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DEVELOPMENT AND USE OF BASELINE MONTHLY UTILITY MODELS FOR EIGHT ARMY INSTALLATIONS AROUND THE UNITED STATES

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ABSTRACT

This report has been prepared for the United States Army Construction Engineering Research Laboratories (USACERL) located in Champaign, IL by the Energy Systems Laboratory (ESL) of Texas A&M University. The first phase of this study, completed in 1995, developed a methodology suitable for tracking and evaluating the extent to which Presidential Executive Order 12902, which mandates a 30% decrease in utility bills from 1985 to 2005, is being met at DoD facilities. The methodology was then applied to clean data from one Army base provided by USACERL. The objectives of the current study were:

(1) to evaluate the methodology when used with monthly mean temperature data and "uncleaned" data available from a central Army database; and

(2) to prepare a primer describing the tracking methodology and its application.

This study used electricity consumption, gas consumption, base area, and population data obtained from the central Defense Energy Information System (DEIS) database by USACERL, and monthly mean temperature data obtained from the National Climatic Data Center in Asheville, NC. The earlier study had used daily temperature data and billing data obtained directly from the Army base. Data for eight DoD installations were obtained from DEIS by USACERL. It was found that the data from DEIS did not include meter reading dates, needed for accurate baseline creation, but a statistical method was developed which adequately estimates the meter reading dates, thereby overcoming this deficiency. It was also found that base population data is not generally useful, but that base area changes should be taken into account while tracking energy use. Estimates of change in energy use determined using DEIS and NCDC input data were very consistent with the results obtained using local billing data and daily temperature data. This indicates that valid estimates of the change in energy use at a particular DoD installation with respect to a baseline year can be reached with DEIS and NCDC data unless these data include transcription errors.

This report also includes a primer which describes the baselining and tracking methodology suitable for use by other analysts who wish to evaluate the changes in energy use at other Army installations.

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DISCLAIMER

This report was prepared by the Energy Systems Laboratory (ESL) of the Texas Engineering Experiment Service (TEES) and was sponsored by the United States Army Construction Engineering Research Laboratories (CERL) located at Champaign, IL. Neither the ESL, TEES or CERL, or any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe on privately-owned rights.

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EXECUTIVE SUMMARY

This report has been prepared for the United States Army Construction Engineering Research Laboratories (USACERL) located at Champaign, IL by the Energy Systems Laboratory (ESL) of Texas A&M University with the objective of developing monthly baseline utility models for electricity and gas use for eight army bases around the U.S. and illustrate their use as screening tools for detecting changes in future utility bills and also to track/evaluate the extent to which Presidential Executive Order 12902 mandating 30% decrease in energy utility bills from 1985 to 2005 is being met.

With the above objective in mind, USACERL commissioned a first study, in mid-1995, with ESL. The objectives were to: (i) to investigate different types of energy modeling software- PRISM and EModel- in order to ascertain which is more appropriate for modeling energy use in DoD installations, (ii) to propose criteria for selecting the baseline year depending on the availability and "cleanliness" of the utility bill data and the associated outdoor temperature data, and (iii) develop/propose statistical equations in order to determine the uncertainty in using these baseline models for predicting monthly (or utility) energy use and annual energy use. For this preliminary study, we wanted to select a base whose utility data had undergone some sort of "reality check". Fort Hood, a large army installation located in central Texas was chosen in view of the fact that extensive data gathering and analyses has been done on this base over the years, and a comprehensive report on utility and services data was available. The results of our previous study, documented in a report by Saman et al.(1995), indicated that reliable baseline models of electricity use, electricity demand, gas use and water use could be identified from utility billing data and that these models were sound enough to be useful as screening tools for detecting changes in future utility bills.

The basic objective of the current study was to apply/evaluate the previous methodology to utility data from eight army bases from various parts of the country. The utility data and other data such as base area and population which were to be used for the analysis were downloaded from the central Defense Energy Information System (DEIS) database by USACERL and sent to the ESL (Table 1). One could not expect such data to be as "clean" as that from Fort Hood since the former is usually not subjected to a careful "reality check" before being entered into the database. Further, unlike the preliminary study where daily mean outdoor temperature data for Temple, TX (a town very close to Fort Hood) was available for the analysis, USACERL decided to use monthly mean temperature data from the National Climatic Data Center (NCDC) at Ashville, NC where such data for numerous sites throughout the U.S. is available to the general public. It was the intent of this study to evaluate whether baseline models identified from DEIS and temperature data are appropriate to use as screening tools

for detecting changes in future utility bills. Further, the data from DEIS did not include meter reading dates, needed for accurate baseline modeling, but a statistical method was developed which adequately estimates the meter reading dates, thereby overcoming this deficiency. We found very consistent estimates of annual change in energy use from both methods. This indicates that conclusive estimates of how energy use in a particular DoD installation varied over the years with respect to a baseline year can be reached with "unproofed" DEIS and NCDC data.

The lack of concurrent temperature and utility bill data for three months of FY85 forced us to reject FY85 as the starting year and choose FY86 instead. The results of our baseline model identification effort are summarized in Table 2. The CV-RMSE of the model is the deciding factor in determining the category of the model fit. We note that of the eight electricity use models, two are excellent, four are good and only one is mediocre. Of the eight gas use models, none is excellent, two are good, four are mediocre and two are poor. Hence, gas use models seem to be generally poorer than electricity use models.

The analyses for all Army bases other than the two Army depots also involved computing percentage changes in annual energy use with respect to baseline year (FY86) normalized by (i) conditioned area, and (ii) conditioned area and population. Though generally the changes in energy use by both means of normalization have more or less similar patterns, the quantitative values are appreciably different during certain years. One cannot place as much confidence in the population values as in the conditioned area values, and so it would probably be better to draw conclusions regarding the extent to which Presidential Executive Order 12902 is being met based on conditioned area normalization only.

The extent to which the annual energy use with respect to the baseline year has changed from the baseline year FY86 until the final year for which data was available, can also be determined from Table 2. We note that of the sixteen gas and electricity use channels evaluated, five showed significant decrease, i.e. showed negative changes larger than the uncertainty, by an average of 37%. Five others were unchanged within the uncertainty, and six had increased significantly (by an average of 40%).

A final objective of this study was to prepare a primer describing our baselining and tracking methodology which can be used by other analysts who wish to perform similar evaluations with data from other army installations. If analyses such as these are to find widespread application, they should be such that they could be applied routinely to all bases every year when annual utility bill data is entered into the central army database.

Table 1. Table giving an indication of the size and energy use of the eight army bases

Serial No.	Army Base	Average Population FY86	Total bldg. area-FY86 ksq.ft	Conditioned area-FY86 ksq.ft	Electricity use-FY86 MWh/yr	Gas use FY86 kcf/yr
1	Fort Bragg, NC	60,006	23,006	19,441	285,056	880,733
2	Fort Carson, CO	25,844	11,344	7,983	96,940	1,417,201
3	Fort Drum, NY	6,694	6,291	4,558	32,750	56,356
4	Fort Hood, TX	66,462	23,840	19,232	307,750	1,416,929
5	Fort Huachuca, AZ	12,484	7,807	6,843	76,498	509,136
6	Fort Ord, CA	37,868	18,037	14,751	122,614	1,203,256
7	Pueblo Army Depot, CO	-	6,245	231	13,340	4,470
8	Sacramento Army Depot, CA	3101*	3,071	505	26,246	109,488

* This value is for FY90

Table 2. Summary of baseline models and change in energy use normalized by conditioned building area.

Army base		Baseline Model				% Change in energy use w.r.t. to baseline year*		
		Baseline year	R^2	CV-RMSE	Model fit	Final Year	% change along with uncertainty++	Comment
Bragg	Elec.	FY86	0.95	4.7	Excellent	FY94	23.3 (3.2)	Significant
	Gas	FY86	0.87	14.4	Mediocre	FY94	9.4 (9.8)	Uncertain
Carson	Elec.	FY86	-	8.0	Good	FY93	1.4 (5.4)	Uncertain
	Gas	FY86	0.94	13.8	Mediocre	FY93	-23.7 (9.3)	Significant
Drum	Elec.	FY86	0.66	10.7	Good	FY94	37.0 (7.3)	Significant
	Gas	FY86	0.69	36.5	Poor	FY94	68.2 (24.8)	Significant
Hood	Elec.	FY86	0.98	5.2	Excellent	FY94	20.6 (3.5)	Significant
	Gas	FY86	0.98	10.1	Good	FY94	-13.3 (6.9)	Significant
Huachu.	Elec.	1985	0.66	7.1	Good	FY90	8.2 (4.6)	Significant
	Gas	1985	0.93	18.4	Mediocre	FY90	11.2 (12.5)	Uncertain
Ord	Elec.	FY86	-	8.3	Good	FY93	-4.0 (5.7)	Uncertain
	Gas	FY86	0.69	16.2	Mediocre	FY93	-8.6 (11.0)	Uncertain
Pueblo	Elec.	FY86	-	17.3	Mediocre	FY93	-43.8 (11.8)	Significant
	Gas	FY86	0.98	9.2	Good	FY92+	85.4 (6.2)	Significant
Sacram.	Elec.	FY86	0.67	7.3	Good	FY94	-52.9 (5.0)	Significant
	Gas	FY86	0.88	26.4	Poor	FY94	-53.6 (17.9)	Significant

* A negative number implies a decrease in energy use and vice versa.

+ Anomalous gas use in FY93 led us to reject the data

++ Defined as the 95% prediction interval

1.0 Background

Presidential Executive order 12902 states that all federal facilities shall reduce energy consumption per gross square foot by 30% from 1985 levels by the year 2005 (Chalifoux et al., 1996). Subsequently the U.S. Army Construction Engineering Research Laboratories (USACERL) at Champaign, IL formulated the Model Energy Installation Program (MEIP). The MEIP is a 5-year pilot project to investigate the feasibility of instituting energy efficiency on an installation-wide (i.e., base-wide) scale in the United States Army (USACERL, 1993). One of the basic intents was to meet the mandate of the above Executive Order in 5 years by reducing the energy consumption and utility bills by 30%.

Each year, the U.S. Army publishes property management data on each of its army bases. Through collection of this property management data, a large database of historic energy utility bills of the numerous installations throughout the country has thus been established over the years. This data is referred to as the Defense Energy Information System (DEIS). A central agency has been charged with gathering the utility bills of the various installations during the previous year and updating the DEIS database each year. Other than a cursory look, no effort is made to assure the accuracy of this data. USACERL wanted to test the feasibility of using this data to track how energy use on a particular installation has been varying, on a year-to-year basis, from some baseline year. This type of ongoing evaluation would provide a "real time" feedback as to the extent to which Presidential Executive Order 12902 is being met.

With the above objective in mind (as well as providing technical advice on the MEIP), USACERL commissioned a first study, in mid-1995, with the Energy Systems Laboratory (ESL) of Texas A&M University. The objectives were to: (i) to investigate different types of energy modeling software- PRISM (Fels et al.,1995) and EModel (Kissock et al., 1994)- in order to ascertain which is more appropriate for baselining energy use on DoD installations, (ii) to propose criteria for selecting the baseline year depending on the availability and "cleanliness" of the utility bill data and the associated outdoor temperature data, and (iii) develop/propose statistical equations in order to determine the uncertainty in using these baseline models for predicting monthly (or utility) energy use and annual energy use. For this preliminary study, we wanted to select a base whose utility data had undergone some sort of "reality check". USACERL instructed the ESL to develop baseline models for Fort Hood. Fort Hood is a large Army installation located in central Texas. It has a daytime population of about 60,000 and contains over 5200 individual buildings covering about 25.5 million square feet. It was chosen in view of the fact that extensive data gathering and analyses has been done on this base over the years and a comprehensive report on utility and services data was available (USACERL, 1993). The results of our previous study, documented in a report by Saman et al.(1995), indicated that sound baseline models of electricity use, electricity demand, gas use and water use could be identified from utility billing data and that these models were good enough to be useful as screening tools for detecting changes in future utility bills.

Developing baseline models is the first step in determining how energy use has been varying over the years. There are also other effects which need to be considered. Total energy use in a building, or even in a group of buildings such as in a DoD installation, is affected by changes in the following five sets of parameters:

(i) climatic variables;

(ii) conditioned building floor area;

(iii) population, i.e., the number of occupants;

(iv) energy efficiency and operation and maintenance (O&M) measures; and

(v) connected load.

What the Presidential Order mandates is that the combined effects of (iv) and (v) should be reduced by 30% from 1985 to 2005. The baseline model only corrects for changes in climatic variables from year to year. Further, energy use from one year to the next needs also to be normalized, i.e., be removed of the effects of parameter sets (ii) and (iii) in order to isolate the effects of parameters (iv) and (v). The procedure to perform the baseline modeling and the above normalization is called the 'baselining methodology'.

2.0 Objectives and Scope

2.1 Objectives

The basic objective of the current study is to apply/evaluate the methodology previously developed for Fort Hood using locally obtained data, to eight army bases using centrally-obtained DEIS data. One could not expect such data to be as "clean" as that obtained directly from Fort Hood, since the former is usually not subjected to careful "reality check" before being entered into the database. Further, unlike the preliminary study where daily mean outdoor temperature data for Temple, TX (a town very close to Fort Hood) was available for the analysis, it was decided to use monthly mean temperature data from the National Climatic Data Center (NCDC,-) where such data for numerous sites throughout the U.S. is available to the general public. The intent of this study was to evaluate whether baseline models identified from DEIS and NCDC data are good enough to use as screening tools for detecting changes in utility bills. Note that the self-imposed condition that only data from such easily accessible sources would be used to evaluate the baseline model development is essential if the present modeling methodology is to find application to DoD facilities nation-wide.

Another objective of this study is to prepare a primer describing our baselining and tracking methodology which can be used by other analysts who wish to perform similar evaluations with data from other Army installations. If baselining analyses such as the analysis presented herein are to find widespread application, they should be simple enough that they could be applied routinely to data from all bases every year when annual utility bill data is entered into DEIS.

2.2 Data provided

USACERL obtained utility data on energy use, building square footage and population from DEIS, and monthly average dry-bulb temperature from NCDC for eight army bases from various parts of the continental U.S. The data were sent to the ESL for analysis. Note that the army maintains such data on a fiscal year (FY) basis (which extends from October of the previous year to September of the current year) rather than on a calendar year basis. Table 2.1 summarizes the data received. Other than Pueblo Army Depot in Colorado and Sacramento Army Depot in California which are army depot centers, the six other bases are densely inhabited. Data from Fort Hood, TX (which was used in the previous study by Saman et al., 1995) was also available for comparative purposes. The intent was to determine how utility and temperature data gathered from different sources would affect the baseline modeling and future tracking evaluation. Table 2.2 shows the size and energy use of the bases for FY86. Fort Hood, TX and Fort Bragg, NC are the largest army bases with about 23 million square feet of total area and populations of over 60,000. Fort Ord, CA is next in size, followed by Fort Carson, CO, Fort Huachuca, AZ and Fort Drum, NY. The latter two bases are much smaller in size than the others.

The data provided by USACERL was complete in terms of building area of the base and utility bill data, i.e., electricity use and gas use. However, population data (also on a month-by-month basis) for the two army depots was incomplete (see Table 2.1 and Table 2.5). The previous study (Saman et al., 1995) had investigated incorporating population data during baseline modeling and found no statistical merit in doing so. USACERL expressed doubts about the usefulness of population data, due to the rather arbitrary manner in which the population of an army base is determined. Hence the year-to-year changes in the size of the Army installations (see Tables 2.3 and 2.4), reflected by changes in population as well as total square footage of buildings, are better captured by the latter variable than by the former. However, we shall not reject population data at this stage, but also perform the analyses with both these variables.

Table 2.1 Summary and status of data received for the eight Army bases. Fiscal year ranges from October of previous year to September of present year.

Serial No.	Army Base	Electricity data	Gas data	Monthly mean temperature	Area	Population
1	Fort Bragg, NC	FY85-94	FY85-94	Jan85-Dec94	FY84-94	FY84-94
2	Fort Carson, CO	FY85-94	FY85-94	Jan85-Dec93	FY84-94	FY84-94
3	Fort Drum, NY	FY85-94	FY85-94	Jan85-Nov94	FY84-94	FY84-94
4	Fort Hood, TX	FY85-94	FY85-94	Jan85-Dec94	FY84-94	FY84-94
5	Fort Huachuca, AZ	FY85-94	FY85-94	Jan85-Aug86 Jan87-Dec90	FY84-94	FY84-94
6	Fort Ord, CA	FY85-94	FY85-94	Jan85-Aug93*	FY84-94	FY84-94
7	Pueblo Army Depot , CO	FY85-94	FY85-94	Jan85-Dec93	FY84-94	No data
8	Sacramento Army Depot, CA	FY85-94	FY85-94	Jan85-Dec94	FY84-94	FY90-94

* Less than 90% of data were available for all months

Table 2.2 Table giving an indication of the size and energy use of the eight Army bases

Serial No.	Army Base	Average Population FY86	Total bldg. area-FY86 ksq.ft	Conditioned area-FY86 ksq.ft	Electricity use-FY86 MWh/yr	Gas use FY86 kcf/yr
1	Fort Bragg, NC	60,006	23,006	19,441	285,056	880,733
2	Fort Carson, CO	25,844	11,344	7,983	96,940	1,417,201
3	Fort Drum, NY	6,694	6,291	4,558	32,750	56,356
4	Fort Hood, TX	66,462	23,840	19,232	307,750	1,416,929
5	Fort Huachuca, AZ	12,484	7,807	6,843	76,498	509,136
6	Fort Ord, CA	37,868	18,037	14,751	122,614	1,203,256
7	Pueblo Army Depot, CO	-	6,245	231	13,340	4,470
8	Sacramento Army Depot, CA	3101*	3,071	505	26,246	109,488

* This value is for FY90

Table 2.3 Annual mean total building areas for all eight Army bases.

	FY86	FY87	FY88	FY89	FY90	FY91	FY92	FY93	FY94
Bragg	23,006	23,760	23,582	26,066	26,723	24,837	25,084	24,958	26,999
Carson	11,344	11,344	11,150	11,598	11,384	12,060	10,460	11,298	10,012
Drum	6,291	6,205	8,474	11,354	12,182	13,075	13,772	12,666	12,487
Hood	23,840	24,181	24,496	24,898	25,545	25,455	25,537	25,696	25,517
Huachuca	7,807	7,991	7,971	7,955	8,020	8,064	8,720	9,045	9,370
Ord	18,037	17,033	18,892	19,962	17,880	18,039	18,039	17,922	5,319
Pueblo	6,245	6,244	6,263	6,254	6,179	6,183	6,233	6,233	6,257
Sacramento	3,071	3,067	3,123	3,123	3,123	3,251	3,118	3,123	3,026

Table 2.4 Annual mean conditioned building areas for all eight Army bases.

	FY86	FY87	FY88	FY89	FY90	FY91	FY92	FY93	FY94
Bragg	19,441	18,906	19,506	21,268	20,359	19,975	19,354	18,967	20,257
Carson	7,983	7,983	7,778	8,976	8,200	9,122	8,169	8,338	7,377
Drum	4,558	4,835	6,512	8,552	9,574	10,172	10,321	9,792	9,655
Hood	19,232	19,163	19,269	19,621	19,602	19,502	19,240	19,178	18,917
Huachuca	6,843	7,028	7,058	7,042	7,056	7,065	7,148	7,937	8,375
Ord	14,751	14,747	15,952	16,463	15,520	15,827	15,827	15,543	3,935
Pueblo	231	229	235	230	222	226	222	222	290
Sacramento	505	500	631	631	631	631	626	631	534

Table 2.5 Annual mean population for all eight Army bases.

	FY86	FY87	FY88	FY89	FY90	FY91	FY92	FY93	FY94
Bragg	60,006	61,772	59,592	61,538	63,874	63,957	64,536	61,172	58,133
Carson	25,844	25,900	25,900	25,900	23,800	23,800	23,500	26,307	24,588
Drum	6,694	13,500	24,329	31,008	31,317	40,687	27,249	26,824	26,643
Hood	66,462	59,878	68,931	67,883	58,314	63,161	50,833	57,187	61,911
Huachuca	12,484	14,286	11,989	13,149	13,235	12,560	12,246	12,567	14,567
Ord	37,868	63,693	17,448	21,990	21,616	23,224	23,224	23,224	-
Pueblo	-	-	-	-	738	642	580	292	264
Sacramento	-	-	-	-	3,101	3,465	3,465	3,465	1,540

Information provided on the building area of the Army base is on an annual (fiscal year) basis rather than on a monthly basis (as were the utility bill data and the population data). So, annual changes in energy use can be normalized for the influence of changes in this variable only. Also, though Presidential Order 12902 requires that the energy reduction be based on gross square footage, it was jointly decided by USACERL and the ESL that building conditioned area would provide a more rational basis for evaluating changes in energy use over the years. An important issue to note is that the DEIS database does not specifically include information about the conditioned building area. The database contains information about square footage of the following categories: (i) buildings, (ii) training, (iii) maintenance and production, (iv) research, development and test, (v) storage building, (vi) hospital and medical, (vii) administration, (viii) bachelor housing, (ix) community, (x) family housing, and (xi) operational buildings. USACERL informed the ESL that the conditioned area would be best represented by subtracting the areas associated with maintenance and production, storage buildings and operational buildings categories from the total area of the base (see Table 2.4). ESL did so with the tacit realization that the conditioned area thus determined had a certain element of uncertainty associated with it. This affects our evaluation of the year-to-year variation in the utility bills (but not the baseline model goodness-of-fit itself since this is done on a monthly level during the baseline year).

There were some serious problems associated with monthly mean outdoor temperature data downloaded from the National Climatic Data Center at Ashville, NC. One problem was that the data sets for all eight bases were from January 1985 and not from October 1984 (which is the start of FY85). The lack of concurrent temperature and utility bill data for three months of FY85 forced us to reject FY85 as the baseline year from which proper analyses could be done and choose FY86 instead. Hence, energy data for a certain number of months at the beginning of the data set (namely January to September 1985) were simply rejected. Further, Fort Carson, Fort Ord and Pueblo Army Depot have temperature data till December 1993 only. Thus, the evaluation of how energy has changed over the years with respect to the baseline year will be curtailed till FY93 only (as against FY94 for the other bases). Also, temperature data for Fort Huachuca is fragmentary (see Table 2.1) and analysis can be done for FY86 and FY88 - FY90 only.

However, the most serious problem has to do with the lack of certainty that the monthly interval during which the daily temperature data is averaged corresponds to the utility bill period. USACERL informed us that utility reading dates are not exactly known but are close to the first day of the calendar month, and that the start and end of the utility bill readings dates can be assumed to be the first and last day respectively of each month. Initially, the ESL manipulated the temperature data based on this assumption. However, our subsequent analysis (described fully later on in this report) revealed this presumption to be false in a number of cases. Though corrective action was taken, a certain amount of uncertainty is still present, thereby compromising the accuracy of our baseline models. Section 3.6 describes how we have tried to correct for this potential mis-match between utility bill period and temperature data.

USACERL also supplied monthly degree-day information (CDD and HDD) for all eight army bases for all the years. However, this data is not directly relevant to our current study since these are to a fixed base of 65 ^{0}F. Our baseline modeling allows for variable base temperatures (ASHRAE, 1993) which renders the modeling more flexible and accurate.

2.3 Scope of study

The reader may recall that the main objective of this study was to determine whether a monthly baseline model of an army base identified from data obtained from general sources, namely utility bill data gathered from DEIS in conjunction with ambient temperature data downloaded from the NCDC database in Ashville, NC is robust enough to provide a meaningful indication of how energy use in that army base has varied over subsequent years. The scope of the study is limited to analyzing such data for eight army bases located in different parts of the continental U.S. The baseline year, due to reasons described above, was chosen as FY86. The baseline models will include both electricity and gas use. We shall also ascertain, albeit in a simplified manner, if the utility bills correspond to calendar months. If not, we will make appropriate corrections as best as possible. The comparative evaluation of two energy analysis software, namely PRISM (Fels et al., 1995) and EModel (Kissock et al., 1994) in a former study (Saman et al., 1995) determined EModel to be more appropriate for baseline modeling of energy use in DoD installations. Consequently, only the EModel software will be used for baseline model development in the framework of the current study. Energy use over different years will be normalized by conditioned square footage (which has a certain amount of uncertainty associated with it) in order to detect changes in utility bills over subsequent years. This screening will be performed for all eight Army installations until FY94 or till such year as data permits. The study shall also present values of fractional changes in energy use over the years as compared to FY86 which have been normalized by year-to-year changes in both building conditioned area and population. Though the Presidential Order makes no mention of population changes, it was deemed necessary that some sort of analysis be also done explicitly with this variable.

3.0 Mathematical Basis of Regression Models

3.1 Pertinent background

An important aspect in identifying statistical models of baseline energy use is the choice of the functional form and that of the independent (or regressor) variables. Extensive studies in the past (for example, see Fels, 1986; or Reddy et al., 1994) have clearly indicated that the outdoor dry-bulb temperature is the most important regressor variable, especially at monthly time scales. Classical linear functions are usually not appropriate because of the presence of functional discontinuities, called "change points". Figure 4.1 shows the various types of single variable (SV) models that have been used to model energy use in commercial and residential buildings (Reddy et al., 1994). One should note how the shape of the functions can be captured by progressively introducing more parameters. A widely adopted convention is to refer to a single variable model with, say, three parameters as a 3P SV model. This study will limit itself to SV models only. Consequently the term SV will not be explicitly mentioned in the rest of this report.

The criteria used to select the most appropriate model is to maximize the goodness-of-fit using the simplest model or combination of models (Draper and Smith,1981). Although several measures of a model's goodness-of-fit are available, we prefer to use the coefficient of determination (R^2) and the coefficient of variation of the root mean square error (CV-RMSE). Though the two measures are related, both are useful indices. When model R^2 is very high or very low, the CV-RMSE may be a more appropriate measure to study.

R^2 can be interpreted as the fraction of the variation in the dependent variable Y (in this study: electricity use and natural gas use) that is explained by the model. It has a maximum value of 1.0. A value of, say, $R^2 = 0.9$ would indicate that 90% of the variation in Y is explained by the model, thus leaving only 10% of the variation in Y unexplained.

Root Mean Square Error (RMSE) is a measure of the deviation of the data from the model and has units similar to the dependent quantity (i.e., for example, cubic feet per month for the gas use model). CV-RMSE is a non-dimensional measure that is found by dividing RMSE by the mean value of Y. It is usually presented as a percentage. Hence, say, a value of 5% would indicate that the variation in Y not explained by the regression model is only 5% of the mean value of Y. RMSE can be calculated as follows:

$$RMSE = \left[\frac{\sum_{i=1}^{n} (Y_i - \hat{Y})^2}{n-p}\right]^{1/2} \tag{3.1a}$$

where $\hat{Y}$ is the value of Y predicted by the regression model, n the number of observations and p is the number of model parameters. For example, for regression models with three parameters, p=3. The CV-RMSE is related to the RMSE as follows:

$$CV - RMSE = \frac{RMSE}{\bar{Y}} \tag{3.1b}$$

In the case of one-parameter, or mean, model, the RMSE is no longer the appropriate statistic to use, and the standard deviation (STD) defined below should be used:

$$STD = \left[\frac{\sum_{i=1}^{n} (Y_i - \bar{Y})^2}{n-1}\right]^{1/2} \tag{3.2a}$$

The associated normalized measure is simply the coefficient of variation of the standard deviation (CV-STD) defined as:

$$CV - STD = \frac{STD}{\bar{Y}} \tag{3.2b}$$

As a rough indication, models with $R^2 \geq 0.7$ and CV-RMSE $\leq$ 7% can be deemed "good" models. In certain cases, the R^2 may be very low indicating that energy use is not much affected by temperature variations. In such cases, regression models with CV-RMSE (or CV-STD) $\leq$12% can still be considered satisfactory. Models with CV-RMSE$\geq$20% can be taken as poor models.

Another important statistical measure is the standard error (SE) which is a measure of how accurately the regression model is able to identify the individual model coefficients (Draper and Smith, 1981). Each coefficient has a SE associated with it, and the smaller the measure, the more confidence you can place on the regression coefficient. Most statistical regression programs always present the SE of the model coefficients along with the output and one does not have to compute this statistic separately. In this report, we shall always present, in conjunction with the regression coefficients, the SE of the coefficients also.

3.2 Simple regression models using EModel

EModel (Kissock et al., 1994) is a tool for the analysis of building energy use data that is especially useful for analyzing hourly or daily data for commercial buildings. It can also be used for monthly data analysis provided the user performs certain data pre-processing steps to calculate average billing period temperature from daily data. EModel integrates the previously laborious tasks of data processing, graphing and modeling in a user-friendly, Microsoft Windows environment. It's easy-to-use features can quickly determine baseline energy consumption. It allows one to edit data files and create new columns of data. Variables can also be plotted as time series data, as relational (XY) plots and as histograms. EModel can apply the following models to data sets: mean, simple linear regression, multiple linear regression, 3 and 4 parameter change- point regression and bin fit.

The dependent variable Y should be taken as the monthly mean daily energy use rather than the monthly total energy use as given by the utility bill. This normalization would remove the small difference in month to month variations in the number of days of each month.

The functional forms of the various models shown in Fig.3.1 are:

(a) Mean or one-parameter (1P) models appropriate for weather independent energy use:

$$Y = \bar{Y} \tag{3.3}$$

(b) Two parameter (2P) models for weather dependent energy use:

- for energy use which increases with increasing outdoor temperature T (like electricity use for air-conditioning):

$$Y = Y_0 + RS * T \tag{3.4a}$$

- for energy use which increases with decreasing outdoor temperature T (like gas use):

$$Y = Y_0 - LS * T \tag{3.4b}$$

where Y_0 is the intercept which represents the value of energy use when $T = 0^0$F (since all our analyses are done with temperature data in degrees Fahrenheit).

(c) Three parameter (3P) models for weather dependent energy use (often used to model residential energy use):

- for energy use which increases with increasing outdoor temperature T:

$$Y = Y_{cp} + RS * (T - X_{cp})^+ \tag{3.5a}$$

- for energy use which increases with decreasing T:

$$Y = Y_{cp} + LS * (T - X_{cp})^- \tag{3.5b}$$

where

$( )^+$ is a mathematical symbolism which denotes that the term within the brackets should be set to zero if it is negative. Y_{cp} is the temperature independent energy use, RS the right-hand slope, LS the

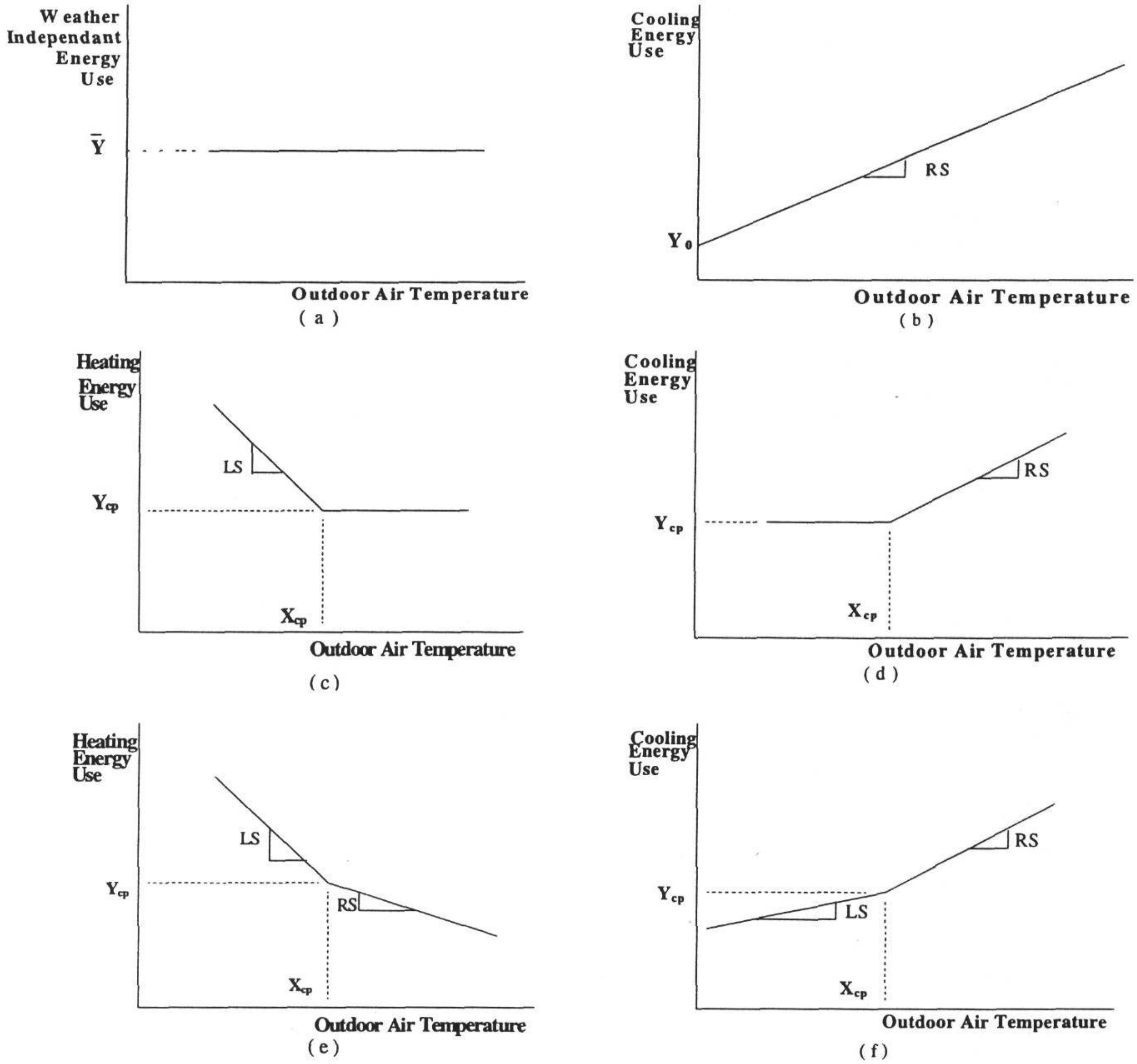

Figure 3.1 Empirical SV energy use models appropriate for building energy use: (a) one-parameter model, (b) two-parameter cooling energy use model, (c) three-parameter heating energy use model, (d) three-parameter cooling energy use model, (e) four-parameter heating energy use model, and (f) four-parameter cooling energy use model.

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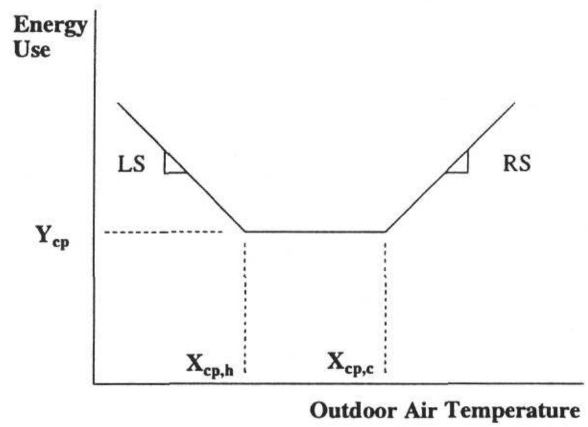
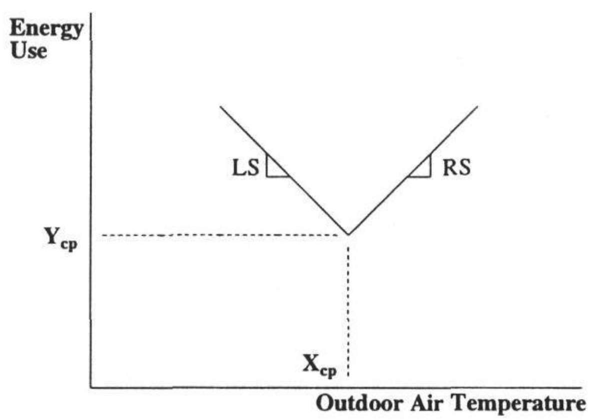


(a)



(b)

Figure 3.2 Other types of empirical SV building energy use models.
(a) Five-parameter model, and (b) Approximation of five-parameter model used in this study (wherever required). Note that this is a special type of four-parameter model shown in Figure 3.1 (e & f).

left hand slope (the values of this coefficient should always be negative), and X_{cp} the change point outdoor temperature. Because Y is a monthly mean daily values, T should be also taken as the monthly mean daily outdoor temperature value. Thus, unlike PRISM where daily mean T for individual days should be known, here one needs to be given monthly mean T values only. Also, EModel while performing a regression with 12 data points representing one year's worth of utility bills automatically presents the user with both R^2 and CV-RMSE of the particular year.

(d) Four-parameter (4P) models for energy use which do not have a constant base-level energy use as do the 3P models (see Fig.3.1). Such variation of energy use with T is often noticed in commercial buildings which have large air-handler units for heating and cooling the supply air stream, and in supermarkets which have large refrigeration loads:

$$Y = Y_{cp} + LS*(T - X_{cp})^{-} + RS*(T - X_{cp})^{+} \tag{3.6}$$

(e) Five parameter (5P) models (see Fig.3.2) for energy use like electricity, which increases both with increasing outdoor temperature (as for air-conditioning) and with decreasing outdoor temperature (as for heat pumps and strip heating);

$$Y = Y_{cp} + LS*(T - X_{cp,h})^{-} + RS*(T - X_{cp,c})^{+} \tag{3.7}$$

where $X_{cp,h}$ and $X_{cp,c}$ are the change point temperatures for heating and cooling respectively. Note that the basic difference between a 4P and a 5P model is that the former has only one change point temperature while a 5P model has two. Physically, one would expect a residence not to use either heating nor cooling over a certain outdoor temperature range, and this behavior is well captured by the 5P model. However, for commercial buildings and for modeling energy use across several buildings of different types (such as whole-base level energy use of an Army installation), one may not be able to detect such a temperature range. Further EModel, in its current form is incapable of modeling such a 5P behavior. Consequently, whenever energy use in a DoD facility does exhibit such a behavior, we shall model it with the functional form shown in Fig.3.2(b). Note that the functional form of such a behavior is given by the 4P equation, namely eq.(3.6).

The functional forms of the regression models discussed above have a certain amount of engineering basis. The interested reader can refer, for example, to Fels (1986) in case of energy use in residences and to Reddy et al., (1995) in case of energy use in commercial buildings.

3.3 Generation of 95% uncertainty bands for individual months

The baseline models developed from one year (in this study, fiscal year 1986 has been chosen) can be used to predict weather-adjusted monthly energy use into the future (or even into the past). Comparison of these projected values with actual monthly use values would provide a means of ascertaining whether actual use has changed as compared to this baseline. Regression-based model predictions invariably have a certain amount of uncertainty, and for the model to be useful as a screening tool, we should be able to ascribe uncertainty bounds to our predictions. The degree of credibility that may be attached to results is expressed by the level of statistical confidence. Specifications of confidence are conventions only. Though 90% confidence levels are the standard in load research (Vine and Kushler, 1995), we shall use bounds of 95% uncertainty bands or 95% prediction interval (PI). Physically, this means that if $\hat{Y}$ is the value predicted by the model, then 95 out of 100 times, the next measured value of Y will be between ($\hat{Y}$+PI) and ($\hat{Y}$-PI). (For a simple linear model (i.e., a 2P SV model), PI for predicting Y for a given X_0 (i.e., for a given month) is well known (Draper and Smith, 1981):

$$PI = t(1-\frac{\alpha}{2}, n-p).RMSE.\sqrt{1+\frac{1}{n}+\frac{(X_0-\bar{X})^2}{\sum_{i=1}^{n}(X_i-\bar{X})^2}} \tag{3.8}$$

where t - the t-statistic evaluated at (1-α/2, n-p)

α -significance level (which for 95% confidence bands is equal to 0.05)

n - number of observations (in this study equal to 12 since utility bills for a year are used)

p - number of parameters in the model

RMSE - root mean square, defined by eq.(3.1)

X_0 - individual independent variable (in this study, the outdoor dry-bulb temperature)

$\bar{X}$ - mean value of X_i (in our case, mean annual value of the outdoor temperature during model identification, i.e., for the baseline year).

For a 3P model with n = 12, the term t(1-α/2, n-p) from statistical tables (Draper and Smith, 1981) is equal to 2.262. Note that for the 3P model using EModel, X is the mean daily outdoor temperature during the billing period.

Predicting PIs for change point SV models such as PRISM and EModel 3P is very complex and is not to be found in textbooks. Simply calculating the PIs for a 3P model using eq.(3.8) would lead to an over-estimation especially for the baseline portion of the fit (i.e., for the months when energy use is independent of outdoor temperature). Our baseline model would then be a rather ineffective screening tool. Though not strictly accurate in the statistical sense, we propose that PIs for 3P models be determined separately for each of the two segments of the model (Hebert and Ruch, 1995). Let n_1 and n_2 be the number of months in the year which respectively fall in the lower temperature portion and in the higher temperature portion of the model. (Note that $n_1 + n_2 = 12$). Then, we suggest that RMSE and $\bar{X}$ be calculated separately for each portion. Subsequently, for the model predictions falling on the lower temperature range (i.e., the left-hand side portion of the model), we shall use

$$PI_1 = t(1-\frac{\alpha}{2}, n-p).RMSE_1.\sqrt{1+\frac{1}{n}+\frac{(X_0-\bar{X}_1)^2}{\sum_{i=1}^{n_1}(X_i-\bar{X}_1)^2}} \qquad (3.9)$$

and, for the higher temperature range (i.e., the right-hand side portion of the model):

$$PI_2 = t(1-\frac{\alpha}{2}, n-p).RMSE_2.\sqrt{1+\frac{1}{n}+\frac{(X_0-\bar{X}_2)^2}{\sum_{i=1}^{n_2}(X_i-\bar{X}_2)^2}} \qquad (3.10)$$

Note that for a 3P model, the value of t will still correspond to n-p = 9 degrees of freedom (n=12, p=3) and that $RMSE_1$ and $RMSE_2$ will be determined using eq.(3.1) with n=12 (and not with n_1 and n_2 respectively). Such a procedure gives more realistic PIs over the entire range of the model and has a certain amount of statistical basis as well (Hebert and Ruch, 1995). Graphically, the two PIs for the 3-P model appear as a band that narrows during the base-level months (i.e., winter months for electricity and water, and summer months for natural gas) and expands during the months when energy use is linearly related to an outdoor temperature difference above the change point.

3.4 Generation of 95% uncertainty bands on an annual basis

The previous section presented relevant equations for calculating PIs on an individual monthly mean daily basis which is appropriate if the baseline models are used as screening tools for detecting month-to-month variations. These equations cannot be used to track year-to-year changes in energy use which is one of the objectives of this study. For this purpose, the annual total energy use along with an estimate of the amount of confidence one can place on these values needs to determined. The total use is easily determined: the twelve monthly mean daily energy use values are simply averaged. However, the 95% PIs for this annual energy use value cannot be determined by simply averaging the PIs of the individual twelve monthly mean daily values since this would lead to a gross over-prediction.

For a simple linear model (i.e., a 2P SV model), Draper and Smith (1981) give the equation for PI of a <u>sum</u> of m number of individual points:

$$PI = t(1-\frac{\alpha}{2}, n-p).RMSE.\sqrt{m+\frac{m}{n}+\frac{\sum_{o=1}^{m}(X_0-\bar{X})^2}{\sum_{i=1}^{n}(X_i-\bar{X})^2}} \quad (3.11)$$

As mentioned earlier in section 3.3, the corresponding equations to calculate PI of 3P change point models are not available. Following a similar development as adopted earlier for monthly predictions, the <u>annual mean daily</u> PI can be determined from the following:

$$PI = \frac{t(1-\frac{\alpha}{2}, n-p)}{m}.[RMSE_1.\sqrt{m_1+\frac{m_1}{n}+\frac{\sum_{o=1}^{m_1}(X_0-\bar{X}_1)^2}{\sum_{i=1}^{n_1}(X_i-\bar{X}_1)^2}}$$

$$+RMSE_2.\sqrt{m_2+\frac{m_2}{n}+\frac{\sum_{o=1}^{m_2}(X_0-\bar{X}_2)^2}{\sum_{i=1}^{n_1}(X_i-\bar{X}_2)^2}}] \quad (3.12)$$

where m_1 and m_2 are the number of months that fall on the left-hand side portion and the right-hand side portion respectively of the model line, and m =12 if all 12 monthly utility bills are available.

Equation (3.12) is rather cumbersome, and we suggest that the following simplified equation be used instead:

$$PI = \frac{t(1-\frac{\alpha}{2}, n-p)}{m}.RMSE.\sqrt{m+\frac{m}{n}} \quad (3.13)$$

In this study where annual predictions are determined by using a monthly baseline model, m=12. The above equation simplifies to

$$PI = \frac{t(1-\frac{\alpha}{2}, n-p)}{12}.RMSE.\sqrt{13} \quad (3.14)$$

We have used eq.(3.14) in determining the 95% PI of the annual mean daily energy use predicted by our baseline monthly models.

Note that the statistical equations presented above for determining uncertainty are subject to an explicit assumption. We have assumed no measurement uncertainty in the temperature variable (i.e., the X variable), an assumption which considerably simplifies the statistical equations. Most statistical textbooks limit their treatment to this case, and though equations are available which can be used to predict model uncertainty when measurement uncertainty in the independent variables of a regression model are present (see for example, Beck and Arnold, 1977), the corresponding equations are complex and outside the purview of the present study.

3.5 Percentage change in normalized energy use on an annual basis

We need to properly define change in energy use on an annual basis since this is one of the objectives of this study. The baseline model described above can be used to correct for changes in energy use due to changes in temperature from one year to the next. As described in section 1, we need also to remove the effects of year to year changes in conditioned area and population in order to determine that the remaining change in energy use is due to energy efficiency and O&M measures in the particular Army base. Normalizing annual mean daily energy use at an Army base due to changes in conditioned area from one year to the next is straight forward since most studies in the literature seem to have consistently assumed a proportional relationship between the two variables. Thus, the area-normalized energy use is merely the annual mean daily energy use divided by the conditioned area for that particular year.

Normalizing energy use for changes in population is not simple since a proportional relationship is obviously incorrect. Energy use in a building, for example, would not double if the number of occupants were doubled. Our earlier attempts (see Saman et al., 1995) at explicitly including population as a variable in our basic regression model of energy and temperature were unsuccessful. Figure 3.3, with data from Fort Bragg indicates no relation between the year-to-year change in annual energy use from FY86 and corresponding changes in population. One could speculate that population could be related to conditioned area, i.e., there could be a tendency to increase the conditioned area if more people had to be accommodated. If this were the case, normalizing energy use by conditioned area would also implicitly normalize energy use for population changes, and no further correction would be needed. We investigated this possibility with data from the various Army bases and unfortunately, found no such relationship. This is illustrated in Fig. 3.4 with data from Fort Bragg. The lack of a relation between the data scatter led us to reject such a possibility.

A second possibility of correcting annual energy use for year to year variations in population is to assume a linear relationship such as the following:

Annual mean daily energy use = a +b* (Population) (3.15)

We shall assume such a relationship, and derive expressions for changes in normalized energy use from year to year w.r.t. to a baseline year.

We shall define annual change in energy $\Delta\tilde{Y}$ for, say FY92, with respect to the baseline year (FY86 has been selected for this study) as follows:

$$\Delta\tilde{Y}(FY92) = \tilde{Y}_{Measured}(FY92) - \tilde{Y}_{Baseline-model}(FY92) \tag{3.16}$$

where $\tilde{Y}_{\text{Baseline model}}$ (FY92) is the conditioned area normalized annual energy determined as the average of the twelve monthly values of normalized energy use predicted by the baseline model using the corresponding monthly mean temperatures for FY92, and $\tilde{Y}_{\text{Measured}}$(FY92) is the conditioned area normalized measured annual mean daily energy use found by averaging the twelve monthly utility bills for FY92 and dividing by the conditioned area for that year.

By defining change in energy use as done above, a positive value of $\Delta\tilde{Y}$ implies a increase in energy use and vice versa. Finally, percentage change on an annual basis is defined as:

$$\%\Delta\tilde{Y}(FY92) = \frac{\Delta\tilde{Y}(FY92)}{\tilde{Y}_{Measured}(FY92)} \times 100 \tag{3.17}$$

Note that one could have used $\tilde{Y}_{\text{Baseline model}}$(FY92) in the denominator of eq.(3.17) instead of $\tilde{Y}_{\text{Measured}}$(FY92) since this would provide a common base when comparing energy use over several years. However, this value is determined from a model and consequently is subject to all the uncertainty (more specifically, bias which any model used for predictive purposes is subject to) which is associated with any model predictions. Hence in order to decrease the uncertainty in our percentage change as far as possible, we deliberately chose to define percentage annual change as given by eq.(3.17).

Note that the above equations are equally valid for energy use normalized by population. When a difference between two years ($\Delta\tilde{Y}$) is taken, one need not explicitly know the value of the intercept a in eq.(3.15). Further, when we are computing a fractional change, i.e., dividing $\Delta \tilde{Y}$ by $\tilde{Y}_{\text{Measured}}$, we need not explicitly know the value of the slope b in eq.(3.15). Thus eq.(3.17) is equally valid for normalizing energy use for population changes provided one simply takes the variable as annual mean daily energy use normalized by conditioned area and divides it by the population value for that year.

Finally, in case one wishes to compute percentage change by the simple utility bill comparison method, i.e., without using a baseline model that accounts for changes in temperature between the baseline and the specific year in question, the following equation should be used in order to be consistent with eqs.(3.16 and 3.17):

$$\%\Delta \tilde{Y}(FY92) = \frac{\tilde{Y}_{Measured}(FY92) - \tilde{Y}_{Baseline-year,measured}}{\tilde{Y}_{Measured}(FY92)} \text{ x } 100 \qquad (3.18)$$

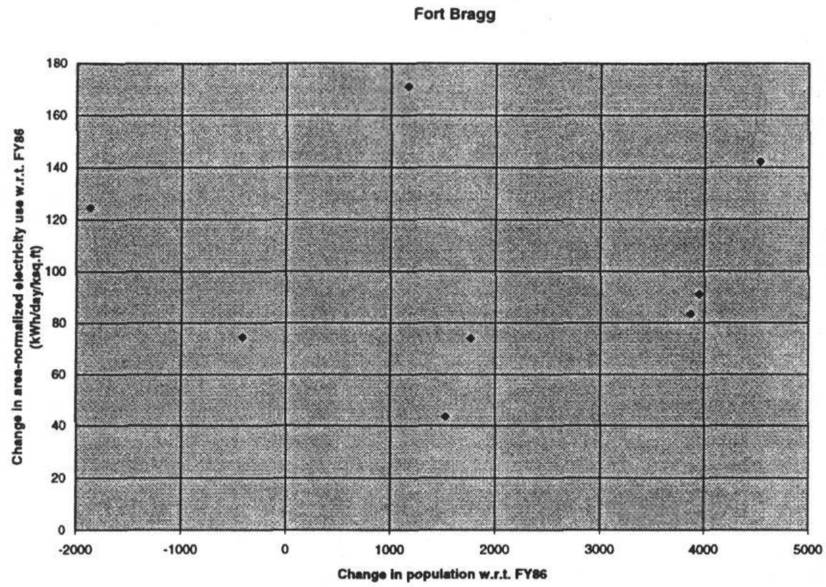


Fig. 3.3. Scatter plot of changes in area-normalized annual electricity use w.r.t. FY86 to those of population over the years for Fort Bragg.

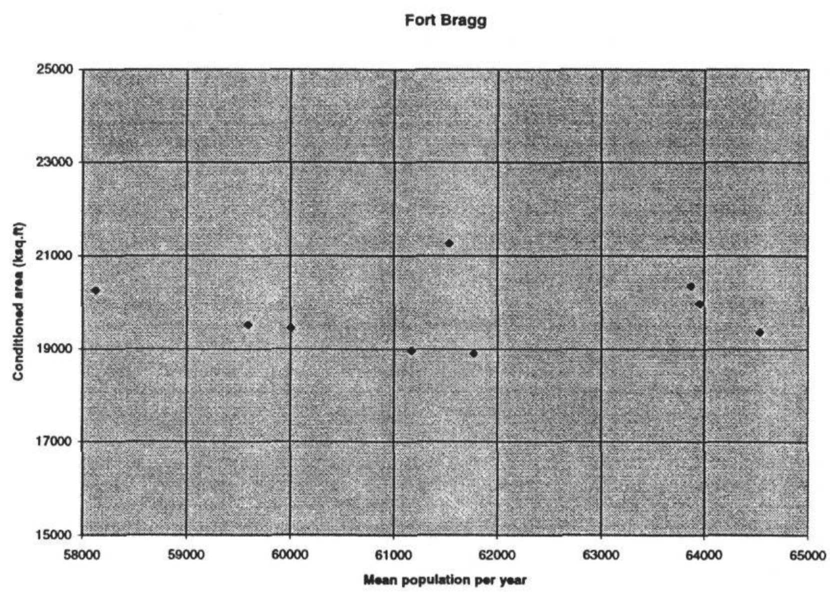


Fig.3.4. Scatter plot of mean annual conditioned area and population over the years for Fort Bragg.

3.6 A statistical means of correcting for mis-match between utility bills and associated temperature data

Perhaps the essential element in our study is the identification of the baseline model, i.e., models for monthly electricity and gas use during the baseline year. As discussed earlier in section 2, the baseline year is chosen as FY86. Also, as discussed in section 2, there is an ambiguity concerning the exact read dates of the utility bills. Our Project Monitor suggested that we assume these to correspond to calendar months since more specific information was not available from the DEIS database. Because choosing the proper concurrent monthly mean outdoor dry-bulb temperature (T) is essential in identifying a proper baseline model, we chose to perform additional regression model runs as follows:

Case 1: We use temperature data corresponding to the same calendar month as the utility bill.

Case 2: Since utility personnel may read the meter in the first few days of a month, a common oversight of a data-entry clerk who subsequently has to transfer the utility bills along with the associated month (without the exact read-day) into a central database would be to associate the energy use with the end-date of the utility bill period. Hence such an oversight could cause a shift of one month (even if we were to assume that utility bills corresponded to calendar month periods). Therefore, the second set of models will be run by using temperature data of the previous month.

Case 3: The two above cases still assumed that read dates more or less corresponded to calendar months. Just as a safety verification, we decided to take the average value of the temperature of the present month (concurrent with the utility bill reading in question) and that of the previous month, and associate that value to the particular utility bill. If the model turns out to be substantially better than the two previous cases, this would imply that the utility bill was read sometime around the middle of the month as against the beginning. Though the same methodology can be used for increments finer than the 15-day period assumed here, we decided that such a procedure (which has still not been tested properly) would be too laborious, and consequently, we have limited the scope of the present search to mid-monthly corrections only.

For each of our baseline models, we shall perform regressions of energy use with the three types of temperature data sets. The one which gives superior statistical fits to the utility data will be taken as the appropriate choice. We have also evaluated this methodology with billing data from a couple of residences and office buildings where utility read dates were known , and it was found that this statistical means was able to properly identify the read dates to within 3-4 days in over two-third of the cases. A more thorough investigation is currently underway. The statistical means of correcting for mis-match between utility bills and associated temperature data does, nevertheless, lack a certain amount of statistical rigor. However, in the face of the time constraints of the project and the intended purpose of evolving the screening methodology to DoD facilities nation-wide where such a problem would exist, both the USACERL Project Monitor and the ESL felt that the above statistical procedure was adequate for the current study.

