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DETERMINING LONG-TERM PERFORMANCE OF COOL STORAGE SYSTEMS FROM SHORT-TERM TESTS

ASHRAE Research Project 1004

LITERATURE REVIEW AND SITE SELECTION

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ABSTRACT

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This is the preliminary report contains the literature review and site selection recommendations for ASHRAE Research Project RP 1004 -- "Determining Long-term Performance of Cool Storage Systems From Short-term Tests".

The literature review covers the relevant literature concerning: 1) different inverse analysis methods, including: building simulation models, regression models, multicollinearity and function forms, 2) methods for predicting long-term performance from short-term measurements, 3) analytical models for chillers, fans and pumps, including a discussion of component-based models versus overall systems models, 4) in-situ testing of chillers, fans and pumps, 5) methods for determining the long-term performance of cool storage systems, including field performance testing, methods for determing annual load frequency distribution, characterization of cool storage system performance, and annual performance projections, and 6) methods for determining the uncertainty associated with measurement and analysis, including: measurement uncertainty, bias and random errors, propagation errors, and regression errors. Information for 14 thermal storage sites is also presented including recommendations for a short list of 5 sites for further study.

This report completes Task 1a (Literature Review), and Task 1b (Preliminary Report), and presents our recommendations for approaching Task 2a (Method to estimate long-term building loads from short-term data), Task 2b (Development of analytical methods for TES), Task 2c (Development of initial list of TES sites and submit to PMS), Task 3c (Uncertainty analysis), and Task 3d (Development of long-term TES performance methodology).

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1.0 INTRODUCTION

This report presents the results of a literature review and preliminary investigation of methods for determining the long-term performance of cool storage systems based on short-term tests. Over 100 cool storage references were reviewed for relevance to this project. Pertinent references are briefly described below, and bibliographic citations are provided under References.

For the purpose of this report, the term "performance" refers to peak energy demand and annual energy usage. In addition, the methods to be developed are intended to determine the "degree of load shifted", which refers to the reduction in the peak energy demand and annual energy usage relative to a comparison system not using cool storage.

2.0 DETERMINE HVAC SYSTEM LOADS FROM SHORT-TERM DATA

2.1 Objective

The specific objective of ASHRAE RP-1004 is to propose and validate a short term in-situ measurement protocol along with associated model development and analysis methods which would provide accurate predictions of the long-term performance of a cool storage system in terms of demand and energy savings. Crucial to this objective is the ability to accurately determine the building loads[1]. This is not only intuitively obvious, but has also been explicitly stated in several studies (for example, Kawashima et al., 1995, 1996) where the ability to predict building loads 24 hours in advance is key to deciding on how to optimally operate the cool storage plant. In this project, the objective is not a 24 hr forecast but, rather, the ability to accurately predict the long-term (i.e., seasonal or annual) hourly cooling loads on the HVAC system from building short-term measurements. This issue is complex because of the effect of diurnal and seasonal variations (i) in the climatic variables that impact building loads (for example, the outdoor dry-bulb temperature, the outdoor humidity and the solar radiation), (ii) in the unpredictability of building internal loads, and (iii) in the manner in which the building HVAC system is operated. Therefore, the intent of this literature review is to discuss the different attempts at modeling HVAC system loads of actual buildings and to summarize the findings of the relatively few studies which have attempted to predict seasonal or long-term hourly building loads from relatively short measurement periods (which in this study are defined as periods ranging from two weeks to three months)

Another sort of distinction needs to be made in terms of model prediction. Forecasting (or prediction) is the technique used to predict future values based upon past and present values (Montgomery and Johnson, 1976). There are two types of forecasts: *expost* and *exante*. In the expost forecast, the forecast period is such that observations of both the driving variables and the response variable are known with certainty. Thus expost forecasts can be checked with existing data and provide a means of evaluating the model. An exante forecast predicts values of the response variable (i.e., building energy use) when those of the influential or regressor variables are either (i) known with certainty (conditional exante forecast), or (ii) not known with certainty

[1] Though there is a connotational difference between the two terms, building loads and HVAC loads, we shall use them interchangeably in this report to mean HVAC loads.

(unconditional exante forecast). Thus the unconditional forecast is more demanding than conditional forecasting since the driving variables need also to be predicted into the future (along with the associated uncertainty which it entails). The studies by Kawashima et al. pertain to unconditional exante forecasts. This is not the objective of this research, rather, we propose to (i) evaluate our building load prediction model approach by means of expost forecasts, and (ii) then, use the model for circumstances pertaining to conditional exante type of forecasts.

2.2 Background

At the onset, one needs to distinguish between forward models and inverse models. Forward modeling describes the traditional computer simulation programs such as DOE-2 or BLAST that calculate building loads. Forward modeling is most often employed for design purposes, such as (i) for calculating the energy performance of a prospective building based on its detailed blueprint description and how the building is likely to be operated, or (ii) for sizing the HVAC equipment to be installed in the new building. Inverse modeling identifies basic building models and model parameters from measured data of building energy use and other influential variables. Inverse modeling is most appropriate for analyzing existing performance data of building energy use either in the framework of statistical models or macro-models of the building energy flows (Rabl, 1988, ASHRAE, 1997). We shall limit the scope of this literature review to inverse models only since it is obviously the one relevant to this research.

The inverse approach to analyzing energy use in buildings is relatively new dating back perhaps 20 years. It arose primarily as a result of the drive to implement energy conservation programs in residential buildings just after the first oil shock in the early 1970s. In one of the earliest methods, data analysts having utility bill data from a residence both prior to and after the retrofit implementation, applied the variable base degree-day (VBDD) concept (ASHRAE, 1997) to normalize energy use for differences in outdoor- dry-bulb temperature prior to and after the retrofit. Analysis methods subsequently developed have increased in number and in sophistication as a result of widening objectives and different types of data availability. The amount of monitored data available for analysis has increased substantially in part due to a dramatic increase in data monitoring technology, but more importantly, due to a motivation arising from the increasing awareness that existing means of predicting energy use in a building using forward models were inadequate and sometimes misleading for the purpose of evaluating the effect of energy conservation programs or for identifying (and correcting) improperly operated buildings. For example, a study by Greely et al. (1990) of 1,700 buildings in the U.S. indicated that the estimated savings in fewer than 16% of the case study buildings came within 20% of the measured savings. Another study by Jamieson and Qualmann (1990) showed an even larger difference (165%) between the predicted and measured energy savings in 16 commercial building retrofits. A common theme in these studies, as well as others of a similar nature, is the need for better measurement methodologies and more complete data which would restore the faith in the prospective efficiency investments. The development of guidelines on measuring retrofit savings has been ongoing during the last few years, and documents are available (NEMVP, 1996; GPC-14P, 1997). These protocols are, however, not appropriate for the purpose of this research since the issue of short-term to long-term load predictions is not addressed at all.

2.3 Different inverse analysis methods

Different authors have chosen to group the various inverse models for building energy use in different ways. One of the preferred grouping is that of MacDonald and Wasserman (1989) who have suggested the following five groups:

(a) annual total energy and energy intensity comparisons (using metered or utility bills),
(b) linear regression and component models (based on monitored data)
(c) multiple linear regression models,
(d) building simulation models, and
(e) dynamic thermal performance models.

When building or HVAC system loads need to be predicted for the purpose of assessing cool thermal storage performance, the "building loads" model ought to be able to predict hourly heating and cooling HVAC system loads. Thus group (a) above which is primarily at monthly time scales is unsuitable. Also, given the complexity and size of commercial buildings, one would like to keep the in-situ monitoring protocol to a minimum. Dynamic models (group e above) would require a level of monitoring and analysis which are too complex to the current objectives (as testified, for example, by the PSTAR method suggested by Subbarao,1988 and limited to heat flows in residential building envelopes). Though attempts have been made to extend PSTAR to commercial buildings, these studies are still limited to smaller size buildings whose loads are primarily determined by the building shell interactions as against the HVAC system effects which are by far the more important determinant of building energy use in large commercial buildings. Hence such protocols are inappropriate for cool thermal storage tests. Other attempts, such as the study by Reichmuth and Robison (1990) are more at the conceptual stage rather than field-tested over several buildings. Hence only groups (b), © and (d) are appropriate for consideration in the framework of the current research study. We shall briefly discuss the concepts and the status of these three methodologies in the sections that follow.

2.3.1 Building simulation models

The building simulation approach relies on adopting a particular engineering simulation model of energy use in a building and "tuning" or adjusting the inputs of the program so that simulated and measured values of building energy use match closely. A simulation program thus calibrated, could then serve as a more reliable means of predicting the energy use of the building when operated under different climatic or different pre-specified operating conditions. One can distinguish two different types of engineering simulation models:

(i) "detailed", general purpose, fixed schematic models such as DOE-2 (Diamond and Hunn, 1981; Norford et al., 1989; Bronson et al., 1992; Bou-Saada, 1994), and BLAST (Manke and Hittle, 1996); or

(ii) the "simplified" fixed schematic HVAC systems models based on the models documented by ASHRAE TC 4.7 (Knebel, 1983) and adopted in slightly different forms by many workers, for example by Katipamula and Claridge (1993), Liu and Claridge (1995). Typically, 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, while the solar heat gains, infiltration heat loss/gain, the conduction gains/losses from the roof are taken to appear as loads on the external zone. Given the internal load schedule, the building description, the type of HVAC system and the climatic parameters, the HVAC system loads can be estimated for each hour of the day and for as many days of the year as needed by the simplified systems model. Since there are fewer parameters to vary, the calibration process is much faster.

The detailed calibrated simulation model approach, on the other hand, 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 under two circumstances: (i) when the analyst would like to model sub-aggregated electric use from monitored whole-building monitored energy use, or (ii) when the quality or length of the data period is not adequate to enable proper regression model identification. Both the detailed and the simplified calibrated model approaches have yet to reach a stage of maturity in methodology development where they can be used routinely and with confidence by people other than skilled analysts. Thus, whenever appropriate, model development using the regression approach is preferred because it is generally the least demanding in effort and user-expertise, yields adequate results and permits uncertainty calculations associated with savings to be quantified using accepted statistical procedures. This is described below.

2.3.2 Regression models

Groups (b) and © stated earlier are essentially similar, except for the number of regressor variables in the model. Both rely on the ability to formulate energy use in a building as a function of one or more driving forces which impact building energy use. An important aspect in identifying statistical models of baseline energy use is the choice of the functional form and that of the independent (or regressor) variables. Extensive studies in the past (for example, see Fels 1986; Kissock 1993; Katipamula et al. 1994) have clearly indicated that the outdoor dry-bulb temperature is the most important regressor variable, especially at monthly time scales, and even at daily time scales. Classical linear functions are usually not appropriate for describing energy use in many commercial buildings because of the presence of functional discontinuities, called "change points". These change-points exist due to the presence of control mechanisms which include, (i) thermostats in residences, (ii) HVAC operating and control schedules, and (iii) economizer cycles in commercial buildings (Reddy et al. 1995). The various types of single variable (SV) models that have been used to model energy use in commercial and residential buildings are described in numerous publications (for example, Kissock, 1993; ASHRAE, 1997; Reddy et al., 1997), and the reader is referred to these publications for additional details. However, the use of multiple linear regression (MLR) models for modeling building energy use is less known by the professional community, and so we shall provide a brief description of MLR below.

2.3.3 Multiple Linear Regression Models (MLR)

Three basic types of MLR models have been used with some success to model the hourly variation of the heating and cooling energy use in commercial buildings for the purpose of long-term prediction[2] (Reddy et al., 1994):

(a) Standard multiple linear or change point regression models where the set of data observations are treated without retaining the time series nature of the data,

(b) Fourier series models which retain the time series nature of the building energy use data and capture the diurnal and seasonal cycles according to which buildings are operated (for example, Seem and Braun, 1991; Dhar et al., 1994), and

(c) ANN or Artificial Neural Network models (for example, Kreider and Wang, 1991; Cohen and Krarti, 1997) where automated algorithms are used to model the time series trend in a non-linear manner.

How the standard MLR and the ANN fare with respect to the others can be gauged from the ASHRAE Energy Predictor II (Haberl and Thamilseran, 1996) where these and other approaches were used to model the same data set of monitored building energy use and then used to predict energy use into a future time period. Monitored building load data being available during the future time period allowed the various modeling approaches to be evaluated against each other in an absolute manner. Given that Fourier series models and ANN models do not have standard software suitable for building energy professionals they are, therefore, limited in their present applicability. Furthermore, since the standard MLR model approach was only marginally less accurate than the ANN models, we have chosen to use this approach in the framework of the present research. We shall discuss the standard MLR models below.

2.3.4 Standard MLR

The goal of modeling energy use by the MLR approach 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 changes in building equipment or building operation intended by the energy retrofit. Environmental variables which meet the above criteria for modeling heating and cooling energy use include outdoor air dry-bulb temperature (To) , 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 electricity used by internal lights and equipment q_i is a good surrogate of the total internal sensible loads (Deng, 1997). For example, when the building is fully occupied, it is also likely to be experiencing high internal electric loads, and vice versa.

[2] Note that the building prediction models in the framework of this study cannot be of the transfer function or the ARIMA type of models (Montgomery and Johnson, 1976). Such models are appropriate only when the forecasts can be updated as the prediction interval slides forward in time.

The use of a single variable (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 degree days. This is a good approximation in case of heating energy use in 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). MLR 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.

2.3.5 Multicollinearity

Although, physically, energy use is dependent on several variables, 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 becomes 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.,1993). Several authors 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., 1993). However, for building energy use, this conclusion is unproved. Stated in simple terms, the significant collinearity between the predictor variables themselves is likely to lead to two different problems:

(a) though the PCA model may provide a good fit to the current data, its usefulness as a reliable predictor of future consumption is suspect; and

(b) the regression coefficients in the PCA model may no longer be proper indicators of the relative physical importance of the regressor parameters.

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 associated with multicollinearity (Draper and Smith, 1981 is one of the few text-books which cautions against indiscriminate use of PCA). The results of the study suggest that multicollinearity may not be as big a problem as originally thought to overcome problem (a) stated above, primarily because multivariate regression models for most buildings with clean data (such as the Texas LoanSTAR program (Claridge et al., 1991, for example) have high values of R^2 (typically higher than 0.8). However, problem (b) stated above still needs to be overcome (as illustrated by the study by Deng, 1997) and so our proposed analysis methodology should explicitly circumvent this limitation.

2.3.6 Functional form

Engineering equations describing the performance of HVAC components and systems are well known (see for example, Knebel, 1983). Studies by Kissock (1993), Reddy et al., (1994) and Katipamula et al., (1994) 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. 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 CV or VAV, for example). Some of these parameters are difficult to estimate or measure in an actual building and hence, they are not good candidates for regressor variables. Further, some of the variables vary but little during the short in-situ monitoring period (or even during a season) and though their effect on energy use may be important, MLR would suggest that they not be retained 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). Since none of the quadratic and cross-product terms of the engineering equations are usually picked up by the MLR 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. Consequently, the use of $(T_{dp} - T_s)^+$ as a regressor in the model is a simplification which seems to yield good accuracy (Katipamula et al., 1994).

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

$$E = \beta_0 + \beta_1 (T_o - \beta_3)^- + \beta_2 (T_o - \beta_3)^+ + \beta_4 (T_{dp} - \beta_6)^- + \beta_5 (T_{dp} - \beta_6)^+ + \beta_7 q_{sol} + \beta_8 q_i \qquad (2.1)$$

Because of the above discussion $\beta_4 = 0$. Introducing indicator variable terminology (Draper and Smith, 1981), the above equation becomes identical to Katipamula et al., (1994) :

$$E = a + b\,T_o + c\,I + d\,I\,T_o + e\,T_{dp}^{+} + f\,q_{sol} + g\,q_i \qquad (2.2a)$$

where the indicator variable (I) is introduced to handle the change in slope of the energy use due to T_o. The variable 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. How the above model is able to remove the effects of patterned residuals (an indication of improper model structure as discussed in most statistical textbooks, for example, Draper and Smith, 1981) is illustrated by Fig. 2.0a with daily monitored cooling data from a Texas LoanSTAR building under VAV operation (Katipamula et al., 1994). The simple 2-P SV model is clearly inadequate, while the model given by eqs. (2.2a, 2.2b) seems to result in a more or less random residual pattern indicating a satisfactory model.

Another finding from the Katipamula et al. study was that though the model given by eq.(2.2a) was appropriate for VAV operation, a simpler model as given below is adequate when the building is operated under CV operation:

$$E = a + b\,T_o + e\,T_{dp}^{+} + f\,q_{sol} + g\,q_i \qquad (2.2b)$$

Note that instead of using $(T_{dp}-T_s)^+$ one could equally use the absolute humidity potential $(w_0 - w_s)^+$ where w_0 is the outdoor absolute humidity and w_s is typically about 0.009 kg/kg. 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 regressor variable set when regressing heating energy use.

Most of the MLR analysis performed as part of the Texas LoanSTAR buildings which are buildings with conservative amounts of glazing, have found the solar term to be statistically insignificant. This is due to the strong correlation between solar radiation and outdoor temperature which results in the latter variable picking up some or all of the contribution of the latter. Thus, we could further simplify the model by dropping the solar term and assuming the solar contribution to be implicitly present in the outdoor temperature contribution (this is also the basis of the ASHRAE modified bin method- see Knebel, 1983).

The MLR model suggested by Katipamula et al. (1994) has been found to be very accurate for daily time scales, and slightly less so for hourly time scales. This is because changes in the way the building is operated during the daytime and the nighttime for example, lead to different relative effects of the various regressors on energy use, which cannot be accurately modeled by one single model. Breaking up the energy use data in hourly bins corresponding to each hour of the day and then identifying 24 individual hourly models lead to appreciably greater accuracy (Katipamula et al., 1994). Unfortunately, this is probably too tedious for the current project, and a method which seems to yield comparable accuracy, is to divide the day into as many periods as there are operating modes. For example, dividing the day into two periods, one corresponding to occupied periods and one to unoccupied periods seems to be an acceptable compromise for buildings operated in more or less two operating modes. Usually not more than two or three such modes are necessary for modeling hourly building energy use. Obviously, it is advisable to determine the number of operating models of a building from monitored data, rather than from hypothetical considerations.

2.4 Short-term to long-term predictions

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 HVAC system loads, a full year of energy consumption data is likely to encompass the entire range of variation of both climatic conditions and 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 problem in such cases is exactly similar to the one faced in in-situ monitoring of the building for the purpose of long-term prediction of building loads. 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 with monitored data by Kissock et al., (1993) for 2-P SV models and by Katipamula et al., (1995) for standard MLR models. Further investigation has also been performed with synthetic energy use data generated from engineering models (Reddy et al., 1998). The same type of general conclusions were reached by all these studies, which are discussed below.

The study by Kissock et al. (1993) limited to three LoanSTAR buildings with constant air volume (CV) systems, and that by Katipamula et al. (1995) where buildings under both CV and VAV operation were selected, found certain general characteristics of how, when and to what extent regression models based on short data-sets incorrectly predict annual energy use in the climate of central Texas.

(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 annual 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. When 2P models are used, cooling models identified from months with above-average temperatures tend to over-predict annual energy and underpredict energy use if identified from months with below-average temperatures. The converse seems to hold for heating models.

Tests with synthetic data found that these observations are applicable for other types of models (say 4P models) as well (Reddy et al., 1998). 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 and with the range of variation of daily temperature values in the data set encompassing as much as the annual variation as possible. 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 a portion of winter and the summer. Figure 2.0b taken from Reddy et al. (1998) illustrates this feature using synthetic cooling energy use data from a heavily scheduled building. The figure shows the monthly range of temperature variation as well as how well the seasonal cooling energy use data are fit by 4P models. The error in using the seasonal models for annual prediction is expressed as a percentage bias which is also indicated in Fig. 2.0b. Though the seasonal models fit the data very well (as shown by the R^2 and CV-RMSE values in Fig.2.0b), only the October-December model is satisfactory for predicting annual energy use as evidenced by its low bias error. Note that judging a model's predictive ability from the goodness-of-fit criteria is erroneous. This is illustrated by the fact that though CV-RMSE is poorer for the model identified from Oct.-Dec. data than that of the April-June and July-Sept. seasonal models, the annual predictive bias is much smaller. The low predictive error of the regression model identified during the Oct.-Dec period may not be too surprising since the variation of outdoor temperature during this period covers most of the annual temperature range (Fig. 2.0b)The best way to avoid the problem of improper long-term prediction is to insure that the outdoor temperature spread in the data set from which the regression model is to be identified captures most of the annual outdoor temperature spread of that location (this is an application of the concept of "proper experimental design" in statistics, (see Montgomery, 1991).

To conclude, the important inferences drawn from the various studies on this issue of short-term to long-term load predictions are that:

(a) only if the monitoring, (in our case, the in-situ tests) are performed during the swing seasons can one expect to have good long-term load predictions, and

(b) there is no way of adjusting regression models to accurately predict annual energy use once improperly identified from short data sets.

These findings and the strategy suggested are, however, unacceptable for the current project since one does not have the luxury of waiting until the climatic conditions are favorable to perform the in-situ tests. Further, practical considerations dictate that in-situ tests (even if they entail non-intrusive monitoring left at site with automated data collection and retrieval) cannot last 3 months, but should be limited to 2-3 weeks at the most. Finally, we reiterate that the objective of this research is to estimate the energy and demand savings from a TES system. Though the long-term building load predictions are likely to be more accurate from models identified from short-term tests performed during the shoulder months, this may not necessarily be the best for characterizing the TES performance. It may be better from the overall TES system point of view to monitor during the peak summer season with a limited range of loads rather than the shoulder seasons where the building loads are relatively low but with greater variability. Therefore, we propose to evaluate a slightly different in-situ testing and monitoring strategy as described below.

2.5 Proposed methodology

One possible approach to predicting long-term building loads from short-term data is to use a calibrated systems model. However, as discussed earlier, this requires specialized skills beyond most energy professionals. Further, HVAC systems have set points (such as the cold or hot deck reset temperatures) which are season dependent, or the building may be operated differently during different seasons of the year which a short-term monitoring protocol will fail to adequately capture unless the analyst acquires such information by other means (say, from the EMCS system or from the building energy manager). Hence, we propose to use a standard MLR model in this research.

Further, the regression model approach, even when a MLR model or a Fourier series model are adopted, is adequate when say 14 days or even 1 month of monitored data are available. We are proposing in this research project a Short-term Monitoring - Long-term Prediction method (SMLP) by using 14 days (two weeks) of monitored hourly data (which can be provided by an non-intrusive or passive in-situ monitoring protocol) supplemented with year-long utility bills of the building. This combination could provide the necessary detailed short-term (i.e., hourly) data as well as the long-term data to meet the objective of this research phase. The short-term data is likely to provide the large variation in internal loads (along with the necessary insight to separate the different operating modes of the building) necessary for proper identification of the regression coefficient associated with this variable, while the utility bills will provide the necessary variability in energy use, outdoor temperature and outdoor humidity levels over an annual cycle to be able to identify the associated model coefficients in a robust fashion.

As a final note, it is important to realize that the SMLP method, or any method based on short-term measurements to predict long-term building energy use, explicitly relies on building operation being consistent within the day-type chosen.

2.5.1 Selection of monitoring periods

In order to evaluate and refine the SMLP method, year-long monitored hourly building energy use data should be available. We could then select different two-week periods (and "assume" that the required in-situ monitored data was gathered during that period) in order to evaluate how the two-week selection process affects the prediction accuracy of long-term building loads. This would give insights into (i) time of the year when the in-situ monitoring is likely to yield a regression model that is most accurate in its long-term predictions, and (ii) the extent to which the accuracy of the building load predictions become poorer when periods other than this optimal period are chosen for the in-situ monitoring period. Given that there are several permutations possible, we have narrowed down the search by selecting time periods using the following objective criteria which are based on findings from past studies (described earlier in section 4), namely that building load prediction accuracy will be best when models are identified from data periods during which the outdoor dry-bulb temperature (which is usually the single most influential driver of building energy use) is closest to the annual mean and has a large day-to-day variability.

These criteria for selecting the "best" two-week period have been quantified as follows:

1. Calculate the yearly average outdoor dry bulb temperature.

2. Among the 52 weeks of the year, choose the weeks where the yearly average temperature lies between the weekly Minimum and Maximum hourly values, i.e., Weekly Min < Yearly Avg < Weekly Max.

3. Narrow down the list of candidate periods to periods where two consecutive weeks satisfy the above condition.

4. Rank them based on how close they are to the yearly average value, (1: for best,....).

5. Rank them based on their hour-to-hour variability, by simply using the range between the Maximum and the Minimum values, (1: for best, ...).

6. Find, for each pair which satisfies step (3), the mean of the ranks of steps (4)and (5). The "best" two-week period will be the one with lowest mean rank (closest to 1).

The "worst" two-week period can also be determined in an analogous manner. Further, how a particular two-week period compares with the best and worst periods can also be evaluated in a quantitative manner.

2.5.2 Modeling variants

The SMLP approach is based on the condition that two weeks of monitored data (entailing chilled water energy use, internal lights and equipment loads, outdoor dry-bulb temperature and outdoor humidity) and 12 monthly utility bills are available for model identification. We have identified four different variants by which the SMLP approach could be implemented statistically to identify the regression model coefficients.

Variant 1: Addition of monthly residuals into an hourly model

Using the two weeks of hourly data for building energy use and corresponding weather conditions, an hourly MLR model assuming a functional form given by eqs.(2.2a, 2.2b) is first developed. This model is then used repetitively for all the hours in a month (or over each utility billing cycle period), and a monthly predicted energy use is determined by aggregating the hourly predictions. The residuals R_k resulting from the difference between the predicted monthly values and the monthly utility bills are then determined for each month (k) of the year. These 12 values are then added to the basic hourly model to get the complete model:

$$E_{i,k} = a + bT_i + c(w_i - 0.009)^+ + d(OCCUP_i) + R_k \qquad (2.3)$$

where, $E_{,I,k}$ is the predicted hourly energy consumption during month k,
R_k is the residual for month k,
T_i is the outdoor dry bulb temperature,
$(w_i - 0.009)^+$ is the adjusted specific humidity difference (set to be zero if negative),

$OCCUP_i$ is an indicator (dummy) variable accounting for occupancy (0 for occupied hours, and 1 for unoccupied hours) which is determined from the monitored internal loads during the 14 day period.

Variant 2: Addition of individual hourly and monthly regression coefficients

Here, we proceed as previously, and using two weeks of hourly data for energy consumption and weather conditions, an hourly MLR model is first developed. The residuals resulting from the difference between the predicted monthly values (aggregated from predicted hourly values) and the monthly utility bills are again regressed against monthly weather conditions and internal loads (monthly values for internal loads might not be available in a real application). The complete model is formed by adding the individual monthly and hourly coefficients of each of the regressor terms.

Variant 3: Weighted regression of hourly and monthly values

Here, unlike the previous two variants, the complete model is identified in one step. First, the monthly utility bill and weather variables are converted to hourly mean values by dividing them by the total number of hours for each month. These 12 hourly-mean monthly values are grouped with the data set of the two-week hourly values. Since the hourly-mean monthly and in-situ hourly values are deduced from different time scales, one needs to distinguish between both during regression by performing a weighted regression (Draper and Smith, 1982). The monthly-mean values can be seen as being an average of (24xj) where j is the number of days in the month. Recall from basic statistics that the sampling distribution of a population varies as the square root of the sample size. Thus the logical manner of regressing the mixed time scale data is to weight the hourly-mean monthly values by $(24 \mathrm{x}\, j)^{1/2}$ and the hourly values by 1.

Variant 4: Two-stage regression model

In order to minimize the confounding effects of collinearity discussed in section 3.3.3, a two-stage approach has been shown to be advantageous in other building related studies (Deng, 1997). This variant involves using the monthly data to identify the coefficients associated with weather variables only, and then using the model residuals at an hourly time scale to identify the occupant and building related diurnal schedules. For instance, a model such as

$$\mathbf{E_k = a + bT_k + c(w_k - 0.009)^+} \quad \text{with } k = 1,........12 \text{ (indicating the 12 months)} \qquad (2.4a)$$

is first identified from utility data. Then an hourly model (**MLR**) is developed using the coefficients **b** and **c** found by the monthly model, and two weeks of hourly energy consumption data (for instance, CW or H -W), internal loads (LTEQ), and an occupancy indicator variable, in the following fashion:

$$E_i - b.\ T_i - c.(w_i - 0.009)^+ = d + e.(LTEQ_i) + f.(OCCUP_i) \qquad (2.4b)$$

This method retains the simplicity in model identification of variant 3 while offering the possibility of identifying more physically-meaningful model coefficient values.

5.3 Proposed variant

The four variants were first evaluated with monitored data from the Fine Arts Building of the University of Arlington monitored by ESL under the LoanSTAR project. It was found that variants (3) and (4) were distinctly better than the other two in terms of ease in model identification effort and in subsequent model prediction accuracy. However, the coefficients of the regressor term of variant (3) were not physical. For example, chilled water use should increase when internal loads increase. A negative regression coefficient was found when variant (3) was used. Consequently, we determined that variant (4) was the best since it had the potential of providing a better physical interpretation of the regression coefficients. The short-term data is likely to provide the large variation in internal loads (along with the necessary insight to separate the different operating modes of the building) necessary for proper identification of the regression coefficient associated with this variable, while the utility bills will provide the necessary variability in energy use, outdoor temperature and outdoor humidity levels to be able to identify the associated model coefficients in a robust fashion. A more complete evaluation along with documented analysis results of all four methods is being done as part of an ongoing Ph.D. thesis at Texas A&M University.

2.6 Evaluation of proposed methodology

The results of an evaluation of the SMLP method using variant (4) is presented in this section. The same data set of the Engineering Center analyzed in the Great ASHRAE Energy Predictor Shootout II (Haberl and Thamilseran 1996) was selected because this would provide an absolute means of evaluating the SMLP method as against other sophisticated modeling techniques proposed by researchers world-wide.

The Engineering Center is an institutional building located in College Station, Texas. It comprises 32,440 m^2 of classes, laboratories, computer rooms, offices, and an unconditioned underground parking garage. It is a heavy structure building with precast concrete walls. The building is occupied on weekdays from 7:30am to 6:30pm and on weekends from 7:30am to 5:30pm. Computer facilities operate 24 hours a day. The building is primarily served with 12 dual-duct air handlers operating 24 hours a day. Chilled and hot water for cooling and heating are supplied to the building by the campus physical plants.

The best two weeks of hourly data of the Engineering Center were chosen according to the criteria described above. Figure 2.1 presents the weekly variations of the outdoor dry bulb temperature for College Station, Texas in the year 1990. Table 2.1 assembles intermediate results obtained during the selection of the "best" two weeks of monitored data. In this manner, the period from May 7th till May 20 th was finally selected.

The monthly utility bills were created by aggregating hourly values available for the Engineering Center. Average monthly weather conditions were also calculating from hourly values. The monthly chilled water use (CW) and the corresponding weather conditions are shown in Table 2.2. Some monthly values could not be used due to large gaps of missing hourly values for those months, and for some months, only a few days were missing. The number of days for each month for which we had clean and complete data are given in Table 2.2 along with monthly mean values of the CW energy use and the climatic regressor variables. The ACW variable which represents CW use on an average day of the month has been determined by only considering the actual number of days per month when data was available.

The following MLR monthly models were fit to the data by ordinary least squares regression:

$$ACW = 29.0706 + 1.5171\,T_i \qquad \text{with } R^2 = 0.7997 \qquad (2.5a)$$

and

$$ACW = 159.379 - 0.8049\,T_i + 4991.4729(w_i - 0.009)^+ \qquad \text{with } R^2 = 0.9019$$

The first model was chosen since the negative coefficient of the outdoor dry bulb temperature in the second model is doubtful and misleading, even though a better correlation was obtained. Since the ACW variable was used instead of the monthly CW, the outdoor dry bulb temperature coefficient (1.5171) was converted to hourly values by dividing by 24.

The hourly MLR model was developed as follows. An hourly variable $[CW_i - (1.517\ T_i)/24]$ was calculated and regressed against the internal loads ($LTEQ_i$) and the occupancy indicator variable ($OCCUP_i$). The variable $OCCUP_i$ was assigned the following values from how the internal load schedule varied at the Engineering Center:

$OCCUP_i$ = 0 for Weekdays, 7:00am - 7:00pm; 1 otherwise
0 for Weekends, Holidays, Semester Breaks, 7:00am - 6:00pm; 1 otherwise.

The following MLR hourly model was finally obtained:

$$CW_i - (1.517 / 24)\,T_i = 1.2581 + 0.00036(LTEQ_i) + 0.02079(OCCUP_i) \qquad (2.6)$$

This hourly model was used to predict CW use during days when monitored CW data was intentionally removed by the organizers of the ASHRAE Energy Predictor Shootout II to evaluate the accuracy of the models developed by the contestants. Time series plots of the removed data in the Shootout competition, predicted with the SMLP method and measured, are shown in Figs. 2.2 - 2.7 different periods of the year. Generally the model seems to be satisfactory, though large differences do appear. Some of the differences between model predicted and observed values could be due to the fact that the building is operated differently that it was during the 14-day period used for model identification. There is often no definite way to determine this, and it is in such cases, that performing an evaluation with synthetically generated data (i.e., using a building energy simulation program) can provide certain insights which actual field data cannot.

A comparison of the accuracy of the SMLP model's prediction with other models is shown in Table 2.3. It is clear that the SMLP is only slightly poorer than the top contestants. The SMLP prediction error on an hourly time scale had a CV (%) of 8.82 and an MBE (%) of 2.63. It is worth mentioning that the top contestants used more sophisticated and involved methods such as neural networks, MLR models for each hour of the day, and inverse binning method (Haberl and Thamilseran 1995). All these methods made use of the approximately full year of hourly data set to identify a model while the SMLP Method utilized only two weeks of hourly data, supplemented by monthly utility bills and weather conditions (that can be obtained in a real situation from the national weather service or from normalized weather conditions). Hence, not only are the predicted hourly values accurate for the SMLP approach, but the results compare very favorably with other more sophisticated approaches.

2.7 Future Work

The above findings are limited to the specific case when the SMLP model used non-intrusive data from the "best" two weeks of the year. We are currently evaluating the prediction accuracy of this method, with other two-week periods. Specifically, we propose to repeat such analyses using the "worst" two weeks as well as a "mediocre" two week period with the same Great Energy Predictor Shootout II data.

Further, we propose to select 6-7 more buildings monitored under the Texas Loan STAR program and repeat the above analyses. We shall select buildings of different types (offices, classes, hospitals, dormitories), different HVAC types (CV, VAV), and different climates (Texas and Minnesota). Actual monitored data presents a challenge in evaluating the proposed prediction method since the operation of the building might (and does) change (without us being cognizant of the fact) from year to year, or even, from season to season. Another problem arises from the availability of clean hourly data covering at least one complete year, and preferably two years (one for model identification, and the other year for evaluating the model prediction accuracy). Since the conclusions of our study would be directly impacted by such considerations, we shall give adequate care to selecting the proper buildings and "clean" data periods for further analysis.

Finally, there are two additional factors which we propose to explicitly consider. Some buildings are monitored by the electric utility and 15 minute demand data may be available to supplement the in-situ measurements. In such cases, a more accurate building load model could be identified than resorting to utility bills. Secondly, the presence of a TES system will affect the proposed building load model identification scheme since the billing data will also implicitly contain the performance of the TES system. How to separate the effect of the TES system from that of the building loads and the chiller needs to be investigated further.

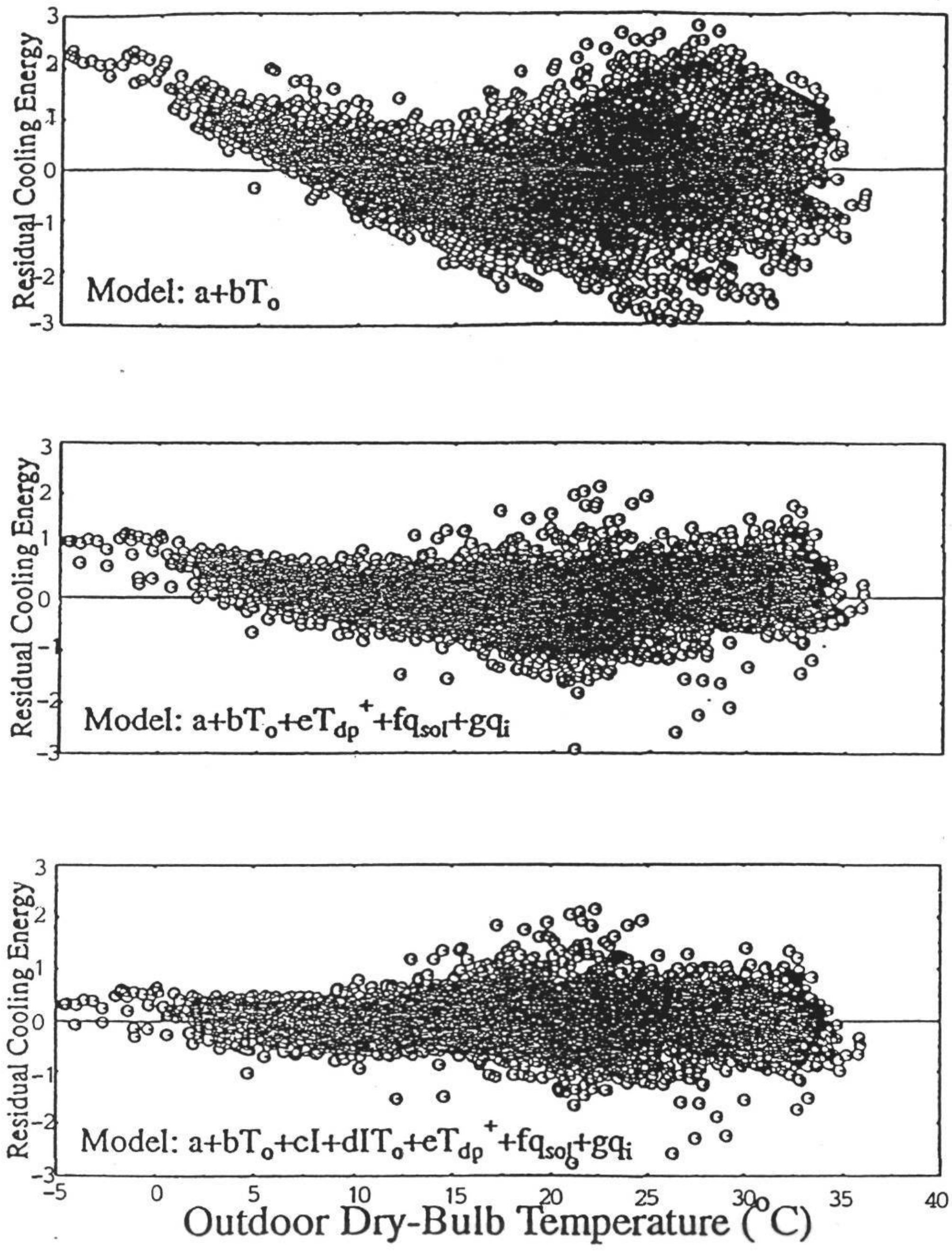
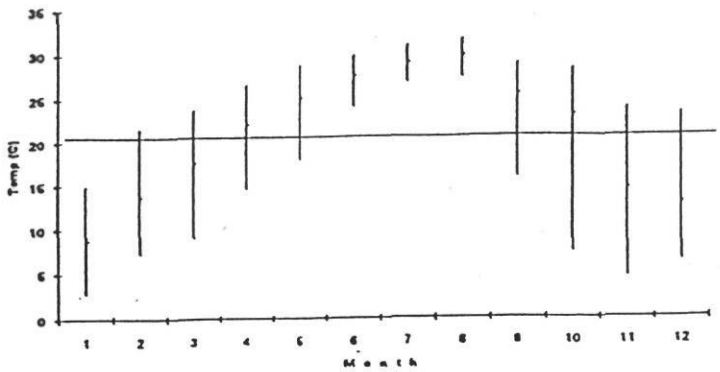
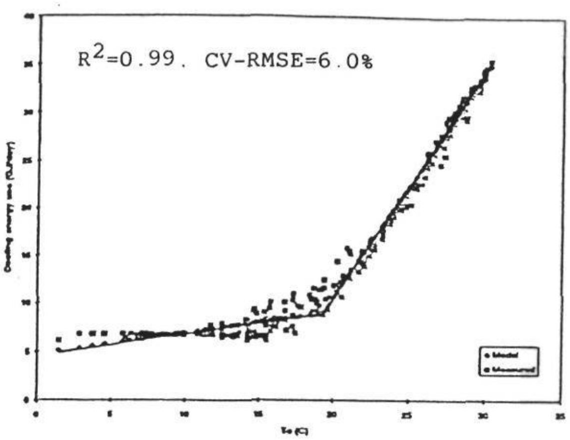


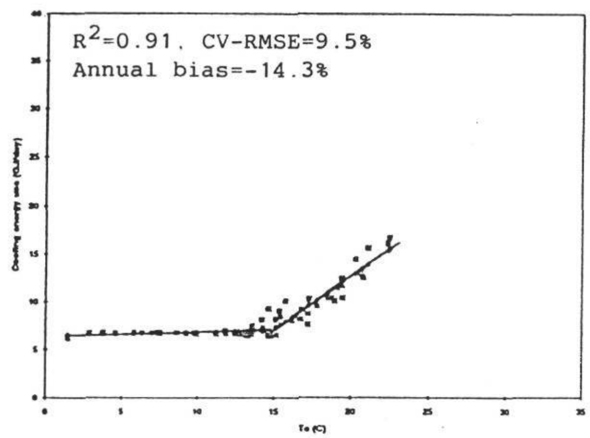
Figure 2.0a. Building Load Report (Katipamula et al. 1994)



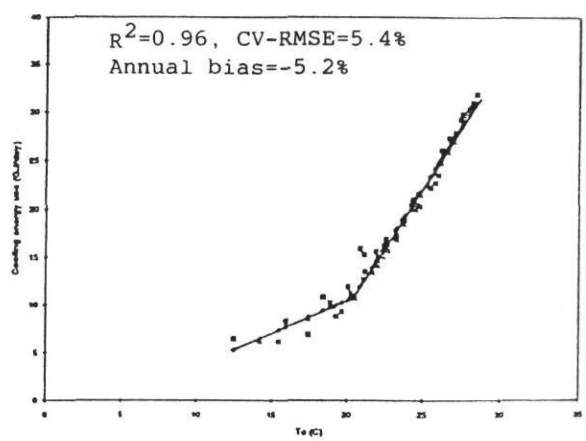
(a) Range of variation of daily T_0 values



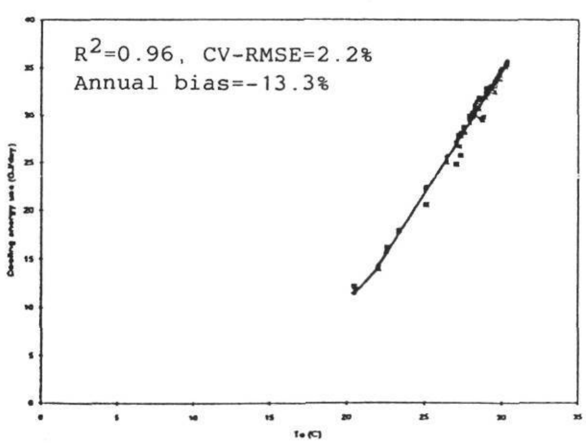
(b) Whole year



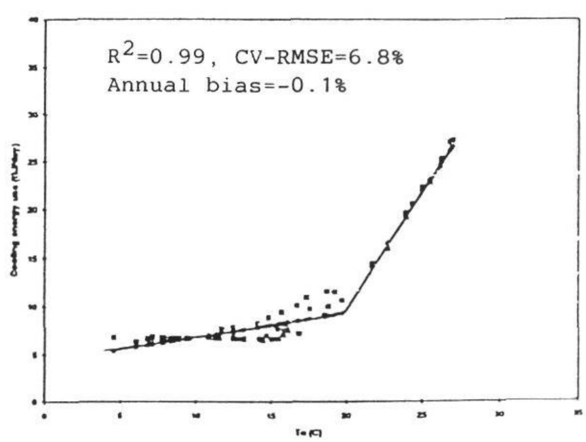
(c) January to March



(d) April to June



(e) July to September



(f) October to December

Figure 2.0b. Building Load Report Statistics.

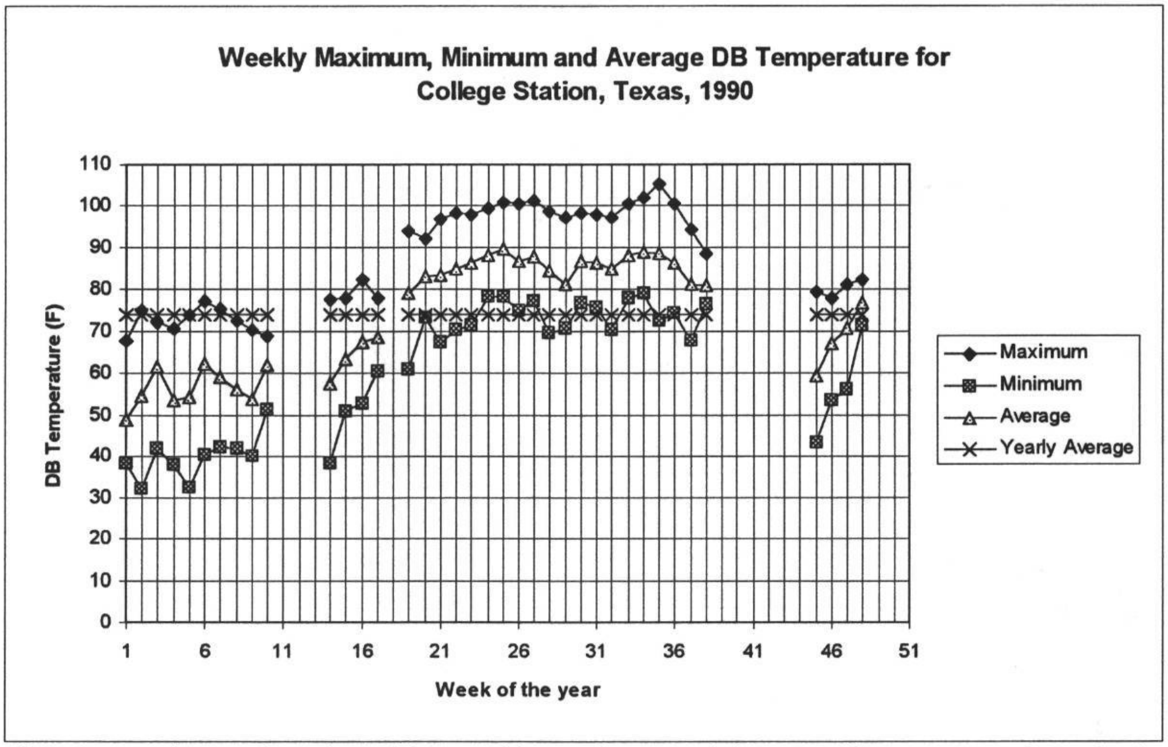


Figure 2.1. Time series plot of the weekly maximum, minimum and average outdoor dry bulb temperature for the Engineering Center case study (for the year 1990).

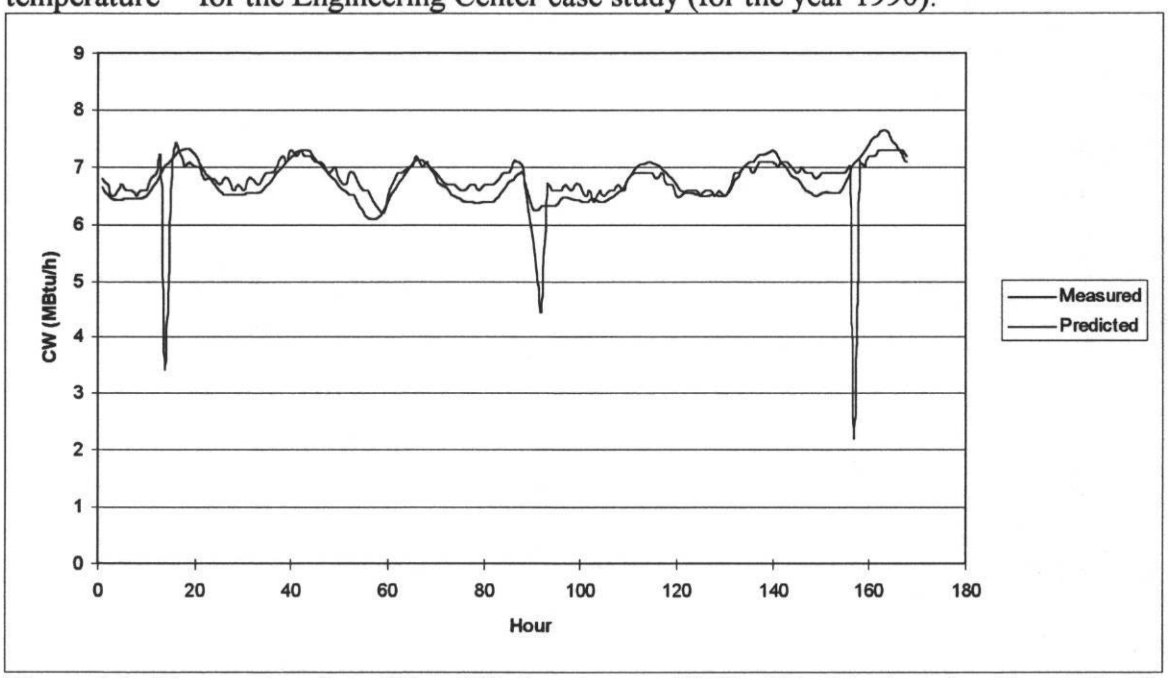


Figure 2.2. Time series plot of the chilled water use (CW) of the Engineering Center for the week of May 15- 21 1990.

