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Improved Analysis Methods For Retrofit Savings And Energy Accounting

Progress Report

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Executive Summary

This report summarizes progress through November, 1990 for ERAP project No. 227, "Improved Analysis Methods for Retrofit Savings and Energy Accounting." The major objectives of this project are to:

1) determine the energy and dollar savings from energy conservation retrofits;

2) reduce energy costs by identifying and correcting operational and maintenance problems at retrofitted facilities;

3) identify savings from individual retrofits to help improve future retrofit selection; and

4) initiate an end-use data base for commercial and institutional buildings to facilitate the comparison and exchange of building energy use information.

A grocery store, two nursing homes, an institutional building, and a high school have been selected as preliminary case study buildings. All of the buildings except the nursing homes have been instrumented to provide sub-metered and total energy use data. Additional buildings in the Texas LoanSTAR program are also instrumented and are being analyzed.

Four preliminary models to predict energy consumption in the case study buildings have been developed and tested. The Princeton Scorekeeping Method Cooling Only (PRISM CO) model is an ambient temperature dependent regression model that provides a good fit ($R^2 = 0.89$ and $R^2 = 0.97$) to the nursing homes' electricity consumption during cooling season months. A four parameter regression change-point model to predict daily electricity consumption at the grocery store has an average daily error of only 1.7% for the period analyzed. Ambient temperature dependent regression models predict hot and chilled water consumption at the institutional building with goodness of fit statistics $R^2 = 0.90$ and $R^2 = 0.87$ respectively. A regression model based on the institutional building's operating hours predicts electricity consumed by lights and receptacles.

The predictive ability of the preliminary models has been tested by comparing predicted energy consumption to measured energy consumption. Models that can accurately predict building energy consumption are essential to the effort to determine retrofit savings and identify and correct operational and maintenance problems. PRISM CO predicted electricity consumption during the cooling months at the nursing homes within 3.3% and 6.3% of measured consumption for the period from April to September 1990. The four parameter change-point model predicted daily electricity consumption at the grocery store for the period from January 1 to October 10, 1990 such that the average residual between measured and predicted electricity consumption was 3.7%. Hot and chilled water consumption at the institutional building was predicted within 5.7% and 0.2% of measured consumption for the period from May 24 to October 10, 1990. The scheduling model for electricity consumed by lights and receptacles at the institutional building had residuals between predicted and measured consumption of less than 15% of the maximum electric demand for the period from August 1989 to August 1990.

In addition to predicting energy use, the end-use breakdown of energy at the case study buildings was estimated using four methods. Peak electric demand was apportioned to different energy using systems by recording energy consumption data from the energy using equipment. An engineering simulation model, A Simplified Energy Analysis Method (ASEAM), estimated the annual energy use break-down at the high school and a nursing home. PRISM CO estimated base-level and temperature dependent energy consumption at the nursing homes. Finally, sub-metered energy consumption data from the institutional building provides the most accurate energy end-use breakdown.

Three new models promise to be statistically rigorous and applicable to a wide range of buildings. A four parameter change-point model that determines model parameters by minimizing mean square error improves the previous four parameter change-point model. A principle component analysis model improves parameter stability compared to standard multiple regression models when the independent variables are correlated. A methodology to identify typical day types for non-weather dependent loads can be used to quickly and accurately develop calibrated input decks for energy simulation models such as DOE-2 and BLAST. Three journal papers that describe these models have been accepted for publication in the Solar Engineering 1991 - Proceedings of the Joint ASME/ISES International Solar Energy Conference1991.

The methodologies developed in this project have immediate application in the Texas LoanSTAR program as part of the effort to determine retrofit savings. Energy savings from this project are conservatively estimated as 2.6×10^{12} Btu/yr by the year 2000 due to improved retrofit selection and identification and correction of operational and maintenance problems. Over 70 requests for information about energy analysis methods and software have been received.

In the next year, efforts will focus on extending the PCA and change-point model analysis and developing systematic methods for identifying and correcting operational and maintenance problems.

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CHAPTER 1
Introduction

Energy use in commercial buildings amounts to about 13% of all U.S. energy use (EIA, 1986). Energy saving retrofits have proven effective at reducing energy related operating costs for building owners and at moderating total U.S. energy consumption growth. A study of over 1,700 building energy retrofits reports a median annual energy savings of 18% of whole-building energy usage with a median payback time of 3.1 years. In over one-half of the projects, whole-building energy use continued to decrease in the years following the retrofit (Greely et al. 1990).

While these results are impressive, fewer than one in six predictions of energy savings came within 20% of measured results (Greely et al. 1990). Reasons for the difficulty in predicting energy savings include the diversity of potential improvements, the diversity of buildings in general, and the high rate of change in the building's use and weather conditions (MacDonald and Wasserman, 1989). The task of predicting building energy consumption could be improved by sharing information about retrofits and building energy use. However, the great diversity in building types, functions, energy using systems, and operating conditions makes comparing the energy use of different buildings even more difficult than predicting an individual building's energy use. Thus, many practitioners currently rely on "their own sense of what constitutes an energy efficient building" (MacDonald and Wasserman, pg. 2, 1989) and "professional judgement" (Greely et al., pg. 3, 1990).

It is apparent that present methods to predict baseline energy use and retrofit energy savings can be significantly improved. The Department of Energy has identified retrofit performance data as a key research need (MacDonald, et al. 1988). With this in mind, the major objectives of this project are to:

1) determine the energy and dollar savings from energy conservation retrofits;

2) reduce energy costs by identifying and correcting operational and maintenance problems at retrofitted facilities;

3) identify savings from individual retrofits to help improve future retrofit selection; and

4) initiate an end-use data base for commercial and institutional buildings to facilitate the comparison and exchange of building energy use information.

This report summarizes the first year's progress towards meeting these goals.

Current Methods to Determine Retrofit Energy Savings

Energy savings are often calculated by direct comparison of pre- and post-retrofit energy consumption. The advantage of this technique is its simplicity. However, direct comparison ignores changes in weather, occupancy, and energy using equipment which may significantly alter post-retrofit energy consumption and estimated savings.

Weather adjusted energy consumption estimates have been shown to differ from measured energy consumption by up to 12% of pre-retrofit consumption (Greely et al. 1990). Since this is comparable to the median energy savings of 18%, it indicates that if not accounted for, changing weather conditions may obscure or amplify estimated savings.

Current single parameter models which consider weather to determine energy savings are best suited to buildings whose energy use is envelope dominated and dry-bulb temperature driven. However, many buildings are influenced by other environmental parameters besides ambient temperature such as latent cooling load and solar-driven influences. To investigate these buildings, we are considering models which also account for dry-bulb temperature, ambient humidity, solar radiation, and wind speed, and other non-environmental factors.

Changes in energy using equipment can also affect retrofit savings estimates. For example, office information equipment (computers, typewriters, copiers, etc.) has been shown to equal or surpass the lighting load in some new commercial buildings (Norford, et al. 1988). If unaccounted for, increased use of this type of equipment can cause significant underestimation of energy savings.

Operational and system parameters influence the energy use in many buildings which are eligible for energy conservation retrofits (Haberl and Claridge, 1987). Operational parameters are occupant related and change frequently, such as occupancy and custodial schedules. System parameters are equipment settings, such as temperature setpoints and economizer damper settings. Operational and system parameters can also be modeled by dual-state models that "switch" between "occupied" and "unoccupied" periods.

Our objective is to develop models which consider these effects and improve our ability to predict the energy consumption of a wider variety of buildings. The new models are based on a combination of measured data, statistical analysis, and engineering design methods. Our approach can be called a "case study" approach, since the models are developed for selected instrumented buildings and then generalized to other buildings.

What's Next

The following chapter describes the buildings that are currently being analyzed and the buildings to be analyzed in the next phase. Next, we report on preliminary models which have been developed for selected buildings. The fourth chapter examines the preliminary models' ability to predict monthly, daily, and hourly energy consumption by comparing predicted to measured energy use. Chapter five reports the energy end-uses for the buildings being analyzed, followed by a chapter which presents the methodology of the change-point, principle component analysis, and scheduling models currently being explored. We then summarize with a market position and technology transfer chapter and close with a discussion of future directions.

CHAPTER 2
Buildings List

This chapter describes the first year, case study buildings, the LoanSTAR buildings for which metered data is available, and buildings being considered for future research. Models are being developed and tested on buildings in the first year case study group. These models will be applied to similar buildings. The pool of LoanSTAR buildings being monitored is a readily accessible group of buildings to which case study results will be applied, tested, and validated. The additional LoanSTAR buildings listed in the third section of this chapter are being considered for new model development and testing.

First Year Case Study Buildings

The primary buildings being analyzed are listed in Table 1.1. The grocery store and nursing homes are parts of commercial chains operating throughout the south central United States. A&M Consolidated High School and the Zachry Engineering Center contain systems which are commonly found in similar buildings throughout the U.S. A short description of each of these buildings follows.

Buildings	Location	Floor Area(ft^2)	Annual Energy Costs	Monitored Data Monthly	Monitored Data Hourly
Grocery store	College Station	40,000	$205,000	39	39
Nursing home	Austin	58,100	$97,700	38	0
Nursing home	Temple	31,000	$45,000	31	0
Zachry Engineering Center	College Station	324,400	$690,300	18	18
A&M Consolidated High School	College Station	209,600	$227,300	13	13

***Table 2.1**; Original buildings analyzed, Texas location, floor area, annual energy costs, and number of months of monthly and hourly energy data currently available.*

Case Study Grocery Store

The grocery store is located in a small shopping center which houses eight businesses. It is open 24 hours per day, every day of the year except Thanksgiving and Christmas.

The building is a single story structure with 16 foot high ceilings and has a total area of 40,000 ft^2 (160 by 250 feet). The front 35,000 ft^2 of space is used for product display, and the rear 5,000 ft^2 holds the space conditioning equipment, the walk-in coolers, and the meat and product preparation areas.

The grocery store shares two interior walls with other businesses on the northwest and southeast sides although the adjacent spaces are currently unconditioned. The northwest and southeast walls are 160 feet in length and are constructed of 6-inch poured concrete, 3.5 inches of interior batt insulation and interior drywall. The northeast and southwest walls are 250 feet long. The northeast wall includes a 60-foot by 16-foot section of glass. The entrance to the street is an L-shaped vestibule with automatic doors. The roof is constructed of a lightweight metal deck which supports a 1-1/2 inch layer of foam insulation, a 2-inch concrete slab and a built-up roof covered with light colored aggregate.

The refrigeration system is the biggest energy using system in the store. It is comprised of twenty R12 compressors in conjunction with 46 refrigeration and freezer cases. The defrost cycle is controlled by 20 time clocks - one for each compressor. The HVAC system consists of two 50 ton units for cooling. Heating is provided by heat reclaim from the refrigeration system and is supplemented by natural gas duct heaters. Natural gas is also used to provide hot water and for ovens in the delicatessen and bakery.

<u>Case Study Nursing Homes</u>

The Temple nursing home is a 100 bed nursing home that was 80 per cent occupied in early 1990. Approximately 40 staff members are present during the day and about 20 during the night. The facility operates 24 hours per day, 365 days per year. Full food and laundry service are provided.

The single story, slab on grade building was built in 1970 and has an approximate floor area of 31,000 ft^2. Exterior walls consist of an eight foot lower section and a four foot upper section. The windows are double glazed, gray glass and cover about 15% of gross wall area. The building has a flat masonry roof with built up roofing and 6" of fiberglass batt insulation.

Most of the space conditioning is provided by eight roof-top air conditioning units. Two of the roof-top units provide heat using electrical resistance heaters and six of the units use natural gas for heating. Vapor compression cooling is used by all units. Heating and cooling is supplemented by six small heat pumps located in individual occupant's rooms.

The Austin nursing home is nearly twice as large: it is a two-story building with approximately 58,000 ft^2 of floor area. Operational schedules and building characteristics are similar to the Temple nursing home.

Space conditioning is primarily provided by 16 roof-top air conditioning units. Some small window air conditioners and heat pumps supplement the roof-top units. All roof top units provide electrical resistance heating and vapor compression cooling.

Case Study Institutional Building

The Zachry Engineering Center (ZEC) is a four-story (plus basement parking level) building on the Texas A&M University campus with approximately 324,400 gross ft^2 of floor area. Major uses of the building include: 1) offices, 2) class rooms, 3) computer rooms, and 4) laboratories. The building also includes hallways and a large atrium area which serves as a common space. It is open 365 days per year, 24 hours per day.

The building is a heavy structure with 6-inch concrete floors and insulated concrete walls. It is heated and cooled by a constant volume dual duct system. Hot water, chilled water, and electricity are supplied by the central campus plant.

Case Study High School

A&M Consolidated High School is a 209,605 ft^2, two-story facility in College Station. School is in session about nine months per year, with vacations in the summer months and during portions of December and January.

The original building was built in 1970, with major additions in 1979 and 1982. It is a primarily concrete structure with brick facia. During the 1982 renovation, the building was reroofed and ceiling insulation was added.

The building uses a combination of HVAC systems. Most of the building is serviced by a constant volume reheat system using centrifugal chillers for cooling and both electrical resistance and natural gas fired boilers for heating. Roof top units using vapor compression cooling and electrical resistance heating provide space conditioning for some class rooms. Electricity dominates energy cost at the school.

LoanSTAR Case Study Buildings

The energy analysis techniques being developed on first year case study buildings will also be applied to selected buildings in Table 1.2. These buildings are currently being monitored or will be monitored as part of the Texas LoanSTAR Program. The Texas LoanSTAR program is an eight year, $98 million revolving loan program, funded by oil overcharge money, for energy conservation retrofits in Texas state, local government, and school buildings (Turner, 1990).

As part of this program, a statewide energy Monitoring and Analysis Program (MAP) has been established. The program's first objective is to determine whether retrofits save as much as estimated in audits. Another objective is to reduce energy costs by evaluating a building's energy-using characteristics. Evidence from Lawerence Berkeley Laboratory (Akbari et al., 1988, and Harrje, 1982), Princeton (Putt et al., 1988), Oak Ridge National Laboratory (MacDonald et al. 1989), and the University of Colorado (Haberl and Claridge, 1987) suggests the potential effectiveness of sub-metering large buildings with major retrofits. The models described in this report are being developed to meet these objectives. The buildings in Table 1.2 provide an readily accessible pool of buildings for model testing and validation.

Agency Name	Location	Projected Savings*	Cost of Monitoring*	# of Bldgs	# of Points
Texas A&M	College Station	$411.1	$42.0	1	45
Texas Dept. of Health	Austin	$60.6	$22.4	5	7
MHMR -El Paso	El Paso	$17.1	$14.2	1	12
MHMR - Austin Hospital	Austin	$336.5	$11.0	1	5
MHMR - Austin School	Austin	$102.9	$20.0	1	3
MHMR - Terrel	Terrel	$343.7	$51.7	6	16
U.T. Arlington	Arlington	$352.2	$56.2	6	39
Texas A&M, Galveston	Galveston	$26.6	$27.0	9	8
U.T. Austin	Austin	$1493.5	$180.8	16	156
U.T. Medical Branch	Galveston	$1100.8	$87.3	8	26
U.T. Health Science Center	Dallas	$283.5	$30.9	4	16
U.T. Dallas	Dallas	$118.4	$34.3	6	10
T.T. Health Science Center	Lubbock	$333.3	$15.0	1	15
U.T. Health Science Center	Houston	$218.3	$32.7	2	12
U.T. Health Science Center	San Antonio	$110.9	$15.0	2	8
Univ. of North Texas	Denton	$65.5	$7.0	1	7
Capitol Complex	Austin	$500.0	$130.4	11	56
	TOTALS:	$5074.8	$779.9	81	441

Table 2.2; *Installations being monitored or having equipment installed in 1990 as part of the Texas LoanSTAR program. * Amounts are in thousands of dollars. (O'Neal, 1990).*

Additional Case Study Buildings

Buildings for which models may be developed and validated in the future are included in Table 1.3. The Texas Technology University Health Center and a government building at the Capital Complex in Austin, are currently enrolled in the LoanSTAR program.

Health Center	Texas Technology University	Lubbock
Government Building	Capital Complex	Austin
Additional grocery stores		Texas

Table 2.3; *Additional buildings for analysis.*

CHAPTER 3
PRELIMINARY MODELS REPORT

Three preliminary models were tested for their ability to predict energy consumption, including: the Princeton Scorekeeping Method (PRISM), temperature dependent models, and scheduling models. The next section describes the Princeton Scorekeeping Method (PRISM) and its application to two nursing homes and A&M Consolidated High School. In the following section, a four-parameter segmented regression model is presented and tested on the grocery store. The final section describes a scheduling model applicable to Zachry Engineering Center and preliminary analysis of A&M Consolidated High School.

The amount of energy saved by a retrofit is determined by comparing a building's post-retrofit energy consumption to an estimate of how much energy the unretrofitted building would have consumed during the same period. Post-retrofit energy consumption is easily determined from the buildings utility bills. The energy prediction methods described in this chapter will be used to estimate how much energy a building would have consumed if it had remained in its pre-retrofit condition.

Accurately predicting building energy consumption can also aid in identifying operational and maintenance problems in buildings. An expert system developed by Haberal and Claridge for this purpose reduced energy consumption by 15% at a campus recreation center (Haberal and Claridge 1987). This method compared the building's measured and predicted energy use and alerted management whenever large deviations occurred.

The models described in this chapter are appropriate for determining retrofit savings and identifying operational and maintenance problems in buildings. For this reason, they are important tools toward achieving the projects objectives.

Princeton Scorekeeping Method

One of the most widely accepted model to determine retrofit savings is the Princeton Scorekeeping Method (Fels 1986). PRISM is a statistical procedure originally developed to provide a weather-adjusted index of energy consumption in residences. PRISM requires whole-building energy consumption data for a building and average daily temperatures at the location. It produces a weather-adjusted Normalized Annual

Consumption (NAC) that is composed of three primary parameters which describe heating-related and non-heating-related consumption. These factors are a slope (kWh/day-F), base-level consumption (kWh/day) and balance-point temperature (F). Variations of PRISM are available which consider cooling energy consumption as well as heating.

PRISM has been adopted as one baseline technique for buildings which are appropriate for analysis with one-, three- and five- parameter segmented linear, change-point models. The versions of PRISM which are available or under development include one-, three- and five- parameter segmented regressions as shown in Figure 3.1.

The one-parameter model is typical of monthly electrical use when heating and cooling influences are absent. It is also typical of sub-metered daily electricity consumption data from many buildings expected in the program. One additional step may include sorting into weekday/weekend data since non-weather dependent use is highly dependent on scheduled use.

The three-parameter PRISM models represent the classic Heating Only (HO) and Cooling Only (CO) models and have been used with some success on the nursing homes.

A five parameter, PRISM Heating and Cooling model (HC), is operational at Princeton. This is a better model for buildings that use one fuel for heating, cooling and base-level purposes. Future analysis will determine the effectiveness of applying this model.

<u>PRISM Models of Nursing Home Electricity Use</u>

The PRISM CO model was applied to monthly electricity consumption data at the two nursing homes. The electric billing data for both facilities are shown in Figure 3.2. Since some heating influence is visible in both data groups, the PRISM cooling only model was used with winter data omitted.

The PRISM CO model coefficients for both nursing homes are listed in Table 3.1. The Temple model provides R^2= 0.89 with a cooling balance-point temperature of 66.8 F. The model is based on fourteen months of electric consumption data. The Austin model provides R^2= 0.97, a cooling base temperature of 74.2 F and is based on seven months of data. The Austin model's higher R^2 results from having fewer data points than the Temple model and does not necessarily imply a better fit. The normalized annual consumption estimated by PRISM is not significant in this case since winter months were not included in the data set.

Electricity consumption versus cooling degree days per day and PRISM's regression estimate for these facilities are shown in Figure 3.3. The PRISM CO model appears to be an adequate estimator of electricity use at both nursing homes during the cooling season.

Model: $T>T_{bal}$: Elec/Day = a + b(T-T_{bal}) $T<T_{bal}$: Elec/Day = a

	T_{bal} (F)	a (kWh/day)	b (kWh/day-F)	Nac (kWh/yr)	R^2
Temple	66.8	1262	54.02	607,250	.89
Austin	74.2	2762	125.83	1,172,688	.97

***Table 3.1**; PRISM coefficients for two nursing homes.*

Other Temperature Dependent Models

PRISM is a segmented, regression model which is appropriate for buildings which exhibt temperature dependencies. Certain buildings may not be well described by PRISM. For example, grocery stores have large amounts of "air cooled" refrigeration equipment with a COP that varies with ambient temperature. Typically, this causes base-level energy consumption to decrease with decreasing ambient temperature. In stores where this condition is significant, a four parameter change-point model with a non-zero slope for the base-level region (RMSE = 169.2) fits the electricity consumption better than the PRISM CO model (RMSE = 277.8).

The following section describes a four parameter change-point model that has been developed to model such energy useage in a grocery store. In the next section chilled water and hot water consumption at Zachry Engineering Center are modeled as functions of ambient temperature and interior lighting and electric loads. The final section describes the results of applying a scheduling model to ZEC electricity use.

A Four Parameter Change-Point Model Of Grocery Store Electricity Consumption

Electricity consumption at the grocery store was recorded at 15-minute intervals and aggregated to provide hourly and daily total consumption. Daily consumption as a function of average daily ambient temperature is shown in Figure 3.4. In the figure, there appears to be two essentially linear regions which meet at about 62 F (called the change point). Physically, the consumption appears to drop slowly with temperature (below 62 F) due to the increasing COP of the refrigeration compressors. As the temperature increases above 62 F, the COP of the compressors drops and air conditioning also becomes necessary, resulting in a sharp increase in the slope of the electricity consumption.