4.0 Analysis of Fort Bragg, NC

4.1 Preliminary data analysis

Time series plots of monthly electricity use and gas use from FY86 to FY94 are shown in Fig.4.1 along with concurrent outdoor temperature. The variation patterns are fairly consistent over the years. As expected, gas use peaks in winter while electricity use seems to be mostly in summer due to air-conditioning. There does seem to be a slight increase in electricity use during the winter months. This leads us to suspect electric heating applications such as heat pumps or electric strip heating in a portion of the buildings.

Figure 4.2 shows the change in total building area and conditioned area (determined as described in section 2.2) over the years. Both these areas seem to have generally increased from FY86 to FY90, decreased abruptly after FY90, remained constant till FY93 and increased again in FY94. Total area exhibits more increase over the years, about 20% from FY86 to FY94. The conditioned area seems to have increased only about 10% during the same period. Annual mean daily population data is also plotted in Fig.4.2. Population seems to have increased by about 8% till FY92 and then decreased to less than the FY86 value by FY94.

Figure 4.3 shows the changes in annual mean daily energy use per unit conditioned area over the years. Except for an increase in gas use in FY87, both gas use and electricity use are fairly consistent over the years. The annual mean outdoor temperature is also plotted in order to enable the reader to associate changes in energy use with temperature changes. For example, FY90 is a hot year and gas use seems to have decreased that year. Plots such as these only provide a general qualitative trend and one should not try to read too much from them.

Figure 4.4 presents time series graphs of monthly electricity and gas use normalized by building conditioned area. We notice, despite consistent temperature patterns, that generally gas use has decreased during summer with the winter use remaining unchanged. However, gas use is lower during FY88 and again in FY91 and FY91. Electricity use seems to show a gradual increase over the years with both troughs and peaks showing an increase.

Figure 4.5 depicts the average monthly outdoor temperatures during a year for all years from FY86 to FY94. We note that the weather during these years seems to be remarkably consistent over the years though certain monthly excursions from the overall annual pattern can be noted.

Temperature data for FY86, our baseline year, seems to be fairly characteristic except for being lower than the average during October and November and above average in December.

Figures 4.6 and 4.7 are time series plots of electricity use and gas use normalized by conditioned area during a year for all years from FY86 to FY94. This type of representation allows clearer visualization of how energy use has changed over the years for a given month. The sharp increases in electricity use in July and gas use during the winter are obvious. One notices the odd behavior of gas use during FY87 where February and March uses are abnormally high as are the uses for June and August. Finally, we notice in Fig.4.6 the slight increase in electricity use during January and February for most years indicating some heating application as discussed earlier.

4.2 Baseline modeling

As described earlier, there is an ambiguity regarding proper match between the utility bill period and the corresponding temperature data supplied to us. In section 3.6, we had suggested a method whereby we would identify the best model from three different sets of runs where the temperature data has been taken in slightly different ways. The criteria for selecting the optimum model among the various runs are as follows:

(i) highest R^2 and lowest CV-RMSE,
(ii) if R^2 values for all models are low, CV-RMSE is to be given more consideration, and
(iii) it would be more appropriate from physical considerations, to select 3-P models rather than 4P models. Only if the improvement in R^2 and CV-RMSE is substantial, would we relax this rule.

Note that both electricity and gas use during the year have been normalized with the conditioned area of the army base during that particular year prior to model identification. The summary model statistics of our baseline model identification effort for all three cases are summarized in Table 4.1. We notice that the improvement in electricity use models is substantial when mid-month temperature values (i.e., case 3 in section 3.6) are used for regression. This leads us to conclude that the electricity bills do not span calendar monthly intervals but are closer to a period from the mid-month to the next. For electricity, the 4P model seems to be the best choice for a baseline model (see Table 4.1). How the model line fits the data points can be noted in Fig. 4.8(a), while how the 4P model compares with the next-best model, namely the 3P cooling model, can be gauged by Fig. 4.8(b).

Regarding the baseline model for gas use, we note from Table 4.1 that using case 1, i.e., temperature data corresponding to the same calendar months as the utility bills, results in best models. Further, the small improvement in R^2 and CV-RMSE as we go from a 3P heating model to a 4P model is not enough to justify using the unphysical 4P model. Consequently, we decided to choose the 3P heating model as our baseline model for gas use. How the individual monthly data points scatter around the 3P heating baseline model line can be seen in Fig. 4.9 (a) while how they are captured by the next-best 4P model can be gauged in Fig. 4.9 (b).

4.3 Baseline models for screening and tracking

Once baseline models have been developed, it is possible to use them as screening tools by comparing forecast levels with actual energy use. Effect of changes in weather from year-to-year (more accurately, outdoor temperature) on the energy use is explicitly accounted for by the baseline model forecasts. Deviations from expectations must be studied to determine whether known extraneous changes have contributed to this variation or whether these changes are a result of energy efficiency measures or DSM programs that have been initiated. How the PIs of the model are to be calculated have been described in section 3.3 for individual months and in section 3.4 on an annual basis. We have used our FY86 baseline models to forecast into the future up to FY94.

Figures 4.10 and 4.12 depict the extent to which the monthly energy use utility bills are bounded by the PIs of the FY86 baseline model for electricity use and gas use respectively. For clearer visualization, we have also shown the residuals (residual = measured value minus model predicted value) along with the PIs. If, say, the utility bill data for a month fall below the lower 95% PI, one can safely affirm that energy use during that month has decreased as compared to model predictions. We note that both electricity and gas use data are well contained within the PIs bands which is not surprising since the models are very good (see Table 4.1).

How well the FY86 baseline models for electricity and gas use are able to predict monthly energy use from FY86 till FY94 can be seen in Figs. 4.11 and 4.13 respectively. Note that the energy use is on a monthly mean daily basis per unit conditioned area but has not been normalized for changes in population from one year to the next. We note that electricity use is consistently above the PIs indicating a large increase in electricity use. Gas, on the other hand, is generally bounded by the PIs (see Fig. 4.13) partly because the PIs for gas are wider than those for electricity (since the model is slightly poorer). So statistically speaking, one cannot draw any definite conclusions about how gas use has varied over the years. However, plots such as this are useful to the energy manager of the corresponding Army base who is in a position to look for (as well as discern and evaluate) changes in energy use as a result of certain specific actions taken (such as O&M measures or say, changes in equipment in the power plants).

On an annual time scale, however, determination of percentage changes in energy use (normalized by conditioned area) with respect to the baseline year (FY86) permit rather well-defined conclusions to be drawn regarding the extent to which the Executive Order 12902 has been met. How these changes are to be determined as well as the 95% PIs of these changes have been described in sections 3.4 and 3.5. Following eqs.(3.16) and (3.17), we have computed the percentage changes on a year by year basis and plotted them in Figs. 4.14 for both electricity and gas. Note that a negative change indicates a decrease in energy use. Both electricity and gas use are clearly positive. Generally electricity use over the years as compared to the baseline year shows an increasing trend, with, however, FY94 use being lower than the two previous years. Gas use, on the other hand, shows a decreasing trend (a small increase in FY94 compared to FY92 and FY93) which is contrary to how electricity use behaved. However, this change is not very significant statistically because of the wide error bands for gas. On the whole, we note that electricity use in FY94 has increased by about 23% ($\pm$3%) with respect to FY86, while gas use has increased by about 9% ($\pm$10%). The uncertainty bands of the change in electricity use are relatively small and we can be confident of our estimates of electricity change. On the other hand, there is a relatively large uncertainty in our estimates of gas use in FY94 as compared to our baseline year of FY86.

4.4 Concluding remarks

The baseline models identified for FY86 for Fort Bragg were found to be very good with the electricity model having R^2 = 0.95 and the gas model R^2 = 0.87. Our analysis indicated that electricity utility bills were read close to mid-month and so a correction had to be made to the calendar monthly mean temperature data that we received. No such correction seems to be necessary for gas use. The best model for electricity was a 4P model, which though slightly unphysical, was so much superior to the next-best 3P cooling model that we had to select it nevertheless. The best model for gas was a 3P heating model.

Using the baseline models to track how energy use has increased (or decreased) over the years required that energy use during each year be normalized by the associated conditioned area of the army installation. (As described above, this quantity is not directly available from the database but had to be inferred from areas of several categories of building types which were listed in the database). This leads to a certain amount of unavoidable uncertainty in our conclusions regarding the screening and tracking aspects of the baseline models. We found that electricity use in FY94 has increased by about 23% (± 3%) with respect to FY86, while gas use has increased by about 9% (± 10%).

We also investigated another issue with the energy use data from Fort Bragg. One could question the need to have such an involved baselining and evaluation methodology as the one adopted here, specially since the month to month variation patterns of outdoor temperature over the years were fairly consistent (see Fig.4.5). One would be curious to ascertain the differences in our estimates of how energy use over the years has changed with respect to a baseline year by the present approach and by a much simpler approach involving direct annual utility bills comparison without any weather correction (see eq.3.18). Figure 4.15 illustrates the amount of differences in percentage changes between the two approaches, namely with and without weather correction. We notice that though the differences are small in certain cases (say FY93 for electricity use), the difference is by no means negligible in cases when the percentage change with respect to the baseline year are small. Differences between both methods are in the range of 3-6% points for electricity and gas. The above comparison serves to underline the need to perform weather correction in order to obtain reliable estimates of how energy use has varied over the years.

Finally, Fig.4.16 and Table 5.4 assemble the year to year percentage changes in annual energy use with respect to baseline year (FY86) normalized by (i) conditioned area, and (ii) conditioned area and population. Though generally the changes in energy use by both means of normalization have more or less similar patterns, the quantitative values are appreciably different during certain years. As described in section 3.5, one cannot place as much confidence in the population values as in the conditioned area values, and so it would probably be better to draw conclusions regarding the extent to which Presidential Executive Order 12902 is being met based on conditioned area normalization only.

Table 4.1. Fort Bragg: model identification summary statistics for baseline year (FY86). Final models selected are shown in bold face.

		3P-Cooling		4P	
	Temperature data used	R^2	CV-RMSE (%)	R^2	CV-RMSE (%)
Electricity	Same month (T_1)	0.79	9.3	0.83	8.9
	Previous month (T_2)	0.67	11.6	0.75	10.6
	Mid-month (T_3)	0.83	8.3*	**0.95**	**4.7***
		3P-Heating		4P	
Gas	Same month (T_1)	**0.87**	**14.4***	0.89	13.8*
	Previous month (T_2)	0.54	27.4	0.56	28.4
	Mid-month (T_3)	0.79	18.6	0.81	18.7

* Plots of these models are shown in the report

Table 4.2. Fort Bragg electricity use: model coefficients (and standard errors) and pertinent regression model statistics for FY86.

Model type	Y_{cp} (kWh/d/ksq.ft)	LS (kWh/d/ksq.ft/F)	RS (kWh/d/ksq.ft/F)	X_{cp} (°F)	R^2	CV-RMSE (%)	RMSE (kWh/d/ksq.ft)	n_1
4P	30.08(4.281)	-0.428(0.0772)	1.352(0.1811)	66.0	0.95	4.7	1.88	6

Table 4.3. Fort Bragg gas use: model coefficients (and standard errors) and pertinent regression model statistics for FY86.

Model type	Y_{cp} (cf/d/ksq.ft)	LS (cf/d/ksq.ft/F)	X_{cp} (°F)	R^2	CV-RMSE (%)	RMSE (cf/d/ksq.ft)	n_1
3P-H	90.89(6.542)	-4.137(0.501)	68.0	0.87	14.4	17.91	7

Table 4.4 Baseline models and percentage change in energy use w.r.t baseline year for Fort Bragg.

Energy type	Baseline year	Model type	Model fit	Year	% change normalized by conditioned area with 95% PI	% change normalized by conditioned area and population
Electric.	FY86	4P	Excellent	FY87	13.95 ± 3.18	11.42
				FY88	15.80	16.38
				FY89	11.94	9.69
				FY90	17.13	11.81
				FY91	17.01	11.55
				FY92	26.53	20.98
				FY93	26.89	25.46
				FY94	23.30	25.69
Gas use	FY86	3P-H	Mediocre	FY87	22.53 ± 9.82	20.25
				FY88	2.48	3.15
				FY89	13.07	10.86
				FY90	4.02	-2.16
				FY91	11.60	5.78
				FY92	7.92	0.97
				FY93	7.64	5.85
				FY94	9.37	12.20

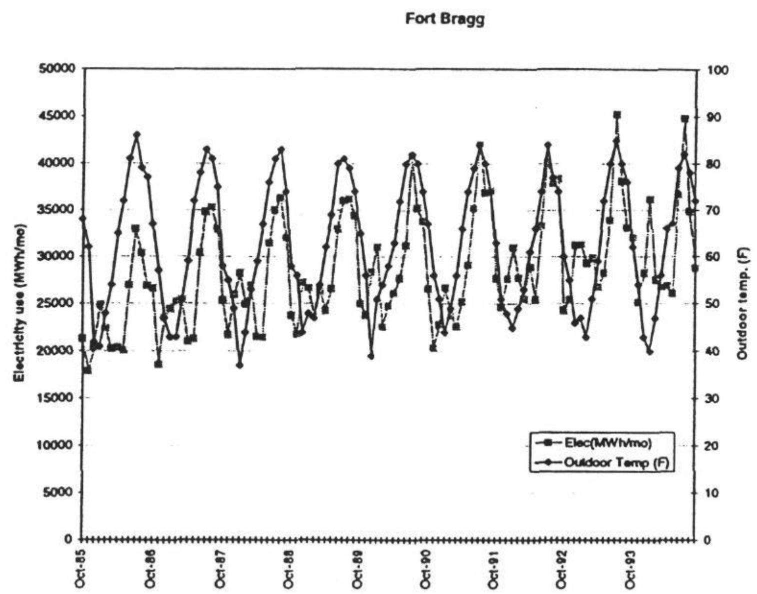


Fig. 4.1(a) Electricity use.

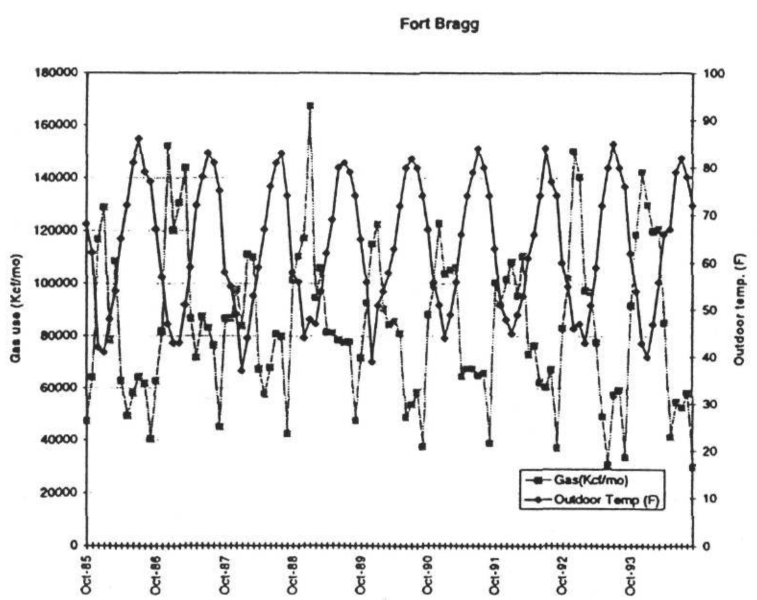


Fig. 4.1(b) Gas use.

Figure 4.1. Time series plots of monthly electricity and gas consumption for Fort Bragg from FY86 to FY94. The concurrent outdoor dry-bulb temperature variation is also shown.

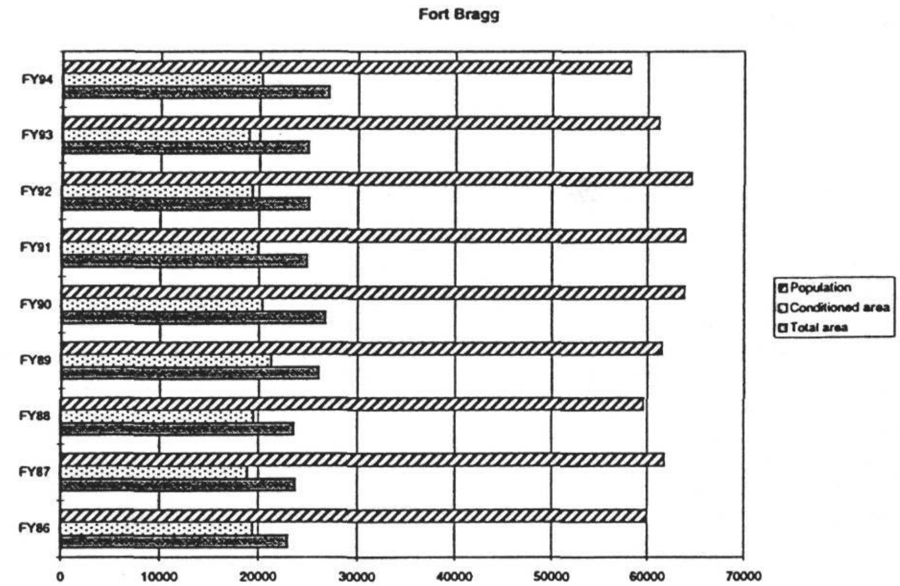


Figure 4.2. Changes in total and conditioned areas (in ksq.ft) and annual mean daily population for Fort Bragg from FY86 to FY94.

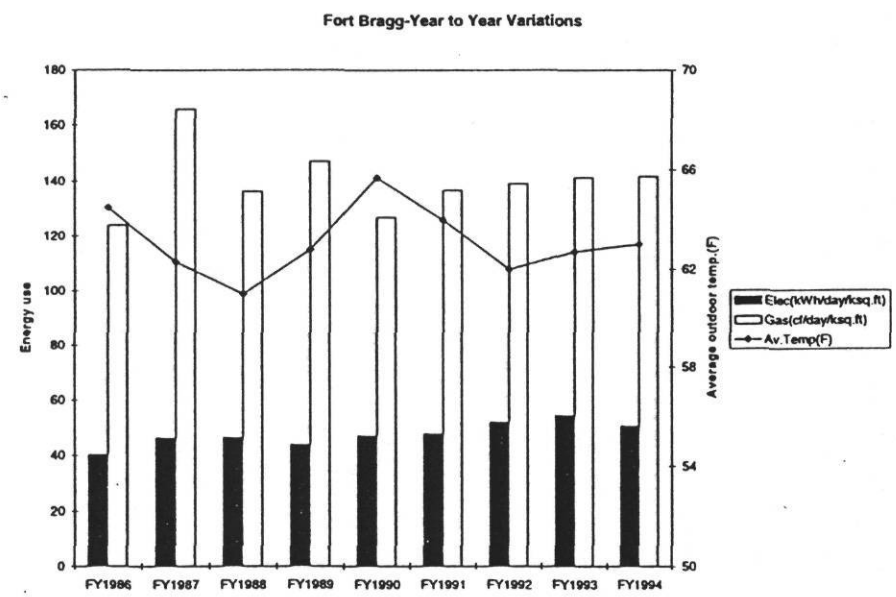


Figure 4.3 Changes in annual mean daily energy use per unit conditioned area and annual mean outdoor temperature for Fort Bragg from FY86 to FY94.

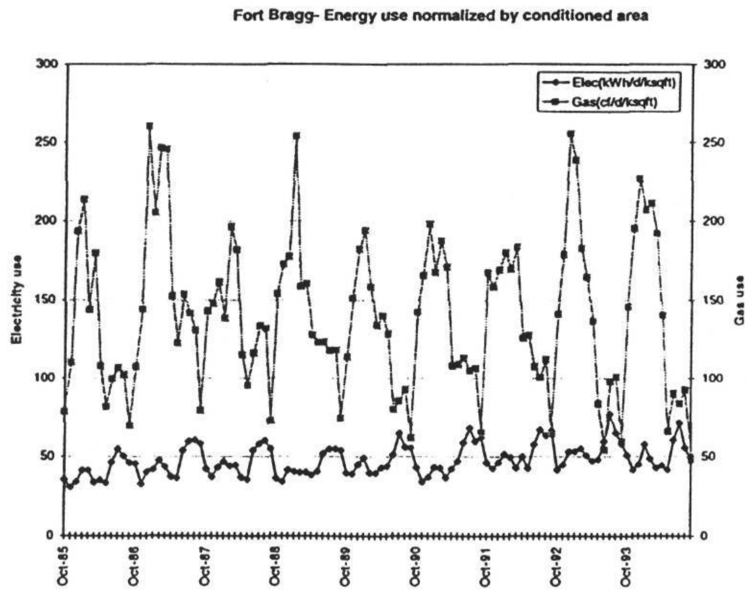


Figure 4.4. Time series graphs of monthly electricity and gas consumption per unit conditioned area for Fort Bragg from FY86 to FY94.

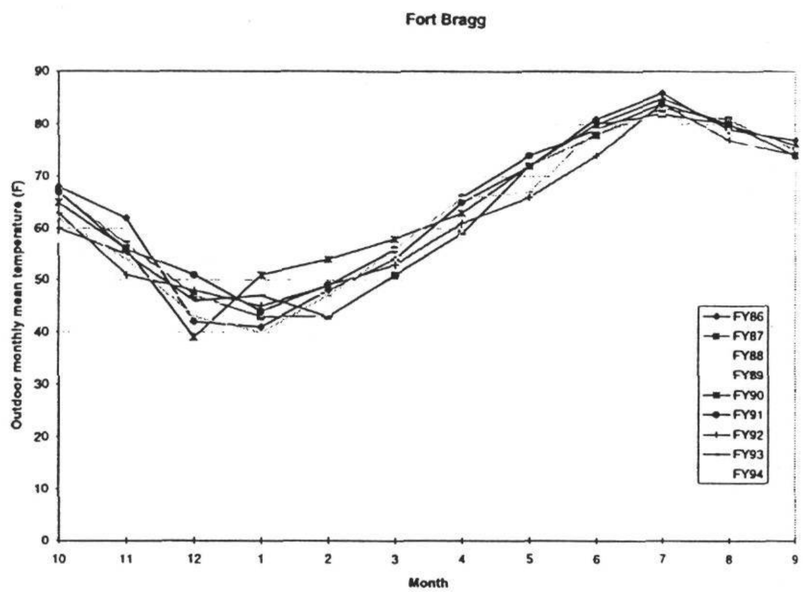


Figure 4.5. Time series plots of average monthly temperatures at Fort Bragg from FY86 to FY94.

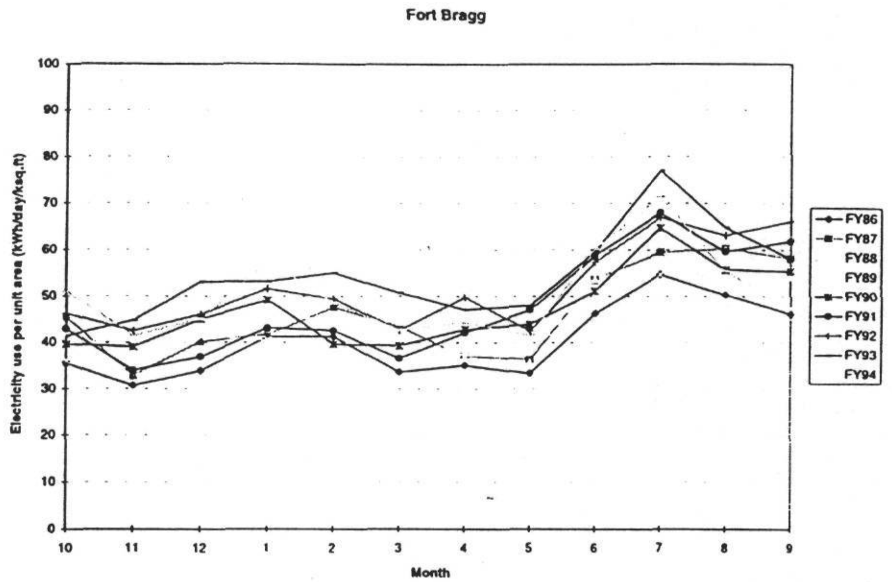


Figure 4.6. Time series plots of electricity use per unit conditioned area for Fort Bragg from FY86 to FY94.

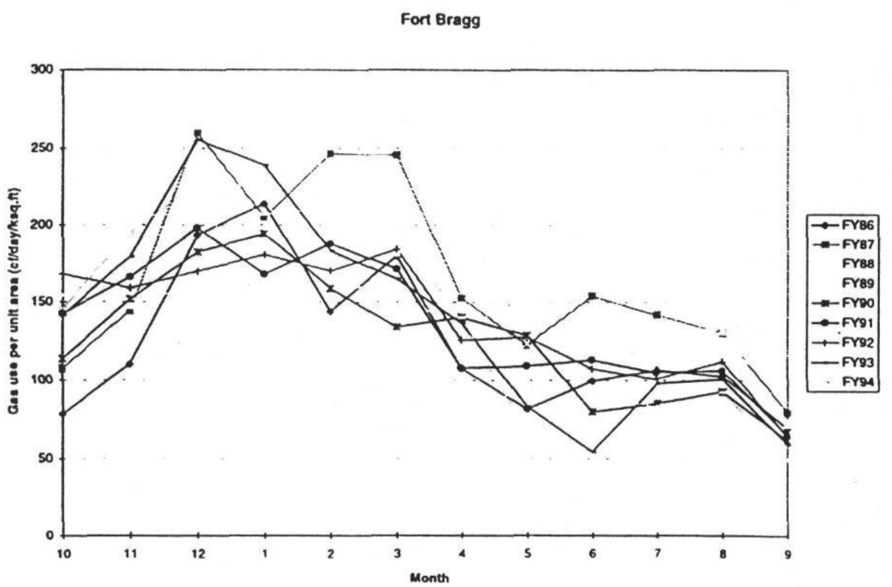
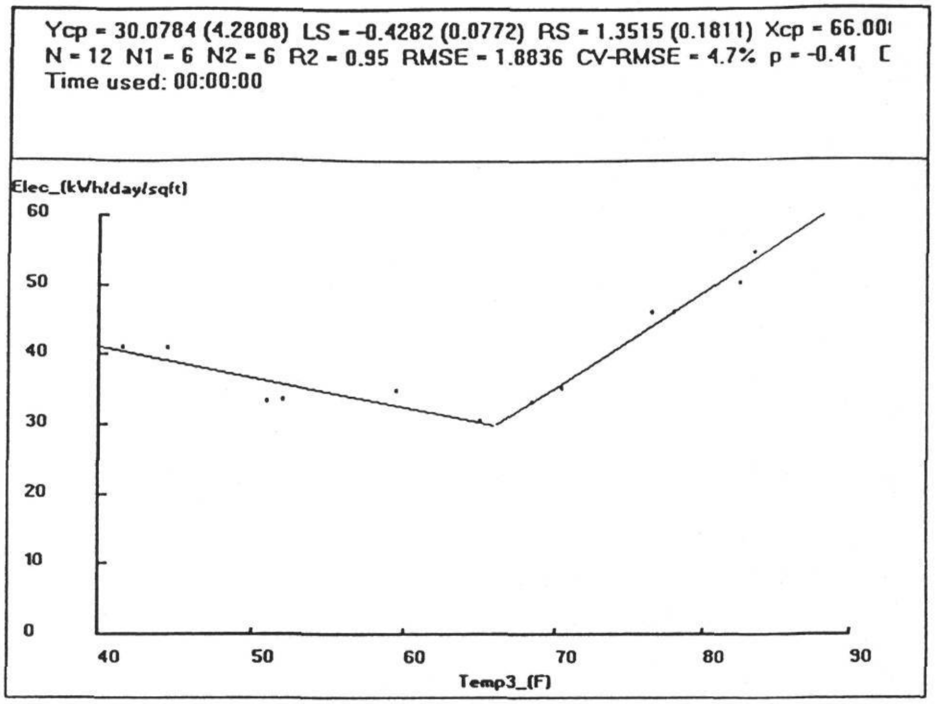


Figure 4.7. Time series plots of gas use per unit conditioned area for Fort Bragg from FY86 to FY94.



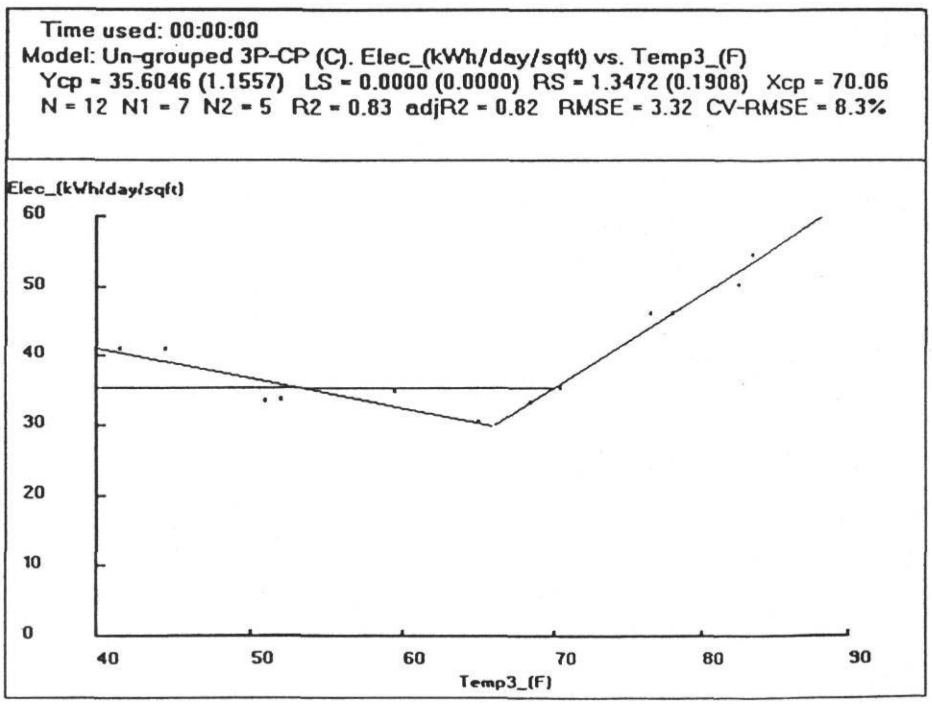
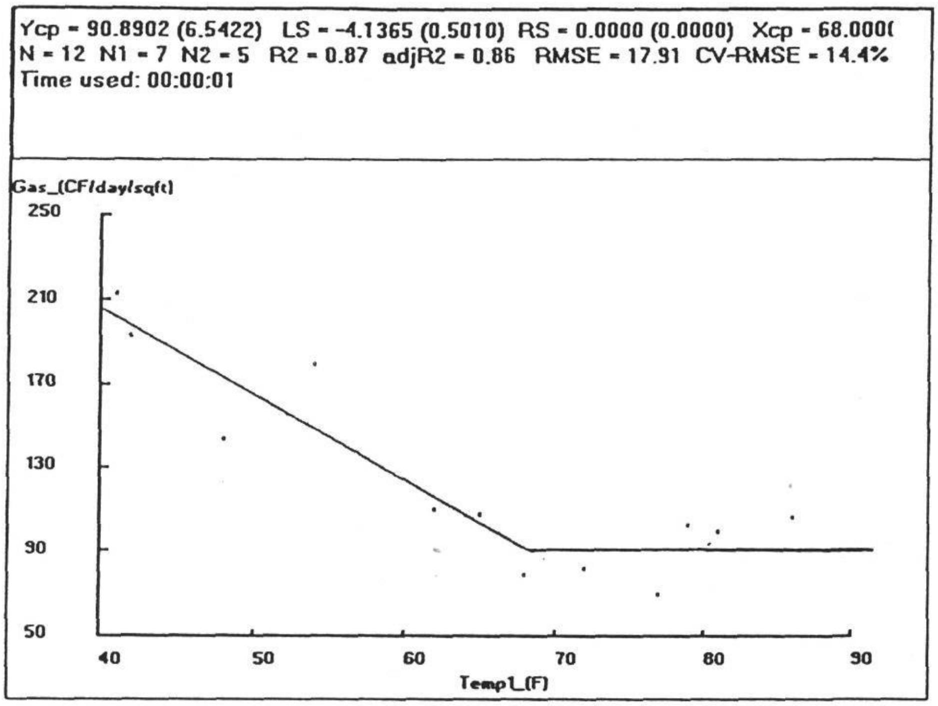


Figure 4.8. EModel change point model line and data points for Fort Bragg electricity consumption for baseline year (FY86). A 15-day shift in temperature led to substantial model improvement. (a) 4P model selected as baseline, (b) 4P model line and next-best model, namely the 3P model line, are shown for comparative purposes.



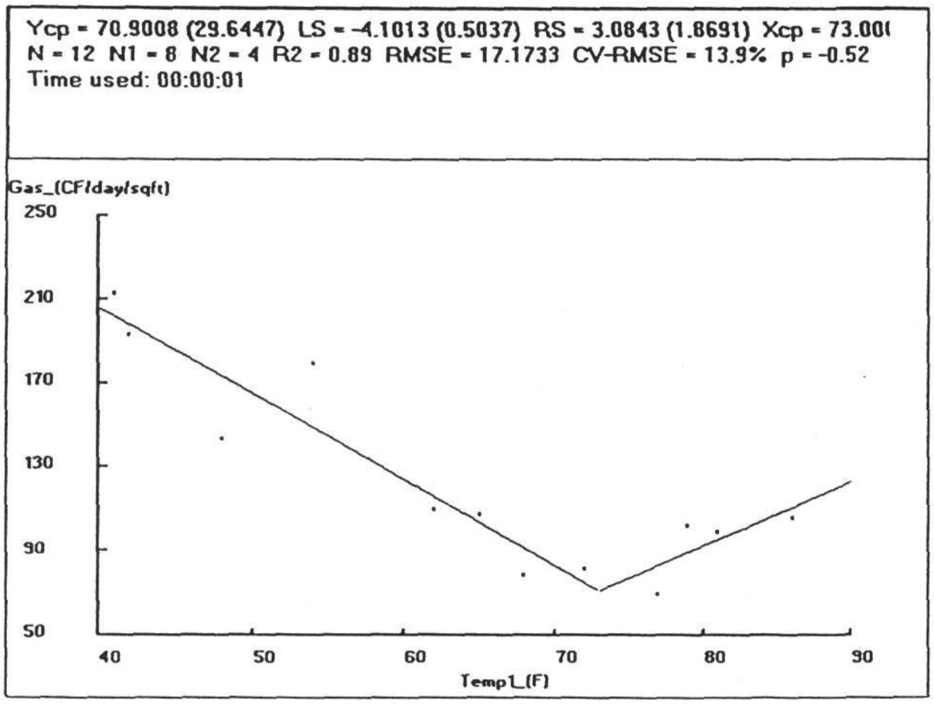


Figure 4.9. EModel change point model line and data points for Fort Bragg natural gas consumption for baseline year (FY86). (a) 3P model selected as baseline, (b) next-best model, namely the 4P model line, is shown for comparative purposes.

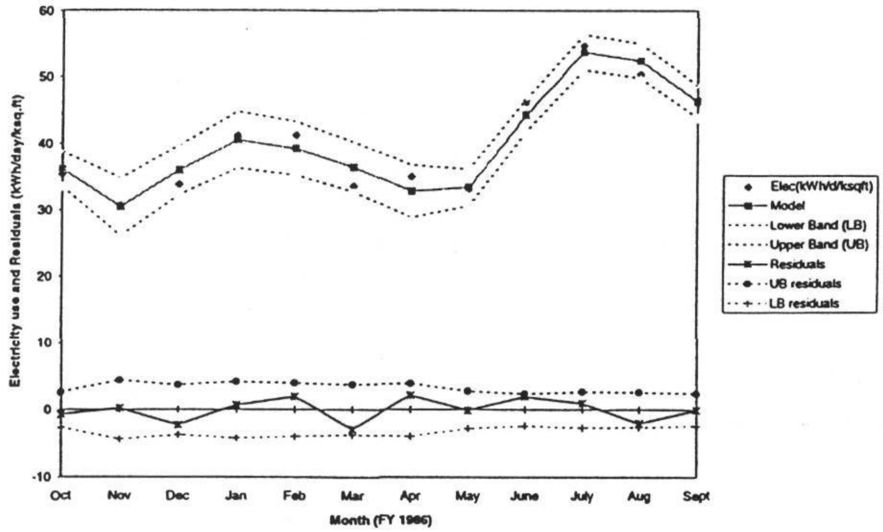


Figure 4.10. Predictive ability of the baseline model (FY86) for Fort Bragg electricity use during FY86. 95% prediction intervals for the model as well as for the model residuals are shown.

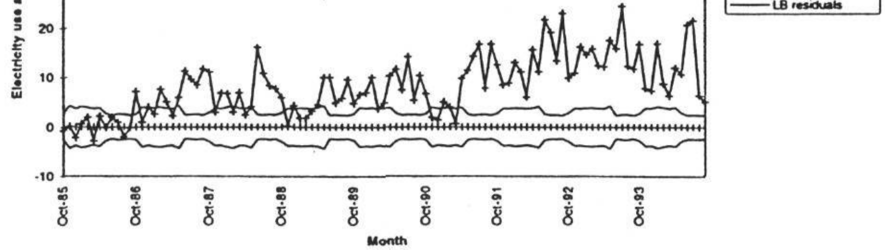


Figure 4.11. Predictive ability of electricity baseline model (FY86) for Fort Bragg from FY86 to FY94. 95% prediction intervals for the model as well as for the residuals are shown.

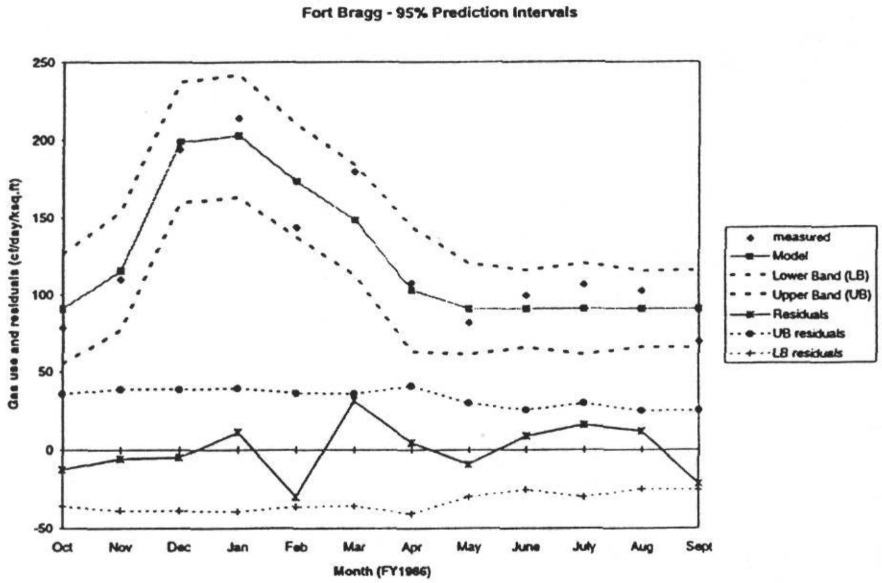


Figure 4.12. Predictive ability of the baseline model (FY86) for Fort Bragg gas use during FY86. 95% prediction intervals for the model as well as for the model residuals are shown.

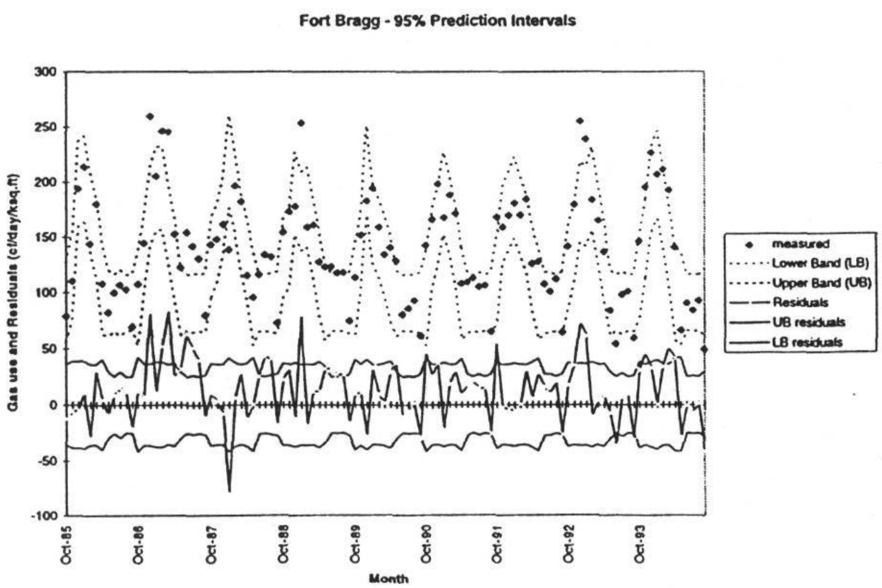


Figure 4.13. Predictive ability of gas baseline model (FY86) for Fort Bragg from FY86 to FY94. 95% prediction intervals for the model as well as for the residuals are shown.

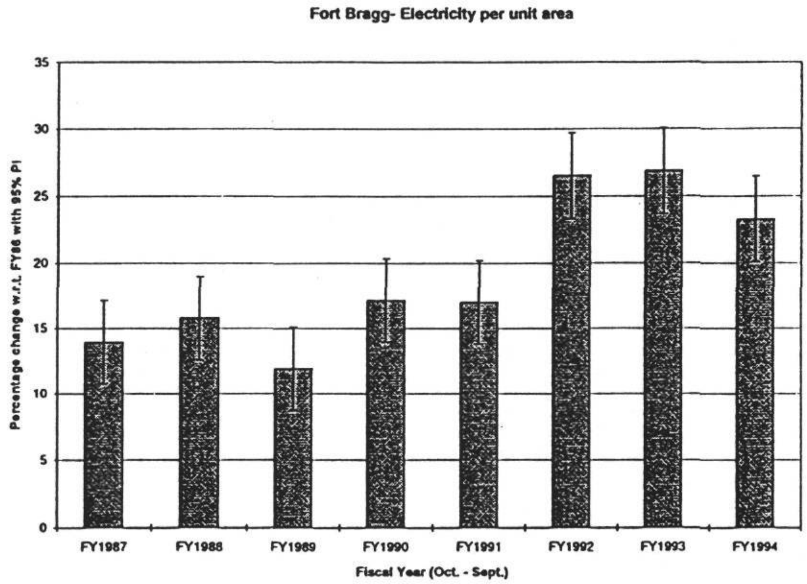


Fig. 4. 14 (a) Electricity use.

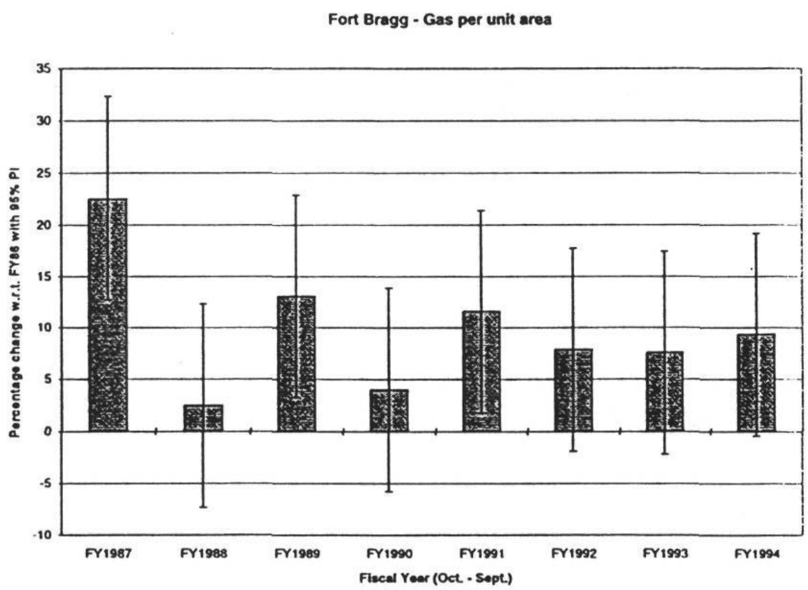


Fig. 4.14 (b) Gas use.

Figure 4.14. Percentage change in annual energy use per conditioned area with respect to baseline year (FY86) for Fort Bragg. Negative change indicates decrease in energy use and vice versa. 95% confidence intervals for the percentage change are also shown.

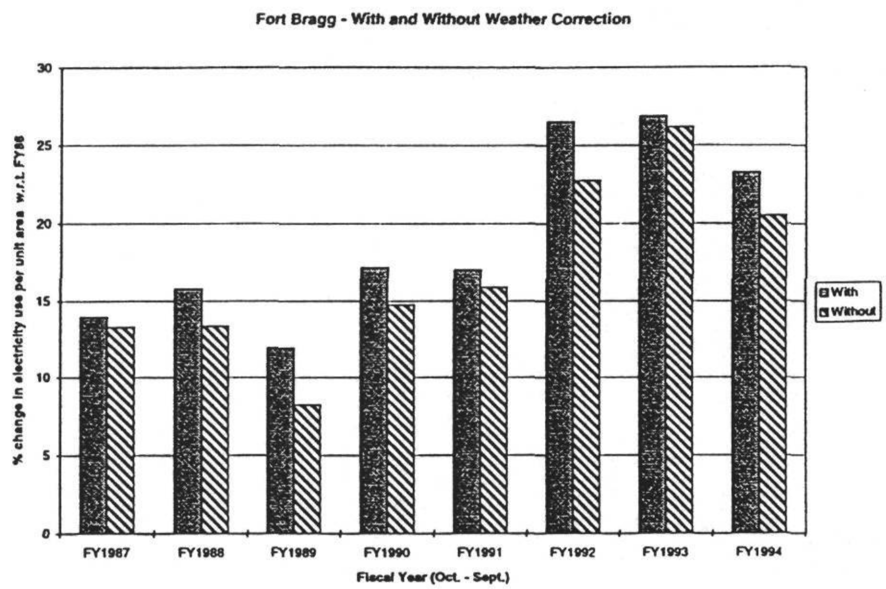


Fig. 4.15 (a) Electricity use.

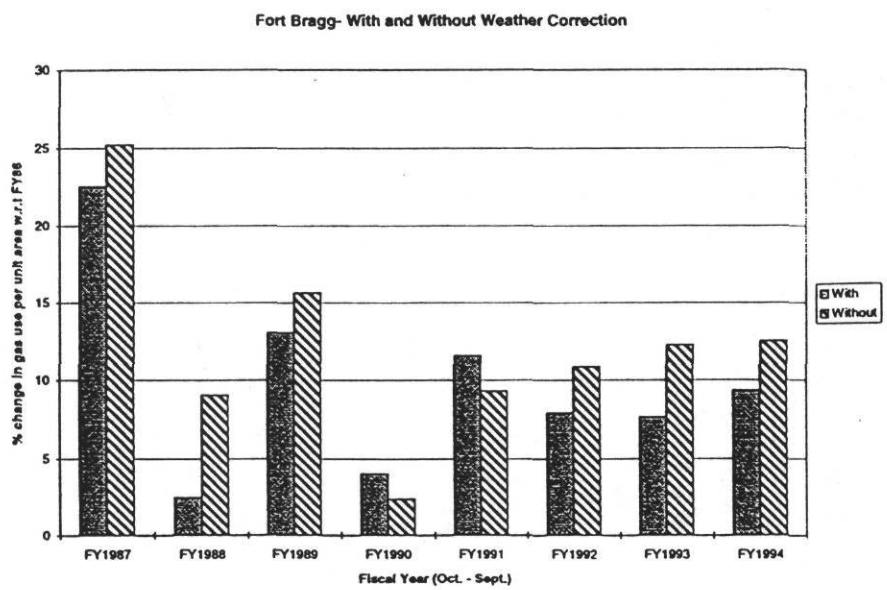


Fig. 4.15(b) Gas use.

Figure 4.15. Differences in percentage change in annual energy use per conditioned area with respect to baseline year (FY86) for Fort Bragg determined by the present methodology and by direct utility bill comparison method. Negative change indicates decrease in energy use and vice versa.

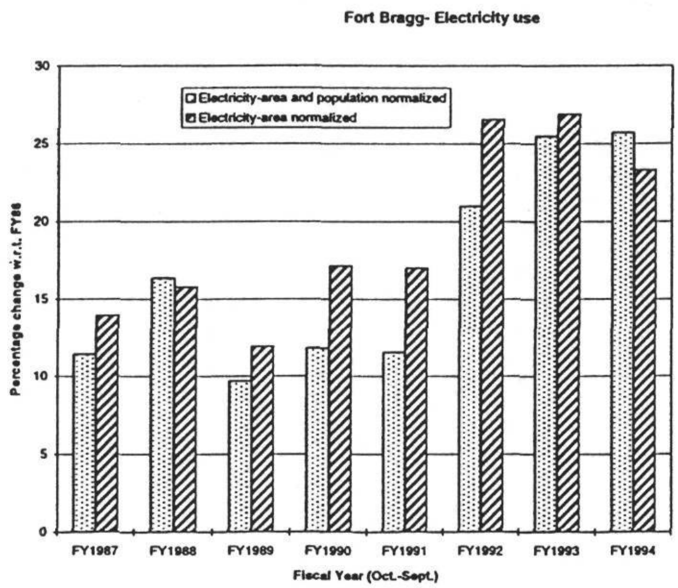


Fig.4.16 (a) Electricity use

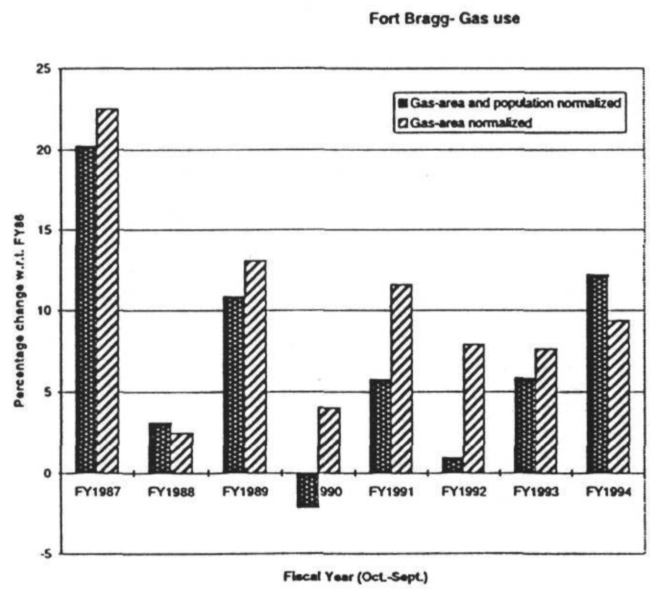


Fig.4.16 (b) Gas use.

Figure. 4.16. Percentage changes in annual energy use with respect to baseline year (FY86) for Fort Bragg with conditioned area normalization as well as with area and population normalization.

5.0 Analysis of Fort Carson, CO

5.1 Preliminary data analysis

Outdoor temperature data provided by USACERL extended only until December 1993, and so all analyses for Fort Carson can be done only until FY93 (i.e., till September 1993). Time series plots of monthly electricity use and gas use from FY86 to FY94 are shown in Fig. 5.1 along with concurrent outdoor temperature. The variation patterns of temperature are fairly consistent over the years while those of electricity do not seem to be very much temperature driven. Gas use is fairly consistent with, as expected, peaks in winter.

Figure 5.2 shows the change in total building area and conditioned area (determined as described in section 2.2) over the years. Both these areas seem to have generally remained constant from FY86 to FY93, though both these areas seem to have had a maximum variation of about 10% over the years. Annual mean daily population data is also plotted in Fig.5.2. Population seems to have remained constant for the first four years, decreased for the next three years, and increased to the FY86 level in FY94.

Figure 5.3 shows the changes in annual mean daily energy use per unit conditioned area over the years. Except for an increase in gas use in FY87 and FY88, gas use seems to have decreased by FY89. Electricity use seems fairly constant over the years. The annual mean outdoor temperature is also plotted in order to enable the reader to associate changes in energy use with temperature changes. For example, FY87 is a cold year and gas use seems to have increased that year. Plots such as these only provide a general qualitative trend and one should not try to read too much from them.

Figure 5.4 presents time series graphs of monthly electricity and gas use normalized by building conditioned area. We notice, despite consistent temperature patterns, that generally gas use has decreased during summer from FY91 onwards with the winter use remaining unchanged. Further gas use in FY86 (our baseline year) exhibits a bi-modal behavior which is strikingly different from all other years shown.

Figure 5.5 depicts the average monthly outdoor temperatures during a year for all years from FY86 to FY93. We note that the weather during these years seems to be also consistent over the years though certain monthly excursions from the overall annual pattern can be noted. Temperature data for FY86, our baseline year, seems to be fairly characteristic except for being lower than the average during November and above average in January and March.

Figures 5.6 and 5.7 are time series plots of electricity use and gas use normalized by conditioned area during a year for all years from FY86 to FY93. This type of representation allows clearer visualization of how energy use has changed over the years for a given month. Clearly, we notice that electricity use has little, if any, seasonal variation and so we do not expect to have a strong temperature dependent model. The sharp increases in electricity use in July and gas use during the winter are obvious. One notices the odd behavior of gas use during FY87 where February and March uses are abnormally high. Finally, we notice in Fig. 5.6 the very slight increase in electricity use during January and February for most years indicating some heating application.

5.2 Baseline modeling

As described earlier, there is an ambiguity regarding proper match between the utility bill period and the corresponding temperature data supplied to us. In section 3.6, we had suggested a method whereby we would identify the best model from three different sets of runs where the temperature data has been taken in slightly different ways. The criteria for selecting the optimum model among the various runs are as follows:

(i) highest R^2 and lowest CV-RMSE,
(ii) if R^2 values for all models are low, CV-RMSE is to be given more consideration, and
(iii) it would be more appropriate from physical considerations, to select 3-P models rather than 4P models. Only if the improvement in R^2 and CV-RMSE is substantial, would we relax this rule.

Note that both electricity and gas use during the year have been normalized with the conditioned area of the army base during that particular year prior to model identification. The summary model statistics of our baseline model identification effort for all three cases are summarized in Table 5.1. We notice by looking at the CV statistics (as is obvious from Fig. 5.6) that a mean electricity use model is as good as the 3P-cooling or the 4P models, and so it would be most appropriate to choose this mean model. In this case the issue of whether the electricity bills span calendar monthly intervals is of no consequence. How the mean model line fits the data points can be noted in Fig. 5.8(a), while how the next-best model, namely the 4P model fits the data points, can be gauged by Fig. 5.8(b).

Regarding the baseline model for gas use, we note from Table 5.1 that using case 1, i.e., temperature data corresponding to the same calendar months as the utility bills, results in best models. Further, there is no improvement in R^2 and CV-RMSE as we go from a 3P- heating model to a 4P model, and consequently, the choice of the 3P heating model as our baseline model for gas use is unambiguous. How the individual monthly data points scatter around the 3P heating baseline model line can be seen in Fig. 5.9. We note that despite the bi-modal behavior in the variation of gas use during the baseline year (see Fig. 5.4) the model identified has a high R^2 (= 0.94) while the CV-RMSE is also on the high side.

