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An Overview of Measured Energy Retrofit Savings Methodologies Developed In The Texas LoanSTAR Program

T. A. Reddy, J. K. Kissock, S. Katipamula,
D. K. Ruch and D. E. Claridge
Energy Systems Laboratory
Texas A&M University, College Station, TX 77843

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ABSTRACT

Development of methodologies to determine energy retrofit savings in commercial buildings (institutional buildings, schools, hospitals, offices, county and state buildings,...) has been the object of active research during the last 5 years in the framework of the Texas LoanSTAR program. We have been able to formulate a global perspective to this problem and identify/develop analysis techniques specific to different sets of conditions. These conditions involve different combinations of: (a) level of monitoring data available (utility bill, whole-building hourly, disaggregated hourly,...); (b) type of energy use (weather or schedule dependent or independent); and (c) amount of data available (length of pre- and post-retrofit periods).

The objective of this report is to present the various analysis techniques in a logical fashion, briefly discussing and illustrating the strengths and weaknesses of each technique with monitored data from several of the LoanSTAR buildings, and providing the reader with complete references of work previously published. As of December 1993, we are reporting retrofit savings on a monthly basis in 34 sites consisting of 50 buildings. Some of the issues addressed relate to determining conditions when statistical regression techniques are preferable to engineering models, to the different forms of single variable and multiple variable regression models and their advantages or disadvantages, to when a specific regression model is to be used and to why inspection of model residuals is important. Other issues such as the uncertainty associated with the savings estimates and the effect of building operating schedules have also been addressed in this report. The framework laid out in this report should be useful for both the practicing professional and the researcher involved or interested in energy conservation as a whole.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Fig.14 Plots showing how cooling and heating energy use vary with T_o.

(a) Normalized monthly temperatures and average cooling NAEUs for JER building.

(b) Inverse of the normalized monthly temperatures and average heating NAEUs for the ZEC building.

Fig. 15 (a) Time series plot of daily AHU electricity use showing pre-retrofit, construction and post-retrofit periods during a CAV to a VAV retrofit at ZEC building

(b) Scatter plot showing pre- and post-retrofit cooling energy use and fitted regression models.

(c) Scatter plot showing pre- and post-retrofit heating energy use and fitted regression models.

Fig.16 (a) Time series plot of daily AHU electricity use showing pre-retrofit, construction and post-retrofit periods during a CAV to a VAV retrofit at EDB, GAR, WAG, BUR, WIN, PAI, WCH and TDH buildings.

(b) Scatter plot showing pre- and post-retrofit cooling energy use and fitted regression models.

(c) Scatter plot showing pre- and post-retrofit heating energy use and fitted regression models

Fig.17 Time series plots of monitored whole-building electricity use in ZEC building during a year. Fourier series model residuals are also shown.

Fig. 18 Schematic of the HVAC and building zone interaction assumed in the simplified systems model approach. Zone E denotes the exterior zone of the two-zone building and zone I is the interior zone.

Fig. 19 Comparison of simulated and measured cooling energy use and residuals in ZEC. Characters on the time axis represent the day of the week during the period of 21 June to 11 July 1991.

Fig. 20 Cumulative measured energy savings from, October 1990 to December 1993, of heating energy (HW), cooling energy (ChW) and electricity (Elec) in 34 sites representing 50 buildings for which retrofits have been completed.

1.0 INTRODUCTION

1.1 Background

There is no single solution to one of the major problems facing mankind today, namely the drastic increase in energy use due to the world-wide population explosion and economic growth, in turn leading to environmental pollution, degradation, climate change and even warfare. Energy conservation, however, is certainly an important aspect of the solution, buying us time to develop renewable energy resources and sustainable economies. Hence it is not surprising that energy conservation is acquiring increasing importance today, in both developing and developed countries alike.

The building sector consumes over a third of the total U.S. energy budget (EIA, 1991) and commercial buildings alone consume nearly 13 Quads (1 Quad=10^{15} Btus) of primary energy, equivalent to 15-16% of the nation's annual energy use. Experts claim that up to 75% of the energy use can be saved by using state of the art equipment technologies and design techniques (Bevington and Rosenfeld, 1990). Energy efficient design of new buildings is an obvious strategy for an energy efficient economy. However, decreasing energy use in existing buildings, operated with equipment designed and installed in an era when energy efficiency was a minor issue, is likely to have a far greater impact over the next decade given that more than two-thirds of the commercial floor space anticipated for the year 2000 is already in place (Greely et al.,1990).

Energy conservation retrofits are typically initiated based on predictions of how much energy and money a retrofit will save. Predicted energy savings are generally estimated using the performance specifications of energy-using equipment and estimates of the physical characteristics and operating conditions of the building. Frequently, several values necessary for these calculations, such as the operating hours of lights and electrical equipment, temperature set-point values, infiltration rates, solar loads and outside-air flow rates for HVAC equipment, are assumed or estimated using "engineering judgment." The calculation procedure or computer algorithm may also make simplifying assumptions in order to reduce the complexity and time required for the calculations. Because of these factors, predicted savings often differ substantially from measured savings. In a study of over 1,700 building energy retrofits, fewer than one in six came within 20% of measured results (Greely et al., 1990). Other examples of major discrepancies between predicted and measured savings abound in the literature. For example, a Swedish study of 306 residences found that glazing retrofits achieved only 48% of the predicted savings, while insulation retrofits and electric heating retrofits achieved only 53% and 83% respectively (Anderlind et al., 1986). Meier and Nordman (1988) examined over 400 residential retrofits and found that predicted savings ranged from 50% to 58% of energy use while measured savings ranged from only 17% to 49% of energy use. The coefficient of determination (R^2 value) between predicted and measured savings in over 300 Minnesota residential retrofits was only 0.11 (Hirst and Goeltz, 1984). Jamieson and Qualmann (1990) found that in a study of 16 commercial retrofits where auditors had been supplied with hourly pre-retrofit data, the mean absolute deviation between predicted and measured savings was 165% even after four buildings with known changes in post-retrofit energy use had been eliminated from the sample. Discrepancies such as these led Hirst et al.,(1986) to conclude that large discrepancies between predicted and actual measured energy use discourage efficiency investments.

Given this backdrop, it is not surprising that the Texas LoanSTAR program, which is a $88.6 million revolving loan program funding energy conserving retrofits in state, local government and school buildings in Texas (Turner, 1990), had established, at its very inception, an energy Monitoring and Analysis Program (MAP). The major objectives of the MAP are to: (i) verify and report energy and dollar savings of the retrofits, (ii) reduce energy costs by identifying operational and maintenance (O&M) improvements at monitored facilities, (iii) improve retrofit selection in future rounds of the LoanSTAR program; and (iv) provide a detailed data base of energy use in commercial/institutional buildings located in Texas. Responsibility for carrying out the MAP objectives has been given to the Energy Systems Laboratory of Texas A&M University.

The scope of this report is limited to objective (i) above. Although the loan repayment schedule is based on the energy savings estimated by the energy audits, the purpose of objective (i) is to determine whether the actual or measured savings from the retrofits are in effect as large as those estimated during the audit process (Heffington et al.,1992). This continuous verification can avoid expensive oversights and assure the proper operation of the building after the retrofit is complete. During the last 4-5 years, we have been developing and refining savings analysis techniques appropriate for different sets of conditions. These conditions involve different combinations of (a) level of monitoring data available, (b) type of energy use, and (c) amount of data available. The primary objective of this report is to present a conceptual framework which would enable the reader to gain a clear understanding of when to use a particular savings analysis technique and its advantages and disadvantages. The report also briefly describes these analysis techniques citing appropriate references for the more interested reader. The scope of this report is limited to retrofit savings. Though retrofit demand savings are also being reported in the LoanSTAR program, the methodology for doing so is still being refined. This report will also not discuss energy savings due to O&M and HVAC recommissioning measures (Liu et al., 1994) into which monitored data is able to provide direct feedback.

Other than the fact that most DSM programs adopt a statistical sampling procedure while retrofit savings are measured on all LoanSTAR buildings, there is an important distinction between the way LoanSTAR reports savings and that done by most DSM programs. The objective of most DSM programs is to determine a single measure, the "Normalized Annual Consumption " (NAC) both during pre- and post-retrofit conditions, and from there deduce the annual savings potential of the energy retrofit over a typical or mean year (Fels and Keating, 1993). Though we have also performed NAC related studies for energy use in commercial buildings (Ruch and Claridge, 1993), the primary concern of the LoanSTAR MAP, on the other hand, is to report actual savings for all retrofits on a continuous monthly basis (Claridge et al., 1991). Consequently LoanSTAR savings analysis uses actual measured climatic data during the reporting period in constrast to extrapolation to a year of "average" weather conditions as in the case of NAC.

At this juncture, we draw the reader's attention to the terminology "measured savings" which is being increasingly used by researchers involved in DSM programs (and which also appears in the title of this report). Since the building has undergone a retrofit, savings cannot be directly measured per se, but are in fact estimated using a baseline model. In this sense, the terminology may be inappropriate. However, the term is being used to emphasize the fact that retrofit savings are determined based on monitored data and not from engineering judgment or audit estimates.

1.2 Levels of Monitoring

While the ASHRAE Handbook (ASHRAE,1991) has a classification scheme for building energy monitoring projects, we shall present a slightly different scheme so that the reader acquires a better perspective of how the LoanSTAR monitoring and analysis approach compares with other programs.

(a) Use of monthly billing data. This approach, the most traditional among DSM programs, is appropriate for residences and small commercial buildings where such monthly billing data are already collected by the concerned energy utility, and where the extra cost of separate monitoring is difficult to justify. The pre-retrofit and post-retrofit utility bills are often compared after normalizing them for differences in weather, occupancy, billing period and schedules between the pre- and post-retrofit periods. A widely used analysis tool for such applications is PRISM (Fels, 1986) which is based on a steady-state model and corrected for pre-post variations in daily outdoor dry-bulb temperature. Although this type of modeling approach is robust, it has five basic limitations: (i) the method assumes a degree-day model (ASHRAE, 1993) of energy use which may not be appropriate for large institutional and commercial buildings; (ii) relatively long pre- and post-retrofit periods, at least 12 months, are required (Rachlin et al., 1986); (iii) analyzing results in individual buildings are likely to be misleading, although the approach is sound for a group of buildings with identical retrofits; (iv) outdoor temperature is assumed to be the only determinant (the effects of other variables such as solar radiation and humidity being either negligible or assumed to be implicitly present in the temperature itself due to collinearity); and (v) limited capability in terms of identifying O&M related problems. Also, PRISM assumes that the operating schedules of the building are constant from month to month during both pre- and post-retrofit periods. A detailed overview of monthly billing analysis techniques to determine electric savings in DSM programs is provided by Fels and Keating (1993).

(b) Use of short-term intrusive monitoring. Various building and climatic parameters are measured at a sub-hourly (intervals less than one hour) level for a few days (3-4 days being typical), both during the pre- and post-retrofit periods. The data are analyzed in the framework of a dynamic inverse modeling approach whereby the various physical parameters of the building, such as heat capacitance, and overall heat loss coefficient, are inferred. The seasonal or yearly use of the building operating under either pre- or post-retrofit conditions can then be deduced by classical macroscopic simulations. There are broadly four different dynamic inverse approaches which one could use (Rabl, 1988): Equivalent Thermal Network (ETP), time series (like ARMA techniques), differential equation and modal analysis. The most important difference between these methods is not in the inherent mathematical formulation, but in the way they are applied to data regression. Historically, the dynamic inverse approach has been used for residences (for example, Sonderegger, 1978; Hammerstein, 1984; Subbarao, 1988; Reddy, 1989) and its current status remains as such. A few studies, for example Rabl (1988) and Burch et al.(1990) have attempted to apply it to commercial building data, but more development work is needed to reach a stage of widespread acceptance.

(c) Use of continuous whole-building monitoring. During the last decade, with the growth of DSM programs and the declining cost of data acquisition equipment and computers, as well as the realization that monitoring data is able to provide near-term feedback to owners and operators that increase operating efficiency (Haberl and Komor, 1989; Liu et al., 1994; Claridge et al., 1994), there has been an increasing number of instances where a non-utility third party monitors several energy channels at the whole-building level, performs the appropriate analysis and transmits the data to the relevant personnel. This monitoring protocol is especially pertinent for large organizations such as government agencies, universities, etc. where often an entire complex of buildings are operated on a single energy meter, their energy needs being supplied from a central physical plant by way of electricity, chilled water and hot water/steam. This level of metering, which is what has been adopted by the Texas LoanSTAR program in the majority of buildings, is a compromise between no monitoring at all and disaggregated continuous monitoring (level d described below). Measurements of whole-building energy use typically provide hourly data of electricity use, chilled water use, hot water/steam use and electricity used by the building's air-handling units and chilled water and hot water pumps. Monitoring equipment to measure such data is installed several months prior to the retrofit and is left in place as long as the retrofit is active. Though the energy conservation benefits of a particular retrofit can be estimated rather accurately with about a year of pre-retrofit data and about a year of post retrofit data, continuous monitoring can also reduce energy costs by identifying and correcting O&M problems and recommissioning or "fine tuning" HVAC systems (Houcek et al., 1993 and Liu et al., 1994), savings which may sometimes be as important as the retrofit savings themselves. Concurrently, pertinent climatic variables are also measured at the site or gathered from national weather stations for the purpose of developing models to estimate the retrofit savings more accurately.

(d) Use of continuous sub-metering. This category involves non-intrusive metering of various pieces of equipment separately, requiring dozens of channels. This level of monitoring is appropriate for research buildings like the Enerplex in New Jersey (Norford et al., 1985), or for demonstration purposes like PG&E's ACT^2 (Kreig and Baker,1992) where the objective is technology assessment. This approach is also widely used by utilities to gather load research data. Though it is usually difficult to justify routine use of such a monitoring approach in building retrofit energy conservation projects, its usefulness in terms of better control and optimizing energy use in specific equipment (see for example, Englander and Norford, 1992) or of the whole HVAC system itself (Braun et al., 1987) is undeniable. The present thinking is that the need for separate metering can be avoided by modifying the way the current generation of EMCS are designed. If EMCS systems are able to store data as well as perform their basic function, namely of proper managing and control of energy use in the building, then the data can be analyzed (i) so that the latter function is performed better, (ii) retrofit savings can be accurately identified without the need to have a dedicated monitoring program such as (c). However, numerous problems preclude general use of the current generation of EMCS for this purpose.

(e) High resolution single channel metering. This approach, still under development and currently applicable to residential and small commercial buildings only (Norford et al., 1992), is to sample the whole-building power consumption at a very high sampling rate (at the milli-second level), and use statistical techniques in conjunction with the on-off signature which characterizes different pieces of electrical equipment, to disaggregate the whole-building signal into individual component consumption. Expensive hardware for sub-metering is avoided but at the cost of having a dedicated micro-processor that is attached to the main electrical service and which performs both the tasks of sampling very frequently and of statistically disaggregating the whole-building signal into its component parts. Presently, the increased difficulty of acquiring, maintaining and manipulating large data sets coupled with data analysis and modeling complexity (for example, dynamic effects of energy storage in the structure may have to be treated) may limit the widespread use of this approach for energy conservation projects.

1.3 Types of energy retrofits in the LoanSTAR program

Monitoring requirements will depend upon the type of retrofits and the level of audit verification required. The projects funded by LoanSTAR primarily include retrofits to lighting, HVAC systems, electric motors, energy management control systems (EMCS), boilers and chillers, energy recovery systems, thermal storage and co-generation systems. As of December 1993, energy savings in 34 LoanSTAR sites representing 50 buildings are being reported. Figure 1 is a pie-chart summarizing the types of buildings being monitored. We note that the majority of these buildings are institutional buildings while a few school districts and thermal energy plants have also come on-line. The buildings located on university campuses vary in size from 49,000 ft^2 to 484,000 ft^2 and house classrooms, offices, laboratories, computer facilities, auditoriums, workshops and a major campus library. Such buildings are usually provided with electricity, chilled water and steam (or hot water) from campus utility plants that are separate from the buildings.

Table 1 is a summary of the various energy conservation retrofit measures (ECRMs) performed by the LoanSTAR program. We note that the primary retrofit in most of the buildings was the conversion of constant air volume (CAV) units to variable air volume (VAV) units. Lighting and EMCS retrofits are the second most important type of retrofits, followed by boiler and chiller retrofits.

While analyzing savings, it is important to distinguish between two types of energy use: weather dependent and weather independent. For example, electricity use by the air handlers of a CAV system is essentially weather independent while that of a VAV system is weather dependent. Lighting energy use is weather independent while energy use by boilers and chillers is, again, weather dependent.

1.4. LoanSTAR monitoring design

The general philosophy of monitoring design in the framework of LoanSTAR is described in this section. Depending on the number of channels being monitored, ensuring the quality of the data may be a formidable task. Meters must be correctly calibrated when installed and recalibrated at periodic intervals to avoid "drift". Detecting bad data can also be difficult. Though certain quality control measures can be automated, proper control requires an inordinate amount of analyst time. Given the financial constraints of the MAP (only 3% of the retrofit cost can be used for monitoring), it was decided that the objectives of LoanSTAR are better served by generally taking fewer channels of good data at the whole-building level rather than at the disaggregated end-use level.

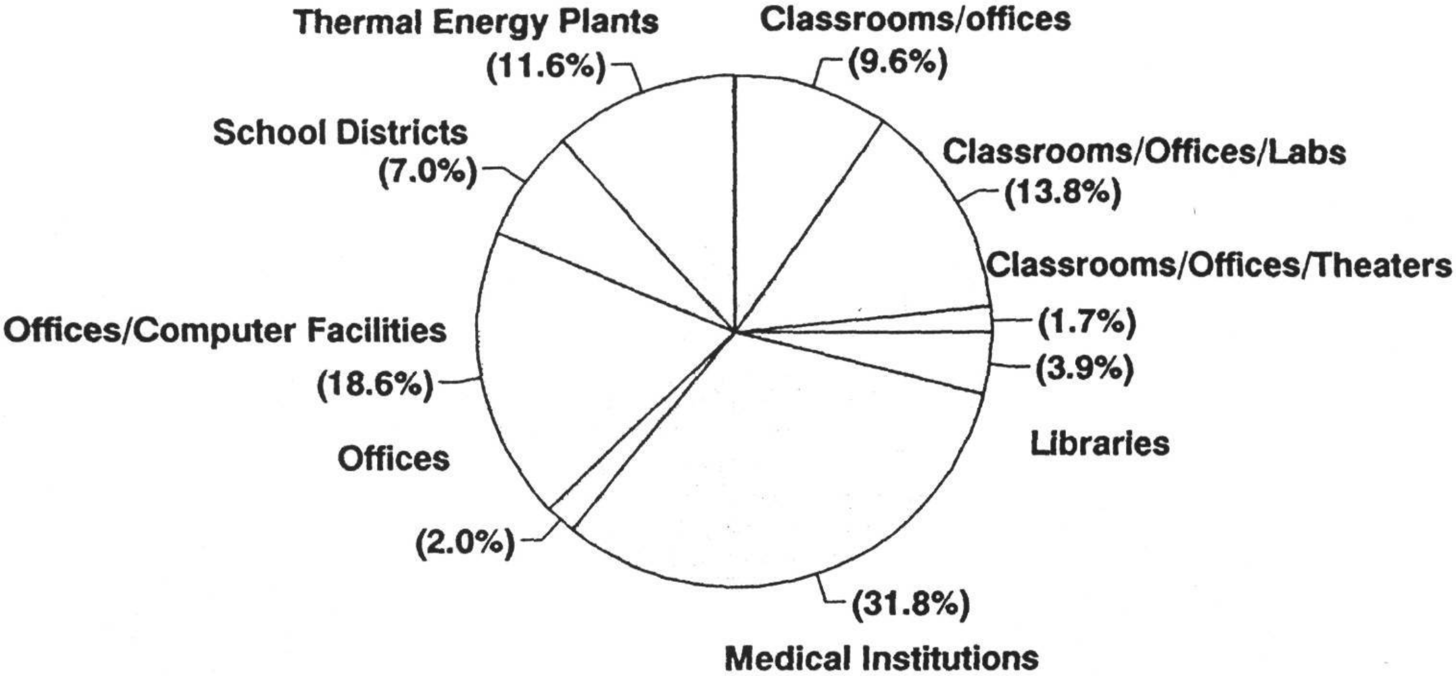


Fig.1 Types of buildings, by percent area, being monitored by the Texas LoanSTAR program as of December 1993. Total floor area monitored is 19.13×10^6 ft^2.

