Non-Intrusive Submetering of Residential Gas Appliances

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A new technique was developed to non-intrusively monitor the use of individual gas appliances in homes. It relied on a very sensitive master gas meter equipped with a pulse meter, data logger, and software. The procedure involves two steps: decomposition and identification of the end uses. The technique is about 95% accurate but the algorithms can still be confused by some relatively common situations. Further improvements in the software are expected to improve accuracy.

The procedure was applied to over 600 homes in Tokyo, Japan. The aggregate data allow more accurate estimates of energy consumption by the major residential gas appliances in addition to their hourly load profiles. Key factors affecting energy demand by each gas appliance were obtained by combining the energy and demographic data. These data are essential for more accurate forecasting of gas consumption, system sizing, and other marketing activities.

The system will not necessarily be as successful in America due to the presence of pilot lights, more appliances per household, and variable-rate gas appliances. Nevertheless, the approach appears promising because it is economical and accurate.

BACKGROUND

The individual metering of gas appliances in homes has always been awkward and expensive. The inability to conveniently submeter gas appliances is responsible for the lack of field data comparable to that available for electric appliances. The absence of such data makes it difficult to accurately forecast gas load and evaluate opportunities to conserve . We report here an entirely new method to gather submetered gas consumption of residential appliances. It does not require expensive equipment or intrusive installations.

There are two conventional approaches to estimating energy use of individual gas appliances. The first requires submetering all or some gas appliances in each home. A recent example of this approach is measurements conducted by Northern Illinois Gas (Menkedic et al. 1993). This approach is expensive, so it is impossible to monitor enough homes in order to obtain a statistically representative sample. As a result, most studies monitor selected appliances in a few homes and settle for ‘‘typical’’ values rather than the average. Other studies have inserted thermal sensors in the major combustion appliances and measured elapsed time. While cheaper than direct metering of gas use, the technique has many drawbacks including greater uncertainty in actual consumption.

An alternative approach relies on monthly gas billing data for a large number of homes combined with details of the appliances present in each home. These conditional demand studies, such as those by Parti et. al. (Parti, Villaflor & Parti 1992) reconcile variations in appliance ownership with differences in energy use. Such studies have been undertaken in both Japan (Murota 1987) and the United States (Energy Information Administration 1994; Energy Information Administration 1996). But when there is little variation in ownership of gas appliances from one house to another (such as is the case in many parts of Japan), the regression coefficients are susceptible to large uncertainties (Nakagami 1987; Nakagami 1993). These uncertainties make it impossible to reliably forecast the increase in consumption due to purchases of new gas appliances, changes in housing stock, and the gradual aging of the Japanese population.

This approach also cannot supply key information, such as the daily or monthly variation in gas use, so it cannot help in facility capacity planning. In Japan, almost all gas is imported as LNG. Each major gas company must therefore own large local storage facilities. From a facilities management perspective, space heating is burdensome for storage but not for pipelines, while water heating is demanding for both facilities. Thus, accurate projections of space and water heating demands will help the gas companies avoid major investments.

Finally, Japanese gas utilities sell gas appliances. More detailed information about consumption behavior allows the utility to design and market appliances that best suit its customers.

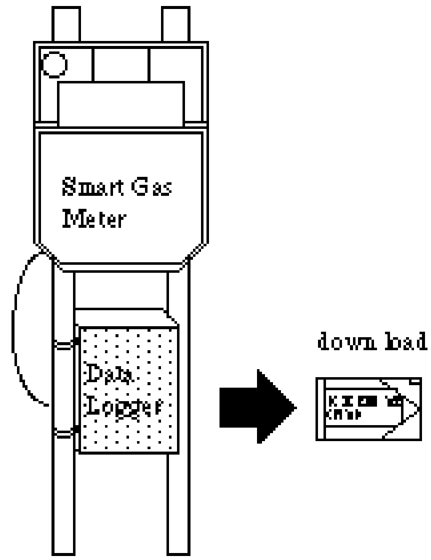
We describe below the details of the new monitoring system. It relies on innovations in both hardware and software. The hardware consists of a sensitive whole-house gas meter and a data logging system. The software consists of a set of algorithms to decompose the whole-house consumption into each appliance's consumption.