5.3 Baseline models for screening and tracking

Once baseline models have been developed, it is possible to use them as screening tools by comparing forecast levels with actual energy use. Effect of changes in weather from year-to-year (more accurately, outdoor temperature) on the energy use is explicitly accounted for by the baseline model forecasts. Deviations from expectations must be studied to determine whether known extraneous changes have contributed to this variation or whether these changes are a result of energy efficiency measures or DSM programs that have been initiated. How the PIs of the model are to be calculated have been described in section 3.3 for individual months and in section 3.4 on an annual basis. We have used our FY86 baseline models to forecast into the future up to FY94.

Figures 5.10 and 5.12 depict the extent to which the monthly energy use utility bills are bounded by the PIs of the FY86 baseline model for electricity use and gas use respectively. For clearer visualization, we have also shown the residuals (residual = measured value minus model predicted value) along with the PIs. If, say, the utility bill data for a month fall below the lower 95% PI, one can safely affirm that energy use during that month has decreased as compared to model predictions. We note that both electricity and gas use data are well contained within the PIs bands which is not surprising since the models are very good (see Table 5.1).

How well the FY86 baseline models for electricity and gas use are able to predict monthly energy use from FY86 till FY94 can be seen in Figs. 5.11 and 5.13 respectively. Note that the energy use is on a monthly mean daily basis per unit conditioned area but has not been normalized for changes in population from one year to the next. We note that electricity use is almost always contained within the PIs indicating no appreciable change over the years in electricity use. A similar behavior is also observed for gas use. So statistically speaking, one cannot draw any definite conclusions about how gas use has varied over the years. However, plots such as this are useful to the energy manager of the corresponding Army base who is in a position to look for (as well as discern and evaluate) changes in energy use as a result of certain specific actions taken (such as O&M measures or say, changes in equipment in the power plants).

On an annual time scale, however, determination of percentage changes in energy use (normalized by conditioned area) with respect to the baseline year (FY86) permit rather well-defined conclusions to be drawn regarding the extent to which the Executive Order 12902 has been met. How these changes are to be determined as well as the 95% PIs of these changes have been described in sections 3.4 and 3.5. Following eqs.(3.16) and (3.17), we have computed the percentage changes on a year by year basis and plotted them in Figs. 5.14 for both electricity and gas. Note that a negative change indicates a decrease in energy use. Both electricity and gas use seem to have increased and decreased over the years. Electricity use during the first two years has increased as compared to the baseline year and then seems to have increased and decreased with respect to the baseline year. Electricity use for FY86 and FY93 seems to be almost unchanged. Gas use, on the other hand, seems to have decreased over the years. Gas use in FY93 is about 24% lower than that of the baseline year, with this change being very significant statistically because error bands for gas are smaller than the magnitude of the variation itself.

5.4 Concluding remarks

The baseline models identified for FY86 for Fort Carson were found to be very good with the mean electricity model having a CV-STD of 8% and the 3P-heating gas model had a $R^2 = 0.94$. Our analysis indicated that correction needs to be made to the calendar monthly mean temperature data that we received.

Using the baseline models to track how energy use has increased (or decreased) over the years required that energy use during each year be normalized by the associated conditioned area of the army installation. (As described above, this quantity is not directly available from the database but has to be inferred from areas of several categories of building types which were listed in the database). This leads to a certain amount of unavoidable uncertainty in our conclusions regarding the screening and tracking aspects of the baseline models. We found almost no change in electricity use in FY93 with respect to FY86, while gas use has decreased by about 24% ($\pm$9%).

Finally, Fig.5.15 and Table 5.4 assemble the year to year percentage changes in annual energy use with respect to baseline year (FY86) normalized by (i) conditioned area, and (ii) conditioned area and population. Though generally the changes in energy use by both means of normalization have more or less similar patterns, the quantitative values are appreciably different during certain years. As described in section 3.5, one cannot place as much confidence in the population values as in the conditioned area values, and so it would probably be better to draw conclusions regarding the extent to which Presidential Executive Order 12902 is being met based on conditioned area normalization only.

Table 5.1. Fort Carson: model identification summary statistics for baseline year (FY 86). Final models selected are shown in bold face.

		Mean	3P-Cooling		4P	
	Temperature data used	CV-St.Dev (%)	R^2	CV-RMSE (%)	R^2	CV-RMSE (%)
Electricity	Same month (T_1)	**8.0***	0.16	7.7	0.41	6.8*
	Previous month (T_2)	-	-	-	0.10	8.4
	Mid-month (T_3)	-	-	-	0.27	7.5
			3P-Heating		4P	
Gas	Same month (T_1)	-	**0.94**	**13.8***	0.94	14.3
	Previous month (T_2)	-	0.76	28.0	0.76	29.4
	Mid-month (T_3)	-	0.94	13.8	0.94	14.6

* Plots of these models are shown in the report

Table 5.2. Fort Carson electricity use: model coefficients (and standard errors) and pertinent regression model statistics for FY86.

Model type	Y_{cp} (kWh/d/ksq.ft)	LS (kWh/d/ksq.ft/F)	X_{cp} (°F)	R^2	CV-St.Dev (%)	St.Dev (kWh/d/ksq.ft)	n_1
Mean	33.3	-	-	-	8.0	2.65	-

Table 5.3. Fort Carson gas use: model coefficients (and standard errors) and pertinent regression model statistics for FY86.

Model type	Y_{cp} (cf/d/ksq.ft)	LS (cf/d/ksq.ft/F)	X_{cp} (°F)	R^2	CV-RMSE (%)	RMSE (cf/d/ksq.ft)	n_1
3P-H	199.34(29.97)	-20.66(1.632)	62.0	0.94	13.7	67.18	9

Table 5.4 Baseline models and percentage change in energy use w.r.t baseline year for Fort Carson.

Energy type	Baseline year	Model type	Model fit	Year	% change normalized by conditioned area with 95% PI	% change normalized by conditioned area and population
Electric.	FY86	Mean	Good	FY87	6.98 ± 5.41	6.78
				FY88	10.48	10.29
				FY89	-6.47	-6.70
				FY90	1.23	9.05
				FY91	-11.97	-3.11
				FY92	-3.95	5.48
				FY93	1.39	-0.38
				FY94	-	-
Gas use	FY86	3P-H	Mediocre	FY87	3.85 ± 9.34	3.64
				FY88	4.57	4.36
				FY89	-15.52	-15.77
				FY90	-1.68	6.36
				FY91	-26.08	-16.11
				FY92	-18.21	-7.49
				FY93	-23.68	-25.89
				FY94	-	-

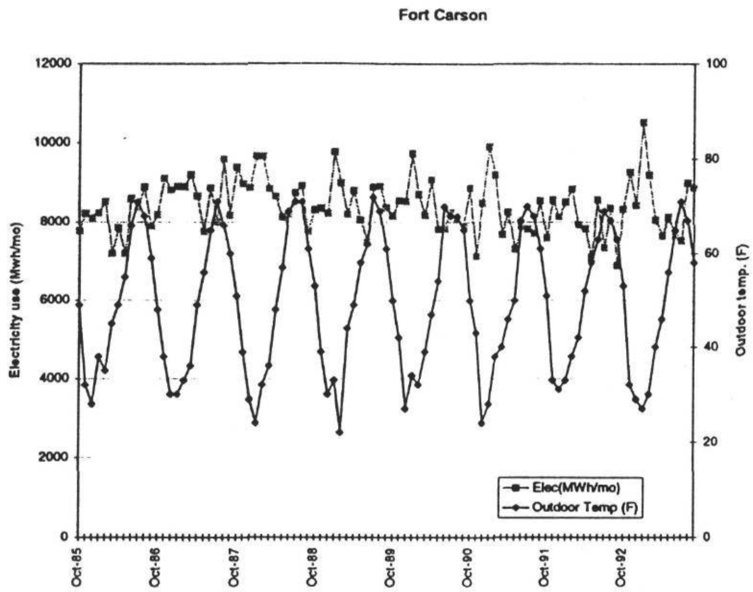


Fig.5.1(a) Electricity use

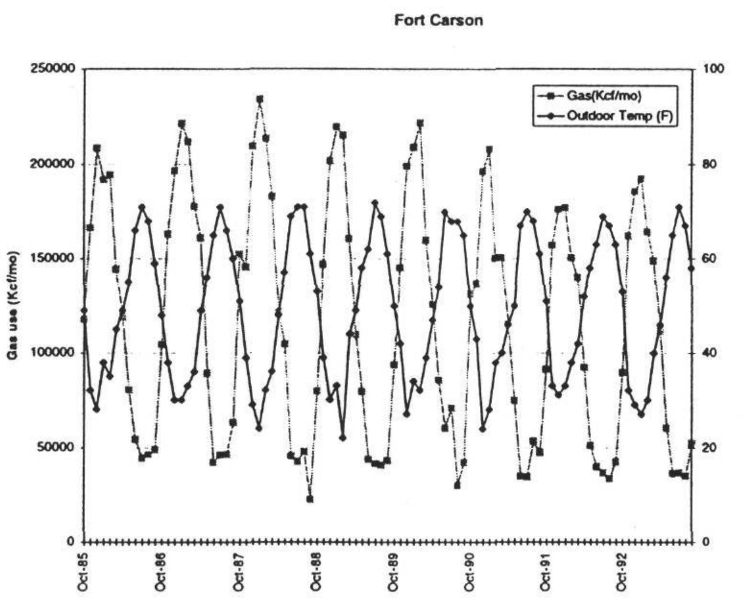


Fig.5.1(b) Gas use

Figure 5.1. Time series plots of monthly electricity and gas consumption for Fort Carson from FY86 to FY93. The concurrent outdoor dry-bulb temperature variation is also shown.

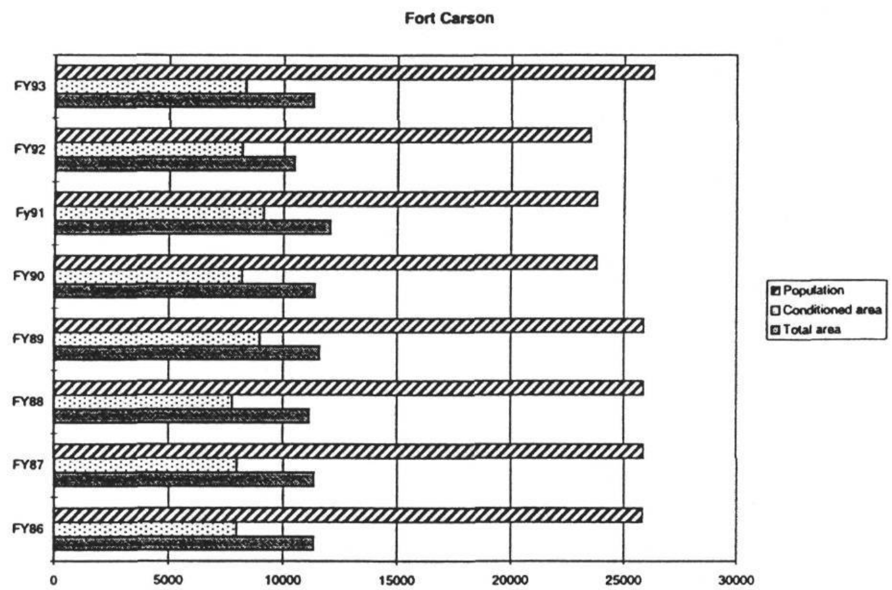


Figure 5.2. Changes in total and conditioned building areas (in ksq.ft) and annual mean daily population for Fort Carson from FY86 to FY93

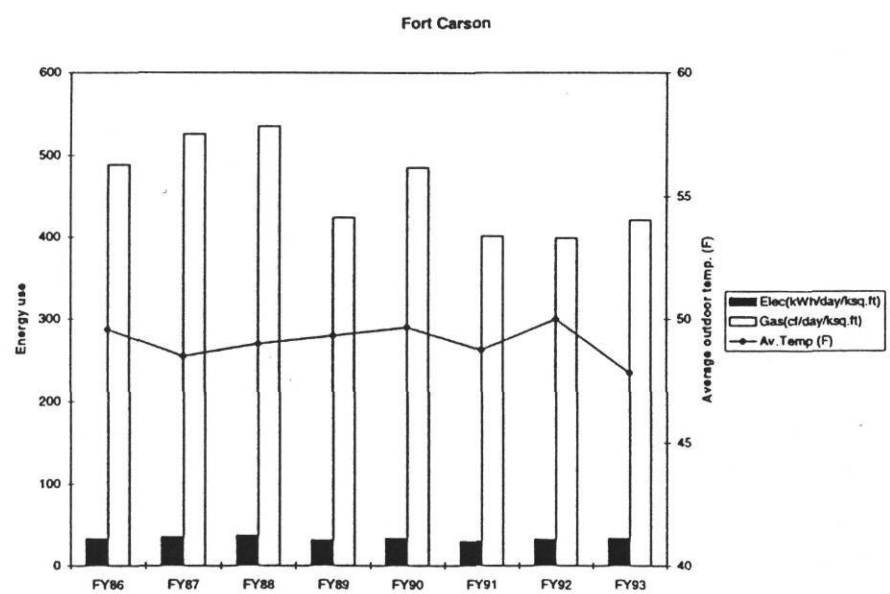


Figure 5.3 Changes in annual mean daily energy use per conditioned area and annual mean outdoor temperature for Fort Carson from FY86 to FY93.

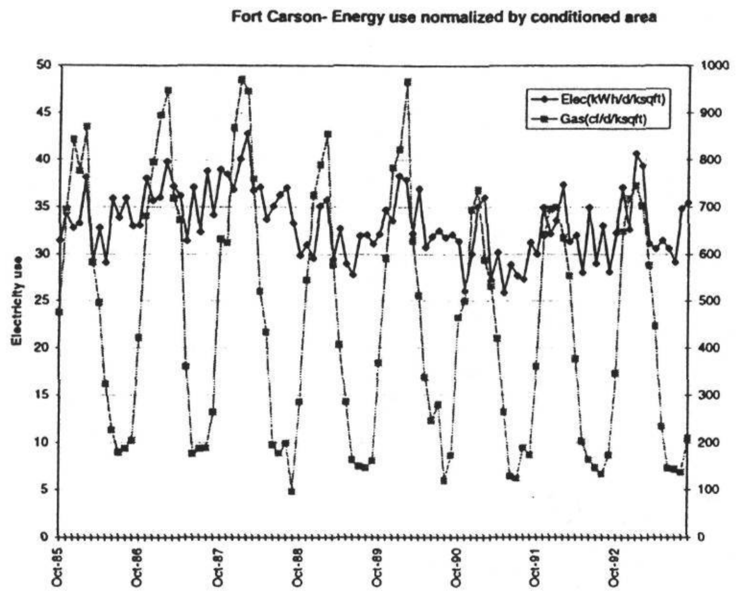


Figure 5.4. Time series graphs of monthly electricity and gas consumption per unit conditioned area for Fort Carson from FY86 to FY93.

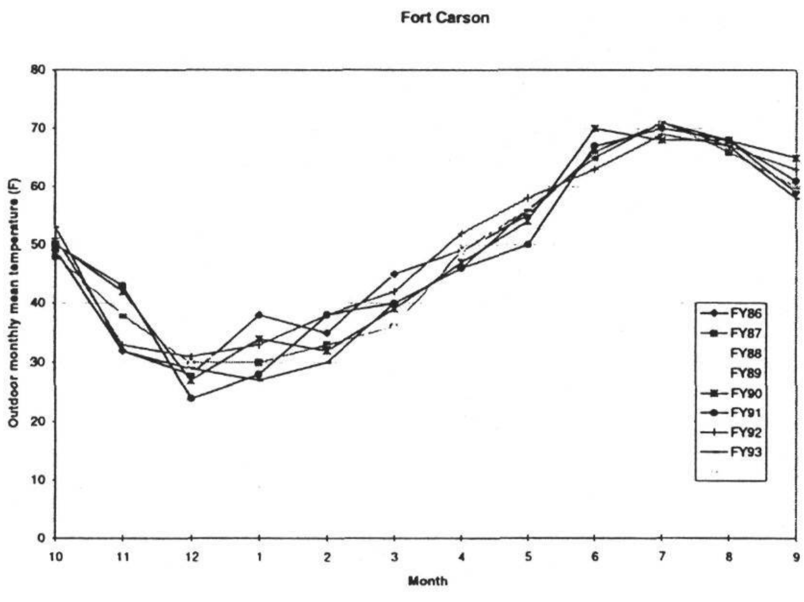


Figure 5.5.Time series plots of average monthly temperatures at Fort Carson from FY86 to FY93.

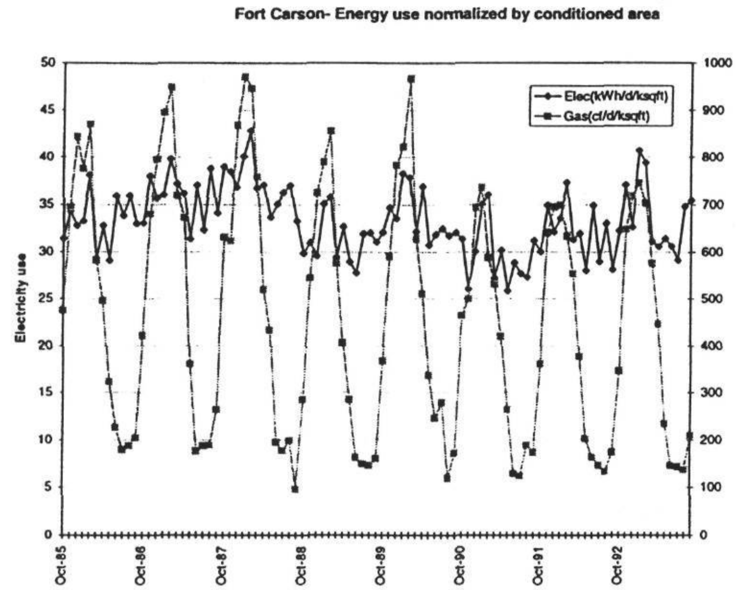


Figure 5.4. Time series graphs of monthly electricity and gas consumption per unit conditioned area for Fort Carson from FY86 to FY93.

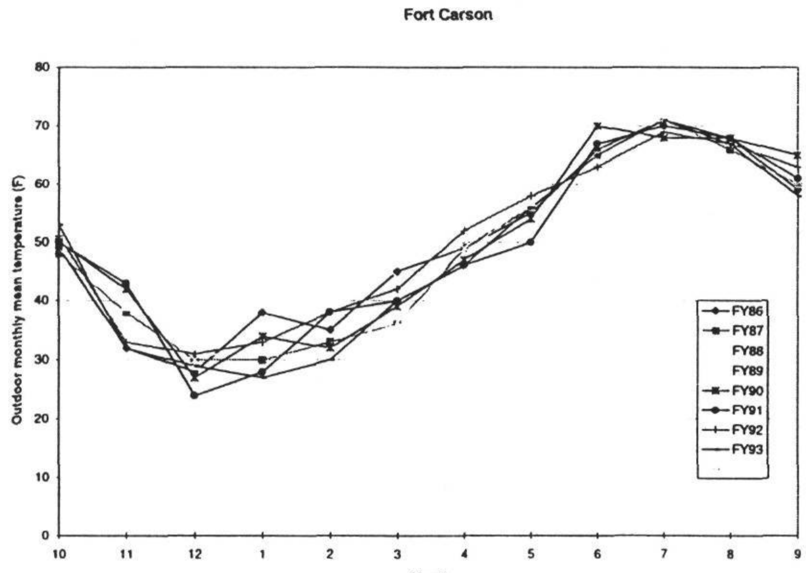


Figure 5.5.Time series plots of average monthly temperatures at Fort Carson from FY86 to FY93.

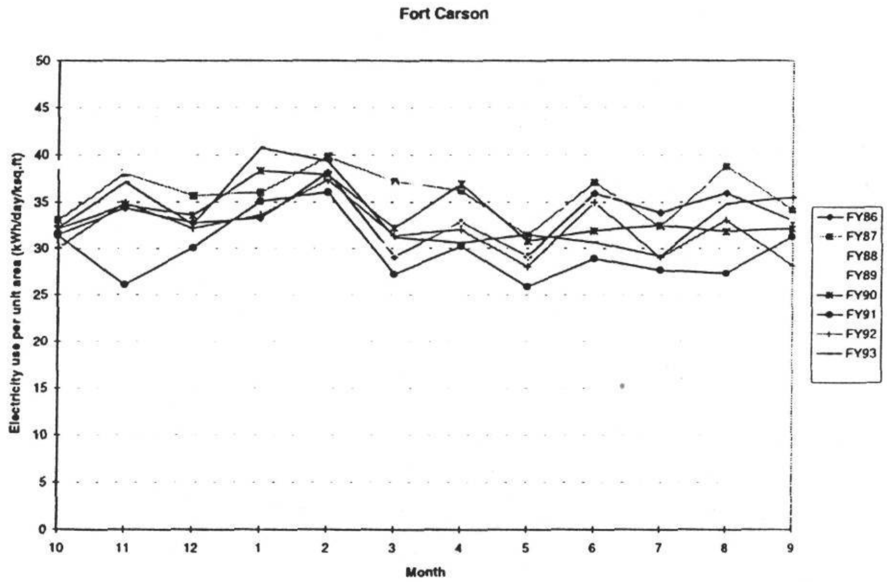


Figure 5.6. Time series plots of electricity use per unit conditioned area for Fort Carson from FY86 to FY93.

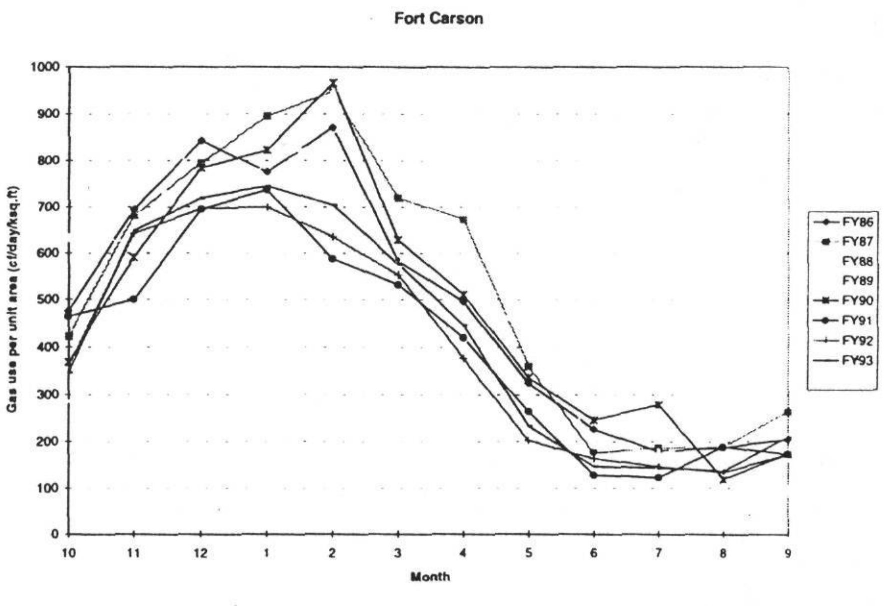


Figure 5.7. Time series plots of gas use per unit conditioned area for Fort Carson from FY86 to FY93.

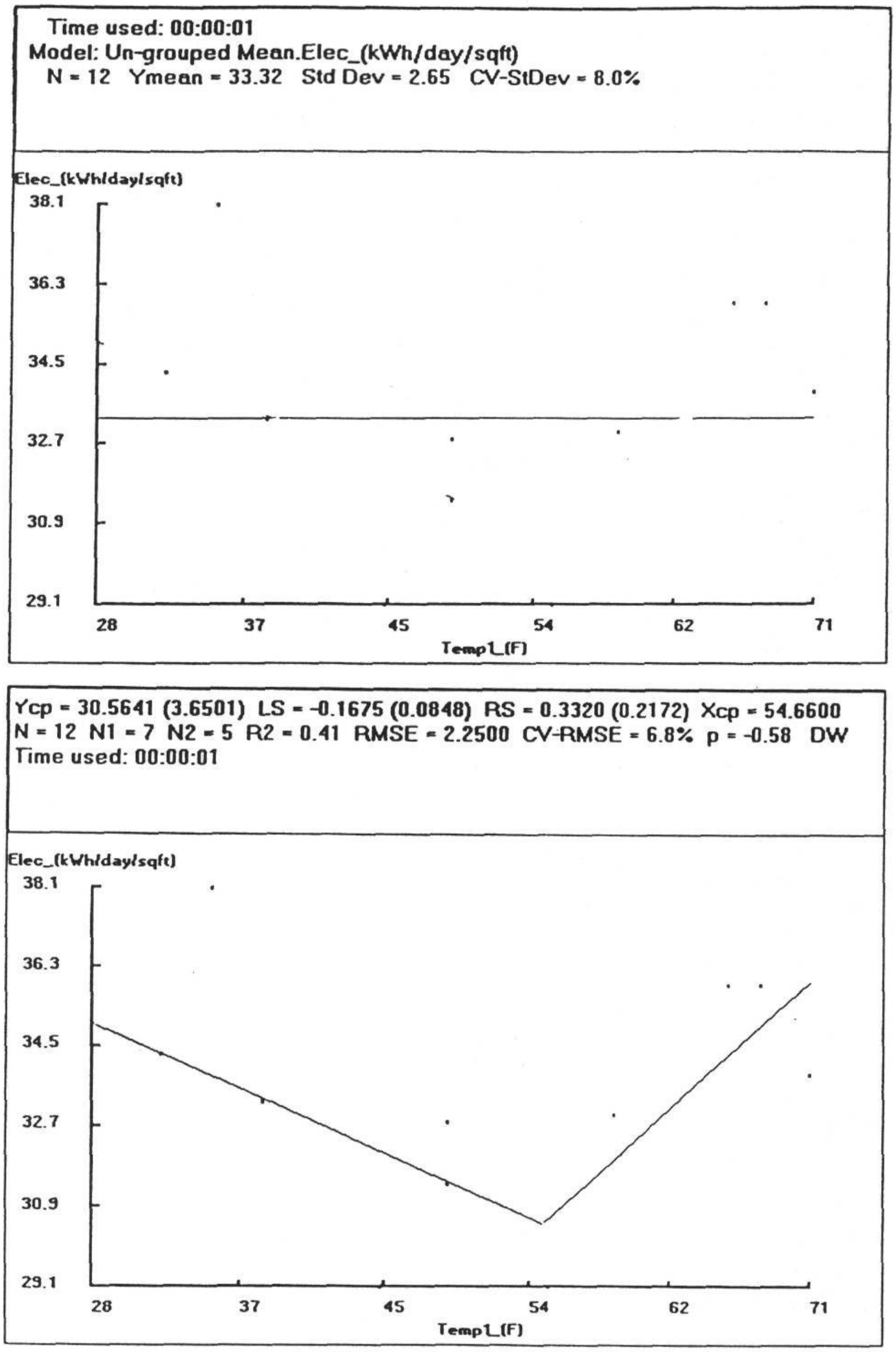


Figure 5.8. EModel change point model line and data points for Fort Carson electricity consumption for baseline year (FY86). No shift in temperature data was needed. (a) mean model selected as baseline, (b) next-best model, namely the 4P model line, and data points are shown for comparative purposes.

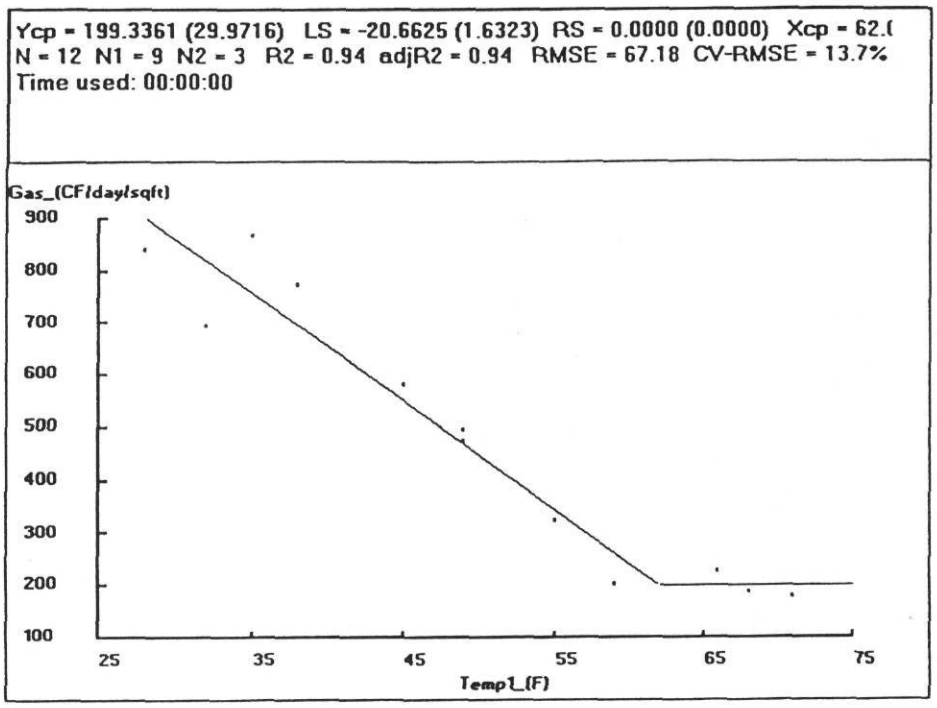


Figure 5.9. EModel change point model line (3-P heating model) and data points for Fort Carson natural gas consumption for baseline year (FY86).

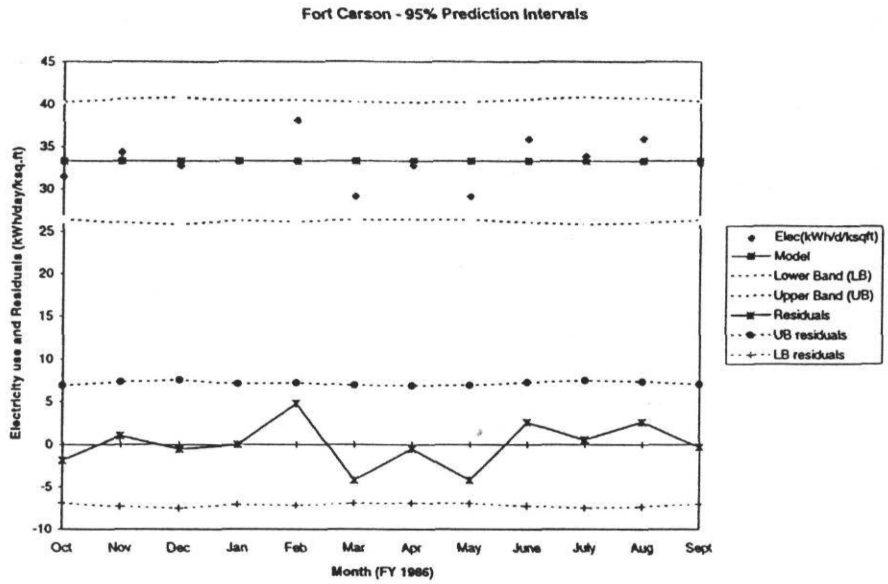


Figure 5.10. Predictive ability of the baseline model (FY86) for Fort Carson electricity use during FY86. 95% prediction intervals for the model as well as for the model residuals are shown.

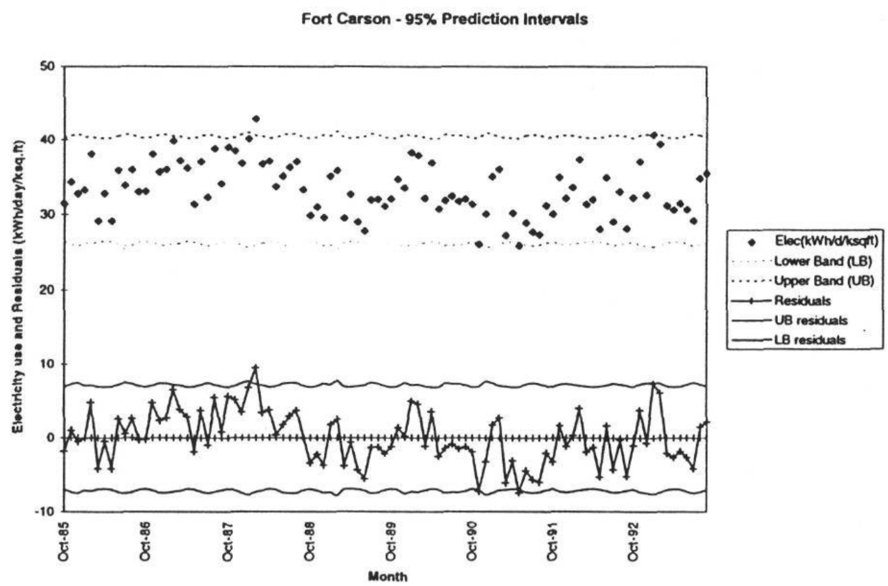


Figure 5.11. Predictive ability of electricity baseline model (FY86) for Fort Carson from FY86 to FY93. 95% prediction intervals for the model as well as for the residuals are shown.

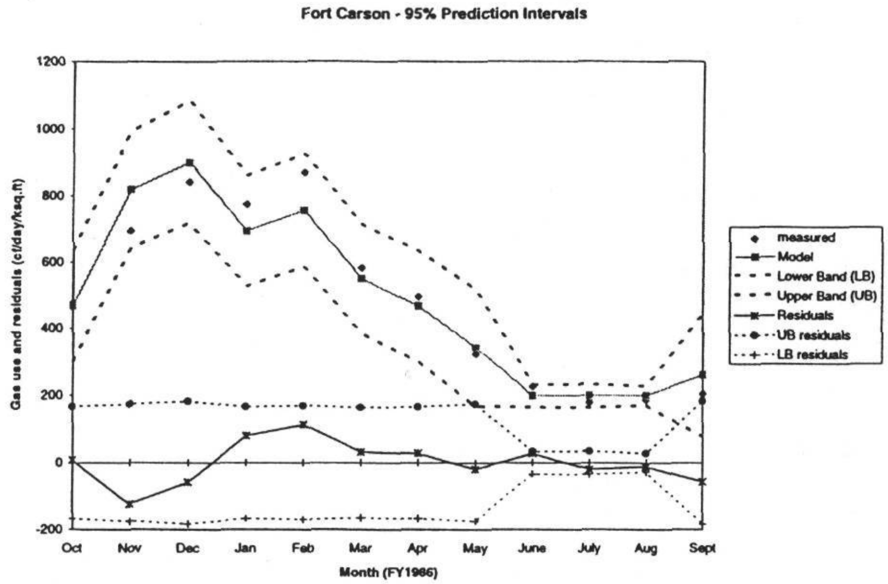


Figure 5.12. Predictive ability of the baseline model (FY86) for Fort Carson gas use during FY86. 95% prediction intervals for the model as well as for the model residuals are shown.

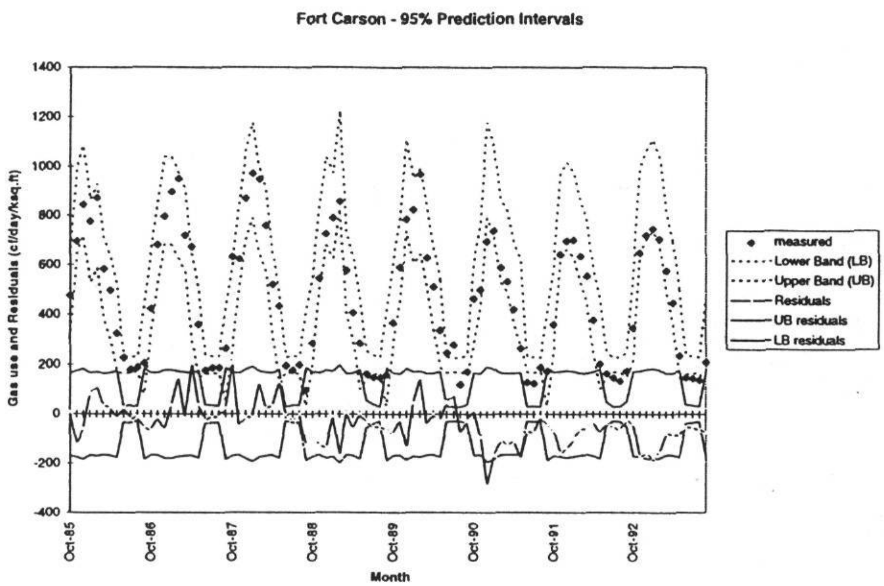


Figure 5.13. Predictive ability of gas baseline model (FY86) for Fort Carson from FY86 to FY93. 95% prediction intervals for the model as well as for the residuals are shown.

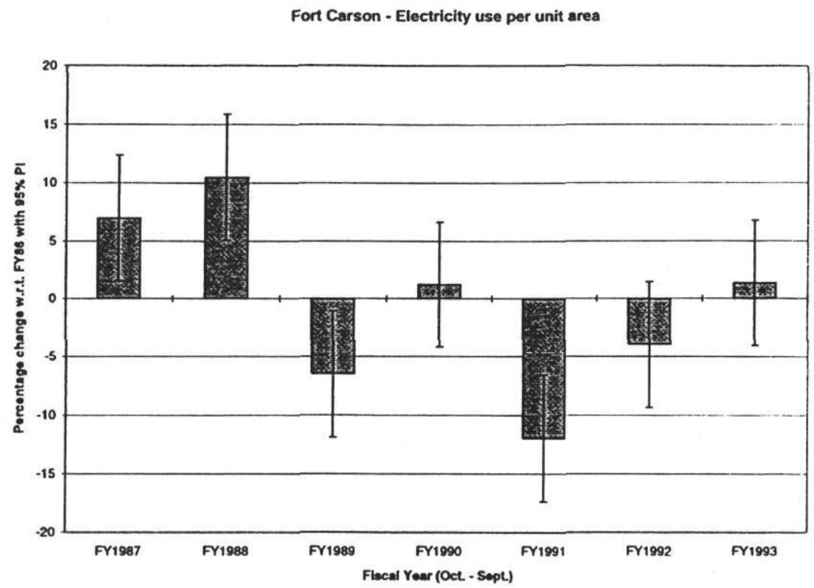


Fig.5.15(a) Electricity use

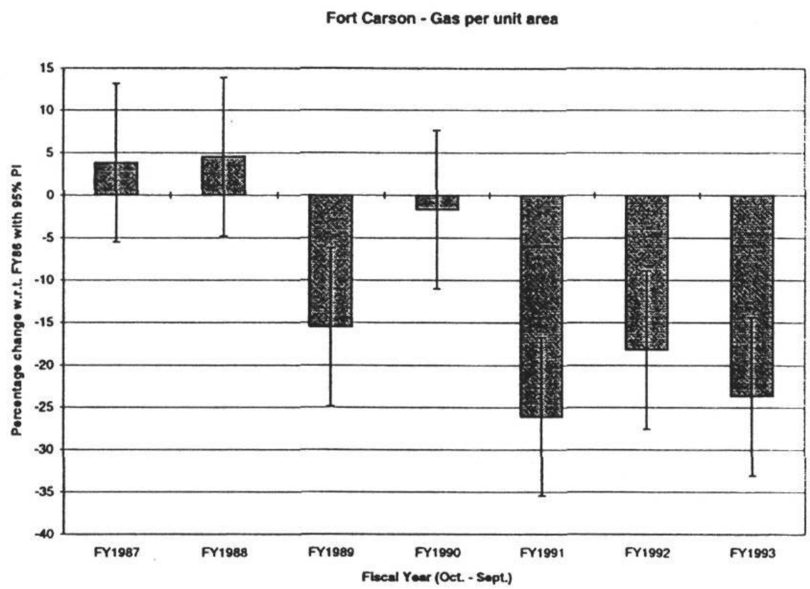


Fig.5.15(b) Gas use

Figure 5.14. Percentage change in annual energy use per conditioned area with respect to baseline year (FY86) for Fort Carson. Negative change indicates decrease in energy use and vice versa. 95% confidence intervals for the percentage change are also shown.

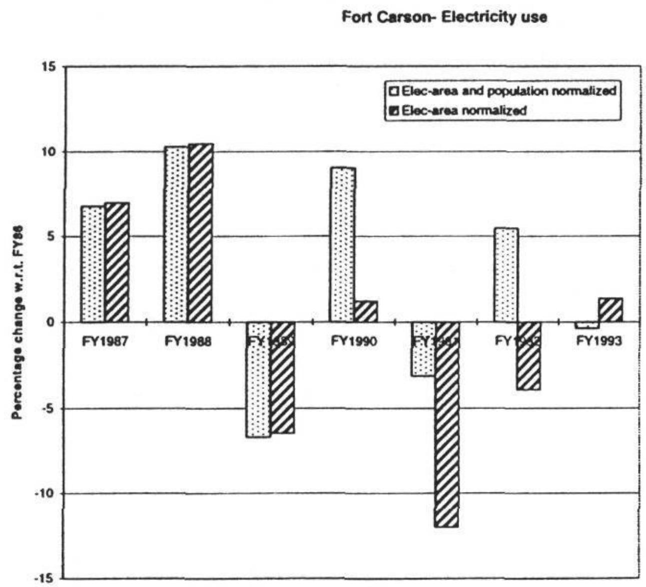


Fig.5.15 (a) Electricity use

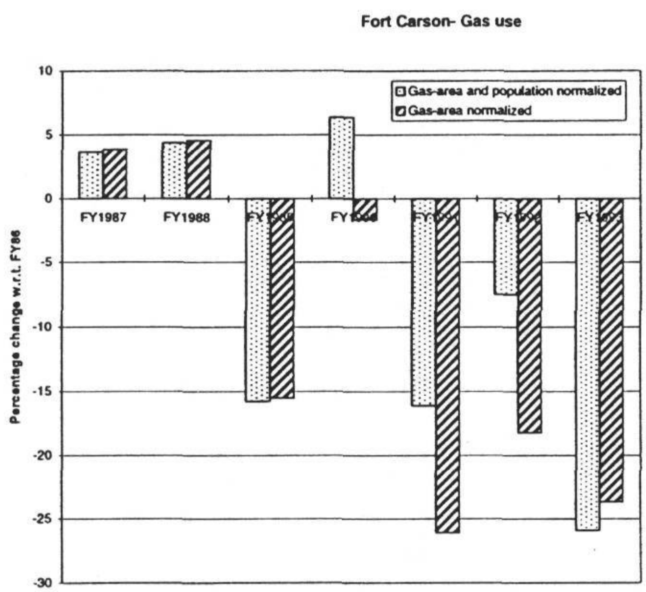


Fig.5.15(b) Gas use

Fig.5.15 Percentage changes in annual energy use with respect to baseline year (FY86) for Fort Carson with conditioned area normalization as well as with area and population normalization.

6.0 Analysis of Fort Drum, NY

6.1 Preliminary data analysis

Time series plots of monthly electricity use and gas use from FY86 to FY94 are shown in Fig. 6.1 along with concurrent outdoor temperature. It is strikingly obvious that gas use has dramatically increased from FY88, with electricity use also increasing four-fold over the years. The variation patterns for temperature are fairly consistent over the years. As expected, gas use peaks in winter while electricity use patterns are more difficult to discern.

Figure 6.2 shows the change in total building area and conditioned building area (determined as described in section 2.2) over the years. Both these areas seem to have dramatically increased from FY86 to FY94, almost doubling over the years. Total area increased by about 60% from FY86 to FY94. The conditioned area increased by about 30% during the same period. Building areas during the last 3-4 years seem to be fairly constant. Annual mean daily population data is also plotted in Fig.6.2. Population also seems to have increased four-fold from FY86 to FY94 with an abnormal increase in FY91.

Figure 6.3 shows the changes in annual mean daily energy use per unit conditioned area over the years. Both gas use and electricity use are fairly consistent over the years. The annual mean outdoor temperature is also plotted in order to enable the reader to associate changes in energy use with temperature changes. For example, FY91 is a hot year and gas use seems to have decreased that year. Plots such as these provide a general qualitative trend and one should not try to read too much from them.

Figure 6.4 presents time series graphs of monthly electricity and gas use normalized by building conditioned area. We notice, despite large increases in conditioned building area that gas use still exhibits the dramatic increase in FY88 seen in Fig. 6.1. Electricity use normalized by conditioned area shows less increase over the years than the total use (see Fig. 6.1), but there is a gradual increase over the years nonetheless.

Figure 6.5 depicts the average monthly outdoor temperatures during a year for all years from FY86 to FY94. We note that the weather during these years seems to be fairly consistent over the years though certain monthly excursions from the overall annual pattern can be noted (FY90 for example). Temperature data for FY86, our baseline year, seems to be fairly characteristic.

Figures 6.6 and 6.7 are time series plots of electricity use and gas use normalized by conditioned area during a year for all years from FY86 to FY94. This type of representation allows clearer visualization of how energy use has changed over the years for a given month. Electricity use is fairly constant during the year with a small increase during winter indicating space heating applications. However, differences from one year to the next in annual electricity patterns are important. Gas use, as expected, peaks in winter. One notices clearly the lower gas use during FY86 and FY87 as compared to the other years. Finally, we notice in Fig. 6.7 the rather abrupt increases in gas use during February for three years for reasons unknown to us.

6.2 Baseline modeling

As described earlier, there is an ambiguity regarding proper match between the utility bill period and the corresponding temperature data supplied to us. In section 3.6, we had suggested a method whereby we would identify the best model from three different sets of runs where the temperature data has been taken in slightly different ways. The criteria for selecting the optimum model among the various runs are as follows:

(i) highest R^2 and lowest CV-RMSE,

(ii) if R^2 values for all models are low, CV-RMSE is to be given more consideration, and

(iii) it would be more appropriate from physical considerations, to select 3-P models rather than 4-P models. Only if the improvement in R^2 and CV-RMSE is substantial, would we relax this rule.

Note that both electricity and gas use during the year have been normalized with the conditioned area of the army base during that particular year prior to model identification. The summary model statistics of our baseline model identification effort for all three cases are summarized in Table 6.1. We notice that the improvement in electricity and gas use models is substantial when previous month temperature values (i.e., case 2 in section 3.6) are used for regression. This leads us to conclude that the electricity bills are mis-matched to utility bills by one month. For electricity, the 3P-heating model seems to be the best choice for a baseline model (see Table 6.1). How the model line fits the data points can be noted in Fig. 6.8(a), while how the 3P model compares with the next-best model, namely the 4P model, can be gauged by Fig. 6.8(b). The model R^2 is rather low though the CV-RMSE is acceptable. These values are basically a reflection of our previous observation that electricity use during the year is not affected much by temperature and is fairly constant.

Regarding the baseline model for gas use, we note from Table 6.1 that using case 2, i.e., temperature data shifted by one month compared to the utility bills, results in best models. Further, the small improvement in R^2 and CV-RMSE as we go from a 3P- heating model to a 4P model is not enough to justify using the unphysical 4P model. Also we preferred to use previous month in order to be consistent with electricity use models rather than adopt case 3 runs which seem slightly better. Consequently, we decided to choose the 3P-heating model as our baseline model for gas use. How the individual monthly data points scatter around the 3P-heating baseline model line can be seen in Fig. 6.9(a) while how they are captured by the next-best 4P model (clearly an unphysical behavior) can be gauged in Fig. 6.9(b). The gas models are very poor (low R^2 and very high CV-RMSE).

The main objective of the modeling effort is to develop models for the baseline year (FY86) for energy use. Instead of limiting ourselves to this year alone, we have also identified models for the years ranging from FY86 to FY94 in an effort to study, (i) how well the models fit the data over the years, and (ii) the extent to which the model coefficients vary from year to year. The model statistical indices R^2 and CV-RMSE which describe the goodness-of-fit of the models identified by EModel, are shown for individual years in Table 6.2 for electricity use and Table 6.3 for gas use. Figures 6.10 and 6.11, which are XY plots of the R^2 values and CV-RMSE values of the 9 electricity and gas models respectively for Fort Drum from FY86 to FY94, permit convenient visualization of how well the models are able to explain the variation in the utility data. As expected, data from different years would have yielded models with different goodness-of-fits. However, except for one year, these models are fairly consistent. It can be seen that for electricity the best model is for FY87, and the worst model is for FY90. For gas, the best model is for FY87 and the worst for FY86 (our baseline year). This suggests that perhaps the choice of the baseline model should not be done simply based on the first year of data availability (FY86 in this study) but based on the goodness-of-fit of models identified from the first few years of data available.

6.3 Baseline models for screening and tracking

Once baseline models have been developed, it is possible to use them as screening tools by comparing forecast levels with actual energy use. Effect of changes in weather from year-to-year (more accurately, outdoor temperature) on the energy use is explicitly accounted for by the baseline model forecasts. Deviations from expectations must be studied to determine whether known extraneous changes have contributed to this variation or whether these changes are a result of energy efficiency measures or DSM programs that have been initiated. How the PIs of the model are to be calculated have been described in section 3.3 for individual months and in section 3.4 on an annual basis. We have used our FY86 baseline models to forecast into the future up to FY94.

Figures 6.12 and 6.14 depict the extent to which the monthly energy use utility bills are bounded by the PIs of the FY86 baseline model for electricity use and gas use respectively. For clearer visualization, we have also shown the residuals (residual = measured value minus model predicted value) along with the PIs. If, say, the utility bill data for a month fall below the lower 95% PI, one can safely affirm that energy use during that month has decreased as compared to model predictions. We note that electricity use data are well contained within the PIs bands. Those for gas are also contained within the PIs, which however are large.

How well the FY86 baseline models for electricity and gas use are able to predict monthly energy use from FY86 till FY94 can be seen in Figs. 6.13 and 6.15 respectively. Note that the energy use is on a monthly mean daily basis per unit conditioned area but has not been normalized for changes in population from one year to the next. We note, as was expected from our observation of the time series plot that electricity use is consistently above the PIs indicating a very large increase in electricity use. Gas use also seems to have increased appreciably. However, plots such as this are useful to the energy manager of the corresponding Army base who is in a position to look for (as well as discern and evaluate) changes in energy use as a result of certain specific actions taken (such as O&M measures or say, changes in equipment in the power plants).

On an annual time scale, however, determination of percentage changes in energy use (normalized by conditioned area) with respect to the baseline year (FY86) permit rather well-defined conclusions to be drawn regarding the extent to which the Executive Order 12902 has been met. How these changes are to be determined as well as the 95% PIs of these changes have been described in sections 3.4 and 3.5. Following eqs.(3.16) and (3.17), we have computed the percentage changes on a year by year basis and plotted them in Fig. 6.16 for both electricity and gas. Note that a negative change indicates a decrease in energy use. Both electricity and gas use are clearly positive. Generally electricity use over the years as compared to the baseline year shows an increasing trend, with, however, FY94 use being lower than the previous years. Gas use has also increased with respect to the baseline, but seems to have remained constant from FY89 onwards. On the whole, we note that electricity use in FY94 has increased by about 37% ($\pm$ 7%) with respect to FY86, while gas use has increased by about 68% ($\pm$ 25%). Though both electricity and gas models are poor (which result in large uncertainty bands), the magnitude of the changes in both quantities are such that we can be confident of our estimates of change in energy use in FY94 as compared to our baseline year of FY86.

6.4 Concluding remarks

The best models for both electricity and gas were 3P-heating models indicating that energy use is predominantly used for space heating. The baseline electricity model identified for FY86 for Fort Drum was found to be mediocre with $R^2 = 0.66$ and CV-RMSE = 10.7%. The baseline gas model was very poor, $R^2 = 0.69$ and CV-RMSE = 36.5%. Our analysis indicated that electricity utility bills were mis-matched by a whole month and so a correction had to be made to the calendar monthly mean temperature data that we received. No such correction seems to be necessary for gas use.

Using the baseline models to track how energy use has increased (or decreased) over the years required that energy use during each year be normalized by the associated conditioned area of the army installation. (As described earlier, this quantity is not directly available from the database but has to be inferred from areas of several categories of building types which were listed in the database). This leads to a certain amount of unavoidable uncertainty in our conclusions regarding the screening and tracking aspects of the baseline models. We found that electricity use in FY94 has increased by about 37% ($\pm$7%) with respect to FY86, while gas use has increased by about 68% ($\pm$25%).

Finally, Fig.6.17 and Table 6.4 assemble the year to year percentage changes in annual energy use with respect to baseline year (FY86) normalized by (i) conditioned area, and (ii) conditioned area and population. Contrary to the earlier bases, the changes in energy use by both means of normalization are drastically different in view of the large increase in population over the years. If normalized according to (ii), both electricity and gas use over the years exhibit a significant decrease. As described in section 3.5, one cannot place as much confidence in the population values as in the conditioned area values, and so it would probably be better to draw conclusions regarding the extent to which Presidential Executive Order 12902 is being met based on conditioned area normalization only.

Table 6.1. Fort Drum: model identification summary statistics for baseline year (FY86). Final models selected are shown in bold face.

		3P-Heating		4P	
	Temperature data used	R^2	CV-RMSE (%)	R^2	CV-RMSE (%)
Electricity	Same month (T_1)	0.44	13.7	0.46	14.2
	Previous month (T_2)	**0.66**	**10.7***	0.68	11.1*
	Mid-month (T_3)	0.62	11.4	0.63	11.9
		3P-Heating		4P	
Gas	Same month (T_1)	0.60	41.4	0.64	41.6
	Previous month (T_2)	**0.69**	**36.5***	0.71	37.2*
	Mid-month (T_3)	0.70	35.7	0.74	35.4

* Plots of these models are shown in the report

Table 6.2. Fort Drum electricity use: 3P-heating model coefficients (and standard errors) and pertinent regression model statistics for all years

Year	Y_{cp} (kWh/d/ksq.ft)	LS (kWh/d/ksq.ft/F)	X_{cp} (°F)	R^2	CV-RMSE (%)	RMSE (kWh/d/ksq.ft)	n_1
FY1986	17.38(0.807)	-0.214(0.0482)	54.0	0.66	10.7	2.11	7
FY1987	24.23(0.568)	-0.171(0.0283)	57.6	0.78	5.4	1.43	7
FY1988	26.01(1.407)	-0.132(0.0474)	70.8	0.44	9.7	2.85	10
FY1989	28.30(1.201)	-0.166(0.1274)	42.0	0.15	11.8	3.46	6
FY1990	25.37(2.587)	-0.166(0.1144)	61.9	0.17	22.1	6.19	8
FY1991	29.82(0.696)	-0.265(0.0763)	44.6	0.55	6.3	1.95	5
FY1992	29.94(0.826)	-1.135(0.4645)	28.2	0.37	8.3	2.55	4
FY1993	29.31(1.301)	-0.140(0.0435)	69.9	0.51	8.2	2.68	10
FY1994	28.40(1.162)	-0.235(0.0503)	57.9	0.69	8.9	2.87	8

Table 6.3. Fort Drum gas use: 3P-heating model coefficients (and standard errors) and pertinent regression model statistics for all years

Year	Y_{cp} (cf/d/ksq.ft)	LS (cf/d/ksq.ft/F)	X_{cp} (°F)	R^2	CV-RMSE (%)	RMSE (cf/d/ksq.ft)	n_1
FY1986	19.65(4.709)	-1.386(0.2926)	53.0	0.69	36.5	12.43	7
FY1987	8.22(1.469)	-1.309(0.0633)	62.0	0.98	11.4	3.47	9
FY1988	17.36(12.345)	-3.328(0.5017)	64.3	0.81	34.8	27.73	10
FY1989	25.08(16.687)	-3.840(0.5730)	70.0	0.82	29.0	33.69	11
FY1990	50.36(18.945)	-3.254(0.6802)	68.8	0.70	33.5	40.65	10
FY1991	33.69(10.106)	-4.240(0.4172)	67.2	0.91	20.2	22.62	10
FY1992	40.01(12.460)	-4.279(0.4929)	65.1	0.88	22.0	27.22	10
FY1993	38.39(21.192)	-3.926(0.7535)	67.6	0.73	36.1	45.23	10
FY1994	32.26(14.545)	-3.476(0.4610)	69.2	0.85	26.3	31.17	11

Table 6.4 Baseline models and percentage change in energy use w.r.t baseline year for Fort Drum.