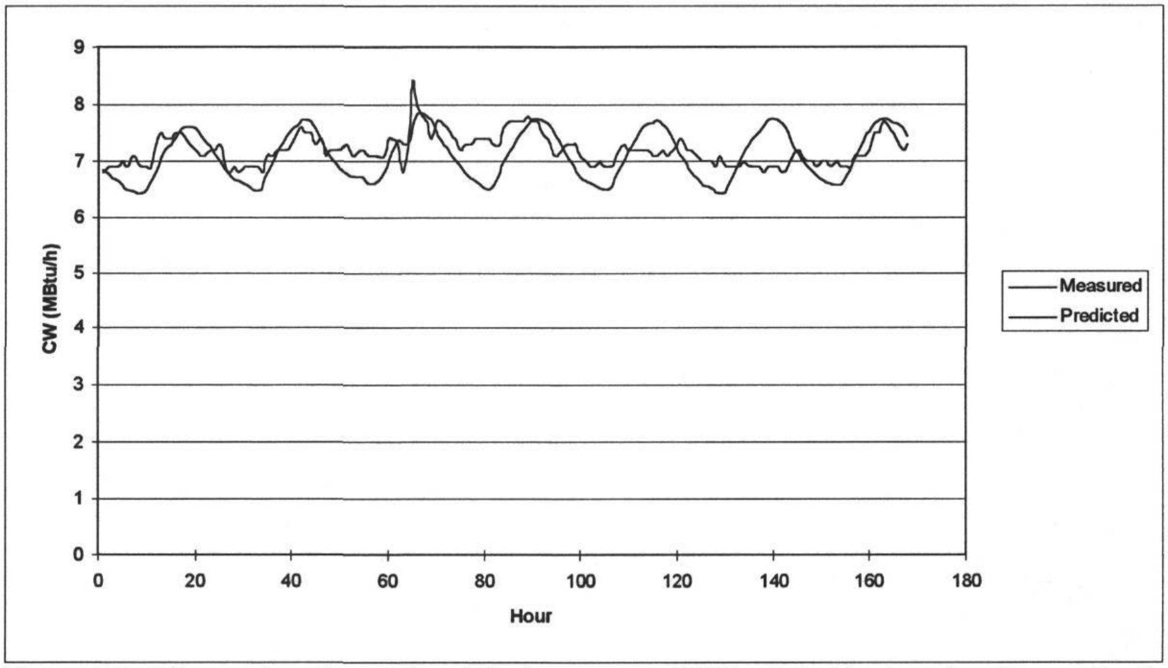


Figure 2.3. Time series plot of the chilled water use (CW) of the Engineering Center for the week of June 12-18 1990.

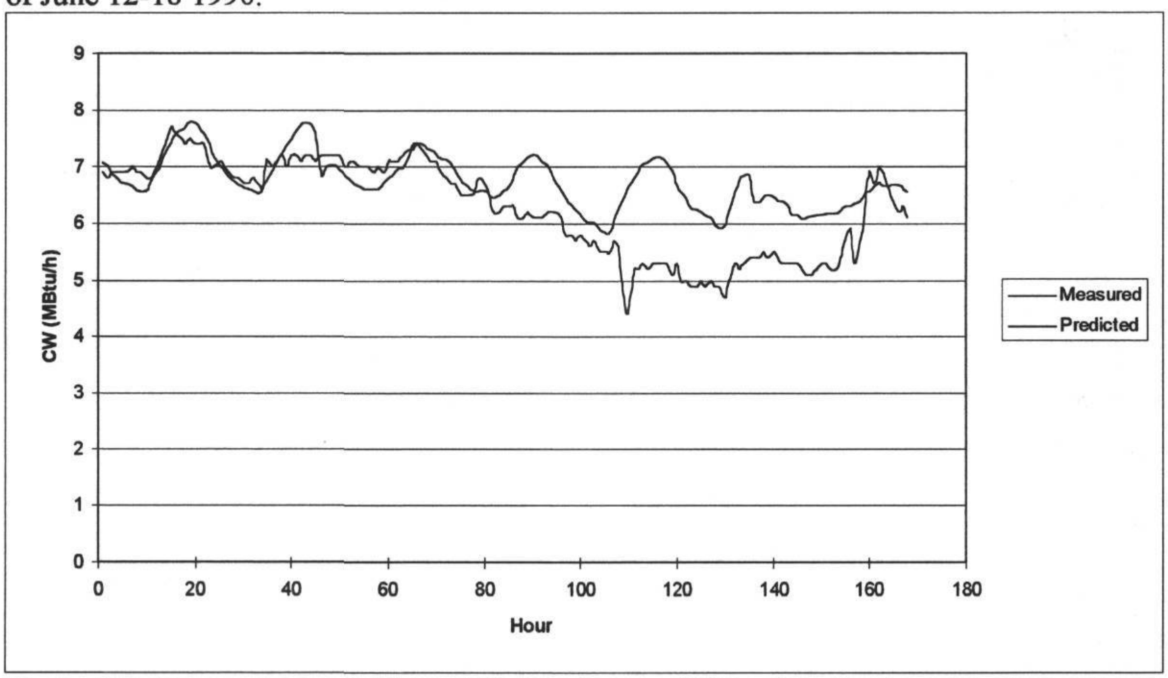


Figure 2.4. Time series plot of the chilled water use (CW) of the Engineering Center for the week of July 7-13 1990.

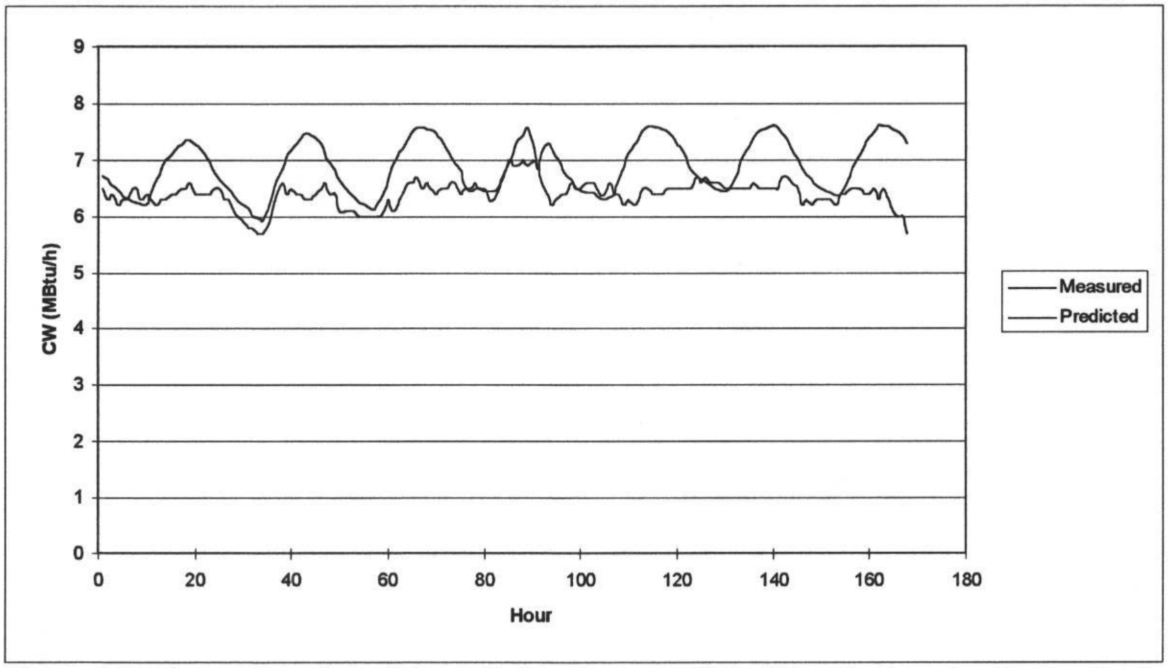


Figure 2.5. Time series plot of the chilled water use (CW) of the Engineering Center for the week of August 7-13 1990. The model overpredicted the energy use during this period which falls in the break between the Summer and the Fall semesters (Aug. 10-26 1990). The model assumed an occupancy during this period similar to the occupancy of the weekends during the semesters.

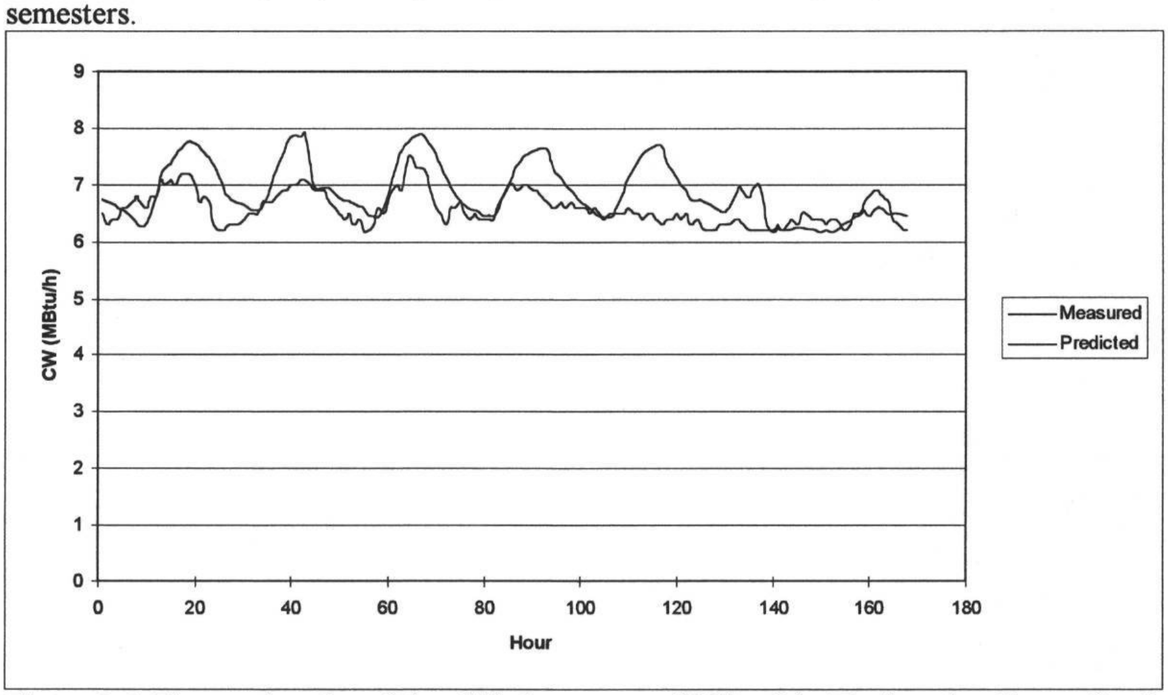


Figure 2.6. Time series plot of the chilled water use (CW) of the Engineering Center for the week of September 4-10 1990.

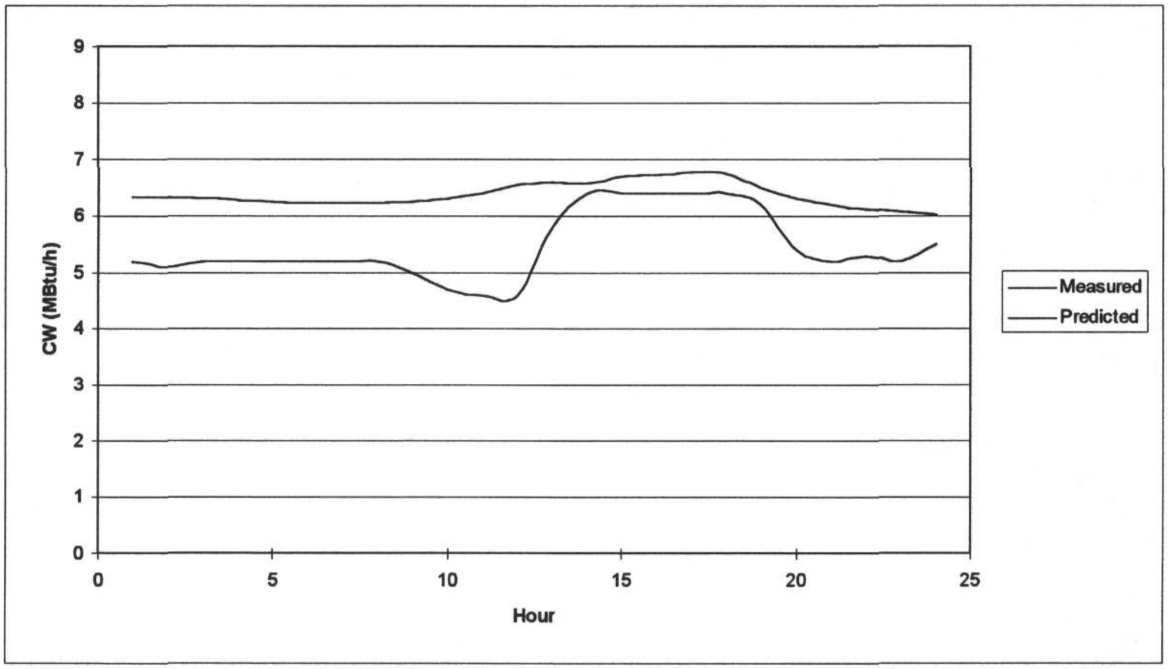


Figure 2.7. Time series plot of the chilled water use (CW) of the Engineering Center for the day of November 27 1990

Table 2.1. The two-weeks period selection procedure for the Engineering Center (College Station, Texas) for the year 1990.

Weeks covering the Yearly Avarage (73.77 F) (Week Min < Year Avg < Week Max)					2 Consecutive Weeks	Rank 1 Average Closest To Yearly Average	Rank 2 Widest Range	Overall Rank = (Rank 1 + Rank 2)/2
Max	Min	Avg	Week #	Date				
75.04	32.1	54.52	2	Jan 8-14				
73.85	32.41	54.43	5	Jan 29-Feb 4		13	1	7
77.17	40.61	62.14	6	Feb 5-11		11	3	7
75.42	42.24	59.05	7	Feb 12-18				
77.48	38.17	57.68	14	Apr 2-8		12	2	7
77.8	51.07	63.43	15	Apr 9-15		5	6	5.5
82.3	52.94	67.23	16	Apr 16-22		3	8	5.5
77.8	60.58	68.57	17	Apr 23-29				
93.82	60.71	79.08	19	May 7-13		4	5	4.5
92.32	73.16	82.98	20	May 14-20		7	9	8
96.76	67.47	83.45	21	May 21-27		8	7	7.5
98.45	70.47	84.82	22	May 28-Jun 3		10	11	10.5
98.08	71.41	86.14	23	Jun 4-10				
98.83	69.6	84.67	28	Jul 9-15		6	10	8
97.2	70.53	81.17	29	Jul 16-22				
97.33	70.22	84.85	32	Aug 6-12				
105.09	72.54	88.55	35	Aug 27-Sep 2				
94.45	67.91	81.29	37	Sep 10-16				
79.49	43.36	59.19	45	Nov 5-11		9	4	6.5
77.9	53.62	66.88	46	Nov 12-18		2	12	7
81.34	56.1	70.49	47	Nov 19-25		1	13	7
82.22	71.33	76.95	48	Nov 26-27				

Table 2.2. Available data for the Engineering Center.

Month	Days	CW (MBtu) (MBtu)	Temp (F)	(w-0.009)+ (lb/lb dryair	ACW (MBtu/day)
Jan-90	31	3537.5	54.26	0.0008	114.11
Feb-90	28	3418.2	58.88	0.0015	122.08
Apr-90	22	2975.7	63.92	0.0029	135.26
May-90	22	3493.04	82.41	0.0139	158.77
Jun-90	30	5111.9	87.60	0.0158	170.40
Jul-90	31	4847.6	85.10	0.0134	156.37
Aug-90	31	4857	87.88	0.0134	156.68
Sep-90	17	2650.7	83.43	0.0129	155.92
Nov-90	21	2301.8	67.25	0.0025	109.61

Table 2.3. Comparison of the accuracy of the models of the top contestants in the Predictor Shootout II competition and the SMLP for the chilled water use (CW) of the Engineering Center.

(E1 to E5 stand for the competition entries, Haberl and Thamilseran 1996).

	E1	E2	E3	E4	E5	SMLP
CV (%)	7.1312	8.2585	8.877	7.0312	9.4499	8.8248
MBE (%)	-0.8917	-3.0309	-3.4214	-1.3372	-1.689	2.6267

3.0 ANALYTICAL MODELS FOR CHILLERS, FANS AND PUMPS

3.1 Background and Objectives

The final intent of the research performed under ASHRAE RP-1004 is to develop a practical methodology for estimating the degree of seasonal and annual electric load (both in terms of energy and demand savings) shifted by a thermal energy storage (TES) system that has been installed in an existing commercial building. The methodology shall be usable by professionals with some expertise in field testing and analysis. The emphasis shall be on practical usefulness and wide applicability rather than on precision. Because of the numerous system and control variants that may exist in the field, this research will devise a framework that defines the recommended approach to tackling this problem. To this end, this research will consist of essentially three major tasks:

(i) developing or evaluating existing methods to perform in-situ short-term tests that includes recommendations on the duration and the time of the year when such tests are to be performed,

(ii) developing or evaluating existing models of the building and the cooling system in the framework of which the in-situ, short-term test results can be analyzed and long-term predictions of the electric load shifted can be predicted; and

(iii) illustrating/validating the merit of the two above tasks with monitored data from 3 TES sites.

Task 1a and 2b of our proposal involve a literature review and a description of the proposed analytical models. The section pertaining to a literature review and proposed methodology of predicting long-term building loads from short-term data is described in a separate document. This document limits itself to the equipment associated with the cooling system that supplies cooling to the HVAC system.

We have suggested, in our proposal, to evaluate two different analytical approaches:

(a) a component based approach that involves developing and characterizing individual components of the system (such as the building, storage tank, chiller, cooling pumps and circulating fans) in terms of climatic variables and other appropriate parameters. The performance of the cooling system under different operating modes is then predicted by assembling these components appropriately and performing a chronological hour-by-hour simulation during the entire season or the entire year;

(b) a lumped model approach where macro-models of the entire cooling system will be developed for each operating mode, and a modified bin-method (ASHRAE, 1997) type of analysis over the pre-specified day-types (typically weekdays and weekends) will be used to determine the seasonal or annual energy and demand savings as a result of the TES system.

This section will limit itself to approach (a) described above, while a separate section will concern itself with analytical approach (b). The objective of this section is to review existing literature of appropriate component models and in-situ measurements for chillers, fans, pumps and TES systems which we deem appropriate to our research, and state the types of models which we shall evaluate with the monitored data collected in the framework of this research.

Much of the literature on testing of HVAC equipment is based on stand-alone testing of a single component in a dedicated test facility with laboratory-grade measurements and limited specific objectives. Accurate evaluation of energy efficiency improvements/alternatives of installed equipment requires their in-situ field performance. Unfortunately, manufacturers' data and laboratory performance measurements are inadequate because often there is considerable differences between the two. Field testing can have many different objectives, as well as involve widely varying equipment configurations and limits on measurement techniques and accuracy. Further, the mathematical models based on which the monitored data will be analyzed in order to characterize the equipment in-situ performance are different than those used for design purposes. They are typically macro-models consisting of a relatively few model parameters whose coefficients need to be identified from the monitored data, usually by regression analysis. This approach falls under "inverse modeling" approach described in ASHRAE (1997).

The effort in performing a literature review on cooling pumps, fans and chillers and in proposing analytical models and in-situ monitoring protocols of such equipment is considerably reduced since the ASHRAE-funded research (RP-827) has recently been completed. The results from this research are documented in Phelan et al. (1994, 1996, 1997 a, b c) and we shall use many of their conclusions and recommendations in the frame work of this research. An overview of the methods, specifically as they relate to this research is briefly presented.

3.2 General approach of the component based model

3.2.1 Overall system model

Typically, a TES system consists of several air handler terminal units in the building which supply the required cooling (and heating) energy to meet the building loads, several pumps, as well as several chillers. In the framework of this research, we shall assume these to be lumped into one piece of equipment of each type as shown in Fig.3.0 Following Braun (1992), the total electrical power consumed in order to provide the necessary cooling energy to the building is given by:

$$E_{total} = E_{ahu} + E_{bldg\ pump} + E_{chiller} + E_{chiller\ pump} + E_{storage\ pump} \tag{3.1}$$

where E_{ahu} is the power consumed by the air handlers in the building,
$E_{bldg\ pump}$ is the power consumed by the pump(s) to circulate chilled water in the building,
$E_{chiller}$ is the power consumed by the chiller(s),
$E_{chiller\ pump}$ is the power consumption of the cooling plant consisting of the condenser

water pump to the cooling tower (and the fan in the cooling tower fan which we assume to be operated under constant air flow rate) , and the pump used to circulate chilled water in the primary loop of the evaporator (which is often different than $E_{bldg\ pump}$), and

$E_{storage\ pump}$ is the pump(s) used by the TES.

The component-based method involves taking in-situ measurements of each of these equipment individually and identifying the empirical coefficients of the appropriate performance models by regressing the monitored data. Subsequently, depending on how the entire system comprising of the building, chiller and TES is operated, the appropriate individual component model equations are simultaneously solved to predict the associate power (or the hourly energy used) by the individual equipment, and consequently that of the entire cooling system. These equations would then directly allow the analyst to determine the seasonal or annual energy and demand in that building for a given set of conditions. If the equations have been developed for the baseline (i.e., non-TES system) and TES cases, then the energy and/or demand reductions can be accurately assessed for normalized conditions.

3.2.2 Approach used in RP-827

The approach adopted in RP-827 is directly pertinent to this research, and a brief description of RP-827 is given below. In 1994, ASHRAE undertook research project RP-827, entitled Methodology Development to Measure In-Situ Chiller, Fan, and Pump Performance. The overall objective of this research was to develop and evaluate methods for performing in-situ testing of mechanical equipment to determine annual energy use characteristics. More specifically, a set of short-term, in-situ test methods were developed to provide performance information that could be used in long-term energy calculations. For fans and pumps, six different test methods were evaluated, such as single point measurements, single point measurements along with manufacturers performance curves, multiple point tests with loads imposed either artificially at the pump or at the building zone level, and passive monitoring methods. The methods generally result in statistical relationships that express power consumption as functions of part-load ratio and, in the case of chillers, system operating temperatures.

The development of these methods was based on the literature survey of laboratory and field testing methods described by Phelan et al. (1994). The methods have been guided by the following philosophy:

(a) There will not be a single best method for all situations. In some situations, limited resources for testing and evaluation may allow only a single field measurement. In other cases, a mechanical system can be monitored for a full day, but the methods cannot intrude on normal system operations. In yet other situations, false loads can be readily imposed on the systems outside of normal operating schedules. Therefore, a set of test procedures has been developed, each having different minimum measurement requirements.

(b) There are many existing standards for experimental measurements and laboratory testing of mechanical equipment performance. The in-situ methods draw on the existing component testing procedures as much as possible, extending these methods to account for the effects of system installation, operation, and control.

(c) The evaluation of annual energy consumption and peak demand characteristics for installed HVAC equipment requires knowledge of the operating load on the system, both at design conditions and throughout the year. However, measurement and characterization of equipment loads were outside the scope of RP-827. (This aspect of building load prediction from short-term tests is explicitly addressed in the framework of the current RP-1004 research). Therefore, the test methods require the user to provide the load distribution, often presented as the number of hours of occurrence of a particular load range.

(d) Annual energy consumption of mechanical equipment is significantly affected by the system control strategy. Therefore, any effort to measure equipment performance for energy characteristics must include the control system within the measurement environment. In particular, any methods of artificially loading the equipment to obtain a rich data set must be applied *outside* the equipment control envelope.

(e) The prediction of annual energy use from in-situ measurements involves several distinct uncertainties. The in-situ test methods should be accompanied by comprehensive methods of uncertainty analysis accounting for each of these sources.

Given the considerations outlined above, a set of in-situ test methods has been developed for chillers, fans, and pumps (Phelan et al., 1996, 1997 a, b). In all cases, a relationship between power consumption and "load", which varies with each equipment type, is developed for the equipment and system using a combination of direct measurements, statistical regression analysis, manufacturer's data, and engineering principles. Details of the protocols for individual measurements, including guidelines for placement of instrumentation and accuracy of instrumentation, are based on accepted industry standards for stand-alone equipment testing.

In general, each testing guideline specifies the following test characteristics:

(i) physical characteristic to be measured (power, flow, pressure, etc.)

(ii) number of data points required

(iii) accuracy of measurements

(iv) reference to existing applicable measurement standards

(v) methods of artificial loading (as required)

(vi) calculation equations and uncertainty analysis.

Several of the methods involve measurements under a range of load conditions. In some methods, the measurements are taken during times of natural load changes while in others, the load variations are imposed by the user. In such cases, the loads are imposed to represent variations as they would normally occur.

The methods developed under RP-827 were evaluated using long-term measured data on fans, pumps, and chillers. Typically, energy consumption estimates were determined by applying the test methods to equipment monitored under the Texas LoanSTAR program (Haberl et al., 1996). (Additional evaluation was also performed using other field data, as necessary.) The suitability of the test methods was evaluated by comparing predicted long-term energy consumption with measured energy use.

3.4 Electric power consumed by building air handling units

The theoretical aspects of calculating fan performance are well understood and documented. Fan capacity and efficiency are calculated from measurements of static pressure, velocity pressure, flow rate, fan speed, and power input. The necessary instrumentation is shown schematically in Fig.2. Measurement techniques and calculations are detailed in the ASHRAE, AMCA, and ASME standards described by Phelan et al. (1997a), and this research proposes to base the measurement protocols on these recommendations if needed.

In order to model electricity used by air-handling units, we need to distinguish between three building air distribution system types and their control (Phelan et al., 1997a):

(a) constant air volume (CV) systems;

(b) variable air volume (VAV) systems with no fan control (i.e., fan operates at constant speed and flow modulation is achieved by means of dampers); and

(c) variable air volume systems (VAV) with fan control (i.e., fan speed is varied along with damper position to regulate flow; this being more energy efficient than (b) above).

In CV systems, E_{ahu} is essentially constant during the period during which the building HVAC system is operated. There may be minor variations in power consumption as the density of the air varies with changes in the air temperature. Hence a one-time measurement during the occupied period of the building (and, perhaps, one during the unoccupied period in case the AHU is shut down) is adequate.

In both cases (b) and (c), E_{ahu} is a function of the building loads, or more specifically the air supplied to the building $m_{air,\,bldg}$. Phelan et al., (1997a) have studied the predictive ability of linear and quadratic models between E_{ahu} and $m_{air,bldg}$ and concluded that though quadratic models are superior in terms of predicting energy use, the linear model seems to be the better overall predictor of both energy and demand (i.e., maximum monthly power consumed by the fan). This is a noteworthy conclusion given that theoretically as well as monitored field data presented by previous authors (for example, Englander and Norford, 1992 and Lorenzetti and Norford, 1993) indicates a third order polynomial. Therefore, we propose to evaluate the linear, quadratic and the third order polynomial functional forms for E_{ahu} and investigate the predictive ability of these models with both $m_{air,bldg}$ and Q_{bldg} as the regressor variables. If models based on the latter variable perform well, then one need not measure $m_{air,bldg}$ during the in-situ measurement protocol. We realize that in a VAV system, there is a one-to-one correlation between these two variables only until the minimum threshold flow rate to the building is reached, and so appropriate corrections need to be included in a model with Q_{bldg} as the regressor variable.

3.5 Power consumed by pump(s)

3.5.1 General considerations

The theoretical aspects of calculating pump performance are well understood and documented. Pump capacity and efficiency are calculated from measurements of pump head, flow rate, and power input. The type of instrumentation needed is shown schematically in Fig.3. These calculations and measurement techniques are detailed in the Standards promulgated by ASME and the Hydraulics Institute, as described by Phelan et al., (1997a). Recommendations on how to perform pump measurements have also been made by Phelan et al., (1997a).

In the same manner as fans, we need to distinguish the operation of circulating pumps in buildings and in cooling equipment depending on how they are modulated during part-load operation for the following types of pumps:

(a) constant flow pump with a three way bypass valve to control the amount of heat transfer in the cooling coils;

(b) variable flow pump with a two-way valve to throttle the flow; and

(c) variable flow pump with a variable speed drive.

3.5.2 Power consumed by the building pump(s)

In constant flow systems, $E_{bldg\ pump}$ is essentially constant during the period in which the building HVAC system is operated in a constant manner (i.e., there are no major pressure variations in the system). Hence a one-time measurement during the occupied period of the building (and, perhaps, one during the unoccupied period) is adequate for those cases where the building pump energy needs to be measured.

However, in both cases (b) and (c), $E_{bldg\ pump}$ is a function of the building loads or more specifically of the fluid flow rate $m_{water,bldg}$. Phelan et al., (1997a) have studied the predictive ability of linear and quadratic models between $E_{bldg\ pump}$ and $m_{water,bldg}$ and concluded that quadratic models are superior to linear models. We propose to evaluate both linear and quadratic functional forms for $E_{bldg,pump}$ and investigate the predictive ability of these models with both $m_{water,bldg}$ and Q_{bldg} as the regressor variables. If models based on the latter variable perform well, then one need not measure $m_{water,bldg}$ during the in-situ measurement protocol. We realize that in a VAV system, there is a one-to-one correlation between these two variables only until the minimum threshold flow rate to the building is reached, and so appropriate corrections need to be included to a model with Q_{bldg} as the regressor variable.

3.5.3 Power consumed by the chiller pump(s)

Normally, there are two separate pumps used by chillers: the condenser pump used to circulate the water to the cooling tower, and the pump which circulates water through the evaporator. More strictly, there are two pumps at the evaporator (Hartman, 1996): one for the primary circuit which maintains a constant chilled-water flow through the chiller, and one for the secondary chilled-water flow to the building. In this section, we deal specifically with the primary loop pump, while the secondary loop pump can be (if present) be combined with the building pump addressed in section 4.2. As discussed by Eppelheimer (1996), controlling head pressure in water-cooled chillers has long been achieved by varying the condenser flow rate. However, flow rate through the evaporators is normally not varied. Though several people have suggested ways and means of modifying the present day controls in order to achieve variable evaporator flow and hence better energy efficiency, the current generation of chillers can be assumed to have constant flow through the evaporator.

3.5.4 Power consumed by the TES pump(s)

The flow rate to the TES whether during charging or during discharging may or may not be constant depending on the specific design. Further, not all TES systems use a separate pump for storage. Such factors need to be explicitly recognized during data collection and model identification.

3.5.5 Aggregated model for all auxiliary equipment

Submetering each and every pump (or fan) and then developing appropriate individual models may be too complex for practical applications. Since the net electricity used by the various pumps is usually small compared to that of the chiller, it would be more practical to only monitor the combined electricity used by all pumps and develop one aggregated model for all the auxiliary equipment. Models as discussed above can be evaluated with gathered data to identify the most appropriate model. This is the approach which we advocate in the framework of this research project.

3.6 Power consumed by chiller

3.6.1 Description of different models

The theoretical aspects of calculating chiller performance are well understood and documented. Chiller capacity and efficiency are calculated from measurements of water flow, temperature difference, and power input (see for example, Liu et al., 1994, Hydeman, 1997, Phelan et al., 1997b). Typical measurement locations are shown schematically in Fig.4. Calculations can also be checked by a heat balance performed on the entire system. These calculations and ARI and other ASHRAE measurement techniques are detailed in Phelan et al., (1997b).

There are basically two types of models to describe chiller performance, polynomial and thermodynamic types. These are described below:

3.6.1.1 Polynomial models

This type of model assumes a polynomial function to correlate chiller (or evaporator) thermal cooling capacity or load Q_{evap} and the electrical power consumed by the chiller (or compressor) P_{comp} with the relevant number of influential physical parameters. For example, based on the functional form of the building simulation software DOE-2 (LBL, 1980) models for part-load performance of energy equipment and plant, P_{comp} can be modeled as the following tri-quadratic model:

$$\begin{aligned} P_{comp} &= a + bxQ_{evap} + cxT_{cond}^{in} + dxT_{evap}^{out} + exQ_{evap}{}^2 + fxT_{cond}^{in}{}^2 + gxT_{evap}^{out}{}^2 \\ &+ hxQ_{evap}xT_{cond}^{in} + ixT_{evap}^{out}xQ_{evap} + jxT_{cond}^{in}xT_{evap}^{out} + kxQ_{evap}xT_{cond}^{in}xT_{evap}^{out} \end{aligned} \tag{3.2}$$

In this model, there are 11 model parameters to identify, but since all of them are unlikely to be statistically significant, a step-wise regression to the sample data set would yield the optimal set of parameters to retain in a given model.

Braun (1992) has used bi-quadratic model with two regressor variables and containing six empirical coefficients, namely cooling load on the chiller (Q_{evap}) and the difference between the ambient wet-bulb temperature T_{wb} and the fluid temperature leaving the evaporator (or the supply temperature to the building) T_{evap}^{out}:

$$P_{comp} = a_0 + a_1 Q_{evap} + a_2 Q_{evap}\hat{}2 + a_3 (T_{wb}- T_{evap}^{out}) + a_4 (T_{wb} - T_{evap}^{out})\hat{}2 + a_5 Q_{evap}(T_{wb} - T_{evap}^{out}) \tag{3.3}$$

The model coefficients a_0 to a_5 are determined by regressing data obtained from actual monitoring. We propose to evaluate slight variants of this model, for example, use the inlet temperature to the condenser or the temperature of the water leaving the cooling tower rather than T_{wb} so as to be consistent with the chiller thermodynamic model described below. This is an important criterion in that models for the different components should be formulated in terms of as few physical and climatic parameters as possible in order to minimize the number of channels that need to be monitored during the in-situ testing. Several other authors (for example Hydeman, 1997) have also proposed slightly different variants of such polynomial models. Therefore, we propose to evaluate these generic models with the monitored data collected in the framework of this research.

3.6.1.2 Thermodynamic models

In contrast to polynomial models, which have no physical basis (merely a convenient statistical one), thermodynamic models are based on thermodynamic considerations for a chiller. Such models are preferred because they generally have fewer model parameters that appear in a functional form with a scientific basis. Hence the model coefficients tend to be more robust, leading to sounder model predictions. Currently there is only one such thermodynamic model, which has appeared in two forms, described below.

3.6.1.2a Complete Gordon-Ng model

The complete chiller model proposed by Gordon and Ng (1994,1995) and by Gordon et al. (1995) is a simple, analytical, universal model for the chiller performance based on thermodynamic considerations and linearization of heat losses. These thermodynamic models were also recommended bin RP-827 (Phelan et al., 1997b). The model predicts the dependence of chiller COP (defined as the ratio of chiller (or evaporator) thermal cooling capacity Q_{evap} divided by the electrical power consumed by the chiller (or compressor) P_{comp}) with certain key (and easily measurable) parameters such as the fluid (water or refrigerant) return temperature from the condenser T^{in}_{cond} , fluid temperature leaving the evaporator (or the chilled water supply temperature to the building) T^{out}_{evap} , and the thermal cooling capacity of the evaporator. The complete Gordon-Ng model is a three-parameter model which takes the following form for model parameter identification by regression:

$$\left(\frac{1}{COP}+1-\frac{T^{in}_{cond}}{T^{out}_{evap}}\right)Q_{evap} = -A_0 + A_1 T^{in}_{cond} - A_2 \frac{T^{in}_{cond}}{T^{out}_{evap}} \qquad (3.4)$$

from which the three parameters are identified by multiple linear regression.

3.6.1.2b Simple Gordon-Ng model

Uniform and systematic procedures for in-situ field measurements of centrifugal chillers were also developed/proposed by Phelan et al. (1997) under the ASHRAE RP-827 project in order to be able to use the Gordon-Ng chiller model to evaluate annual electrical energy consumption and peak demand loads. They found that many chiller systems, in which in-situ tests are being performed during one season of the year, do not exhibit the required variation in T^{in}_{cond} and T^{out}_{evap} to support a model such as given by eq.(3.4). Under such conditions a simpler two-parameter model has been advocated, namely:

$$\frac{1}{COP} = -c_0 + \frac{c_1}{Q_{evap}} \qquad (3.5)$$

3.7 In-situ testing of chillers

Phelan et al. (1997b) also found that the simple Gordon-Ng model identified from in-situ data does an excellent job of predicting the total electricity consumed by the chiller (a difference of only 0.54% is reported on a seasonal basis) while the predicted maximum demand is poorer but acceptable (with a difference of 4.3% from the measured maximum). Haberl et al. (1997) have also presented results of an analysis involving predicting electricity use and demand of a chiller during different summer months of the year using chiller parameters identified from in-situ chiller measurements. Since the results of this study are directly relevant to the objectives of this research, we shall describe the procedure and the conclusions of the Phelan et al.,(1997b) and Haberl et al., (1997) studies.

Haberl et al. (1997) used hourly monitored data during the entire cooling season to determine predictive accuracy of three chiller modeling approaches, namely: (i) the complete Gordon and Ng model (Gordon and Ng, 1994, 1995), (ii) the simplified Gordon and Ng model (which was advocated by Phelan et al. (1997b) in the framework of the ASHRAE RP-827 in-situ chiller measurement project), and (iii) the quadratic functional form used by DOE-2 to model part-load equipment and plant performance. The comparison has been made by identifying chiller model parameters from monitored hourly data of chiller under passive conditions, (i.e, normal operation from two different periods): (a) from the first 10 days of May, and (b) from two days each of May, June, July, August and September, in order to illustrate the corresponding differences in prediction accuracy which may result from the choice of the time of the year during which the in-situ test is performed.

The study by Haberl et al., (1997) applied the three above models to monitored data from the ASHRAE RP-827 site in Texas in order to predict chiller power during a complete summer period. The site is Victoria High School located in Victoria, Texas, and is the same one used by Phelan et al., (1997b). Two water-cooled centrifugal chillers supply cooling to approximately 257,000 square feet of conditioned space. All HVAC equipment operate only during occupied hours, i.e. from 6:00 a.m. till 8:00 p.m.. The HVAC system is manually shut down during unoccupied periods and weekends. The analysis which follows is based on monitored data from one chiller only.

Monitoring equipment was installed as part of the Texas LoanSTAR program (Haberl et al., 1996) which included monitoring the following at an hourly time scale:

(a) evaporator thermal load, Q_{evap}

(b) compressor power, P_{comp}

(c) Supply and return chilled water flows (only the supply temperature T_{evap}^{out} is actually needed by the model)

(d) cooling water supply and return temperatures (only the inlet temperature to the condenser T_{cond}^{in} is actually needed by the model)

(e) other quantities such as electricity used by the pumps and the flow rate to the evaporator are also measured, but do not appear in the model.

The procedure to evaluate how well the three chiller models fare as in-situ models consists of identifying the model parameters from a relatively short data period (akin to an in-situ test) and determining the accuracy of the model in predicting hourly P_{comp} values during an entire summer, (specifically May to September 1996). Since model parameters of building energy related equipment are usually better identified from regressor data, an earlier premise was that the in-situ test procedure would yield more representative model parameters if the monitoring time scale of one hour be reduced so that initial transients would provide the needed variability. Thus, one minute data was gathered during two days in summer for model parameter identification. The one minute data was not compatible with the resolution of the digital measuring instrument and so 5 minute averaging of the data was performed as described by Figueroa (1997). However, it was found that the model identified from one day's data gave a bias in predicting P_{comp} when applied to data from the other test data. Since the Gordon-Ng model is applicable to steady-state performance, it is clear that the model parameters should not be identified from a start-up transient test (which contain dynamic conditions) in an effort to obtain a larger scatter in the range of variation of the regressor variables (namely, T_{evap}^{out}, T_{cond}^{in} and Q_{evap}). It is better to use part of the hourly monitored data itself, and study the predictive accuracy of the corresponding model over the entire summer period.

In a effort to systematically study the prediction accuracy of the three chiller models whose parameters have been identified from in-situ data, Haberl et al. (1997) have considered two different periods containing the same number of hourly data: (a) data taken from one season only (first 10 days of May 1996), and (b) data taken from several months (2 days each from the 5 months, namely May, June, July, August and September). It is obvious that in-situ test (b) would provide a wider range of variation in the regressor variables than would 5 days in May alone, and hence allow more representative model parameters to be identified. The general conclusions of the study were as follows:

(a) the simple Gordon-Ng model (eq. 3.5) allows accurate prediction of monthly chiller electricity use and demand irrespective of the time of the year from which in-situ tests are performed in order to determine model parameters. The prediction accuracy for monthly energy use is less than 3% while that for demand is less than 3.5%. Both these findings are in general agreement with those of Phelan et al. (1997b).

(b) the tri-quadratic model (eq. 3.2) is very accurate only when the model parameters are identified from monitored data that cover the full range of variation of climatic and load variation which the chiller is likely to experience; otherwise it is very unstable and can give grossly misleading predictions.

(c) the complete Gordon-Ng model (eq. 3.4) has little to recommend it in predictive accuracy. For water cooled chillers, the variation in the water entering the chiller may not be enough to support such a model. Hence only in climates and for chillers which are operated and controlled such that they experience large variations in T_{evap}^{out} and T_{cond}^{in} during the year is there a merit in considering such a model.

(d) It is very important to realize that the Gordon-Ng model is strictly applicable for steady-state operation of the chiller and should not be used to predict COP or power use during start up or shut-down periods (which may be of the order of one hour or more in many cases). Note that the model was originally developed and validated from steady-state data gathered from laboratory tests by Gordon and Ng (1994, 1995). Though Gordon et al., (1995) have applied the model to chiller data in the field as a case study, there seems to be a need for energy and chiller equipment professionals to better understand and appreciate the finer nuances of analyzing in-situ chiller performance data in the framework of the various chiller models. We propose to passively analyze monitored chiller data from another site the same way as described in the Haberl et al. (1997) paper for the site of Victoria, TX, in order to assure ourselves of the generality of these conclusions.

3.8 Summary of Analytical Models for Chillers, Fans and Pumps

This document reviewed existing literature on in-situ test methods for fans, pumps and chillers so that appropriate performance models can be identified to be used for long-term performance prediction. Since an ASHRAE project (RP-827) was recently completed, we propose to largely use their recommendations. However, there are some alternate models for fans, pumps and chillers which have been described in this document, and which we shall evaluate with monitored data gathered in the framework of this research project. The thrust of this research is towards developing and evaluating in-situ test methods and models for the TES system, while those of the associated equipment are less of a concern given that it was researched by RP-827.

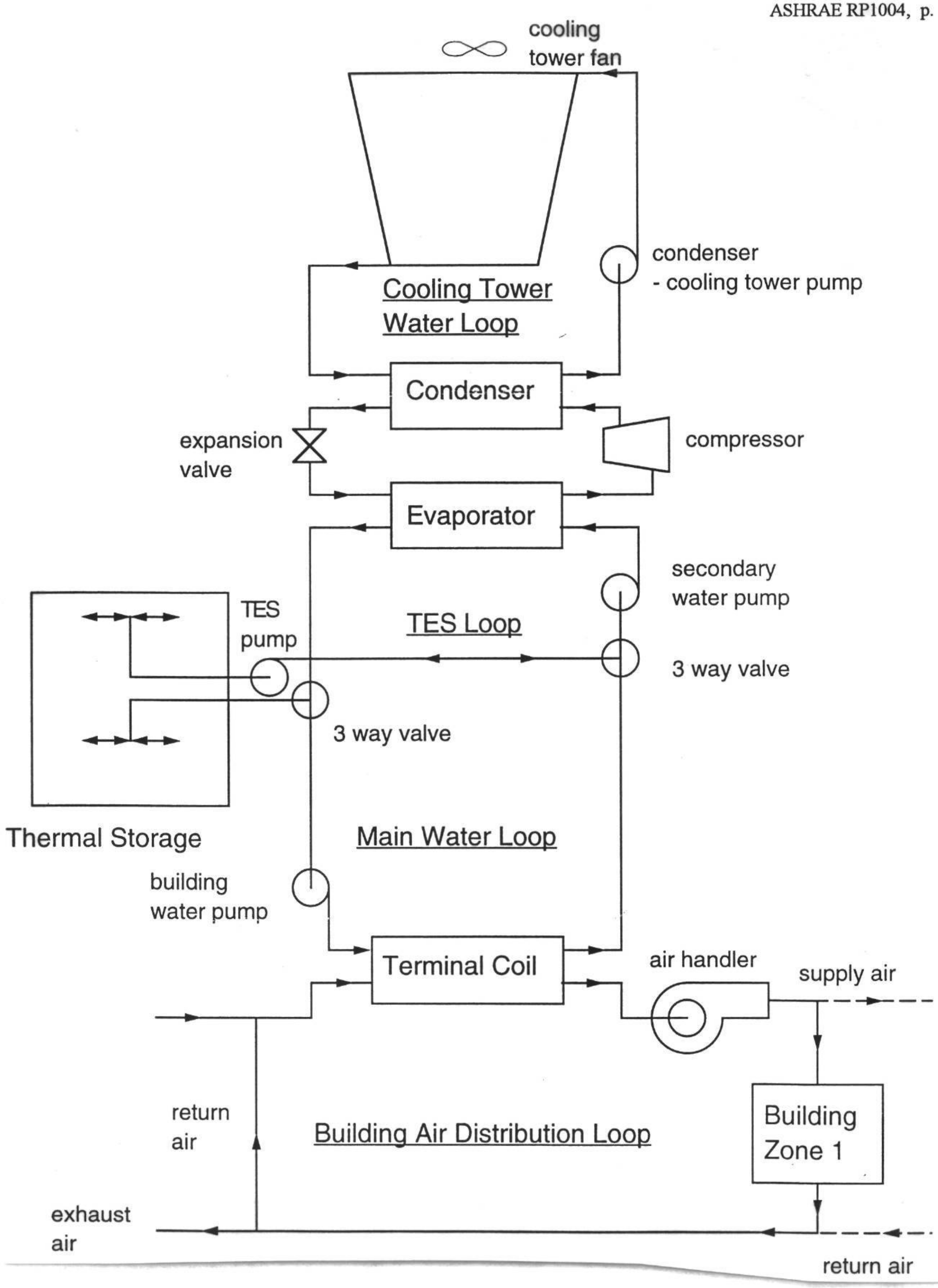


Figure 3.0 Schematic of combined building HVAC system and thermal storage system (Braun 1992).

