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EPA DOE

ENERGY STAR® Partnerships Program

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Pacific Northwest National Laboratory
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Summary

The New York Power Authority (NYPA), the New York City Housing Authority (NYCHA), and the U.S. Departments of Housing and Urban Development (HUD) and Energy (DOE) have joined in a project to replace refrigerators in New York City public housing with new, highly energy-efficient models. This project laid the ground work for the Consortium for Energy Efficiency (CEE) and DOE to enable housing authorities throughout the United States to bulk-purchase energy-efficient appliances.

DOE helped develop and plan the program through the ENERGY STAR® Partnerships program conducted by its Pacific Northwest National Laboratory (PNNL). PNNL was subsequently asked to conduct the savings evaluations for 1996 and 1997. PNNL designed the metering protocol and occupant survey, supplied and calibrated the metering equipment, and managed and analyzed the data.

The 1996 metering study of refrigerator energy usage in New York City public housing (Pratt and Miller 1997) established the need and justification for a regression-model-based approach to an energy savings estimate. The *need* originated in logistical difficulties associated with sampling the population and performing a stratified analysis. Commonly, refrigerators[(a)] with high representation in the population were missed in the sampling schedule, leaving significant holes in the sample and difficulties for the stratified analysis. The *justification* was found in the fact that strata (distinct groups of identical refrigerators) were not statistically distinct in terms of their label ratio (ratio of metered consumption to label rating). This finding suggested a general regression model could be used to represent the consumption of all refrigerators in the population. In 1996 a simple two-coefficient regression model, a function of only the refrigerator label rating, was developed and used to represent the existing population of refrigerators.

A key concept used in the 1997 study grew from findings in a small number of apartments metered in 1996 with a detailed protocol. Fifteen-minute time-series data of ambient and compartment temperatures and refrigerator power were analyzed and demonstrated the potential for reducing power records into three components. This motivated the development of an analysis process to divide the metered consumption into baseline load, occupant-associated load, and defrosting load. The baseline load is the consumption that would occur if the refrigerator were on but had no occupant usage load (no door-opening events) and the defrosting mechanism was disabled. The motivation behind this component reduction process was the hope that components could be more effectively modeled than the total. We reasoned that the components would lead to a better (more general and more significant) understanding of the relationships between consumption, the characteristics of the refrigerator, and its operating environment.

The 1997 metering study was directed at developing the data reduction and modeling procedures conceived in 1996. The objective of the 1997 metering study was to achieve a more complete understanding of savings as a function of refrigerator label ratings, occupant effects, indoor and

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(a) As distinguished by manufacturer and model numbers.

compartment temperatures, and characteristics (such as size, defrost features, and age). Ideally the regression models would be applicable to future project years and potentially other sites and cities.

A durable six-sensor metering protocol was implemented to collect detailed time-series data on ambient and compartment temperatures, compartment door-opening activities, and power usage. Metering and demographic data were collected and reduced from 120 NYCHA apartments. Regression models were developed from this database. These models were then applied to the population of refrigerators removed and installed in NYCHA housing in the 1997 project year (Pratt and Miller 1997).

Conclusions

Key conclusions of the analysis are summarized below.

- The ***baseline component*** correlates strongly with label rating and the age of the refrigerator. Evidence of refrigerator degradation is significant in the baseline data. Older refrigerators are more degraded. (See Section 3.3.)

- A categorical variable, which indicates if the apartment building is predominately populated by elderly occupants, was shown to be significant in the correlation with the ***baseline component***, indicating that refrigerator degradation is related to the age of the occupants. Apparently the refrigerators in the elderly apartments are better maintained. (See Section 3.3.)

- Occupant activity strongly affects the magnitude of the ***occupant component***. A categorical variable that describes whether the apartment buildings are predominantly populated by elderly occupants was found to be an adequate indicator of refrigerator usage. (See Section 3.3.)

- ***Refrigerators with automatic defrost have higher occupant consumption (on a label-normalized basis) per unit of occupant activity than refrigerators with manual defrost***. The fans in refrigerators with automatic defrost appear to significantly increase air exchange with the room during times that doors are open. This effect is not represented in label ratings determined from closed-door testing. A categorical variable that represents whether the refrigerator is automatic or manual is critical to account for variance in the occupant component. (See Section 3.3.)

- The propensity for occupant consumption per unit of occupant activity was expected to be primarily driven by the volume of the refrigerator and the characteristics of its compressor. The aggregate of these characteristics is indirectly represented in the refrigerator's label rating. But in terms of explaining variance in the sample data, the baseline component itself appears to be the best fundamental characteristic, perhaps because it better reflects the vapor-compression cycle's degradation with age. ***Volume may appear in future studies as a more significant descriptive variable if there is more diversity in refrigerator volume in the population (and sample)***. (See Section 3.3.)

- The ***defrost component*** correlates well with the sum of the baseline and occupant components. (See Section 3.3.)

- ***Accounting for differences between the characteristics of the metered sample and the general population is important for the accuracy of the savings estimate***. Significant differences were found in several characterizing parameters: age of existing refrigerators, concentration of manual-defrost refrigerators, building characteristics (e.g., whether predominantly occupied by elderly or nonelderly occupants). All of these effects contributed to significantly higher modeled savings for the population in comparison to the metered sample averages. (See Section 3.4.)

- For refrigerators metered in the ***summer***, the peak load occurred at ***9:00 p.m***. ***The load at summer peak was 13% higher than the average load.*** For refrigerators metered in the ***winter***, the peak load occurred at ***4:00 p.m***. ***The load at winter peak was 9% times higher than the average load.*** (See Section 3.5.)

- The regression models can be applied to future program years in New York City. If future replacement units are significantly different in design or volume it is recommended that the regression models be applied only to the existing units and that a sample of replacement units be monitored (see Section 4.0).

- The regression models should not generally be applied to other cities. Constraints in application originate in the limited capabilities of the regression models to represent effects driven by occupant usage and refrigerator volume. With caution, the models can be applied in sites characterized as similar to NYCHA housing in New York. Similarity needs to be judged based on demographics, apartment building characteristics and operation, refrigerator volume, and weather (see Section 4.0).

Contents

Figures

Tables

1.0 Introduction

The New York Power Authority (NYPA), the New York City Housing Authority (NYCHA), and the U.S. Departments of Housing and Urban Development (HUD) and Energy (DOE) have joined in a project to replace refrigerators in New York City public housing with new, highly energy-efficient models. This project laid the ground work for the Consortium for Energy Efficiency (CEE) and DOE to enable housing authorities throughout the United States to bulk-purchase energy-efficient appliances (Wisniewski and Pratt 1997). This document describes the analysis of annual energy cost savings achieved from replacing 20,000 refrigerators in 1997, the second year of the program.

DOE helped develop and plan the program through the ENERGY STAR® Partnerships program conducted by its Pacific Northwest National Laboratory (PNNL). PNNL was subsequently asked to conduct the savings evaluations for 1996 and 1997. PNNL designed the metering protocol and occupant survey, supplied and calibrated the metering equipment, and managed and analyzed the data.

The 1996 metering study of refrigerator energy usage in New York City public housing (Pratt and Miller 1997) established the need and justification for a regression-model-based approach to an energy savings estimate. The *need* originated in logistical difficulties associated with sampling the population and performing a stratified analysis. Commonly, refrigerators[a] with high representation in the population were missed in the sampling schedule, leaving significant holes in the sample and difficulties for the stratified analysis. The *justification* was found in the fact that strata (distinct groups of identical refrigerators) were not statistically distinct in terms of their label ratio (ratio of metered consumption to label rating). This finding suggested a general regression model could be used to represent the consumption of all refrigerators in the population. In 1996 a simple two-coefficient regression model, a function of only the refrigerator label rating, was developed and used to represent the existing population of refrigerators.

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understanding of savings as a function of refrigerator label ratings, occupant effects, indoor and compartment temperatures, and characteristics (such as size, defrost features, and age). Ideally the regression models would be applicable to future project years and potentially other sites and cities.

A durable six-sensor metering protocol was implemented to collect detailed time-series data on ambient and compartment temperatures, compartment door-opening activities, and power usage. Metering and demographic data were collected and reduced from 120 NYCHA apartments. Regression models were developed from this database. These models were then applied to the population of refrigerators removed and installed in NYCHA housing in the 1997 project year (Pratt and Miller 1997).

The remainder of this report includes five sections and appendices. Section 2.0 discusses the data collection efforts and other data sources used in this analysis. Section 3.0 describes the analysis procedure and discusses the results. Section 4.0 discusses the application of the regression model in future years and other cities. Section 5.0 highlights the conclusions drawn from the analysis. Section 6.0 contains a list of references cited in this report. Appendix A discusses the method used to monitor power consumption, occupant door events, and ambient and refrigerator compartment temperatures in 121 apartments. Appendix B is a discussion of the survey of information relating to refrigerator performance taken in each monitored apartment. The method used to process time-series data is outlined in Appendix C. The method used to determine the age of high duty cycle refrigerators is discussed in Appendix D. Appendix E contains the metered and surveyed field data for each metered refrigerator. Appendix F provides a summary of occupant density in NYCHA housing developments.

Figures 1.1 through 1.5 illustrate the installation of the new refrigerators and the recycling of the existing refrigerators.

Figure 1.1. Typical New York City Housing Authority Development

Figure 1.2. Unloading New Refrigerators

Figure 1.3. New Refrigerators Outside Development Waiting for Installation

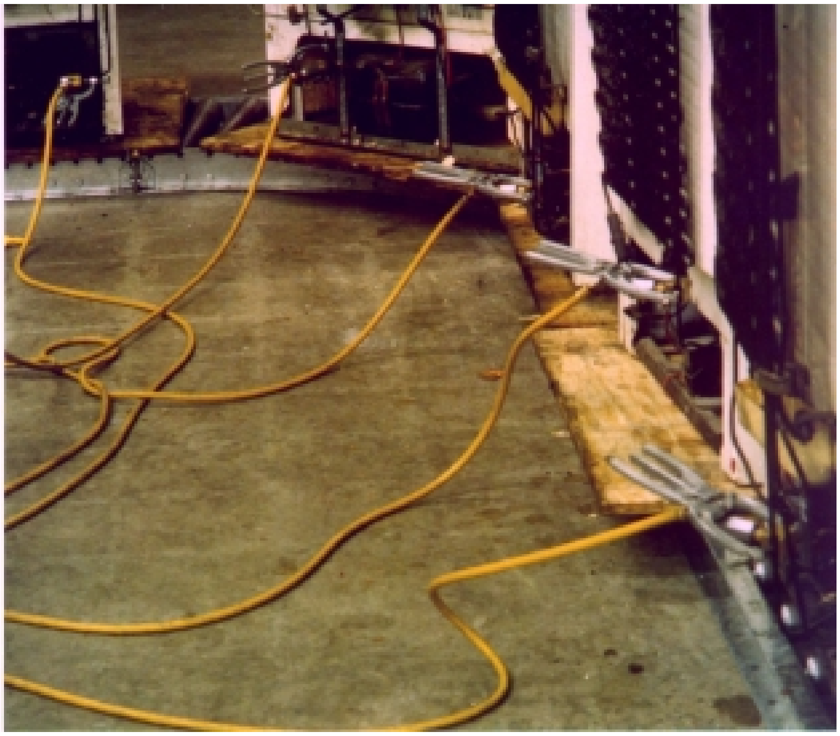

Figure 1.4. Removing Refrigerant from Existing Refrigerators

Figure 1.5. Draining Oil from Existing Refrigerators

2.0 Data Collection

PNNL's development of the regression-model tools for calculating the program energy savings involved the integration of several data sources:

- detailed 15-minute time-series metering of power usage, ambient and compartment temperatures, and occupant door-opening activity for refrigerators in the field over about a one-week period for a sample of new and existing refrigerators

- infrared-scanner measurements of ambient indoor-air temperature and fresh-food and freezer compartment temperatures at the beginning and end of the monitoring period

- a survey of occupant, apartment, and refrigerator characteristics

- a database of refrigerator characteristics including model numbers, DOE-label rating test results, rated volumes, defrost features, and year of production as reported by refrigerator manufacturers

- daily outdoor temperatures (during field testing) and long-term-average monthly outdoor temperatures for New York City from National Weather Service data posted on the Internet

- occupant data (numbers by four age categories) for each of the NYCHA housing developments involved in 1997.

The following sections describe these different types of data and how they were obtained.

2.1 Refrigerator Label Ratings and Characteristics Data

A database of refrigerator characteristics was used to find DOE-label ratings for refrigerators replaced by the program. For many years manufacturers have been required to provide DOE the results of energy consumption tests conducted in an environmental chamber for use as consumer label ratings (10 CFR 430). The label rating test consists of placing the refrigerator in a chamber maintained at an elevated temperature (90°F) to simulate door openings. After repeating the test at two control settings and measuring the resulting energy consumption and freezer temperatures, the results are interpolated to estimate annual consumption at a freezer temperature of 5°F. After testing several refrigerators off the production line, the average of their annualized consumption is issued as the label rating for a given refrigerator model. DOE sets standards for maximum label ratings as a function of refrigerator volume. The Association of Home Appliance Manufacturers (AHAM) maintains an appliance database listing each refrigerator by brand and model, DOE-label rating, rated volume, year of production, and the refrigerator's defrost features (AHAM 1990).

All possible model numbers do not appear in this database. Manufacturers use parts of model numbers to specify submodel information like color, which side of the door is hinged, and place of production. A lapse also occurred in federally mandated reporting of label ratings in the late '70s, and labels were not required at all prior to 1975. Some manufacturers produce refrigerators that are essentially identical but are sold under a variety of brand names with different model numbers. These refrigerators appear separately in the database.

2.2 Field Data Collection

PNNL developed and managed the data collection process. PNNL designed the metering protocol and occupant survey, supplied and calibrated the metering equipment, and managed and analyzed the data.

Planergy installed meters on 104 existing refrigerators and 17 new Maytag high-efficiency replacement refrigerators. These meters recorded energy consumption, ambient and compartment temperatures, and occupant door-opening activity over a period of approximately one week (see Appendix A). The monitoring produced detailed time-series data at 15-minute intervals. This data was collected to form the basis for understanding variations in consumption data as affected by operating conditions. The time-series data also served to quantify peak-load impacts.

For each metered refrigerator, Planergy collected a variety of characteristic information (see Appendix B). This information included refrigerator model number and manufacturer, relative condition (state of repair) of the refrigerator, apartment characteristics, and the number and age of occupants. Snapshot data, at the beginning and end of the monitoring week, were recorded based on observations of the refrigerator control settings, visual estimates of the degree of food loading in each compartment, and infrared scanner (radiometer) measurements of ambient and compartment temperatures. These data quantify the state of the refrigerator and establish the nature of its operating environment.

No formal sampling scheme was established; residents were recruited for metering on an informal basis by knocking on doors or talking to residents, resident association leaders, or superintendents. Apartments on various floors in the buildings were sampled because ambient temperatures may be higher on the upper floors. Although the sample is not random in a formal statistical sense, a reasonably representative sample of occupant refrigerator usage was achieved.

After screening for data quality problems, some metered records had to be eliminated. Eight sites showed extremely low (near zero) energy usage during the week, indicating an instrumentation sensor problem or a malfunctioning refrigerator (either unplugged or not operating). These power records were not included in the analysis.

Various other logger failures were documented for each site (see comment code in Appendix E). The degree to which missing data affected the analysis depended mainly on whether the refrigerator was performing within normal bounds or was showing signs of malfunction (see Appendix C). Data requirements for malfunctioning refrigerators were lower because they could not be processed with the normal approach. These refrigerators were processed with a simplified analysis depending only on temperature and total power measurements (see Section 3.4). After considering missing data, the power records from all but eight sites were used in the savings estimate.

The label for one of the 104 existing units monitored by PNNL could not be identified. This unidentified refrigerator, along with eight sites with missing power data, resulted in 95 (103-8) existing refrigerators for use in the savings analysis.

Two new refrigerators were malfunctioning. These refrigerators had high consumption and detailed records clearly indicated high duty cycle behavior. It appeared that the controls on these refrigerators had failed and they were running continuously. The occupants complained of freezing problems in the fresh-food compartment (based on the occupants' complaints, these refrigerators were replaced after the monitoring period). These refrigerators were excluded from both the normal and simplified analysis process paths. This handling contrasts with that of the malfunctioning existing refrigerators. It is asserted that the malfunctioning behavior of the new refrigerators would not be allowed to persist. For this reason, Table 2.1 shows 15 (out of 17 monitored) new refrigerators used in the savings analysis.

In addition, NYPA collected simple total energy data on 51 new Maytag refrigerators. The data was not detailed 15-minute interval data but rather lumped weekly totals. These data could not be directly used in the primary analysis process but were used as a secondary check against totals derived from the detailed PNNL data.

The disposition of all the metered data is summarized in Table 2.1.

Table 2.1. Metered Data Collected and Used in the Savings Analysis

Metered Data	Existing Refrigerators Removed, (various models)	New Refrigerators Delivered (Maytag)
PNNL, total	104	17
Data used, total	95	15
NYPA, total	0	51
Data used, total	0	0

Also, PNNL noted early in the metering effort that the infrared radiometer used to take the snapshot temperature measurements produced consistently warmer readings than those from a thermistor, particularly at the low temperatures in the freezer compartment. A correction relationship was produced based on these measurements, as discussed in Appendix B. The corrected radiometer measurements were only used at those sites where thermistor-based time-series readings were not available.

2.3 Occupant Data

Occupant data was provided by NYCHA for each of the housing developments involved in the 1997 project year. The average number of occupants per apartment for each development was provided for each of four age categories: children (0-9), teenagers (10-20), adults (21-61), and elders (62 and older).

3.0 Analysis

The objective of the 1997 analysis was to develop tools for estimating the annual energy and demand savings associated with replacing refrigerators in NYCHA housing. The 1997 analysis also provided a more complete understanding of savings as a function of refrigerator label ratings, occupant effects, indoor and compartment temperatures, and refrigerator characteristics (such as size, defrost features, and age).

PNNL's analysis had to account for two effects not directly represented in the raw data:

- Ambient indoor-air temperatures during week-long metering periods do not generally represent annual average conditions. It is important to account for this effect in estimating annual savings because refrigerator energy consumption is largely proportional to the temperature difference between the compartments and the ambient temperatures.

- Many more existing refrigerator models were replaced than could be metered with any meaningful sample, and the efficiency of existing refrigerators, as evidenced by their DOE-label ratings, varies widely (by more than a factor of two).

To conduct the analysis, PNNL performed the following steps:

1. Analyze the raw data to determine the components of total consumption:

    - *Baseline*: energy conducted through the walls of the refrigerator when the door is closed

    - *Occupant*: energy from warm food or air entering through the compartment doors

    - *Defrost*: energy injected into and subsequently removed from the refrigerator for melting ice buildup on the coil

2. Adjust the metered consumption of each refrigerator from the temperature conditions during the metering period to that which would occur under annual average conditions.

3. Construct a relationship between the components of refrigerator energy consumption and site/refrigerator characteristics so that consumption could be estimated for refrigerator models not represented in the metered sample.

4a. Use the relationship developed in Step 3 to estimate energy savings for each model of refrigerator replaced.

4b. Use the records of the number of refrigerators of each model demanufactured to compute an average total per-unit savings for the program in 1997.

5. Estimate the electricity consumption of refrigerators during the hours of peak building demand.

Details of these analysis steps are presented in the corresponding subsections (3.1−3.5) which follow.

3.1 Determining Components of Total Consumption

To improve the modeling effort used in the 1996 analysis, a significant step was added to the analysis process (see Appendix C). This step allowed the results to be generalized and potentially applied to future project years and other sites and cities. Fundamental to this new approach was the division of refrigerator energy usage into three primary components of thermal load: baseline (conduction through the shell), occupant door-opening activity and associated food and air cooling, and defrosting. Detailed metering of the refrigerator supported component-wise division of total consumption. These components led to a better (more complete and more significant) understanding of the relationships between consumption, the characteristics of the refrigerator, and its operating environment.

To illustrate the advantage of working with components instead of total consumption, consider the contrast between the baseline load and the occupant load. The baseline energy flows through the walls of the refrigerator shell. The occupant energy comes in through the open door. While both loads are essentially driven by the temperature difference between the interior set point and the room temperature, the similarities nearly stop there.

The baseline load has little, if any, relationship to the number of occupants or their food usage patterns. The baseline load is strongly related to the label rating because both are indicators of the refrigerators' ability to resist (with insulation) and remove (with the compressor) energy flowing in through the shell. State-of-repair issues related to refrigerator age and the condition of the shell and seals will be reflected in a higher baseline load.

The occupant load has little, if any, relationship to the shell (and its insulation) but rather is a reflection of occupant usage and how efficiently the compressor can remove the associated food and door-opening energy. Occupant characteristics, such as age and number, that affect usage patterns should correlate with the occupant load.

Defrost events occur in response to the baseline and occupant loads. Defrost events are triggered by the accumulation of compressor run time, and so the defrost load is expected to correlate strongly with the sum of the baseline and occupant loads.

The process of separating these three load types begins with identifying the baseline load. At any given point in time, the refrigerator may be responding to one or all three of these load types. However, in the early morning hours of each day before the occupants begin to use the refrigerator, the refrigerator will remove all occupant-related loads and reach a steady state. Consumption will be at a minimum (except for the occasional defrost event). At these times the consumption is purely in response to the baseline load and is roughly proportional to the temperature difference across the refrigerators shell.

Using this information, a time-series for the baseline load can be established using monitored compartment and ambient temperatures. A time series of the temperature difference (ΔT) across the shell is calculated. Then the ΔT record is simply scaled with a proportionality constant until it coincides with the total power records during these times of pure baseline load (see Figure C.4).

Defrost periods are identified by analyzing the time-series records of freezer temperature and total power usage (see Appendix C.2). Sudden rises in freezer temperature and power usage are generally a clear indicator of the start of the defrost period.

The components of energy usage are then calculated by time-based integration of the total and baseline components. The total energy usage is the integral of the total power time series. The baseline energy is the integration of the baseline time series. The defrost energy is calculated from a time series of the difference between the total and the baseline load, and knowledge of the start and end times for each defrost event (see Section C.5). After the baseline and defrost components have been identified, the remaining component of the total is the occupant load.

3.2 Adjusting Metered Consumption for Annual Average Conditions

To best determine the savings that would occur under annual average conditions in New York City public housing, the metered consumption recorded at each site was adjusted using a correction factor (see the linear adjustment method in Section B.2 of the first project-year report [Pratt and Miller 1997]).

$$E_{\text{annual average}} = E_{\text{site}} \frac{\Delta T_{\text{annual average}}}{\Delta T_{\text{site}}} \tag{3.1}$$

where ΔT = T_{amb} - T_{int}
T_{amb} = room temperature
T_{int} = surface area-weighted average of the two compartment temperatures.

Annual average ambient and compartment temperatures are estimated and then subtracted to form an annual average temperature difference ($\Delta T_{\text{annual average}}$). Consumption at sites with ΔT conditions higher or lower than the annual average is adjusted by the ratio of the annual-average ΔT to the site's measured ΔT. Consumption at sites with unusually warm room temperature is reduced and consumption at mild sites is increased by this adjustment factor.