Energy type	Baseline year	Model type	Model fit	Year	% change normalized by conditioned area with 95% PI	% change normalized by conditioned area and population
Electric.	FY86	3P-H	Good	FY87	25.20 ± 7.27	-50.85
				FY88	31.74	-148.10
				FY89	31.70	-216.39
				FY90	29.67	-229.05
				FY91	37.68	-278.77
				FY92	35.58	-162.22
				FY93	38.69	-145.67
				FY94	37.01	-150.73
Gas use	FY86	3P-H	Poor	FY87	-15.24 ± 24.78	-132.40
				FY88	55.64	-61.22
				FY89	69.51	-41.24
				FY90	71.95	-31.23
				FY91	71.13	-75.49
				FY92	71.75	-14.98
				FY93	71.24	-15.24
				FY94	68.19	-26.60

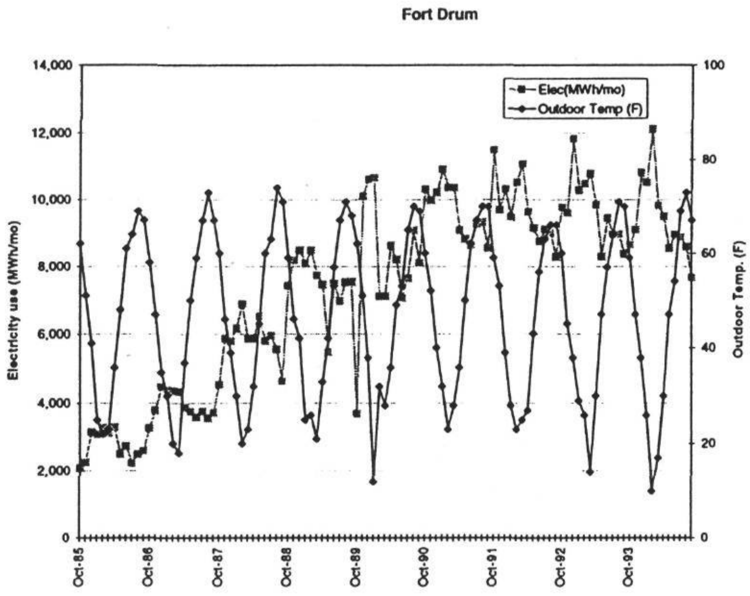


Fig.6.1(a) Electricity use.

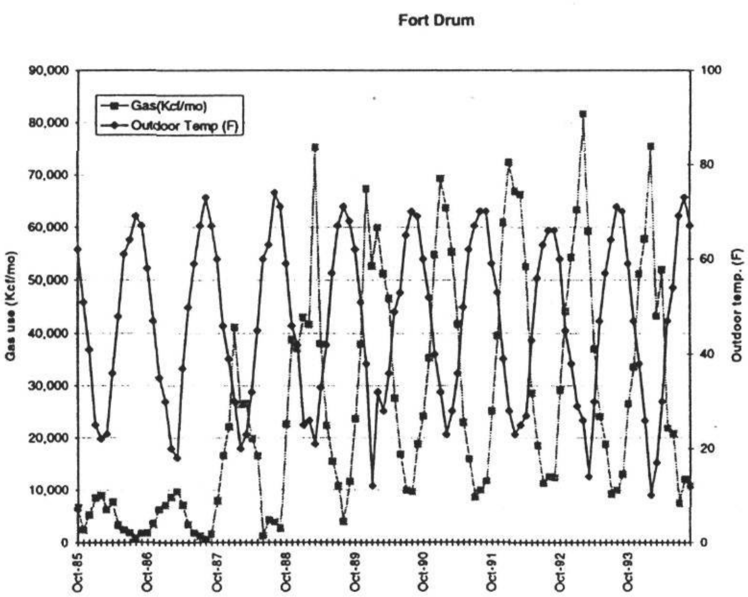


Fig.6.1(b) Gas use

Figure 6.1. Time series plots of monthly electricity and gas consumption for Fort Drum from FY86 to FY94. The concurrent outdoor dry-bulb temperature variation is also shown.

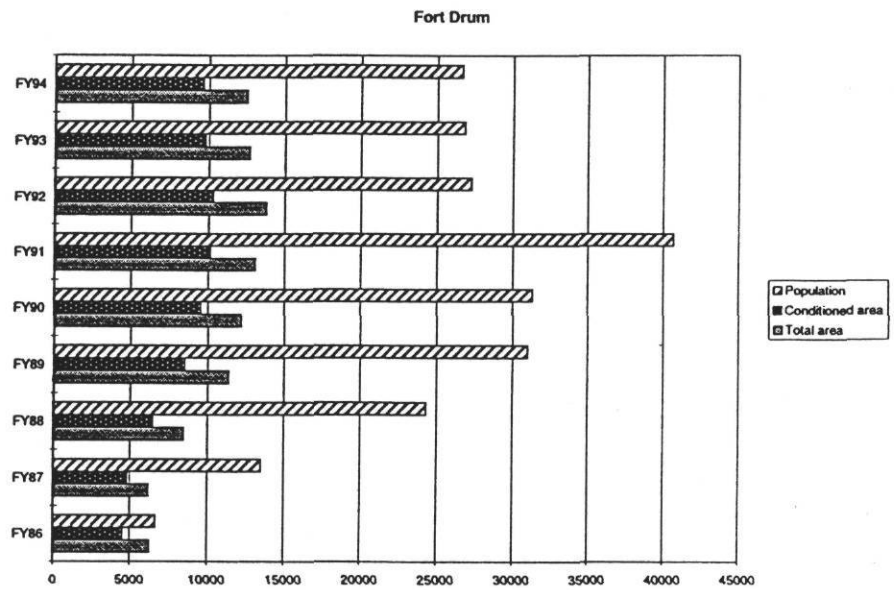


Figure 6.2. Changes in total and conditioned areas (in ksq.ft) and annual mean daily population for Fort Drum from FY86 to FY94.

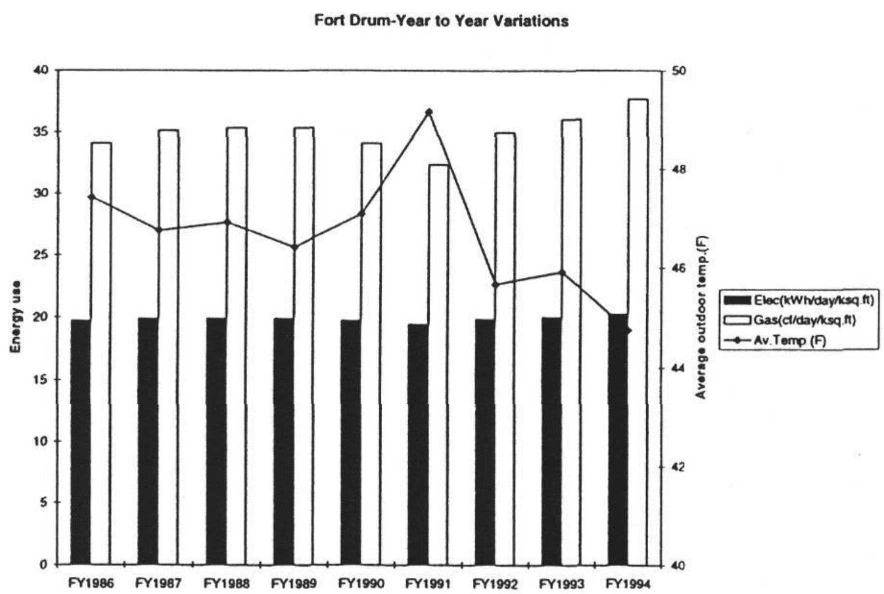


Figure 6.3 Changes in annual mean daily energy use per conditioned area and annual mean outdoor temperature for Fort Drum from FY86 to FY94.

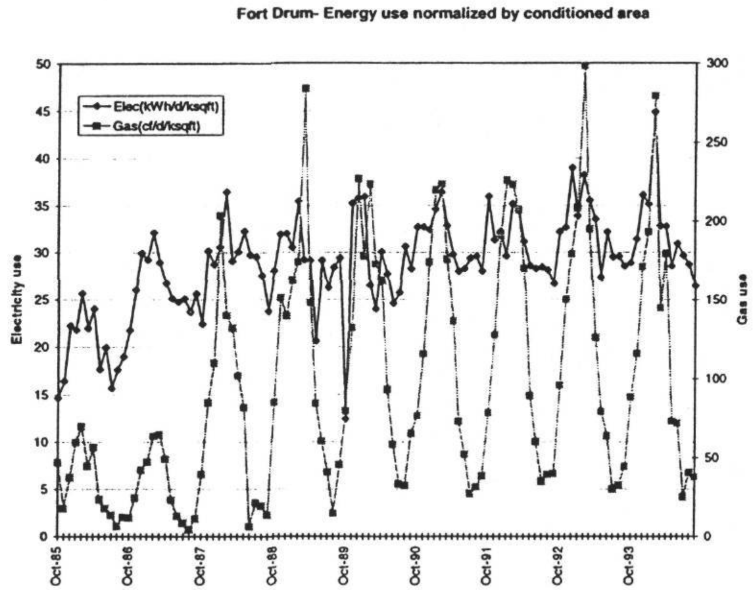


Figure 6.4. Time series graphs of monthly electricity and gas consumption per unit conditioned area for Fort Drum from FY86 to FY94.

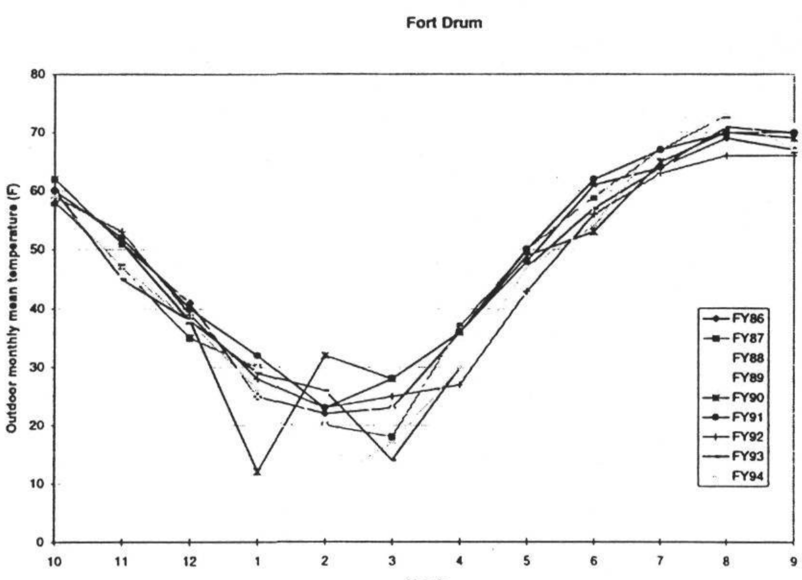


Figure 6.5. Time series plots of average monthly temperatures at Fort Drum from FY86 to FY94.

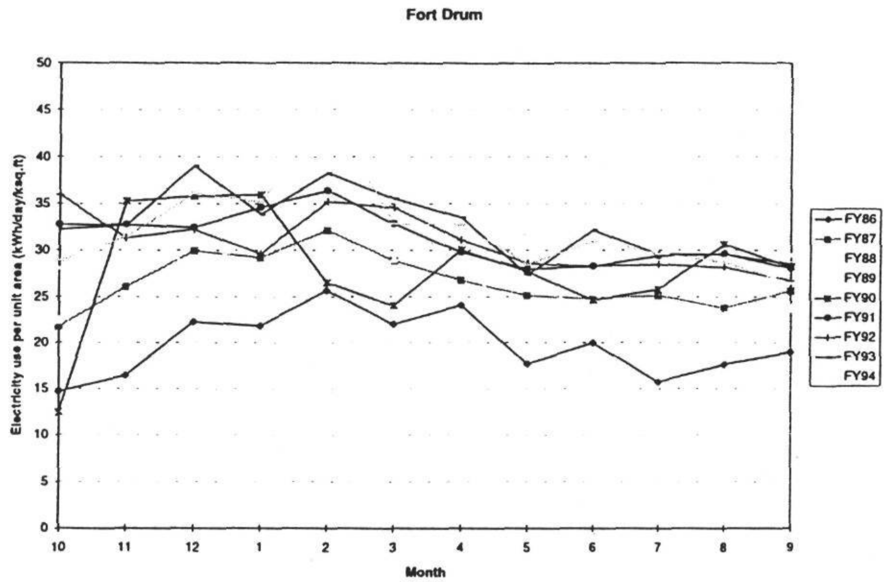


Figure 6.6. Time series plots of electricity use per unit conditioned area for Fort Drum from FY86 to FY94.

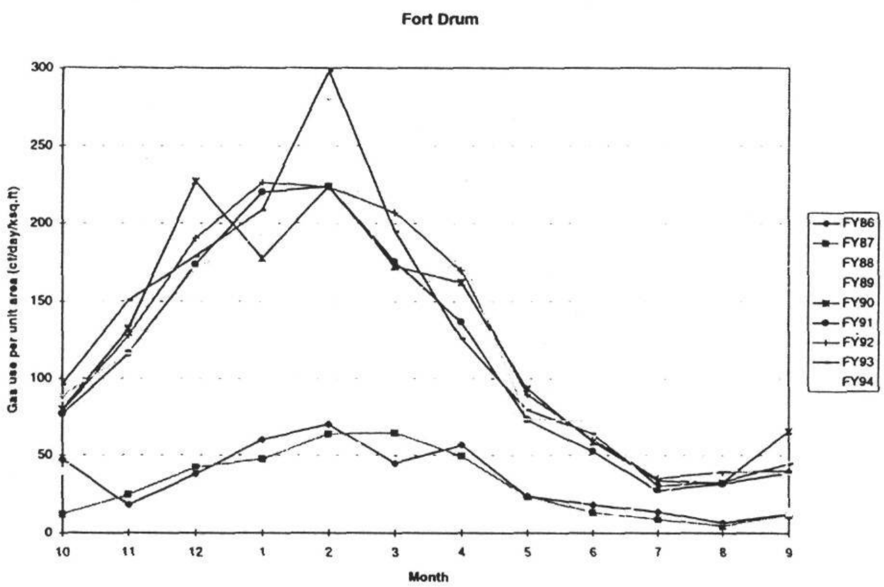


Figure 6.7. Time series plots of gas use per unit conditioned area for Fort Drum from FY86 to FY94.

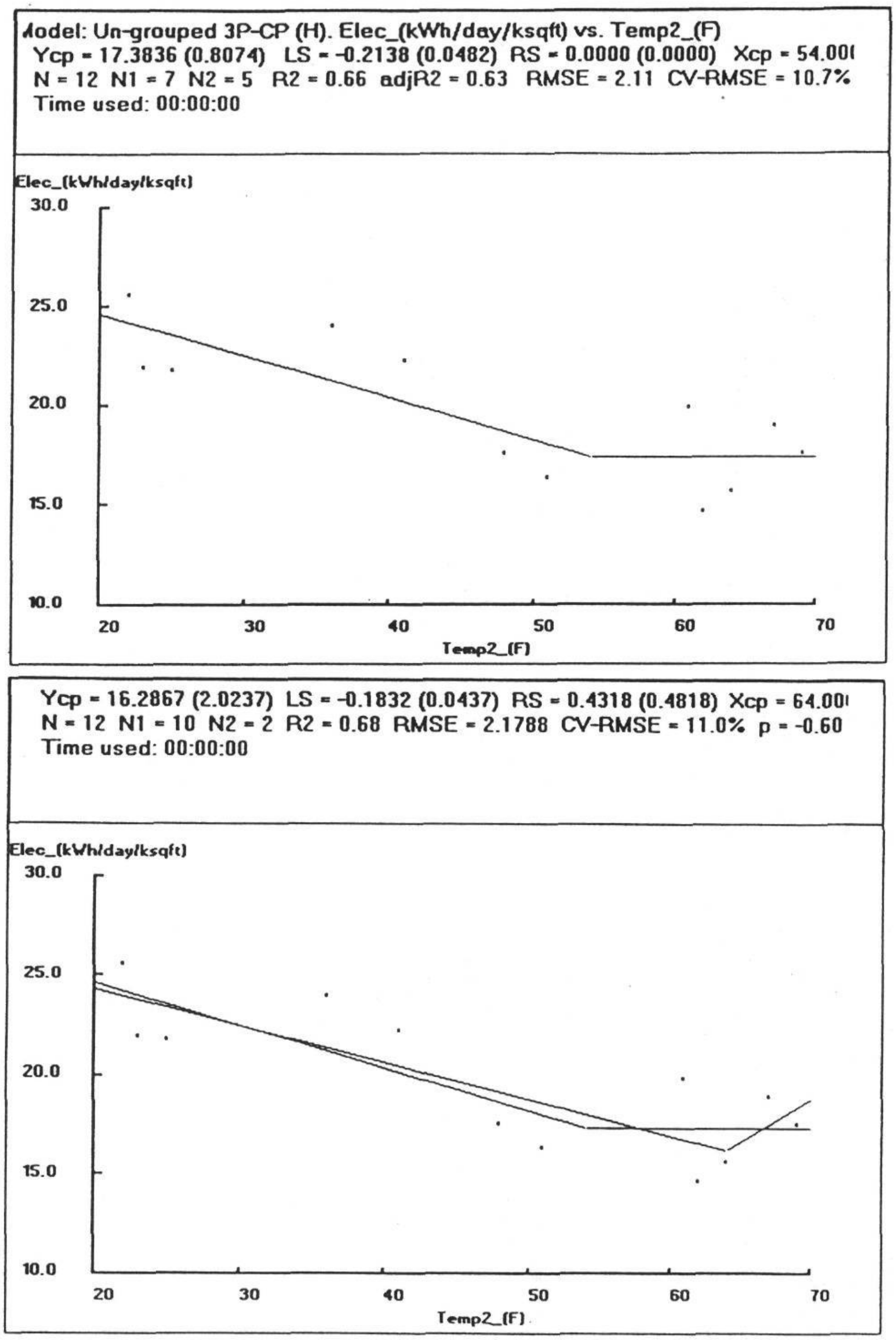


Figure 6.8. EModel change point model line and data points for Fort Drum electricity consumption for baseline year (FY86). A one-month shift in temperature led to substantial model improvement. (a) 3P-heating model selected as baseline, (b) 3P model line and next-best model, namely the 4P model line, are shown for comparative purposes.

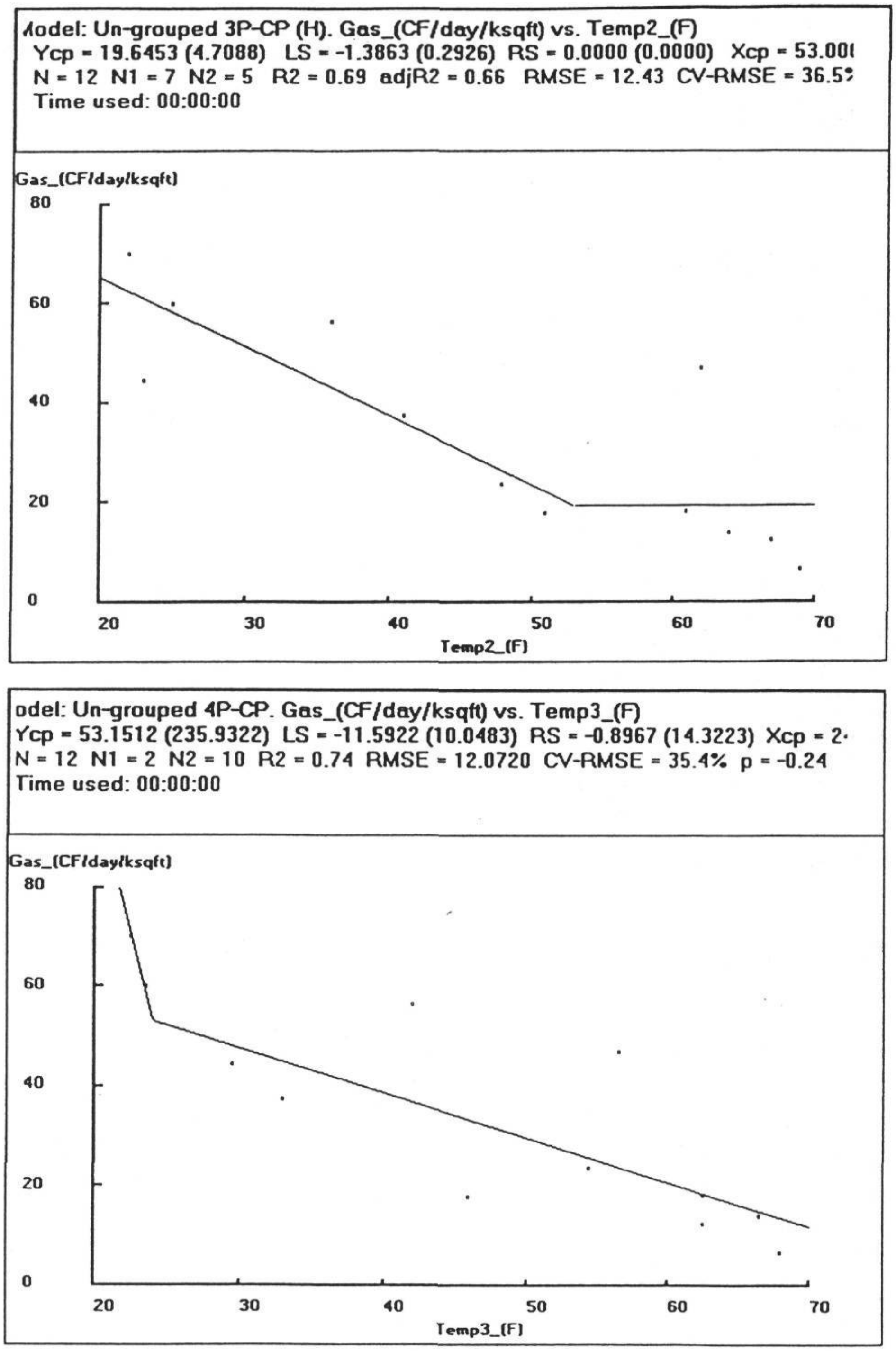


Figure 6.9. EModel change point model line and data points for Fort Drum natural gas consumption for baseline year (FY86). A one-month shift in temperature led to substantial model improvement. (a) 3P-heating model selected as baseline, (b) next-best model, namely the 4P model line, is shown for comparative purposes.

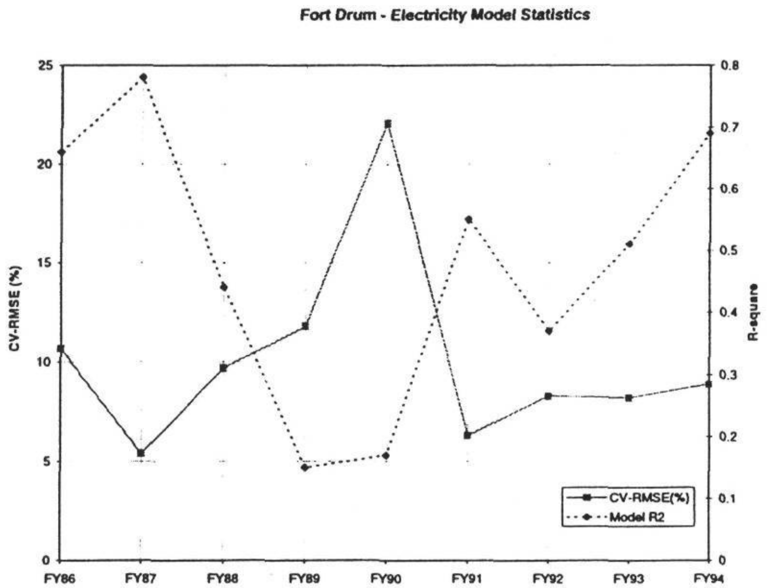


Figure 6.10. R^2 and CV-RMSE of electricity models for the years from FY86 to FY94 for Fort Drum.

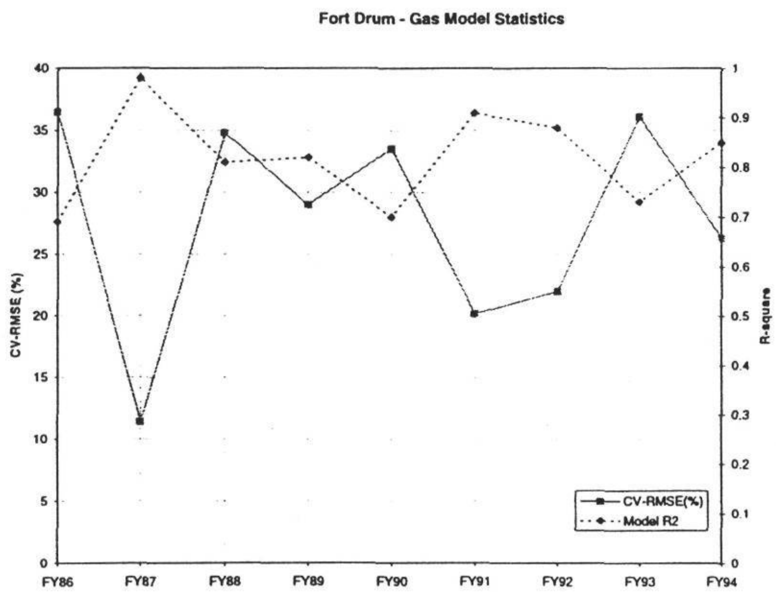


Figure 6.11 R^2 and CV-RMSE of gas models for the years from FY86 to FY94 for Fort Drum.

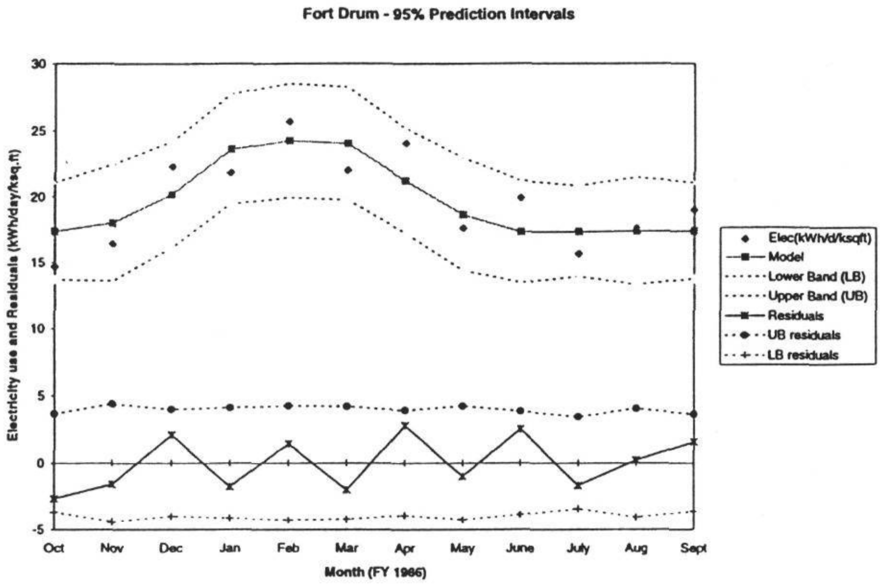


Figure 6.12. Predictive ability of the baseline model (FY86) for Fort Drum electricity use during FY86. 95% prediction intervals for the model as well as for the model residuals are shown.

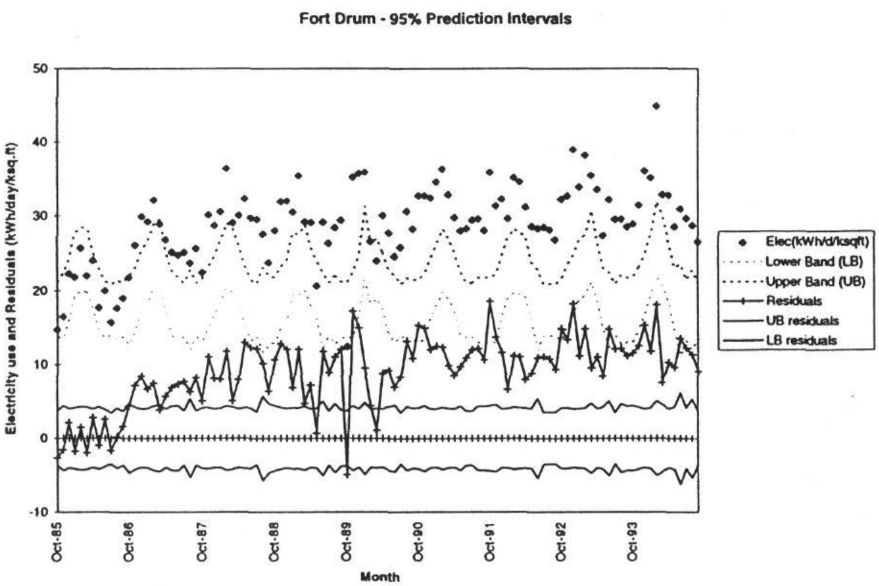


Figure 6.13. Predictive ability of electricity baseline model (FY86) for Fort Drum from FY86 to FY94. 95% prediction intervals for the model as well as for the residuals are shown.

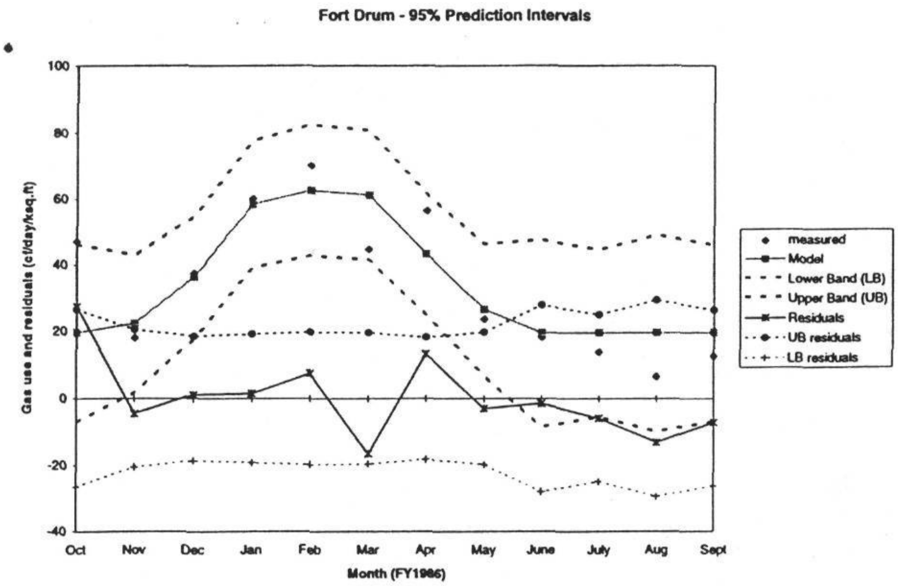


Figure 6.14. Predictive ability of the baseline model (FY86) for Fort Drum gas use during FY86. 95% prediction intervals for the model as well as for the model residuals are shown.

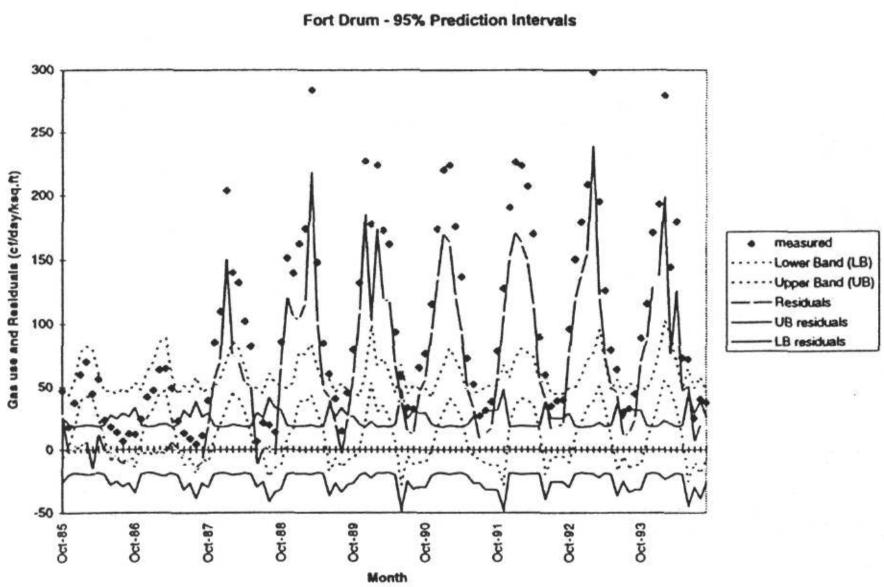


Figure 6.15. Predictive ability of gas baseline model (FY86) for Fort Drum from FY86 to FY94. 95% prediction intervals for the model as well as for the residuals are shown.

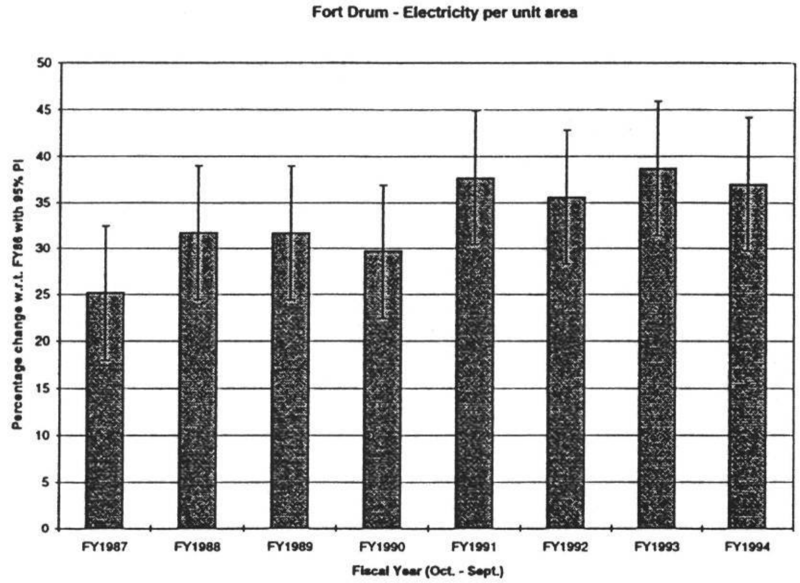


Fig.6.16(a) Electricity use

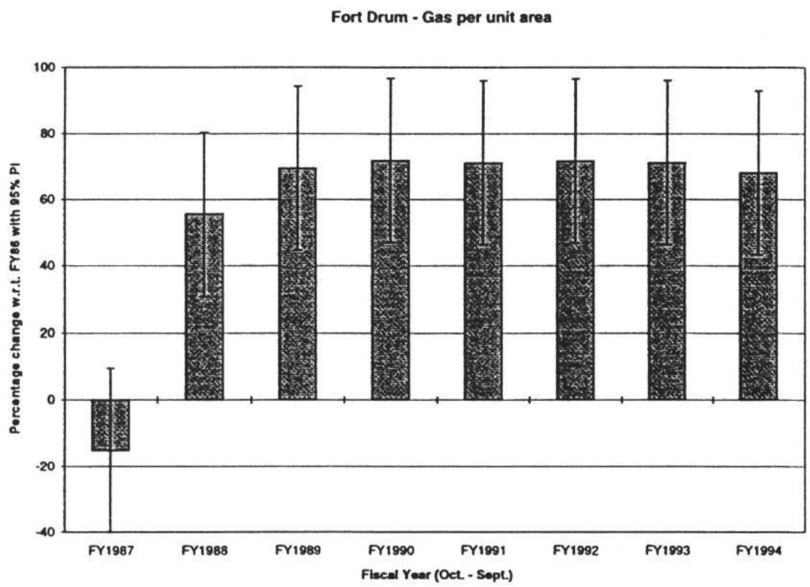


Fig.6.16(b) Gas use

Figure 6.16. Percentage change in annual energy use per conditioned area with respect to baseline year (FY86) for Fort Drum. Negative change indicates decrease in energy use and vice versa. 95% confidence intervals for the percentage change are also shown.

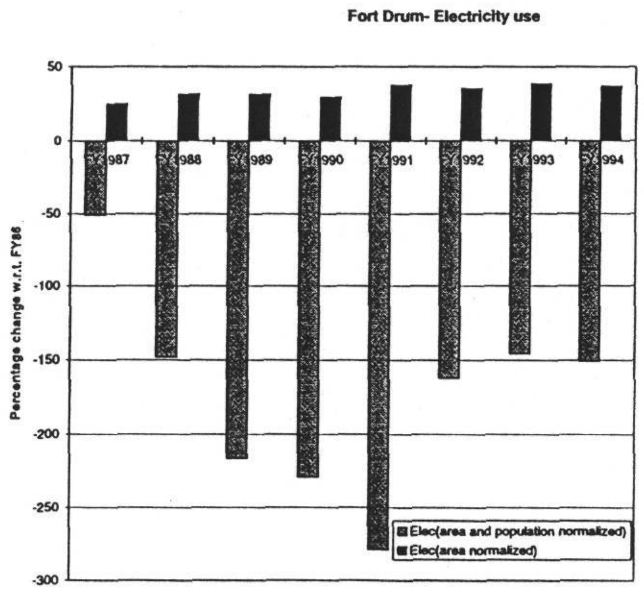


Fig.6.17(a) Electricity use

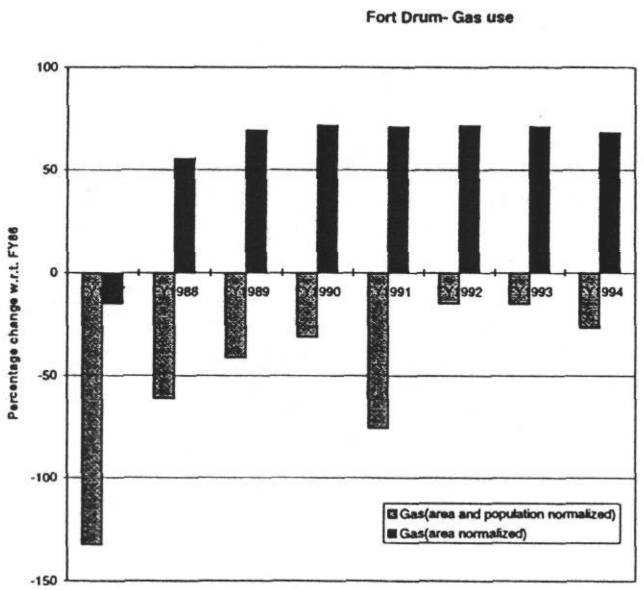


Fig6.17(b) Gas use

Figure 6.17. Percentage changes in annual energy use with respect to baseline year (FY86) for Fort Drum with conditioned area normalization as well as with area and population normalization.

7.0 Analysis of Fort Hood, TX

7.1 Preliminary data analysis

Time series plots of monthly electricity use and gas use from FY86 to FY94 are shown in Fig. 7.1 along with concurrent outdoor temperature. The variation patterns of all three channels are fairly consistent over the years. As expected, gas use peaks in winter while electricity use seems to be mostly in summer due to air-conditioning. There does seem to be a slight increase in electricity use during the winter months also leading us to suspect electric heating applications such as heat pumps or electric strip heating in a portion of the buildings.

Figure 7.2 shows the change in total building area and conditioned area (determined as described in section 2.2) over the years. Both these areas seem to have been generally constant over the years. Total building area has increased a little over the years, about 8% from FY86 to FY94. The conditioned area does not seem to have changed at all over the years. Annual mean daily population data is also plotted in Fig.7.2. Population seems to have decreased by about 8% from FY86 till FY94 with increases and decreases occurring over the years.

Figure 7.3 shows the changes in annual mean daily energy use per unit conditioned area over the years. Except for an increase in gas use in FY87, both gas use and electricity use are fairly consistent over the years. The annual mean outdoor temperature is also plotted in order to enable the reader to associate changes in energy use with temperature changes. For example, FY87 is a cold year and gas use seems to have increased that year. Plots such as these provide a general qualitative trend and one should not try to read too much from them.

Figure 7.4 presents time series graphs of monthly electricity and gas use normalized by building conditioned area. We notice that generally gas use has been constant until FY91 and then decreased from FY92 onwards. Electricity use seems to have increased gradually over the years.

Figure 7.5 depicts the average monthly outdoor temperatures during a year for all years from FY86 to FY94. We note that the weather during these years seems to be remarkably consistent over the years. Temperature data for FY86, our baseline year, seems to be fairly characteristic except for November which is hotter and January and September which is cooler than other years.

Figures 7.6 and 7.7 are time series plots of electricity use and gas use normalized by conditioned area during a year for all years from FY86 to FY94. This type of representation allows clearer visualization of how energy use has changed over the years for a given month. The sharp increases in electricity use in July and gas use during the winter are obvious. One notices the odd behavior in both electricity and gas uses during FY94 as compared to the rest of the years.

7.2 Baseline modeling

As described earlier, there is an ambiguity regarding proper match between the utility bill period and the corresponding temperature data supplied to us. In section 3.6, we had suggested a method whereby we would identify the best model from three different sets of runs where the temperature data has been taken in slightly different ways. The criteria for selecting the optimum model among the various runs are as follows:

(i) highest R^2 and lowest CV-RMSE,

(ii) if R^2 values for all models are low, CV-RMSE is to be given more consideration, and

(iii) it would be more appropriate from physical considerations, to select 3-P models rather than 4-P models. Only if the improvement in R^2 and CV-RMSE is substantial, would we relax this rule.

Note that both electricity and gas use during the year have been normalized with the conditioned area of the army base during that particular year prior to model identification. The summary model statistics of our baseline model identification effort for all three cases are summarized in Table 7.1. We notice that the utility bill and the associated temperature data are well matched and so no correction is required (i.e., case 1 in section 3.6) are used for regression. For electricity, the 3P-cooling model seems to be the best choice for a baseline model (see Table 6.1). How the model line fits the data points can be noted in Fig.7.8. The model is excellent with R^2 = 0.98 and CV-RMSE = 5.2 %.

Regarding the baseline model for gas use, we note from Table 7.1 that using case 1, i.e., temperature data corresponding to the same calendar months as the utility bills, results in best models. Further, the small improvement in R^2 and CV-RMSE as we go from a 3P-heating model to a 4P model is not enough to justify using the unphysical 4P model. Consequently, we decided to choose the 3P heating model as our baseline model for gas use. How the individual monthly data points scatter around the 3P heating baseline model line can be seen in Fig. 7.9(a) while how they are captured by the next-best 4P model can be gauged in Fig. 7.9(b). The model is very good with R^2 = 0.98 and CV-RMSE = 10.1 %.

7.3 Baseline models for screening and tracking

Once baseline models have been developed, it is possible to use them as screening tools by comparing forecast levels with actual energy use. Effect of changes in weather from year-to-year (more accurately, outdoor temperature) on the energy use is explicitly accounted for by the baseline model forecasts. Deviations from expectations must be studied to determine whether known extraneous changes have contributed to this variation or whether these changes are a result of energy efficiency measures or DSM programs that have been initiated. How the PIs of the model are to be calculated have been described in section 3.3 for individual months and in section 3.4 on an annual basis. We have used our FY86 baseline models to forecast into the future up to FY94.

Figures 7.10 and 7.12 depict the extent to which the monthly energy use utility bills are bounded by the PIs of the FY86 baseline model for electricity use and gas use respectively. For clearer visualization, we have also shown the residuals (residual = measured value minus model predicted value) along with the PIs. If, say, the utility bill data for a month fall below the lower 95% PI, one can safely affirm that energy use during that month has decreased as compared to model predictions. We note that both electricity and gas use data have rather narrow PIs bands which is not surprising since the models are very good (see Table 7.1).

How well the FY86 baseline models for electricity and gas use are able to predict monthly energy use from FY86 till FY94 can be seen in Figs. 7.11 and 7.13 respectively. Note that the energy use is on a monthly mean daily basis per unit conditioned area but has not been normalized for changes in population from one year to the next. We note that electricity use is generally contained within the PIs indicating no consistent increase in electricity use. The only exception is during FY94 where an abnormal increase can be noticed. Gas use is also generally bounded by the PIs (see Fig. 7.13) with however, gas use showing a statistically significant decrease both in summer of FY93 and FY94. However, plots such as this are useful to the energy manager of the corresponding Army base who is in a position to look for (as well as discern and evaluate) changes in energy use as a result of certain specific actions taken (such as O&M measures or say, changes in equipment in the power plants).

On an annual time scale, however, determination of percentage changes in energy use (normalized by conditioned area) with respect to the baseline year (FY86) permit rather well-defined conclusions to be drawn regarding the extent to which the Executive Order 12902 has been met. How these changes are to be determined as well as the 95% PIs of these changes have been described in sections 3.4 and 3.5. Following eqs.(3.16) and (3.17), we have computed the percentage changes on a year by year basis (see Table 7.4) and plotted them in Figs. 7.14 for both electricity and gas. Note that a negative change indicates a decrease in energy use. Generally electricity use over the years as compared to the baseline year shows an increasing trend, with a rather large increase in FY94. Gas use, on the other hand, has decreased specially from FY91 - FY94 with respect to the baseline year. Interestingly, gas use in FY94 has increased compared to FY92 and FY93. On the whole, we note that electricity use in FY94 has increased by about 21% ($\pm$ 3%) with respect to FY86, while gas use has decreased by about 13% ($\pm$ 7%).

7.4 Concluding remarks

The baseline models identified for FY86 for Fort Hood were found to be very good with the electricity model having R^2 = 0.98 and CV-RMSE = 5.2%, and the gas model having R^2 = 0.98 and CV-RMSE = 10.1%. Our analysis indicated that no correction was necessary between utility bills and calendar monthly mean temperature data that we received. This observation is consistent with our previous study done at Fort Hood (Saman et al., 1995). The best model for electricity was a 3P-cooling model while the best model for gas was a 3P-heating model.

Using the baseline models to track how energy use has increased (or decreased) over the years required that energy use during each year be normalized by the associated conditioned area of the army installation. (As described earlier, this quantity is not directly available from the database but has to be inferred from areas of several categories of building types which were listed in the database). This leads to a certain amount of unavoidable uncertainty in our conclusions regarding the screening and tracking aspects of the baseline models. We found that electricity use in FY94 has increased by about 21% ($\pm$ 3%) with respect to FY86, while gas use has decreased by about 13% ($\pm$ 7%).

In our previous Fort Hood study (Saman et al., 1995), we had used calendar year (not fiscal year as done in this study) for all analyses. Further, we used 1987 as the baseline year (while here we have used FY86 as the baseline year), and compared annual changes in electricity use and gas use till calendar year 1993. Despite these differences, we can still acquire an indication as to the extent to which the results of both studies differ with each other. Recall that the former study used carefully monitored on-site data which was subsequently "reality-checked" while the temperature data was acquired by ESL from Temple, TX (a nearby location). The data of the current study was from general sources such as the army central utility bills database and the NCDC climatic data. One of the objectives of this study was also to investigate the extent to which data from such general sources would yield reliable estimates of how energy use in a particular DoD installation is varying over the years. The previous study found that electricity use normalized by conditioned area from calendar year

1987 till 1993 increased by 4.7% while gas use decreased by 20.4%. Looking at Fig. 7.14, we find that the difference in electricity use between FY93 and FY87 suggests an increase of about 7%, while that for gas use is about 20%. These figures are fairly consistent with those of the previous study thereby indicating that conclusive estimates of how energy use in a particular DoD installation has varied over the years with respect to a baseline year can be reached even with "unproofed" data obtained from general sources.

We also investigated another issue with the energy use data from Fort Hood. One could question the need to have such an involved baselining and evaluation methodology as the one adopted here specially since the month to month variation patterns of outdoor temperature over the years were fairly consistent (see Fig. 7.5). One would be curious to ascertain the differences in our estimates of how energy use over the years has changed with respect to a baseline year by the present approach and by a much simpler approach involving direct annual utility bills comparison without any weather correction (see eq.3.18). Figure 7.15 illustrates the amount of differences in percentage changes between the two approaches, namely with and without weather correction. We notice that though the differences are small during certain years, these are very large during other years (for example, gas use during FY87 and FY93). More importantly, these seems to be no pattern to the differences in percentage changes between both methods. The above comparison serves to reinforce a similar conclusion reached with Fort Bragg data (see Fig. 4.15), namely that weather correction is absolutely necessary in order to obtain reliable estimates of how energy use has varied over the years.

Finally, Fig.7.16 and Table 7.4 assemble the year to year percentage changes in annual energy use with respect to baseline year (FY86) normalized by (i) conditioned area, and (ii) conditioned area and population. The changes in energy use by both means of normalization are very different, the difference being pronounced for gas. As described in section 3.5, one cannot place as much confidence in the population values as in the conditioned area values, and so it would probably be better to draw conclusions regarding the extent to which Presidential Executive Order 12902 is being met based on conditioned area normalization only.

Table 7.1. Fort Hood: model identification summary statistics for baseline year (FY86). Final models selected are shown in bold face.

		3P-Cooling		4P	
	Temperature data used	R^2	CV-RMSE (%)	R^2	CV-RMSE (%)
Electricity	Same month (T_1)	**0.98**	**5.2***	0.98	5.4
	Previous month (T_2)	0.72	19.1	0.72	19.9
	Mid-month (T_3)	0.92	10.2	0.92	10.5
		3P-Heating		4P	
Gas	Same month (T_1)	**0.98**	**10.1***	0.99	8.8*
	Previous month (T_2)	0.60	49.0	0.60	51.5
	Mid-month (T_3)	0.87	27.3	0.88	28.2

* Plots of these models are shown in the report

Table 7.2. Fort Hood electricity use: model coefficients (and standard errors) and pertinent regression model statistics for FY86.

Model type	Y_{cp} (kWh/d/ksq.ft)	RS (kWh/d/ksq.ft/F)	X_{cp} (°F)	R^2	CV-RMSE (%)	RMSE (kWh/d/ksq.ft)	n_1
3P-C	31.46(0.871)	2.142(0.0992)	67.0	0.98	5.2	2.28	5

Table 7.3. Fort Hood gas use: model coefficients (and standard errors) and pertinent regression model statistics for FY86.

Model type	Y_{cp} (cf/d/ksq.ft)	LS (cf/d/ksq.ft/F)	X_{cp} (°F)	R^2	CV-RMSE (%)	RMSE (cf/d/ksq.ft)	n_1
3P-H	87.11(7.620)	-16.50(0.689)	71.0	0.98	10.1	20.44	7

Table 7.4 Baseline models and percentage change in energy use w.r.t baseline year for Fort Hood.

Energy type	Baseline year	Model type	Model fit	Year	% change normalized by conditioned area with 95% PI	% change normalized by conditioned area and population
Electric.	FY86	3P-C	Excellent	FY87	3.88 ± 3.54	13.40
				FY88	2.56	-1.06
				FY89	6.75	4.75
				FY90	9.82	20.88
				FY91	5.00	9.72
				FY92	8.54	30.05
				FY93	10.90	23.33
				FY94	20.62	26.06
Gas use	FY86	3P-H	Good	FY87	1.03 ± 6.86	10.83
				FY88	-6.84	-10.81
				FY89	3.03	0.95
				FY90	1.25	13.35
				FY91	-11.61	-6.07
				FY92	-14.00	12.81
				FY93	-19.05	-2.43
				FY94	-13.32	-5.56

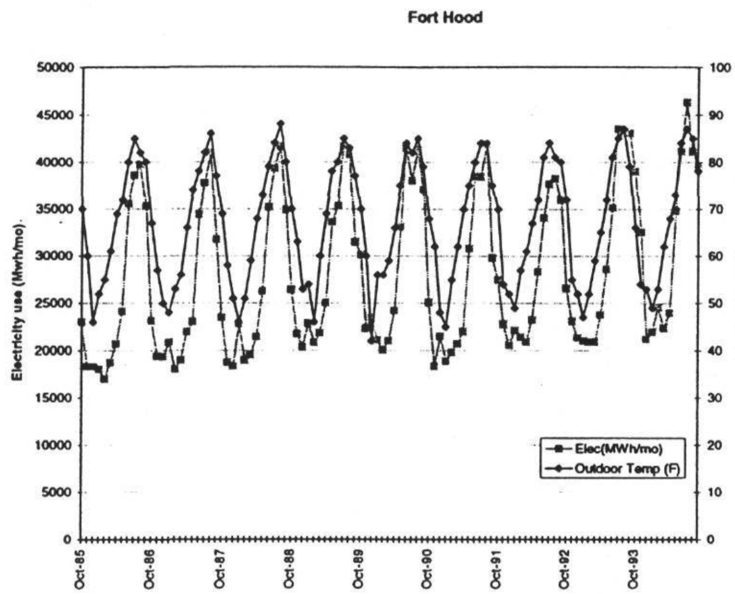


Fig.7.1(a) Electricity use

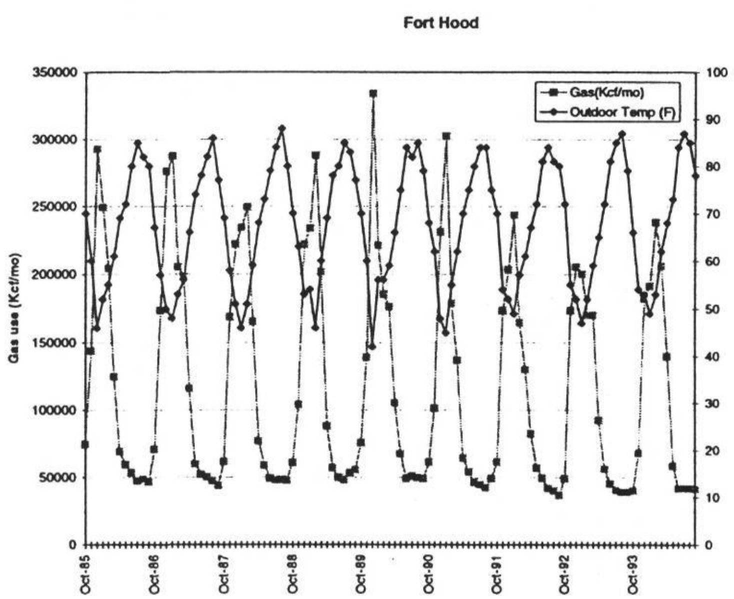


Fig.7.1(b) Gas use

Figure 7.1. Time series plots of monthly electricity and gas consumption for Fort Hood from FY86 to FY94. The concurrent outdoor dry-bulb temperature variation is also shown.

