Methodology Development for Determining Long-Term Performance of Cool Storage Systems from Short-Term Tests

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ABSTRACT

This paper and its companion (Elleson et al. 2002) report the results of ASHRAE Research Project RP-1004: Determining long-term performance of cool storage systems from short-term tests. The overall objective of this research was to develop a generalized methodology for determining the long-term performance of an existing cool storage system based on short-term field measurements. Specifically, this involved:

i. *the development of an analysis methodology for determining energy and demand savings of the cooling plant due to the cool-storage system as compared to an otherwise identical one without such a cool-storage system. The analysis was to be based as much as possible on monitored data as against conventional methods that rely on simplified calculations of "typical" days during summer and winter which are then extrapolated to the whole year; and*

ii. *recommendations for formulating a short-term measurement and verification (M&V) plan. This includes issues such as what specific measurements to make, the time of the year in which to make them (i.e., how one season may be more suitable than another), and the duration of the short-term monitoring period.*

Such a methodology has been developed and tested using monitored data from three case study sites, resulting in significant advances in the analysis of in-situ cool storage system performance. This methodology will simplify the evaluation of existing cool storage systems, which will enhance the application of cool storage technology. It will also provide a basis for the development of evaluation methodologies for other technologies; for example, thermal heating storage systems used in areas where expensive electrical energy is used for heating. While the companion paper describes the validation of field data used for the performance evaluation (Elleson et al. 2002), this paper describes details of the analysis methodology and presents the results of applying the methodology to the three case study sites. Recommendations for future work are also included.

INTRODUCTION

Energy performance contracts often require verification by actual monitoring of the energy and cost savings resulting from implementing energy efficiency projects. These M&V efforts are needed because there is significant uncertainty regarding how well such projects perform relative to their design predictions. This has been especially true with non-steady-state systems, including HVAC&R systems, and in particular those that incorporate cool storage. Many cool storage systems are completely or partially dependent upon field assembly of components that cannot be pre-rated or tested prior to assembly. The performance of this equipment is also highly dependent on how it is operated as a system, which may be different from the way it was designed. For these systems, field testing is the only way to ensure that the installed systems meet the specified performance predictions. At present, though there are several design guides (e.g., Dorgan and Elleson 1993) and other pertinent documents, including FEMP (1996), IPMVP (1997), ARI (1998), Standard 150-2000 (ASHRAE 2000), and Guideline 14P (ASHRAE 2001), there are no widely accepted standard methods or protocols to conduct long-term evaluations of entire cool storage systems in the field (i.e., *in-situ*). Therefore, investigators must develop custom measurement plans and analysis procedures

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for each project, increasing evaluation costs and diminishing quality assurance.

OBJECTIVE AND SCOPE

The objective of this research was therefore to develop a generalized methodology or tool for determining the long-term performance of existing cool storage systems using field monitored data gathered for that specific purpose. The tool would consist of recommendations of what data channels need to be metered and what time of the year to monitor the cooling system, along with a framework of analytical models for analyzing the data and determining energy and demand savings and their associated uncertainty. The outcome of this research should not be a pre-packaged or "black-box" type of software package but should be a well documented and defensible monitoring and analysis methodology that can lead to procedures and algorithms that can be widely used by ASHRAE members.

The scope of this project is limited to: (i) existing cool storage systems, as opposed to projects where a cool storage system is being evaluated as an alternative, and (ii) savings associated with electricity use (as against gas or oil use) and electric demand.

Though there are numerous types of cool storage systems and modes of operation, this research was limited to the study of three cool storage systems, the selection of which was approved by the RP-1004 Project Monitoring Subcommittee. The cool storage systems at the test sites selected were representative of reasonably well-engineered and well-operated systems, versus "excellent" or "optimal" systems. The scope of this project is not to diagnose system operation or to suggest optimal cool storage operation and control strategies but to study a cool storage system as it is currently operated. This paper describes the details of the analysis methodology and presents the results of applying the methodology to the three case study sites. Recommendations for future work are also included. The companion paper describes the validation of field data used for the performance evaluation (Elleson et al. 2002).