DETAILS OF THE NON-INTRUSIVE MONITORING SYSTEM

The gas meter used in Japan translates the movement of the diaphragm into a cyclic crank rotation and then transmits it to the digital indicator. Thus the minimum value of mechanically distinguishable unit of flow is equivalent to one crank rotation. A magnet attached to the gas meter emits an electronic pulse as the crank rotates. Another device detects the pulse and is connected to a microcomputer in the gas meter. Between two pulses, 0.0318 ft^3 of gas flows through a standard size meter. In Table 1, we list typical Japanese gas appliances, their rated input and elapsed time (in seconds) necessary for one pulse emission at the rated consumption.

Each gas meter is equipped with a data logger; when the microcomputer in the gas meter receives a pulse, it transmits a time stamp to the logger with the elapsed time between consecutive pulses. Figure 1 illustrates the system configuration.

Figure 1 *Data Logging System Configuration*



The number of pulses emitted per day varies with use, but typically ranges from tens to thousands. The logger has 0.5M bytes RAM, so we can easily download the data on IC memory card in a few seconds via I/O interface. We schedule data collection from each customer site at most four times a year by utility personnel. At the utility offices, we decompress the data before proceeding to the analysis step. Table 2 contains an example of decompressed, pre-analysis data, and Figure 2 shows an example load data.

Table 1. *Elapsed Time Between Two Pulses for a Certain Amount of Gas Flow*

Input (Btu/h)	Elapsed Time Between Pulses (seconds)	Appliances Corresponding to Inputs
2,000	70.7	
4,000	35.4	Rice cooker
8,000	17.7	Cooking stove, Dryer
12,000	11.8	Stove
20,000	7.1	Oven
40,000	3.5	Bath heater Instantaneous water heater (small)
120,000	1.2	Instantaneous water heater (large)

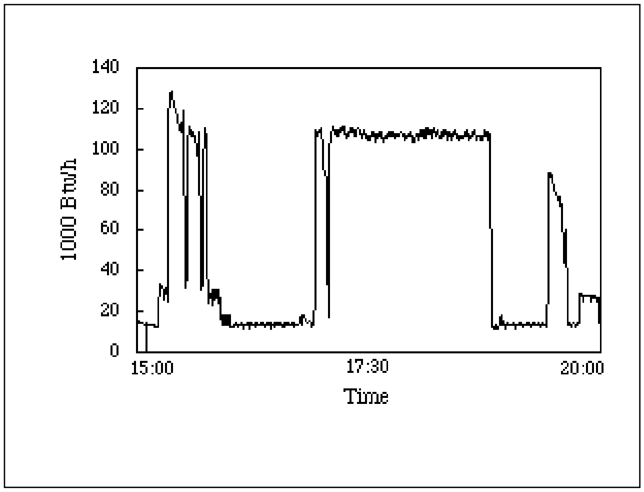
ESTIMATION OF FINAL DEMANDS

Estimation of end uses consists of two steps: decomposition and identification. In the decomposition step, we disaggre-

Table 2. *Example of Pre-Analysis Data*

Time hr/mn/sec	Gas Flow (kBtu/h)	Interval (sec)	Pulse Counts
06/23/10	10.5	25.89	1
06/23/36	10.4	52.72	2
06/24/29	14.4	18.94	1
06/24/48	13.2	2.07	1
06/24/50	15.8	3.47	2
06/24/53	151.0	1.81	1
06/24/55	140.0	1.95	1

Figure 2 *An Example of Load Data*



gate the flow assuming not more than one appliance is turned on or turned off instantaneously. In other words, if there is a significant increase (decrease) in the aggregated flow, we assume one appliance is turned on (off). At the same time, the computer keeps track of the number of active appliances and gas consumption by each appliance.

