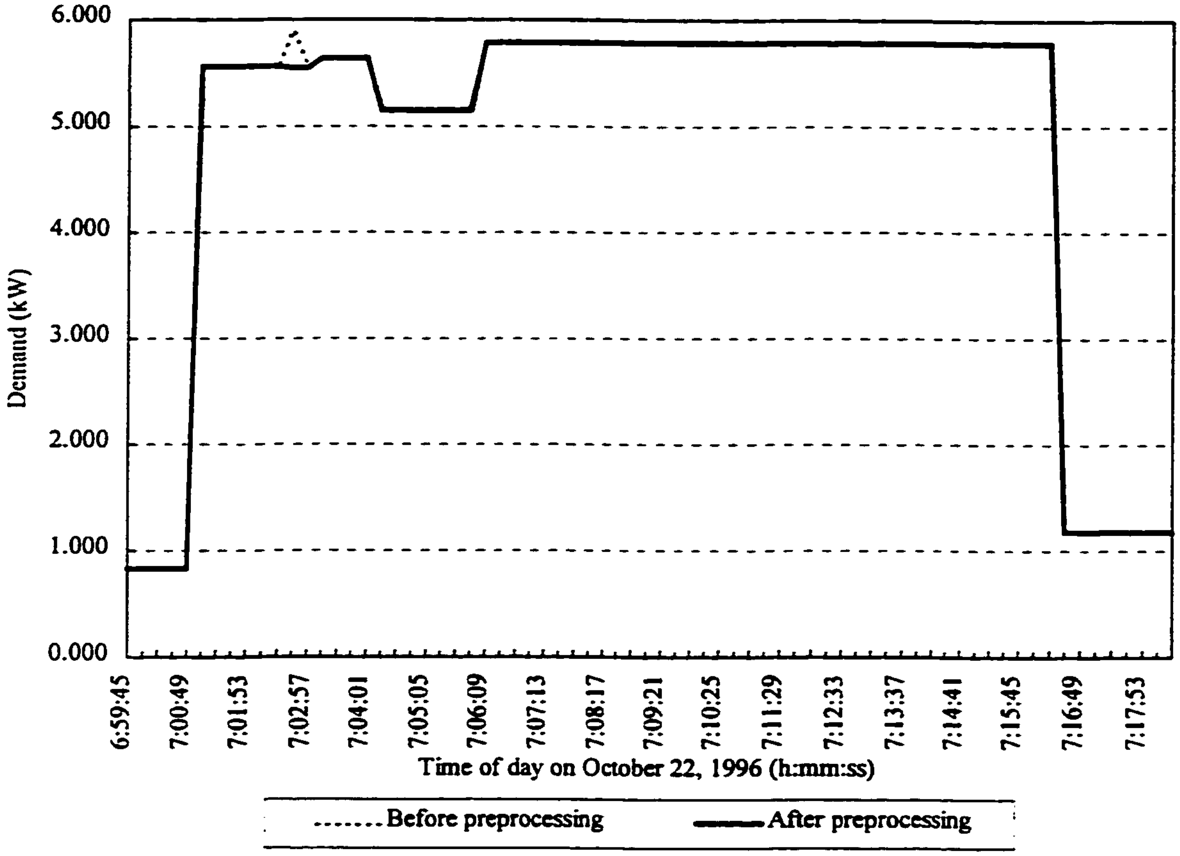


Figure 15. Symmetrical spikes removed by preprocessor.

4.4 BLOCK 3: APPLIANCE-LOAD RECOGNITION ALGORITHM

The third block of the load disaggregation computer program contains the appliance-load recognition algorithm. This block contains all the operations required in the *evaluation mode*. Its input is the filtered signal from the preprocessors and the statistics gathered during the sampling mode. This section first explains the assumptions made during the development of the algorithm; then, the details of the algorithm are described.

The algorithm basically compares each change in the total demand to each appliance operating range. If the value of the change is within an appliance range, the change is attributed to that appliance. A step increase in the total demand signal indicates that an appliance has turned on. A step decrease indicates that an appliance has turned off. Developing the basic algorithm led to the creation of a number of checking subroutines. There are five checking subroutines that check if an ON or OFF signal has been missed or if a consecutive pair of ON signals actually represents one single ON signal. They are (i) the average duration check, (ii) the maximum duration checks, (iii) the zero demand check, (iv) backtracking, and (v) the *consecutive pair-of-ON signals* check.

4.4.1 Assumptions

The following assumptions were made during the development of the algorithm. In each case, the reasons for making these assumptions are explained.

4.4.1.1 Statistical range

After the original input signal has been preprocessed, the resulting output signal is free of most anomalous fluctuations. Therefore, all the variations in the filtered signal should be due to an appliance turning on or off. Any particular appliance has a limit to the amount of current it draws from the main supply lines. Therefore, the variations in total electric demand that are caused by a particular appliance should fall within a predictable range of that appliance's operating level. For data that is approximately normally distributed

[Mendenhall and Sincich, 1992], 95% of the measurements will lie within two standard deviations of their mean. Therefore, when the variation in electric demand is compared with $\mu \pm 2 \bullet \sigma$, as obtained for each appliance during the sampling mode, it is anticipated that 95% of the ON and OFF signals will be recognized.

4.4.1.2 Coincident signals

The appliance load recognition algorithm assumes that there are no coincident ON or OFF signals, that is, it assumes that there is never more than one appliance turning on or off during the same time interval. When there are coincident signal, one or more of the signals may not be recognized, or the combined effect of the coincident events may lead to a falsely identified appliance event. This assumption is valid as long as the time interval is short. The longer the time interval, the greater is the chance that there will be coincident signals.

4.4.1.3 Washing machines

The dishwasher and the clothes washer have similar operating characteristics. So it is difficult to distinguish between the two based on their load profiles. But since they both perform similar functions, they can be lumped together as one appliance in the appliance-load recognition algorithm. However, this now creates the potential problem of simultaneous usage of these two appliances. Therefore, another assumption is that the dishwasher and the clothes washer are never used at the same time. The data confirms that this assumption is valid.

4.4.1.4 OFF signal decreases total demand

A final assumption, that at first glance seems obvious, led to the development of the average duration checking subroutine. The assumption is this: whenever there is a decrease in the total demand, an appliance has turned off. This appliance that has just turned off may or may not be one of the monitored appliances. If the appliance-load recognition algorithm fails to recognize that an appliance has turned off because the decrease in total demand does not match any appliance range, then there is a decrease in total demand that is unaccounted for. Although it is possible that this decrease is due to a non-monitored appliance turning off, the actions of the preprocessors make this unlikely. Therefore, a decrease in total demand that does not match an appliance range can serve as a flag to indicate a potentially missed event. This checking routine is discussed in detail in Section 4.4.3.1.

4.4.2 Core of computer program: appliance-load recognition algorithm

Figure 16 is a flowchart of the principal elements of the algorithm. Each appliance event is characterized by an ON signal, an OFF signal, and a duration. The program reads the first set of values from the input file into the variables time_{n-1}, date_{n-1}, demand_{n-1}. The subscript n-1 means *at time n minus one*, in other words, the *previous* values. Then the program reads the next set into the variables time_n, date_n, demand_n. The subscript n means *at time n*, that is, the *present* values. These two sets of data are referred to as a *successive pair* of measurements. So the program compares every successive pair of demand measurements. The difference is the change in demand: $\Delta d = \text{demand}_n - \text{demand}_{n-1}$. There are three possible outcomes and each will follow a different course of action. If Δd is positive, there is an increase in demand. If Δd is negative, there is a decrease in demand. And if Δd is zero, there is no change in demand. When Δd is positive, the algorithm compares the magnitude of the increase to each appliance range in an attempt to determine which appliance has turned on. When Δd is negative, the algorithm again compares the magnitude of the decrease to each appliance range, but now in an attempt to determine which appliance has turned off. When there is no change in demand, the algorithm performs the maximum duration check. At every time step, the program keeps track of how long each appliance has been identified as being ON by incrementing a duration counter by the magnitude of the time interval. Then the set of values are incremented so that the newest set becomes the oldest set, that is, demand_n becomes demand_{n-1}. The next set of values are read and they become the newest set. The program repeats the complete loop until the end of the file is reached. The details of each course of action and the checking subroutines are explain next.

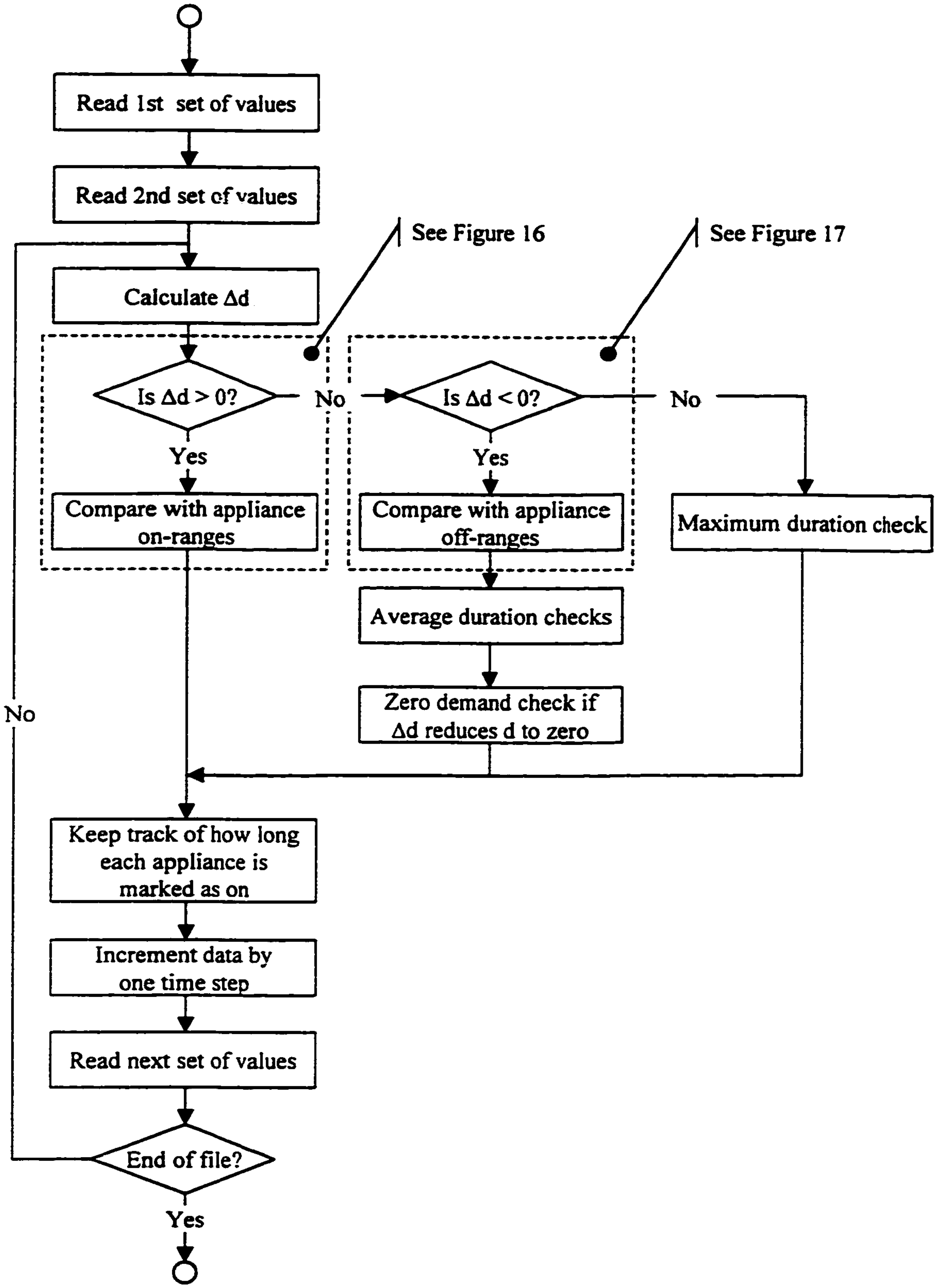


Figure 16. Flowchart showing the principal elements of the appliance-load recognition algorithm.

4.4.2.1 Increase in total demand

Figure 17 shows the details of the algorithm for the increase-in-demand condition. The algorithm compares the magnitude of the increase to each appliance range until a match is found. To avoid the complications that would arise if two or more appliance ranges overlap, the algorithm compares the increase to each appliance range in the following order: water heater (HW), baseboard heater (PL), washing machines (W), refrigerator (FR). For example, if an increase falls within both the baseboard heater range and the washing machines range, the increase would be attributed to the baseboard heater because it has the higher priority. The order of priority is arranged in order of decreasing average operating demand. When an increase is within an appliance range, that appliance is marked as *turned ON*. If the increase does not match the operating range of any appliance (obtained during the sampling period), the increase is assumed to be caused by other appliances and the increase is attributed to a variable called *residual*. Two components of the backtracking subroutine are integrated with the increase-in-demand procedure. They will be explained later in Section 4.4.4.

4.4.2.2 Decrease in total demand

Figure 18 shows the details of the algorithm for the decrease-in-demand condition. Just like for the increase condition, the algorithm compares the magnitude of the decrease to each appliance range in the same order as before, that is, HW, PL, W, and FR. When an OFF signal matches an appliance range and the appliance is marked as ON, the appliance is marked as *turned OFF*. If an OFF signal matches an appliance range but the appliance is not marked as ON, the backtracking subroutine is initiated. This procedure is explained later in Section 4.4.4. If the decrease does not match any appliance range, the average duration checking subroutine is initiated. This subroutine is explained in Section 4.4.3.1. If the decrease can not be attributed to one of the measured appliances turning off, it is assumed to be caused by an appliance that was not measured. In either case, the residual is adjusted by the magnitude of the decrease in demand. Finally, if a decrease reduces the total demand to zero, the zero demand checking subroutine is initiated. This checking algorithm is explained in Section 4.4.3.3.

4.4.2.3 No change in total demand

Figure 19 shows the flow chart for the situation when there is no change in the total demand. In this case, when the demand is constant, the maximum duration checking subroutine is performed. Then the durations of all appliances that are marked as ON are increased by the magnitude of the time step, Δt.

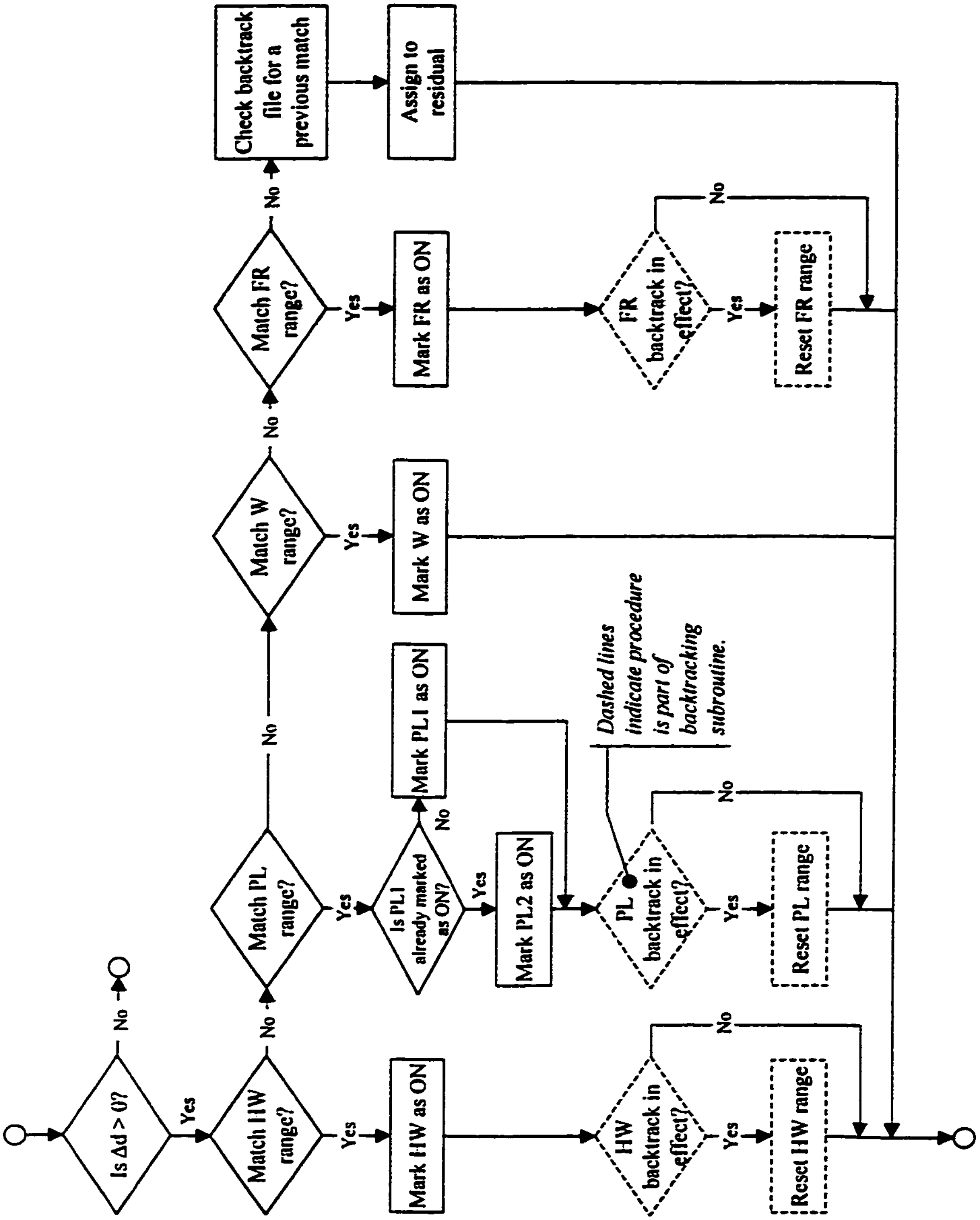


Figure 17. Increase in demand.

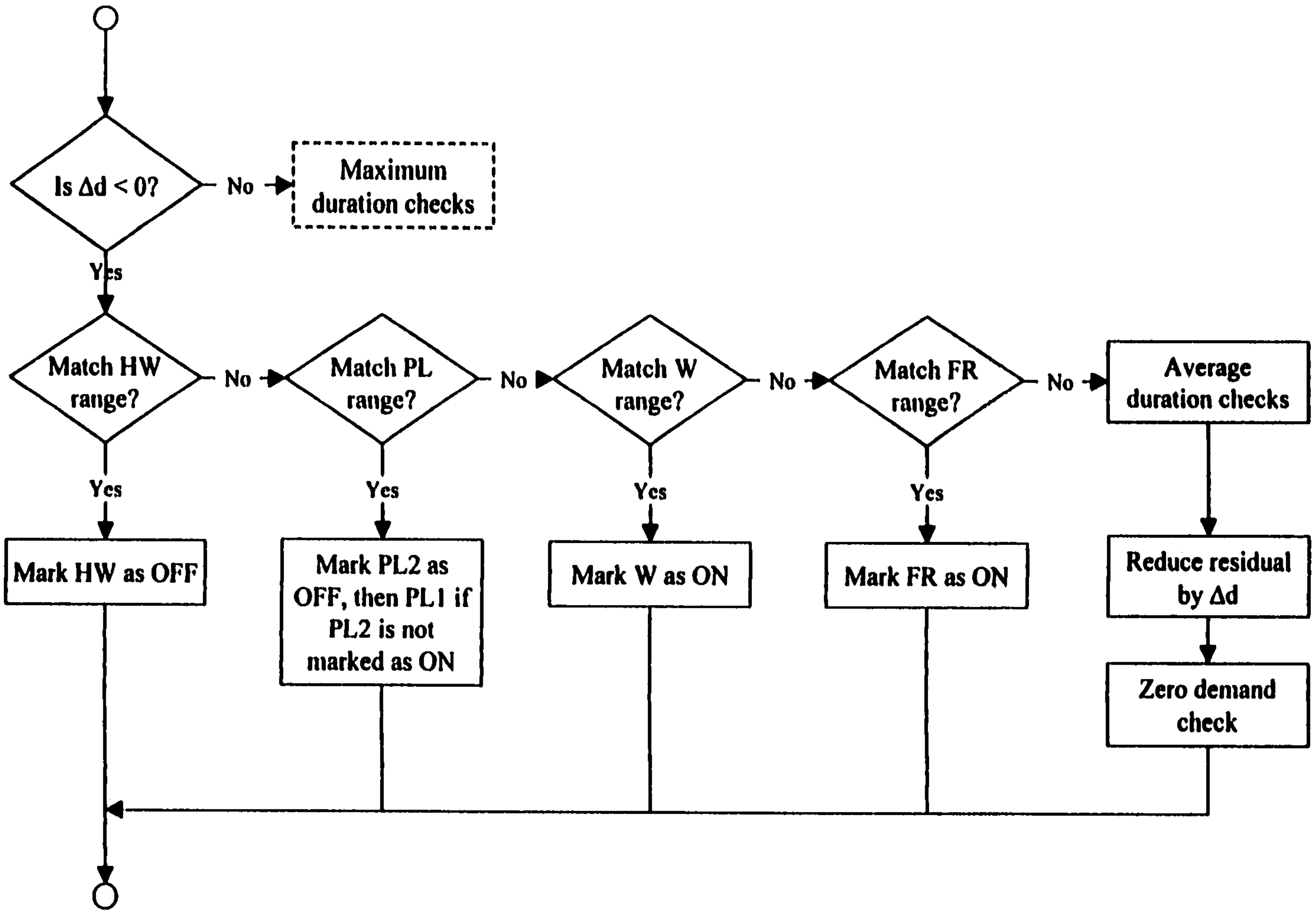


Figure 18. Decrease in demand.