PRACTICAL CONSIDERATIONS

This tool was developed with the following general considerations in mind:

- The tool should be *readily implemented* by practitioners with some experience in field measurement, testing, and commissioning, as well as in statistical data analysis, modeling, and in basic engineering uncertainty determination.
- The tool should be *cost-effective*. The total cost of the entire evaluation, including measurement equipment, testing, and analysis time, should be in the range of 5-10% of the total cost of the cool storage system.
- The tool should provide *acceptable accuracy* in terms of cool storage savings in energy and demand. The uncertainty in the savings determined should not exceed +50% as measured against the total performance of the cool storage system. This threshold is deemed acceptable based on similar threshold values specified in Guideline 14P (ASHRAE 2001).

DESCRIPTION OF THE ANALYSIS METHODOLOGY

Requirements

The benefit in using thermal storage in a cooling plant is primarily for demand reduction during the peak period of the day. Furthermore, energy use cost savings may also result, which may be partly due to difference in the electric rate structure between on-peak and off-peak hours of the day and also because load leveling over the day can lead to more efficient chiller operation. Finally, the efficiency of the chiller may also improve due to lower condenser temperatures during the evening charging hours. Hence, the first and basic requirement of the analysis approach is that it has to distinguish between on-peak and off-peak periods vis-à-vis both energy costs and demand costs.

A second requirement of the analysis methodology is that it should be based, as much as possible, on the monitored data, reflecting actual system performance rather than optimal operation, and not rely on simplified calculations of energy and demand savings gleaned from "typical" days in summer or winter, which are then extrapolated to a whole year. Though such a procedure is often adopted by practicing professionals, it is difficult to develop it into a consistent methodology without some amount of arbitrariness.

A third requirement of the analysis methodology is that the performance of the "baseline" cooling system without thermal storage be determined, if possible, from the monitored data of the actual facility under study and not on speculative engineering "judgment" or from the manner in which it was designed and "supposed" to be operated. This can be achieved if the necessary models are to be developed from data periods when the TES does not contribute to meeting the building loads along with the building chillers. This requirement was explicitly stipulated in the request for proposal to cover the case when no performance data are available prior to installation of the TES system. In case such baseline data are available, it is obvious that one would use such data for modeling baseline performance. The methodology advocated in this paper still applies subject to minor modifications that will become obvious to the reader.

Specific Considerations

The development of the analysis methodology for determining energy and demand savings due to the TES system has been influenced by the following considerations:

- Since electric utilities generally bill their customers monthly with utility rates likely to change seasonally, savings should be calculated on a month-by-month basis.

- Instead of an analytical approach using characteristic or prototypical day-types for summer and winter, a monthly mean daily computational approach is used that captures enough of the year-round variability while minimizing the amount of computational effort required.
- While demand savings need to rely on the utility's monthly peak data interval (often 15, 30, or 60-minute data), energy use savings need to be inferred from the monthly mean daily data (separated into on-peak and off-peak periods during the day). Analysis at the 15-minute level for energy use modeling is not recommended since unacceptable, unknown variations (i.e., statistical noise) are introduced into the data because of such factors as the relatively large thermal capacity of the chilled water in the water loop, control dynamics, and part-hour usage when one period contains part of an on-cycle and part of an off-cycle. Note that no such averaging is done while modeling and determining demand savings.

