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

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Abstract

This paper presents a new computer program for nonintrusive disaggregation of the total electricity consumption of a house into the major end uses. The computer program has two modes: (1) sampling and (2) evaluation. In the sampling mode, the operating characteristics (of each end use are determined from data collected over a period of several days using at least one current sensor per appliance. In the evaluation mode, only the main electric entrance of the house is monitored, and the electric signal is analyzed to disaggregate the total energy consumption. The errors in estimating the energy shares of three major end uses (water heater, baseboard heater and refrigerator) are less than 10% for most evaluation scenarios. © 2000 Elsevier Science Ltd. All rights reserved.

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1. Introduction

Home owners are often unaware of how renovations, aging appliances, newly installed appliances and changes in occupant behavior affect the energy performance of their house. For example, installing a more efficient furnace will not necessarily reduce energy bills if the occupants stop turning down the thermostat at night [1].

The continuous monitoring of energy consumption is the only approach that can provide

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useful feedback to the home owner, the utility company and the energy auditor. Utility companies should offer new services to their customers to remain competitive in an increasingly deregulated energy market. Among these new services, a high priority should be given to the installation of Energy Monitoring and Management Systems (EMMS) in houses. These systems will (i) continuously monitor and quantify the real long term energy impact of renovations, purchases and changes in occupant behavior, (ii) increase awareness of energy performance and (iii) provide helpful recommendations to the home owner for improving the house's energy performance. To reduce the initial cost of the system, the minimum number of monitoring sensors should be used.

Over the past several years, researchers have developed methods of disaggregating the total energy consumption of a house into its major end uses. Load disaggregation is a method of extracting its constituent parts from the total load. It yields information about the energy consumption of end uses without measuring the end uses directly for long periods of time; therefore, fewer sensors are needed, and less data is collected. Consequently, monitoring, storage and transmission costs are lower.

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

Hart [2] introduced the topic of electric load disaggregation and listed an exhaustive bibliography of research in the areas of nonintrusive appliance load monitoring. He presented the concept of an appliance signature, and defined it 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. "A nonintrusive signature is one that can be measured by passively observing the operation of a load" [2]. There are two types of nonintrusive signature: steady state and transient. A steady state signature is derived from the difference between the steady state properties of an appliance's operating states. For example, the steady state power signature of a baseboard heater is the power difference between its off state and on state. 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 can provide additional information to steady state signatures. An intrusive signature requires some form of active interference at the energy consumer's property. There are two types of intrusive signature: physical and electrical. A physically intrusive signature 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 operating state of the appliance [3]. An electrically intrusive signature is generated at the electricity meter by injecting a signal such as a voltage harmonic. Changes in the current waveform contain information about the end uses active at that moment.

The nonintrusive appliance load monitor (NALM) developed by Hart [2] determines the energy consumption of individual appliances in a house based on analysis of the current and voltage measured at the electricity meter. The NALM 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 intervals in which the input does not vary by more than 15 W (or 15 VAR for reactive power). The values within the steady periods are averaged, thereby minimizing the effect of electrical noise. The difference between two successive steady periods is the step change in power. The algorithm groups the observed step changes into clusters. Ideally, each of these clusters represents one kind of state change for one appliance. The algorithm matches the observed step changes with the operating characteristics of each appliance, thereby recognizing the operation of each appliance. Field testing of the prototype NALM compared its performance with data collected conventionally [4]. The average error for total household energy consumption was −6.3%. In another field test [5], the difference between the NALM estimates for monthly electricity consumption and data from direct measurement was less than 10% for pumps and refrigerators and less than 15% for all other appliances.

Norford et al. [6] described the results of a field test of a residential nonintrusive load monitor (Res-NILM) device in four houses that were also sub-metered. The results showed errors between 11 and 24% for refrigerators, 2 and 17% for water heaters and 2 and 52% for electric heaters. Quantum Consulting Inc. [7] developed a computer program to obtain the end use load profiles from premise level data, that is, the total household electric power measured at the electricity meter. The algorithm rules are based on pattern recognition. The input to the program is the premise level load data, information about standard appliances obtained through surveys with the customer and assumptions about the customer's behavior. Forty houses were evaluated during four summer months using the program [8,9]. The peak values of the disaggregated air conditioner load, averaged over all households for all summer days, differs from the peak of the average metered profile by less than 5%. The average energy consumption of an air conditioner, derived from the heuristic load profiles, differs from the actual consumption by less than 10%. This 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 biggest advantage is that it can use load research data that utilities may have already collected.