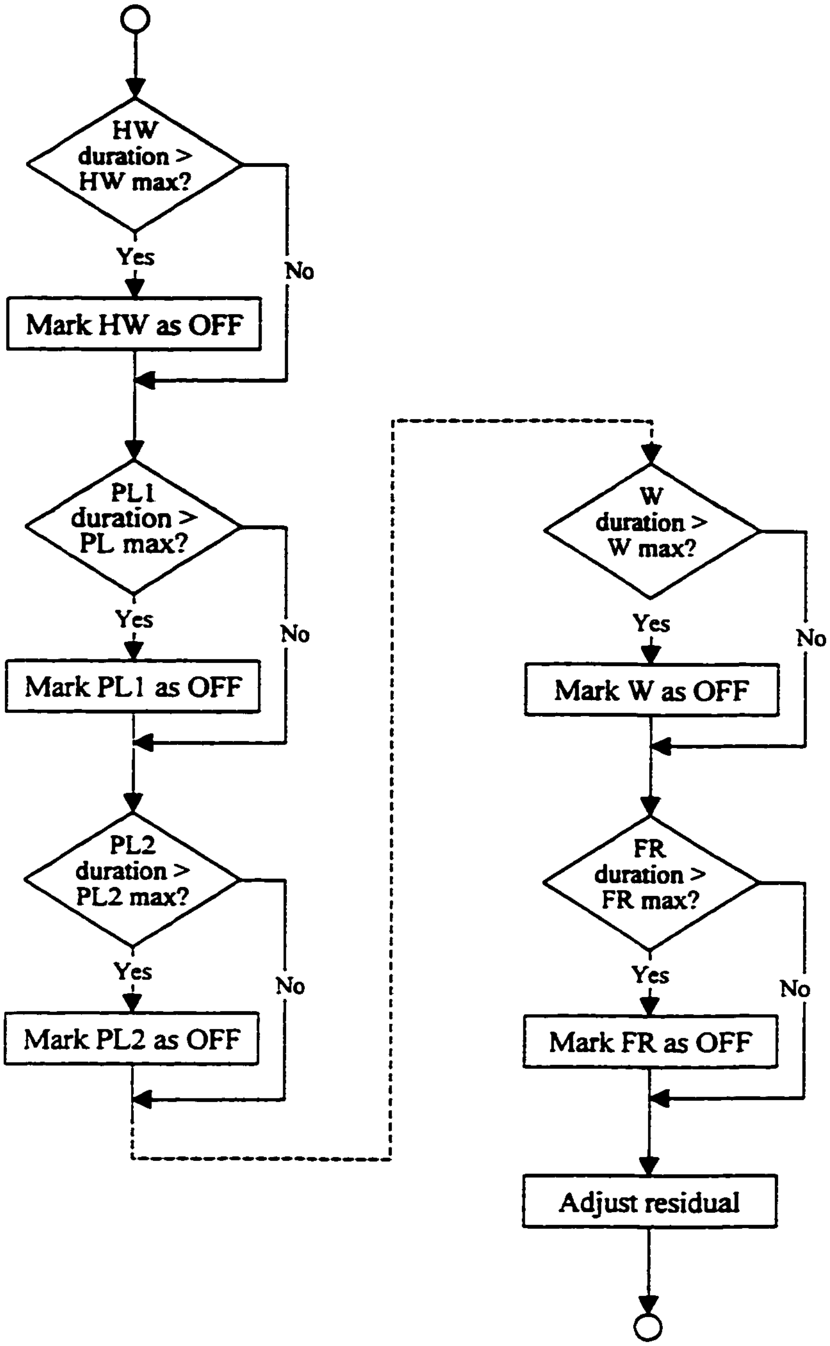


Figure 19. Maximum duration check when there is no change in demand.

4.4.3 Duration checks

There are three duration checking subroutines. The statistics used in the duration checks come from the statistics gathered during the sampling period.

4.4.3.1 Average duration check

The average duration check is performed every time there is a decrease in the total demand that is not assigned to an appliance. Figure 20 shows the sequence of steps in this subroutine. Like the increase-in-demand and decrease-in-demand subroutines, the average duration subroutine checks the appliances in a predetermine sequence. The sequence was initially arranged in decreasing order of the appliances' average duration. But during the early stages of development, it was found that the present sequence of water heater, washing machines, baseboard heaters, and refrigerator yield the best results. During subsequent development, it was found that the average duration check resulted in an underestimation of energy consumption of the water heater and the refrigerator because of erroneous and premature OFF signal recognition. So the average duration variable was replaced with the maximum duration variable for the water heater and refrigerator only. If an appliance is marked as ON *and* it has been marked as ON longer than the average duration (or maximum duration if it is the water heater or the refrigerator) that was observed during the sampling period, it is marked as turned OFF. The appliance's operating-state variable and its duration counter are reset to zero, and the backtrack enabling variable is reset to one.

4.4.3.2 Maximum duration check

When there is no change in total-household demand, the maximum duration checking subroutine is performed. It checks the duration of each appliance that is marked as ON. If it has been marked as ON longer than the observed maximum duration for that appliance, then it is marked as turned OFF. The reasoning behind this is: if an OFF signal is missed, the next possible OFF signal will come at the end of the next event. If this happens, the appliance would have been marked as ON for a long time. So to avoid large overestimates of energy consumption, it is important to ensure that if an OFF signal is missed, the appliance is marked as turned OFF as soon as possible. Then its duration counter is reset to zero and the backtracking enabling variable is reset to one.

4.4.3.3 Zero demand check

If a decrease in total demand reduces the total demand to zero, the zero demand checking subroutine is initiated. Figure 21 shows the outline of this subroutine. This subroutine is necessary to prevent the possibility that an OFF signal might still be missed, even after the two duration checks. If the total demand is zero, there can be no appliance consuming energy. So when a step decrease reduces the total demand to zero, all appliances are marked as OFF, the duration counters are reset to zero, and the backtrack enabling variables are reset to one.

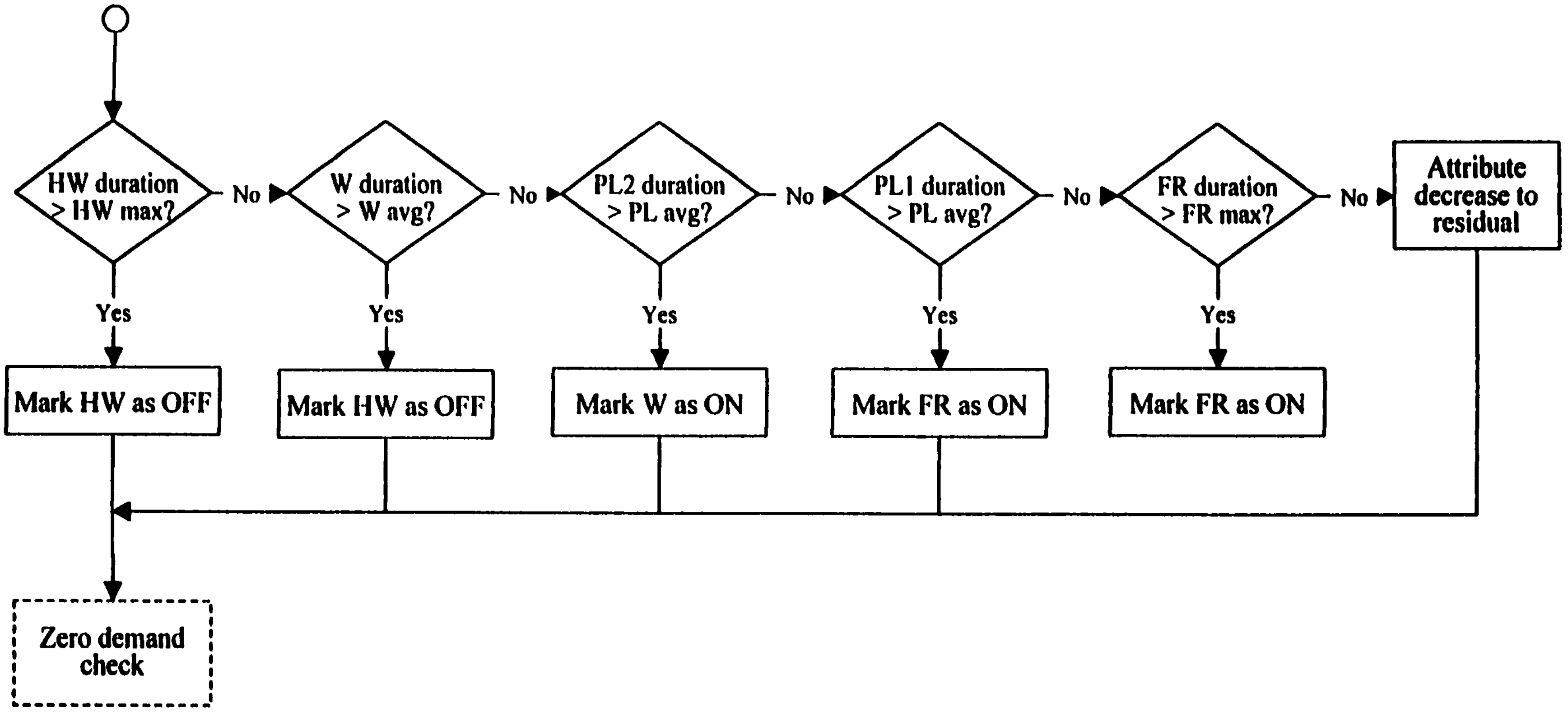


Figure 20. Average duration check.

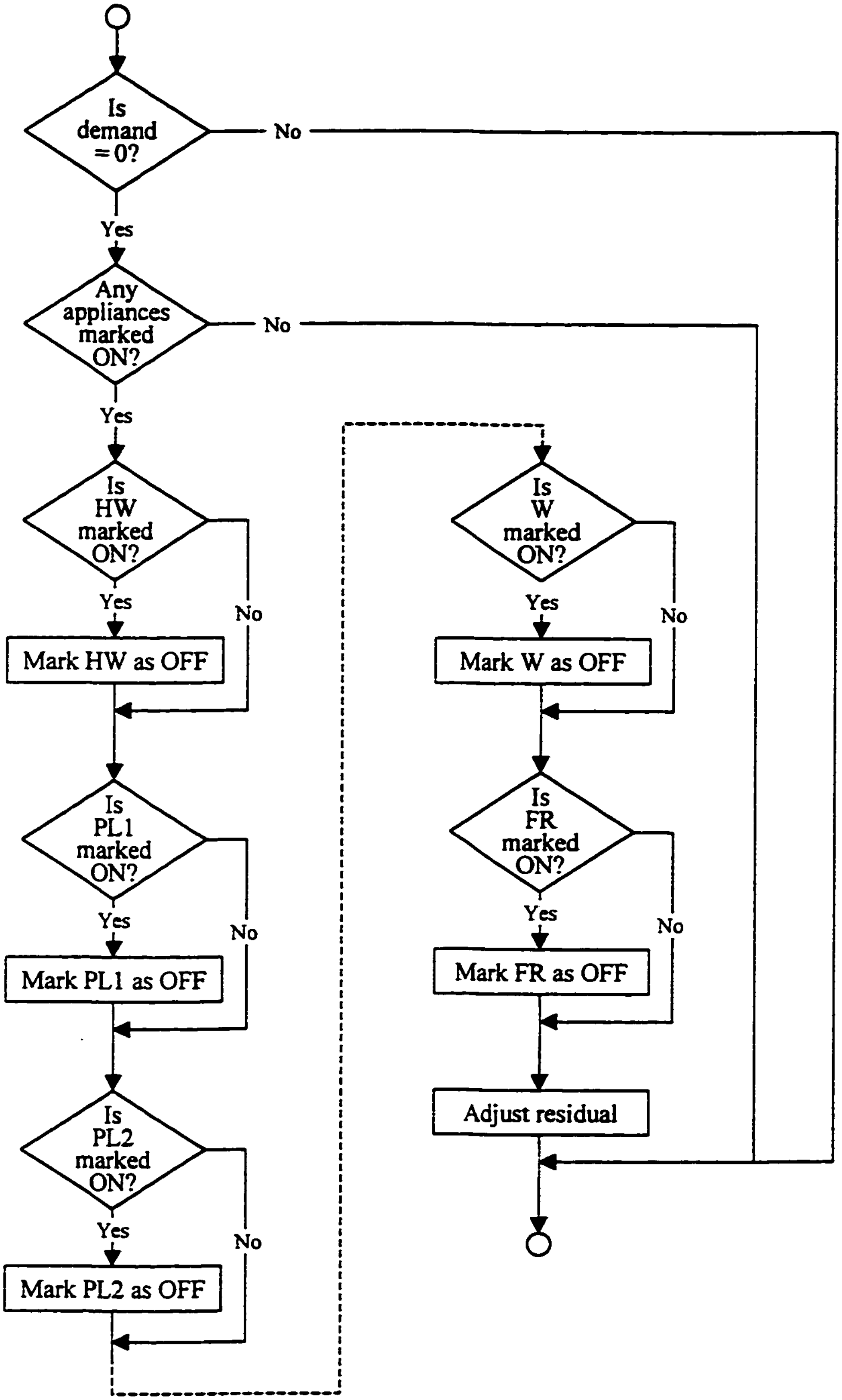


Figure 21. Zero demand check.

4.4.4 Backtracking

If an OFF signal matches an appliance range but that appliance is not marked as ON, the program *backtracks* through the input file and looks for the presumably missed ON signal using wider selection criteria. Backtracking will reposition the file position pointer in the input file back to a time no earlier than the current time, that is, the time at which backtracking is initiated, minus the maximum duration of the appliance that initiated backtracking. Only three appliances have backtracking components: the water heater, the first baseboard heater and the refrigerator. Unlike the other checking subroutines, backtracking is not a subroutine. Its statements are not clustered in the same block of code. Instead, its components occur throughout the algorithm. So the sequence of the explanation to follow is based on the sequence of events that occur when backtracking is initiated.

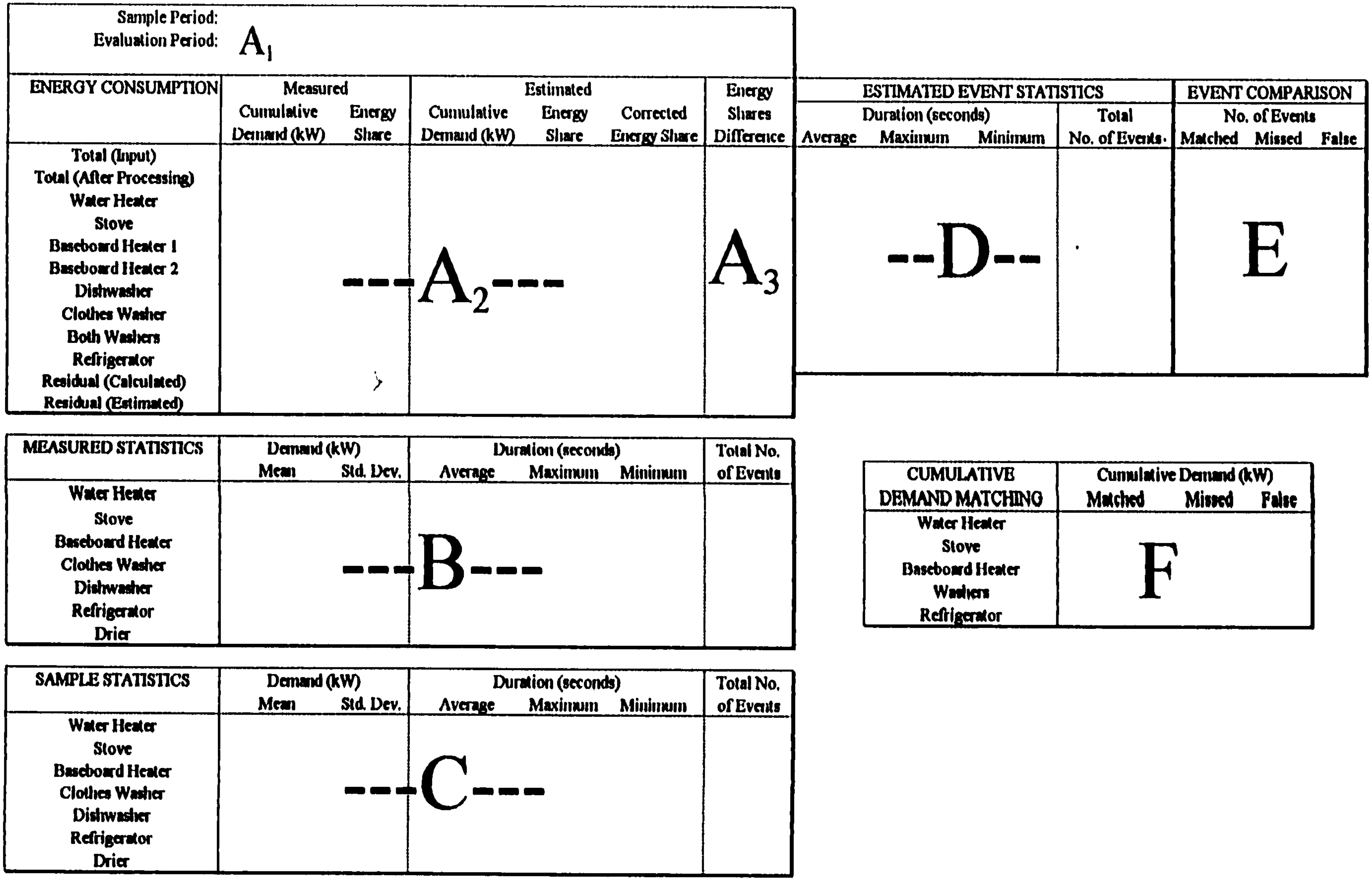
There are three criteria that must be satisfied before backtracking is initiated. The first is that a an appliance ON signal must be missed. This occurs when the decrease in demand matches an appliance range but that particular appliance is not marked as ON. The second criterion is that backtracking must be allowed; that is, the appliance's backtrack enabling variable must be equal to one. The third criterion was created to ensure that the program does not enter a programming loop that has no logical exit: The program compares the time that backtracking was last initiated for the appliance under consideration, *time_backtrack_initiated*, to the time at the current time step, *time_now*. If *time_backtrack_initiated* is later than *time_now* then backtracking is not allowed. If it is allowed, the file position pointer in the input file is repositioned to the time that corresponds to the time now (the time the pointer currently points to) minus the maximum duration of the appliance responsible for invoking backtracking. For example, if a water heater ON signal is missed, the file position pointer is repositioned to *time_now - hw_max_duration.* The output file position pointer is similarly repositioned but to one time step before *time_now - hw_max_duration.* The operating state and the operating duration of each appliance are read from the output file at this time step. These values now represent *the previous time step.* Then the water heater's probable operating range is increased. For example, the standard deviation coefficient may be increased from 2 to 3 so that the program looks for a increase in the range of $\mu \pm 3\ \sigma$. The program proceeds as before. When it encounters an increase that matches the new water heater range, it first disables backtracking to avoid an infinite loop (which would be created if backtracking is initiated a second time while within the first loop), and then it marks the water heater as ON. In the marking an appliance as ON sequence, a check detemines whether it is marked as ON because the ON signal matches the new appliance operating range or the original operating range. If it is because it matches the new range, the appliance operating range is reset to the default values and the backtrack enabling variable is reset to one. Then, when the OFF signal that triggered backtracking is encountered for the second time, the water heater is marked as OFF as usual. The duration counter is reset to zero, the backtrack enabling variable is reset to one and the backtrack-in-effect variable is reset to zero. If, however, no ON signal was found that matches the unpaired OFF signal, when the OFF signal is encountered a second time, the recognition range is reset to the default range. Then the program proceeds with the average duration checks. From this point onwards, the program proceeds as before.