An earlier study by Katipamula et al. (1998) investigated the effect of estimating energy savings from building air-handler unit retrofits using regression models determined from monitored data that were averaged monthly, daily, or hourly. The major findings of that study were that even when hourly or subhourly data are available, baseline models identified from daily averaged data were more likely to provide better insight into building operation from day to day and were the most robust (because outliers can be weeded out). Such averaging yielded data sets that allowed more statistically sound models since there is a sufficient—but not excessive (as with hourly data)—number of data points to work with. Furthermore, daily averaged data did not suffer from the strong diurnal operating schedules under which most buildings operate—a factor that confounds simple hourly models that do not possess separate daytime and nighttime models. Thus, in order to reduce the variability in the hourly observations, we chose to identify energy use models and perform the energy use analysis on a daily basis using daily mean hourly models. Hence, energy use models are best identified as mean models (i.e., based on daily averaged hourly data). A report prepared as part of RP-1004 (Reddy et al. 2000) illustrates the reduction in data scatter when going from hourly to daily averaged data. Peak or maximum hourly (or 15-minute) data were, however, used for demand modeling.

- As stated above, one of the requirements of this research project was to emphasize the development of a simplified method that could be widely applied by HVAC practitioners. Detailed component models to predict chiller electricity use and to model the state of charge of TES tanks were evaluated with monitored data (Haberl et al. 1997; Reddy et al. 1999b). However, it was felt that though such modeling approaches were useful, they were not appropriate for the objective of this project since the effort involved in using calibrated HVAC component models is too great and the required analysis capabilities beyond the competencies of most practitioners. Hence, a simpler approach called the "lumped model" approach has been proposed and evaluated as part of this research.

  The lumped model approach derives its name from the fact that all cooling plant electricity use (i.e., building chillers, auxiliary, TES chiller, and TES pump electricity use) are combined into a total electricity use (E_{plant}), and only this "lumped" use is considered further. The distinctive manner in which the particular cooling plant is operated and controlled during different times of the day is implicitly captured in the lumped methodology since a different set of models are identified for each of the different periods. Thus, the set of lumped models corresponding to the on-peak period would predict a lower value of E_{plant} than that corresponding to the off-peak period for the same outdoor temperature value.

- Normally, demand rate charges are based on the peak monthly electricity use during a 15-minute window corresponding to the total building electricity use and not just to the cooling plant electricity use. In this analysis, however, we limit ourselves to monthly peak demand values of the cooling plant only as the basis for determining avoided demand due to the TES system, assuming that building electricity use remains unaltered.
- The lumped model analysis approach adopted in this study requires determining averages over daily and monthly time periods, as well as maximum monthly values. During the course of the analysis, it was found that reliance on a spreadsheet program as the only platform for data analysis was problematic. Therefore, some of the analysis was performed in a relational database program. The convenience provided by a relational database, which allows such features as data manipulation and sorting using data queries, was found to be very advantageous and is therefore strongly recommended. However, the subsequent steps of identifying regression models and performing month-by-month analyses are still best performed using spreadsheets.

Mathematical Description of Savings Calculation

The basic paradigm in the methodology to characterize actual cooling plant performance is to divide the year into monthly periods (so as to be consistent with the manner in which energy is billed) and to identify a set of corresponding, simple regression models. The above considerations suggested that energy use of the cooling system be modeled based on daily averaged hourly data separated into weekday on-peak, weekday off-peak, and weekends/holiday periods. In many TES systems, the weekday off-peak and weekend/holiday operation are similar, but in others they differ, and it is just as convenient to maintain this distinction as to perform a separate evaluation to verify this aspect. For each of the three periods, two sets of nested energy use models are developed:

- one for building cooling load Q_{Bldg} as a function of outdoor dry-bulb temperature T_0, and
- one for cooling plant electric use E_{Plant} as a function of Q_{Bldg}.

Finally, performance data corresponding to those hours when the TES is idle (i.e., neither being discharged nor charged) are extracted, from which the baseline model for E_{Plant} as a function of Q_{Bldg} is identified.