Yamagami et al. [10] presented the results of disaggregation of total household gas demand in Japan. The algorithm was first used on about five houses in which 20 pairs of gas meters and data loggers were installed. The detailed monitored data allowed the researchers to test and improve their algorithm, which was later applied to 600 homes. The authors suggested that a look backward capability might be able to improve the identification of variable rate gas appliances. At the time when the article was written, the authors were satisfied with the performance (about 95% accurate).

Another approach, based on pattern recognition techniques, showed a promising potential for application in residential buildings [11]. The results proved that the whole house electricity consumption can be disaggregated into its major end uses, using a pattern recognition approach and only one sensor installed on the main electric entrance of the house. It also requires a one time sub-metering of the target appliances during the sampling period, of about a week, to find the electric characteristics of the appliances. The results are provided in terms of daily load profiles, energy consumption, and energy contribution of the selected appliances. The errors in evaluating the daily energy consumption are between −10.5% and 15.9% for both the water heater and the refrigerator.

This paper presents a new computer program that disaggregates the total electricity consumption in a house into the major end uses based on the analysis of current, measured at the main entrance.

2. Data acquisition

The data for developing the algorithm were collected at 16 s intervals in a single family house in Montreal from October 1996 to January 1997. Clamp-on current sensors, line splitters and data loggers were used to measure and record the current in (i) the main supply lines and in the following major appliances: (ii) hot water tank, (iii) stove, (iv) baseboard heaters, (v) dishwasher, (vi) clothes washer, (vii) drier and (viii) refrigerator. Note that the baseboard heaters are used only for supplementary heating. The major appliances consume about 85% of the total household electricity. Lights, small appliances and the clothes drier consume the remaining 15%. Sixteen seconds was found to be a convenient sampling rate. At this sampling rate, data could be collected in the data loggers for up to a week before the information had to be downloaded. In Quebec, the electric utility company supplies electricity to houses at a nominal 120 V in each of two legs. Power, or demand, is calculated assuming the voltage supplied is constant. The variations in voltage, as sometimes occur, do not affect the final results, which are presented as the percentage contribution of each appliance to the total energy consumption of the house.

Preliminary data analysis consisted of observing how the electric demand of each appliance varies over time and then comparing it to the total electric demand. For example, Fig. 1 shows a snapshot in time of such a comparison. The thick line is the total demand and the thin lines are the individual demands of each appliance. The load profiles of the individual appliances are reflected in the load profile of the total. Observing several days of data also revealed that each appliance has a characteristic load profile. For example, the refrigerator has a long low rectangular profile with a relatively large initial spike and a short period of decreasing demand at the end of the event. The baseboard heater, however, is more clearly a perfect rectangle with little variation in current from start to end. Each appliance event is characterized by an ON signal, an OFF signal and a duration.

Obvious patterns were identified and rules for predicting them were organized into an algorithm called the appliance load recognition algorithm. The computer program has two major modes: (1) sampling and (2) evaluation. 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. In the evaluation mode, the appliance load recognition algorithm analyzes the electric current measured at the main entrance using the previously identified statistics of each appliance. Only two current sensors are required to collect the total current data in the evaluation mode, that is, one on each supply line.

The program is written in the C programming language and has four principal components, or blocks (Fig. 2). The input is a set of data files which contain a series of electricity demand values in kW and their date and time labels. There is one data file for each major 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. The results are also presented as the estimated contribution of each appliance to the total electricity consumption of the house. These percentage contributions are simple referred to as energy shares.

2.1. Sample statistics

The first 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.

2.2. 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 is used. All seven preprocessors smooth out small or erratic variations in the total