4.4.5 Consecutive pair of ON signals check

This is the final checking subroutine. It performs a function similar to the third preprocessor: the one that fills in gaps in a step increase. If the sum of two consecutive step increase signals is within the water range and if neither of the signals are attributed to an appliance, the water heater is marked as ON.

4.5 BLOCK 4: ENERGY CONSUMPTION CALCULATIONS

Finally, the fourth block calculates the energy consumption of each appliance by integrating the electric demand over time. There is a lot of data output from the computer program. For example, an evaluation period of one day results in over 80 000 individual data. So in order to evaluate the accuracy of the program, the output data is summarized in an *output table*. Figure 22 shows the general features of the output table. Sections 4.5.1 to 4.5.6 describe the information contained within each area of the table.



Sample Period:
Evaluation Period:

ENERGY CONSUMPTION	Measured		Estimated			Energy Shares Difference	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
							Duration (seconds)			Total No. of Events	No. of Events		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share		Average	Maximum	Minimum		Matched	Missed	False
Total (Input)													
Total (After Processing)													
Water Heater													
Stove													
Baseboard Heater 1													
Baseboard Heater 2													
Dishwasher													
Clothes Washer													
Both Washers													
Refrigerator													
Residual (Calculated)													
Residual (Estimated)													

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater						
Stove						
Baseboard Heater						
Clothes Washer						
Dishwasher						
Refrigerator						
Drier						

CUMULATIVE DEMAND MATCHING	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater			
Stove			
Baseboard Heater			
Washers			
Refrigerator			

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater						
Stove						
Baseboard Heater						
Clothes Washer						
Dishwasher						
Refrigerator						
Drier						

Figure 22. General features of output table.

4.5.1 Energy shares

The shaded area A in Figure 21 shows the measured and the estimated energy consumption. The subarea A_1 shows the sampling period and the evaluation period. The subarea A_2 shows the measured and estimated cumulative demand and energy shares of each appliance. The total estimated cumulative demand is the total measured cumulative demand after it has been preprocessed. To get the energy consumption, multiply the cumulative demand by the size of the time step per hour:

$$energy\,consumption[kW\cdot h] = cumulative\,demand[kW]\times\frac{time\,step}{hour}\left[\frac{16\,s}{3600\,s/hr}\right].$$

The estimated energy shares are corrected with a correction factor so that they represent energy shares based on the total measured cumulative demand not the total estimated cumulative demand. The correction factor is the measured cumulative demand divided by the estimated cumulative demand:

$$correction\,factor = \frac{measured\ cumulative\ demand}{estimated\ cumulative\ demand}.$$

The subarea A_3 shows the difference between the measured energy shares and the estimated energy shares. The first measure of accuracy is the energy shares difference.

4.5.2 Measured operating characteristics

Area B shows the measured operating characteristics of the major appliances during the user-selected **evaluation** period. This information comes from the appliance files. It is available now for validation, but it will not be available in the final version of the program, because it will be the actual output sought. For each appliance, the demand columns show mean demand and demand standard deviation, and the duration columns show average, minimum and maximum event durations. The last column shows total number of events for each appliance.

4.5.3 Sampling period operating characteristics

Area C shows the measured operating characteristics of the major appliances during the user-selected **sampling** period. This area contains the same kinds of information as Section B, but unlike Section B, this information will be shown in the final version.

4.5.4 Estimated operating characteristics

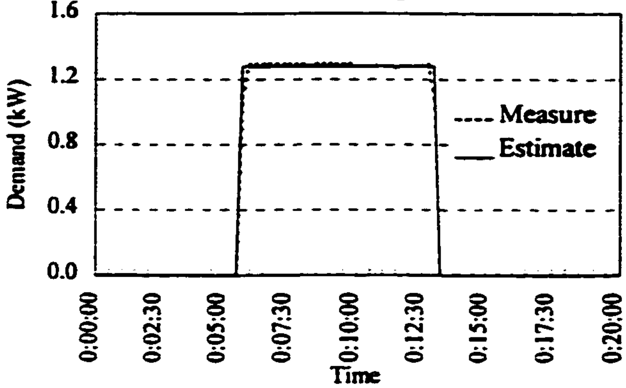
Area D shows the summary of the appliance events estimated by the program. Unlike areas B and C, the mean and standard deviation are not shown, because they are known: The program assumes that each appliance draws a constant current; therefore, once an ON signal is detected, it assigns the appropriate appliance mean from the sample statistics as the estimated operating demand. So the mean is equal to the assigned demand and the standard deviation is zero.

4.5.5 Event comparison

Area E shows how many estimated events match measured events. It also shows the number of missed and false events. This section is necessary for validation because it shows the accuracy of the program in recognizing appliance events. If the program is one hundred percent accurate, the start and end of each estimated event would correspond to the start and end of each measured event. However, this is rarely the case. When an event is estimated, there are two conditions to consider before one can say that the estimated event matches a measured event. These are the timing of the ON and OFF of each estimated event.

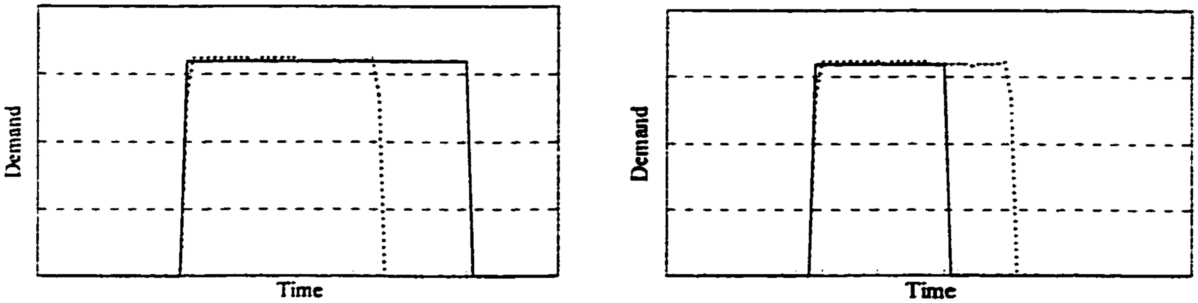
If the ON of the estimated event corresponds to the ON of a measured event, and if the OFF of the estimated event corresponds to the OFF of the same measured event, then the program has correctly estimated the occurrence of that event. But what if the OFF events do not occur at the same time? Say the estimated event is turned OFF too soon. Should this mean that the measured event is missed? It depends on the desired use of the program. Figures 23 to 25 show the cases representing the possible arrangements of ON and OFF event-matching. Essentially the definition of a match is this: if an ON signal, an OFF signal, or a matching pair of ON and OFF signals is detected, then an event match is made. If an estimated ON or OFF signal is within five time steps (5 × 16 seconds = 80 seconds) of the actual signal, then it is considered a match. The cases in Figure 23 are considered to be matches, because it is some information about the real event, either the ON, the OFF or both, embedded in the total signal that contributes to the identification of the estimated event. Figure 24 shows the cases where there are two matches. In Figure 24a, one measured event is identified by two estimated events. In Figure 24b, two measured events are identified by one estimated event. The cases in Figure 25 are considered to be false events, because none of the information of the measured event embedded in the total signal is used to identify the estimated event.

a. ON and OFF recognized.



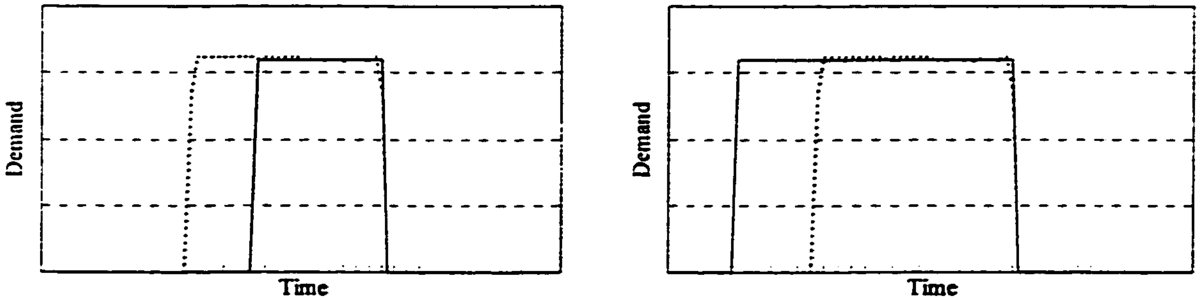
b. ON recognized but OFF missed.

c. ON recognized but false OFF.



d. ON missed but OFF identified.

e. Already ON but OFF identified.



f. Two estimated events for one measured event.

g. Match with second baseboard heater only.

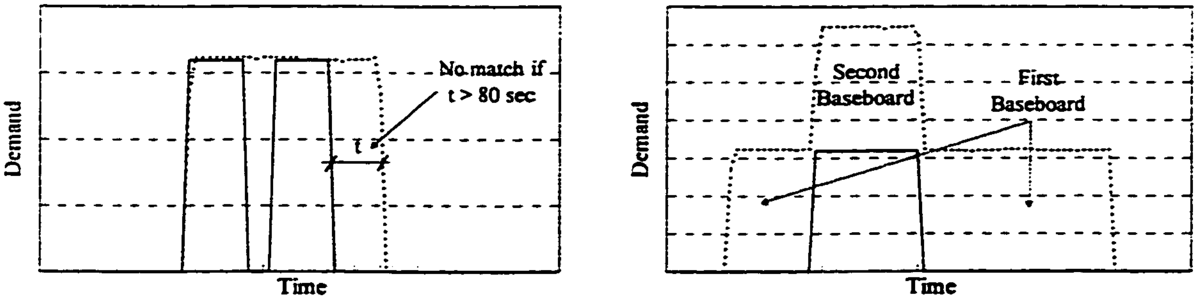
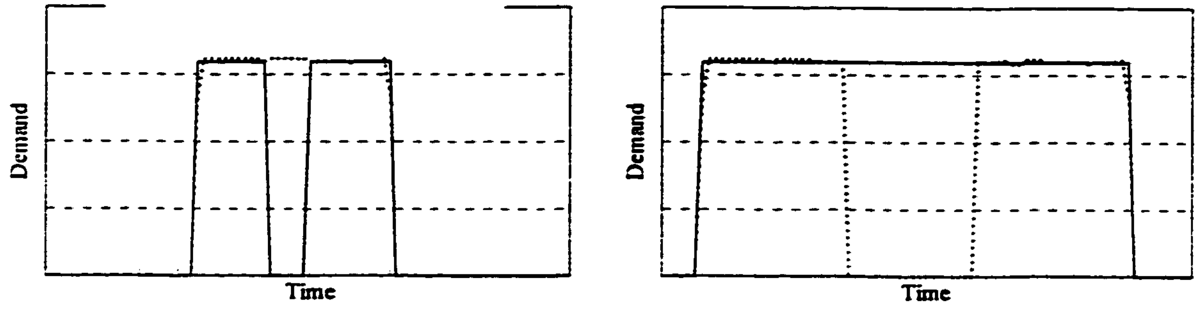


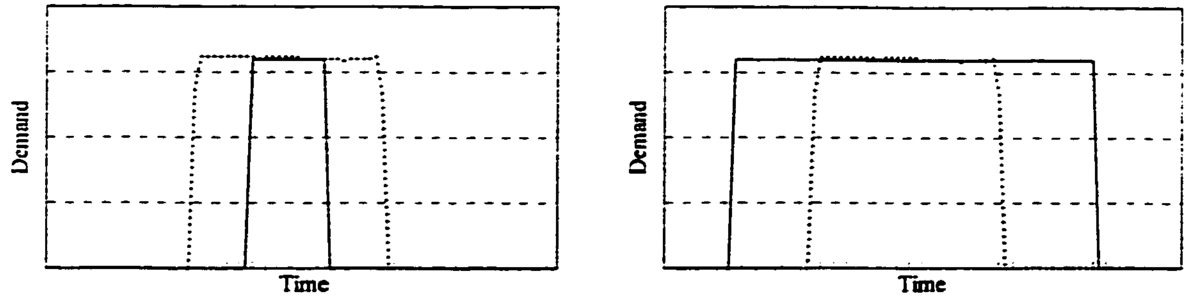
Figure 23. Event-matching cases representing one match.



a. One measured event identified with two estimated events.

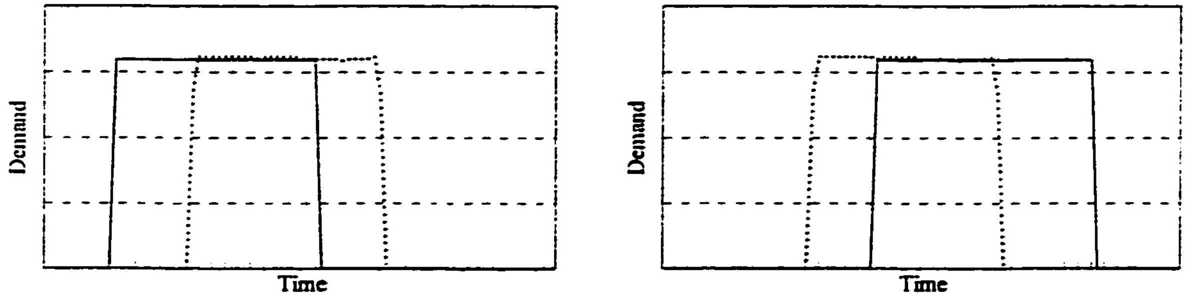
b. One estimated event for two measured events.

Figure 24. Event-matching cases representing two matches.



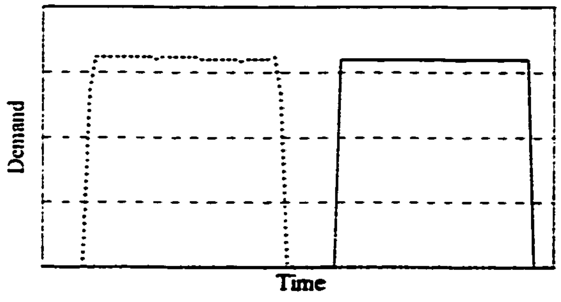
a. ON missed and false OFF.

b. Already ON and OFF missed.



c. Already ON and fasle OFF.

d. ON missed and OFF missed.



e. Both ON and OFF missed.

Figure 25. No-match cases representing false events.

Area E in the output table also shows the stove's total number of measured, sampled, and estimated events should be ignored for now. Preprocessor 5 (described in Section 4.3.6), identifies the component of the total demand signal that is characteristic of the stove and removes it from the total signal. However, unlike the load disaggregation algorithm, which identifies one event at a time, preprocessor 5 identifies a group of events as one event. So, for example, the program could estimate ten measured events correctly yet assign them to just one estimated event; therefore, it would appear as if nine events were missed. So to avoid misrepresentation of results, the stove's total number of measured, sampled, and estimated events should be ignored in the percentages that follow; however, these statistics are still included because they are useful for coming up with future strategies to identify the stove signal.

Another apparent discrepancy that arises will not be evident until actual results are presented. Figure 24 shows two cases where there are two matches: Figure 24a shows two estimated events that match one measured event, and Figure 24b shows one estimated event that matches two measured events. These two cases are defined as matches because they are each a combination of two simple cases: Figure 24a is a combination of Figure 23c and d; and Figure 24b is a combination of Figure 23b and e. The apparent discrepancy will arise when the users attempts to check the results by adding the number of matched events with the number of missed events to see if they equal the number of estimated events, or by adding the number of matched events to the number of false events to see if they equal the number of measured events. If the cases represented in Figures 24a or 24b occur, this checking will not work. And the total number of missed and false events will be off by the number of events that are matched according to Figures 24a and 24b.

4.5.6 Cumulative demand comparison

Although event comparison is useful, the large number of rules defining a match means that it must be done manually. Event matching that does not take into account the timing of events is called cumulative demand matching. It is less informative than event matching, but it has the advantage that it can done automatically, that is, it is a component of the computer program.

Area F (Figure 22) shows the amount of matched, missed, and false cumulative estimated demand, and Table 2 shows how the calculations are performed. Columns D and E show the measured and estimated baseboard heater demand, respectively. Column F shows the portion of the measured baseboard heater demand that the program correctly identified, column G shows the portion of the measured baseboard heater demand that it missed, and column H shows the portion of the estimated baseboard heater demand that it falsely attributed to the baseboard heater.

Like the information in Area B, cumulative demand comparison can only be used to validate the computer program because appliance demand will not have been measured beyond the sampling period.

Table 2. Comparing measured demand with estimated demand.

A	B	C	D	E	F	G	H
	Demand (kW)				Compared to Mean Demand		
Time	Measured Total-Household	Total-Household After Pre-processing	Measured Baseboard Heater	Estimated Baseboard Heater	Estimated Match	Missed	False
22:36:33	1.216	1.216	0	0		0	0
22:36:49	1.216	1.216	0	0		0	0
22:37:05	1.216	1.216	0	0		0	0
22:37:21	2.385	2.385	1.253	0		1.253	0
22:37:37	2.694	2.679	1.296	0		1.296	0
22:37:53	2.694	2.679	1.296	0		1.296	0
22:38:09	2.668	2.679	**1.296**	***1.258***	***1.258***	0.038	0
22:38:25	2.668	2.679	**1.296**	***1.258***	***1.258***	0.038	0
22:38:41	2.668	2.679	**1.282**	***1.258***	***1.258***	0.024	0
22:38:57	2.694	2.679	**1.282**	***1.258***	***1.258***	0.024	0
22:39:13	8.545	8.577	**1.267**	***1.258***	***1.258***	0.009	0
22:39:29	6.937	8.577	**0.843**	***1.258***	***1.258***	0	0.415
22:39:45	6.458	5.868	0	1.258		0	1.258
22:40:01	5.868	5.868	0	1.258		0	1.258
22:40:17	6.030	6.472	0	1.258		0	1.258
22:40:33	6.458	6.472	0	0		0	0
22:40:49	6.485	6.472	0	0		0	0
22:41:05	5.868	5.882	0	0		0	0
TOTAL:	**74.768**	**76.293**	**11.111**	**11.318**	**7.546**	**3.980**	**4.187**

CHAPTER 5

VALIDATION OF NONINTRUSIVE LOAD DISAGGREGATION COMPUTER PROGRAM

This chapter presents the validation of the nonintrusive load disaggregation computer program. There are two measures of accuracy that must be considered in order to validate the performance of the computer program: the accuracy in estimating energy consumption and the accuracy in identifying appliance events. Both measures of accuracy must also be considered concurrently in order to completely describe the accuracy of the program. Since the purpose of the thesis is to develop a working prototype, computer processing time will not be discussed.

5.1 EVALUATION PERIODS

Table 3 shows twenty-five combinations of sampling period and evaluation period that are used to test the performance of the computer program. Each pair of sampling period and evaluation period is called a *scenario*. Running the program for a particular scenario is called a *run*. The output from each run is documented in Appendix B.

5.2 PRESENTATION OF RESULTS

Tables 4 to 9 summarize the results from all twenty-five runs and group them by appliance. For example, Table 4 shows the results for the water heater. The first two columns (A and B) show the run number and the evaluation scenario. The next three columns (C, D, and E) show the measured and estimated energy shares and their difference. The next three columns (F, G, and H) show the measured and estimated energy consumption and the percentage error. The last five columns (I to M) show the event detection statistics.

Table 3. Twenty-five scenarios for validation of computer program.