Table 1. Summary of ECRMs for buildings monitored in the LoanSTAR program as of December 1993.

ECRM Recommendations	Impl. Cost $	% of Total Imp. Cost	Cost Savings $	% of Total Cost Savings	Simple Payback Yrs
HVAC System Retrofits	$10,504,625	32.3	$3,256,227	34.0	3.2
Boiler & Steam Retrofits	$1,439,646	4.4	$1,116,516	11.7	1.3
Motor/VSD/VSP Conversion	$4,679,163	14.4	$1,172,166	12.3	4.0
Chiller & CHW Retrofits	$1,936,886	6.0	$362,643	3.8	5.3
Lighting Retrofits	$4,841,987	14.9	$1,605,062	16.8	3.0
EMC Systems	$3,368,158	10.4	$736,918	7.7	4.6
Pumping System Retrofits	$1,752,647	5.4	$655,057	6.8	2.7
Others	$3,997,383	12.3	$662,291	6.9	6.0
Total	$32,520,495	100	$9,566,880	100	3.4

To provide the best measure of energy savings, the energy use of each type of equipment being retrofitted should be separately monitored. For example, if CAV air handlers are being converted to VAV, the total electricity used by the air-handlers should be metered. This can often be accomplished by metering the electricity used by a distribution panel (often called a motor-control center) which distributes electricity to all of the air-handlers in the building.

If the energy savings generated by lighting retrofits are to be exactly measured, then all of the electrical feeds to the lighting fixtures must be identified and metered. In practice, this is often difficult and expensive since lighting feeds are usually distributed throughout the building. A less expensive method is to meter the whole-building electricity use and the air-handler electricity use separately. The difference between the two channels (provided no large appliances are situated outside the building) is the lighting and equipment use (q_i). Comparing q_i (even over a short period since this use is essentially weather independent) immediately before and after the retrofit, will yield a good estimate of the electricity saved by the retrofit. Over a long period of time, however, this estimate of savings may be less accurate as other electrical equipment may be added or removed from the building.

If a retrofit is expected to reduce the heating and cooling energy use, these channels should also be metered. In buildings where heating and cooling are generated on-site, metering the energy supplied to the heating (say, in the form of volume of natural gas) or the cooling (say, electricity in the case of a vapor compression chiller and natural gas in the case of an absorption chiller) equipment is adequate. If the building subscribes to district heating and/or cooling (like institutional buildings do) then whole-building heating and/or cooling energy use can be measured separately by individually metering heating and cooling fluid streams as they enter and leave the building. This involves measuring the fluid flow rate <u>and</u> the temperature difference between the supply and return streams. We recommend that both these quantities (flow rate and energy use) be monitored and retained as separate channels since this allows corrections (such as flow rate) to be made at a later time if manufacturer calibration factors are found to be astray, something which occurred in the LoanSTAR program (O'Neal et al.,1990).

Typically, the following channels are used during retrofit savings calculations: chilled water use, steam or hot water use, whole-building electricity, air handler electricity use, chilled water pump electricity use, natural gas to boilers and climatic variables (outdoor dry bulb temperature, relative humidity and global horizontal solar radiation).

2. OVERVIEW OF LOANSTAR RETROFIT SAVINGS MEASUREMENT METHODOLOGY

Figure 2 provides a general overview of the various retrofit savings analysis techniques developed in the LoanSTAR program. The primary breakdown depends on whether monitored post-retrofit data are available or not. If not available, analysis of utility billing data or an engineering judgment approach have to be adopted. These approaches are well documented in the current literature (see for example, Fels and Keating, 1993) and though we have had to adopt some of these techniques in a few of the LoanSTAR buildings, this report will not address these. Rather, we shall expand on analysis techniques where a certain amount of monitored post-retrofit data are available. The next branching off in Fig. 2 has to do with whether monitored pre-retrofit data are available, and this determines whether to use regression models or some sort of calibrated model. The rest of this report describes these approaches at length and provides complete reference to pertinent publications.

2.1 Weather dependence and schedule dependence

One way of estimating retrofit savings is to directly compare the unadjusted pre-retrofit energy use to the post-retrofit energy use. Though this method may yield a first-order evaluation, it is often considered to be too simplistic because the effect of the retrofit on energy use may be largely or entirely masked by changes between the pre- and the post-retrofit periods of certain important parameters influencing energy use (the most important often being the climatic variables and the building operating schedule). Consequently, in order to incorporate the effects of such changes into the energy savings calculation, a theoretical model capable of predicting energy use of the building under pre-retrofit or baseline operation needs to be developed. Though pre-retrofit utility bills may provide the basis for such a model, most of the LoanSTAR buildings which are institutional do not have such data. Consequently the pre-retrofit monitored data provides both a base-line and the basis for the model. The hourly data collected by LoanSTAR is generally superior to monthly data for creating baseline models (an issue which will be discussed in section 3.3.).

As mentioned earlier, certain types of energy use in commercial buildings, such as q_i and CAV system air handler electricity use, are insensitive to variations in weather and are primarily determined by the occupancy or operating schedule of the building. In many cases, these weather independent types of energy use are relatively constant during each operating schedule period and may be accurately modeled as the mean energy use during each period. A common example occurs when air handlers are partially shut down on weekends. In this case, air handler electricity use is modeled with separate mean (or one-parameter) models for weekdays and weekends. For greater accuracy, a classification more involved than a mere weekday-weekend separation is advised for weather independent energy use. A procedure called "day grouping", shown in Fig. 3, is followed. This involves performing the Duncan

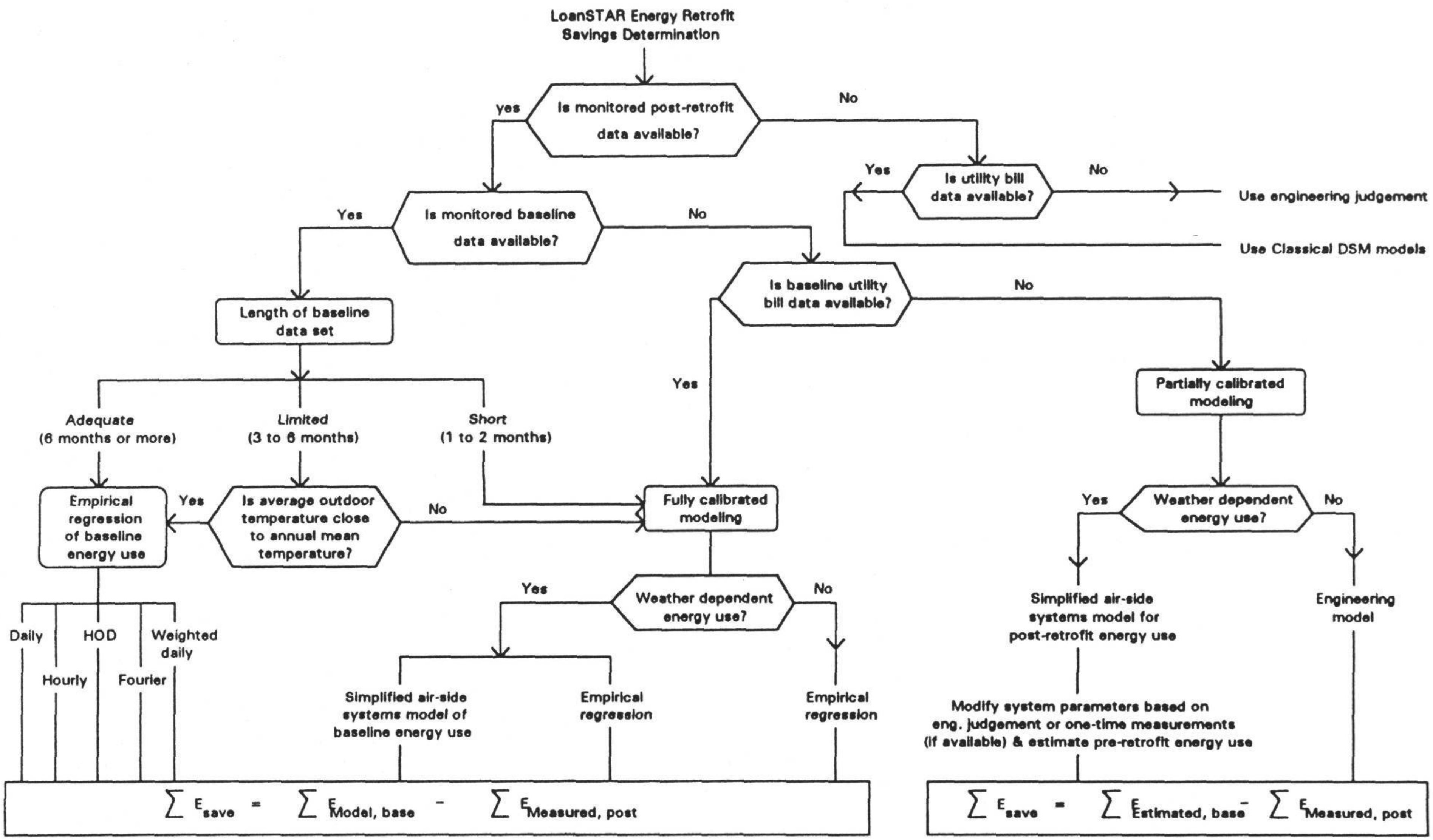


Figure 2. Overview of the Energy Retrofit Savings Determination Approaches Used in LoanSTAR

statistical test (Ott,1988) in order to determine whether daily mean energy use during weekdays, weekends, holidays and semester breaks (in case of education buildings) are different enough to justify separate models. In case of weather dependent energy use, such as cooling and heating energy use, we found a weekday-weekend separation to be generally adequate. The annual periodicity present in the data and the relatively small impact of daily total internal load variations due to scheduling effects on weather dependent energy use seem to have the result of not requiring a rigorous day-typing procedure (Dhar et al., 1994).

The use of separate models for different operating or occupancy schedules enhances the resolution of the savings but does not affect the determination of how much energy is saved. However, it does decrease the uncertainty of the retrofit savings, thus making it desirable to perform proper day-typing before model identification (Kissock, 1993).

2.2 Choice of time scale

In many instances, the time scale of the data used to measure savings may be determined simply by what type of data are available. For example, if only utility billing data are available, the analyst has no choice but to use the monthly time scale. However, the increasing use of dedicated metering equipment and EMCS in commercial buildings has dramatically increased the availability of high resolution energy use data. In these cases, the selection of the time-interval of data used to measure savings involves a subjective trade-off between the information content of the savings, and the modeling and computational effort required to derive the savings. For example, hourly data if properly modeled, can provide high time-resolution savings information in which savings during particular hours of the day can be determined (Katipamula et al., 1994 a&b). This information can be useful for O&M identification, something which coarser time-resolution models cannot provide. Engineering judgment backed by sample calculations (Kissock, 1993) indicate that dynamic effects due to thermal mass effects due to scheduling and diurnal climatic swings are certainly important at the hourly time scale, while their effect is minimal or even negligible at the daily time scale. A study by Katipamula et al.(1994 a&b), described later in section 3.3, indicates that the model accuracy is in fact improved in most cases when daily time scales are assumed. Hence the daily time scale seems to be most appropriate for retrofit savings analysis in general, though there are special circumstances when hourly models are more appropriate. The above study is the only one of its kind, and we are currently evaluating this issue more rigorously.

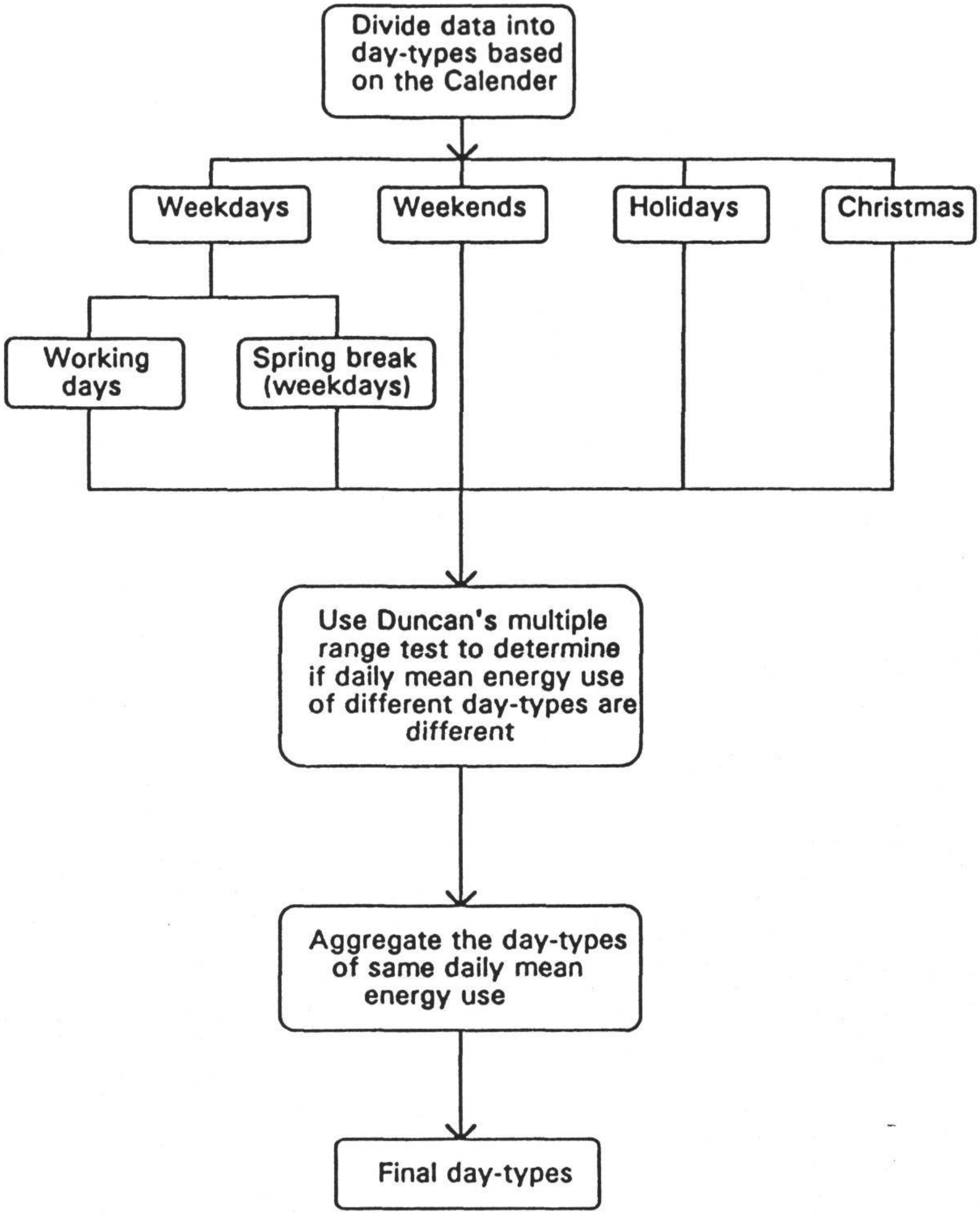


Fig.3 Flow chart of the day-typing procedure used to statistically distinguish between days when a commercial building is operated differently. A separate model is then identified for each day-group.

2.3 General approach

The methodology currently used to report retrofit savings in LoanSTAR buildings basically involves the following steps (Kissock et al., 1992 a&b):

(i) Identification of the baseline, construction and post retrofit periods

This is done both from talks with site personnel and inspection of the hourly time series plots of pertinent energy use. For example, in the case of an air-side HVAC retrofit from CAV to VAV operation, it is best to study air handler electricity use. As illustrated in Fig. 4, changes in consumption patterns are very distinct during these three stages and consequently there is little ambiguity. In the baseline period, air-handler electricity use is almost constant, while electricity use behavior during the construction period is erratic. Finally, after the VAV system is complete, air-handler use follows a regular but varying pattern depending upon the building loads. In case of weather independent energy use, say lighting, the same type of erratic behavior will mark the onset of the construction period. Once the construction is complete, the lighting signal will revert back to a steady (or periodic) trace which will be lower than the baseline energy use.

(ii) Preliminary data handling

The entire data set from each building is comprised of hourly averaged or summed observations. Each of these channels is screened and converted into daily averaged data (Lopez and Haberl,1992). As described earlier, this is the time scale most often (but not always) used in the LoanSTAR program because of the following reasons: (i) it retains the resolution required to observe variation in energy use with climatic conditions and building operating modes, (ii) it avoids the complexity introduced by dynamic effects, i.e., the thermal mass effects of the building shell and the strong diurnal scheduling patterns of q_i, and (iii) significantly reduces the amount of data to be manipulated and interpreted as compared to hourly data, while remaining large enough for robust statistical analysis, and (iv) results in models more accurate than hourly or monthly models. Some of these issues are addressed at length in section 3.3.

(iii) Model identification

Statistical models of baseline energy use of each energy type influenced by the retrofit are developed. Typically, this would include daily cooling energy use, heating energy use, and electricity use models. The functional form of each model is determined both by our physical understanding of how a particular type of energy use should vary with time and also by the operating schedules. The latter effect is explicitly accounted for by developing models for each day-type separately. A complete description of the various types of regression models is given in section 3.2.

The criteria used to select the most appropriate model is to maximize the goodness-of-fit using the simplest model or combination of models. Although several measures of a model's goodness-of-fit are available, we prefer to use the coefficient of variation of the root mean square error (CV-RMSE) (Draper and Smith, 1981) where

$$\mathrm{CV-RMSE} = 100 * \frac{\left[\sum_{d=1}^{n}\left(E_d - \hat{E}_d\right)^2 / (n-p)\right]^{1/2}}{\overline{\mathrm{E}}} \tag{1}$$

where $\overline{E}$ is the mean daily energy use and $\hat{E}_d$ is the daily energy use predicted by the baseline model, E_d is the measured daily energy use, *n* is the number of days and *p* the number of regression parameters in the model. For a one parameter or mean model, $\hat{E}_d = \overline{E}$ and *CV-RMSE* is identical to the coefficient of variation of the standard deviation (CV-SD). The *CV-RMSE* index is preferable to the widely used coefficient of determination (R^2) because it ascribes an absolute statistical order of merit to the variation in the independent variable not explained by the regressor parameters, while R^2 is a relative predictor describing how the particular model fares with respect to a mean model. Hence two data sets with very different amounts of scatter can have similar R^2 values if the importance of the relative predictor variables in each model are similar.

(iv) Predicting energy use of unretrofitted building

The set of baseline models (usually identified by regression using daily data) are then used to predict daily energy consumption of the unretrofitted building under building operation and weather conditions corresponding to each day of the post-retrofit period. Because the building has already undergone retrofits, the use of a model is unavoidable and leads to model prediction uncertainties which subsequently impact retrofit savings estimates. Section 3.4 discusses model uncertainty effects more fully.