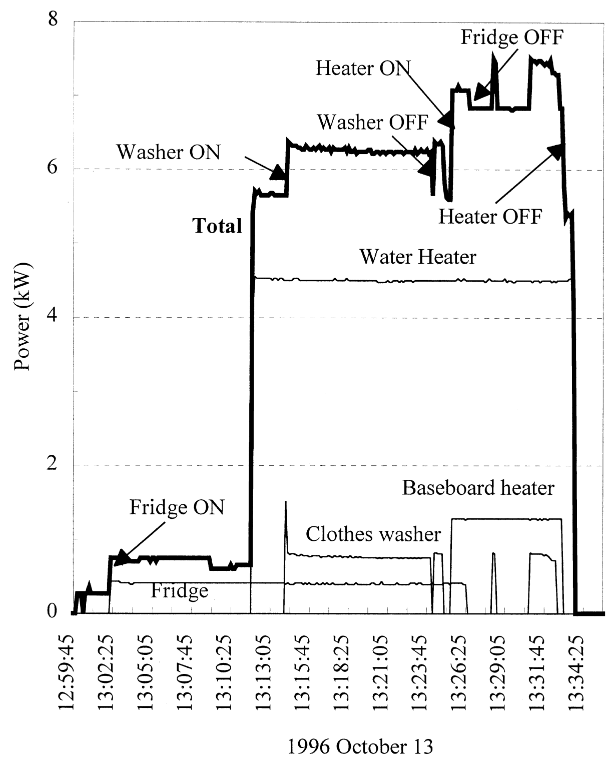

Fig. 1. Sample of electric demand in the test house.

demand signal. 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.

1. The first preprocessor eliminates monitoring errors by adjusting the total signal so that it is never less than the sum of the demands of all the monitored appliances.
2. The second preprocessor removes fluctuations in the total signal while they are within ± 0.1 kW (Fig. 3). 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 [2].
3. The third preprocessor removes the effect of sampling rate while an appliance is turning on. Because the sampling rate is 16 s, an appliance's ON signal does not necessarily appear to occur instantaneously. 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

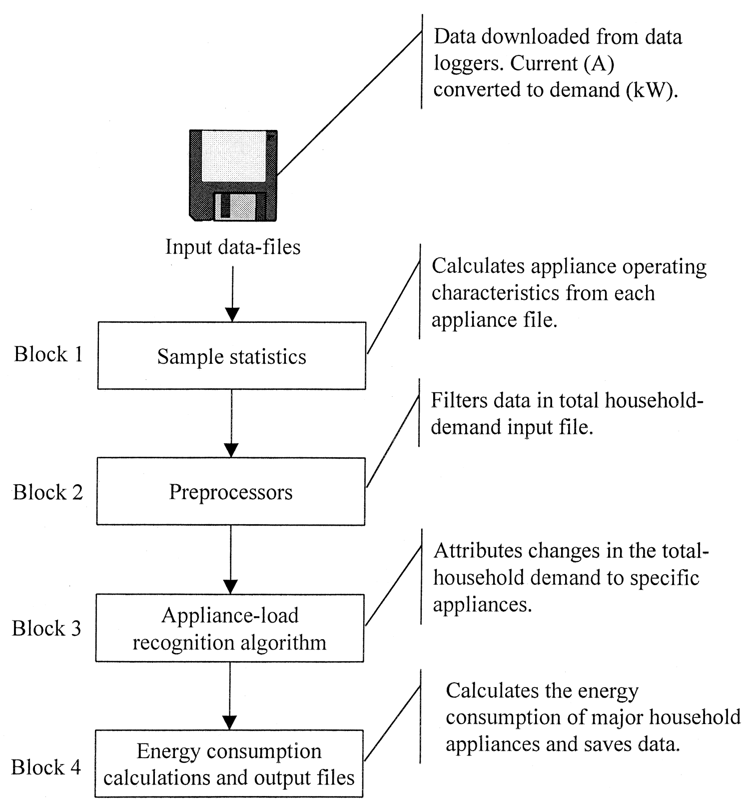

Fig. 2. Four main components of load disaggregation computer program.

operating limits.

4. The fourth preprocessor removes the effect of sampling rate while an appliance is turning off.
5. The fifth preprocessor might well be called the stove load recognition algorithm. 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. Therefore, the stove signal component of the total signal is isolated and removed. One of the characteristics of the stove signal is that it has a large amplitude and a short period. The portions removed are stored in a temporary file which will be used later in block four to estimate the stove's energy consumption.
6. The sixth preprocessor removes individual asymmetrical spikes from the total signal if they are followed by relatively long periods of constant demand. Spikes in the total demand are occasionally observed when appliances with a reactive component come on, such as a refrigerator or a washer. Generally, an asymmetrical spike indicates the beginning of an event, and can be used as a characteristic parameter to identify these appliances. However, it is not known if these spikes always occur when the appliance comes on because the 16 s data sampling rate is sometimes greater than the duration of these spikes. Therefore, the