	Sample Period			Evaluation Period		
Run Number	Start*	End	Number of Days	Start	End	Number of Days
1	Tue, Oct 15, 1996	Tue, Oct 15, 1996	1	Tue, Oct 15, 1996	Tue, Oct 15, 1996	1
2	Wed, Oct 16, 1996	Wed, Oct 16, 1996	1	Wed, Oct 16, 1996	Wed, Oct 16, 1996	1
3	Thu, Oct 17, 1996	Thu, Oct 17, 1996	1	Thu, Oct 17, 1996	Thu, Oct 17, 1996	1
4	Fri, Oct 18, 1996	Fri, Oct 18, 1996	1	Fri, Oct 18, 1996	Fri, Oct 18, 1996	1
5	Tue, Oct 15, 1996	Fri, Oct 18, 1996	4	Tue, Oct 15, 1996	Fri, Oct 18, 1996	4
6	Mon, Nov 25, 1996	Mon, Nov 25, 1996	1	Mon, Nov 25, 1996	Mon, Nov 25, 1996	1
7	Tue, Nov 26, 1996	Tue, Nov 26, 1996	1	Tue, Nov 26, 1996	Tue, Nov 26, 1996	1
8	Wed, Nov 27, 1996	Wed, Nov 27, 1996	1	Wed, Nov 27, 1996	Wed, Nov 27, 1996	1
9	Thu, Nov 28, 1996	Thu, Nov 28, 1996	1	Thu, Nov 28, 1996	Thu, Nov 28, 1996	1
10	Fri, Nov 29, 1996	Fri, Nov 29, 1996	1	Fri, Nov 29, 1996	Fri, Nov 29, 1996	1
11	Sat, Nov 30, 1996	Sat, Nov 30, 1996	1	Sat, Nov 30, 1996	Sat, Nov 30, 1996	1
12	Mon, Nov 25, 1996	Sat, Nov 30, 1996	6	Mon, Nov 25, 1996	Sat, Nov 30, 1996	6
13	Tue, Jan 7, 1997	Tue, Jan 7, 1997	1	Tue, Jan 07, 1997	Tue, Jan 07, 1997	1
14	Wed, Jan 8, 1997	Wed, Jan 8, 1997	1	Wed, Jan 08, 1997	Wed, Jan 08, 1997	1
15	Thu, Jan 9, 1997	Thu, Jan 9, 1997	1	Thu, Jan 09, 1997	Thu, Jan 09, 1997	1
16	Fri, Jan 10, 1997	Fri, Jan 10, 1997	1	Fri, Jan 10, 1997	Fri, Jan 10, 1997	1
17	Sat, Jan 11, 1997	Sat, Jan 11, 1997	1	Sat, Jan 11, 1997	Sat, Jan 11, 1997	1
18	Sun, Jan 12, 1997	Sun, Jan 12, 1997	1	Sun, Jan 12, 1997	Sun, Jan 12, 1997	1
19	Tue, Jan 7, 1997	Sun, Jan 12, 1997	6	Tue, Jan 07, 1997	Sun, Jan 12, 1997	6
20	Tue, Nov 19, 1996	Mon, Nov 25, 1996	7	Tue, Nov 19, 1996	Mon, Nov 25, 1996	7
21	Tue, Nov 19, 1996	Mon, Nov 25, 1996	7	Tue, Nov 19, 1996	Sat, Nov 30, 1996	14
22	Tue, Nov 19, 1996	Mon, Nov 25, 1996	7	Tue, Nov 19, 1996	Mon, Dec 09, 1996	21
23	Tue, Nov 19, 1996	Mon, Nov 25, 1996	7	Tue, Nov 19, 1996	Wed, Dec 18, 1996	28**
24	Tue, Nov 19, 1996	Mon, Nov 25, 1996	7	Tue, Nov 19, 1996	Fri, Jan 24, 1997	54**
25	Tue, Nov 19, 1996	Mon, Nov 25, 1996	7	Tue, Oct 15, 1996	Fri, Jan 24, 1997	72**

*The start is always 0:00:00 h and the end is always 23:59:45 h.

**Data do not contain a series of consecutive days with no interruptions.

Table 4. Results for the water heater from all 25 runs.

A	B	C	D	E	F	G	H	I	J	K	L	M
	WATER HEATER	Energy Shares (%)			Energy Use (kWh)			Event Detection				
Run Number	Scenario	Measured	Estimated (Corrected)	Difference E-M	Measured	Estimated	Percent Error (E-M)/M	Total Measured	Total Estimated	Matched	Missed	False
1	Tue, Oct 15, 1996	38.32	36.59	-1.73	11.115	10.678	-3.93	13	12	12	1	0
2	Wed, Oct 16, 1996	48.47	48.11	-0.36	12.229	12.209	-0.16	10	10	10	0	0
3	Thu, Oct 17, 1996	40.61	49.61	9.00	10.179	12.535	23.14	10	8	8	2	0
4	Fri, Oct 18, 1996	39.69	40.79	1.10	8.569	8.846	3.24	11	12	11	0	1
5	All Oct	41.72	46.40	4.68	42.092	47.137	11.98	43	41	40	3	1
6	Mon, Nov 25, 1996	38.32	40.91	2.59	9.984	10.798	8.16	13	12	11	2	1
7	Tue, Nov 26, 1996	45.92	44.40	-1.52	15.854	15.407	-2.82	13	13	13	0	0
8	Wed, Nov 27, 1996	63.91	60.87	-3.04	20.117	19.221	-4.46	10	9	9	1	0
9	Thu, Nov 28, 1996	26.89	21.40	-5.49	10.646	8.513	-20.04	12	8	8	4	0
10	Fri, Nov 29, 1996	51.71	48.92	-2.79	22.060	20.999	-4.81	12	7	6	6	1
11	Sat, Nov 30, 1996	49.75	29.72	-20.03	30.732	18.471	-39.90	15	8	8	7	0
12	All Nov	46.34	48.49	2.15	109.394	115.132	5.25	74	64	62	12	6
13	Tue, Jan 07, 1997	43.76	45.41	1.65	16.929	17.644	4.23	11	13	11	0	2
14	Wed, Jan 08, 1997	49.15	47.63	-1.52	22.357	21.783	-2.57	14	13	13	1	0
15	Thu, Jan 09, 1997	34.25	38.67	4.42	11.237	12.814	14.04	11	16	11	0	5
16	Fri, Jan 10, 1997	45.74	47.16	1.42	19.031	19.706	3.55	14	15	14	6	1
17	Sat, Jan 11, 1997	45.61	36.95	-8.66	39.606	32.093	-18.97	15	7	6	9	1
18	Sun, Jan 12, 1997	42.14	44.89	2.75	28.180	30.191	7.14	15	15	10	5	5
19	All Jan	43.98	48.62	4.64	137.339	152.371	10.94	79	79	66	13	14
20	7:7	38.15	40.48	2.33	105.342	112.668	6.95	84	92	74	10	19
21	7:14	43.35	43.96	0.61	260.654	265.718	1.94	181	176	158	27	23
22	7:21	44.94	46.01	1.07	386.846	398.255	2.95	269	270			
23	7:28	45.36	46.57	1.21	517.482	534.074	3.21	365	362			
24	7:54	45.51	47.45	1.94	1075.680	1127.696	4.84	693	681			
25	7:72	40.48	40.01	-0.47	1351.965	1342.209	-0.72	912	807			

Table 5. Results for the stove from all 25 runs.

Run Number	STOVE Evaluation scenario	Energy Shares (%) Measured	 Estimated (Corrected)	 Difference E-M	Energy Use (kWh) Measured	 Estimated	 Percent Error (E-M)/M
1	Tue, Oct 15, 1996	5.28	4.75	-0.53	1.532	1.386	-9.51
2	Wed, Oct 16, 1996	0.00	0.00	0.00	0.000	0.000	
3	Thu, Oct 17, 1996	2.53	0.00	-2.53	0.635	0.000	-100.00
4	Fri, Oct 18, 1996	1.52	0.00	-1.52	0.328	0.000	-100.00
5	All Oct	2.47	2.54	0.07	2.495	2.584	3.53
6	Mon, Nov 25, 1996	7.49	1.87	-5.62	1.951	0.493	-74.73
7	Tue, Nov 26, 1996	13.64	5.28	-8.36	4.708	1.833	-61.07
8	Wed, Nov 27, 1996	0.00	0.00	0.00	0.000	0.000	
9	Thu, Nov 28, 1996	7.31	4.28	-3.03	2.895	1.704	-41.13
10	Fri, Nov 29, 1996	7.44	0.00	-7.44	3.173	0.000	-100.00
11	Sat, Nov 30, 1996	9.99	1.38	-8.61	6.173	0.859	-86.09
12	All Nov	8.01	2.06	-5.95	18.900	4.879	-74.19
13	Tue, Jan 07, 1997	2.50	0.00	-2.50	0.967	0.000	-100.00
14	Wed, Jan 08, 1997	1.18	0.50	-0.68	0.537	0.226	-57.91
15	Thu, Jan 09, 1997	7.34	2.50	-4.84	2.408	0.830	-65.52
16	Fri, Jan 10, 1997	3.57	2.60	-0.97	1.484	1.088	-26.68
17	Sat, Jan 11, 1997	6.40	15.94	9.54	5.559	13.850	149.12
18	Sun, Jan 12, 1997	9.81	13.11	3.30	6.558	8.816	34.43
19	All Jan	5.61	7.51	1.90	17.513	23.550	34.47
20	7:7	8.91	2.47	-6.44	24.594	6.865	-72.09
21	7:14	7.75	3.25	-4.50	46.611	19.671	-57.80
22	7:21	6.92	3.08	-3.84	59.549	26.699	-55.16
23	7:28	6.54	2.74	-3.80	74.657	31.381	-57.97
24	7:54	5.32	3.64	-1.68	125.654	86.427	-31.22
25	7:72	40.48	4.80	-35.68	166.304	160.918	-3.24

Table 6. Results for the baseboard heater from all 25 runs.

Run	BASEBOARD	Energy Shares (%)			Energy Use (kWh)			Event Detection				
Number	HEATER Evaluation scenario	Measured	Estimated (Corrected)	Difference E-M	Measured	Estimated	Percent Error (E-M)/M	Total Measured	Total Estimated	Matched	Missed	False
1	Tue, Oct 15, 1996	7.50	11.30	3.80	2.174	3.298	51.67	12	21	10	3	11
2	Wed, Oct 16, 1996	8.99	7.89	-1.10	2.269	2.003	-11.74	13	15	12	1	3
3	Thu, Oct 17, 1996	16.37	13.45	-2.92	4.103	3.400	-17.14	19	19	16	3	3
4	Fri, Oct 18, 1996	17.32	15.36	-1.96	3.740	3.331	-10.92	18	26	18	0	8
5	All Oct	12.18	14.97	2.79	12.286	15.205	23.76	61	86	59	5	29
6	Mon, Nov 25, 1996	11.60	10.42	-1.18	3.023	2.750	-9.03	9	9	8	1	1
7	Tue, Nov 26, 1996	12.00	26.37	14.37	4.143	9.152	120.91	5	28	4	0	23
8	Wed, Nov 27, 1996	6.03	11.53	5.50	1.897	3.644	92.11	4	23	3	1	20
9	Thu, Nov 28, 1996	30.46	31.66	1.20	12.061	12.593	4.41	13	31	18	3	13
10	Fri, Nov 29, 1996	17.20	18.51	1.31	7.339	7.946	8.26	38	40	35	3	5
11	Sat, Nov 30, 1996	3.44	9.43	5.99	2.122	5.863	176.26	10	30	7	3	23
12	All Nov	12.96	19.46	6.50	30.585	46.193	51.03	76	201	77	9	124
13	Tue, Jan 07, 1997	18.49	20.62	2.13	7.155	8.012	11.98	16	41	18	1	23
14	Wed, Jan 08, 1997	20.74	6.82	-13.92	9.433	3.119	-66.93	15	11	8	8	3
15	Thu, Jan 09, 1997	19.24	14.28	-4.96	6.310	4.731	-25.02	16	10	6	10	4
16	Fri, Jan 10, 1997	12.05	12.54	0.49	5.014	5.244	4.58	18	22	14	4	8
17	Sat, Jan 11, 1997	11.29	7.34	-3.95	9.807	6.376	-34.99	12	10	2	10	8
18	Sun, Jan 12, 1997	10.77	9.52	-1.25	7.200	6.398	-11.14	22	23	7	15	16
19	All Jan	14.38	15.05	0.67	44.918	47.166	5.00	94	165	69	25	97
20	7:7	19.32	28.65	9.33	53.357	79.742	49.45	159	326	162	8	164
21	7:14	16.23	22.05	5.82	97.577	133.297	36.61	257	598	274	16	324
22	7:21	14.60	20.82	6.22	125.649	180.206	43.42	369	826			
23	7:28	13.50	19.51	6.01	154.039	223.793	45.28	429	1044			
24	7:54	13.67	19.60	5.93	323.026	465.740	44.18	853	2080			
25	7:72	12.10	18.32	6.22	404.180	614.351	52.00	1011	2733			

Table 7. Results for both washers from all 25 runs.

Run Number	BOTH WASHERS Evaluation scenario	Energy Shares (%) Measured	Estimated (Corrected)	Difference E-M	Energy Use (kWh) Measured	Estimated	Percent Error (E-M)/M	Event Detection Total Measured	Total Estimated	Matched	Missed	False
1	Tue, Oct 15, 1996	1.56	5.19	3.63	0.453	1.513	234.31	5	20	3	2	17
2	Wed, Oct 16, 1996	0.00	0.00	0.00	0.000	0.000		0	0	0	0	0
3	Thu, Oct 17, 1996	0.00	0.00	0.00	0.000	0.000		0	0	0	0	0
4	Fri, Oct 18, 1996	2.16	3.96	1.80	0.467	0.858	83.92	6	11	3	3	8
5	All Oct	0.91	3.57	2.66	0.919	3.624	294.29	11	35	6	5	29
6	Mon, Nov 25, 1996	0.00	0.00	0.00	0.000	0.000		0	0	0	0	0
7	Tue, Nov 26, 1996	1.11	3.83	2.72	0.384	1.328	246.22	5	13	0	5	13
8	Wed, Nov 27, 1996	0.62	0.33	-0.29	0.196	0.103	-47.62	6	1	0	6	1
9	Thu, Nov 28, 1996	0.00	0.00	0.00	0.000	0.000		0	0	0	0	0
10	Fri, Nov 29, 1996	1.05	2.23	1.18	0.449	0.955	112.50	6	10	4	2	6
11	Sat, Nov 30, 1996	2.70	1.84	-0.86	1.667	1.145	-31.30	40	20	14	26	6
12	All Nov	1.14	1.28	0.14	2.696	3.053	13.24	57	32	9	48	24
13	Tue, Jan 07, 1997	0.00	0.00	0.00	0.000	0.000		0	0	0	0	0
14	Wed, Jan 08, 1997	1.01	1.60	0.59	0.460	0.733	59.44	6	11	3	3	8
15	Thu, Jan 09, 1997	0.00	0.00	0.00	0.000	0.000		0	0	0	0	0
16	Fri, Jan 10, 1997	1.60	2.97	1.37	0.665	1.238	86.10	11	19	8	4	11
17	Sat, Jan 11, 1997	2.28	2.45	0.17	1.987	2.124	6.89	39	50	9	30	41
18	Sun, Jan 12, 1997	2.37	2.75	0.38	1.578	1.855	17.51	37	33	11	26	22
19	All Jan	1.50	2.46	0.96	4.690	7.709	64.36	93	139	33	60	107
20	7:7	0.85	2.23	1.38	2.369	6.223	162.75	30	43	6	24	38
21	7:14	1.25	1.70	0.45	7.485	10.295	37.54	133	77	17	116	61
22	7:21	1.05	1.82	0.77	9.085	15.728	73.11	159	120			
23	7:28	0.96	1.82	0.86	10.885	20.898	91.99	188	162			
24	7:54	0.94	1.84	0.90	22.423	43.691	94.85	388	346			
25	7:72	0.85	1.68	0.83	28.117	56.439	100.73	483	446			

Table 8. Results for the refrigerator from all 25 runs.

Run Number	REFRIGERATOR Evaluation scenario	Energy Shares (%) Measured	Estimated (Corrected)	Difference E-M	Energy Use (kWh) Measured	Estimated	Percent Error (E-M)/M	Event Detection Total Measured	Total Estimated	Matched	Missed	False
1	Tue, Oct 15, 1996	19.30	13.56	-5.74	5.597	3.960	-29.25	41	40	26	15	14
2	Wed, Oct 16, 1996	22.31	19.67	-2.64	5.629	4.989	-11.36	41	39	31	10	8
3	Thu, Oct 17, 1996	21.85	15.85	-6.00	5.477	4.006	-26.86	43	35	30	13	5
4	Fri, Oct 18, 1996	26.20	21.12	-5.08	5.656	4.582	-18.99	42	41	36	7	5
5	All Oct	22.16	17.71	-4.45	22.359	17.989	-19.54	167	149	126	41	23
6	Mon, Nov 25, 1996	22.20	14.02	-8.18	5.782	3.701	-36.00	40	25	21	19	4
7	Tue, Nov 26, 1996	15.87	9.06	-6.81	5.478	3.144	-42.60	42	29	23	18	6
8	Wed, Nov 27, 1996	16.57	14.41	-2.16	5.215	4.550	-12.75	44	41	33	11	8
9	Thu, Nov 28, 1996	13.60	12.01	-1.59	5.384	4.777	-11.27	43	33	26	17	7
10	Fri, Nov 29, 1996	12.57	8.91	-3.66	5.364	3.823	-28.74	43	40	27	16	13
11	Sat, Nov 30, 1996	9.50	7.41	-2.09	5.870	4.610	-21.47	36	31	24	12	7
12	All Nov	14.02	10.28	-3.74	33.094	24.404	-26.26	243	193	142	101	52
13	Tue, Jan 07, 1997	14.14	11.56	-2.58	5.470	4.492	-17.89	45	37	33	13	4
14	Wed, Jan 08, 1997	12.01	8.56	-3.45	5.463	3.918	-28.28	46	35	32	14	3
15	Thu, Jan 09, 1997	18.02	9.66	-8.36	5.910	3.201	-45.84	40	25	24	16	1
16	Fri, Jan 10, 1997	15.30	9.60	-5.70	6.365	4.011	-36.98	35	36	22	13	15
17	Sat, Jan 11, 1997	7.23	3.37	-3.86	6.279	2.928	-53.37	36	25	17	19	8
18	Sun, Jan 12, 1997	9.15	5.09	-4.06	6.118	3.420	-44.09	38	31	20	18	11
19	All Jan	11.40	7.29	-4.11	35.606	22.874	-35.76	237	196	146	92	56
20	7:7	14.42	10.33	-4.09	39.819	28.742	-27.82	267	191	140	127	53
21	7:14	13.28	9.62	-3.66	79.859	58.149	-27.19	531	412	309	224	112
22	7:21	13.92	9.91	-4.01	119.822	85.779	-28.41	796	651			
23	7:28	13.98	9.77	-4.21	159.512	112.052	-29.75	1067	850			
24	7:54	13.29	9.35	-3.94	314.197	222.261	-29.26	2096	1712			
25	7:72	12.42	8.37	-4.05	414.938	280.837	-32.32	2825	2297			

Table 9. Results for the residual from all 25 runs.

	RESIDUAL	Energy Shares (%)			Energy Use (kWh)		
Run Number	Evaluation scenario	Measured	Estimated (Corrected)	Difference E-M	Measured	Estimated	Percent Error (E-M)/M
1	Tue, Oct 15, 1996	28.04	28.62	0.58	8.133	8.354	2.71
2	Wed, Oct 16, 1996	20.22	24.33	4.11	5.103	6.173	20.98
3	Thu, Oct 17, 1996	18.63	21.09	2.46	4.670	5.328	14.08
4	Fri, Oct 18, 1996	13.11	18.78	5.67	2.830	4.073	43.93
5	All Oct	20.55	14.81	-5.74	20.737	15.042	-27.46
6	Mon, Nov 25, 1996	20.39	32.79	12.40	5.312	8.656	62.95
7	Tue, Nov 26, 1996	11.46	11.06	-0.40	3.955	3.838	-2.97
8	Wed, Nov 27, 1996	12.87	12.84	-0.03	4.051	4.054	0.08
9	Thu, Nov 28, 1996	21.74	30.65	8.91	8.606	12.192	41.67
10	Fri, Nov 29, 1996	10.03	21.44	11.41	4.277	9.204	115.18
11	Sat, Nov 30, 1996	24.63	50.21	25.58	15.214	31.210	105.14
12	All Nov	17.54	18.44	0.90	41.416	43.775	5.70
13	Tue, Jan 07, 1997	21.11	22.41	1.30	8.165	8.705	6.61
14	Wed, Jan 08, 1997	15.90	34.89	18.99	7.234	15.955	120.57
15	Thu, Jan 09, 1997	21.15	34.88	13.73	6.939	11.556	66.53
16	Fri, Jan 10, 1997	21.74	25.14	3.40	9.044	10.505	16.16
17	Sat, Jan 11, 1997	27.18	33.96	6.78	23.600	29.498	24.99
18	Sun, Jan 12, 1997	25.78	24.64	-1.14	17.236	16.570	-3.86
19	All Jan	23.13	19.05	-4.08	72.217	59.698	-17.34
20	7:7	18.34	15.84	-2.50	50.636	44.078	-12.95
21	7:14	18.15	19.41	1.26	109.128	117.346	7.53
22	7:21	18.57	18.36	-0.21	159.830	158.892	-0.59
23	7:28	19.66	19.58	-0.08	224.257	224.578	0.14
24	7:54	21.26	18.12	-3.14	502.502	430.679	-14.29
25	7:72	29.17	26.83	-2.34	974.047	899.911	-7.61

5.3 DISCUSSION OF RESULTS

5.3.1 One-day results

Daily results refer to the runs where the sampling period and the evaluation period are both one day. Daily evaluation was done to fine-tune the computer program. The daily results show how the computer program performs for a particular day, because the sample statistics are calculated for that day and then used to disaggregate that same day's energy consumption. Only when the sampling period is applied to longer evaluation periods, do we start to see how the program works for any group of days.