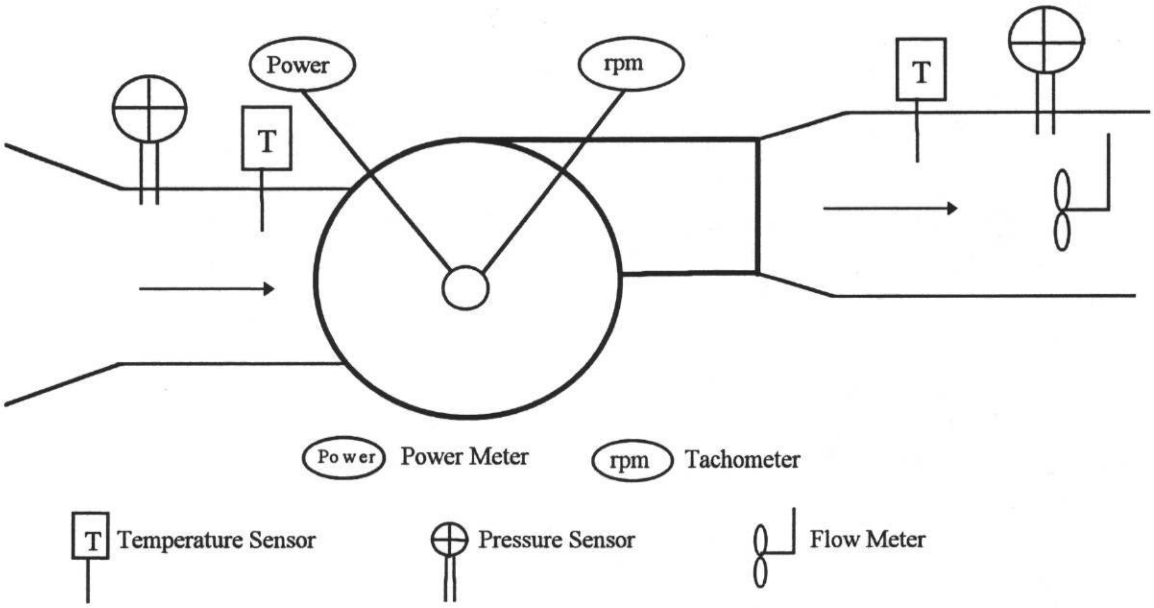
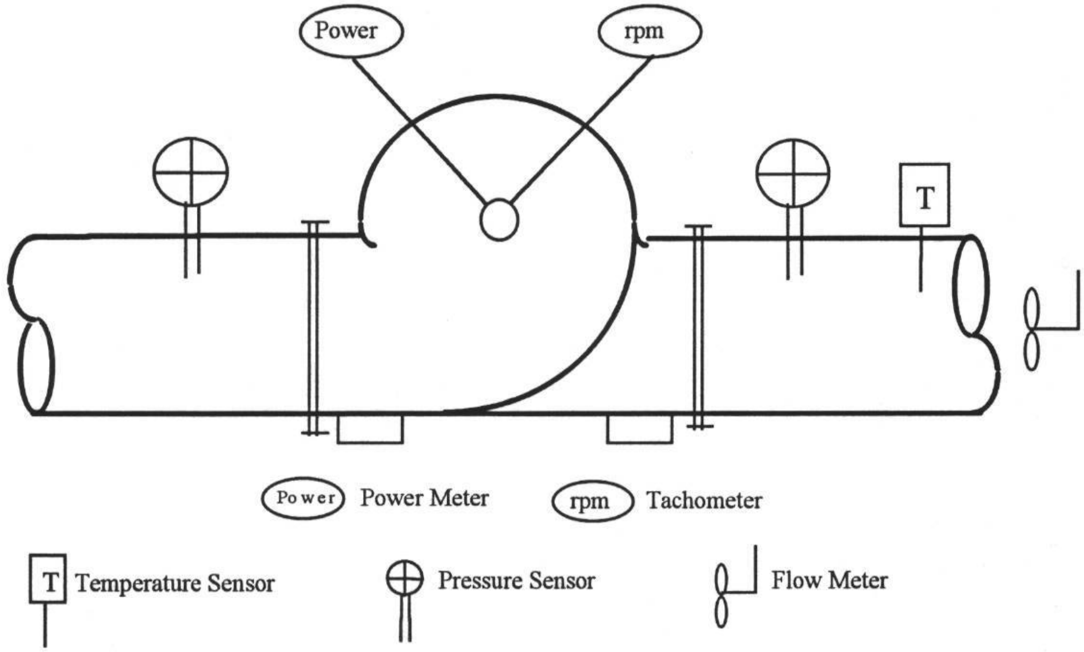


Figure 3.1: Typical Centrifugal Fan with Minimum Required Instrumentation (from Phelan et al., 1997a)



Figure

Figure 3.2: Typical Centrifugal Pump with Minimum Required Instrumentation (from Phelan et al., 1997a)

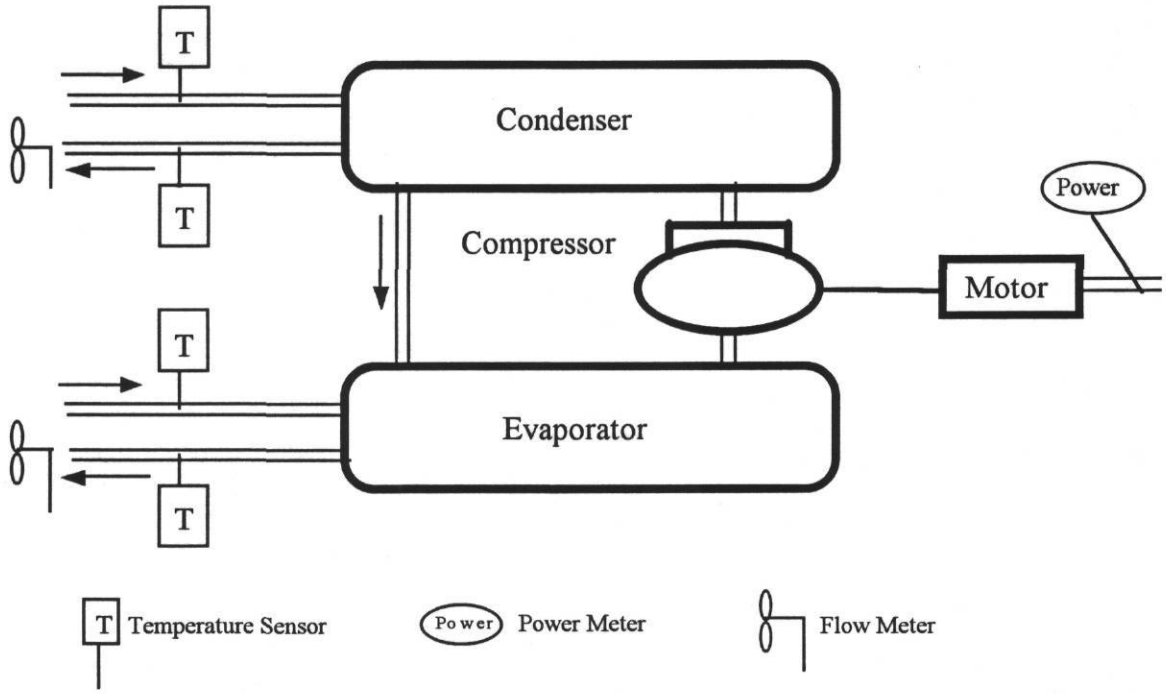


Figure 3.3: Typical Chiller with Minimum Required Instrumentation (from Phelan et al., 1997b)

4.0 DETERMINATION OF THE LONG-TERM PERFORMANCE OF COOL STORAGE SYSTEMS

4.0 Background.

A method for determining the long-term performance of cool storage systems should include the following steps:

- Carry out field performance testing. This step requires definition of the following:

    a. Data points to be monitored

    b. Appropriate monitoring period

    c. Data collection procedures

- Determine the annual load frequency distribution.
- Characterize the performance of the cool storage system during the monitoring period.
- Estimate the annual performance of the cool storage system with the annual load distribution.
- Define an appropriate comparison system.
- Characterize the performance of the comparison system.
- Estimate the annual performance of the comparison system with the annual load distribution.

Each of these steps is discussed below.

4.1 Field Performance Testing

ARI (n.d.) described a laboratory test method for the purpose of rating cool storage devices at a specific test condition. NAESCO (1993) outlined a basic method of determining thermal storage system energy and demand savings. ASHRAE Standard 150P (ASHRAE n.d.) included instrumentation requirements, methods for verifying instrument accuracy, and information required prior to testing. EPRI (1988) provided recommendations for monitoring cool storage systems. Gillespie (1997) described instrumentation selection, installation, and uncertainty issues for monitoring a cool storage system. Hensel et al. (1991) determined flow to and from a chilled water storage tank by correlating pitot-tube measurements with a mass balance based on orifice-plate measurements at other locations in the system. Dorgan and Dorgan (1995) and Dorgan et al. (1995) described methods for data verification and post-processing.

4.1.1 Data Points to be Monitored

Our review indicates that minimum data points to be monitored include the electric demand and energy use of the chiller(s) and auxiliaries, and the thermal energy (cooling) supplied to or from storage, chiller(s), and load. Requirements for monitoring individual temperatures and flow rates will be determined in Task 2 for the specific analytical approach(es) evaluated under that task. Instrumentation requirements will be defined according to the recommendations of ASHRAE Standard 150P (ASHRAE n.d.).

4.1.2 Appropriate Monitoring Period

The monitoring period must be short enough that it will be practical to apply. However, it must be long enough, and occur at an appropriate time of year, to capture sufficient variation in loads to accurately predict long-term performance. A two-week data collection period is proposed as a starting point. The length and appropriate season of the data collection period will be evaluated in Task 2.

4.1.3 Data Collection Procedures

The specific data to be collected will be determined by the selected approach for characterizing the system performance. The test methods will be in accordance with the requirements of ASHRAE Standard 150P (ASHRAE n.d.) where applicable.

4.2 Determine the Annual Load Frequency Distribution

Depending on the selected analytical approach, the load frequency distribution may be defined in terms of day-type, outdoor temperature-time of day bins, or mode of system operation. Determination of load frequency distributions is discussed in detail in a separate section of the report.

4.3 Characterize the Performance of the Cool Storage System During the Monitoring Period.

Two possible simulation schemes have been identified for characterizing the cool storage system performance:

- Chronological or hour-by-hour simulation, performing a calculation for each of 8760 hours in the year.

- Characteristic daily profile approach, whereby the cool storage system operation is characterized on the basis of 24-hour daily cycles.

Bou Saada and Haberl (1995a, 1995b) described the use of weather daytyping for characterizing building energy usage. Baughman et al. (1993) developed a “characteristic days method” for evaluating cool storage system performance. Daily cooling coil loads (kBtu/day) were found to be correlated with the peak daily temperature. A set of fifteen days was selected to represent the range of variation of cooling coil loads over the year. Performance of a cool storage system was estimated for each of these days using a computer model. Each month of the year was characterized according to the number of each of the characteristic day-types occurring in the month. (Presumably weather data for a typical year was used to perform this characterization.) The storage system demand and energy use for each month was determined from the maximum demand and total energy use of the day-types in the month.

We anticipate that the characteristic daily profile approach will involve defining a number of representative daily load profiles, in terms of the daily peak load, the high temperature for the day, or some other appropriate parameter. The response of the cool storage system to each of these daily load profiles is modeled in detail. Monthly and annual load distributions are defined in terms of the number of occurrences of each of the representative daily profiles. Annual performance is determined by multiplying the results for each profile by the number of occurrences. Details of this approach will be developed under Task 2.

Elovitz (1990) used a spreadsheet-based method to estimate savings of several proposed thermal storage systems, using a degree-hour method based on bin data to estimate annual load distributions. This concept will be considered for applicability to the Task 2 development of methodologies.

In addition to the two simulation schemes, we shall consider three different types of modeling approaches:

- Individual component models of each piece of equipment
- Simplified lumped component physical models for each mode of system operation
- Simplified lumped regression or "black-box" models for each mode of system operation

The two component modeling approaches involve selecting appropriate model parameters to characterize the cool storage system operation and its performance in response to building loads, and in that sense, are similar to the calibrated simulation approach of ASHRAE Guideline 14P (ASHRAE n.d.).

The individual component modeling approach would simulate the performance of each individual chiller, pump, heat rejection device, and storage device, in response to the appropriate temperatures and flow rates, for each time step. Simulation of these components is discussed in a separate section of the report.

The storage device model should capture the heat transfer and fluid dynamic processes in the storage tank. Several authors have described models for simulation of cool storage devices. Jekel (1991), Jekel et al. (1993), Vick et al. (1996a, 1996b), Neto and Krarti (1997a, 1997b), and Drees and Braun (1995) have developed models for internal melt ice-on-coil systems. Silver et al. (1989) modeled an external melt ice-on-coil system. Strand et al. (1994) and Pederson et al. (n.d.) describe the development of models for internal melt, encapsulated ice, and ice harvester systems, and their implementation in the BLAST program. Gretarsson et al. (1994) developed a model for stratified thermal storage. Zurigat (1989) surveyed stratified thermal storage tank models and compared several of the models against experimental data.

The component model approach also requires a characterization of the cool storage system operating strategy. Braun (1992), Drees and Braun (1996), Ruchti et al. (1996), and Kawashima et al. (1996) discussed conventional and optimized cool storage operation and control strategies. We will use these references, and recent unpublished work by Elleson, to incorporate appropriate modeling of operating strategies.

The simplified lumped component model would be limited to simulation of four generalized components:

- building loads,
- chiller,
- storage, and
- auxiliaries (pumps and fans).

Several authors have addressed the use of single indices to describe cool storage system performance. Tran et al. (1989) described the use of the Figure of Merit to characterize the measured thermal performance of six chilled water storage systems. Rosen et al. (1988) discussed the use of exergy analysis, rather than energy analysis, for the evaluation of sensible thermal energy storage systems. Rosen (1992) developed several definitions of energy and exergy efficiency for sensible thermal energy storage, for the overall storage process and for charging, storing, and discharging periods. These indices may be applicable for use with the simplified lumped component model approach.

The "black-box" models would be based on empirical or semi-empirical correlations of the system's responses to load conditions. The system model, developed by regression, ANN, or other techniques, returns the daily cooling system demand and energy use as a function of maximum daily load, and possibly of day of week, time of year, or other parameters. The load frequency distribution is expressed in terms of the maximum daily load as a function of weather, and possibly of day of week, time of year, or other parameters.

The two component modeling approaches can be used in conjunction with either the hour-by-hour or characteristic daily profile simulation schemes. The "black-box" modeling approach would be most effectively used with the characteristic daily profile simulation scheme.

In Task 2, the simulation schemes and modeling approaches will be evaluated in more detail and compared in terms of implementation cost, reliability, and uncertainty.

4.4 Estimate the Annual Performance of the Cool Storage System

The annual system performance is determined by combining the cool storage system model with the load frequency distribution.

- For the *component model* approach, the model is run with hourly loads for the year.

- For the *characteristic daily profiles* approach, the performance for each characteristic profile is multiplied by the number of occurrences of each of the representative daily profiles.

- For the *lumped system model* approach, the model is run with the daily peak loads for the year.

4.5 Define an Appropriate Comparison System

The primary goals of the proposed RP1004 methodology are to determine energy savings and demand shift. Therefore, it will be critical to address how the comparison system or "base case" is to be defined.

The simplest case is one where: 1) the storage system uses a chiller that is clearly of the same type that would have been used in a non-storage system, and 2) there is some operation of the storage chiller at "conventional" chilling temperatures. The practitioner can determine the chiller performance for conventional operation, and apply this performance to the annual loads.

The problem is more difficult in cases where

1. The storage cooling plant is of a different type than the most likely non-storage alternative. For example, chiller vs. DX, air-cooled vs. water-cooled, multiple chiller types or sizes. The methodology must address how to determine the comparison system's performance characteristics.

2. There is no obvious choice for the system type that "would-have-been" installed in place of the storage system. The methodology must address how to determine the comparison system type.

3. The storage system has been designed with a "total system" approach, incorporating design features such as a large chilled water temperature range, cold air distribution, an innovative pumping configuration, or a nonstandard condenser flow rate. The methodology must address to what extent auxiliary energy savings stemming from these features are credited to the cool storage system, or whether they might also have been achieved with a non-storage system.

4. Actual performance falls short of the design intent or the manufacturers' equipment ratings. The methodology must address whether a non-storage system would also have fallen short.

Akbari and Sezgen (1992) provided a methodology for comparing measured TES performance with modeled nonstorage system performance. EPRI (1988) provided recommendations for defining a simulated nonstorage system for performance comparison. Merten et al. (1989) described measured performance of six cool storage systems monitored during 1987, and seven systems monitored during 1988, and also describe a method for determining the appropriate efficiency for the simulated nonstorage comparison system. Liu et al. (1994) used an average kW/ton vs. percent full load performance curve, based on field data from 30 centrifugal chillers, to determine base-case system performance for comparison with cool storage field data collected by Merten et al. (1989). Sohn (1989, 1991a, 1991b) described the results of field monitoring of three ice storage systems, and a comparison with nonstorage system performance. Abbas et al. (1995) and Abbas et al. (1996) presented results of field monitoring at seven cool storage sites.

Our intention is for the RP1004 methodology to provide guidance for addressing these issues, but it would be impossible to provide prescriptive methods that would apply to every case. Ultimately, the basis for defining the base case that determines "savings" and "demand shift" will need to be specified up front by the party that is interested in determining these quantities. Therefore, we will seek guidance from the RP 1004 Project Monitoring Subcommittee regarding this issue.

4.6 Characterize the Performance of the Comparison System

The performance of the comparison system is characterized by the same method as that of the cool storage system.

4.7 Estimate the Annual Performance of the Comparison System

The annual performance of the comparison system is determined by the same method as that of the cool storage system.

5.0 PROPOSED METHODOLOGIES FOR PERFORMING UNCERTAINTY ANALYSIS

5.1 Objectives

The need for uncertainty analysis and its methodology is well documented in the literature, and there are several textbooks which treat this subject with varying levels of detail. A proper uncertainty analysis can be very complex and cumbersome especially if the potential user strives to be very meticulous. There are three good references in the HVAC literature which we draw attention to: ASHRAE Guideline 2-1986 (ASHRAE, 1990), ASHRAE RP-827 (Phelan et al.,1997) and Appendix B of ASHRAE Standard 150P on cool storage performance testing (ASHRAE, 1997). The last reference is especially pertinent to this research given that it applies to thermal energy storage (TES) systems and that a simplified and fairly complete treatment of the various sources of uncertainty and simplified ways to deal with them is provided.

The objective of this document is to outline how we propose to deal with the issue of uncertainty in the framework of the current research. We shall start with a brief discussion of the concept of uncertainty, present the causes of uncertainty in what we think is a novel outlook, outline how we propose to deal with (i) measurement errors in equations, (ii) errors related to the use regression models, (iii) errors arising from both measurement errors **and** the use of regression models, and (iv) errors in time series data.

5.2 Introduction

The concept of uncertainty is better understood in terms of confidence limits. Confidence limits define the range of values which can be expected to include the true value with a stated probability of obtaining that value (ASHRAE, 1990). Thus, a statement that the 95% confidence limits are 5.1 to 8.2 implies that the true value will be contained between the interval bounded by 5.1 and 8.2 in 19 out of 20 predictions, or more loosely, that we are 95% confident that the true value lies between 5.1 and 8.2. For a given set of n observations with normal or gaussian error distribution, the total variance (**var**) about the mean predicted value ($\bar{X}'$) provides a direct indication of the confidence limits. Thus the "true" mean value $\bar{X}$ of the random variable is bounded by:

$$\text{bounds of } \bar{X} = \bar{X}' \pm (t_{\alpha/2,n-1} \cdot \text{var}) = \bar{X}' \pm \frac{(t_{\alpha/2,n-1} \cdot \sigma)}{\sqrt{n}} \qquad (5.1)$$

where $t_{\alpha/2,n-1}$ is the t-statistic with probability of $(1-\alpha/2)$ and (n-1) degrees of freedom (tabulated in most statistical textbooks), and σ^2 is the estimated variance.

There are two separate sources of uncertainty or error (terms which we shall use interchangeably though others like Phelan et al., 1997a distinguish between both) when dealing with analysis of observed data such as that encountered in the framework of this research: (i) measurement errors, and (ii) prediction error due to the regression model. A clear conceptual understanding of when these arise is provided below.

Consider a model such as: $y = a_0 + a_1 . x_1 + a_2 . x_2$ where the x's are the independent variables and a's are model coefficients. An uncertainty in the variable y can arise from three sources:

(a) in case the coefficients a_0 , a_1 and a_2 are known with zero uncertainty (i.e., either they are constants or are values which one can look up from tables such as steam tables, for example). The uncertainty in the derived variable y is then only due to the measurement uncertainties present in the x's. How to determine the uncertainty in y for such models or equations is given by the "propagation of errors" formulae which most engineers are familiar with (and which is presented in section 3). An example of this type of uncertainty is when charging capacity of the TES system is deduced from measurements of mass flow rate and inlet and outlet temperature differences.

(b) when the x's are assumed to have no error in themselves but the coefficients a_0, a_1 and a_2 have some inherent error (as a result of identifying them from regression to measured data). We have prediction errors in the y variable under such a case since any regression model cannot explain the entire variation in the regressor variable (this source of error, called model prediction error, is addressed in section 4). An example of this source of uncertainty is when a simple regression model is used to predict building loads from outdoor temperature (T). If the measurement error in T is so small as to be negligible, then the uncertainty in predicting building loads falls in this category.

when both the x's and the coefficients a's have uncertainties, the former due to measurement errors and the latter because a regression model is identified from monitored data. The standard practice in classical regression analyses is to assume no measurement error in the regressor variables. Such an assumption is perhaps inadmissible for this research since we may then be placing too much confidence in our predictions, i.e., underestimating the uncertainty. An example of this source of uncertainty is when a polynomial model is used to predict pump electricity consumption from measured values of fluid flow rate (which inherently have non-negligible measurement errors). Although the statistical complexity is substantially enhanced when dealing with this case, we shall address this issue in the current research (see section 5 below).

Finally, we shall try, at a later stage during this research project, to simplify some of these formulae so as to be more usable by the ASHRAE community. This simplification will, however, not be attempted in this document but later on as monitored data becomes available and the validity of the simplifications can be tested.

5.3 Measurement uncertainty

5.3.1 Bias and random errors

Both measurement and model uncertainties consist of two types of error: a systematic or biased error (b) and a random or "white noise" error (ε). The terms accuracy and precision are often used to distinguish between bias and random errors. A set of measurements with small bias errors is said to have high accuracy, while a set of measurements with small random errors is said to have high precision (ASHRAE,1990). Since bias and random errors are usually uncorrelated, we can express measurement variance as:

$$\sigma^2_{meas}(b_m, \varepsilon_m) = \sigma^2(b_m) + \sigma^2(\varepsilon_m) \qquad (5.2)$$

The error sources of monitoring equipment can be further divided into: (i) calibration errors, (ii) data acquisition errors, and (iii) data reduction errors. The interested reader can refer to ANSI/ASME standard (1990) for a more complete discussion. Bias errors include: (i) those which are known and can be calibrated out by adjusting the data points after the measurements are made, (ii) those which are negligible and are ignored, and (iii) those which are estimated and are included in the uncertainty analysis.

It is usually cumbersome to perform an uncertainty analysis with data having known biases and this is treated in ASHRAE (1997). It is far simpler to remove known biases from the data prior to data analysis and only treat random errors. This is what will be done in the framework of this research.

As for the random errors, the well-known Kline and McClintock (1953) method, described in section 3.2, is widely used to determine measurement uncertainties in the derived variables.

5.3.2. Propagation of random errors (Kline and McClintock, 1953).

The uncertainty in a measurement or variable x is described by specifying the expected or mean value $\bar{x}$ for the variable followed by the absolute uncertainty Δx at a certain confidence level (usually 90% or 95%). This is written as: $x = \bar{x} \pm \Delta x$. In general, the uncertainty Δy of a function $y = y(x_1, x_2, .., x_n)$ whose independently measured variables are all given with the same confidence level, is obtained by the first order expansion of the Taylor series (ASHRAE, 1997):

$$\Delta y = [(\sum_{i=1}^{n} \frac{\partial y}{\partial x_i} \Delta x_i)^2]^{1/2} \qquad (5.3)$$

For some of the basic operations:

addition or subtraction: $y = (x_1 \pm x_2),\ \Delta y = (\Delta x_1^2 + \Delta x_2^2)^{1/2}$ (5.4)

multiplication: $y = (x_1) * (x_2),\ \Delta y = [(\frac{\Delta x_1}{x_1})^2 + (\frac{\Delta x_2}{x_2})^2]^{1/2}$ (5.5)

division: $y = (x_1) / (x_2),\ \Delta y = \frac{\Delta x_1}{\Delta x_2}[(\frac{\Delta x_1}{x_1})^2 + (\frac{\Delta x_2}{x_2})^2]^{1/2}$ (5.6)

For multiplication and division, the fractional error is given by the same expression. Say R = xy/z. Then

$$\frac{\Delta R}{R} = [\frac{\Delta x^2}{x^2} + \frac{\Delta y^2}{y^2} + \frac{\Delta z^2}{z^2}]^{1/2} \qquad (5.7)$$

In many cases, deriving partial derivatives of complex analytical functions could be a tedious affair and is error-prone mathematically. A simple computer routine could be written to perform the task of calculating uncertainties without resorting to analytical methods (Holman and Gajda, 1994). Such a method is based on approximating partial derivatives by finite differences as follows.

Let $y = y(x_1, x_2, \ldots x_n)$. Then

$$\frac{\delta y}{\delta x_1} = \frac{y(x_1 + \Delta x_1, x_2 \ldots x_n) - y(x_1, x_2 \ldots x_n)}{\Delta x_1}$$
$$\frac{\delta y}{\delta x_2} = \frac{y(x_1, x_2 + \Delta x_2 \ldots x_n) - y(x_1, x_2 \ldots x_n)}{\Delta x_2} \qquad \text{etc..} \qquad (5.8)$$

These approximations can be introduced into any equation to determine the uncertainty in the result. This method is most convenient for complicated functional forms or for sets of simultaneous equations. The types of equations encountered in this research are usually simple equations or polynomials, which we shall use to a large extent.

5.4 Uncertainty due to regression models

5.4.1 Different sources of error

The determination of prediction errors from using regression models is subject to different types of problems. The various sources of error can be classified into three categories (Reddy et al.,1992):

(a) Model mis-specification errors which are due to the fact that the functional form of the regression model is usually an approximation of the true driving function of the response variable. Typical causes are: (i) inclusion of irrelevant regressor variables or non-inclusion of important regressor variables (for example, neglecting humidity effects); (ii) assumption of a linear model, when the physical equations suggest non-linear interaction among the regressor variables; and (iii) incorrect order of the model, i.e., either a lower order or a higher order model than the physical equations suggest. Engineering insight into the physical behavior of the system helps minimize this type of error.

(b) 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. In essence, this uncertainty arises because even though the "exact" functional form of the regression model may be known, the model parameters are random variables as a result of randomness in the regressor and response variables.

(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. Models identified from short data sets, which do not satisfactorily represent the annual behavior of the system, will be subject to this source of error. Although we cannot quantify this error in statistical terms alone, but we can suggest experimental conditions to be satisfied which are likely to lead to accurate predictive models. The prediction of building loads from short-term in-situ tests will suffer from this type of error.

Both sources (a) and (c) are likely to introduce bias and random error in the predictions. If ordinary least squares (OLS) regression is used for parameter estimation and if the model is subsequently used for prediction, error due to source (b) will be purely random with no bias. Thus, models identified from short data sets and used to predict seasonal or annual energy use are affected by both (a) and (c) sources of error. The best way to minimize all the above sources of error is to calibrate the instruments properly (so as not to have any bias errors) and increase the number of data observations (or sampling points) and take observations under different operating conditions that cover the entire range of variation of system operation.

It should be noted that no statistical assumptions regarding the errors need be made in obtaining OLS parameter estimates. Information regarding the model residuals or errors is required only when one wishes to specify confidence limits of these parameter estimates (Beck and Arnold, 1977).

Finally, the statistically efficient way of dealing with improper residual behavior (i.e., residuals which have non-constant variance or show distinct patterns implying a serial correlation) is not to use OLS but to use other regression schemes which will yield unbiased parameter estimates and narrower confidence intervals. This is probably too demanding statistically for most ASHRAE members, and an alternative approach, is to use OLS parameter estimates but to widen the confidence intervals. Papers by Reddy et al., (1994), Ruch et al., (1997) and Reddy et al., (1998) discuss these issues, especially as they pertain to statistical models for building energy use. Such sources of error are usually secondary compared to the model prediction error and make the error analysis much more complex. We propose to evaluate such effects with the data gathered in this research project, and overlook such effects if they are small.

5.5 Prediction error of single variate linear models

Let us consider a simple linear model given by $y = a + b.x$ which has been used to perform a least squares regression to monitored x and y data. This regression equation can be used to predict future values of y provided the x value is within the domain of the original data from which the model was identified. We differentiate between the two types of predictions, as follows:

A mean response is where we would like to predict the mean value of y for a large number of repeated x_0 values. The mean value is directly deduced from the regression equation while the variance is (Draper and Smith, 1982):

$$\mathrm{var}(\hat{y}_0) = MSE.[\frac{1}{n} + \frac{(x_0 - \bar{x})^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}] \tag{5.9}$$

where MSE is the mean square error of the model, given by

$$MSE = \sum (y_i - a - b.x_i)^2 / (n-2) \tag{5.10}$$

in the case of the simple linear model with two parameters.

(b) <u>An individual or specific response</u> where we would like to predict the specific value of y for a specific value x_0. The specific response is directly deduced from the regression equation but its variance is larger than the previous case and is given by (Draper and Smith, 1982):

$$\mathrm{var}(\hat{y}_0) = MSE.[1 + \frac{1}{n} + \frac{(x_0 - \bar{x})^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}] \tag{5.11}$$

Thus the 95% confidence interval for the individual response at level X_0 is:

$$\mu_0 = \hat{y}_0 \pm t_{0.025}.\mathrm{var}(\hat{y}_0) \tag{5.12}$$

where $t_{0.025}$ is the value of the t-student distribution at an error level of 0.025 or 2.5% (i.e., a two-tailed error distribution is assumed). In eq.(5.12) the confidence intervals for individual responses will be wider than those of the mean response

(c) <u>sum of values</u> where we would like to determine the error in the sum of n values. For example, we would like to determine the uncertainty in the electric power consumed by a pump during the entire year where the hourly pump consumption is determined by using a regression model. If the sum is made up of n predictions, we could determine the uncertainty in each prediction and then use eq. (3.3.) to determine the uncertainty in the sum. It is often simpler to do a bin type of calculation, and the appropriate equations are presented by Phelan et al. (1997).

<u>5.6 Prediction error of multi-variate (or polynomial) regression models (Draper and Smith, 1981)</u>

When dealing with multiple regression, it is advantageous to resort to matrix algebra because of the compactness and ease of manipulation it offers. Consider a data set of n readings that include k regressor variables. The corresponding multiple linear regression model is:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + \varepsilon \tag{5.13}$$

Note that the same model formulation (as well as the subsequent error analysis provided the prediction range is within the range used to identify the model) is equally valid to polynomial models of the following type (Montgomery and Runger, 1994):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_1^2 + \ldots + \beta_k x_1^k + \varepsilon \qquad (5.14)$$

Let x_{ij} denote the i[th] observation of parameter j. Then eq.(4.13) can be re-written as a linearized equation:

$$y = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} + \varepsilon_i \qquad (5.15)$$

In matrix notation (with **y'** denoting the transpose of **y**), eq.(4.13) can be expressed as follows (with the matrix dimension shown as subscripted brackets):

$$\mathrm{Y}_{(n,1)} = \mathrm{X}_{(n,p)} \beta_{(p,1)} + \varepsilon_{(n,1)} \qquad (5.16)$$

where p is the number of parameters in the model = k+1

and $\mathrm{Y}' = [y_1\ y_2 \ldots y_n]$, $\beta' = [\beta_0\ \beta_1 \ldots \beta_k]$, $\varepsilon' = [\varepsilon_1\ \varepsilon_2\ \ldots \varepsilon_n]$

$$\text{and } \mathrm{X} = \begin{bmatrix} 1 & x_{11} & .. & x_{1k} \\ 1 & x_{21} & .. & .. \\ .. & .. & .. & .. \\ 1 & x_{n1} & .. & x_{nk} \end{bmatrix} \qquad (5.17)$$

The classical least-squares approach used by the majority of analysts is the OLS method where the parameter set β is determined such that the sum of squares function is minimized. This results in the regression coefficients being determined from the following equation:

$$\hat{b} = (\mathrm{X}'\mathrm{X})^{-1}\mathrm{X}'\mathrm{Y} \qquad (5.18)$$

provided matrix **X** is non-singular and where **b** is the least square estimator matrix of β

Pure regression models, even when they fit the data extremely well, should not be blindly used for predictions outside the range of variation of the original data. One has a better chance of doing so with models based on engineering (such as thermodynamic or heat transfer) considerations specially if the model parameters are estimated accurately. It is practically impossible to statistically determine the uncertainty or variance of predictions outside the range of variation of the original data. Hence, the short-term to long-term prediction of building loads, for example, which is part of this research, defies a rigorous uncertainty analysis. The only recourse is to estimate the prediction uncertainty under specific case studies during which year-long monitored data is available, and assume that the error would be approximately the same for other instances as well. (This type of reasoning is what has been implicitly done in the framework of the ASHRAE RP-827 research, Phelan et al., 1997). Also, since we shall be comparing two alternatives, i.e., without (the baseline case) and with the TES system, the large uncertainty in the load profile determination is likely to affect both alternatives equally, thus minimizing its importance to this research.

However, for predictions within the range of variation of the original data, the equations for determining the variance in model predictions are well known.

(a) For the mean response at a specific set of x_0 values, the variance is:

$$\mathrm{var}(\hat{y}_0) = \sigma^2 [\mathbf{X_0}(\mathbf{X'}\,\mathbf{X})^{-1}\mathbf{X'_0}] \qquad (5.19)$$

where **1** is a column vector of unity.

Confidence limits at a significance level α are: $y_0 \pm t(n-k, \alpha/2).\,\mathrm{var}^{1/2}(\hat{y}_0)$ (5.20)

(b) The variance of an individual prediction is

$$\mathrm{var}(\hat{y}_0) = \sigma^2 [\mathbf{1} + \mathbf{X_0}(\mathbf{X'}\,\mathbf{X})^{-1}\mathbf{X'_0}] \qquad (5.21)$$

(c) For the sum of m individual responses, the prediction error is given by Theil (1971):

$$\mathrm{var}[\sum_{j=1}^{m}(y_j)] = \sigma^2 \{\mathbf{1'}[\mathbf{X_0}(\mathbf{X'X})^{-1}\mathbf{X'_0} + \mathbf{I}].\mathbf{1}\} \qquad (5.22)$$

where **I** is an identity matrix, i.e., a diagonal matrix of unity. Note that pre and post multiplying the matrix within the square brackets by an unit vector is akin to summing all the elements of the matrix.

5.7 Uncertainty of models identified with error in the regressor variables

How to determine prediction uncertainty of models identified from data where the regressor variables had inherent measurement errors is extremely complex statistically. Most of the standard text-books (for example, Draper and Smith, 1982) do no more than cursorily acknowledge this case without providing the appropriate mathematical equations. However, this type of uncertainty has direct bearing on this research; for example, the electric power consumed by a fan or pump is a polynomial function of the fluid flow rate, which can only be measured to within 8-10% uncertainty in the field. We have been able to identify a book (Fuller, 1987) which treats this subject thoroughly. We shall apply the equations in that book to the current research.

5.8 Uncertainty in time series data

Time series data used to determine charging or discharging capacity of TES systems needs to be handled differently from the cases described above. A fairly complete discussion is provided in Annex B of the proposed ASHRAE standard 150P (ASHRAE,1997). We propose to use the procedures described in that standard as a starting point for our own research.

5.9 Concluding remarks

This document reviews the various sources of uncertainty which have to be explicitly considered in our research. Appropriate equations of how we propose to determine the uncertainty in our predictions are also presented. We realize that the statistical equations to determine prediction uncertainty of regression models other than the simple one variable regression model are complex and may be beyond the comprehension of most energy professionals. Consequently, as part of this research, we shall forsake some statistical rigor and endeavor to simplify these equations to a level that practicing engineers could use.

6.0 CANDIDATE TEST SITES

This section of the contains a complete list of sites that were considered candidates for monitoring for the ASHRAE RP 1004 project. In the first column is the agency or university where the system is located followed by the site contact, phone and FAX number. In the next column the design engineering firm and design engineer are then listed with phone and FAX number. This is followed by the chiller capacity, thermal storage capacity, chiller type, chiller manufacturer, storage type, storage manufacturer. Finally, each site was asked whether or not they would be willing to participate in the ASHRAE project and whether or not the plans were available for photocopying.

Table 6.1: Complete list of Thermal Storage sites considered for the RP 1004 project.

Site	Site Contact	Site Phone #	Site Fax #	Design Engineer	Design Phone #	Chiller Capacity	Thermal Capacity	Chiller Type	Chiller Manuf	Storage Type	Storage Manufacturer	Willing to Monitor?	Plan Availability
Del Mar	Mike Snyder	512-886-1642	512-886-1920	ACR Engr	512-440-8333	2 @ 1000	16700 ton-h	centrifugal	Trane,	CHW	CBI	Y	Y
College				Austin, TX	Rajeesh	tons each	(calculated)		Westinghouse				
					Kapileshwari								
Midland County	Bill Decker	915-688-8940	915-688-8903	FEULS	512-331-5181	1 @ 250	8 @ 160	screw	Trane	Ice	Calmac	Y	Y
Courthouse				Austin, TX	David Parr	tons	ton-h each			Internal melt			
Ward Memorial	Maynard Clark	915-943-2511	915-943-3679	Fannin&Fannin	806-745-2533	1 @ 130	1100 ton-h	rotary	Trane	CHW	Scott Manuf.	undecided	Y
Hospital				Lubock, TX	Jack Roberts	tons	ton-h						
TSTC	Jerry Behrens	956-425-0687	956-425-0688	Gomez-Garza	956-546-0110	450 ton	5560 ton-h	screw	Trane	H2O	Built on-site	N	??
				Brownsville, TX	Pete Garza	500 ton	(calculated)	centrifugal	McQuay		Converted from		
											water treatment plant		
UH Clear Lake	Doug Willenberg	281-283-2250	281-283-2257	Cohn & Daniels		475 ton	6800 ton-h	screw	Vilter	Ice		undecided	Y
				OR Joe Consella	214-337-8300					Exter. melt			
Oppe Elementary	Justin Gordon	409-762-8181	409-765-6248	Building Environmental		1 @ 188	665 ton-h	D/X	York	ice	N/A	N	Y
School				Engineering		1 @ 45							
				Ft. Worth									
Weis Middle	Justin Gordon	409-762-8181	409-765-6248	Building Environmental		2 @ 120	902 ton-h	D/X	York	ice	N/A	N	Y
School				Engineering		1 @ 60							
				Ft. Worth									
Parker Elementary	Justin Gordon	409-762-8181	409-765-6248	Building Environmental		3 @ 100	862 ton-h	D/X	York	ice	N/A	N	Y
School				Engineering		1 @ 60							
				Ft. Worth									
Morgan Elementary	Justin Gordon	409-762-8181	409-765-6248	Building Environmental		3 @ 100	1038 ton-h	D/X	York	ice	N/A	N	Y
School				Engineering		1 @ 70							
				Ft. Worth									
Rosenberg Elementary	Justin Gordon	409-762-8181	409-765-6248	Building Environmental			800 ton-h	D/X	York	N/A	N/A	N	Y
School				Engineering									
				Ft. Worth									
Austin Convention	Rudy Farias	512-404-4300	512-404-4352	Page-Southerland-	512-472-6721	2 @ 600	8260 ton-h	centrifugal	McQuay	Ice	Fafco	Y	Y
Center				Page Austin, TX		tons each				Internal melt			
EPCC Valle Verde	Cecil Lance	915-594-2556	915-594-2551	RBM Engr	915-584-9934	1 @ 300	5475 ton-h	centrifugal	Trane	ice	N/A	Y	Y
						ton							

Site	Site Contact	Site Phone #	Site Fax #	Design Engineer	Design Phone #	Chiller Capacity	Thermal Capacity	Chiller Type	Chiller Manuf	Storage Type	Storage Manufacturer	Willing to Monitor?	Plan Availability
EPCC Trans Mountain	Cecil Lance	915-594-2556	915-594-2551	RBM Engr	915-584-9934	1 @ 200	2280 ton-h	screw	Trane	ice	N/A	Y	Y
						ton							
MHMR 673 Terrel	Ken McDonald	972-563-6452	972-551-0101	ACR Engr	512-440-8333	1 @ 200	7000 ton-h	rotary	Trane	CHW	PDM	Y	Y
				Austin, TX	Rajeesh	ton	supplied by						
					Kapileshwari	1 @ 120	a combination	screw	Multistack	CHW		Y	Y
						ton	of the six						
MHMR 676 Terrel	Ken McDonald	972-563-6452	972-551-0101	ACR Engr	512-440-8333	1 @ 240	chillers in 4	screw	Multistack	CHW	PDM	Y	Y
				Austin, TX	Rajeesh	ton	different						
					Kapileshwari		mechanical						
MHMR 680 Terrel	Ken McDonald	972-563-6452	972-551-0101	ACR Engr	512-440-8333	1 @ 275	rooms	rotary	Trane	CHW	PDM	Y	Y
				Austin, TX	Rajeesh	ton							
					Kapileshwari								
MHMR 686 Terrel	Ken McDonald	972-563-6452	972-551-0101	ACR Engr	512-440-8333	2 @ 425		centrifugal	Carrier	CHW	PDM	Y	Y
				Austin, TX	Rajeesh	ton each							
					Kapileshwari								
USA CERL	Chang Sohn	217-398-5424	217-373-3430	Univ of Illinois/CERL		2@175	1700	screw	York	encap		Y	Y
						ton each	ton-hours			Ice			

The sites in Table 6.1 were evaluated according to the following criteria:

- Over 1000 ton-hours storage capacity
- Provides for diversity in storage technologies
- Load profile is representative of common storage applications
- Available and accessible for testing
- Owner willing to cooperate
- Currently instrumented with all or most of required instrumentation.

The most promising sites are listed in the following table.

Table 6.2 Short List of Sites for RP1004 project.

Site	Storage Medium	Storage Technology	Storage Capacity (ton hours)
Midland County Courthouse	Ice	Ice internal melt	1160 TH
Del Mar College	Chilled Water	Stratified tank	One million gallons (7-10,000 TH)
Austin Convention Center	Ice	Ice internal melt	6000 TH
University of Houston, Clear Lake	Ice	Ice external melt	6,800 TH
CERL	Ice	Encapsulated Ice	1,700 TH

These sites will be further evaluated for their suitability for testing, and the final candidates will be selected with the concurrence of the PMS. The sites will be evaluated according to the following criteria:

- Over 1000 ton-hours storage capacity
- Provides for diversity in storage technologies
- Load profile is representative of common storage applications
- Available and accessible for testing
- Owner willing to cooperate
- Currently instrumented with all or most of required instrumentation.
- Datalogger
- Storage flow
- Temperature entering storage
- Temperature leaving storage
- Load Btu measurement, or flow and entering/leaving temperatures
- Chiller power
- Auxiliaries power

7.0 NOMENCLATURE

b	bias error
k	number of regression parameters in the model
n	number of observation points (months, days, hours,...)
p	number of model parameters (=k+1)
t	t-statistic
$\overline{X}$	mean value of X
$\hat{X}$	model predicted value of X
α	significance level
ε	random error
σ^2	estimated variance of the model error
var	model prediction uncertainty

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APPENDIX

Specific information for selected thermal storage monitoring sites.

SITE No.	SITE NUMBER	LOCATION	TYPE OF ST(
143	Delmar College	Corpus Christi, TX	Chilled water
144	Midland County Courthouse	Midland, TX	Internal melt -
230	Austin Convention Center	Austin, TX	Internal melt -
322	University of Houston - Clearlake	Houston, TX	External melt-

Site #143

Delmar College
Corpus Christi, TX

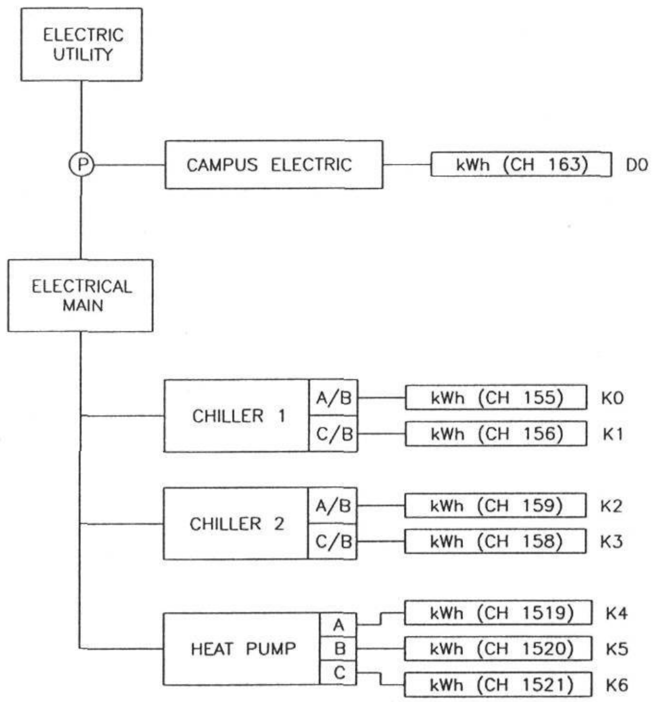
Chilled Water

)/YY)DD)	Time HH:mm	Raw-Data lin pos	coln pos	Arch coln pos	Name of Channel	Archive Units	Arch Format	Conv'n Code	Conv'n Constants	Error Code	Error Constants	Channel Description
/91	00:00	1	0	0	Begin	Del Mar						Beginning date
/91	00:00	1	1	1	Bldg. #	XX	I3	2	0 143	0		Building Number
/91	00:00	1	1	2	Mon-Raw	MM	I3	1		0		Month
/91	00:00	1	2	3	Mon-Raw	DD	I3	1		0		Day
/91	00:00	1	3	4	Mon-Raw	YY	I3	1		0		Year
/91	00:00	1	3	5	Greg-Jul	MMDDYY	I5	24	1 2	0		Gregorian Date to Julian
/91	00:00	1	4	7	Time	HH mm	I5	16	5	0		Time
/91	00:00	1	3	6	Greg-Dec	DDD.frac	F10.4	28		0		Gregorian Date to Jul.Decimal
/91	00:00	1	6	8	Chl AB	F9.3	F9.3	1		1	-5 500	Chiller 1 AB (kWh/h)
/91	00:00	1	7	9	Chl CB	F9.3	F9.3	1		1	-5 500	Chiller 1 CB (kWh/h)
/91	00:00	1	8	10	Ch2 AB	F9.3	F9.3	1		1	-5 500	Chiller 2 AB (kWh/h)
/91	00:00	1	9	11	Ch2 CB	F9.3	F9.3	1		1	-5 500	Chiller 2 CB (kWh/h)
/91	00:00	1	10	12	Chl S T	F9.3	F9.3	1		1	-5 200	Chl 1 Sup Temp (F)
/91	00:00	1	11	13	Chl R T	F9.3	F9.3	1		1	-5 200	Chl 1 Ret Temp (F)
/91	00:00	1	12	14	Ch2 S T	F9.3	F9.3	1		1	-5 200	Chl 2 Sup Temp (F)
/91	00:00	1	13	15	Ch2 R T	F9.3	F9.3	1		1	-5 200	Chl 2 Ret Temp (F)
/91	00:00	1	14	16	Campus E	F9.3	F9.3	1		1	0 15000	Campus Elec (kWh/h)
/91	00:00	1	15	17	Campus G	F9.3	F9.3	1		1	0 100000	Campus Gas (MCF)
/91	00:00	1	16	18	ChW1 Btu	F9.3	F9.3	1		1	0 100000	Chl 1 Energy (kBtu)
/91	00:00	1	17	19	ChW1Flow	F9.3	F9.3	1		1	0 100000	Chl 1 Flow (gal)
/91	00:00	1	18	20	ChW2 Btu	F9.3	F9.3	1		1	0 100000	Chl 2 Energy (kBtu)
/91	00:00	1	19	21	ChW2Flow	F9.3	F9.3	1		1	0 100000	Chl 2 Flow (gal)
/99	23:00	1	0	0	End	Del Mar						

DEL MAR COLLEGE
ELECTRICAL MONITORING DIAGRAM

LEGEND

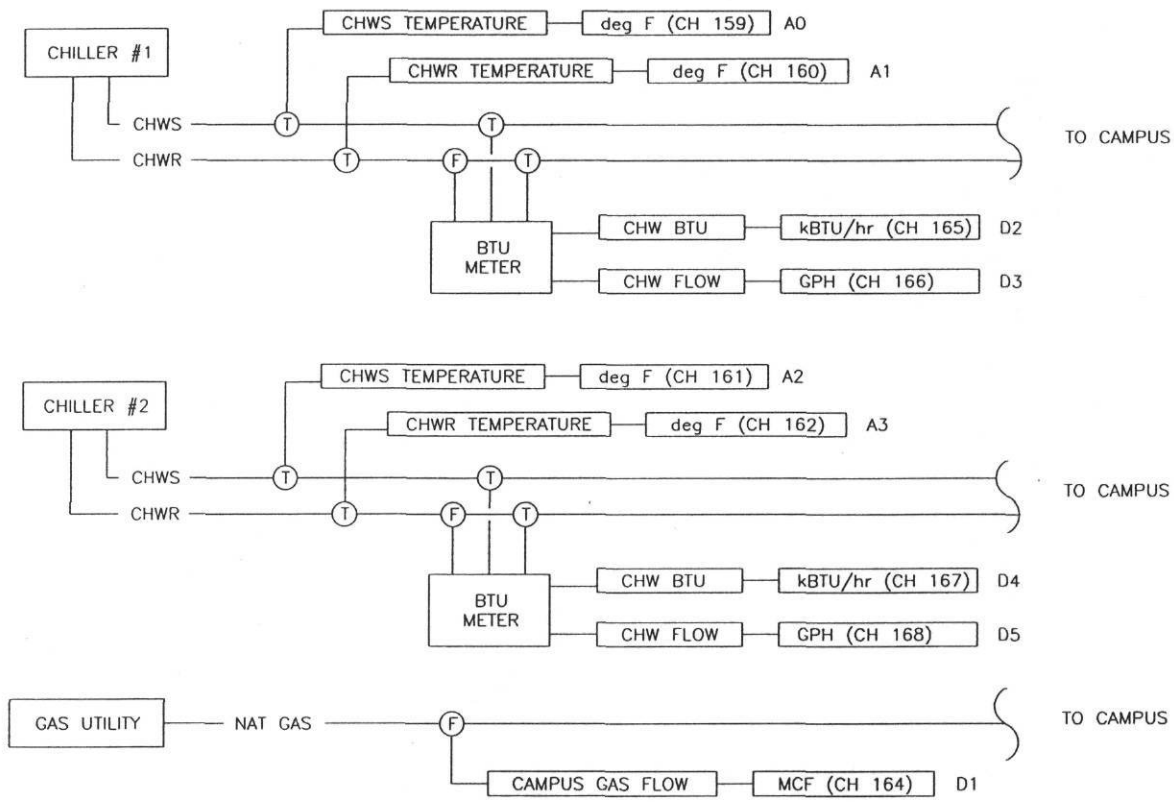
K=KWH CHANNEL
A=ANALOG CHANNEL
D=DIGITAL CHANNEL
P=PULSE METER



DEL MAR COLLEGE
THERMAL MONITORING DIAGRAM

LEGEND

K=KWH CHANNEL
A=ANALOG CHANNEL
D=DIGITAL CHANNEL
F=FLOW METER
GPH=GALLONS PER HOUR
CHWS=CHILLED WATER SUPPLY
CHWR=CHILLED WATER RETURN