We also considered using one model between E_{Plant} and T_0 directly, rather than a nested model approach involving two models. The main reason that this approach was rejected is that it does not allow the diagnostic ability to identify the source of excessive scatter, and also it cannot compensate for changes in the building thermal loads over time. Hence, though it involves more effort and cost, installing metering to explicitly measure thermal cooling load in the building is advocated. It is worth noting that an increasing number of building owners and energy managers are generally requesting ESCOs to install such metering in order to better track, manage, and lower their cooling loads by better building operation.

The basis of the savings methodology can be summarized as follows:

$$\text{Annual savings} = \sum_{month}\begin{bmatrix}(\text{Baseline system energy cost})\\-(\text{Actual system energy cost})\end{bmatrix} + \sum_{month}\begin{bmatrix}(\text{Baseline system demand cost})\\-(\text{Actual system demand cost})\end{bmatrix}$$

or, in equation form,

$$\$_{save,\,annual} = \sum_{q=m_1}^{m_2} \$_{save,\,monthly} = \sum_{q=m_1}^{m_2}\left[\sum_{p=1}^{s} n_{p,\,q}h_{p,\,q}c_{p,\,q}(E_{p,\,q} - E^*_{p,\,q})\right] + d_q(D_q - D^*_q)$$

where

$\$_{save,annual}$	total annual savings in electricity cost
$\$_{save,\,monthly}$	total monthly savings in electricity cost
q	a particular month during the year
m_1, m_2	index of month of year when storage is used to shift load from on-peak hours. For example, if storage is used to shift load year-round, m_1=1 and m_2=12.
p	particular period during the day/week/year with a distinct cool storage operating mode
s	number of different periods with distinct cool storage operating modes. A typical case is s=3: weekday on-peak, weekday off-peak, and weekend/holiday.
$h_{p,q}$	number of hours during period p and month q
n	number of days in the period p and month q
$c_{p,q}$	unit cost of electricity use during period p and month q
E	daily mean hourly baseline energy use without thermal storage
E^*	daily mean hourly energy use with thermal storage
d_q	on-peak demand rate during month q
D	on-peak monthly demand for the baseline cooling system
D^*	on-peak monthly demand for the actual cooling system

Uncertainty Analysis

As part of this research project, an earlier study was undertaken to develop a methodology for estimating the engineering uncertainty in savings due to a particular energy conservation measure as compared to a baseline system (Reddy et al. 1999a). A notable feature of the previous study was that all pertinent uncertainty equations were presented in the form of a nomograph consisting of six interconnected graphs, whereby a user can graphically determine the final uncertainty in savings by selecting appropriate values of the various sources of uncertainty. This nomograph can be quickly and conveniently used to estimate the uncertainty in the energy and demand savings.

Analysis with Short Data Sets

A few studies discussed in the RP-1004 literature review (Reddy et al. 1998b) investigated the annual predictive accuracy of short data set models (i.e., data sets that do not span a complete year). Though most of these studies pertain to the baseline modeling of building cooling and heating thermal energy use, the conclusions of these previous studies are relevant to the current study.

There are no absolute rules for determining the minimum acceptable length of the monitoring to accurately predict long-term HVAC system loads. However, one could speculate that 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 and would provide the best estimates of savings associated with thermal storage.

The accuracy with which temperature-dependent regression models of energy use identified from short data sets are able to predict annual energy use has been investigated with monitored data by Kissock et al. (1998) for two-parameter single variable models and by Katipamula et al. (1995) for standard multivariate models. The study by Kissock et al. (1998) was limited to three buildings in Texas with constant air volume (CV) systems. The study 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 correctly predict annual energy use in the climate of central Texas.

Tests with synthetic data found that these observations are applicable for other types of models (i.e., four-parameter models) as well (Reddy et al. 1998a). In that study, the best predictors of both cooling and heating annual energy use were 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. Therefore, 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 or summer.

Regression models identified from data that span less than one complete year (which we refer to as "short-term" data) result in model coefficients different from those identified with year-long data due to the limited spread in variation in T_0. This tends to bias the energy use and demand predictions by regression models that use the coefficients derived from short-term data when extrapolated to the whole year. It is, in fact, the magnitude of this bias (which directly impacts the resulting energy and demand savings estimates) that we are attempting to minimize.