5.3.1.1 Sample of one-day to one-day results

Table 10 shows the results of one particular run. Both the sampling period and the evaluation period are Friday, October 18, 1996. The difference between the measured and the estimated energy shares is never greater than 6%. Out of 77 measured events (11+18+0+6+42), 88% ({11+18+3+36}÷77) are correctly identified, and 13% ({0+0+3+7}÷77) are missed. Out of all estimated events, 24% ({1+8+8+5}÷77) are false. All of the water heater and the baseboard heater events are recognized, while 86% (36÷42) of the refrigerator events are recognized. Only 8% (1÷12) of the estimated water heater events are false. However, 31% (8÷26) of the estimated baseboard heater events are false. Twelve percent (5÷41) of the estimated refrigerator events are false and 17% (7÷42) of the measured refrigerator events are missed. Half the washer events are successfully identified (3÷6) and half are missed (3÷6). However, 73% (8÷11) of the estimated washer events are false.

Table 10. Example of the results of one run.

Sample Period:	Fri, October 18, 1996	to	Fri, October 18, 1996
Evaluation Period:	Fri, October 18, 1996	to	Fri, October 18, 1996

ENERGY CONSUMPTION	Measured		Estimated			Energy Shares	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
							Duration (seconds)			Total No.	No. of Events		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share	Difference	Average	Maximum	Minimum	of Events	Matched	Missed	False
Total (Input)	4857.597	na	na	na									
Total (After Processing)	na	na	4880.495	100.47	100.00								
Water Heater	1927.963	39.69	1990.443	40.98	40.79	-1.10	595	1152	208	12	11	0	1
Stove	73.805	1.52	0.000	0	0.00	1.52	0	0	0	0			
Baseboard Heater 1	841.456	17.32	749.543	15.43	15.36	1.96	356	1328	32	26	18	0	8
Baseboard Heater 2	841.456	17.32	0.000	0	0.00		0	0	0	0			
Dishwasher	105.016	2.16	na	na	na								
Clothes Washer	0.000	0.00	na	na	na								
Both Washers	na	na	193.141	3.98	3.96	-1.80	383	880	32	11	3	3	8
Refrigerator	1272.595	26.20	1030.884	21.22	21.12	5.08	974	3472	16	41	36	7	5
Residual (Calculated)	636.762	13.11	na	na	na								
Residual (Estimated)	na	na	916.483	18.87	18.78	-5.67							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.463	0.317	628	1152	336	11
Stove	1.604	1.271	61	240	16	12
Baseboard Heater	1.295	0.247	577	3232	400	18
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.734	0.088	381	896	96	6
Refrigerator	0.413	0.023	1173	3792	544	42
Drier	na	na	na	na	na	na

DEMAND MATCHING	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	1905.257	22.706	85.186
Stove	0.000	73.805	0.000
Baseboard Heater	589.956	251.500	159.588
Washers	87.542	17.474	105.599
Refrigerator	971.839	300.756	59.045

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.463	0.317	628	1152	336	11
Stove	1.604	1.271	61	240	16	12
Baseboard Heater	1.295	0.247	577	3232	400	18
Clothes Washer	0.734	0.088	381	896	96	6
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.413	0.023	1173	3792	544	42
Drier	0.000	0.000	0	0	0	0

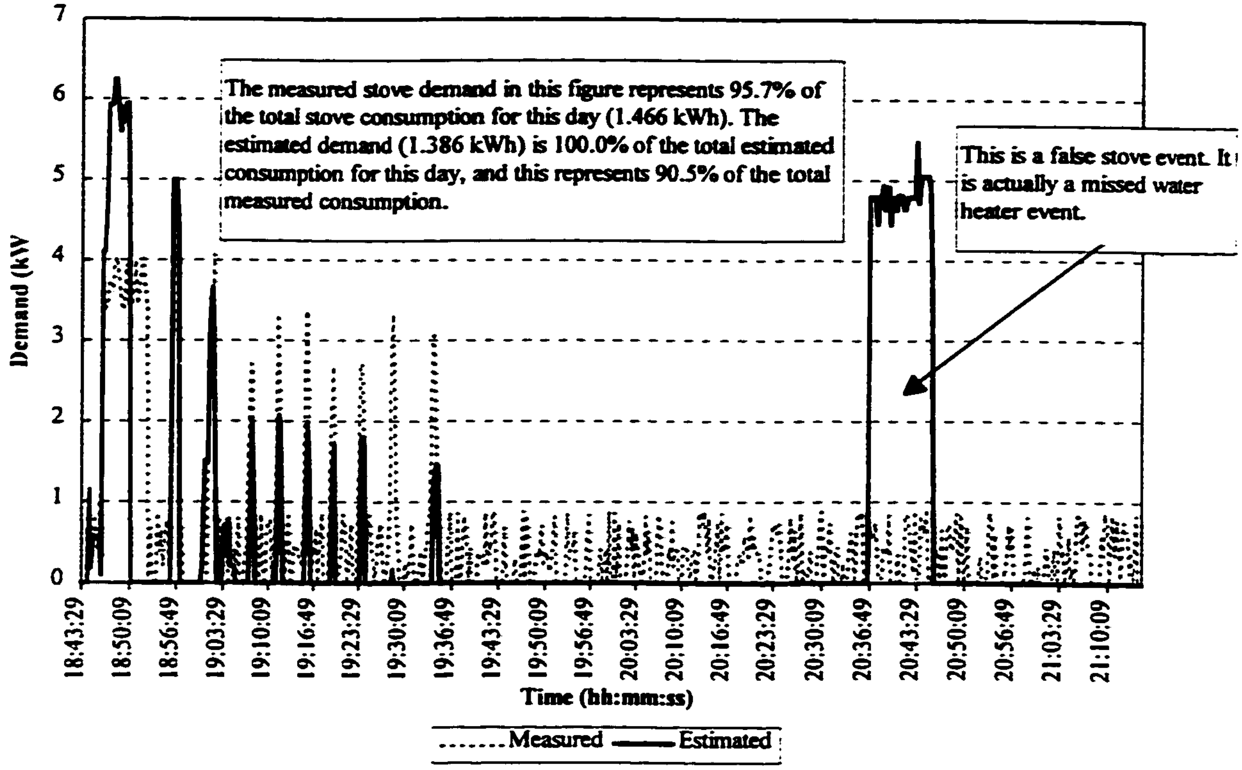
5.3.1.2 Individual appliance energy consumption and event recognition

5.3.1.2.1 Water heater

The differences in energy shares of one-day to one-day runs (Table 4) show that for some runs, the program performs very well, for example run 2 on Wednesday, October 16, 1996, the difference is -0.36%. Yet on other days, for example run 11 on Saturday, November 30, 1996, the difference is 20.03%. On average though, the difference in percent is 4.25%. Note to that the worst day in terms of matching consumption is a Saturday. And the worst days in terms of matching events is also a Saturday. Saturday is a day, presumably, when the occupants are home making frequent use of the hot water. However, on weekdays, when they are presumably away most of the day, the activation of the water heater is mostly to make up for standby losses, which follow a regular cycle.

5.3.1.2.2 Stove

The best results for the stove occur when the program is run 2 on Wednesday, October 16, 1996 (Table 5). The difference between measured and estimated stove energy shares is only -0.53%. And even in absolute terms, this represents just a -9.51% ({4.75-5.28}÷5.28) error in energy consumption. Figure 26 shows that the program identifies, but underestimates, most of the large stove-spikes; and that it misses completely most of the smaller stove-spikes. Like the water heater, the worst day for estimating the stove energy consumption is a Saturday: run 17 on January 11, 1997. The energy shares difference is 9.54%, which is an absolute error of 149.12% ({15.94-6.40}÷6.40) in energy consumption. But, let us look more closely at two of the reasons for this large error and at their consequence.



The measured stove demand in this figure represents 95.7% of the total stove consumption for this day (1.466 kWh). The estimated demand (1.386 kWh) is 100.0% of the total estimated consumption for this day, and this represents 90.5% of the total measured consumption.

This is a false stove event. It is actually a missed water heater event.

Figure 26. Stove demand on October 15, 1996.

Figure 27 shows the stove demand during a five-minute period on this day. This figure highlights a very important observation: the total household signal does not always correspond exactly to the sum of the measured appliances even when the measured appliances are the only ones that are on. In the figure, the thin line with square markers is the total household demand, and the thin dashed line is the measured stove demand. In this instance, 100% of the total household demand is due to the stove because no other monitored appliances are ON. The magnitude of the total household spikes suggests that indeed not even any of the non-monitored appliances are ON. Yet even in this case, the stove consumption is overestimated by 15.87%. So although the numbers may show that the program has not performed well overall, it is clear that for particular periods, it does perform exactly as intended.

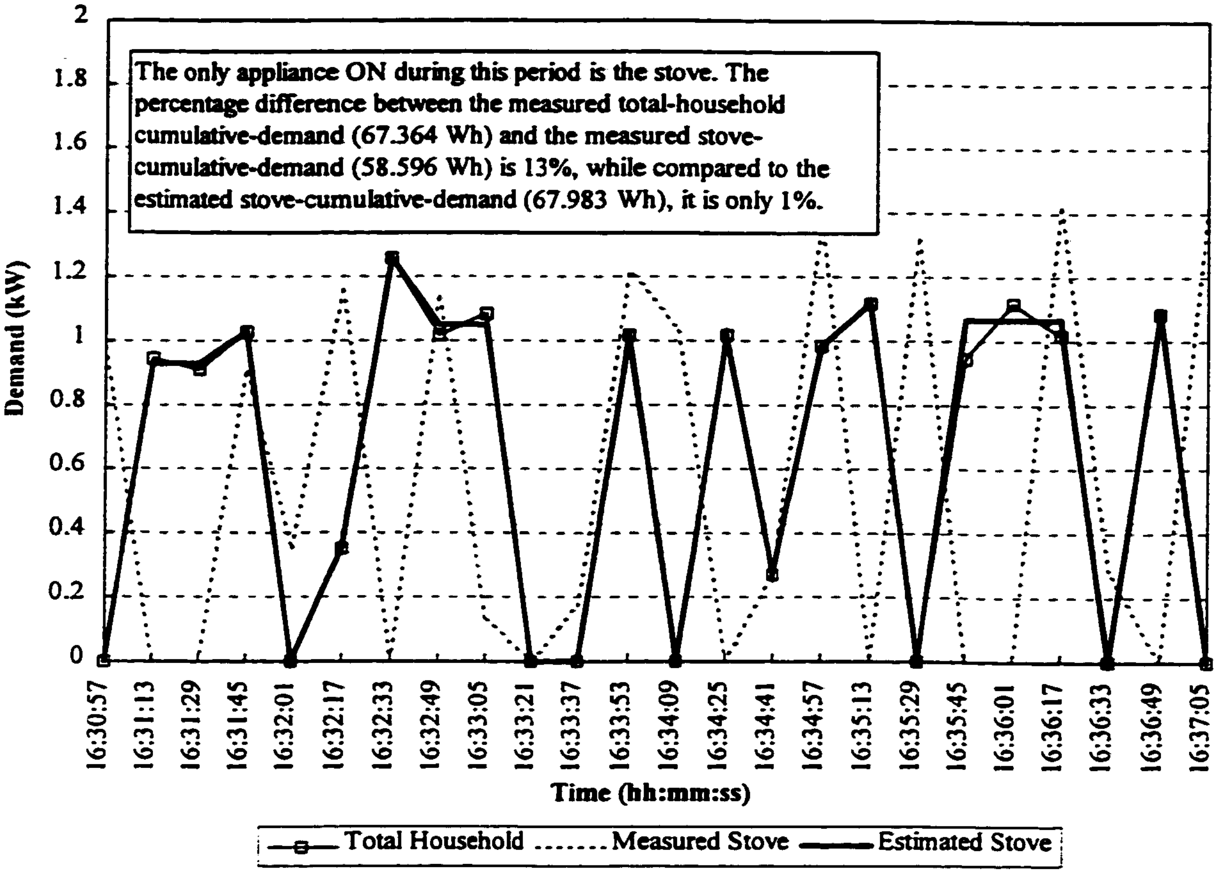

The only appliance ON during this period is the stove. The percentage difference between the measured total-household cumulative-demand (67.364 Wh) and the measured stove-cumulative-demand (58.596 Wh) is 13%, while compared to the estimated stove-cumulative-demand (67.983 Wh), it is only 1%.

Figure 27. Stove consumption on January 11, 1997.

Throughout this entire day, five hot water events are erroneously attributed to the stove. Therefore, of the 8.288 kW·h that should have gone to the water heater, 6.534 kW·h is erroneously attributed to the stove. Because the computer program follows an appliance turn-on preference hierarchy when attributing portions of the total household demand load to particular appliances, an error in recognizing one appliance can result in an error in recognizing another appliance. For example, if the program falsely identifies a water heater event as a stove event, the stove energy consumption is overestimated by the magnitude of this event and the water heater is underestimated by the magnitude of this event. Again, the accuracy in recognizing one appliance's energy consumption can affect the accuracy in recognizing other appliances' energy consumption.

5.3.1.2.3 ***Baseboard heater***

The best day for energy-shares matching is run 16 on Friday, January 10, 1997 (Table 6). The difference is only 0.49%. In terms of energy consumption, this is an absolute error of 4.58% ({12.54-12.05}÷12.05). The best day for matching events is run 6 on Monday, November 25, 1996 because almost 90% (8÷9) of the events are matched, only one is missed and only one is false. The worst day for event matching is again a Saturday: run 17 on January 11 this time. The worst day for energy shares is Tuesday, November 26, 1996. The difference is 14.37%, representing an absolute error in energy consumption of over 100% ({26.37-12.00}÷12.00). Therefore, although 80% (4÷5) of the events are recognized, 82% (23÷28) of all recognized events are false.

5.3.1.2.4 ***Washers***

The energy shares difference for the washer is always less than 4% (Table 7). Yet, in general, only about half the events are successfully matched. Furthermore, the actual energy-consumption absolute errors can be quite large, as large as 246.22%, in fact (run 7 on Tuesday, November 26). However, because the washers' energy shares are relatively small, the difference in cost between measured and estimated energy consumption is accordingly relatively small.

5.3.1.2.5 ***Refrigerator***

The best day for estimating energy shares and consumption is run 9 on Thursday, November 28, 1996 (Table 8). The energy-shares difference is only -1.59% while the energy-consumption absolute error is 1.27%. The program consistently recognizes about 65% of events and of all estimated events, 23% are generally false.

5.3.1.2.6 ***Summary***

Results of daily runs show that the program accurately estimates the energy consumption of the water heater, and it correctly identifies most water heater events. The program generally overestimates baseboard heater and washer consumption, and it consistently underestimates refrigerator consumption.

Furthermore, any particular day is not representative of all other days. The sample statistics for a particular day may be such that the total signal can be successfully analyzed, or they may not. Therefore, to avoid the particular anomalies of a particular day, a longer period should be chosen. The evaluation for all days (runs 5, 12, and 19) shows that selecting a larger sampling period can minimize the effect. Compared to the all-one-day runs, there is no conclusive difference in energy consumption. However, there is equal and better event recognition. In other words, the longer the sampling period, the greater the likelihood that it is representative of average conditions.

5.3.2 Multiple-days results

Multiple-days refer to the runs where the sampling period was kept constant and the evaluation period was extended (runs 20 to 25). The sampling period, as Table 3 shows, is Tuesday, November 19 to Monday, November 25, 1996; and the evaluation period starts with this same week and gradually it is extended. The difference in energy-shares, except for the baseboard heater and one instance of the stove, is always less than 5% (Table 4 to 9). The difference in energy-shares is always less than 10% for the baseboard heater. The average energy-consumption absolute error for the water heater is 3.43%. The average energy-consumption absolute error for the baseboard heater is 45.16%. The energy-consumption absolute error for the refrigerator is consistently about 30%. The energy-consumption absolute error for the stove and the washers is not consistent. It varies from 3.24% to 72.09% for the stove and from 37.54% to 162.75% for the washers. About 25% of the false refrigerator events are one minute or less in duration. Because the refrigerator demand in relatively small compared to the other major appliances, it is possible that smaller appliances are mistakenly identified as the refrigerator.

5.3.3 Optimum sampling-period to evaluation-period ratio

The long evaluation-period results in Tables 4 to 9 indicate that increasing the evaluation period while the sampling period is held constant at one week has no effect on accuracy. The significance is that one week is long enough to get a statistically representative sample of each appliance's operating characteristics. Of course, the data is from the colder fall and winter months. Further research is needed to test the program under summer conditions, that is, in the warmer months. The present results show that the ideal sampling period is seven consecutive days. It has been shown that day-of-the-week occupant behavior has a large effect on appliance frequency of use and hence energy consumption.

CHAPTER 6

CONCLUSIONS

The appliance-load disaggregation computer program described in this thesis estimates the energy consumption of major household appliances. The following conclusions concern the runs where the sampling period is one week and evaluation periods is from one to several weeks. The difference in energy-shares, for all appliances except for the baseboard heater and one instance of the stove, is always less than 5%. The difference in energy-shares is always less than 10% for the baseboard heater. The average energy-consumption absolute error is 3.43% for the water heater, 45.16% for the baseboard heater, and consistently about 30% for the refrigerator. The energy-consumption absolute error for the stove and the washers varies between less than 5% and more than 100%. About 25% of the false refrigerator events are one minute or less in duration. Furthermore, one week is long enough to get a statistically representative sample of each appliance's operating characteristics.

Finally, in meeting the stated objective of developing the methodology and related computer program for nonintrusive load disaggregation, the following conclusions have been drawn.

1. Electric current alone is sufficient a signature to identify the major appliances in a house.

2. Using the combination of data loggers and current probes described in Chapter 3 is a simple and inexpensive way to measure and collect the data. Installation can be done in less than an hour, and it does not require an electrician.
3. The preprocessing algorithms described in this chapter are based on simple calculations. Complex equations and transformations from the field of signal processing are not necessary.
4. The look-backward approach (backtracking) is an excellent way of increasing the accuracy of the appliance-load recognition algorithm when an appliance event is missed.
5. At the present time, the only hindrance to real-time load disaggregation is the backtracking subroutine. If the accuracy of the program can be increased without using backtracking, real-time load disaggregation is possible.
6. The algorithm is capable of disaggregation load data collected at any rate as long as it is consistent. Further research is needed to measure the accuracy of the program at longer sampling rates. However, the 16-second sampling rate is not fast enough to rely on transient signatures in residential appliances as an indicator of appliance activation

CHAPTER 7

RECOMMENDATIONS FOR FURTHER RESEARCH

The following recommendations are suggestions to other researchers interested in furthering the goals of this research.

1. The downloading time, both in duration and frequency, should be minimized, and all data loggers should be synchronized so that they start recording at the same time to avoid downloading time and synchronization-related problems in the future

2. A *post*-processing algorithm should be added between program blocks 3 and 4 to further increase the accuracy of the computer program. This algorithm would analyze the output data and remove short duration events (defined by the minimum durations in the sampling mode) from the disaggregated output file, and add them to the residual.

3. The program should be tested with data collected during the summer months to ensure that its performance is consistent with the results obtained using winter data.

4. The program should also be tested with data from other houses. If any modifications to the program are to be undertaken, it should be restructured so that the user can select which preprocessors and which checking subroutines to implement, and the order of appliance turn-on and turn-off sequence.

