Development of Baseline Monthly Utility Models for Fort Hood, Texas+

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ABSTRACT

The Fort Hood Army base in central Texas has more than 5,200 buildings and can be considered as typical of large Department of Defense Army bases in the continental United States. The annual utility bill of the base exceeds $25 million. Baseline monthly models for electricity use, electricity demand, gas use, and water use for the three cantonment areas of Fort Hood have been developed. Such models can be used as screening tools for detecting changes in future utility bills and also to track/evaluate the

12902, mandating 30% decrease in energy utility bills from 1985 to 2005, is being met. In this analysis, 1990 has been selected as the baseline year to illustrate the predictive capability of the models. Since ascertaining the uncertainty of our predictions is very important for meaningful evaluations, we have also presented the relevant equations for computing the 95% prediction intervals of the regression models and illustrated their use with measured data over the period 1989 - 1993.

This study also evaluated two different types of energy modeling software- the Princeton Scorekeeping method (PRISM) and EModel- in order to ascertain which is more appropriate for baseline modeling of large Army installations such as Fort Hood. It was found that the EModel software, which has more flexibility to handle different types of linear single variate change point models, gave more accurate modeling results.

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. Subsequently, the Army Corps of Engineers of the United States Construction Engineering

Champaign, IL formulated the Model Energy Installation Program (MEIP) (USACERL, 1993). 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. One of the basic intents was to meet the mandate of the above Executive Order in only 5 years by reducing the energy consumption and utility bills at Fort Hood, Texas, by 30%, as compared to 1993 levels.

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Fort Hood is a large army base located in central Texas, about 70 miles north of Austin. It has a daytime population of approximately 65,000 which shrinks to 40,000 at night. Its building stock is diverse, totaling over 5,200 individual buildings and covers about 25.5 million square feet, 8.5 million of which is family housing. Its utility bills for Fiscal Year 1993 were $16 million for electricity and $5 million for natural gas. The base is composed of three separate and physically distinct cantonment areas: Main Fort Hood, West Fort Hood and North Fort Hood. Main's building stock covers about 23.6 million square feet (91% of the total). West Fort Hood is located four miles west of Main Fort Hood and contains about 1.4 million square feet of buildings (5.4% of the total). North Fort Hood, located 20 miles north of Main Fort Hood, is comprised of about 0.82 million square feet of buildings (3.2% of the total), most of which are occupied during the summer months when the National Guard training is in progress. Approximately 500 buildings scattered throughout the three cantonment areas are individually metered for electric power consumption.

Utility electric power to Fort Hood is metered in three locations: Main Fort Hood, West Fort Hood and North Fort Hood, where separate substations have been installed. Natural gas is metered in only two locations: one gas meter records the combined gas usage of Main and West cantonment areas, and the other gas meter records usage at North Fort Hood. Water metering is similar to gas meter: one meter for Main and West combined, and another for North only.

2.0 Objectives and Scope

The objectives of the study were to develop baseline monthly models of (i) electricity use, (ii) electricity demand, (iii) gas use, and (iv) water use for the three cantonment areas of Fort Hood, TX and illustrate their use as screening tools for detecting changes in future utility bills. These baseline models will also be used to track/evaluate the extent to which the Executive Order mandating 30% decrease in energy consumption is being met. This study will also evaluate two 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 baseline modeling of large Department of Defense (DoD) installations.

A certain amount of effort has been placed in narrowly defining the scope of this study because extensive monitored data are available. For example, hourly data for several years for more than 20 electric feeders are available. The primary objective was to develop baseline models capable of evaluating the extent to which energy conservation measures at Fort Hood are reducing energy consumption and thereby meeting the target set by the Executive Order. Since models developed for Fort Hood through the MEIP initiative are intended to be easily extrapolated to energy use in other DoD facilities nation-wide, USACERL decided it would be best to develop monthly-level models. Such data are readily available for DoD installations, while hourly or daily data are not. USACERL directed that disaggregation of electricity use, electrical demand, natural gas use and water use beyond the cantonment-area level was not required in this study. Disaggregation of Fort Hood total electricity use into its component end uses (e.g. cooling, fans, pumps, lights, plug loads, etc.) is currently underway through another research contract. Further, it was felt that, since Fort Hood is experiencing (and has experienced) changes in population as well as total square footage of buildings over the years, the influence of these two variables should be explicitly studied.

Finally, regarding the issue of which year to use for baseline model development, three choices were available. Since the Executive Order set the goal based on year 1985, one could have chosen this year as the baseline year. However, utility data for 1985 were not readily available. Since obtaining the data would have postponed the initiation of this study, USACERL decided to use a later year. The second choice was to choose year 1993 (the first year of the MEIP effort) as the baseline year, as done in the CERL report (Chalifoux et al., 1996). In 1991, the Energy Office at Fort Hood instituted a very successful demand shedding initiative via frequency modulated (FM) cycling of residential air conditioning units (the "FM Load Management System"). USACERL and the Fort Hood Energy Office wanted to baseline Fort Hood energy use sometime previous to 1991 as a means of further validating the effects of the demand shedding effort. Hence it was decided to use 1990 data for baseline model development at the cantonment-level and for subsequent screening purposes in this study.