(v) Estimation of savings

Finally, the savings over a certain number of post-retrofit days are estimated by subtracting the daily measured energy consumption from the daily energy consumption predicted by the baseline model and summing the daily savings over the time period in question.

The entire procedure for computing total savings of either chilled water, hot water or electricity, at the daily time scale, can be summarized by:

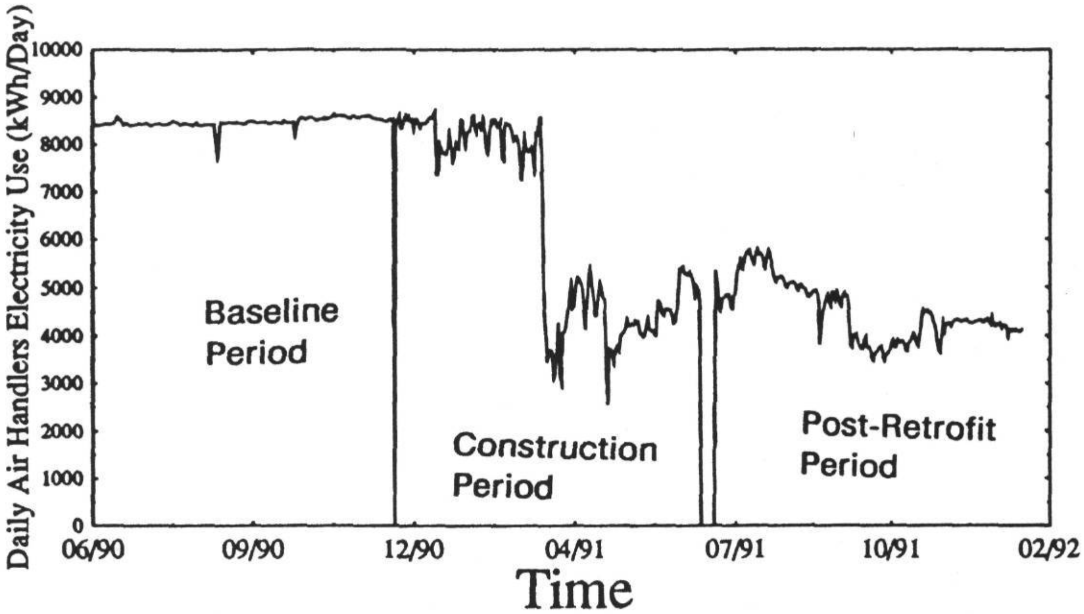


Fig. 4 Pump and air handler unit electricity use at a site where a CAV to VAV conversion was performed. The baseline, construction and post-retrofit periods are clearly identified by changing energy use patterns.

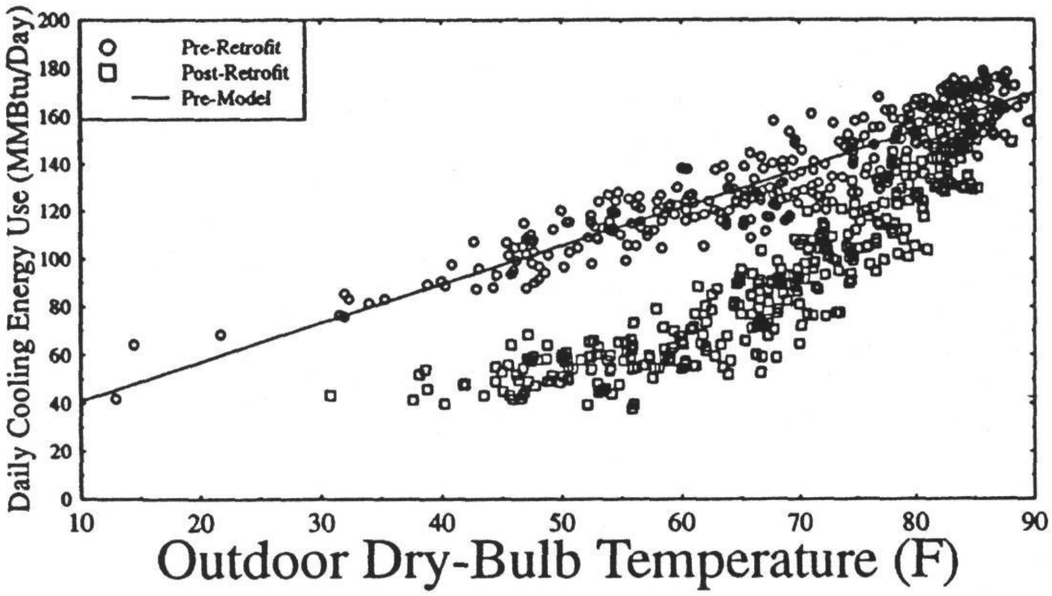


Fig. 5 Typical scatter plot showing baseline and post-retrofit cooling energy use versus T_o for the case when adequate baseline data is available. Savings are measured as the difference between a pre-retrofit baseline model (shown as a linear plot) and measured post-retrofit energy use.

$$\sum_{j=1}^{m} E_{Save,j} = \sum_{j=1}^{m} \hat{E}_{Base,j} - \sum_{j=1}^{m} E_{Meas,j} \tag{2a}$$

or

$$E_{Save,Tot} = \hat{E}_{Base,Tot} - E_{Meas,Tot} \tag{2b}$$

where

j	- subscript representing a particular day over the post-retrofit period,
m	- number of post-retrofit days over which savings are estimated,
$E_{Save,j}$	- energy savings over day j,
$\hat{E}_{Base,j}$	- model predicted baseline daily energy use of unretrofitted building,
$E_{Meas,j}$	- measured post-retrofit daily energy use, and
Tot	- subscript denoting total over the entire retrofit period.

The above procedure is illustrated by Fig. 5 which shows a typical scatter plot of baseline and post-retrofit cooling energy use versus T_o. The regression model is fitted to the pre-retrofit daily data points, while the differences between each point (representing daily post-retrofit energy use) and the regression line determines the energy savings on that particular day. Summing the daily values over m days yields the net energy savings during a certain time interval.

3.0 REGRESSION MODELING METHODS

3.1 Basic Considerations

It is clear from the above discussion that the regression model identification phase is crucial in the entire retrofit savings process. The Texas LoanSTAR program requires that data acquisition equipment to monitor building energy use be installed for a suitable period before the retrofits are carried out (Claridge et al., 1991) and remain in the building possibly throughout the retrofit life. Consequently, estimates of the retrofit energy savings can be based on the regression model approach. There are, however, buildings for which, due to a variety of reasons, the baseline data period is either too short or even entirely spurious. As discussed at more length in section 3.5, statistical models based on less than about 3 to 6 months of data are usually unreliable. Only in such instances is the calibrated simplified systems model approach (described in section 4) considered for use in the LoanSTAR program (Katipamula and Claridge, 1993). The calibrated detailed simulation model approach is more tedious and requires knowledge of how the mechanical systems of the building are operated and a certain proficiency in using the particular building energy code. It is typically resorted to during analysis of monitored data only when the quality or length of the data period is not adequate to enable proper regression model identification. This approach has yet to reach a stage of maturity in methodology development where it can be used routinely and with confidence by people other than skilled analysts. Whenever appropriate, model development using the regression approach is used because it is generally the least demanding in effort and user-expertise, yields adequate results and permits uncertainty associated with savings to be quantified using accepted statistical procedures. Consequently, our efforts have been largely directed towards the regression model approach.

The goal of modeling energy use to measure savings is to characterize building energy use with a few readily available and reliable input variables. In addition, each independent variable must be unaffected by the retrofit so that the model can accurately predict the energy use that would have occurred if the retrofit had not taken place. Environmental variables which meet the above criteria for modeling heating and cooling energy use include outdoor air dry-bulb temperature, solar radiation and specific humidity. In commercial buildings, internally generated loads, such as the heat given off by people,lights and electrical equipment, also impact heating and cooling energy use. Such internal loads are difficult to measure in their entirety given the ambiguous nature of people loads and latent loads. However, we find that the monitored q_i is a good surrogate of the total internal sensible loads. For example, when the building is fully occupied, q_i is also likely to be high, and vice versa.

Although, physically, energy use is dependent on several variables that influence energy use, there are strong practical incentives for identifying the simplest model that results in acceptable accuracy. Multivariable models require more metering and are unusable if even one of the variables is unavailable. In addition, some of the regressor variables may be linearly correlated. This condition, called multicollinearity, can result in large uncertainty in the estimates of the regression coefficients, and can also lead to poorer model prediction accuracy as compared to a model where the regressors are not linearly correlated (Ruch et al.,1993a). Several authors (for example, Draper and Smith, 1981) recommend using Principal Component Analysis (PCA) to overcome multicollinearity effects. Analysis of multi-year monitored daily energy use in a grocery store found a clear superiority of PCA over multivariate models (Ruch et al., 1993a; Cox, 1993). However, a more general evaluation by Reddy and Claridge (1994) of both analysis techniques using synthetic data from four different geographic locations in the U.S. found that injudicious use of PCA may exacerbate rather than overcome problems associate with multicollinearity. The results of the study suggest that multicollinearity may not be as big a problem as originally thought, primarily because multivariate regression models for most of the LoanSTAR models have high values of R^2 (typically higher than 0.8).

3.2 Overall classification

Engineering equations describing the performance of HVAC components and systems are well known (see for example, Knebel, 1983). Recent studies by Kissock (1993), Reddy et al., (1994) and Katipamula et al., (1994a) specially aimed at investigating the functional basis of energy use in HVAC systems with monitoring data analysis in mind, indicate that no single empirical model is appropriate for all energy types and HVAC systems. This is in contrast to residential buildings where a single variable three-parameter, degree-day model such as PRISM is widely applicable (Fels, 1986).

In commercial buildings, we find that some types of energy use are weather independent and are appropriately modeled as the mean energy use in each operating period. Weather dependent energy use is strongly influenced by system type, control options, climatic variables, and the physical and operational characteristics of the building such as the building loss coefficient and internal loads. Although the mathematical models suggest quadratic and cross-product relationships between the regressor variables (Reddy et al., 1994), these effects have been found to be usually small since a multiple linear model when regressed to actual data yields excellent fits (Katipamula et al., 1994 a&b). Consequently, linear regression can be adopted without much, if any, loss in model accuracy.

Linear regression models relevant for LoanSTAR analysis can be divided into two categories: single variable (SV) models and multiple variable (MV) models.

3.2.1. SV models

In this class of models, outside air dry-bulb temperature T_0 is taken as the only regressor variable. Like the choice of time scales, this is a subjective trade-off. Some accuracy is lost as compared to multiple regression, but the simplicity and relatively good accuracy of such models coupled with the fact that T_0 is widely available, make them highly desirable.

There arises, however, a small dilemma. Many of the DSM utility bill analysis methods use the average of the daily maximum and the daily minimum hourly T_o values to characterize daily T_o values. Such a practice originated because it was easier to obtain and use such "min-max" data that was routinely provided by meteorological locations throughout the U.S. in hard copy form. With hourly data being now freely available in electronic form, either from monitoring by the retrofit analysis contractor or from the National Weather Services, it would be physically more accurate to use hourly averages over the day to characterize daily T_o data. The dilemma is how best to characterize T_o in order for models to be most meaningful. We have found the differences in both modeling approaches to be very minor, and, thus, any approach could be adopted with negligible differences provided one is consistent with how T_o was defined during model identification and during prediction.

(a) Mean or one-parameter (1-P) models appropriate for weather independent energy use, (for example, lighting or air handler electricity use for CAV systems). The model is simply

$$E = \beta_0 \tag{3}$$

(b) Two-parameter (2-P) models for weather dependent energy use such as cooling and heating energy use in CAV systems without control options such as economizer cycles and hot deck reset schedules and with small amounts of outdoor air intake, typically 10-20% (Knebel, 1983):

$$E = \beta_0 + \beta_1 T_o \tag{4}$$

where the two coefficients are determined by regression.

(c) Segmented linear regression models, which can be further sub-divided into:

- Three parameter (3-P) or PRISM-type models (Fels, 1986)
- Four parameter or 4-P models (Ruch and Claridge, 1992) expressed as:

$$E = \beta_0 + \beta_1 (T_o - \beta_3)^- + \beta_2 (T_o - \beta_3)^+ \tag{5}$$

where the symbols $(\,)^-$ and $(\,)^+$ indicate that the quantities within the parenthesis should be set to zero when they are negative and positive respectively. β_0 is the energy consumption at the change point temperature β_3 , while β_1 and β_2 and are the low and high temperature slopes (Fig. 6). When β_1 is constrained to be zero, we get the 3-P change-point model which is the basis of the heating only PRISM model (Fels,1986). In this light, the 3-P model can be viewed as a special (but important for residential buildings) case of the more general 4-P model. Such models are appropriate for cooling and heating energy use in CAV systems with economizer operation or hot deck reset schedules, and VAV systems.

Note that separate models need to be identified for each day-group (see Section 2.1). A compact way of doing this is to introduce indicator variables (Draper and Smith, 1981) for each day-group and identify one single model describing all day-groups <u>simultaneously</u>. Though this is statistically more formal, we have found it more convenient to separate the daily data into sub-groups and develop individual models for each day-group. The results by either method are identical.

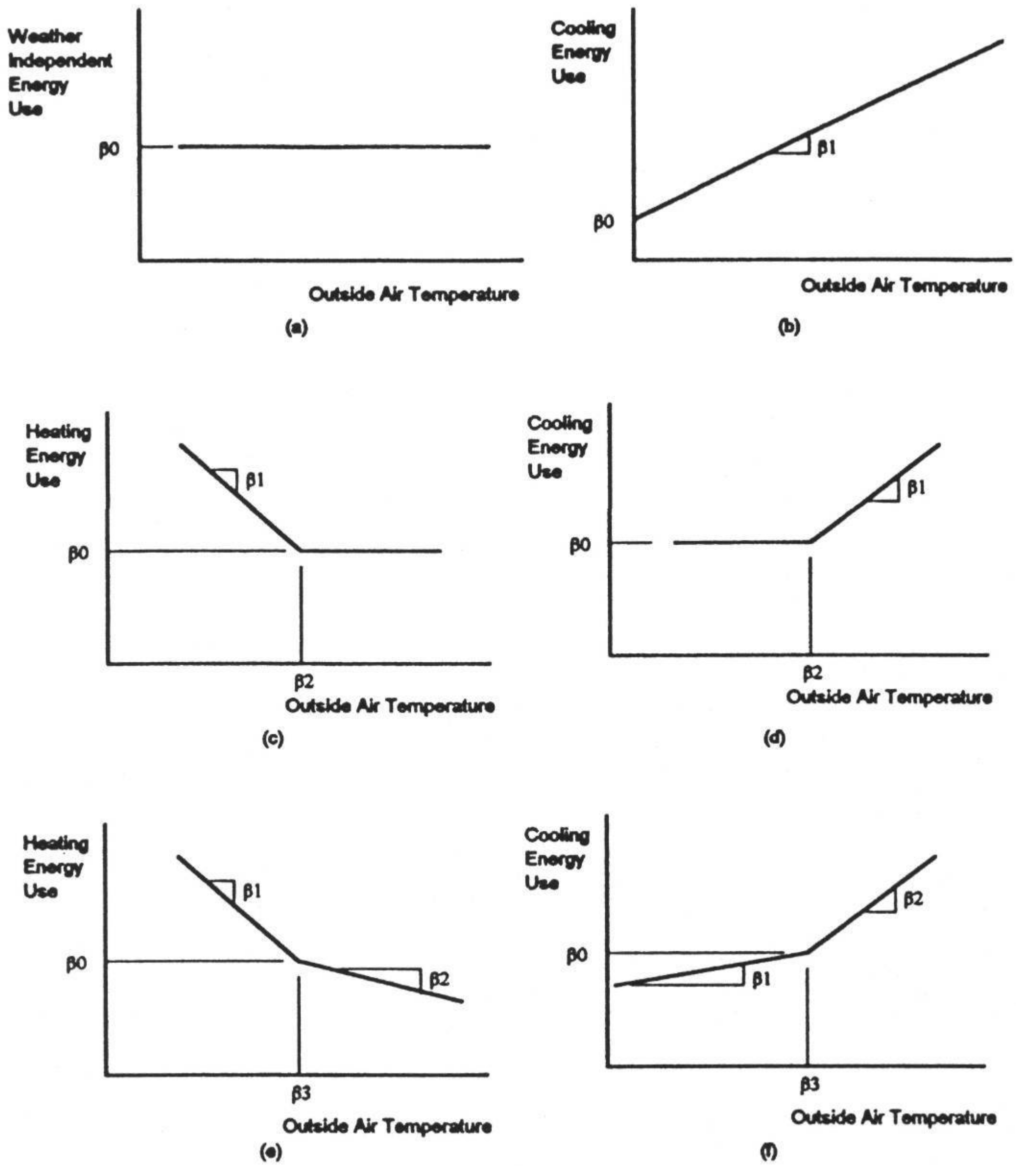


Fig.6 Empirical SV energy use models appropriate for commercial building energy use: (a) one-parameter model, (b) two-parameter model shown for cooling energy use, (c) three-parameter heating energy use model, (d) three-parameter cooling energy use model, (e) four-parameter heating energy use model, and (f) four-parameter cooling energy use model.

Identification of model types (a) and (b) is relatively straightforward and can be done in standard packages (for example, SAS,1989 and STATGRAPHICS, 1991). Though linear segmented models are special cases of a much larger set of models, called spline functions (Pindyck and Rubenfeld, 1981), these commercial packages do not, however, allow segmented linear regression modeling to be investigated in a framework convenient enough for building energy analysis. This is because the change point needs to be known and specified in order to use classical spline regression. Because this is not known a priori for buildings (in fact, this is one of the parameters being identified by regression), these general commercial regression packages cannot be used directly. Another deficiency in these packages is the lack of proper error diagnostics for spline regression models. Consequently, specially written computer programs, like PRISM (Fels, 1986) or EModel (Kissock et al., 1993b), are used. The computational algorithm of the 4-P model used in EModel involves a search method whereby the best least square fit is determined. More specifically, the residual sum of squares over each of the two segments are computed separately for each incremental variation in the change point temperature, and then added together. The particular value which minimizes this sum is the sought-after change-point temperature (Ruch and Claridge, 1992).

3.2.2 MV Models

The use of a SV 3-P model like the PRISM model (Fels, 1986) has a physical basis only when energy use above a base level is linearly proportional to either T_0 or to degree days. This is a good approximation in case of residential buildings. Commercial buildings, in general, have higher internal heat generation with simultaneous heating and cooling energy use and are strongly influenced by HVAC system type and control strategy. This makes energy use in commercial buildings to be less strongly influenced by T_o alone. It is not surprising that blind use of SV models has had mixed success at modeling energy use in commercial buildings (MacDonald and Wasserman, 1989). Multiple variable (MV) regression models are a logical extension to SV models provided the choice of the variables to be included and their functional forms are based on the engineering principles on which HVAC systems and other systems in commercial buildings operate.