The identification step combines audit information and the decomposed consumption data. When the meter is installed, we survey the house's gas appliances and record their capacities. Heuristic rules are then applied to match appliances with gas use. These rules rely on both flow rate and duration. At the installation of the logging devices at each customer, we survey all appliances with its rated input. For the most part, we rely on the rate of gas use and the duration of use to identify the appliances. These procedures are similar to those used by Hart (Hart 1991; Hart 1992) and Norford (Norford, Tabors & Byrd 1992) to decompose electricity consumption based on whole-building electrical consumption and equipment data.

In Japanese homes, the major appliances can be associated with the following flow and duration characteristics:

- Water heating: a high but short flow
- Space heating: a stable, long and/or periodical flow
- Cooking: a low, short flow.

Here, 'high' and 'short' imply somewhat more than 40 kBtu/h and less than an hour respectively, of course they depend on operational characteristics of each appliance, though. Figure 3 illustrates an idea of decomposition and Figure 4 shows a result of decomposition algorithm applied to the data shown in Figure 2. Note that these appliances are generally either on or off; that is, they exhibit no variable rate consumption. In addition, Japanese appliances rarely have pilot lights.

RESULTS

We installed twenty data loggers in the houses and apartments of the utility employees to test the hardware and procedures. By comparing the estimates with the actual data which were obtained through the interview, we improved the algorithm. Later examination with the logged data from the different samples shows at least 95% accuracy in estimation. The algorithms can still be confused by some relatively common situations. Further improvements in the software are expected to improve accuracy. Nevertheless, this was judged sufficiently accurate to apply the procedure to a larger group of homes. By 1996, a representative sample of over

Figure 3 *An Example of the Decomposition Algorithm*

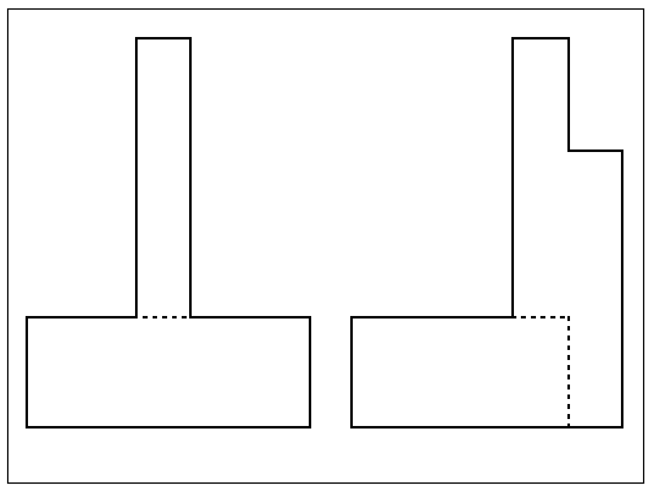
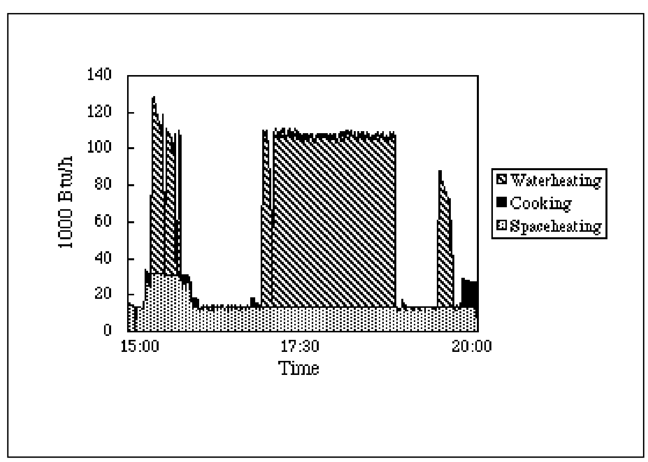


Figure 4 *A Result of the Decomposition Algorithm*



600 homes in Tokyo had been monitored with the non-intrusive technique. Some of the results are described below.