3.0 Previous Studies

There has been extensive data gathering and analyses work done at Fort Hood over the years. A comprehensive report on Fort Hood Utility and services data has been prepared (USACERL, 1993). Historical energy consumption data from as far back as 1983 are available for electricity, gas and other services. Complete details about the electrical distribution, water distribution and storage, sewage treatment, gas distribution, air conditioning and refrigeration equipment, and chiller and boiler equipment are also available. The various building categories and types and statistics relating to each of these are also documented.

The MEIP is a multi-faceted endeavor with efforts ranging from technology assessments to technical training to resident energy education. The focus during the first year was to commission numerous consultants to perform well-defined base-wide studies of the major building mechanical and electrical technologies and to determine specific energy retrofit technologies that would result in maximum energy savings. During the second year, a computer program called Building Use Categorization and Scale-up (BUCS) system was developed that allows for the empirical and systematic selection of prototype buildings for auditing and/or computer modeling purposes with the objective of projecting probable energy usage of the whole installation from the audited subset. Project funding was also applied for and received during the second year of the MEIP. The third year, which is currently underway, involves continuing training programs for Fort Hood maintenance personnel and assisting Fort Hood in implementing various retrofits identified during the first two years of the MEIP. It is in the framework of this research objective that the current study with Energy Systems Laboratory (ESL) of the Texas Engineering Experiment Station (TEES) at Texas A&M University was initiated.

Lister et al.(1996) have determined energy conservation opportunities and associated cost savings for the military family housing neighborhoods at Fort Hood, which is estimated to account for 25% of the total annual energy consumption. A collaborative design process under the direction of a multi-disciplinary team has proposed design alternatives of prototypical energy efficient residential units that would have least environmental impact and pleasing living conditions (Deal and Adams, 1996). Studies aimed at disaggregating, by end use, the specific electric feeders at Fort Hood have also been done in an effort to more accurately identify energy conservation of specific processes such as space cooling, air-handling units, fans, cold and hot water pumps, cooking, lighting, etc. (Akbari and Konopacki, 1995; Konopacki et al., 1995).

4.0 Data Used for Analysis

The various types of utility use and associated cost figures of the three cantonment areas of Fort Hood were sent to ESL by USACERL in electronic form. USACERL informed ESL that utility read dates are not exactly known but are close to within 2-3 days of the calendar month. So the start and end of the utility bill readings dates were assumed to be the first and last day respectively of each month. Though the data was from October 1986 to June 1995, USACERL decided to start with January 1989, due to reasons explained earlier.

To perform weather corrections to the energy and water use, ESL required daily average values of outdoor dry-bulb temperature at Fort Hood. The closest meteorological station was Temple, TX some 30 miles away, and so ESL acquired relevant outdoor temperature data for Temple from the National Weather Service. However, readily-available weather data for Temple, Texas covered only through May 1994. In view of the objectives of this study, it was decided to limit the present analysis at the cantonment area level from January 1989 to December 1993 data only.

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'.

We started the analysis by studying time series plots of the monthly electricity use, electricity demand, gas use and water use for the Main, West and North substations. As seen in Fig.1, which pertains to the Main cantonment area, the plots seem to generally depict consistent annual patterns and little variation over the years. Also, electric use (consisting mainly of lighting, equipment and chillers) seems to show small blips during the winter months leading us to suspect electric heating applications such as heat pumps or electric strip heating.

The decrease in demand from 1991 (when the DSM load shedding program was activated) is very clear for the Main cantonment area (Fig.1) though a slight take-back in 1992 and 1993 for all three cantonment areas is evident. This take-back effect is especially marked for the West cantonment area.

Inspection of the average monthly outdoor temperatures in Temple during 1989 to 1993 revealed that the weather seems to have behaved fairly consistently over the years except for a couple of outliers. We were informed that the population data on a monthly basis may not be as accurate as other types of data since it is estimated by several individuals on the army base who were responsible for certain sections of the base. On a daily basis, the population seems to have been between 40,000 and 45,000. There are no marked seasonal patterns. The population seems to have decreased from 1988 to 1992 by about 14%, and again increased abruptly in 1993 to the 1989 value. The annual population for the year 1990 is lower by about 7% as compared to 1989 and 1993, and higher by about 7% as compared to 1992.