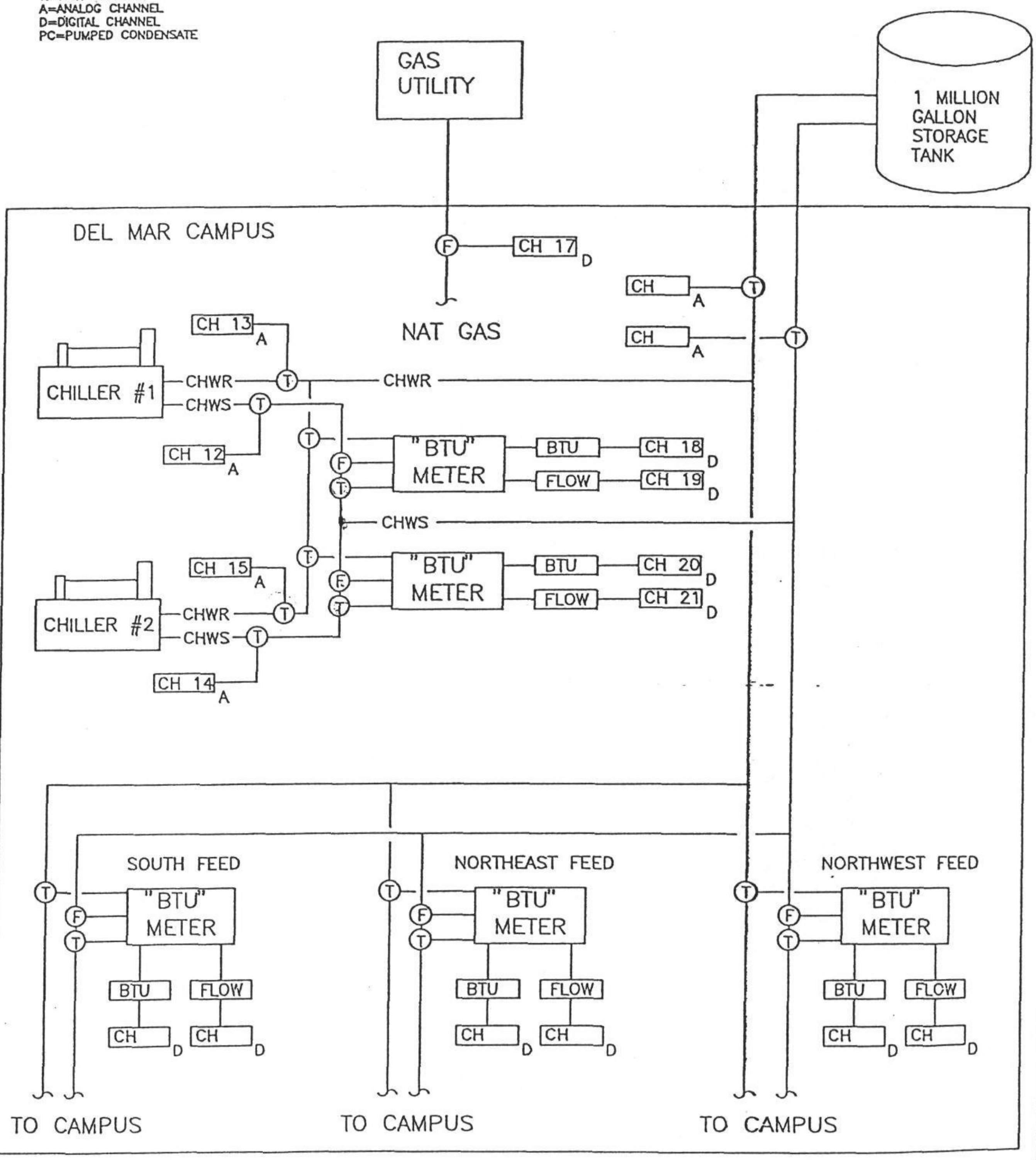


THERMAL MONITORING DIAGRAM

DEL MAR COLLEGE

LEGEND

K=KWH CHANNEL
A=ANALOG CHANNEL
D=DIGITAL CHANNEL
PC=PUMPED CONDENSATE



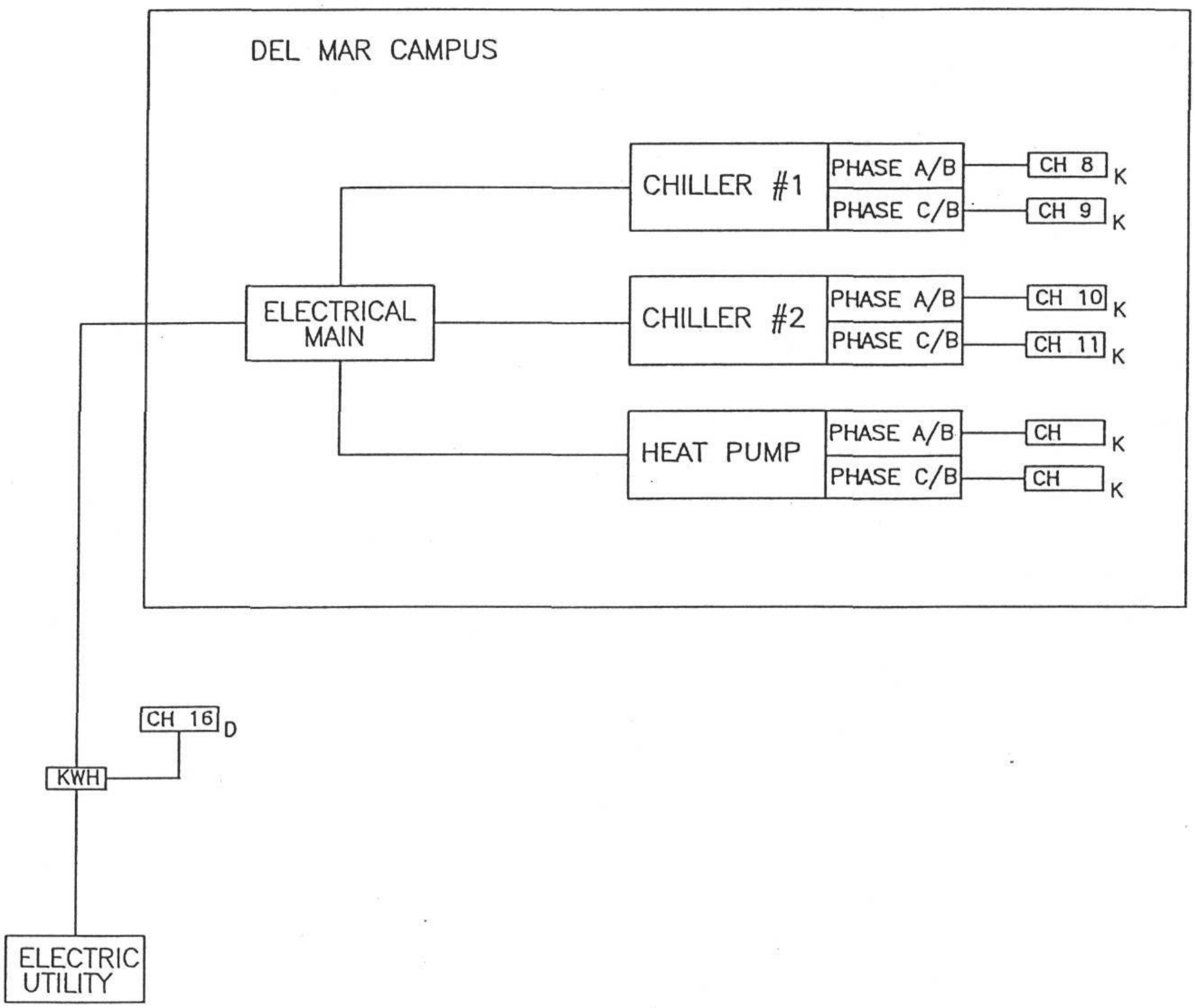
DEL MAR COLLEGE – SITE 143

ELECTRICAL MONITORING DIAGRAM

DEL MAR COLLEGE

LEGEND

K=KWH CHANNEL
A=ANALOG CHANNEL
D=DIGITAL CHANNEL



DEL MAR COLLEGE – SITE 143

DELMAR COLLEGE

Building Envelope:
- 681,592 sq. ft.
- 23 buildings, built in in 1940-present
- Conditioned floor area: 636,707 sq. ft.
- walls: variable construction
- windows: N/A
- roof: built-up flat

Building Schedule:
- Monday - Friday 7:30 am to 12:00 pm
- Saturday and Sunday - some buildings partially occupied

Building HVAC and Auxiliary Equipment
- Information for the individual AHUs in each building is not available. Campus has a mixture of single duct, double duct constant volume, variable volume and DX units. All the new buildings have variable volume system with DDC control.
- 1 - 1000 ton Trane Centrifugal Chiller
- 1 - 1000 ton Westinghouse Centrifugal Chiller
- Several DX units, total cooling capacity 300 tons
- 2 hot water boilers, 300 hp each

HVAC Schedule
- 24 hrs/day

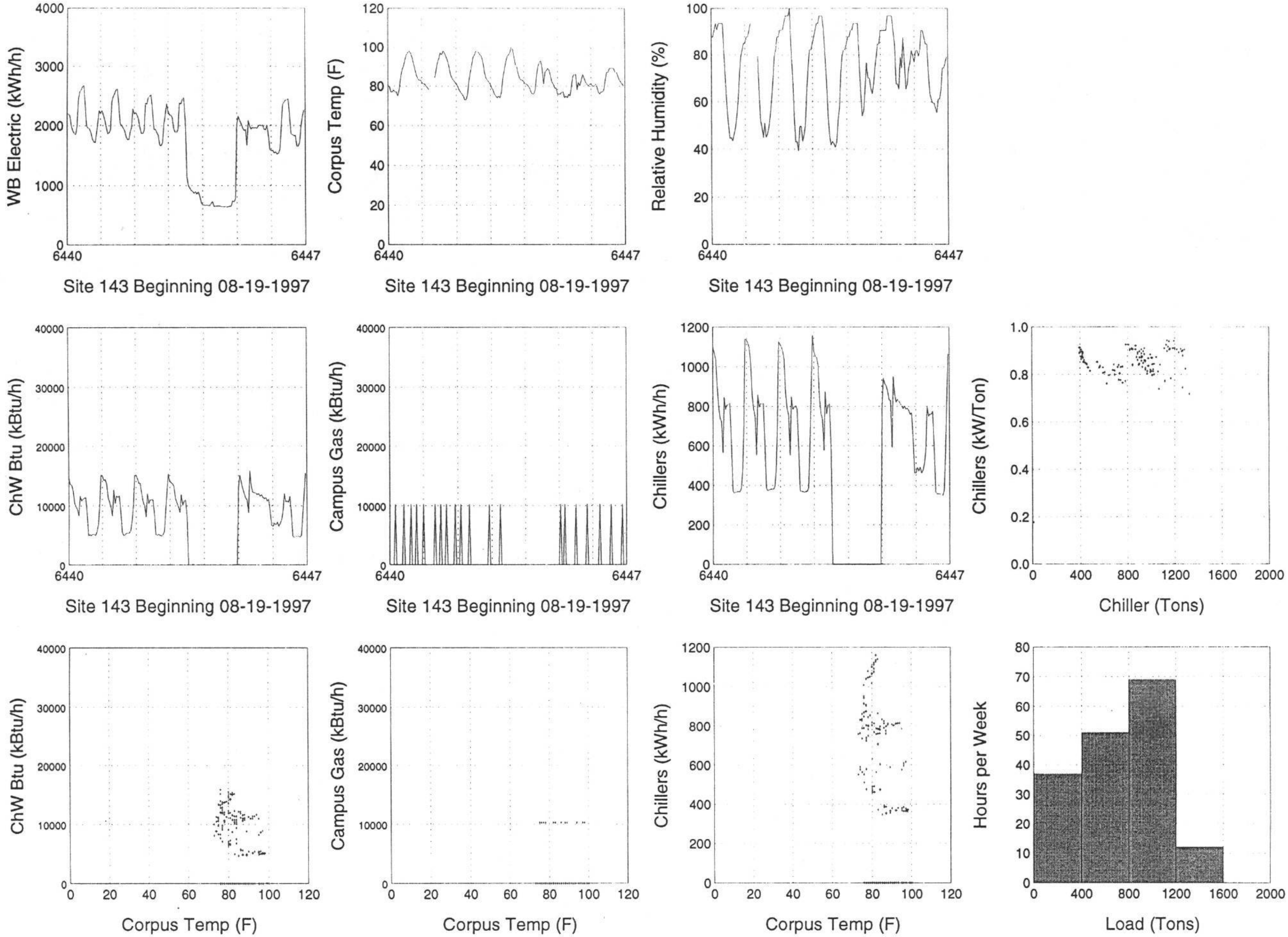
Lighting
- mixture of florescent, incandescent in the classrooms, offices, and corridors
- metal halides, H.P. sodium and L.P. sodium in the Gym, swimming pool, for parking and security lights.

Proposed Maintenance and Operation Measures
- None

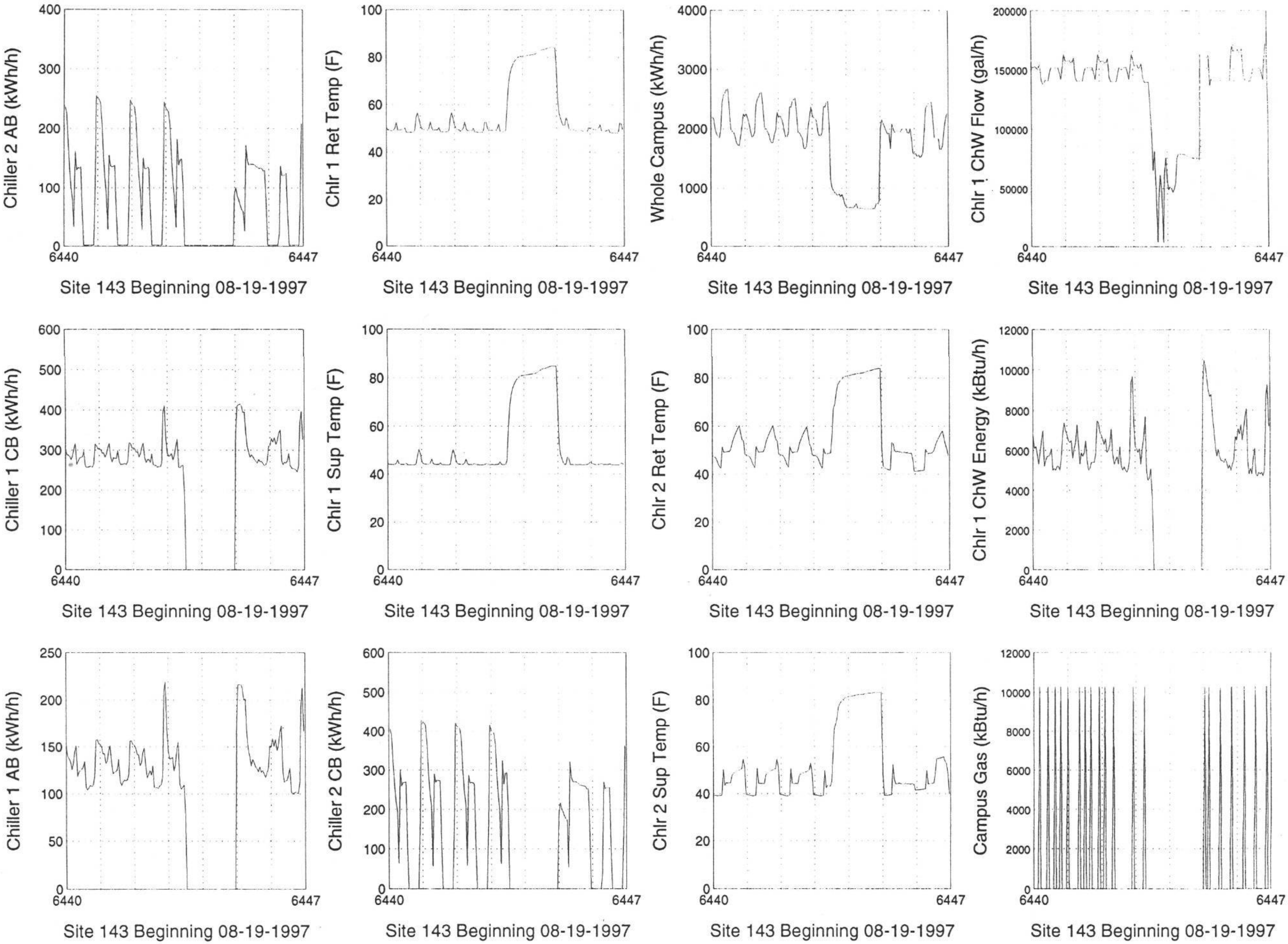
Proposed Retrofits
- thermal energy storage/industrial water source heat pump
- capacitors for power factor improvement
- interior lighting controls
- exterior lighting conversions
- fixture relamping
- Total loan amount $1,157,404 with audit estimated savings of $287,930/yr

Status of Retrofits
- Capacitors were installed in July 1992.
- Thermal storage system will be completed in November 1993. Heat pump became operational on June 30, 1993.

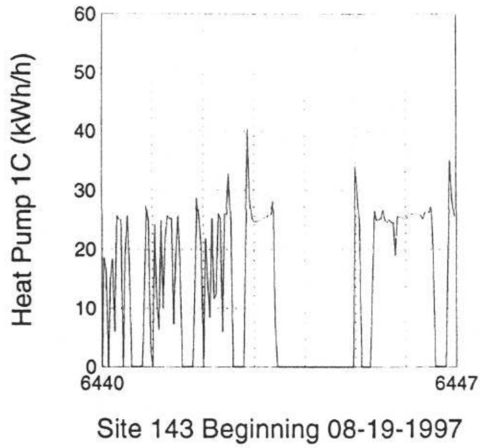
Site 143 Page 1

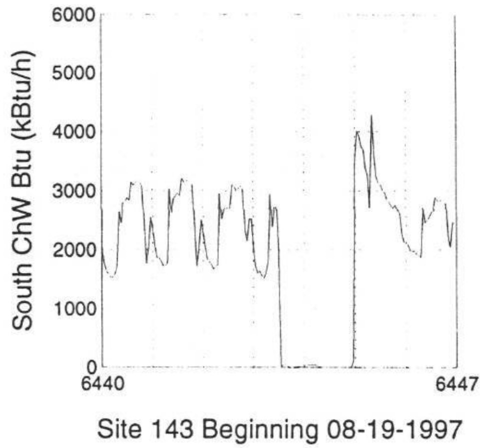


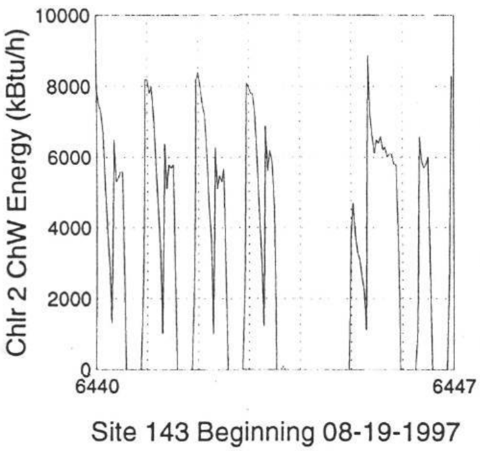
Site 143 Page 2

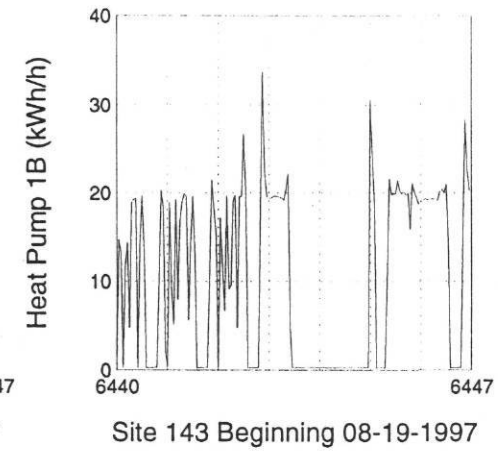


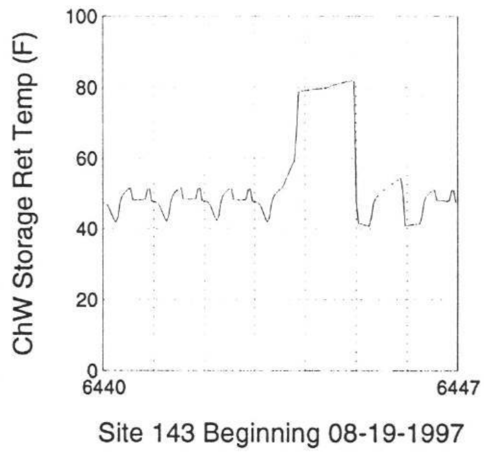
Site 143 Page 3

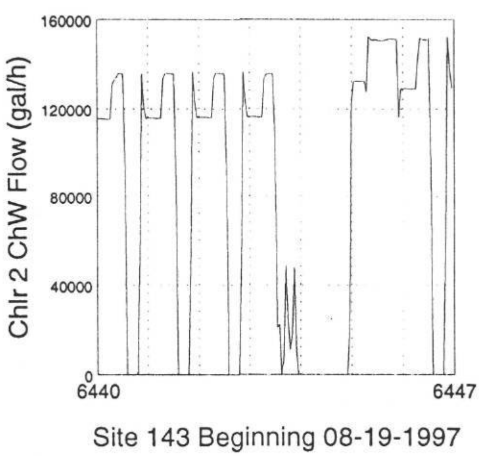


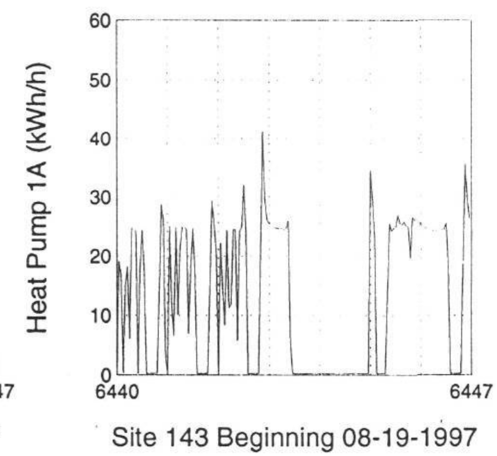


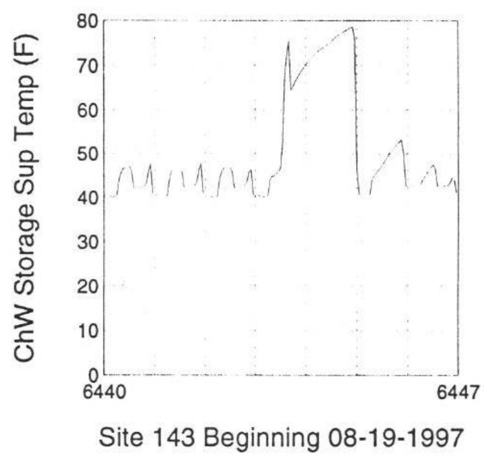


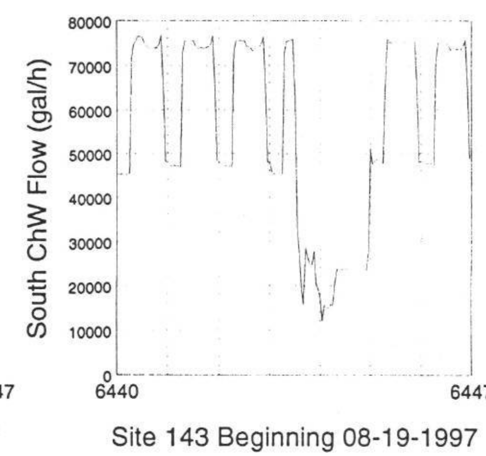












Delmar College

Whole Campus
636,702 square feet

Site Contact	LoanSTAR Metering Contact
Mr. Johnny L. White	Aamer Athar or Namir Saman
Director of Physical Facilities	053 WERC
Delmar College	Texas A&M University
Baldwin & Ayers	College Station, TX 77843-3123
Corpus Cristi, TX 78404	(409) 845–9213
(512) 886–1242	

Summary of Energy Consumption

	Measured Use	% hours reported	Unit Cost	Estimated Cost
Electricity	1446293 kWh	100	$0.02940	$42521
Peak 60 Minute Demand	2845 kW	100	$13.52	$38461
Chilled Water	6886.3 MMBtu	100	$6.000	$41318
Natural Gas	1699.5 MMBtu	100	$3.940	$6696

Peak 60 minute demand was recorded at 1200 Tuesday 06/17/97.
There were 720 hours in this month.

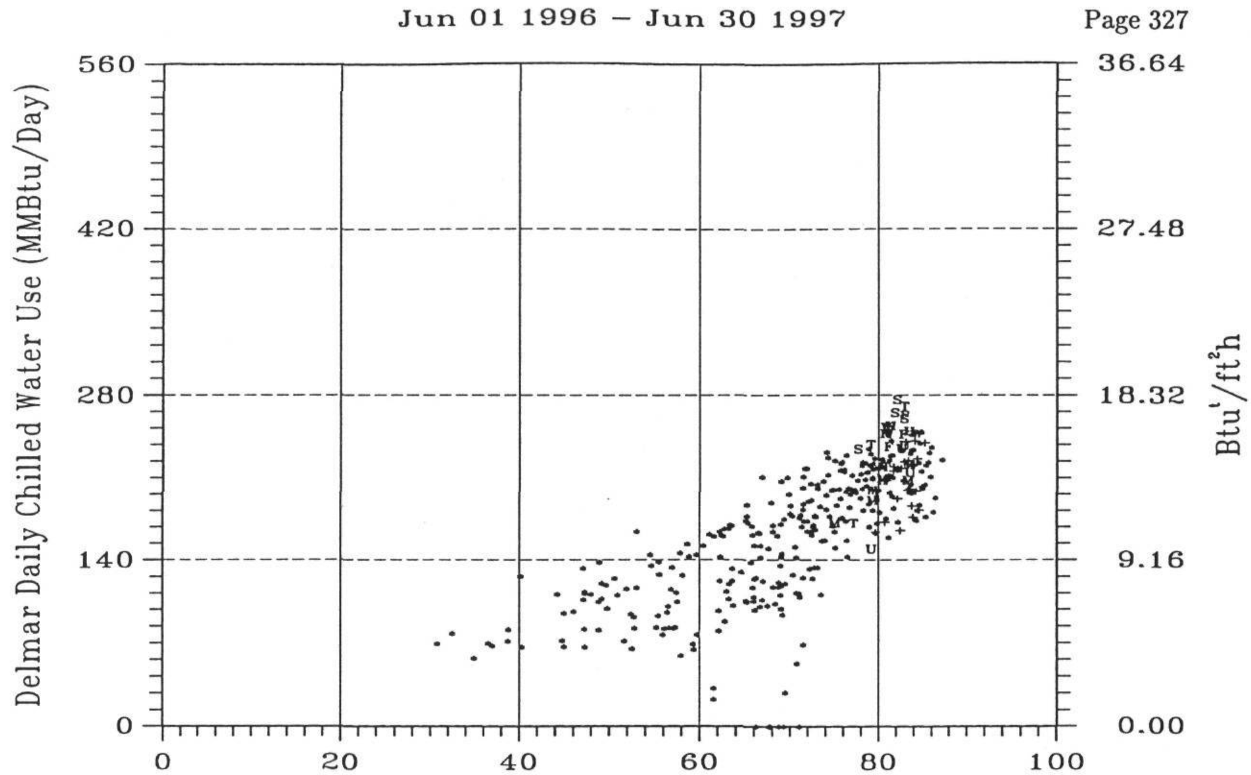
Monthly Retrofit Savings

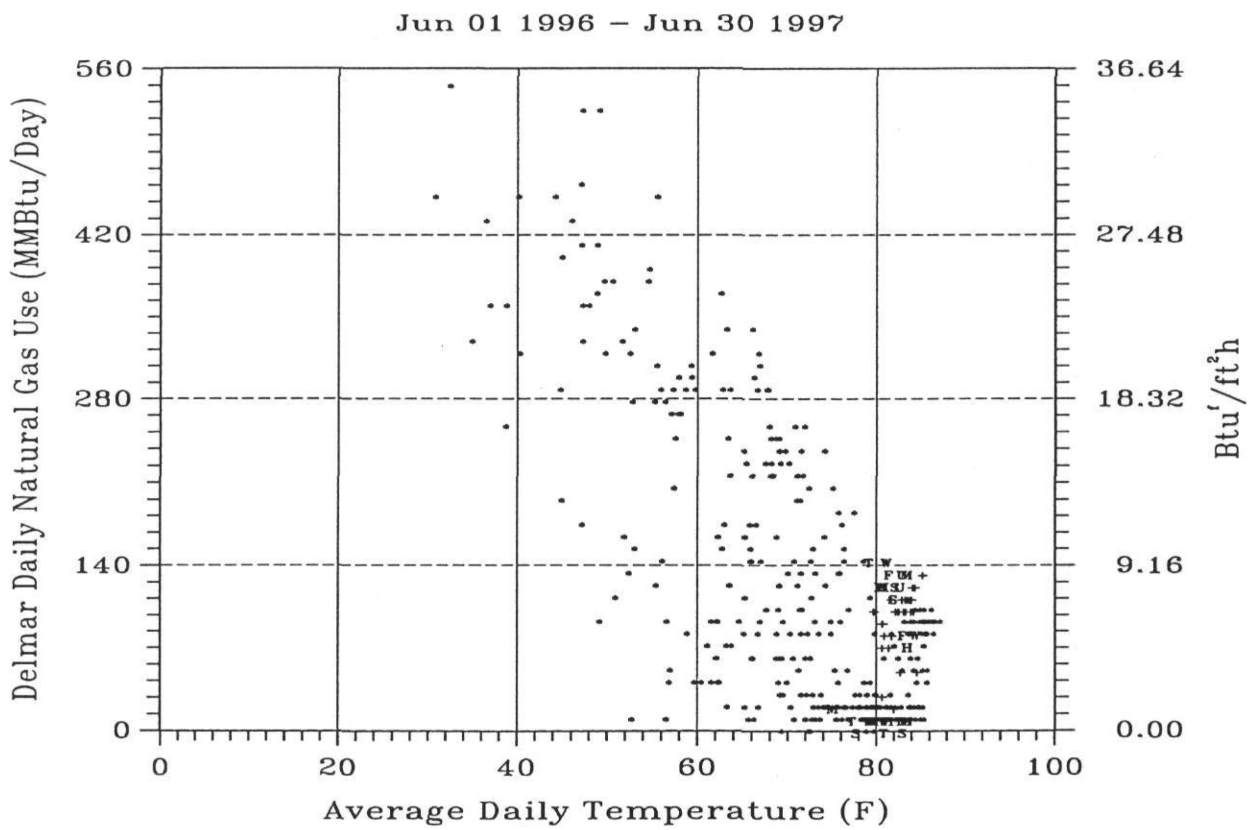
	Measured Savings		Audit Estimated Savings	
Electricity (kWh)	-38202	$-1123	-127565	$-3750
Electricity Demand (kW)	834	$11276	1139	$15399
Cond./H.W./N.G. (MMBtu)	3932	$15492	2079	$8191
Monthly Total		$25645		$19840
Total to Date*	(51 months)	$1468182	(48 months)	$844531

*Measured savings include construction period. Audit estimated savings do not.

Comments

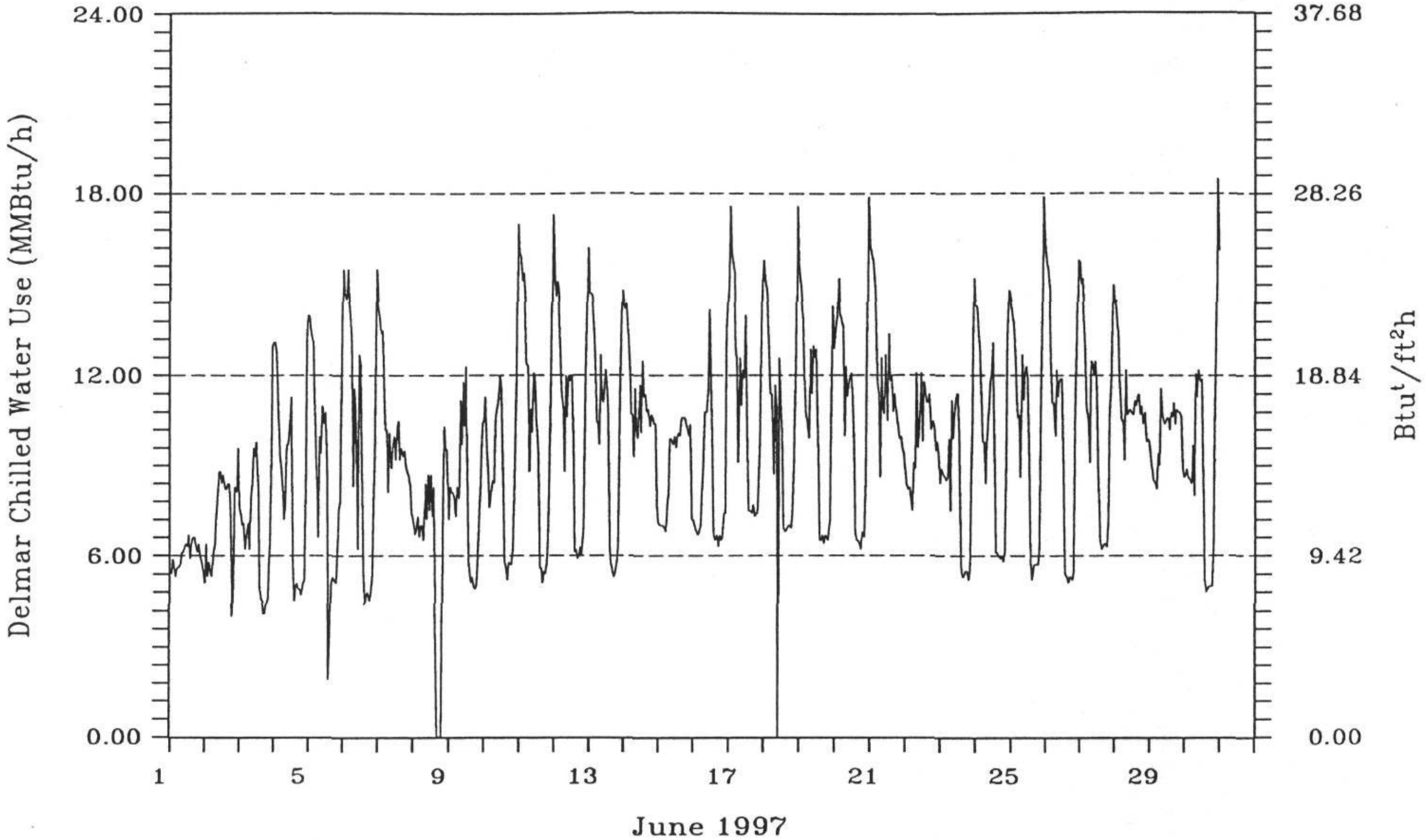
★ **Chilled water energy use increased when compared to June 1996.**

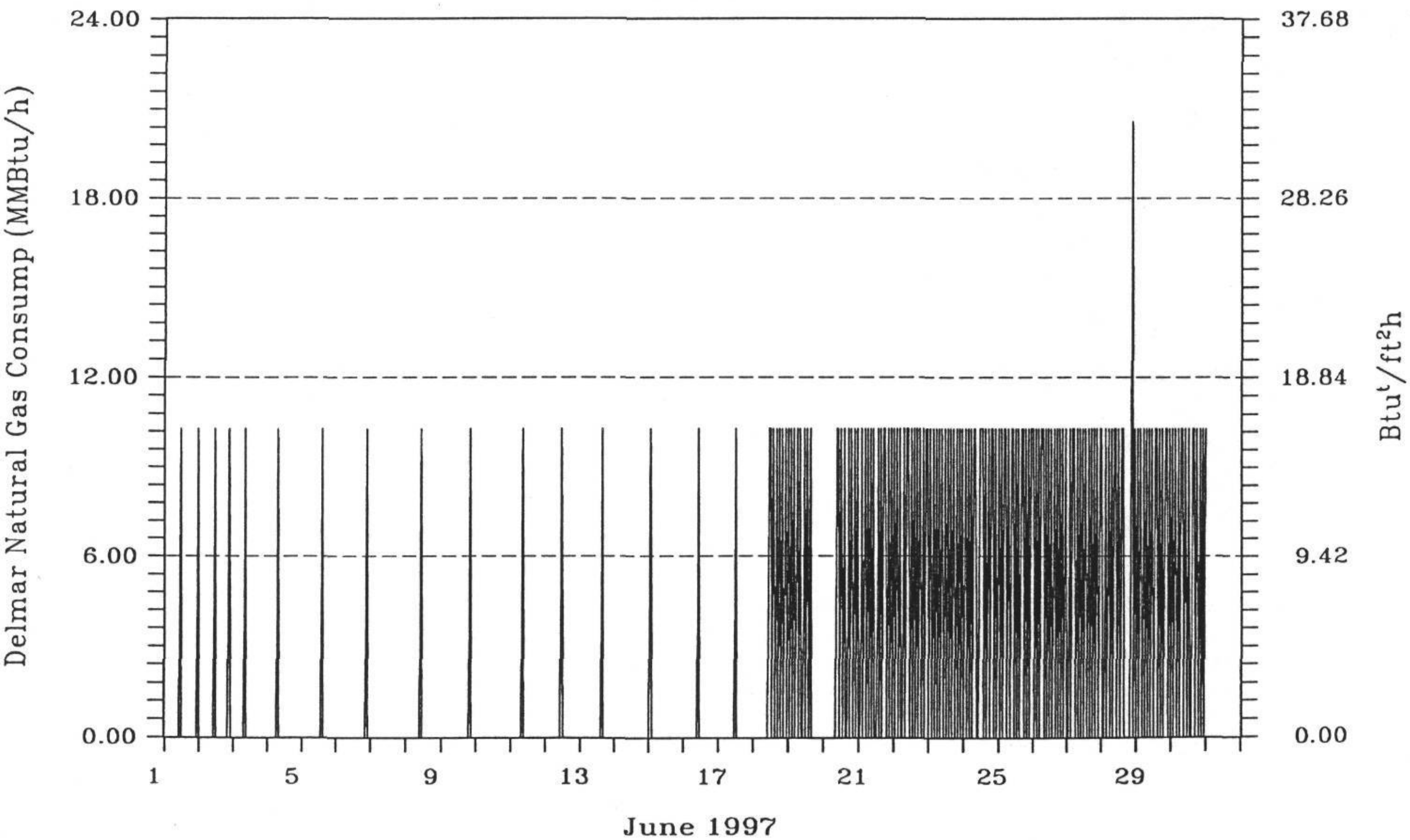




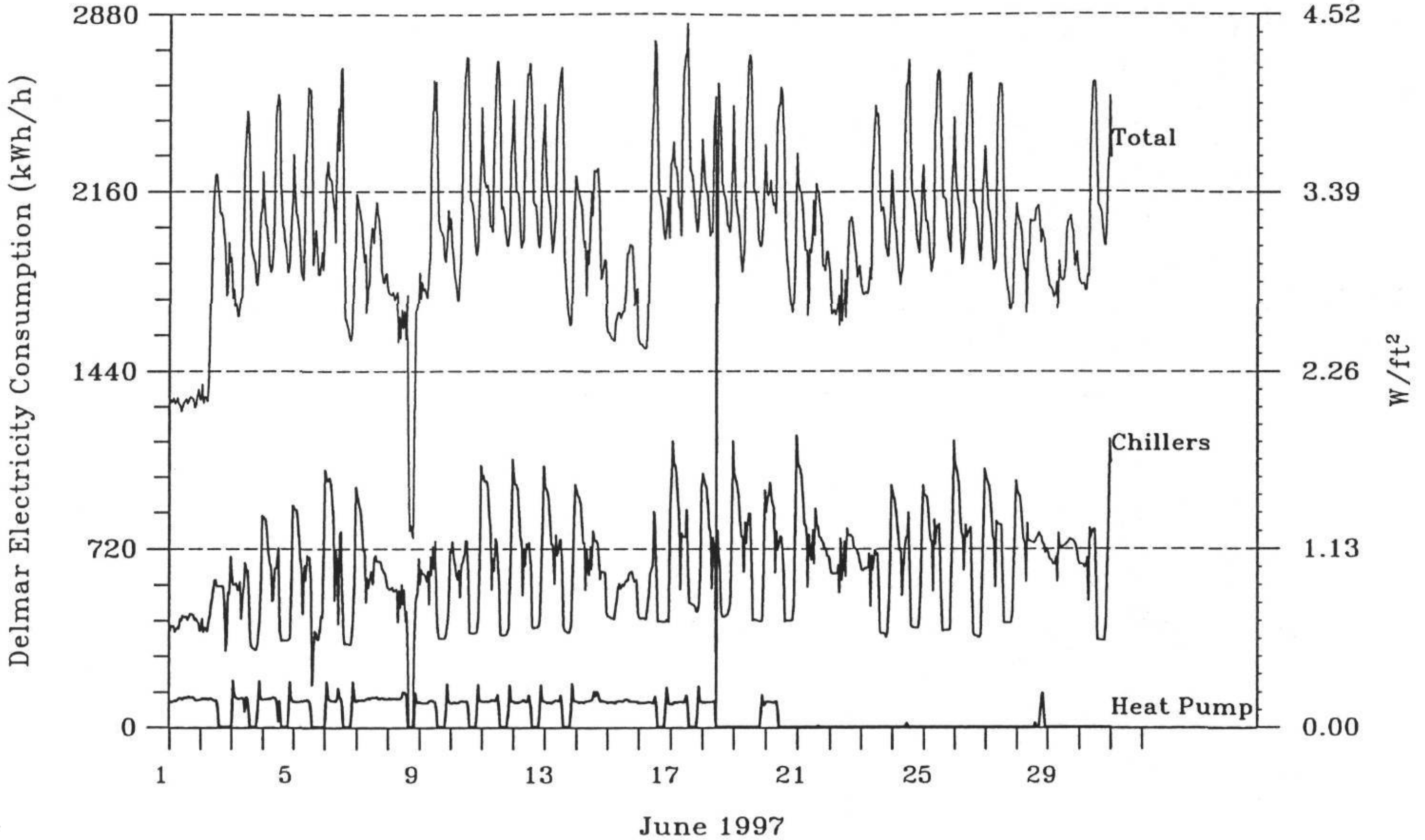
Data points for the current month are shown as letters. Monday through Sunday are represented as M,T,W,H,F,S,U.

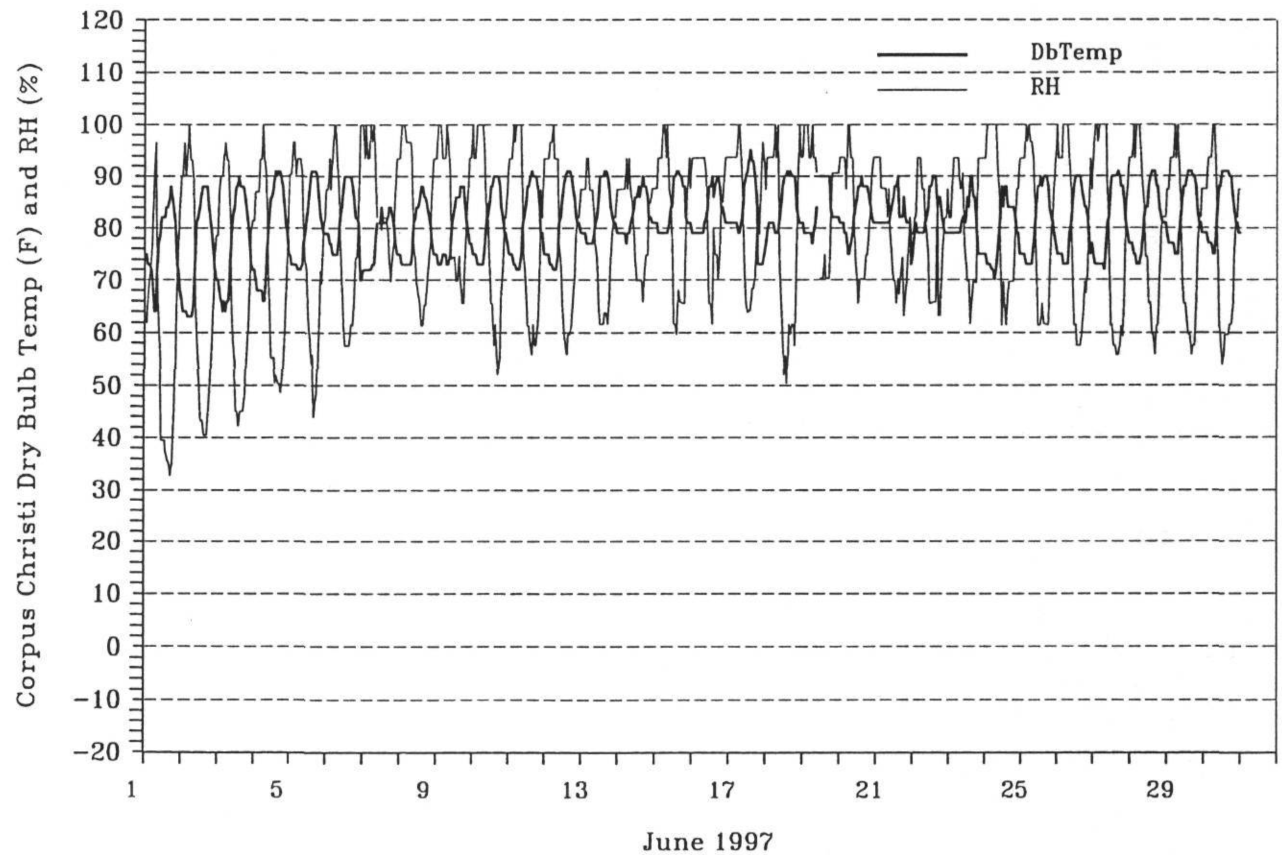
Points from this month last year are shown as +. All other points are shown as *.