Consequently, the data were divided into two groups: those collected when the ambient temperature (as recorded at the local airport) was above 62 F and those collected when the temperature was at or below 62 F. Each set was then regressed against the dry bulb temperature to obtain a unique slope.

This process resulted in a four-parameter regression model for the daily average electricity consumption. The parameters are: (1) a slope for the non-cooling regime, (2) a slope for the cooling regime, (3) a change-point temperature, and (4) a baseload plus refrigeration consumption at the change point temperature, T_{cp}. The daily average electricity consumption, E_d, can then be expressed as:

$$E_d = E_{cp} + B_r*(T_d - T_{cp}) \quad T_d <= 62 \text{ F}$$
$$E_d = E_{cp} + B_c*(T_d - T_{cp}) \quad T_d > 62 \text{ F}$$

where T_d is the average daily temperature, E_{cp} is the electricity consumption at the change point of 62 F and B_r and B_c are the slope coefficients. The model parameters obtained are:

$$E_{cp} = 310 \text{ kWh/day}$$
$$B_r = 0.868 \text{ kWh/day-F}$$

$$B_c = 4.976 \text{ kWh/day-F.}$$

The ability of the daily predictor model to estimate consumption during April 1989 is shown in Figure 3.5. The model appears to track actual consumption very well. Excluding anomalies on April 4, 8 and 9, the average residual consumption is 8.6 kWh or 1.7% of the total whole-building electricity use. A more extensive discussion is provided in Schrock and Claridge (1989).

A Model Of ZEC Chilled Water Consumption

The chilled water consumption for ZEC depends primarily on the ambient temperature as can be seen in Figure 3.6. There appears to be a slight difference between weekdays and weekends - physically we expect this difference to be due to lower internal heating due to lower electricity consumption on weekends.

Table 3.2 shows our pre-retrofit model for chilled water consumption at the ZEC, determined using SAS (SAS 1985). Models are shown which depend on temperature (T) only and which depend on temperature, T, as well as electrical consumption for lights and office equipment, LE. The second model has a slightly higher R^2 parameter and may be preferable since lights and office equipment contribute to the cooling load and therefore have a physical basis for being included in the model.

	$CW = a + bT$	$CW = \alpha + b_t T + b_e LE$
R^2	$R^2 = 0.86$	$R^2 = 0.87$
Intercept	$a = 221.8$	$a = 35.5$
Slope	$b = 16.4$	b_t=16.2 b_e=0.01
Prob Param = 0	$P_a = 0.0001$ $P_b = 0.0001$	$P_a = 0.4799$ $P_{bt} = 0.0001$ $P_{be} = 0.0001$

Table 3.2; *Model parameters and statistics for two models of chilled water consumption at the Zachry Engineering Center.* R^2 *indicates the fraction of variability in the data explained by the model. The second model provides a slightly better fit to the data. The positive slopes indicate the chilled water consumption increases as ambient temperature increases. The low probabilities (P) indicate that all of the parameters except the intercept of the lights and equipment model are statistically significant.*

Note that the chilled water consumption does not show a change-point. It simply decreases as temperature decreases. It <u>might</u> show a change point at sufficiently low temperatures, however, the available data includes some of the coldest weather ever experienced in College Station and no change point is evident. Therefore we conclude that a two- parameter model without a change point is appropriate.

<u>A Model Of ZEC Hot Water Consumption</u>

The hot water consumption is similar to the chilled water consumption, except that hot water consumption decreases as ambient temperature increases. This behavior is shown in Figure 3.7. The data appear to exhibit a slight dependence on the electricity consumption for lights and equipment as shown in Table 3.3. In this case the dependence on electricity use is about three times stronger than for chilled water.

	$HW = a + bT$	$HW = a + b_tT + b_eLE$
R^2	$R^2 = 0.87$	$R^2 = 0.90$
Intercept	$a = 1808.8$	$a = 2178.3$
Slope	$b = -19.5$	$b_t = -19.2$ $b_e = -0.03$
Prob Param = 0	$P_a = 0.0001$ $P_b = 0.0001$	$P_a = 0.0001$ $P_{bt} = 0.0001$ $P_{be} = 0.0001$

***Table 3.3**; Model parameters and statistics for two models of hot water consumption at the Zachry Engineering Center.* R^2 *indicates the fraction of variability in the data explained by the model. The second model provides a slightly better fit to the data. The negative slopes indicate that hot water consumption increases as ambient temperature decreases. The low probabilities (P) indicate that all of the model parameters are statistically significant.*

Scheduling Models

Energy use in many buildings is heavily dependent on the building's operating schedule. In some cases, a model for predicting energy consumption can be developed simply by correlating measured energy use with the building's operating schedule (Haberl and Komor, 1989). The next two sections describe scheduling models for electricity consumption for the Zachry Engineering Center and the applicability of a scheduling model for A&M Consolidated High School.

A Model Of ZEC Electricity Consumption

The electrical consumed by lights and recepticles at the ZEC from July 1989 through May 1990 is shown in Figure 3.8. The figure shows hours of the day from front-to-back, Julian day of the year from right-to-left and hourly electricity use on the vertical axis. The building is open seven days a week, 24 hours a day, and the HVAC systems are operated continuously. Light and recepticles electricity consumption shows a diurnal pattern which varies from a minimum level near 600 kW to a peak of 1 MW on weekdays with a slightly lower minimum and much lower peak on weekends. Some gross characteristics of the data are evident in the figure. Proceeding from right to left, consumption is seen to be lower during the break period just before Autumn Semester begins. Christmas vacation period is very evident as the "canyon" near the middle of the figure. The other "canyons" in the left half of the figure represent missing data.

The data were used to define an average hourly schedule for weekdays and weekends when school is in session as shown in Figure 3.9(b). This may be compared with the measured consumption for February 1990, shown in Fig. 3.9(a). The positive residuals and absolute values of the negative residuals are shown in Figs 3.9(c) and 3.9(d). The residual plots indicate: 1) that light and recepticle electricity use is generally well-described by this simple model (+/- 100 KW out of 1500 kW); 2) that there is a consistent over-prediction of electricity use on Friday afternoons (days 32,39,46 and 53 of Fig. 3.9(d)); and 3) that Saturday consumption is sometimes higher than expected (days 40 and 54 of Fig. 3.9(c)).

<u>A&M Consolidated High School Electricity Use</u>

Electricity use at A&M Consolidated High School appears to be dominated more by scheduling and operational influences than by ambient temperature. Figure 3.10 depicts electricity use as a function of ambient temperature for the Spring semester. The data are divided into day types with 0,1, and # representing Saturday, Sunday, and holidays respectively. Weekdays are represented by numbers 2 through 6. Electricity use is clearly higher on weekdays than on weekends or holidays; however, no significant dependence on temperature is evident. Figure 3.11 shows hourly electrical use for most of the school year. A load shape that corresponds to school operating times is clearly evident.

Because the building energy use is not highly temperature dependent, we expect low PRISM R^2 values. PRISM analysis of the data is consistent with these conclusions.

This analysis suggests that electricity use at A&M Consolidated High School may be more appropriately modeled using a scheduling model such as the load-shape methodology described in chapter six.

CHAPTER 4
Model Predictive Ability

The preliminary models described in chapter three have been used to predict energy consumption in selected buildings. Energy predicting models in three different time frames are presented here: monthly, daily, and hourly. The models' prediction of energy consumption is compared to actual energy consumption in the sections that follow.

Monthly Nursing Home Electricity Use

The PRISM CO model described in chapter three was used to predict electricity use at the nursing homes during the summer of 1990. For the Temple nursing home, the model parameters are based on 14 months of data between February, 1988 and August, 1989. In Figure 4.1a, those model parameters are used to predict electricity consumption in a subsequent period between April and September, 1990. These predicted values are compared to measured data for this period in Figure 4.1.

Electricity consumption predicted by PRISM CO closely follows the trend of actual electricity consumption. One method to quantify how close predicted consumption is to actual consumption is to find the difference between the values and divide by the actual consumption. This method yeilds an average deviation between actual and predicted consumption of 6.3% of measured consumption. The small deviation between actual and predicted electricity consumption indicates that PRISM CO is a good predicter of electricity consumption at this nursing home. The total predicted consumption for the period shown was 3.3% less than the measured consumption.

Figure 4.1b shows measured and predicted electricity consumption at the Austin nursing home. For this run, the PRISM CO model parameters were based on seven months of data between March and October, 1989. These parameters are then used to predict electricity consumption in a subsequent period between April and September, 1990.

It appears that PRISM CO slightly over-predicts energy use for this period. However, the nursing home underwent a lighting retrofit that reduced the power required to light the building after the original parameters were determined. In this case, the bias shown in Figure 4.1b actually represents electricity saved by the lighting retrofit. PRISM CO indicates an average monthly savings of 6.2% of measured consumption. The total electricity savings during this period was 6.3% of measured consumption.

Daily Grocery Store Electricity Use

The four parameter change-point model described in chapter three was developed using data from March, 1988 to April, 1989. This model was then applied to electricity use and temperature data for a new period beginning January 1, 1990 and ending October 10, 1990 to test its ability to predict electricity use at the grocery store. Actual consumption and the model's predicted consumption are shown in Figure 4.2.

Two regions of differing temperature dependence (slope) are evident in the measured consumption. The model appears to slightly under-predict electricity consumption, especially below the change-point. A physical explanation appears plausible, since a large refrigerated room was added to the store after the model was developed. It is also possible that sales volume may have increased since the original model was developed. Although this points to the weakness of models dependent only on temperature, the model still provides a good fit to the data. The average deviation between measured and predicted electricity use is 3.7% of measured use.

Daily ZEC Chilled Water Consumption

The ZEC chilled water use model described in chapter three was developed using data from September 1, 1989 to May 23, 1990. It was applied to new data from May 24, 1990 to October 10, 1990 to test its predictive ability. Both the model's prediction and measured data from this period are depicted in Figure 4.3 as a function of ambient temperature.

The model is sensitive to ambient temperature and internal cooling required because of lights and receptacle use. However, the dependence on lighting and receptacle electricity is so small in this model that the predicted energy consumption appears in Figure 4.3 as a straight line dependent only on temperature. The average deviation between measured and predicted consumption is 5.1% of measured consumption. The total predicted consumption for the period was within 0.2% of measured consumption, indicating that the model was an excellent predictor of chilled water consumption during this period.

Daily ZEC Hot Water Consumption

The chapter three model for hot water consumption at the ZEC was also tested against measured data from the most recent time period. The results are depicted in Figure 4.4, again as a function of temperature. In the hot water model, the inverse dependence on lighting and receptacle electricity use is much greater than in the chilled water model. Because of this, the model's predicted consumption appears as a region partly dependent on temperature and partly dependent on lighting and receptacle electricity use in Figure 4.4.

The average deviation between measured and predicted consumption was 83.2% of measured consumption. The high average error is not particularly troublesome because the model has been applied to a set of days with daily temperatures which do not represent the daily temperatures that the model was originally developed for. Most of the daily temperatures in the new set of data are above 80 F, with correspondingly small predictions hot water consumption. The model was developed for a data set with a more even distribution of daily temperatures and larger amounts of hot water consumption. The total predicted hot water consumption for the period shown was 5.6% greater than measured consumption.

Hourly ZEC Electricity Use

A methodology to identify typical day types for a building using monitored end-use data for non-weather dependent electric load (i.e. lights, equipment, etc.) has been developed. This scheduling model was tested on data from the ZEC with good results.

Electricity consumption at the ZEC can be accurately represented with five typical load shapes: (a) three in a "LOW" group, (b) one in a "NORMAL" group and (c) one in a "HIGH" group. Figure 4.5 shows the number of days in each day type. A comparison of the actual and predicted electric consumption is shown in Figure 4.6. The predicted electric consumption was calculated from the five typical load shapes. The residual plots indicate: (a) the predicted consumption is close to the actual consumption (+/- 100 kW), and (b) the residuals during the holidays/vacations are consistently higher.

CHAPTER 5
END-USE DISAGGREGATION

Whole-building energy consumption represents the sum of many energy end-uses within a building. Some of these end-uses such as heating and air conditioning are driven by the weather. Some, such as lighting and office equipment are driven by the scheduled use of the building. Accurate models to predict whole building energy use must consider all of these different energy end uses. To do this, accurate information on the breakdown of energy consumption within a building is necessary.

In this chapter, the energy consumption of the five original buildings is divided into end-uses using four different techniques. In the first section, the peak demand is disaggregated into end-uses at a nursing home, the grocery store, and the high school using data from equipment name plates. The next section describes an engineering simulation model's estimates of energy end-use consumption at the Temple nursing home and at A&M Consolidated High School. Then statistical model estimates of base-level and cooling related electricity use at the nursing homes are presented. In the last section, sub-metering at the ZEC provides a breakdown of the building's annual energy consumption.

Peak Electric Demand Method

Energy using equipment has been inventoried at the grocery store, nursing homes, and high school. The rated electric demand of each piece of equipment is obtained from the name plate or by contacting the manufacturer of the equipment. From this information, the building's electric demand during theoretical peak operation can be apportioned to the different energy using equipment.

Figure 5.1 shows the estimated contribution of each category during peak operation at the grocery store. The estimated end-use breakdown of the several electrical systems in the store is: refrigeration cases and compressors (44.3%), air conditioning (24.6%), lighting (15.8%), food preparation (12.6%), point-of-sale registers (1.2%) and miscellaneous end uses (1.5%). Clearly, the best candidates for energy savings are the systems which use the most energy in the store. Of the total energy use, 84.7% can be attributed to three systems: refrigeration, air conditioning and lighting.

The peak electric demand breakdown at the Temple nursing home is depicted two ways in Figure 5.2. Figure 5.2a shows electricity use by electricity using systems. Air conditioning is the largest load, representing 57.4% of total demand, followed by lighting (20.2%), food preparation (18.1%), and laundry services (4.2%).

Electric demand is divided into functional areas within the building in Figure 5.2b. The estimated peak electric demand end-use breakdown by functional area is: resident areas (46.5%), utility areas (34.3%), and lobby and dining areas (19.2%). Of the three areas, the resident areas make up the largest fraction of total floor area (59%), accounting for the large fraction of peak demand. The utility areas (kitchen and laundry) make up the smallest amount of floor area (9%), and have the highest power density in the building.

The peak demand used by major energy using systems at A&M Consolidated High School is shown in Figure 5.3. Peak end-use demand is estimated as: chillers (65.1%), lights (16.7%), air handling units (9.0%), pumps (6.7%), and condenser (2.5%). Miscellaneous energy using equipment is not included in this breakdown.

Engineering Simulation Models

The energy consumed by a building's energy using systems can also be estimated by engineering simulation models. The building energy use in A&M Consolidated High School and the Temple nursing home was simulated using A Simplified Energy Analysis Method (ASEAM, ACEC, 1987) computer software. ASEAM uses the modified bin method of energy analysis.

ASEAM estimated the annual energy consumption end-uses at the Temple nursing home as (Figure 5.4): HVAC (50%), lighting (26%), and food preparation and laundry services (24%). These are estimates of the total annual energy use including electricity (on a site basis) and natural gas.

ASEAM estimates of the electricity use at A&M Consolidated High School are shown in Figure 5.5. The electricity consumption breakdown is cooling (36.7%), miscellaneous equipment (25.8%), lighting (16.5%), fans (15.0%), heating (3.1%), and pumps (3.0%).

Not included in this breakdown is additional heating for space conditioning and hot water that is supplied by natural gas.

Statistical Models

PRISM estimates annual base-level (or temperature independent) energy consumption and energy consumed to heat or cool a building. The results of the PRISM CO analysis for cooling months at the nursing homes is shown in Figure 5.6. PRISM CO estimates that cooling requires 28.8% of electricity consumption at the Temple nursing home. Electricity for cooling is estimated to be 14.0% of total electricity consumption at the Austin nursing home.

Measured Data

Energy end-use data has been collected for the ZEC since May 1989. Electricity, hot water, and chilled water are provided by the Texas A&M physical plant. The energy consumption estimates listed here are on a site basis and do not include losses incurred at the physical plant or in transportation from the physical plant to the ZEC.

For the period from September 1, 1989 to August 31, 1990, the ZEC used 9,727,000 kWh of electricity. The maximum electric demand during the year was 1,395 kW. Air handlers, pumps, and main frame computers accounted for 42.7%, and lights and 'plug in" loads accounted for 57.3% of annual consumption (Figure 5.7a).

The breakdown of the thermal energy use at ZEC is shown in Figure 5.7b. 48,725 million Btu of chilled water and 17,291 million Btu of hot water was used. Chilled water accounted for 73.8% of the thermal load and hot water accounted for 26.2%.

CHAPTER 6
Model Development

Significant progress has been achieved in developing models for buildings which exhibit change-point, multivariable dependent, and operational and scheduling dependent energy use. The following three sections of this chapter describe these three types of models. Each model was developed to overcome limitations of a preliminary model. These models promise to be both statistically rigorous and applicable to a wide range of buildings.

The first model, a four parameter change-point model, grew out of PRISM's limitations at predicting grocery store energy consumption. The grocery store data showed that "base-level" electricity consumption increases with temperature. PRISM attempts to force a temperature independent line through these data, resulting in an improper fit. The change-point model identifies the change-point temperature, change-point energy consumption, and slopes that give the lowest least square error over the entire data set for a segmented regression of energy consumption and temperature. The model is described in the next section of this chapter.

Ambient dry-bulb temperature is a strong predictor of weather-related energy consumption in many buildings. However, other environmental, system, and operating parameters also influence energy consumption and may be useful predictors of energy consumption when incorporated in a multiple regression model. A persistent problem with previous attempts to do this has been intercorrelation between predicting variables. This leads to unstable parameter estimates and may cause large errors when the model is used to predict energy use for a subsequent period. For example, solar radiation may contribute a large part of the air conditioning load in a building with large areas of glazing. However, if both solar radiation and temperature were used in the same multiple regression model the two variables would be highly intercorrelated, increasing and decreasing in similar diurnal patterns. This may lead to unreliable estimates of the model parameters. In the second section, a statistical technique that removes the collinearity between independent variables and still retains much of the information content of the original variables is described. This technique is combined with the change-point model described above and is called a change-point principle component analysis (CP/PCA) model. This model is described in the second section of this chapter.

The last section describes a methodology to identify day-types for non-weather dependent loads from metered data. Hourly energy simulation programs such as DOE-2 and BLAST have been used to predict energy savings from building retrofits. Such calibrated computer models require information from equipment inventories, operating schedules, etc., to estimate scheduled electric loads (e.g., lighting, equipment, fans). With the use of a day-typing routine, monitored hourly data for these loads can be used to accurately identify typical day types for a building, from which a calibrated input deck can be prepared quickly and inexpensively, enhancing the wide use of these models to predict the performance of conservation retrofits.

A Four Parameter Change-Point Model

Change-point behavior characterizes energy use in many buildings. This is because most buildings use some type of thermostatic control to switch systems on and off. Furthermore, examination of the fundamental equations governing air-side systems shows that constant-volume reheat systems (with preheat below a specified outdoor temperature), and systems which reduce outdoor air intake below a specified outdoor temperature also exhibit some form of change-point behavior.

The four parameter change-point model is shown in general form in Figure 6.1. It has two linear regions of differing slopes joined at the "change point." The slopes may be either positive as shown on the left side of the figure or negative as shown on the right side. Since the independent variable is ambient temperature, the two regions can appropriately be called the "low temperature region" and the "high temperature region." For the specific cooling-related case treated in this report, temperatures below the change point will be referred to as the "refrigeration" region and those above the change point will be referred to as the "cooling region" corresponding to the dominant temperature dependent loads in each temperature region.

The expected electricity consumption per day, E_d, is given by

$$E_d = a + b_c(T_d - T_{cp})^+ - b_r(T_{cp} - T_d)^+ \quad (1)$$

where b_c is the cooling slope, b_r is the refrigeration slope, T_d is the average daily temperature, and T_{cp} is the change-point temperature. The superscript "+" indicates zero if the term inside the parentheses is negative. These parameters are shown graphically in Figure 6.2.

For a given set of data, parameter estimates are chosen that give the best least-squares fit to the data. A computer program has been developed to determine these parameters from electricity and temperature data. To initiate the program, a reasonable temperature interval [RTMIN, RTMAX] that contains the change-point temperature T_{cp} must be specified. The program then implements an algorithm that outputs:

1) the parameter estimates b_r, b_c , a, T_{cp},
2) the R^2 statistics for the entire model and each segment,
3) the root mean-square error (RMSE) for each segment,
4) confidence intervals for the parameter estimates.

Statistical Analysis

Some important statistical problems involved in estimating the model parameters with variable T_{cp} were first solved by Hudson (1966). Several of Hudson's theoretical results are utilized in this algorithm. The algorithm finds the optimal value of T_{cp} by searching within an interval [RTMIN, RTMAX] known to contain T_{cp}. For each such feasible value of T_{cp}, corresponding values of b_r, b_c , and a are found that give the best least-squares fit to the data. From this collection of fits to the data, the algorithm chooses the one with the best least squares fit (i.e. with a minimum mean-square error).

The reliability of the parameter estimates can be gauged by confidence intervals returned by the program. The confidence intervals for T_{cp} with significance level e are defined such that there is a 100 x (1 - e) percent chance that the true value of T_{cp} is bounded by the confidence intervals.