Energy use as a function of T_o exhibits a change point in several buildings which is generally between 15°and 22° C (Kissock et al., 1992a). Subsequent studies based on physical system behavior (Kissock, 1993; Reddy et al., 1994 and Katipamula et al., 1994a) have indicated that the change point in CAV systems is due to a combination of latent loads (for cooling use), hot deck scheduling and economizer cycle operation. In the case of VAV systems, an additional, and perhaps most influential, factor is the outdoor temperature at which the minimum design supply air flow rate is reached. Thus the energy use is a complex function of climatic conditions, internal loads, building characteristics (such as loss coefficient and heat capacity), HVAC system characteristics (air flow rate, outdoor air fraction, economizer operation and control options like deck settings and scheduling,...), and HVAC type (whether CAV or VAV, for example). Some of these parameters are difficult to estimate in an actual building and hence, they are not good candidates for regressor variables. Further, some of the variables vary but little during a season and though their effect on energy use may be important, a stepwise regression would not retain them in the final set of regressor variables, their effect being implicitly lumped into the constant parameter of the regression model.

The functional basis of air-side heating and cooling use in various HVAC system types has been addressed by Reddy et al. (1994) and subsequently applied to monitored data in commercial buildings (Katipamula et al., 1994 a&b). Since none of the quadratic and cross product terms of the engineering equations are usually picked up by the MV models, we are left with models for energy use which are strictly linear.

In addition to T_o, internal loads q_i, solar loads q_{sol} and latent effects via the outdoor dew point temperature T_{dp} are candidate regressor variables. In commercial buildings, a major portion of the latent load is due to fresh air ventilation. However, this load appears only when the outdoor air dew point temperature exceeds the cold deck temperature. Hence the term $(T_{dp} - T_s)^+$ where the + sign indicates that the term is to be set to zero if negative, and T_S is the mean surface temperature of the cooling coil (typically about 11 - 13°C) is a more realistic descriptor of the latent loads than is T_{dp} alone. The above aspect is illustrated by Fig. 7 which shows how the simulated cooling energy use in a building with a dual duct CAV system and constant internal loads is likely to vary with different T_o values and different values of outdoor relative humidity. We note clearly the inadequacy of 2-P and 3-P models and the fact that the change point does not strictly occur at one specific value of T_o, but changes with the outdoor humidity level. Consequently, the use of $(T_{dp} - T_s)^+$ as a regressor in the model is a simplification which seems to yield adequate accuracy.

Thus a MV regression model with an engineering basis has the following structure:

$$E = \beta_0 + \beta_1 (T_o - \beta_3)^- + \beta_2 (T_o - \beta_3)^+ + \beta_4 (T_{dp} - \beta_6)^- + \beta_5 (T_{dp} - \beta_6)^+ + \beta_7 q_{sol} + \beta_8 q_i \qquad (6a)$$

Because of the above discussion $\beta_4 = 0$. Introducing indicator variable terminology (Neter et al., 1989), the above equation is identical to (Katipamula et al., 1994a) :

$$E = a + b T_o + c I + d I T_o + e T_{dp}^+ + f q_{sol} + g q_i \qquad (6b)$$

Table 2. Comparison of the predictive ability of different models using eq.(6b).

Site	Modeling Period Identification	Modeling Period Prediction	Indice	Monthly	Daily	Hourly	HOD
MSB (DDCV)	Jan. - Dec. '92	Jan. - Dec. '93	CV	8.4	4.8	5.8	5.1
			MBE	-2.2	-0.6	-0.7	-0.9
BUR (VAV)	Jan. - Dec. '92	Jan. - Dec. '93	CV	9.9	7.5	9.1	9.1
			MBE	-8.2	-6.5	-6.4	-7.7
WIN (VAV)	Jan. - Dec. '92	Jan. - Dec. '93	CV	15.3	15.2	15.7	15.5
			MBE	-12.6	-12.0	-10.7	-11.8

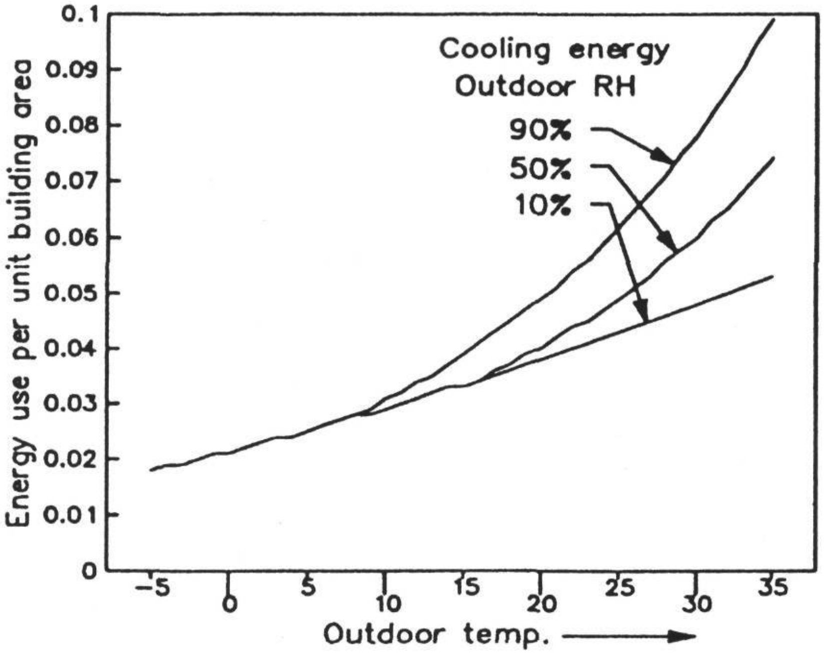


Fig.7 Simulated variation of total cooling energy consumption (kW/m^2) versus T_0 (^oC) for a dual-duct CAV system.

where the indicator variable I is introduced to handle the change in slope of the energy use due to T_o. I is set equal to 1 for T_o values to the right of the change point (i.e., for high T_o range) and set equal to 0 for low T_o values. As for the SV segmented models (i.e., 3-P and 4-P models), a search method is used in order to determine the change point which minimizes the total sum of squares. The interpretation of the coefficients c and d which represent the change in slope at the T_o change point is exactly similar to that of the 4-P model described in section 3.2.1. How the above model is able to remove the effects of patterned residuals (an indication of improper model structure as discussed in section 3.4) is illustrated by Fig. 8 with daily monitored cooling data from a LoanSTAR building under VAV operation (Katipamula et al., 1994a). The simple 2-P SV model is clearly inadequate, while the model given by eq. (6b) seems to result in a more or less random residual pattern indicating a satisfactory model. A final aspect to be kept in mind is that, contrary to cooling energy use, latent loads do not appear on the heating coil of the HVAC system and hence the term T^+_{dp} should be omitted from the model structure when regressing heating energy use.

3.3.Comparison of various models and effect of time resolution

As mentioned in section 2.2, we have also investigated the effect of time resolution on model goodness-of-fit and model accuracy (Katipamula et al., 1994b). When hourly monitored data are available, one has four choices in terms of time resolution: monthly, daily, hourly and individual hourly or hour of day (HOD). Thus, the first three choices would involve one model for each day-type while the HOD approach would entail identifying 24 models for each day-type, i.e., one for each hour of the day. Figure 9 illustrates how the process of averaging and summing decreases the scatter in the data as one goes from hourly to monthly data. The scatter in hourly energy use above a T_o value of about 16° C is very pronounced in large part due to latent loads. This effect, as well as day-to-day variation in hourly q_i, contribute to greater scatter at an occupied hour (namely 1 p.m.) for HOD models than at an unoccupied hour (4 a.m. shown).

Year long monitored data of cooling energy use from six LoanSTAR sites, three with dual duct CAV systems and three with VAV systems, were modeled following eq. (6b) at all four time scales (Katipamula et al., 1994b). The decrease in CV-RMSE, defined in eq. (1), with inclusion of additional regressor parameters in the model for all four scales is summarized in Fig. 10. With little variation to capture, the monthly models consistently have the lowest CV. Only T_o and T^+_{dp} variables are needed to adequately model energy use because the CV does not decrease when further variables are added to the model. In all time scales, T_o and T^+_{dp} account for over 90% of the variation in cooling energy use. The daily models have the next lowest CV, followed by HOD models and hourly models in order of increasing

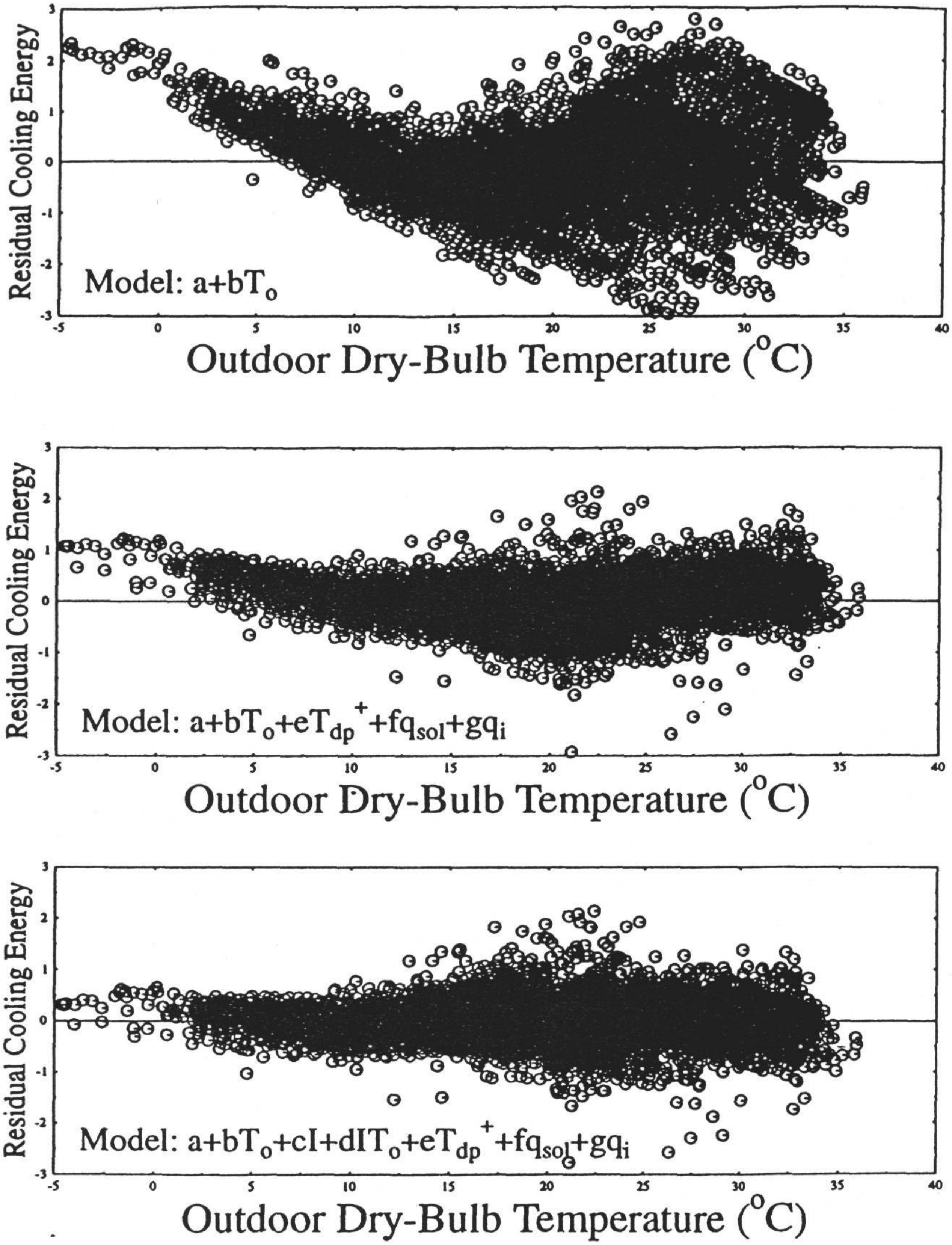


Fig.8 Comparison of residuals (i.e., measured minus model predicted) cooling energy use from three different models for the ZEC building under VAV operation.

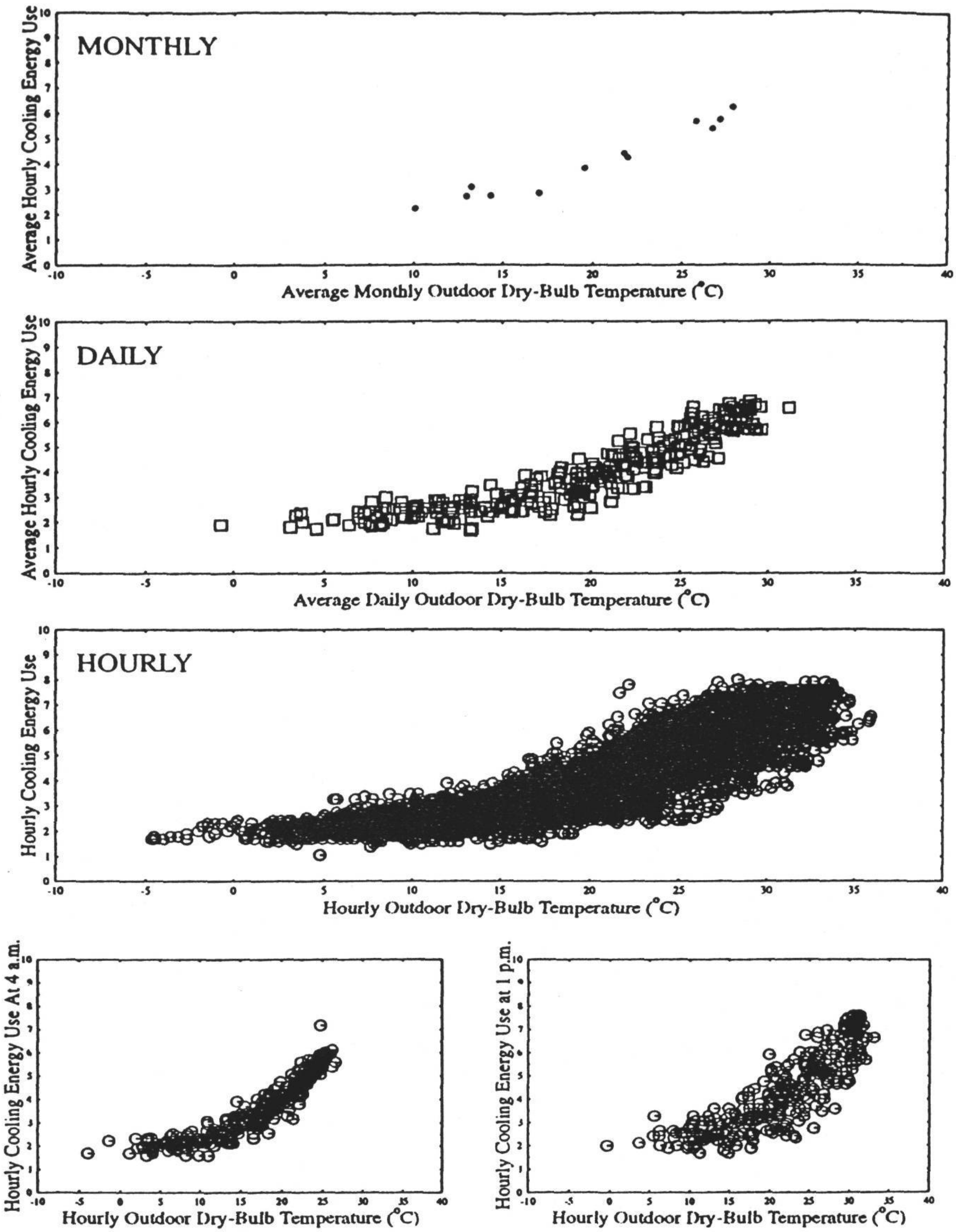


Fig.9 Cooling energy use (GJ/hr) as a function of T_0 for different time scales at the ZEC building under VAV operation.

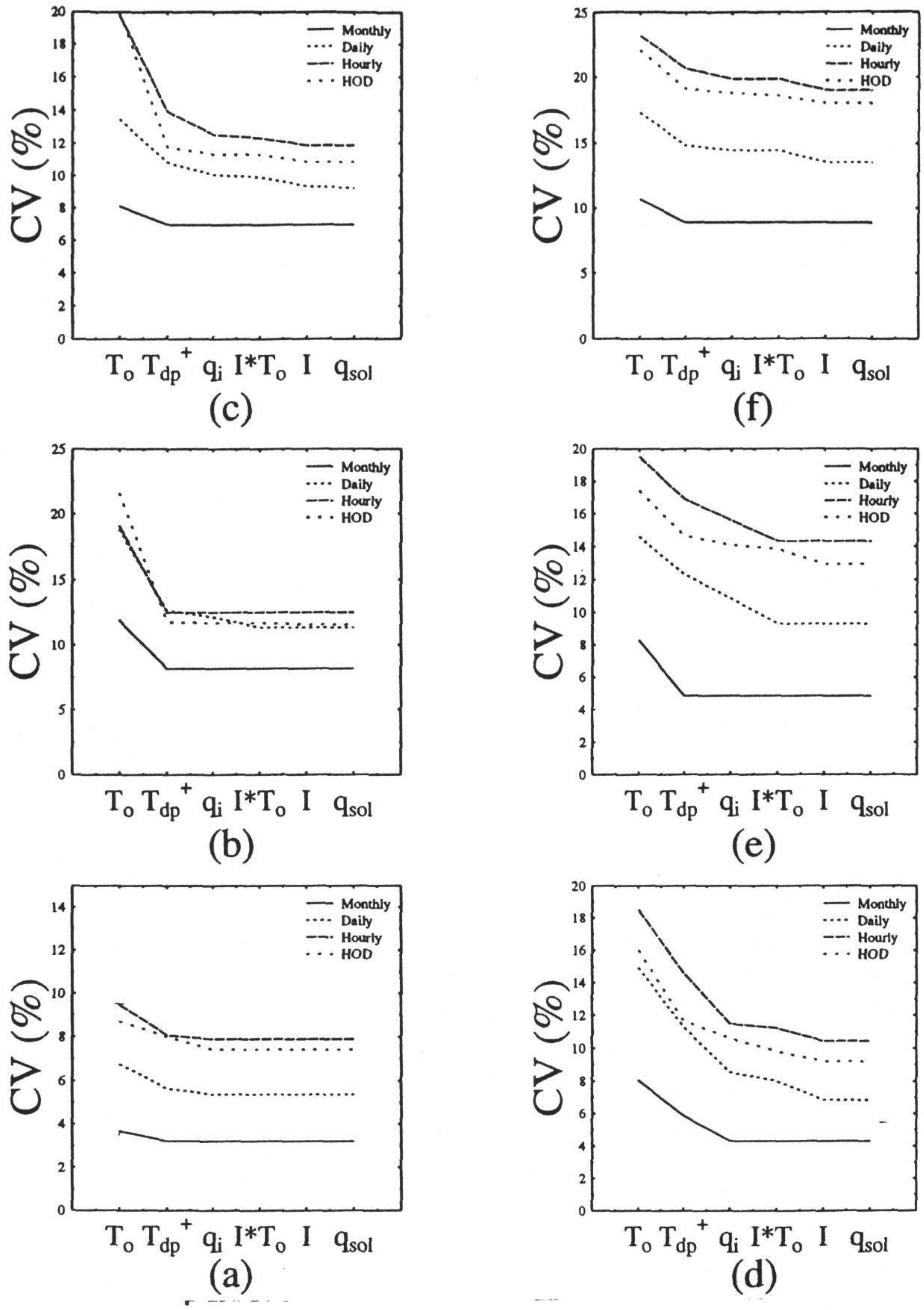


Fig.10 Change in CV with addition of independent variables to the models given by eq.(1). (a) ZEC building under dual-duct CAV operation, (b) WEL building under dual-duct CAV operation, (c) MSB building under VAV operation, (d) MSB building under dual-duct CAV operation, (e) BUR building under VAV operation, and (f) WIN building under VAV operation.