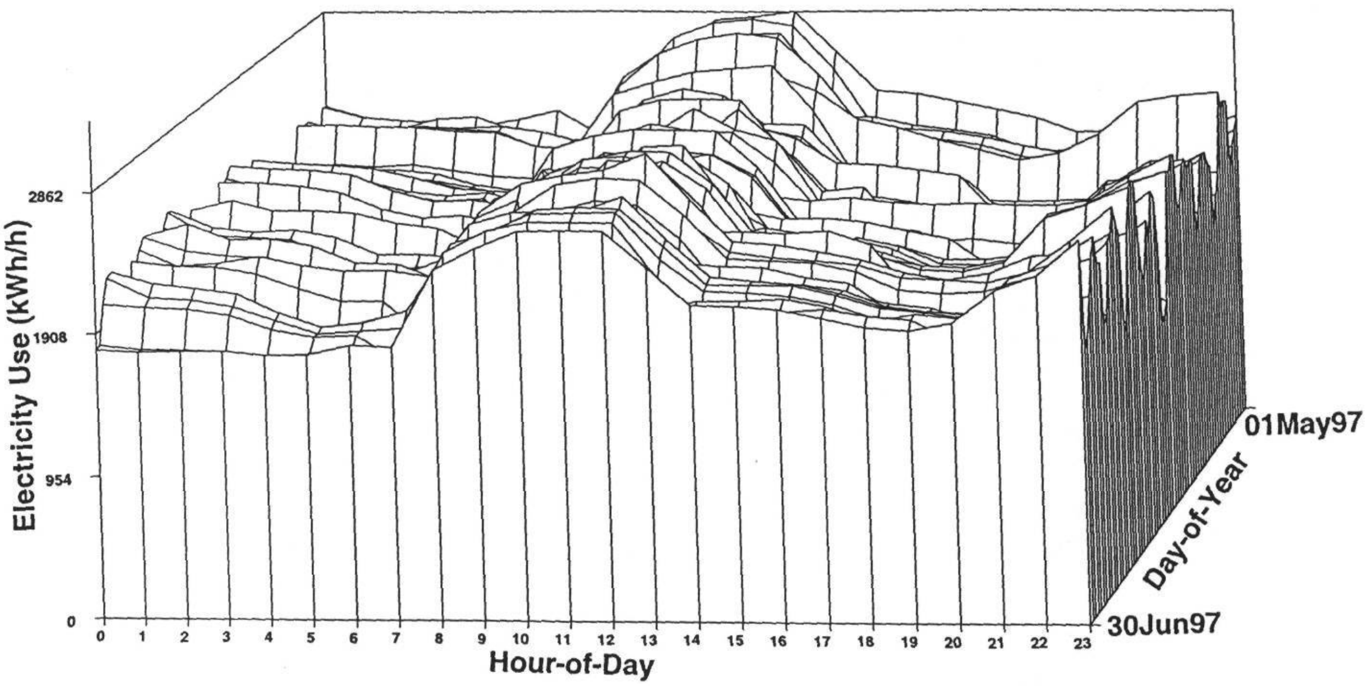
Delmar College - Whole Campus - June 1997



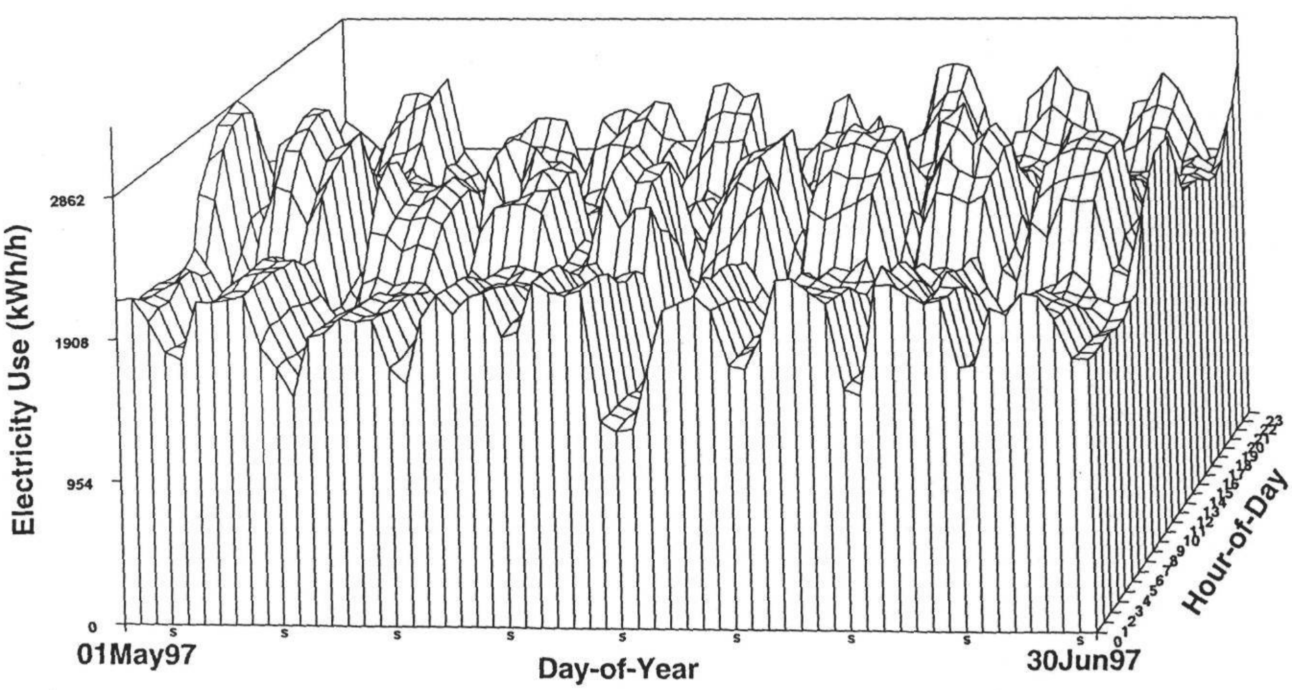


Delmar College - Whole Campus - June 1997

Whole–Building Electric



Whole–Building Electric



Sundays are marked with an "S"

DEL MAR COLLEGE

Building Envelope:
- 681,592 sq.ft.
- 23 buildings, built in 1940-present
- conditioned floor area: 636,707 sq.ft.
- walls: variable construction
- windows: N/A
- roof: built-up flat

Building Schedule:
- Monday - Friday 7:30 am to 12:00 midnight
- Saturday and Sunday - some buildings partially occupied

Building HVAC and Auxiliary Equipment
- information for the individual AHUs in each building is not available. Campus has a mixture of single duct, double duct constant volume, variable volume and DX units. All the new buildings have variable volume system with DDC control
- 1 - 1000 ton Trane Centrifugal Chiller
- 1 - 1000 ton Westinghouse Centrifugal Chiller
- several DX units, total cooling capacity 300 tons
- 2 hot water boilers, 300 hp each

HVAC Schedule
- 24 hrs/day

Lighting
- mixture of fluorescent, incandescent in the classrooms, offices, and corridors
- metal halides, H.P. sodium and L.P. sodium in the Gym, swimming pool, for parking and security lights

Proposed Maintenance and Operation Measures
- none

Proposed Retrofits
- thermal energy storage/industrial water source heat pump
- capacitors for power factor improvement
- interior lighting controls
- exterior lighting conversions
- fixture relamping
- total loan amount $1,157,404 with audit estimated savings of $287,930/yr

Status of Retrofits
- capacitors were installed in July 1992
- thermal storage system was completed in November 1993. The heat pump became operational on June 30, 1993

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636,702 square feet

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Corpus Cristi, TX 78404
(512) 886–1242

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Aamer Athar or Namir Saman
053 WERC
Texas A&M University
College Station, TX 77843-3123
(409) 845–9213

1996 Summary of Measured Energy Consumption and Savings

	Electricity				Electricity Demand				Hot Water/Steam/NG				Total	
	Consumption			Savings	Consumption			Savings	Consumption			Savings	Monthly	Cumulative
Month	kWh	$	%	$	kW	$	%	$	MMBtu	$	%	$	Savings	Savings
Jan	1186845	$34893	100	$-11	2460	$33262	100	$24661	7540	$29706	100	$12060	$36710	$36710
Feb	1275017	$37486	100	$-703	2741	$37059	100	$30518	7251	$28570	100	$8038	$37853	$74563
Mar	1243228	$36551	100	$-1233	2901	$39220	100	$27730	6365	$25080	100	$13215	$39712	$114275
Apr	1411140	$41488	100	$-1809	2732	$36942	100	$9723	3152	$12418	100	$18159	$26073	$140348
May	1420786	$41771	100	$-343	2771	$37468	100	$6852	3492	$13757	100	$10413	$16922	$157270
Jun	1438269	$42285	100	$-90	2847	$38490	100	$9180	2853	$11241	100	$9909	$18999	$176269
Jul	1516371	$44581	100	$-45	2935	$39687	100	$7363	2472	$9740	100	$10603	$17921	$194190
Aug	1523911	$44803	100	$-1276	2970	$40154	100	$8223	1452	$5722	100	$15579	$22526	$216716
Sep	1470262	$43226	100	$-1962	2942	$39775	100	$9255	525	$2070	100	$20740	$28033	$244749
Oct	1534345	$45110	100	$-2201	2959	$40008	100	$32127	680	$2678	100	$24460	$54386	$299135
Nov	1413828	$41567	100	$-2283	2957	$39979	100	$31934	2173	$8563	100	$23699	$53350	$352485
Dec	1167231	$34317	100	$-1618	2501	$33817	100	$21186	5140	$20250	100	$18727	$38295	$390780
Total	16601233	$488078		$-13574	33716	$455861		$218752	43095	$169795		$185602		$390780
EUI	26.1	$\frac{kWh}{ft^2yr}$			52954	$\frac{Btu}{ft^2yr}$			67684	$\frac{Btu}{ft^2yr}$				

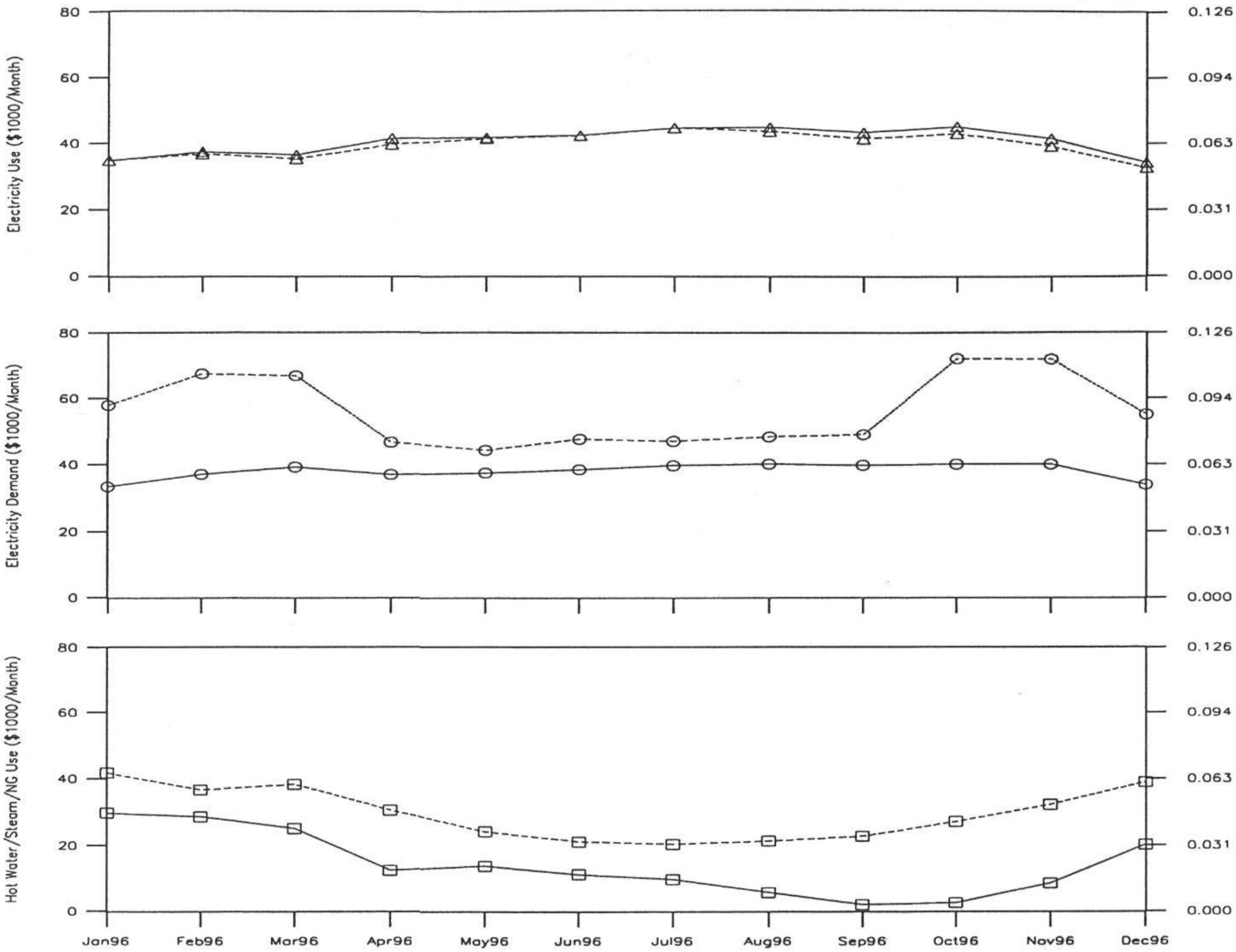
Comments

★ **The percent columns indicate the number of hours reported in that month.**

★ **The LoanSTAR monitoring began in November 1991.**

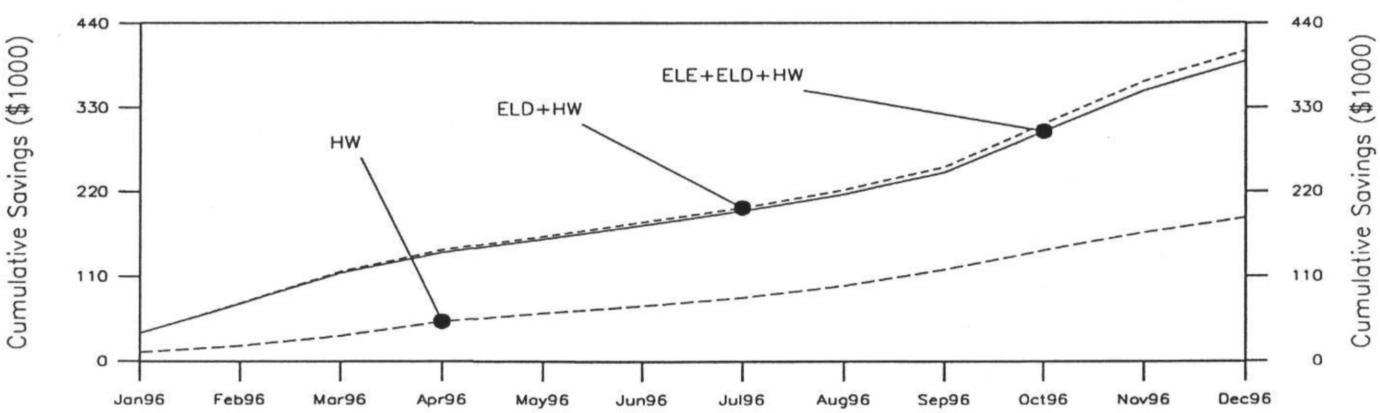
★ **The unit cost used for estimating the electricity costs are: $0.02940/kWh (ELE), $6.00/MMBtu (CW), and $3.94/MMBtu (NG).**

★ **The audit estimated savings for the thermal storage and heat pump retrofit are: $98,292 (NG), $184,788 (ELED), -$45,000 (ELE), and $238,000 (Total).**



Solid line represents measured energy use while the dashed line indicates the energy that would have been consumed had the retrofit not been installed

△ Electric ○ Cooling □ Heating



DEL MAR COLLEGE

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- capacitors for power factor improvement
- interior lighting controls
- exterior lighting conversions
- fixture relamping
- total loan amount $1,157,404 with audit estimated savings of $287,930/yr

Status of Retrofits
- capacitors were installed in July 1992
- thermal storage system was completed in November 1993. The heat pump became operational on June 30, 1993

Site #144

Midland County Courthouse
Midland, TX

Internal melt - ice

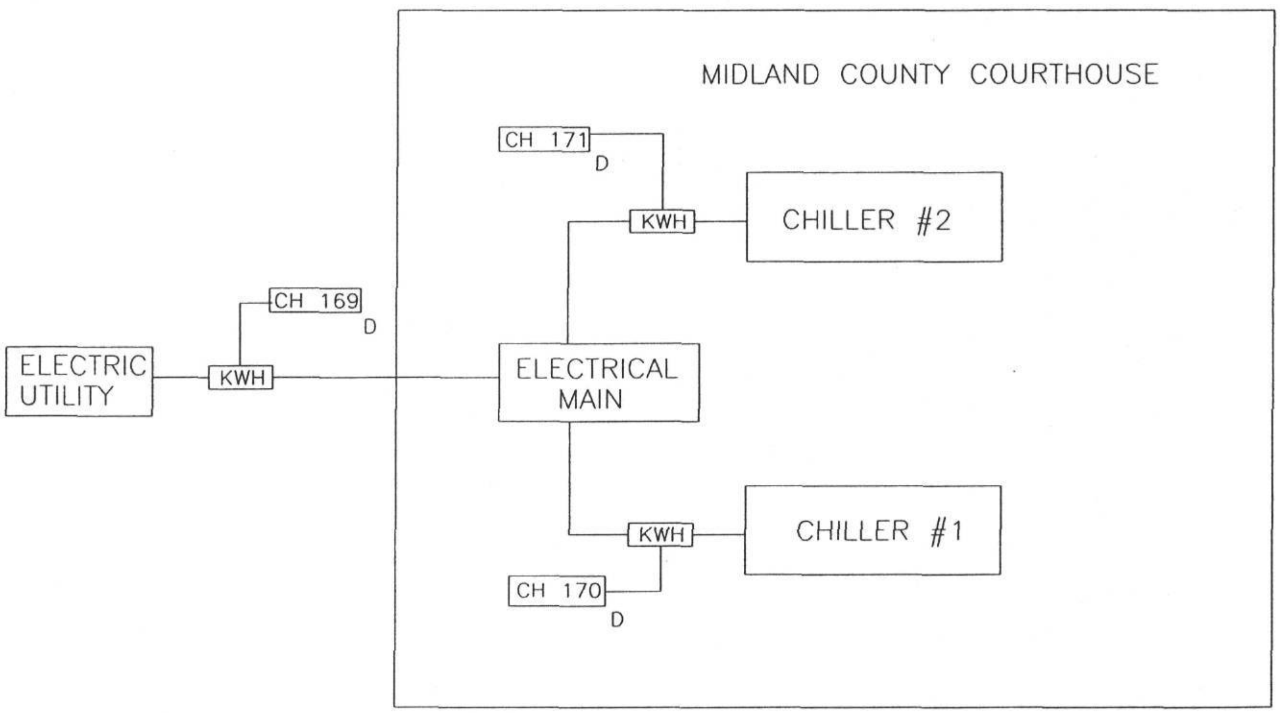
d	cp	Description
9	1	Whole Bldg (kWh/h)
)	2	Chiller #1 (kWh/h)
L	3	Chiller #2 (kWh/h)

D/YY DDD)	Time HH:mm	Raw-Data lin pos	coln pos	Arch coln pos	Name of Channel	Archive Units	Arch Format	Conv'n Code	Conv'n Constants	Error Code	Error Constants	Channel Description
2/90	00:00	1	0	0	Begin	MidlandCounty						Beginning date
2/90	00:00	1	1	1	Site	-	I3	2	0 144	0		Site #
2/90	00:00	1	1	2	Mon-Raw	MM	I3	1		0		Month
2/90	00:00	1	2	3	Mon-Raw	DD	I3	1		0		Day
2/90	00:00	1	3	4	Mon-Raw	YY	I3	1		0		Year
2/90	00:00	1	3	5	Greg-Jul	MMDDYY	I5	24	1 2	0		Gregorian Date to Julian
2/90	00:00	1	4	7	Time	HH mm	I5	16	5	0		Time
2/90	00:00	1	3	6	Greg-Dec	DDD.frac	F10.4	28		0		Gregorian Date to Jul.Decimal
2/90	00:00	1	6	8	WBldg	F9.3	F9.3	1		1	0 5000	Whole Bldg (kWh/h)
2/90	00:00	1	7	9	Chlr 1	F9.3	F9.3	1		1	0 5000	Chiller #1 (kWh/h)
2/90	00:00	1	8	10	Chlr 2	F9.3	F9.3	1		1	0 5000	Chiller #2 (kWh/h)
./99	23:00	1	0	0	End	MidlandCounty						

ELECTRICAL MONITORING DIAGRAM
MIDLAND COUNTY COURTHOUSE

LEGEND

K=KWH CHANNEL
A=ANALOG CHANNEL
D=DIGITAL CHANNEL

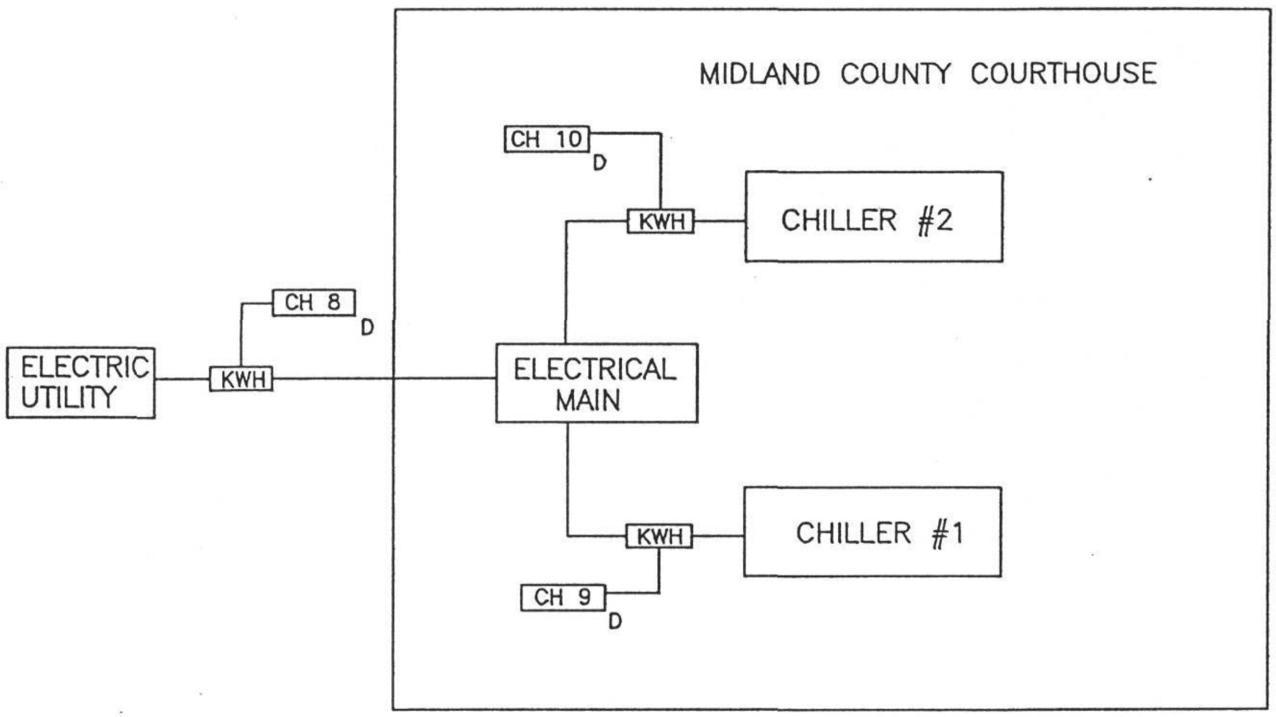


ELECTRICAL MONITORING DIAGRAM

MIDLAND COUNTY COURTHOUSE

LEGEND

K—KWH CHANNEL
A—ANALOG CHANNEL
D—DIGITAL CHANNEL



MIDLAND CO. COURTHOUSE – SITE 144

Midland County, Courthouse

Courthouse:
- 90,100 sq.ft. Five story and a basement, constructed in 1930.
- The building is constructed with reinforced concrete foundation, structure, and walls.
- Exterior walls have plaster and interior walls are wood or metal studs with painted gypsum board.
- Windows are slightly tinted, single glaze with metal frame.
- Flat roof is built up with gravel ballast. Roof is insulated.
- Fifth floor houses a jail. Other floors house courtrooms and offices for support personnel.
- Jail operates 24 hours/day. 365 days/year.
- Other floors usually operate from 6:00a.m. to 8:00p.m. 6 days/week.

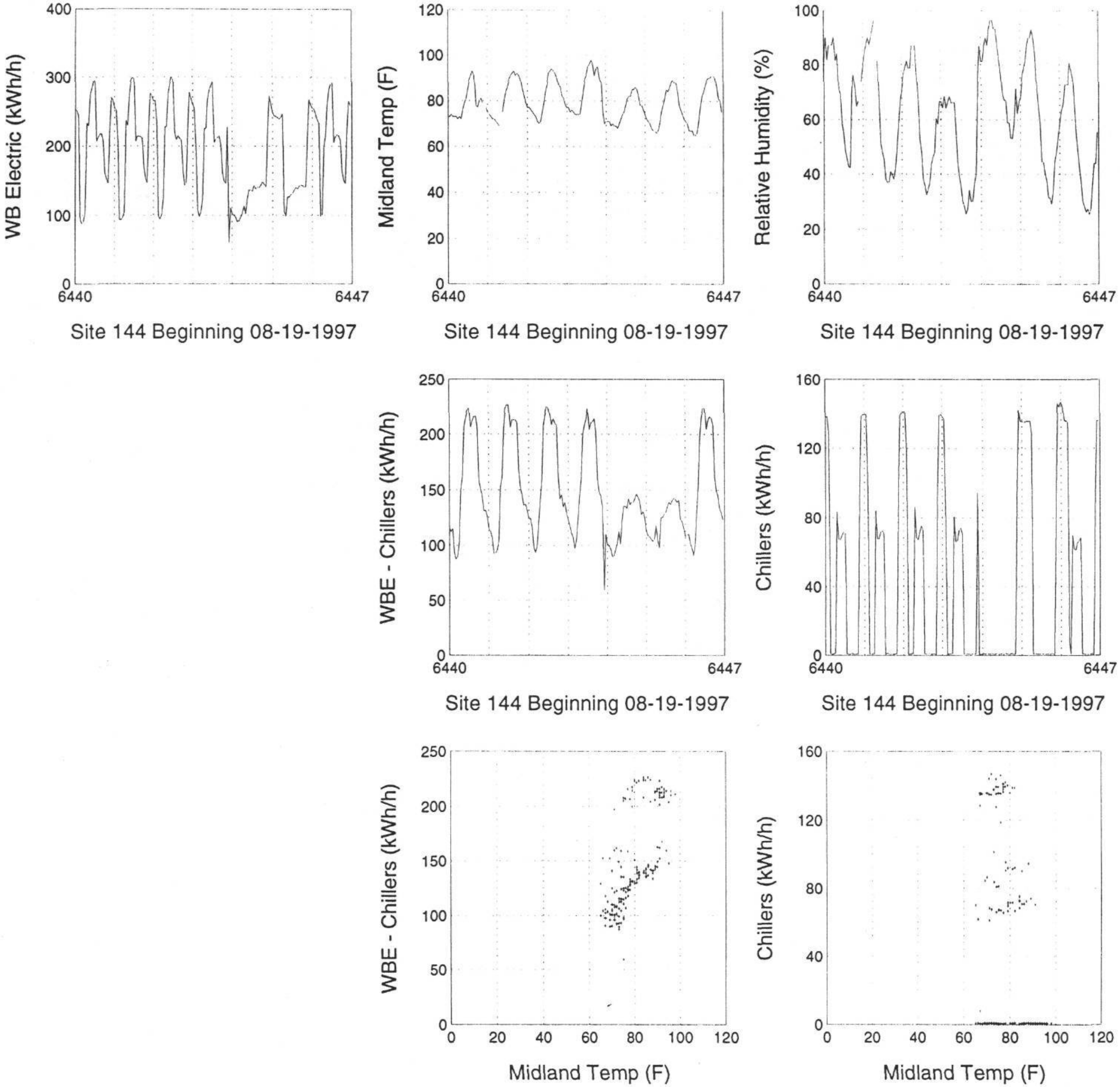
HVAC Equipment:
- 4 15 h.p. AHU's
- 1 10 h.p. AHU
- 1 3 h.p. AHU's
- 1 43 h.p. heating strip
- 7 rooftop packaged air conditioning units
- 1 3.4 MMBtu (input) boiler
- 1 7.5 h.p. CWP
- 1 210 ton screw chiller

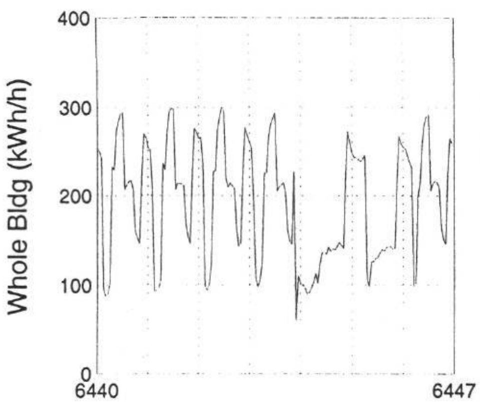
Lighting:
- 945 2 lamp fixtures (34 watts) (operates 2756 hours/year)
- 142 2 lamp fixtures (34 watts) (operates 8760 hours/year)

Recommended ECRMs:
- Energy Management System
- Occupancy senors
- Modify chiller piping and control
- Electronic ballasts

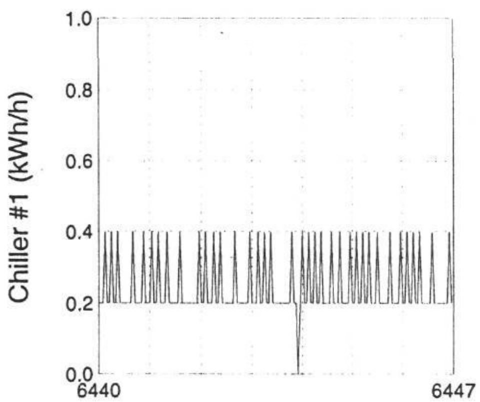
Date of Retrofit:
- Energy Management System & thermal storage was completed in August 1992
- 2-85 ton chillers were replaced by one 210 ton screw chiller on 5/14/92. One of the old chillers has been taken out while one will be used as a backup.
- Lighting modifications are still in progress

Site 144 Page 1

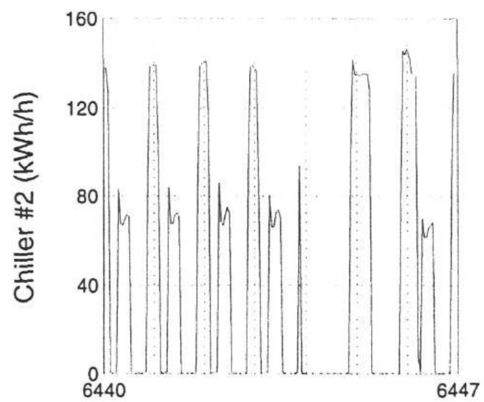




Site 144 Beginning 08-19-1997



Site 144 Beginning 08-19-1997



Site 144 Beginning 08-19-1997

Midland County Courthouse

90,100 square feet

Site Contact
Mr. Bill Decker
Facility Management Director
Suite 003
Midland County Courthouse
200 West Wall
Midland, TX 79701
(915) 688–8940

LoanSTAR Metering Contact
Aamer Athar or Namir Saman
053 WERC
Texas A&M University
College Station, TX 77843-3123
(409) 845–9213

Summary of Energy Consumption

	Measured Use	% hours reported	Unit Cost	Estimated Cost
Electricity	131372 kWh	100	$0.03000	$3941
Peak 60 Minute Demand	312 kW	100	$10.72	$3345
Chiller Electricity	30546.1 kWh	100	$0.030	$916

Peak 60 minute demand was recorded at 1200 Monday 06/30/97.
There were 720 hours in this month.

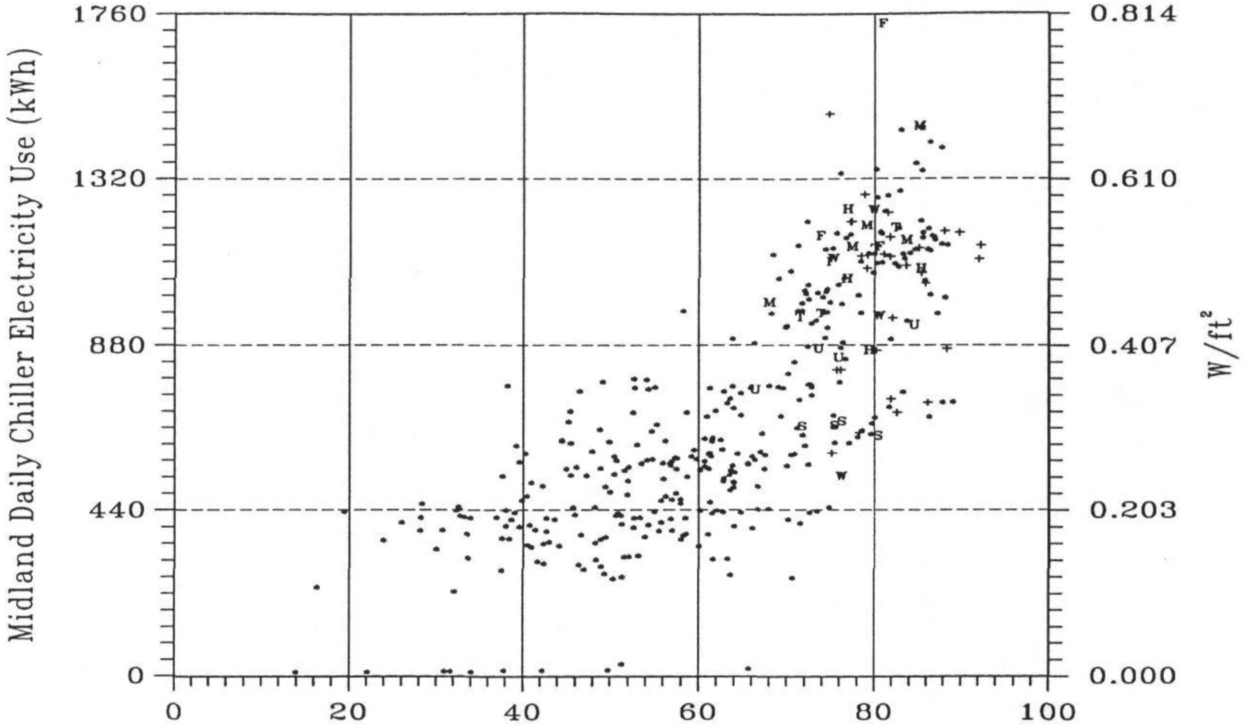
Monthly Retrofit Savings

	Measured Savings		Audit Estimated Savings	
Electricity (kWh)	44227	$1327	37913	$1137
Electricity Demand (kW)	120	$1286	145	$1554
Monthly Total		$2613		$2691
Total to Date*	(57 months)	$109916	(57 months)	$151889

*Measured savings include construction period. Audit estimated savings do not.

Comments

Jun 01 1996 – Jun 30 1997



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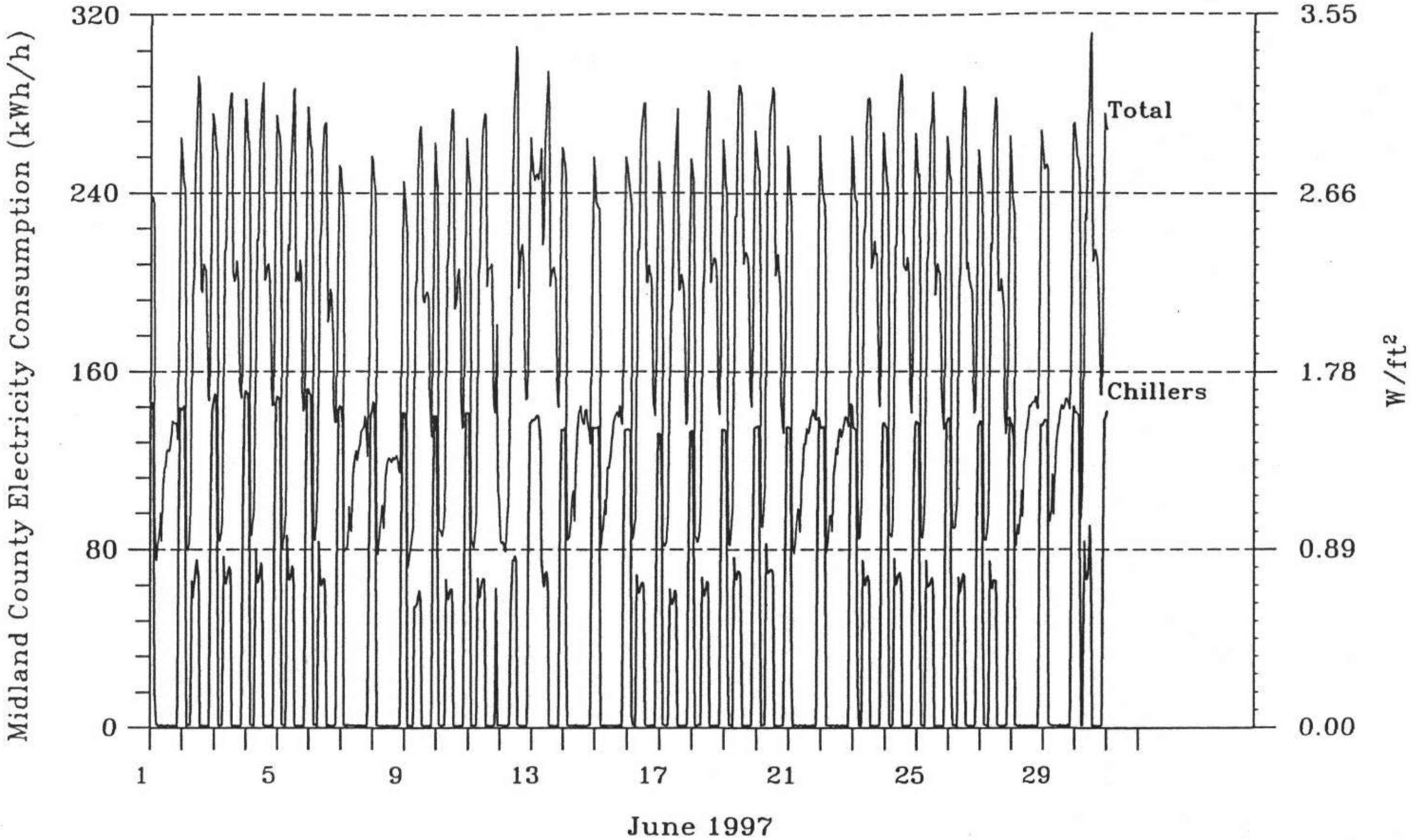
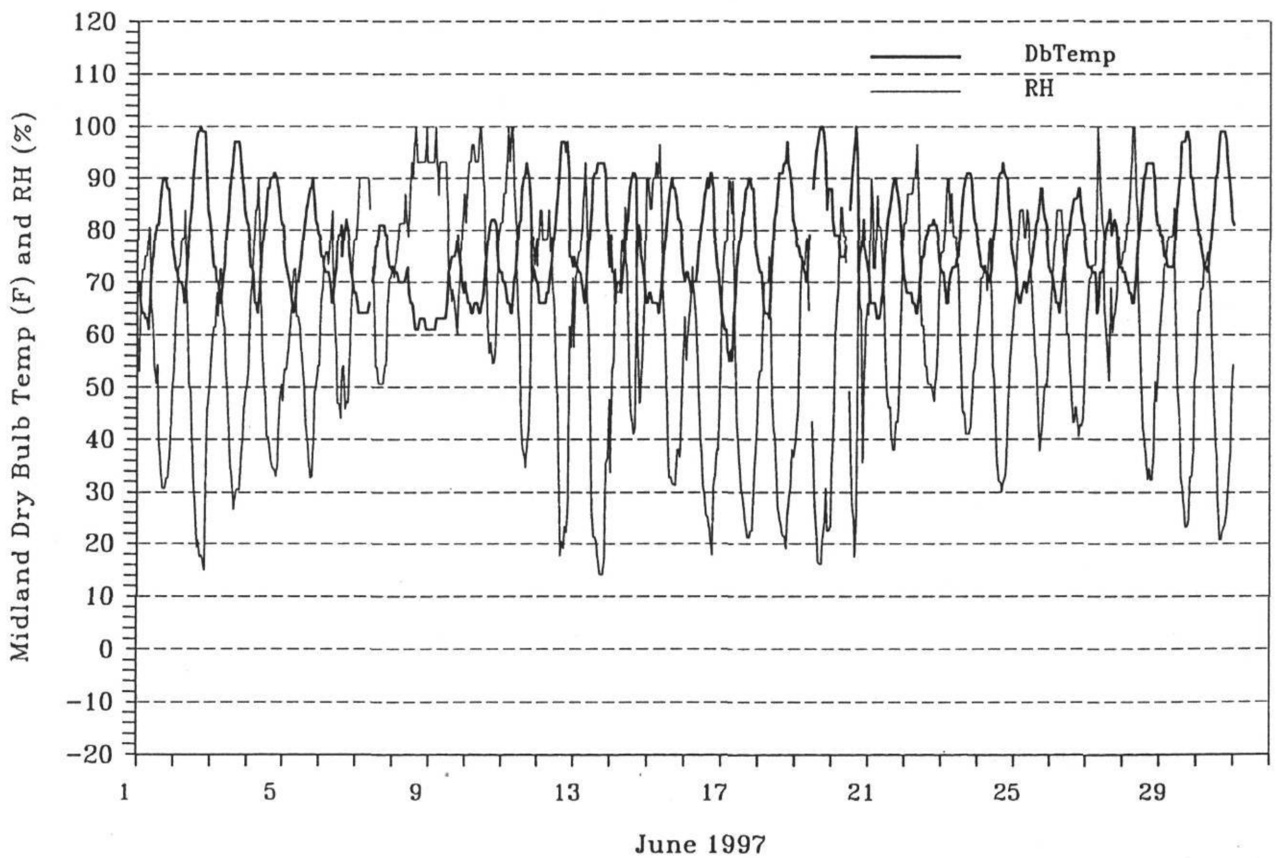
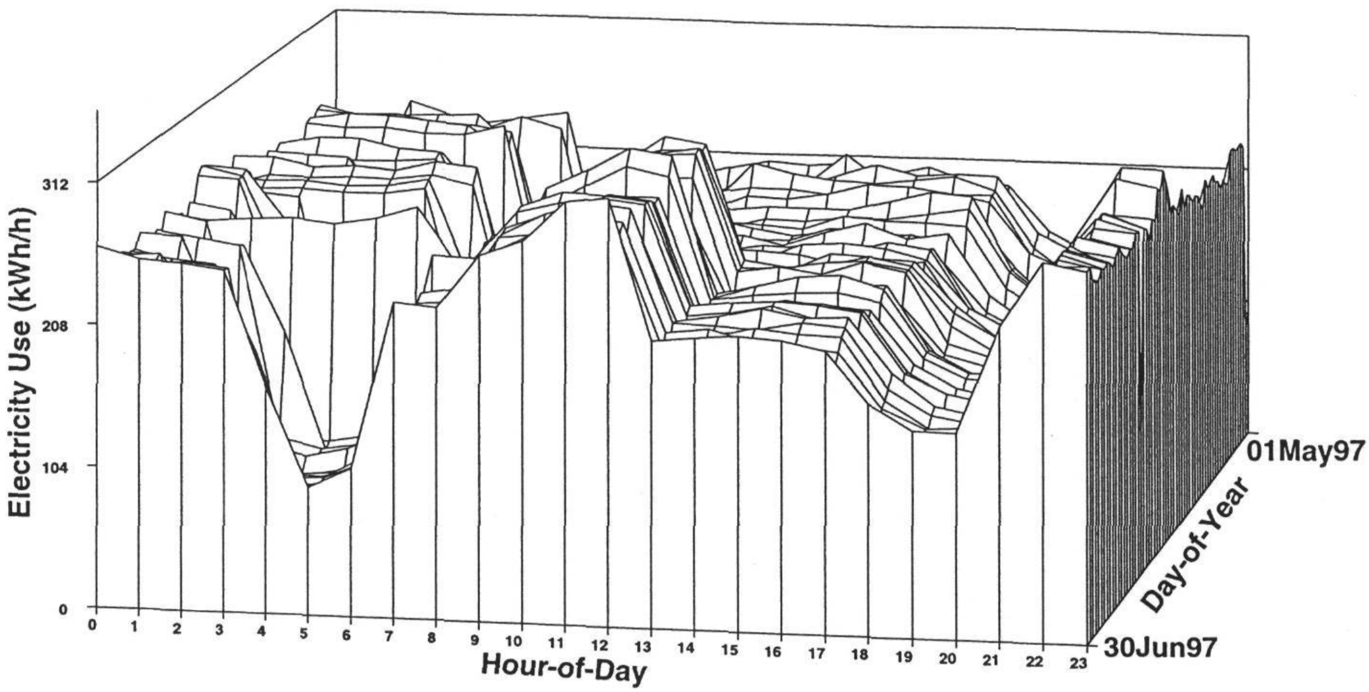


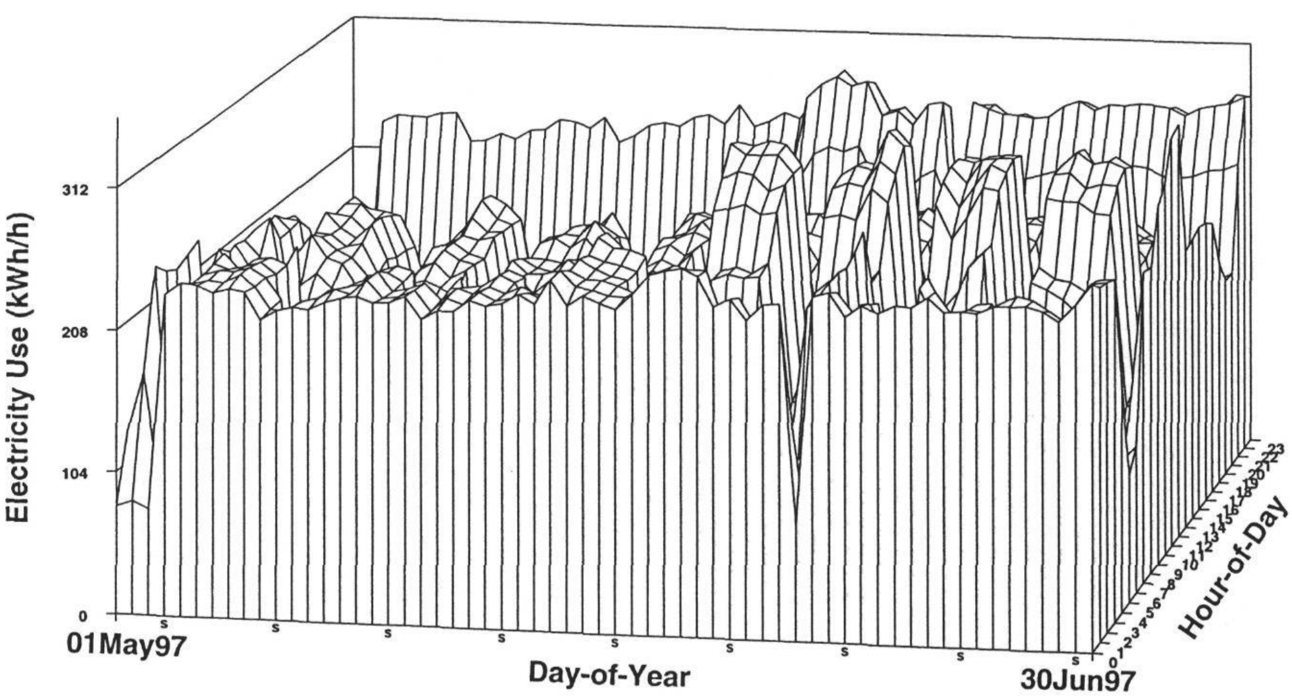


Midland County Courthouse - June 1997

Whole–Building Electric



Whole–Building Electric



Sundays are marked with an "S"

MIDLAND COUNTY COURTHOUSE

Courthouse:
- 90,100 sq.ft.
- five story and a basement; constructed in 1930
- the building is constructed with reinforced concrete foundation, structure, and walls
- exterior walls have plaster and interior walls are wood or metal studs with painted gypsum board
- windows are slightly tinted, single glaze with metal frame
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- fifth floor houses a jail. Other floors house courtrooms and offices for support personnel
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- 1 43 h.p. heating strip
- 7 rooftop packaged air conditioning units
- 1 3.4 MMBtu (input) boiler
- 1 7.5 h.p. CHWP
- 1 210 ton screw chiller

Lighting:
- 945 2 lamp fixtures (34 watts) (operates 2756 hours/year)
- 142 2 lamp fixtures (34 watts) (operates 8760 hours/year)

Recommended ECRMs:
- Energy Management System
- occupancy sensors
- modify chiller piping and control
- electronic ballasts

Date of Retrofit:
- Energy Management System & thermal storage was completed in August 1992
- 2-85 ton chillers were replaced by one 210-ton screw chiller on 5/14/92. One of the old chillers has been taken out while one will be used as a backup
- lighting modifications are still in progress

Comments:
- the W/ft^2 scale on the electricity consumption graph is only valid for the total electricity consumption
- demand reported on the first page is the peak demand. It is not used for calculating the demand savings from the thermal storage system. Billed demand based on the on-peak demand is used to calculate the demand savings

Midland County Courthouse

90,100 square feet

Site Contact
Mr. Bill Decker
Facility Management Director
Suite 003
Midland County Courthouse
200 West Wall
Midland, TX 79701
(915) 688–8940

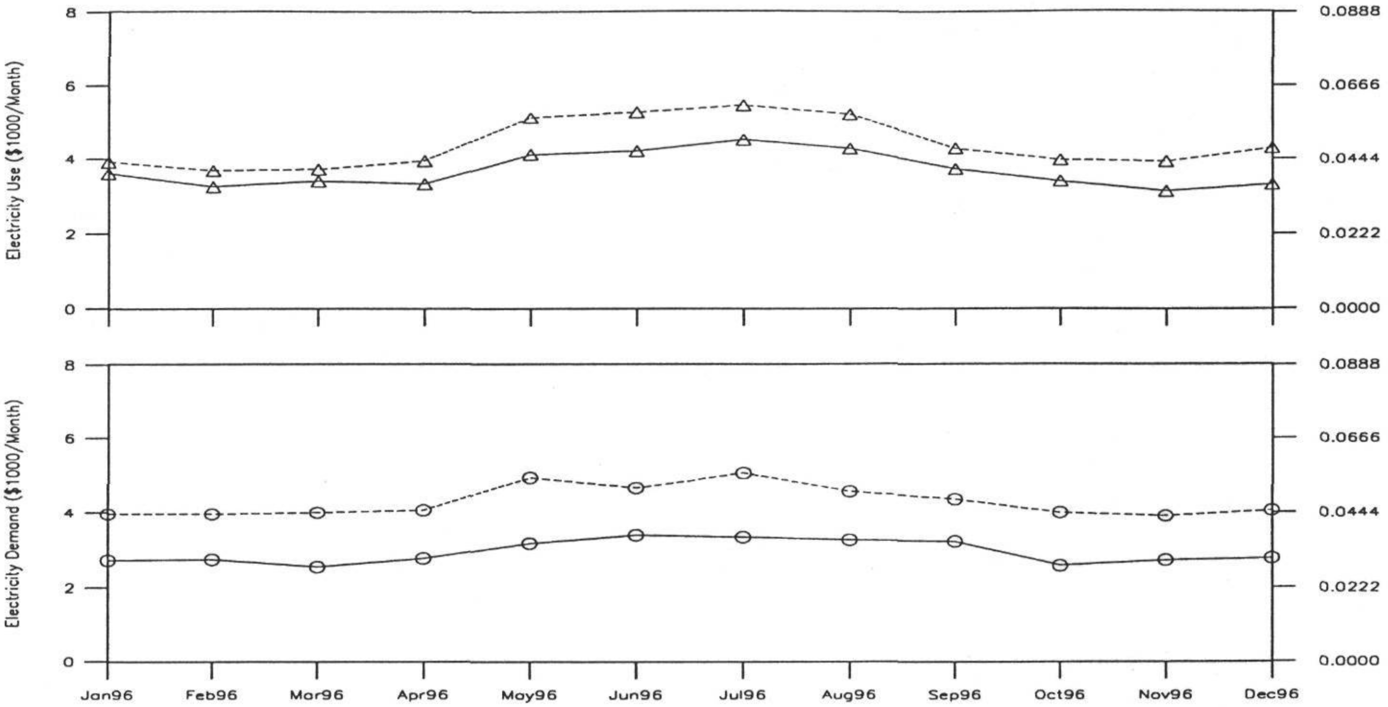
LoanSTAR Metering Contact
Aamer Athar or Namir Saman
053 WERC
Texas A&M University
College Station, TX 77843-3123
(409) 845–9213