Aggregate Data

Table 3 lists the average annual demands in millions of Btu (MBtu) per family in the three categories as derived from the non-intrusive monitoring program. The type of building structure (e.g., detached vs. multifamily) significantly influences heat demand although the influence of floor area is no doubt also reflected in the house/apartment difference. Figure 5 shows monthly demands of each category , while Figure 6 and Figure 7 show hourly load profiles for typical summer and winter days. (For competitive reasons, the scales on Figures 6-9 are arbitrary)

It is also possible to combine the submetered data with demographic data, and better understand the factors determining demand. For example, Figures 8 and 9 illustrate the merging of water heating and space heating energy data and floor areas.

Table 3. *Average Annual Demands Per Family (MBtu)*

Type of Structure	Space Heating	Water Heating	Cooking	Total
House	4.3	18.4	3.2	25.9
Apartment	1.7	9.8	2.1	13.6
Condo	1.5	14.5	2.5	18.5

Figure 5 *Monthly Demands*

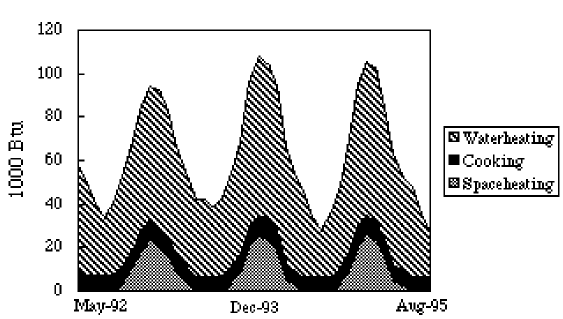


Figure 6 *Daily Load Curve in Winter*

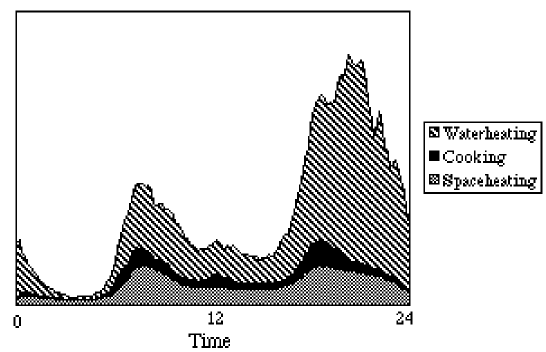


Figure 7 *Daily Load Curve in Summer*

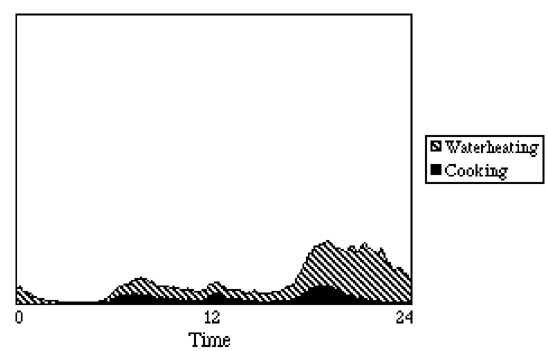


Figure 8 *Annual Water Heating Demands Vs Family Size*

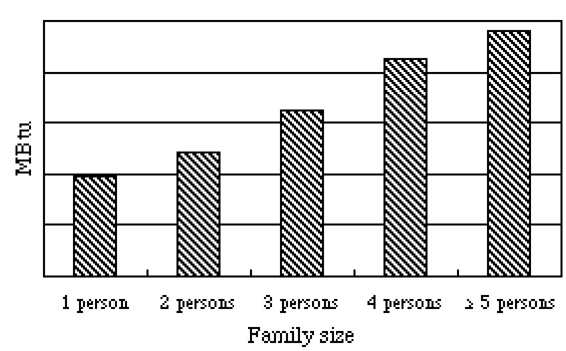
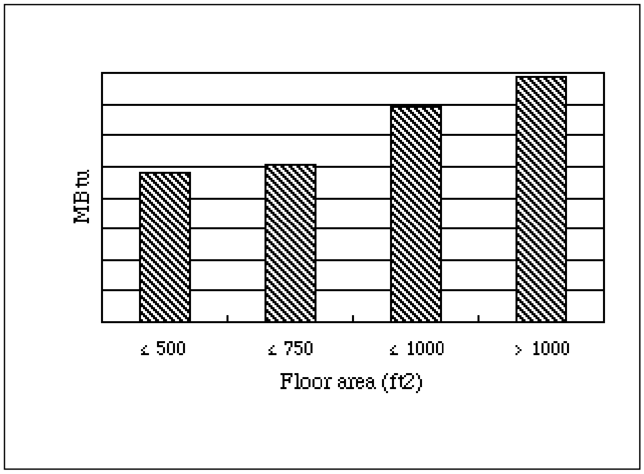


Figure 9 Space Heating Demands Vs House Size



DEMAND MODELS

The value of the submetered data is most apparent in the demand models that can be constructed with the energy and survey data collected as part of a project. A detailed model of water heating demand was created through a regression analysis. The model structure was:

$$\text{water heating demands} = \text{family size} + \text{number of faucets} + \text{configuration}$$

The effect of each factor is shown in Figure 10. The annual average water heating demand for the samples is 14.7 MBtu; if a family consists of three persons, the demand is 1 MBtu less than 14.7 MBtu. From this regression, we found that 'family size' and 'number of faucets' are the most significant predictors of water heating energy use. Curiously, the type of water heater was not significant, even though there are several, very different, water heating configurations in Japanese homes.

Similarly, we obtained the following model for space heating:

$$\text{space heating demand} = \text{family size} + \text{floor area} + \text{presence of non-gas space heater} + \text{building construction}$$

Figure 11 shows the effect of each factor. Here, 'floor area' is much more critical than the other factors. In Japan, central heating systems are not as popular as in the United States and 'building construction' does not have much influence.

For cooking demands, we have:

$$\text{cooking} = \text{family size} + \text{age of householer}$$

We show the result in Figure 12. Of all three categories, cooking demands are the least, both in average and in variance.

Some of the results stated above could have been anticipated beforehand, but the submetering approach allows quantification. The linear models exhibited in this section, however,