Even when three months of data are used, there are enough daily data points to allow the set of nested regression models of energy use to be identified. This is not so with demand models where one has only one data point for one month. Further, the effect of the bias in demand models, identified from short-term data, tends to impact the total savings estimates more drastically than that of energy use since the effect of the former is, by far, the more influential. Our analysis revealed that it is impossible to identify realistic electric demand models between E_{Plant} and Q_{Bldg} using three months of data (i.e., three data points). Faced with this dilemma, we investigated different alternatives, and we recommend the following approach, subject to the realistic assumption that the 12 most recent utility bills for the whole facility (which relates to $E_{Bldg+Plant}$) can be obtained:

1. Define a new variable called "Ratio" (= $E_{Plant}/E_{Bldg+Plant}$) on a monthly basis and calculate the corresponding values for the three months for which monitored data are available.

2. Identify a simple linear regression model of "Ratio" against T_0 (or Q_{Bldg}) using these three data points.

3. Use the above identified model to predict the monthly values of "Ratio" using the available 12 monthly values of T_0 (or Q_{Bldg}).

4. Finally, knowledge of the 12 utility bills allows the 12 monthly E_{Plant} values to be deduced.

We reiterate that the objective of this research is to estimate the annual energy and demand savings of a cooling plant with a TES system. One could argue that 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. Therefore, it may be better from the overall cooling plant 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. This specific issue, as well as allied ones, have been specifically investigated during the course of this research and is discussed in subsection (e) of the case study section.

STEP-BY-STEP PROCEDURE

Step 1. Obtain the following data and perform data quality checks as described by Elleson et al. (2002):

(a) *Mandatory data*

- *Utility bills:* the most recent 12 consecutive utility bills of the facility
- *Facility electricity use* ($E_{Bldg+Plant}$): the sum of the total building-related equipment (i.e., lights, equipment, etc.) and that of the cool storage plant (i.e., chillers, pumps, cooling tower fans, etc.). This should be the same as that provided by the utility bills.
- *Cool plant electricity use* (E_{Plant}): the sum of all electricity used by the equipment in the cooling plant including pumps and auxiliaries associated with the thermal storage system. This is equal to ($E_{Chiller} + E_{Aux}$)
- *Building cooling load* (Q_{Bldg}): the building thermal load in tons, calculated from the flow rate and supply and return temperatures of the chilled water serving the building load. Flow and temperature data should be available as separate channels for validation purposes.
- *Outdoor dry-bulb temperature* (T_0). This should be recorded on site and checked against the nearest NWS weather station for drift.
- *Separate metering of chillers and pumps*: If the thermal storage subsystem has a separate chiller and pump, their electricity use also needs to be monitored.
- Binary variable indicating whether the TES is being operated (either being charged or discharged) or idle.

(b) *Optional data*

- *Building chiller electricity use* ($E_{Chiller}$): the sum of the electric use of the chillers only, excluding auxiliaries.
- *Auxiliary electricity use* (E_{Aux}): the electric use of all