CV. Also noteworthy is the fact that under CAV operation, addition of variables other than T_o and T^{+}_{dp} improves the results only marginally, if at all. Under VAV operation (and other than monthly models) inclusion of additional variables improves the model considerably. The solar variable is found to be unimportant in all of the buildings studied.

Although monthly models show the lowest CV during model identification, their prediction uncertainty is high (Katipamula et al., 1994b). This conclusion was arrived at by developing different time scale models of cooling energy use at three different LoanSTAR locations (one under CAV operation and two under VAV operation) with one year of measured data, and then using these models to predict energy use into the future months during which monitored data were also available. This allowed the predictive ability of different models to be compared without ambiguity. The CV-RMSE and the mean bias error (MBE) shown in Table 2 indicate that monthly models are the poorest, with daily and hourly models being the best. That the monthly models are poor is explained by the fact that too much information is probably lost by the averaging process. The independent variables effecting energy use vary so little on a monthly basis that they do not get included in a monthly model and valuable interactions are not captured by the monthly model. However, averaging on a daily time scale has the positive effect of removing some, but not too much, of the variation in the regressor variables. Consequently daily models seem to have the lowest predictive error of all time scales. For example, the large difference between the MBE of daily and monthly models for MSB building (located in the hot and humid climate of Houston, TX) is due to the outdoor humidity effects because of the large outdoor air fraction, namely over 80%.

Inspection of Table 2 reveals that the MBE and CV-RMSE for MSB building is acceptable (about 2% for monthly, and less than 1% for the other time scales) while the MBE for the two other sites are generally high and negative (i.e., model is overpredicting energy use). This is atypical and has to do with the fact that both BUR and WIN buildings had O&M changes during the predictive period where the operating hours of air handler units were decreased during the unoccupied hours of the day.

The major conclusion in this section is that daily models are most appropriate for retrofit savings analysis where both model identification and prediction accuracy are critical issues. Another factor which supports this choice (rather than monthly time scales) is that, due to data quality issues and monitoring problems (which are bound to occur even in the most careful of programs involving continuous monitoring of several buildings), certain periods of data may have to be rejected during the analysis. This effect is likely to be more of a problem with monthly data than with daily data. The reader should, however, realize that HOD models, though not advisable for retrofit savings analysis, are most appropriate for O&M fault detection and dynamic control (with say an EMCS system) where time resolution finer than daily time scales are advantageous (Liu et al., 1994). A final issue impacting the choice of which time scale models to use, has to do with how crucial it is in the retrofit program to identifying why a particular retrofit is not performing to expectation. It is very difficult to glean out such insights from monthly data while it is often rather straight forward to do so with hourly data (Liu et al., 1994).

3.4. Uncertainty in Savings Determination

In statistics, ascertaining the uncertainty of a prediction is as important as the prediction itself. Hence determining the uncertainty in our retrofit savings estimate is imperative. Model identification has direct bearing on determining the uncertainty because the same issues equally affect the nature and magnitude of errors. The uncertainty in savings can be attributed to measurement errors (both in the independent and dependent variables) and to errors in the regression model. The former are relatively well known to engineers and the methodology of estimating their effect is adequately covered in classical engineering textbooks. Errors in regression models, on the other hand, are more complex and arise from several sources. Reddy et al. (1992) have classified these into three categories which are briefly mentioned below:

(a) Model prediction errors which arise due to the fact that a model is never "perfect". Invariably a certain amount of the observed variance in the response variable is unexplained by the model. This variance introduces an uncertainty in prediction even when the range of variation in the regressor variable is within the range over which the model was identified.

(b) Model mis-specification errors which are due to: i) inclusion or non-inclusion of certain regressor variables (neglecting humidity effects , for example); ii) assumption of a linear model, when the physical equations suggest non-linear interaction among the regressor variables; iii) incorrect order of the model, i. e., either a lower order or a higher order than the physical equations suggest.

(c) Model extrapolation errors which arise when a model is used for prediction outside the region covered by the original data from which the model has been identified.

It is difficult to handle category (c) in a purely statistical manner. Insights gained from studies involving physical or engineering models (Kissock, 1993; Reddy et al., 1994 or Katipamula et al., 1994 a&b) are the only way that such effects can be reduced. The net result of categories (a) and (b) is improper residual behavior. This may partially or even entirely invalidate some of the major assumptions made during least-squares regression (Draper and Smith, 1981), namely that the residuals have: (i) zero mean; (ii) constant variances, i.e., heteroscedasticity is not present; (iii) are uncorrelated, i.e., no serial correlation or autocorrelation is present; and, (iv) a near-normal distribution.

The method of least squares can be used to estimate the parameters in a linear regression model regardless of the form of the distribution of errors (Draper and Smith, 1981), and so the last assumption (iv) is not relevant in our current savings calculation methodology. Assumption (i) is also not a serious criteria because it is satisfied in most cases. The normal manner to deal with heteroscedasticity is to perform a weighted regression with the observations inversely weighted with their variance (Draper and Smith, 1981). Data from the LoanSTAR buildings do not seem to generally exhibit strong heteroscedasticity (Ruch and Claridge, 1992), and consequently this issue may also be overlooked.

The issue of autocorrelation which manifests itself by patterned residuals is, however, serious. Most of the SV models developed at the daily time scale seem to suffer from autocorrelated residual behavior, probably because of neglecting all variables other than T_o as well as due to seasonal changes in the operation of the HVAC system and the building. Though model redesign can alleviate this to a certain extent (Ruch et al., 1993b; Kaipamula et al., 1994a), we have found that autocorrelation effects still remain strong in most SV regression models. This is illustrated in Fig. 11 where the residuals of the SV cooling model in ZEC, a large institutional building, have an autocorrelation strength of 0.76. The practical implication of neglecting serial correlations in the data is that equations presented in elementary statistical textbooks for model prediction uncertainty (say, Draper and Smith, 1981) will <u>underestimate</u> the true model uncertainty. We would then be placing more confidence in our savings estimates than is strictly warranted, and hence the need to treat this issue properly.

A study by Ruch et al.(1993b) has addressed this issue and suggested a hybrid model approach consisting of a combination of ordinary least squares (OLS) model and an autoregressive (AR) model, which though akin to OLS in predictive ability has more realistic error diagnostics than OLS. The statistical theory of the hybrid model approach is developed from fundamental statistical concepts and though involving a certain amount of mathematical sophistication in terms of matrix algebra, can be "conveniently" programmed in a PC-based computer routine (like EModel, Kissock et al., 1993b).

The first step in the hybrid model approach, as depicted in the flow chart of Fig. 12, is to perform an OLS fit to the data. An analysis of the residuals is next undertaken to check for autocorrelation, a widely used index being the Durbin-Watson statistic (Draper and Smith,1981). If the test indicates that the residuals are uncorrelated, the OLS model can be used for both prediction and error diagnostics. If autocorrelation exists, every effort is made to redesign the model (by looking for time-dependent

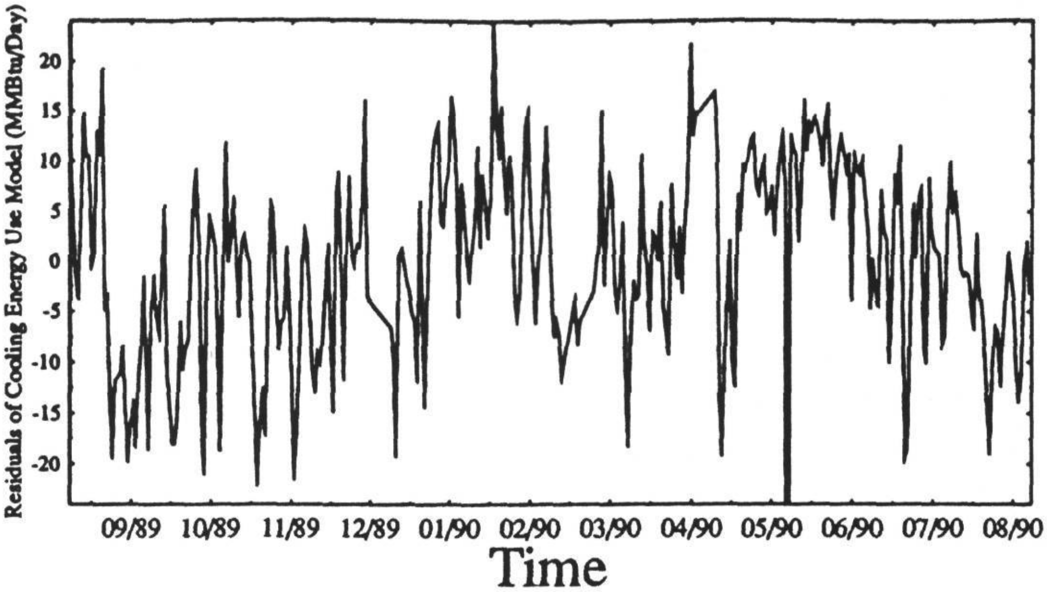


Fig.11 Figure illustrating the strong patterned residuals in the cooling model for ZEC (autocorrelation of 0.76). Most of the daily SV regression models suffer from this phenomenon.

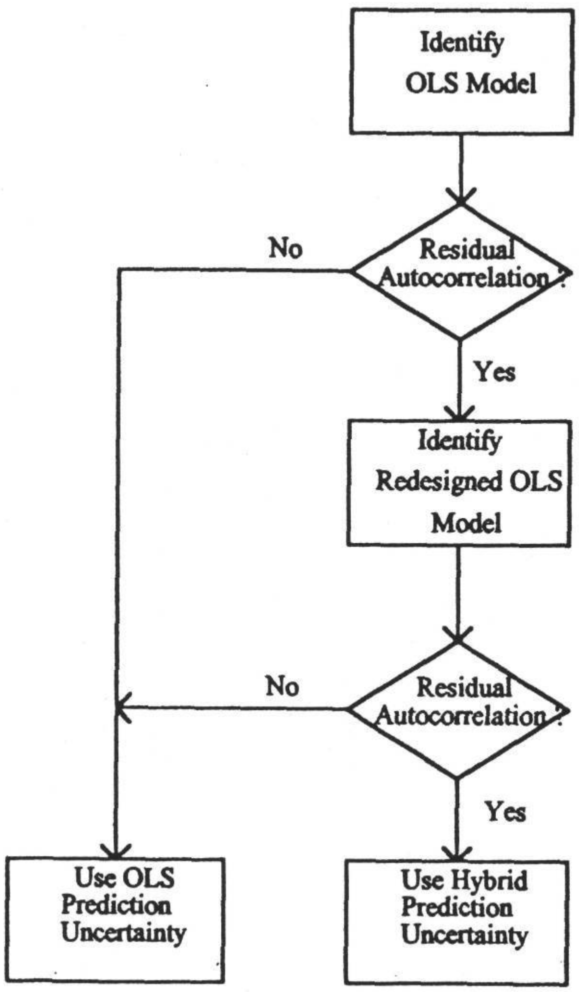


Fig.12 Flow chart summarizing regression model fitting procedure and uncertainty determination..

operational changes or omitted variables, for example). If model redesign does not remove the autocorrelation effects, an AR model is fit to the data set. If the R^2 of this model is close to that of the OLS model, the AR model can be used as the predictor model. However, this has never been the case in any of the LoanSTAR buildings and so this step is not shown explicitly in the flowchart of Fig. 12. Finally, the OLS model is used to predict daily energy use under post-retrofit climatic conditions while the uncertainty of the predictions is determined by the error diagnostics provided by the AR model.

Comparisons between OLS and hybrid error diagnostics have also been performed with measured data from three buildings (Ruch et al., 1993b). Data sets of cooling and heating energy use at ZEC from the Texas A&M University campus, cooling energy use at a library (PCL) and heating energy use at a classroom building, both at the University of Texas at Austin, were examined. In each case, energy use appeared to be a nearly linear function of T_o, and no additional independent variable data were available. For each building, the data were split into two parts: hypothetical "pre" and "post" periods with energy use modeling done on the "pre" data and the models tested on the "post" data. The "pre" data were selected so that the range of daily T_o was as representative as possible of the annual temperature variation for the region. The specific dates for all four channels are given in Table 3. Both OLS and hybrid models were fit to each building's "pre" period data set. The models were then used to predict the cumulative energy use for the "post" period, and the prediction error bounds were calculated at the 95% and 99% confidence levels. The results are listed in Table 3. In each case, the hybrid model provided far more accurate error estimates of the model prediction than did ordinary OLS. The OLS model consistently underestimates the actual prediction error, while those of the hybrid model are more realistic.

3.5. Effect of Short Pre-retrofit Data sets

Although there are no absolute rules for determining the minimum acceptable length of the pre-retrofit period for the regression model to accurately predict long-term system performance, intuitively one would use at least a full year of energy consumption. The data are then likely to encompass the entire range of variation of both climatic conditions and in the different operating modes of the building and of the HVAC system. However, in many cases a full year of data are not available and one is constrained to develop models using less than a full year of data. The accuracy with which temperature-dependent regression models of energy use identified from short data sets (i.e., data sets of less than one year) are able to predict annual energy use has been investigated (Kissock et al., 1993a). Certain general characteristics of how, when and to what extent temperature-dependent models based on short data-sets incorrectly predict annual energy use have been identified.

Table 3. Uncertainty estimates of OLS and hybrid models compared to actual data. The percentages are relative to the actual energy use. For a correct estimate of uncertainty, the actual prediction error should be less than the prediction error bound at the given confidence level. ρ is the autocorrelation coefficient.

Building & Energy Type	Model Type	Dates of "Pre" Data	Dates of "Post" Data	ρ	Predicted Energy Use (GJ)	Actual Energy Use (GJ)	Actual Prediction Error	95% Prediction Error Bound (%)	99% Prediction Error Bound (%)
Library Cooling	OLS	1/15/90 - 6/30/90	7/1/90-11/27/90	.78	8419	7779	8	3	4
	Hybrid	6/1/90 - 10/31/90	11/1/90-11/27/90					8	11
Eng. Ctr. Heating	OLS	8/7/91-1/31/92	2/1/92-4/30/92	.96	1268	1569	19	7	9
	Hybrid							33	44
Eng.Ctr. Cooling	OLS			.73	3244	3435	6	4	5
	Hybrid							9	12
Class Rm. Heating	OLS	12/5/90-4/30/91	11/11/91-3/16/92	.94	2194	2609	16	3	4
	Hybrid							17	22

Monitored daily data of cooling and heating energy use from three LoanSTAR buildings with CAV systems have been selected. The energy use appear to be linearly related with $T_{o,}$ thus making the use of change-point models unnecessary. The first step was to construct temperature-dependent linear regression models of daily energy use from one, three, and five month sliding data-sets. Then the annual energy use predicted by these models was compared to the annual energy use predicted by a model based on an entire year of data. A Normalized Annual Energy Use (NAEU) index was defined as the ratio of annual energy use predicted by a model based on a short data-set to that predicted by the full year model. Time plots of the NAEU for the different buildings and for different time periods are shown in Fig. 13. It shows that annual heating energy use can be up to 400% greater than the annual energy use predicted by models from short data sets. In addition, in the climate of Central Texas, models of heating energy use typically have prediction errors 4-5 times greater than those of cooling energy models.

Two characteristics of data-sets were identified which influence their ability to predict annual energy use.

(a) As expected, longer data sets provide a better estimate of annual energy use than shorter data sets. In the sample of buildings chosen, the average cooling prediction error of short data sets decreased from 7.3% to 3.0% and the average annual heating prediction error decreased from 27.5% to 12.9% as the length of data sets increased from one month to five months.

(b) More important than the length of the data set, however, was the season during which it occurred. Cooling models identified from months with above-average temperatures tend to over-predict annual energy and vice-versa. The converse seems to hold for heating models. As is illustrated in Fig. 14., the NAEUs are strongly influenced by T_o. The best predictors of both cooling and heating annual energy use are models from data-sets with mean temperatures close to the annual mean temperature. The range of variation of daily temperature values in the data set seems to be of secondary importance. One month data sets in spring and fall, when the above condition applies, are frequently better predictors of annual energy than five month data sets from winter and summer.

The physical basis of the above observations and how models identified from short data-sets could be "corrected" to yield more accurate estimates of the annual energy use, are issues currently being investigated. Our current recommendation (from our analysis of energy use data for commercial buildings in Texas) is that regression models are accurate predictors of annual energy use when developed from data of six months or more. However, even three months of data would be adequate <u>provided</u> the mean T_o value during the period is close to the annual mean value. These recommendations are the basis of the retrofit savings decision tree shown in Fig. 2.

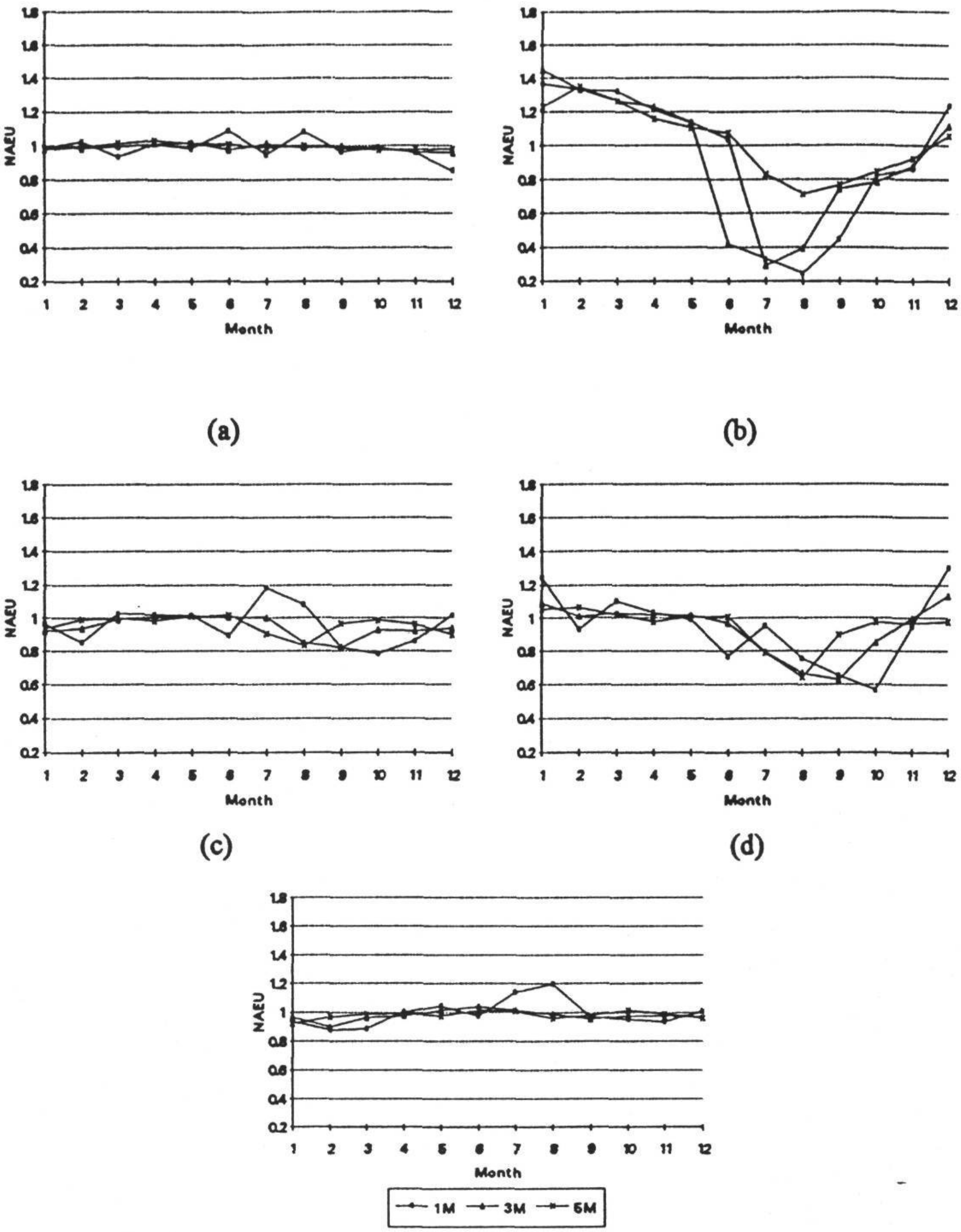
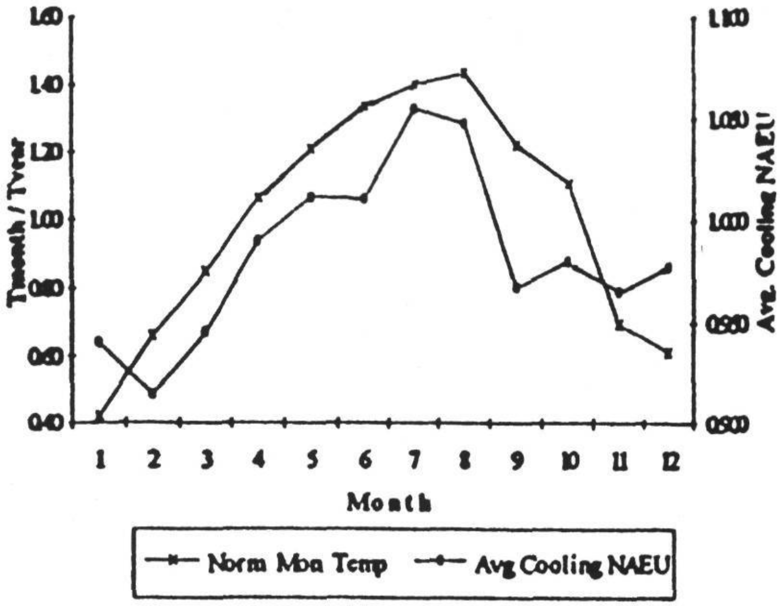


Fig. 13 Normalized annual energy use (NAEU) for one, three and five month sliding windows in different buildings, (a) ZEC cooling energy use, (b) ZEC heating energy use, (c) MSB cooling energy use, (d) MSB heating energy use, and (e) JER chiller electricity use.