Floor areas of permanent, semi-permanent and temporary buildings have changed on an annual basis from 1985 to 1995. Though the Presidential Order requires that the energy use reduction be based on gross square footage, it was decided that building conditioned area would provide a more rational basis for evaluating changes in energy use over the years. Following discussions with USACERL and the Fort Hood Energy Office, it was decided that the sum of permanent and semi-permanent floor space would best reflect the total conditioned building area of the base. Hence this value should be used for normalizing annual energy consumption values. During the years 1987 to 1993, conditioned building area has been increasing steadily from about 20.5 million square feet in 1987 to about 22.3 million square feet in 1993.

5.0 Mathematical Basis of Regression Models

5.1 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". A widely adopted convention is to refer to a single variable model with, say, three parameters as a 3-P SV model. This study will limit itself to SV models only, and 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. As a rough indication, models with $R^2 > 0.7$ and CV-RMSE < 8% can be considered "good" models.

5.2 Variable degree day method and PRISM models

The PRInceton Scorekeeping Method (PRISM) (Fels, 1986) and the associated computer software (Fels et al., 1995) is widely used for determining energy savings in conservation programs. It is based on the steady-state energy balance of a residence operated as a one-zone building. Though it has been applied to commercial and institutional buildings and also to whole campus level (Haberl, 1992), it is most suitable for shell-dominated buildings such as residences and small commercial buildings wherein energy use is not strongly influenced by the non-linear behavior exhibited by chillers, refrigerators and boilers. PRISM uses the readily-available data of whole-house consumption based on utility billing data and average daily outdoor temperature data from the closest weather station (for the period being studied as well as long-term periods for the calculation of variable degree days) to determine a weather adjusted index of consumption, the Normalized Annual Consumption (NAC). NAC is analogous to the miles-per-gallon rating for automobiles. The NAC represents annual energy consumption during a year of average weather conditions. Total energy savings due to the implementation of energy conserving measures is then derived as the difference in the NACs for the periods before and after retrofit implementation.

The functional form of the PRISM models are:

- for electricity use, electricity demand and water use (uses which increase with outdoor temperature T):

$$Y = \alpha + \beta_c * DD(\tau_c) \quad (1)$$

- for gas use (which increases with decreasing T):

$$Y = \alpha + \beta_h * DD(\tau_h) \quad (2)$$

-for electricity use that increases with both increase and decrease in T (say, heat pumps)

$$Y = \alpha + \beta_h * DD(\tau_h) + \beta_c * DD(\tau_c) \quad (3)$$

where DD (τ) are the degree-days to the base τ , and the subscripts c and h stand for cooling and heating respectively. Note that eqs. (1) and (2) represent a model with three regression parameters, i.e, a 3-P model, while eq.(3) represents a 5-P model.

The latest version of the PRISM software (Fels et al., 1995) is fairly user friendly and is run from a Microsoft Windows environment. It directly gives R^2 values of the models fitted. However, it only calculates the CV-RMSE of the NAC value and not of the individual model identified from the 12 utility bill readings that characterize the year under study. Hence we are forced to calculate the CV-RMSE separately in a spreadsheet for each year in the framework of the present study.

It must also be pointed out that in order to remove variations in the number of days during each billing period (utility meters are usually not read on exactly the same day each month but may vary by a couple of days), PRISM divides the utility bill energy use by the actual number of days during that billing period. Hence the dependent variable Y in eqs.(1) - (3) are monthly mean daily values and not monthly total values.

5.3 Simple 3-P regression model (use of 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. Its 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 functional form of the model most appropriate for the monthly data being analyzed in this study is as follows:

- for electricity use, electricity demand and water use (uses which increase with outdoor temperature T):

$$Y = Y_{cp} + RS * (T - X_{cp})^{+} \qquad (4)$$

- for gas use (which increases with decreasing T):

$$Y = Y_{cp} + LS * (T - X_{cp})^{-} \qquad (5)$$

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 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 sum of daily values, T should be 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.

Finally, comparison of PRISM and EModel regression models and coefficients is more easily done if energy consumption used in EModel is also divided by the number of days in the billing period. The variable Y in eqs.(4) and (5) is then the monthly mean daily energy (and water) use value instead of the monthly total value.

5.4 Generation of 95% uncertainty bands for individual months

The baseline models developed from one year (in this study, year 1990 has been chosen) can be used to predict weather-adjusted monthly energy and water 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 most commonly used convention of fixing these bounds is by computing the 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 2-P SV model), PI for predicting Y for a given X_0 (i.e., for a given month) is well known (Draper and Smith,1981):

$$PI = t(1-\frac{\alpha}{2}, n-p).RMSE. \sqrt{1+\frac{1}{n}+\frac{(X_0-\bar{X})^2}{\sum_{i=1}^{n}(X_i-\bar{X})^2}} \qquad (6)$$

where

t - the t-statistic evaluated at ($1-\alpha/2$, 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 error,