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APPENDIX A

LEGEND TO INPUT FILES

	Actual day	Renamed	
	Tue, Oct 15, 1996	Mon, Jan 01, 1996	
	Wed, Oct 16, 1996	Tue, Jan 02, 1996	
	Thu, Oct 17, 1996	Wed, Jan 03, 1996	
	Fri, Oct 18, 1996	Thu, Jan 04, 1996	
	Mon, Oct 21, 1996	Fri, Jan 05, 1996	
	Tue, Oct 22, 1996	Sat, Jan 06, 1996	
	Wed, Oct 23, 1996	Sun, Jan 07, 1996	
	Thu, Oct 24, 1996	Mon, Jan 08, 1996	
	Fri, Oct 25, 1996	Tue, Jan 09, 1996	
	Fri, Nov 08, 1996	Wed, Jan 10, 1996	
	Sat, Nov 09, 1996	Thu, Jan 11, 1996	
	Sun, Nov 10, 1996	Fri, Jan 12, 1996	
	Mon, Nov 11, 1996	Sat, Jan 13, 1996	
	Tue, Nov 12, 1996	Sun, Jan 14, 1996	
	Wed, Nov 13, 1996	Mon, Jan 15, 1996	
	Thu, Nov 14, 1996	Tue, Jan 16, 1996	
	Fri, Nov 15, 1996	Wed, Jan 17, 1996	
	Sat, Nov 16, 1996	Thu, Jan 18, 1996	
	Tue, Nov 19, 1996	Fri, Jan 19, 1996	Week 1
	Wed, Nov 20, 1996	Sat, Jan 20, 1996	
	Thu, Nov 21, 1996	Sun, Jan 21, 1996	
	Fri, Nov 22, 1996	Mon, Jan 22, 1996	
	Sat, Nov 23, 1996	Tue, Jan 23, 1996	
	Sun, Nov 24, 1996	Wed, Jan 24, 1996	
	Mon, Nov 25, 1996	Thu, Jan 25, 1996	
	Tue, Nov 26, 1996	Fri, Jan 26, 1996	Week 2
	Wed, Nov 27, 1996	Sat, Jan 27, 1996	
	Thu, Nov 28, 1996	Sun, Jan 28, 1996	
	Fri, Nov 29, 1996	Mon, Jan 29, 1996	
	Sat, Nov 30, 1996	Tue, Jan 30, 1996	
	Sun, Dec 01, 1996	Wed, Jan 31, 1996	
	Mon, Dec 02, 1996	Thu, Feb 01, 1996	
	Tue, Dec 03, 1996	Fri, Feb 02, 1996	Week 3
	Wed, Dec 04, 1996	Sat, Feb 03, 1996	
	Thu, Dec 05, 1996	Sun, Feb 04, 1996	
	Fri, Dec 06, 1996	Mon, Feb 05, 1996	
	Sat, Dec 07, 1996	Tue, Feb 06, 1996	
	Sun, Dec 08, 1996	Wed, Feb 07, 1996	
	Mon, Dec 09, 1996	Thu, Feb 08, 1996	
	Tue, Dec 10, 1996	Fri, Feb 09, 1996	Week 4
Missing Dec 11 and 12	Wed, Dec 11, 1996	Sat, Feb 10, 1996	
	Sat, Dec 14, 1996	Sun, Feb 11, 1996	
	Sun, Dec 15, 1996	Mon, Feb 12, 1996	
	Mon, Dec 16, 1996	Tue, Feb 13, 1996	
	Tue, Dec 17, 1996	Wed, Feb 14, 1996	
	Wed, Dec 18, 1996	Thu, Feb 15, 1996	
	Thu, Dec 19, 1996	Fri, Feb 16, 1996	
	Wed, Dec 25, 1996	Sat, Feb 17, 1996	
	Thu, Dec 26, 1996	Sun, Feb 18, 1996	
	Fri, Dec 27, 1996	Mon, Feb 19, 1996	
	Sat, Dec 28, 1996	Tue, Feb 20, 1996	
	Sun, Dec 29, 1996	Wed, Feb 21, 1996	
	Tue, Dec 31, 1996	Thu, Feb 22, 1996	

Actual day	Renamed
Wed, Jan 01, 1997	Fri, Feb 23, 1996
Thu, Jan 02, 1997	Sat, Feb 24, 1996
Fri, Jan 03, 1997	Sun, Feb 25, 1996
Sat, Jan 04, 1997	Mon, Feb 26, 1996
Tue, Jan 07, 1997	Tue, Feb 27, 1996
Wed, Jan 08, 1997	Wed, Feb 28, 1996
Thu, Jan 09, 1997	Thu, Feb 29, 1996
Fri, Jan 10, 1997	Fri, Mar 01, 1996
Sat, Jan 11, 1997	Sat, Mar 02, 1996
Sun, Jan 12, 1997	Sun, Mar 03, 1996
Mon, Jan 13, 1997	Mon, Mar 04, 1996
Tue, Jan 14, 1997	Tue, Mar 05, 1996
Wed, Jan 15, 1997	Wed, Mar 06, 1996
Thu, Jan 16, 1997	Thu, Mar 07, 1996
Mon, Jan 20, 1997	Fri, Mar 08, 1996
Tue, Jan 21, 1997	Sat, Mar 09, 1996
Wed, Jan 22, 1997	Sun, Mar 10, 1996
Thu, Jan 23, 1997	Mon, Mar 11, 1996
Fri, Jan 24, 1997	Tue, Mar 12, 1996

APPENDIX B

COMPUTER PROGRAM OUTPUT FILE: SUMMARIES FOR 25 RUNS

Sample Period: Tue, October 15, 1996 to Tue, October 15, 1996
Evaluation Period: Tue, October 15, 1996 to Tue, October 15, 1996

ENERGY CONSUMPTION	Measured		Estimated			Difference	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
	Cumulative	Energy	Cumulative	Energy	Corrected	in Energy	Duration (seconds)			Total No.	No. of Events		
	Demand (kW)	Share	Demand (kW)	Share	Energy Share	Shares	Average	Maximum	Minimum	of Events	Matched	Missed	False
Total (Input)	6526.013	na	na	na									
Total (After Processing)	na	na	6567.531	100.64	100.00								
Water Heater	2500.826	38.32	2402.579	36.82	36.59	1.73	717	1248	352	12	12	1	0
Stove	344.735	5.28	311.954	4.78	4.75	0.53	116	544	16	13			
Baseboard Heater 1	489.207	7.50	630.059	9.65	9.59	-3.80	445	912	32	18	10	3	11
Baseboard Heater 2			111.927	1.72	1.71		475	608	224	3			
Dishwasher	101.814	1.56	na	na	na								
Clothes Washer	0.000	0.00	na	na	na								
Both Washers	na	na	340.371	5.22	5.19	-3.63	366	848	48	20	3	2	17
Refrigerator	1259.412	19.30	891.066	13.65	13.56	5.74	861	2736	96	40	26	15	14
Residual (Calculated)	1830.019	28.04	na	na	na								
Residual (Estimated)	na	na	1879.574	28.80	28.62	-0.58							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.466	0.379	689	1216	352	13
Stove	0.939	1.013	62	512	16	95
Baseboard Heater	1.258	0.094	519	912	416	12
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.743	0.088	438	896	96	5
Refrigerator	0.414	0.023	1188	3872	544	41
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	2314.858	185.968	87.721
Stove	118.812	225.923	193.142
Baseboard Heater	339.741	149.466	402.245
Washers	75.175	26.639	265.196
Refrigerator	743.576	515.836	147.490

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.466	0.379	689	1216	352	13
Stove	0.939	1.013	62	512	16	95
Baseboard Heater	1.258	0.094	519	912	416	12
Clothes Washer	0.743	0.088	438	896	96	5
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.414	0.023	1188	3872	544	41
Drier	0.000	0.000	0	0	0	0

Sample Period: Wed, October 16, 1996 to Wed, October 16, 1996
Evaluation Period: Wed, October 16, 1996 to Wed, October 16, 1996

ENERGY CONSUMPTION	Measured		Estimated			Difference	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share	in Energy Shares	Duration (seconds) Average	Maximum	Minimum	Total No. of Events	No. of Events Matched	Missed	False
Total (Input)	5676.655	na	na	na									
Total (After Processing)	na	na	5709.247	100.57	100.00								
Water Heater	2751.558	48.47	2747.040	48.39	48.11	0.36	973	4752	304	10	10	0	0
Stove	0.000	0.00	0.000	0	0.00	0.00	0	0	0	0			
Baseboard Heater 1	510.547	8.99	436.898	7.70	7.66	1.10	400	784	64	14	12	1	3
Baseboard Heater 2			13.731	0.24	0.24		176	176	176	1			
Dishwasher	0.000	0.00	na	na	na								
Clothes Washer	0.000	0.00	na	na	na								
Both Washers	na	na	0.000	0	0.00	0.00	0	0	0	0	0	0	0
Refrigerator	1266.447	22.31	1122.580	19.78	19.67	2.64	1104	3856	48	39	31	10	8
Residual (Calculated)	1148.103	20.22	na	na	na								
Residual (Estimated)	na	na	1388.997	24.47	24.33	-4.11							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.518	0.265	974	4752	304	10
Stove	0.000	0.000	0	0	0	0
Baseboard Heater	1.248	0.084	503	1200	128	13
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.417	0.026	1185	3856	528	41
Drier	na	na	na	na	na	na

CUMULATIVE	Cumulative Demand (kW)		
DEMAND MATCHIN	Matched	Missed	False
Water Heater	2724.184	27.374	22.856
Stove	0.000	0.000	0.000
Baseboard Heater	410.721	99.826	39.909
Washers	0.000	0.000	0.000
Refrigerator	1007.234	259.213	115.346

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.518	0.265	974	4752	304	10
Stove	0.000	0.000	0	0	0	0
Baseboard Heater	1.248	0.084	503	1200	128	13
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.417	0.026	1185	3856	528	41
Drier	0.000	0.000	0	0	0	0

Sample Period: Thu, October 17, 1996 to Thu, October 17, 1996
Evaluation Period: Thu, October 17, 1996 to Thu, October 17, 1996

ENERGY CONSUMPTION	Measured		Estimated			Difference in Energy Shares	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
							Duration (seconds)			Total No. of Events	No. of Events		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share		Average	Maximum	Minimum		Matched	Missed	False
Total (Input)	5639.657	na	na	na									
Total (After Processing)	na	na	5685.353	100.81	100.00								
Water Heater	2290.356	40.61	2820.281	50.01	49.61	-9.00	1256	3616	368	8	8	2	0
Stove	142.942	2.53	0.000	0	0.00	2.53	0	0	0	0			
Baseboard Heater 1	923.169	16.37	764.947	13.56	13.45	2.92	517	1104	64	19	16	3	3
Baseboard Heater 2			0.000	0	0.00		0	0	0	0			
Dishwasher	0.000	0.00	na	na	na								
Clothes Washer	0.000	0.00	na	na	na								
Both Washers	na	na	0.000	0	0.00	0.00	0	0	0	0	0	0	0
Refrigerator	1232.356	21.85	901.331	15.98	15.85	6.00	997	3040	32	35	30	13	5
Residual (Calculated)	1050.834	18.63	na	na	na								
Residual (Estimated)	na	na	1198.794	21.26	21.09	-2.46							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.491	0.281	814	3616	352	10
Stove	2.343	1.301	89	544	16	11
Baseboard Heater	1.246	0.074	624	3952	400	19
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.413	0.025	1110	3984	496	43
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	2058.939	231.417	761.342
Stove	0.000	142.942	0.000
Baseboard Heater	568.964	354.205	195.983
Washers	0.000	0.000	0.000
Refrigerator	770.135	462.221	131.196

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.491	0.281	814	3616	352	10
Stove	2.343	1.301	89	544	16	11
Baseboard Heater	1.246	0.074	624	3952	400	19
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.413	0.025	1110	3984	496	43
Drier	0.000	0.000	0	0	0	0

Sample Period: Fri, October 18, 1996 to Fri, October 18, 1996
Evaluation Period: Fri, October 18, 1996 to Fri, October 18, 1996

ENERGY CONSUMPTION	Measured		Estimated			Difference in Energy Shares	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
							Duration (seconds)			Total No. of Events	No. of Events		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share		Average	Maximum	Minimum		Matched	Missed	False
Total (Input)	4857.597	na	na	na									
Total (After Processing)	na	na	4880.495	100.47	100.00								
Water Heater	1927.963	39.69	1990.443	40.98	40.79	-1.10	595	1152	208	12	11	0	1
Stove	73.805	1.52	0.000	0	0.00	1.52	0	0	0	0			
Baseboard Heater 1	841.456	17.32	749.543	15.43	15.36	1.96	356	1328	32	26	18	0	8
Baseboard Heater 2			0.000	0	0.00		0	0	0	0			
Dishwasher	105.016	2.16	na	na	na								
Clothes Washer	0.000	0.00	na	na	na								
Both Washers	na	na	193.141	3.98	3.96	-1.80	383	880	32	11	3	3	8
Refrigerator	1272.595	26.20	1030.884	21.22	21.12	5.08	974	3472	16	41	36	7	5
Residual (Calculated)	636.762	13.11	na	na	na								
Residual (Estimated)	na	na	916.483	18.87	18.78	-5.67							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.463	0.317	628	1152	336	11
Stove	1.604	1.271	61	240	16	12
Baseboard Heater	1.295	0.247	577	3232	400	18
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.734	0.088	381	896	96	6
Refrigerator	0.413	0.023	1173	3792	544	42
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	1905.257	22.706	85.186
Stove	0.000	73.805	0.000
Baseboard Heater	589.956	251.500	159.588
Washers	87.542	17.474	105.599
Refrigerator	971.839	300.756	59.045

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.463	0.317	628	1152	336	11
Stove	1.604	1.271	61	240	16	12
Baseboard Heater	1.295	0.247	577	3232	400	18
Clothes Washer	0.734	0.088	381	896	96	6
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.413	0.023	1173	3792	544	42
Drier	0.000	0.000	0	0	0	0

Sample Period: Tue, October 15, 1996 to Fri, October 18, 1996
Evaluation Period: Tue, October 15, 1996 to Fri, October 18, 1996

ENERGY CONSUMPTION	Measured		Estimated			Difference in Energy Shares	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share		Duration (seconds)			Total No. of Events	No. of Events		
							Average	Maximum	Minimum		Matched	Missed	False
Total (Input)	22699.922	na	na	na									
Total (After Processing)	na	na	22855.783	100.69	100.00								
Water Heater	9470.703	41.72	10605.753	46.72	46.40	-4.68	923	4752	208	41	40	3	1
Stove	561.482	2.47	581.313	2.56	2.54	-0.07	250	1456	16	26			
Baseboard Heater 1	2764.379	12.18	2871.721	12.65	12.56	-2.79	479	3728	32	76	59	5	29
Baseboard Heater 2			549.340	2.42	2.40		696	2704	32	10			
Dishwasher	206.830	0.91	na	na	na								
Clothes Washer	0.000	0.00	na	na	na								
Both Washers	na	na	815.502	3.59	3.57	-2.66	505	896	32	35	6	5	29
Refrigerator	5030.810	22.16	4047.600	17.83	17.71	4.45	1049	3984	16	149	126	41	23
Residual (Calculated)	4665.718	20.55	na	na	na								
Residual (Estimated)	na	na	3384.556	14.91	14.81	5.74							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.486	0.314	785	4752	304	43
Stove	1.185	1.186	64	544	16	118
Baseboard Heater	1.263	0.152	574	7200	128	61
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.739	0.088	407	896	96	11
Refrigerator	0.414	0.024	1163	3984	496	167
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	9108.027	362.676	1497.725
Stove	226.043	335.439	355.270
Baseboard Heater	2042.021	722.358	1379.040
Washers	167.455	39.375	648.047
Refrigerator	3574.375	1456.435	473.224

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.486	0.314	785	4752	304	43
Stove	1.185	1.186	64	544	16	118
Baseboard Heater	1.263	0.152	574	7200	128	61
Clothes Washer	0.739	0.088	407	896	96	11
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.414	0.024	1163	3984	496	167
Drier	0.000	0.000	0	0	0	0

Sample Period: Mon, November 25, 1996 to Mon, November 25, 1996
Evaluation Period: Mon, November 25, 1996 to Mon, November 25, 1996

ENERGY CONSUMPTION	Measured		Estimated			Difference in Energy Shares	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
							Duration (seconds)			Total No. of Events	No. of Events		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share		Average	Maximum	Minimum		Matched	Missed	False
Total (Input)	5861.659	na	na	na									
Total (After Processing)	na	na	5939.483	101.33	100.00								
Water Heater	2246.307	38.32	2429.501	41.45	40.91	-2.59	743	2000	320	12	11	2	1
Stove	438.955	7.49	110.930	1.89	1.87	5.62	1008	1008	1008	1			
Baseboard Heater 1	680.099	11.60	532.042	9.08	8.96	1.18	884	1280	480	8	8	1	1
Baseboard Heater 2			86.667	1.48	1.46		1152	1152	1152	1			
Dishwasher	0.000	0.00	na	na	na								
Clothes Washer	0.000	0.00	na	na	na								
Both Washers	na	na	0.000	0	0.00	0.00	0	0	0	0	0	0	0
Refrigerator	1301.062	22.20	832.695	14.21	14.02	8.18	1306	3760	32	25	21	19	4
Residual (Calculated)	1195.236	20.39	na	na	na								
Residual (Estimated)	na	na	1947.648	33.23	32.79	-12.40							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.362	0.350	633	1968	320	13
Stove	3.885	2.714	139	688	16	13
Baseboard Heater	1.204	0.095	1004	2976	496	9
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.408	0.024	1275	4512	512	40
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	1532.358	713.949	897.142
Stove	36.968	401.987	73.962
Baseboard Heater	456.078	224.021	162.632
Washers	0.000	0.000	0.000
Refrigerator	722.961	578.101	109.735

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.362	0.350	633	1968	320	13
Stove	3.885	2.714	139	688	16	13
Baseboard Heater	1.204	0.095	1004	2976	496	9
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.408	0.024	1275	4512	512	40
Drier	0.000	0.000	0	0	0	0

Sample Period: Tue, November 26, 1996 to Tue, November 26, 1996
Evaluation Period: Tue, November 26, 1996 to Tue, November 26, 1996

ENERGY CONSUMPTION	Measured		Estimated			Difference in Energy Shares	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share		Duration (seconds) Average	Maximum	Minimum	Total No. of Events	No. of Events Matched	Missed	False
Total (Input)	7767.575	na	na	na									
Total (After Processing)	na	na	7808.143	100.52	100.00								
Water Heater	3567.256	45.92	3466.585	44.63	44.40	1.52	975	2576	320	13	13	0	0
Stove	1059.362	13.64	412.420	5.31	5.28	8.36	180	1344	16	27			
Baseboard Heater 1	932.172	12.00	1747.651	22.50	22.38	-14.37	970	3408	32	21	4	0	23
Baseboard Heater 2			311.639	4.01	3.99		519	1888	64	7			
Dishwasher	86.318	1.11	na	na	na								
Clothes Washer	0.000	0.00	na	na	na								
Both Washers	na	na	298.849	3.85	3.83	-2.72	507	896	48	13	0	5	13
Refrigerator	1232.482	15.87	707.409	9.11	9.06	6.81	961	3024	32	29	23	18	6
Residual (Calculated)	889.985	11.46	na	na	na								
Residual (Estimated)	na	na	863.590	11.12	11.06	0.40							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.377	0.292	1003	2576	304	13
Stove	3.053	1.383	463	1952	16	12
Baseboard Heater	1.373	0.421	2170	3664	496	5
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.725	0.147	381	896	96	5
Refrigerator	0.406	0.026	1156	3920	496	42
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	3367.538	199.718	99.047
Stove	405.708	653.654	6.712
Baseboard Heater	488.315	443.857	1570.975
Washers	0.000	86.318	298.849
Refrigerator	646.686	585.796	60.723

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.377	0.292	1003	2576	304	13
Stove	3.053	1.383	463	1952	16	12
Baseboard Heater	1.373	0.421	2170	3664	496	5
Clothes Washer	0.725	0.147	381	896	96	5
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.406	0.026	1156	3920	496	42
Drier	0.000	0.000	0	0	0	0

Sample Period: Wed, November 27, 1996 to Wed, November 27, 1996
Evaluation Period: Wed, November 27, 1996 to Wed, November 27, 1996