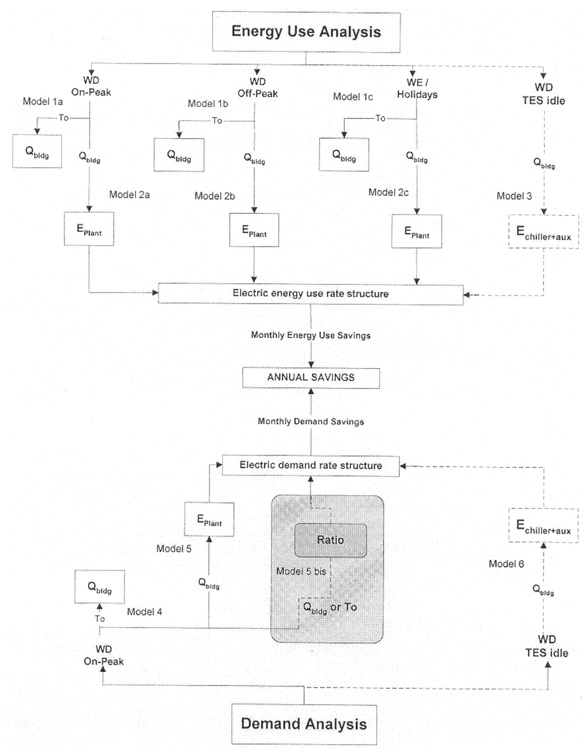

Figure 1 *Flow chart of the basic lumped model analysis approach to characterize actual cooling plant performance.*

pumps and cooling tower fans. It does not include building AHU fans or any secondary circulating pumps not required to move fluid through the chillers and storage.

Step 2. Perform exploratory analysis to verify schedules and operating strategies, and identify patterns in system operation:

(a) Relative magnitude of energy use of various equipment (on a monthly basis).

(b) Correlation patterns between outdoor temperature, building cooling loads, and electric use (on a monthly basis).

(c) Differences in building operating schedules during weekdays (WD) and weekends (WE).

(d) Treatment of holidays and abnormal days (whether to bin with WD data, WE data, or to reject).

(e) Consistency of the operating schedule on a diurnal basis with data binned into WD and WE/holidays.

(f) On-peak and off-peak times of day (and of season) as well as day-to-day variability in cool plant and TES operation.

Step 3. Query database for each calendar month of the year separately in order to obtain the data sets to be used in succeeding steps.

(a) *For demand analysis*: Separate annual data into calendar months and determine monthly maximum values of the outdoor dry-bulb temperature, building cooling load, and cool plant total electric use.

(b) *For energy analysis*: Separate the records for each month into three subsets for weekday on-peak, weekday off-peak, and weekend/holiday periods. For each subset determine the daily mean values of the outdoor dry-bulb temperature, building cooling load, and cooling plant total electric use.

(c) *For the baseline model*: Extract the records for times during weekdays when thermal storage is neither being charged nor discharged. Determine monthly maximum and mean values of outdoor dry-bulb temperature, building cooling load, and cooling plant total electric use.

Step 4. Develop the following sets of models from the data sets created in step 3 above (see the flowchart shown in Figure 1).

Important: *Identify linear models only (rather than second order models), since calculations for energy savings are performed on a monthly mean daily basis. However, models can be multi-variate (i.e., have more than one independent variable), though most often multiple variables are not required. As a general rule of thumb, models having coefficient of variation (CV) values <10% are considered good, and those with CV values >20% are considered poor. These values pertain to field-monitored HVAC&R data used for M&V purposes and are not appropriate for other instances.*

(a) *Demand Models.* Identify the nested set of demand regression models using monthly maximum data from 3(a). Do not use daily averaged data for this step. See the flow chart shown in Figure 1.

- Building cooling thermal loads versus outdoor dry-bulb temperature
- Cooling plant electricity use versus building cooling thermal load

(b) *Energy Use Models.* Identify three sets of nested energy use regression models, for weekday on-peak, weekday off-peak, and weekend/holiday periods, using monthly average data from 3(b).

- Building cooling thermal loads versus outdoor dry-bulb temperature
- Cooling plant electric use versus building cooling thermal load

(c) *Baseline Models.* Identify a demand model and an energy use model of the baseline cooling plant when TES is idle, using data from 3(c):

- Cooling plant electric use versus building cooling thermal load

Step 5. Calculate monthly energy use and demand for the monitored system and the baseline system using the models identified in Step 4. Calculate energy and demand savings for each month by subtracting the values for the monitored system from those for the baseline system.