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 3-P model with n = 12, ($1-\alpha/2$, n-p) from statistical tables (Draper and Smith, 1981) is equal to 2.262. Note that for the PRISM model, X is the variable degree-day (DD), while for the 3-P 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 3-P is very complex and is not to be found in textbooks. Simply calculating the PIs for a 3-P model using eq.(6) would lead to an over-estimation specially for the baseline portion of the fit (i.e., for the months when energy use is independent of outdoor temperature). This is because the monthly energy use during the baseline portion tends to show little month to month variability as compared to energy use during the other months of the year. So the statistical equations for predicting the PIs should take this physical behavior into consideration if they are to be realistic. Though not strictly accurate in the statistical sense, we propose that PIs for 3-P 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 baselevel portion and in the linear 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. Then, for the model predictions falling on the base portion of the model, we shall use

$$PI_1 = t(1-\frac{\alpha}{2}, n-p).RMSE_1. \sqrt{1+\frac{1}{n}+\frac{(X_0-\bar{X}_1)^2}{\sum_{i=1}^{n_1}(X_i-\bar{X}_1)^2}} \qquad (7)$$

and, for the linear portion of the model

$$PI_2 = t(1-\frac{\alpha}{2}, n-p).RMSE_2. \sqrt{1+\frac{1}{n}+\frac{(X_0-\bar{X}_2)^2}{\sum_{i=1}^{n_2}(X_i-\bar{X}_2)^2}} \qquad (8)$$

Note that 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 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 (though it will tend to under-estimate the PI bands) 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 baselevel months (i.e., winter months for electricity and water, and summer months for natural gas) and expands during the months when energy use is linear with outdoor temperature.

5.5 Generation of 95% uncertainty bands on an annual basis

The previous section presented relevant equations for calculating PIs on an individual monthly 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 and water use which is one of the objectives of this study. For this purpose, the annual total energy (and water) use along with an estimate of the amount of confidence one can place on these values must be determined. The total use is easily determined: the twelve monthly mean daily energy use values are simply averaged together. However, the 95% PIs for this annual mean daily energy use value cannot be determined by simply averaging the PIs of the individual twelve months since this would lead to a gross over-prediction.

For a simple linear model (i.e., a 2-P SV model), Draper and Smith (1981) give the equation for PI of a sum of m number of individual points (m=12 if annual energy use values are sought):

$$PI = t(1-\frac{\alpha}{2}, n-p).RMSE.\sqrt{m + \frac{m}{n} + \frac{\sum_{o=1}^{m}(X_0 - \bar{X})^2}{\sum_{i=1}^{n}(X_i - \bar{X})^2}} \quad (9)$$

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

$$PI = \frac{t(1-\frac{\alpha}{2}, n-p)}{m} .[RMSE_1\sqrt{m_1 + \frac{m_1}{n} + \frac{\sum_{o=1}^{m_1}(X_0 - \bar{X}_1)^2}{\sum_{i=1}^{n_1}(X_i - \bar{X}_1)^2}} + RMSE_2.\sqrt{m_2 + \frac{m_2}{n} + \frac{\sum_{o=1}^{m_2}(X_0 - \bar{X}_2)^2}{\sum_{i=1}^{n_2}(X_i - \bar{X}_2)^2}}] \quad (10)$$

where m_1 and m_2 are the number of months that fall on the baselevel and on the linear portion of the model line respectively.

Equation (10) is rather cumbersome to use, and since monthly mean annual temperatures do not vary by much from year to year, we suggest that the following simplified equation be used instead:

$$PI = \frac{t(1-\frac{\alpha}{2}, n-p)}{m}.RMSE.\sqrt{m + \frac{m}{n}} \quad (11)$$

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

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

We have used eq.(12) in determining the 95% PI of the annual mean daily energy (and water) 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.

5.6 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 earlier, 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 attempts at explicitly including population as a variable in our basic regression model of energy and temperature were unsuccessful (Reddy et al., 1996). 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 Fort Hood and several other Army bases and, unfortunately, found no such relationship (Reddy et al., 1996). In view of the above and due to the uncertainty in the determination of population, it was decided not to explicitly include this variable in the framework of the present study.

We shall define annual change in energy $\Delta\tilde{Y}$ for, say FY92, with respect to the baseline year (FY90 has been selected for this study) as follows:

$$\Delta\tilde{Y}(FY92) = \tilde{Y}_{Measured}(FY92) - \tilde{Y}_{Baseline-model}(FY92) \qquad (13)$$

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 $\tilde{Y}_{Measured}$(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:

$$\%\Delta \tilde{Y}(FY92) = \frac{\Delta \tilde{Y}(FY92)}{\tilde{Y}_{Measured}(FY92)} x100 \quad (14)$$