1996 Summary of Measured Energy Consumption and Savings

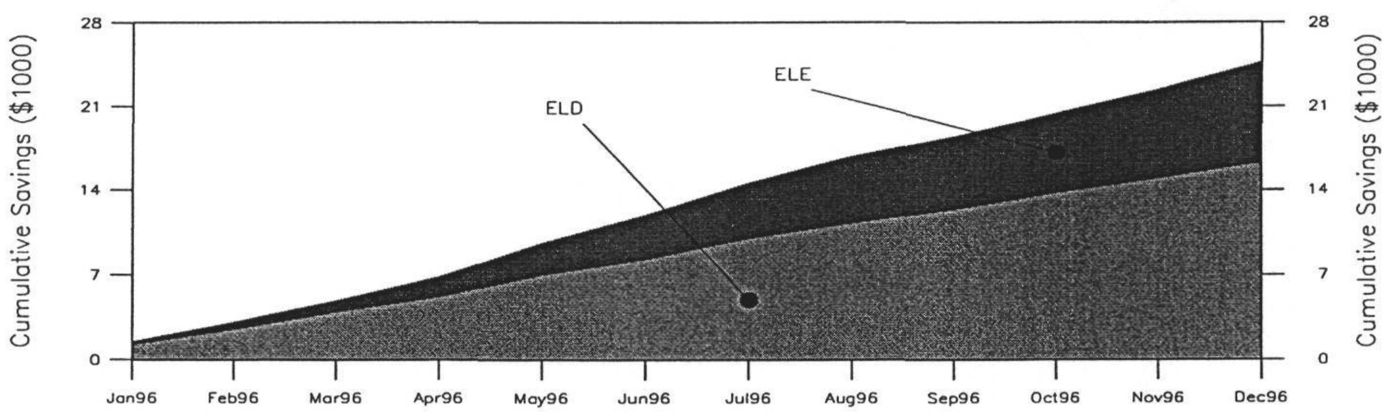
	Electricity				Electricity Demand				Hot Water/Steam/NG				Total	
	Consumption			Savings	Consumption			Savings	Consumption			Savings	Monthly	Cumulative
Month	kWh	$	%	$	kW	$	%	$	MMBtu	$	%	$	Savings	Savings
Jan	120372	$3611	100	$315	254	$2727	100	$1233	not metered			N/A	$1548	$1548
Feb	108345	$3250	100	$437	256	$2749	100	$1211	not metered			N/A	$1648	$3196
Mar	112932	$3388	100	$327	238	$2551	100	$1447	not metered			N/A	$1774	$4970
Apr	110920	$3328	100	$621	259	$2774	100	$1286	not metered			N/A	$1907	$6877
May	137421	$4123	100	$1006	296	$3173	100	$1758	not metered			N/A	$2764	$9641
Jun	140172	$4205	100	$1066	317	$3396	100	$1265	not metered			N/A	$2331	$11972
Jul	150185	$4506	100	$940	312	$3340	100	$1715	not metered			N/A	$2655	$14627
Aug	142717	$4282	100	$937	304	$3263	100	$1297	not metered			N/A	$2234	$16861
Sep	124158	$3725	100	$551	301	$3229	100	$1126	not metered			N/A	$1677	$18538
Oct	112796	$3384	100	$573	241	$2586	100	$1415	not metered			N/A	$1988	$20526
Nov	103962	$3119	100	$799	254	$2727	100	$1179	not metered			N/A	$1978	$22504
Dec	110496	$3315	100	$977	259	$2779	100	$1276	not metered			N/A	$2253	$24757
Total	1474476	$44236		$8549	3291	$35294		$16208						$24757
EUI	16.4	$\frac{kWh}{ft^2 yr}$			36526	$\frac{Btu}{ft^2 yr}$								

Comments

- ★ **The percent columns indicate the number of hours reported in that month.**
- ★ **The LoanSTAR monitoring began in December 1991.**
- ★ **All the proposed retrofits were completed in August 1992.**
- ★ **The unit costs used for estimating the audit and measured savings are: $0.0300/kWh and $10.72/kW-mo (ELED).**
- ★ **Audit estimated savings from the completed retrofits are: $12,600 (ELE), $18,300 (ELED), and $30,900 (Total).**



Solid line represents measured energy use while the dashed line indicates
the energy that would have been consumed had the retrofit not been installed
△ Electric ○ Cooling



Site #230

Austin Convention Center
Austin, TX

Internal melt - ice

d	cp	Description
5	1	MSBA Elec EGY MTRA(kWh/15min)
6	2	MSBB Elec EGY MTRB(kWh/15min)
7	3	Chil Elec EGY Chil(kWh/15min)
8	4	Chiller Flow(gal/15min)
9	5	Chiller Btu (kBtu/15min)
0	6	Bldg Chwflow(gal/15min)
1	7	Bldg ChwBtu(kBtu/15min)
2	8	WBE Elec EGY MTRC(kWh/15min)

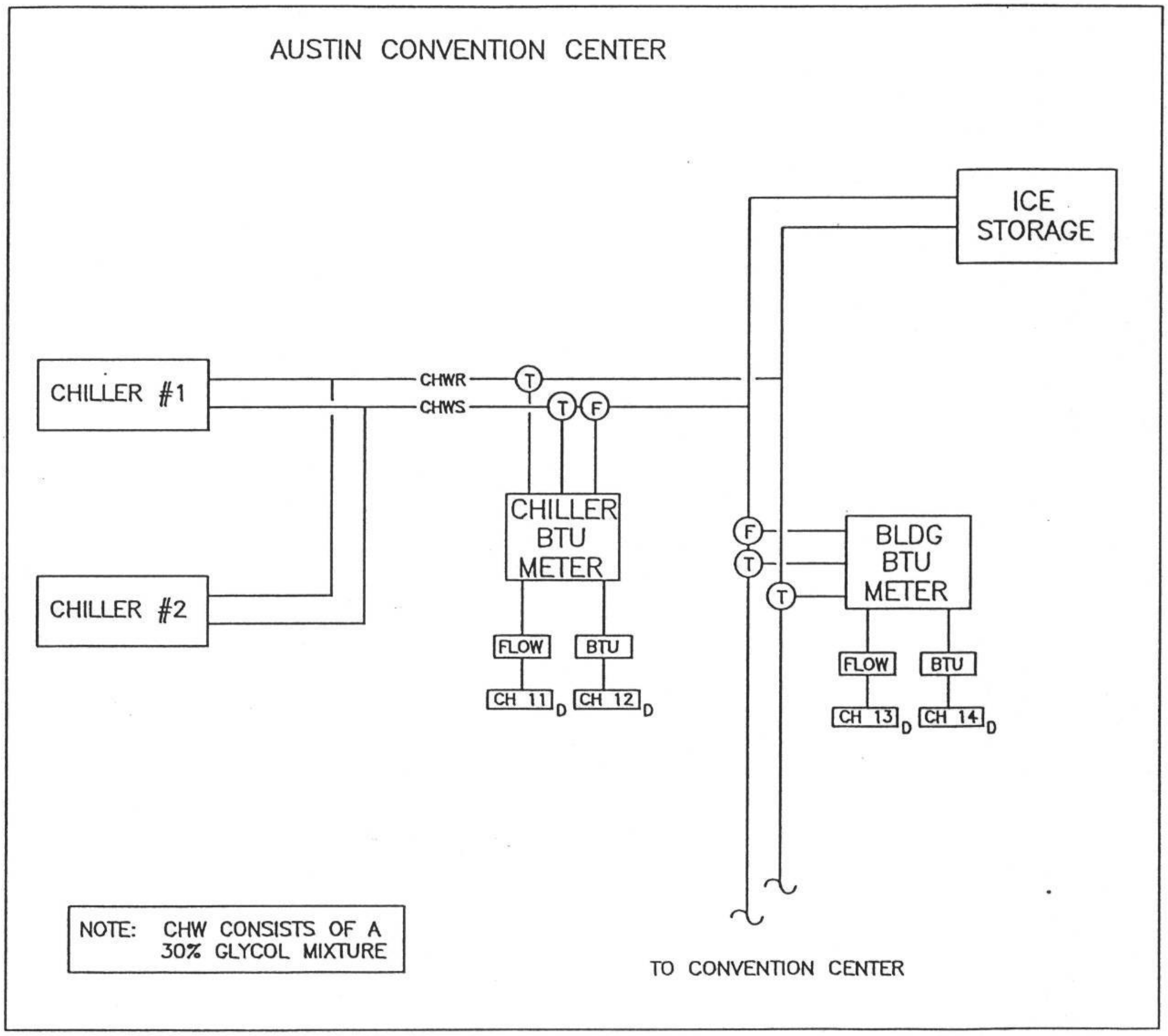
23090001.cht   Fri Oct 8 15:32:45 1993   1

Date MM/DD/YY (YY DDD)	Time HH:mm	Raw-Data lin pos	coln pos	Arch coln pos	Name of Channel	Archive Units	Arch Format	Conv'n Code	Conv'n Constants	Error Code	Error Constants	Channel Description
#												
07/03/90	00:00	1	0	0	Begin	ACC					Beginning date	
07/03/90	00:00	1	1	1	Bldg. #	XX	I3	2	0 230	0		Building Number
07/03/90	00:00	1	1	2	Mon-Raw	MM	I3	1		0		Month
07/03/90	00:00	1	2	3	Mon-Raw	DD	I3	1		0		Day
07/03/90	00:00	1	3	4	Mon-Raw	YY	I3	1		0		Year
07/03/90	00:00	1	3	5	Greg-Jul	MMDDYY	I5	24	1 2	0		Gregorian Date to Julian
07/03/90	00:00	1	4	7	Time	HH mm	I5	16	5	0		Time
07/03/90	00:00	1	3	6	Greg-Dec	DDD.frac	F10.4	28		0		Gregorian Date to Jul.Decimal
07/03/90	00:00	1	6	8	MSBA MTA	F9.3	F9.3	1		1	-1 5000	MSBA Elec EGY MTRA(kWh/15min)
07/03/90	00:00	1	7	9	MSBB MTB	F9.3	F9.3	1		1	-1 5000	MSBB Elec EGY MTRB(kWh/15min)
07/03/90	00:00	1	8	10	ChlrElec	F9.3	F9.3	1		1	-1 5000	Chil Elec EGY Chil(kWh/15min)
07/03/90	00:00	1	9	11	ChlrChwf	F9.3	F9.3	1		1	-1 100000	Chiller Flow(gal/15min)
07/03/90	00:00	1	10	12	ChlrBtu	F9.3	F9.3	1		1	-1 5000	Chiller Btu (kBtu/15min)
07/03/90	00:00	1	11	13	BldgChwf	F9.3	F9.3	1		1	-1 100000	Bldg Chwflow(gal/15min)
07/03/90	00:00	1	12	14	BldgBtu	F9.3	F9.3	1		1	-1 5000	Bldg ChwBtu(kBtu/15min)
07/03/90	00:00	1	13	15	WBE MTC	F9.3	F9.3	1		1	-1 5000	WBE Elec EGY MTRC(kWh/15min)
03/11/99	23:00	1	0	0	End	ACC						

THERMAL MONITORING DIAGRAM
AUSTIN CONVENTION CENTER

LEGEND

K=KWH CHANNEL
A=ANALOG CHANNEL
D=DIGITAL CHANNEL

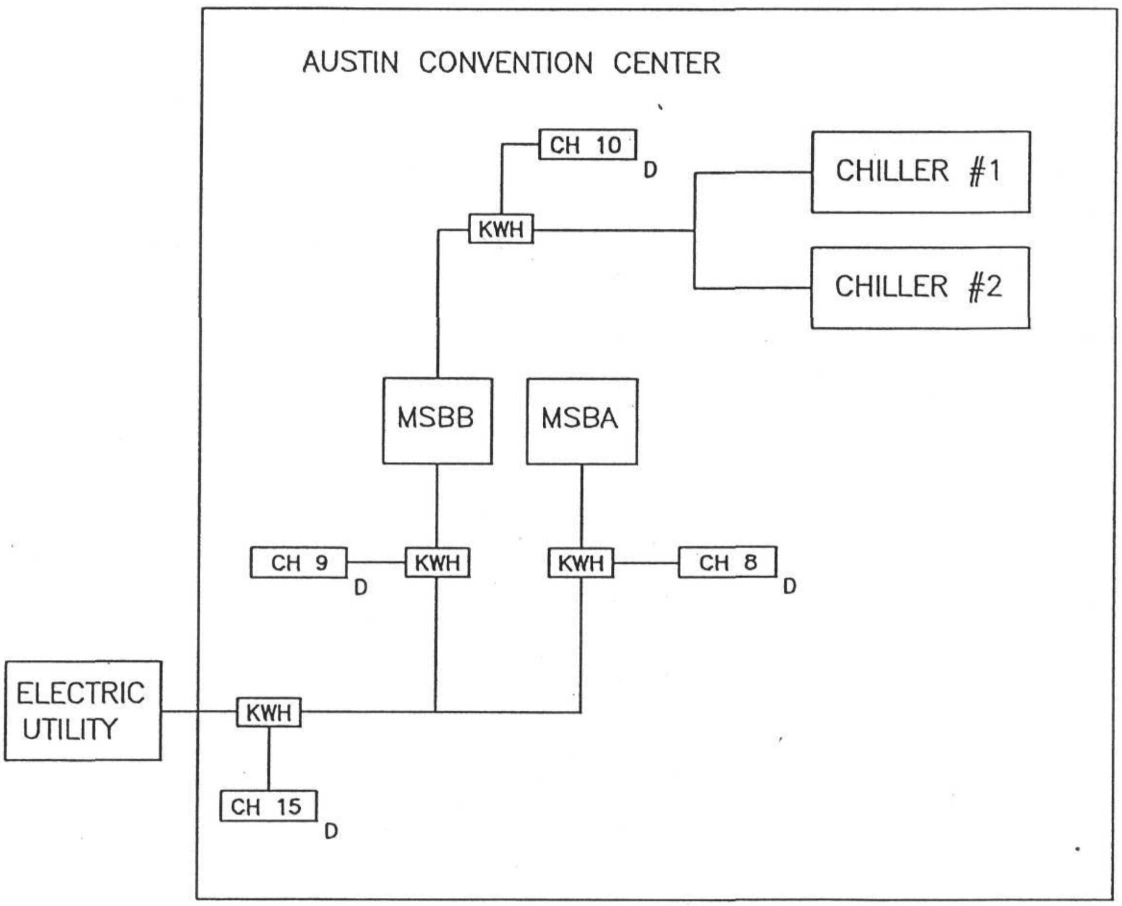


ELECTRICAL MONITORING DIAGRAM

AUSTIN CONVENTION CENTER

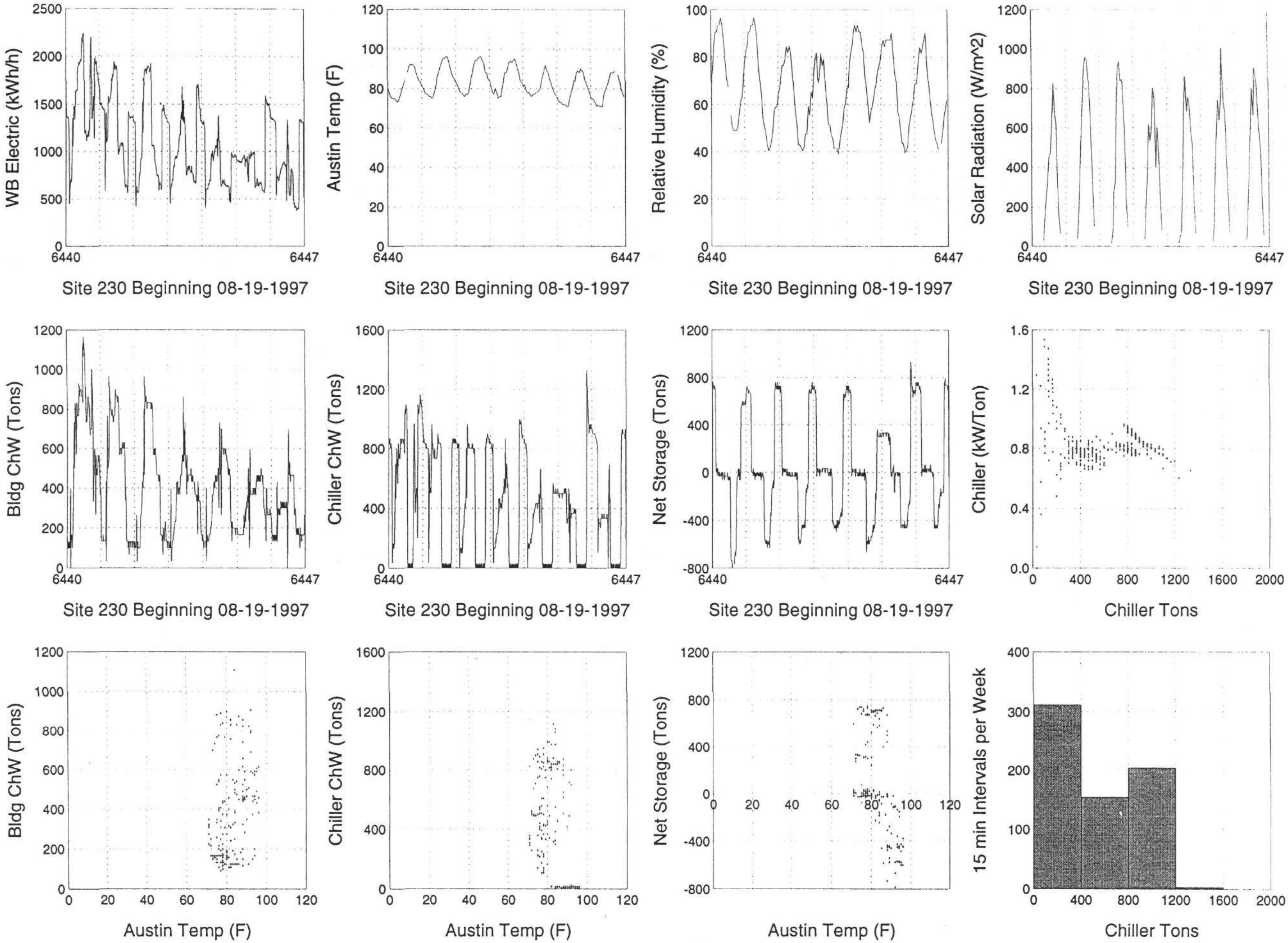
LEGEND

K=KWH CHANNEL
A=ANALOG CHANNEL
D=DIGITAL CHANNEL

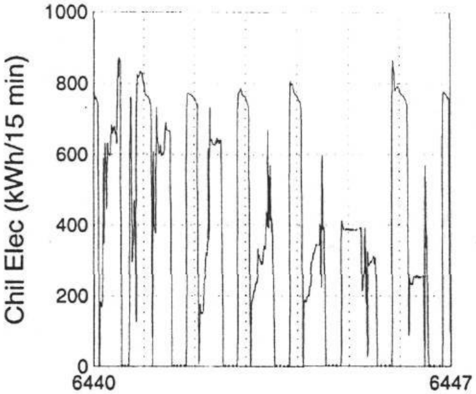


AUSTIN CONVENTION CENTER – SITE 230

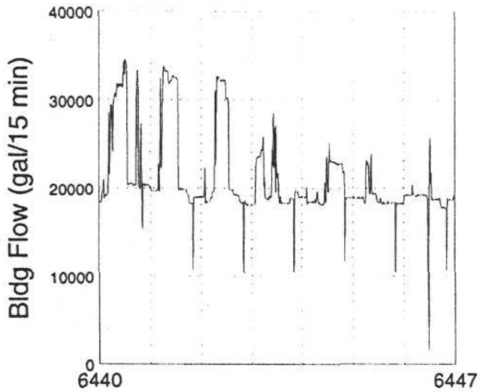
Site 230 Page 1



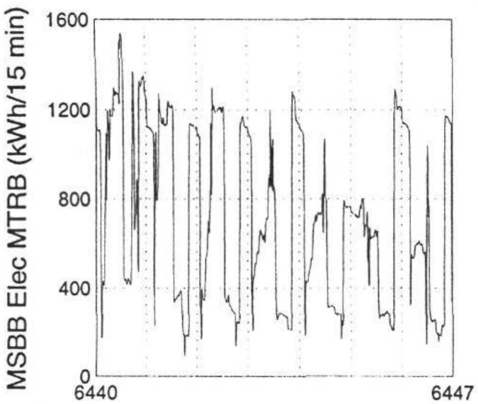
Site 230 Page 2



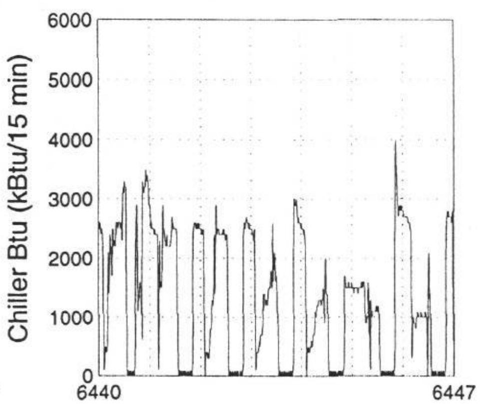
Site 230 Beginning 08-19-1997



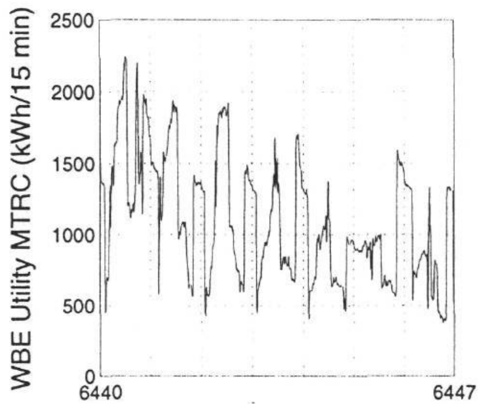
Site 230 Beginning 08-19-1997



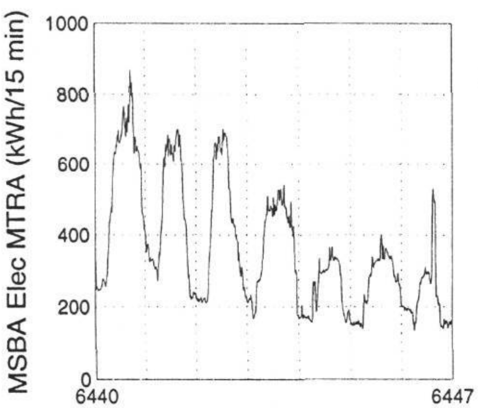
Site 230 Beginning 08-19-1997



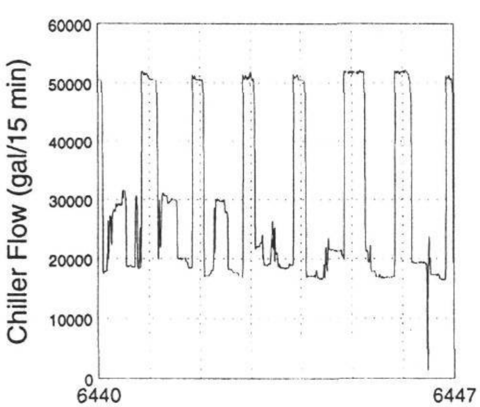
Site 230 Beginning 08-19-1997



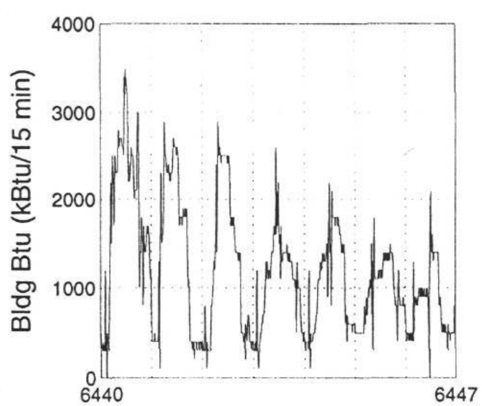
Site 230 Beginning 08-19-1997



Site 230 Beginning 08-19-1997



Site 230 Beginning 08-19-1997



Site 230 Beginning 08-19-1997

Austin Convention Center

City of Austin

174,456 square feet

Site Contact

Mr. Rudy Farias
Facilities Maintenance Manager
Austin Convention Center
500 East First Street
Austin, TX 78701
(512) 404–4300

LoanSTAR Metering Contact

Aamer Athar or Namir Saman
053 WERC
Texas A&M University
College Station, TX 77843-3123
(409) 845–9213

Summary of Energy Consumption

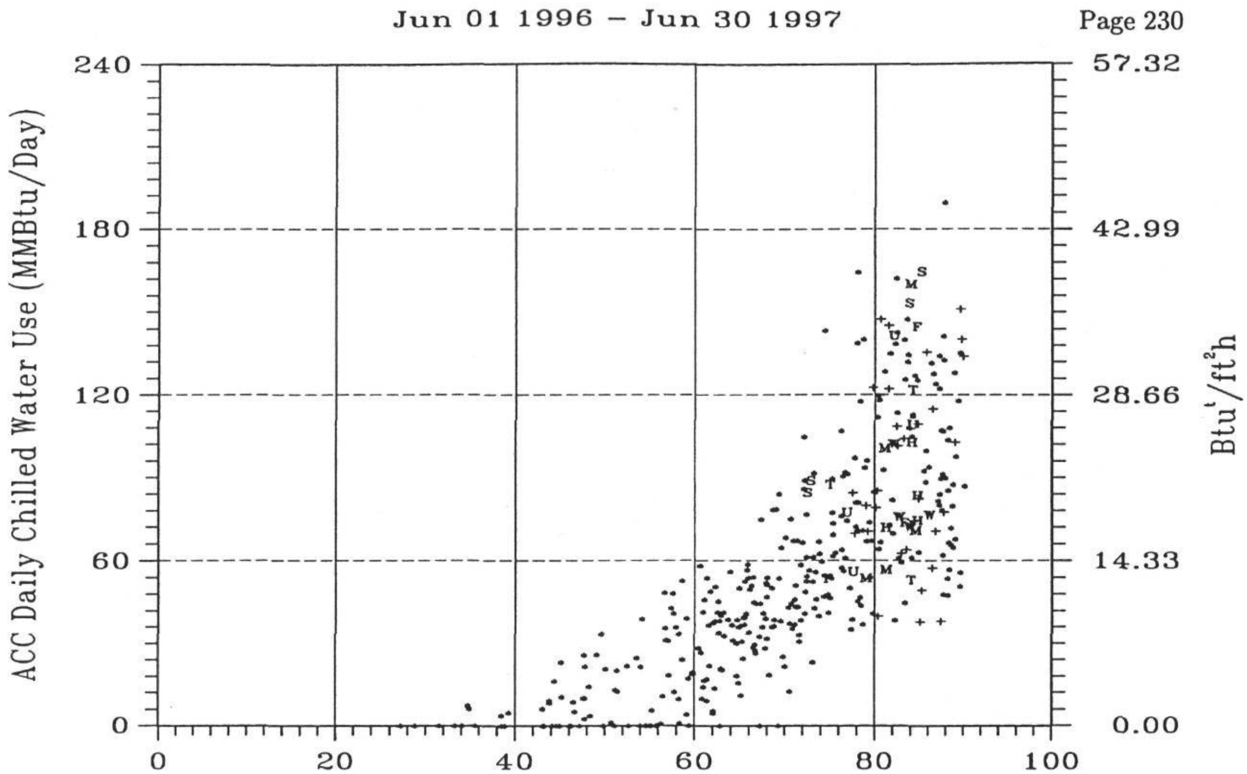
	Measured Use	% hours reported	Unit Cost	Estimated Cost
Electricity	671033 kWh	100	$0.06130	$41134
Peak 15 Minute Demand	2060 kW	100	-	-
Chilled Water Usage	2766.4 MMBtu	100	$5.000	$13832
Chilled Water Prod	3072.7 MMBtu	100	$5.000	$15364

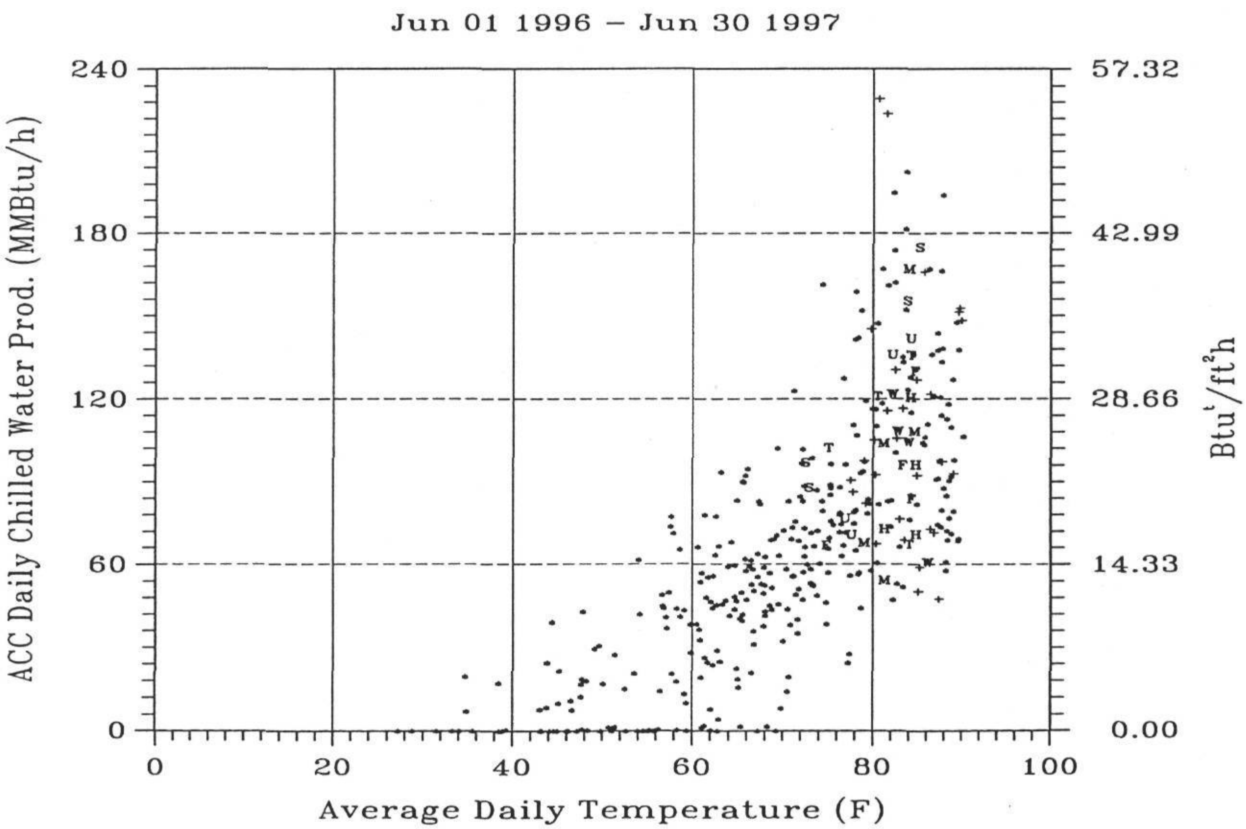
Peak 15 minute demand was recorded at 1930 Saturday 06/14/97.
There were 720 hours in this month.

Monthly Retrofit Savings

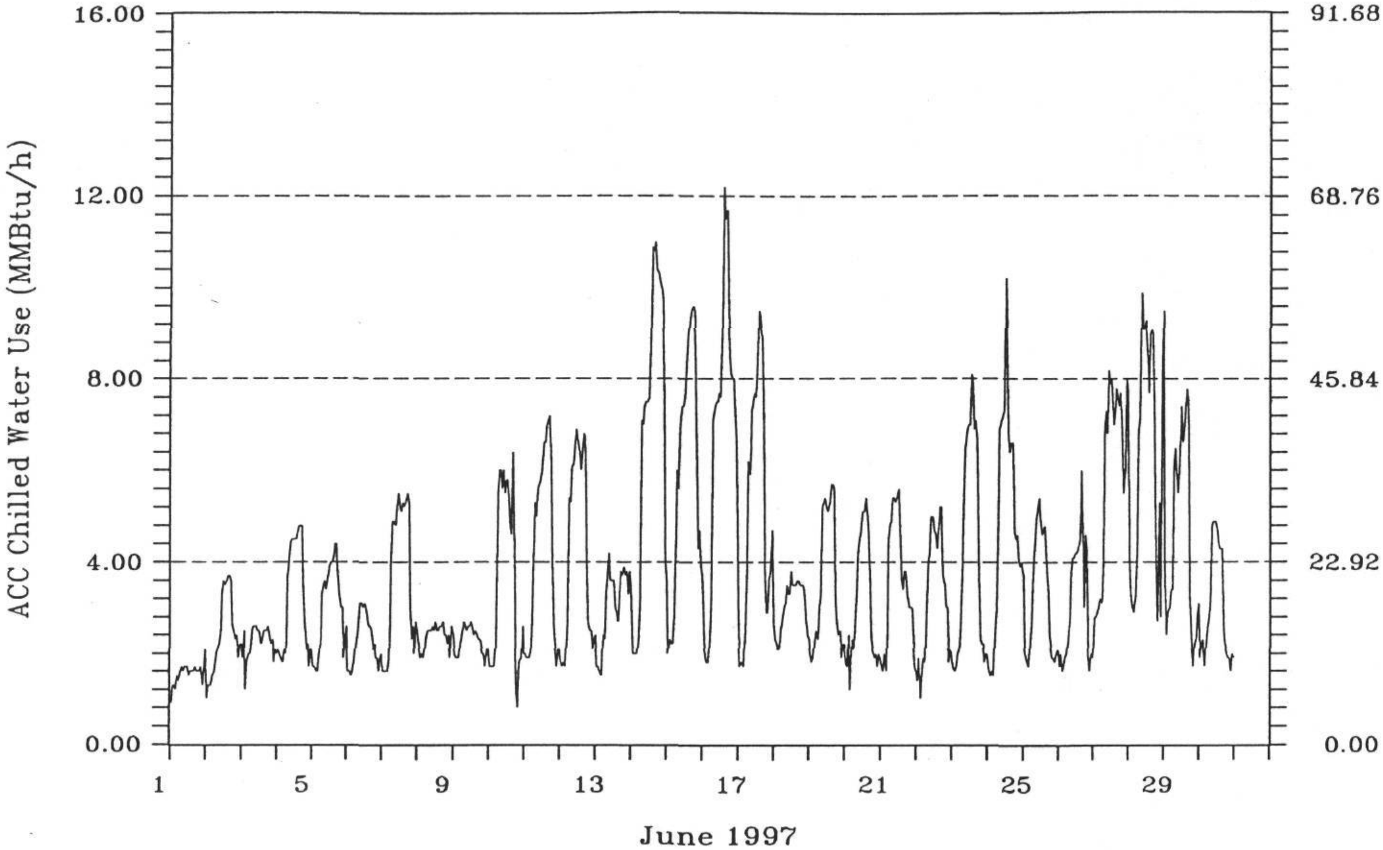
* All retrofits are in the bidding phase.
* Expected start date of construction is December 1997.

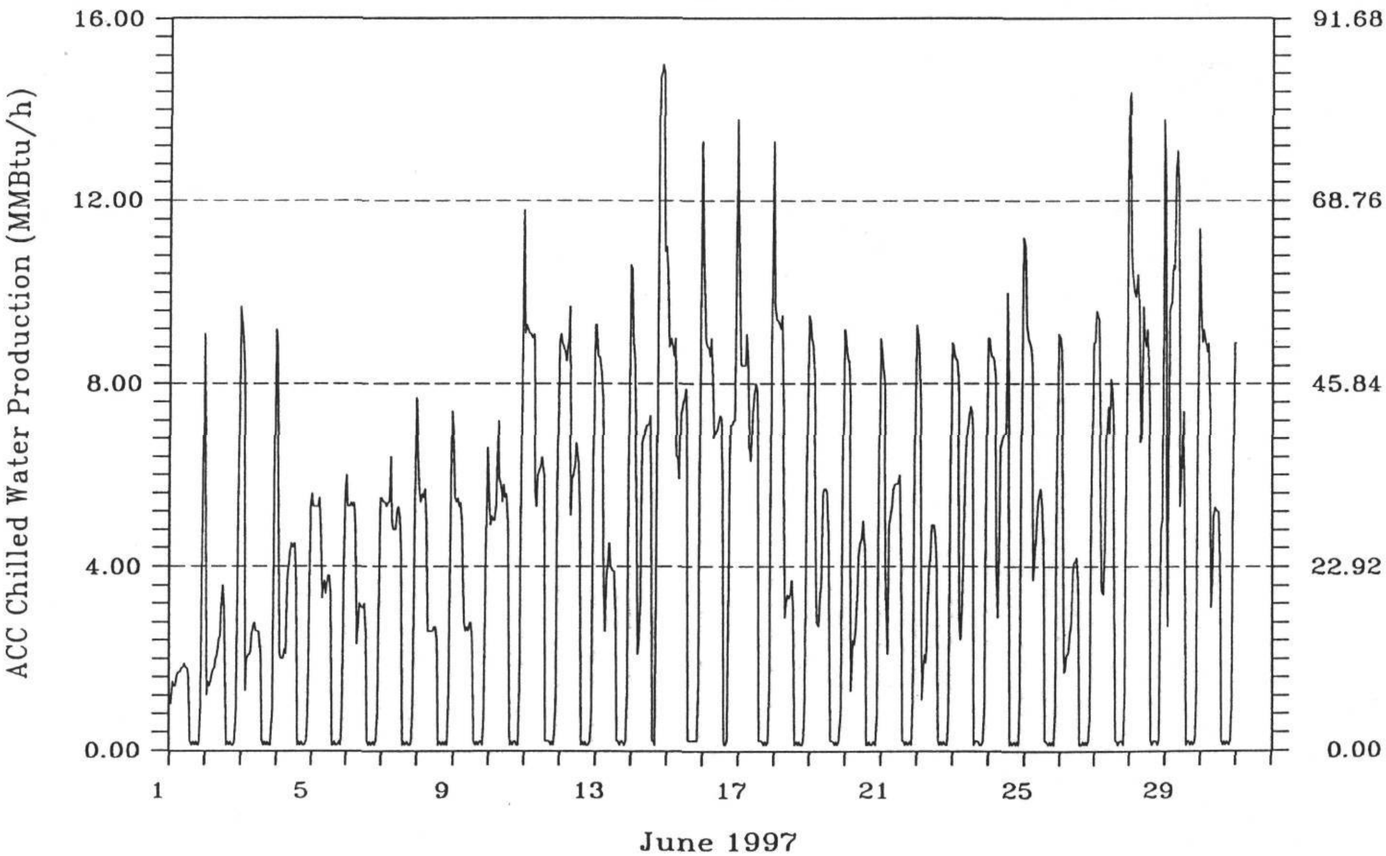
Comments



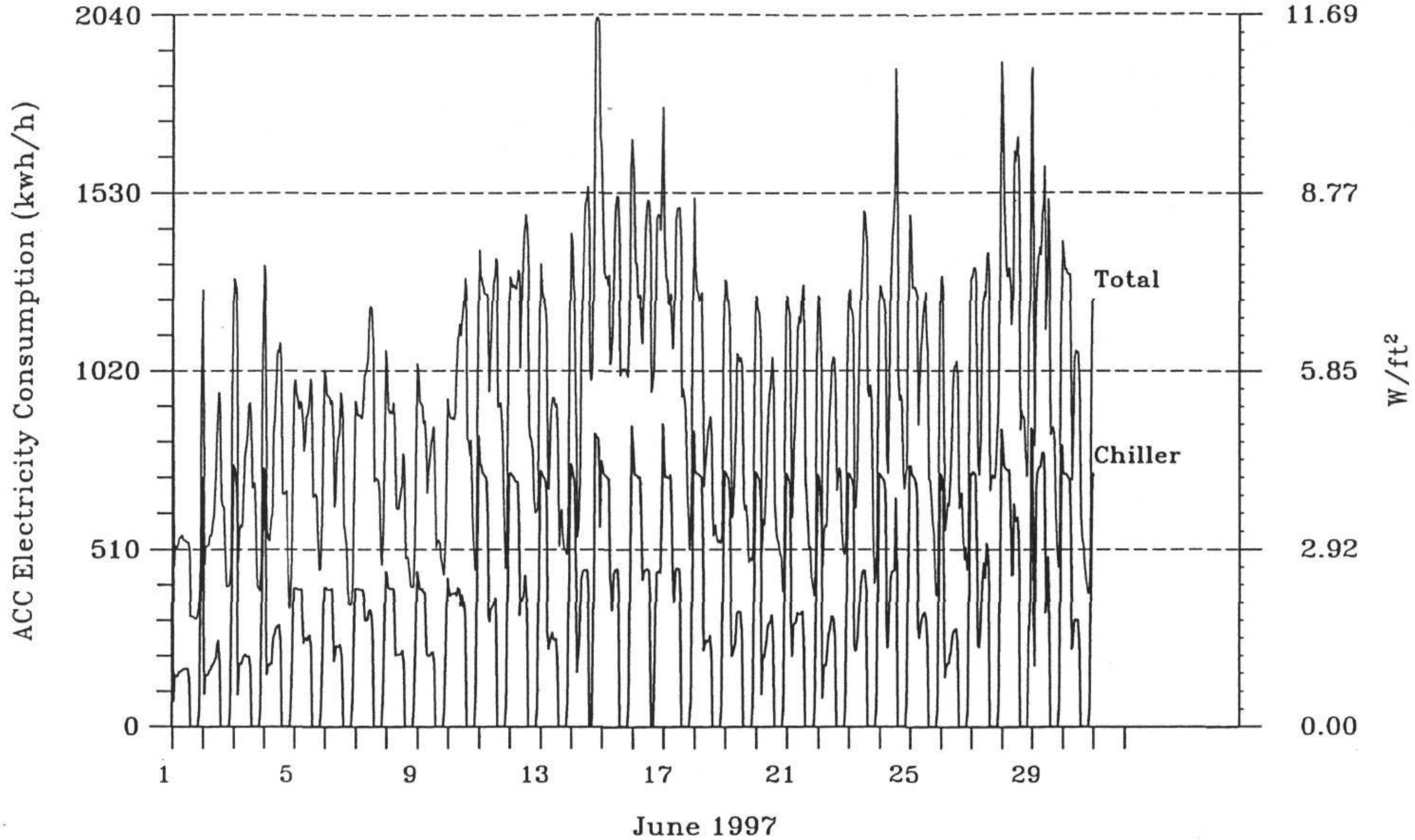


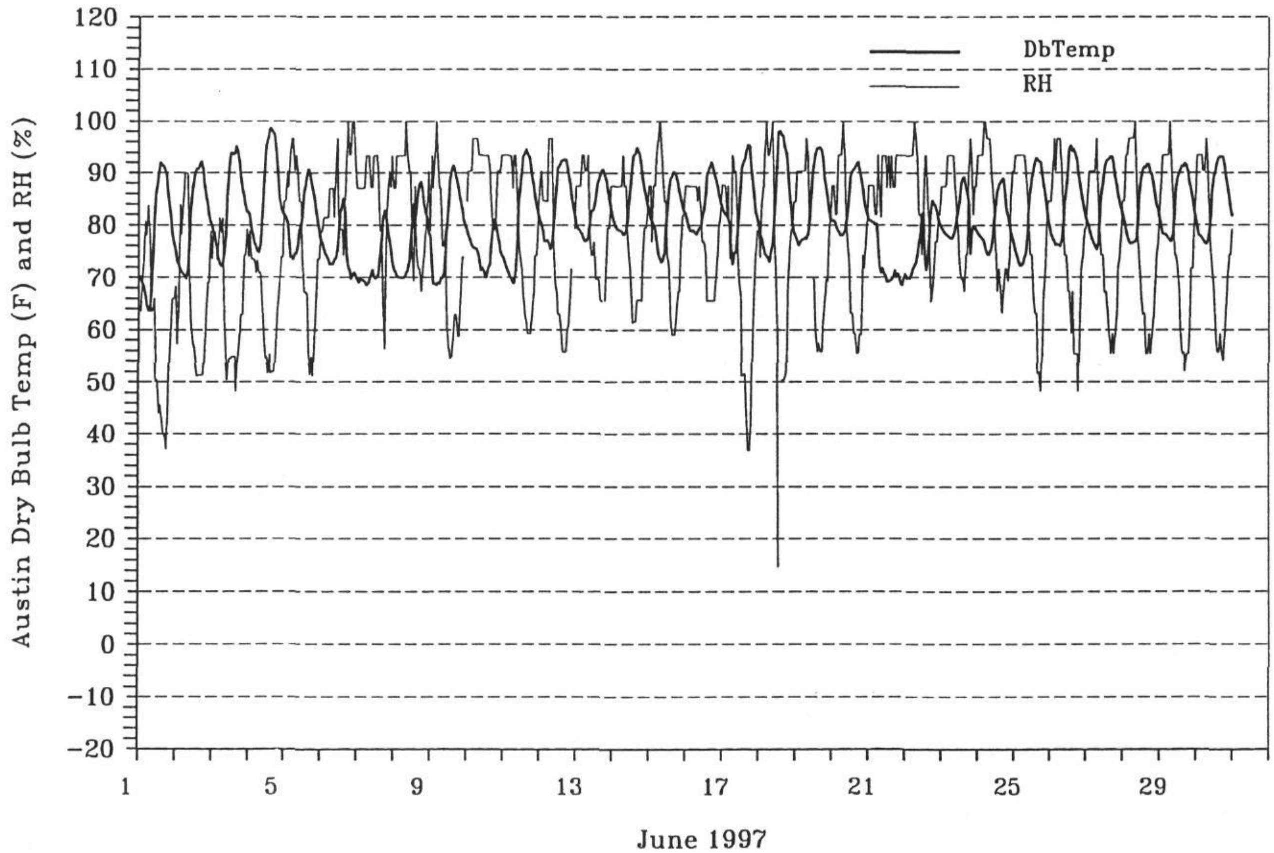
Data points for the current month are shown as letters. Points from this month last year are shown as +.
Monday through Sunday are represented as M,T,W,H,F,S,U. All other points are shown as *.