To estimate annual average ambient condition ($T_{\text{amb annual average}}$ in Equation 3.1), a relationship between indoor and outdoor temperatures for public housing in New York City is established. This relationship is based on measurements of indoor temperature and the daily outdoor temperature records from the National Climate Data Center (see Figure 3.1 and Section 4.2 of the 1996 project-year report [Pratt and Miller 1997]). The data used here include the snap-shot scanner measurements made in 1996 and the detailed logger measurements made in 1997. As shown in Figure B.1, in measurements of room temperature, snapshot scanner data correlates well with the daily averages produced from the logger data.

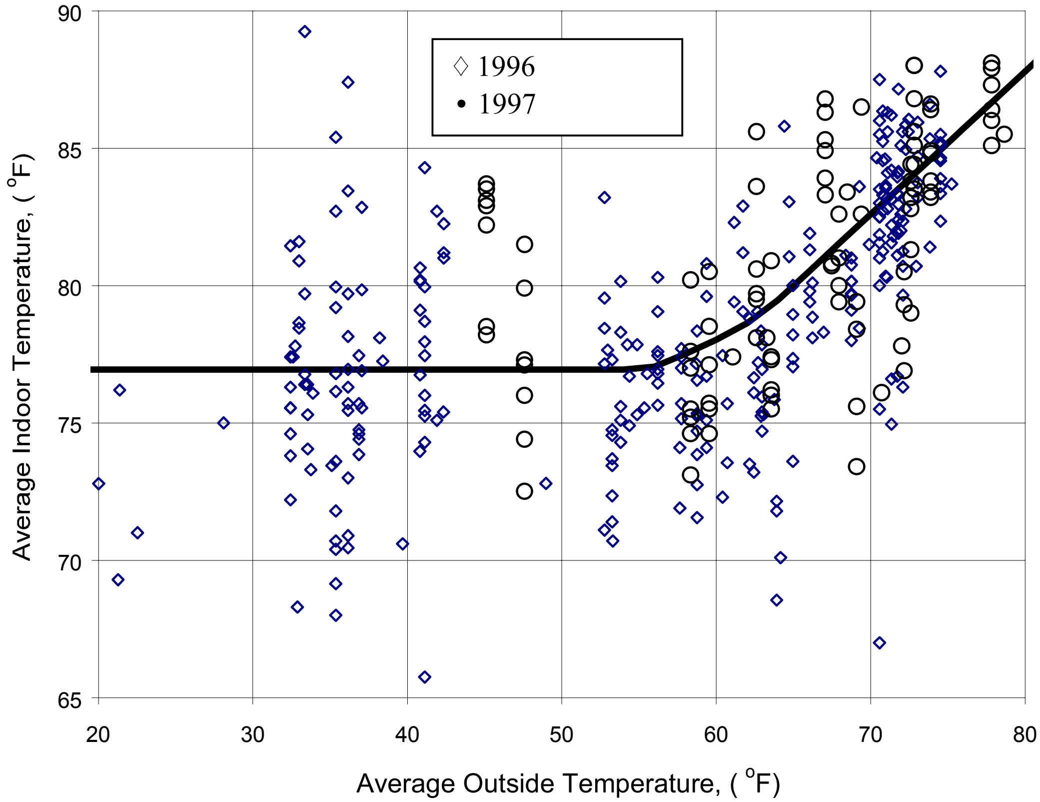

Figure 3.1. Relationship Between Indoor and Outdoor Temperatures

This relationship between indoor and outdoor temperature is used to produce a long-term average indoor temperature for the typical public-housing apartment in New York City. This average temperature is determined by driving the relationship with long-term average monthly outdoor temperature data (see Outdoor trace in Figure 3.2). The results are predictions of the indoor temperature by month (see Indoor trace in Figure 3.2). These 12 indoor points are then averaged to produce an annual average indoor temperature of 79.3°F.

The annual average interior temperature was set to 28.1°F ($T_{int\ annual\ average}$ in Equation 3.1). This value is derived from a surface area weighted average of a 38°F fresh-food temperature and a 5°F freezer compartment temperature (0.7*38 + 0.3*5). These compartment temperatures are common set points used in testing (10 CRF 430). This interior target is very close to the average of the interior temperature recorded for the existing automatic-defrost refrigerators, excluding malfunctioning refrigerators (28.3°F = 39.16*0.7 + 3.1*0.3). It is assumed that the controls in the refrigerators keep the interior temperatures relatively constant throughout the year.

The ambient and internal annual targets are combined to produce a target ΔT of 51.2°F. For site ΔT near 50°F, a 1°F change in target ΔT results in approximately a 2% change in savings (1 part in 50).

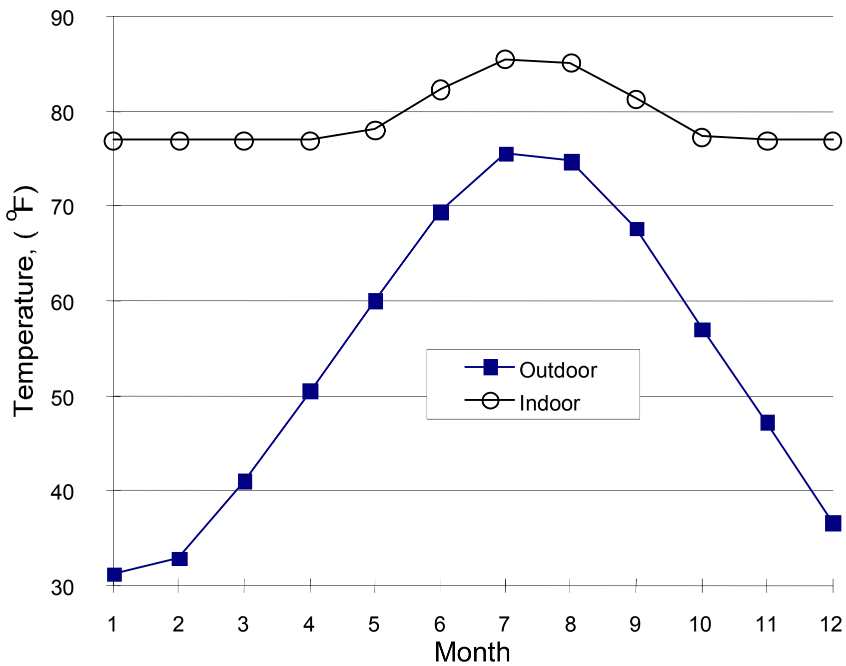

Figure 3.2. Response of Indoor Conditions to Outdoor Conditions

3.3 Constructing Relationships Between Consumption and Site/Refrigerator Characteristics

The development of consumption models starts with analyzing patterns and relationships in the metered sample. These relationships are needed so that consumption can be estimated for refrigerator models not represented in the metered sample.

3.3.1 Categorical Effects

Total consumption, components of consumption, and various parameters that describe the operating environment are presented in Table 3.1. This summary is organized to illustrate differences in consumption as affected by two key categorical variables[a]—the type of refrigerator (manual or automatic) and the type of occupants (elderly or not).

(a) Continuous variables represent quantitative data having a continuous range of values. Categorical variables, by contrast, represent qualitative data and are discrete, meaning they can assume only certain fixed numeric or nonnumeric values.

Table 3.1. Summary of Field Data by Defrost Characteristics and Occupant Age

Parameter		New	Existing	Existing					
				Automatic			Manual		
				Young	Elderly	E&Y[(a)]	Young	Elderly	E&Y
Label data on sample	Label, kWh/yr	437	792	715	646	709	887	919	898
	Year	1997	1987	1992	1993	1992	1980	1980	1980
	Age	0	10	5	4	5	17	17	17
	Volume, cft	15.0	13.1	13.8	13.6	13.8	12.1	12.0	12.1
Misc data	Food [1-4]	1.73	1.52	1.68	1.40	1.66	1.47	1.13	1.34
	Frost, in.	0.00	0.20	0.00	0.00	0.00	0.48	0.39	0.45
Usage as fraction of label	Total usage	1.11	1.10	1.20	1.11	1.19	1.11	0.72	0.96
	Occupant	0.41	0.28	0.38	0.26	0.37	0.19	0.11	0.15
	Baseline and defrost	0.70	0.72	0.71	0.85	0.73	0.83	0.61	0.71
	Defrost	0.087	0.048	0.078	0.082	0.079	0.00	0.00	0.00
Usage	Total usage, kWh/yr	484	859	876	715	862	961	664	850
	Occupant, kWh/yr	179	215	280	167	267	169	98	131
	Baseline, kWh/yr	270	543	457	496	461	750	566	661
	Defrost, kWh/yr	38	35	56	52	56	0	0	0
Temps	Ambient, °F	80.9	80.3	80.7	77.6	80.4	80.4	79.7	80.1
	Fresh Food, °F	38.7	40.5	40.1	37.2	39.8	40.2	43.1	41.3
	Freezer, °F	1.3	6.1	5.0	-2.5	4.3	7.5	10.1	8.4
Door openings	Frig counts/day (n)	33.4 (9)	46.7 (71)	51.5 (40)	48.8 (2)	51.3 (42)	44.3 (20)	28.6 (8)	39.8 (28)
	Frez counts/day (n)	10.1 (11)	14 (70)	15.8 (41)	5.9 (3)	15.1 (44)	16 (17)	4.8 (9)	12.1 (26)
	Frig open time, % (n)	0.94 (9)	0.9 (71)	0.97 (40)	0.86 (2)	0.96 (42)	0.92 (20)	0.44 (8)	0.78 (28)
	Frez open time, % (n)	0.21 (11)	0.31 (71)	0.26 (42)	0.09 (3)	0.25 (45)	0.4 (17)	0.45 (9)	0.42 (26)
Count	Sample	15	103	53	5	58	29	16	45
	High duty cycle	0	14	7	0	7	7	0	7

(a) Elderly and young.

The elderly classification is determined at the development level and is an indicator of whether the development is predominately elderly or not.[(a)] The elderly classification was assigned to all housing developments with an elderly/total count ratio greater than 0.25 and total/family count ratio less than 2.0. These developments include Laguardia, Haber, and Wise.

(a) Data on the number of occupants and their ages were collected at each apartment in the sample. These data were not used in this analysis because the quality of the data was questionable based on difficulties in data collection.

The effects of refrigerator type and occupant age are seen clearly in both total consumption and the occupant-consumption component when expressed as consumption ratios (fraction of label rating). The existing automatic refrigerators show a 24% ((1.19-0.96)/0.96) higher total-consumption ratio when compared with the existing manual-defrost refrigerators. The existing automatic refrigerators show a 150% ((0.37-0.15)/0.15) higher occupant-consumption ratio when compared with the existing manual refrigerators. For automatic refrigerators, the apartments in buildings populated mostly by nonelderly occupants showed a 46% ((0.38-0.26)/0.26) higher occupant-consumption ratio when compared with those populated mainly by elderly occupants. For manual refrigerators, the apartments in buildings populated mostly by nonelderly occupants showed a 73% ((0.19-0.11)/0.11) higher occupant-consumption ratio when compared with those populated mainly by elderly occupants.

Higher consumption ratios for automatic refrigerators and nonelderly occupants are also reflected in the food-loading and door-opening activity data. Higher occupant activity for the nonelderly is indicated in all the activity variables except for freezer door-open time for manual refrigerators. Higher consumption for automatic refrigerators, independent of occupant age, is shown by the higher consumption for the automatic refrigerators compared with the manual refrigerators in the nonelderly-occupied apartments.

3.3.2 Continuous Effects

The refrigerator's label rating is expected to be the strongest predictor of consumption among the variables describing the operating environment or characteristics of the refrigerator. However, as seen in Figure 3.3, the label rating is not, by itself, an excellent predictor of total consumption. The label rating fails to account for most of the large amount of variation in total consumption. Seventy-five percent of the variation is unaccounted for with the R^2 of 0.25 achieved with this simple relationship. This is expected because occupant activity is not at all represented in the label rating but is known to strongly affect total energy consumption.

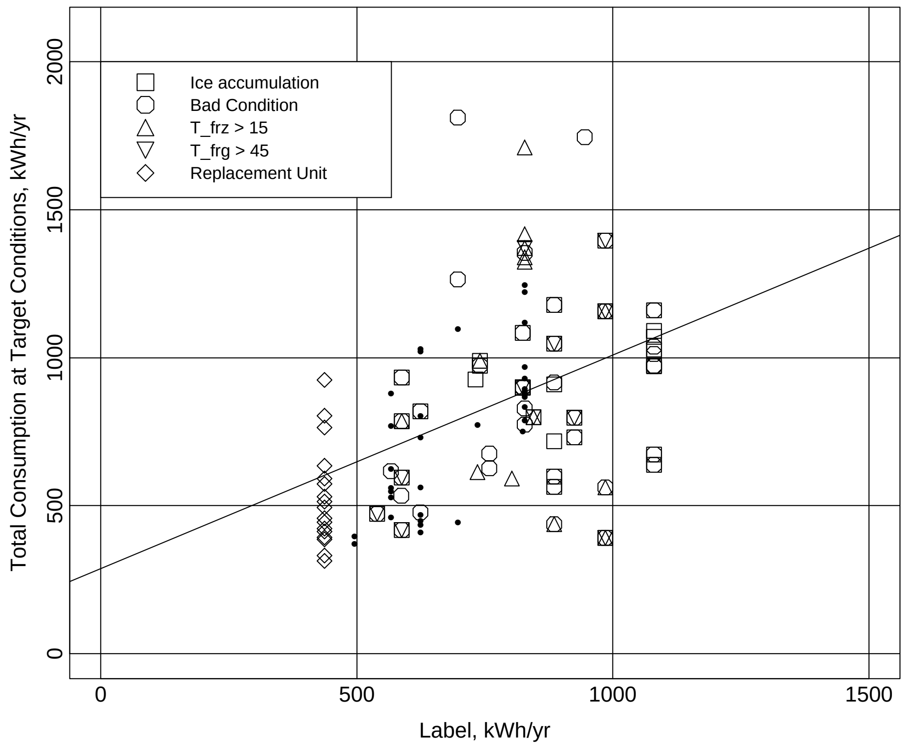

Figure 3.3. Total Consumption Modeled by Label Rating

A plot of the baseline component by itself yields a much stronger correlation ($R^2 = 0.56$) with the label rating (Figure 3.4). A large reduction in scatter is seen when Figure 3.3 is compared with Figure 3.4. This reduction is especially distinct when considering the new refrigerators plotted in each figure at a label rating of 437 kWh/yr.

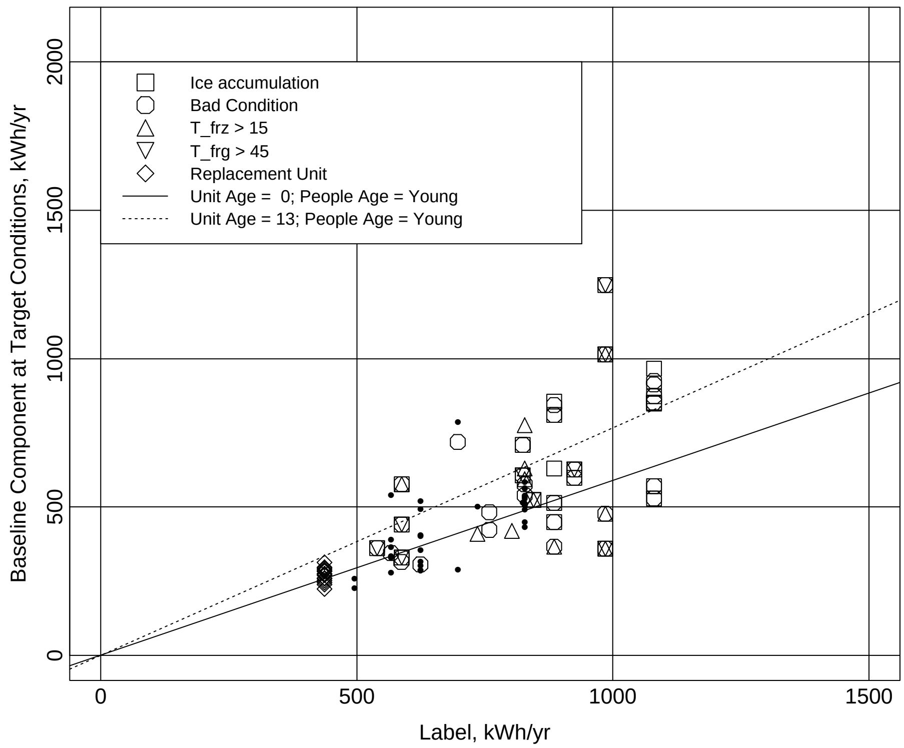

Figure 3.4. Baseline Component Modeled by Label Rating

The age of the refrigerator is also expected to account for part of the variation in the baseline component. Older refrigerators are more likely to have damaged seals or walls, or wet insulation. The prediction lines in Figure 3.4 result from including age in a regression model of the baseline component (see Section 3.3.4). The top line is a prediction for refrigerators 13 years of age. The lower line is a prediction for new refrigerators (age 0 years).

The response of the occupant-consumption ratio to door-opening events is shown in Figures 3.5 through 3.9. These plots show the occupant-consumption ratio increasing with door-opening counts or door-open duration. Figure 3.5 shows the occupant-consumption ratio's relationship to the sum of the fresh-food and freezer door-opening counts. The points in Figure 3.6 are a subset of those in Figure 3.5 and represent only refrigerators with automatic defrost. The points in Figure 3.7 are a subset of those in Figure 3.5 and represent only the refrigerators with manual defrost.

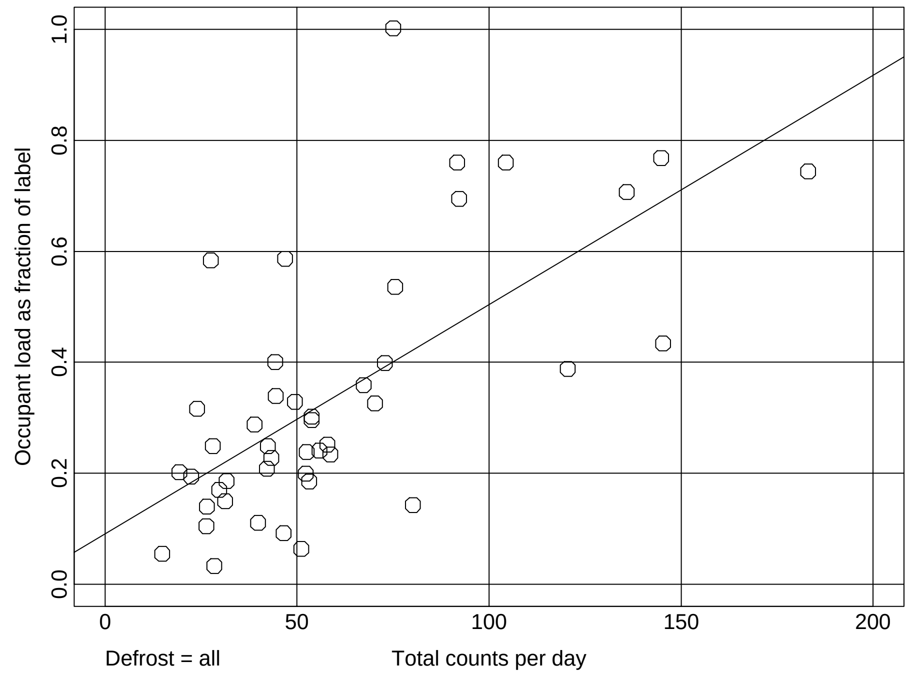

Figure 3.5. Occupant Component for Automatic and Manual Refrigerators

The automatic refrigerators have a higher response to occupant activity than do the manual refrigerators. This result further supports observations made in the previous section. Even when normalized by the label ratings, the automatic refrigerators show higher occupant loads than manual refrigerators at the same level of occupant activity. This difference in occupant load is evidence of a physical difference between the manual and automatic refrigerators that is not represented in the label rating.

Improved correlation between the occupant-consumption ratio and the occupant activity variables can be achieved by regressing against combinations of the occupant activity variables. Through regression techniques, the best fit can be found and insignificant variables (those that do not help account for variance in occupant-consumption ratio) can be dropped. The best fits for automatic and manual refrigerators are shown in Figures 3.8 and 3.9, respectively. The improvement in correlation can be seen when these two plots are compared with Figures 3.6 and 3.7. Again, evidence of a physical difference between the manual and automatic refrigerators exists that is not represented in the label rating. The automatic refrigerators show a significant response to door-open duration that is not seen in the manual refrigerators. The manual refrigerators respond mainly to the number of freezer-door openings. A discussion of the differences between refrigerators with manual and automatic defrost is given in Section 3.3.3.