ENERGY CONSUMPTION	Measured		Estimated			Difference in Energy Shares	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
							Duration (seconds)			Total No. of Events	No. of Events		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share		Average	Maximum	Minimum		Matched	Missed	False
Total (Input)	7082.111	na	na	na									
Total (After Processing)	na	na	7103.690	100.30	100.00								
Water Heater	4526.409	63.91	4324.650	61.06	60.87	3.04	1753	6224	352	9	9	1	0
Stove	0.000	0.00	0.000	0	0.00	0.00	0	0	0	0			
Baseboard Heater 1	426.817	6.03	770.156	10.87	10.84	-5.50	538	2400	32	17	3	1	20
Baseboard Heater 2			49.818	0.70	0.70		99	304	32	6			
Dishwasher	0.000	0.00	na	na	na								
Clothes Washer	44.097	0.62	na	na	na								
Both Washers	na	na	23.098	0.33	0.33	0.29	528	528	528	1	0	6	1
Refrigerator	1173.303	16.57	1023.717	14.45	14.41	2.16	991	3104	16	41	33	11	8
Residual (Calculated)	911.485	12.87	na	na	na								
Residual (Estimated)	na	na	912.251	12.88	12.84	0.03							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.386	0.228	1650	6208	352	10
Stove	0.000	0.000	0	0	0	0
Baseboard Heater	1.346	0.395	1264	2912	624	4
Clothes Washer	0.700	0.074	168	528	16	6
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.403	0.027	1058	3472	448	44
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	4259.840	266.569	64.810
Stove	0.000	0.000	0.000
Baseboard Heater	207.566	219.251	612.408
Washers	0.000	44.097	23.098
Refrigerator	864.430	308.873	159.287

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.386	0.228	1650	6208	352	10
Stove	0.000	0.000	0	0	0	0
Baseboard Heater	1.346	0.395	1264	2912	624	4
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.700	0.074	168	528	16	6
Refrigerator	0.403	0.027	1058	3472	448	44
Drier	0.000	0.000	0	0	0	0

Sample Period: Thu, November 28, 1996 to Thu, November 28, 1996
Evaluation Period: Thu, November 28, 1996 to Thu, November 28, 1996

ENERGY CONSUMPTION	Measured		Estimated			Difference in Energy Shares	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
							Duration (seconds)			Total No. of Events	No. of Events		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share		Average	Maximum	Minimum		Matched	Missed	False
Total (Input)	8908.184	na	na	na									
Total (After Processing)	na	na	8950.305	100.47	100.00								
Water Heater	2395.462	26.89	1915.497	21.5	21.40	5.49	878	2096	384	8	8	4	0
Stove	651.411	7.31	383.489	4.30	4.28	3.03	405	1328	32	6			
Baseboard Heater 1	2713.698	30.46	2186.647	24.55	24.43	-1.20	1271	3440	32	20	18	0	13
Baseboard Heater 2			646.774	7.26	7.23		684	1904	32	11			
Dishwasher	0.000	0.00	na	na	na								
Clothes Washer	0.000	0.00	na	na	na								
Both Washers	na	na	0.000	0	0.00	0.00	0	0	0	0	0	0	0
Refrigerator	1211.369	13.60	1074.804	12.07	12.01	1.59	1294	3408	16	33	26	17	7
Residual (Calculated)	1936.244	21.74	na	na	na								
Residual (Estimated)	na	na	2743.094	30.79	30.65	-8.91							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.363	0.286	732	2096	384	12
Stove	2.808	2.186	155	704	16	24
Baseboard Heater	1.376	0.440	2427	16240	544	13
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.403	0.024	1119	3408	496	43
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	1428.028	967.434	487.469
Stove	148.195	503.216	235.294
Baseboard Heater	1804.169	909.529	1029.252
Washers	0.000	0.000	0.000
Refrigerator	866.980	344.389	207.824

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.363	0.286	732	2096	384	12
Stove	2.808	2.186	155	704	16	24
Baseboard Heater	1.376	0.440	2427	16240	544	13
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.403	0.024	1119	3408	496	43
Drier	0.000	0.000	0	0	0	0

Sample Period: Fri, November 29, 1996 to Fri, November 29, 1996
Evaluation Period: Fri, November 29, 1996 to Fri, November 29, 1996

ENERGY CONSUMPTION	Measured		Estimated			Difference in Energy Shares	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share		Duration (seconds)			Total No. of Events	No. of Events		
							Average	Maximum	Minimum		Matched	Missed	False
Total (Input)	9599.259	na	na	na									
Total (After Processing)	na	na	9658.478	100.62	100.00								
Water Heater	4963.393	51.71	4724.768	49.22	48.92	2.79	2489	10016	304	7	6	6	1
Stove	713.934	7.44	0.000	0	0.00	7.44	0	0	0	0			
Baseboard Heater 1	1651.373	17.20	1741.493	18.14	18.03	-1.31	602	1536	464	38	35	3	5
Baseboard Heater 2			46.277	0.48	0.48		304	480	128	2			
Dishwasher	101.137	1.05	na	na	na								
Clothes Washer	0.000	0.00	na	na	na								
Both Washers	na	na	214.916	2.24	2.23	-1.18	490	896	32	10	4	2	6
Refrigerator	1206.990	12.57	860.071	8.96	8.91	3.66	857	3888	32	40	27	16	13
Residual (Calculated)	962.432	10.03	na	na	na								
Residual (Estimated)	na	na	2070.953	21.57	21.44	-11.41							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.339	0.185	1525	10032	288	12
Stove	5.900	1.449	161	528	16	12
Baseboard Heater	1.218	0.189	571	1616	464	38
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.702	0.111	384	896	96	6
Refrigerator	0.402	0.026	1118	3888	544	43
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	4324.732	638.661	400.036
Stove	0.000	713.934	0.000
Baseboard Heater	1380.684	270.689	407.086
Washers	86.757	14.380	128.159
Refrigerator	684.059	522.931	176.011

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.339	0.185	1525	10032	288	12
Stove	5.900	1.449	161	528	16	12
Baseboard Heater	1.218	0.189	571	1616	464	38
Clothes Washer	0.702	0.111	384	896	96	6
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.402	0.026	1118	3888	544	43
Drier	0.000	0.000	0	0	0	0

Sample Period: Sat, November 30, 1996 to Sat, November 30, 1996
Evaluation Period: Sat, November 30, 1996 to Sat, November 30, 1996

ENERGY CONSUMPTION	Measured		Estimated			Difference in Energy Shares	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share		Duration (seconds)			Total No. of Events	No. of Events		
							Average	Maximum	Minimum		Matched	Missed	False
Total (Input)	13900.191	na	na	na									
Total (After Processing)	na	na	13985.456	100.61	100.00								
Water Heater	6914.787	49.75	4155.924	29.90	29.72	20.03	1886	6128	352	8	8	7	0
Stove	1388.891	9.99	193.175	1.39	1.38	8.61	83	352	16	17			
Baseboard Heater 1	477.482	3.44	998.372	7.18	7.14	-5.99	552	1376	32	24	7	3	23
Baseboard Heater 2			320.733	2.31	2.30		709	1072	176	6			
Dishwasher	0.000	0.00	na	na	na								
Clothes Washer	375.022	2.70	na	na	na								
Both Washers	na	na	257.649	1.85	1.84	0.86	288	544	32	20	14	26	6
Refrigerator	1320.834	9.50	1037.245	7.46	7.41	2.09	1312	4624	240	31	24	12	7
Residual (Calculated)	3423.175	24.63	na	na	na								
Residual (Estimated)	na	na	7022.358	50.52	50.21	-25.58							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.407	0.164	1674	6128	336	15
Stove	4.354	2.430	160	1168	16	32
Baseboard Heater	1.206	0.141	634	1376	464	10
Clothes Washer	0.716	0.082	210	656	16	40
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.408	0.023	1438	4624	496	36
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	3256.644	3658.143	899.280
Stove	191.086	1197.805	2.090
Baseboard Heater	339.076	138.406	980.029
Washers	159.803	215.219	97.846
Refrigerator	896.581	424.253	140.665

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.407	0.164	1674	6128	336	15
Stove	4.354	2.430	160	1168	16	32
Baseboard Heater	1.206	0.141	634	1376	464	10
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.716	0.082	210	656	16	40
Refrigerator	0.408	0.023	1438	4624	496	36
Drier	0.000	0.000	0	0	0	0

Sample Period: Mon, November 25, 1996 to Sat, November 30, 1996
Evaluation Period: Mon, November 25, 1996 to Sat, November 30, 1996

ENERGY CONSUMPTION	Measured		Estimated			Difference	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
						in Energy	Duration (seconds)			Total No.	No. of Events		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share	Shares	Average	Maximum	Minimum	of Events	Matched	Missed	False
Total (Input)	53118.979	na	na	na									
Total (After Processing)	na	na	53423.032	100.57	100.00								
Water Heater	24613.614	46.34	25904.693	48.77	48.49	-2.15	1480	9520	112	64	62	12	6
Stove	4252.553	8.01	1097.747	2.07	2.06	5.95	190	1344	16	51			
Baseboard Heater 1	6881.641	12.96	8300.938	15.63	15.54	-6.50	703	3440	16	145	77	9	124
Baseboard Heater 2			2092.488	3.94	3.92		459	2912	16	56			
Dishwasher	187.455	0.35	na	na	na								
Clothes Washer	419.119	0.79	na	na	na								
Both Washers	na	na	686.870	1.29	1.28	-0.14	481	896	64	32	9	48	24
Refrigerator	7446.040	14.02	5490.965	10.34	10.28	3.74	1124	4640	16	193	142	101	52
Residual (Calculated)	9318.557	17.54	na	na	na								
Residual (Estimated)	na	na	9849.332	18.54	18.44	-0.90							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.377	0.237	1216	10032	288	74
Stove	3.757	2.263	195	1952	16	93
Baseboard Heater	1.302	0.350	1113	16240	464	76
Clothes Washer	0.714	0.081	204	656	16	46
Dishwasher	0.713	0.129	383	896	96	11
Refrigerator	0.405	0.025	1210	4624	496	243
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	18395.018	6218.596	7509.675
Stove	780.836	3471.717	316.911
Baseboard Heater	4593.350	2288.291	5800.076
Washers	114.985	491.589	571.885
Refrigerator	4526.893	2919.147	964.071

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.377	0.237	1216	10032	288	74
Stove	3.757	2.263	195	1952	16	93
Baseboard Heater	1.302	0.350	1113	16240	464	76
Clothes Washer	0.713	0.129	383	896	96	11
Dishwasher	0.714	0.081	204	656	16	46
Refrigerator	0.405	0.025	1210	4624	496	243
Drier	0.000	0.000	0	0	0	0

Sample Period: Tue, January 07, 1997 to Tue, January 07, 1997
Evaluation Period: Tue, January 07, 1997 to Tue, January 07, 1997

ENERGY CONSUMPTION	Measured		Estimated			Difference in Energy Shares	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
							Duration (seconds)			Total No. of Events	No. of Events		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share		Average	Maximum	Minimum		Matched	Missed	False
Total (Input)	8704.449	na	na	na									
Total (After Processing)	na	na	8741.924	100.43	100.00								
Water Heater	3808.951	43.76	3969.893	45.61	45.41	-1.65	1093	4720	112	13	11	0	2
Stove	217.643	2.50	0.000	0	0.00	2.50	0	0	0	0			
Baseboard Heater 1	1609.844	18.49	1461.586	16.79	16.72	-2.13	575	1680	16	31	18	1	23
Baseboard Heater 2			341.124	3.92	3.90		416	688	32	10			
Dishwasher	0.000	0.00	na	na	na								
Clothes Washer	0.000	0.00	na	na	na								
Both Washers	na	na	0.000	0	0.00	0.00	0	0	0	0	0	0	0
Refrigerator	1230.806	14.14	1010.665	11.61	11.56	2.58	1058	3984	32	37	33	13	4
Residual (Calculated)	1837.205	21.11	na	na	na								
Residual (Estimated)	na	na	1958.657	22.50	22.41	-1.30							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.471	0.231	1239	4736	352	11
Stove	2.981	0.651	117	448	16	10
Baseboard Heater	1.312	0.353	1226	7280	544	16
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.413	0.024	1059	3984	512	45
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	3780.193	28.758	189.700
Stove	0.000	217.643	0.000
Baseboard Heater	995.068	614.776	807.642
Washers	0.000	0.000	0.000
Refrigerator	845.222	385.584	165.442

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.471	0.231	1239	4736	352	11
Stove	2.981	0.651	117	448	16	10
Baseboard Heater	1.312	0.353	1226	7280	544	16
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.413	0.024	1059	3984	512	45
Drier	0.000	0.000	0	0	0	0

Sample Period: Wed, January 08, 1997 to Wed, January 08, 1997
Evaluation Period: Wed, January 08, 1997 to Wed, January 08, 1997

ENERGY CONSUMPTION	Measured		Estimated			Difference	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share	in Energy Shares	Duration (seconds)			Total No.	No. of Events		
							Average	Maximum	Minimum	of Events	Matched	Missed	False
Total (Input)	10233.821	na	na	na									
Total (After Processing)	na	na	10290.054	100.55	100.00								
Water Heater	5030.415	49.15	4901.087	47.89	47.63	1.52	1353	5024	352	13	13	1	0
Stove	120.796	1.18	50.846	0.50	0.50	0.68	464	464	464	1			
Baseboard Heater 1	2122.376	20.74	698.134	6.82	6.78	13.92	918	1360	128	10	8	8	3
Baseboard Heater 2			3.649	0.04	0.04		48	48	48	1			
Dishwasher	103.413	1.01	na	na	na								
Clothes Washer	0.000	0.00	na	na	na								
Both Washers	na	na	164.882	1.61	1.60	-0.59	332	784	32	11	3	3	8
Refrigerator	1229.254	12.01	881.578	8.61	8.56	3.45	976	3008	32	35	32	14	3
Residual (Calculated)	1627.567	15.90	na	na	na								
Residual (Estimated)	na	na	3589.879	35.08	34.89	-18.99							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.460	0.275	1288	5024	352	14
Stove	2.279	0.871	212	624	16	4
Baseboard Heater	1.216	0.076	1860	6064	912	15
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.723	0.100	381	896	96	6
Refrigerator	0.413	0.025	1035	3008	368	46
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	4469.379	561.036	431.708
Stove	40.005	80.791	10.841
Baseboard Heater	645.911	1476.465	55.872
Washers	52.936	50.477	111.947
Refrigerator	831.733	397.521	49.845

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.460	0.275	1288	5024	352	14
Stove	2.279	0.871	212	624	16	4
Baseboard Heater	1.216	0.076	1860	6064	912	15
Clothes Washer	0.723	0.100	381	896	96	6
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.413	0.025	1035	3008	368	46
Drier	0.000	0.000	0	0	0	0

Sample Period: Thu, January 09, 1997 to Thu, January 09, 1997
Evaluation Period: Thu, January 09, 1997 to Thu, January 09, 1997

ENERGY CONSUMPTION	Measured		Estimated			Difference	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
							Duration (seconds)			Total No.	No. of Events		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share	in Energy Shares	Average	Maximum	Minimum	of Events	Matched	Missed	False
Total (Input)	7381.056	na	na	na									
Total (After Processing)	na	na	7454.829	101.00	100.00								
Water Heater	2528.298	34.25	2883.147	39.06	38.67	-4.42	650	2656	112	16	11	0	5
Stove	541.800	7.34	186.832	2.53	2.50	4.84	784	784	784	1			
Baseboard Heater 1	1419.840	19.24	904.526	12.25	12.13	4.96	1705	2816	624	7	6	10	4
Baseboard Heater 2			160.050	2.17	2.15		704	1280	144	3			
Dishwasher	0.000	0.00	na	na	na								
Clothes Washer	0.000	0.00	na	na	na								
Both Washers	na	na	0.000	0	0.00	0.00	0	0	0	0	0	0	0
Refrigerator	1329.738	18.02	720.120	9.76	9.66	8.36	1114	5120	160	25	24	16	1
Residual (Calculated)	1561.380	21.15	na	na	na								
Residual (Estimated)	na	na	2600.153	35.23	34.88	-13.73							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.436	0.329	829	2656	288	11
Stove	2.325	0.911	133	768	48	28
Baseboard Heater	1.213	0.079	1170	5520	624	16
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.414	0.023	1285	9152	432	40
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	2499.369	28.929	383.778
Stove	75.428	466.372	111.404
Baseboard Heater	554.708	865.132	509.869
Washers	0.000	0.000	0.000
Refrigerator	667.101	662.637	53.019

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.436	0.329	829	2656	288	11
Stove	2.325	0.911	133	768	48	28
Baseboard Heater	1.213	0.079	1170	5520	624	16
Clothes Washer	0.000	0.000	0	0	0	0
Dishwasher	0.000	0.000	0	0	0	0
Refrigerator	0.414	0.023	1285	9152	432	40
Drier	0.000	0.000	0	0	0	0

Sample Period: Fri, January 10, 1997 to Fri, January 10, 1997
Evaluation Period: Fri, January 10, 1997 to Fri, January 10, 1997

ENERGY CONSUMPTION	Measured		Estimated			Difference in Energy Shares	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share		Duration (seconds)			Total No. of Events	No. of Events		
							Average	Maximum	Minimum		Matched	Missed	False
Total (Input)	9360.558	na	na	na									
Total (After Processing)	na	na	9403.205	100.46	100.00								
Water Heater	4281.891	45.74	4433.858	47.37	47.16	-1.42	1058	3520	352	15	14	6	1
Stove	333.806	3.57	244.758	2.61	2.60	0.97	344	880	128	4			
Baseboard Heater 1	1128.167	12.05	1102.937	11.78	11.73	-0.49	734	2272	32	20	14	4	8
Baseboard Heater 2			76.893	0.82	0.82		512	944	80	2			
Dishwasher	105.701	1.13	na	na	na								
Clothes Washer	43.983	0.47	na	na	na								
Both Washers	na	na	278.559	2.98	2.97	-1.37	336	880	32	19	8	4	11
Refrigerator	1432.198	15.30	902.577	9.64	9.60	5.70	976	4992	32	36	22	13	15
Residual (Calculated)	2034.812	21.74	na	na	na								
Residual (Estimated)	na	na	2363.623	25.25	25.14	-3.40							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.470	0.280	1095	3520	352	14
Stove	2.736	1.282	195	656	32	10
Baseboard Heater	1.201	0.123	834	3248	496	18
Clothes Washer	0.698	0.081	202	576	32	5
Dishwasher	0.739	0.138	381	880	96	6
Refrigerator	0.411	0.023	1592	7008	512	35
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	4243.586	38.305	190.272
Stove	182.338	151.468	62.419
Baseboard Heater	753.945	374.222	425.885
Washers	115.163	34.521	163.396
Refrigerator	815.522	616.676	87.055

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.470	0.280	1095	3520	352	14
Stove	2.736	1.282	195	656	32	10
Baseboard Heater	1.201	0.123	834	3248	496	18
Clothes Washer	0.739	0.138	381	880	96	6
Dishwasher	0.698	0.081	202	576	32	5
Refrigerator	0.411	0.023	1592	7008	512	35
Drier	0.000	0.000	0	0	0	0

Sample Period: Sat, January 11, 1997 to Sat, January 11, 1997
Evaluation Period: Sat, January 11, 1997 to Sat, January 11, 1997

ENERGY CONSUMPTION	Measured		Estimated			Difference in Energy Shares	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share		Duration (seconds) Average	Maximum	Minimum	Total No. of Events	No. of Events Matched	Missed	False
Total (Input)	19538.578	na	na	na									
Total (After Processing)	na	na	19545.446	100.04	100.00								
Water Heater	8911.351	45.61	7220.960	36.96	36.95	8.66	3701	13168	352	7	6	9	1
Stove	1250.876	6.40	3116.183	15.95	15.94	-9.54	220	2144	16	59			
Baseboard Heater 1	2206.499	11.29	1088.219	5.57	5.57	3.95	2069	3776	32	7	2	10	8
Baseboard Heater 2			346.306	1.77	1.77		1536	2640	32	3			
Dishwasher	108.217	0.55	na	na	na								
Clothes Washer	338.911	1.73	na	na	na								
Both Washers	na	na	477.952	2.45	2.45	-0.17	211	896	16	50	9	30	41
Refrigerator	1412.784	7.23	658.774	3.37	3.37	3.86	1018	4240	32	25	17	19	8
Residual (Calculated)	5309.940	27.18	na	na	na								
Residual (Estimated)	na	na	6637.052	33.97	33.96	-6.78							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.460	0.203	2131	13152	352	15
Stove	1.182	0.819	49	1616	16	342
Baseboard Heater	1.202	0.053	2445	14480	544	12
Clothes Washer	0.724	0.083	234	768	16	32
Dishwasher	0.762	0.141	325	896	16	7
Refrigerator	0.414	0.021	1516	4176	496	36
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	5737.161	3174.190	1483.799
Stove	573.218	677.658	2542.964
Baseboard Heater	171.577	2034.922	1262.948
Washers	160.616	286.512	317.335
Refrigerator	567.580	845.204	91.194