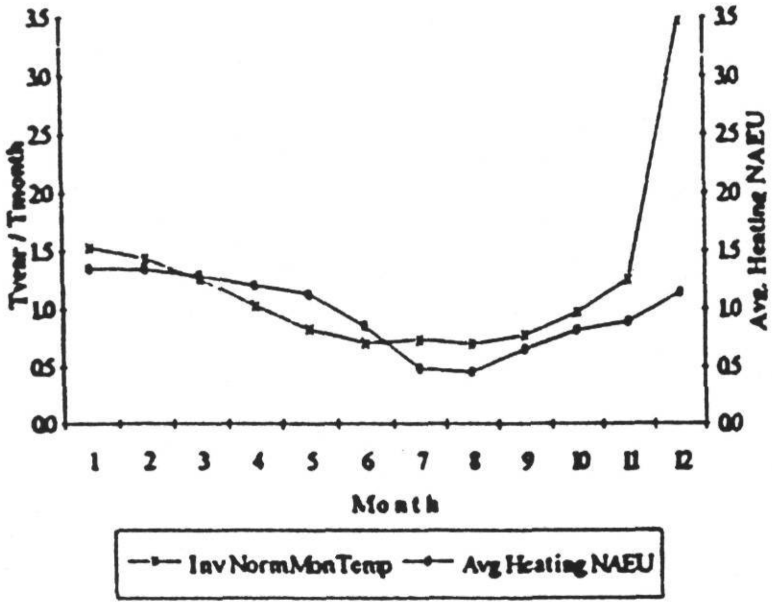


Fig.14 Plots showing how cooling and heating energy use vary with T_o.

(a) Normalized monthly temperatures and average cooling NAEUs for JER building.

(b) Inverse of the normalized monthly temperatures and average heating NAEUs for the ZEC building.

3.6 Case studies

In this section, we shall present results of applying the regression modeling approach to nine LoanSTAR sites (Kissock, 1993) using an integrated, user-friendly PC-based software program, called EModel (Kissock et al., 1993b) which is especially suited for exploration and modeling of energy data. Information about the building size, use and type of retrofit is given in Table 4. In every case, except at GAR and WCH buildings, the pre-retrofit baseline period is either greater than one year in length or spans the spring months when average T_o are close to the annual value. Thus, for these buildings we anticipate little error in the baseline models due to short data sets. For GAR and WCH, however, we would expect the baseline model for cooling energy use to underestimate annual cooling energy use (resulting in lesser savings than expected) and vice versa for heating models.

Figure 15(a) depicts time plots of AHU daily electricity use in the ZEC building as the HVAC system is retrofit from CAV to VAV operation. Scatter plots of daily cooling and heating energy use with T_o are also shown as well as the SV regression models identified for both pre- and post-retrofit periods. Though the post-retrofit models are not directly used for savings determination in the LoanSTAR program, these have been shown here in order to impart a better visual assessment of the extent of savings. The post-retrofit models have been found to be useful to fill in gaps in our post-retrofit data as a result of monitoring problems. Also they are necessary if NAC values are to be estimated (Fels, 1986; Ruch and Claridge, 1993). Figure 16 depicts the same type of information as Fig. 15 did for the remaining eight buildings in order to illustrate how energy use models vary across sites. Summary statistics from the pre-retrofit SV daily models are listed in Table 5. The CV-RMSE values listed in the table are weighted averages which account for the number of weekdays and weekends in the pre-retrofit period. We note, that on an average the CV-RMSE for mean (i.e., weather independent energy use), for cooling and for heating models are 3.3%, 11.4% and 14.1% respectively. The fallacy of merely deciding on the "best" model based on the R^2 value is also clearly demonstrated by cooling energy use at the EDB building where the CV-RMSE is only 8.9% despite a very low R^2 of 0.39. The savings are summarized in Table 6. The mean percent reductions in energy costs are 38.8%, the majority of which result from reducing cooling energy use.

In order to give the reader an indication of the amount of uncertainty prevalent in our retrofit savings determination, let us consider the ZEC building (Fig. 15).

(a) <u>Cooling energy</u>. During the 389 days of post-retrofit data, the cooling energy savings are 17,130 GJ. The autocorrelation coefficient of the residuals is 0.60 and the residuals fail the Durbin-Watson test indicating the need for the hybrid model to determine uncertainty. Using the procedure outlined in Ruch

Table 4. Description of case-study buildings.

Building Name (Abbreviation)	Use	Conditioned Floor Area (m^2)	Primary Retrofit	Pre-Retrofit Period
Zachry (ZEC)	offices, labs, classrooms	23,000	CAV to VAV	11/1/89 - 11/27/90
Education (EDB)	offices, classrooms	23,300	CAV to VAV	10/24/90 - 4/29/91
Garrison (GAR)	offices, classrooms, auditorium	5,000	CAV to VAV	10/21/90 - 2/28/91
Waggener (WAG)	offices, labs, classrooms	5,400	CAV to VAV	10/16/90 - 5/22/91
Burdine (BUR)	offices, labs, classrooms	9,600	CAV to VAV	10/16/90 - 5/14/91
Winship (WIN)	offices, theater classrooms	10,100	CAV to VAV	10/16/90 - 7/1/91
Painter (PAI)	offices, labs, classrooms	11,900	CAV to VAV	10/16/90 - 5/31/91
Hogg (WCH)	offices, classrooms, auditorium	4,500	CAV to VAV	10/16/90 - 1/31/91
Texas Dept. Health (TDH)	offices, labs, computers	22,800	Added EMCS	7/15/91 - 8/15/92

Table 5. Summary of SV daily model statistics for case study buildings. Weighted averages of weekday and weekend statistics are presented. The last row shows the mean and standard deviation of each column.

	Electricity		Cooling			Heating		
	Model Type	CV-SD (%)	Model Type	R^2	CV-RMSE (%)	Model Type	R^2	CV-RMSE (%)
ZEC	1	1.7	2	.85	8.0	2	.88	26.1
EDB	1	5.1	3	.39	8.9	4	.88	13.1
GAR	1	3.0	4	.82	11.6	2	.90	8.2
WAG	1	2.2	4	.87	14.7	2	.73	23.3
BUR	1	3.2	3	.67	12.2	4	.95	11.9
WIN	1	3.5	4	.90	10.1	4	.86	10.0
PAI	1	2.5	4	.89	13.1	4	.76	10.0
WCH	1	4.9	4	.60	14.3	4	.42	11.9
TDH	1	3.9	2	.90	9.6	4	.92	12.7
Mean		3.3 (1.2)		.77 (.18)	11.4 (2.4)		.81 (.16)	14.1 (6.3)

Table 6. Summary of 1992 savings for case-study buildings. Electricity savings at the Education Building (EDB) include a lighting retrofit. Savings at TDH are from September through December. The last row shows the mean and standard deviation for each column.

	Electricity		Cooling Energy		Heating Energy		Total
	Average Daily Savings (W/m^2)	Percent Reduction in Energy Use	Average Daily Savings (W/m^2)	Percent Reduction in Energy Use	Average Daily Savings (W/m^2)	Percent Reduction in Energy Use	Percent Reduction in Energy Costs
ZEC	7.5	15.4	22.1	31.1	19.7	82.9	30.6
EDB	13.8	59.8	19.3	46.8	4.8	28.6	49.7
GAR	6.6	48.9	21.1	56.6	8.4	74.0	56.3
WAG	4.4	16.1	9.6	26.5	5.6	47.9	23.4
BUR	7.2	39.3	20.1	46.8	2.7	17.3	39.6
WIN	10.1	37.4	44.2	56.6	25.4	58.6	51.4
PAI	7.3	23.9	12.5	21.9	10.0	34.6	25.0
WCH	7.5	41.1	36.2	57.6	30.4	66.4	56.1
TDH	3.7	10.8	26.8	27.3	2.7	9.1	17.0
Mean	7.6 (3.0)	32.5 (16.8)	23.5 (10.9)	41.2 (14.5)	12.2 (10.4)	46.6 (25.8)	38.8 (15.2)

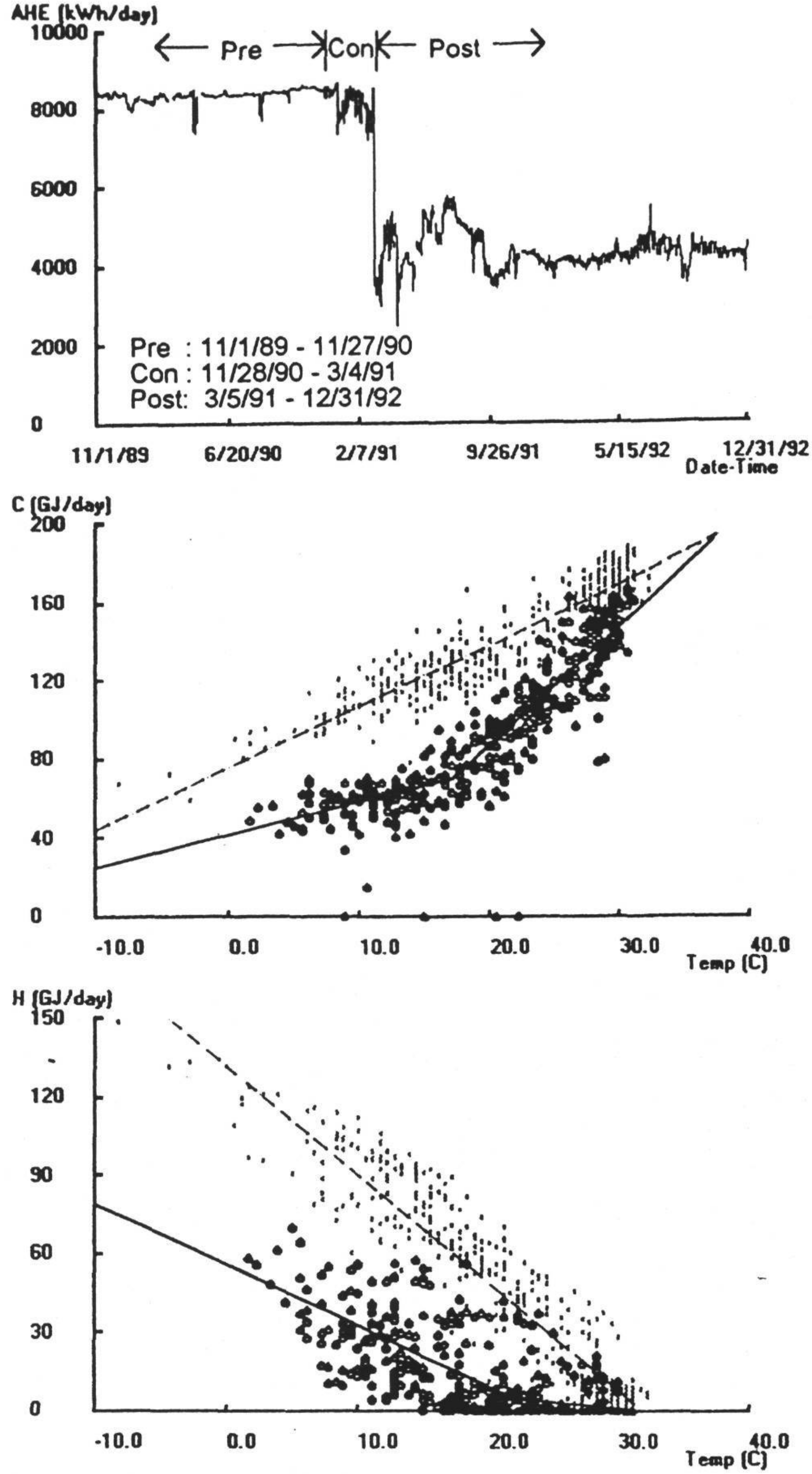


Fig. 15 (a) Time series plot of daily AHU electricity use showing pre-retrofit, construction and post-retrofit periods during a CAV to a VAV retrofit at ZEC building

(b) Scatter plot showing pre- and post-retrofit cooling energy use and fitted regression models.

(c) Scatter plot showing pre- and post-retrofit heating energy use and fitted regression models.

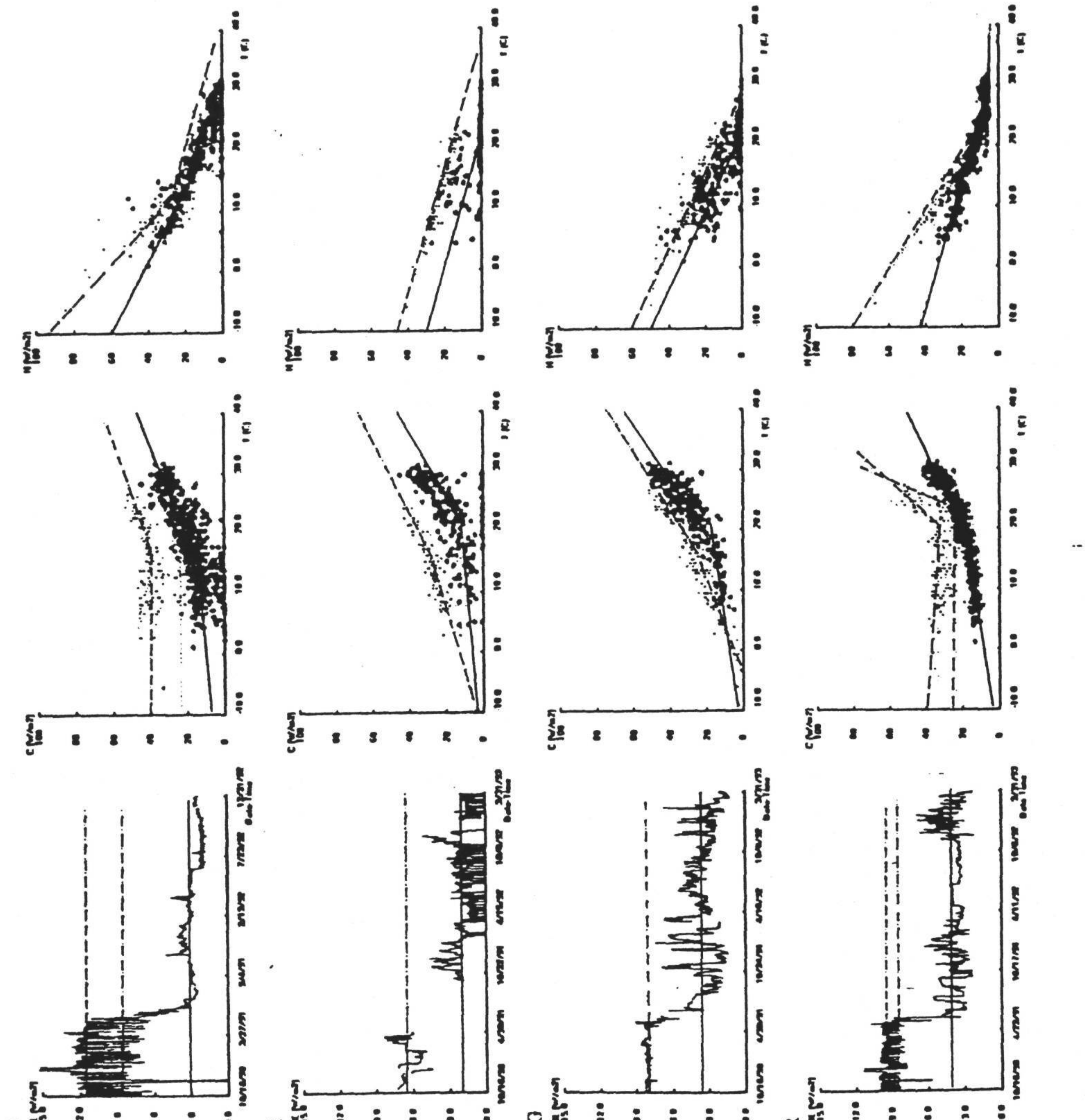


Fig.16 (a) Time series plot of daily AHU electricity use showing pre-retrofit, construction and post-retrofit periods during a CAV to a VAV retrofit at EDB, GAR, WAG, BUR, WIN, PAI, WCH and TDH buildings.

(b) Scatter plot showing pre- and post-retrofit cooling energy use and fitted regression models.