6.0 Baseline Modeling

PRISM and EModel software were used to identify monthly models for electricity use, electric demand, gas use and water use for each of the three cantonment areas on a yearly basis. A clearer visual comparison of the performance of both pieces of software is provided by Fig.2 which assembles the CV-RMSE values for all four channels, for all years and for all the models. Note that in most cases EModel performs better than PRISM, and even in the few cases where it did not, the difference was very little. The reason for this phenomenon is unclear and could be partly due to PRISM being more sensitive than EModel to the 2-3 day discrepancy between utility read dates for electricity and calendar month periods. Another possible cause is that PRISM is most appropriate for shell-dominated buildings like residences. Because housing only constitutes about 25% of the total energy use at Fort Hood, energy use in "other" types of buildings may be closer to that of commercial and institutional buildings which is better modeled by functional forms used by EModel than by PRISM. Yet another reason could be that EModel software uses a finer search grid for the change point than does the PRISM software. Whatever the cause, it seems that EModel is more appropriate for modeling energy and water consumption of DoD installations. We have decided to adopt EModel results for all subsequent analyses.

Table 1 assembles the 3-P model coefficients and the R^2 and CV-RMSE of the 14 baseline models for 1990. The water use model for North campus is very poor and we do not recommend that it be used. Three other models, namely (i) electricity use by the North substation, (ii) gas use in the Main and West cantonments, and (iii) gas use in the North cantonment, are to be used with caution (CV-RMSE > 10%).

Regression models at the whole base level are better than those for each of the three cantonment areas separately because of the fact that aggregate energy use values usually behave more consistently than disaggregated ones.

We note that despite high R^2 values for all four gas models ($R^2 > 0.90$), the gas models cannot be said to be very good because of the high CV-RMSE values (greater than 20%). The R^2 statistic (which represents the fractional variation in the monthly data points about their mean annual value that is explained by the regression model) is misleading in this case due to the large seasonal variation exhibited by gas use.

7.0 Use of Baseline Models for Screening

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 (for example, changes in population, square footage,...) or whether these changes are a result of energy efficiency measures or Demand-Side Management (DSM) programs that have been initiated. How the PIs of the model are to be calculated have been described earlier. We have used our 1990 baseline models to forecast into the future up to 1993 and also backcast into the past until 1989.

Figures 3 and 4 depict the extent to which the monthly utility bills are bounded by the PIs of the 1990 baseline model. 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 falls below the lower 95% PI, one can safely affirm that energy use during that month has decreased as compared to model predictions. Salient observations from each figure are reported below:

(i) Main substation electricity use.

We note that on the whole, the observed energy use is bounded by the PIs of the 1990 baseline model (see Fig.3). Inspection of the residual plots reveal that there are certain periods , namely April, May and July of 1991, April-July of 1992, May-July 1993 where the observed energy use is definitely lower than that baseline model-predicted values (as a result of initiating the FM Load Management System), while energy use during Sept-Oct. 1993 is higher.

(ii) Main substation electricity demand.

Figure 4 clearly indicates the benefit of the DSM program since we see a substantial reduction from March 1991. Because of the ratchet clause on the peak demand, the billed peaks in winter are also lower from 1991-92 onwards. It is only during Sept-Oct. 1993 that demand seems to have crept up again.

The whole-installation baseline models can be used to determine whether energy and water use efficiency has increased over the years. This type of analysis capability is crucial if one wishes to ascertain the extent to which the Executive Order 12902 has been met. Using monthly mean daily temperature data for 1993, the 1987 models have been used as the baseline models to predict 1993 energy and water use and compare them with measured values. Figure 5 depicts the change in annual values of electricity use, electricity demand, gas use and water use for the entire installation normalized by conditioned building square footage from 1987 to 1993. The changes in annual consumption has been computed following eqs.(13) and (14). Note that a negative change indicates a decrease in energy use, and vice versa. We note that consumption normalized by conditioned area shows the following behavior from 1987 to 1993: (i) electricity use has increased by 4.7%, (ii) demand has decreased by 1.8%, (iii) gas has decreased by 20.4%, and (iv) water use has decreased by 15.5%.

The uncertainty, i.e., the 95% PIs of these changes have also been computed following eq.(12) and are shown in Fig.5. We note that these PIs are relatively small, 2.8% for electricity use, 1.7% for electricity demand, 0.2% for gas use and 0.3% for water use. Hence we can place a certain amount of confidence in our estimates of the extent to which normalized energy and water use for Fort Hood have changed from 1987 to 1993.

8.0 Future Work

The present baselining methodology has been extended to eight Army bases in the continental United States (Reddy et al., 1996). Based on the experience acquired from such a study, a primer document describing the data analysis, model development and screening procedures is being prepared so that energy managers at specific army bases could perform similar analyses by themselves.