Figure 10 Water Heating Demand Model

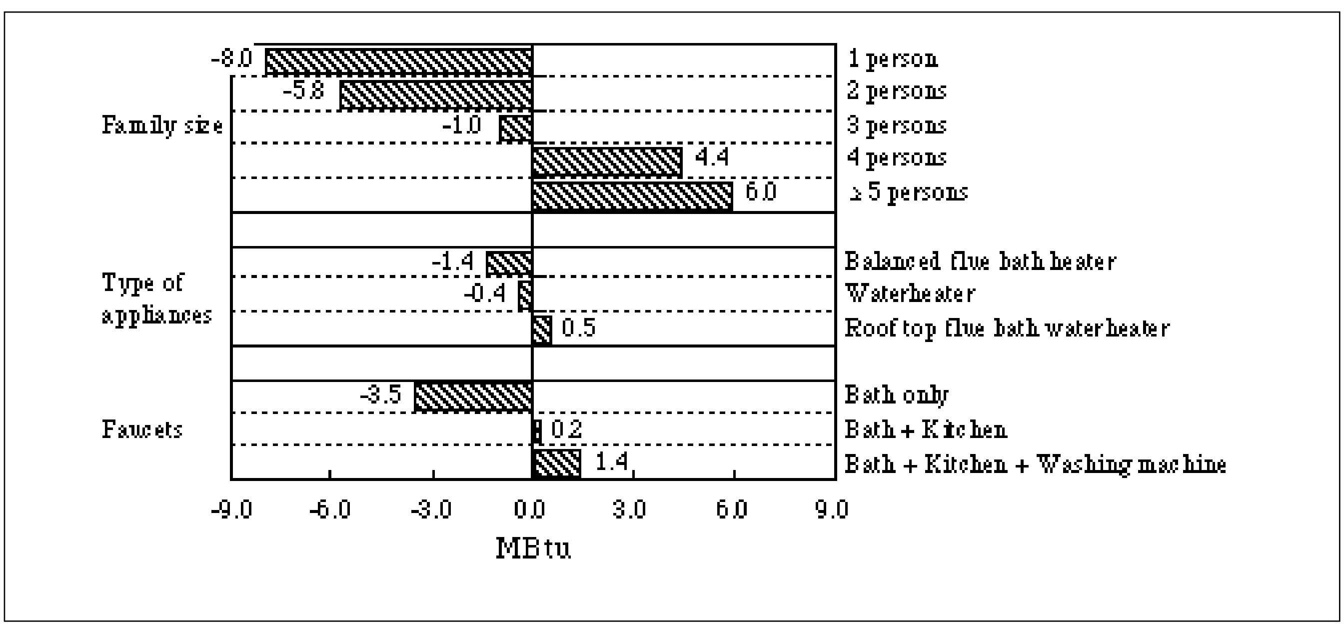


Figure 11 Space Heating Demand Model

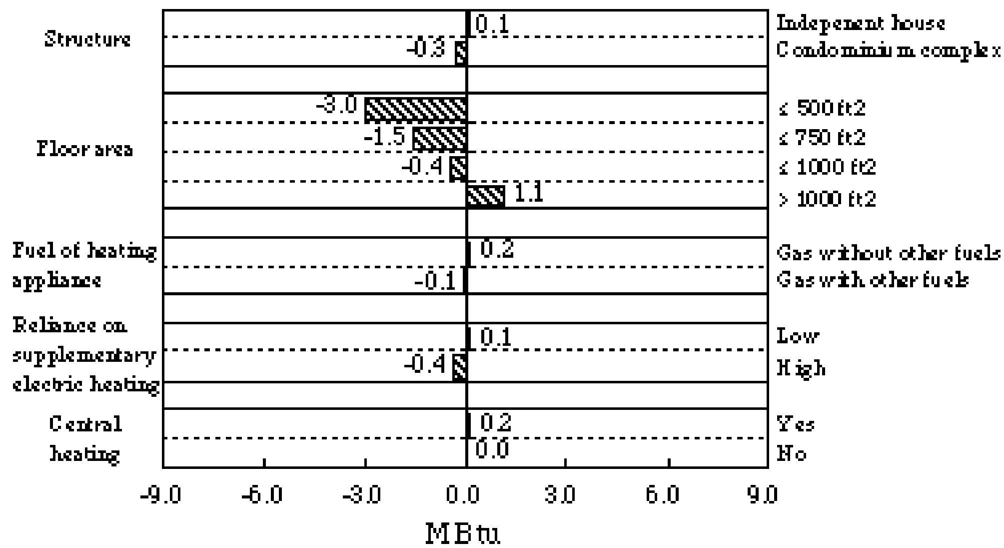
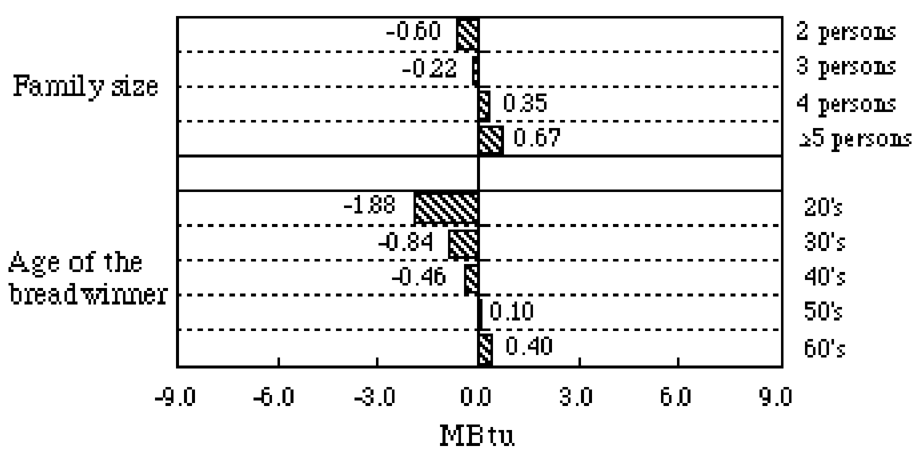