Perform the above calculation using a spreadsheet program with the table set up as shown in Table 6. The table allows an analyst to study intermediate values and also make changes if necessary to certain parameters. Note that the regression model parameters, the monthly electric rate structures, and the monthly mean and maximum T_0 values are needed to initiate the calculations.

Step 6. Perform uncertainty analysis on savings determined in Step 5 using the nomograph developed by Reddy et al. (1999a) and illustrated in Figure 7.

Step 7. If data are less than one whole year, a slightly different procedure is adopted for the demand model as depicted by the shaded area in Figure 1 and labeled model 5-bis.

With one year of monitoring, 12 monthly values are usually adequate to obtain good models. If short-term monitoring is adopted, we find that the first model can be determined even with three data points if three months are used. However, the relationship between E_{Plant} and Q_{Bldg} is not accurate enough for annual predictions if only three points are available. To obtain an acceptable model, we suggest using the peak demand information contained in the utility bills, which is why we had proposed in Step 1 that the most recent 12 monthly utility bills be collected. How to perform the analysis has been previously described in the section entitled "Analysis with Short Data Sets."

CASE STUDY RESULTS

Table 1 provides a convenient summary of the type of facilities and the cooling plants studied. All three are large systems (3,000-6,000 ton-hour) located in two different geographic locations. The facilities include a large hotel, a campus with a cluster of separate buildings, and a convention center and are representative of the various types of sites where TES is usually implemented. The case studies include one chilled water system (#2) and two ice-on-coil internal melt systems (#1 and #3). Finally, the three case studies also include two common types of operation for cooling plants with TES systems: uniform year-round operation of the TES system (#1 and #3) and load-shifting operation during the summer season only (#2). Hence, the three case studies selected cover a wide variety of type, location, and operational characteristics generally found in cooling plants with TES systems.

Table 1 also provides details of the exact period when monitoring was performed, as well as the specific period used for data analysis. We note that one year of data was used for the two sites whose TES systems were operated year-round, while the entire four summer months of operation were used for the other. This satisfied the original requirements of the project in terms of performance data to be gathered within the framework of this research.

TABLE 1
Summary Description of the Three Sites and Their Cooling Plants

	Site #1	Site #2	Site #3
Location	San Francisco, Calif.	Corpus Christie, Texas	Austin, Texas
Size of bldg/facility	—	681,592 ft^2	—
Type of bldg/facility	Large hotel	Community college	Convention center
Size of cooling plant (no. of chillers and size)	2 × 900 ton	1 × 800 ton; 1 × 1000 ton	2 × 650 ton
Type of TES system	Internal melt ice-on-coil	Stratified chilled water	Internal melt ice-on-coil
Capacity of TES	3000 ton-hour (6 tanks)	1.2 million gallons	6000 ton-hour (42 tanks)
No. and size of dedicated TES chiller	1 × 150 ton	None	None
TES operation cycle	Weekly	Daily	Daily
Diurnal TES on-peak period during weekdays	12:00 - 19:00 h	12:30 - 19:30 h	14:00 - 20:00 h
Seasonal TES operation	Year-round operation, seasonal electric rates	Load-shifting from June-Sept. only	Year-round operation, constant electric rates
Comments	Site was on RTP, data analysis was modified accordingly	Plant includes a 300T industrial heat recovery heat pump	About 26 weekdays data had to be removed since TES was not operated during those days
Data collection period	4/94 - 12/97	5/98 - 10/99	5/98 - 12/99
Data period used for analysis	Jan. - Dec. 1997	June - Sept. 1999	Oct. - Sept. 1999
Time scale of data collection	15 min	1 h	1 h