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Nomenclature

LS	left slope of a multiple slope model
m	number of model predicted values that are summed
n	number of observations in the model
n_1	number of observations on the base portion of the model
n_2	number of observations on the variable portion of the model
R^2	coefficient of determination
RS	right slope of a multiple slope model
T	outdoor dry-bulb temperature
X	independent or regressor variable
Xcp	X change-point of a multiple slope model
Y	dependent variable (electricity use, demand, gas use and water use on a monthly mean daily basis)
Ycp	Y change point of a multiple slope model
$\hat{Y}$	model-predicted value of Y

<u>Greek</u>

α	intercept or base energy use of the PRISM model
β_c	slope for the PRISM cooling model
β_h	slope for the PRISM heating model
τ_c	base temperature for the PRISM cooling model
τ_h	base temperature for the PRISM heating model

<u>Acronyms</u>

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

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Table 1. Final 1990 Baseline 3-P Regression Model Coefficients and Goodness-of-fit Indices

		Ycp	Slope	Xcp	R^2	CV-RMSE
Whole-base	Elec.	662 MWh/day	26 MWh/°F-day	58.2 °F	0.99	3.80%
	Demand	56,115 kW/mo	559 kW/°F-mo	58.2 °F	0.99	1%
	Gas	1,794 Mcf/day	-265 Mcf/°F-day	68.3 °F	0.91	20.20%
	Water	$4{,}643\times10^3$ Gallons/day	248×10^3 Gallons /°F-day	66.6 °F	0.92	9.20%
Main	Elec.	492 MWh/day	20 MWh/°F-day	58.2 °F	0.98	4.5%
	Demand	43,571 kW/mo	548 kW/°F-mo	62.4 °F	0.98	1.5%
	Gas	1,755 Mcf/day	-259 Mcf/°F-day	68.3 °F	0.91	20.4%
	Water	$4{,}490\times10^3$ Gallons/day	232×10^3 Gallons /°F-day	65.8 °F	0.93	9.0%
West	Elec.	158 MWh/day	6 MWh/°F-day	57.4 °F	0.99	3.3%
	Demand	11,186 kW/mo	81 kW/°F-mo	45.6 °F	0.71	5.6%
North	Elec.	12 MWh/day	0.43 MWh/°F-day	64.9 °F	0.59	20.3%
	Demand	1,123 kW/mo	6 kW/°F-mo	55.7 °F	0.45	6.7%
	Gas	48 Mcf/day	-8 Mcf/°F-day	61.6 °F	0.94	15.9%
	Water	139×10^3 Gallons/day	6×10^3 Gallons /°F-day	72.5 °F	0.11	52.9%