The confidence intervals returned by the four-parameter model are approximations to likelihood-based confidence intervals. In an effort to confirm the accuracy of our method of approximating the confidence intervals, numerical experiments on the four-parameter model's error diagnostics using Monte Carlo computer simulations were carried out.

In our Monte Carlo study of the four-parameter model, the errors were assumed to be identically, independently and normally distributed. Two hundred synthetic data sets were randomly distributed in their respective cooling regimes. The refrigeration regime is where the models differ significantly in their predicted electrical use.

At temperatures below 59.65 F, the four-parameter model has a RMSE (169.2) significantly lower than PRISM's (277.8). In addition, the residuals of the PRISM CO model (Figure 6.4) are clearly not randomly distributed because of the model's zero slope in the base-level regime.

	T_{cp}	a	b_r	b_c
PRISM	57.14	7262.53	0	94.8474
	(1.29)	(65.34)	*	(4.66)
4-par.	59.65	7459.98	19.87	96.22
model	(58.25, 63.25)	(7358, 7693)	(14.52, 27.48)	(92.04, 104.34)

Table 6.1; *Parameter values and error diagnostics for each model of the grocery store electricity consumption. The 75% confidence intervals shown for the 4-parameter model are skewed, reflecting the nature of the curve-fit. Standard errors are given in parentheses for PRISM. A standard confidence interval for* T_{cp}*, say, is (55.85, 58.43).*

In contrast, the four-parameter model's residuals, shown in Figure 6.5, appear randomly and independently distributed. A standard statistical test for heteroskedasticity (non-constant error variance) was carried out which confirmed this observation.

However, the four-parameter model's RMSE is significantly higher for the cooling regime (382) than for the refrigeration regime (169.2). An F test at a significance level of 0.01 indicated that the variance of the two regimes were unequal. In order to get reliable error diagnostics for this case study, a weighted least squares (WLS) analysis was undertaken.

While the WLS analysis results in biased parameter estimates, the (weighted) errors are randomly distributed, with constant variance. As a consequence, the confidence intervals for the parameters are valid (Draper and Smith 1981). WLS offers reliable error diagnostics in compensation for biased parameter estimates. In order to take this into account, the model (1) must be altered slightly. A reasonable energy model fitting the case study is

$$
\begin{aligned}
E_d &= a - b_r(T_d - T_{cp})^+ + e_1 \quad \text{if } T_d \leq T_{cp} \\
E_d &= a + b_c(T_d - T_{cp})^+ + e_2 \quad \text{if } T_d > T_{cp}
\end{aligned}
\tag{4}
$$

generated. Each such data set consisted of 200 observations using random normal deviates with parameter values $T_{cp} = 59.5$, $b_r = 19.9$, $b_C = 93$, $a = 7530.5$, and variance $s^2 = 320$. Temperature values $T_1, \ldots T_{200}$ were chosen randomly from a one year data set of average daily temperatures in the Bryan/College Station area. The results suggest that the approximate confidence intervals found according to our algorithm are highly accurate, since they contain the actual parameter values at essentially the percentage rate expected by the likelihood confidence intervals.

Grocery Store Results

The model was applied to data from the grocery store and compared to PRISM runs for the same data. Clean data were selected from June 1989 through May 1990 resulting in 191 days for which complete electric and weather data were available. As noted earlier, when plotted as a function of daily average ambient temperature, these data show two distinct regions of non-zero slope (Figure 6.3). This physically represents the behavior of the refrigeration equipment which cools the refrigerated food display cases and frozen food cases in the store at low temperatures with the addition of the air conditioning load above the change point.

The model of electricity use for the grocery store data provided by the four parameter curve-fitting algorithm is:

$$E_d = 7459.98 + 96.22(T_d - 59.65)^+ - 19.87(59.65 - T_d)^+ \quad (2)$$

It is noted that determination of the change point by minimizing RMSE resulted in a change point 2.35 F lower than the 62 F visually estimated by Schrock and Claridge (1989).

The electricity use predicted by PRISM CO is

$$E_d = 7262.53 + 94.85(T_d - 57.14)^+ \quad (3)$$

By forcing the base-level slope to be zero, PRISM CO estimates T_{cp} to be 2.51 F less than our estimate of 59.65 F. An examination of the two models shows them to be nearly in agreement at temperatures above 59 F, with predicted electrical use differing by at most 40 kW (9% of maximum use) in the 59 - 90 F range. The residuals of both models appear

The observations are weighted for a WLS analysis according to their respective regime. The estimate of T_{cp} was found to be unchanged (59.65), whereas the other parameter estimates were altered slightly. The electrical use predicted using WLS was found to be

$$E_d = 7459.67 + 96.26(T_d - 59.65)^+ - 19.86(59.65 - T_d)^+ \quad (5)$$

An application of White's test and an examination of the weighted residuals show that heteroskedasticity has been eliminated, which makes the weighted estimates' error diagnostics reliable. A comparison of these estimates with those of unweighted least-squares shows the weighted parameter estimates are not too different from the unweighted estimates. The weighted method increases the model's R^2 statistic from 0.9068 to 0.9423; the respective RMSE's are not comparable due to the weighting.

These error diagnostics, while reliable, are made under the assumption that T_{cp} is fixed at 59.65 F, an assumption not made under normal circumstances, (i.e. when the variance is constant and an unweighted least-squares fit is satisfactory). A future report will attempt to determine reliable error diagnostics for all parameter estimates with variable T_{cp}.

Change-Point Model Summary

In summary, a rigorous procedure for determining the change point for a general four parameter linear change-point model of energy use has been presented and applied to a case study grocery store. It is shown that determination of the change point by minimizing RMSE resulted in a change point 2.3 F lower than the visual estimate reported earlier. For the case study data, it is shown that the four parameter model provides a comparable fit to PRISM CO above the change point, but provides an RMSE of 169.2 kWh/day vs 277.8 kWh/day provided by PRISM CO below the change point. Furthermore, the residuals of the four parameter model were shown to be randomly distributed. Standard errors were obtained for the model parameters after performing a weighted least squares analysis to eliminate heteroskedasticity due to differences in RMSE in the cooling and base-level regimes. The four parameter model appears to provide a highly satisfactory model for the electricity use of the case study grocery store.

A Change-Point Principal Component Analysis (CP/PCA) Model

Numerous investigators have attempted to use multiple linear regression analysis to develop improved models of building energy consumption. These attempts have often been frustrated by the significant collinearity between the predictors used. Principal Component Analysis (PCA) has been used to tackle similar problems for some time by climatologists and more recently by Hadley and Tomich (1986) to examine influences on heating energy consumption in residences. This approach appears promising as a way of combining physical models and insight with measured data to achieve improved empirical models for determining retrofit savings.

The CP/PCA model described in this section combines the change point methodology described in the last section with the flexibility to incorporate other variables besides temperature which may affect electricity consumption. Temperature, humidity, solar radiation, and sales are regressed against electrical consumption for data from each of the two segments of the electrical consumption versus temperature line shown in Figure 6.6. If standard multiple regression were used, the variances in the estimates of each regression coefficient would be large because the "independent" variables are highly correlated. PCA is a mathematical transformation that removes this correlation and decreases the error in the regression parameters. This improves our confidence in the parameters when used as predictors for a new set of data. The trade-off that PCA imposes for decreased parameter error is a less accuracy fit (R^2) to the original data set.

The PCA Method

Standard Multiple Linear Regression (MLR) may suffer from significant stability problems when predictor variables in the regression analysis are intercorrelated. The collinearity of the variables will cause the variances of some of the estimated regression coefficients to be quite large, resulting in an unstable and misleading estimate of the regression equation.

The PCA method transforms the original variables into an uncorrelated set of orthogonal variables that are linear combinations of the original variables (the mathematical details of this transformation are described at length in Jolliffe [1986]). Together these new variables, called principal components (PCs), retain all of the information found in the original variables.

The PCs can be mathematically ranked according to their ability to "explain" variance in the data set. A PC with sufficiently low variance rank can be eliminated from the data base without losing a significant amount of information. It is advantageous to eliminate PCs with low variance rank to increase the stability of the model. Most authors suggest 70 - 80% as a minimal level of the generalized variance explained by a PCs (see Jolliffe [1986], Section 6.1).

While the importance of a PC can be judged using its variance rank, there is another - and sometimes conflicting - measure of the importance of a PC : its merit as a predictive variable. The goal is to use the minimum number of PCs while maximizing the predictive ability. That is, deleting a well-chosen PC will greatly reduce the standard error of the regression coefficients of the original variables. The trade-off is that this statistically stable model will not fit the given data quite as well as the unstable standard MLR model, so deleting PCs must be done with care. *If none of the PCs are deleted, the resulting regression equation is equivalent to the standard MLR model.*

PCA Applied To The Grocery Store

Variables which could plausibly influence electrical consumption and for which data are available are temperature, humidity, solar radiation, and sales. These data were available for 191 days between June 1989 and May 1990.

Dry-bulb temperature is the dominant non-scheduled predictor of changes in electricity consumption for most buildings. Ambient specific humidity is a major contributor to the latent load in buildings when there is excess moisture in the outdoor air that must be removed at the cooling coils. Enthalpy was tried as a combined measure of temperature and humidity, but separate treatment of these variables proved superior. The case study building has only a small amount of glazing, but as a single story building has a large horizontal roof exposure; consequently, horizontal solar radiation is a logical predictor. Sales data is plausibly correlated with door openings on refrigeration cases, and other restocking activity as well as internal gain from occupants; so it was also tested as a predictive variable.

Cooling Regime Model

For the range of temperature data above the change-point temperature (which includes space-cooling, refrigeration, and base-level electrical loads), the intercorrelation between temperature, solar gain and humidity was great enough to consider a PCA approach. In addition, these variables were all significantly correlated with electrical consumption, confirming their predictive value. The correlation between electricity and sales was insignificant, with a correlation coefficient of -0.07. Sales would thus contribute only "noise" to the model and so was dropped from consideration. For these reasons, electricity consumption in the cooling regime was modeled as a linear function of temperature, humidity and solar radiation. A PCA analysis was performed, followed by a regression of electricity consumption against the resulting PCs.

As shown in Table 6.2, the first two PCs, PC1 and PC2, have high variance ranks and a collective variance rank (94.67%) well above the required 70%, whereas PC3 has a low variance rank and contributes little to the collective variance rank. Because of this, two models of electricity use were considered: as a function of all three PCs (Model 1), and as a function of only PC1 and PC2 (Model 2). Referring to Table 6.3, note that PC3 can be deleted with a negligible drop in the R^2 statistic, and only a 5.33% drop in the variance rank. Moreover, PC3 has an unstable regression coefficient: its standard error is more than 50% of the coefficient itself. For these reasons, the optimal solution for our modeling problem in the cooling regime is to express electrical consumption as a linear function of the first two PCs only:

$$E = 482.20(PC1) + 106.41(PC2) + 9349.12 \quad (1)$$

While this regression equation does not give the best fit to this particular data set, it is more stable than a MLR fit, and hence, we can be confident of its reliability with a new set of data. By dropping PC3, the stability of the model has been improved, which should result in a better predictor of future electrical consumption.

	Component		
variable	PC1	PC2	PC3
Normalized Temperature	.732	.178	-.658
Normalized Humidity	.660	-.425	.619
Normalized Solar	.170	.887	.428
R^2 Contribution	.7158	.0245	.0088
Variance Rank	.556	.391	.053

Table 6.2; *Principal Components in the Cooling Regime. The first three entries of each column define the eigenvector v_i associated with the given PC.*

	Model 1	Model 2	St. MLR Model
variables	PC1, PC2, PC3	PC1, PC2	Temp, sph, solar
temp coef/std error	*	*	71.71 / 9.30
sph coef/std error	*	*	36001 / 13098
solar coef/st error	*	*	1.48 / 0.71
PC1 coef/std error	482.20 / 27.86	482.20 / 28.21	*
PC2 coef/std error	106.41 / 33.26	106.41 / 33.68	*
PC3 coef/std error	-172.59 / 90.08	*	*
Constant coef/std error	9349.12 / 35.83	9349.12 / 36.28	2838.55 / 525.05
R^2	0.7490	0.7403	0.7490
Root MSE	374.08	378.76	374.08
Variation % Explained	100	94.67	100

Table 6.3; *Cooling Regime regression summary. Note that Model 1 is equivalent to the standard MLR model since none of the PCs are deleted.*

The model for the cooling regime found using standard multiple linear regression without PCA is

$$E = 71.71(\text{temp F}) + 1.48(\text{solar W/m}^2) + 36001(\text{sph lb-mois/lb-air}) + 2838.55 \quad (2)$$

where daily average values are used for all predictive variables. Referring again to Table 6.3, note the significant standard errors of the standard MLR model's regression coefficients. These large standard errors reflect the high collinearity between the variables, and indicate instability in the MLR model. The PCA model (Model 2) has substantially better stability, while maintaining a goodness-of-fit competitive with the standard MLR model. Further insight into the PCA model is gained by a transformation of PC1 and PC2 back into the physical variables, which yields

$$E = 54.90(\text{temp}) + 2.55(\text{solar}) + 59227(\text{sph}) + 3666.68 \quad (3)$$

It is interesting that the importance of the solar and humidity variables is nearly doubled in the PCA model.

<u>The Refrigeration Regime Model</u>

The regime below the change-point temperature contains refrigeration and base-level electrical loads, with the refrigeration loads being temperature dependent. Among the 133 days in the complete data set, 24 fell into this regime. Proceeding as in the cooling regime, the correlation between each of the potential predictor variables was examined. As before, both humidity and temperature appeared to be significant (see Table 6.4).

	temp	**sph**	**sales**	**solar**	**elec.**
variable					
temp	1.00	0.69	0.27	0.24	0.77
sph		1.00	0.29	-0.06	0.67
sales			1.00	0.10	0.56
solar				1.00	0.17
elec.					1.00

Table 6.4; *Correlation coefficients for the refrigeration regime*

Variable	PC1	Component PC2	PC3
Normalized Temperature	.628	-.342	.700
Normalized Humidity	.634	-.298	-.714
Normalized Sales	.452	.891	.030
R^2 Contribution	.4870	.0283	.0744
Variance Rank	.594	.267	.140

Table 6.5; *Principal Components in the Refrigeration Regime. The first three entries of each column define the eigenvector v_i associated with the given PC.*

	Model 1	**Model 2**	**St. MLR Model**
variables	PC1, PC2, PC3	PC1, PC3	Temp, sph, sales
temp coef/std error	*	*	29.96 / 9.51
humidity coef/std error	*	*	-4182 / 29125
sales coef/std error	*	*	4.96 / 1.80
PC1 coef/std error	118.74 / 24.37	118.74 / 24.59	*
PC2 coef/std error	42.74 / 36.37	*	*
PC3 coef/std error	95.74 / 50.24	95.74 / 50.69	*
Constant coef/std error	7269.51 / 31.84	7269.51 / 32.13	5416.84 / 440.61
R^2	.5898	.5615	.5898
Root MSE	155.97	157.38	155.97
Variance Rank	100	73.34	100

Table 6.6; Refrigeration *Regime 24 day regression summary. Model 1 is equivalent to the standard MLR model since it uses all three PCs.*

In contrast with the cooling situation, solar gain was statistically insignificant in the refrigeration regime. This makes sense physically because the space-cooling systems are not active in this regime; only the refrigeration systems, lights and equipment are consuming electricity. Heating is primarily provided by a constant volume system with heat recovery from the refrigeration system and so has a negligible impact on electrical consumption. Thus for both statistical and physical reasons, solar was not included as a predictor.

On the other hand, sales -- an indicator of occupancy gain, (i.e., opening and closing of refrigeration doors, etc.) appears to be moderately correlated with electrical use in the refrigeration regime (0.56) and was consequently included as a predictor variable. This flip-flopping of the significance of sales and solar gain between the regimes is noteworthy, and further substantiates the usefulness of the change-point data separation.

From this analysis, it was determined that electricity use in the base-level regime could best be modeled as a linear function of temperature, humidity, and sales. The high correlation between humidity and temperature (0.69) made a PCA analysis worthwhile. Of the three PCs, PC1 was clearly most important in variance rank and R^2 contribution (Table 6.5). The predictive power of PC3 was also significant, so it was also included as a variable in the two models considered. Observe that PC1 and PC3 have a collective variance rank of 73.34%, a satisfactory level according to our criterion.

Model 1 is equivalent to the standard MLR equation since it uses all three PCs. It has a variance rank of 100%, but the (85%) standard error of PC2 indicates high statistical instability (Table 6.6). In addition, the R^2 contribution of PC2 is quite small (see Table 6.5). The statistical instability of Model 1, which is largely due to PC2, makes it an unsatisfactory model.

Model 2, using only PC1 and PC3, looks more promising. Its Root MSE and R^2 statistic are comparable with those of the standard MLR model, however, Model 2 does not suffer from the standard MLR model's severe statistical instability (note in particular that the standard error of the humidity coefficient is approximately seven times the coefficient itself). If the PCs are transformed back into the physical variables, Model 2 is

$$E = 33.14(\text{temp}) + 2.96(\text{sales}) + 5347.85(\text{sph}) + 5320.70 \quad (4).$$

A Comparison of the Goodness-of-fit In The Two Regimes

The reader may have noticed that the PCA model has a significantly higher R^2 value in the cooling regime (.7403) than in the refrigeration regime (.5615). This is not disturbing, for the electrical consumption in the base-level regime is relatively flat, and a low R^2 value is expected when the dependent variable is near-zero slope (Draper and

Smith 1981). For this reason, we argue that an acceptable R^2 value depends on the temperature regime.

Another way to compare the fits is by examining the model's RMSE in each regime. A smaller RMSE indicates a more precise prediction, and is independent of the flatness of the consumption. The refrigeration-level's RMSE (157.38) is quite low, indicating a good fit. The somewhat larger RMSE in the cooling regime (378.76) reflects the greater volatility of the electrical consumption in this regime. Events that are difficult to measure, e.g. leaving store doors open for deliveries, affect the electrical consumption much more in the cooling regime, and consequently raise the RMSE in this temperature range.

Discussion Of PCA Model

The change-point PCA model has several advantages over standard MLR for the case-study data. In the case of significantly correlated predictor variables, a transformation of these variables into uncorrelated PCs, followed by the elimination of unstable PCs, allows construction of a more statistically stable predictor model. This method sacrifices a small drop in the model's explanation of the current data set in return for greatly reducing the high variability of the parameter estimates often seen in a standard MLR.

The use of a change point enables better selection of predictor variables. For example, solar radiation was a significant influence on consumption in the cooling regime, but would only have contributed "noise" to the model in the refrigeration regime. Temperature was an important linear predictor in both regimes, but its influence changed dramatically at the change point, a phenomenon that the change-point method incorporated into the model.

While a CP/PCA model is not trivially simple, its construction is systematic. Depending on the relationship between consumption and temperature, the optimal data split into two regimes, can be easily found using the four parameter change point model (Ruch and Claridge 1991). A standard statistical software package will do the PCA analysis, and then the PCs to be dropped can be chosen according to clear criteria: the PC's variance rank, contribution to the model's R^2, and the standard errors of the regression coefficients.

A Load Shape Methodology For Non-Weather Dependent Electricity Use

This section summarizes a methodology to identify typical day types for a building using monitored end-use data for non-weather dependent electric load (i.e. lights, equipment, etc.). Load shapes can be generated from the data for each typical day type and used as schedules in building energy simulation models such as DOE-2 and BLAST. These simulation models can then be used to estimate retrofit savings.

To start the process, one year of hourly non-weather dependent electric consumption data (i.e. lights, equipment, etc.) is preferred. Calculate the mean and the standard deviation at each hour for the entire data set (i.e. 24 separate calculations). The regularity index, given by Eq. 1, provides a good measure of the lack of regularity within a sample.

$$RI = \frac{100\text{xStandard Deviation}}{\text{Hourly Mean}} \qquad (1)$$

The choice of the maximum acceptable RI depends on how much variation is permissible within a given day type. It is felt that 10% variation is acceptable for buildings considered in this report. If the RI for all 24 hours stays within a pre-determined value of X, then the building is classified as 7-day type (i.e. all seven days of the week have identical load shape).

In addition, if the mean across each hour for the day type is identical, then the building is classified as continuously operating type. If the building is not a 7-day type, the total data set is then sorted into day type groups, with days in each group having similar consumption patterns.

One way to sort the data is by comparing daily consumption patterns. To accomplish this the hourly data are summed to daily data. The mean daily consumption and standard deviation are then calculated and the days are divided into three groups: (a) LOW_D, which are days with daily consumption less than average daily consumption minus 10% of one standard deviation, (b) HIGH_D, which are days with daily consumption greater than average daily consumption plus 10% of one standard deviation and (c) NORMAL_D, the remaining days. Once the three groups are formed, typical day types are identified within each group.

For a typical commercial building the days in the LOW group would generally be: weekends, holidays, vacation days, special events and erratic days. The next step is to sort the days in the LOW group into weekdays (WD) and weekends (WE). This is done by calculating the model using a calendar time line. Next, every day in the weekday group is checked to determine if it is either a holiday (H), a vacation day (V), or a special event (S). This is performed by comparing time line dates to a pre-assembled list of known holidays. The days which is not a holidays, vacations or special events, are classified as erratic events (E). A flag (H, V, S, & E) is then attached to each day in the weekday group. Next, the weekday group is sorted into Mon. through Fri. and the weekend group is sorted into Sat and Sun. bins. Then the mean and the standard deviation for each hour are calculated for all bins.