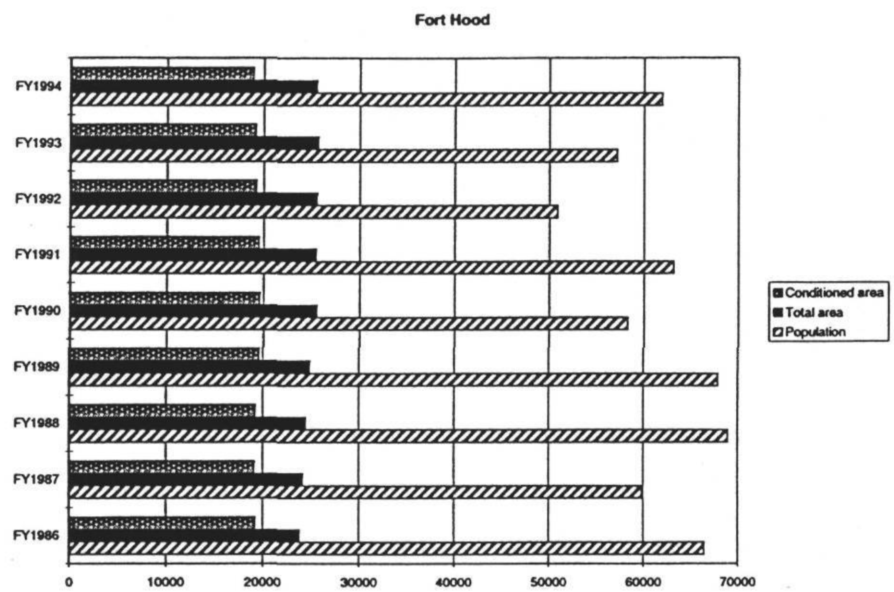


Figure 7.2. Changes in total and conditioned areas (in ksq.ft) and annual mean daily population for Fort Hood from FY86 to FY94.

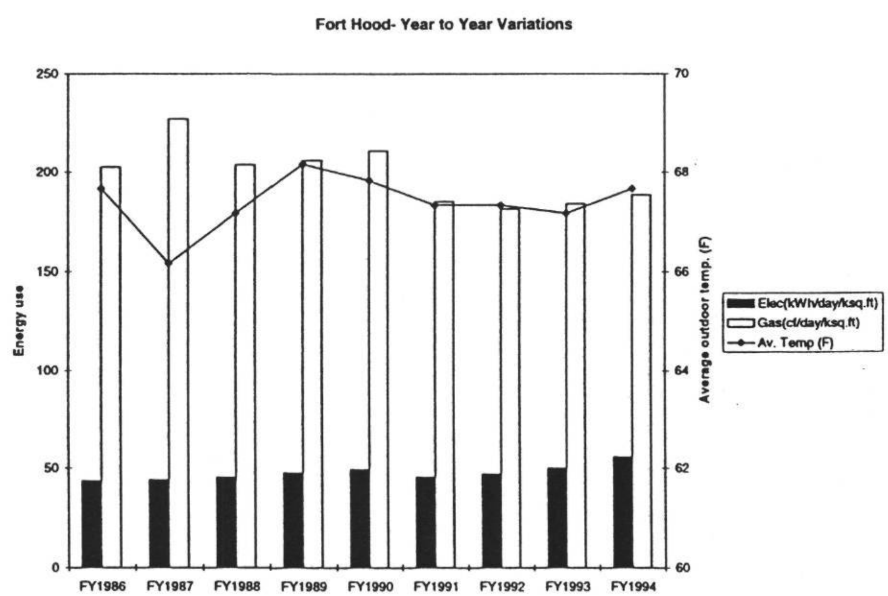


Figure 7.3 Changes in annual mean daily energy use per conditioned area and annual mean outdoor temperature for Fort Hood from FY86 to FY94.

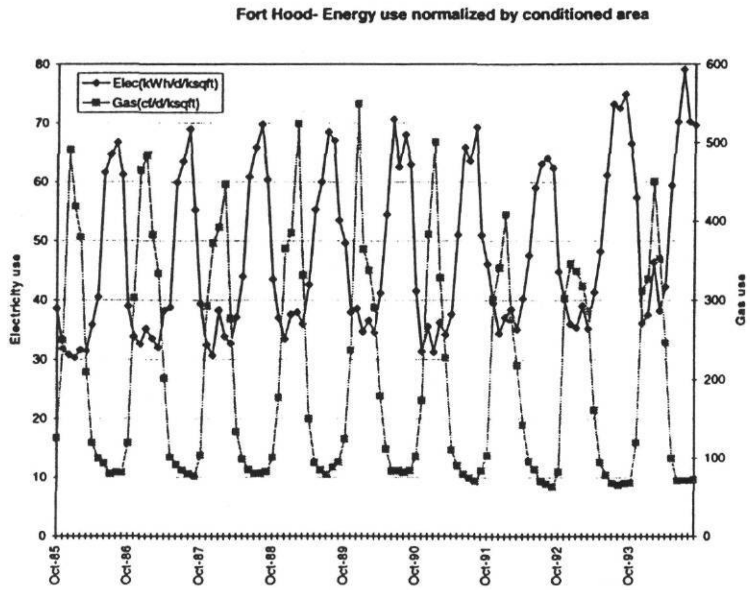


Figure 7.4. Time series graphs of monthly electricity and gas consumption per unit conditioned area for Fort Hood from FY86 to FY94.

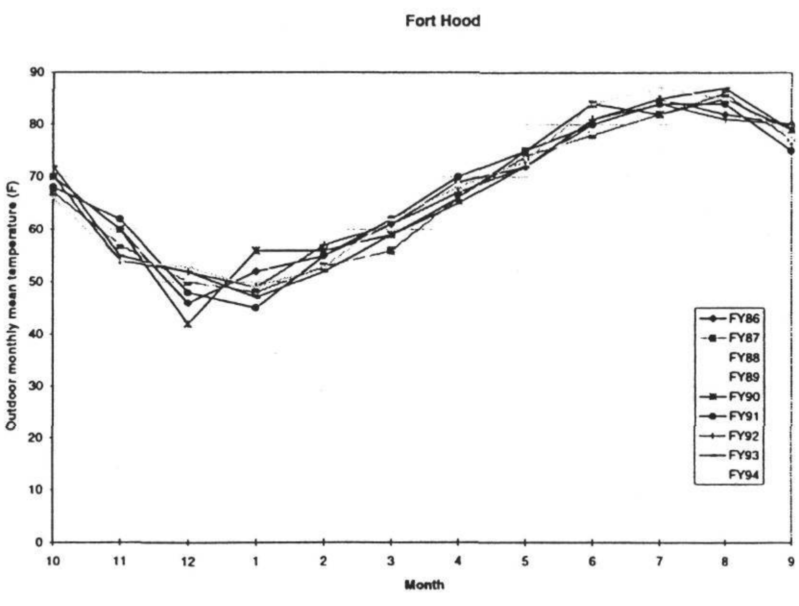


Figure 7.5. Time series plots of average monthly temperatures at Fort Hood from FY86 to FY94

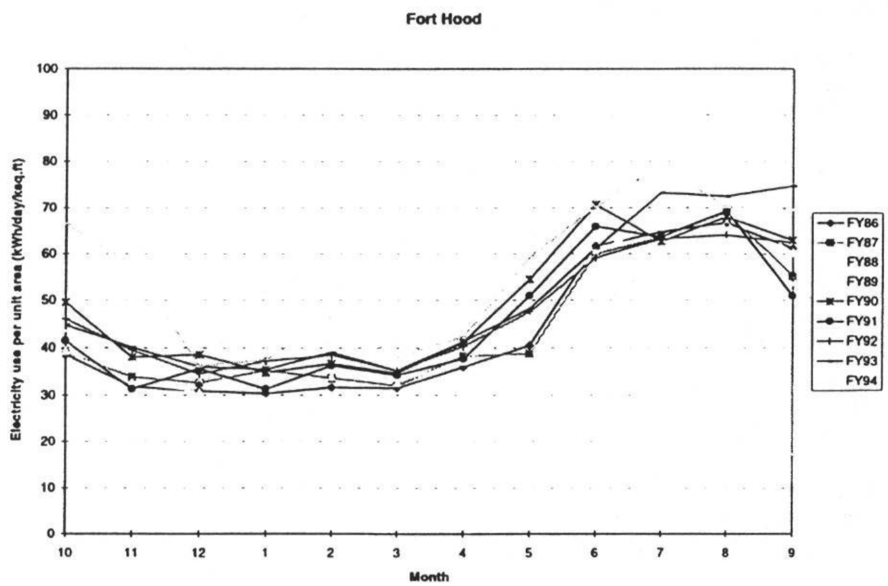


Figure 7.6. Time series plots of electricity use per unit conditioned area for Fort Hood from FY86 to FY94.

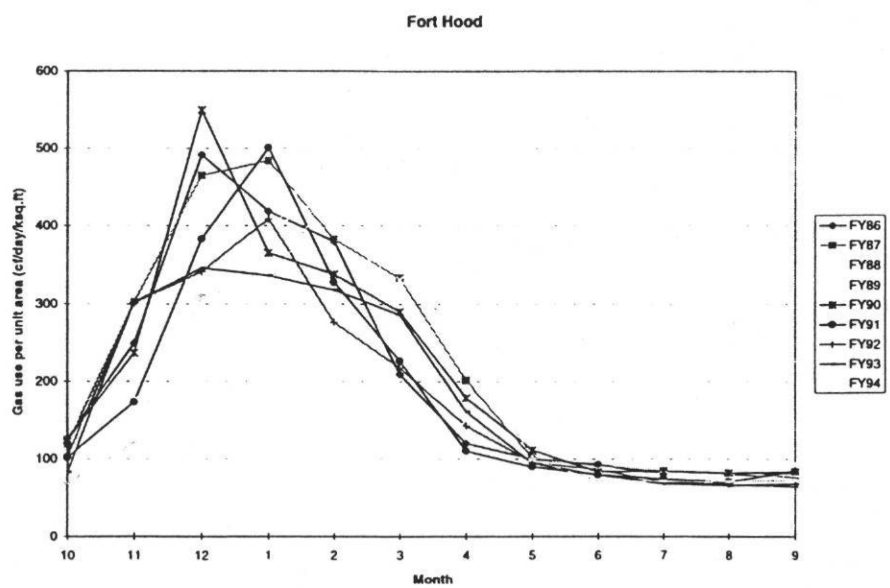


Figure 7.7. Time series plots of gas use per unit conditioned area for Fort Hood from FY86 to FY94.

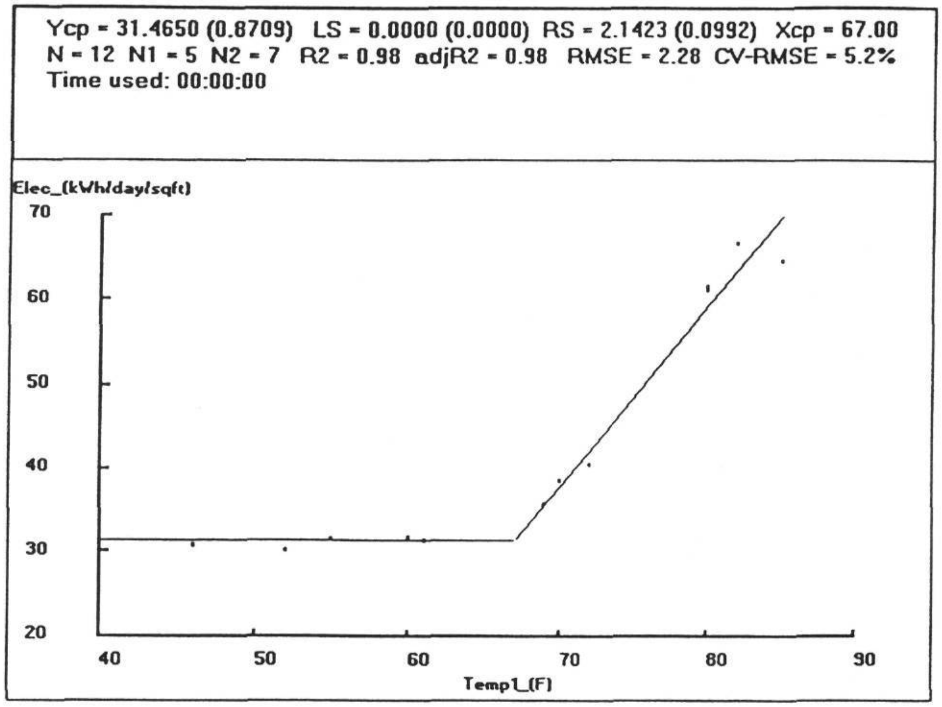


Figure 7.8. EModel change point model line and data points for Fort Hood electricity consumption for baseline year (FY86). 3P-cooling model selected as baseline.

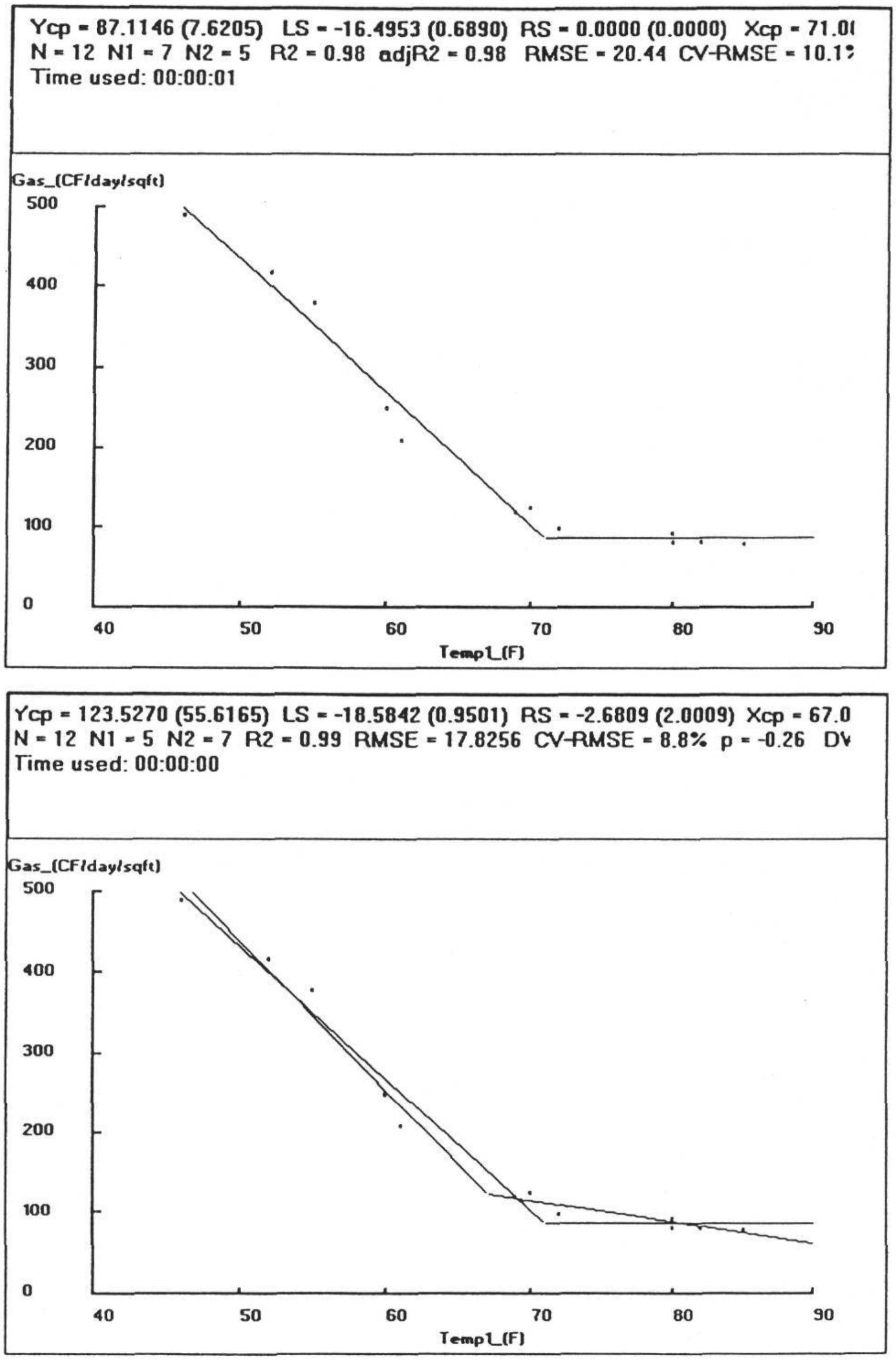


Figure 7.9. EModel change point model line and data points for Fort Hood natural gas consumption for baseline year (FY86). (a) 3P-heating model selected as baseline, (b) next-best model, namely the 4P model line, is shown for comparative purposes.

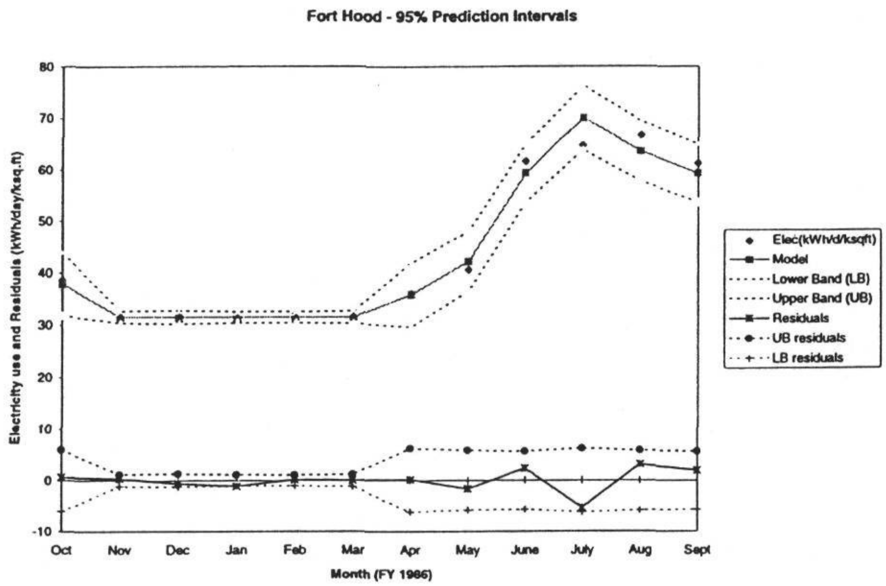


Figure 7.10. Predictive ability of the baseline model (FY86) for Fort Hood electricity use during FY86. 95% prediction intervals for the model as well as for the model residuals are shown.

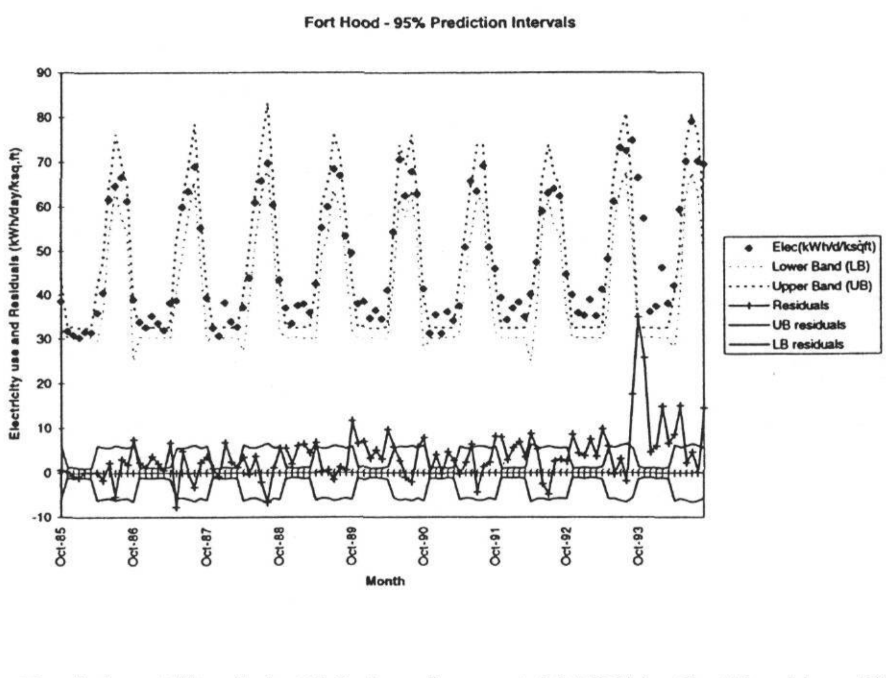


Figure 7.11. Predictive ability of electricity baseline model (FY86) for Fort Hood from FY86 to FY94. 95% prediction intervals for the model as well as for the residuals are shown.

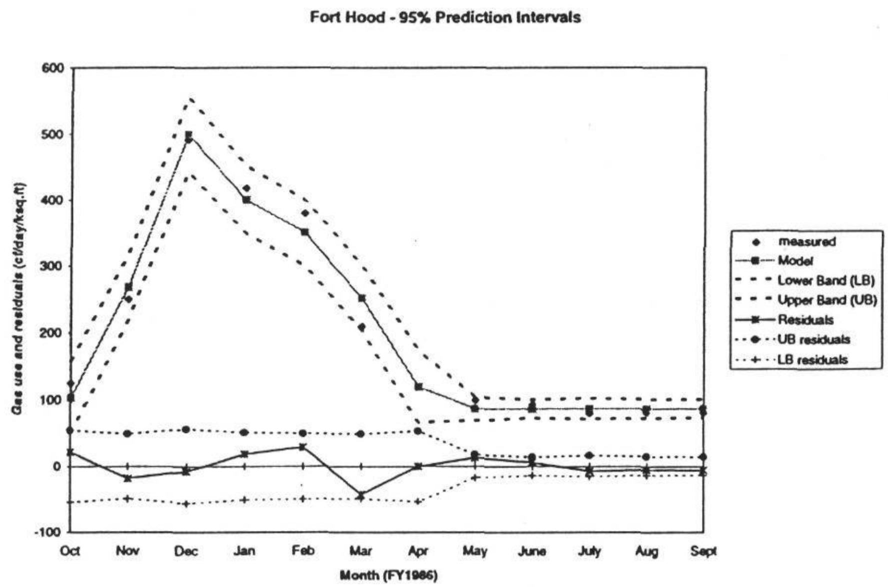


Figure 7.12. Predictive ability of the baseline model (FY86) for Fort Hood gas use during FY86. 95% prediction intervals for the model as well as for the model residuals are shown.

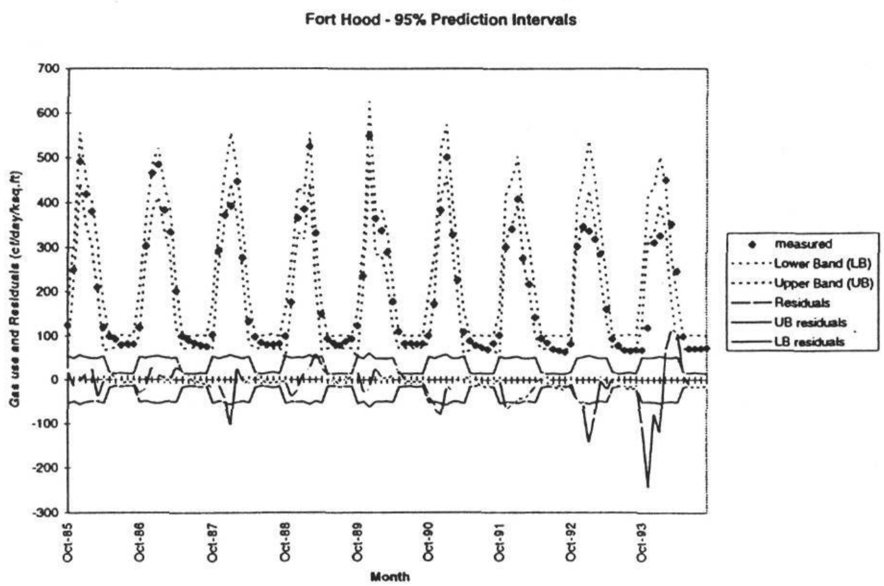


Figure 7.13. Predictive ability of gas baseline model (FY86) for Fort Hood from FY86 to FY94. 95% prediction intervals for the model as well as for the residuals are shown.

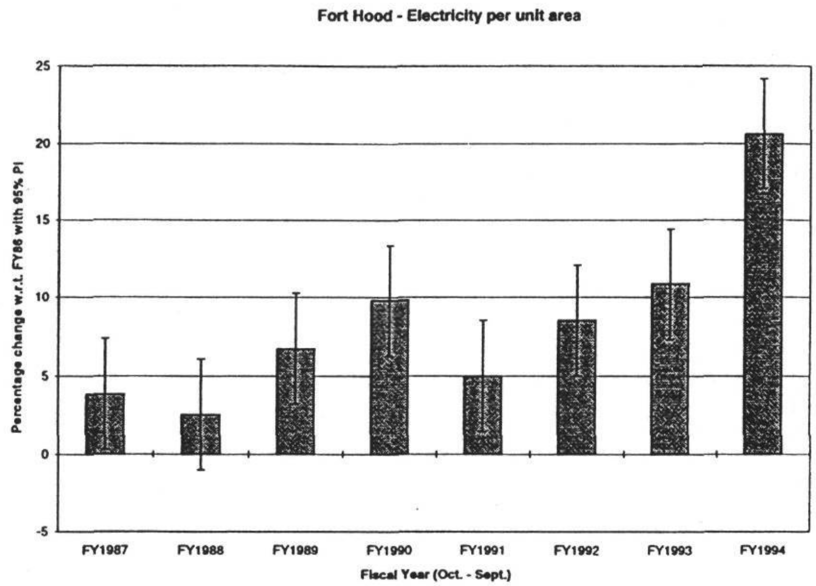


Fig.7.14(a) Electricity use

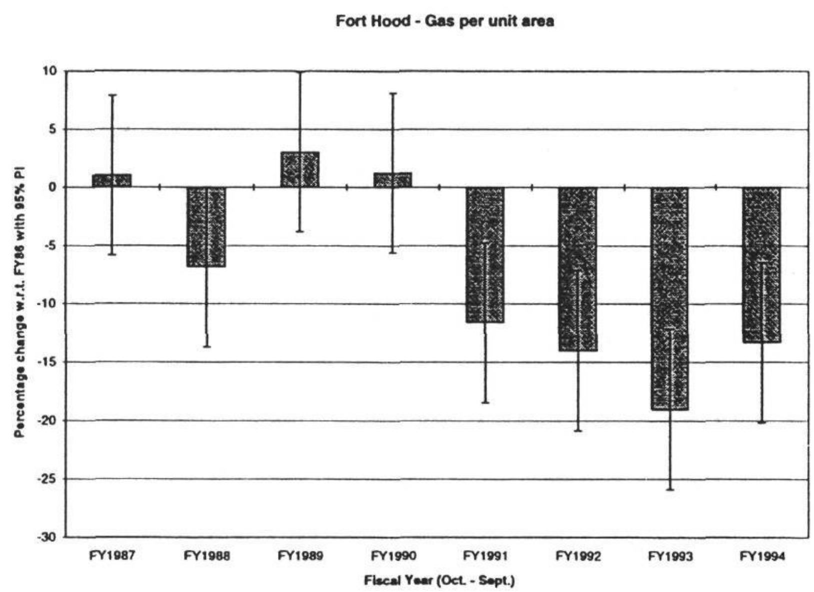


Fig.7.14(b) Gas use

Figure 7.14. Percentage change in annual energy use per conditioned area with respect to baseline year (FY86) for Fort Hood. Negative change indicates decrease in energy use and vice versa. 95% confidence intervals for the percentage change are also shown.

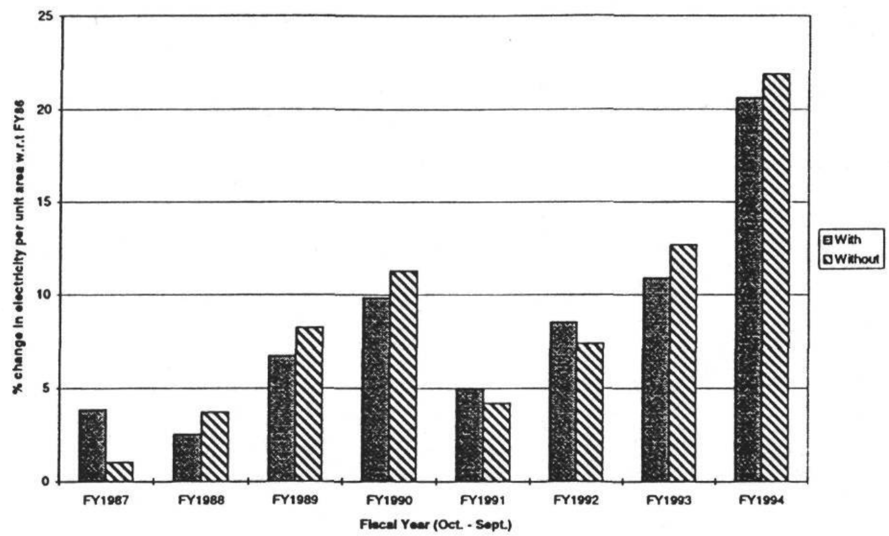


Fig.7.15(a) Electricity use

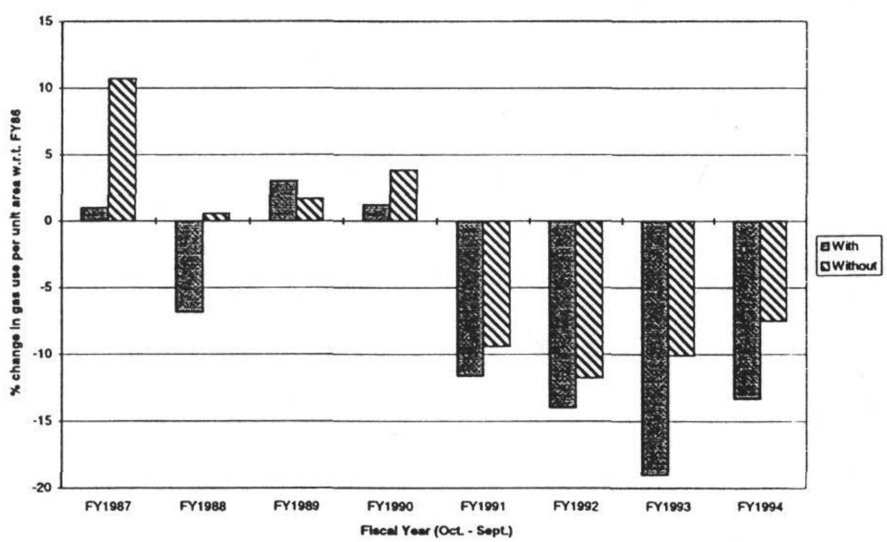


Fig.7.15(b) Gas use

Figure 7.15. Differences in percentage change in annual energy use per conditioned area with respect to baseline year (FY86) for Fort Hood determined by the present methodology and by direct utility bill comparison method. Negative change indicates decrease in energy use and vice versa.

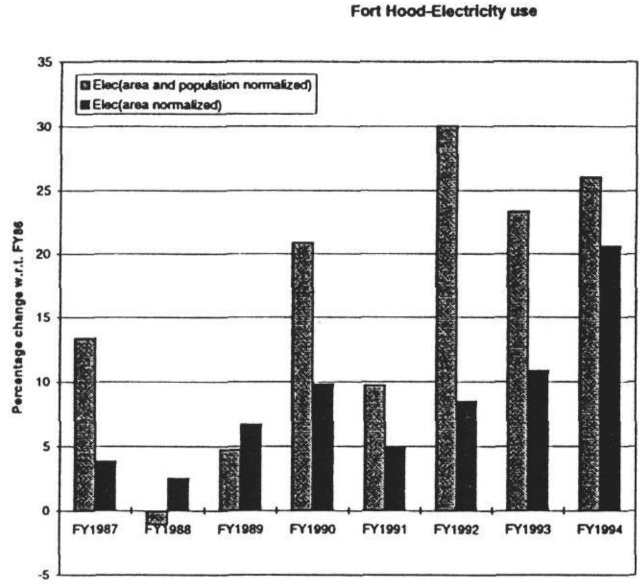


Fig.7.16(a) Electricity use

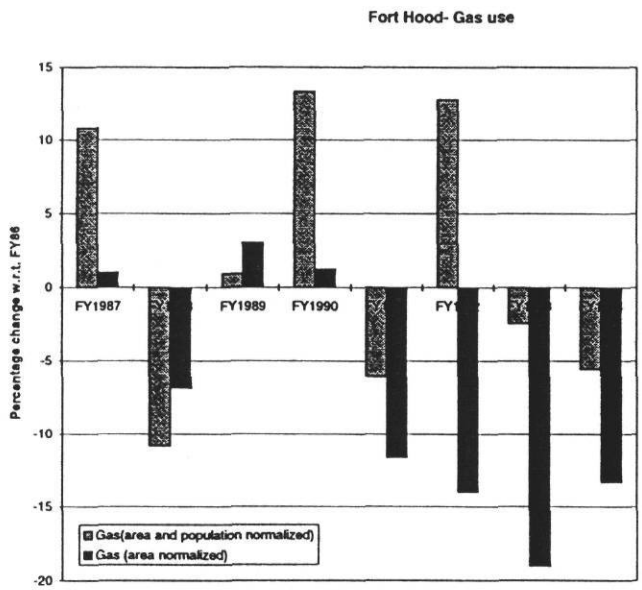


Fig.7.16(b) Gas use

Figure 7.16. Percentage changes in annual energy use with respect to baseline year (FY86) for Fort Hood with conditioned area normalization as well as with area and population normalization.

8.0 Analysis of Fort Huachuca, AZ

8.1 Preliminary data analysis

Though energy utility bill data for this installation are complete till FY94, temperature data is fragmentary (see Table 2.1). Consequently our evaluations can only be done till FY90. Further temperature data from September 1986 till December 1986 is missing. Hence a baseline model for FY86 (as was chosen for all other installations in this study) is difficult to identify since 3 months of data (October - December 1995) would be missing. Hence, we decided to identify the model from calendar year 1985 and use it for evaluating energy use over subsequent fiscal year basis. Time series plots of monthly electricity use and gas use from January 1985 to FY94 are shown in Fig. 8.1 along with concurrent outdoor temperature (which, however, is missing from January 1991 onwards). The temperature variation patterns are fairly consistent over the years. As expected, gas use peaks in winter while electricity use seems to be mostly in summer due to air-conditioning. Gas use during several years is rather erratic: bi-modal over several years and abnormal during summer of 1986. Our decision to use calendar year 1985 as our baseline year seems to have been wise since this would avoid the abnormal behavior in gas use seen during summer of 1986.

Figure 8.2 shows the change in total building area and conditioned area (determined as described in section 2.2) over the years. Both these areas seem to have generally remained constant till FY91 and then increased from FY92 onwards. Since our evaluation is limited till FY90, we can assume for our purpose that conditioned area over the years has remained unchanged. Annual mean daily population data is also plotted in Fig.8.2. Population seems to have been fairly constant over the years, except for FY87 and FY94.

Figure 8.3 shows the changes in annual mean daily energy use per unit conditioned area over the years. The energy use seems fairly constant. The annual mean outdoor temperature is also plotted in order to enable the reader to associate changes in energy use with temperature changes. For example, FY87 is a hot year and gas use seems to have decreased that year. Plots such as these provide a general qualitative trend and one should not try to read too much from them.

Figure 8.4 presents time series graphs of monthly electricity and gas use normalized by building conditioned area. Gas use has decreased from FY92 onwards but will not appear in our analysis results because of our cut-off year of FY90. Electricity use is fairly erratic with a gradual increase over the years

Figure 8.5 depicts the average monthly outdoor temperatures during a year for all years from January 1985 to FY90. We note that despite the limited data the weather during these years seems to be fairly consistent over the years.

Figures 8.6 and 8.7 are time series plots of electricity use and gas use normalized by conditioned area during a year for all years from FY86 to FY94. This type of representation allows clearer visualization of how energy use has changed over the years for a given month. Electricity use in rather erratic from month to month and shows no pronounced seasonal effect, though one can detect a slight increase in summer use (presumably due to air-conditioning). Gas use is obviously for space heating as it is higher during the winter. One notices the odd behavior of gas use during FY86 where December use is abnormally high.

8.2 Baseline modeling

As described earlier, there is an ambiguity regarding proper match between the utility bill period and the corresponding temperature data supplied to us. In section 3.6, we had suggested a method whereby we would identify the best model from three different sets of runs where the temperature data has been taken in slightly different ways. The criteria for selecting the optimum model among the various runs are as follows:

(i) highest R^2 and lowest CV-RMSE,

(ii) if R^2 values for all models are low, CV-RMSE is to be given more consideration, and

(iii) it would be more appropriate from physical considerations, to select 3P models rather than 4P models. Only if the improvement in R^2 and CV-RMSE is substantial, would we relax this rule.

Note that both electricity and gas use during the year have been normalized with the conditioned area of the army base during that particular year prior to model identification. As discussed earlier, calendar year data for 1985 has been used for identifying the baseline model. The summary model statistics of our baseline model identification effort for all three cases are summarized in Table 8.1. We notice that the improvement in electricity use models is substantial when mid-month temperature values (i.e., case 3 in section 3.6) are used for regression. This leads us to conclude that the electricity bills do not span calendar monthly intervals but are closer to a period from the mid-month to the next. For electricity, the 3P-cooling model seems to be the best choice for a baseline model (see Table 8.1). How the 3P model line fits the data points can be noted in Fig. 8.8(a), while how the 3P model compares with the next-best model, namely the 4P model, can be gauged by Fig. 8.8(b).

Though the model R^2 is low ($R^2 = 0.66$), the low CV-RMSE (= 7.1%) makes the electricity use model satisfactory.

Regarding the baseline model for gas use, we note from Table 8.1 that using case 1, i.e., temperature data corresponding to the same calendar months as the utility bills, results in best models. Further, the 3P heating model is clearly the best and so we have selected it as our baseline model for gas use. How the individual monthly data points scatter around the 3P heating baseline model line can be seen in Fig. 8.9. Though the model R^2 is high ($R^2 = 0.93$), the high CV-RMSE (= 18.4%) makes the gas model a poor one.

8.3 Baseline models for screening and tracking

Once baseline models have been developed, it is possible to use them as screening tools by comparing forecast levels with actual energy use. Effect of changes in weather from year-to-year (more accurately, outdoor temperature) on the energy use is explicitly accounted for by the baseline model forecasts. Deviations from expectations must be studied to determine whether known extraneous changes have contributed to this variation or whether these changes are a result of energy efficiency measures or DSM programs that have been initiated. How the PIs of the model are to be calculated have been described in section 3.3 for individual months and in section 3.4 on an annual basis. We have used our 1985 baseline models to forecast into the future up to FY90.

Figures 8.10 and 8.12 depict the extent to which the monthly energy use utility bills are bounded by the PIs of the 1985 baseline model for electricity use and gas use respectively. For clearer visualization, we have also shown the residuals (residual = measured value minus model predicted value) along with the PIs. If, say, the utility bill data for a month fall below the lower 95% PI, one can safely affirm that energy use during that month has decreased as compared to model predictions. We note that electricity use data have strayed outside the PIs bands in February. Some of the gas data points are also outside the PI bands. This deviation (not seen in data from any of the other bases) should not be a cause of undue concern since the data points are for FY86 while the PIs pertain to the calendar 1985 baseline model.

How well the calendar 1985 baseline models for electricity and gas use are able to predict monthly energy use from FY86 till FY90 can be seen in Figs. 8.11 and 8.13 respectively. Note that the energy use is on a monthly mean daily basis per unit conditioned area but has not been normalized for changes in population from one year to the next. We note that electricity use is consistently above the PIs from FY89 onwards indicating a large increase in electricity use. Gas use, on the other hand, seems generally bounded by the PIs (see Fig. 8.13). The large seasonal fluctuations in gas use and the relatively large 95% PI bands make the figure difficult to read and thence draw statistically sound conclusions. However, plots such as this are useful to the energy manager of the corresponding Army base who is in a position to look for (as well as discern and evaluate) changes in energy use as a result of certain specific actions taken (such as O&M measures or say, changes in equipment in the power plants).

On an annual time scale, however, determination of percentage changes in energy use (normalized by conditioned area) with respect to the baseline year (1985) permit rather well-defined conclusions to be drawn regarding the extent to which the Executive Order 12902 has been met. How these changes are to be determined as well as the 95% PIs of these changes have been described in sections 3.4 and 3.5. Following eqs.(3.16) and (3.17), we have computed the percentage changes on a year by year basis and plotted them in Figs. 8.14 for both electricity and gas. Note that a negative change indicates a decrease in energy use. Both electricity and gas use are clearly positive. Generally electricity use over the years as compared to the baseline year (calendar 1985) has increased, with, however, FY94 use being lower than the previous year. Gas use, on the other hand, shows a decreasing trend in FY90 which, however, is still higher than that in 1985. The relatively poorer model for gas use has resulted in wider error bands for gas. On the whole, we note that electricity use in FY90 has increased by about 8% ($\pm$5%) with respect to 1985, while gas use has increased by about 11% ($\pm$13%). The uncertainty bands of the change in electricity use are relatively small and we can be confident of our estimates of electricity change. On the other hand, there is a relatively large uncertainty in our estimates of gas use in FY90 as compared to our baseline year of 1985.

8.4 Concluding remarks

The baseline models identified for calendar year 1985 for Fort Huachuca were found to be satisfactory for the electricity model (CV-RMSE = 7.1% for a 3P-cooling model) and unsatisfactory for the gas model (CV-RMSE=18.4% for a 3P-heating model). Our analysis indicated that electricity utility bills were read close to mid-month and so a correction had to be made to the calendar monthly mean temperature data that we received. No such correction seems to be necessary for gas use.

Using the baseline models to track how energy use has increased (or decreased) over the years required that energy use during each year be normalized by the associated conditioned area of the army installation. (As described earlier, this quantity is not directly available from the database but has to be inferred from areas of several categories of building types which were listed in the database). This leads to a certain amount of unavoidable uncertainty in our conclusions regarding the screening and tracking aspects of the baseline models. We found that electricity use in FY90 has increased by about 8% ($\pm$5%) with respect to calendar year 1985, while gas use has increased by about 11% ($\pm$13%). Given the relative size of the error bands, we can be fairly confident of our conclusions regarding change in electricity use while we need to be more cautious about that of gas use.

Finally, Fig.8.15 and Table 8.4 assemble the year to year percentage changes in annual energy use with respect to baseline year (FY86) normalized by (i) conditioned area, and (ii) conditioned area and population. Though generally the changes in energy use by both means of normalization have more or less similar patterns, the quantitative values are appreciably different during certain years. As described in section 3.5, one cannot place as much confidence in the population values as in the conditioned area values, and so it would probably be better to draw conclusions regarding the extent to which Presidential Executive Order 12902 is being met based on conditioned area normalization only.

Table 8.1. Fort Huachuca: model identification summary statistics for baseline year (calender year 1985). Final models selected are shown in bold face.

		3P-Cooling		4P	
	Temperature data used	R^2	CV-RMSE (%)	R^2	CV-RMSE (%)
Electricity	Same month (T_1)	0.64	7.3	0.64	7.7
	Previous month (T_2)	0.54	8.3	0.54	8.8
	Mid-month (T_3)	**0.66**	**7.1***	0.67	7.4*
		3P-Heating		4P	
Gas	Same month (T_1)	**0.93**	**18.4***	0.93	19.4
	Previous month (T_2)	0.75	34.0	0.80	32.0
	Mid-month (T_3)	0.90	21.7	0.92	20.3

* Plots of these models are shown in the report

Table 8.2. Fort Huachuca electricity use: model coefficients (and standard errors) and pertinent regression model statistics for calender year 1985

Model type	Y_{cp} (kWh/d/ksq.ft)	RS (kWh/d/ksq.ft/F)	X_{cp} (°F)	R^2	CV-RMSE (%)	RMSE (kWh/d/ksq.ft)	n_1
3P-C	27.11(0.751)	0.493(0.1119)	64.4	0.66	7.1	2.07	6

Table 8.3. Fort Huachuca gas use: model coefficients (and standard errors) and pertinent regression model statistics for calender year 1985.

Model type	Y_{cp} (cf/d/ksq.ft)	LS (cf/d/ksq.ft/F)	X_{cp} (°F)	R^2	CV-RMSE (%)	RMSE (cf/d/ksq.ft)	n_1
3P-H	74.38(15.854)	-12.94(1.151)	70.7	0.93	18.4	37.62	8

Table 8.4 Baseline models and percentage change in energy use w.r.t baseline year for Fort Huachuca.

Energy type	Baseline year	Model type	Model fit	Year	% change normalized by conditioned area with 95% PI	% change normalized by conditioned area and population
Electric.	Calender-85	3P-C	Good	FY86	-3.30 ± 4.59	-3.30
				FY87	2.74	-11.29
				FY88	7.04	10.73
				FY89	13.84	9.26
				FY90	8.15	9.98
				FY91	-	-
				FY92	-	-
				FY93	-	-
Gas use	Calender-85	3P-H	Mediocre	FY86	31.34 ± 12.51	31.34
				FY87	25.72	15.00
				FY88	9.50	13.09
				FY89	10.99	6.25
				FY90	11.22	12.99
				FY91	-	-
				FY92	-	-
				FY93	-	-

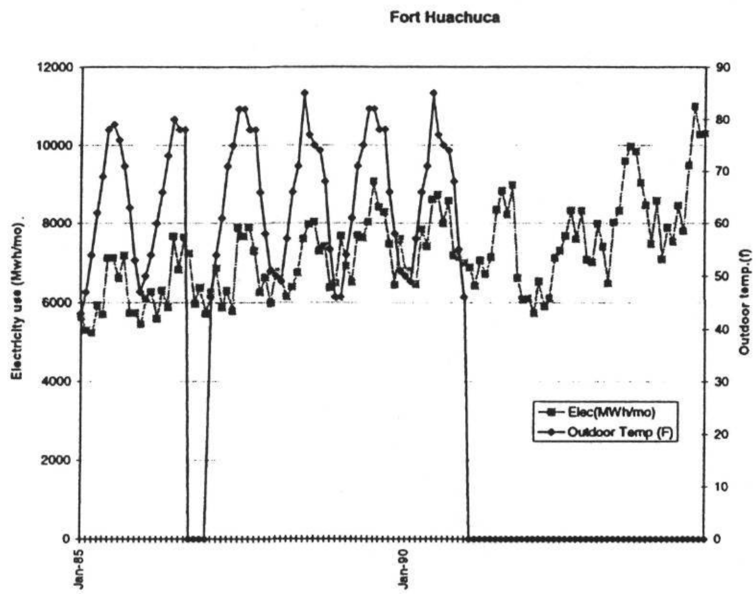


Fig.8.1(a) Electricity use

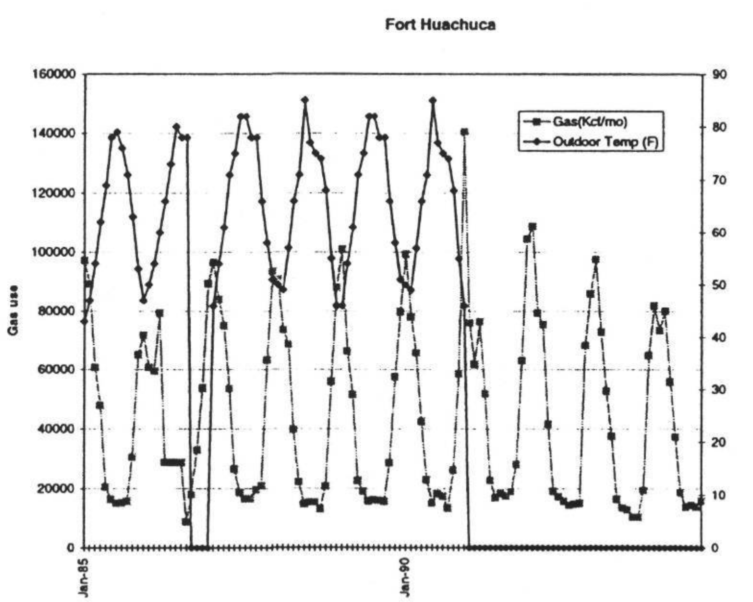


Fig8.1(b) Gas use

Figure 8.1. Time series plots of monthly electricity and gas consumption for Fort Huachuca from January 1985 to FY94. Note that the concurrent outdoor dry-bulb temperature data is fragmentary and extends only till Decmber 1990.

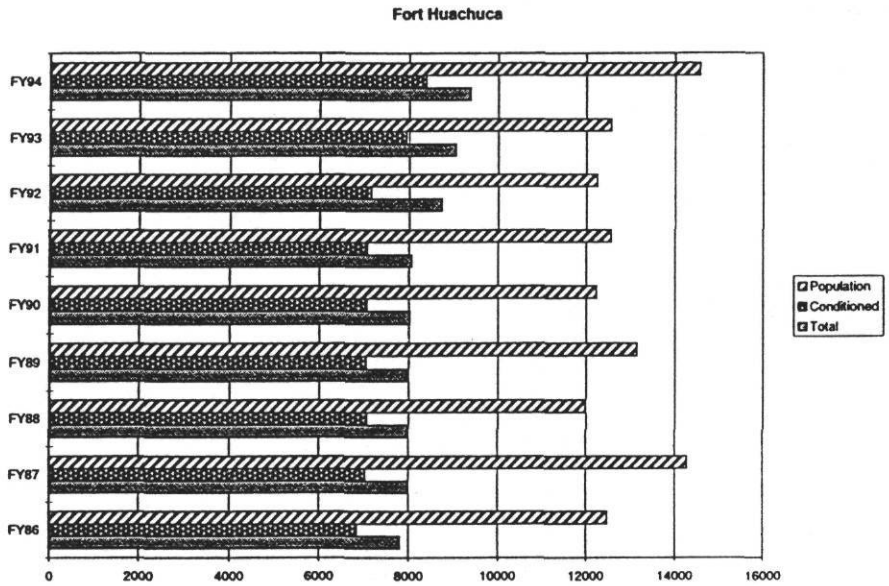


Figure 8.2. Changes in total and conditioned areas (in ksq.ft) and annual mean daily population for Fort Huachuca from FY86 to FY94.

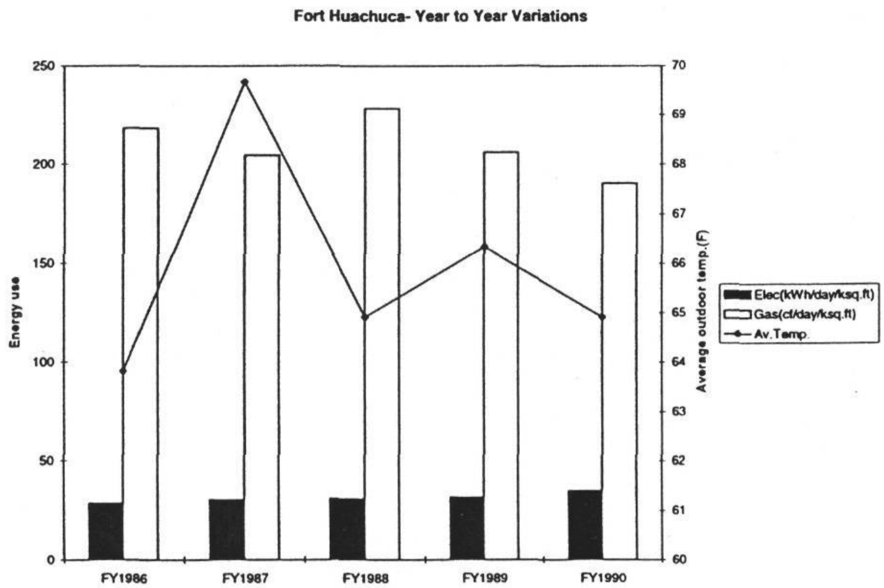


Figure 8.3 Changes in annual mean daily energy use per conditioned area and annual mean outdoor temperature for Fort Huachuca from FY86 to FY90.

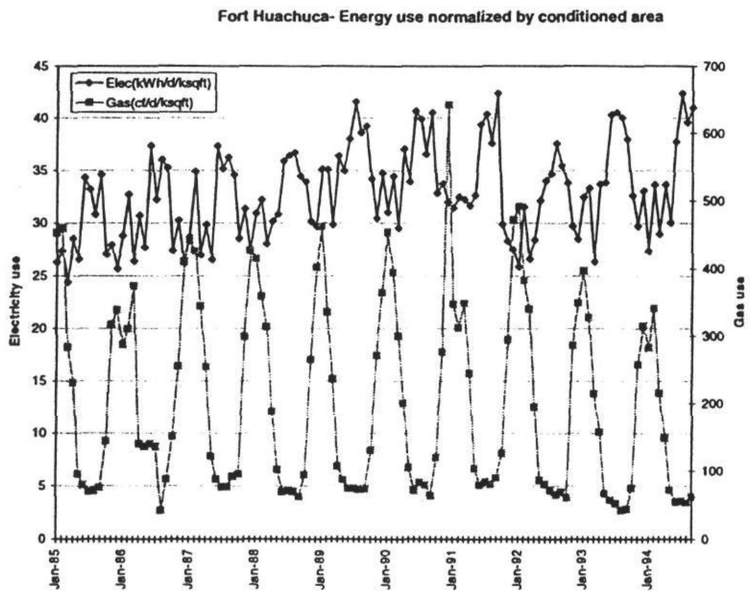


Figure 8.4. Time series graphs of monthly electricity and gas consumption per unit conditioned area for Fort Huachuca from January 1985 to FY94.

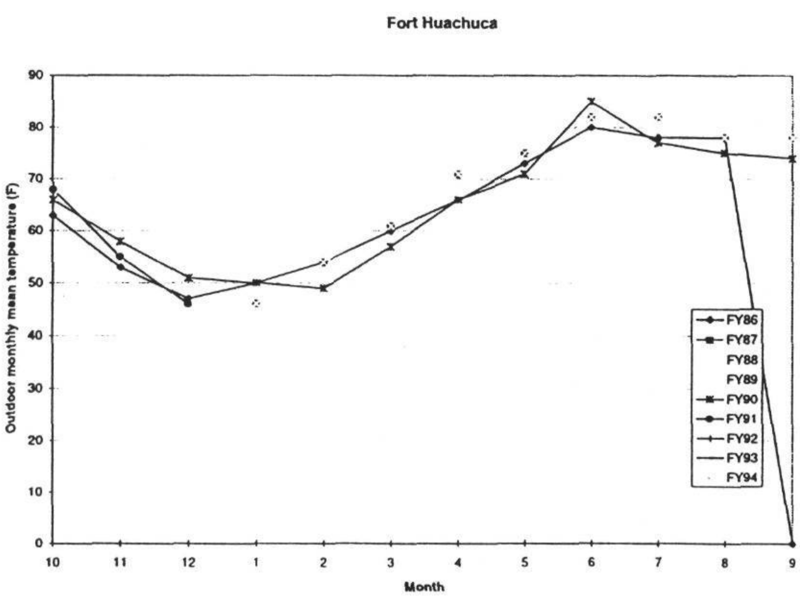


Figure 8.5. Time series plots of average monthly temperatures at Fort Huachuca from FY86 to FY90.