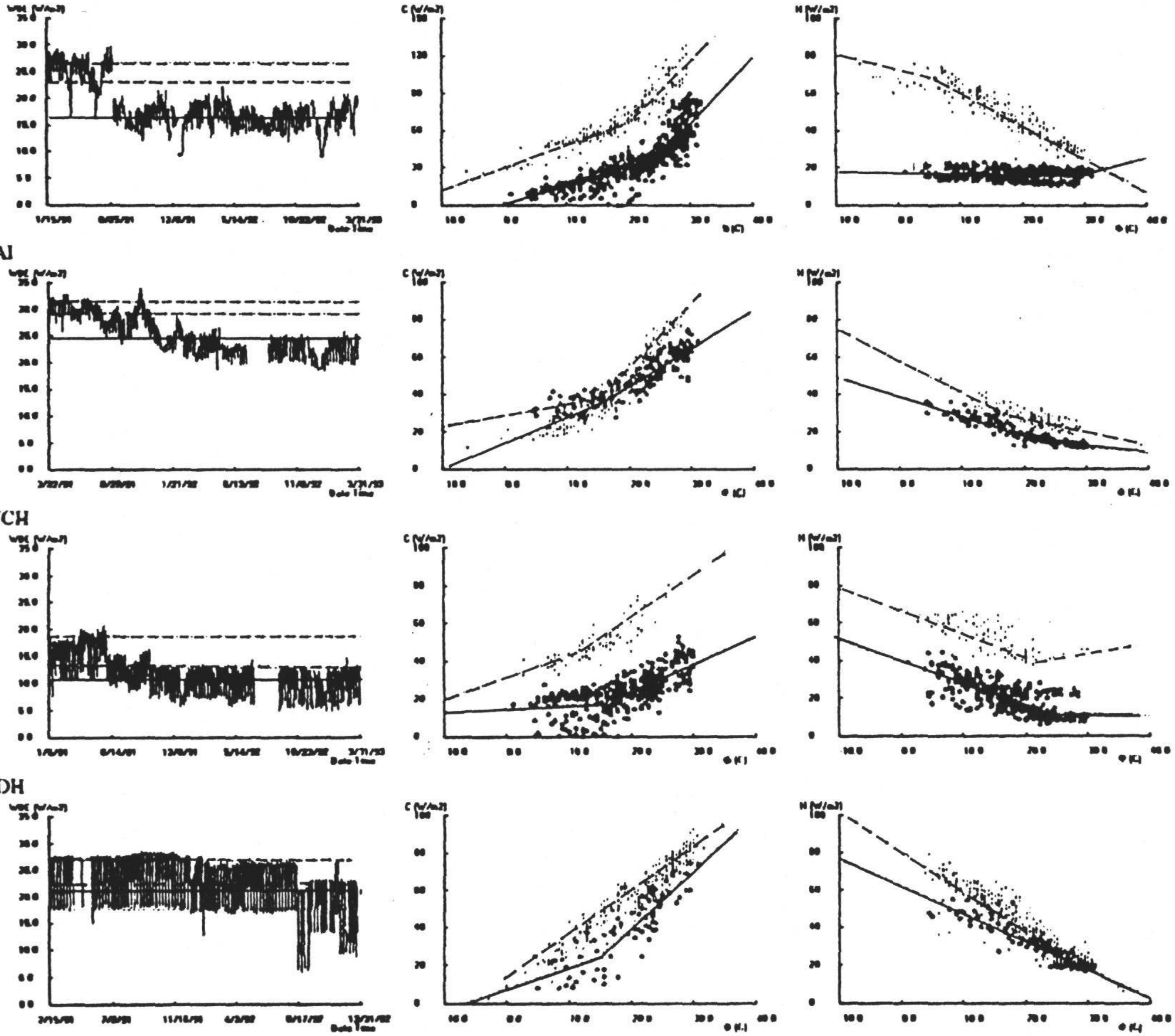
(c) Scatter plot showing pre- and post-retrofit heating energy use and fitted regression models

WIN

PAI

WCH

TDH



et al.(1993b), the baseline model uncertainty at the 95% confidence level is +-1,240 GJ. Assuming measurement error to be +-5% of post-retrofit energy use (i.e., 1835 GJ), the post-retrofit measurement uncertainty is equal to $[1240^2 + 1835^2]^{1/2}$ = +-2,214 GJ. Consequently, the average daily savings are 44.0+-5.7 GJ/day with an uncertainty of +-12.9%.

(b) Heating energy. Over the 455 days of available data in the post-retrofit period, savings were 16,928 GJ. Again, the autocorrelation coefficient is high (0.77) and uncertainty following the hybrid model needs to be calculated. At the 95% confidence level, the uncertainty in the baseline model is +-2,186 GJ. Assuming a +-5% hot water measurement error, the average daily heating energy savings are 37.2+-4.8 GJ/day with an uncertainty of +-13.0%.

4. SPECIALIZED APPROACHES

4.1 Seasonal scheduling changes

As mentioned in section 2.1, building scheduling effects are much more influential in commercial buildings than in residences and explicit consideration of their effects is taken via day-typing. For school buildings, the scheduling effects are even stronger, with distinct differences in energy use between school days and non-school days. Also, schools are unoccupied or only partially occupied during the summer (June through August), and so energy use patterns in the summer are distinctly different from those of spring and fall. Further, there are also lengthy school breaks (for example, 3 weeks at Christmas). Finally, there were certain schools and commercial buildings where a special kind of day grouping was needed. The hours of operation during a day changed on a seasonal basis. For example, in a few schools the fall season had longer operating hours than the spring. In another commercial building which had multiple chillers, certain of the chillers were shut down during non-summer periods. To properly treat seasonal variations in energy use due to different daily operating schedules, analysis of daily data alone would yield a poor model. One alternative is to develop separate models for each seasonal operating schedule which is, however, tedious. More importantly, the periods may not contain sufficient data for sound regression modeling. To overcome these difficulties, we have developed two approaches for such instances: the Fourier Series approach and the weighted daily approach.

4.2 Fourier Series Models

Seasonal changes in the daily peak demand and daily operating schedule of the building can be conveniently modeled by the Fourier series approach because such changes are handled implicitly. This approach has other benefits as well. It can yield insight into the basic frequencies under which different types of buildings operate, and hence is an useful tool for load research programs. Further, the Fourier series approach is a very convenient way of performing day-typing more rigorously than our present methods. Finally, it is a compact way of modeling hourly energy use for O&M identification and dynamic control.

Both weather independent energy use (like internal loads) and weather dependent loads (like comfort cooling and heating thermal energy use) are strongly periodic, both diurnally and annually, because of systematic scheduling effects under which buildings operate and also because of the inherent periodicity of the primary forcing functions. The annual periodicity is illustrated by time series plots in Fig.17 which shows whole building electricity (E_{wbe}) use over a year in a large university building (ZEC) in central Texas. E_{wbe}, in this case, includes internal loads and electricity to operate the air-handlers but does not include any cooling or heating energy use. Note the distinct drops during weekends, during spring, summer and fall semester breaks, and finally during the Christmas- New Year period. Also, E_{wbe} keeps increasing slowly from the beginning of a semester and drops gradually towards the end.

The Fourier series is a powerful and elegant mathematical tool for analyzing periodic data. Climatic data (i.e., solar radiation and outdoor temperature) are periodic and have been analyzed using Fourier series by several researchers (Philips, 1984; Hittle and Pederson, 1981). Trigonometric models with hour of the day as the primary variable have been proposed in the classical literature (Pandit and Wu, 1983). Attempts at Fourier series modeling of hourly energy use in commercial buildings are relatively few, the most important being perhaps that by Seem and Braun (1991) who chose a week as the maximum period of the Fourier series. The regression fit was poor, however, partly because of the choice of the maximum period. Commercial buildings undergo major operating changes from weekdays to weekends, and a week may not be the logical period to choose.

An improved Fourier series approach to modeling hourly energy use in commercial buildings has been developed by Dhar et al., (1994). It yields superior regression fits partly because of the care taken to separate days in the year during which the building is operated differently and partly because of the functional form of the regression model proposed in the study. The rationale of the study was not merely to achieve a better statistical fit to monitored hourly data. An allied objective was to determine commonalties in diurnal and seasonal schedules in different types of buildings, for example, commercial, institutional, schools, hospitals, etc. The Fourier series approach then provides direct insight into how the building is operated.

When data have both annual and diurnal periodicities, the model for weather independent energy use at day d of the year and hour h of the day could be written as:

$$E_{d,h} = \beta_0 + \sum_{k=1}^{k_{max}} \left[\alpha_k \sin\frac{2\pi k}{365} d + \beta_k \cos\frac{2\pi k}{365} d \right] + \sum_{j=1}^{j_{max}} \left[\gamma_j \sin\frac{2\pi j}{24} h + \delta_j \cos\frac{2\pi j}{24} h \right] \quad (7)$$

where the first Fourier series with subscript k represents the annual periodicity and the second Fourier series with subscript j represents the diurnal periodicity. We have also investigated the choice of daily data (i.e., using daily energy use values during regression) in order to model seasonal variation. For example, weekly-mean daily or monthly-mean daily values of monitored energy use could have given a "smoother" seasonal variation pattern which could have yielded a more accurate and "robust" regression model. Analysis with data from several buildings has revealed that using daily data is most accurate (Dhar et al., 1994).

Equation 7 provides the model structure for weather independent energy use. A suitable model for weather dependent energy use, that will incorporate the effects of both scheduling and periodicity in the weather variables has also been developed by combining the weather variables with the Fourier series (Dhar et al., 1994). Following a similar approach as that described in section 3.2.2. a general linear equation for modeling thermal cooling energy use at each individual hour h (and for each day-type) is:

$$E_h = a_h + b_h T_{o,h} + c_h W^+_{o,h} + d_h q_{sol,h} \quad (8)$$

where a_h, b_b, c_h, and d_h are the regression coefficients, and $W^+_o = (W_o - W_s)^+$ with $^+$ signifying that W^+_o should be set to zero if $W_o < W_s$ kg per kg of dry air. A typical value of W_s is 0.0092 kg/kg. Subscript h stands for a particular hour of day and can be arbitrarily assumed to be 0 at midnight, 1 at 1 a.m. and so on. When heating energy use is being modeled, the term $(c_h W_{0,h})^+$ should be omitted from the regression (i.e., set to zero).

The coefficients of the above model vary significantly from one hour to the next over the day. A model such as eq.(8), if used for all hours of the day (without distinguishing between individual hours), forces the coefficients to assume "mean" values which are oblivious to the strong diurnal schedules according to which the building is operated. As a result, less accurate fits are obtained, i.e., coefficient of variation of such hourly regression models are usually higher than models which distinguish between individual hours (Katipamula et al.,1994b). More importantly, physical insight into the building operating schedule is lost. Again, analysis of monitored data from several Texas LoanSTAR buildings has suggested that the diurnal variation of each of these coefficients is also conveniently modeled by a

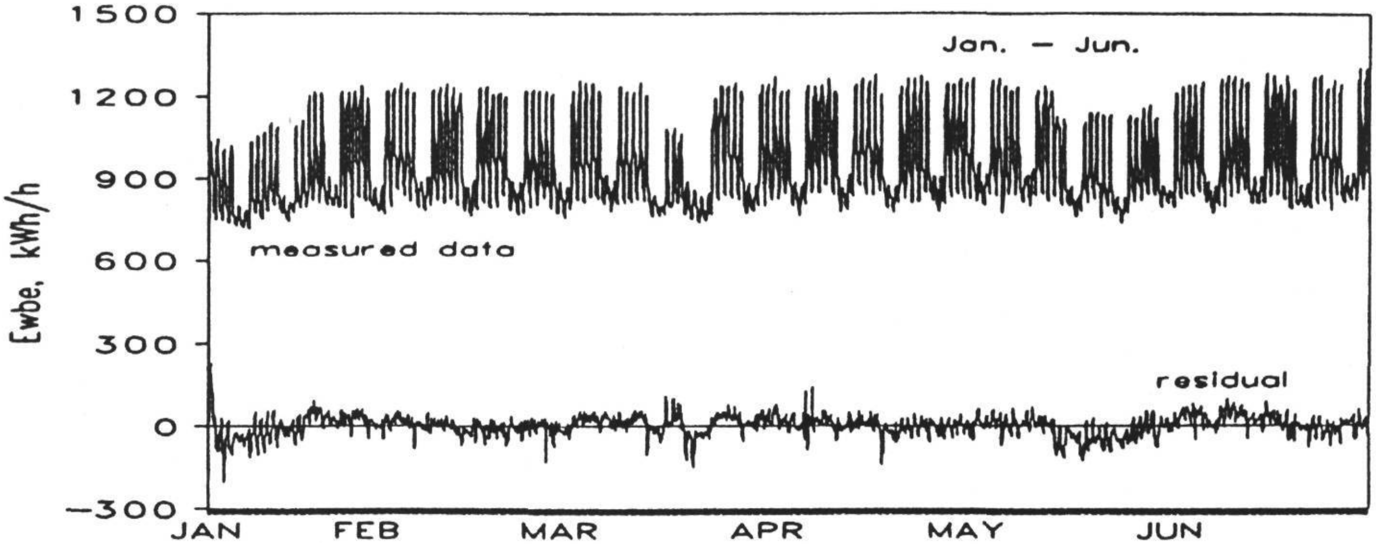


Figure 1a

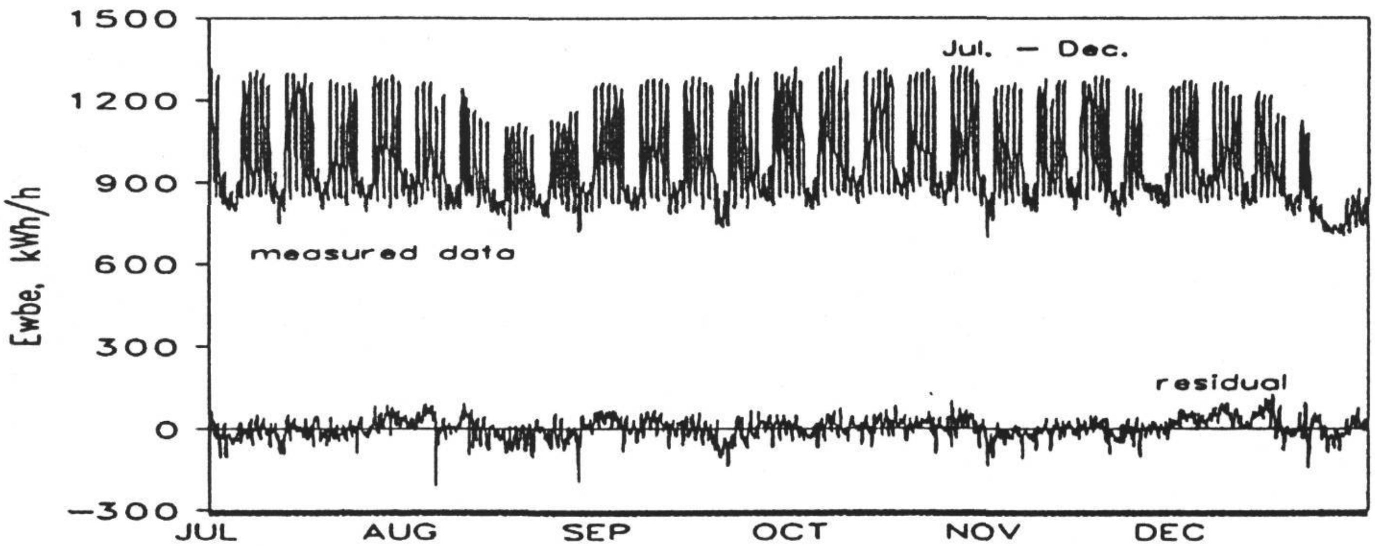


Fig.17 Time series plots of monitored whole-building electricity use in ZEC building during a year. Fourier series model residuals are also shown.

Fourier series. Consequently, the complete general model equation for weather dependent energy use takes the following functional form:

$$E_h = \beta_0 + \sum_{n=1}^{11}\left[\alpha_n \sin\frac{2\pi n}{24}h + \beta_n \cos\frac{2\pi n}{24}h\right] + T_{o,h}\sum_{n=0}^{11}\left[\gamma_n \sin\frac{2\pi n}{24}h + \delta_n \cos\frac{2\pi n}{24}h\right]$$
$$+W^{+}{}_{o,h}\sum_{n=0}^{11}\left[\phi_n \sin\frac{2\pi n}{24}h + \psi_n \cos\frac{2\pi n}{24}h\right] + q_{sol,h}\sum_{n=0}^{11}\left[\eta_n \sin\frac{2\pi n}{24}h + \varsigma_n \cos\frac{2\pi n}{24}h\right] \qquad (9)$$

with the specific humidity terms being omitted in heating energy use models.

It will be noted that no Fourier series terms are included in eq. (9) to account for annual variation. The primary reason for this is that the weather variables in the model inherently contain seasonal frequency information and their variation is able to satisfactorily capture the annual periodicity in energy use, thus yielding good model fits. Eq. (9) is the complete model, but as will be discussed below, the data will only support a regression model with fewer terms. The choice of which terms to retain is based both on statistical tests and on an arbitrary, but realistic, cut-off criteria of the partial R^2 value.

The models were applied to energy use in several LoanSTAR buildings with very good results. It was found that only 3 or 4 frequencies adequately capture most of the hourly variation of weather dependent energy use. For weather independent energy use 8 to 12 terms are needed, although use of the first 4 or 5 terms seem to capture most of the variation in the data. For example, the model fit to E_{wbe} data shown in Fig.17 resulted in a CV-RMSE value of 4.9% and R^2 of 0.90 during weekdays. The ability of the Fourier model to capture the hourly variation is clearly illustrated by the residual plot also shown in Fig.17.

4.2 Weighted daily regression

The weighted daily regression approach (Liu, 1993) is specifically applicable to buildings with seasonally varying diurnal operating patterns. It is basically a simplification of the HOD modeling approach in that only two models, one for occupied hours of the day and one for unoccupied hours, are determined instead of 24 models (one for each hour) needed by the HOD approach. Hourly monitored energy use and hourly T_o values are used to generate two sets of data weighted by the number of hours during the day that the building is occupied or unoccupied. Let E_h (with h = 1 to 24) represent the hourly energy use for hour h, and let E_{max} and E_{min} be the maximum hourly and minimum hourly energy use. A simple way of determining whether a particular hour of the day would correspond to the occupied period would be to see if $E_h > 0.5^* (E_{max} + E_{min})$. After the operational patterns are determined, the hourly data of the occupied period are averaged to get a single data point representative of the mean energy use during that period. The same process is repeated for the unoccupied period. The corresponding T_0 values are also determined in like fashion. In this manner, we are able to obtain a new set of daily mean energy use data consisting of two data points for each day which distinguish between the two different building operational modes. Two separate models are then identified and used to predict energy use under post-retrofit conditions in order to determine retrofit savings. This approach retains all the simplicity of the daily regression approach while distinguishing between seasonal changes in operating schedules.

5. CALIBRATED MODELS

5.1 Preamble

In some buildings, the pre-retrofit monitoring data were so short that a proper statistical model could not be developed. Even more drastic was the fact that in a few buildings, retrofits were completed before the monitoring instrumentation was even installed. In such cases a forward model (as against an inverse modeling approach, Rabl, 1988) which explicitly contains audit or measured data of various parameters is used in conjunction with a set of engineering models describing the various components of the system to estimate energy use. The model is then compared and "fine tuned" with monitored post-retrofit data. In the case of weather independent energy savings like lighting savings, the problem of assessing retrofit savings involves determining the wattage and number of lights that have been changed during the retrofit and estimating the operating hours. This approach is well known among DSM professionals. For chiller and boiler retrofits, the problem is a little more complex because equipment performance is non-linear with part-load operation. This issue has not been specifically addressed in the LoanSTAR program, and so we shall not discuss this here.

5.2 Simplified HVAC system models

In the case of air-side retrofits to the HVAC system, the problem of retrofit savings determination is not as straightforward as the other two cases discussed above because of the strong weather dependency of heating and cooling energy use and because of the complexity of HVAC system operation. Though a detailed computer model like DOE-2 (1981) could be used for prediction purposes (Hsieh, 1988; Bronson et al., 1992) the approach has had mixed success given the very large number of input parameters required by such models. The analyst has great difficulty in deciding which parameters to tune and by how much in order to make the simulations more realistic. The large number of calibration runs make the approach too laborious and inappropriate for routine retrofit saving analysis. The simplified calibrated model approach (Katipamula and Claridge, 1993) developed based on the ASHRAE modified bin method (Knebel, 1983) has been found to be far more appropriate for our purpose given that it is a compromise between model prediction accuracy and the number of simulation parameters to calibrate. The accuracy obtained by this approach has been found to be acceptable for savings determination (Katipamula and Claridge, 1993) as well as for HVAC fine-tuning (Liu et al., 1994). Appropriate cases for applying this approach are summarized in the decision tree shown in Fig. 2.