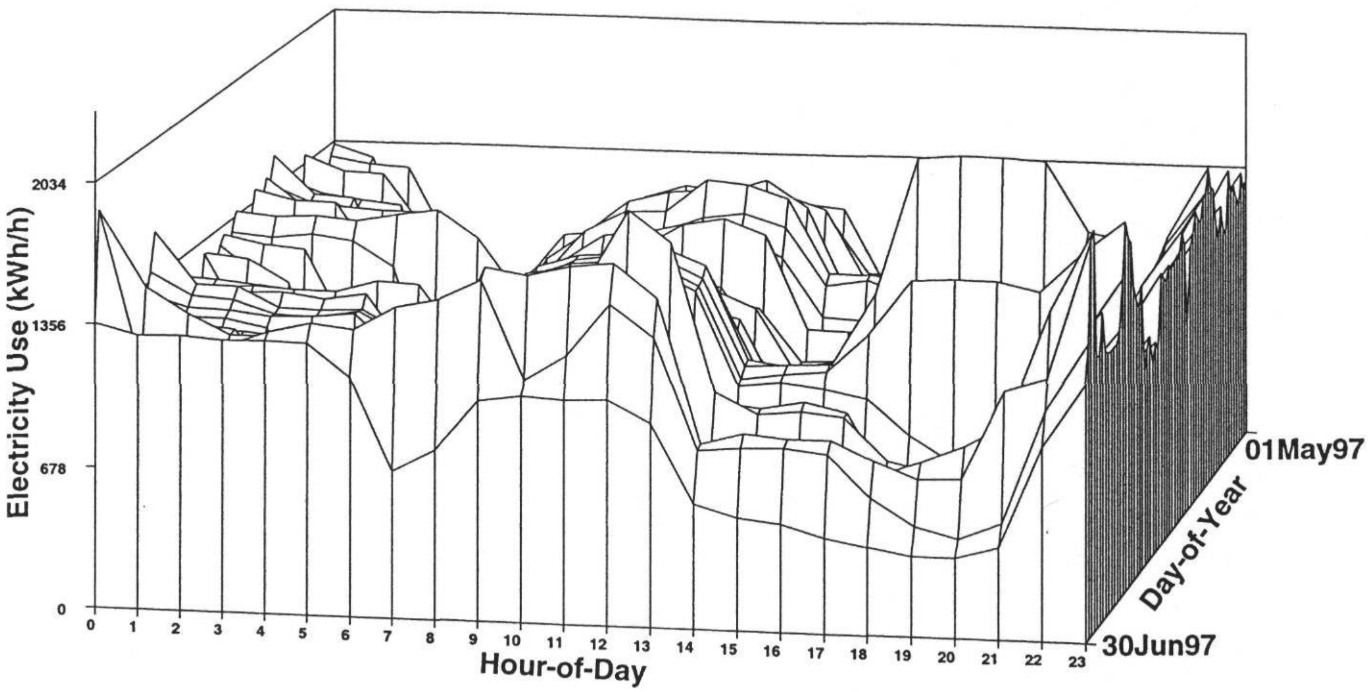
Austin Convention Center - City of Austin - June 1997



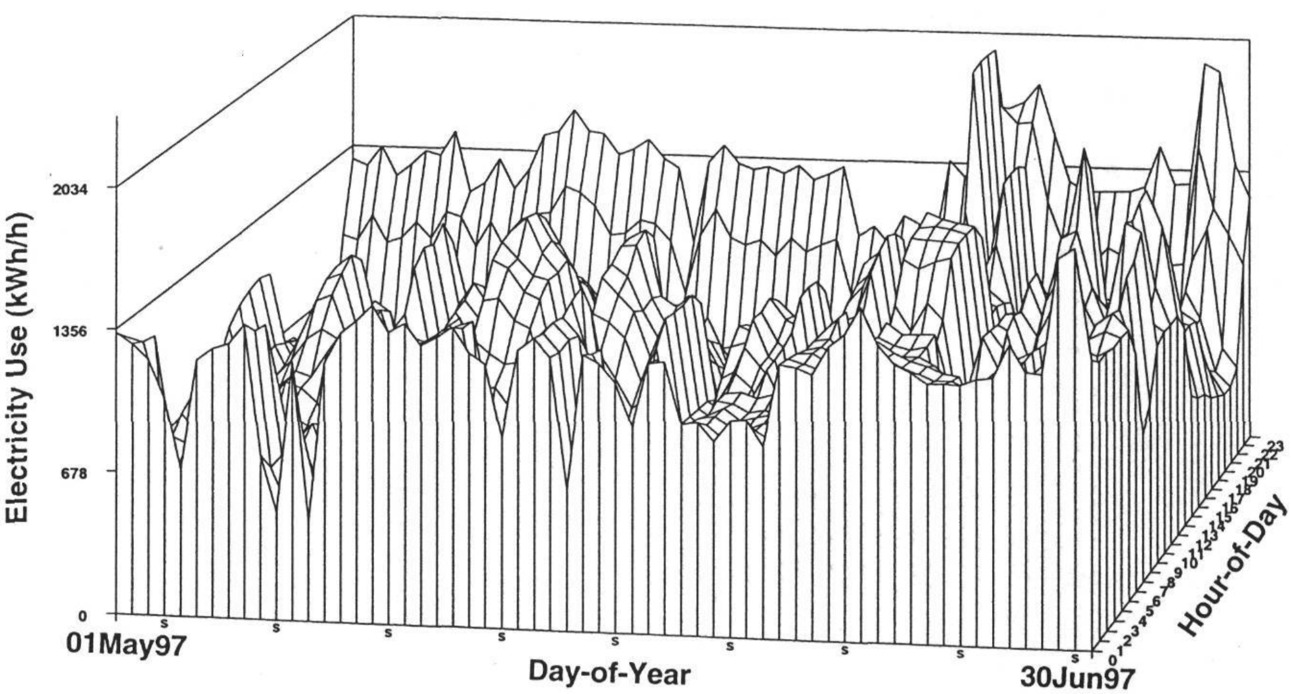


Austin Convention Center - City of Austin - June 1997

Whole–Building Electric



Whole–Building Electric



Sundays are marked with an "S"

CITY OF AUSTIN

Austin Convention Center

Building Envelope:
- 411,000 gross sq.ft.; 174,456 sq.ft. conditioned area
- 3 floors; comprised of Exhibit Halls, Ballrooms and Meeting rooms
- walls: granite with no insulation
- roof: flat built-up roof

Building Schedule:
- occupancy depends on events scheduleed, varies a lot. No events at night

Building HVAC and Equipment:
- two electric centrifugal chillers
- one 150Hp gas boiler
- several AHU's ranging from 5Hp to 50Hp
- several pumps ranging from 30Hp to 125Hp
- 2-spd, 40Hp CT fans

HVAC Schedule:
- not available

Lighting:
- metal halides, incandescent and fluorescent

Proposed Retrofits:
- lighting controls
- variable volume pumping conversion
- control modifications for building pressurization

Status of Retrofits:
- all retrofits are in the bidding phase. Expected start date of construction is December 1997

Other Information:
- lighting can be programmed through computer

Austin Convention Center

City of Austin
174,456 square feet

Site Contact

Mr. Rudy Farias
Facilities Maintenance Manager
Austin Convention Center
500 East First Street
Austin, TX 78701
(512) 404–4300

LoanSTAR Metering Contact

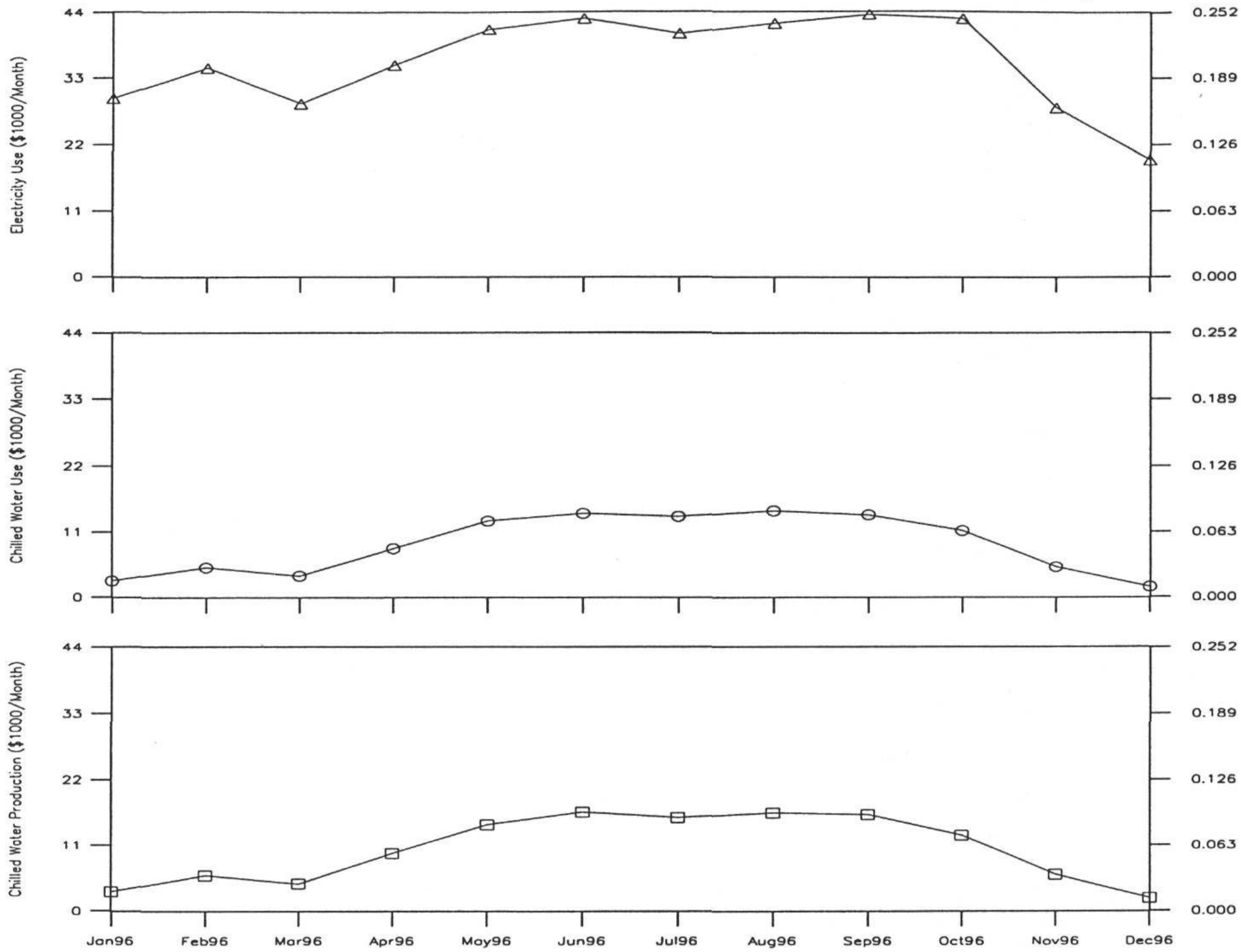
Aamer Athar or Namir Saman
053 WERC
Texas A&M University
College Station, TX 77843-3123
(409) 845–9213

1996 Summary of Measured Energy Consumption

	Electricity Consumption			Chilled Water Consumption			Chilled Water Production		
Month	kWh	$	%	MMBtu	$	%	MMBtu	$	%
Jan	483106	$29614	100	554	$2771	100	648	$3242	100
Feb	564930	$34630	100	999	$4997	100	1187	$5937	100
Mar	468100	$28695	100	723	$3615	100	908	$4538	100
Apr	573552	$35159	100	1642	$8209	100	1928	$9641	100
May	671325	$41152	100	2562	$12809	100	2889	$14447	100
Jun	700275	$42927	100	2819	$14096	100	3317	$16583	100
Jul	658037	$40338	100	2721	$13607	100	3137	$15683	100
Aug	686022	$42053	100	2907	$14535	100	3291	$16456	100
Sep	709785	$43510	100	2770	$13848	100	3235	$16177	100
Oct	698542	$42821	100	2234	$11170	100	2537	$12683	100
Nov	458585	$28111	100	1013	$5063	100	1211	$6054	100
Dec	318290	$19511	100	354	$1770	100	432	$2158	100
Total	6990549	$428521		21298	$106490		24720	$123599	
EUI	40.1	$\frac{kWh}{ft^2yr}$		122082	$\frac{Btu}{ft^2yr}$		141697	$\frac{Btu}{ft^2yr}$	

Comments

- ★ **The percent columns indicate the number of hours reported in that month.**
- ★ **The LoanSTAR monitoring began in July 1993.**
- ★ **The unit costs used for estimating energy costs are: $0.0613/kWh and $5.00/MMBtu (CW).**



The solid line indicates measured energy consumption

△ Electric ○ Cooling □ Chilled Water

CITY OF AUSTIN

Austin Convention Center

Building Envelope:
- 411,000 gross sq.ft., 174,456 sq.ft. conditioned area
- 3 floors, comprised of Exhibit Halls, Ballrooms and Meeting rooms
- walls: granite with no insulation
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Building Schedule:
- occupancy depends on events scheduleed, varies a lot. No events at night

Building HVAC and Equipment:
- two electric centrifugal chillers
- one 150Hp gas boiler
- several AHU's ranging from 5Hp to 50Hp
- several pumps ranging from 30Hp to 125Hp
- 2-spd, 40Hp CT fans

HVAC Schedule:
- not avaliable

Lighting:
- metal halides, incandescent and fluorescent

Proposed Retrofits:
- lighting controls
- variable volume pumping conversion
- control modifications for building pressurization

Status of Retrofits:
- all retrofits are in construction phase

Other Information:
- lighting can be programmed through computer

Site #322

University of Houston - Clearlake
Houston, TX

Ice on coil

d	cp	Description
9	1	Whole Bldg Elec (kW)
0	2	Whole Bldg Gas (mcf/h)
1	3	Whole Bldg Chw (kBtu/h)
2	4	Whole Bldg Chw flow (gal/h)
3	5	Chiller 1 Elec (kW)
4	6	Chiller 2 Elec (kW)
5	7	Chiller 3 Elec (kW)
6	8	Ice Store Chw (kBtu/h)

32290001.cht Tue Jan 31 13:13:57 1995 1

Date MM/DD/YY (YY DDD)	Time HH:mm	Raw-Data lin pos	coln pos	Arch coln pos	Name of Channel	Archive Units	Arch Format	Conv'n Code	Conv'n Constants	Error Code	Error Constants	Channel Description
#												
08/23/94	00:00	1	0	0	Begin	UHCL/Bayou Building						Beginning date
08/23/94	00:00	1	1	1	Site	-	I3	2	0 322	0		Site #
08/23/94	00:00	1	1	2	Mon-Raw	MM	I3	1		0		Month
08/23/94	00:00	1	2	3	Mon-Raw	DD	I3	1		0		Day
08/23/94	00:00	1	3	4	Mon-Raw	YY	I3	1		0		Year
08/23/94	00:00	1	3	5	Greg-Jul	MMDDYY	I5	24	1 2	0		Gregorian Date to Julian
08/23/94	00:00	1	4	7	Time	HH mm	I5	16	5	0		Time
08/23/94	00:00	1	3	6	Greg-Dec	DDD.frac	F10.4	28		0		Gregorian Date to Jul.Decimal
08/23/94	00:00	1	6	8	WBELEC	F9.3	F9.3	1		1	-5 9999999	Whole Bldg Elec (kW)
08/23/94	00:00	1	7	9	WBGAS	F9.3	F9.3	1		1	-5 9999999	Whole Bldg Gas (mcf/h)
08/23/94	00:00	1	8	10	WBCHWB	F9.3	F9.3	1		1	-5 9999999	Whole Bldg Chw (kBtu/h)
08/23/94	00:00	1	9	11	WBCHWF	F9.3	F9.3	1		1	-5 9999999	Whole Bldg Chw flow (gal/h)
08/23/94	00:00	1	10	12	CHL1	F9.3	F9.3	1		1	-5 9999999	Chiller 1 Elec (kW)
08/23/94	00:00	1	11	13	CHL2	F9.3	F9.3	1		1	-5 9999999	Chiller 2 Elec (kW)
08/23/94	00:00	1	12	14	CHL3	F9.3	F9.3	1		1	-5 9999999	Chiller 3 Elec (kW)
08/23/94	00:00	1	13	15	ICECHWB	F9.3	F9.3	1		1	-5 9999999	Ice Store Chw (kBtu/h)
12/31/99	23:00	1	0	0	End	UHCL/Bayou Building						

Ice storage is run from 1:15 pm - 12:45 am
will be done on post retrofit

University of Houston-Clear Lake: Bayou Building

Building Envelope:
- 460,576 sq. ft.
- Walls: precast
- Roof: built up
- Year of construction: 1975

Building Schedule:
- The average occupancy schedule is 8 am to 5 pm Monday through Friday

Building HVAC and Equipment:
- 3 chilled water pumps ranging from 40 - 50Hp
- 32 AHUs ranging from 30 - 75Hp
- 3 cooling tower fans, 50Hp each

HVAC Schedule:
- All HVAC equipment operates for 5,450 hours annually and is controlled by automation. Operating hours are 6:00 am to 10:00 pm

Lighting:
- 12,210 two lamp 40W fixtures

Completed Retrofits:
- Thermal Storage - December 1995

Other Information:
- Electricity is supplied by Houston Lighting & Power and natural gas is supplied by General Land Office.

Building Envelope:
- 460,576 sq. ft.
- Walls: precast
- Roof: built up
- Year of construction: 1975

Building Schedule:
- The average occupancy schedule is 8 am to 5 pm Monday through Friday

Building HVAC and Equipment:
- 3 chilled water pumps ranging from 40 - 50Hp
- 17 AHUs ranging from 30 - 75Hp
- 3 cooling tower fans, 50Hp each

863 Ch 1 Tons
863 Ch 2 Tons

HVAC Schedule:
- All HVAC equipment operates for 5,450 hours annually and is controlled by automation.

Lighting:
- 12,210 two lamp 40W fixtures

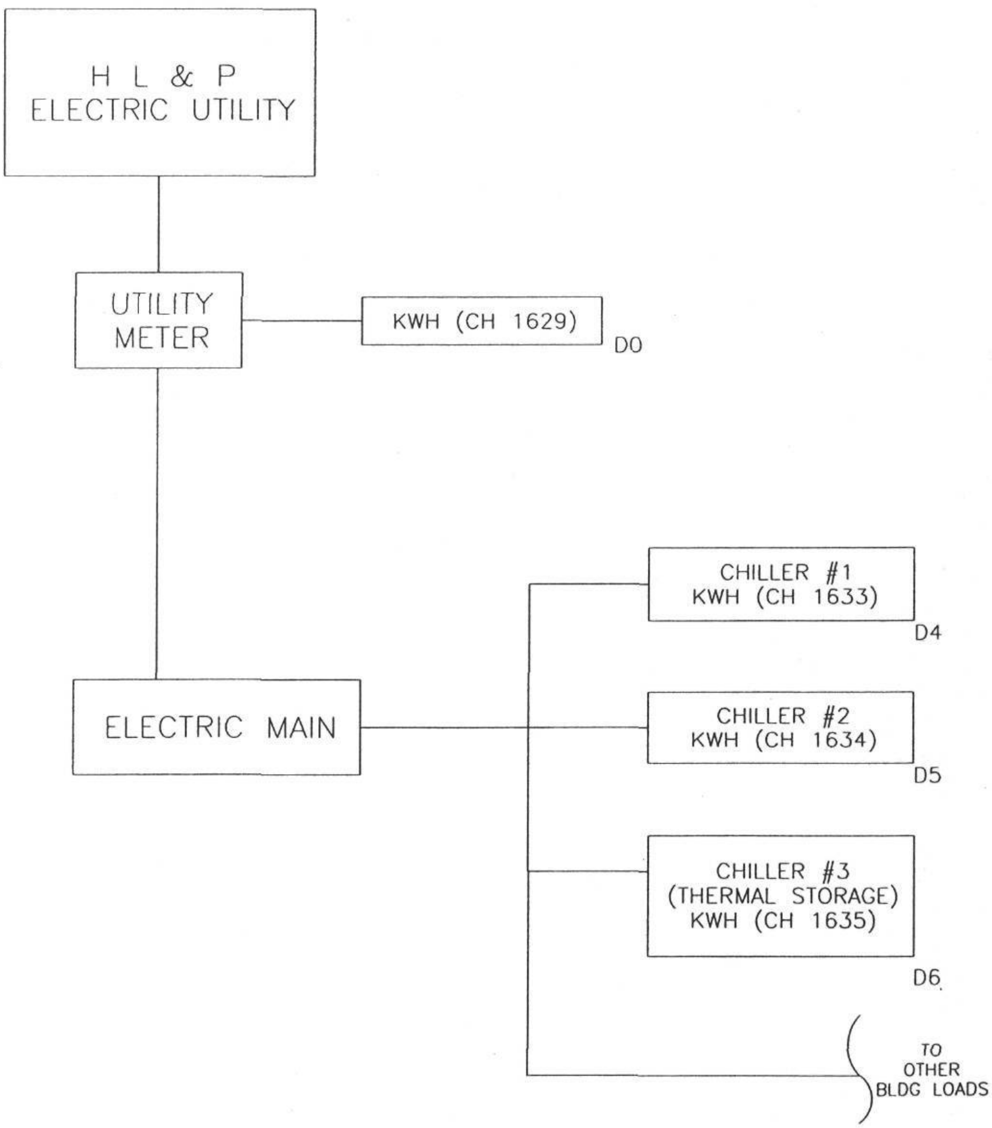
Proposed Retrofits:
- Thermal Storage

Other Information:
- Electricity is supplied by Houston Lighting & Power and natural gas is supplied by General Land Office.

UNIVERSITY OF HOUSTON
CLEAR LAKE
ELECTRICAL MONITORING DIAGRAM

LEGEND

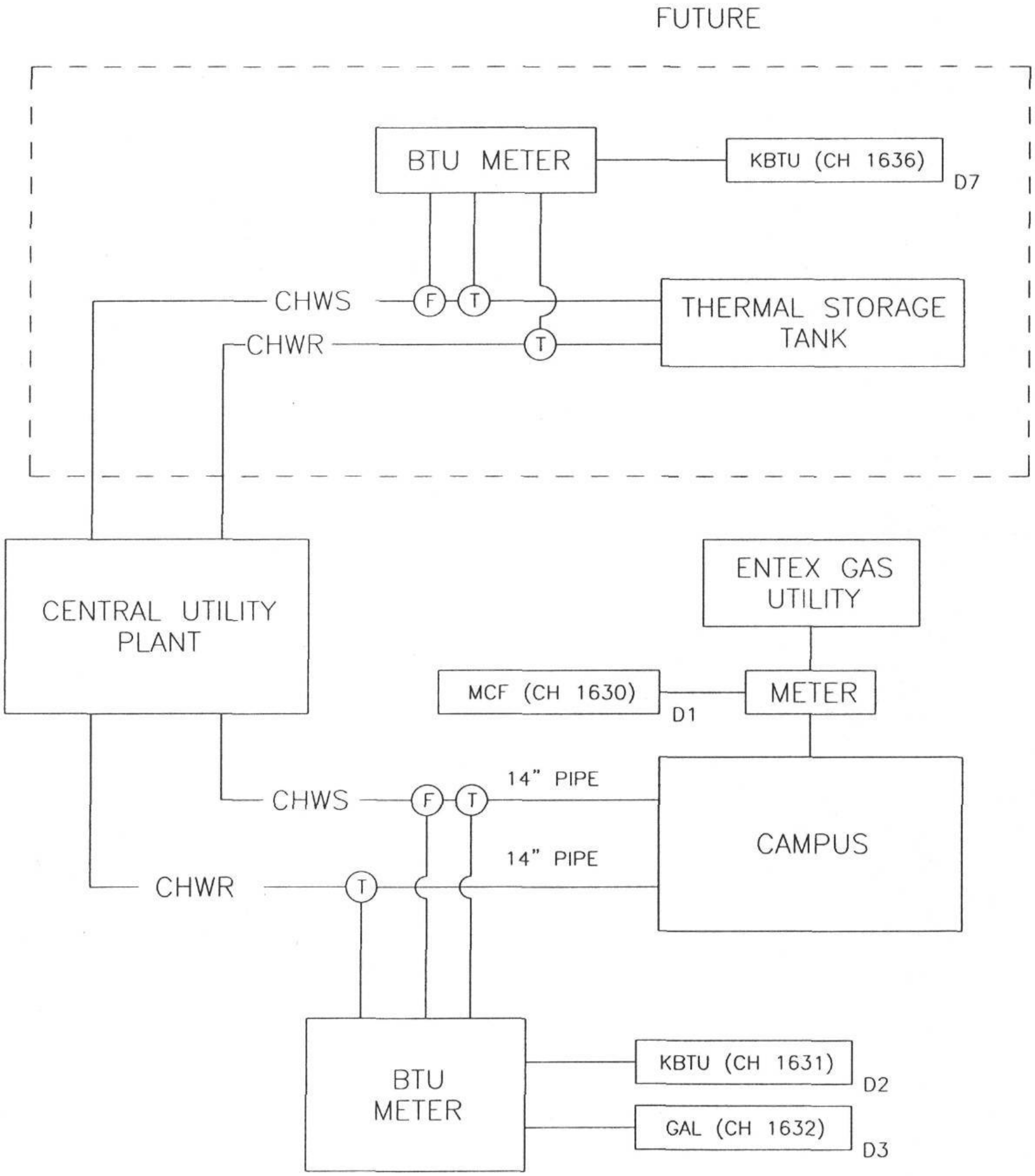
K=KWH CHANNEL
A=ANALOG CHANNEL
D=DIGITAL CHANNEL



UNIVERSITY OF HOUSTON CLEAR LAKE
THERMAL MONITORING DIAGRAM

LEGEND

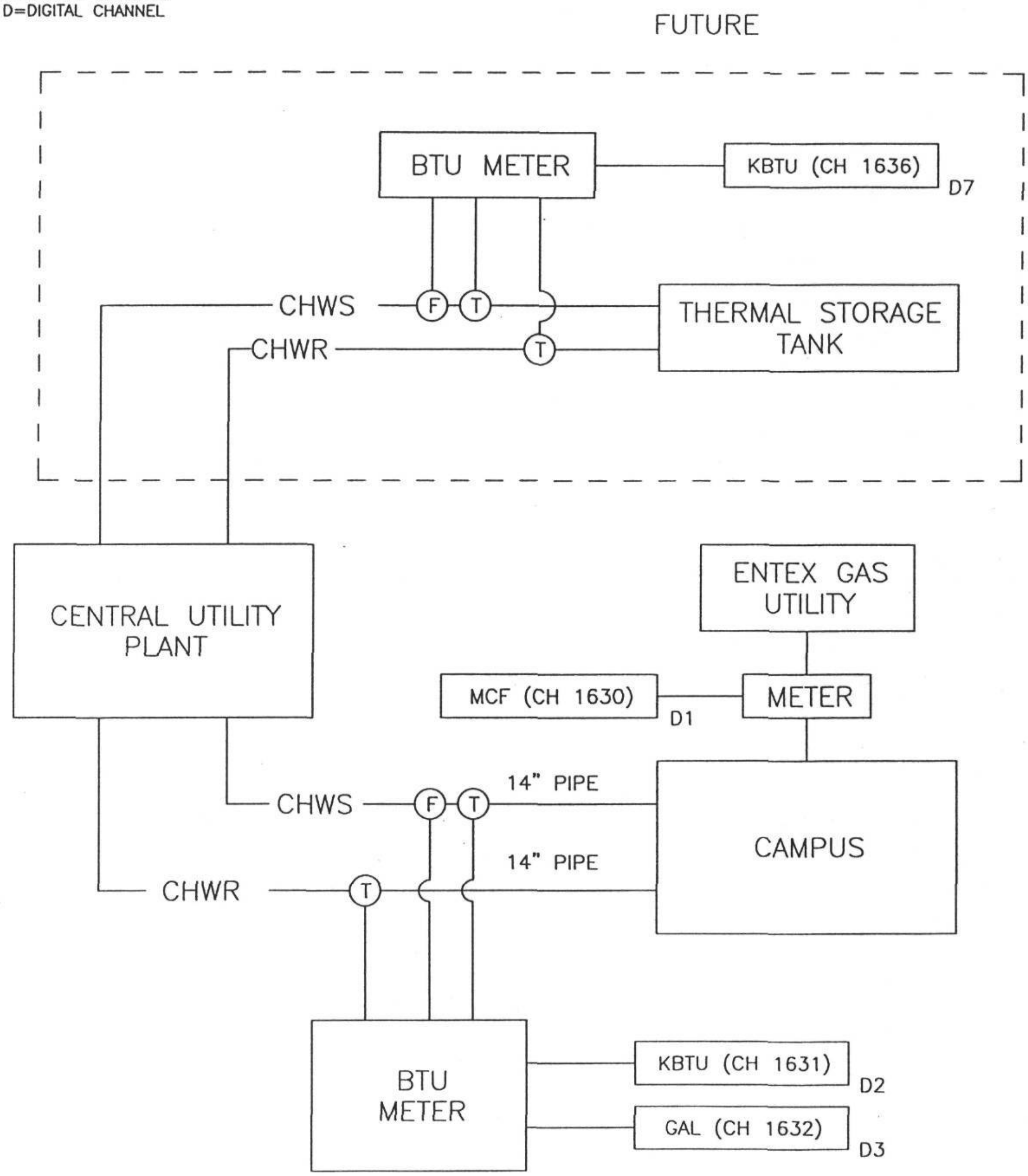
K=KWH CHANNEL
A=ANALOG CHANNEL
D=DIGITAL CHANNEL



THERMAL MONITORING DIAGRAM
UNIVERSITY OF HOUSTON CLEAR LAKE

LEGEND

K=KWH CHANNEL
A=ANALOG CHANNEL
D=DIGITAL CHANNEL

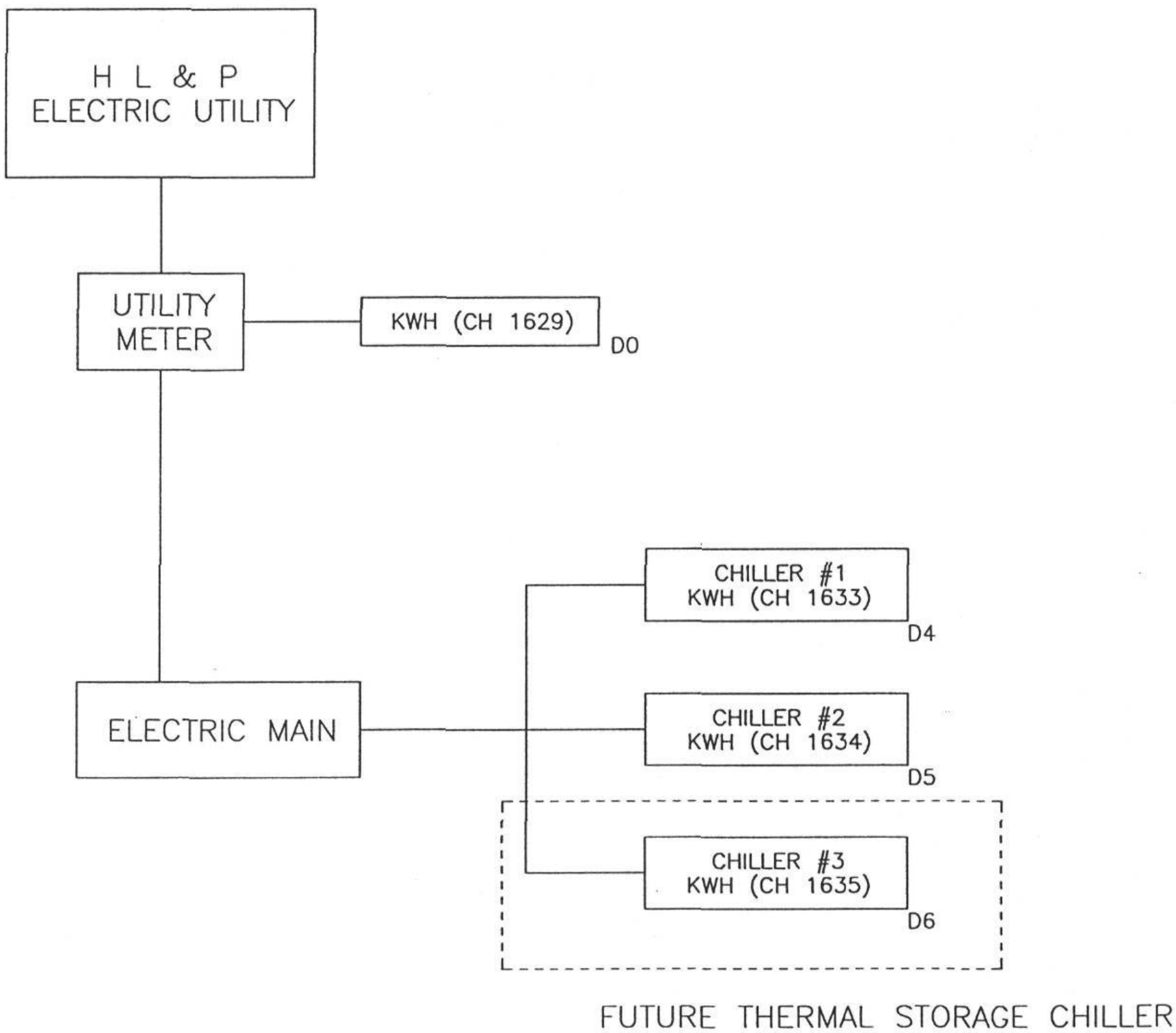


UNIVERSITY OF HOUSTON\CLEAR LAKE – SITE 322 (HOURLY DATA)

ELECTRICAL MONITORING DIAGRAM
UNIVERSITY OF HOUSTON CLEAR LAKE

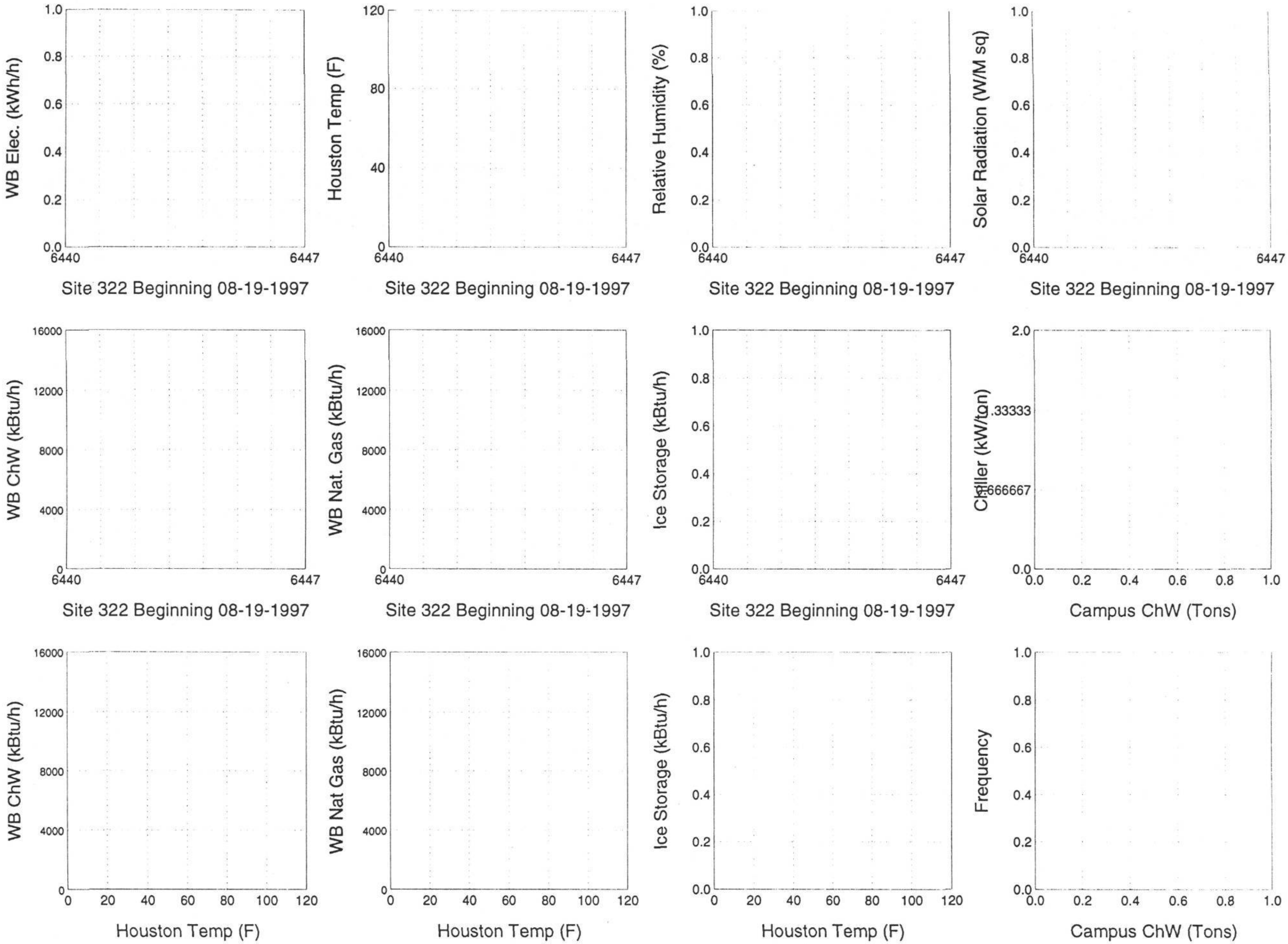
LEGEND

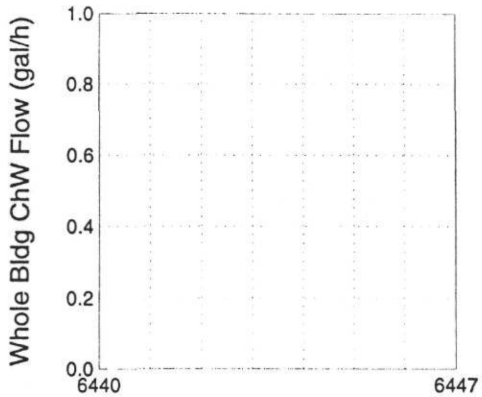
K=KWH CHANNEL
A=ANALOG CHANNEL
D=DIGITAL CHANNEL



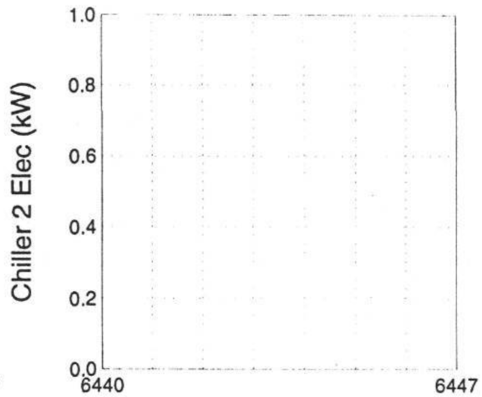
UNIVERSITY OF HOUSTON\CLEARLAKE – SITE 322 (HOURLY DATA)

Site 322 Page 1

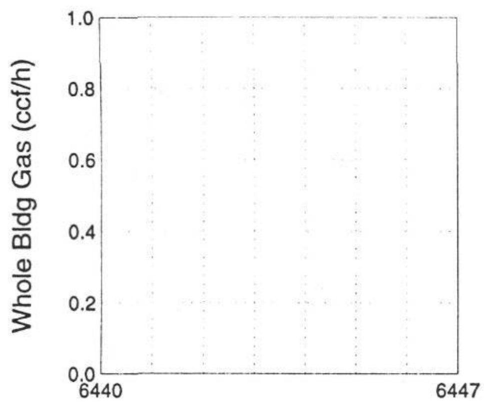




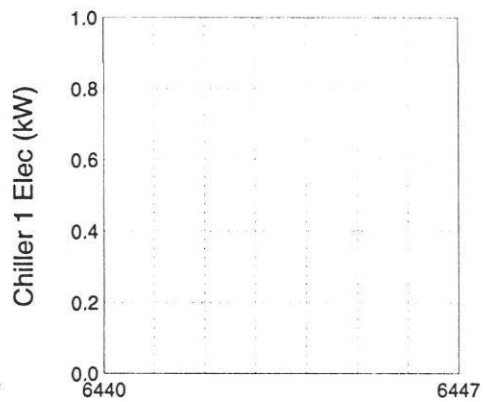
Site 322 Beginning 08-19-1997



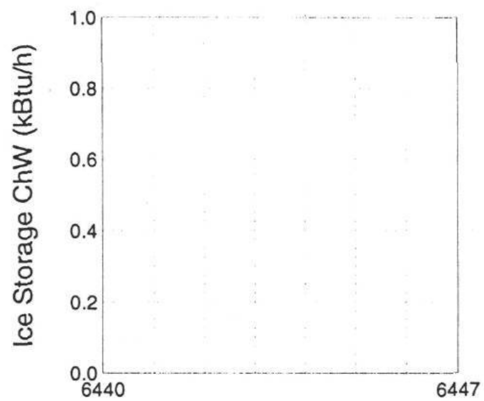
Site 322 Beginning 08-19-1997



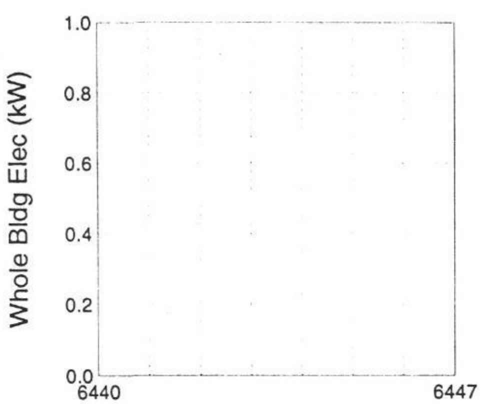
Site 322 Beginning 08-19-1997



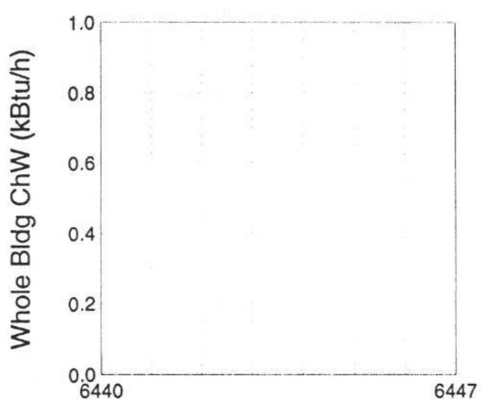
Site 322 Beginning 08-19-1997



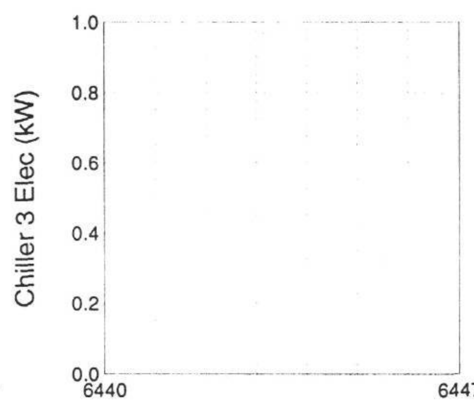
Site 322 Beginning 08-19-1997



Site 322 Beginning 08-19-1997



Site 322 Beginning 08-19-1997



Site 322 Beginning 08-19-1997

University of Houston - Clear Lake

460,576 square feet

Site Contact	LoanSTAR Metering Contact
Mr. Herald Johnson	Aamer Athar or Namir Saman
Director of Physical Plant	053 WERC
University of Houston - Clear Lake	Texas A&M University
2700 Bay Area Blvd. Box 222	College Station, TX 77843-3123
Houston, TX 79430	(409) 845-9213
(713) 283-2250	

Summary of Energy Consumption

	Measured Use	% hours reported	Unit Cost	Estimated Cost
Electricity	- kWh	-	$0.02700	-
Peak 60 Minute Demand	- kW	-	$12.19	-
Chilled Water	3952.9 MMBtu	77	$5.000	$19765
Natural Gas	107.1 MMBtu	77	$3.378	$362

No peak 60 minute demand was recorded this month.
There were 720 hours in this month.

Monthly Retrofit Savings

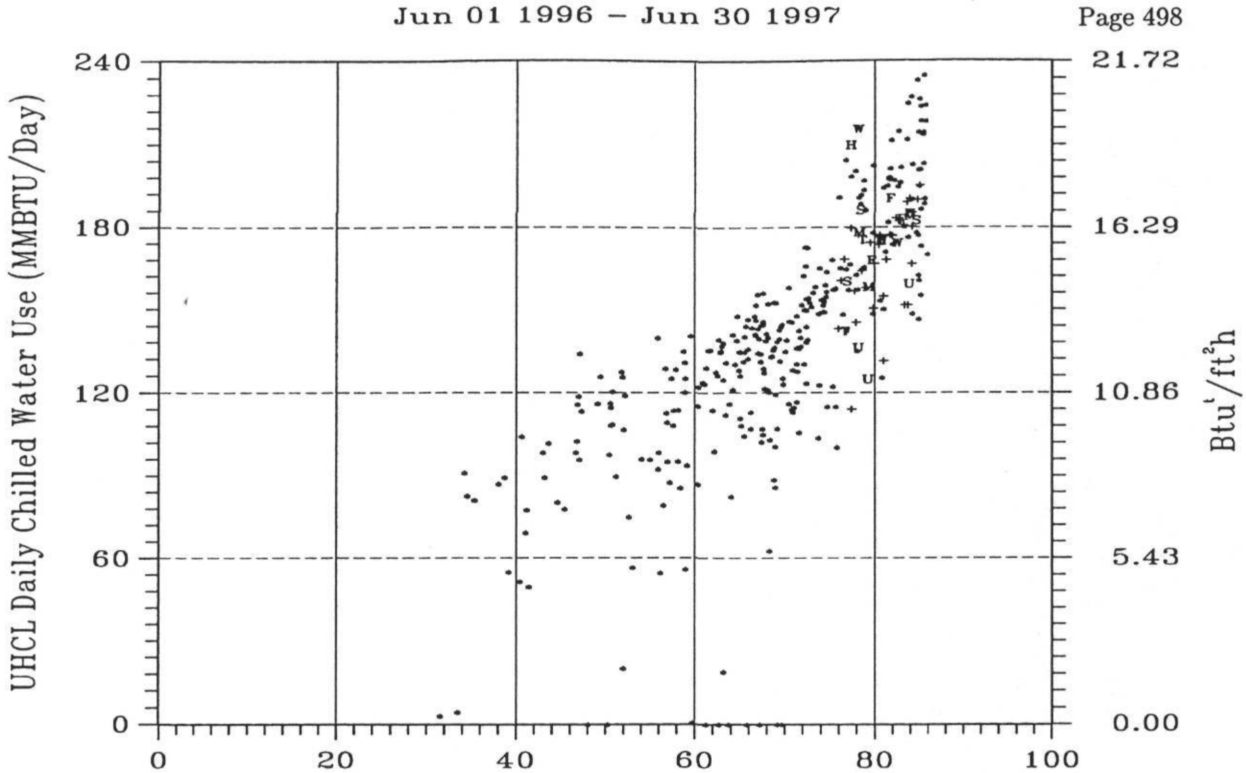
	Measured Savings		Audit Estimated Savings	
Electricity Demand (kW)	907	$11056	524	$6388
Monthly Total		$11056		$6388
Total to Date*	(17 months)	$128440	(14 months)	$89426

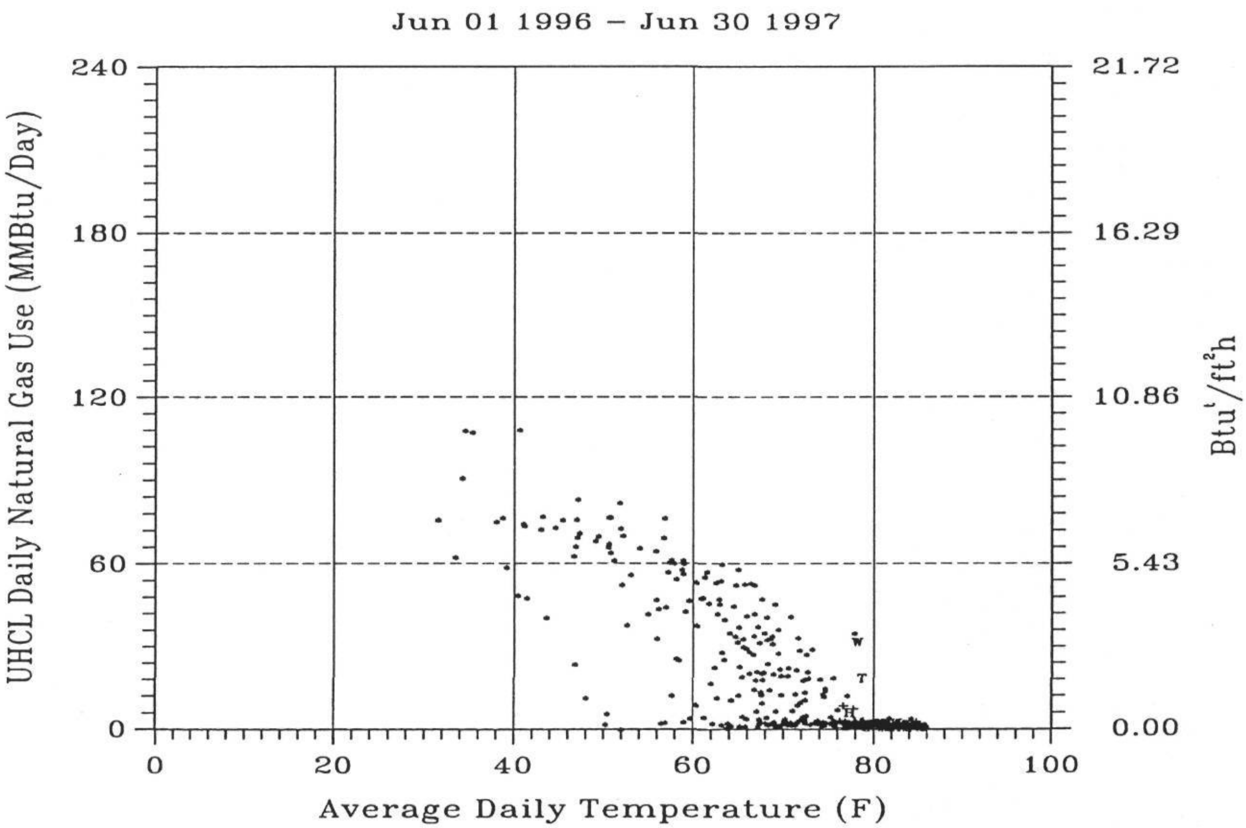
*Measured savings include construction period. Audit estimated savings do not.