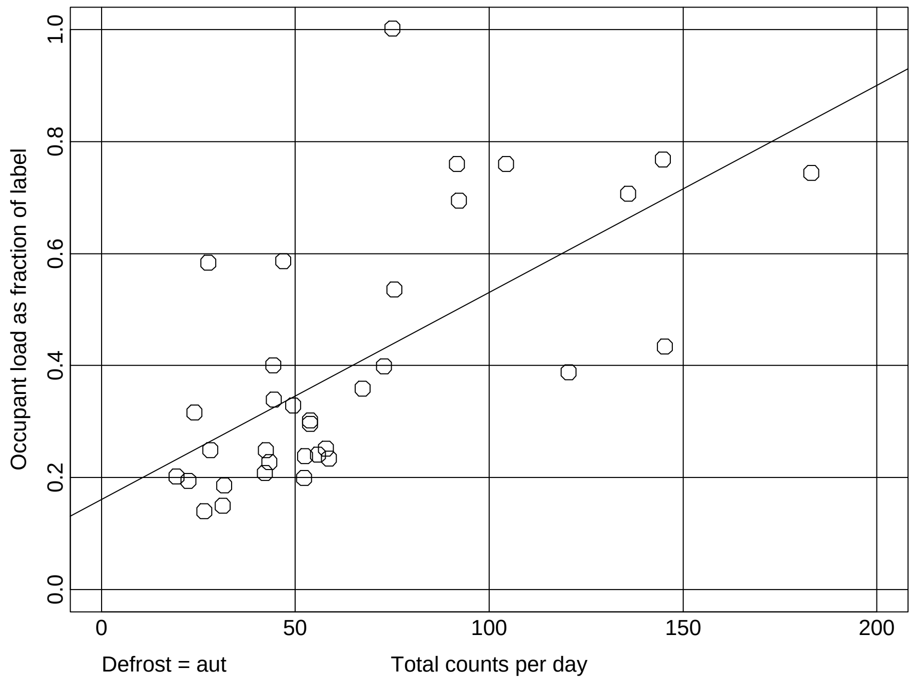

Figure 3.6. Occupant Component for Automatic Refrigerators

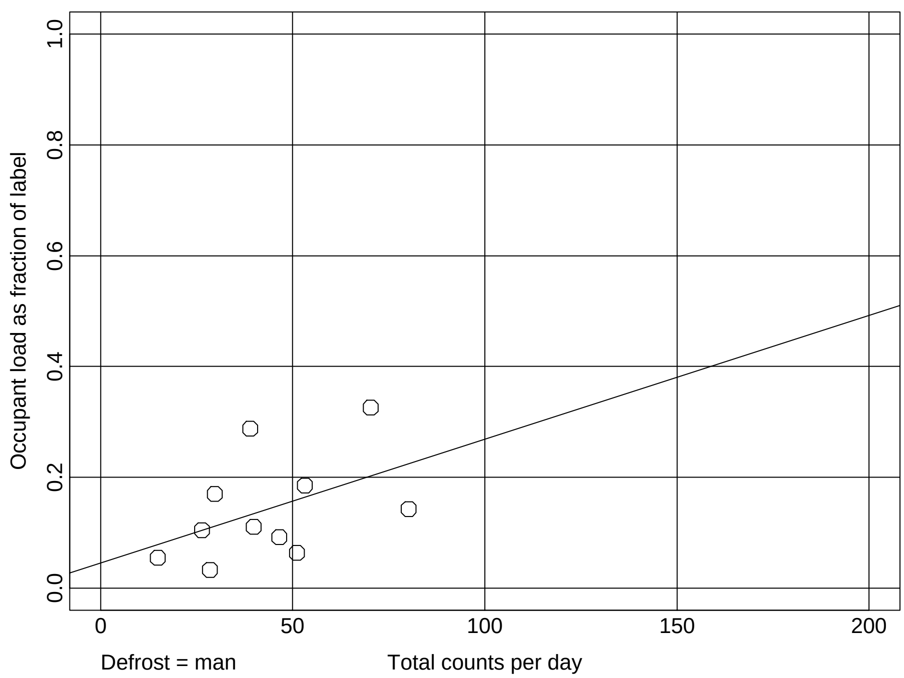

Figure 3.7. Occupant Component for Manual Refrigerators

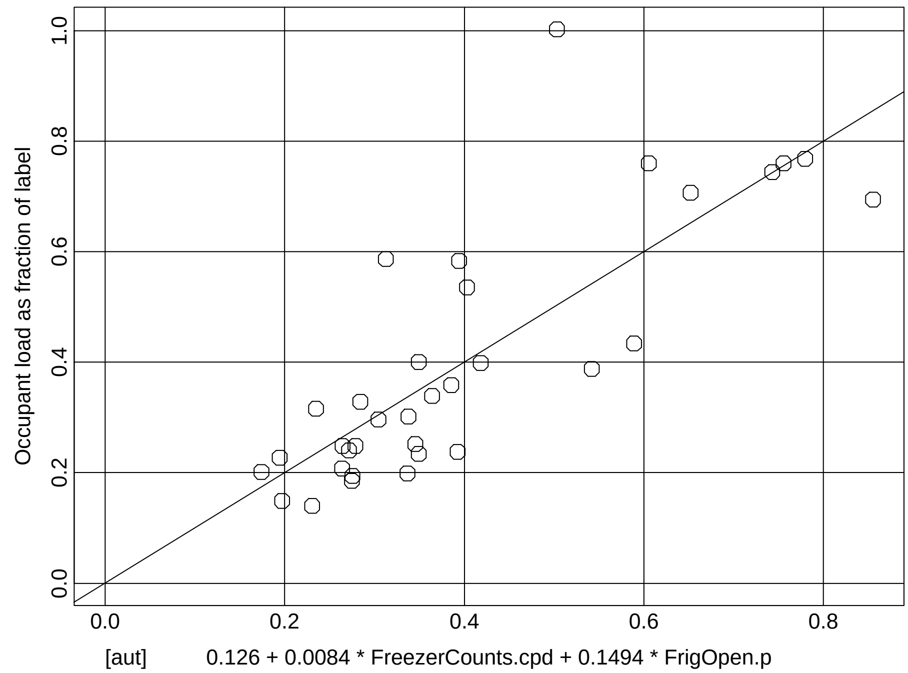

Figure 3.8. Occupant Component and Model of Automatic Refrigerators

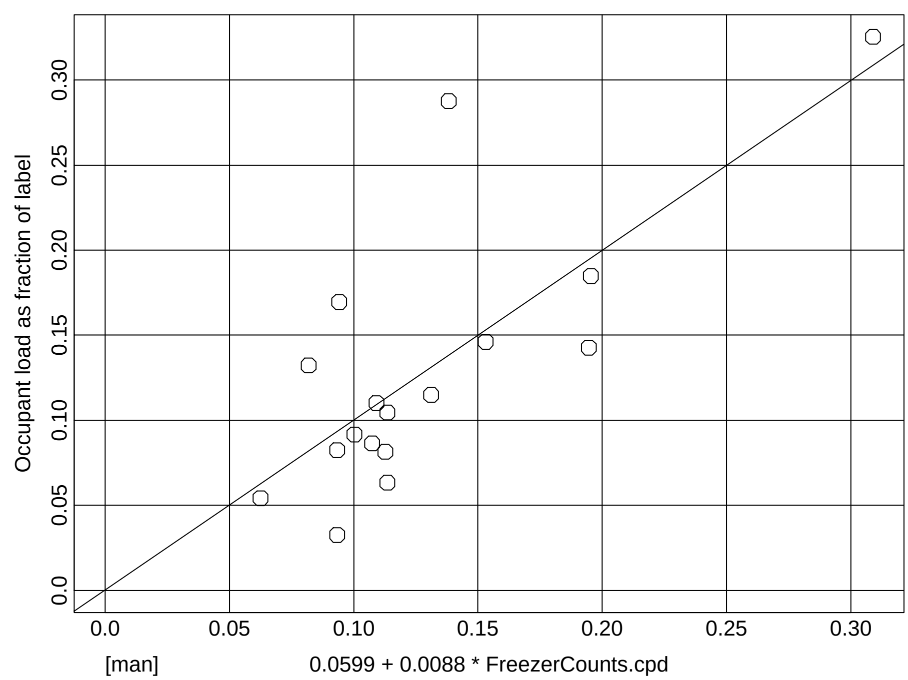

Figure 3.9. Occupant Component and Model of Manual Refrigerators

The defrost component relates strongly to the sum of the baseline and occupant components. This relationship is shown in Figure 3.10, and reflects the fact that the defrost events are triggered by a compressor run-time accumulator. Defrost events are initiated whenever the accumulator reaches a set threshold. The duration of the defrost event is determined by a coil-temperature sensor that terminates the event when the temperature reaches a target level. If there is no ice to melt, the duration will be relatively constant from one event to the next. The remaining variance in Figure 3.10 is probably due to differences in manufacturers' defrost hardware and variations in the amount of humidity (and associated propensity for ice accumulation) in different apartments.

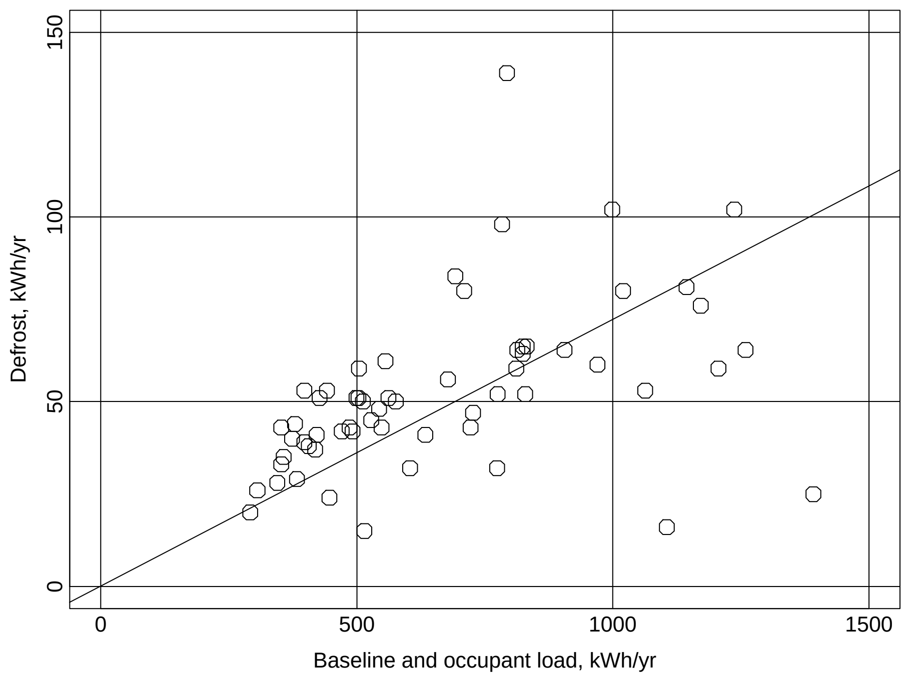

Figure 3.10. Defrost as Modeled by Sum of Baseline and Occupant Components

3.3.3 Discussion: Differences Between Manual and Automatic Defrost

As is seen in the summaries of the categorical data (Table 3.1) and the plots of the continuous data (Figure 3.5 through 3.9), the manual refrigerators appear to have less of an energy penalty (per unit of label) associated with opening the fresh-food compartment than the automatic refrigerators. A manufacturer of refrigerators was presented with these observations and PNNL requested an interpretation. In discussions with the manufacturer, several physical differences generally found between manual and automatic refrigerators, that are not accounted for in normal label rating testing, were identified:

1. Manual refrigerators have no fan. Automatic refrigerators have a fan that blows air over the evaporator coil and distributes air to the fresh-food and freezer compartments. When the doors are opened, this fan will continue to run if the compressor is on, or will start to run as warm room air comes into contact with the thermostat control. No feature exists to disable the compressor and fan

when the door is open. As a result, the fan operation greatly increases the heat exchange through the open door. Basically, cold air is being blown out into the room. It was suggested that the strength of this effect may be proportional to the volume of the refrigerator (the larger automatic refrigerators have more cold air to exchange).

2. Newer automatic refrigerators tend to have larger light bulbs than older manual refrigerators.

3. Ice accumulation in the manual refrigerators may be causing an artifact interaction with the analysis process. If manual refrigerators have some ice accumulation, this accumulation may reduce their capacity and raise the fraction of the total consumption that is identified as baseline because quiet times (time of equilibrium) are less likely to be reached during the night (see Appendix C, Section C.3). The potential result is an overestimate of the baseline load and an equal underestimate of the occupant load. Some evidence of this effect is apparent in Table 3.1 when comparing the automatic-young category with the manual-young category: the manual refrigerators have lower occupant load (as fraction of label) but higher baseline load. However, when the automatic-elderly and young (E&Y) category is compared with the manual-E&Y category, this pattern is not seen—the occupant load is significantly lower for the manual refrigerators and the baseline load is approximately the same. This effect appears to be secondary to effects 1 and 2 above.

The manufacturer observed that the metered estimates of defrost energy appeared somewhat low. The difficulties associated with identifying the defrost component are discussed in Appendix C. At sites with high occupant usage, the estimated defrost component is probably lower than the actual defrost component [and the estimate of the occupant component is higher than actual]. If process bias were the major cause of the higher occupant component for the automatic refrigerators, the effect would not be seen strongly in the totals. However, the behavior is clearly seen in the label-normalized usage totals in Table 3.1 (the total consumption ratio was 1.19 for automatic refrigerators and 0.96 for manual refrigerators).

Section C.5 discusses a test that was run to estimate the sensitivity of the savings estimate to the split between the occupant and defrost components. The sensitivity test showed the modeled-savings estimate to be very insensitive to the split between defrost and occupant components. A 50% increase in the defrost component caused a relatively small 1% increase in the savings estimate.

3.3.4 Regression: Model Structure and Constants

Observations discussed in Sections 3.3.1 and 3.3.2, along with an additional exploratory regression analysis, led to the functional form for a consumption model shown in Equation 3.2 and Table 3.2. This functional form reflects the key findings from the analysis of the metered sample:

Table 3.2. Summary of Model Coefficients

Variable		Coefficient	t-value
Baseline	L	$a_1 = 0.589$	15.9
	$L{*}N_{age}$	$a_2 = 0.0137$	4.1
	$L{*}C_{elderly}$	$a_3 = -0.0844$	NA
	$L{*}N_{age}{*}C_{elderly}$	$a_4 = -0.00196$	NA
Occupant	Intercept	$a_5 = 169$	5.7
	$C_{defrost}$	$a_6 = -222$	-4.2
	$E_{baseline}{*}C_{defrost}$	$a_7 = 0.750$	7.5
	$C_{elderly}$	$a_8 = -66.7$	NA
	$C_{defrost}{*}C_{elderly}$	$a_9 = 87.7$	NA
	$E_{baseline}{*}C_{defrost}{*}C_{elderly}$	$a_{10} = -0.296$	NA
Defrost	$(E_{baseline}+E_{occupant}){*}C_{defrost}$	$a_{11} = 0.0714$	21.4

Baseline Component

- The baseline component correlates well with label rating.

- Evidence of refrigerator degradation is significant in the baseline data. Older refrigerators are more degraded.

- Refrigerator degradation is also related to the ages of the occupants, indicating the refrigerators in the elderly apartments are better maintained.

Occupant Component

- The propensity for occupant consumption per unit of occupant activity is expected to be primarily driven by the volume of the refrigerator and the characteristics of its compressor. The aggregate of these characteristics is indirectly represented in the refrigerator's label rating. But in terms of explaining variance in the sample data, the baseline component itself appears to be the best fundamental characteristic, perhaps because it better reflects the vapor-compression cycle's degradation with age.

- The propensity for occupant consumption per unit of occupant activity is also strongly affected by whether the refrigerator automatically or manually defrosts. This effect is distinct from the label rating (or baseline component) because the behavior is more clearly seen in label-normalized data. A categorical variable that represents whether the refrigerator is automatic or manual is critical to account for variance in the occupant component.

- Occupant activity strongly affects occupant consumption. A categorical variable that describes whether the apartment buildings are predominantly populated by elderly people is a good indicator of refrigerator usage.

Defrost Component

- The defrost component correlates well with the sum of the baseline and occupant components.

$$E_{total} = E_{baseline} + E_{occupant} + E_{defrost} \tag{3.2}$$

where $E_{baseline}$ = f(label rating, refrigerator age, elderly)
$E_{occupant}$ = f($E_{baseline}$, defrost type, elderly)
$E_{defrost}$ = f($E_{baseline} + E_{occupant}$)

or more explicitly

$$E_{baseline} = L \cdot (a_1 + a_2 N_{age} + a_3 C_{elderly} + a_4 N_{age} C_{elderly})$$
$$E_{occupant} = a_5 + a_6 C_{defrost} + a_7 E_{baseline} C_{defrost} + a_8 C_{elderly} + a_9 C_{defrost} C_{elderly} + a_{10} E_{baseline} C_{defrost} C_{elderly}$$
$$E_{defrost} = a_{11} \cdot (E_{baseline} + E_{occupant})$$

where E_{total} = total annual energy consumption, kWh/yr
$E_{baseline}$ = baseline component of total energy consumption, kWh/h
$E_{occupant}$ = occupant component of total energy consumption, kWh/h
$E_{defrost}$ = defrost component of total energy consumption, kWh/h
L = label rating, kWh/yr
N_{age} = age of refrigerator, years
$C_{elderly}$ = categorical variable [elderly(1), nonelderly(0)]
$C_{defrost}$ = categorical variable [automatic(1), manual(0)].

The categorical variables $C_{elderly}$ and $C_{defrost}$ are binary. For example, $C_{defrost}$ is 1 for refrigerators with automatic defrosting and 0 for manuals. The contribution from a model term with categorical variables is zero unless all the categorical variables in that term are 1. For example, the last term in the occupant component model, E_{cond}*$C_{defrost}$*$C_{elderly}$, is zero for apartments with manual refrigerators or apartments in buildings with primarily elderly occupants.

The model is structured so that each term with a $C_{elderly}$ categorical variable has a corresponding term but without the $C_{elderly}$ variable. Because of this parallel structure, the terms with $C_{elderly}$ act as modifiers to their corresponding nonelderly terms. For nonelderly cases the elderly term drops out; for elderly cases the elderly term acts as a modifier to the nonelderly term. For example, the second and forth terms in the baseline model are a pair of this nature. This parallel structure is used to accommodate elderly effects in the baseline and occupant models.

The coefficients for all terms that include the $C_{elderly}$ categorical variable are derived from the regression coefficients for the nonelderly sites and field component data observed at the elderly sites.

This method was used in part to resolve regression difficulties resulting from the small number of elderly sites that had automatic refrigerators. It is applied to both the baseline and occupant component models.

The approach is to model the elderly sites by applying a correction factor to the form regressed from the nonelderly sites. The correction factor is simply the mean of the ratio of the observed field component data to the predicted component data at the elderly sites:

$$G_{\text{correction}} = \overline{\left(\frac{C_i}{F(\vec{x}_i)}\right)} \tag{3.3}$$

where F = model of energy component (based on nonelderly sides)
C_i = metered component of consumption at elderly site i
$\vec{x}_i$ = model input parameters at elderly site i.

For example, for the baseline model the correction factor is 0.857 and for the occupant model the correction factor is 0.605. Correction factors less than 1 indicate that models based purely on the nonelderly sites overestimate the consumption observed at the elderly sites.

The coefficients of the terms with the $C_{elderly}$ categorical variable can then be derived using the correction factor. It is assumed that the model terms with the categorical variable $C_{elderly}$ are linearly related, though a factor "k," to those derived using nonelderly sites. Then the additive modifiers of the categorical terms must equal the product of the correction factor and nonelderly model.

$$G_{\text{correction}} \cdot F(\vec{x}_i) = F(\vec{x}_i) + k \cdot F(\vec{x}_i) \tag{3.4}$$

Reducing the equation gives the result for the term factor that will derive elderly coefficients from the nonelderly coefficients.

$$k = G_{\text{correction}} - 1 \tag{3.5}$$

For example, the coefficient of the term $LC_{elderly}$ in the baseline model is calculated from the coefficient on the L terms as follows (see Table 3.2):

$$-.084 = (0.857 - 1) \cdot 0.589 \tag{3.6}$$

3.4 Estimating Energy Savings

This section illustrates how the regression relationships of Section 3.3.4 can be applied to estimate the energy savings in a replacement program. The example presented here uses the 1997 replacement program in NYCHA housing.

The regression models predict the total annual consumption of each existing and corresponding new refrigerator in the replacement program, which includes refrigerator models not represented at all in the metered sample. The relationship for total annual energy consumption (Equation 3.2) is evaluated for the population of refrigerators; i.e., for all distinct models of existing refrigerators found in each housing development. The characteristics of each distinct refrigerator model and the type of occupants in the building in which the refrigerators are located (dominated by elderly or nonelderly occupants) are inputs to the regression models. Sample and population average values of these parameters are shown in Table 3.3.

Table 3.3. Sample and Population Average Modeling Parameters

Parameter	Sample				Population		
	New	Existing					
	Automatic	All	Manual	Automatic	All	Manual	Automatic
Label, kWh/yr	437	792	898	709	862	910	728
Age	0.0	10.1	16.7	5.0	13.0	15.5	5.8
Volume, ft^3	15.0	13.1	12.1	13.8	12.7	12.4	13.6
Count	15	103	45	58	14,080	10,401	3679
Part of total	100%	100%	44%	56%	100%	74%	26%
Elderly Count	0	21	16	5	748	682	66
Part of subtotal	0%	20%	36%	9%	5%	7%	2%

For each distinct model of refrigerator (j), the corresponding counts, n_j of that refrigerator, are used to produce a count-weighted average for existing and new refrigerators (Equations 3.7 and 3.8).[a]

$$\overline{E}_{new} = \sum_j E_{new\,@\,j} \cdot \frac{n_j}{n_{total}} \tag{3.7}$$

$$\overline{E}_{existing} = \sum_j E_{existing\,@\,j} \cdot \frac{n_j}{n_{total}} \tag{3.8}$$

Refrigerators in the population with high duty cycle behavior (malfunctioning) cannot be represented with the component models. As discussed in Section C.6, the components of energy consumption for these refrigerators could not be established in the metered sample, and therefore the component models do not in any way represent the higher consumption levels of these malfunctioning refrigerators.

Rather, high duty cycle behavior is accounted for by estimating the consumption level of typical high duty cycle refrigerators in the population and the high duty cycle refrigerator fraction of the population.

(a) When either a model number was unknown or a label rating could not be found for an existing refrigerator, the refrigerator is excluded from the savings analyses (4% are excluded in 1997).

Their consumption level is estimated as the product of their label ratio in the sample and the average label of the existing refrigerators in the population (Equation 3.9).

$$\overline{E}_{hdc} = \overline{R}_{existing} \cdot \overline{\left(\frac{E_{total}}{R}\right)}_{hdc-sample} \qquad (3.9)$$

Their fraction in the population (x_{hdc}=0.173) is estimated by scaling the fraction found in the metered sample ($x_{hdc\text{-}sample}$=0.135) with age (Equation 3.10). If the population is older than the sample, the high duty cycle fraction in the sample is scaled up by the age ratio to represent the population.

$$x_{hdc} = x_{hdc-sample} \cdot \left(\frac{\overline{N}_{age-population}}{\overline{N}_{age-sample}}\right) \qquad (3.10)$$

The overall average consumption for the existing refrigerators is then calculated with the high duty cycle fraction for the population. It is represented as the blended average of those existing refrigerators having high duty cycle behavior and those that do not (Equation 3.11, and the column titled "Blend" in Table 3.4).

$$\overline{E}'_{existing} = (1 - x_{hdc})\overline{E}_{existing} + x_{hdc}\overline{E}_{hdc} \qquad (3.11)$$

The estimated per-unit savings is then calculated as the difference between the average consumption for the existing refrigerators and the average consumption for the new refrigerators (Equation 3.12). The results for 1997 are given in Table 3.4.

$$\overline{E}_{savings} = \overline{E}'_{existing} - \overline{E}_{new} \qquad (3.12)$$

Table 3.4. Energy Savings Estimate for the Population

Parameter	Existing			New	Difference
	High Duty Cycle	Normal	Blend		
Fraction of population	17%	83%	100%	100%	0%
Label, kWh/yr	862	862	862	437	425
Baseline, kWh/yr	NA	664	NA	256	NA
Occupant, kWh/yr	NA	203	NA	136	NA
Defrost, kWh/yr	NA	15	NA	28	NA
Total, kWh/yr	1351	882	**963**	**420**	**543**
Label Ratio	1.57	1.02	1.12	0.96	0.16

Differences between the characteristics of the sample and the population are summarized in Table 3.3. The sample consisted of 56% automatic refrigerators while the population actually had only 26% automatic refrigerators. Of the apartments sampled with existing refrigerators, 20% of the refrigerators were in buildings classified as elderly, while in the population only 5% were classified as elderly. The average age in the sample was 10.1 years but was significantly higher at 13.0 years in the population.

The average label for the existing refrigerators in the sample was 792 kWh/yr but was significantly higher in the population at 862 kWh/yr. The higher average label in the population mainly reflects the higher concentration of older manual refrigerators, but also the manual and automatic label averages in the population are slightly higher than their corresponding averages in the sample.

These differences between the characteristics of the sample and the characteristics of the population are the fundamental reason why the modeled result for the population savings (543 kWh/yr) is substantially different than the savings indicated directly in the sample data (361 kWh/yr, raw with no ΔT adjustment; 375 kWh/yr, ΔT adjusted). Higher refrigerator age and a lower concentration of elderly in the population will increase the modeled estimate of consumption (and corresponding savings) for the population.