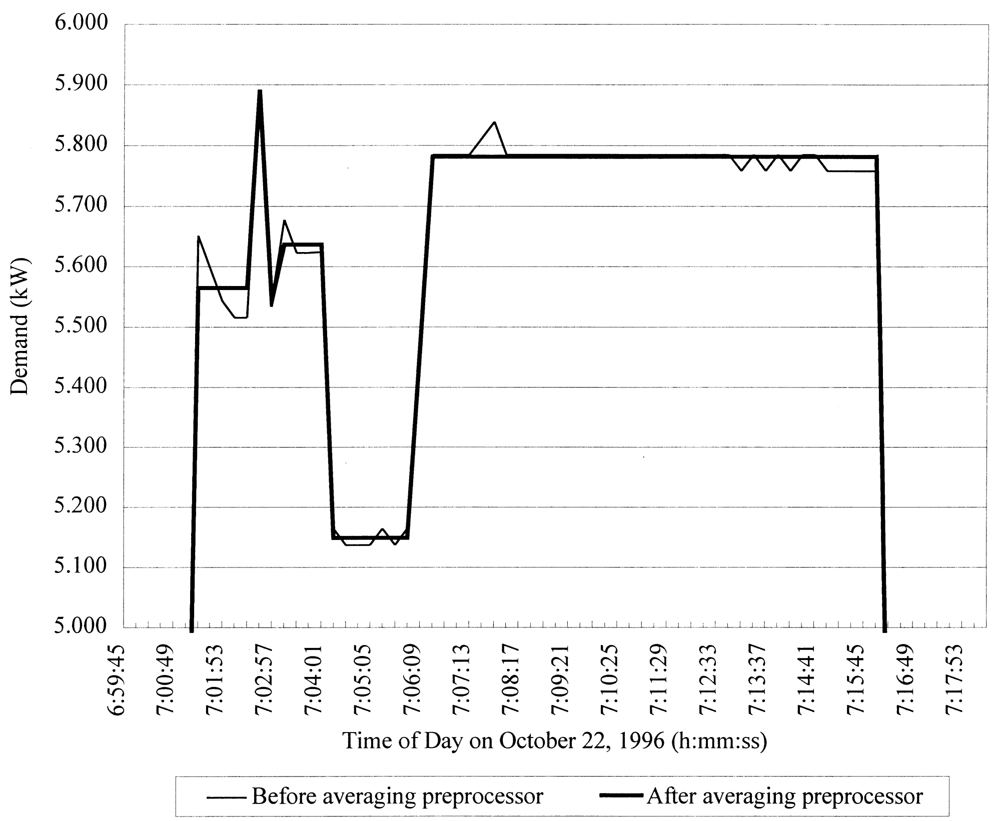

Fig. 3. Detail of averaging preprocessor.

program cannot rely on the presence of these spikes as appliance event indicators. So, the sixth preprocessor removes the asymmetrical spikes.

7. The seventh preprocessor removes individual symmetrical spikes from the total signal. Short duration spikes may be caused by appliances that were not measured, random surges in the current or occupant behavior.

2.3. Appliance load recognition algorithm

The third block of the load disaggregation computer program (Fig. 2) contains the appliance load recognition algorithm. This block of the computer program contains all the operations required in the *evaluation mode*. It requires, as input, the filtered signal from the preprocessors and the statistics gathered during the sampling mode.

The algorithm compares each change in the total signal to each appliance operating range. If the magnitude of the change is within the range of an appliance operating level, that is, the mean demand plus or minus two standard deviations, the change is attributed to that appliance. Therefore, assuming that there are no coincident ON or OFF signals, at least 95% of the ON and OFF signals should be recognized. The algorithm compares changes in the total signal to each appliance range in the following order of decreasing average operating demand: water heater (HW), baseboard heater (PL), washing machine (W) and refrigerator (FR). For example, if an increase is within both the baseboard heater range and the washing machine range, the increase is attributed to the baseboard heater. When an increase falls within an appliance range, that appliance is marked as *turned ON*. If the increase does not match the operating range of any monitored appliance, the increase is assumed to be caused by an appliance that was not monitored, and the increase is attributed to a variable called *residual*.

The algorithm contains a number of checking subroutines:

1. The average duration check is performed every time when there is a decrease in the total demand that is not attributed to a monitored appliance. The average duration subroutine checks the appliances in a predetermine sequence. The sequence was initially arranged in decreasing order of the appliances' average duration. However, during the early stages of development, it was found that the following sequence yields the best results: water heater, washing machine, baseboard heater and refrigerator. During subsequent development, it was found that the average duration check resulted in an underestimation of the 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.
2. The maximum duration checking is performed when there is no change in total household demand. 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.