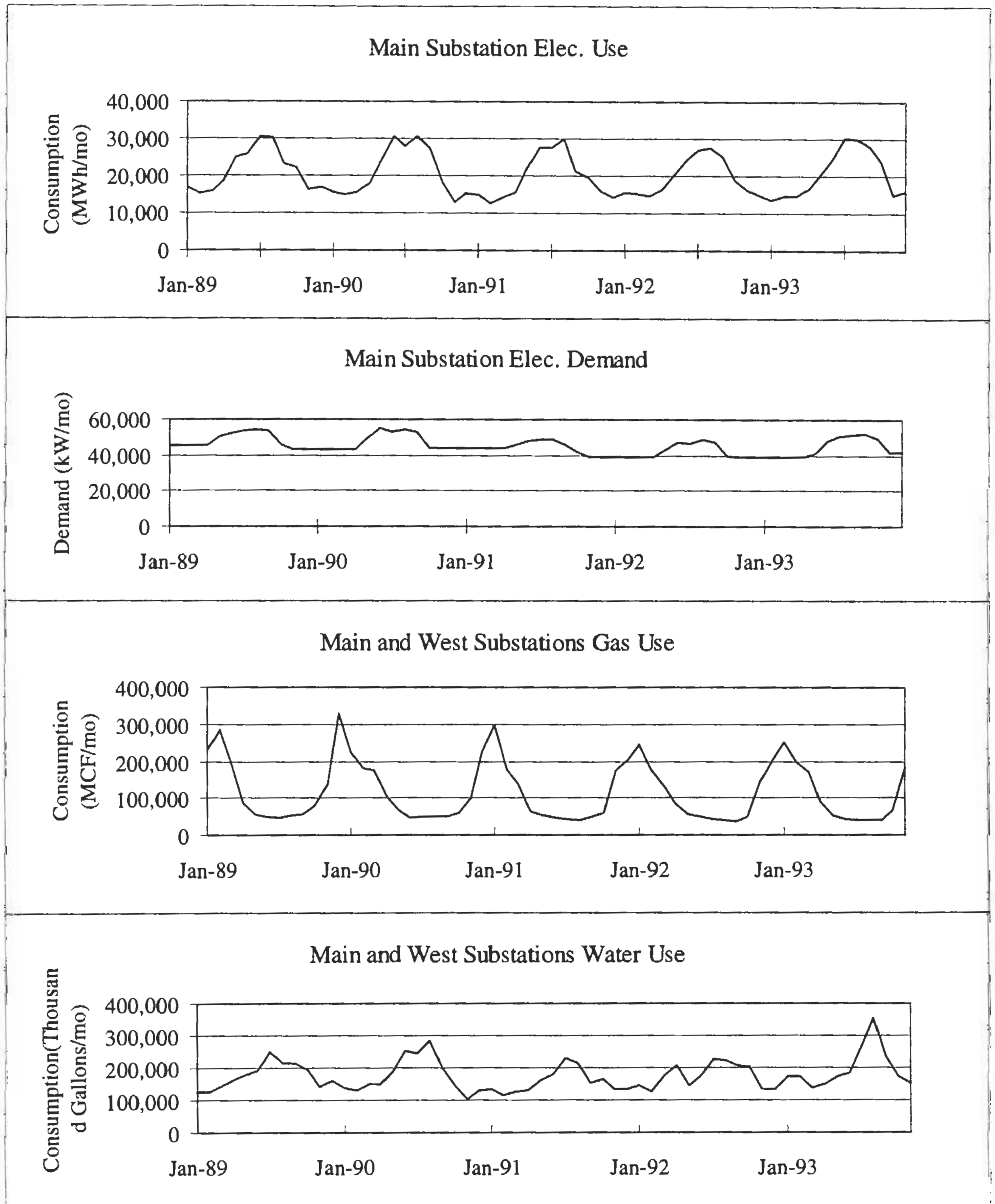

Figure 1.Time series graphs for Fort Hood Main Substation (serving Main Fort Hood cantonment area only) and Gas and Water use for Main and West cantonment areas since these have common gas and water meters.