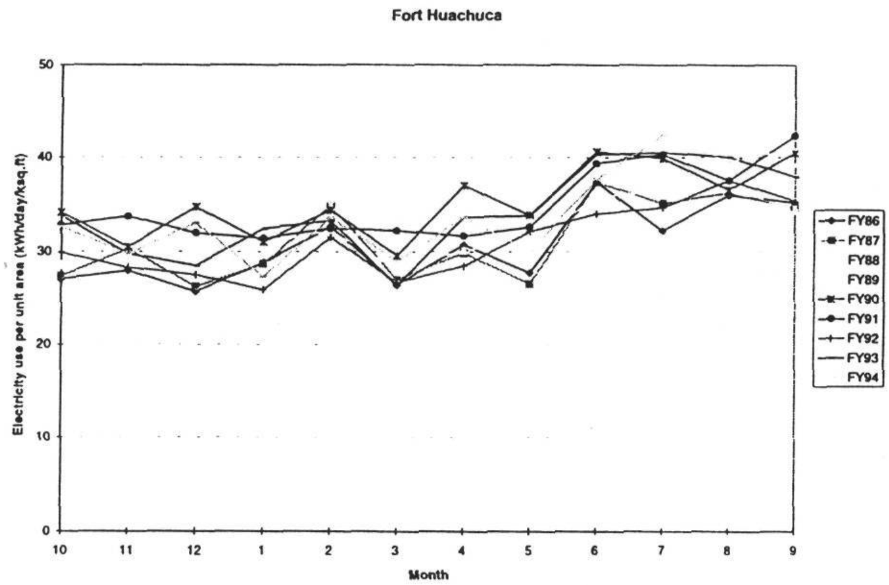


Figure 8.6. Time series plots of electricity use per unit conditioned area for Fort Huachuca from FY86 to FY94.

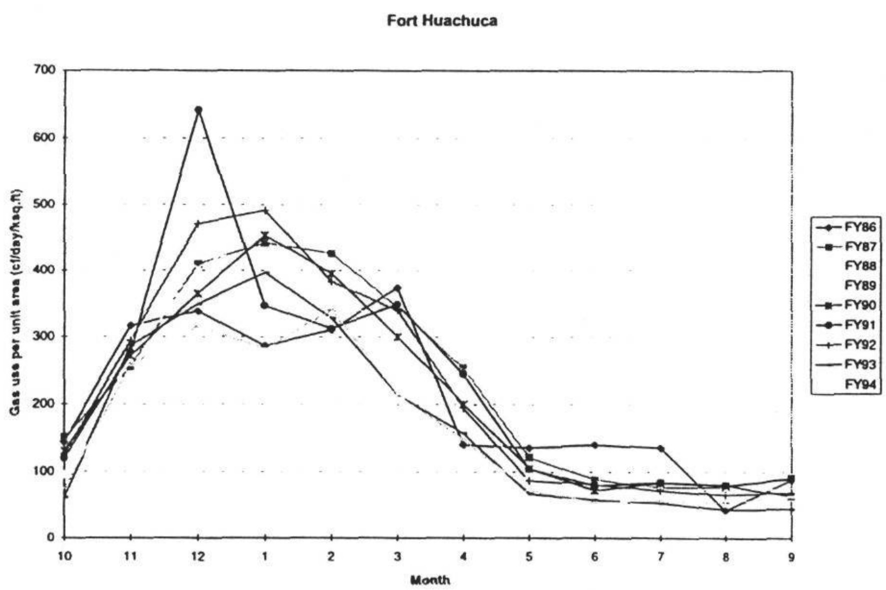
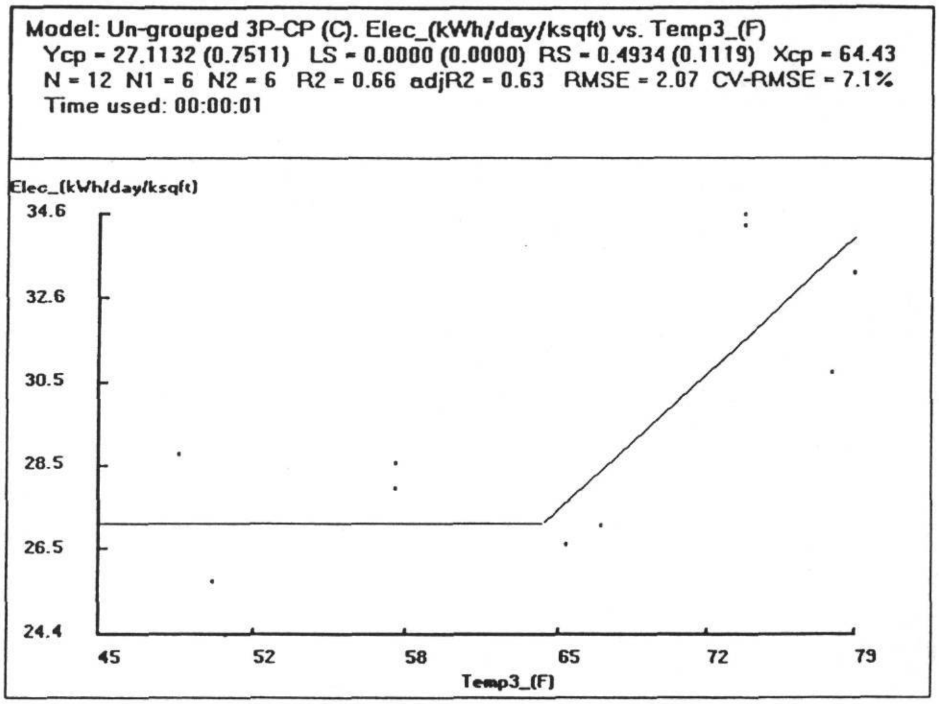


Figure 8.7. Time series plots of gas use per unit conditioned area for Fort Huachuca from FY86 to FY94.



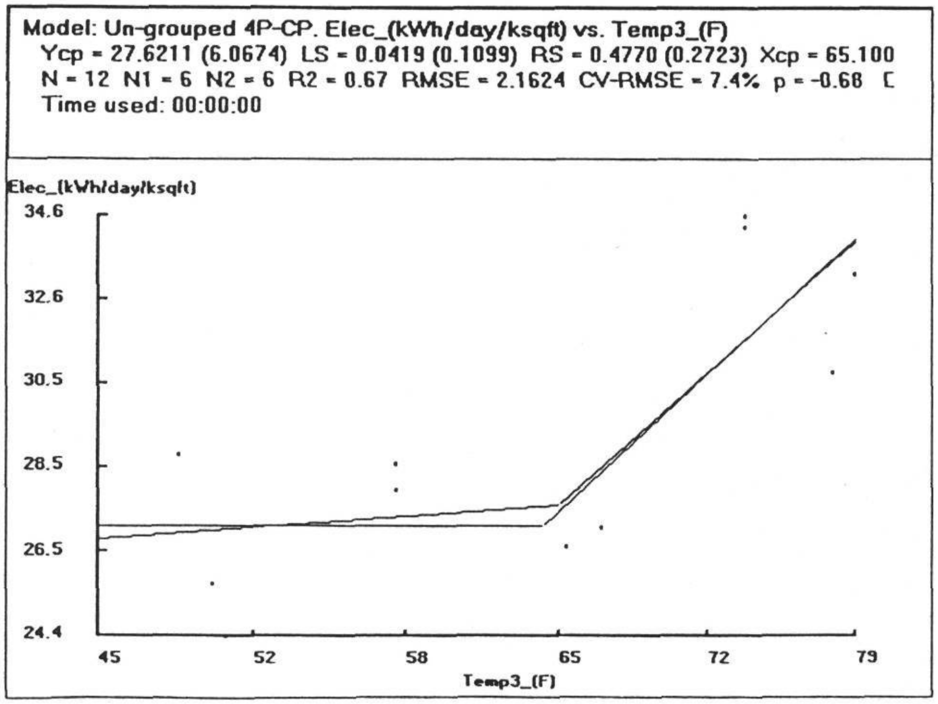


Figure 8.8. EModel change point model line and data points for Fort Huachuca electricity consumption for baseline year (calendar year 1985). A 15-day shift in temperature led to substantial model improvement. (a) 3P-cooling model selected as baseline, (b) 3P cooling model line and next-best model, namely the 4P model line, are shown for comparative purposes.

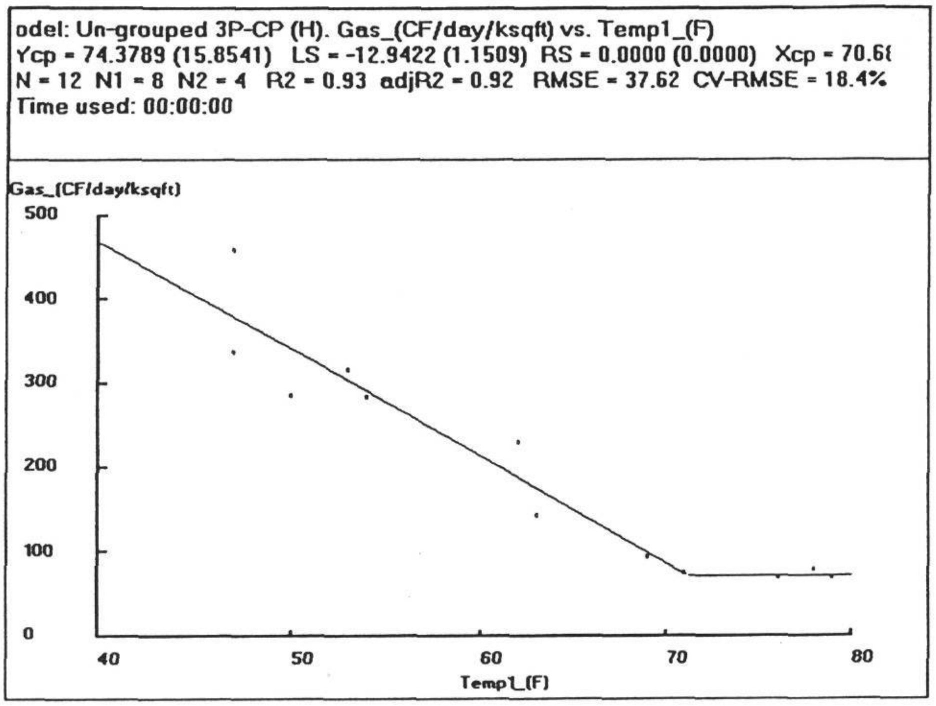


Figure 8.9. EModel change point model line and data points for Fort Huachuca natural gas consumption for baseline year (calendar year 1985). 3P model selected as baseline.

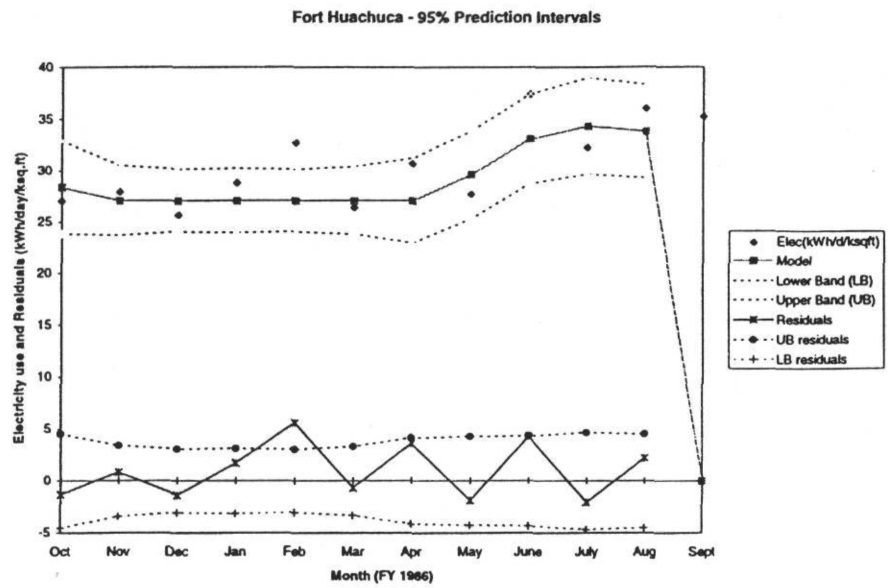


Figure 8.10. Predictive ability of the baseline model (calendar year 1985) for Fort Huachuca electricity use during FY86. 95% prediction intervals for the model as well as for the model residuals are shown.

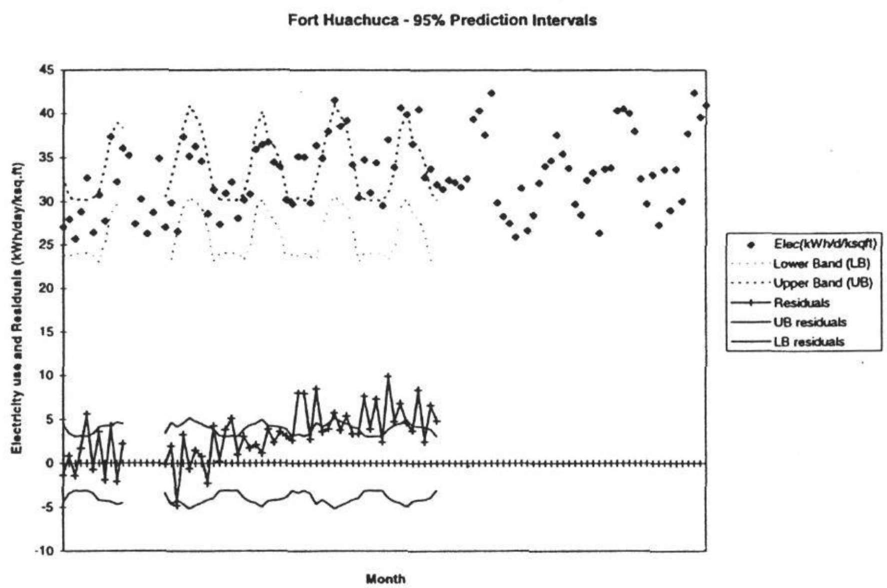


Figure 8.11. Predictive ability of electricity baseline model (calendar year 1985) for Fort Huachuca from FY86 to FY90. 95% prediction intervals for the model as well as for the residuals are shown.

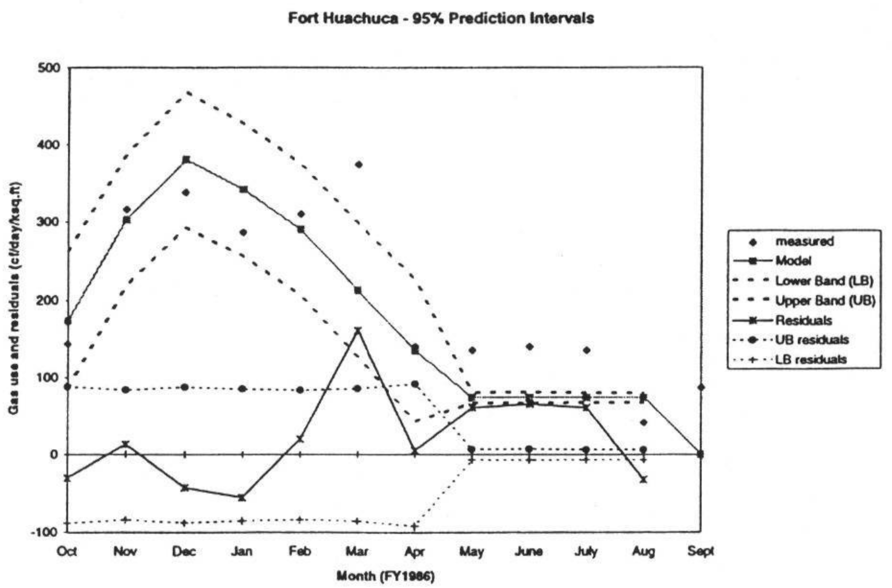


Figure 8.12. Predictive ability of the baseline model (calendar year 1985) for Fort Huachuca gas use during FY86. 95% prediction intervals for the model as well as for the model residuals are shown.

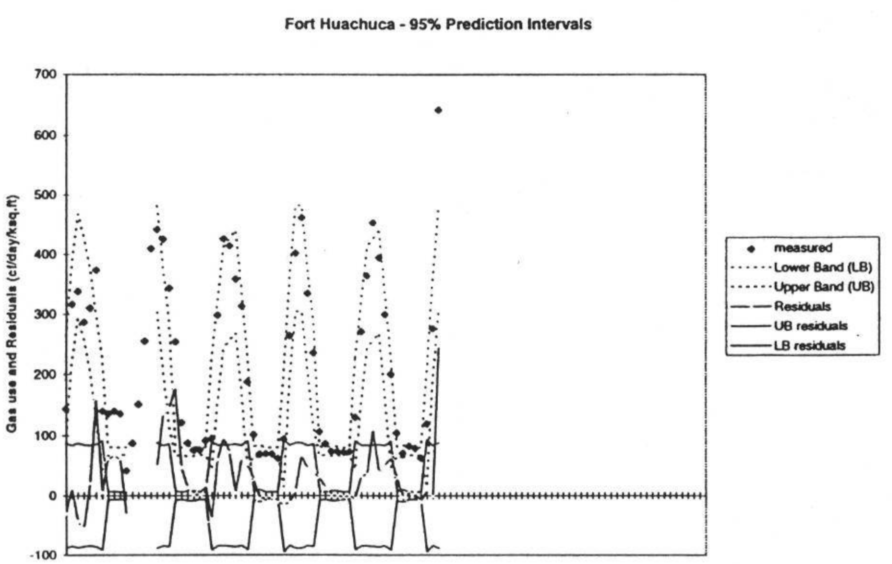


Figure 8.13. Predictive ability of gas baseline model (calendar year 1985) for Fort Huachuca from FY86 to FY90. 95% prediction intervals for the model as well as for the residuals are shown.

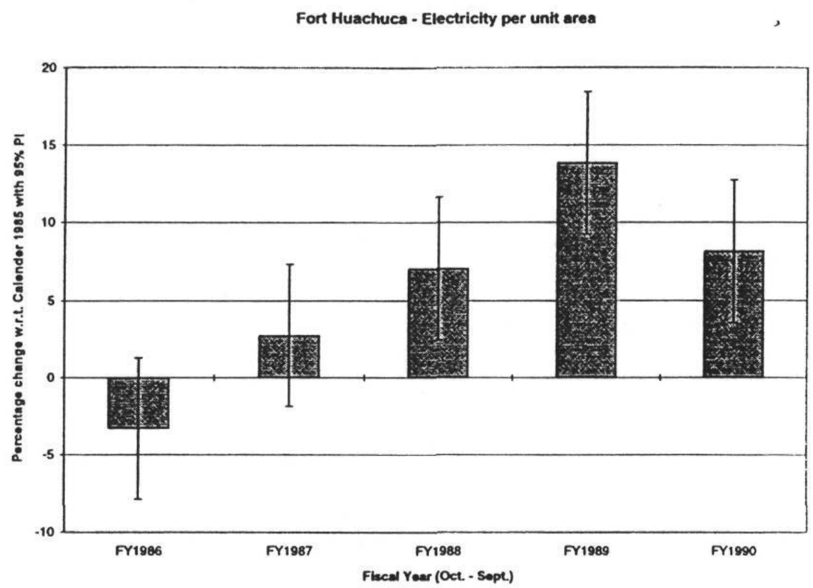


Fig.8.14(a) Electricity use

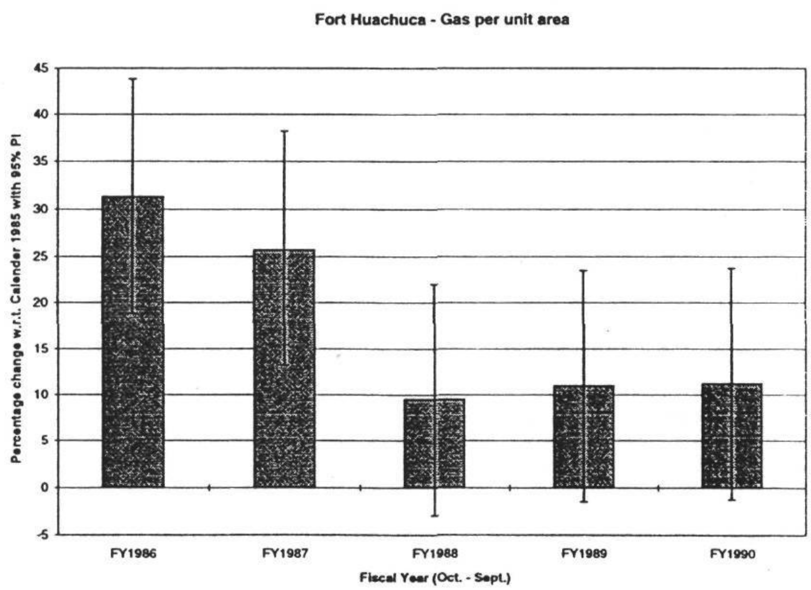


Fig.8.14(b) Gas use

Figure 8.14. Percentage change in annual energy use per conditioned area with respect to baseline year (calendar year 1985) for Fort Huachuca. Negative change indicates decrease in energy use and vice versa. 95% confidence bands are also shown.

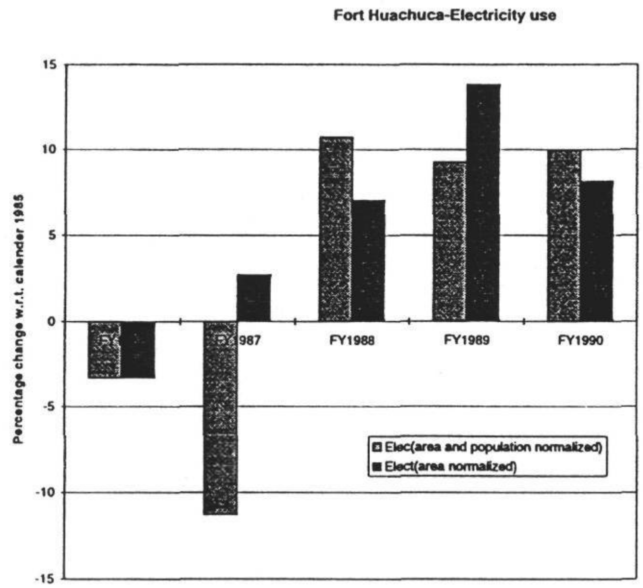


Fig.8.15(a) Electricity use

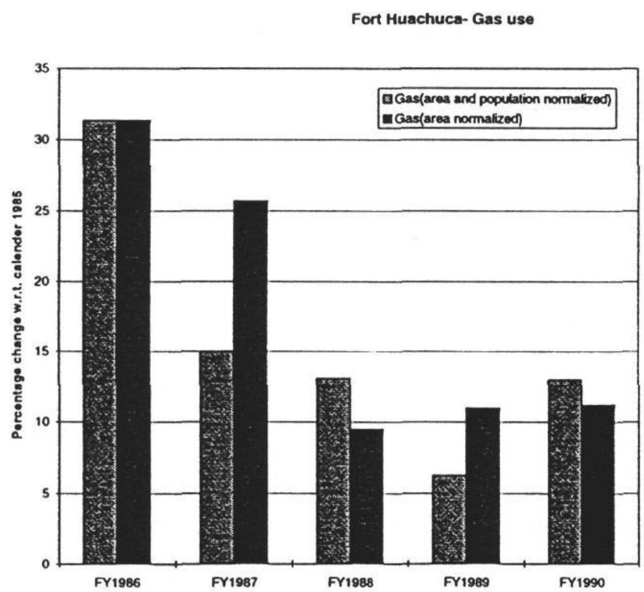


Fig.8.15(b) Gas use

Figure 8.15. Percentage changes in annual energy use with respect to baseline year (FY86) for Fort Huachuca with conditioned area normalization as well as with area and population normalization.

9.0 Analysis of Fort Ord, CA

9.1 Preliminary data analysis

Outdoor temperature data provided to us extended only until December 1993, and so all analyses at Fort Ord can be done only until FY93. Time series plots of monthly electricity use and gas use from FY86 to FY94 are shown in Fig. 9.1 along with concurrent outdoor temperature. The variation patterns for gas use are not very consistent over the years. As expected, gas use peaks in winter while electricity use seems to be very flat signifying little seasonal change as well as little year to year changes.

Figure 9.2 shows the change in total building area and conditioned area (determined as described in section 2.2) over the years. Total area decreased during FY87, then increased to a maximum during FY89 and has remained constant ever since. The conditioned area seems to have generally followed the same trend and has increased by about 7% from FY86 to FY93. Annual mean daily population data is also plotted in Fig.9.2. Population seems to have increased suddenly in FY87 as compared to FY86, and then decreased to a constant value over the last 5 years.

Figure 9.3 shows the changes in annual mean daily energy use per unit conditioned area over the years. Gas use exhibits variations over the years, while electricity use is fairly constant. The annual mean outdoor temperature is also plotted in order to enable the reader to associate changes in energy use with temperature changes. For example, FY88 and FY89 are cold years and gas use seems to have increased during those years. Plots such as these provide a general qualitative trend and one should not try to read too much from them.

Figure 9.4 presents time series graphs of monthly electricity and gas use normalized by conditioned area. Gas use has increased from FY88 onwards and remained more or less constant from then. Electricity use shows little seasonal variation but has shown a long term patterns of decrease and increase over the years

Figure 9.5 depicts the average monthly outdoor temperatures during a year for all years from FY86 to FY93. We note, as mentioned earlier, smaller swings and more year-to-year. Temperature data for FY86, our baseline year, does not seem to be very characteristic as it is lower than the other years during November, March and April, and higher in January than the other years.

Figures 9.6 and 9.7 are time series plots of electricity use and gas use normalized by conditioned area during a year for all years from FY86 to FY93. This type of representation allows clearer visualization of how energy use has changed over the years for a given month. Electricity use is fairly constant over the year and over the years, while gas use during the winter months is high due to space heating applications. There is also more variability from year to year.

9.2 Baseline modeling

As described earlier, there is an ambiguity regarding proper match between the utility bill period and the corresponding temperature data supplied to us. In section 3.6, we had suggested a method whereby we would identify the best model from three different sets of runs where the temperature data has been taken in slightly different ways. The criteria for selecting the optimum model among the various runs are as follows:

(i) highest R^2 and lowest CV-RMSE,

(ii) if R^2 values for all models are low, CV-RMSE is to be given more consideration, and

(iii) it would be more appropriate from physical considerations, to select 3-P models rather than 4P models. Only if the improvement in R^2 and CV-RMSE is substantial, would we relax this rule.

Note that both electricity and gas use during the year have been normalized with the conditioned area of the army base during that particular year prior to model identification. The summary model statistics of our baseline model identification effort for all three cases are summarized in Table 9.1. We note that the R^2 values of the 3P-heating and cooling models and of the 4P models are very low indicating almost no temperature dependence. The mean model seems to be the best choice for the baseline model even though the 4P model has slightly lower CV-RMSE. How the mean model line fits the data points can be noted in Fig. 9.8(a), while how the mean model compares with the next-best model, namely the 4P model, can be gauged by Fig. 9.8(b). The mean model is satisfactory since the CV-STD is low indicating not much variability in the utility bills from month to month.

Regarding the baseline model for gas use, we note from Table 9.1 that using case 1, i.e., temperature data corresponding to the same calendar months as the utility bills, results in best models. Further, the small improvement in R^2 as we go from a 3P-heating model to a 4P model is not enough to justify using the unphysical 4-P model. Consequently, we decided to choose the 3P-heating model as our baseline model for gas use. How the individual monthly data points scatter around the 3P-heating baseline model line can be seen in Fig. 9.9. The model is not very good with R^2 = 0.69 and CV-STD = 16.2%.

9.3 Baseline models for screening and tracking

Once baseline models have been developed, it is possible to use them as screening tools by comparing forecast levels with actual energy use. Effect of changes in weather from year-to-year (more accurately, outdoor temperature) on the energy use is explicitly accounted for by the baseline model forecasts. Deviations from expectations must be studied to determine whether known extraneous changes have contributed to this variation or whether these changes are a result of energy efficiency measures or DSM programs that have been initiated. How the PIs of the model are to be calculated have been described in section 3.3 for individual months and in section 3.4 on an annual basis. We have used our FY86 baseline models to forecast into the future up to FY93.

Figures 9.10 and 9.12 depict the extent to which the monthly energy use utility bills are bounded by the PIs of the FY86 baseline model for electricity use and gas use respectively. For clearer visualization, we have also shown the residuals (residual = measured value minus model predicted value) along with the PIs. If, say, the utility bill data for a month fall below the lower 95% PI, one can safely affirm that energy use during that month has decreased as compared to model predictions. We note that the PIs for the gas use are rather wide since the model is not very good (see Table 9.1).

How well the FY86 baseline models for electricity and gas use are able to predict monthly energy use from FY86 till FY93 can be seen in Figs. 9.11 and 9.13 respectively. Note that the energy use is on a monthly mean daily basis per unit conditioned area but has not been normalized for changes in population from one year to the next. We note that electricity use is bounded by the PIs indicating no statistical increase in electricity use over the years. Gas use also exhibits similar behavior (see Fig. 9.13). So statistically speaking, one cannot draw any definite conclusions about how gas use has varied over the years. However, plots such as this are useful to the energy manager of the corresponding Army base who is in a position to look for (as well as discern and evaluate) changes in energy use as a result of certain specific actions taken (such as O&M measures or say, changes in equipment in the power plants).

On an annual time scale, however, determination of percentage changes in energy use (normalized by conditioned area) with respect to the baseline year (FY86) permit rather well-defined conclusions to be drawn regarding the extent to which the Executive Order 12902 has been met. How these changes are to be determined as well as the 95% PIs of these changes have been described in sections 3.4 and 3.5. Following eqs.(3.16) and (3.17), we have computed the percentage changes on a year by year basis (see Table 9.4) and plotted them in Figs. 9.14 for both electricity and gas. Note that a negative change indicates a decrease in energy use. Electricity use over the years seems to have varied considerably. There was a statistically significant increase in energy use from FY90 till FY92 as compared to the baseline year FY86. Subsequently, energy use during FY93 seems to have decreased. Gas use, on the other hand, seems to have been always less than that during the baseline year, with a rather abrupt decrease in FY93. However this change is not very significant statistically because of the wide error bands for gas. On the whole, we note that electricity use in FY93 has decreased by about 4% ($\pm$6%) with respect to FY86, while gas use has decreased by about 9% ($\pm$11%). The uncertainty bands of the change in electricity use and gas use are wider than the extent of energy decrease and so one cannot place much confidence in these savings estimates.

9.4 Concluding remarks

The electricity baseline model identified for FY86 for Fort Ord was a mean model with CV-STD= 8.3%, while the 3P-heating gas model with R^2 = 0.69 and CV-RMSE = 16.2% was quite poor. Our analysis indicated that no correction to the utility bill data is necessary in order to match them with the calendar monthly mean temperature data that we received.

Using the baseline models to track how energy use has increased (or decreased) over the years required that energy use during each year be normalized by the associated conditioned area of the army installation. (As described earlier, this quantity is not directly available from the database but has to be inferred from areas of several categories of building types which were listed in the database). This leads to a certain amount of unavoidable uncertainty in our conclusions regarding the screening and tracking aspects of the baseline models. We found that electricity use in FY93 has decreased by about 4% ($\pm$6%) with respect to FY86, while gas use has decreased by about 9% ($\pm$11%). Since the uncertainty bands are wider than our estimates of energy decrease from FY86, not much confidence can be placed on these estimates.

Finally, Fig.9.15 and Table 9.4 assemble the year to year percentage changes in annual energy use with respect to baseline year (FY86) normalized by (i) conditioned area, and (ii) conditioned area and population. The changes in energy use by both means of normalization are widely. Population over the years having decreased from the FY86 value, normalization by approach (ii) would suggest that energy use has increased substantially as compared to FY86. As described in section 3.5, one cannot place as much confidence in the population values as in the conditioned area values, and so it would probably be better to draw conclusions regarding the extent to which Presidential Executive Order 12902 is being met based on conditioned area normalization only.

Table 9.1. Fort Ord: model identification summary statistics for baseline year (FY86). Final models selected are shown in bold face.

		Mean	3P		4P	
	Temperature data used	CV-St.Dev (%)	R^2 Cool/Heat	CV-RMSE (%) Cool/Heat	R^2	CV-RMSE (%)
Electricity	Same month (T_1)	**8.3***	0.14/0.06	8.1/8.5	0.38	7.2*
	Previous month (T_2)	-	0.12/0.05	8.2/8.5	0.26	7.9
	Mid-month (T_3)	-	0.10/0.03	8.3/8.6	0.11	8.7
			3P-Heating		4P	
Gas	Same month (T_1)	-	**0.69**	**16.2***	0.71	16.4
	Previous month (T_2)	-	0.45	21.6	0.50	21.8
	Mid-month (T_3)	-	0.71	15.7	0.72	16.2

* Plots of these models are shown in the report

Table 9.2. Fort Ord electricity use: model coefficients (and standard errors) and pertinent regression model statistics for FY86.

Model type	Y_{cp} (kWh/d/ksq.ft)	LS (kWh/d/ksq.ft/F)	X_{cp} (°F)	R^2	CV-St.Dev (%)	St.Dev (kWh/d/ksq.ft)	n_1
Mean	22.80	-	-	-	8.3	1.90	-

Table 9.3. Fort Ord gas use: model coefficients (and standard errors) and pertinent regression model statistics for FY86.

Model type	Y_{cp} (cf/d/ksq.ft)	LS (cf/d/ksq.ft/F)	X_{cp} (°F)	R^2	CV-RMSE (%)	RMSE (cf/d/ksq.ft)	n_1
3P-H	162.85(16.62)	-15.306(3.2228)	59.0	0.69	16.2	36.25	9

Table 9.4 Baseline models and percentage change in energy use w.r.t baseline year for Fort Ord.

Energy type	Baseline year	Model type	Model fit	Year	% change normalized by conditioned area with 95% PI	% change normalized by conditioned area and population
Electric.	FY86	Mean	Good	FY87	2.33 ± 5.66	-64.28
				FY88	-2.90	52.59
				FY89	-0.59	41.59
				FY90	5.81	46.24
				FY91	7.73	43.41
				FY92	5.79	42.22
				FY93	-3.95	36.25
				FY94	-	-
Gas use	FY86	3P-H	Mediocre	FY87	-0.53 ± 10.99	-69.10
				FY88	-5.75	51.27
				FY89	-3.02	40.17
				FY90	-3.25	41.06
				FY91	-0.91	38.11
				FY92	-0.17	38.57
				FY93	-8.58	33.41
				FY94	-	-

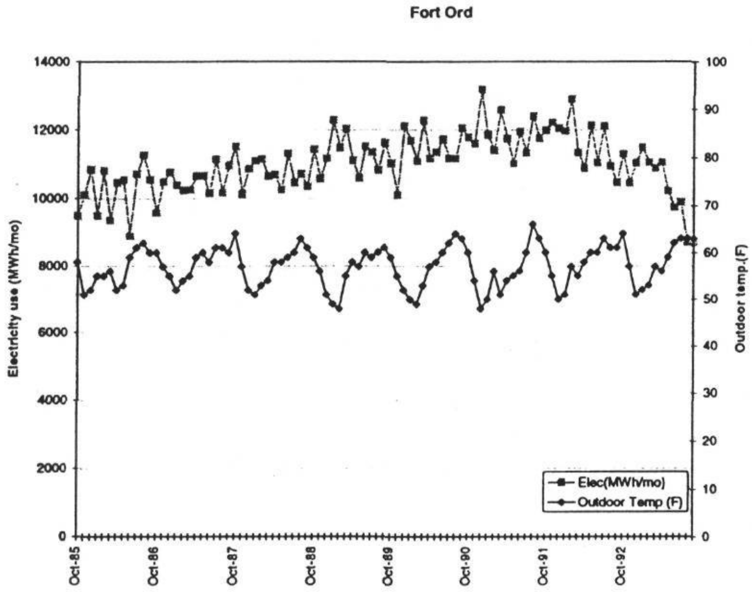


Fig.9.1(a) Electricity use

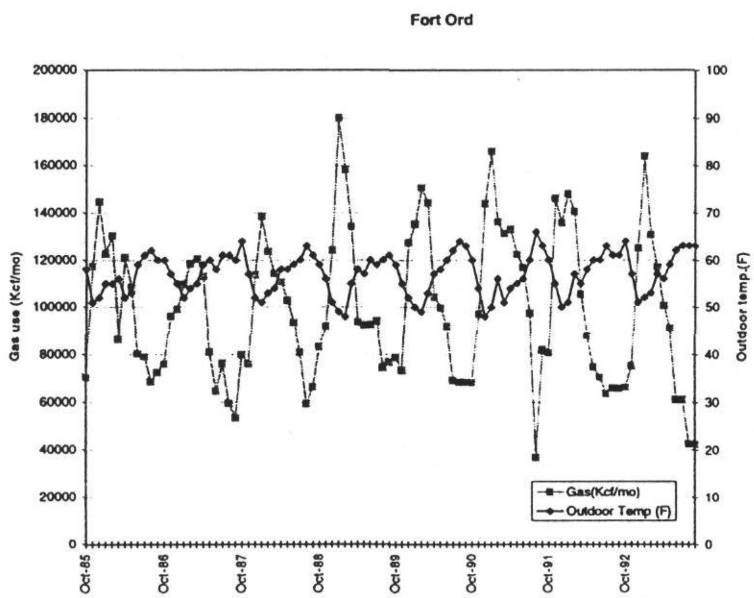


Fig.9.1(b) Gas use.

Figure 9.1. Time series plots of monthly electricity and gas consumption for Fort Ord from FY86 to FY93. The concurrent outdoor dry-bulb temperature variation is also shown.

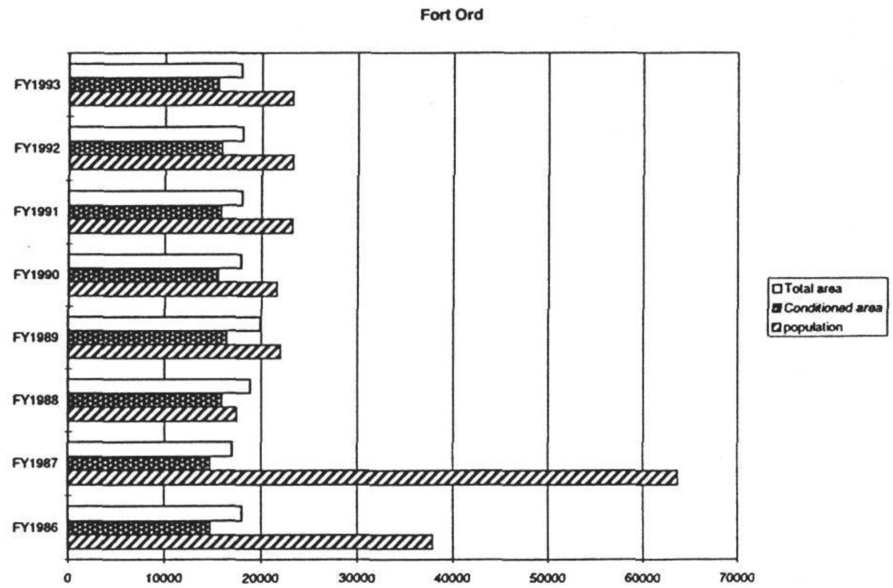


Figure 9.2. Changes in total and conditioned areas (in ksq.ft) and annual mean daily population for Fort Ord from FY86 to FY93.

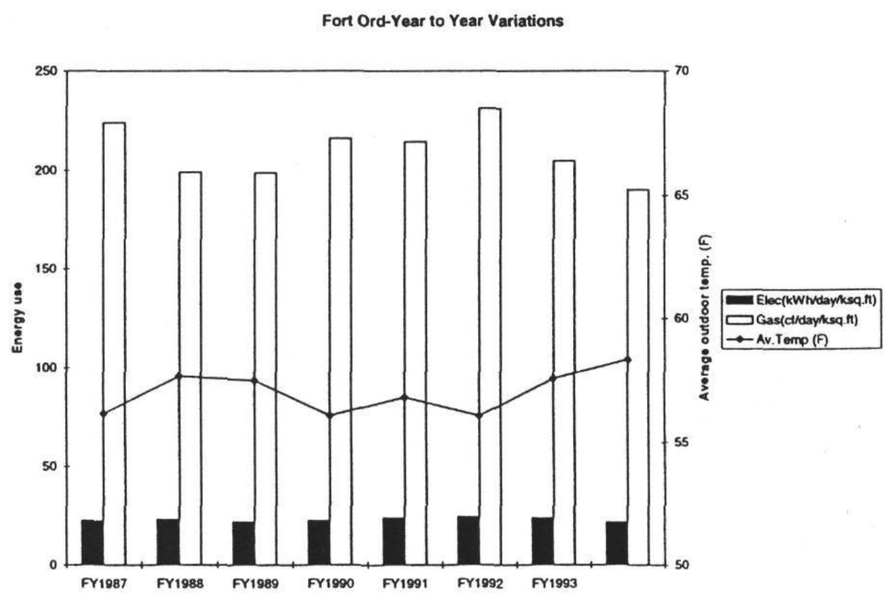


Figure 9.3 Changes in annual mean daily energy use per unit conditioned area and annual mean outdoor temperature for Fort Ord from FY86 to FY94.

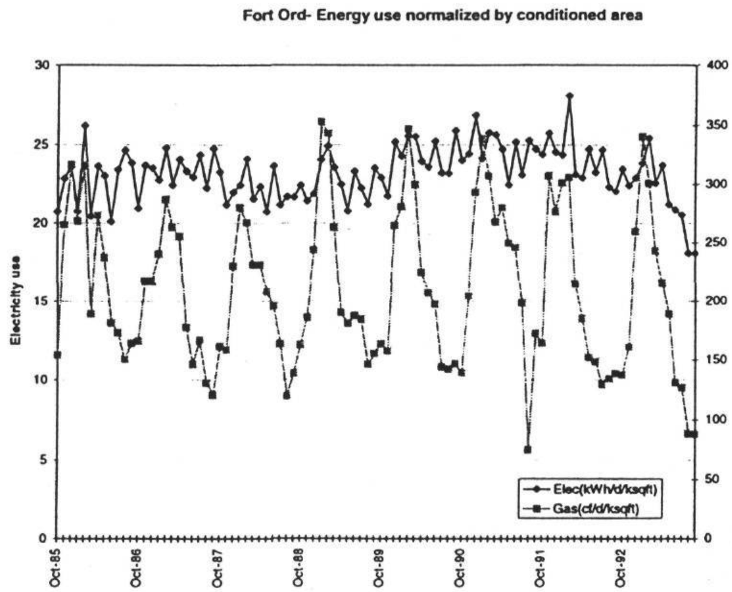


Figure 9.4. Time series graphs of monthly electricity and gas consumption per unit conditioned area for Fort Ord from FY86 to FY93.

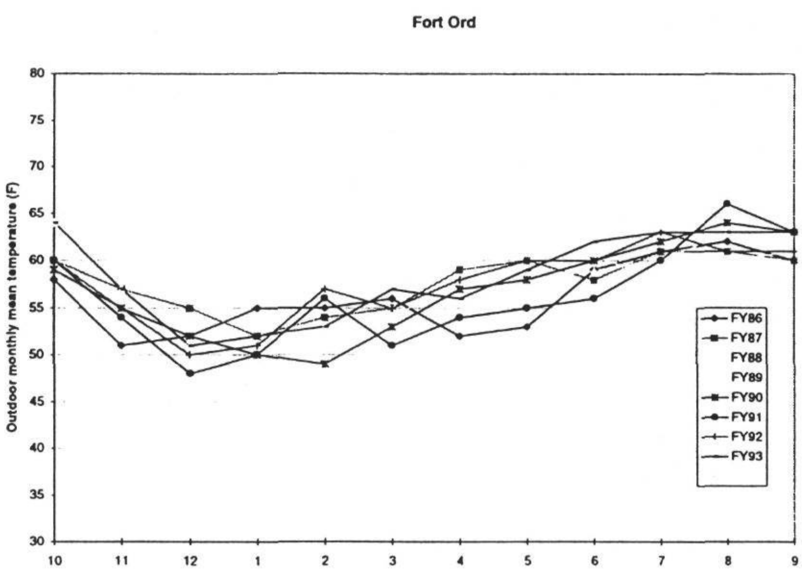


Figure 9.5. Time series plots of average monthly temperatures at Fort Ord from FY86 to FY93.

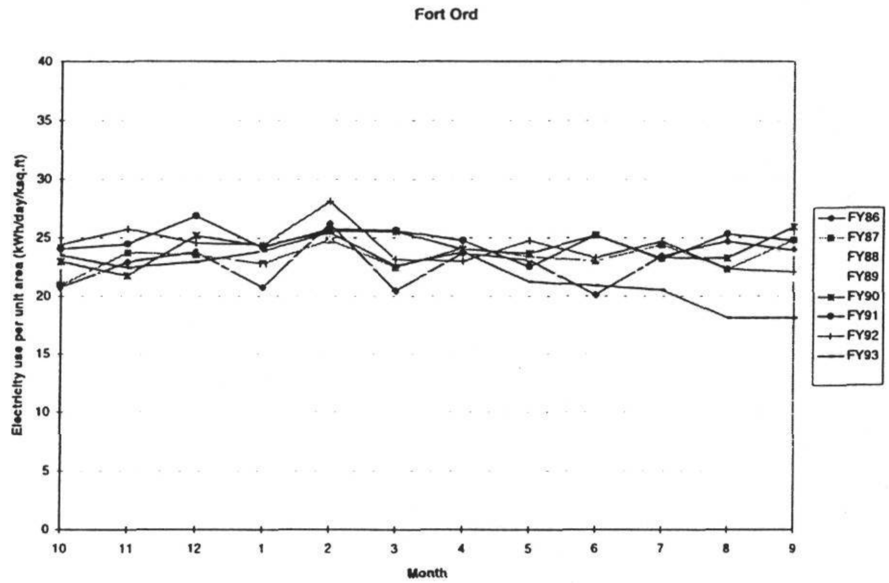


Figure 9.6. Time series plots of electricity use per unit conditioned area for Fort Ord from FY86 to FY93.

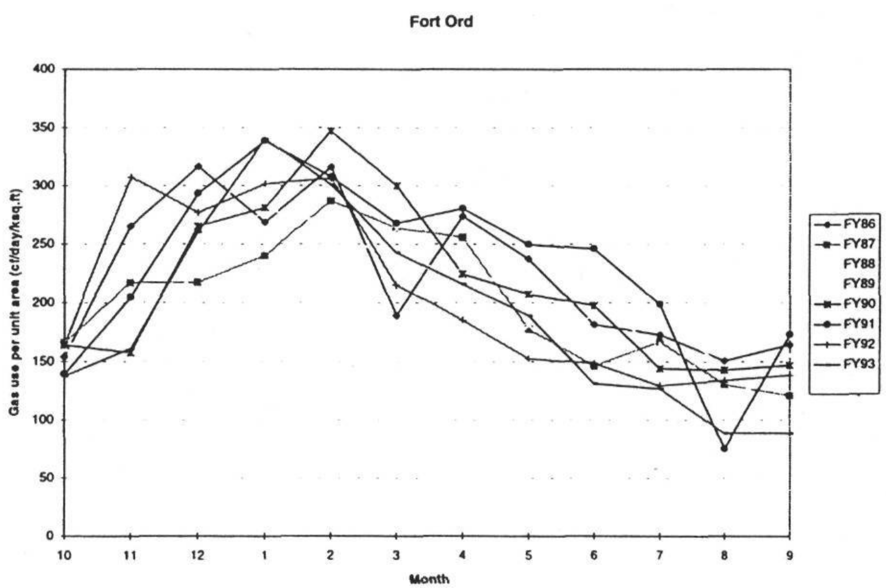
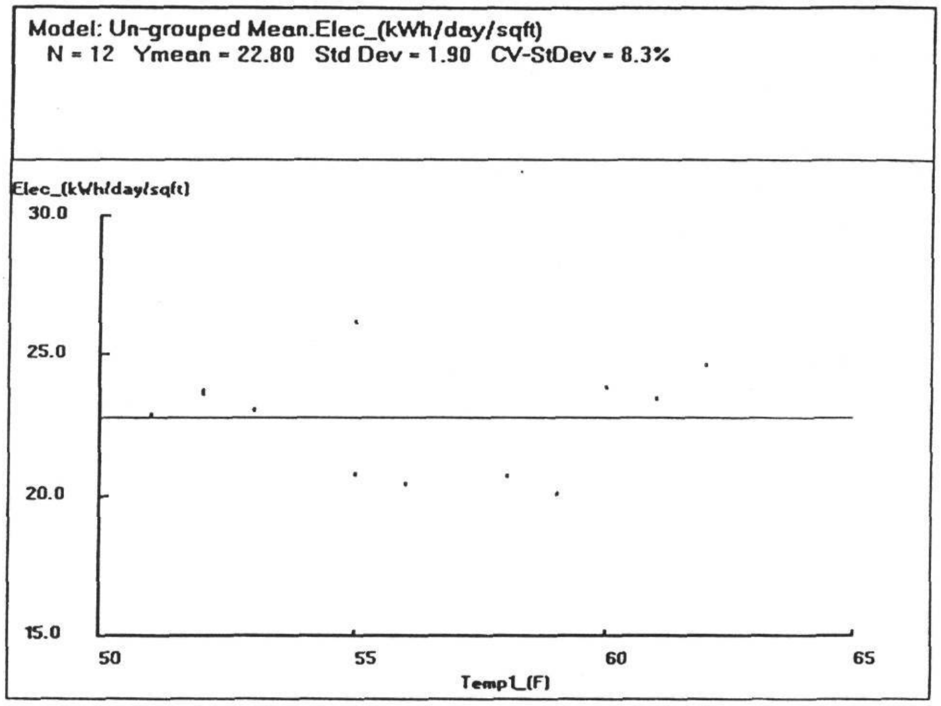


Figure 9.7. Time series plots of gas use per unit conditioned area for Fort Ord from FY86 to FY93.



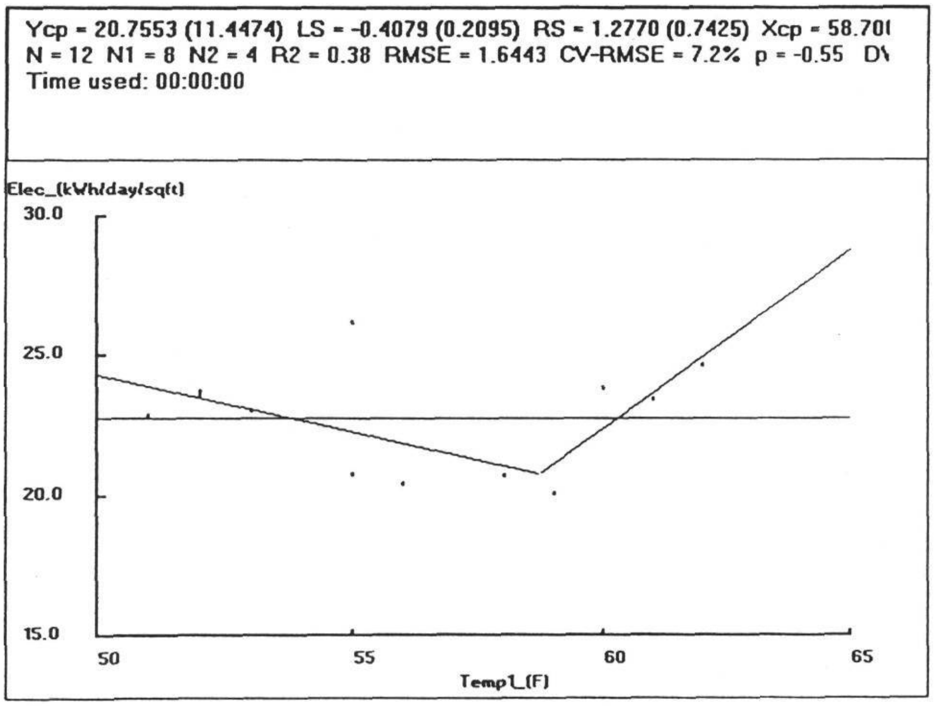


Figure 9.8. EModel change point model line and data points for Fort Ord electricity consumption for baseline year (FY86). (a) Mean model selected as baseline, (b) mean model line and next-best model, namely the 4P model line, are shown for comparative purposes.

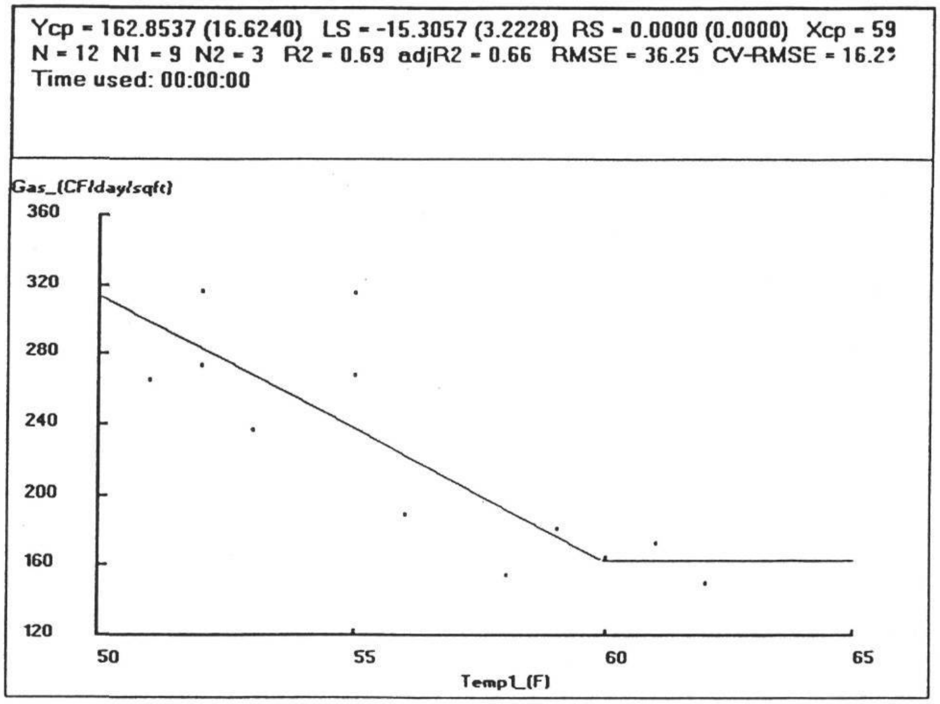


Figure 9.9. EModel change point model line and data points for Fort Ord natural gas consumption for baseline year (FY86). 3P-heating model selected as baseline.

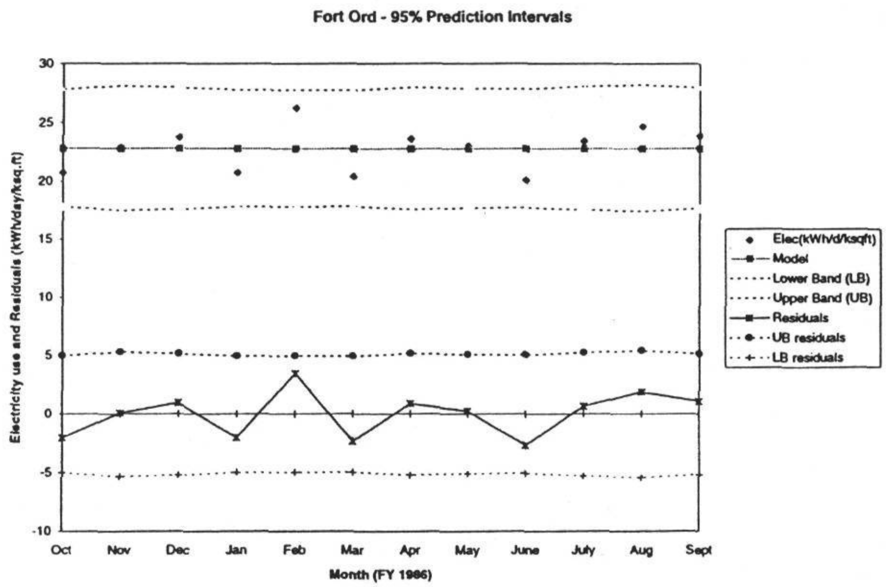


Figure 9.10. Predictive ability of the baseline model (FY86) for Fort Ord electricity use during FY86. 95% prediction intervals for the model as well as for the model residuals are shown.