The higher representation by the manual refrigerators in the population impacts the modeled savings estimates in two opposing ways. The higher label ratio of the existing manual refrigerators increases the savings estimate but the lower occupant consumption associated with manual refrigerators decreases it. However, the label effect is more dominant. The higher concentration of manual refrigerators in the population is responsible for part of the higher (than the sample) modeled-population consumption (and corresponding savings).

The new refrigerators are significantly larger than the average replaced refrigerators (15.0 ft^3 compared to 12.7 ft^3), providing considerable added amenity for the residents. Because refrigerator heat loss and hence energy consumption are directly proportional to surface area, savings would be even higher if the new refrigerators were the same size as the existing refrigerators. A simple estimate of the extra energy savings that would have occurred had the existing refrigerators been as large as the new refrigerators (based on the ratio of the volumes) is 174 kWh/yr.

$$\text{volume effect} = 963\left(\frac{15.0\ \text{ft}^3}{12.7\ \text{ft}^3}\right) - 963 = 174\ \text{kWh/yr}$$

3.5 Demand Savings by Time of Day and Year

This section describes the development of the time-of-day load-shape curves from refrigerators monitored in New York City in 1997. It also presents an example (NYCHA Housing 1996) of how these load curves can be used with building peak data in estimating demand savings.

3.5.1 Demand Savings and Load Shapes

Coincident peak demand for the refrigerators in this project are calculated based on their contribution to the building load at the time of building-peak power usage:

$$P_{peak} = P_{average} F_{peak/average}(t_{coincident}) \qquad (3.13)$$

where P_{peak} = annual average power at time of building peak, kW
$P_{average}$ = annual average refrigerator power consumption, kW
$F_{peak/avearage}$ = ratio of hourly average to total average (by time of day)
$t_{coincident}$ = time of day for building peak (coincidence information).

$P_{average}$ is based on gross power-usage records (either metered or modeled) for each model of refrigerator and is simply the annual load estimate divided by the number of hours in a year.

$$P_{average} = \frac{E_{annual}}{8760} \qquad (3.14)$$

where E_{annual} = annualized energy consumption (kWh/yr).

The $F_{peak/average}$ is determined from detailed field monitoring on 94 refrigerators (each logged at 15-minute intervals for approximately six or more days). A plot of $F_{peak/average}$ is shown in Figure 3.11 as a function of time of day. Each point on this plot is determined by the average consumption for a specific hour divided by the average consumption for all 24 hours.

To remove cycling variations (and anomalous contribution to the load shape), the individual time-series data are first smoothed by substituting the average values resulting from a moving window (see Section C.1). Each of the 94 time series is averaged by hour of day. These 94 load shapes are then given equal weight in determining the overall average load shapes. This averaging of the averages is necessary to avoid giving higher weight to the refrigerators with longer monitoring periods.

The refrigerators were monitored for a week each during the period January to September. If the results are separated into two seasons, winter and summer (summer start dates ranging from 5/15 to 9/15), the load shapes appearing in Figure 3.11 result. For refrigerators metered in the summer, the peak load (maximum value of $F_{peak/average}$) occurred at 9 p.m. The load at summer peak was 1.132 times higher than the average load. For refrigerators metered in the winter, the peak load occurred at 4 p.m. The load at winter peak was 1.094 times higher than the average load.

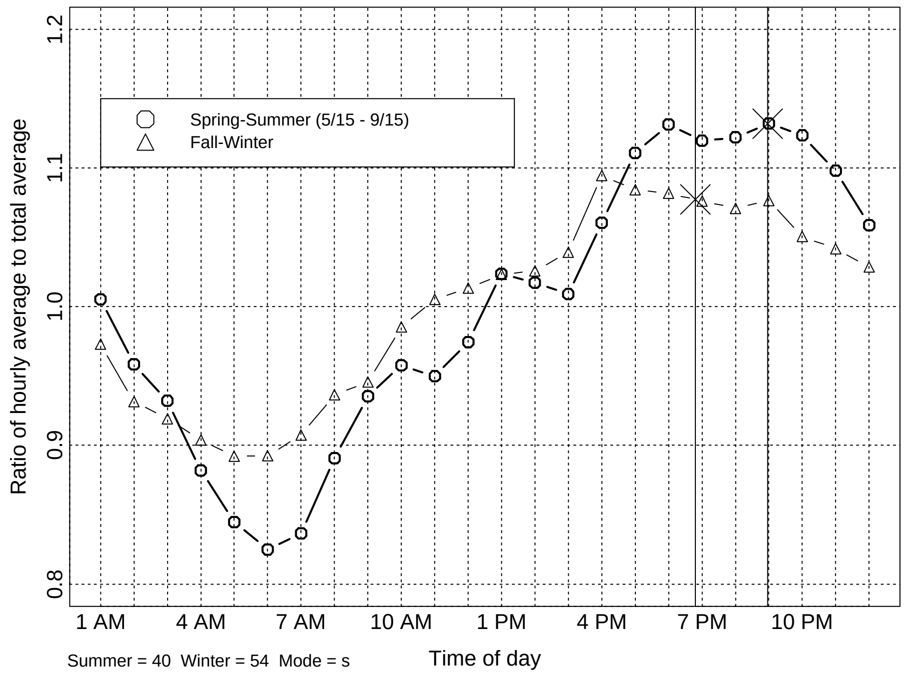

Figure 3.11. Seasonal Variations in Coincident Demand Peak

3.5.2 Summer and Winter Coincident Peak

$F_{peak/average}$ ($t_{coincident}$) is then determined as the value of $F_{peak/average}$ at the time of building peak consumption. For example, this can be done for both summer and winter periods using the average of building peak-time data from 10 buildings in New York City. (See Table C.1 on building data in the final report from project year 1996 [Pratt and Miller 1997].)

The building summer peak (8:58 p.m.) and the building winter peak (6:48 p.m.) are shown with vertical lines in Figure 3.11. The coincident peak in the refrigerator's seasonal-load shapes is marked with an X. The time-weighted average of these two F values, 1.095, is used to represent the whole year.

$$1.095 = \frac{(1.077 \cdot 8 + 1.132 \cdot 4)}{12}$$

The annual average demand power at building peak is then the product of $F_{peak/average}$ and the annual average refrigerator wattage (annual kWh/8760). These demand power values are calculated and shown for both existing and new refrigerators in Table 3.5.

Table 3.5. Energy and Demand Consumption and Savings

Refrigerator Group	Label kWh/yr	Label Ratio	Energy kWh/yr	Demand kW
Existing, Consumption	862	1.12	963	0.120
New, Consumption	437	0.96	420	0.053
Savings			543	0.068

4.0 Future Applications of the Regression Models

The following sections discuss the application of the regression models in estimating savings in future years in New York City and in other cities. Limitations of the models are identified and discussed. These sections also serve to point to future work that could extend the applicability of the regression models.

4.1 Primary Limitations

The regression models have only very simple demographic capabilities. The most significant shortcoming in the data collection process was in characterizing the occupants in the metered apartments. As was mentioned in Section 3.3.1, the quality of the survey of occupant characteristics, in the metered apartments, was determined to be low. Mainly for this reason, only a gross categorical variable was used to describe the demographics of the sample and population: predominately elderly or not. This fundamentally limited our capability to model the occupant component of the load. A consequence, likely related to the demographic issue, is the lack of significance of the volume characteristic in the regressions.

Refrigerator volume did not appear significant in our analysis. This might be expected because of the relatively small spread in refrigerator sizes in the population (constrained by kitchen size and layout). A more diverse population of refrigerator sizes would likely give added strength to volume terms in the regression models. However, it is expected that volume and demographic variables interact (high-volume refrigerators, per unit of label, with high door-opening usage will have a higher occupant component, per unit of label, than a corresponding smaller refrigerator). And so it is thought that the lack of significance of the volume terms may be partially caused by variance left in the regression model due to the weak demographics.

An obvious action to improve the occupant characteristics in the metering database is to either re-survey those apartments using different survey methods or to use existing NYCHA demographic data on those apartments. As time goes by, an after-the-fact survey will deviate from the actual demographics existing during the 1997 metering. The NYCHA demographics records hold the most promise for better representation.

Moisture (humidity) is not accounted for in the regression models. Discussions with refrigerator manufacturers informed us that high humidity could significantly increase the defrost component. However, this study shows the defrost component to be less than ten percent of the totals in New York City and therefore, a significant change in the defrost component might be expected to cause as much as a ten percent increase or decrease in bottom-line savings.

The regression models do not account for significant design changes whose impact might not be seen in standard label testing procedures. A design change that affects field performance but does not affect label testing (no door openings) performance, would not be accounted for in these models. For example, if a switch was installed to disable the fan and compressor when the door is open, this would reduce the occupant component but would have no impact on the label rating.

4.2 New York City in Future Years

If the replacement refrigerators are identical to those used in the 1997 project year, there are no significant changes that would diminish the validity of the models. The existing refrigerators that are removed may be somewhat different in age and model type than those removed in 1997. But it is thought that subtle changes in the characteristics of population (as the program moves on to different NYCHA developments) can be accounted for in the regression models.

If the compartment-to-ambient temperature difference is significantly different in subsequent years, the models' outputs must be adjusted. For example, if in some future year air-conditioning is installed in all apartments, the target ΔT_{1997} used in this analysis would not be appropriate; the savings estimate would be too high. The regression model estimate of savings should be corrected by the following factor:

$$F = \frac{\Delta T_{future}}{\Delta T_{1997}} \tag{4.1}$$

If the replacement refrigerator has a significantly different design or volume (from the replacement refrigerator in 1997) then the model should be applied only to the existing units. The least costly approach, in this case, is to meter a small sample of new units (20 to 30) and use a simple temperature-corrected average of their annualized total energy usage. Caution should be used in selecting the apartments for monitoring; the apartments selected should be those that best represent the population. For example, if the population is not predominately elderly, do not meter units that are occupied by elderly people.

4.3 Other Cities

The regression models should only be applied in another city if it can be characterized as similar to New York. The similarity must be in the areas where the model is the weakest: demographics and refrigerator volume. Some changes in climate can accommodated.

If the monthly outdoor temperatures are significantly different from New York, but the apartment buildings and their operation are similar, the relationship shown in Figure 3.1 could be used to develop a new annual average kitchen temperature.

There is no method at this time to estimate the impact of a change to a high- or low-humidity climate.

It is thought that a calibration/test exercise would be a prudent first step before applying the regression models to other sites. In this exercise, the model is compared to the results of a metering study in another city.

5.0 Conclusions

- The ***baseline component*** correlates strongly with label rating and the age of the refrigerator. Evidence of refrigerator degradation is significant in the baseline data. The magnitude of the effect is related to the age of the refrigerator. (See Section 3.3.)

- A categorical variable, which indicates if the apartment building is predominately populated by elderly occupants, was shown to be significant in the correlation with the ***baseline component***, indicating that refrigerator degradation is related to the age of the occupants. Apparently the refrigerators in the elderly apartments are better maintained. (See Section 3.3.)

- Occupant activity strongly affects the magnitude of the ***occupant component***. A categorical variable that describes whether the apartment buildings are predominantly populated by elderly occupants was found to be an adequate indicator of refrigerator usage. (See Section 3.3.)

- ***Refrigerators with automatic defrost have higher occupant consumption (on a label-normalized basis) per unit of occupant activity than refrigerators with manual defrost***. The fans in refrigerators with automatic defrost appear to significantly increase air exchange with the room during times that doors are open. This effect is not represented in label ratings determined from closed-door testing. A categorical variable that represents whether the refrigerator is automatic or manual is critical to account for variance in the occupant component. (See Section 3.3.)

- The propensity for occupant consumption per unit of occupant activity was expected to be primarily driven by the volume of the refrigerator and the characteristics of its compressor. The aggregate of these characteristics is indirectly represented in the refrigerator's label rating. But in terms of explaining variance in the sample data, the baseline component itself appears to be the best fundamental characteristic, perhaps because it better reflects the vapor-compression cycle's degradation with age. ***Volume may appear in future studies as a more significant descriptive variable if there is more diversity in refrigerator volume in the population (and sample)***. (See Section 3.3.)

- The ***defrost component*** correlates well with the sum of the baseline and occupant components. (See Section 3.3.)

- ***Accounting for differences between the characteristics of the metered sample and the general population are important for the accuracy of the savings estimate***. Significant differences were found in several characterizing parameters: age of existing refrigerators, concentration of manual refrigerators, building characteristics (predominantly occupied by elderly or nonelderly occupants). All of these effects contributed to significantly higher modeled savings for the population in comparison to the metered sample averages. (See Section 3.4.)

- For refrigerators metered in the ***summer***, the peak load occurred at ***9:00 p.m***. ***The load at summer peak was 1.132 times higher than the average load.*** For refrigerators metered in the ***winter***, the peak load occurred at ***4:00 p.m***. ***The load at winter peak was 1.094 times higher than the average load.*** (See Section 3.5.)

- The regression models can be applied to future program years in New York City. If future replacement units are significantly different in design or volume it is recommended that the regression models be applied only to the existing units and that a sample of replacement units be monitored (see Section 4.0).

- The regression models should not generally be applied to other cities. Constraints in application originate in the limited capabilities of the regression models to represent effects driven by occupant usage and refrigerator volume. With caution, the models can be applied in sites characterized as similar to NYCHA housing in New York. Similarity needs to be judged based on demographics, apartment building characteristics and operation, refrigerator volume, and weather (see Section 4.0).

6.0 References

10 CFR 430, Subpart B. App. A1. 1995. Code of Federal Regulations. *Uniform Test Method for Measuring the Energy Consumption of Electric Refrigerators and Electric Refrigerator-Freezers.*

Association of Home Appliance Manufacturers (AHAM). 1995. *1995 Directory of Certified Refrigerators and Freezers*.

Pratt, R. G. and J. D. Miller. 1997. *The New York Power Authority's Energy-Efficient Refrigerator Program for the New York City Housing Authority – Savings Evaluation*, PNNL-11643, Pacific Northwest National Laboratory, Richland, Washington.

Wisniewski, E. J. and R. G. Pratt. 1997. *Impacts of CEE's 1996-1997 Super-Efficient Apartment-Sized Refrigerator Initiative*. Presented at the National Energy Program Evaluation Conference, August 29, 1997, Chicago, Illinois.

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Appendix A

Monitoring Equipment

Appendix A

Monitoring Equipment

Detailed monitoring of power consumption, occupant door events, and ambient and refrigerator compartment temperatures was done in each of 121 apartments. Instrumentation included seven sets of data loggers. Each of the seven sets of loggers was deployed weekly. Each set includes six loggers:

1. power
2. room temperature
3. fresh-food compartment temperature
4. freezer compartment temperature
5. fresh-food door events
6. freezer door events.

After four rounds of deployment (4 weeks, 28 apartments), the loggers were shipped to Richland, Washington for downloading and analysis of the data. The empty loggers were then returned to New York City for another month of monitoring. This process was repeated five times throughout a period starting in April 1997 and ending in November 1997.

Each logger is set to record a sample average every 15 minutes. The result from each logger is a time series of 15-minute averages (96 points per day).

All loggers can operate off internal batteries. This feature offers protection from the somewhat irregular power in the public housing apartment buildings in New York City and insures a continuous time series record even in the case of a power outage.

A.1 Power Consumption

The power logger records a time series of voltage, current, true power, and power factor (Pacific Science and Technology; Elite-1 Logger). Voltage and current are sampled at a rate of 7.68 kHz (128 points per waveform). Sampled data are used to calculate true power and power factor. Data are averaged and recorded every fifteen minutes. The result is a time series with four averages recorded every hour (96 points per day).

The power logger has 12-bit resolution (1 part in 4096), corresponding to a resolution of 0.1 volts on the voltage measurement. A 20-amp current transformer (CT) is used with the logger yielding a 0.005-amp resolution (0.5% on a 1-amp load).

The power logger is powered by either a D.C. transformer (wall plug-in) or on its internal batteries. If wall power fails, the refrigerator continues to sample, but at a reduced rate, using its internal battery. In either mode, the refrigerator yields a 15-minute average.

The power loggers can take 32000 readings. In each 15-minute period, one reading is logged for each of four elements of the data record (voltage, current, power, power factor), yielding 96, 15-minute records in a day. In this configuration the logger can make a continuous time series with a maximum length of 83.3 days (32000/96/4).

The power instrumentation consists of two elements: the logger electronics (right side in Figure A.1) and the CT box, power strip, and D.C. power supply (left side in Figure A.1). The refrigerator is plugged into the CT box, which in turn is plugged into the power strip. The CT box contains a CT and electrical connections for the line voltage sampling. Current measurements are made on the power lines that pass through the CT. Data is recovered from the logger via an RS-232 interface seen on the front edge of the logger box.

A.2 Occupant Door Events

The event loggers make a time-stamp record of contact openings and closings in a reed switch (Brultech Research Inc; EL-100 Event logger). The reed switch is mounted on the main body of the refrigerator and the magnet is mounted on the door (Figure A.2). When the door opens (Figure A.3) and the magnet separates from the switch, the contact state of the switch changes. Each opening or closing produces a time-stamp record in the logger.

This log of transitions can be post-processed to develop a time series of door events. The time series can be binned at 15-minute intervals to give a time series of door-opening counts and door-open time.

The event loggers have internal memory sufficient to hold up to 8000 transitions. For a high rate of transition, 800 per week (refrigerator door opened 400 times in a week), the logger memory would support 70 days of monitoring (8000/(800/7)).

A.3 Compartment Temperature

The electronics for each temperature logger is contained in a small matchbox-size shell (Onset Computer Corporation; StowAway XTI logger). An external thermistor is plugged into the logger. The thermistor is then attached to the inner surface of a moisture-proof canister (Figure A.4). Before sealing the logger inside the canister, desiccant is enclosed. The size of the sealed canister is slightly smaller than a small soda can (Figure A.5).

The temperature loggers can hold 7944 records. For a 15-minute interval time series, this memory capacity gives a maximum deployment time of 82.75 days (7944/96). Accuracy is reported by the manufacturer to be better than ±1.0°C over its applicable range of –39°C to + 75°C.

Figure A.1. Current Transformer Box and Power Logger

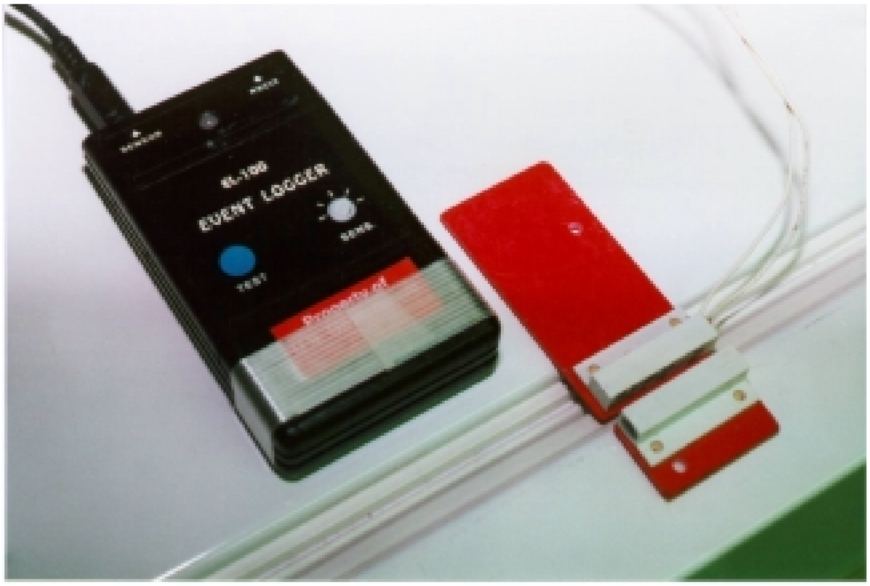

Figure A.2. Event Logger, Magnet, and Reed Switch Mounted on Refrigerator

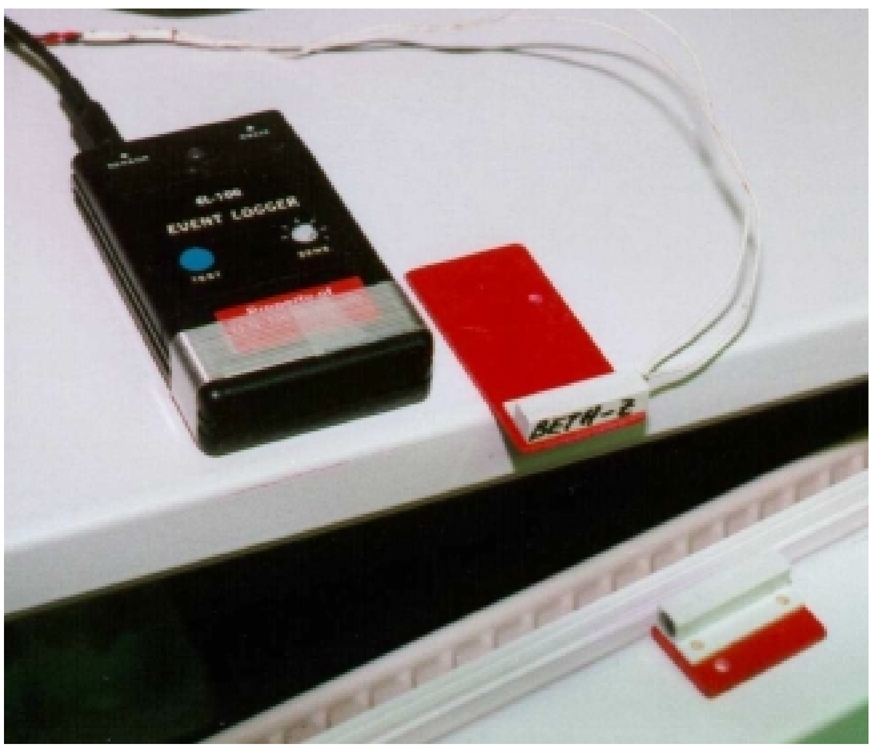

Figure A.3. Event Logger, Magnet, and Reed Switch Mounted on Refrigerator – Refrigerator Door Open

Figure A.4. Temperature Logger, Moisture-Proof Canister, and Desiccant Bags

Figure A.5. Temperature Logger Inside of Closed Canister

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Appendix B

Occupant Survey

Appendix B

Occupant Survey

A survey of information relating to refrigerator performance was taken in each monitored apartment. Survey data were collected at the beginning and end of the monitoring period. These data serve to quantify the state of the refrigerator and establish the nature of the operating environment of both the existing and replacement refrigerators. Data were collected on the refrigerator, apartment characteristics, and occupants (see Figure B.1)

B.1 Existing Refrigerator Data

Characteristics of the refrigerator were collected, including the manufacturer's name and the refrigerator's model number. Also, data reflecting the relative condition of the refrigerator and the degree of food loading were recorded. These data were collected through visual observation of the refrigerator's shell, seals, state of defrost, and stacking of food on shelves.

B.2 Infrared Scanner Measurements

Room and fresh-food and freezer compartment and temperatures were also measured with an infrared scanner (Exergen microscanner model D501). These snapshot measurements were made at the time of installation and removal of the metering equipment. For the compartment temperature measurements, the scanner was set to record the minimum temperature during a scan and hold that value in memory. All exposed surfaces in each compartment were then scanned and the value for the lowest surface temperature was recorded.