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.460	0.203	2131	13152	352	15
Stove	1.182	0.819	49	1616	16	342
Baseboard Heater	1.202	0.053	2445	14480	544	12
Clothes Washer	0.762	0.141	325	896	16	7
Dishwasher	0.724	0.083	234	768	16	32
Refrigerator	0.414	0.021	1516	4176	496	36
Drier	0.000	0.000	0	0	0	0

Sample Period: Sun, January 12, 1997 to Sun, January 12, 1997
Evaluation Period: Sun, January 12, 1997 to Sun, January 12, 1997

ENERGY CONSUMPTION	Measured		Estimated			Difference in Energy Shares	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share		Duration (seconds)			Total No. of Events	No. of Events		
							Average	Maximum	Minimum		Matched	Missed	False
Total (Input)	15045.630	na	na	na									
Total (After Processing)	na	na	15131.364	100.57	100.00								
Water Heater	6340.469	42.14	6793.042	45.15	44.89	-2.75	1633	6144	80	15	10	5	5
Stove	1475.543	9.81	1983.617	13.18	13.11	-3.30	1531	3392	16	7			
Baseboard Heater 1	1619.916	10.77	972.192	6.46	6.42	1.25	803	1232	112	16	7	15	16
Baseboard Heater 2			467.330	3.11	3.09		882	1680	128	7			
Dishwasher	104.607	0.70	na	na	na								
Clothes Washer	250.512	1.67	na	na	na								
Both Washers	na	na	417.285	2.77	2.75	-0.38	288	880	32	33	11	26	22
Refrigerator	1376.569	9.15	769.601	5.12	5.09	4.06	957	3488	32	31	20	18	11
Residual (Calculated)	3878.014	25.78	na	na	na								
Residual (Estimated)	na	na	3728.297	24.78	24.64	1.14							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.437	0.242	1524	6144	352	15
Stove	1.629	0.945	296	3888	16	49
Baseboard Heater	1.211	0.083	972	7632	544	22
Clothes Washer	0.704	0.089	190	624	16	30
Dishwasher	0.737	0.141	325	896	96	7
Refrigerator	0.415	0.022	1397	4272	672	38
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	4975.345	1365.124	1817.697
Stove	883.820	591.723	1099.797
Baseboard Heater	365.543	1254.373	1073.979
Washers	121.225	233.894	296.060
Refrigerator	682.386	694.183	87.214

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.437	0.242	1524	6144	352	15
Stove	1.629	0.945	296	3888	16	49
Baseboard Heater	1.211	0.083	972	7632	544	22
Clothes Washer	0.737	0.141	325	896	96	7
Dishwasher	0.704	0.089	190	624	16	30
Refrigerator	0.415	0.022	1397	4272	672	38
Drier	0.000	0.000	0	0	0	0

Sample Period: Tue, January 07, 1997 to Sun, January 12, 1997
Evaluation Period: Tue, January 07, 1997 to Sun, January 12, 1997

ENERGY CONSUMPTION	Measured		Estimated			Difference in Energy Shares	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
							Duration (seconds)			Total No. of Events	No. of Events		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share		Average	Maximum	Minimum		Matched	Missed	False
Total (Input)	70264.092	na	na	na									
Total (After Processing)	na	na	70507.729	100.35	100.00								
Water Heater	30901.375	43.98	34283.371	48.79	48.62	-4.64	1558	13152	80	79	66	13	14
Stove	3940.464	5.61	5298.837	7.54	7.51	-1.90	420	3392	16	54			
Baseboard Heater 1	10106.642	14.38	8333.851	11.86	11.82	-0.67	885	3344	16	123	69	25	97
Baseboard Heater 2			2278.433	3.24	3.23		709	4720	32	42			
Dishwasher	421.938	0.60	na	na	na								
Clothes Washer	633.406	0.90	na	na	na								
Both Washers	na	na	1734.546	2.47	2.46	-0.96	280	896	16	139	33	60	107
Refrigerator	8011.349	11.40	5146.636	7.32	7.29	4.11	1016	6672	16	196	146	92	56
Residual (Calculated)	16248.918	23.13	na	na	na								
Residual (Estimated)	na	na	13432.054	19.12	19.05	4.08							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.456	0.250	1405	13152	288	79
Stove	1.612	1.034	89	3888	16	442
Baseboard Heater	1.224	0.160	1405	16096	496	94
Clothes Washer	0.714	0.086	212	768	16	67
Dishwasher	0.740	0.132	351	896	16	26
Refrigerator	0.413	0.023	1308	9152	496	237
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	26684.708	4216.667	7598.663
Stove	1443.320	2497.144	3855.517
Baseboard Heater	5288.475	4818.167	5323.810
Washers	376.757	678.587	1357.789
Refrigerator	4487.310	3524.039	659.326

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.456	0.250	1405	13152	288	79
Stove	1.612	1.034	89	3888	16	442
Baseboard Heater	1.224	0.160	1405	16096	496	94
Clothes Washer	0.740	0.132	351	896	16	26
Dishwasher	0.714	0.086	212	768	16	67
Refrigerator	0.413	0.023	1308	9152	496	237
Drier	0.000	0.000	0	0	0	0

Sample Period: Tue, November 19, 1996 to Mon, November 25, 1996
Evaluation Period: Tue, November 19, 1996 to Mon, November 25, 1996

ENERGY CONSUMPTION	Measured		Estimated			Difference	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
							Duration (seconds)				No. of Events		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share	in Energy Shares	Average	Maximum	Minimum	Total No. of Events	Matched	Missed	False
Total (Input)	62126.516	na	na	na									
Total (After Processing)	na	na	62621.712	100.80	100.00								
Water Heater	23701.904	38.15	25350.313	40.80	40.48	-2.33	1003	8432	48	92	74	10	19
Stove	5533.725	8.91	1544.580	2.49	2.47	6.44	435	2960	16	19			
Baseboard Heater 1	12005.414	19.32	14013.957	22.56	22.38	-9.33	728	3824	16	242	162	8	164
Baseboard Heater 2			3927.981	6.32	6.27		588	2288	32	84			
Dishwasher	369.414	0.59	na	na	na								
Clothes Washer	163.507	0.26	na	na	na								
Both Washers	na	na	1400.253	2.25	2.23	-1.38	723	1248	96	43	6	24	38
Refrigerator	8959.341	14.42	6466.972	10.41	10.33	4.09	1330	5712	32	191	140	127	53
Residual (Calculated)	11393.211	18.34	na	na	na								
Residual (Estimated)	na	na	9917.655	15.96	15.84	2.50							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.396	0.287	1027	10000	304	84
Stove	4.290	2.426	94	1440	16	219
Baseboard Heater	1.273	0.303	949	10528	256	159
Clothes Washer	0.720	0.057	454	928	32	8
Dishwasher	0.730	0.103	368	896	80	22
Refrigerator	0.407	0.025	1318	5712	16	267
Drier	na	na	na	na	na	na

CUMULATIVE	Cumulative Demand (kW)		
DEMAND MATCHIN	Matched	Missed	False
Water Heater	20166.640	3535.264	5183.673
Stove	1142.397	4391.328	402.184
Baseboard Heater	9868.631	2136.783	8073.307
Washers	137.433	395.488	1262.820
Refrigerator	5259.839	3699.502	1207.133

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.396	0.287	1027	10000	304	84
Stove	4.290	2.426	94	1440	16	219
Baseboard Heater	1.273	0.303	949	10528	256	159
Clothes Washer	0.730	0.103	368	896	80	22
Dishwasher	0.720	0.057	454	928	32	8
Refrigerator	0.407	0.025	1318	5712	16	267
Drier	0.000	0.000	0	0	0	0

Sample Period: Tue, November 19, 1996 to Mon, November 25, 1996
Evaluation Period: Tue, November 19, 1996 to Sat, November 30, 1996

ENERGY CONSUMPTION	Measured		Estimated			Difference in Energy Shares	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
							Duration (seconds)			Total No. of Events	No. of Events		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share		Average	Maximum	Minimum		Matched	Missed	False
Total (Input)	135295.758	na	na	na									
Total (After Processing)	na	na	136007.189	100.53	100.00								
Water Heater	58647.104	43.35	59786.650	44.19	43.96	-0.61	1236	9520	48	176	158	27	23
Stove	10487.422	7.75	4425.964	3.27	3.25	4.50	226	2960	16	116			
Baseboard Heater 1	21954.838	16.23	23562.796	17.42	17.33	-5.82	686	3824	16	432	274	16	324
Baseboard Heater 2			6429.110	4.75	4.73		487	2608	16	166			
Dishwasher	725.329	0.54	na	na	na								
Clothes Washer	958.853	0.71	na	na	na								
Both Washers	na	na	2316.469	1.71	1.70	-0.45	668	1248	32	77	17	116	61
Refrigerator	17968.349	13.28	13083.429	9.67	9.62	3.66	1247	5856	16	412	309	224	111
Residual (Calculated)	24553.863	18.15	na	na	na								
Residual (Estimated)	na	na	26402.771	19.51	19.41	-1.26							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.391	0.267	1181	10032	288	181
Stove	3.114	2.429	113	2448	16	475
Baseboard Heater	1.314	0.365	1040	16496	256	257
Clothes Washer	0.711	0.073	240	928	16	90
Dishwasher	0.728	0.112	371	896	80	43
Refrigerator	0.406	0.025	1333	15168	16	531
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	46980.385	11666.719	12806.265
Stove	2377.509	8109.913	2048.455
Baseboard Heater	15756.608	6198.230	14235.298
Washers	409.106	1275.076	1907.363
Refrigerator	10790.080	7178.269	2293.349

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No. of Events
	Mean	Std. Dev.	Average	Maximum	Minimum	
Water Heater	4.396	0.287	1027	10000	304	84
Stove	4.290	2.426	94	1440	16	219
Baseboard Heater	1.273	0.303	949	10528	256	159
Clothes Washer	0.730	0.103	368	896	80	22
Dishwasher	0.720	0.057	454	928	32	8
Refrigerator	0.407	0.025	1318	5712	16	267
Drier	0.000	0.000	0	0	0	0

Sample Period: Tue, November 19, 1996 to Mon, November 25, 1996
Evaluation Period: Tue, November 19, 1996 to Mon, December 09, 1996

ENERGY CONSUMPTION	Measured		Estimated			Difference	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
							Duration (seconds)			Total No.	No. of Events		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share	in Energy Shares	Average	Maximum	Minimum	of Events	Matched	Missed	False
Total (Input)	193675.928	na	na	na									
Total (After Processing)	na	na	194750.967	100.56	100.00								
Water Heater	87040.386	44.94	89607.445	46.27	46.01	-1.07	1208	10016	48	270			
Stove	13398.539	6.92	6007.348	3.10	3.08	3.84	223	2960	16	188			
Baseboard Heater 1	28271.122	14.60	31661.870	16.35	16.26	-6.22	667	3824	16	597			
Baseboard Heater 2			8884.416	4.59	4.56		488	2608	16	229			
Dishwasher	993.857	0.51	na	na	na								
Clothes Washer	1050.346	0.54	na	na	na								
Both Washers	na	na	3538.809	1.83	1.82	-0.77	655	1248	16	120			
Refrigerator	26959.925	13.92	19300.309	9.97	9.91	4.01	1165	5856	16	651			
Residual (Calculated)	35961.753	18.57	na	na	na								
Residual (Estimated)	na	na	35750.770	18.46	18.36	0.21							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.412	0.357	1173	10032	64	269
Stove	2.706	2.186	112	3120	16	709
Baseboard Heater	1.292	0.326	949	16496	64	369
Clothes Washer	0.712	0.074	234	928	16	101
Dishwasher	0.730	0.108	375	896	80	58
Refrigerator	0.407	0.025	1331	15168	16	796
Drier	na	na	na	na	na	na

CUMULATIVE	Cumulative Demand (kW)		
DEMAND MATCHIN	Matched	Missed	False
Water Heater	71722.500	15317.886	17884.945
Stove	3098.997	10299.542	2908.350
Baseboard Heater	20682.440	7588.682	19863.846
Washers	586.719	1457.484	2952.090
Refrigerator	16255.355	10704.570	3044.954

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.396	0.287	1027	10000	304	84
Stove	4.290	2.426	94	1440	16	219
Baseboard Heater	1.273	0.303	949	10528	256	159
Clothes Washer	0.730	0.103	368	896	80	22
Dishwasher	0.720	0.057	454	928	32	8
Refrigerator	0.407	0.025	1318	5712	16	267
Drier	0.000	0.000	0	0	0	0

Sample Period: Tue, November 19, 1996 to Mon, November 25, 1996
Evaluation Period: Tue, November 19, 1996 to Wed, December 18, 1996
Note: no data for December 11 and 12.

ENERGY CONSUMPTION	Measured		Estimated			Difference in Energy Shares	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
							Duration (seconds)			Total No.	No. of Events		
	Cumulative Demand (kW)	Energy Share	Cumulative Demand (kW)	Energy Share	Corrected Energy Share		Average	Maximum	Minimum	of Events	Matched	Missed	False
Total (Input)	256687.065	na	na	na									
Total (After Processing)	na	na	258024.977	100.52	100.00								
Water Heater	116433.498	45.36	120166.727	46.81	46.57	-1.21	1208	10016	48	362			
Stove	16797.790	6.54	7060.797	2.75	2.74	3.80	212	2960	16	232			
Baseboard Heater 1	34658.767	13.50	38714.671	15.08	15.00	-6.01	654	3824	16	744			
Baseboard Heater 2			11638.840	4.53	4.51		488	2608	16	300			
Dishwasher	1200.405	0.47	na	na	na								
Clothes Washer	1248.679	0.49	na	na	na								
Both Washers	na	na	4702.086	1.83	1.82	-0.86	645	1248	16	162			
Refrigerator	35890.134	13.98	25211.700	9.82	9.77	4.21	1165	5856	16	850			
Residual (Calculated)	50457.792	19.66	na	na	na								
Residual (Estimated)	na	na	50530.156	19.69	19.58	0.08							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.429	0.338	1152	10032	64	365
Stove	2.452	1.999	103	3120	16	1063
Baseboard Heater	1.304	0.339	991	23216	64	429
Clothes Washer	0.714	0.074	241	944	16	116
Dishwasher	0.730	0.108	365	896	80	72
Refrigerator	0.410	0.024	1314	15168	16	1067
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	95992.520	20440.978	24174.208
Stove	3474.731	13323.059	3586.066
Baseboard Heater	24394.321	10264.446	25959.190
Washers	670.717	1778.367	4031.369
Refrigerator	21373.255	14516.879	3838.445

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.396	0.287	1027	10000	304	84
Stove	4.290	2.426	94	1440	16	219
Baseboard Heater	1.273	0.303	949	10528	256	159
Clothes Washer	0.730	0.103	368	896	80	22
Dishwasher	0.720	0.057	454	928	32	8
Refrigerator	0.407	0.025	1318	5712	16	267
Drier	0.000	0.000	0	0	0	0

Sample Period: Tue, November 19, 1996 to Mon, November 25, 1996
Evaluation Period: Tue, November 19, 1996 to Fri, January 24, 1997
Note: no data for December 11 and 12.

ENERGY CONSUMPTION	Measured		Estimated			Difference	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
	Cumulative	Energy	Cumulative	Energy	Corrected	in Energy	Duration (seconds)			Total No.	No. of Events		
	Demand (kW)	Share	Demand (kW)	Share	Energy Share	Shares	Average	Maximum	Minimum	of Events	Matched	Missed	False
Total (Input)	531783.637	na	na	na									
Total (After Processing)	na	na	534711.497	100.55	100.00								
Water Heater	242028.086	45.51	253731.712	47.71	47.45	-1.94	1356	15008	32	681			
Stove	28272.241	5.32	19446.146	3.66	3.64	1.68	263	9216	16	428			
Baseboard Heater 1	72680.956	13.67	79717.907	14.99	14.91	-5.93	686	9184	16	1460			
Baseboard Heater 2			25073.655	4.72	4.69		508	9056	16	620			
Dishwasher	2791.667	0.52	na	na	na								
Clothes Washer	2253.510	0.42	na	na	na								
Both Washers	na	na	9830.586	1.85	1.84	-0.90	631	1312	16	346			
Refrigerator	70694.275	13.29	50008.752	9.40	9.35	3.94	1147	7328	16	1712			
Residual (Calculated)	113062.902	21.26	na	na	na								
Residual (Estimated)	na	na	96902.738	18.22	18.12	3.14							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.440	0.294	1259	17056	64	693
Stove	2.107	1.658	103	3888	16	2085
Baseboard Heater	1.286	0.307	1060	35760	16	853
Clothes Washer	0.714	0.078	225	944	16	224
Dishwasher	0.736	0.108	370	896	16	164
Refrigerator	0.412	0.024	1309	15184	16	2096
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	200443.384	41584.702	53288.329
Stove	7401.487	20870.754	12044.659
Baseboard Heater	48945.171	23735.785	55846.391
Washers	1248.987	3796.190	8581.599
Refrigerator	42750.435	27943.840	7258.317

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.396	0.287	1027	10000	304	84
Stove	4.290	2.426	94	1440	16	219
Baseboard Heater	1.273	0.303	949	10528	256	159
Clothes Washer	0.730	0.103	368	896	80	22
Dishwasher	0.720	0.057	454	928	32	8
Refrigerator	0.407	0.025	1318	5712	16	267
Drier	0.000	0.000	0	0	0	0

Sample Period: Tue, November 19, 1996 to Mon, November 25, 1996
Evaluation Period: Tue, October 15, 1996 to Fri, January 24, 1997
Note: no data for December 11 and 12.

ENERGY CONSUMPTION	Measured		Estimated			Difference	ESTIMATED EVENT STATISTICS				EVENT COMPARISON		
	Cumulative	Energy	Cumulative	Energy	Corrected	in Energy	Duration (seconds)			Total No.	No. of Events		
	Demand (kW)	Share	Demand (kW)	Share	Energy Share	Shares	Average	Maximum	Minimum	of Events	Matched	Missed	False
Total (Input)	751399.063	na	na	na									
Total (After Processing)	na	na	754799.742	100.45	100.00								
Water Heater	304192.162	40.48	301997.091	40.19	40.01	0.47	1362	15008	32	807			
Stove	37418.503	4.98	36206.514	4.82	4.80	0.18	219	9216	16	817			
Baseboard Heater 1	90940.441	12.10	105172.141	14.00	13.94	-6.22	683	9184	16	1935			
Baseboard Heater 2			33056.902	4.40	4.38		521	9056	16	798			
Dishwasher	3657.708	0.49	na	na	na								
Clothes Washer	2668.599	0.36	na	na	na								
Both Washers	na	na	12698.801	1.69	1.68	-0.83	632	1312	16	446			
Refrigerator	93361.005	12.42	63188.308	8.41	8.37	4.05	1081	7328	16	2297			
Residual (Calculated)	219160.645	29.17	na	na	na								
Residual (Estimated)	na	na	202479.986	26.95	26.83	2.34							

MEASURED STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.438	0.293	1203	17056	64	912
Stove	2.251	1.761	105	3888	16	2537
Baseboard Heater	1.293	0.311	1113	35760	16	1011
Clothes Washer	0.715	0.079	221	944	16	270
Dishwasher	0.737	0.107	373	896	16	213
Refrigerator	0.412	0.024	1283	15184	16	2825
Drier	na	na	na	na	na	na

CUMULATIVE DEMAND MATCHIN	Cumulative Demand (kW)		
	Matched	Missed	False
Water Heater	228952.461	75239.701	73044.631
Stove	11172.264	26246.239	25034.249
Baseboard Heater	58453.287	32487.154	79775.756
Washers	1539.499	4786.808	11159.302
Refrigerator	53859.372	39501.633	9328.937

SAMPLE STATISTICS	Demand (kW)		Duration (seconds)			Total No.
	Mean	Std. Dev.	Average	Maximum	Minimum	of Events
Water Heater	4.396	0.287	1027	10000	304	84
Stove	4.290	2.426	94	1440	16	219
Baseboard Heater	1.273	0.303	949	10528	256	159
Clothes Washer	0.730	0.103	368	896	80	22
Dishwasher	0.720	0.057	454	928	32	8
Refrigerator	0.407	0.025	1318	5712	16	267
Drier	0.000	0.000	0	0	0	0