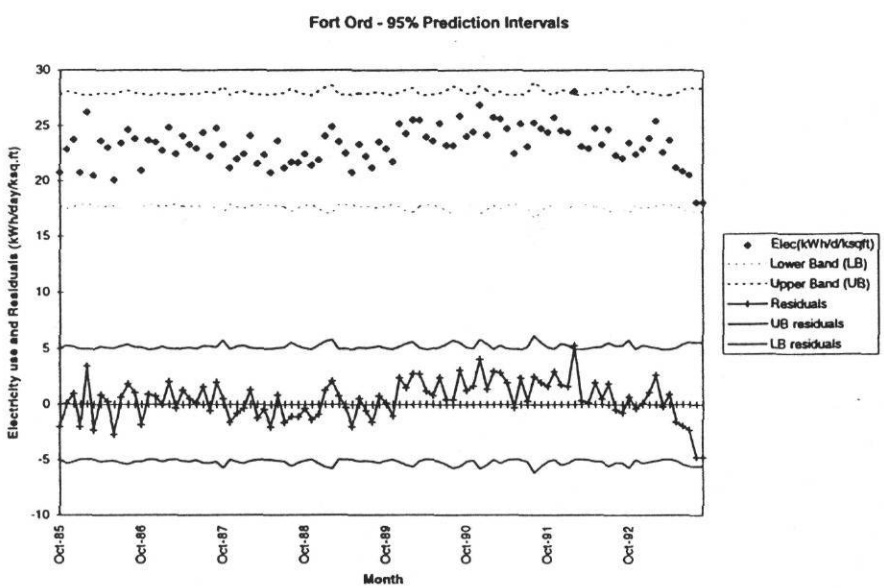


Figure 9.11. Predictive ability of electricity baseline model (FY86) for Fort Ord from FY86 to FY93. 95% prediction intervals for the model as well as for the residuals are shown.

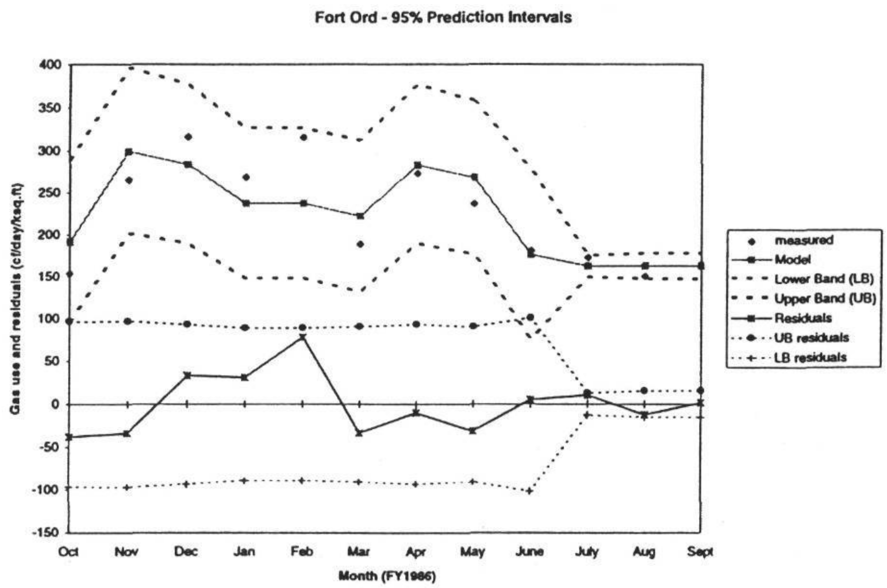


Figure 9.12. Predictive ability of the baseline model (FY86) for Fort Ord gas use during FY86. 95% prediction intervals for the model as well as for the model residuals are shown.

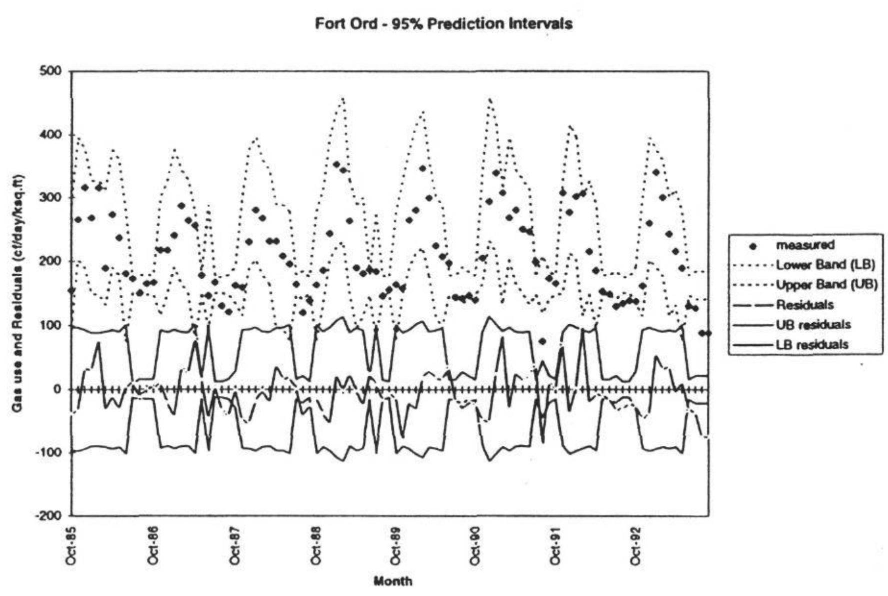


Figure 9.13. Predictive ability of gas baseline model (FY86) for Fort Ord from FY86 to FY93. 95% prediction intervals for the model as well as for the residuals are shown.

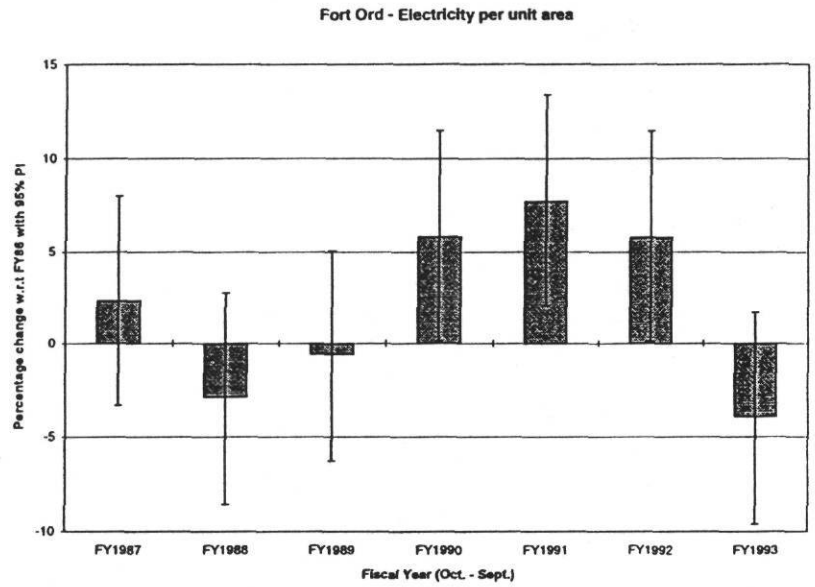


Fig.9.14(a) Electricity use

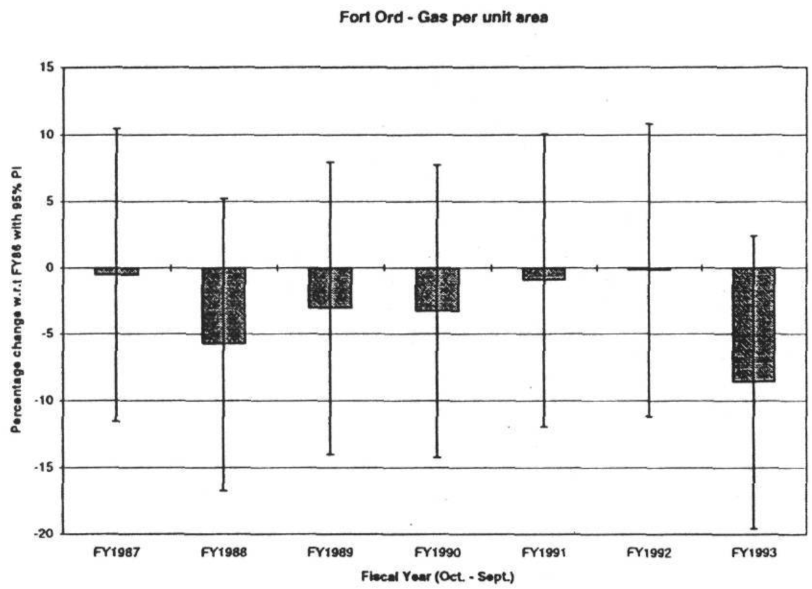


Fig.9.14(b) Gas use

Figure 9.14. Percentage change in annual energy use per conditioned area with respect to baseline year (FY86) for Fort Ord. Negative change indicates decrease in energy use and vice versa. 95% confidence intervals for the percentage change are also shown.

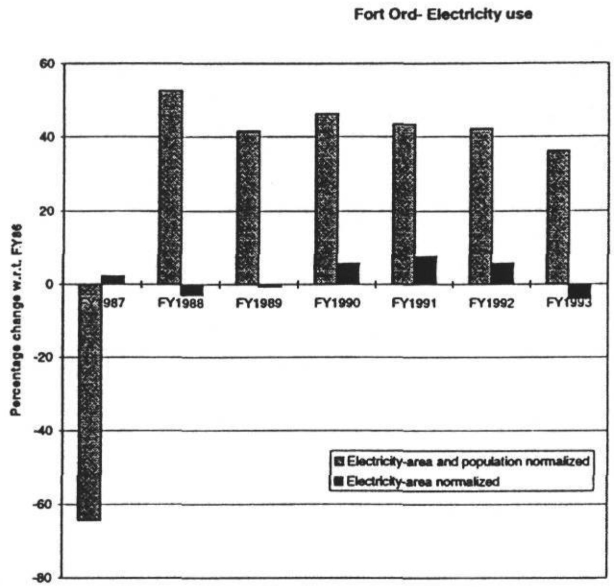


Fig.9.15 (a) Electricity use.

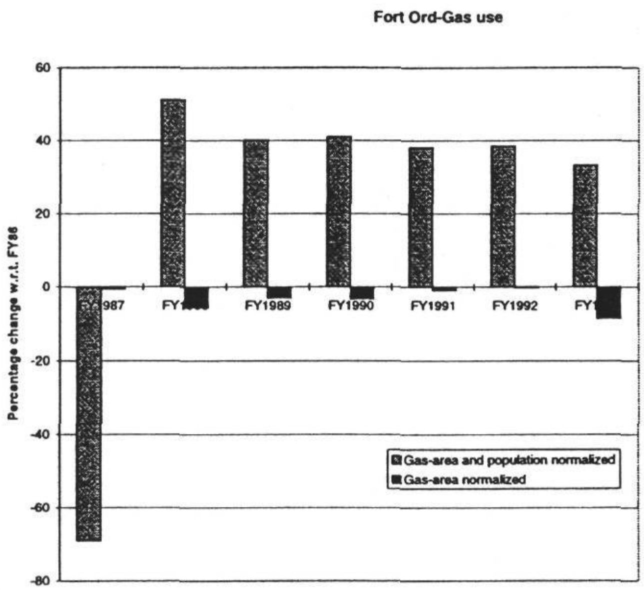


Fig.9.15 (b) Gas use

Figure 9.15. Percentage changes in annual energy use with respect to baseline year (FY86) for Fort Ord with conditioned area normalization as well as with area and population normalization.

10.0 Analysis of Pueblo Army Depot , CO

10.1 <u>Preliminary data analysis</u>

Outdoor temperature data till December 1993 only was provided to us and so all analyses at Pueblo Army Depot can be done only until FY93. Time series plots of monthly electricity use and gas use from FY86 to FY93 are shown in Fig. 10.1 along with concurrent outdoor temperature. The variation patterns of outdoor temperature and gas use are fairly consistent over the years except for a very large increase in the gas use during FY93. The magnitude of order increase leads us to suspect a transcription error in the decimal point while entering gas utility bills into the database, but we shall leave this as is until we get a confirmation on our speculation. Electricity use seems to be fairly constant seasonally but does show variability over the years.

Recall that this installation is an army depot center which is probably sparsely populated (population data for this installation was unavailable, see Table 2.2). Figure 10.2 which shows the change in total building area and conditioned area (determined as described in section 2.2) over the years, is striking in two respects. The conditioned area is only about 5% of the total building area, and both the areas have remained unchanged over the years. Annual mean daily population data is also plotted in Fig.10.2. from FY90 onwards. As expected, the population is low but does exhibit a variation from year to year.

Figure 10.3 shows the changes in annual mean daily energy use per unit conditioned area over the years. Electricity use seems to be gradually decreasing while gas use (except for FY93 as mentioned earlier) is fairly consistent over the years. The annual mean outdoor temperature is also plotted in order to enable the reader to associate changes in energy use with temperature changes. Plots such as these provide a general qualitative trend and one should not try to read too much from them.

Figure 10.4 presents time series graphs of monthly electricity and gas use normalized by conditioned area. With conditioned area constant over the years, these plots are almost identical to those in Fig. 10.1.

Figure 10.5 depicts the average monthly outdoor temperatures during a year for all years from FY86 to FY94. We note that the weather during these years seems to be fairly consistent over the years though certain monthly excursions from the overall annual pattern can be noted. Temperature data for FY86, our baseline year, seems to be fairly characteristic except for being higher than the rest during January.

Figures 10.6 and 10.7 are time series plots of electricity use and gas use normalized by conditioned area during a year for all years from FY86 to FY93. This type of representation allows clearer visualization of how energy use has changed over the years for a given month. Electricity use in July is almost constant throughout the year and fairly erratic. Gas use from FY86 till FY92 is very consistent while the order of magnitude increase in FY93 has already been pointed out earlier.

10.2 Baseline modeling

As described earlier, there is an ambiguity regarding proper match between the utility bill period and the corresponding temperature data supplied to us. In section 3.6, we had suggested a method whereby we would identify the best model from three different sets of runs where the temperature data has been taken in slightly different ways. The criteria for selecting the optimum model among the various runs are as follows:

(i) highest R^2 and lowest CV-RMSE,

(ii) if R^2 values for all models are low, CV-RMSE is to be given more consideration, and

(iii) it would be more appropriate from physical considerations, to select 3-P models rather than 4P models. Only if the improvement in R^2 and CV-RMSE is substantial, would we relax this rule.

Note that both electricity and gas use during the year have been normalized with the conditioned area of the army base during that particular year prior to model identification. The summary model statistics of our baseline model identification effort for all three cases are summarized in Table 10.1. We note that the R^2 values of the 3P-heating and cooling models and of the 4P models are very low indicating almost no temperature dependence. The mean model, though having slightly higher CV values than the others, seems to be the best choice. How the model line fits the data points can be noted in Fig. 10.8(a), while how the next-best model, namely the 4P model fits the data points, can be gauged by Fig. 10.8(b). The mean model is not very good, having a CV-STD = 17.3%, which is large.

Regarding the baseline model for gas use, we note from Table 10.1 that using case 1, i.e., temperature data corresponding to the same calendar months as the utility bills, results in best models. Further, the R^2 and CV-RMSE of the 3P- heating model are so good, and the model line fits the data points so well (see Fig. 10.9), that investigation with a 4P model was deemed unnecessary. The 3P-heating model is very good with $R^2 = 0.98$ and CV-RMSE = 9.2%.

10.3 Baseline models for screening and tracking

Once baseline models have been developed, it is possible to use them as screening tools by comparing forecast levels with actual energy use. Effect of changes in weather from year-to-year (more accurately, outdoor temperature) on the energy use is explicitly accounted for by the baseline model forecasts. Deviations from expectations must be studied to determine whether known extraneous changes have contributed to this variation or whether these changes are a result of energy efficiency measures or DSM programs that have been initiated. How the PIs of the model are to be calculated have been described in section 3.3 for individual months and in section 3.4 on an annual basis. We have used our FY86 baseline models to forecast into the future up to FY93.

Figures 10.10 and 10.12 depict the extent to which the monthly energy use utility bills are bounded by the PIs of the FY86 baseline model for electricity use and gas use respectively. For clearer visualization, we have also shown the residuals (residual = measured value minus model predicted value) along with the PIs. If, say, the utility bill data for a month fall below the lower 95% PI, one can safely affirm that energy use during that month has decreased as compared to model predictions. We note that electricity use has very wide PIs bands which is not surprising since the model was rather poor (see Table 10.1). The gas use model (which was very good) has narrow 95% uncertainty bands.

How well the FY86 baseline models for electricity and gas use are able to predict monthly energy use from FY86 till FY93 can be seen in Figs. 10.11 and 10.13 respectively. Note that the energy use is on a monthly mean daily basis per unit conditioned area but has not been normalized for changes in population from one year to the next. We note that electricity use is well contained within the PIs while showing a decrease from FY90 onwards. Gas use also seems well bounded by the PIs (see Fig. 10.13) except for the very large increase in FY93. Plots such as this are useful to the energy manager of the corresponding Army base who is in a position to look for (as well as discern and evaluate) changes in energy use as a result of certain specific actions taken (such as O&M measures or say, changes in equipment in the power plants).

On an annual time scale, however, determination of percentage changes in energy use (normalized by conditioned area) with respect to the baseline year (FY86) permit rather well-defined conclusions to be drawn regarding the extent to which the Executive Order 12902 has been met. How these changes are to be determined as well as the 95% PIs of these changes have been described in sections 3.4 and 3.5. Following eqs.(3.16) and (3.17), we have computed the percentage changes on a year by year basis (Table 10.4) and plotted them in Figs.10.14 for both electricity and gas. Note that a negative change indicates a decrease in energy use. Clearly electricity use has decreased over the years. Though FY87 - FY89 do not exhibit statistically conclusive decreases in energy use with respect to FY86 (since the 95% PI bands are wider than the estimates of change themselves), decrease in electricity use from FY90 onwards is significant. Gas use, on the other hand, does not seem to have varied over the years except for FY93 which we suspect to be erroneous as discussed above.

On the whole, we note that electricity use in FY93 has decreased by about 44% ($\pm$ 12%) with respect to FY86, while gas use in FY92 (omitting the anomalous use in FY93), has increased by about 4% ($\pm$ 6%). While electricity use decrease is statistically significant, that for gas is not.

10.4 Concluding remarks

The mean electricity baseline model identified for FY86 for Pueblo Army Depot was found to be quite poor with CV-STD = 17.3%. The 3P-heating gas model was fairly good with R^2 = 0.98 and CV-RMSE = 9.2%. Our analysis indicated that there was no mis-match between the utility bills and the calendar monthly mean temperature data that we received.

Using the baseline models to track how energy use has increased (or decreased) over the years required that energy use during each year be normalized by the associated conditioned area of the army installation (a quantity which is not directly available from the database but which had to be inferred from areas of several categories of building types which were listed in the database). This leads to a certain amount of unavoidable uncertainty in our conclusions regarding the screening and tracking aspects of the baseline models. We found that electricity use in FY93 has decreased by about 44% ($\pm$ 12%) with respect to FY86, while gas use, omitting the anomalous FY93, has increased by about 4% ($\pm$ 6%) from FY86 till FY92 which is, however, statistically uncertain. Since data for population was missing for a number of years, and since this variable would have little effect on energy use in an Army depot, we have not done any investigation with energy normalizing by population as was done in the previous bases.

Table 10.1. Pueblo Army Depot: model identification summary statistics for baseline year (FY86). Final models selected are shown in bold face.

		Mean	3P		4P	
	Temperature data used	CV-St.Dev (%)	R^2 Cool/Heat	CV-RMSE (%) Cool/Heat	R^2	CV-RMSE (%)
Electricity	Same month (T_1)	**17.3***	0.06/0.20	17.6/16.3	0.24	16.7*
	Previous month (T_2)	-	0.16/0.01	16.6/18.1	0.25	16.6
	Mid-month (T_3)	-	0.01/0.09	18.1/17.4	0.17	17.4
			3P-Heating		4P	
Gas	Same month (T_1)	-	**0.98**	**9.2***	-	-
	Previous month (T_2)	-	0.98	9.2	-	-
	Mid-month (T_3)	-	0.98	9.2	-	-

* Plots of these models are shown in the report

Table 10.2. Pueblo Army Depot electricity use: model coefficients (and standard errors) and pertinent regression model statistics for FY86.

Model type	Y_{cp} (kWh/d/ksq.ft)	LS (kWh/d/ksq.ft/F)	X_{cp} (°F)	R^2	CV-St.Dev (%)	St.Dev. (kWh/d/ksq.ft)	n_1
Mean	158.4	-	-	-	17.3	27.45	-

Table 10.3. Pueblo Army Depot gas use: model coefficients (and standard errors) and pertinent regression model statistics for FY86.

Model type	Y_{cp} (cf/d/ksq.ft)	LS (cf/d/ksq.ft/F)	X_{cp} (°F)	R^2	CV-RMSE (%)	RMSE (cf/d/ksq.ft)	n_1
3P-H	17.29(2.123)	-2.447(0.1077)	65.6	0.98	9.2	4.90	9

Table 10.4 Baseline models and percentage change in energy use w.r.t baseline year for Pueblo Army Depot. Data for population was missing for a certain number of years and so percentage change numbers normalized by population were not calculated

Energy type	Baseline year	Model type	Model fit	Year	% change normalized by conditioned area with 95% PI
Electric.	FY86	Mean	Mediocre	FY87	2.20 ± 11.78
				FY88	-3.85
				FY89	-3.29
				FY90	-11.52
				FY91	-16.57
				FY92	-30.44
				FY93	-43.81
				FY94	-
Gas use	FY86	3P-H	Good	FY87	8.91 ± 6.25
				FY88	8.85
				FY89	1.90
				FY90	4.41
				FY91	-1.18
				FY92	3.52
				FY93	85.44
				FY94	-

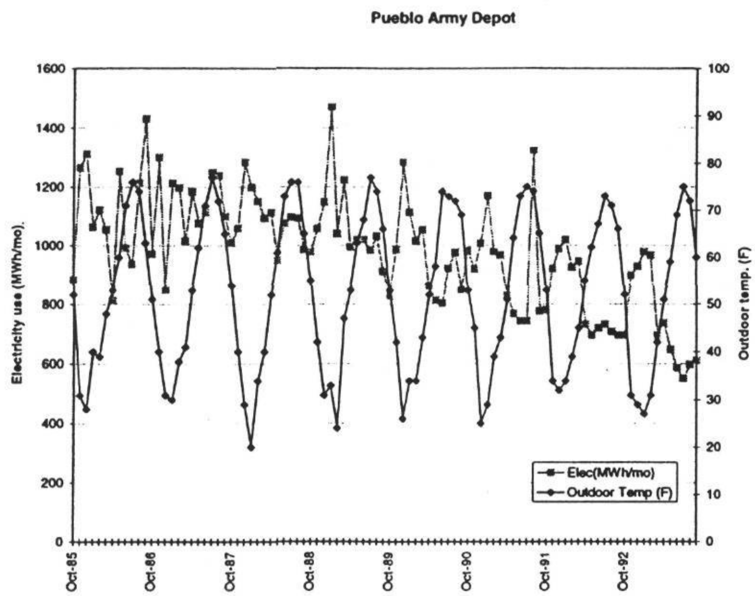


Fig.10.1(a)

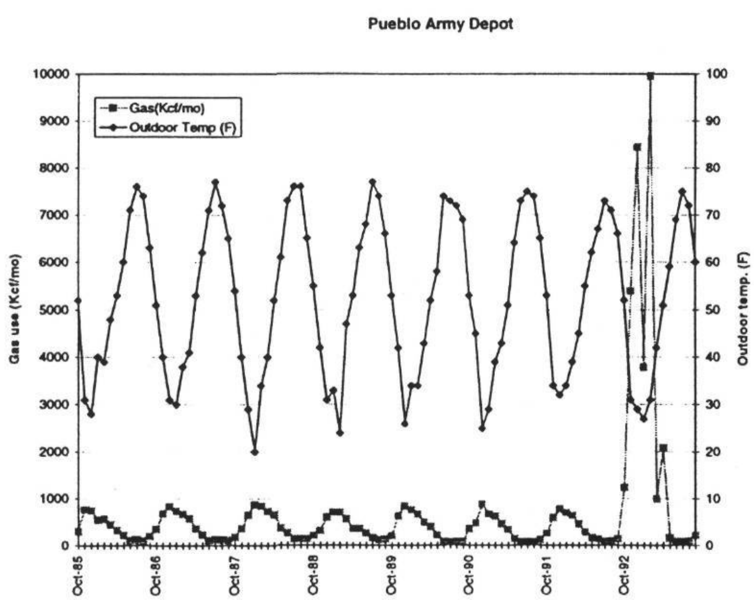


Fig.10.1(b)

Figure 10.1. Time series plots of monthly electricity and gas consumption for Pueblo Army Depot from FY86 to FY93. The concurrent outdoor dry-bulb temperature variation is also shown.

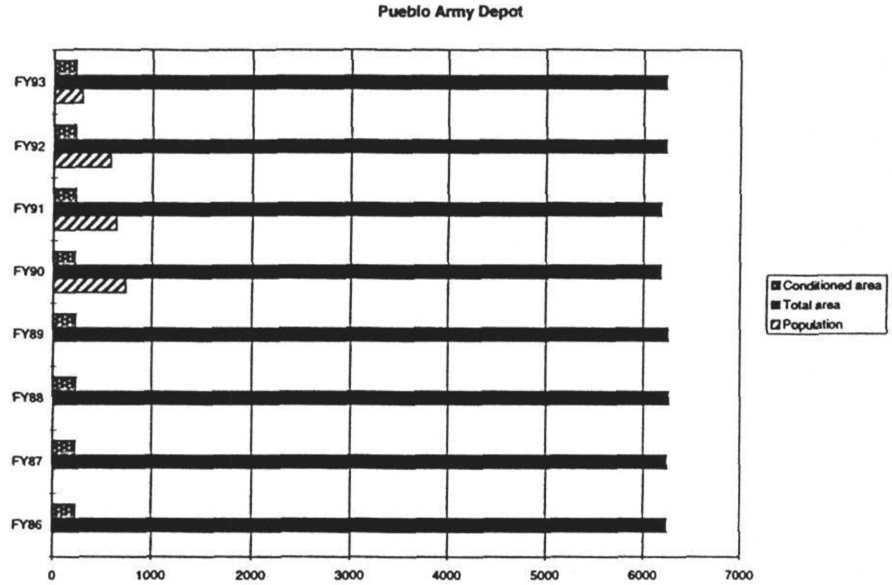


Figure 10.2. Changes in total and conditioned areas (in ksq.ft) and annual mean daily population for Pueblo Army Depot from FY86 to FY93.

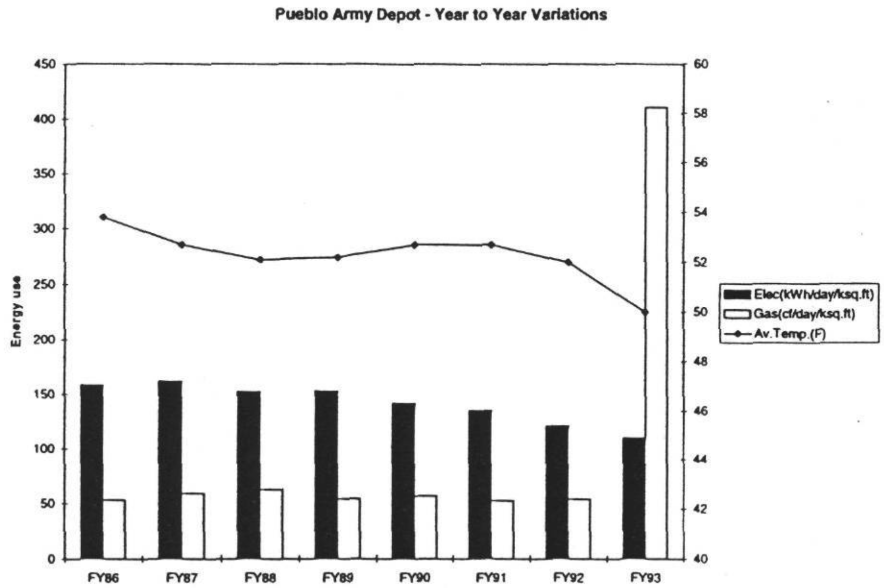


Fig.10.3 Changes in annual mean daily energy use per unit conditioned area and annual mean outdoor temperature for Pueblo Army Depot from FY86 to FY93.

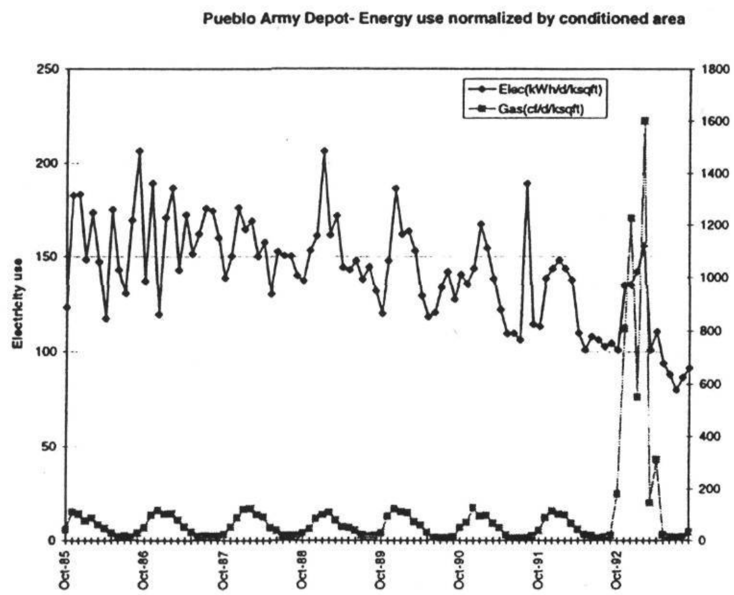


Figure 10.4. Time series graphs of monthly electricity and gas consumption per unit conditioned area for Pueblo Army Depot from FY86 to FY93.

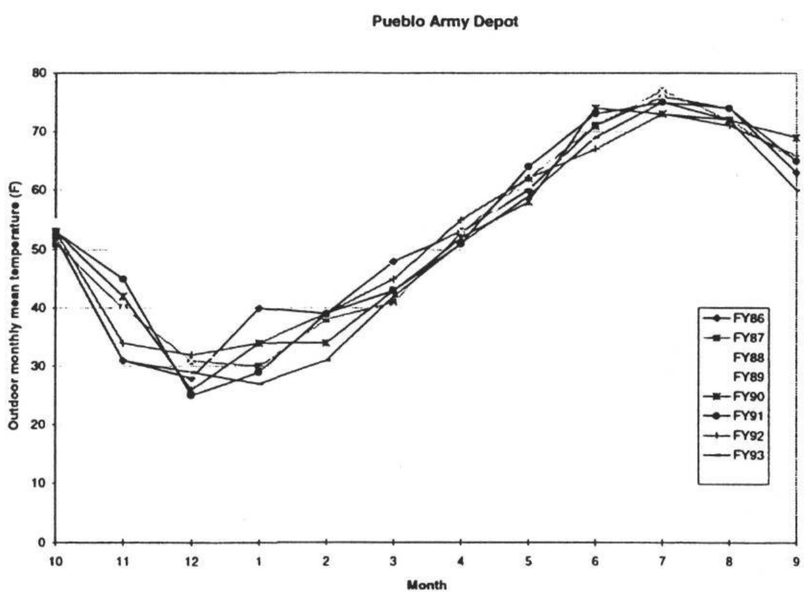


Figure 10.5. Time series plots of average monthly temperatures at Pueblo Army Depot from FY86 to FY93.

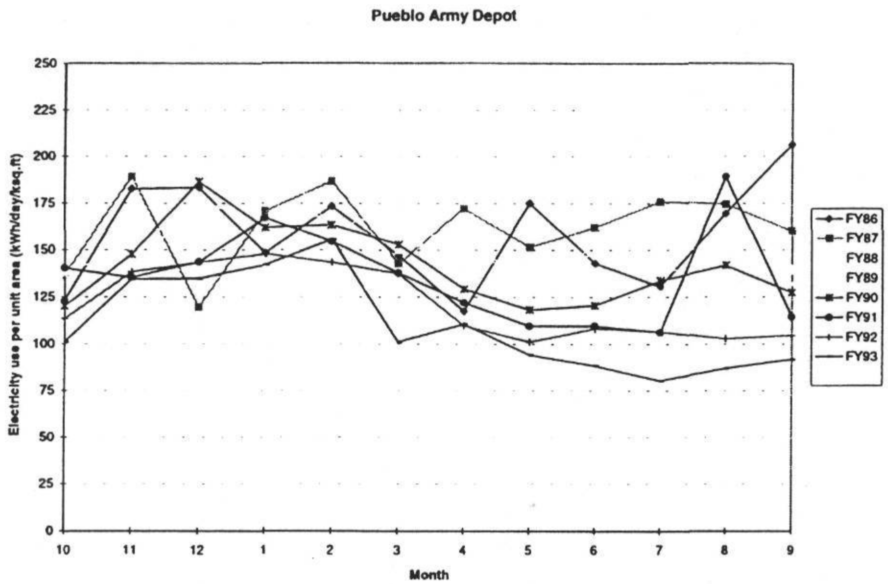


Figure 10.6.Time series plots of electricity use per unit conditioned area for Pueblo Army Depot from FY86 to FY93.

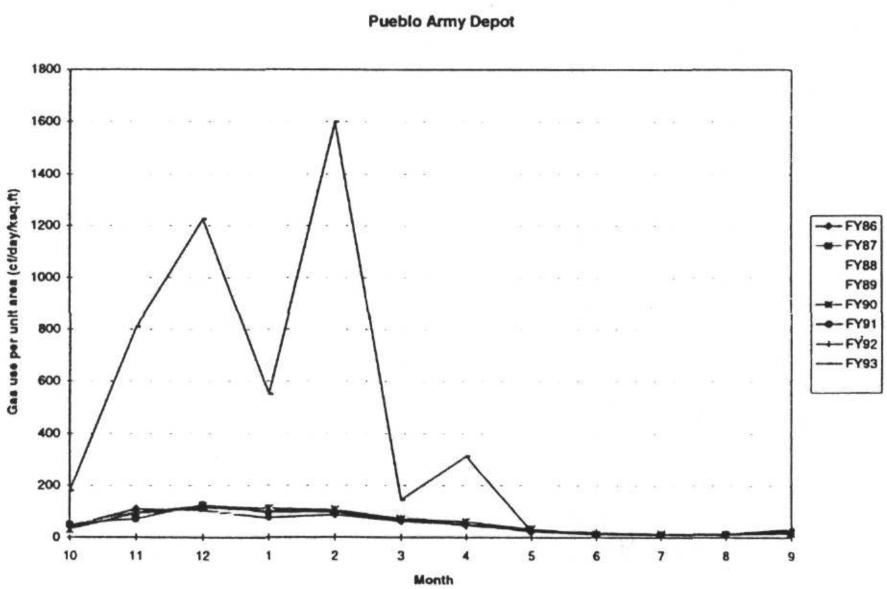


Figure 10.7. Time series plots of gas use per unit conditioned area for Pueblo Army Depot from FY86 to FY93.

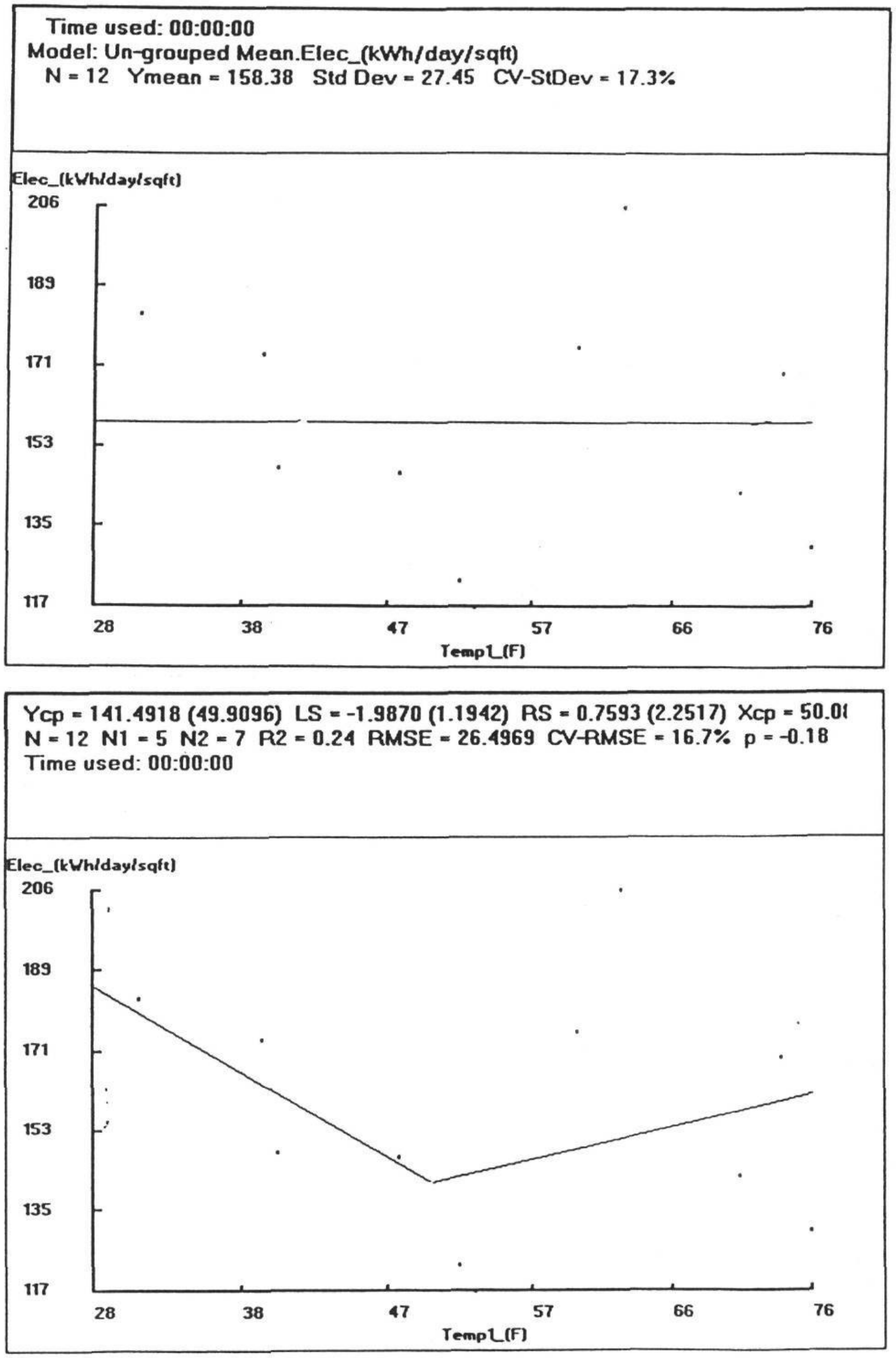


Figure 10.8. EModel change point model line and data points for Pueblo Army Depot electricity consumption for baseline year (FY86). (a) Mean model selected as baseline, (b) next-best model, namely the 4P model line, are shown for comparative purposes.

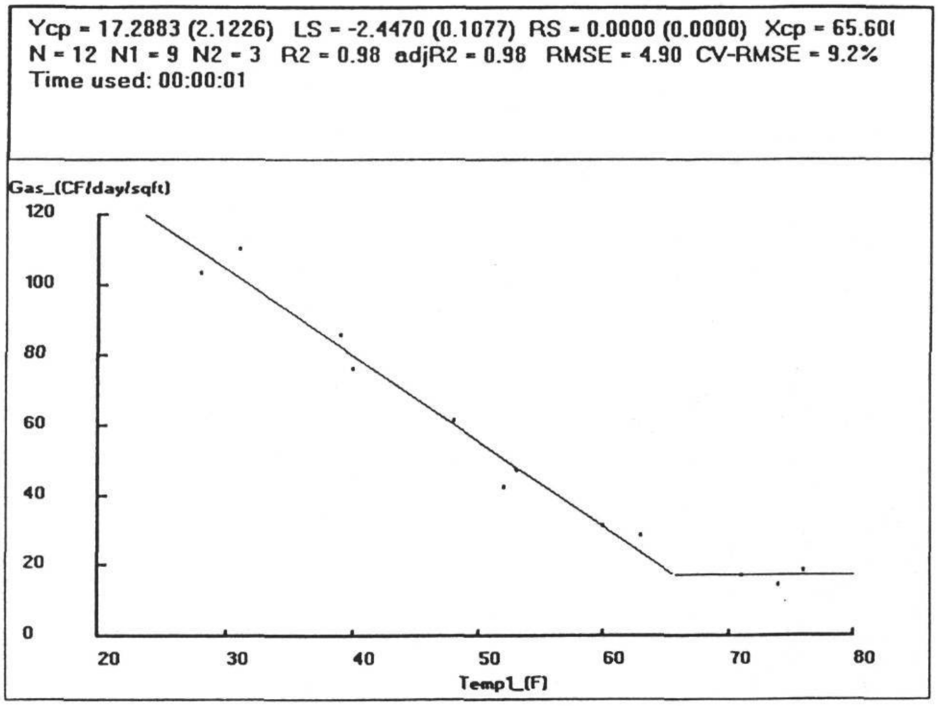


Figure 10.9. EModel change point model line and data points for Pueblo Army Depot natural gas consumption for baseline year (FY86). 3P-heating model selected as baseline.

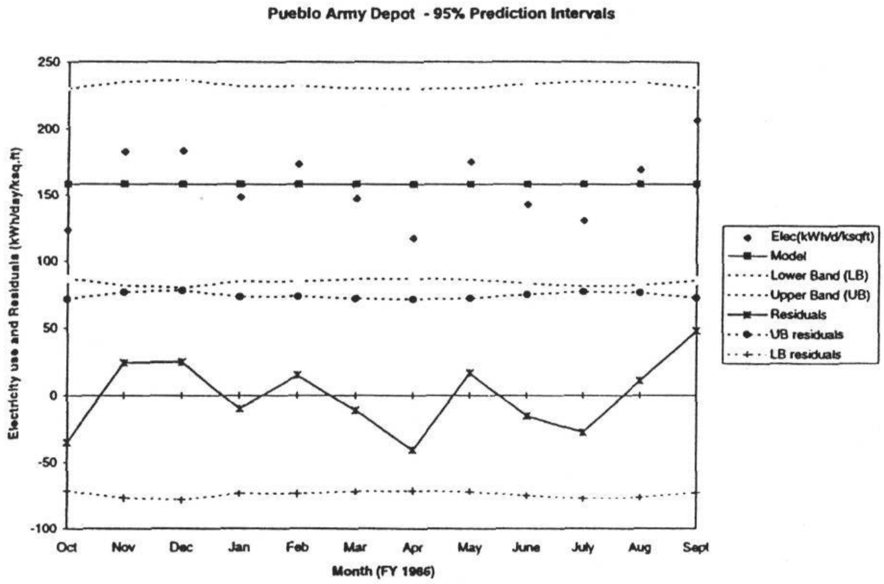


Figure 10.10.Predictive ability of the baseline model (FY86) for Pueblo Army Depot electricity use during FY86. 95% prediction intervals for the model as well as for the model residuals are shown.

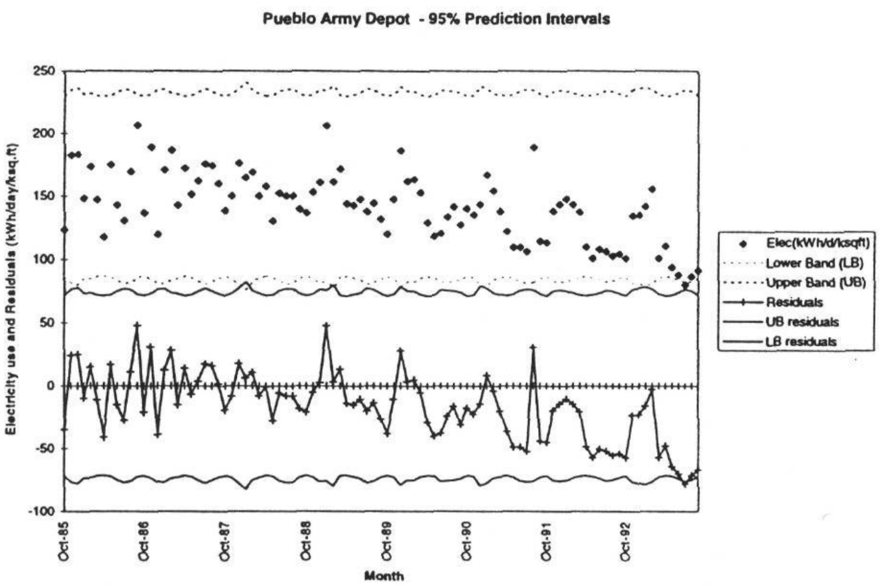


Figure 10.11. Predictive ability of electricity baseline model (FY86) for Pueblo Army Depot from FY86 to FY93. 95% prediction intervals for the model as well as for the residuals are shown.

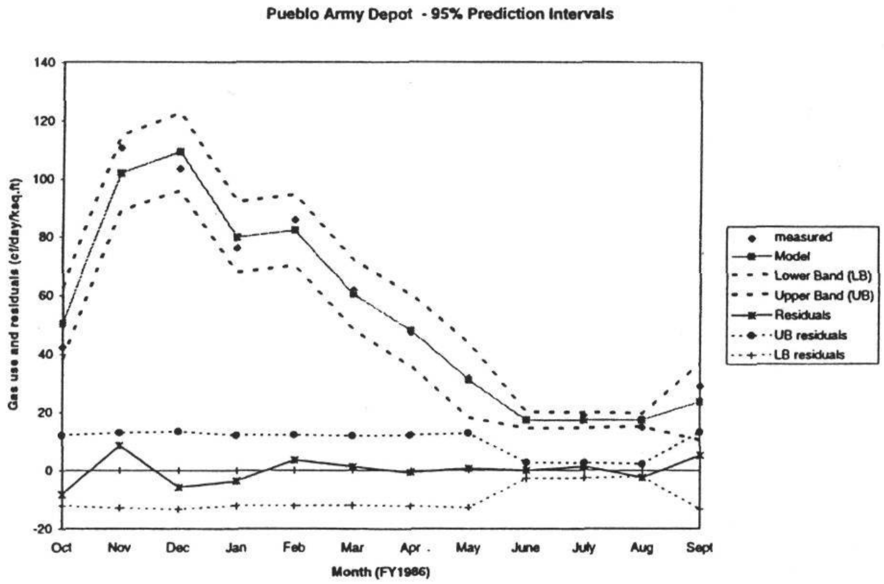


Figure 10.12. Predictive ability of the baseline model (FY86) for Pueblo Army Depot gas use during FY86. 95% prediction intervals for the model as well as for the model residuals are shown.

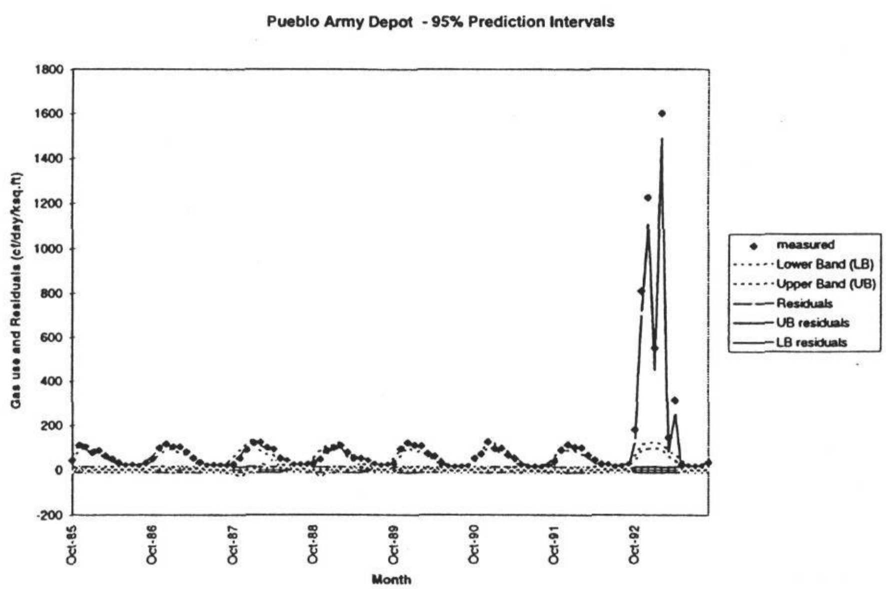


Figure 10.13. Predictive ability of gas baseline model (FY86) for Pueblo Army Depot from FY86 to FY93. 95% prediction intervals for the model as well as for the residuals are shown.

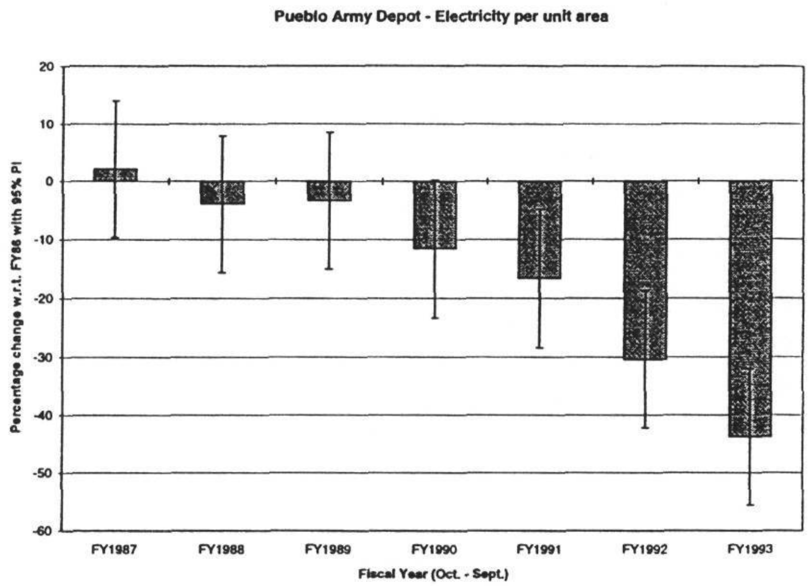


Fig.10.14(a) Electricity use

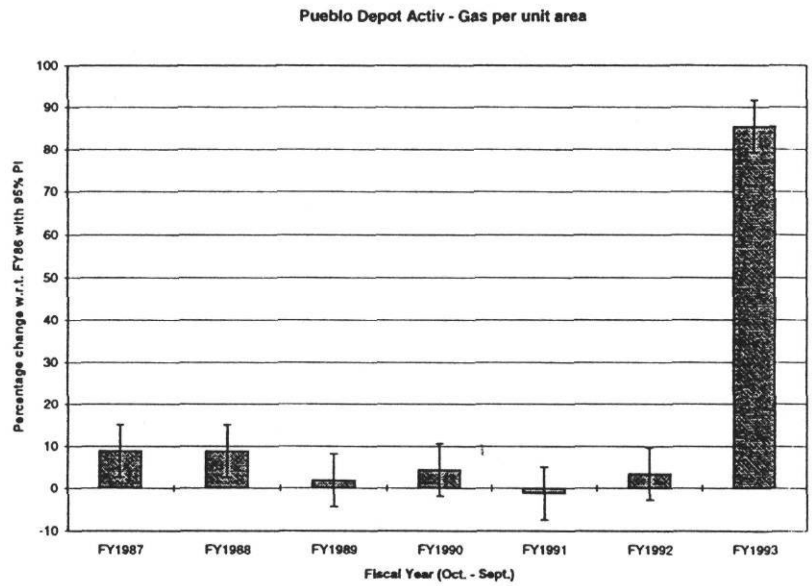


Fig.10.14(b) Gas use

Figure 10.14. Percentage change in annual energy use per conditioned area with respect to baseline year (FY86) for Pueblo Army Depot . Negative change indicates decrease in energy use and vice versa. 95% confidence intervals for the percentage change are also shown.

11.0 Analysis of Sacramento Army Depot, CA

11.1 Preliminary data analysis

Time series plots of monthly electricity use and gas use from FY86 to FY94 are shown in Fig. 11.1 along with concurrent outdoor temperature. The variation patterns for gas and temperature are fairly consistent over the years. As expected, gas use peaks in winter. Electricity use seems to be constant over the year while a general increase and then a decrease over the years is noticeable.

Sacramento Army Depot is an army depot and one would except a relatively small fraction of the total building area to be conditioned. Figure 11.2 shows the change in total area and conditioned area (determined as described in section 2.2) over the years. Both these areas seem to have generally increased from FY86 to FY90, and then decreased again so that the values in FY94 are close to those in FY86. The conditioned area seems to be about 15% of the total building area of the base. Annual mean daily population data from FY90 is also plotted in Fig.11.2. Population seems to have dropped significantly in FY94.

Figure 11.3 shows the changes in annual mean daily energy use per unit conditioned area over the years. Both gas use and electricity use are variable over the years. The annual mean outdoor temperature is also plotted in order to enable the reader to associate changes in energy use with temperature changes. Plots such as these provide a general qualitative trend and one should not try to read too much from them.

Figure 11.4 presents time series graphs of monthly electricity and gas use normalized by conditioned area. We notice that generally gas use has decreased during summer with the winter use remaining unchanged till FY93 and then decreased in FY94. Also, gas use during FY91 is lower and also bi-modal. Electricity use seems to show a gradual decrease over the years.

Figure 11.5 depicts the average monthly outdoor temperatures during a year for all years from FY86 to FY94. We note that the weather during these years seems to be fairly consistent over the years though certain monthly excursions from the overall annual pattern can be noted. Temperature data for FY86, our baseline year, seems to be fairly characteristic except for being higher than the rest of the years during January.

Figures 11.6 and 11.7 are time series plots of electricity use and gas use normalized by conditioned area during a year for all years from FY86 to FY94. This type of representation allows clearer visualization of how energy use has changed over the years for a given month. Electricity use looks fairly constant over the year with, however, important year to year variations. We note that electricity use data for FY94 is much lower than that during the other years. Gas is obviously used largely for space heating since it peaks in winter. One notices the odd behavior of gas use during January 1986 and from January till September 1994 where gas use is lower than in the other years.

11.2 Baseline modeling

As described earlier, there is an ambiguity regarding proper match between the utility bill period and the corresponding temperature data supplied to us. In section 3.6, we had suggested a method whereby we would identify the best model from three different sets of runs where the temperature data has been taken in slightly different ways. The criteria for selecting the optimum model among the various runs are as follows:

(i) highest R^2 and lowest CV-RMSE,
(ii) if R^2 values for all models are low, CV-RMSE is to be given more consideration, and
(iii) it would be more appropriate from physical considerations, to select 3-P models rather than 4P models. Only if the improvement in R^2 and CV-RMSE is substantial, would we relax this rule.