Comments

★ **Electricity consumption data are missing from 6/1/97 to 6/30/97 due to a monitoring hardware problem.**

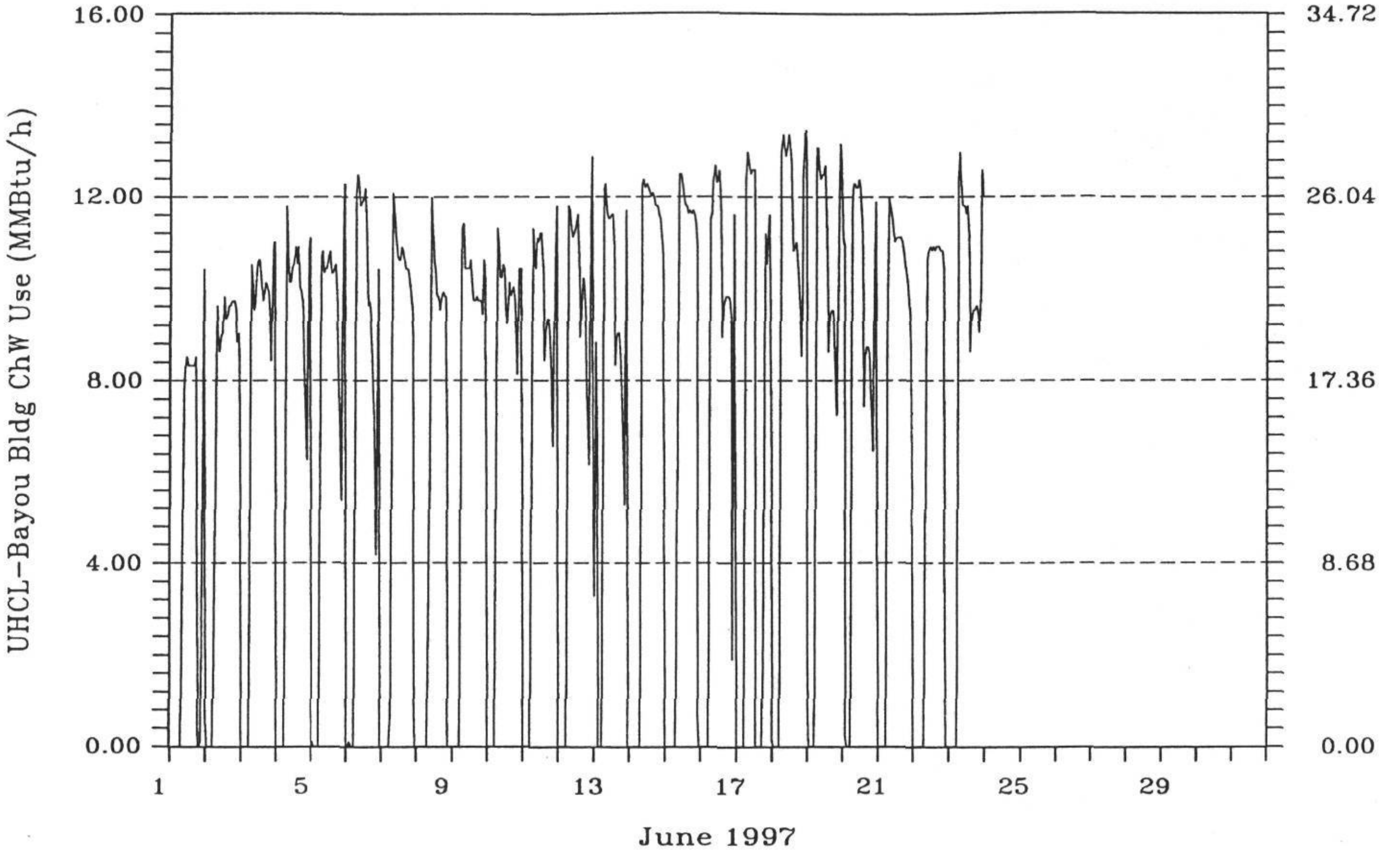
★ **Chilled water and natural gas energy use data are missing from 6/24/97 to 6/31/97 due to a monitoring hardware problem.**

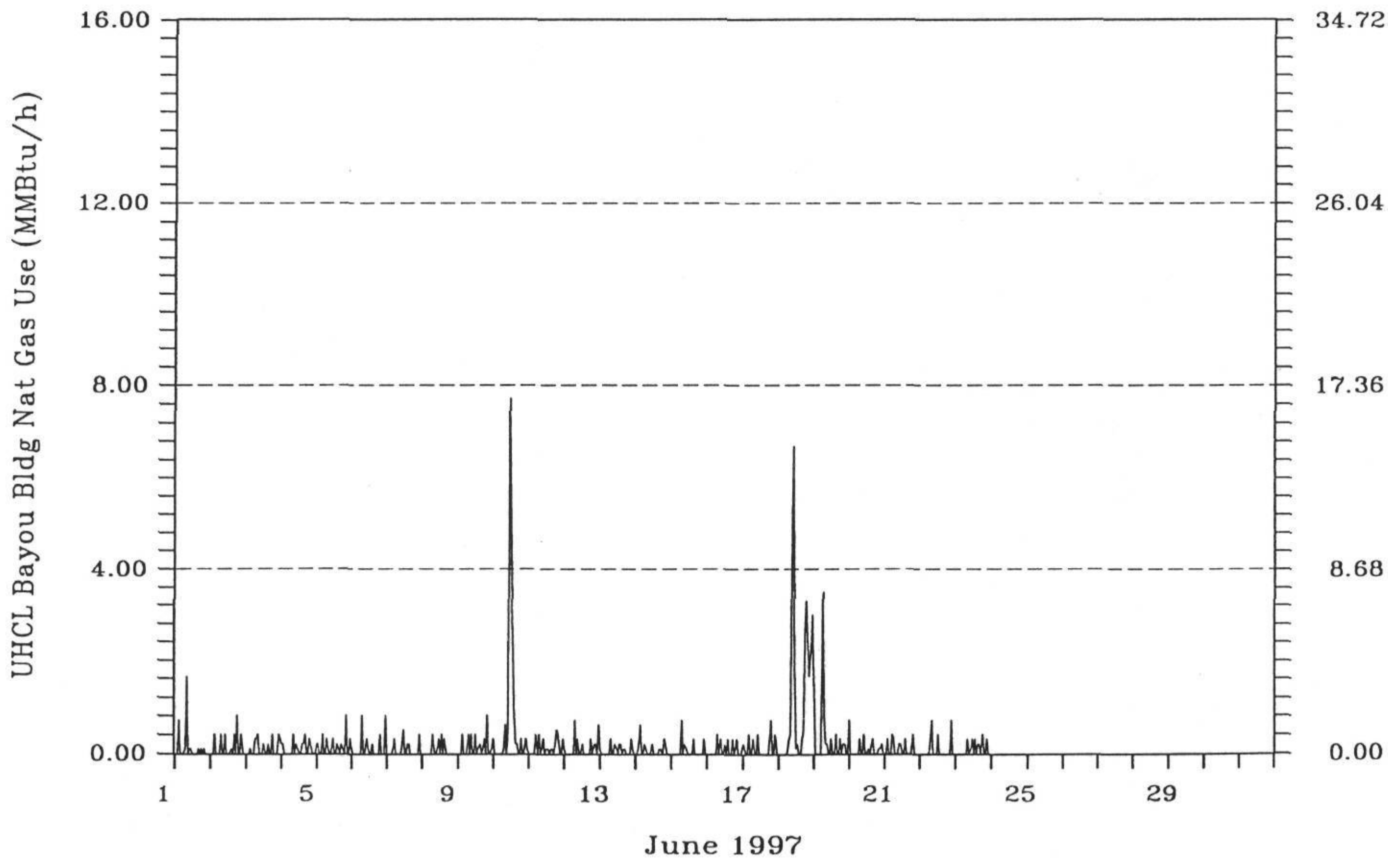




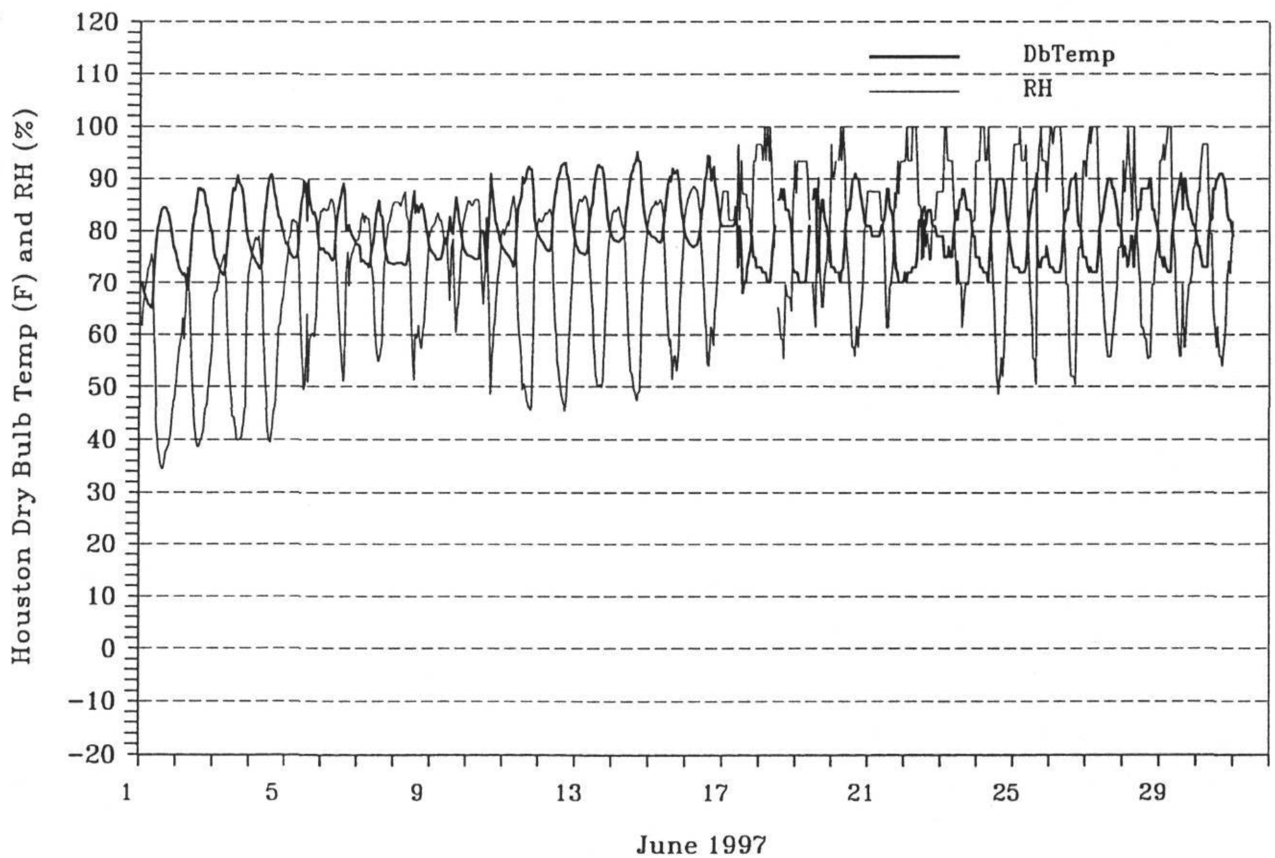
Data points for the current month are shown as letters. Monday through Sunday are represented as M,T,W,H,F,S,U.

Points from this month last year are shown as +. All other points are shown as *.





University of Houston - Clear Lake - June 1997


Houston Dry Bulb Temp (F) and RH (%)
120
110
100
90
80
70
60
50
40
30
20
10
0
-10
-20
DbTemp
RH
1
5
9
13
17
21
25
29
June 1997

UNIVERSITY OF HOUSTON-CLEAR LAKE

Bayou Building

Building Envelope:
- 460,576 sq.ft.
- walls: precast
- roof: built up
- year of construction: 1975

Building Schedule:
- the average occupancy schedule is 8 am to 5 pm Monday through Friday

Building HVAC and Equipment:
- 3 chilled water pumps ranging from 40 - 50 hp
- 32 AHUs ranging from 30 - 75 hp
- 3 cooling tower fans, 50 hp each

HVAC Schedule:
- all HVAC equipment operates for 5,450 hours annually and is controlled by automation. Operating hours are 6:00 am to 10:00 pm

Lighting:
- 12,210 two lamp 40W fixtures

Completed Retrofits:
- thermal storage - December 1995

Other Information:
- electricity is supplied by Houston Lighting & Power and natural gas is supplied by General Land Office

University of Houston - Clear Lake

460,576 square feet

Site Contact

Mr. Herald Johnson
Director of Physical Plant
University of Houston - Clear Lake
2700 Bay Area Blvd. Box 222
Houston, TX 79430
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LoanSTAR Metering Contact

Aamer Athar or Namir Saman
053 WERC
Texas A&M University
College Station, TX 77843-3123
(409) 845–9213

1996 Summary of Measured Energy Consumption and Savings

	Electricity				Electricity Demand				Hot Water/Steam/NG				Total	
	Consumption			Savings	Consumption			Savings	Consumption			Savings	Monthly	Cumulative
Month	kWh	$	%	$	kW	$	%	$	MMBtu	$	%	$	Savings	Savings
Jan	1232280	$33272	100	N/A	2890	$35230	100	$353	1854	$6262	100	N/A	$353	$353
Feb	1237974	$33425	100	N/A	3102	$37810	100	$-1874	1058	$3573	100	N/A	$-1874	$-1521
Mar	1282004	$34614	100	N/A	3171	$38653	100	$-1839	1089	$3679	100	N/A	$-1839	$-3360
Apr	1295690	$34984	100	N/A	3162	$38548	100	$-1124	675	$2280	100	N/A	$-1124	$-4484
May	1366308	$36890	100	N/A	2078	$25331	100	$10753	137	$464	100	N/A	$10753	$6269
Jun	1368385	$36946	100	N/A	2078	$25331	100	$11370	91	$306	100	N/A	$11370	$17639
Jul	1537861	$41522	100	N/A	2078	$25331	100	$12762	40	$134	100	N/A	$12762	$30401
Aug	1515457	$40917	57	N/A	2078	$25331	57	$9851	41	$137	84	N/A	$9851	$40252
Sep	1488129	$40179	39	N/A	2065	$25172	39	$10947	154	$519	39	N/A	$10947	$51199
Oct	1471375	$39727	100	N/A	2674	$32596	100	$1962	315	$1064	100	N/A	$1962	$53161
Nov	1282487	$34627	100	N/A	2601	$31706	100	$4259	461	$1556	100	N/A	$4259	$57420
Dec	1025366	$27685	100	N/A	2156	$26282	100	$10780	1024	$3459	100	N/A	$10780	$68200
Total	16103316	$434788		$0	30133	$367321		$68200	6939	$23433		$0		$68200
EUI	35.0	$\frac{kWh}{ft^2yr}$			65424	$\frac{Btu}{ft^2yr}$			15065	$\frac{Btu}{ft^2yr}$				

Comments

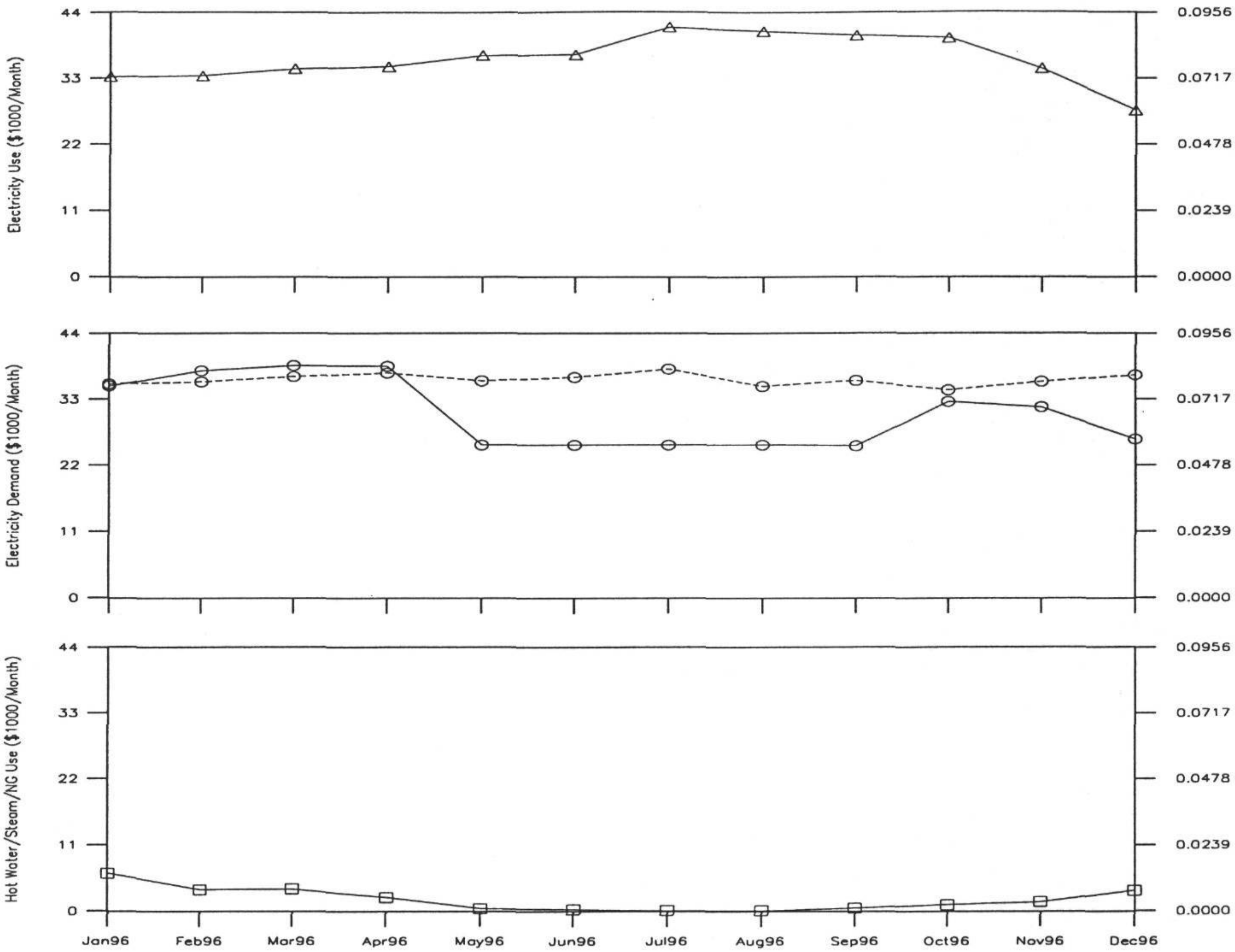
★ **The percent columns indicate the number of hours reported in that month.**

★ **The LoanSTAR monitoring began in August 1994.**

★ **The unit costs used for estimating the energy costs and savings are: $0.027/kWh (ELE), $12.19/kW-mo (ELED), $5.00/MMBtu (CW), and $3.378/MMBtu (NG).**

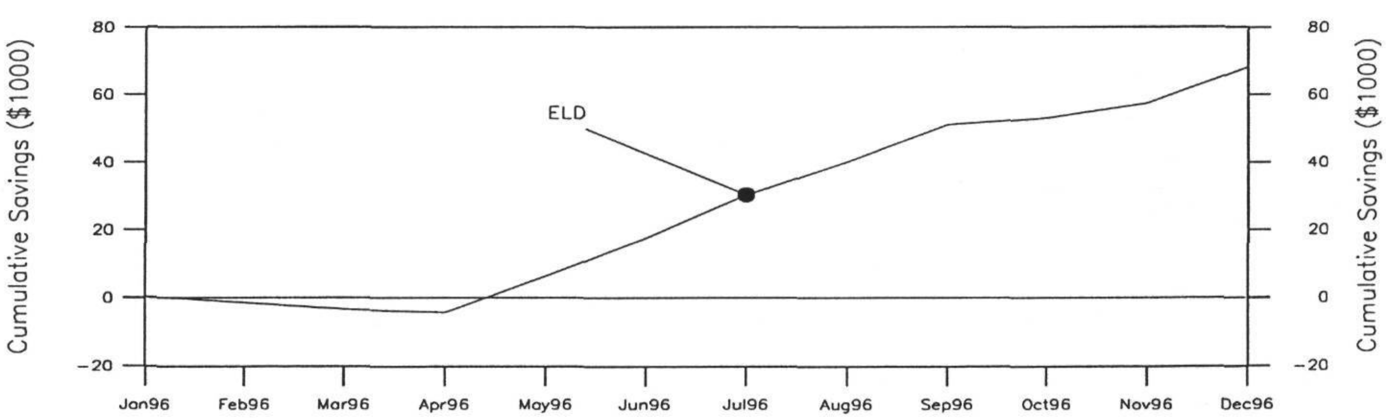
★ **Electricity, chilled water and natural gas consumption data for parts of August and September 1996 are missing due to a monitoring hardware problem.**

★ **The audit estimated savings for the completed thermal storage system are $76,700 (ELED).**



Solid line represents measured energy use while the dashed line indicates
the energy that would have been consumed had the retrofit not been installed

△ Electric ○ Cooling □ Heating



UNIVERSITY OF HOUSTON-CLEAR LAKE

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Completed Retrofits:

- thermal storage - December 1995

Other Information:

- electricity is supplied by Houston Lighting & Power and natural gas is supplied by General Land Office

University of Houston - Clear Lake

460,576 square feet

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Summary of Energy Consumption

	Measured Use	% hours reported	Unit Cost	Estimated Cost
Electricity	867660 kWh	84	$0.02700	$23427
Peak 60 Minute Demand	3171 kW	84	$12.19	$38653
Chilled Water	4254.1 MMBtu	71	$5.000	$21270
Natural Gas	34.1 MMBtu	84	$3.378	$115

Peak 60 minute demand was recorded at 1200 Thursday 08/01/96.
There were 744 hours in this month.

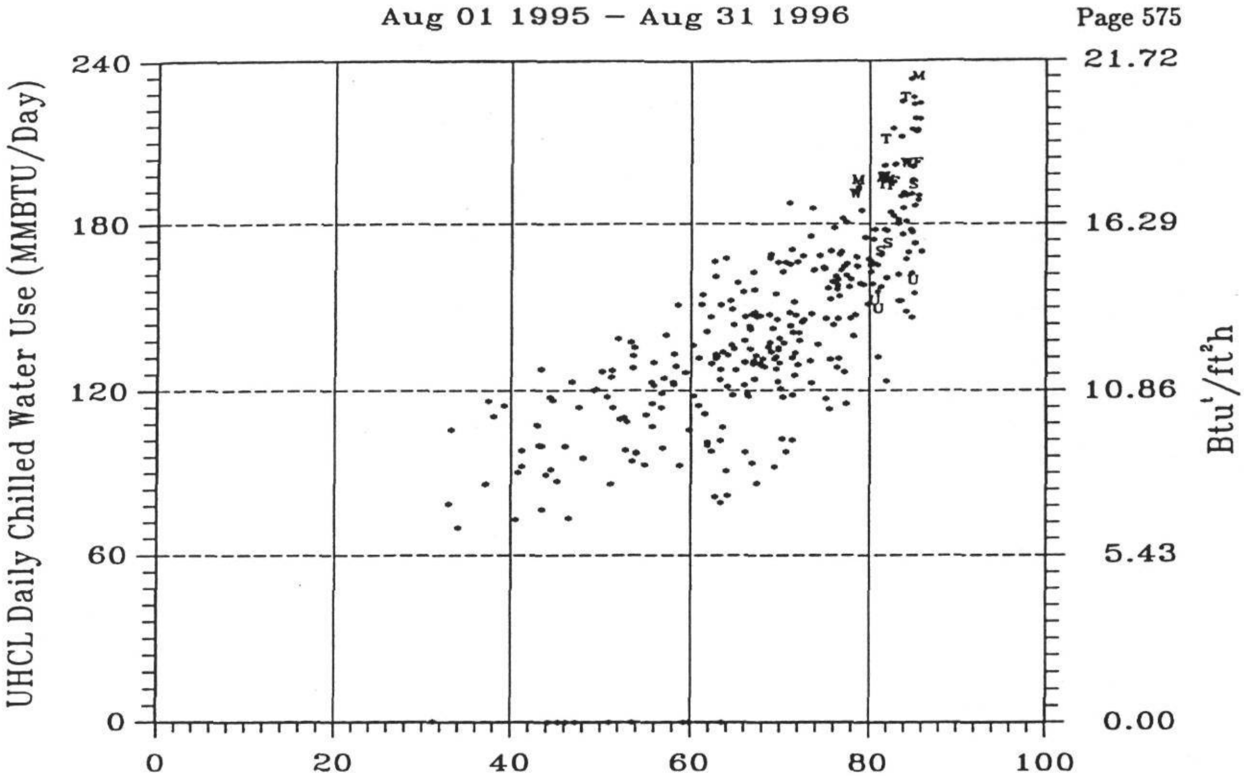
Monthly Retrofit Savings

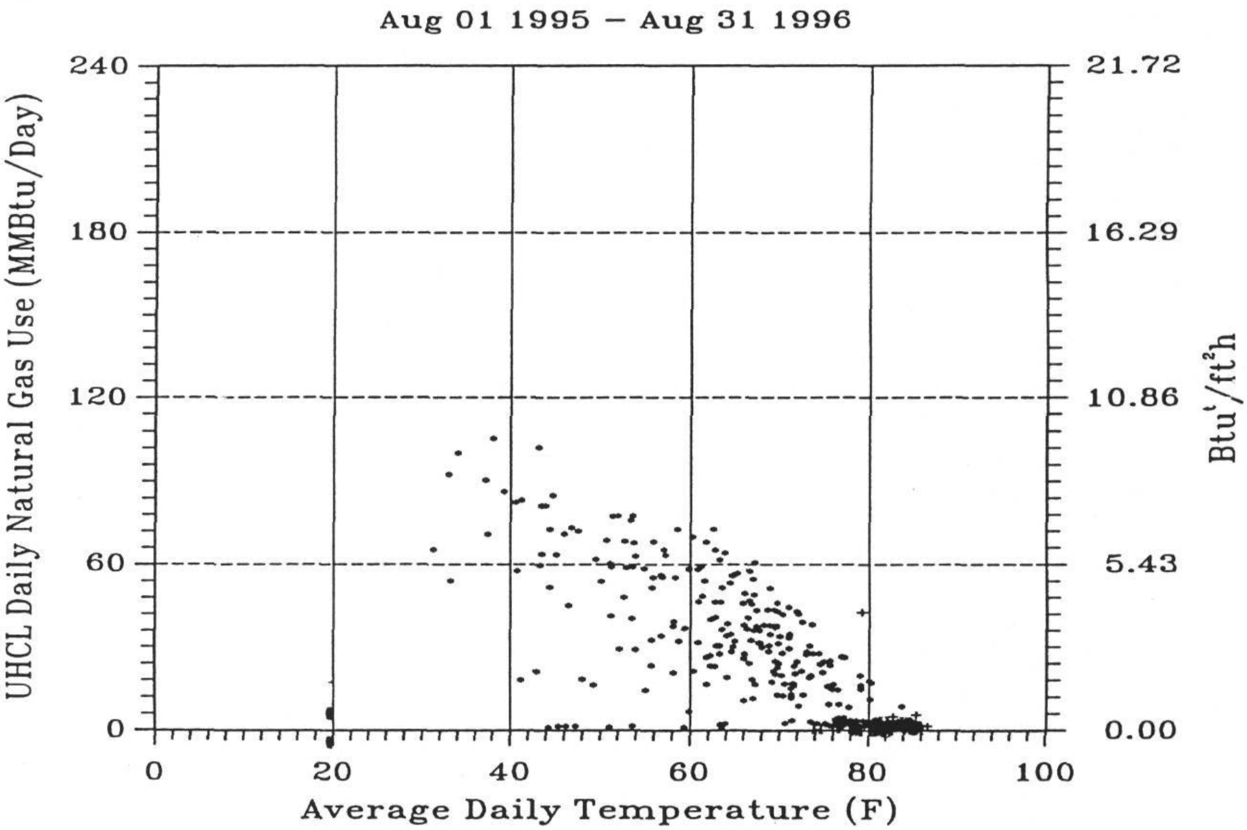
	Measured Savings	Audit Estimated Savings
Monthly Total		
Total to Date*		

*Measured savings include construction period. Audit estimated savings do not.

Comments

★ Chilled water energy use data are missing from 8/23/96 to 8/31/96, natural gas use data are missing from 8/27/96 to 8/31/96, and electricity use data are missing from 8/8/96 to 8/17/96 and from 8/27/96 to 8/31/96 – due to a monitoring hardware problem.





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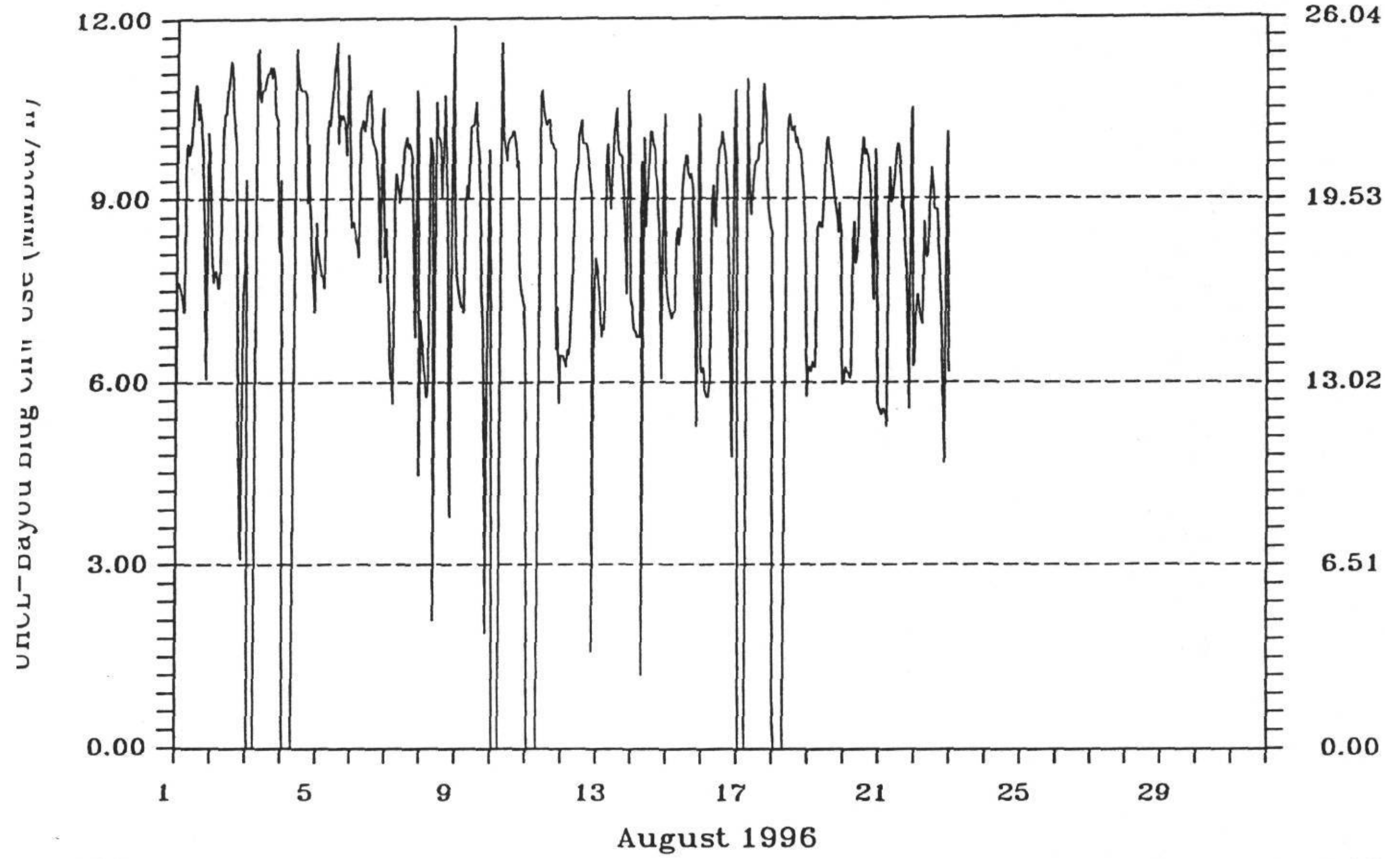
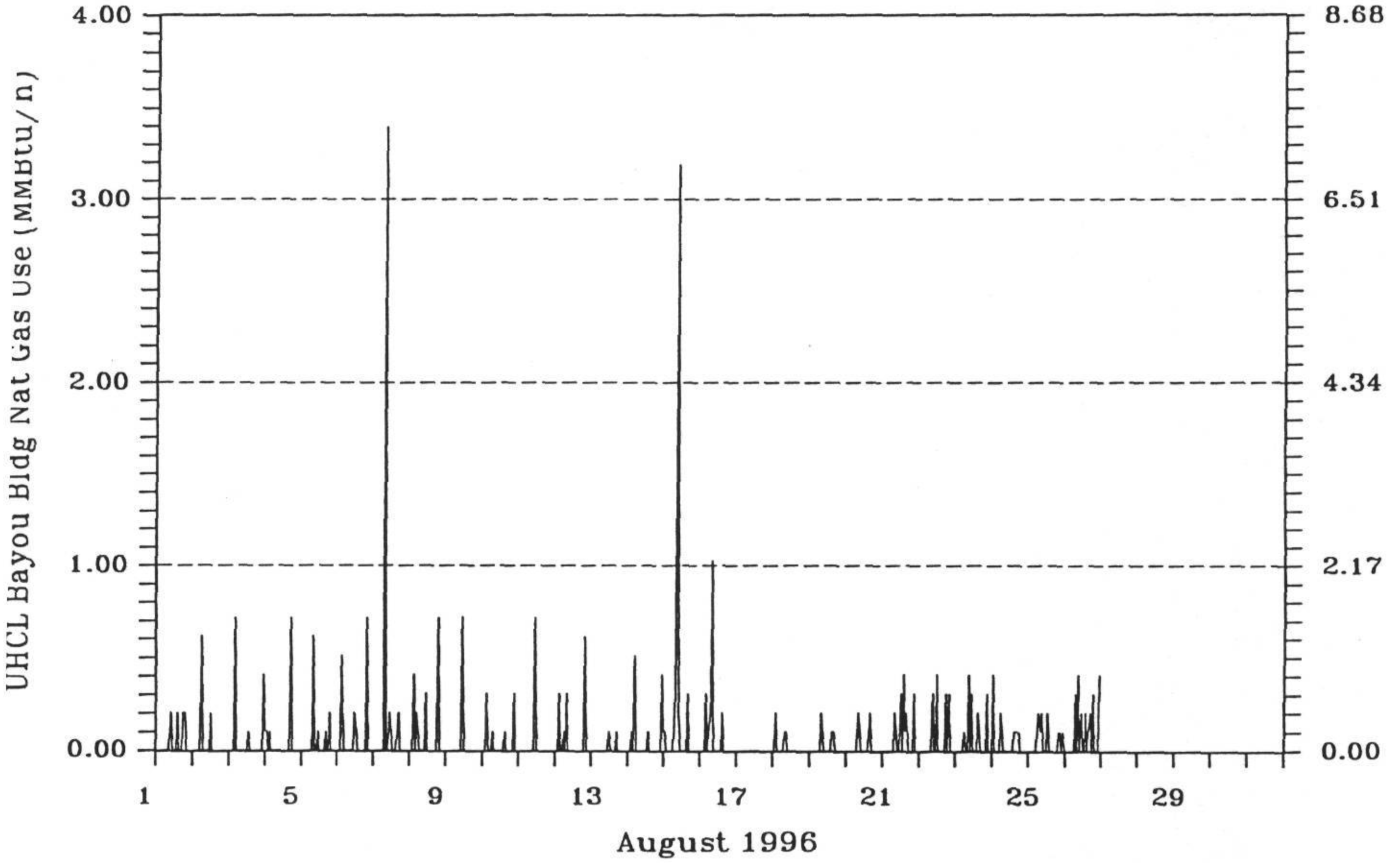
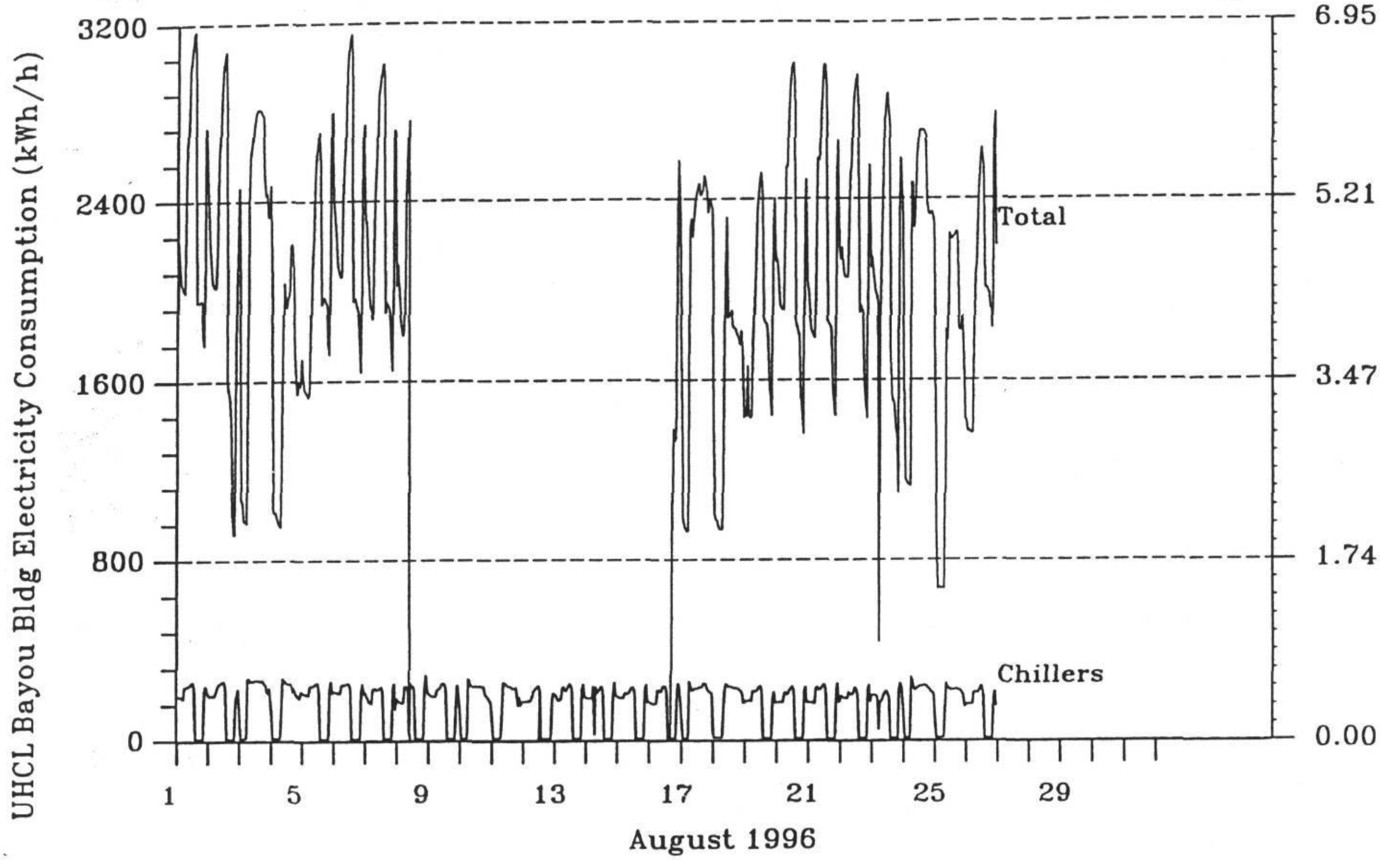
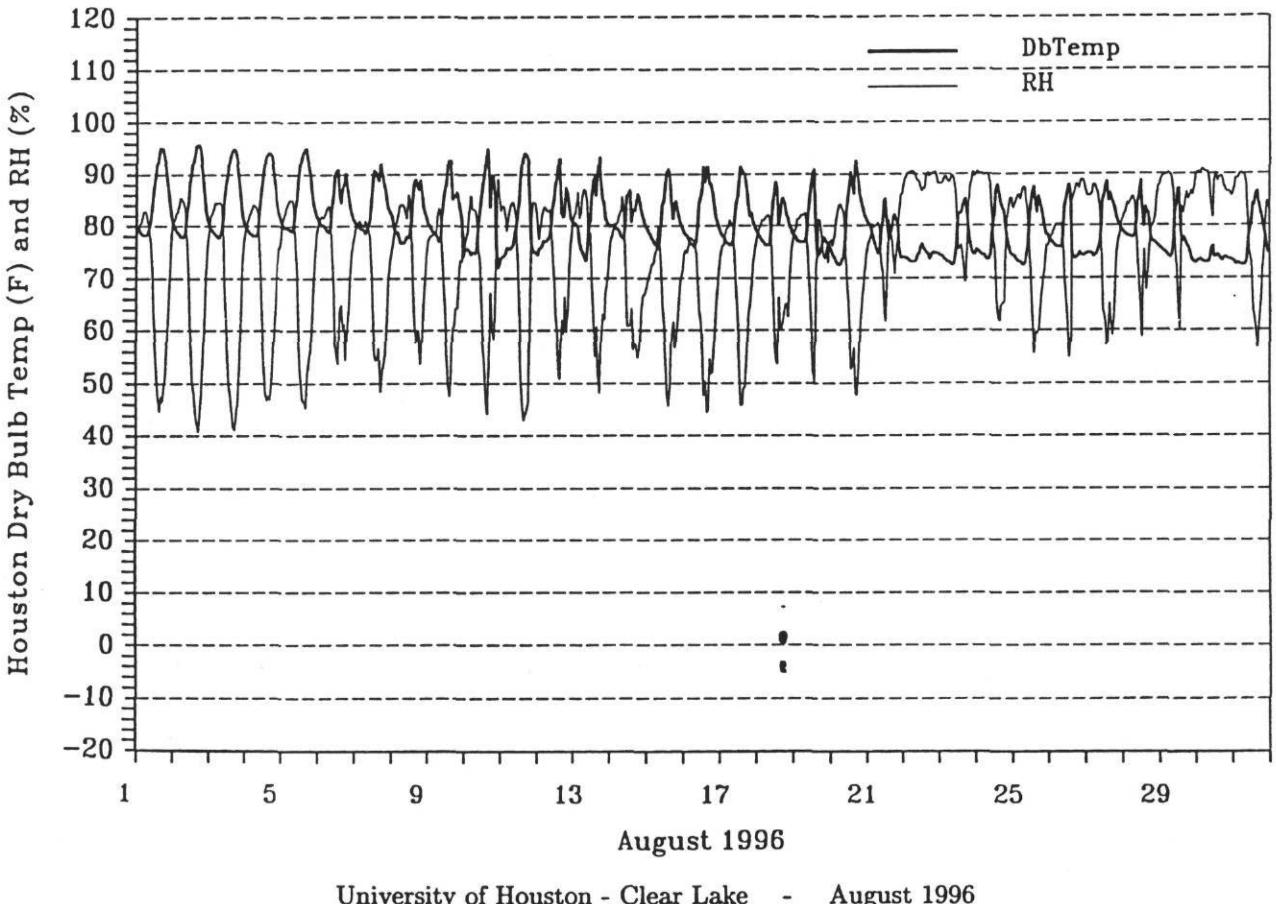

12.00
9.00
6.00
3.00
0.00
26.04
19.53
13.02
6.51
0.00
Btu^t/ft²h
1
5
9
13
17
21
25
29
August 1996


UHCL Bayou Bldg Nat Gas Use (MMBtu/h)
4.00
3.00
2.00
1.00
0.00
8.68
6.51
4.34
2.17
0.00
1
5
9
13
17
21
25
29
August 1996

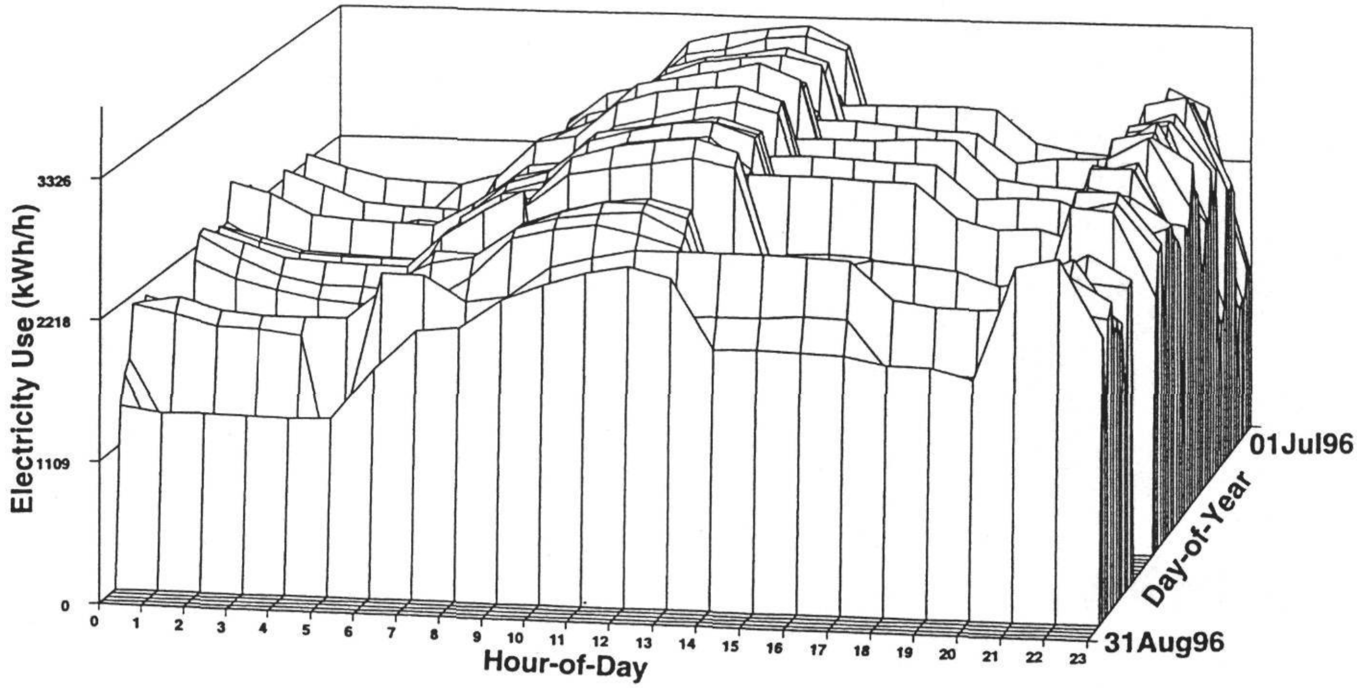


UHCL Bayou Bldg Electricity Consumption (kWh/h)
W/ft²
3200
2400
1600
800
0
6.95
5.21
3.47
1.74
0.00
Total
Chillers
1
5
9
13
17
21
25
29
August 1996

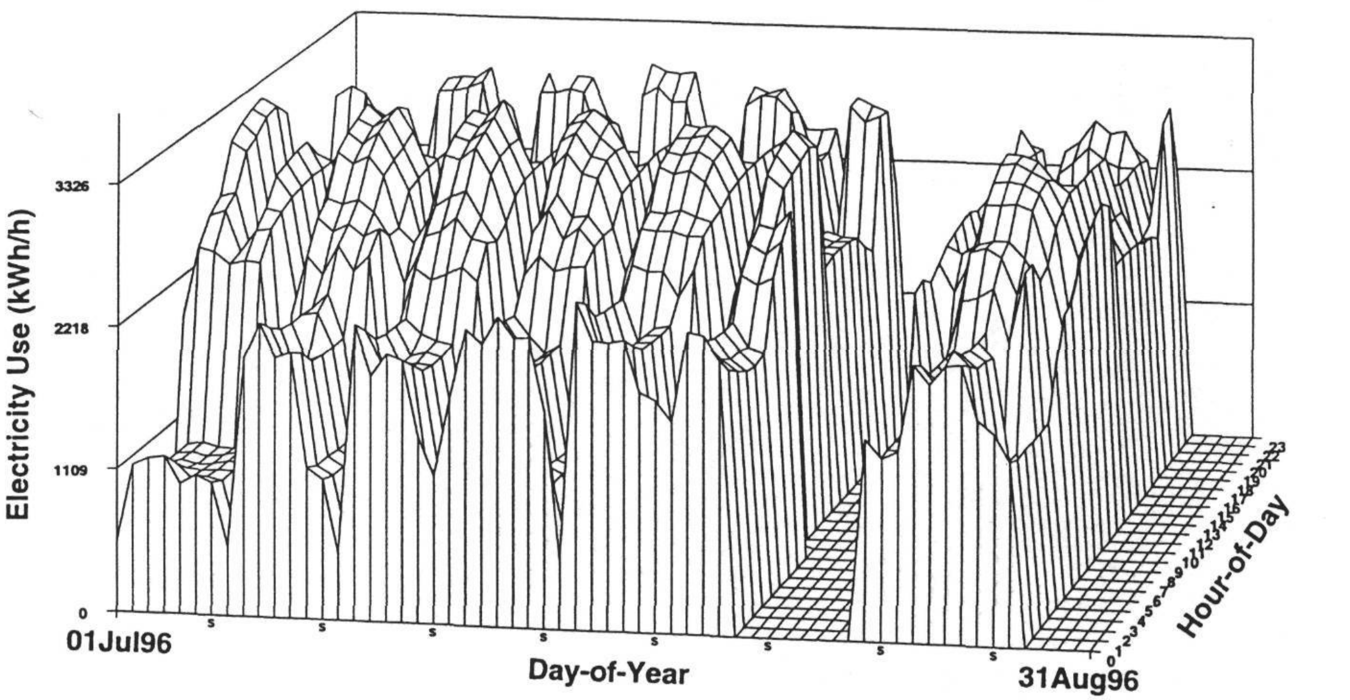


Houston Dry Bulb Temp (F) and RH (%)
DbTemp
RH
120
110
100
90
80
70
60
50
40
30
20
10
0
−10
−20
1
5
9
13
17
21
25
29
August 1996

Whole-Building Electric



Whole-Building Electric



Sundays are marked with an "S"

UNIVERSITY OF HOUSTON-CLEAR LAKE

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