At this stage we have seven load shapes (Mon. - Sun.) for the LOW group. Using a similar procedure, the data can then be further grouped as LOW_LOW_XX, LOW_HIGH_XX and LOW_NORMAL_XX where XX can be WD, WE or a combination of days. If groups still remain that do not satisfy the RI criteria, another level of groups may be required.

The NORMAL-D and HIGH_D groups can be similarly subdivided. Load shapes for all of these groups can then be generated.

Day-Type Methodology Applied To ZEC

This procedure has been applied to the ZEC with good results. Those results are presented in chapter four.

CHAPTER 7
Technology Transfer and Energy Saving Potential

The methodologies developed and tested in this project have immediate application in Texas LoanSTAR Program. This program is an eight year, $98 million revolving loan program, funded by oil overcharge money which provides energy conservation retrofits in Texas state, local government and school buildings (Turner, 1990). The program began in 1989 and the first retrofits were installed in the latter part of 1990. Institutions and agencies participating in the program must repay the conservation loans according to estimated savings from an energy audit.

A statewide energy Monitoring and Analysis Program (MAP) has been established as part of the LoanSTAR Program. The major objectives of the MAP are to: 1) verify energy and dollar savings of the retrofits, 2) reduce energy costs by identifying operational and maintenance improvements, 3) improve retrofit selection in future rounds of the LoanSTAR Program, and 4) initiate a data base of energy use in institutional and commercial buildings in Texas. Texas A&M is the prime contractor for the MAP, so any methodologies developed in this ERAP Project will be immediately implemented within the LoanSTAR MAP.

Improved models should provide better estimates of the energy savings achieved by the retrofits, but the energy savings from this project will come from improved abilities to use the monitored data from the buildings to identify and diagnose operational improvements. Previous work (Haberl and Claridge, 1987; Haberl and Vadja, 1988; MacDonald and Wasserman, 1989; Haberl and Komor, 1989) has shown that careful analysis of monitored building consumption data can identify operational changes which lead to energy cost savings of 5-15%. The LoanSTAR Program hopes to achieve significant operational savings as a result of data analysis in addition to those from the capital measures installed. This will be the first large scale application of these techniques, so average savings are expected to be somewhat lower than those achieved in heavily analyzed pilot studies. However, the analysis developments resulting from this ERAP project are expected to augment the savings which would have been identified without this project.

Energy savings due to this project are conservatively estimated as 2.6×10^{12} Btu by the year 2000, considering only the buildings which will participate in the LoanSTAR Program. Details of this calculation are provided in Appendix A.

Additional savings can be expected from implementation of these techniques in other public and private sector buildings. There is a very high level of interest in the techniques and software being developed in both the private and public sectors. Over 70 inquiries have already been received. Individuals and groups requesting information as of December 1, 1990 are shown in Appendix B.

CHAPTER 8
Future Plans

During the next year, effort will focus on three areas:

1) Examination of PCA methodology on buildings with submetered data;

2) Development and implementation of systematic methods for identifying operational improvements in buildings; and

3) Examination of the change-point model in at least one more building and identification of building/system types where this approach is expected to be useful.

The overall progress on this project is meeting or exceeding the milestone descriptions and dates listed in the Project WorkPlan. This report summarizes completion of the following tasks:

1) Select preliminary SRDLP buildings for analysis;

2) Select and instrument one grocery store and one nursing center;

3) Develop preliminary models for energy use of buildings in task 1 and 2;

4) Test predictive ability of models of Task 3;

5) Assemble end-use data for preliminary buildings;

6) Select and analyze additional buildings;

7) Refine predictive models based on data from Task 6.

In addition, major progress has been made on Task 11 "Develop generalized predictive model framework" and the stated milestone 13 "Publication of at least three papers at conferences and in journals" by 1/93 has already been achieved with publication of three conference papers and acceptance of three more for publication in March, 1991.

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Figures

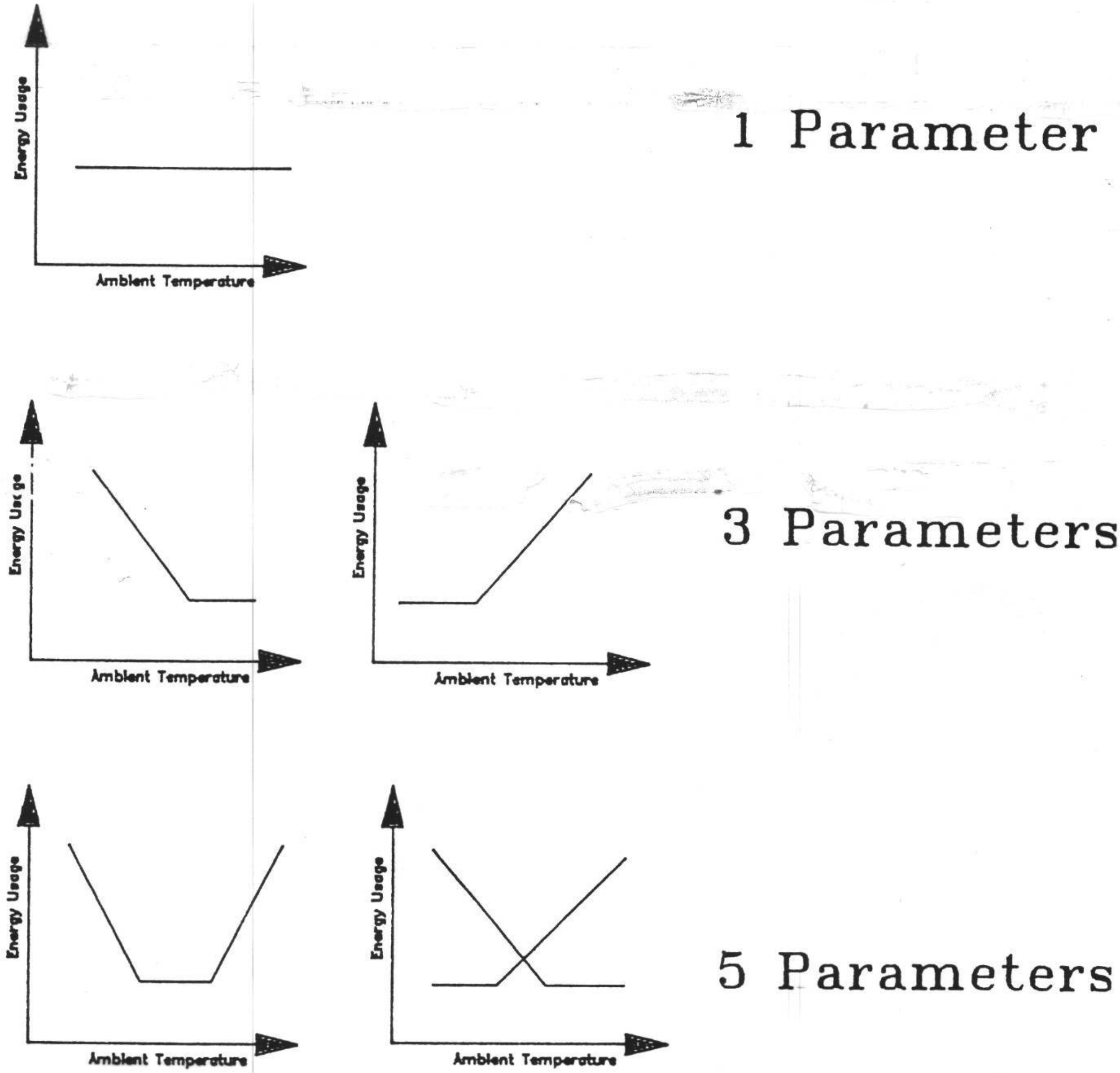

Figure 3.1; PRISM model types. *One-, three-, and five-parameter models of energy use as implemented in the Princeton Scorekeeping Method (PRISM) are shown.*

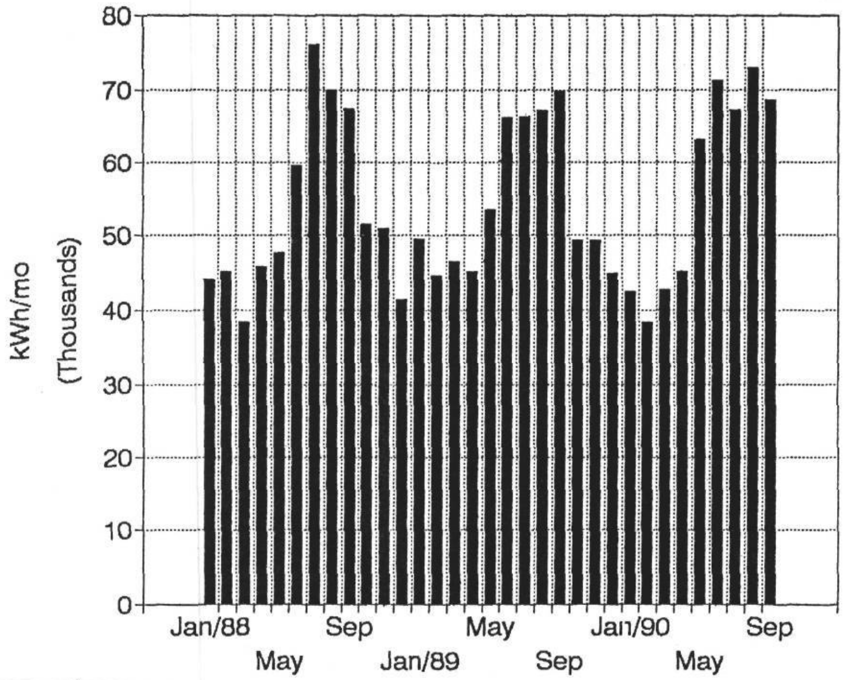

Figure 3.2a; Electric utility billing history for Temple nursing home.

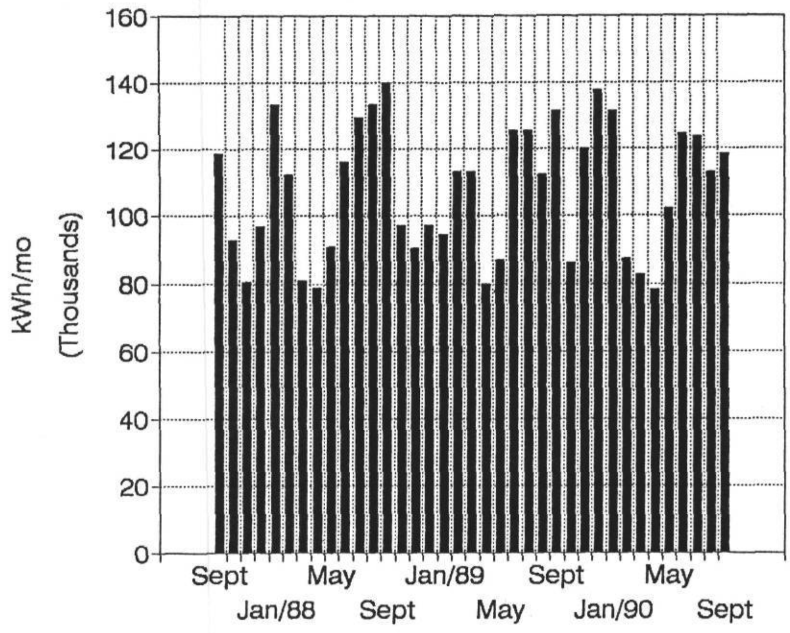

Figure 3.2b; Electric utility billing history for Austin nursing home.

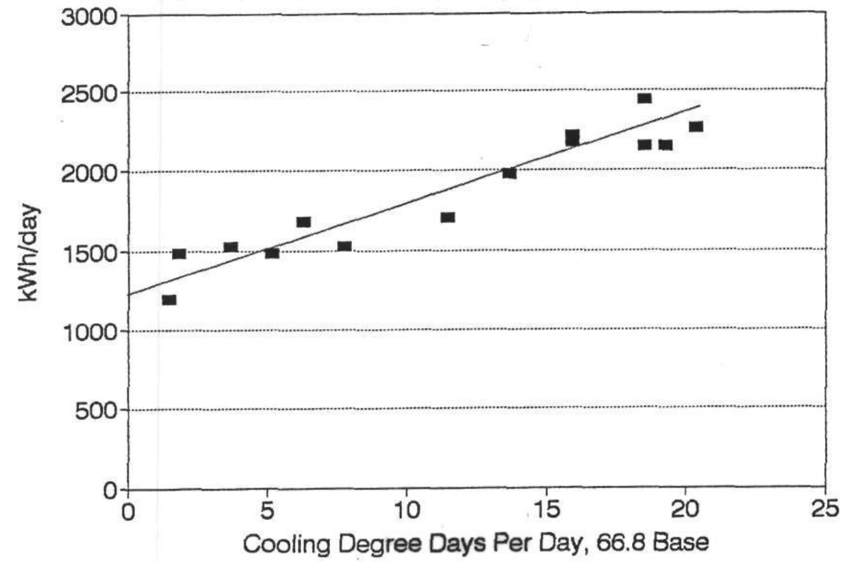

Figure 3.3a; Electricity consumption vs. cooling degree days for Temple nursing home. *PRISM CO model for cooling season month sfrom March, 1988 to August, 1989.*

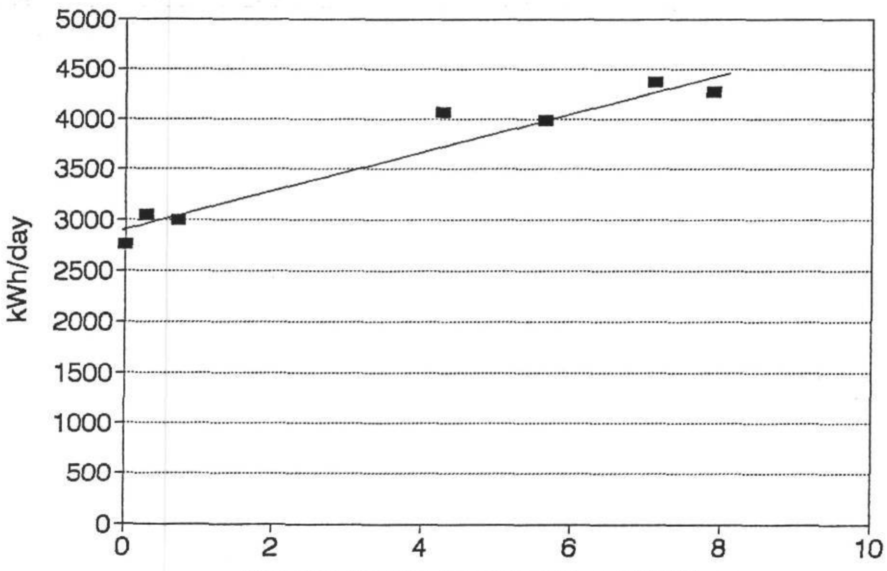

Figure 3.3b; Electricity consumption vs. cooling degree days for Austin nursing homes. *PRISM CO model for cooling seasons months from April, 1989 to October, 1989.*

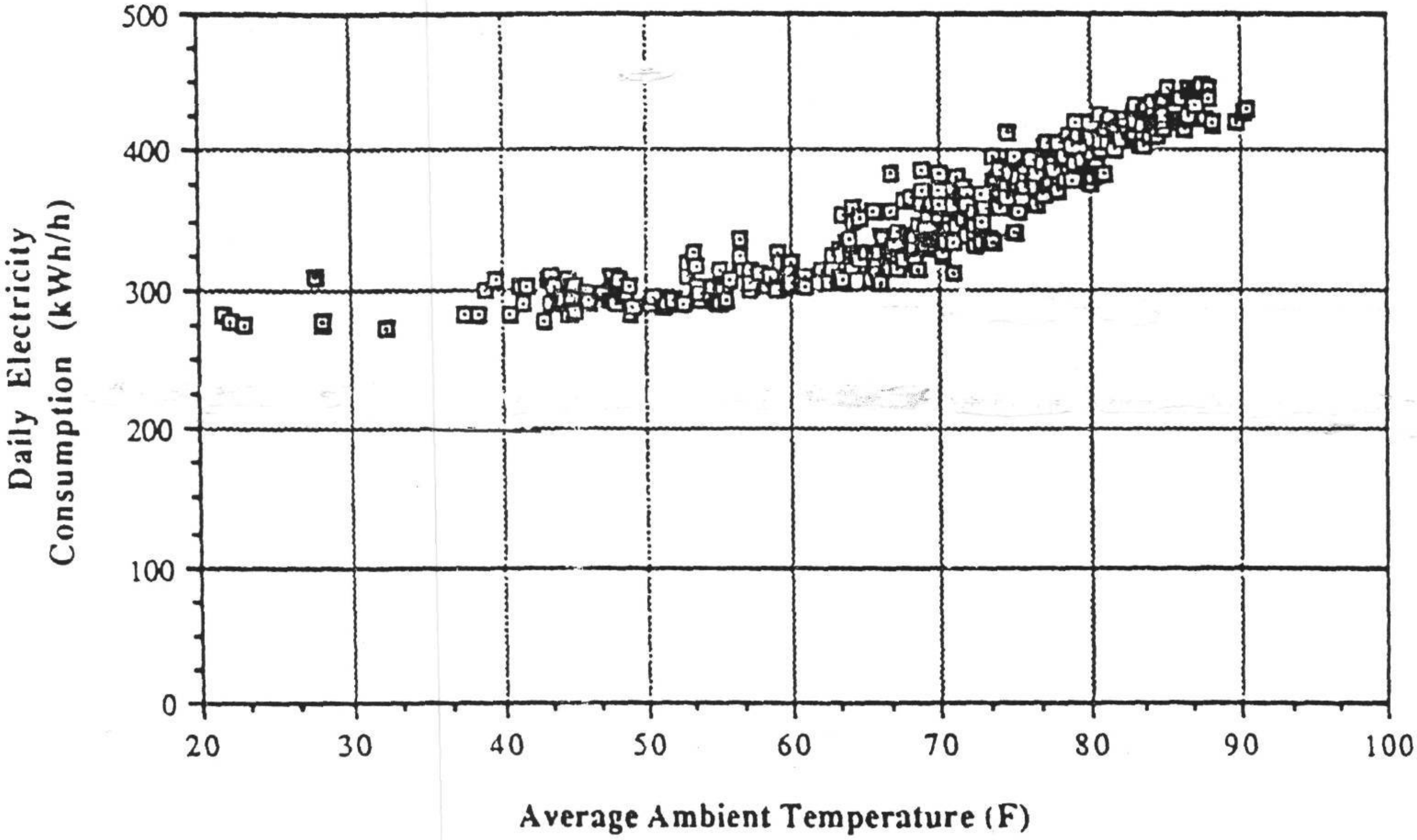

Figure 3.4; Grocery store daily electricity use vs. average daily ambient temperature for March 1988 to April 1989.

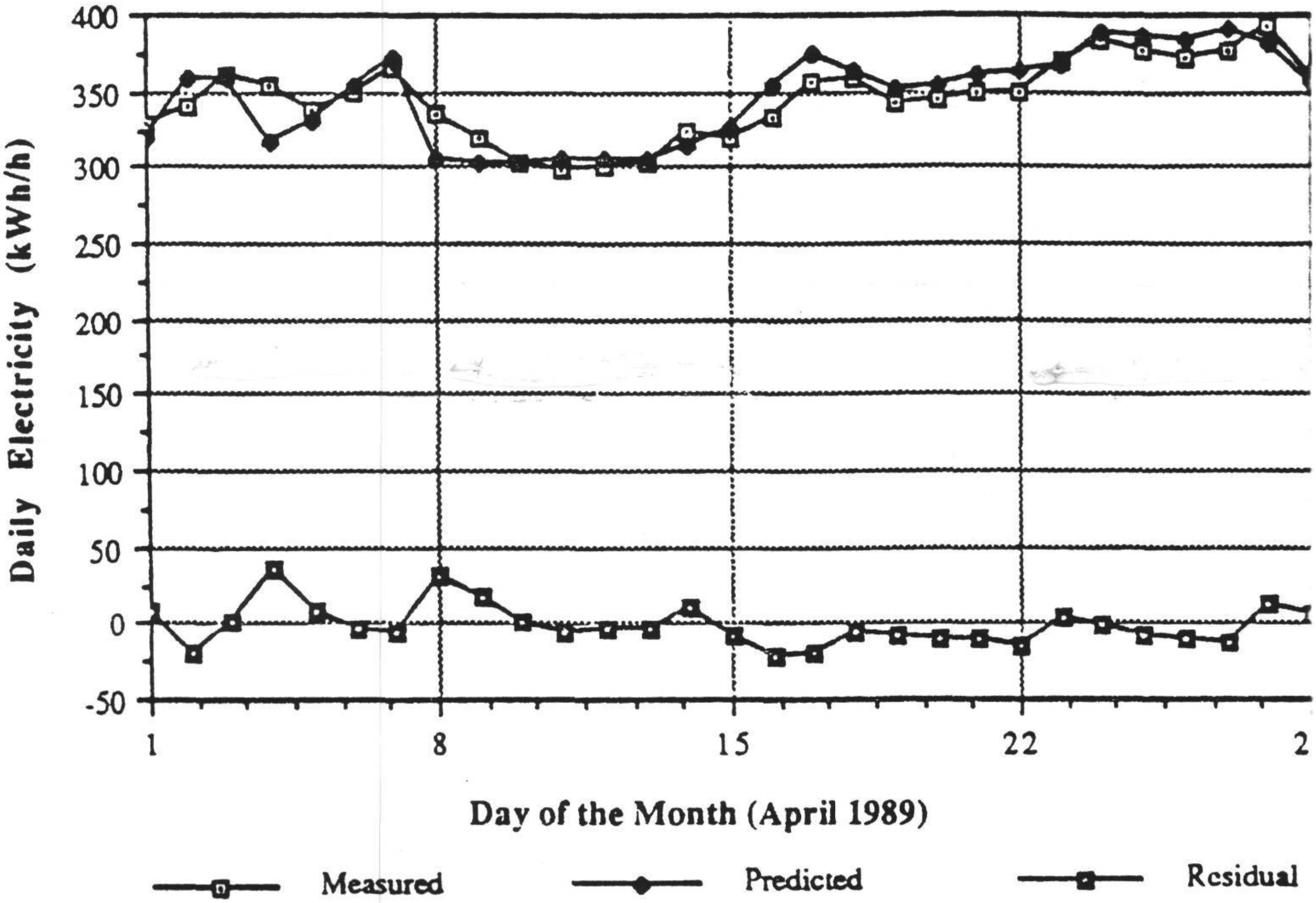

Figure 3.5; Measured, predicted, and residual daily electricity use for the grocery store for April 1989.