3. The zero demand checking is performed if a decrease in total demand reduces the total demand to zero. The use of this subroutine prevents 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.
4. 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. Only three appliances have backtracking subroutines: the water heater, the baseboard heater and the refrigerator.
5. The final checking subroutine is the consecutive pair of ON signals checking. If the sum of two consecutive step increases is within the water heater range, and if neither of the signals are attributed to an appliance, then the water heater is marked as ON.

Finally, the fourth block of the computer program (Fig. 2) calculates the energy consumption of each appliance by integrating the electric demand over time. Related statistics such as the number of estimated events, the energy shares, and the maximum, minimum and average duration of each event, are also calculated. Blocks three and four perform the calculations required in the evaluation mode.

3. Validation of the computer program

Two measures of accuracy were used to validate the computer program: (i) the estimated energy consumption and (ii) the number of events recognized.

Table 1 shows 25 combinations of sample period and evaluation period that were used for the validation of the computer program. Each pair of sample period and evaluation period is called a *scenario*.

Tables 2–4 summarize the results from all 25 scenarios for three appliances: water heater, baseboard heater and refrigerator.

3.1. One-day scenarios

These scenarios have a one day sampling period and a one day evaluation period. The results 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 the baseboard heater and washer consumption; and consistently underestimates the refrigerator consumption. There is a high rate of correct event detection for the water heater and refrigerator events.

The differences between the estimated and measured energy shares of the water heater (Table 2) are less than 6% for all scenarios except three (scenarios 3, 11 and 17). For example, in scenario 2, on Wednesday, October 16, 1996, the difference is −0.36%. On average, the difference for all one day scenarios is 3.49%. In terms of water heater energy consumption, the error is less than 9% for most cases, with seven exceptions.

Table 1
223Twenty-five scenarios for validation of computer program

Run Number	Sample period			Evaluation period		
	Start[a]	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[b]
24	Tue, Nov 19, 1996	Mon, Nov 25, 1996	7	Tue, Nov 19, 1996	Fri, Jan 24, 1997	54[b]
25	Tue, Nov 19, 1996	Mon, Nov 25, 1996	7	Tue, Oct 15, 1996	Fri, Jan 24 1997	72[b]

[a] The start is always 0:00:00 h and the end is always 23:59:45 h.
[b] Data do not contain a series of consecutive days with no interruptions.

Table 2
Results for the water heater from all 25 scenarios

Scenario Number	Water heater	Energy shares (%)			Energy use (kWh)			Event detection				
	Evaluation scenario	Measured	Estimated	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 3
Results for the baseboard heater from all 25 scenarios

Scenario Number	Baseboard heater	Energy shares (%)			Energy use (kWh)			Event detection				
	Evaluation scenario	Measured	Estimated	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 4
Results for the refrigerator from all 25 scenarios

Scenario Number	Refrigerator	Energy shares (%)			Energy use (kWh)			Event Detection				
	Evaluation scenario	Measured	Estimated	Difference $E-M$	Measured	Estimated	Percent error $(E-M)/M$	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			

For the baseboard heater, the errors in estimating the energy shares are less than 10% with two exceptions (Table 3), while for the refrigerator, the errors are less than 9% for all scenarios (Table 4). For both the baseboard heater and the refrigerator, there are larger errors in estimating the absolute energy consumption in kWh.

3.2. Multiple days scenarios

These scenarios have a constant sampling period of seven days and extended evaluation period (scenarios 20 to 25). The sampling period, as Table 1 shows, is Tuesday, November 19 to Monday, November 25, 1996; and the evaluation period starts with the same week and gradually is extended. The difference in energy shares, for the water heater and the refrigerator (Tables 2 and 4) is less than 5%, and less than 10% for the baseboard heater. In terms of average energy consumption, the average absolute error is 3.43% for the water heater, 45.16% for the baseboard heater, and about 30% for the refrigerator.

3.3. Optimum sample period to evaluation period ratio

The results of scenarios 20 to 25 indicate that the sampling period of one week is long enough to obtain statistically representative operating characteristics for each appliance. Since the results were obtained for the fall and winter periods, further research is needed to test the program under warmer climatic conditions.

4. Conclusions

The nonintrusive load disaggregation computer program described in this paper could 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 behavior, (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.

The errors in estimating the energy shares of three major appliances (water heater, baseboard heater and refrigerator) are less than 10% for most evaluation scenarios.

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