These data served as a backup to the time-series logger measurements of the compartment temperatures. Logger measurements were made with thermistors and recorded every 15 minutes throughout the monitoring period (see Appendix A).

At sites where both snapshot scanner and time-series thermistor measurements were taken, a relationship between the two types of measurements was developed (see Figure B.2). Each point on the plot represents the average of the two snapshot scanner readings (x-axis) and the average of the roughly 672 (4*24*7) thermistor readings (y-axis).

The compartment data points are regressed to form a linear correction relationship, to allow for a correction of the scanner readings so they can be used at sites where temperature logger data were unavailable. This relationship is also useful in establishing compatibility with the data collected during the 1996 project year. The fit is shown as the solid line in the plot. The highest group of points is from room air measurements; the lowest group is from freezer compartment measurements. The infrared

Figure B.1. 1997 NY Refrigerator Project Survey Data Form

Site

Weekly Installation No. (a,b,c or d): ☐

Name: ☐

Apt No.: ☐

Building: ☐

Development: ☐

Borough: ☐

Phone: ☐

Floor: ☐ of ☐ (ex.: 2 of 10)

No. Bedrooms: ☐

Side of bldg: ☐N ☐S ☐E ☐W

Temperatures

	Installation	Removal
Fresh Food:	☐ °F	☐ °F
Freezer:	☐ °F	☐ °F
Kitchen:	☐ °F	☐ °F

Logger Lights:

Power ☐ Room Temp. ☐

Frig-Events ☐ Freezer-Events ☐

Loggers

☐ Sara ☐ Mary ☐ Beth ☐ Ruth ☐ Karl ☐ Pete ☐ Gary

Installation Completed: Date: / /97 Time: : m

Removal Started: Date: / /97 Time: : m

No. of Occupants

Total number: ☐

Children (age: 0-9): ☐

Teenagers (10-20): ☐

Adults (21-64): ☐

Elders (65 and up): ☐

Typical number home 9am-3pm weekdays ☐

Comments:

- note any nearby heat sources
- other

Refrigerator

New ☐ **Existing** ☐ **Size** ☐ **ft^3**

Model No.: ☐

Brand: ☐ **No. Doors:** ☐ 1 ☐ 2

Condition: ☐ OK (age appropriate but still in good shape)

☐ Bad (doors don't close well, bad seals, dents)

Built: Label: ☐ Est.: ☐ 1990s ☐ 1980s ☐ 1970s

Frost Build Up in Freezer: ☐ in. of ice thickness

Anti-Sweat Switch: ☐ On ☐ Off ☐ No Switch

Fresh Food start	end		**Temperature Control Settings**		**Freezer** start	end
		full scale		full scale		
☐	☐	☐		☐	☐	☐

start	end	**Compartment Food Loadings**	start	end
☐	☐	Very High (100% full & stacked)	☐	☐
☐	☐	High (shelves >90% full, not stacked)	☐	☐
☐	☐	Medium (shelves <90% >25% full)	☐	☐
☐	☐	Low (shelves <25% full)	☐	☐

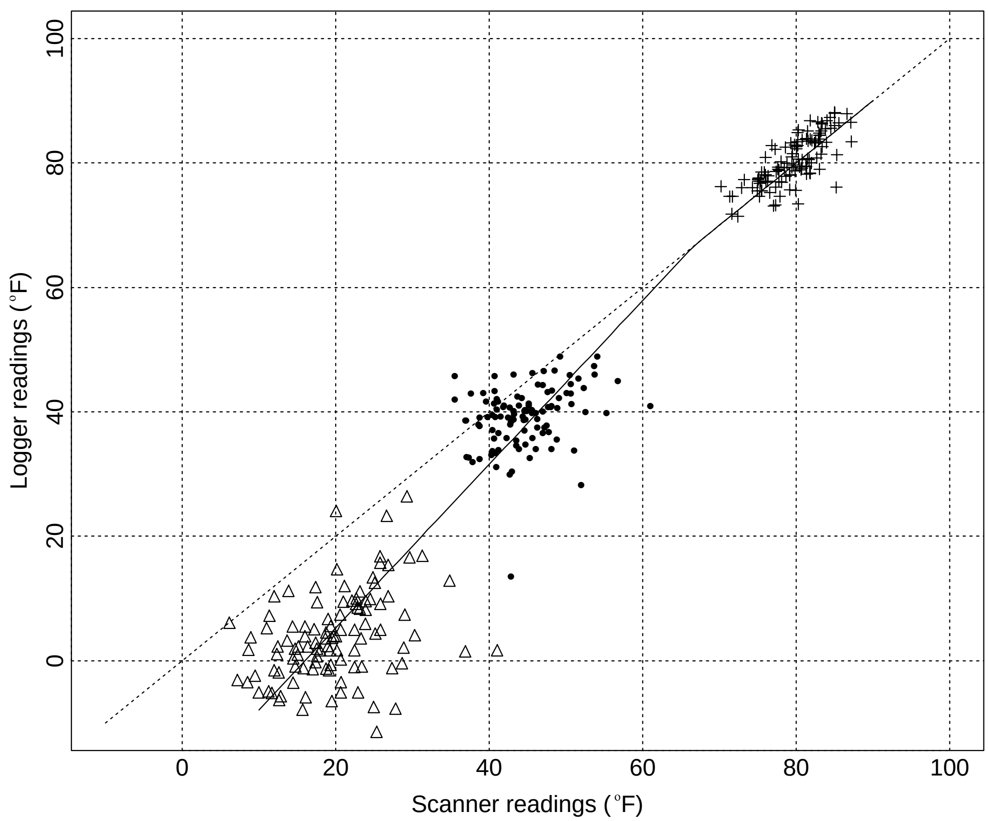

Figure B.2. Comparison of Logger and Scanner Data (+Ambient, •Fresh-Food, and ΔFreezer)

scanner shows good agreement with the thermistor for the room temperature measurements. However, in the compartment measurements the scanner shows significantly higher readings than the thermistor. This difference may result from a partial fogging of the refrigerator air and/or condensation on solid surfaces in the refrigerator compartments. Better correlation might be achieved in future measurements if the scanner is placed in contact with an exposed surface. Also, the infrared scanner is known to be biased by differences between the warm ambient kitchen temperature (with which the scanner electronics are in thermal equilibrium) and the cold surface temperature that it is measuring.

B.3 Occupant Data

We originally planned to directly ask the occupants of each monitored apartment questions about the number and ages of occupants in the apartment. Also, one question was designed to collect information on the number of people home during the day. However, early in the project, the surveyor was uncomfortable with the nature of these questions (especially questions relating to when the apartments would be unoccupied). As a result, the surveyor developed an indirect method of collecting this information. Indirect questions and observations were used to estimate the occupant data.

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Appendix C

Processing the Time-Series Data

Appendix C

Processing the Time-Series Data

Field measurements of refrigerator energy consumption, ambient conditions, and occupant usage are averaged (or summed) every 15 minutes to produce time-series records throughout a week-long period of monitoring. These time-series records are processed to yield annualized estimates of total load and its three components: baseline, occupant usage, and defrost.

The primary element of the process is establishing the baseline load. The baseline load is the consumption that would occur if the refrigerator were on but had no occupant usage load (no door-opening events) and no defrost load (defrosting features turned off). The baseline load is roughly proportional to the temperature difference across the shell of the refrigerator. It is essentially the load that is conducted through the shell of the refrigerator (the variations in efficiency of the vapor-compression cycle affect it somewhat). Consumption at levels above the baseline is caused by occupant usage or defrost events.

An additional step is to distinguish between occupant usage and defrost load. Defrost periods can be identified by analyzing sudden rises in freezer temperatures and power levels. These processes are described below.

C.1 Smoothing the Time Series

Interactions between the cycling frequency of the refrigerator and the logging frequency (once every 15 minutes) cause artifact variations in the raw-power time series that are not due to variations in load. As shown in Figure C.1, the raw time series commonly varies from observation of zero wattage to wattage between 100 and 150. A beat pattern in the raw-power time series can be clearly seen in the raw data after day 249.

To clearly observe variations in consumption that are due to variations in load, the time series is smoothed. The smoothing process involves a running average where a point in the resulting smoothed time series is the average of a set of n points in the raw time series. The set of n raw points is chosen to be centered around the time of the smoothed point. The smoothing process is implemented so that it can be performed twice. The heavy-line trace in Figure C.1 is a result of this double-smoothing operation on the raw time series. An initial smoothing with a 7-point (1.75-hour window) running average is followed with a 5-point (1.25-hour window) smoothing operation. The double-smoothing operation offers added flexibility in removing the artifact variations. The degree of smoothing (size of the smoothing window) is chosen by increasing it until the fluctuations in plotted power usage, during times of low occupant activity, are small (compared to variations caused by occupant activity).

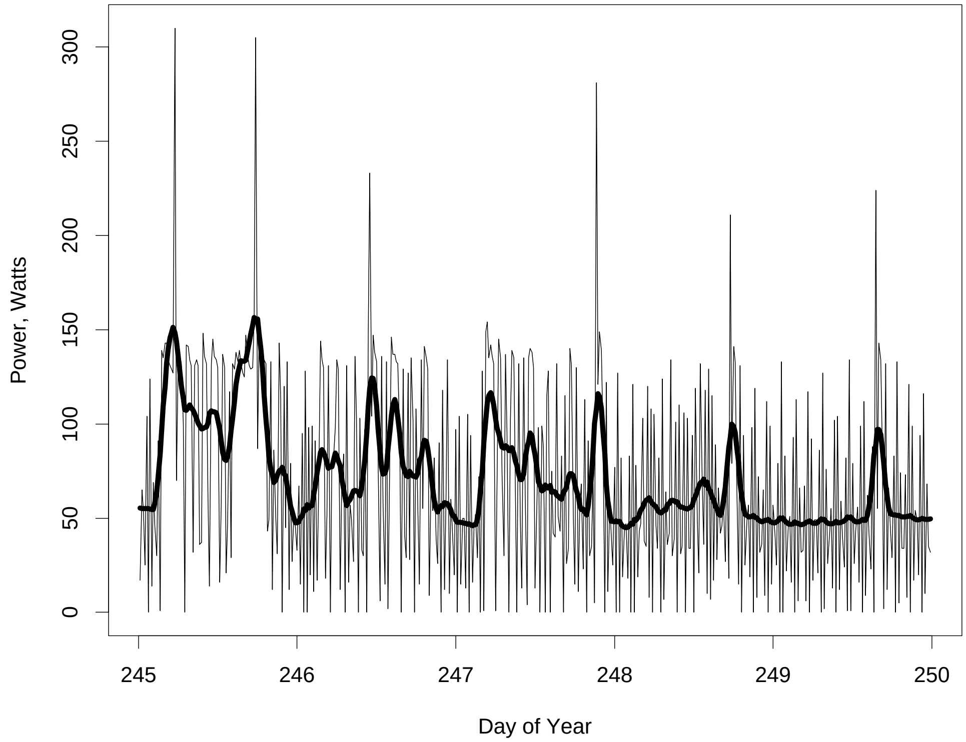

Figure C.1. Raw and Smoothed Times Series Record of Refrigerator Power Usage

Smoothing is done on the temperature and power records. Because the temperature data loggers are also recording at 15-minute intervals, the choice of window size in the running average is similar to that for the power records. The choice of a smaller window size for the temperature data can be made to compensate for added thermal lag and natural smoothing resulting from the canisters that protect the temperature loggers. In general, the choice of temperature window size tracks with the power window size and is only one step tighter. In the example that follows, the temperature windows are 5 and 5 (one increment tighter than the 7 and 5 used on the power time series).

When observing the smoothed time series, consideration must be given to the fact that, in addition to removing artifact noise, the smoothing operation spreads out spike-like events. Two very distinct defrost events can be seen in Figure C.1 (see times 248.8 and 249.8). These events are by nature very much like a step function on the leading edge. There is a sudden rise in power draw as the compressor timer triggers the beginning of the defrost action. The trailing edge of the event has a more gradual slope as the defrosting terminates and is followed by cycling of the refrigerator to remove the injected defrost heat. The smoothing operation converts this raw step response with a sloping trailing edge into a triangle response. The leading edge now has a noninfinite slope and the slope of the trailing edge is reduced. Also the duration of the smoothed defrost event (and associated cool-down period that follows) appears to be roughly twice as long as in the raw time series.

The spreading of spike-like events in the smoothing operation is not a problem because the process of quantifying the three components of consumption involves *integration* of the time series data. All of the analysis is done with smoothed data.

C.2 Identifying Defrost Periods

Defrost events are identified by analyzing the freezer-compartment temperature data and the power data. The onset of defrost is identified by the sudden rise in freezer-compartment temperature and the sudden rise in power draw. The completion of the defrost event is identified when the injected heat has been removed from the compartment and the temperature and power return to predefrost levels. The set of points in the temperature time series that falls between these two conditions identifies the defrost event (shown with box marks in Figure C.2). This plot shows the smoothed freezer-compartment temperatures and the corresponding smoothed-power readings.

The particular site data presented here is instructive because it is known that the occupants had moved out of the apartment several days after the onset of the monitoring period. As a result, several defrost events were observed without any complicating occupant activity. Figure C.2 shows that the last defrost event (without occupants) is simpler to identify than the first one. Coincidental door-opening or food-loading activity can make it difficult to isolate the defrost spike. However, using peripheral information, such as the fact that the onset of defrost is triggered periodically by accumulations of compressor run time and that the duration of defrost events is relatively constant throughout a week of monitoring, reasonable judgements can be made in defining the events.

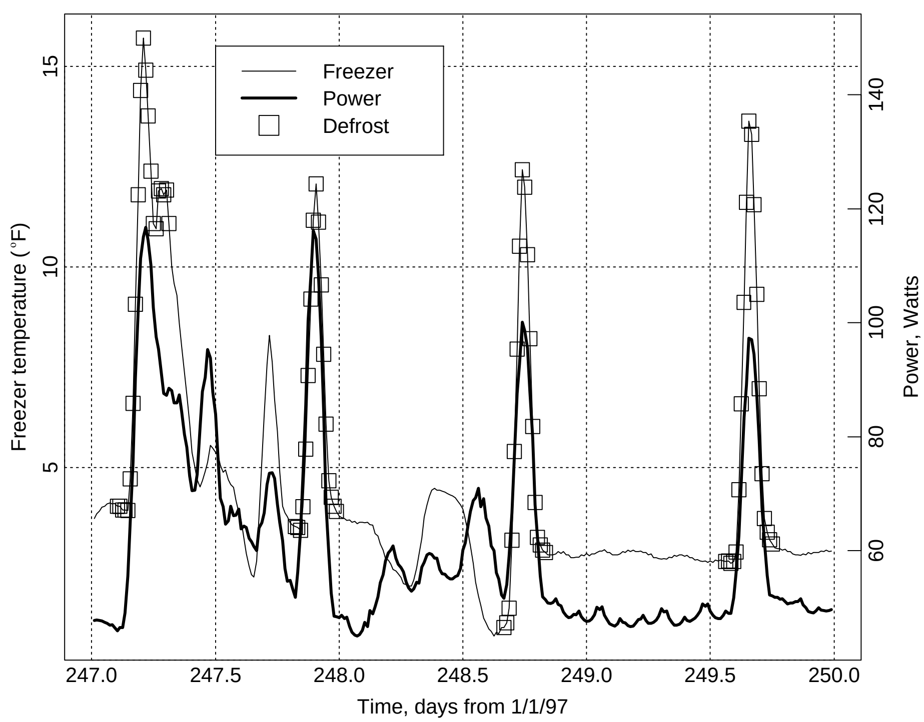

Figure C.2. Superimposed Freezer Temperature and Power Time Series

The process of identifying the events is implemented using an automated onset detector and a manual defrost-set editor. The onset detector looks for sudden rises in freezer-compartment temperatures. It is controlled by chosen sensitivity and duration parameters that determine when the set of defrost points starts and how many points will be in the set. These parameters are adjusted by site to best represent the varying characteristics of the refrigerators. Finally, a manual screen-based editor is used to add or remove points from each defrost-event set.

C.3 Establishing the Baseline

Temperature data from the room and the fresh-food and freezer compartments of the refrigerator are used to establish the baseline time series. The baseline power usage is roughly proportional to the temperature difference across the shell of the refrigerator (Equation C.1). A temperature difference (Equation C.2) is calculated using an effective internal temperature (Equation C.3). This internal temperature is the surface-area-weighted average of the two compartment temperatures. In most refrigerators 70% of the surface area is in the fresh-food compartment.

$$P_{baseline} = k\Delta T \tag{C.1}$$

$$\Delta T = T_{room} - T_{int} \tag{C.2}$$

$$T_{int} = 0.7 * T_{freshfood} + 0.3 * T_{freezer} \tag{C.3}$$

The proportionality constant k (in Equation C.1) can be established by plotting the $k\Delta T$ data (estimate of $P_{baseline}$) with its corresponding power time series. The $k\Delta T$ time series is developed by combining the raw temperature time series in Figure C.3 using Equations C.2 and C.3. The constant k can be determined by requiring that the power time series coincide with the $k\Delta T$ time series during times when the refrigerator is not defrosting, there is no occupant usage, and after all occupant loads accumulated during the day have been satisfied. Periods of this type, with pure baseline loads, often occur early in the morning just before the occupants start the day and make breakfast.

In Figure C.4, the constant k has been varied until the power series (thin line) coincides with the $k\Delta T$ series (bold line) during "quiet times." Such periods of pure baseline load are clearly seen starting on day 249, the time that the occupants are known to have moved out of the apartment. Additional "quiet time" is seen briefly, in the early morning periods, in each of the previous four days. The time axis at the top of the plot shows local New York City time, the time axis at the bottom of the plot shows logger time (Pacific Standard Time). Occupant behavior is best considered with respect to the local time axis. Data from the event loggers, the sum of open-door time for the fresh-food and freezer compartments, during each 15-minute period, is represented by dots; open-door time is scaled on the right axis.

C.4 Calculating the Components of Energy Consumption

After k has been determined, the three components of energy consumption can be calculated through integration of the power time-series data. The baseline energy is the integral of the $k\Delta T$ data, the area

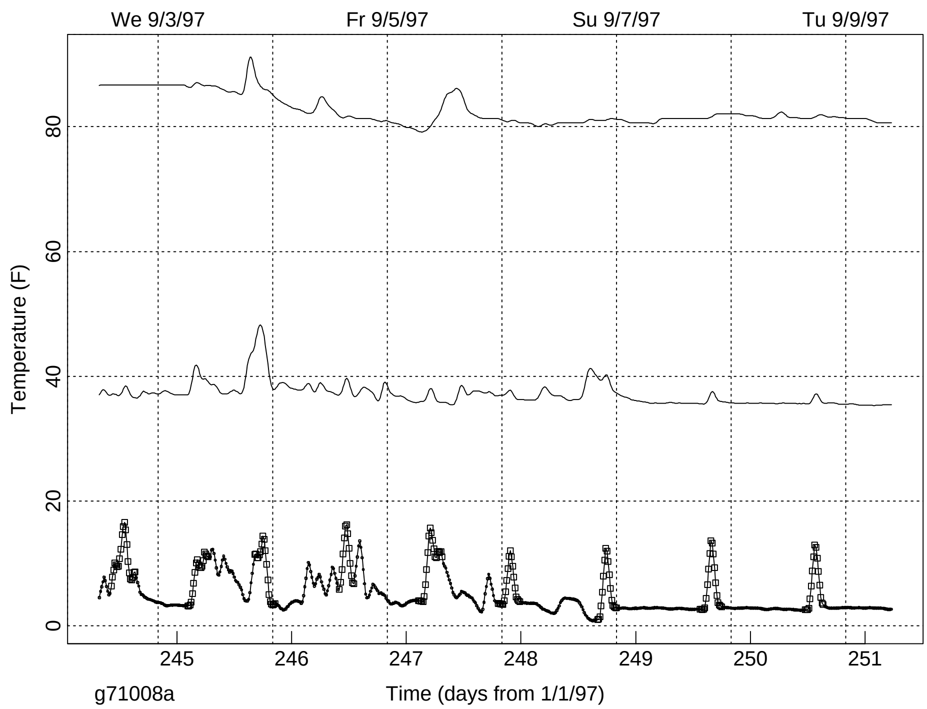

Figure C.3. Room, Fresh-Food, and Freezer Compartment Temperatures

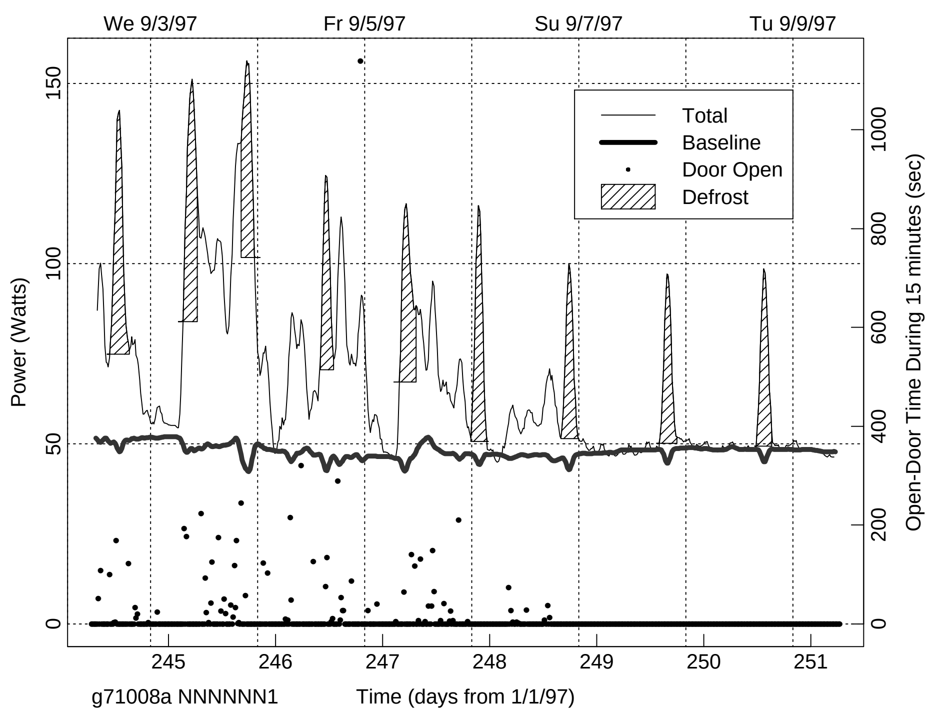

Figure C.4. Baseline, Occupant Usage, and Defrost Components beneath the kΔT trace. Energy associated with occupant activity and defrost events is represented by the area above the kΔT trace and below the total power trace. The occupant usage is calculated by subtracting defrost energy from this occupant and defrost total.

The defrost periods are represented in Figure C.4 by the cross-hatched shading. At the base of each shaded area is a line segment that defines the length of the defrost period. The y coordinate of this horizontal line is determined by the average of the starting and ending wattage during the corresponding defrost period. The area above this horizontal line and below the total-power traces is shaded. The defrost energy is not simply an integration of this shaded area. Nor is it the area, during defrost, under the total-power trace and above the kΔT trace. Instead, consideration is given to the fact that occupant activity can occur during periods of defrost. That is, defrost loads are often superimposed on top of occupant loads.