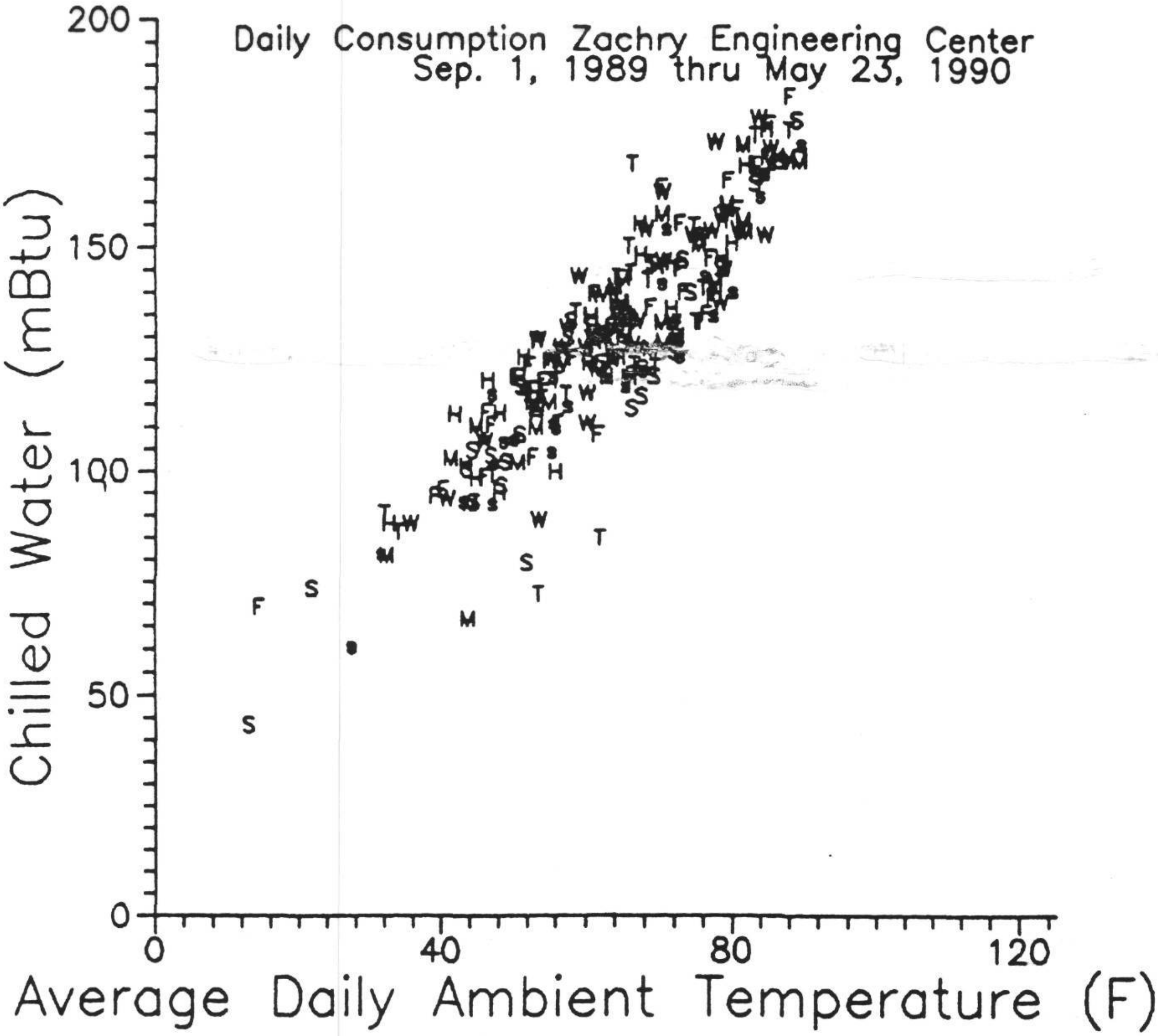

Figure 3.6; Daily chilled water use vs. ambient temperature for the ZEC from September 1, 1989 to May 23, 1990.

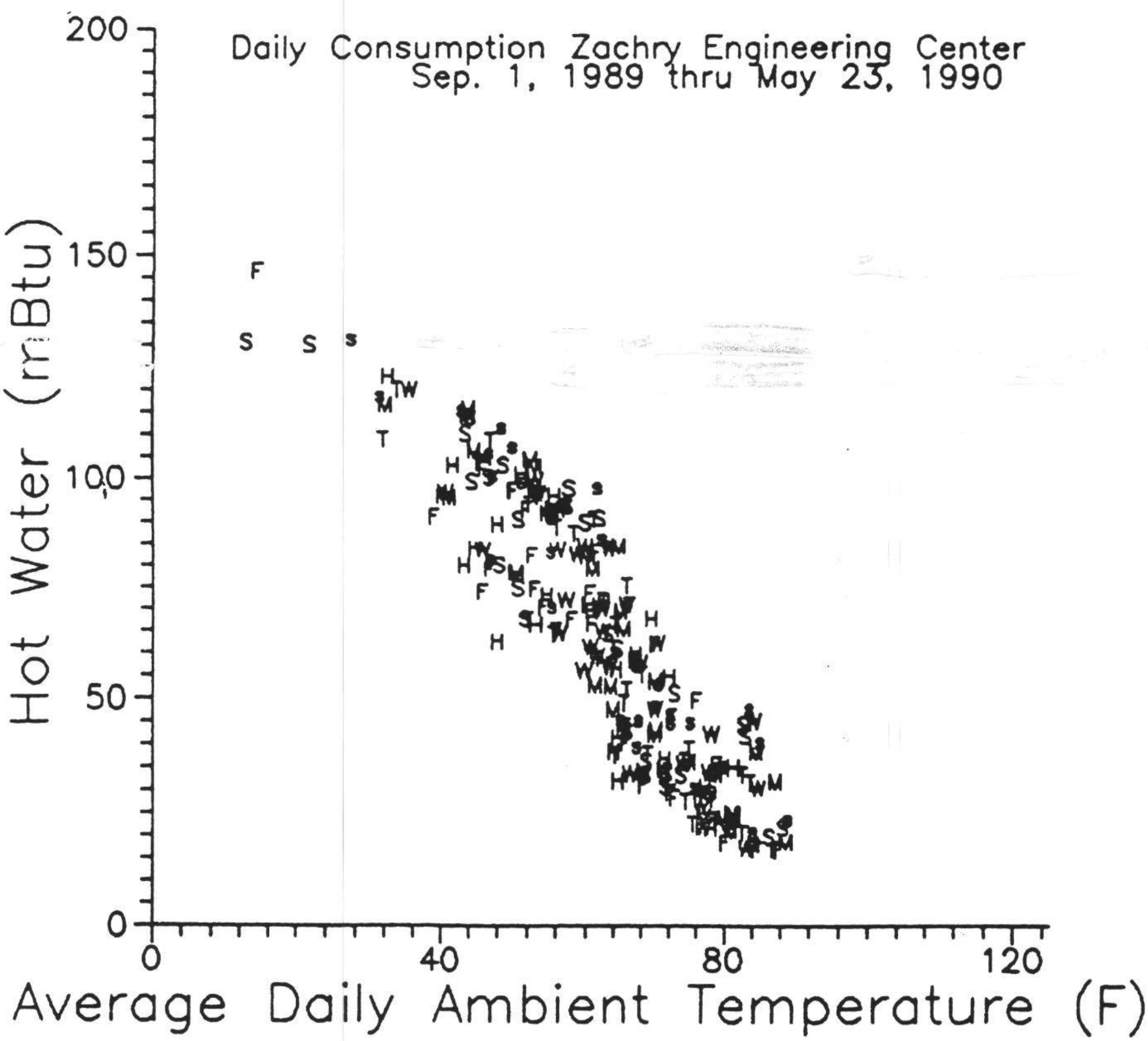

Figure 3.7; Daily hot water use vs. ambient temperature for the ZEC from September 1, 1989 to May 23, 1990.

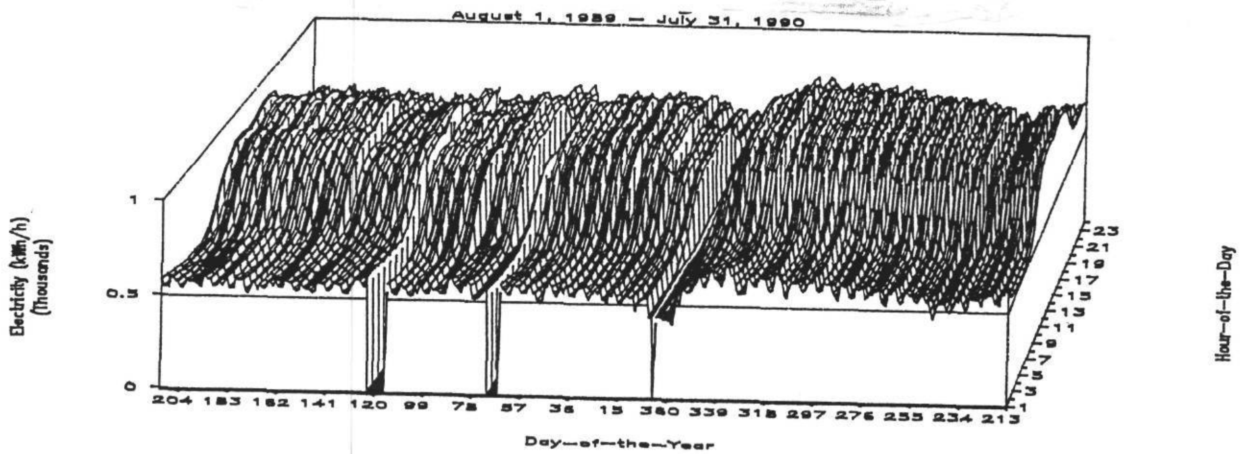

Figure 3.8; Hourly lights and receptacles electricity consumption for the ZEC from August 1, 1989 to July 31, 1990. *The day of the year forms the x-axis and the hour of the day forms the y-axis. Hourly lights and receptacles electricity use is displayed as the height above the x-y plane.*

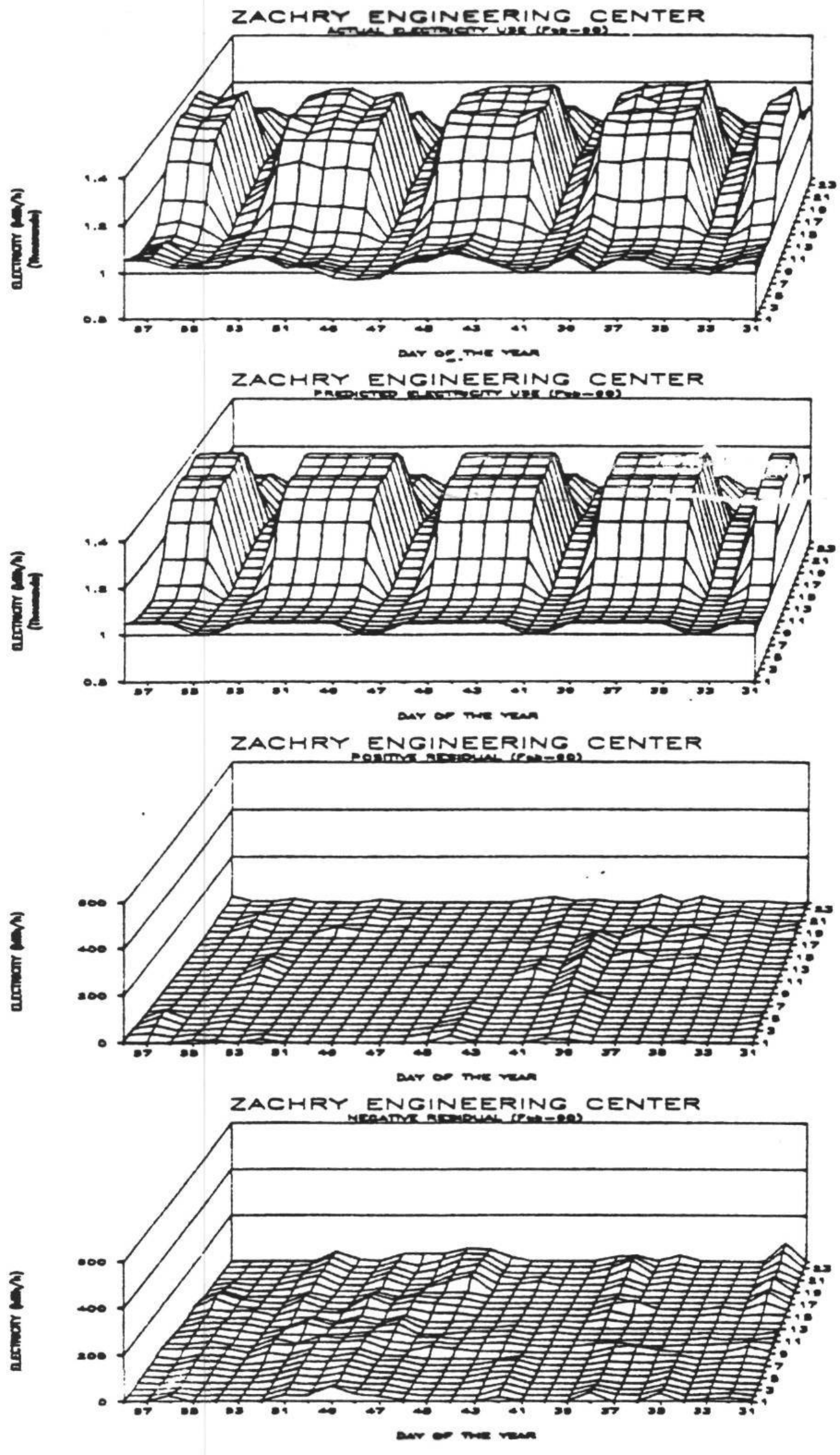

Figure 3.9; Measured, predicted and residual hourly whole-building electricity use for the ZEC for February, 1990. *The day of the year forms the x-axis and the hour of the day forms the y-axis. Hourly whole building electricity use is displayed as the height above the x-y plane.*

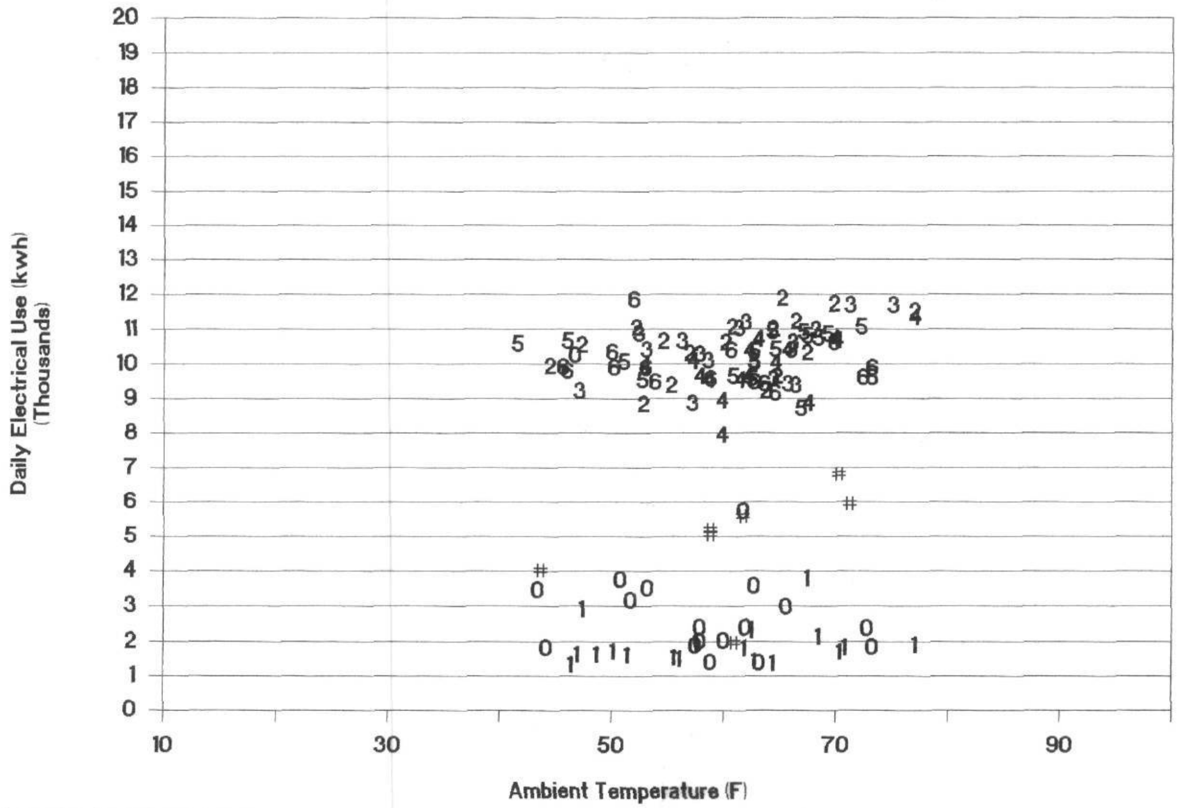

Figure 3.10; Daily electricity use vs. ambient temperature for A&M Consolidated High School from January 1, 1990 to May 8, 1990. *Data labels are: (0-1) weekends, (2-6) weekdays, and (#) holidays. Electricity use is much more dependent on scheduling than on ambient temperature.*

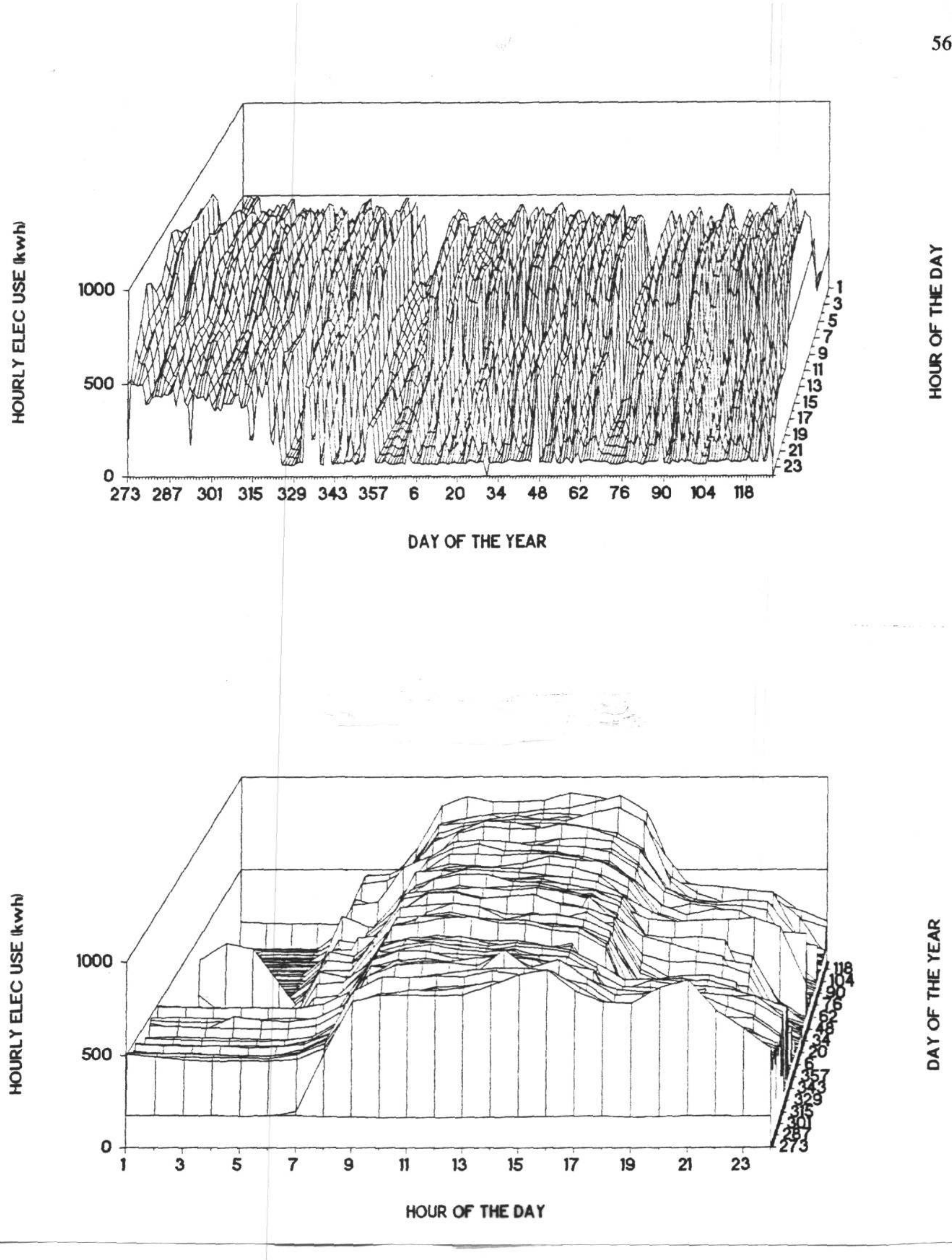

Figure 3.11; Hourly electricity use for A&M Consolidated High School from October 1, 1989 to May 8, 1990.