Figure 12 Cooking Demand Model



are naive versions, and other factors such as income, energy prices, and so on apparently have influence on final demand. Thus, revision of the models in order to improve estimation accuracy remains a future problem.

TIME SERIES ANALYSIS

Some of the households have been monitored for more than a couple of years, so it is possible to see changes in demand due to changes in appliances, size of family, and climate. This gives us a marginal effect of each factor, and in a sense, measured effects are more accurate than the estimates obtained in the previous section since no sample errors (or heterogeneity of samples) arise. The following two examples demonstrate the power of this information.

One home was observed to greatly increase its winter gas use. Figure 13 shows a monthly profile of gas consumption for 1993 and 1994. The total demand rose in 1994, but there was no clue as to 'what' demand and 'why'. According to

Figure 13 *Monthly Gas Meter Reading*

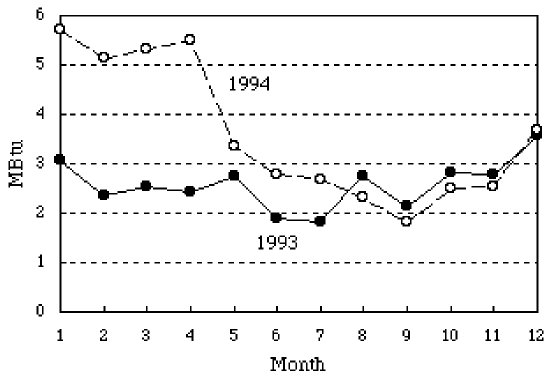
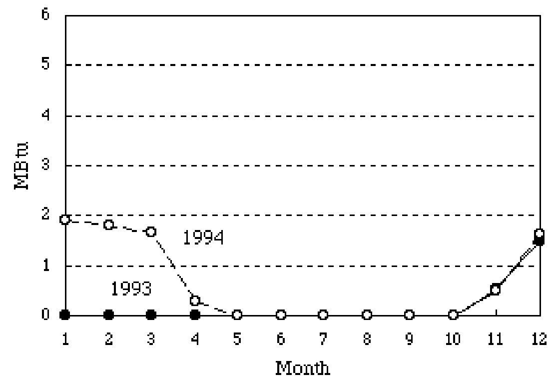


Figure 14 *Monthly Space Heating Demands*



questionnaires administered to the occupants, the occupants bought a gas heater in the Fall of 1993. (Before then, the household had only an electric heat pump.). Table 4 also shows a drastic change in space heating demand. Figure 14 shows a drastic increase in monthly space heating demands.

In another home, a decrease in total gas use was observed (Figure 15). The questionnaires revealed that one family member left in the second year (from four to three members). Submetered data (Table 3) reveal the impact of a smaller family, both in terms of reduced water heating (significant), space heating (small), and cooking (none).