Note that both electricity and gas use during the year have been normalized with the conditioned area of the army base during that particular year prior to model identification. The summary model statistics of our baseline model identification effort for all three cases are summarized in Table 11.1. We notice that the improvement in electricity use models is substantial when previous month temperature values (i.e., case 2 in section 3.6) are used for regression. This leads us to conclude that the electricity bills do not span calendar monthly intervals but have been shifted by one month. For electricity, the 4P model seems to be the best choice for a baseline model (see Table 11.1). How the model line fits the data points can be noted in Fig. 11.8. Though the R^2 value is poor (= 0.67), CV-RMSE = 7.3% which makes the baseline electricity model a good one.

Regarding the baseline model for gas use, we note from Table 11.1 that using case 2, i.e., temperature data shifted by one month compared to the utility bills, results in best models. Further, from the R^2 and CV-RMSE values, a 3P-heating model is clearly the best choice. How the individual monthly data points scatter around the 3P-heating baseline model line can be seen in Fig. 11.9.

Though the R^2 value is satisfactory (R^2 = 0.88), the CV-RMSE =26.4% which is very large. Consequently, the model has to be deemed unsatisfactory.

11.3 Baseline models for screening and tracking

Once baseline models have been developed, it is possible to use them as screening tools by comparing forecast levels with actual energy use. Effect of changes in weather from year-to-year (more accurately, outdoor temperature) on the energy use is explicitly accounted for by the baseline model forecasts. Deviations from expectations must be studied to determine whether known extraneous changes have contributed to this variation or whether these changes are a result of energy efficiency measures or DSM programs that have been initiated. How the PIs of the model are to be calculated have been described in section 3.3 for individual months and in section 3.4 on an annual basis. We have used our FY86 baseline models to forecast into the future up to FY94.

Figures 11.10 and 11.12 depict the extent to which the monthly energy use utility bills are bounded by the PIs of the FY86 baseline model for electricity use and gas use respectively. For clearer visualization, we have also shown the residuals (residual = measured value minus model predicted value) along with the PIs. If, say, the utility bill data for a month fall below the lower 95% PI, one can safely affirm that energy use during that month has decreased as compared to model predictions. We note that the 95% PI bands for electricity use are relatively narrow which is not surprising since the model is satisfactory with low CV-RMSE (see Table 10.1). The prediction bands for gas use, on the other hand, are relatively large since the model is a poor one.

How well the FY86 baseline models for electricity and gas use are able to predict monthly energy use from FY86 till FY94 can be seen in Figs. 11.11 and 11.13 respectively. Note that the energy use is on a monthly mean daily basis per unit conditioned area but has not been normalized for changes in population from one year to the next. We note that electricity use is generally contained within the PIs till FY92 and then seems to have decreased subsequently. Gas use data, on the other hand, is generally bounded by the PIs (see Fig. 11.13) partly because the PIs for gas are wider than those for electricity (since the model is slightly poorer). So statistically speaking, one cannot draw any definite conclusions about how gas use has varied over the years. However, plots such as this are useful to the energy manager of the corresponding Army base who is in a position to look for (as well as discern and evaluate) changes in energy use as a result of certain specific actions taken (such as O&M measures or say, changes in equipment in the power plants).

On an annual time scale, however, determination of percentage changes in energy use (normalized by conditioned area) with respect to the baseline year (FY86) permit rather well-defined conclusions to be drawn regarding the extent to which the Executive Order 12902 has been met. How these changes are to be determined as well as the 95% PIs of these changes have been described in sections 3.4 and 3.5. Following eqs.(3.16) and (3.17), we have computed the percentage changes on a year by year basis (see Table 11.4) and plotted them in Figs. 11.14 for both electricity and gas. Note that a negative change indicates a decrease in energy use. Clearly both electricity and gas use have decreased with respect to FY86. Except for FY87 when electricity use has increased from that of FY86, electricity use has progressively decreased more so from FY90 onwards. Gas use also has decreased from FY93 onwards. The changes during the last two years, for both electricity and gas use, are significant statistically in view of the relatively narrow uncertainty bands. On the whole, we note that electricity use in FY94 has decreased by about 53% ($\pm$ 5%) with respect to FY86, while gas use has decreased also by about 54% ($\pm$ 18%). The uncertainty bands of the change in electricity use are relatively smaller than those of the gas, but nonetheless both these estimates of change compared to our baseline year of FY86 are significant.

11.4 Concluding remarks

The 4P electricity baseline model identified for FY86 for Sacramento Army Depot was found to be satisfactory in terms of acceptable CV-RMSE value though the R^2 value was low. On the other hand, the gas model has high R^2 (= 0.88), but since the CV-RMSE = 26.4%, the model was deemed unsatisfactory. Our analysis indicated that both electricity and gas utility bills were recorded with a one month mis-match with the calendar monthly mean temperature data that we received.

Using the baseline models to track how energy use has increased (or decreased) over the years required that energy use during each year be normalized by the associated conditioned area of the army installation. (As described earlier, this quantity is not directly available from the database but has to be inferred from areas of several categories of building types which were listed in the database). This leads to a certain amount of unavoidable uncertainty in our conclusions regarding the screening and tracking aspects of the baseline models. We found that electricity use in FY94 has decreased by about 53% ($\pm$ 5%) with respect to FY86, while gas use has decreased also by about 54% ($\pm$ 18%). Since data for population was missing for a number of years, and since this variable would have little effect on energy use in an Army depot, we have not done any investigation with energy normalizing by population as was done in the previous bases.

Table 11.1. Sacramento Army Depot: model identification summary statistics for baseline year (FY86). Final models selected are shown in bold face.

		Mean	3P		4P	
	Temperature data used	CV-St.Dev (%)	R^2 Cool/Heat	CV-RMSE (%) Cool/Heat	R^2	CV-RMSE (%)
Electricity	Same month (T_1)	11.6	0.02/0.08	12.1/11.7	0.11	12.1
	Previous month (T_2)	-	0.09/0.38	11.6/9.6	**0.67**	**7.3***
	Mid-month (T_3)	-	0.05/0.29	11.9/10.2	0.44	9.6
			3P-Heating		4P	
Gas	Same month (T_1)	-	0.53	51.6	0.53	54.4
	Previous month (T_2)	-	**0.88**	**26.4***	0.88	27.8
	Mid-month (T_3)	-	0.82	32.1	0.82	33.8

* Plots of these models are shown in the report

Table 11.2. Sacramento Army Depot electricity use: model coefficients (and standard errors) and pertinent regression model statistics for FY86.

Model type	Y_{cp} (kWh/d/ksq.ft)	LS (kWh/d/ksq.ft/F)	RS (kWh/d/ksq.ft/F)	X_{cp} (°F)	R^2	CV-RMSE (%)	RMSE (kWh/d/ksq.ft)	n_1
4P	118.35(28.28)	-2.05(0.491)	3.10(1.362)	68.0	0.67	7.3	10.45	8

Table 11.3. Sacramento Army Depot gas use: model coefficients (and standard errors) and pertinent regression model statistics for FY86.

Model type	Y_{cp} (cf/d/ksq.ft)	LS (cf/d/ksq.ft/F)	X_{cp} (°F)	R^2	CV-RMSE (%)	RMSE (cf/d/ksq.ft)	n_1
3P-H	222.97(63.58)	-50.59(6.021)	67.2	0.88	26.4	157.46	8

Table 11.4 Baseline models and percentage change in energy use w.r.t baseline year for Sacramento Army Depot. Data for population was missing for a certain number of years and so percentage change numbers normalized by population were not calculated.

Energy type	Baseline year	Model type	Model fit	Year	% change normalized by conditioned area with 95% PI
Electric.	FY86	4P	Good	FY87	9.65 ± 4.98
				FY88	-15.84
				FY89	-11.56
				FY90	-0.36
				FY91	-2.42
				FY92	-6.15
				FY93	-17.70
				FY94	-52.92
Gas use	FY86	3P-H	Poor	FY87	-10.71 ± 17.94
				FY88	-29.68
				FY89	-12.76
				FY90	-8.80
				FY91	-14.72
				FY92	8.66
				FY93	-32.81
				FY94	-53.60

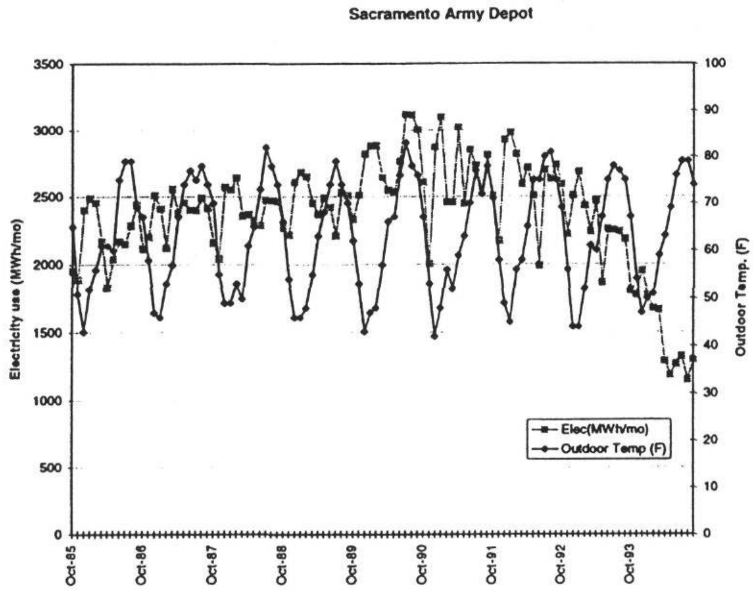


Fig.11.1(a)

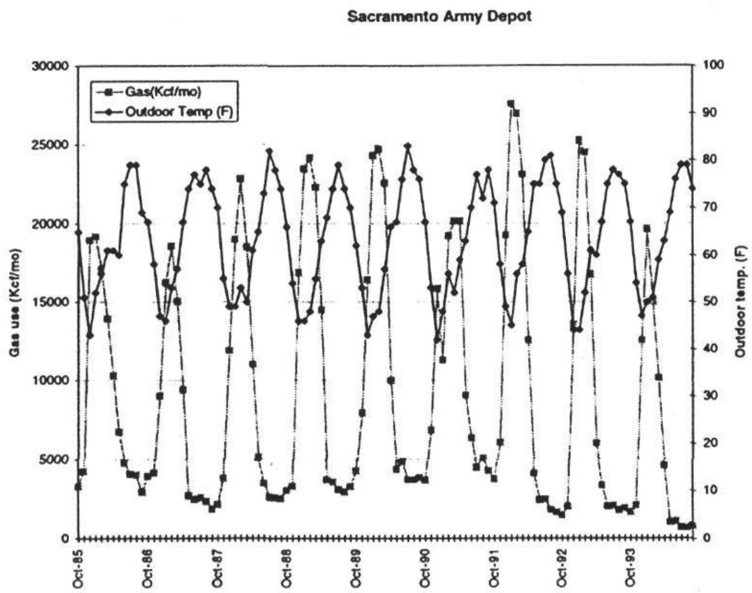


Fig.11.1(b)

Figure 11.1. Time series plots of monthly electricity and gas consumption for Sacramento Army Depot from FY86 to FY94. The concurrent outdoor dry-bulb temperature variation is also shown.

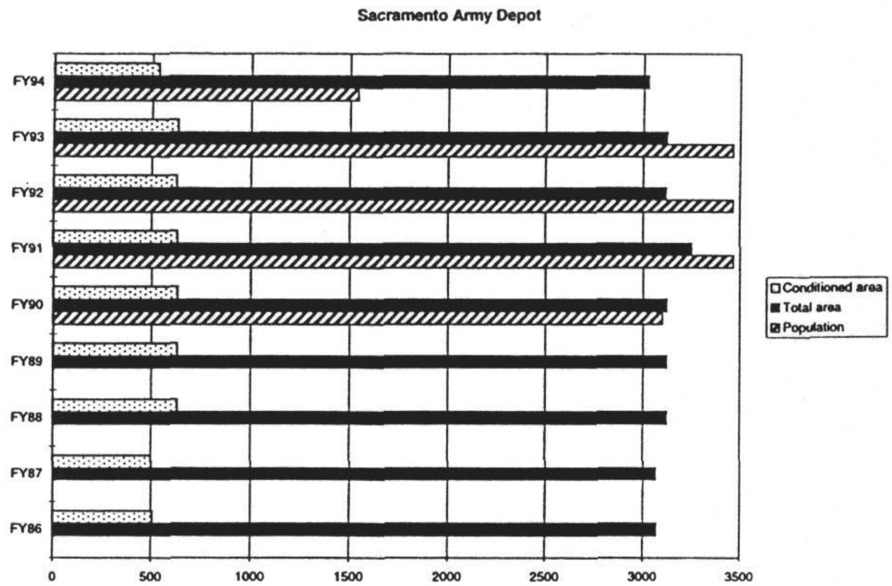


Figure 11.2. Changes in total and conditioned areas (in ksq.ft) and annual mean daily population for Sacramento Army Depot from FY86 to FY94.

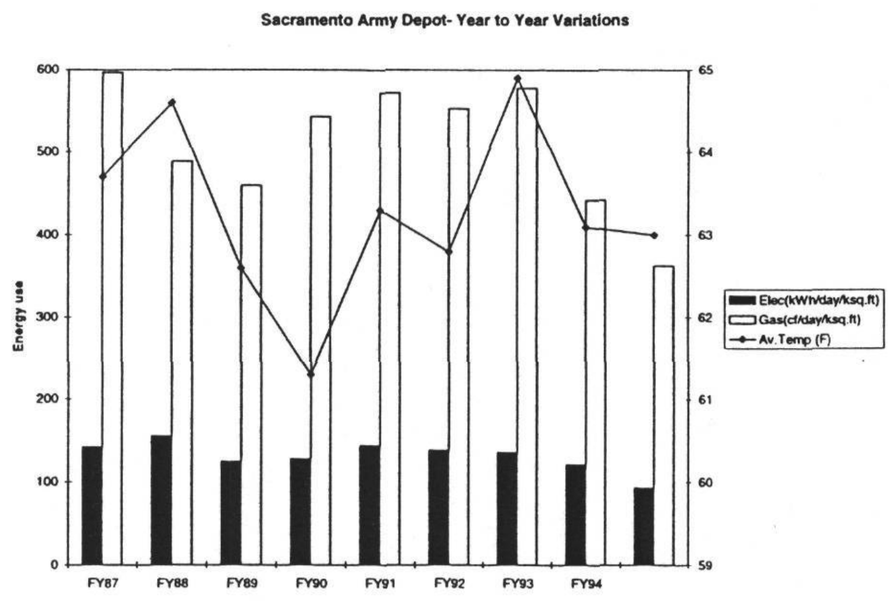


Fig.11.3 Changes in annual mean daily energy use per unit conditioned area and annual mean outdoor temperature for Sacramento Army Depot from FY86 to FY94.

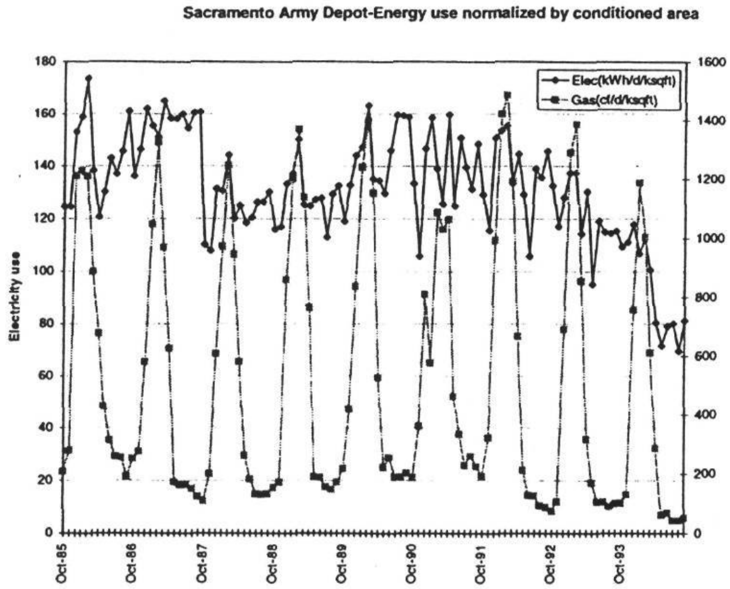


Figure 11.4. Time series graphs of monthly electricity and gas consumption per unit conditioned area for Sacramento Army Depot from FY86 to FY94.

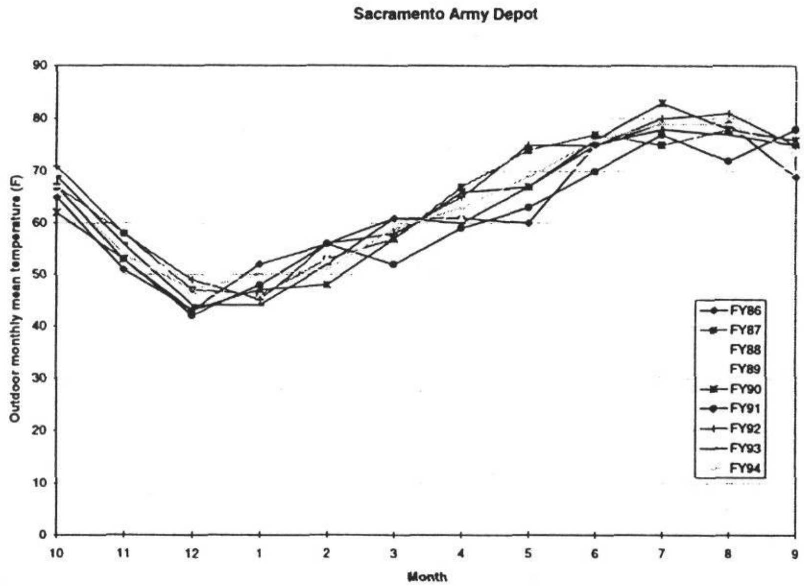


Figure 11.5. Time series plots of average monthly temperatures at Sacramento Army Depot from FY86 to FY94.

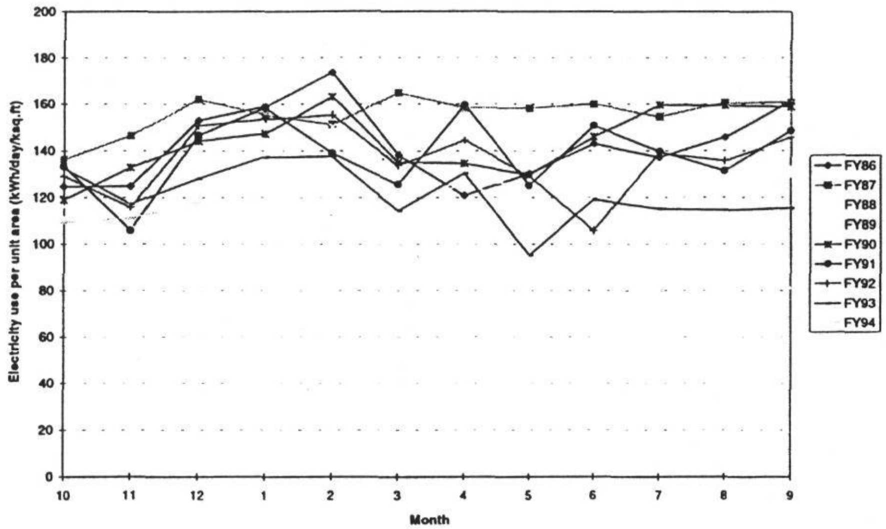


Figure 11.6. Time series plots of electricity use per unit conditioned area for Sacramento Army Depot from FY86 to FY94.

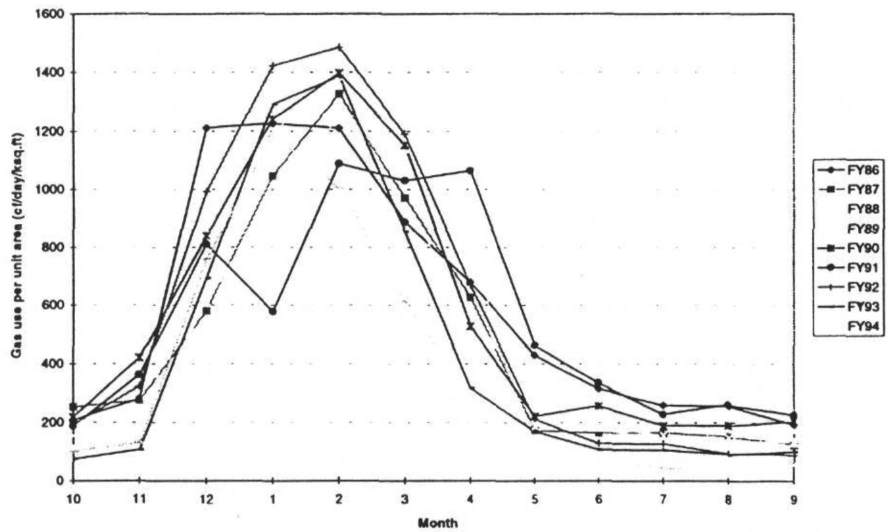


Figure 11.7. Time series plots of gas use per unit conditioned area for Sacramento Army Depot from FY86 to FY94.

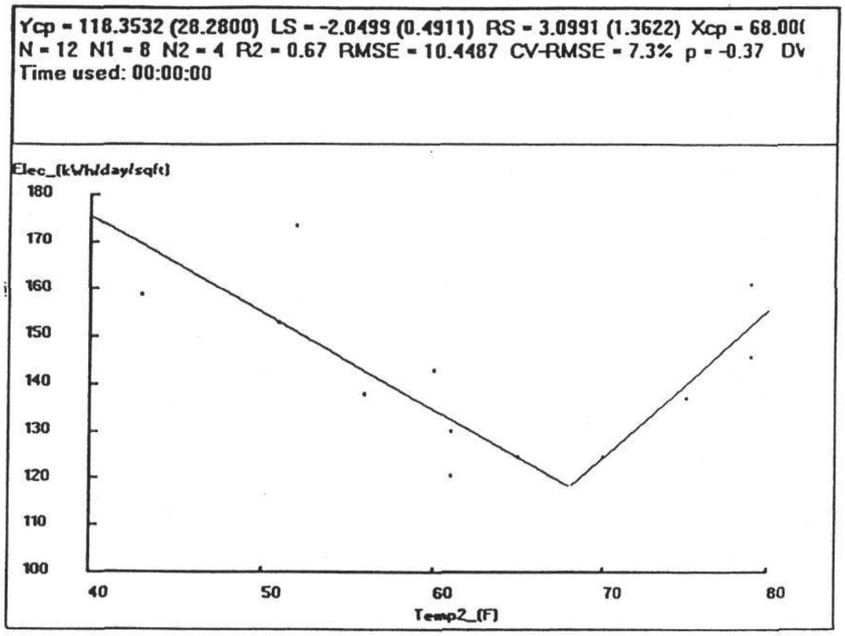


Figure 11.8. EModel change point model line and data points for Sacramento Army Depot electricity consumption for baseline year (FY86). A one-month shift in temperature led to substantial model improvement. 4P model selected as baseline.

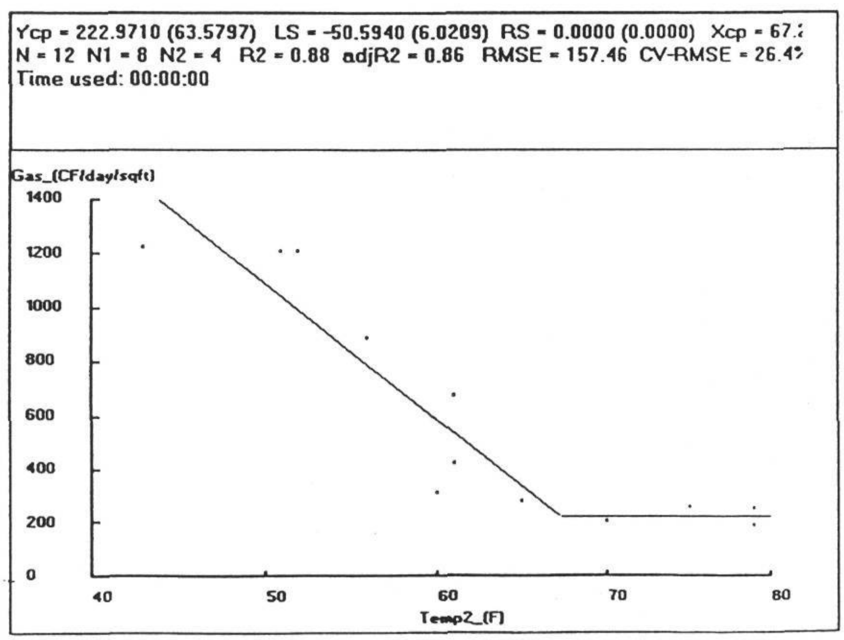


Figure 11.9. EModel change point model line and data points for Sacramento Army Depot natural gas consumption for baseline year (FY86). A one-month shift in temperature led to substantial model improvement. 3P-heating model selected as baseline.

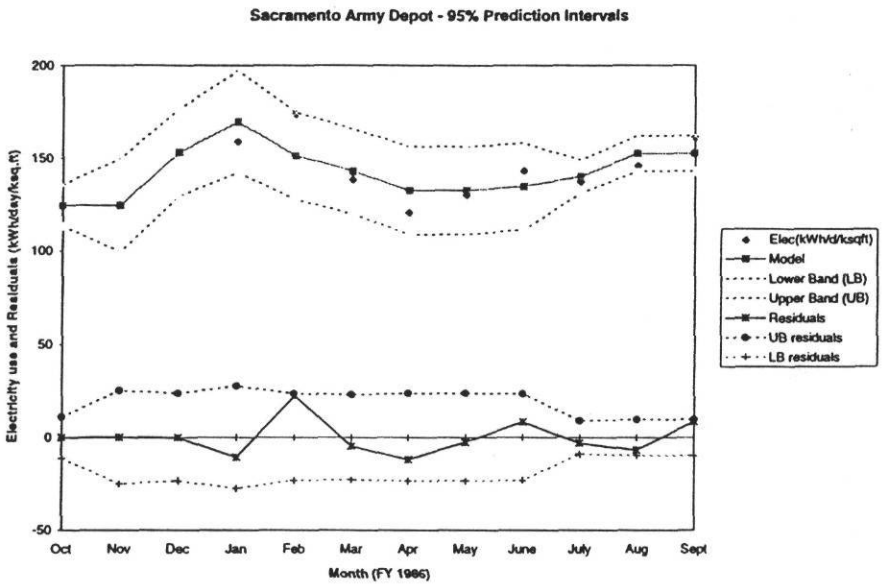


Figure 11.10. Predictive ability of the baseline model (FY86) for Sacramento Army Depot electricity use during FY86. 95% prediction intervals for the model as well as for the model residuals are shown.

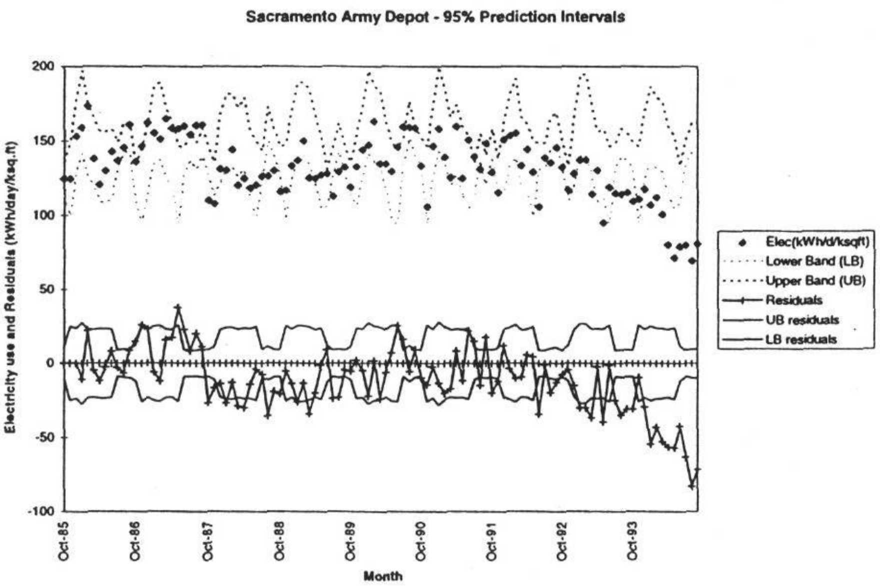


Figure 11.11. Predictive ability of electricity baseline model (FY86) for Sacramento Army Depot from FY86 to FY94. 95% prediction intervals for the model as well as for the residuals are shown.

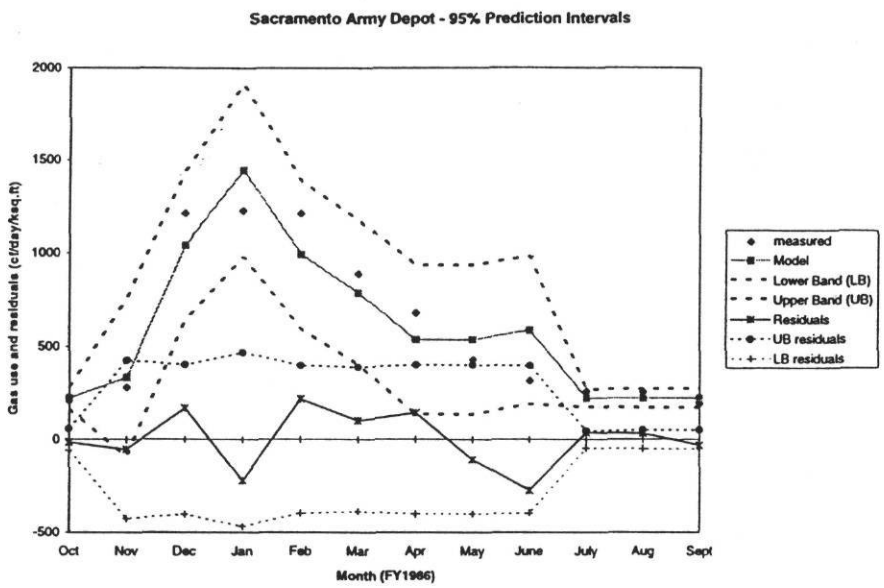


Figure 11.12. Predictive ability of the baseline model (FY86) for Sacramento Army Depot gas use during FY86. 95% prediction intervals for the model as well as for the model residuals are shown.

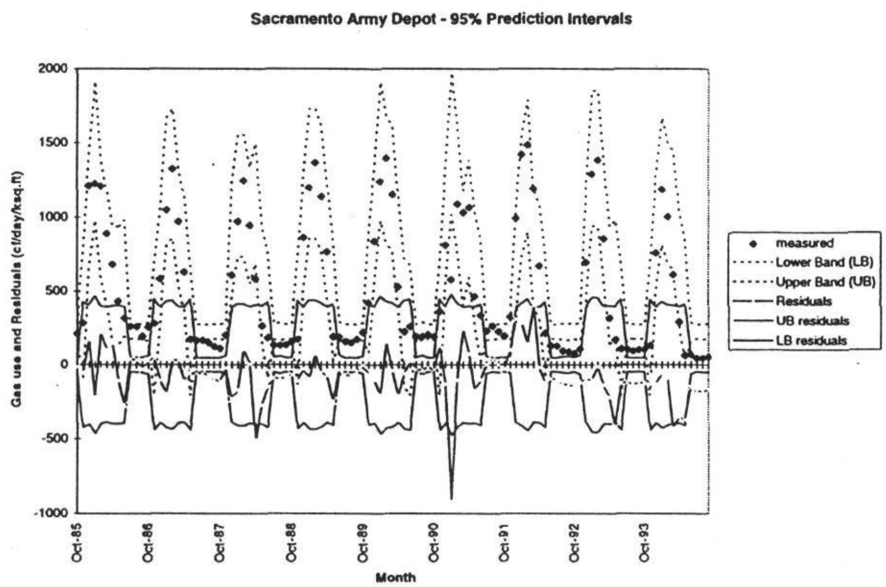


Figure 11.13. Predictive ability of gas baseline model (FY86) for Sacramento Army Depot from FY86 to FY94. 95% prediction intervals for the model as well as for the residuals are shown.

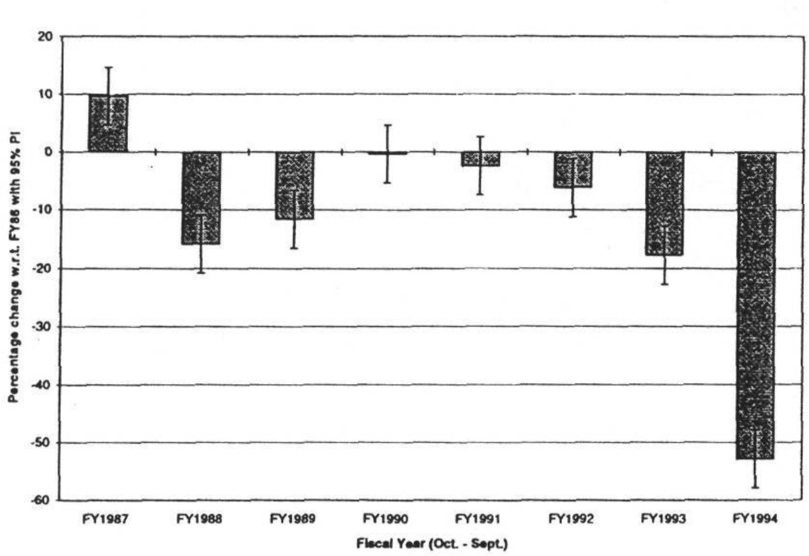


Fig.11.14(a) Electricity use

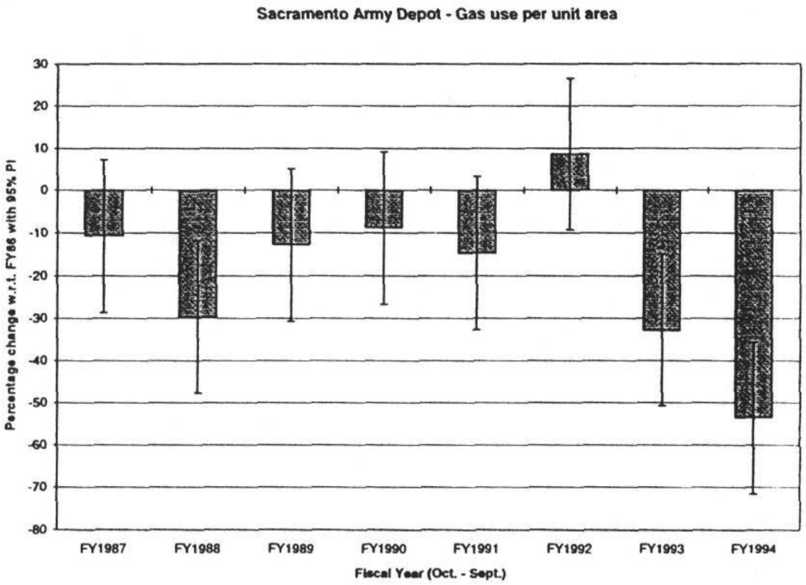


Fig.11.14(b) Gas use

Figure 11.14. Percentage change in annual energy use per conditioned area with respect to baseline year (FY86) for Sacramento Army Depot. Negative change indicates decrease in energy use and vice versa. 95% confidence intervals for the percentage change are also shown.

12.0 Overall Summary and Conclusions

This report has been prepared for the United States Army Construction Engineering Research Laboratories (USACERL) located at Champaign, IL by the Energy Systems Laboratory (ESL) of Texas A&M University with the objective of developing monthly baseline utility models for electricity and gas use for eight army bases around the U.S. and illustrate their use as screening tools for detecting changes in future utility bills and also to track/evaluate the extent to which Presidential Executive Order 12902 mandating 30% decrease in energy utility bills from 1985 to 2005 is being met.

With the above objective in mind , USACERL commissioned a first study, in mid-1995, with ESL. The objectives were to: (i) to investigate different types of energy modeling software- PRISM and EModel- in order to ascertain which is more appropriate for modeling energy use in DoD installations, (ii) to propose criteria for selecting the baseline year depending on the availability and "cleanliness" of the utility bill data and the associated outdoor temperature data, and (iii) develop/propose statistical equations in order to determine the uncertainty in using these baseline models for predicting monthly (or utility) energy use and annual energy use. For this preliminary study, we wanted to select a base whose utility data had undergone some sort of "reality check". Fort Hood, a large army installation located in central Texas was chosen in view of the fact that extensive data gathering and analyses has been done on this base over the years, and a comprehensive report on utility and services data was available. The results of our previous study, documented in a report by Saman et al.(1995), indicated that reliable baseline models of electricity use, electricity demand, gas use and water use could be identified from utility billing data and that these models were sound enough to be useful as screening tools for detecting changes in future utility bills.

The basic objective of the current study was to apply/evaluate the previous methodology to utility data from eight army bases from various parts of the country. The utility data and other data such as base area and population which were to be used for the analysis were downloaded from the central Defense Energy Information System (DEIS) database. One could not expect such data to be as "clean" as that from Fort Hood since the former is usually not subjected to careful "reality check" before being entered into the database. Further, unlike the preliminary study where daily mean outdoor temperature data for Temple, TX (a town very close to Fort Hood) was available for the analysis, USACERL decided to use monthly mean temperature data from the National Climatic Data Center (NCDC) at Ashville, NC where such data for numerous sites throughout the U.S. is available to the general public. It was the intent of this study to evaluate whether baseline models identified from DEIS and temperature data are appropriate to use as screening tools for detecting changes in future utility bills. Note the self-imposed condition that only data from such easily accessible sources would be used to generate and evaluate the baseline models. The intent was to determine if the baseline modeling methodology, used with success on locally obtained data at Fort Hood, is applicable to DoD facilities nation-wide using data easily obtained from the DEIS and NCDC databases.

A final objective of this study was to prepare a primer describing our baselining and tracking methodology which can be used by other analysts who wish to perform similar evaluations with data from other army installations. If analyses such as these are to find widespread application, they should be such that they could be applied routinely to all bases every year when annual utility bill data is entered into the central army database.

USACERL sent utility data (i.e., monthly energy use data) for eight army bases from various parts of the continental U.S. Note that the army maintains such data on a fiscal year (FY) basis (which extends from October of the previous year to September of the current year) rather than on a calendar year basis. The names of the bases and the size and energy use of the bases is provided by Table 12.1. Data from Fort Hood, TX (which was obtained directly from Fort Hood and used in the previous study by Saman et al., 1995) was also sent for comparative purposes in order to determine how utility and temperature data gathered from different sources would affect the baseline modeling and future tracking evaluation.

There were some serious problems associated with monthly mean outdoor temperature data downloaded from the National Climatic Data Center at Ashville, NC. One problem was that the data sets for all eight bases were from January 1985 and not from October 1984 (which is the start of FY85, the baseline year for the Presidential Executive Order). The lack of concurrent temperature and utility bill data for three months of FY85 forced us to reject FY85 as the starting year and choose FY86 instead. Further, Fort Carson, Fort Ord and Pueblo Army Depot have temperature data till December 1993 only. Thus the evaluation of how energy has changed over the years with respect to the baseline year has been curtailed till FY93 only (as against FY94 for the other bases). Also, temperature data for Fort Huachuca is fragmentary and analysis was done for FY86 and FY88 - FY90 only.

However, the most serious problem was the lack of certainty that the monthly interval during which the daily temperature data is averaged corresponds to the utility bill period. USACERL informed us that utility reading dates are not exactly known but are close to the first day of the calendar month, and that the start and end of the utility bill readings dates can be assumed to be the first and last day respectively of each month. Initially, the ESL manipulated the temperature data based on this assumption. However, our subsequent analysis (described fully later on in this report) revealed this presumption to be false in a number of cases. Though corrective action was taken, a certain amount of uncertainty was present, thereby compromising the accuracy of our baseline models. How the ESL proceeded to detect, and if necessary correct, for this potential mis-match between utility bill period and temperature data is also described in this report.

Our previous study concluded that the EModel software developed by the Energy Systems Laboratory to model baseline energy use in commercial buildings has more flexibility to handle different types of linear, single-variate change-point models than PRISM . EModel also gave more accurate modeling results. Hence EModel software was used to develop all the models presented in this report.

The results of our baseline model identification effort are summarized in Table 12.2. The model type and whether an adjustment was needed (to match the temperature data with the utility bill period) is also indicated. We note that both electricity and gas use at Fort Carson and Sacramento Army Depot needed an adjustment of one month, while electricity use at Fort Bragg and Fort Huachuca needed a 15-day adjustment.

How well the models fit the data can be ascertained from Table 12.2. The CV-RMSE of the model is the deciding factor in determining the category of the model fit. We note that of the eight electricity use models, two are excellent, four are good and only one is mediocre. Of the eight gas use models, none is excellent, two are good, four are mediocre and two are poor. Hence, gas use models seem to be generally poorer than electricity use models. Finally, we note that all gas models are 4P-heating models while electricity use models are mixed.

The analyses for all Army bases other than the two Army depots also involved computing percentage changes in annual energy use with respect to baseline year (FY86) normalized by (i) conditioned area, and (ii) conditioned area and population. Though generally the changes in energy use by both means of normalization have more or less similar patterns, the quantitative values are appreciably different during certain years. As described in section 3.5, one cannot place as much confidence in the population values as in the conditioned area values, and so it would probably be better to draw conclusions regarding the extent to which Presidential Executive Order 12902 is being met based on conditioned area normalization only.

The extent to which the annual energy use with respect to the baseline year has changed from the baseline year FY86 till the final year for which data was available, can also be determined from Table 12.2. We note that overall, nine of the eighteen gas and electricity use estimates are positive (i.e., energy use has increased), five of the estimates being very large (more than 20%). Only in five of the sixteen estimates of annual percentage change in energy use are the 95% prediction intervals larger than the estimates themselves implying than one should not place much confidence in these estimates.

We also investigated another issue with the energy use data from Fort Bragg and Fort Hood. One could question the need to have as involved a baselining and evaluation methodology as the one adopted here specially since the month to month variation patterns of outdoor temperature over the years is generally fairly consistent. One would be curious to ascertain the differences in our estimates of how energy use over the years has changed with respect to a baseline year by the present approach and by a much simpler approach involving direct annual utility bills comparison without any weather. We notice that though the differences in fractional change in annual energy use are small in certain years, they are relatively very important during other years. More importantly, there seems to be no pattern to the differences in percent change in annual energy consumption calculated by both methods. Such a comparison served to underline the need to perform weather correction in order to obtain reliable estimates of how energy use has varied over the years.

A final issue that we studied was the extent to which our estimates of annual energy changes with respect to a baseline year would be affected by "unproofed" data such as that used in the framework of the present study. This was possible since the previous study used carefully monitored utility data from Fort Hood along with specially obtained temperature data, while the current study used data from DEIS and NCDC. We found very consistent estimates of annual change in energy use from both methods. This indicates that conclusive estimates of how energy use in a particular DoD installation varied over the years with respect to a baseline year can be reached with "unproofed" DEIS and NCDC data.

Table 12.1. Table giving an indication of the size and energy use of the eight army bases

Serial No.	Army Base	Average Population FY86	Total bldg. area-FY86 ksq.ft	Conditioned area-FY86 ksq.ft	Electricity use-FY86 MWh/yr	Gas use FY86 kcf/yr
1	Fort Bragg, NC	60,006	23,006	19,441	285,056	880,733
2	Fort Carson, CO	25,844	11,344	7,983	96,940	1,417,201
3	Fort Drum, NY	6,694	6,291	4,558	32,750	56,356
4	Fort Hood, TX	66,462	23,840	19,232	307,750	1,416,929
5	Fort Huachuca, AZ	12,484	7,807	6,843	76,498	509,136
6	Fort Ord, CA	37,868	18,037	14,751	122,614	1,203,256
7	Pueblo Army Depot, CO	-	6,245	231	13,340	4,470
8	Sacramento Army Depot, CA	3101*	3,071	505	26,246	109,488

* This value is for FY90

Table 12.2. Summary of baseline models and change in energy use normalized by conditioned building area.

Army base		Baseline model						% Change in energy use w.r.t. to baseline year*		
		Baseline year	Model type	Temp. shift	R^2	CV-RMSE	Comment	Final Year	% change along with 95% PI	Comment
Bragg	Elec.	FY86	4P	15 days	0.95	4.7	Excellent	FY94	23.3 (3.2)	Significant
	Gas	FY86	3P-H	None	0.87	14.4	Mediocre	FY94	9.4 (9.8)	Uncertain
Carson	Elec.	FY86	Mean	None	-	8.0	Good	FY93	1.4 (5.4)	Uncertain
	Gas	FY86	3P-H	None	0.94	13.8	Mediocre	FY93	-23.7 (9.3)	Significant
Drum	Elec.	FY86	3P-H	1 month	0.66	10.7	Good	FY94	37.0 (7.3)	Significant
	Gas	FY86	3P-H	1 month	0.69	36.5	Poor	FY94	68.2 (24.8)	Significant
Hood	Elec.	FY86	3P-C	None	0.98	5.2	Excellent	FY94	20.6 (3.5)	Significant
	Gas	FY86	3P-H	None	0.98	10.1	Good	FY94	-13.3 (6.9)	Significant
Huachu.	Elec.	1985	3P-C	15 days	0.66	7.1	Good	FY90	8.2 (4.6)	Significant
	Gas	1985	3P-H	None	0.93	18.4	Mediocre	FY90	11.2 (12.5)	Uncertain
Ord	Elec.	FY86	Mean	None	-	8.3	Good	FY93	-4.0 (5.7)	Uncertain
	Gas	FY86	3P-H	None	0.69	16.2	Mediocre	FY93	-8.6 (11.0)	Uncertain
Pueblo	Elec.	FY86	Mean	None	-	17.3	Mediocre	FY93	-43.8 (11.8)	Significant
	Gas	FY86	3P-H	None	0.98	9.2	Good	FY92+	85.4 (6.2)	Significant
Sacram.	Elec.	FY86	4P	1 month	0.67	7.3	Good	FY94	-52.9 (5.0)	Significant
	Gas	FY86	3P-H	1 month	0.88	26.4	Poor	FY94	-53.6 (17.9)	Significant

* A negative number implies a decrease in energy use and vice versa.

+ Anomalous gas use in FY93 led us to reject the data

Nomenclature

LS	left slope of a multiple slope model
m	number of model predicted values that are summed (mostly m = 12)
n	number of observations in the model (mostly n = 12)
n_1	number of observations in the lower temperature range of the model
n_2	number of observations in the higher temperature range of the model
p	number of parameters in the regression model
R^2	coefficient of determination
RS	right slope of a multiple slope model
T	monthly mean daily outdoor dry-bulb temperature
X	independent or regressor variable (which is T in this study)
X_{cp}	X change-point of a multiple slope model
Y	dependent variable (monthly mean daily values of the utility bills)
Y_0	intercept of a 2P model (i.e., energy use value when $T = 0^0$ F)
Y_{cp}	Y change point of a multiple slope model
$\bar{Y}$	mean value of Y
$\hat{Y}$	model-predicted value of Y
$\tilde{Y}$	annual sum of monthly energy use values

<u>Acronyms</u>

CDD	cooling degree days
CV-RMSE	coefficient of variation of the root mean square error
CV-STD	coefficient of variation of the standard deviation
DD	degree days
EModel	Software developed by Energy Systems Laboratory to perform change point regressions
HDD	heating degree days
PI	prediction intervals
PRISM	Princeton Scorekeeping Method and software
RMSE	root mean square error
SE	standard error
STD	standard deviation
SV	single variate model

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Appendix A: Baseline Model Development Primer

This primer provides a step-by-step procedure by which a user can identify the most appropriate baseline model from monthly utility bills of a facility, and then use it for discerning changes or verifying energy savings from future utility bills. The user is assumed to have basic statistical expertise, be able to use the EModel energy software developed by the Energy Systems Laboratory of Texas A&M University, and be familiar with a spreadsheet program from which most of the calculations and plotting will be done.

A1. Determine objectives of modeling

The first step is to define the objective or the purpose for which baseline modeling is to be done. For example, the objective may be to evaluate the extent to which Presidential Executive Order 12902 (which mandates that all federal facilities shall reduce energy consumption per gross square foot by 30% from 1985 levels by the year 2005) is being met on a "real time" basis. Another example may be that the Energy Manager of the facility has initiated certain Demand Side Management practices, or O&M measures, or replaced existing equipment by high-efficiency equipment, and he wishes to determine or verify the amount of energy saved as a result. Yet another example could be that it would facilitate the implementation of performance based shared energy savings contracts. At this step, the user should also choose a tentative baseline year.

A2. Obtain relevant data

This second step involves gathering the relevant utility bill data (in energy units, not dollars). If both electricity use and gas use need to be modeled, then utility bills of both types of energy uses should be gathered. It would be preferable to obtain at least 1-2 years of utility bills prior to and following the baseline year tentatively chosen in step 1. Also, the user should obtain all utility bills for each year following the chosen baseline year, through the present year, and enter this data into the spreadsheet. Usually, utility bills specify the exact read dates of the billing period. This information for each bill should also be entered into the spreadsheet. If this information is lacking, then the user will have to resort to a statistical procedure as described in section 3.6 of this report. This procedure, however, will introduce uncertainty in our baseline modeling, and should be performed only as a last resort.

The user should obtain daily mean outdoor dry-bulb temperature for the specific location (or a nearby location) for the period of analysis. Using these daily mean dry-bulb temperatures, the user should calculate the monthly mean hourly outdoor dry-bulb temperatures corresponding to each monthly utility bill period . (The National Weather Service often provides users with the mean of the daily maximum and minimum hourly values, and these are also adequate provided the user consistently uses these values throughout the entire analysis.)

In case daily mean hourly values cannot be obtained, the following simplified procedure can be followed. The monthly mean values (corresponding to the calender months) for the specific or nearby location, are more easily obtained from published handbooks. Usually the read dates of the utility bills over the years are consistent to within a few days. Hence the two monthly temperature values of the two straddling months are weighted according to the number of days during each month contained in the billing period. For example, let the utility bill read date be the 10th of the month. Then the monthly mean temperature value of the previous month is weighted by a factor of two, added to the mean monthly temperature of the current month and divided by three in order to give the weighted monthly mean temperature. This weighting is then done for all the months during which the energy bills need to be analyzed.

In case conditioned building area or occupancy rates change from month to month (or year to year), such information should also be entered into the spreadsheet. The user should also determine, by talking to the relevant personnel, the procedure used to obtain occupancy and square footage data. This will also provide an indication of the accuracy of the data.

A3. Preliminary data analysis

At this stage, the monthly utility bill data and corresponding outdoor temperature, conditioned building area and occupancy rates have been entered in columnar form into the spreadsheet. The user should first generate time series plots of these quantities and study these plots for discrepancies or abnormal behavior. Often the latter is due to erroneous or spurious data, in which case, plotting the data would serve to flag such occurrences. The data during the chosen baseline year and for a year on either side of the baseline year
should be paid particular attention.

Next, the user should normalize monthly energy use data into energy use per day by dividing the utility bill by the number of days in that particular billing period (due care for leap years to be taken). This would remove the effect, albeit small, of the month to month differences in the number of days.

If data showing changes in conditioned area are available only on an annual basis (this is most common), another column should be created in the spreadsheet for billed energy *use per day per square foot.* This normalization should remove the effect of changes in conditioned area from year to year. This energy use data will be used in all subsequent analysis.

Normalizing energy use for the effect of occupancy is difficult because of the nebulous nature of this variable. Occupancy rates are not explicitly measured, and even a "best guess" estimate may have enough uncertainty in it to "smother" a lot of the year to year differences in energy use which the user is trying to discern. Further, one could speculate that (i) small changes (say about 20% or so) in occupancy rates would not affect the conditioned building area, while (ii) large changes would result in additional conditioned area being built to accommodate the increased occupancy rate, or in buildings being shut down if occupancy rates decrease. Hence, one would expect some inter-dependency between conditioned building area and occupancy rates only if any one of them varies significantly. Thus, it is suggested that the user normalize energy use by both variables, resulting in energy *use per day per conditioned area per occupant,* only if sufficient confidence can be placed in the occupancy rate data <u>and</u> if the variation in conditioned building area is not substantial. Otherwise, it is recommended that the user limit himself to analyzing energy use normalized by conditioned building area only.

A4. <u>Choice of baseline year and model identification</u>

Once the utility bills have been normalized by the number of days of the billing period and by conditioned area, the user is ready to proceed to model identification. (Note that if changes in occupancy rates are important and well determined on a month by month basis, it is advisable to normalize energy use for this variable also prior to model identification. If only annual values of occupancy are known, then it is better not to normalize for this variable at this stage, but to do so when percentage change in annual energy use is determined according to the equations described in section 3.5 of the main report.)

It could so happen that the year chosen for the preliminary baseline year has abnormal behavior (due to a number of reasons, known or unknown), and so a model identified from monthly data for the baseline year would be either poor or unrepresentative. In the former case, the subsequent uncertainty bands would be too large and have limited diagnostic capability. In the latter case, the baseline model would have a large bias which negates whatever benefits the baseline model may have to offer in terms of predictive ability. Therefore it is advisable to identify models for each of the following three years: (i) one year prior to the baseline year, (ii) the baseline year, and (iii) one year subsequent to the baseline year. The model identification is to be done with all twelve monthly normalized utility bills. The entire year should be rejected even if the bill for one month is missing or is spurious. Further, the user should be careful in using periods of one year only and not have billing data for the same month during successive years (say, in an effort to have twelve data points when data for one month had to be rejected for some reason or another) because this would introduce a bias in our baseline model.

EModel software should be used with the twelve monthly data points and the twelve monthly outdoor temperature data points, to identify the most appropriate regression model. The identification process involves performing 1P (i.e., mean), 2P, 3P and 4P regressions for each of the three years and then selecting the optimum functional form based on the following criteria:

(i) highest R^2 and lowest CV-RMSE,
(ii) if R^2 values for all models are low, CV-RMSE is to be given more consideration, and
(iii)it would be more appropriate from physical considerations, to select 3-P models rather than 4P models. Only if the improvement in R^2 and CV-RMSE is substantial, would the user relax this rule.

If the optimum regression model for the preliminary baseline year is better, or only slightly poorer, than those of the other two years, the baseline year model can be chosen as the final baseline model. If not, the user has to decide which of the three yearly models is most appropriate.

Though there is little the user can do at this stage to improve a model, he should at least make a note of how "good" the baseline model is, since this would provide an indication of how good his subsequent detection and screening process is likely to be. As a rough indication, models with $R^2 \geq 0.7$ and CV-RMSE $\leq$ 7% can be deemed "good" models. In certain cases, the R^2 may be very low indicating that energy use is not much affected by temperature variations. In such cases, regression models with CV-RMSE (or CV-STD) $\leq$12% can still be considered satisfactory. Models with CV-RMSE$\geq$20% can be taken as poor models.

It must be pointed out that EModel software also yields, apart from the R^2 and the CV-RMSE values, other statistics as well. There are two statistical indices which the user should make a careful note of: the Root Mean Square Error (RMSE) and the number of data points (n_1 in the main report) which fall on the lower temperature region of the change point regression line based on 3P and 4P models (the latter is not required for 1P and 2P models). Since there are 12 data points, the number of data points falling on the right side of the change point (n_2 in the main report) is easily deduced.