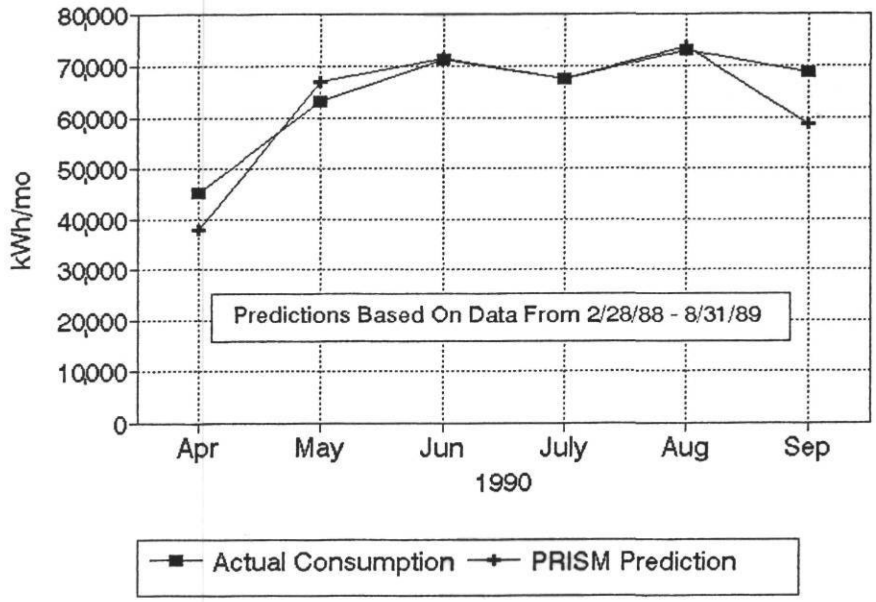

Figure 4.1a; Predicted and measured monthly electricity use for the Temple nursing home.

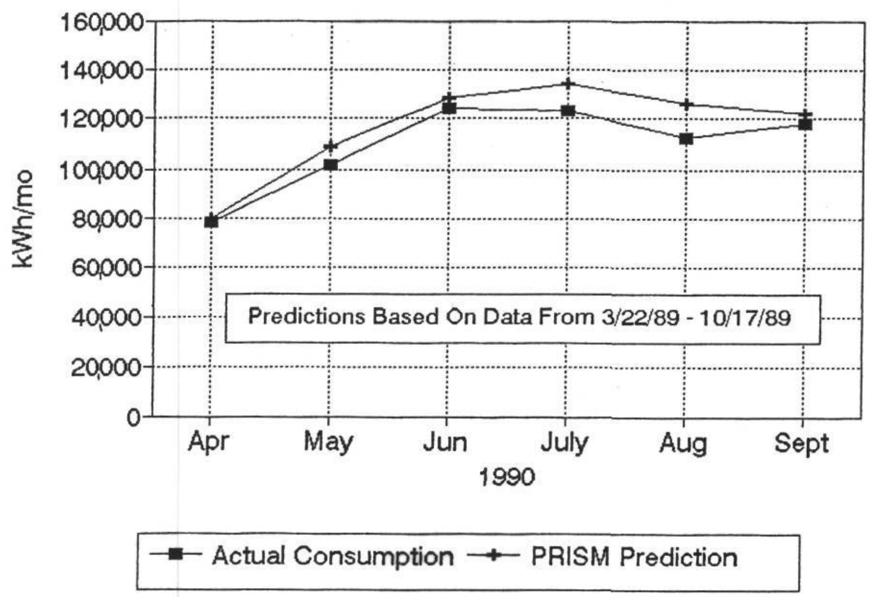

Figure 4.1b; Predicted and measured monthly electricity use for the Austin nursing home.

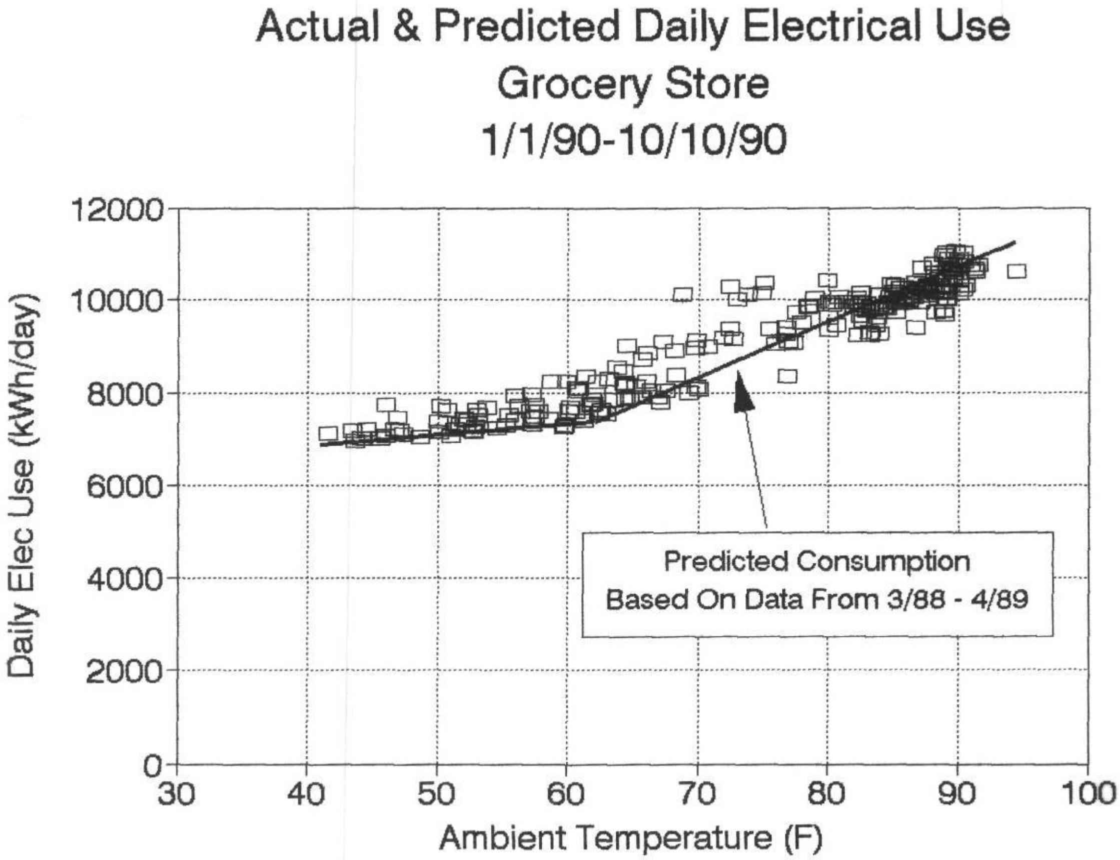

Figure 4.2; Predicted and measured daily electricity use for the grocery store.

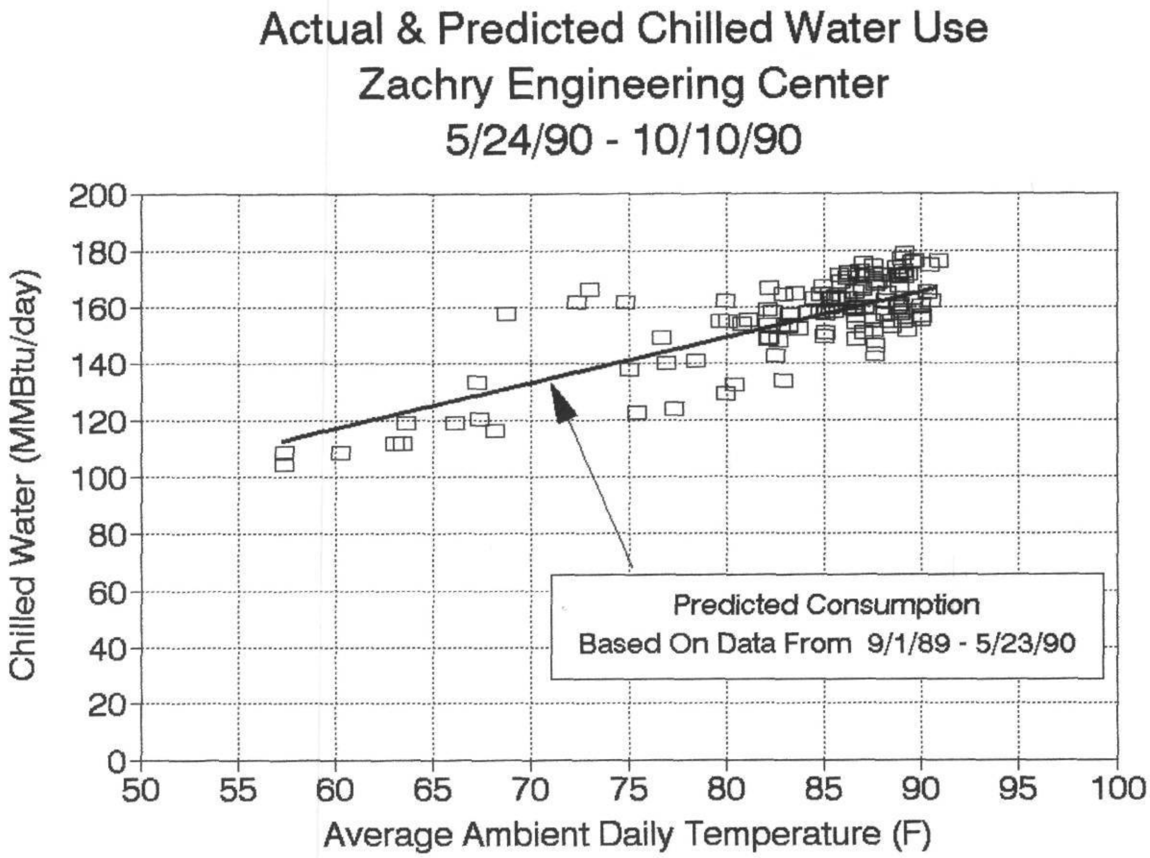

Figure 4.3; Predicted and measured daily chilled water use for the ZEC.

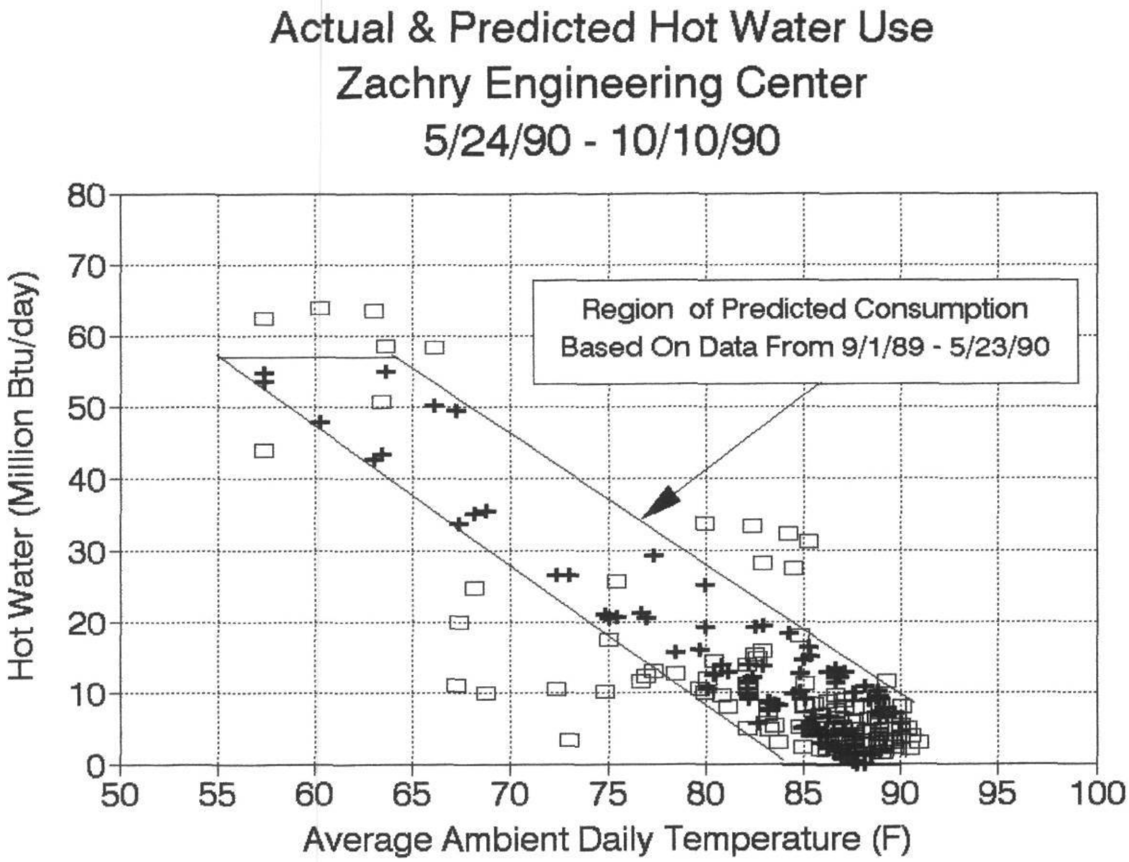

Figure 4.4; Predicted and measured daily hot water use for the ZEC.

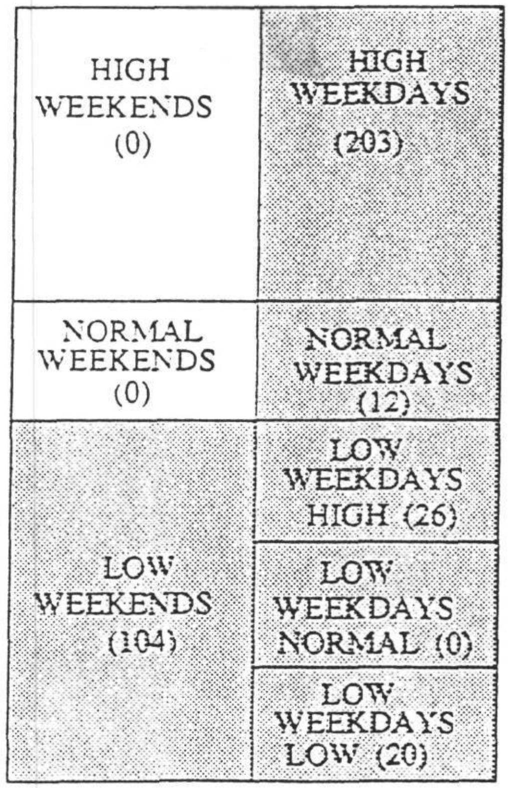

Figure 4.5; Number of days in the five primary day types for the ZEC.

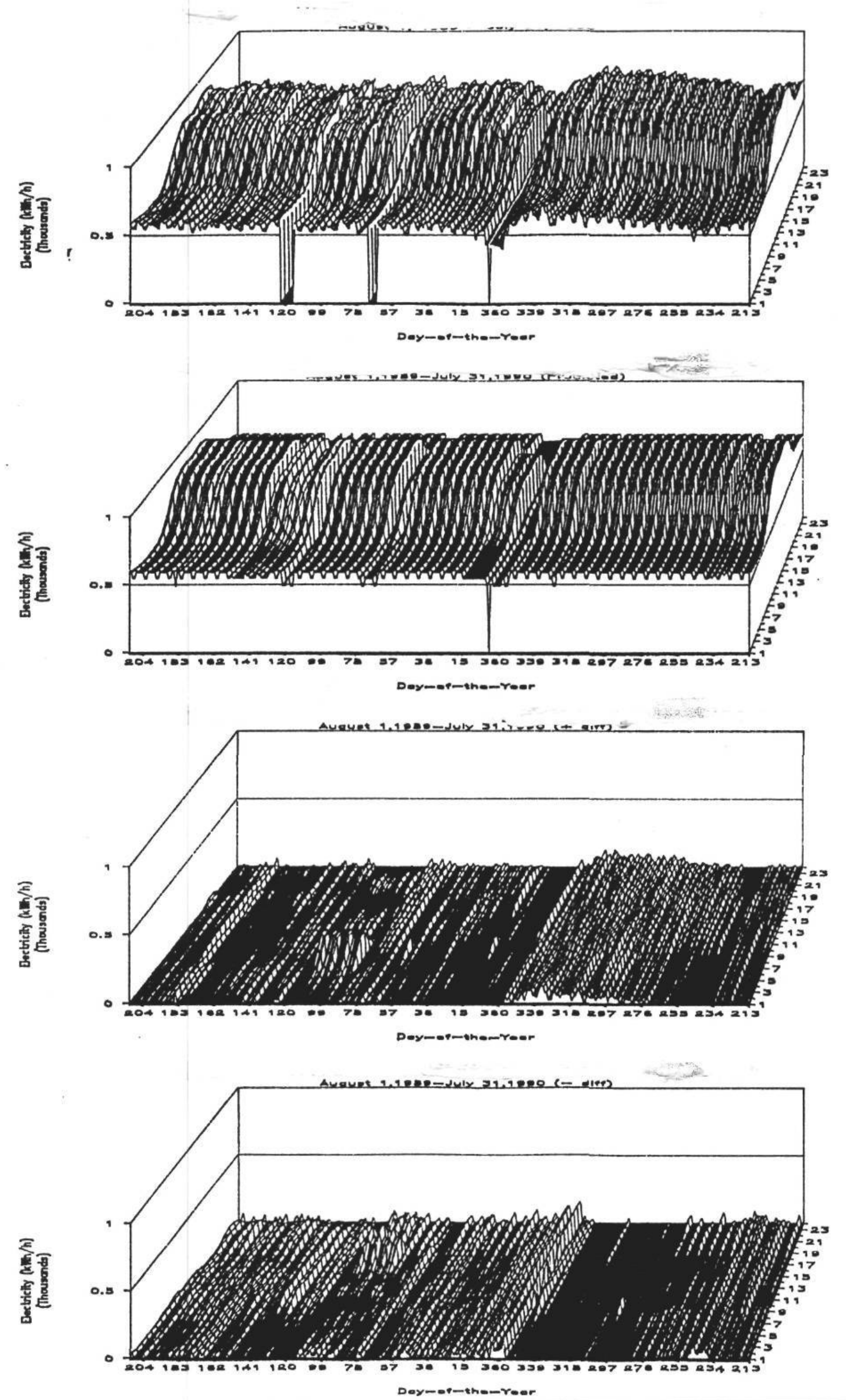

Figure 4.6; Actual, predicted and residual lights and receptacles electricity use for the ZEC. *A graphical analysis such as this can help identify changes in operating and maintenance practices. The positive residuals occuring between days 300 and 270 resulted from the removal of a computer center from the ZEC.*

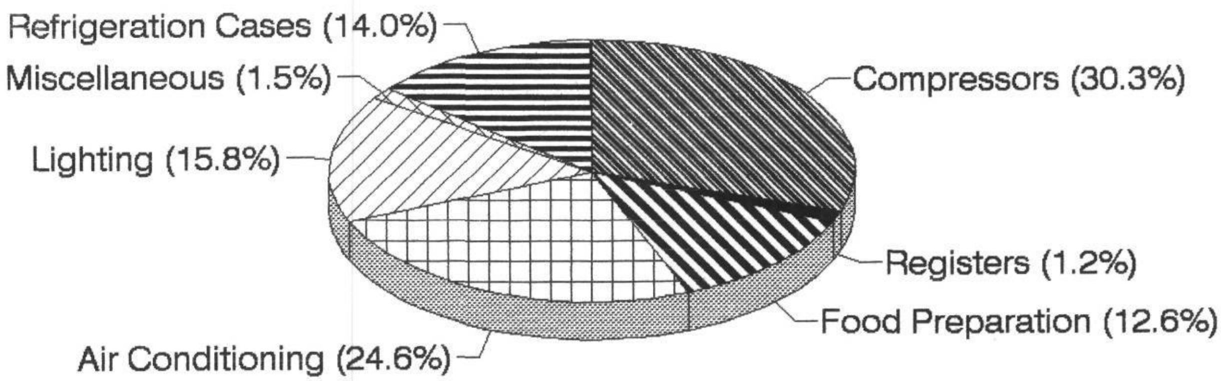

Figure 5.1; Grocery store estimated peak electricity use. *This figure shows the estimated breakdown of electrical systems in the store. The breakdown is for the peak electric demand of the store which could occur during refrigeration defrost cycles.*

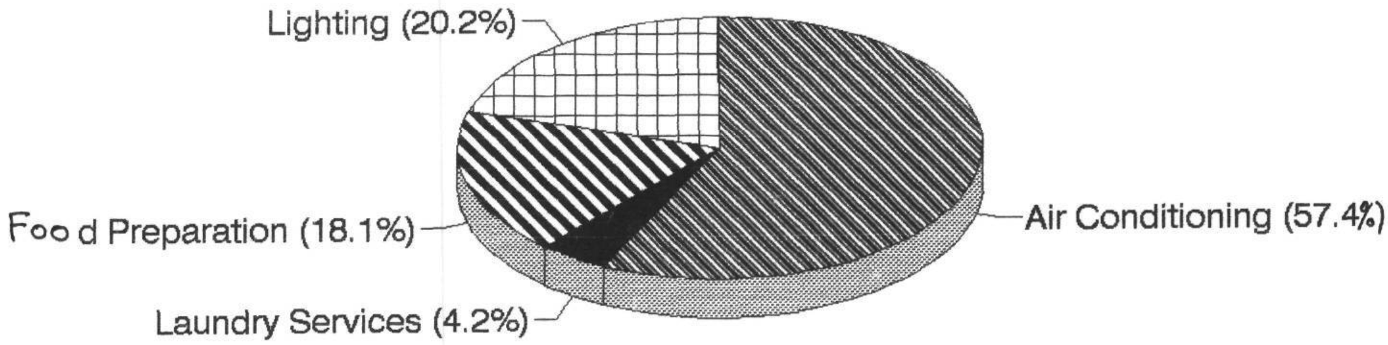

Figure 5.2a; Estimated Temple nursing home peak electricity use by function.