Defrost energy is calculated using the average occupant wattage during periods of no defrost. This average occupant wattage is the average of the difference between the total wattage and the baseline wattage during periods of no defrost. It is asserted that this level of occupant load has equal probability of occurring during periods of defrost as well during periods of no defrost. As a result, the defrost wattage can be calculated during periods of defrost as the difference between the total wattage and the average occupant wattage. Then the defrost energy is calculated as the time integral[(a)] of the defrost wattage.

In this way the time-series records from the six data loggers installed at each site are processed to determine total energy usage and its three components. The results are then annualized based on the duration of the monitoring period. Finally, the results are normalized to a target temperature difference (see Section 3.2).

C.5 Sensitivity of Modeling Result to Estimates of Defrost Energy

As discussed in Section C.2, distinguishing defrost events from occupant activity can be difficult. In sites where a very high level of occupant activity exists, the defrost spikes become less distinct and the identification process tends to underestimate the duration of the defrost event.

To quantify the impact of this uncertainty, a test was run to check the sensitivity of the savings estimate (see Section 3.4) to errors in estimating the defrost period by adjusting the defrost and occupant components with a correction factor:

$$E'_{occupant} = E_{occupant} - d \cdot E_{defrost} \tag{C.4}$$

$$E'_{defrost} = E_{defrost} + d \cdot E_{defrost} \tag{C.5}$$

(a) This is *not* the shaded area. The shaded area visually highlights the defrost period. As described above, the line segment under the shaded area identifies the starting and ending of the defrost period.

The adjustment takes a portion of the orginal defrost energy and subtracts that amount from the occupant component and moves it to the defrost component. This redistribution process is applied to each site in the metered-sample database. Then the regression models are reregressed with the adjusted data and the savings estimate is then recalculated.

The test showed that the savings estimate is quite insensitive to the accurcy of the split between the occupant and defrost components. For d of 0.5 (50% increase in defrost component) the change in the savings estimate is only 1%.

C.6 Processing Refrigerators with High Duty Cycle

The process of determining the three consumption components is dependent on successfully establishing the baseline power time series. If no periods exist where the refrigerator appears to have satisfied the occupant load, the process fails. In this case all that can be determined is the total energy usage.

Situations where the process fails can be classified as high load or low capacity. In high-load cases the refrigerators may succeed in maintaining good control of the compartment air temperatures but never fully remove all the excess energy in the food during the week of monitoring. They are controlling well but never quite reach equilibrium (all food cooled to set-point temperatures). These cases were very rare.

In low-capacity cases the occupant load may be low or moderate but for some reason the refrigerator is malfunctioning. Perhaps the refrigerant charge is low, the compressor is failing, or the refrigerator has severe ice accumulation. Structural changes to a refrigerator, such as deteriorating seals or a damaged shell and resulting wet insulation, can also make the refrigerator appear low in capacity. In these cases the refrigerator may run nearly continuously, referred to as high duty cycle operation: high run-time, low off-time. These cases were much more common.

When the refrigerator is running nearly continuously, unusual patterns appear in plots of total watts and $k\Delta T$ (k and ΔT are defined in Section C.3). As seen in the high duty cycle case in Figure C.5, the watts and $k\Delta T$ traces appear to be nearly mirror images of each other.

For example, occupant usage in day 195 is indicated by dots of open-door events. Because the refrigerator is running continuously it can no longer respond directly (by running more) to variation in load; it cannot run more than 100% of the time. More load without more cooling causes higher temperatures at the evaporator coil (lower ΔT between room and compartment). Higher temperatures at the coil increase power draw from the compressor. The resulting power trace shows a symmetric increase with the corresponding decrease in ΔT.[a]

(a) The conclusion that these refrigerators are running nearly all the time is supported by observing that their time series plots look essentially the same whether the data is smoothed or in its raw form.

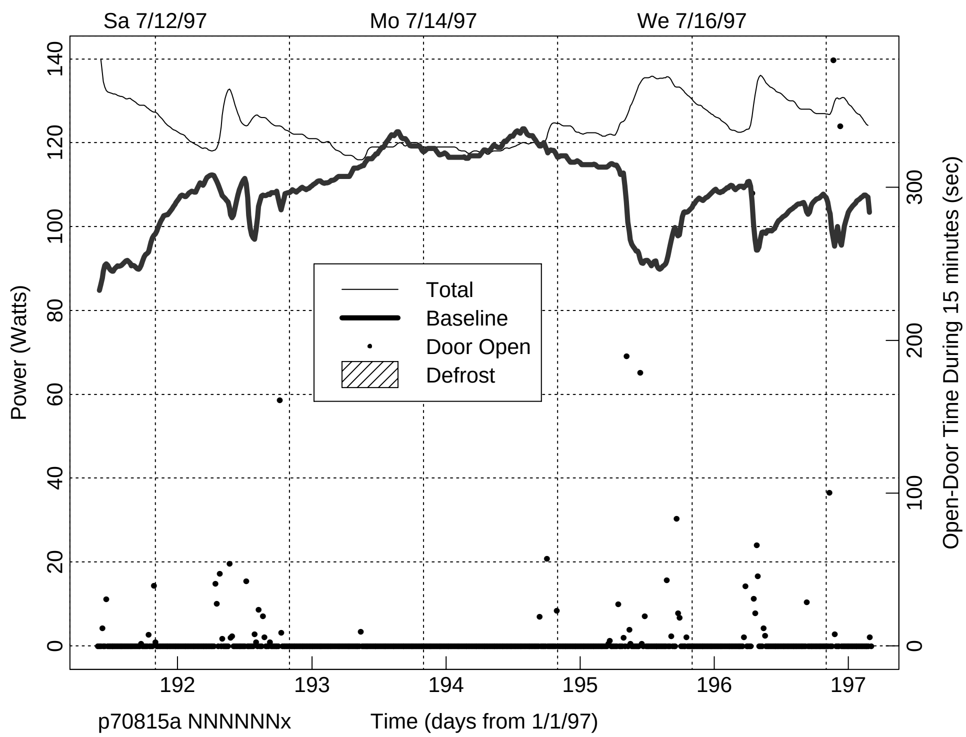

Figure C.5. Malfunctioning Refrigerator with High Duty Cycle

In these high duty cycle cases, it is not possible to establish the baseline consumption levels in the way defined above. Quiet times are never really achieved. The occupant load is never quite satisfied, and if it is, it may be days after the time of the occupant activity. This behavior makes any attempted estimates of baseline load artificially high and estimates of occupant load artificially low. The occupant load is essentially smeared out over the whole time series. There is relatively small variation in the total wattage throughout the monitoring week.

High duty-cycle cases can not be processed into components as described above; instead they are processed as totals. Their total wattage data is time integrated and projected to target ΔT conditions. Since we are unable to discern the three components of their load, these refrigerators cannot be represented in any of the component-modeling work (Section 3.3.3). However, these malfunctioning refrigerators are included in the savings estimates through a performance indicator (the ratios of their average total consumption to label) and a simplified relationship between refrigerator age and the likelihood of malfunction (see Section 3.4 and Appendix D).

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Appendix D

Age of High Duty Cycle Refrigerators

Appendix D

Age of High Duty Cycle Refrigerators

Of the 104 existing refrigerators monitored, 14 were identified as having unusual cycling behavior. These refrigerators appeared to be running nearly continuously and were failing to maintain compartment temperatures at set point. These high duty cycle units (high on-time, low off-time) demonstrated reduced capacity and corresponding need for maintenance or repair.

The high run times of these refrigerators frustrated attempts to divide the consumption into baseline, occupant, and defrost loads. Essentially the refrigerators never completely satisfy the occupant load that occurs during the day and as a result never operate purely on the baseline load (see Section C.6). Without these quiet times, usually occurring early in the morning before any new occupant use at the start of the day, the baseline load cannot be established. Consequently, the high duty cycle units were excluded from the mainstream analysis and modeling.

To represent the high duty cycle refrigerators in the savings estimate, a method was needed for establishing the probability that any given refrigerator in the population is afflicted by high duty cycle behavior and corresponding high consumption. This probability would need to be represented as a function of the refrigerator's age. In an attempt to do this, an analysis was made of the age of the high outliers in the pooled collection of the 1996 and 1997 field data samples. The 1996 data (Pratt and Miller 1997) was included in this analysis in an effort to increase the significance of the derived probability relationships.

D.1 Identifying High Outliers

A linear regression of total consumption against the label rating for consumption is used as the basis for establishing outliers. If a unit's consumption is higher than the product of the predicted value and an outlier threshold factor, it is considered a high outlier. The set of high outliers can be thinned by using a more stringent (higher) threshold factor. Figure D.1 and Figure D.2 illustrate the identification process for the 1996 and 1997 data sets. In these cases the threshold factor is set to 1.3. Any site with consumption higher than the product of the factor 1.3 and the predicted value is included in the high-outlier set. These high-outlier sites are plotted with an octagon.

The 1997 sites known to have high duty cycle refrigerators are shown in Figure D.2 (plotted with an X). This identification can be made for the 1997 data because of the availability of compartment-temperature time-series data.

The units that are common to both the high-outlier set and the high duty cycle set are marked with a superimposed X and octagon in Figure D.2. The total count common to both sets, N_{xo}, can be expressed

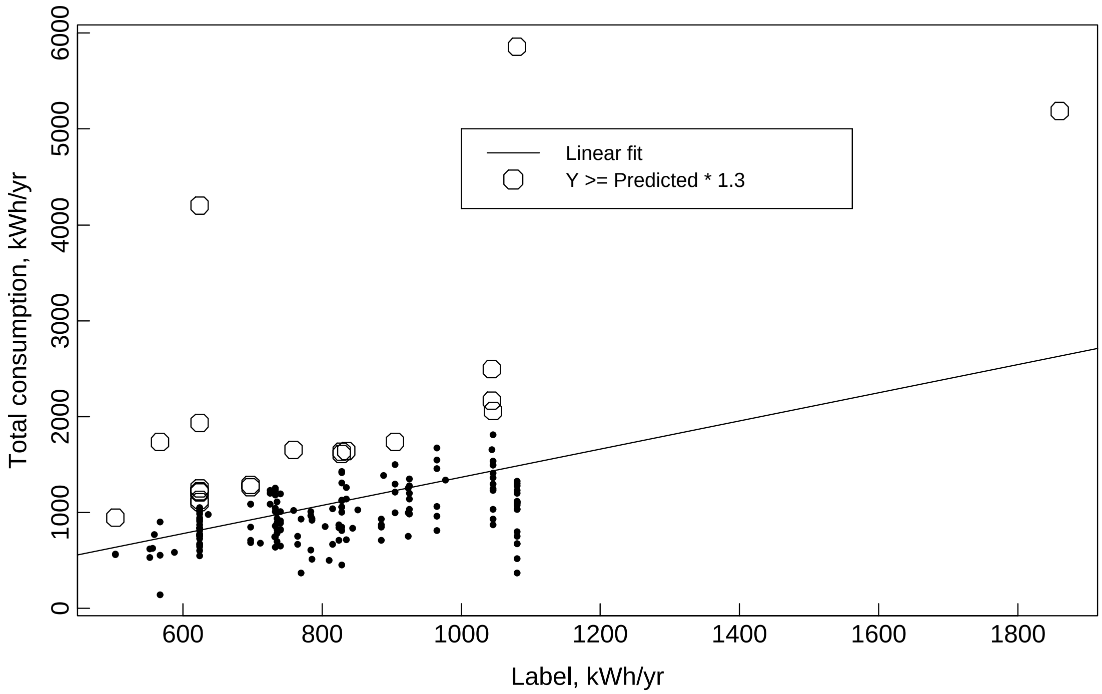

Figure D.1. High-Outlier Selection in 1996 Field Sample

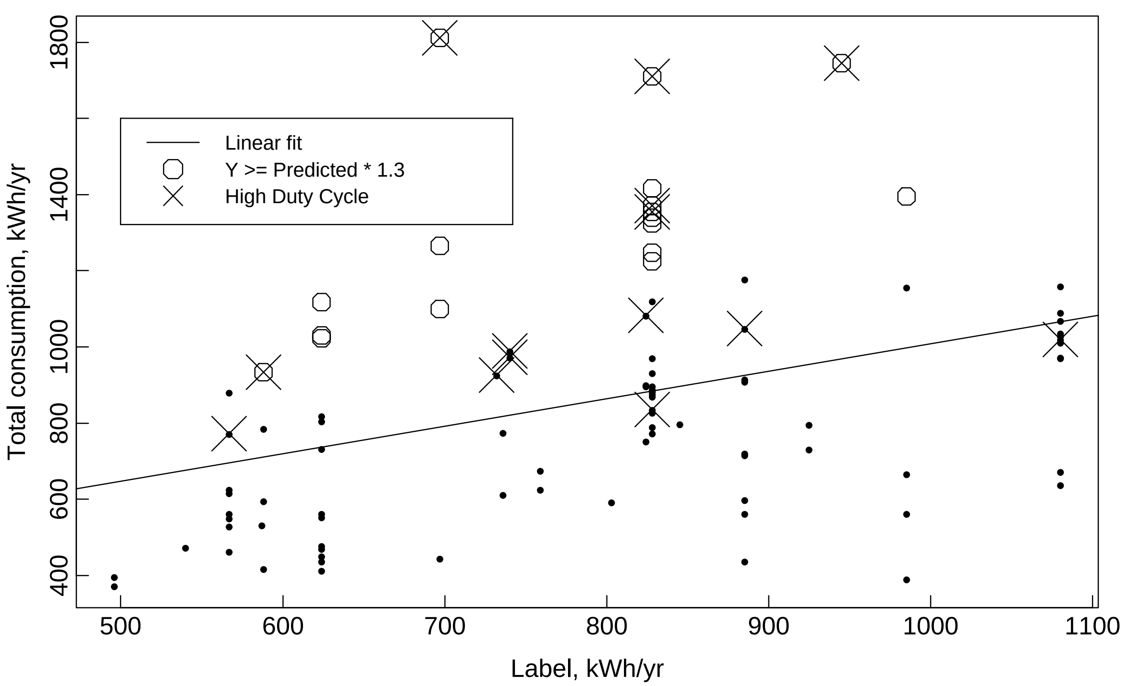

Figure D.2. High-Outlier Selection in 1997 Field Sample as a fraction of the total count in either set: N_x high-duty cycle, or N_o high outliers. As the outlier threshold factor becomes more stringent, the concentration of high duty cycle units in the high-outliers set becomes higher.

These fractions are indicators of how well the high-outlier set represents the high duty cycle set. A high N_{xo}/N_o ratio is good because it indicates that most of the refrigerators in the high-outlier set are in fact high duty cycle refrigerators. A high N_{xo}/N_x ratio is good because it indicates that a high percentage of the high duty cycle refrigerators are being found by the selection process; few are being overlooked. Values of these fractions for outlier thresholds ranging from 1.0 to 1.5 are found in Table D.1.

Table D.1. Outliers and Units with High Duty Cycles in the 1997 Field Sample

Outlier factor	N_x	N_o	N_{xo}	N_x/N_o	N_{xo}/N_x	N_{xo}/N_o
1.0	14	40	12	0.35	0.86	0.30
1.1	14	29	12	0.48	0.86	0.41
1.2	14	22	8	0.64	0.57	0.36
1.3	14	17	6	0.82	0.43	0.35
1.4	14	11	5	1.27	0.36	0.45
1.5	14	9	5	1.56	0.36	0.56

N_o/N_{total} , a third parameter, is also used in determining the usefulness of the selected set. This is simply an indicator of the relative size of the selected set. The larger the set, the more likely a significant age relationship will be observed when counting high outliers in a sequence of age bins.

A calculation of these three parameters is made from the 1997 data set. A plot of the results in Figure D.3 shows that it is not possible to select an outlier threshold factor where all the parameters are high. This is because the high duty cycle refrigerators are not simply found to be extreme high outliers but rather are found throughout the high-outlier domain (outlier threshold factor greater than 1.0). A few refrigerators are even found at consumption levels below the linear fit prediction. This dispersion of the high duty cycle refrigerators reflects variations in the severity of the maintenance problems and the variability of the occupant load.

D.2 Binning High Outliers by Date of Manufacture

To search for a relationship with age, the set of high outliers in the 1996 and 1997 data is binned by date of manufacture. The high-outlier count in each date bin is divided by the total number of units in each bin. This fraction is then normalized by the ratio of high duty cycle counts to high-outlier counts in the 1997 data. The result is an estimate of the fraction of the population that will have high-duty cycle behavior. This is calculated for each in a sequence of 5-year time bins, j (see Equation D.1).

$$\frac{n_{x_j}}{n_{total_j}} = \left(\frac{n_{o_j}}{n_{total_j}}\right)_{pooled} \left(\frac{n_x}{n_o}\right)_{1997} \tag{D.1}$$

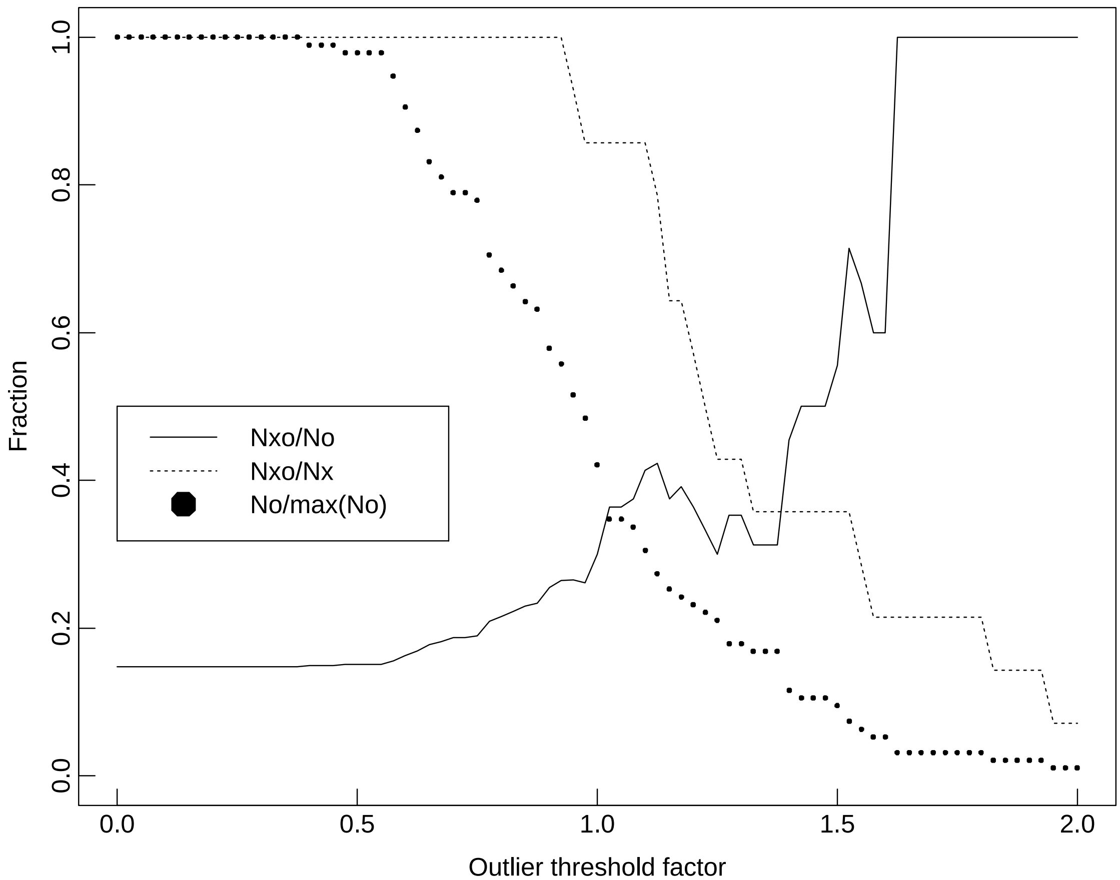

Figure D.3. Refrigerators Common to High-Outlier and High Duty Cycle Sets in 1997 Field Sample

These normalized-outlier fractions are plotted in Figure D.4 for outlier thresholds ranging from 1.0 to 1.5. The normalization factor, n_x/n_o is shown in Table D.1. If n_{total} is less than 10 in a particular bin, the corresponding normalized fraction is not plotted.

As the outlier threshold is raised, the normalized-outlier fractions shift from decreasing with age to increasing with age (except for the 1990-1995 bin, which always appears high). The increasing with age pattern seen with outlier thresholds greater than 1.3 is the expected behavior; however, at these higher thresholds the pooled outlier set is quite small (36 @ 1.3, 17 @1.5).

D.3 Binning by Age Determined to be Inconclusive

Due to the severity of the thinning required to see the expected behavior in the outlier set (Section D.2), the binning analysis is considered inconclusive as a quantitative indicator of the frequency of high duty cycling as a function of age. A pattern described in Section D.1 is considered to be the underlying cause of this difficulty in the binning analysis: “high duty cycle refrigerators are not simply found to be extreme high outliers but rather are found throughout the high-outlier domain.”

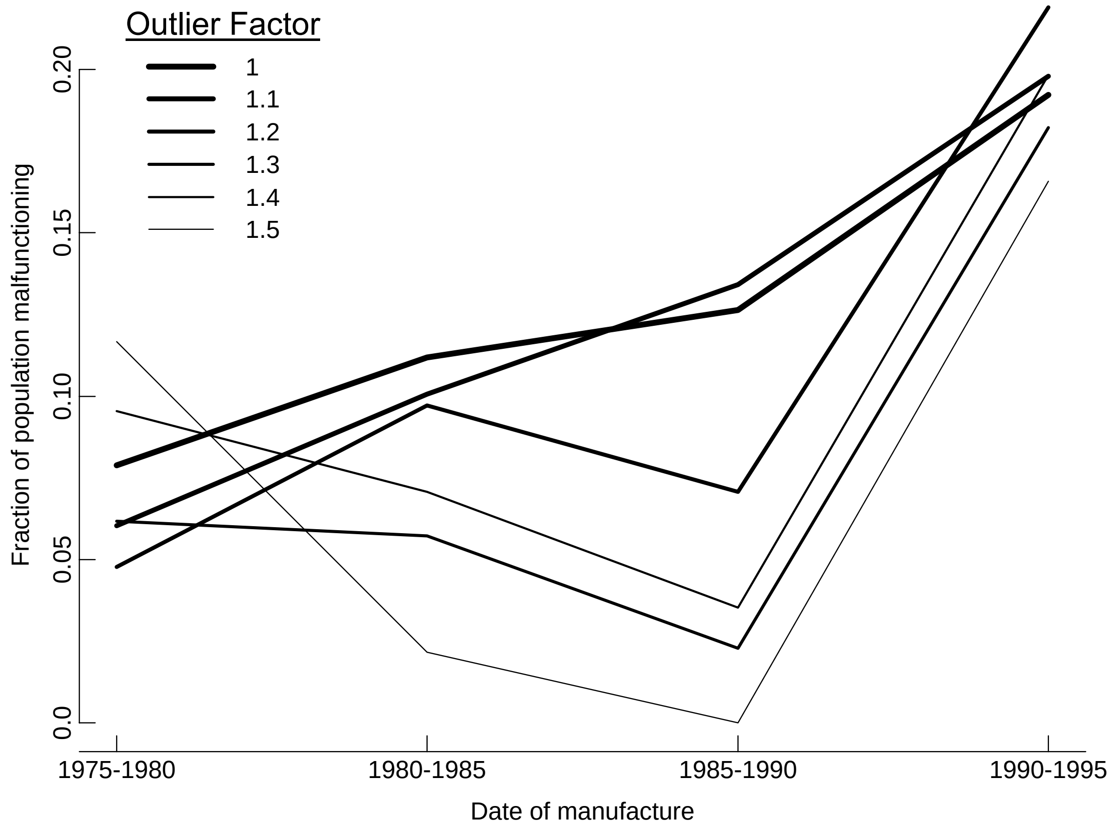

Figure D.4. 1996 and 1997 Normalized Outlier Fractions Binned by Production Date

Because of the difficulties in the binning analysis, a simplified relationship between age and high duty cycle behavior is assumed and described in the following section.