This method involves developing simplified HVAC system models consistent with the pre-retrofit system of the building under study. Though a typical commercial building would have a large number of separate air handler units servicing different zones of the building (a LoanSTAR building with about 30,000 m^2 of conditioned area has more than a dozen air handlers), the approach involves lumping all similar air handler units into one large unit. Figure 18 is a schematic of how the simplified systems model views the interaction between an HVAC system (a dual duct system is assumed) and the building zones. The building is divided into two zones: an exterior or perimeter zone and an interior or a core zone. The core zone is assumed to be insulated from the envelope heat losses/gains, solar heat gains and infiltration heat loss/gain, the conduction gains/losses from the roof are lumped with the external zone. Each zone is supplied with the required amount of hot and cold air such that the mixed air stream is able to meet the required zone loads. The hot and cold streams are conditioned by the cooling and heating coils whose performance is dictated by how the controls of the deck schedules are set.

Next, simplified HVAC system models of the building and of the HVAC system are written following the general approaches described in Knebel (1983), Katipamula and Claridge (1993) and Reddy et al. (1994). However, these equations are generic and the analyst will have to adapt and modify them to the particular variant and the control strategy of his specific building. Thus, one of the constraints of this approach is that the analyst must be familiar with the various HVAC component models and be able to assemble them into a system which he or she can then simulate.

Given the internal load schedule, the building description and the climatic parameters, the analyst estimates parameters such as the overall heat loss coefficient of the building shell, measure (or failing which estimate) various quantities such as air flow rate, fresh air fraction, cold deck and hot deck settings. (The need to know these parameters accurately often justifies the cost of metering at least one of the air-handlers, and a paper by Katipamula and Claridge (1992) highlights the importance of doing so.) The HVAC heating and cooling use for each hour of the day and for as many days of the year as monitored pre-retrofit data is available are next determined by system simulation. The analyst then computes CV-RMSE and mean MBE between monitored and simulated heating and cooling data separately, and if these indices are unacceptably high, some of the simulation inputs are altered and the

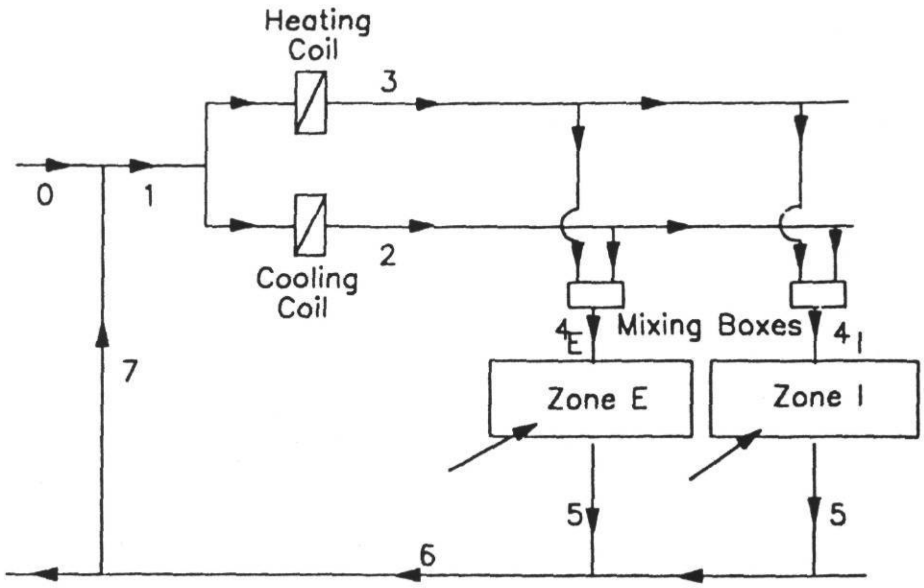


Fig. 18 Schematic of the HVAC and building zone interaction assumed in the simplified systems model approach. Zone E denotes the exterior zone of the two-zone building and zone I is the interior zone.

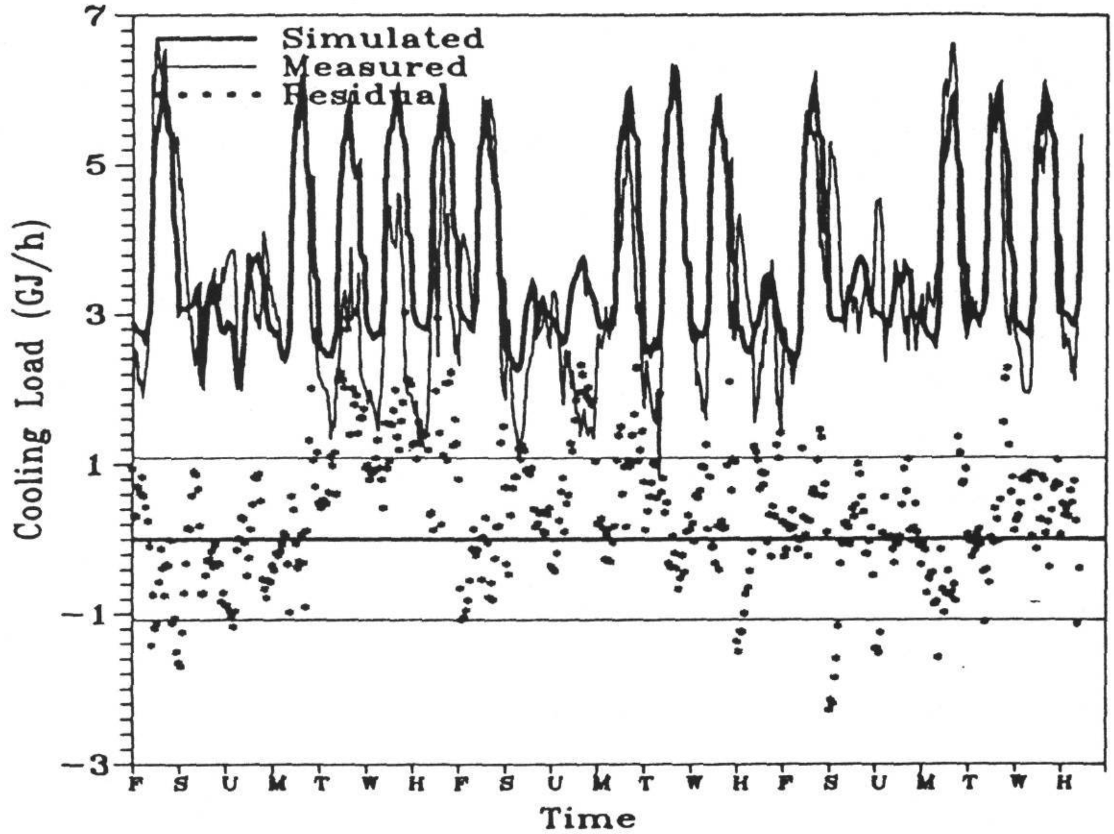


Fig. 19 Comparison of simulated and measured cooling energy use and residuals in ZEC. Characters on the time axis represent the day of the week during the period of 21 June to 11 July 1991.

simulation repeated. This process of trial and error, called calibration, is repeated until the statistical indices are acceptable. We have found that values of CV-RMSE and MBE of about 10% or lower and 1% or lower respectively to be achievable without too much effort. Figure 19, taken from Katipamula and Claridge (1993) illustrates how well the simplified systems approach predicts cooling energy use in a large commercial building during a 3 week summer period.

Another simplification reduces much of the tediousness in the calibration process. Time constants of HVAC systems are much less than an hour while those of the building shell are longer. Hence accurate prediction of the building loads, and subsequently of the system loads, would involve using hourly time scale for simulations and explicitly considering transient conduction effects. Though this was what was done in the original study by Katipamula and Claridge (1993), subsequent studies (for example, Kissock, 1993) have indicated that acceptable accuracy can still be achieved in most calibrations by (i) overlooking dynamic effects and treating all heat interactions as steady state, and (ii) adopting daily time scales instead of hourly. Though the hour by hour differences between simulated and monitored energy use may be slightly higher (i.e., CV-RMSE may be higher), the long-term prediction accuracy (i.e., the MBE) is only slightly affected.

We are currently trying to develop guidelines of which parameters to alter depending on the magnitude of the CV-RMSE and the MBE of heating and cooling energy use. This would further shorten the calibration process and lead to the development of automated routines (similar to RESEM developed by Hitchcock et al.,1991) which can perform the entire calibration task with minimal analyst time and effort. Further, there are no established formulae or procedures to estimate the prediction uncertainty of simplified system calibrated models. This is also an area of future research.

5.3 Difference between fully calibrated and partially calibrated models

Recall that the simplified systems calibration method is adopted only when a small amount of pre-retrofit monitored data (typically less than about three months) are available (see Fig. 2). The calibration process basically permits more accurate prediction of the long-term (or yearly) pre-retrofit system energy use than that provided by the regression approach, and hence retrofit savings are more accurately determined. Thus, being able to calibrate the model with measured (either utility bills or hourly monitored) data is required to qualify as <u>fully calibrated</u> models (see Fig.2).

On the other hand, the simplified systems approach can also be used when <u>no</u> pre-retrofit data are available, though one should expect more uncertainty in our retrofit saving estimates. Say a CAV system is retrofit into a VAV system but no pre-retrofit data are available. Energy use models for VAV operation are developed and calibrated with the post-retrofit monitored data. The calibrated building loads and specific parameters not affected by the retrofit can then be used with some confidence to predict energy use under pre-retrofit CAV condition. However, one is never entirely sure of how the building and the HVAC system was operated and controlled in the pre-retrofit period and so the process can at best provide limited confidence in retrofit savings. This approach, whereby data are unavailable to calibrate the pre-retrofit model, has been referred to as the partially calibrated approach (see Fig. 2).

6. SUMMARY

Measurement of savings is a crucial aspect of any energy conservation retrofit program. Accurate measurement of savings which documents the success of a program is a powerful tool for continuation and implementation of retrofits in additional buildings as well as helping to improve the selection of future retrofits. The approach used in the Texas LoanSTAR program to identify savings involves monitoring the energy consumption in both the pre-retrofit and post-retrofit periods by installing appropriate dedicated equipment. Models, either regression based or engineering system based, are then developed from the pre-retrofit data to serve as baseline energy consumption (see Fig. 2). These models are then used to predict the amount of energy the building would have consumed during the post-retrofit period had not the retrofit taken place. The difference between the baseline predicted energy use and the monitored energy consumption in the post-retrofit period is the energy saved. However, in certain buildings, due to delays in installing the monitoring equipment or due to equipment malfunction, there are cases when little or no monitored pre-retrofit data are available. In such cases, fully calibrated or partially calibrated models which make use of utility bills (if available) enhance the accuracy in determining retrofit savings. Table 7 summarizes the various types of models being used in the LoanSTAR program as of December 1993. We note that the majority are daily regression models. In a couple of buildings, hourly regression models, calibrated simplified systems models, weighted regression models calibrated with utility bills and pure utility bill models are also used. Demand savings are also being reported at a few sites largely by direct utility bill comparison, but this area has not been discussed in this report. Cumulative measured savings in the 34 sites as of December 1993, amount to $6.6 million (see Fig. 20), which is 25.4% of the pre-retrofit energy use. More specifically, savings in electricity are 37%, in chilled water energy 43% and in hot water energy 20% of the total measured savings. We also note that measured savings are higher than audit estimated savings by about 20% (which is contrary to most previous studies, as was discussed in section 1 of this report). O&M savings and constant feedback to facility personnel on the energy use behavior of their buildings may be some of the likely causes for this unexpected benefit.

	Electricity	Chilled Water	Hot Water/ Steam/Nat. Gas	Total
Pre-Retrofit Use	$14,860,000	$8,227,000	$3,271,000	$26,358,000
Post-Retrofit Use	$12,423,000	$5,405,000	$1,917,000	$19,745,000
Measured Savings	$2,437,000	$2,822,000	$1,354,000	$6,613,000
% of Pre-Retrofit Use	16.4	34.3	41.4	25.4
% of Total Measured Savings	36.9	42.7	20.5	100.0
Audit Estimated Savings	$2,548,600	$1,463,000	$1,479,000	$5,490,600

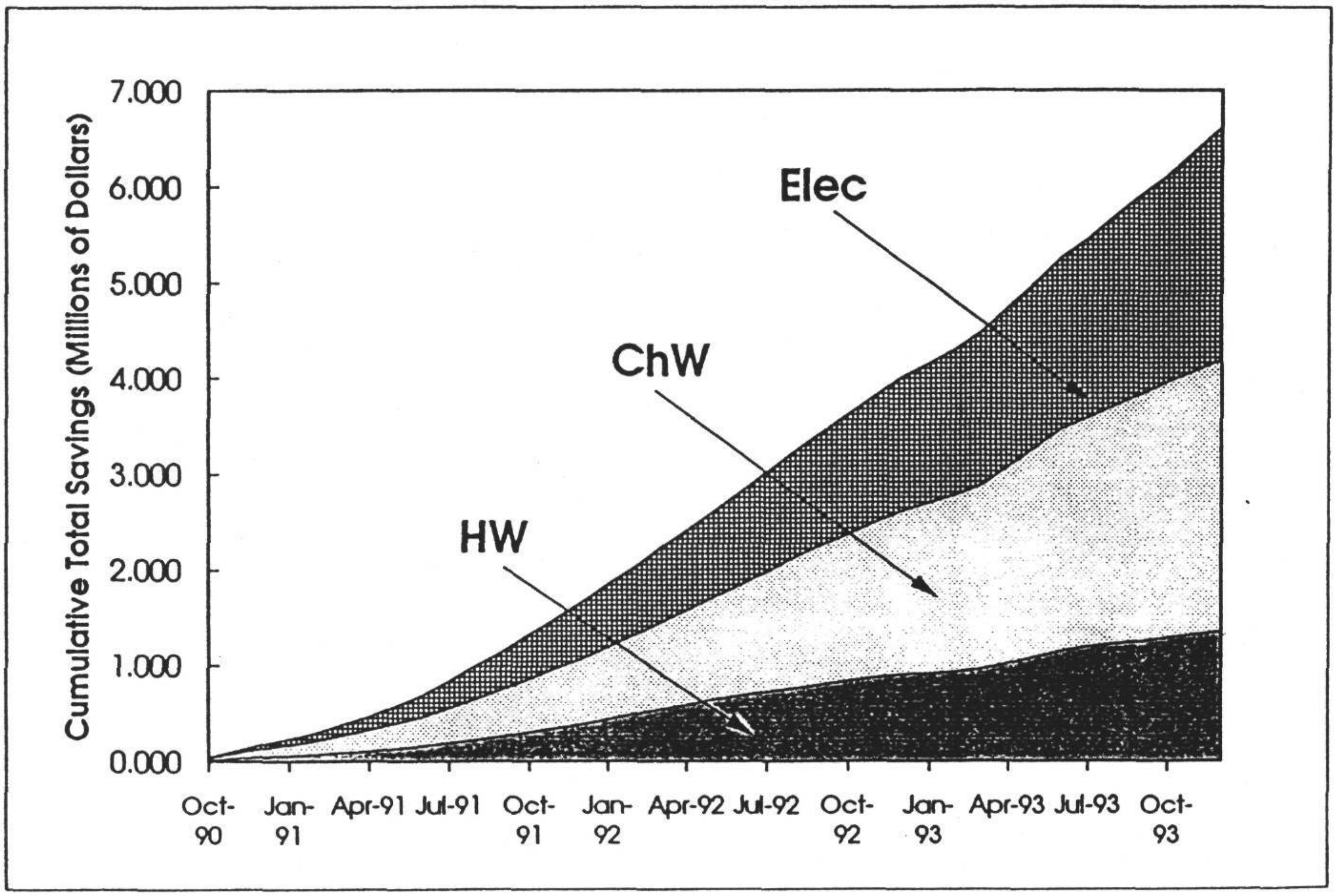


Fig. 20 Cumulative measured energy savings from, October 1990 to December 1993, of heating energy (HW), cooling energy (ChW) and electricity (Elec) in 34 sites representing 50 buildings for which retrofits have been completed.

Table 7. Types of LoanSTAR energy savings models as of December 1993.

	Regression	Simplified systems	Utility bill
Lighting electricity	5	-	2
Air-handler electricity	19	2	-
Chilled/hot water pump electricity	10	-	-
Cooling energy	16	3	-
Heating or gas energy	19	3	-
Electrical demand	-	-	7

The objective of this report was to present an overview (see Fig. 2) of the various analysis approaches developed in the framework of the LoanSTAR program in order to determine retrofit savings. This report limited itself to analysis approaches which we felt were not of limited scope and which would be of general interest to the practicing professional or the energy conservation researcher. An integrated, user-friendly PC-based software program, called EModel (Kissock et al., 1993b) has also been developed which is especially suited for exploration and modeling of energy data.

We have had, on occasion, to use conventional utility bill analysis approaches, but these are well described in the literature (see for example, Fels and Keating, 1993) and have not been addressed in this report. There have also been LoanSTAR retrofits which were so specific that we left them out of this report. For example, there were two schools where monitoring began after part of the retrofit was already completed. Specifically, a gas-fired absorption chiller was replaced by a vapor compression chiller which supplemented the cooling provided by already existing roof-top units. Monitoring began after the chiller retrofit was complete. A few months later, an EMCS system was installed. The determination of how much energy saving was due to the chiller and the EMCS separately was an interesting problem which is fully described by Liu (1993). Such specific circumstances are bound to occur in any major retrofit program and though one could try to document as comprehensively as possible all the techniques that have been attempted so that they are available to the community at large, it would be easier for each individual to develop and refine some of the variants as the need arises. What is needed is not so much the laying down of firm rules by which to determine retrofit savings, but rather enhancing the awareness of the conservation community as a whole by presenting what we have learned regarding the types of issues involved and the types of approaches, tools and insight developed in the framework of the LoanSTAR program.

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NOMENCLATURE

E	energy use
I	indicator variable
m	number of post-retrofit observation points (months, days, hours,...)
n	number of pre-retrofit observation points (months, days, hours,...)
p	number of regression parameters in the model
q_i	lighting and equipment use internal to the building
q_{sol}	global horizontal solar radiation
T_{dp}	outdoor dew point temperature
T^+_{dp}	$=(T_{dp} - T_s)^+$
T_o	outdoor dry-bulb temperature
T_s	*mean surface temperature of the cooling coil of the* HVAC system
W_o	outdoor specific humidity
$\bar{X}$	mean value of X
$\hat{X}$	model predicted value of X

Subscripts

d	daily
i	index for observation during the pre-retrofit period
j	index for observation during the post-retrofit period
save	saved
tot	total

Acronyms

AR	auto-regressive
CAV	constant air volume
CV-RMSE	coefficient of variation of the root mean square error (defined by eq.1)
CV-SD	coefficient of variation of the standard deviation (for a mean or one parameter model)
ECRM	energy conserving retrofit measures
HVAC	heating, cooling and air-conditioning
MBE	mean bias error
MV	multi-variate model
NAEU	*normalized annual energy use index*
OLS	ordinary least squares
PRISM	PRInceton Score keeping Method
R^2	coefficient of determination
SV	single variate model
VAV	variable air volume

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