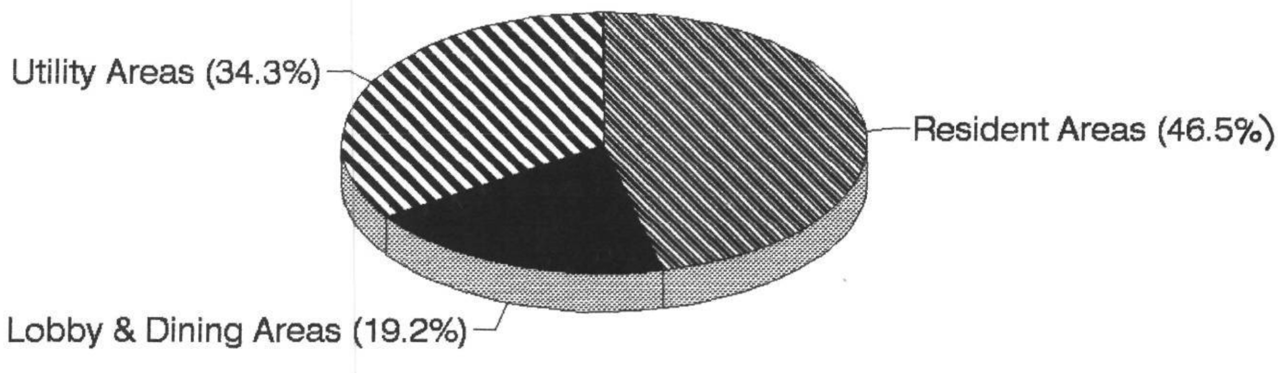

Figure 5.2b; Estimated Temple nursing home peak electricity use by area.

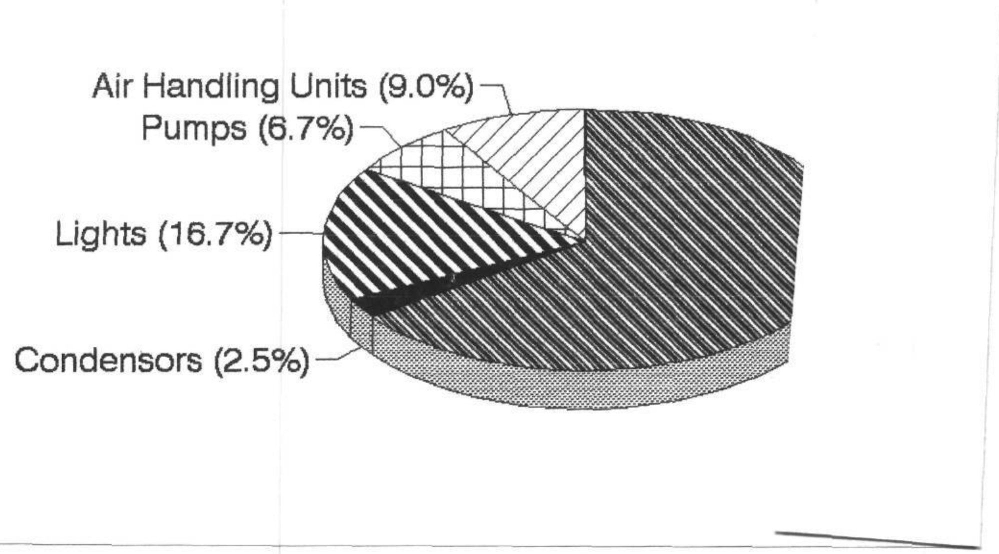

Figure 5.3 A&M Consolidated High School estimated peak electricity use. *This figure shows the estimated breakdown of major electrical systems in the school. It does not include smaller miscellaneous loads.*

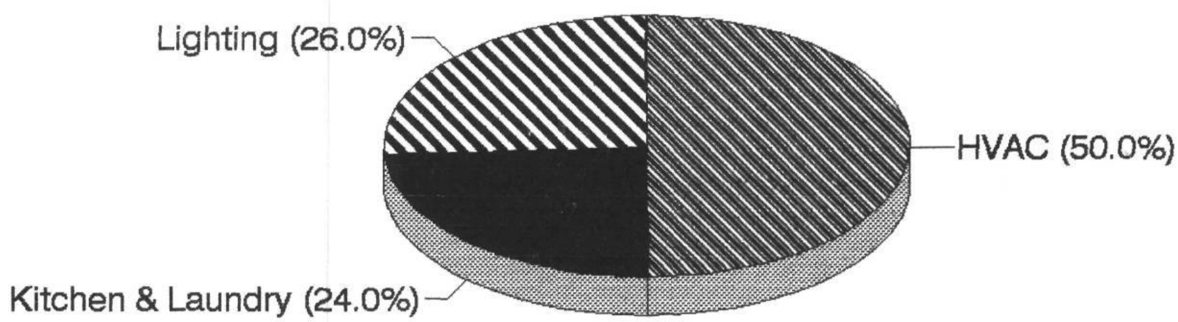

Figure 5.4; ASEAM estimate of annual Temple nursing home electricity use.

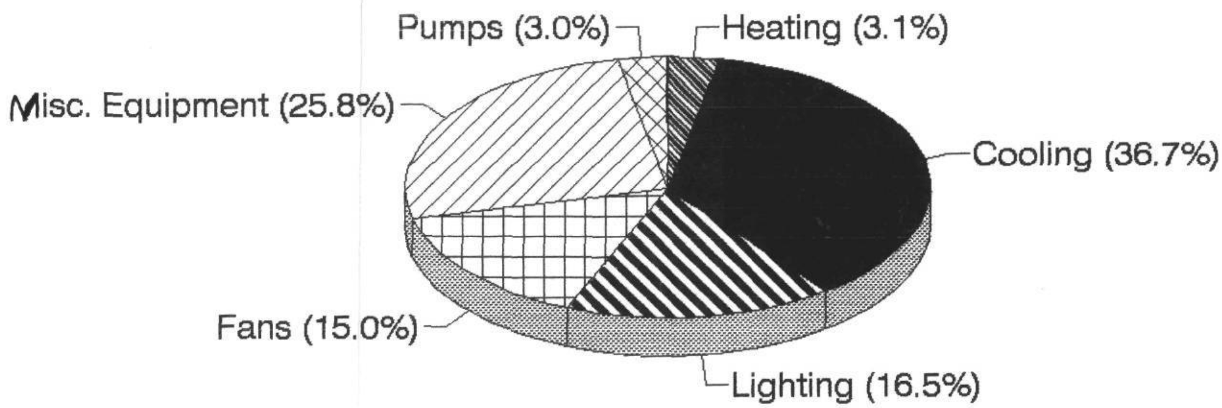

Figure 5.5; ASEAM estimate of annual A&M Consolidated High School electricity use.

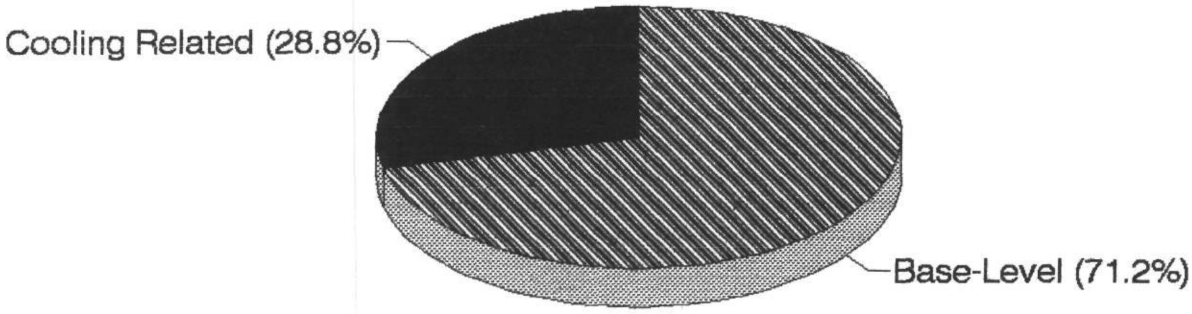

Figure 5.6a; PRISM estimate of Temple nursing home base-level and cooling electricity use.

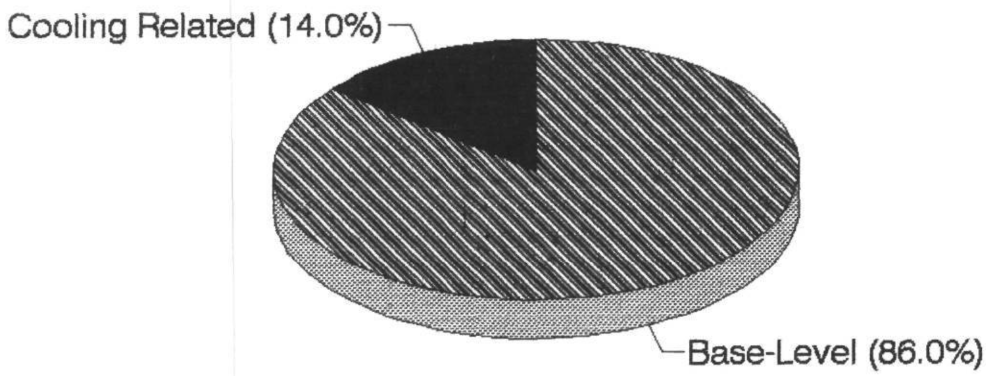

Figure 5.6b; PRISM estimate of Austin nursing home base-level and cooling electricity use.

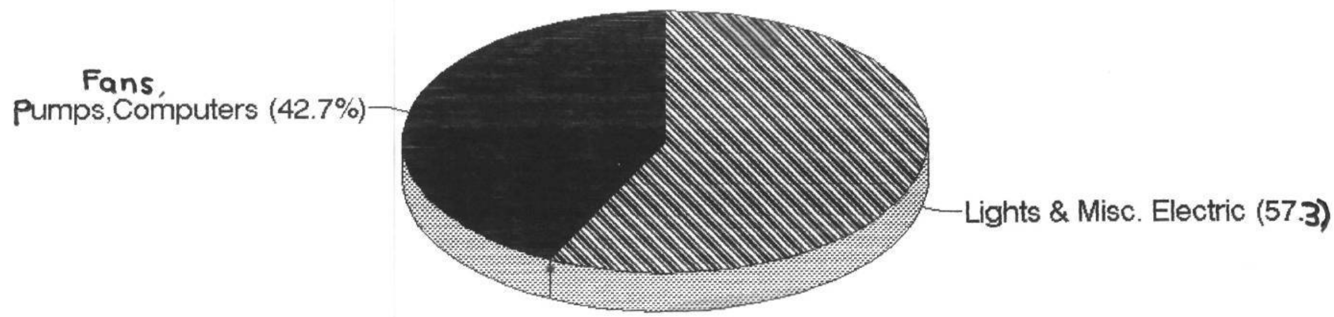

Figure 5.7a; Measured breakdown of ZEC electricity use. *Misc. Electric includes all "plug in" loads at wall receptacles.*

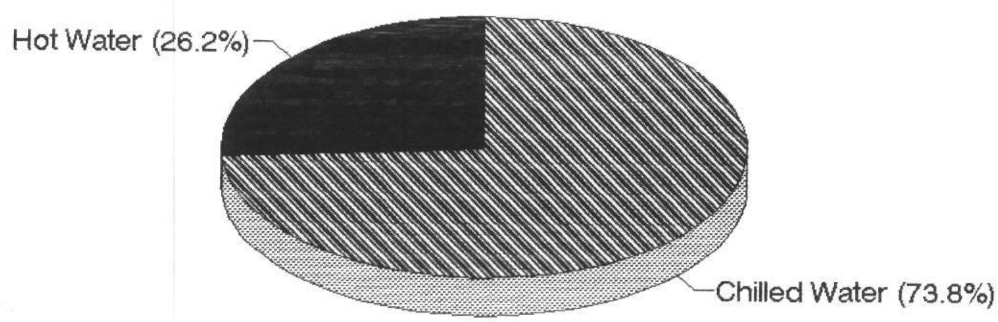

Figure 5.7b; Measured breakdown of the ZEC thermal energy use. *Hot and chilled water are supplied by the Texas A&M physical plant.*

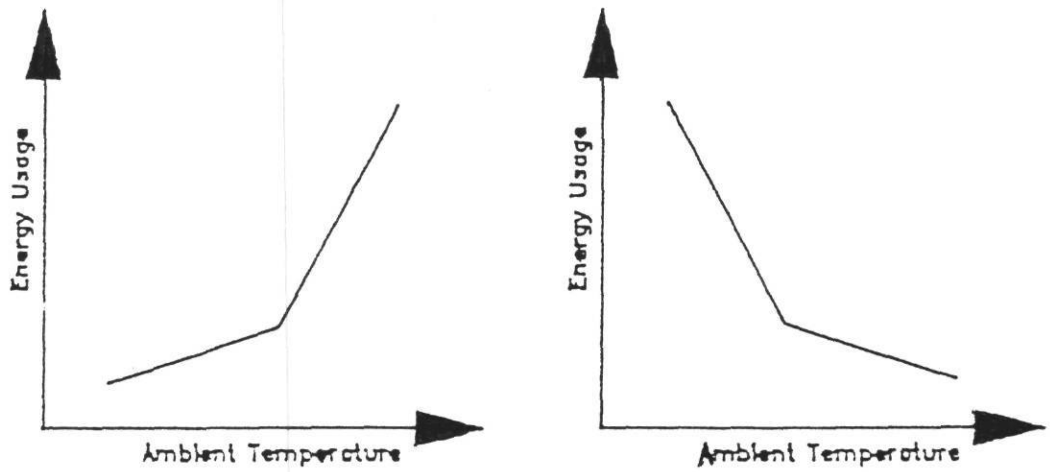

Figure 6.1; Generalized four parameter models of energy use with positive and negative slopes.

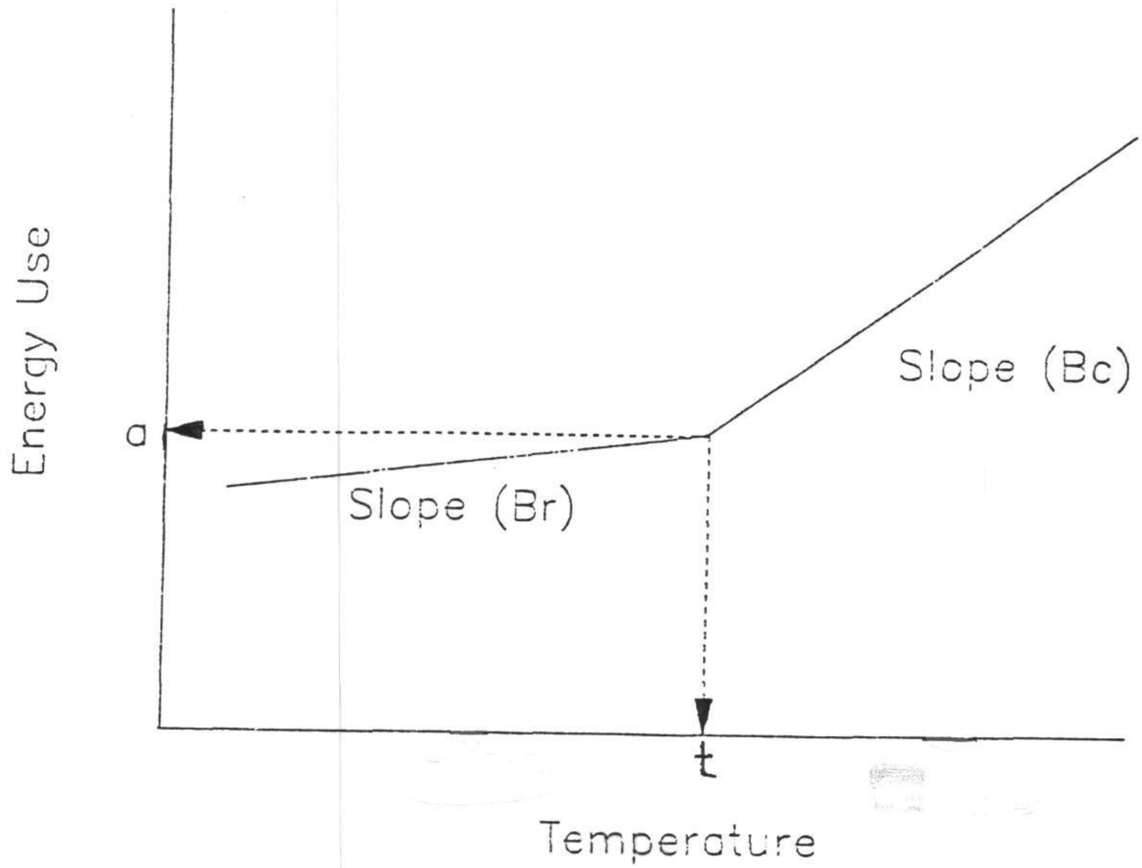

Figure 6.2; Generalized change-point model and parameters.

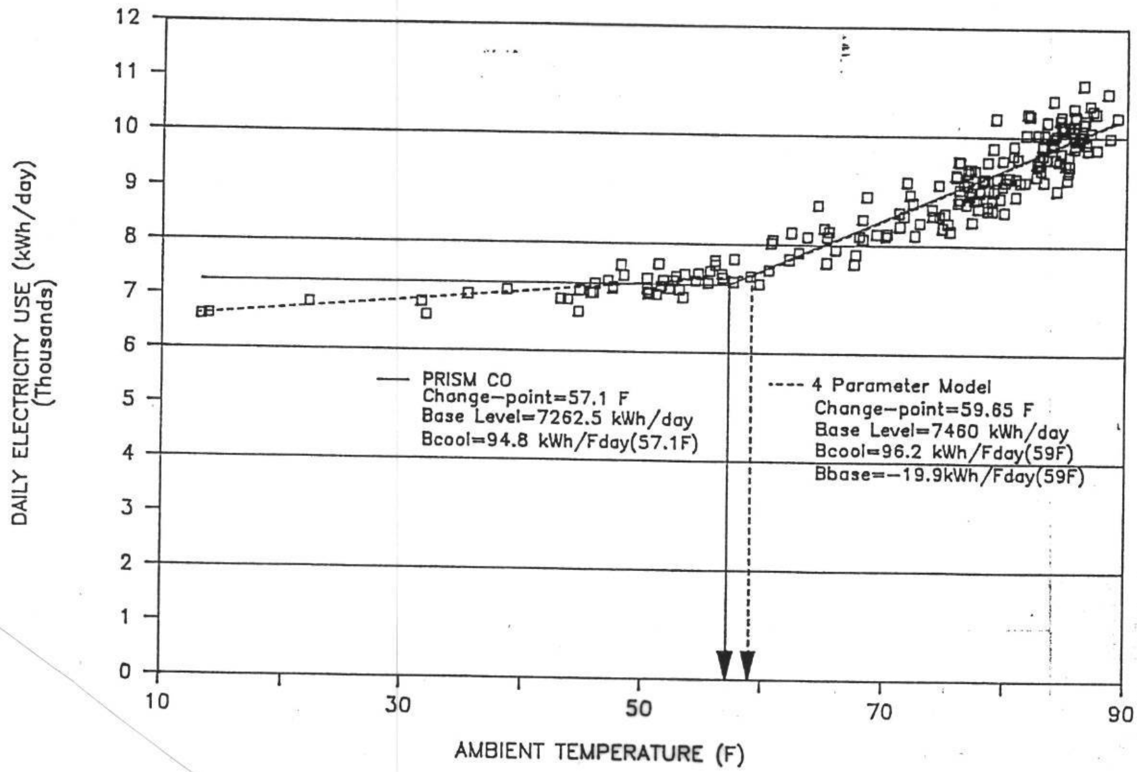

Figure 6.3; Change-point model and PRISM CO model fits to grocery store data.