We have not yet had enough samples to conduct a systematic analysis of time series data. However, as the number of monitors increases and time passes, we will have more and more cases of ’change’. For example, the utility sells more than 200,000 space heaters each year, corresponding to 2.5% of the utility’s customers. In four years, 10% of the customers, and hence by law of large numbers, 10% of our samples

Figure 15 *Monthly Gas Meter Reading*

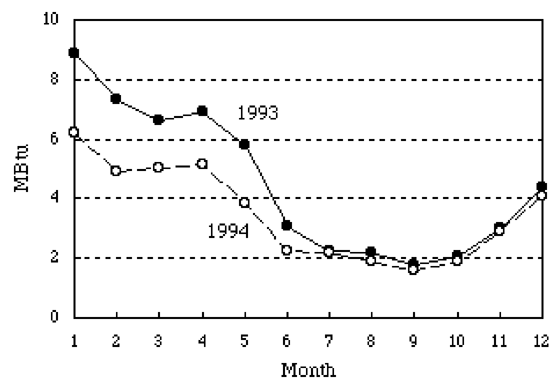


Table 4. *Comparison of Final Demands of a Family in 1993 and 1994 (MBtu)*

Year	Water Heating	Space Heating	Cooking
1993	25.6	2.0	5.2
1994	28.9	7.8	5.9
Differences	3.4	5.8	0.7

Table 5. *Comparison of Final Demands of Smaller Family in 1993 and 1994 (kBtu)*

Year	Water Heating	Space Heating	Cooking
1993	26.8	19.9	4.1
1994	20.7	17.4	4.2
Fluctuation	− 6.1	− 2.5	− .1

buy new gas heaters. Assuming 1000 data loggers in the field, there will be 100 cases of monitored homes with space heater installations. This is sufficient for confident inference of impacts.

APPLICABILITY TO AMERICA

The non-intrusive monitoring system has been tried in over 600 Japanese homes with a high degree of success. However, the system will not necessarily be as successful in America. Three aspects require further investigation: pilot lights, impact of more appliances, and variable-rate gas appliances. Pilot lights are not used in Japan, but they are common in America. In principle, the algorithms should be easily adjusted to account for the constant load created by pilot lights. The algorithms will not be able to determine the amount of energy consumed by each appliance's pilot; this may require additional measurements during the audit.

American homes often have more gas appliances than Japanese homes. The extra appliances include a gas clothes dryer, decorative fireplaces, pool and spa heaters, and exterior radiant heating elements. Disaggregation becomes more complicated, and computing requirements increase substantially with the number of appliances present.

Some American appliances have variable combustion rates (that is, furnaces and stoves). A variable rate of gas combustion could confuse the detection algorithms. Improved algorithms, with a ''look backward'' capability, might be able to improve identification of variable-rate gas appliances.

CONCLUSIONS

We have demonstrated that gas consumption of individual appliances can be reliably estimated from whole-house measurements. This non-intrusive technique requires a sensitive gas meter and special software to identify the individual end uses. In addition, a simple audit is needed to inventory the gas appliances and their capacities. A multi-step procedure is required to disaggregate the whole-house consumption data into consumption profiles for each appliance. The equipment is significantly easier to install and does not disturb the occupants during the monitoring period.

The technique is about 95% accurate but the algorithms can still be confused by some relatively common situations. Further improvements in the software are expected to improve accuracy.

The value of the monitoring system has already been demonstrated after collecting data from over six hundred Japanese homes. The end use data have allowed the gas utility to more accurately quantify the variables affecting the demand for gas in Japanese homes. This permits more efficient operation of the supply and distribution system and more accurate forecasting of demand. In addition, the impacts of fuel switching, retrofits, and behavioral changes can be easily observed.

Several technical problems need to be resolved before the approach can be used in America, including the ability of the system to accommodate more appliances, pilot lights, and variable-rate appliances. None of these appear to be insurmountable obstacles.

ACKNOWLEDGMENTS

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