D.4 Simplified Relationship Between Age and Likelihood of Malfunction

In an effort to develop a quantitative relationship that could be used on the general population of refrigerators, a simplifying assumption is used. It is asserted that the likelihood of a refrigerator malfunctioning is directly proportional to its age. The proportionality factor is calculated as the ratio of the fraction of high duty cycle refrigerators in the 1997 sample of existing refrigerators to the average age of those refrigerators:

$$f = \left(\frac{n_x / n_{total}}{\overline{X}_{age}} \right)_{existing-'97} \tag{D.2}$$

Then the fraction of refrigerators in the general population that have high duty cycle behavior are calculated using this factor and the average age of the population:

$$n_x / n_{total} = f \cdot \left(\overline{X}_{age}\right)_{population} \tag{D.3}$$

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Appendix E

Site Field Data

Appendix E

Site Field Data

Table E.1 contains the primary metered and surveyed field data collected by PNNL and Planergy in 1997. Each row represents a metered refrigerator. The index in Table E.2 describes each of the columns in Table E.1.

The refrigerators are sorted by the date when data was downloaded, the logger name, and the site index. All three of these parameters are contained in the "Site Code" field. The first letter in this field identifies the logger, the next five numbers are the download date, and the last letter indicates which week the refrigerator was monitored. For example, 70428 refers to 4/28/1997. Monitoring was generally done in 4-week batches. The site index ranges from a to d for weeks 1 to 4.

All columns in Table E.1 relating to either the total or the components of consumption are ΔT adjusted (except for the column labeled "Raw"). Equation (3.1) was used to project the raw consumption to an annual average ΔT of $51.2^{o}F$. The actual average ΔT recorded at the site is shown in the second to the last column in Table E.1. For example, in the first row of the table, the raw consumption of 437 is projected to annual average conditions by multiplying by the ratio of target to actual ΔT [413 = 437*(51.2/54.2)]. All consumption in the table (except for the single raw column) is calculated as if the refrigerator had been operating at a ΔT of $51.2^{o}F$.

The comment field indicates the success of the loggers, sensors, and the splitting process used in identifying the components of total consumption. This field is seven characters long, with the first six characters referring to each of six data loggers at the site and the seventh character referring to the split process (see Table E.3).

Table E.1. Field-Monitoring Results

No.	Site Code	Develop	Manufacturer	Model	Proxy	Aut	Days	Consump. Raw (kWh/yr)	Consump. Adj (kWh/yr)	DOE Label (kWh/yr)	Label Ratio	Load Splits Cond (kWh/yr)	Load Splits Occup (kWh/yr)	Load Splits Defr (kWh/yr)	Openings Refg (1/day)	Openings Frzr (1/day)	Duration Refg (%)	Duration Frzr (%)	Temperatures Amb (°F)	Temperatures Refg (°F)	Temperatures Frzr (°F)	Temp Diff (°F)	Comment
New Refrigerators																							
1	b70428.a	SMITH	MAGIC CHEF	CTN1511AEW	CTL1511AEW	1	6.8	437	413	437	0.95	284	99	29	NA	9	NA	0.1%	82.2	39.2	1.8	54.2	NNNNbN1
2	g70428.a	SMITH	MAGIC CHEF	CTN1511AEW	CTL1511AEW	1	6.7	626	592	437	1.35	314	230	48	NA	NA	NA	NA	83.5	41.1	1.9	54.2	NNNNbe1
3	k70428.a	SMITH	MAGIC CHEF	CTN1511AEW	CTL1511AEW	1	6.9	448	444	437	1.02	275	NA	NA	NA	8.3	NA	0.1%	78.5	41.7	-7.9	51.7	NeNesNz
4	m70428.a	SMITH	MAGIC CHEF	CTN1511AEW	CTL1511AEW	1	6.8	416	386	437	0.88	261	92	33	21	NA	0.6%	NA	83.7	39.3	3.2	55.2	NNNNNb1
5	p70428.a	SMITH	MAGIC CHEF	CTN1511AEW	CTL1511AEW	1	6.7	451	423	437	0.97	258	121	44	30.5	NA	1.4%	NA	83.1	38.4	5.5	54.6	NsNNNe1
6	r70428.a	SMITH	MAGIC CHEF	CTL1511AEW	CTL1511AEW	1	6.8	329	313	437	0.72	223	69	20	NA	0.6	NA	0.1%	78.2	33.8	2.3	53.9	NNNNbm1
7	s70428.a	SMITH	MAGIC CHEF	CTL1511AEW	CTL1511AEW	1	6.9	371	332	437	0.76	245	61	26	22	4.5	0.5%	0.1%	82.9	35.0	4.0	57.2	NNsNNN1
8	b71008.b	SEDGWICK	MAGIC CHEF	CTN1511AEW	CTL1511AEW	1	6.0	519	530	437	1.21	252	234	43	65.6	9.9	1.3%	0.1%	76.9	38.9	-1.5	50.1	NNNNNN1
9	b71008.c	SEDGWICK	MAGIC CHEF	CTL1511AEW	CTL1511AEW	1	5.8	627	635	437	1.45	293	311	32	NA	10.3	NA	0.1%	79.4	39.7	3.6	50.5	NNsNhN1
10	k71008.b	SEDGWICK	MAGIC CHEF	CTN1511AEW	CTL1511AEW	1	6.9	1015	924	437	2.11	NA	NA	NA	52.9	16.2	1.0%	0.1%	77.8	33.5	-6.3	56.2	NNNNNNx
11	k71008.c	SEDGWICK	MAGIC CHEF	CTL1511AEW	CTL1511AEW	1	5.0	472	457	437	1.05	271	148	37	33.2	11.3	1.0%	0.1%	80.7	39.3	1.0	52.9	NNNNNN1
12	m71008.c	SEDGWICK	MAGIC CHEF	CTN1511AEW	CTL1511AEW	1	5.5	430	393	437	0.90	238	119	35	22.7	NA	0.3%	NA	80.0	34.1	0.2	56.1	NNNNNh1
13	p71008.b	SEDGWICK	MAGIC CHEF	CTL1511AEW	CTL1511AEW	1	6.0	573	573	437	1.31	273	255	45	22.4	5.1	1.5%	0.1%	79.3	41.0	-1.9	51.2	NNNNNN1
14	p71008.c	SEDGWICK	MAGIC CHEF	CTL1511AEW	CTL1511AEW	1	4.4	530	513	437	1.17	296	175	42	25.9	18.4	0.5%	0.1%	80.8	39.0	1.9	52.9	NNNNNN1
15	r71008.b	SEDGWICK	MAGIC CHEF	CTN1511AEW	CTL1511AEW	1	5.9	1137	803	437	1.84	NA	NA	NA	82.6	13.5	2.6%	0.1%	80.5	13.6	-5.2	72.5	NNNNNNx
16	r71008.c	SEDGWICK	MAGIC CHEF	CTN1511AEW	CTL1511AEW	1	5.9	772	764	437	1.75	284	438	43	57.2	17.9	1.5%	0.1%	81.0	41.1	1.7	51.7	NNNNNN1
17	s71008.c	SEDGWICK	MAGIC CHEF	CTL1511AEW	CTL1511AEW	1	5.9	525	494	437	1.13	289	153	53	NA	15.6	NA	0.1%	82.6	38.8	3.6	54.4	NNNNsN1
Existing Refrigerators																							
18	b70428.b	SOUNDVIEW	WHITE WESTINGHOUSE	WRT15CGAZ	WRT15CGA**	1	7.2	399	451	624	0.72	318	80	53	NA	2.7	NA	0.1%	76.0	40.2	8.5	45.3	NNNNbN1
19	g70428.b	SOUNDVIEW	WHITE WESTINGHOUSE	RT114LLW5	RT114L	1	6.8	485	592	803	0.74	420	128	43	NA	NA	NA	NA	77.1	46.3	9.1	42.0	NNNNbe1
20	k70428.b	SOUNDVIEW	WHITE WESTINGHOUSE	MRT15CNBWO	MRT15CNB**	1	6.9	921	1023	624	1.64	522	NA	NA	23.7	NA	0.4%	NA	72.5	38.1	-0.9	46.1	NeNeswz
21	m70428.b	SOUNDVIEW	WHIRLPOOL	ET12PCXLWR0	ET12PCXL	0	6.9	782	910	885	1.03	855	56	0	45	6.1	0.5%	0.1%	77.3	44.5	7.2	44.0	NNNNNw1
22	p70428.b	SOUNDVIEW	WHITE WESTINGHOUSE	WRT15CGAZ0	WRT15CGA**	1	6.6	700	733	624	1.17	404	274	56	62.1	NA	1.2%	NA	74.4	37.8	-3.1	48.9	NsNNNe1
23	r70428.b	SOUNDVIEW	WHITE WESTINGHOUSE	BA13000974	NA	NA	6.8	1101	1102	NA	NA	740	259	102	45.2	NA	1.7%	NA	81.5	42.3	2.4	51.2	NNNNbw1
24	s70428.b	SOUNDVIEW	HOTPOINT	CTXY14CMELWH	CTXY14CM	1	6.8	878	776	736	1.05	504	188	84	49.4	NA	0.6%	NA	79.9	31.2	0.4	57.9	NNsNNs1
25	b70624.a	MITCHEL	GENERAL ELECTRIC	TA12SNB	TA12SR	0	7.1	821	933	588	1.59	NA	NA	NA	78.7	NA	1.1%	NA	74.6	36.7	12.9	45.0	NNNNNux
26	b70624.b	MITCHEL	HOT POINT	CTH14CYXLRWH	CTH14CYT	1	6.7	349	373	496	0.75	229	116	28	41.9	16.8	0.6%	0.1%	75.7	38.7	2.3	47.9	NNNNNN1
27	b70624.c	SEDGWICK	ROPER	RT12VDKDW00 B0	RT12DK*A*0*	1	5.7	462	463	567	0.82	281	141	41	15.4	12.7	0.3%	0.1%	80.6	40.3	4.5	51.0	NNNNNN1
28	b70624.d	SEDGWICK	WHIRLPOOL	EET122PTWOLO	EET121DT	0	5.8	1231	1028	1080	0.95	848	180	0	38.2	NA	0.3%	NA	86.3	38.9	-7.4	61.3	NNNNNu1
29	g70624.a	MITCHEL	GIBSON	RD12C1WMGC	RD12C1*MGC	0	6.9	865	898	824	1.09	709	189	0	22	NA	0.3%	NA	77.6	40.9	-1.2	49.3	NNNNNe1

Table E.1. (contd)

No.	Site Code	Develop	Manufacturer	Model	Proxy	Aut	Days	Consump.		DOE	Label Ratio	Load Splits			Openings		Duration		Temperatures			Temp Diff	Comment
								Raw	Adj	Label		Cond	Occup	Defr	Refg	Frzr	Refg	Frzr	Amb	Refg	Frzr		
								kWh/yr		kWh/yr		kWh/yr			1/day		(%)		(°F)			(°F)	
30	g70624.b	MITCHEL	WHITE WESTINGHOUSE	ATG15ONCW1	ATG150N**1	1	6.8	997	1099	697	1.58	789	231	80	69.4	NA	0.7%	NA	77.1	40.3	8.2	46.4	NNNNNe1
31	g70624.c	SEDGWICK	WHIRLPOOL	EET122DTWRO	EET121DT	0	5.8	1101	1012	1080	0.94	924	88	0	NA	6	NA	0.1%	83.6	39.4	1.1	55.7	NNNNbN1
32	g70624.d	SEDGWICK	WHIRLPOOL	EET122DTWRO	EET121DT	0	5.8	1222	1091	1080	1.01	966	124	0	NA	8.1	NA	0.1%	83.9	37.6	0.7	57.4	NNNNbN1
33	k70624.a	MITCHEL	WHITE WESTINGHOUSE	ATG150NLW2	ATG150N**2	1	6.9	1250	1265	697	1.81	719	487	59	43	NA	1.1%	NA	75.5	35.9	-0.7	50.6	NNNNNb1
34	k70624.b	MITCHEL	GENERAL ELECTRIC	TA12SRB	TA12SR	0	6.6	502	595	588	1.01	441	154	0	88.4	NA	0.8%	NA	75.5	39.4	15.7	43.2	NNNNNb1
35	k70624.c	SEDGWICK	WHIRLPOOL	EET122DWR0	EET121DT	0	5.3	1037	1037	1080	0.96	913	NA	NA	43.7	NA	2.5%	NA	78.1	42.1	-8.6	51.2	NNNlNbz
36	k70624.d	SEDGWICK	GENERAL ELECTRIC	TA12SLB	TA12SR	0	5.8	752	786	588	1.34	577	NA	NA	79.8	NA	1.5%	NA	83.3	45.9	7.3	49.0	NNNlNbz
37	m70624.a	MITCHEL	GIBSON	RD12C1WMGC	RD12C1*MGC	0	6.9	1088	1083	824	1.31	NA	NA	NA	47.9	12.3	1.1%	0.1%	77.0	35.9	1.5	51.4	NNNNNNx
38	m70624.b	MITCHEL	WHITE WESTINGHOUSE	MTR15CNBW1	MRT15CNB**	1	6.7	448	471	624	0.75	290	157	24	43.5	14.4	0.7%	0.1%	78.5	40.5	5.0	48.7	NNNNNN1
39	m70624.c	SEDGWICK	ROPER	RT12DKXAWOO	RT12DK*A*0*	1	5.8	646	626	567	1.10	367	NA	NA	84.5	19.6	1.6%	0.1%	79.5	39.7	-3.8	52.9	NNllNNz
40	m70624.d	SEDGWICK	WHIRLPOOL	EET122DTWRO	EET121DT	0	5.8	1225	1160	1080	1.07	NA	NA	NA	47.1	19.9	1.3%	0.1%	85.3	41.6	7.1	54.1	NNllNNo
41	p70624.a	MITCHEL	GIBSON	RD12C1WMGC	RD12C1*MGC	0	7.0	633	900	824	1.09	606	NA	NA	65.3	NA	2.1%	NA	75.2	43.6	28.9	36.0	NNNlNez
42	p70624.b	MITCHEL	GIBSON	RD12C1WMGC	RD12C1*MGC	0	6.8	NA	NA	824	NA	NA	NA	NA	NA	NA	NA	NA	74.6	33.8	29.1	42.2	sNllhed
43	p70624.c	SEDGWICK	WHIRLPOOL	503621017.0	81362*0	1	5.8	1748	1745	945	1.85	NA	NA	NA	53.7	NA	1.3%	NA	79.7	43.9	-7.7	51.3	NNllNhx
44	p70624.d	SEDGWICK	WHIRLPOOL	ET12PCXLWLO	ET12PCXL	0	6.0	1097	1048	885	1.18	NA	NA	NA	16.8	2.7	0.3%	0.1%	86.8	40.1	17.2	53.6	NNllNNx
45	r70624.a	MITCHEL	GIBSON	RD12C1WMGC	RD12C1*MGC	0	6.4	718	753	824	0.91	517	237	0	30	8.9	0.5%	0.1%	80.2	43.1	4.1	48.8	NNNNNN1
46	r70624.b	MITCHEL	WHITE WESTINGHOUSE	WRT15CGAZO	WRT15CGA**	1	6.8	752	819	624	1.31	NA	NA	NA	56.2	18	0.8%	0.1%	80.5	43.0	11.2	47.0	NNNNNNo
47	r70624.c	SEDGWICK	ROPER	RT12DKYAWOO	RT12DK*A*0*	1	6.0	854	772	567	1.36	NA	NA	NA	10.6	19.2	0.1%	0.1%	78.1	34.0	-7.7	56.6	NNNNNNx
48	r70624.d	SEDGWICK	WHITE WESTINGHOUSE	ATG150NCW1	ATG150N**1	1	7.8	1731	1811	697	2.60	NA	NA	NA	11.6	3.2	0.1%	0.1%	83.4	43.5	13.4	48.9	NNNNNNx
49	s70624.a	MITCHEL	WHITE WESTINGHOUSE	ATG150NLW2	ATG150N**2	1	6.8	367	445	697	0.64	292	114	38	NA	6.9	NA	0.1%	73.1	39.6	10.4	42.3	NNNNbm1
50	s70624.b	MITCHEL	WHIRLPOOL	ET12PCXLWLO	ET12PCXL	0	1.2	NA	NA	885	NA	NA	NA	NA	NA	33.2	NA	0.1%	77.4	58.1	34.7	26.3	sNNNbmd
51	s70624.c	SEDGWICK	WHIRLPOOL	EET122DTWL0	EET121DT	0	5.8	NA	NA	1080	NA	NA	NA	NA	NA	NA	NA	NA	85.6	41.1	10.0	53.8	slNNbbd
52	s70624.d	SEDGWICK	WHIRLPOOL	ET12PCXLWRO	ET12PCXL	0	5.8	NA	NA	885	NA	NA	NA	NA	NA	NA	NA	NA	84.9	38.1	-0.9	58.5	slNNbbd
53	b70815.a	BARUCH	WHIRLPOOL	EFT121DTWRO	EHT121DT	0	6.9	778	798	845	0.94	523	275	0	42	28.3	1.2%	0.1%	86.4	45.5	15.4	49.9	NNNNNN1
54	b70815.b	BARUCH	WHITE WESTINGHOUSE	RT141GLWA	RT141G**A	1	6.9	1507	1416	828	1.71	775	616	25	152.3	30.8	2.4%	0.1%	85.6	45.9	-3.4	54.5	NNNNNN1
55	b70815.c	BARUCH	WHITE WESTINGHOUSE	RT141GCWA	RT141G**A	1	6.7	1198	1339	828	1.62	593	644	102	NA	NA	NA	NA	81.3	46.8	9.1	45.8	NNNNss1
56	b70815.d	BARUCH	HOT POINT	CTH14CYLLWH	CTH14CYS	1	6.8	414	397	496	0.80	261	92	43	27.3	4.4	0.8%	0.1%	83.2	40.3	5.2	53.4	NNNNNN1
57	g70815.a	BARUCH	WHITE WESTINGHOUSE	WRT15CGAWO	WRT15CGA**	1	7.0	1126	1030	624	1.65	496	474	60	69.8	34.6	2.3%	0.1%	87.3	39.7	11.8	56.0	NNNNNN1
58	g70815.b	BARUCH	WHITE CONSELID	MRT15CNBWO	MRT15CNB**	1	6.8	630	563	624	0.90	357	155	50	37.1	5.3	0.6%	0.1%	84.4	35.5	7.4	57.3	NNNNNN1
59	g70815.c	BARUCH	WHITE WESTINGHOUSE	RT141GLWA	RT141G**A	1	6.9	1255	1324	828	1.60	630	629	64	50.8	40.9	0.9%	0.1%	82.8	45.5	8.1	48.5	NNNNNN1
60	g70815.d	BARUCH	WHITE WESTINGHOUSE	RT141GCWA	RT141G**A	1	6.9	1012	897	828	1.08	535	297	65	53.1	14.2	0.9%	0.1%	84.9	39.2	-1.0	57.8	NNNNNN1

Table E.1. (contd)