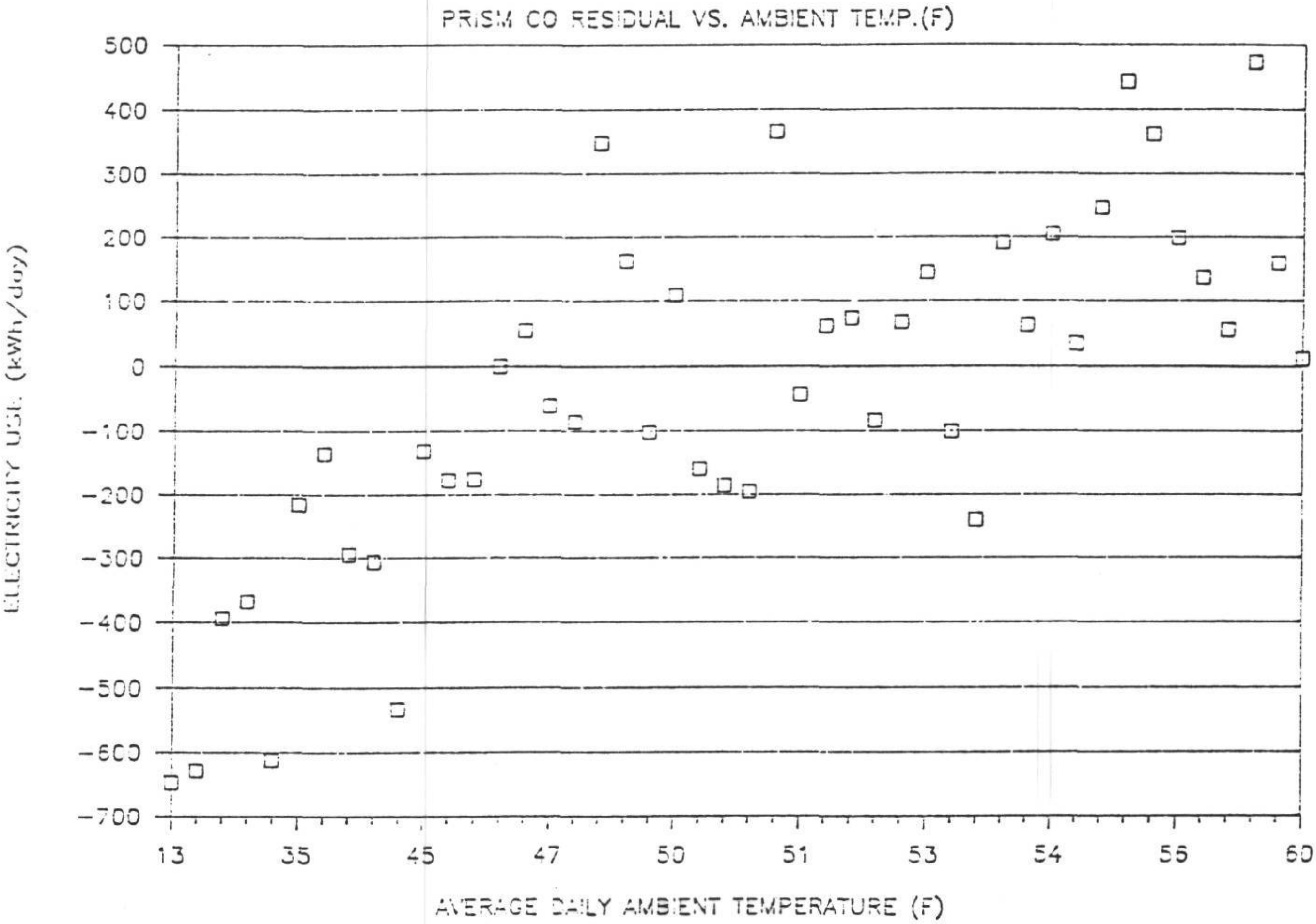

Figure 6.4; PRISM CO model residuals for base-level regime of the grocery store.
Note the trend of residuals increasing with temperature.

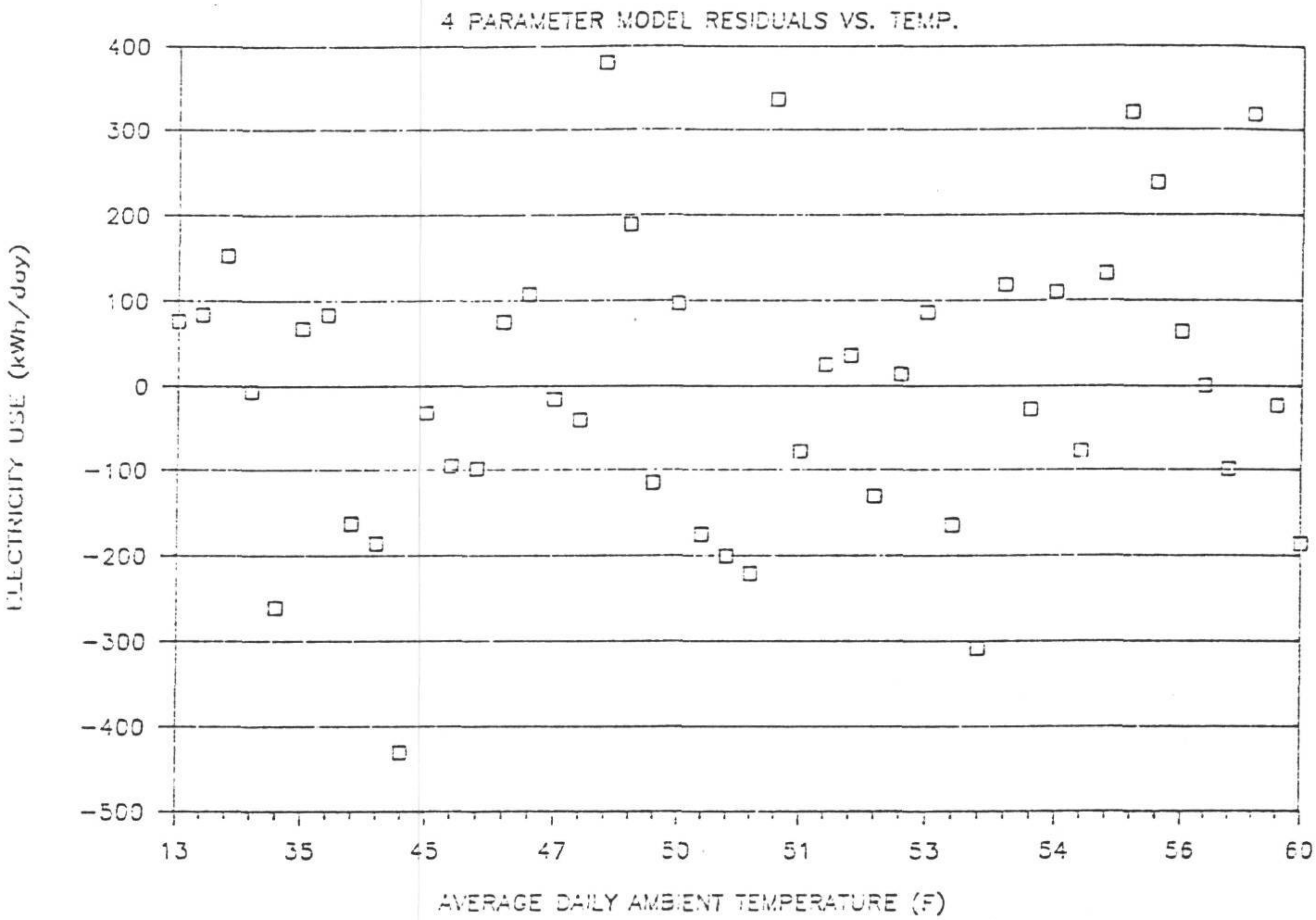

Figure 6.5; Change-point model residuals for refrigeration regime of the grocery store. *Residuals are nearly normally distributed.*

Appendix A
ERAP Energy Savings Worksheet

ERAP ENERGY SAVINGS WORKSHEET

Date: 12-5-90 *ERAP Project No.:* 327 *PI:* D. E. Claridge

Project Title: Improved Analysis Methods ... *Evaluator:* ______

Expected Date of Proof of Concept 1 (*Month*) 93 (*Year*)

		1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	
Targeted BTUs	Source		7.34	7.45	7.72	7.92	8.13	8.13	8.36	8.57	8.77	
	Site		2.16	2.19	2.27	2.33	2.39	2.39	2.46	2.52	2.58	X 10^{14}/yr
X												
Savings Factor			0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	
X												
Feasibility Factor		0.5	0.55	0.75	1.0	1.0	1.0	1.0	1.0	1.0	1.0	
X												
Penetration Factor			.008	.016	.024	.032	.040	.048	.052	.052	.052	
X												
Adoption Factor*			1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	
=												
Calculated Energy Savings			2.94	8.94	18.5	25.3	32.5	39.0	43.5	44.6	45.6	X 10^{10}

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
***Default Adoption Factors From Product Acceptance Curve**										
	*Time Corrected***									

** *Time correction determined by date of proof of concept. Time correction adoption factors determined by multiplying adoption factors by time correction. (See tables)*

TEN YEAR TOTAL BTU'S SAVED

2.6 X 10^{12}

REFERENCES AND SOURCES OF ESTIMATES

ERAP ENERGY SAVINGS WORKSHEET

Targeted BTU's:

Commercial sector electric consumption estimates from Public Utility Commission of Texas, "End-Use Modeling Project Interim Report" February 1989.

Savings Factor:

10% savings typical based on Haberl & Claridge, ASHRAE Trans 1987. We estimate ERAP work will inprove from 10% to 11% for incremental savings of 1%.

Feasibility Factor:

Concept will be implemented beginning in 1991. We assign 0.5 for 1991, reading 1.0 in 1993.

Penetration Factor:

The penetration factor is based on the energy consumption of buildings expected to participate in the Texas LoanSTAR Program. Additional use of techniques by private sector may improve this impact.

Adoption Factor:

Assumed to be 1.0 for LoanSTAR buildings where contract is in place to implement these techniques.

Notes:

Appendix B
Requests for Information
About Energy Analysis Methods and Software

REQUESTS FOR INFORMATION
ABOUT ENERGY ANALYSIS METHODS AND SOFTWARE

no.	date mailed	name/address mailed to	what was mailed
1	5-25-89	Michael N. Hart President Energy Engineering Associates, Inc. PO Box 49134 Austin, TX 78765	information about Zachry Engineering Center: monthly plots of dry bulb temperature, solar radiation, electric consumption, chilled and hot water consumption; channel table for data logger; building survey data; assumption used for modeling building and typical measured load profiles
2	7-9-90	Raj Gopal The Anco Group 231 W. Michigan Ave. #P141 Milwaukee, WI 53203	list of software packages
3	7-9-90	Robert Tyls AT&T Contract Services One Oak Way Rm. 3Wc135 Berkeley Heights, NJ 07922	lists of software packages
4	7-9-90	Dominick Chirico Stone & Webster Engineering 250 W. 34th Street New York, NY 10119	lists of software packages
5	7-9-90	James Elleson, P.E. Dorgan & Associates 5610 Medical Cir. #31 Madison, WI 53719-1227	lists of software packages
6	7-9-90	Lew Harriman Mason-Grant Company PO Box 6547 Portsmouth, NH 03801	lists of software packages
7	7-9-90	Robert Hough, P.E. The Fleming Group 6310 Fly Road East Syracuse, NY 13057	lists of software packages
8	7-9-90	Dr. Hiroshi Yoshino Department of Architecture Tohoku University AOBA SENDAI 980 JAPAN	lists of software packages

9	7-9-90	Ernie Freeman U.S.D.O.E. 1000 Independence S.W. Washington, D.C. 20585	lists of software packages
10	7-9-90	Lester Shen Underground Space Center Civil & Mineral Engr. Bldg. 500 Pillsbury Dr. SE University of Minnesota Minneapolis, MN 55455	lists of software packages
11	7-9-90	Charles Cromar, P.E. Florida Solar Energy Center 300 State Road #401 Cape Canaveral, FL 32920-4099	lists of software packages
12	7-9-90	Harry Misurello The Fleming Group 1511 K. Street NW #331 Washington, DC 20005	lists of software packages
13	7-9-90	William Mixon O.R.N.L. MS 6070 PO Box 2008, Bldg. 3147 Oak Ridge, TN 37831	lists of software packages
14	7-9-90	Robert McDowell, P.E. Physical Plant 89 Freedman Crescent Winnipeg, Manitoba CANADA Canada R3T 2N2	lists of software packages
15	7-9-90	David Saum Infiltec PO Box 1533 Falls Church, VA 22041	lists of software packages
16	7-9-90	Robert Briggs Battelle PNL Battelle Boulevard Richland, WA 99352	lists of software packages
17	7-9-90	William Fleming The Fleming Group 6310 Fly Road East Syracuse, NY 13057	lists of software packages
18	7-9-90	Julie Oliver U.S.D.O.E. 1000 Independence S.W. Washington, D.C. 20585	lists of software packages

19	7-9-90	Dr. Jan Krieder ICEM/CEAE University of Colorado Boulder, CO 80309-0428	lists of software packages
20	7-9-90	Richard Mazzucchi Battelle PNL Battelle Boulevard Richland, WA 99352	lists of software packages
21	8-15-90	Jeff Wheless 180 Technology Road Norcross, GA 300092 Schlumberger, Inc.	Hot & Humid preprints
22	10-08-90	Ken Keating U.S. Department of Energy Bonneville Power Administration PO Box 3621 Portland, OR 97208-3621	Hot & Humid preprints and copies of recent articles concerning an exploratory analysis of the energy audit process
23	10-08-90	Jim Vajda U.S.D.O.E. 1000 Independence Ave. SW Washington, DC 20585	Hot & Humid preprints and ASHRAE Journal articles
24	10-8-90	David Feng Civil Engineering Department University of Colorado Boulder, CO 80309-0428	ASHRAE Journal articles
25	10-11-90	Howard Reichmuth Pacific Power 920 SW 6th Ave., 440 PFFC Portland, OR 97204	Hot & Humid preprints
26	10-11-90	William Jones Ontario Hydro 800 Kipling Ave. KR263 Toronto, Ontario M8Z 5S4 CANADA	Hot & Humid preprints
27	10-11-90	Michael Kaplan Kaplan Engineering 623 Atwater Road Lake Oswego, OR 97034	Hot & Humid preprints
28	10-11-90	Mukesh Khattar EPRI - Commercial Applications 3412 Hillview Ave. PO Box 10412 Palo Alto, CA 94303	Hot & Humid preprints

29	10-11-90	M. J. DeLaHunt BR Associates, Inc. 2323 Eastlake Ave. East Seattle, WA 98102	Hot & Humid preprints
30	10-11-90	Ron Wendland EPRI - Thermal Storage Technology 3412 Hillview Ave. PO Box 10412 Palo Alto, CA 94303	Hot & Humid preprints
31	10-11-90	Manuel Carabott PRISM Engineering 145 West 15th Street #102 North Vancouver, B.C. V7M 1R9 CANADA	Hot & Humid preprints
32	10-11-90	John Proctor 45 Massasoit St. #102 San Francisco, CA 94110	Hot & Humid preprints
33	10-11-90	Chris Soper 1126 Sinex Ave. Pacific Grove, CA 93950	Hot & Humid preprints
34	10-11-90	David Myers Honeywell MN63-C010 Sensor and System Development Cent 1000 Boone Ave. Golden Valley, MN 55427	Hot & Humid preprints
35	10-11-90	Stuart Harrison Domestic Automation 353 D. Vintage Park Drive Foster City, CA 94404	Hot & Humid preprints
36	10-11-90	George Baird School of Architecture Victoria University of Wellington PO Box 600 Wellington, New Zealand	Hot & Humid preprints
37	10-11-90	Paul Meagher EPRI - Demand Side Planning 3412 Hillview Ave. PO Box 10412 Palo Alto, CA 94303	Hot & Humid preprints

38	10-11-90	Laurence Carmichael EPRI 3412 Hillview Ave. PO Box 10412 Palo Alto, CA 94303	Hot & Humid preprints
39	10-11-90	Arne Boysen Arne Boysen AB Hersbyvagen 23 S-181 42 Lidingo SWEDEN	papers for publication in his proceedings: reprints of articles from ASHRAE, Hot & Humid, ACEEE proceedings
40	10-16-90	Mark Opal Sycom Corporation 1050 Thomas Jefferson St. NW (6th floor) Washington, D.C. 20007	preprints of papers describing the program & related papers
41	10-16-90	Edward McGee Bramalea Texas 901 Main Street Dallas, TX 75202	preprints of papers describing the program & related papers
42	10-16-90	Larry Kramer TU Electric PO Box 151325 Irving, TX 75015-1325	preprints of papers describing the program & related papers
43	10-16-90	Jack Wolpert Environmental Research Group 1536 Cole Boulevard #145 Golden, CO 80401	paper dealing with potential DOE-2.1c problems; Forrestal & shopping center papers;
44	10-16-90	Davor Novosel Gas Research Institute 8600 West Bryn Mawr Ave. Chicago, IL 60631	paper on study done grocery store in Texas
45	10-16-90	Mark Krebs Southern Union Gas 400 West 15th Street Austin, TX 78701	background papers on techniques developed for tracking, analyzing and displaying building energy usage and early study done on a grocery store
46	10-16-90	Alan Ash The Trane Company PO Box 814609 (75381-4609) Dallas, TX 75234	background papers on techniques developed for tracking, analyzing and displaying building energy usage
47	10-16-90	George Grant Grant Engineering 990 Bennett Ave. Winter Park, FL 32789	background papers on techniques developed for tracking, analyzing and displaying building energy usage; Forrestal & New Jersey shopping center papers

48	10-18-90	Richard Flora Fermitek Corporation 25117 SW Parkway Ave. Wilsonville, OR 97070	Hot & Humid preprints
49	10-19-90	Michael Anderson Landis & Gyr 3601 Sagamore Parkway North PO Box 7180 Lafayette, IN 47903	Hot & Humid preprints
50	10-19-90	Ed Cunnie Gulton Industries -- Rustrak Gulton Industrial Park East Greenwich, RI 02818	Hot & Humid preprints
51	10-19-90	Ron Gumina Synergistics Control Systems, Inc 6600 Plaza Drive, Suite 200 New Orleans, LA 70124	Hot & Humid preprints
52	10-19-90	Ralph Kellar Process Systems 24 Starway Willis, TX 77378	Hot & Humid preprints
53	10-19-90	Dave Repko Campbell Scientific, Inc. PO Box 551 Logan, UT 84321	Hot & Humid preprints
54	10-22-90	Dave Simms SERI - Wind Systems 1617 Cole Blvd. Golden, CO 80401	Hot & Humid preprints
55	10-23-90	Joe Holzer ServiceMaster 5340 S. Quebec St. Englewood, CO 80111	Hot & Humid preprints
56	10-24-90	Herb Muther Honeywell, Inc. Honeywell Plaza Minneapolis, MN 55408	Hot & Humid preprints
57	10-25-90	Barbara Trent ASHRAE Program 1791 Tullie Circle NE Atlanta, GA 30329	information concerning recent research

58	10-25-90	Don Peavy GFE Energy Management 1980 Post Oak Blvd. #1495 houston, TX 77056	Hot & Humid preprints
59	10-30-90	Bruce Long Engineering Division Prudential Realty Group Three Gateway Center Newark, NJ 07102-4082	Hot & Humid proceedings & related articles and the ESL brochure
60	10-30-90	Dr. Gideon Shavit Honeywell Commercial Buildings Group 1500 W. Dundee Rd. Arlington Heights, Illinois 60004	Hot & Humid preprints & ESL brochure
61	10-31-90	John Short Lambert Engineering 601 NW Harmon Bend, OR 97701	hot & Humid preprints
62	10-31-90	Dr. Peter Brothers Johnson Controls 507 East Michigan St. PO Box 423 Milwaukee, WI 53201	Hot & Humid preprints
63	11-8-90	Scott Seitz PEPSI Route 35 and 100 Somers, New York 10589	Hot * Humid papers & recent ASHRAE Journal articles
64	11-8-90	Ms. Sandy Robinson Meta Systems 1 Kendall Square #2200 Cambridge, MA 02139	Hot & Humid papers
65	11-15-90	Ms. Marisa Gurjao Pinheiro Fundacao Centro Tecnologico De Minas Gerias CETEC, Setor de Informacao Tecnologico STI Av. Jose Candido da Sliveira, 2000, Horto Ramal 346, Caixa Postal 2306 31170 Belo Horizonte - MG, BRAZIL	copies of articles referenced in the 8/90 and 9/90 ASHRAE Journal articles & copies of papers describing work done here
66	11-20-90	Gary Lawson Washington Water Power PO Box 3727 Spokane, WA 99220-3727	Hot & Humid papers, Thermal Envelopes IV paper, draft copy of the PSC Final report, 1990 ACEEE poster paper

67	11-20-90	Moncef Krarti Steven Winter Associates 50 Washington Street Norwalk, CT	Hot & Humid papers, ASME preprints
68	11-20-90	Martha Hewett C. E. U. E. 510 1st Avenue North #400 Minneapolis, MN 55403	Hot & Humid papers, 3 ASME preprints
69	11-23-90	Dr. Forrest Stoddard Alternative Energy Institute WTSU Box 248 Canyon, TX 79016-0248	several preprints, printout of weather channels
70	11-28-90	Professor David Klett Mechanical Engineering North Carolina AT&T State Universtiy Greensboro, NC 27411	copies Hot & Humid and ASME preprints
71	11-28-90	Prof. Bill Beckman 240 ME Building University of Wisconsin Madison, WI 53706	copies Hot & Humid and ASME preprints
72	11-28-90	Boyce Farror, P. E. 6931 Lakewood Blvd. Dallas, TX 75214	copies Hot & Humid and ASME preprints