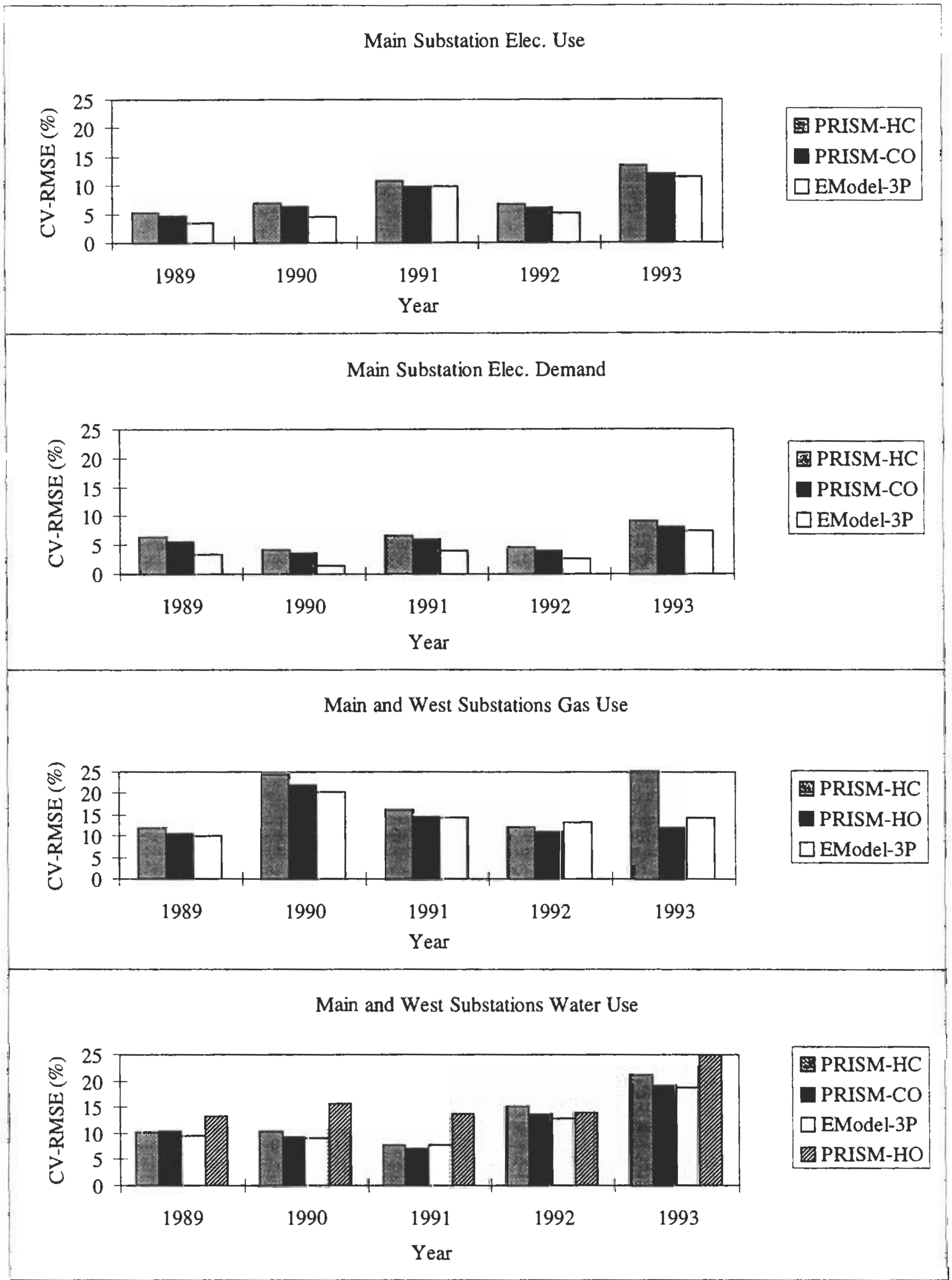

Figure 2. Comparison of CV-RMSE of different models evaluated.

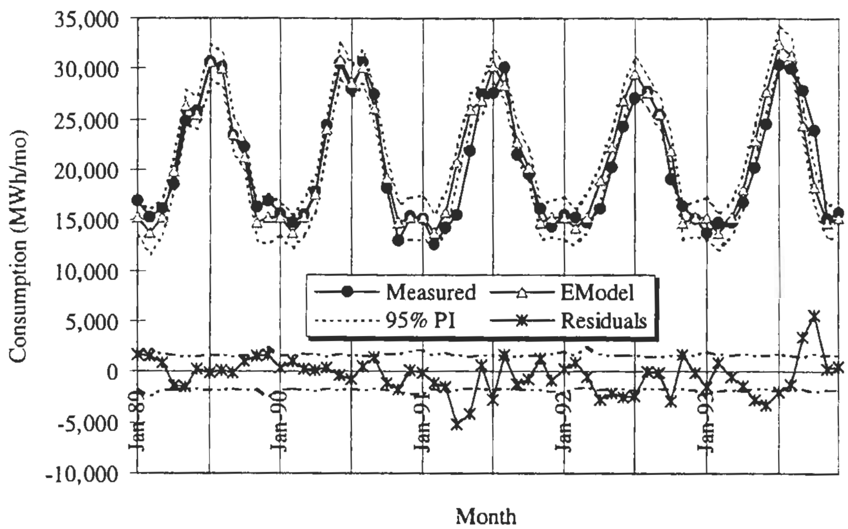

Figure 3. Predictive ability of 1990 baseline 3-P regression model for Main Substation electricity use. 95% prediction intervals for the model as well as for the residuals are shown.

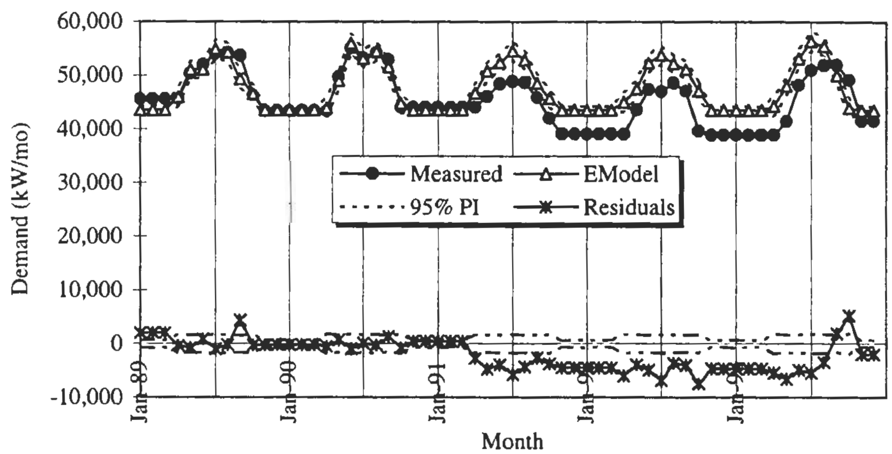

Figure 4. Predictive ability of 1990 baseline 3-P regression model for Main Substation electricity demand. 95% prediction intervals for the model as well as for the residuals are shown.

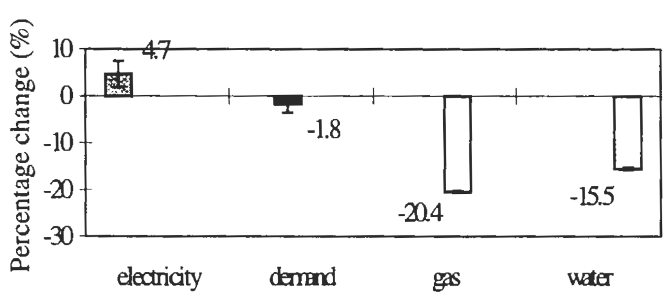

Figure 5. Percentage change in annual energy use and water use from 1987 to 1993 normalized by total conditioned building area. Negative change indicates a decrease in use and vice versa. 95% confidence intervals for the percentage change are also shown.