No.	Site Code	Develop	Manufacturer	Model	Proxy	Aut	Days	Consump. Raw (kWh/yr)	Consump. Adj (kWh/yr)	DOE Label (kWh/yr)	Label Ratio	Load Splits Cond (kWh/yr)	Load Splits Occup (kWh/yr)	Load Splits Defr (kWh/yr)	Openings Refg (1/day)	Openings Frzr (1/day)	Duration Refg (%)	Duration Frzr (%)	Temperatures Amb (°F)	Temperatures Refg (°F)	Temperatures Frzr (°F)	Temp Diff (°F)	Comment
61	k70815.a	BARUCH	WHIRLPOOL	ET12CCRSWOO	ET12CC*S*0	0	6.8	1085	990	740	1.34	NA	NA	NA	34.8	6.4	1.6%	0.1%	88.1	46.7	-2.4	56.1	NNNNNNx
62	k70815.b	BARUCH	WHITE WESTINGHOUSE	RT141GLWA	RT141G**A	1	6.9	1750	1710	828	2.07	NA	NA	NA	NA	25.3	NA	0.1%	85.1	46.0	1.7	52.4	NNNNsNx
63	k70815.c	BARUCH	WHITE WESTINGHOUSE	RT141GCWA	RT141G**A	1	6.8	932	882	828	1.07	450	334	98	NA	7.2	NA	0.1%	83.2	39.9	3.9	54.1	NNNNsN1
64	k70815.d	BARUCH	WHITE WESTINGHOUSE	RT141GLWA	RT141G**A	1	6.8	1008	888	828	1.07	509	315	65	NA	6.2	NA	0.1%	86.4	40.8	-0.9	58.1	NNNNsN1
65	m70815.a	BARUCH	HOT POINT	CTX14CMCR	CTX14CM	1	6.9	599	613	736	0.83	409	153	51	31.8	10.4	0.3%	0.1%	87.9	49.0	12.0	50.0	NNNNNN1
66	m70815.b	BARUCH	WHITE WESTINGHOUSE	RT141GCWA	RT141G**A	1	6.9	833	791	828	0.96	513	197	80	45.3	7.2	1.4%	0.1%	88.0	44.4	9.9	54.0	NNNNNN1
67	m70815.c	BARUCH	WHITE WESTINGHOUSE	RT141GLHA	RT141G**A	1	6.7	1113	1371	828	1.66	NA	NA	NA	47.1	12.4	0.6%	0.1%	83.8	49.0	26.4	41.6	NNNNNNx
68	m70815.d	BARUCH	WHITE WESTINGHOUSE	RT141GLWA	RT141G**A	1	6.9	841	774	828	0.93	539	188	47	40.8	2.5	0.3%	0.1%	84.8	40.7	2.3	55.6	NNNNNN1
69	p70815.a	BARUCH	KENMORE	106.866 (211)	86621**	0	5.8	1091	973	740	1.31	NA	NA	NA	18.4	8.3	0.4%	0.1%	85.5	42.2	-4.9	57.4	NNNNNNx
70	p70815.b	BARUCH	WHITE WESTINGHOUSE	RT141GCWA	RT141G**A	1	6.8	939	870	828	1.05	566	245	59	41.8	12	0.5%	0.1%	86.8	41.0	9.5	55.3	NNNNNN1
71	p70815.c	BARUCH	WHITE WESTINGHOUSE	RT141GCNA	RT141G**A	1	6.9	953	971	828	1.17	563	343	64	NA	11.7	NA	0.1%	79.0	41.7	-1.4	50.2	NNNNhN1
72	p70815.d	BARUCH	WHITE WESTINGHOUSE	RT141GCWA	RT141G**A	1	6.8	961	886	828	1.07	494	330	63	55	17.9	1.0%	0.1%	83.4	39.1	1.7	55.5	NNNNNN1
73	r70815.a	BARUCH	WHITE WESTINGHOUSE	WRT15CGAWO	WRT15CGA**	1	6.9	497	438	624	0.70	305	93	39	27.8	3.5	0.3%	0.1%	86.0	36.9	6.7	58.2	NNNNNN1
74	r70815.b	BARUCH	WHITE WESTINGHOUSE	RT141GCWA	RT141G**A	1	6.9	1432	1248	828	1.51	586	585	76	109.9	26	2.1%	0.1%	88.0	40.1	3.9	58.8	NNNNNN1
75	r70815.c	BARUCH	WHITE WESTINGHOUSE	RT141GLWA	RT141G**A	1	6.8	987	877	828	1.06	541	272	64	42	7.5	0.6%	0.1%	83.2	37.1	-1.2	57.6	NNNNNN1
76	r70815.d	BARUCH	WHITE WESTINGHOUSE	RT141GCWA	RT141G**A	1	6.7	1492	1354	828	1.64	NA	NA	NA	70.4	16.1	1.6%	0.1%	86.6	41.5	3.8	56.4	NNNNNNx
77	s70815.a	BARUCH	WHIRLPOOL	ET12CCLSWOO	ET12CC*W*0*	0	6.9	1078	926	732	1.27	NA	NA	NA	38.3	20.5	0.3%	0.1%	85.1	37.9	-3.5	59.6	NNNNNNx
78	s70815.b	BARUCH	WHITE WESTINGHOUSE	RT141GCWA	RT141G**A	1	6.8	1310	1225	828	1.48	508	636	81	101.3	43.5	1.9%	0.1%	83.5	38.7	5.5	54.8	NNNNNN1
79	s70815.c	BARUCH	WHITE WESTINGHOUSE	RT141GLHA	RT141G**A	1	6.9	953	932	828	1.13	434	359	139	110.8	34.5	1.2%	0.1%	84.4	40.4	12.5	52.4	NNNNNN1
80	s70815.d	BARUCH	WHITE WESTINGHOUSE	RT141GCWA	RT141G**A	1	6.8	1210	1121	828	1.35	530	575	16	70.1	22.1	3.6%	0.1%	83.8	40.9	-0.4	55.3	NNNNNN1
81	b71008.a	SEDGWICK	WHITE WESTINGHOUSE	MRT15CNBW	MRT15CNB**	1	7.9	907	806	624	1.29	408	366	32	37.8	9.1	0.7%	0.1%	78.4	33.1	-7.9	57.6	NNNNNN1
82	b71008.d	SOUNDVIEW	WHIRLPOOL	ET12PCXLWLO	ET12PCXL	0	7.8	1043	1178	885	1.33	810	369	0	NA	NA	NA	NA	76.2	41.5	6.1	45.3	NNNNss1
83	g71008.a	SEDGWICK	ROPER	RD12DKXAWOO	RT12DK*A*0*	1	7.0	604	562	567	0.99	393	111	59	14.7	7.7	0.6%	0.1%	82.6	37.2	5.1	55.0	NNNNNN1
84	k71008.a	SEDGWICK	WHITE WESTINGHOUSE	CTL11OWK1	CTN110	1	8.3	NA	NA	759	NA	NA	NA	NA	NA	NA	NA	NA	73.4	70.4	70.0	3.1	sNmmssd
85	k71008.d	SOUNDVIEW	WHIRLPOOL	ET12PCXLWRO	ET12PCXL	0	7.9	880	916	885	1.04	843	73	0	NA	3.8	NA	0.1%	76.0	36.7	3.7	49.2	NNNNhN1
86	m71008.a	SEDGWICK	ROPER	RD12DKXAWOO	RT12DK*A*0*	1	13.9	593	550	567	0.97	332	167	51	31.1	NA	0.3%	0.1%	76.1	32.0	-5.1	55.2	NNNNNN1
87	m71008.d	SOUNDVIEW	WHITE WESTINGHOUSE	RT143SCWO	RT143SC**	1	7.9	969	836	828	1.01	NA	NA	NA	NA	7.5	NA	0.1%	77.3	28.4	-6.5	59.4	NNNNsNx
88	p71008.a	SEDGWICK	WHIRLPOOL	EET122DTWRD	EET121DT	0	7.8	1055	1020	1080	0.94	NA	NA	NA	17.2	11.9	0.1%	0.1%	75.6	32.9	-1.3	53.0	NNNNNNx
89	p71008.d	SOUNDVIEW	WHITE WESTINGHOUSE	RT114LLH-8	RT114L	1	7.8	579	626	759	0.82	423	153	50	15.7	3.6	0.1%	0.1%	77.4	43.0	-0.2	47.4	NNNNNN1
90	r71008.a	SEDGWICK	ROPER	RD12DKXAWOO	RT12DK*A*0*	1	7.8	1002	881	567	1.55	542	287	52	NA	43.6	NA	0.1%	79.4	32.8	-5.9	58.2	NNNNsN1
91	r71008.d	SOUNDVIEW	WHIRLPOOL	EET122DTWRO	EET121DT	0	7.9	1007	1070	1080	0.99	NA	NA	NA	29.3	65.3	0.4%	0.1%	80.9	44.6	5.0	48.2	NNNNNNb

Table E.1. (contd)

No.	Site Code	Develop	Manufacturer	Model	Proxy	Aut	Days	Consump. kWh/yr		DOE Label kWh/yr	Label Ratio	Load Splits kWh/yr			Openings 1/day		Duration (%)		Temperatures (°F)			Temp Diff (°F)	Comment
								Raw	Adj			Cond	Occup	Defr	Refg	Frzr	Refg	Frzr	Amb	Refg	Frzr		
92	s71008.a	SEDGWICK	ROPER	RD12DKXAWOO	RT12DK*A*0*	1	7.0	615	530	567	0.93	336	179	15	18.3	5.7	0.4%	0.1%	86.5	32.5	14.7	59.3	NNNNNN1
93	s71008.d	SOUNDVIEW	WHITE WESTINGHOUSE	RT114LLH-8	RT114L	1	7.8	675	676	759	0.89	483	151	41	40.2	12.1	0.7%	0.1%	75.5	33.9	2.1	51.1	NNNNNN1
94	b71202.a	BETANCES	WHIRLPOOL	ETH141DTWRO	EHT141DT	0	3.8	740	797	925	0.86	626	171	0	37.8	15.4	1.5%	0.1%	78.9	37.6	16.8	47.5	NNNNNN1
95	b71202.b	WISE TOWERS	WHIRLPOOL	EET122DTWRO	EET121DT	0	6.9	606	673	1080	0.62	529	145	0	NA	NA	NA	NA	77.9	42.3	7.4	46.1	NNNNsh1
96	b71202.c	WISE TOWERS	WHIRLPOOL	ET12PCXLWLO	ET12PCXL	0	1.0	NA	NA	885	NA	NA	NA	NA	NA	NA	NA	NA	78.3	61.5	29.7	26.3	sNNNssd
97	b71202.d	WISE TOWERS	WHIRLPOOL	EHT121PTWL0	EHT121PT	0	6.9	507	562	985	0.57	477	85	0	NA	5.4	NA	0.1%	82.3	47.5	9.6	46.2	NNNNhN1
98	g71202.a	BETANCES	WHITE WESTINGHOUSE	WRT15CGAWO	WRT15CGA**	1	3.8	419	554	624	0.89	261	242	51	95.7	24.8	1.4%	0.1%	71.8	43.1	9.7	38.7	NNNNNN1
99	g71202.b	WISE TOWERS	FRIGIDARE	MTR13CRBW2	MRT13CRB**	1	6.9	606	533	587	0.91	315	177	42	47.6	6.2	1.1%	0.1%	79.0	31.2	-3.4	58.2	NNNNNN1
100	g71202.c	WISE TOWERS	WHIRLPOOL	ET12PCXLWLO	ET12PCXL	0	6.9	546	563	885	0.64	514	48	0	14.6	0.3	0.1%	0.1%	79.3	39.9	5.6	49.7	NNNNNN1
101	g71202.d	WISE TOWERS	WHIRLPOOL	EHT121PTWLO	EHT121PT	0	6.8	348	391	985	0.40	359	32	0	24.7	3.8	0.6%	0.1%	82.8	46.1	16.6	45.6	NNNNNN1
102	k71202.a	BETANCES	WHITE WESTINGHOUSE	WRT15CGAZO	WRT15CGA**	1	3.8	NA	NA	624	NA	NA	NA	NA	55.2	22.4	1.7%	0.1%	77.1	35.8	-5.1	53.6	sNNNNNd
103	k71202.b	WISE TOWERS	ROPER	RT12DKYAWOO	RT12DK*A*0*	1	6.9	613	617	567	1.09	344	212	61	NA	NA	NA	NA	73.2	34.1	-5.1	50.9	NNNNss1
104	k71202.c	WISE TOWER	GENERAL ELECTRIC	TA12SRN	TA12SR	0	6.8	413	417	588	0.71	330	87	0	NA	NA	NA	NA	78.7	32.7	16.9	50.7	NNNNbs1
105	k71202.d	WISE TOWERS	WHIRLPOOL	EHT121PTWLO	EHT121PT	0	6.0	1122	1157	985	1.17	1014	144	0	NA	10.6	NA	0.1%	86.3	45.4	16.3	49.6	NNNNbN1
106	m71202.a	BETANCES	WHITE WESTINGHOUSE	WRT15CGAZO	WRT15CGA**	1	3.8	368	413	624	0.66	289	85	40	NA	NA	NA	NA	71.4	34.9	4.4	45.7	NNNNss1
107	m71202.b	WISE	WHIRLPOOL	EET122DTWRO	EET121DT	0	6.9	1104	973	1080	0.90	873	99	0	41.9	4.6	0.8%	0.1%	81.4	35.7	-5.7	58.1	NNNNNN1
108	m71202.c	WISE TOWERS	WHIRLPOOL	ET12PCXLWLO	ET12PCXL	0	4.9	402	437	885	0.49	367	70	0	NA	NA	NA	NA	82.5	46.1	10.4	47.1	NNNNss1
109	m71202.d	WISE TOWERS	WHIRLPOOL	EHT121PTWL0	EHT121PT	0	6.9	623	666	985	0.68	563	103	0	20.3	6.1	0.4%	0.1%	76.7	40.4	1.7	47.9	NNNNNN1
110	p71202.a	BETANCES	WHIRLPOOL	EHT121PTWLO	EHT121PT	0	3.9	1326	1395	985	1.42	1248	146	0	NA	NA	NA	NA	76.9	30.0	24.1	48.7	NNNNss1
111	p71202.b	WISE TOWERS	WHIRLPOOL	EET122DTWRO	EET121DT	0	7.0	933	971	1080	0.90	852	119	0	34.3	5.6	0.4%	0.1%	78.0	39.9	2.9	49.2	NNNNNN1
112	p71202.c	WISE TOWER	WHIRLPOOL	ET12PCXLWLO	ET12PCXL	0	6.9	483	599	885	0.68	449	150	0	25.8	3.9	0.4%	0.1%	76.1	45.0	11.1	41.3	NNNNNN1
113	p71202.d	WISE TOWERS	WHITE WESTINGHOUSE	WRT15CGAZD	WRT15CGA**	1	6.9	431	478	624	0.77	306	121	51	NA	5.7	NA	0.1%	77.8	42.6	5.9	46.2	NlNNsN1
114	r71202.a	BETANCES	WHITE WESTINGHOUSE	WRT15CGAWO	WRT15CGA**	1	3.8	NA	NA	624	NA	NA	NA	NA	NA	NA	NA	NA	74.6	34.7	5.0	48.8	sNNNssd
115	r71202.b	WISE TOWERS	WHIRLPOOL	EET122DTWRO	EET121DT	0	6.9	577	638	1080	0.59	570	68	0	16.1	NA	0.2%	NA	79.1	43.3	8.4	46.3	NNNNNs1
116	r71202.c	WISE TOWER	WHIRLPOOL	ET12PCXLWLO	ET12PCXL	0	6.9	660	717	885	0.81	629	88	0	NA	NA	NA	NA	78.6	40.9	9.4	47.2	NNNNss1
117	r71202.d	WISE TOWERS	WHIRLPOOL	EEL131CTWRO	EEL131CT	0	6.9	393	473	540	0.88	362	111	0	51.2	NA	0.6%	NA	78.5	41.4	23.3	42.5	NNNNNe1
118	s71202.a	BETANCES	WHIRLPOOL	ETH141DTWLO	EHT141DT	0	3.8	767	731	925	0.79	599	132	0	64.9	15.3	0.6%	0.1%	74.6	30.5	-1.5	53.7	NNNNNN1
119	s71202.b	WISE TOWERS	WHITE WESTINGHOUSE	RT143SCWO	RT143SC**	1	6.9	775	828	828	1.00	576	199	52	50	5.8	0.7%	0.1%	79.2	43.9	1.7	48.0	NNNNNN1
120	s71202.c	WISE TOWER	WHIRPOOL	ET12PCXLWLO	ET12PCXL	0	7.3	697	721	885	0.81	603	117	0	NA	2.5	NA	0.1%	78.3	41.9	-1.9	49.5	NNNNsN1
121	s71202.d	WISE TOWERS	WHITE WESTINGHOUSE	WRT15CGAWO	WRT15CGA**	1	5.9	1273	1117	624	1.79	937	126	53	NA	NA	NA	NA	78.8	34.1	-11.4	58.4	NNNNss1

Table E.2. Description of Columns in Field-Monitoring Results Table

Column Heading	Description
No.	Row number
Site Code	Logger name, download date, and site index
Develop	NYCHA development name
Manufacturer	Manufacturer of the refrigerator
Model	Model number recorded at the site
Proxy	Best match in the AHAM refrigerator database
Aut	Automatic defrost (1), manual defrost (2)
Days	Length of monitoring period, days
Consumption-Raw	Raw total consumption, kWh/yr
Consumption-Adj	ΔT-adjusted consumption, kWh/yr (see Section 3.2), $\Delta T_{annual\ average}$ = 51.2°F
DOE-Label	Label rating of annual consumption, kWh/yr
Label-Ratio	Ratio of adjusted consumption to label rating
Load Splits-Cond	Conduction component of the ΔT-adjusted total consumption, kWh/yr
Load Splits-Occup	Occupant component of the ΔT-adjusted total consumption, kWh/yr
Load Splits-Defr	Defrost component of the ΔT-adjusted total consumption, kWh/yr
Openings-Refg	Fresh-food compartment door-opening events, counts/day
Openings-Frzr	Freezer compartment door-opening events, counts/day
Duration-Refg	Fraction of time fresh-food door is open, % of total
Duration-Frzr	Fraction of time freezer door is open, % of total
Temperatures-Amb	Average ambient (room) temperature, °F
Temperatures-Refg	Average fresh-food compartment temperature, °F
Temperatures-Frzr	Average freezer compartment temperature, °F
Temp Diff	Difference between ambient and interior temperature, °F, $T_{amb} - (0.7*T_{refg} + 0.3*T_{frzr})$
Comment	Code describing the success of the loggers, sensors, and process (see Table E.3)

Table E.3. Comment Key

Character No:		
	1	Power Data
	2	Ambient temperature logger
	3	Frig compartment logger
	4	Freezer compartment logger
	5	Frig compartment event logger (door openings)
	6	Freezer compartment event logger (door openings)
	7	Splitting process
Letter Codes:		
Power	N	Normal
	s	Sensor problem or logger not installed correctly at site (possible CT wire problem)
Temperatures	N	Normal
	l	File was low on data (stopped on its own before the download)
	e	Empty logger (appears to not have been launched)
	m	Logger moved or removed by occupant (e.g., logger removed from frig. or freezer and set in room)
	s	Thermistor cable must have been loose. Raw temperature data shows repeated measurement over extended period
Events	N	Normal
	w	Frig. and freezer sensors appear to be switched
	b	Battery interruption, battery became disconnected
	m	Mild battery interruption, but end events are reconstructed from front time stamp to within 5 minutes of actual
	s	Sensor does not seem to be responding to door openings (set-up problem or defective sensor)
	u	The sensor was indicated by the logger to be unplugged for a significant portion of the week
	e	Empty: logger not deployed (out for repair)
	h	Sensor problem causing very high door-opening durations
Split Process	1	Ok, process can be used to determine baseline, door-opening, and defrost consumptions
	z	Ok, but no freezer data: baseline can be estimated, but split between door opening and defrost load cannot be estimated
	x	Failed: Control or capacity problem
	a	Failed: Difficult to establish baseline (high door-opening loads day and night)
	d	Failed: Not enough data
	o	Failed: Extended OFF periods

F. Level 1 Heading

THIS PAGE CONTAINS A LEVEL 1 HEADING WHICH ACTIVATES THE APPENDIX LETTER IN THE PAGE NUMBER. THE HEADING 1 STYLE MUST BE MODIFIED IN ORDER TO CHANGE THE APPENDIX LETTER.

PLEASE RECYCLE THIS PAGE.

Appendix F

Occupant Density in NYCHA Housing Developments

Appendix F

Occupant Density in NYCHA Housing Developments

The New York City Housing Authority (NYCHA) provided occupant count data for each housing development in the 1997 project year in each of four age categories: children (0-9), teenagers (10-20), adults (21-61), and elders (62 and older). This data is summarized in Table F.1. The column identified as "Elderly" has a value of 1 for those developments that are occupied mainly by elderly people (0 indicates not elderly). To be assigned the elderly classification, the development must have an elderly/total fraction greater than 0.25 and a total/residence ratio of less than 2.0.

In a letter from NYCHA to Pacific Northwest National Laboratory (PNNL), the official count of people in all NYCHA developments was identified as 431,500 people living in 173,660 units (2.5 per unit). However, this count is know to be conservative because it is estimated that roughly 105,000 additional unofficial residents are in these apartments. Therefore, the best estimate of the true occupant density in NYCHA developments is 3.1 [(431,500 + 105,000)/173,660] persons per dwelling unit.

Table F.1. NYCHA Occupant Data for Each Development in the 1997 Project Year

		Count per Family					Fraction of Total				Development Size		
Indexing Name	**Elderly**	**Child**	**Teen**	**Adult**	**Elders**	**Total**	**Child**	**Teen**	**Adult**	**Elders**	**Dev**	**NYCHA Name**	**Families**
Albany	0	0.55	0.65	1.10	0.28	2.58	0.21	0.25	0.43	0.11	85	ALBANY I AND II	1135
Baruch	0	0.45	0.62	1.18	0.35	2.59	0.17	0.24	0.45	0.14	60	BARUCH	2134
Berry	0	0.34	0.38	0.88	0.47	2.06	0.16	0.18	0.42	0.23	52	BERRY	500
Betances	0	0.43	0.69	1.30	0.21	2.63	0.17	0.26	0.49	0.08	285	BETANCES VI	145
Campos	0	0.40	0.71	1.43	0.34	2.88	0.14	0.25	0.50	0.12	286	CAMPOS PLAZA II	223
Chelsea	0	0.35	0.55	1.12	0.44	2.46	0.14	0.22	0.45	0.18	134	CHELSEA	420
Clinton	0	0.49	0.63	1.10	0.39	2.61	0.19	0.24	0.42	0.15	123	CLINTON	742
	0	0.47	0.69	1.09	0.33	2.58	0.18	0.27	0.42	0.13	69	COOPER PARK	697
Douglas-Add	0	0.37	0.47	0.98	0.45	2.27	0.16	0.21	0.43	0.20	148	DOUGLASS & ADDITION	1420
Douglas-Reh	0	0.37	0.47	0.98	0.45	2.27	0.16	0.21	0.43	0.20	148	DOUGLASS & ADDITION	1420
Gravesend	0	0.73	0.76	1.14	0.17	2.80	0.26	0.27	0.41	0.06	68	GRAVESEND	605
Haber	1	0.00	0.00	0.21	0.99	1.21	0.00	0.00	0.17	0.82	142	HABER	368
HarlemRiver	0	0.33	0.31	0.79	0.42	1.86	0.18	0.17	0.42	0.23	147	HARLEM RIVER I & II	634
HighBridge	0	0.57	0.67	1.19	0.25	2.68	0.21	0.25	0.44	0.09		HIGHBRIDGE	662
Hope	0	0.33	0.54	1.00	0.47	2.34	0.14	0.23	0.43	0.20	247	HOPE GARDENS	316
Langston	0	0.66	0.61	1.19	0.20	2.66	0.25	0.23	0.45	0.08	168	HUGHES	494
Independence	0	0.82	0.78	1.03	0.63	3.26	0.25	0.24	0.32	0.19	140	INDEPENDENCE	707
Isaacs	0	0.30	0.36	0.95	0.49	2.10	0.14	0.17	0.45	0.23	139	ISAACS	635
KingTowers	0	0.47	0.54	1.09	0.39	2.49	0.19	0.22	0.44	0.16	30	KING TOWERS	1332
LaGuardia-Add	1	0.00	0.00	0.11	1.06	1.17	0.00	0.00	0.09	0.91	152	LAGUARDIA ADDITION	140
SethLow	0	0.73	0.78	1.25	0.20	2.96	0.25	0.26	0.42	0.07	169	LOW, SETH	517
Melrose	0	0.52	0.68	1.06	0.30	2.56	0.20	0.26	0.42	0.12	28	MELROSE	951
Mitchel	0	0.46	0.50	0.93	0.36	2.25	0.20	0.22	0.41	0.16	145	MITCHEL	1603
Rangel	0	0.43	0.47	0.96	0.42	2.28	0.19	0.21	0.42	0.18	37	RANGEL(COLONIALPARK)	926
Richmond	0	0.93	0.80	1.16	0.13	3.01	0.31	0.27	0.38	0.04	117	RICHMOND TERRACE	468
Sedgwick	0	0.41	0.46	1.07	0.27	2.21	0.18	0.21	0.48	0.12	45	SEDGWICK	745
Smith	0	0.29	0.43	1.09	0.57	2.38	0.12	0.18	0.46	0.24	27	SMITH	1896
	0	0.55	0.68	1.15	0.26	2.64	0.21	0.26	0.44	0.10		SOUNDVIEW	1204
SouthBeach	0	0.50	0.59	1.05	0.35	2.49	0.20	0.24	0.42	0.14	35	SOUTH BEACH	417
	0	0.50	0.56	1.01	0.41	2.48	0.20	0.23	0.41	0.16	38	ST. NICHOLAS	1471
Wise	1	0.18	0.29	0.83	0.60	1.90	0.10	0.15	0.43	0.31	127	WISE	386
	1	0.31	0.34	0.82	0.53	2.00	0.15	0.17	0.41	0.27	174	WSUR VEST POCKETS	383

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