TABLE 2
Electric Rate Structures for the Three Sites

	Site #1			Site #2			Site #3		
	Energy Use ($/kWh)			Energy Use ($/kWh)			Energy Use ($/kWh)		
	On-peak	Off-peak	Demand ($/kW)	On-peak	Off-peak	Demand ($/kW)	On-peak	Off-peak	Demand ($/kW)
Jan.	0.08	0.05	14.0	0.028	0.028	*	0.0348	0.0348	9.48
Feb.	0.08	0.05	14.0	0.028	0.028	*	0.0348	0.0348	9.48
Mar.	0.08	0.05	14.0	0.028	0.028	*	0.0348	0.0348	9.48
Apr.	0.08	0.05	14.0	0.028	0.028	*	0.0348	0.0348	9.48
May	0.10	0.05	14.0	0.028	0.028	*	0.0348	0.0348	9.48
June	0.10	0.05	14.0	0.028	0.028	12.41	0.0348	0.0348	9.48
July	0.10	0.05	14.0	0.028	0.028	12.41	0.0348	0.0348	9.48
Aug.	0.10	0.05	14.0	0.028	0.028	12.41	0.0348	0.0348	9.48
Sept.	0.10	0.05	14.0	0.028	0.028	12.41	0.0348	0.0348	9.48
Oct.	0.10	0.05	14.0	0.028	0.028	*	0.0348	0.0348	9.48
Nov.	0.08	0.05	14.0	0.028	0.028	*	0.0348	0.0348	9.48
Dec.	0.08	0.05	14.0	0.028	0.028	*	0.0348	0.0348	9.48

The electric utility rate structures for the three sites are summarized in Table 2. Site #1, which is operated year-round, is subject to a real-time pricing schedule. Since this type of pricing was outside the objective of this research, we adopted a standard time-of-use rate schedule that would otherwise apply to this facility (this was determined subsequent to discussions with the facility personnel). The rate schedule has uniform rates in off-peak energy use and in demand, but has a seasonal energy use rate for on-peak periods. At Site #2, the demand charge is applied only during four months of summer. There are no demand charges for the remaining eight months, so the TES system is not consistently used to shift load during these months. Site #3, which is operated year-round, is owned and operated by the municipal utility. Therefore, uniform utility rates were assumed for both energy use (on-peak and off-peak) and demand.

(a) *Exploratory Data Analysis*

The objectives of the exploratory analysis are:

- to determine the number of operating modes of the cooling plant (for example, on-peak, off-peak, during weekdays [WD] and weekends [WE]),
- to identify the on-peak and off-peak hours of the day and to study the differences in energy use between both periods,
- to determine how consistently the cooling plant and its various pieces of equipment are operated on a day-to-day basis, and
- to visually inspect overall patterns and correlations between outdoor temperature, building/loop cooling thermal loads, and cooling plant electricity use.

This section presents examples from the exploratory analysis for Case Study Site #3. Detailed analysis results for all three sites can be found in Reddy et al. (2000) for Case Study #1, and in Reddy et al. (2001) for Case Studies #2 and #3.

The variables monitored hourly as part of this project are described and listed in Elleson et al. (2002). The complete data set ranged from Sept. 10, 1998, till Sept. 24, 1999. We evaluated the option of splicing the last week of Sept. 1998 to the first three weeks of Sept. 1999 so as to obtain a full month of September. However, it was found that such an approach was not justified given that the operation of the cooling plant in the two months seems to have been very different, and so it was decided not to use the Sept. 1998 data in this analysis. Consequently, all analyses described below are based on data from Oct. 1998 through Sept. 1999 (with the last week of data missing).

Analysis of the data revealed that the facility, which is a convention center, is operated the same on weekends as on weekdays. The cooling plant seems to be operated in a like manner during both periods, and exhibits the same on-peak period: from 14:00 till 20:00 during all days. Hence, the hourly data set was separated into three subsets:

- on-peak periods (during WD and WE),
- off-peak periods (during WD and WE),
- baseline periods, i.e., when the TES was not operated.

This system is typically operated with the chillers shut down during the on-peak period, and the TES is discharged so as to meet the entire building thermal cooling load by itself. All electricity use during the on-peak period is essentially due to the auxiliary equipment (pumps and fans). However, a

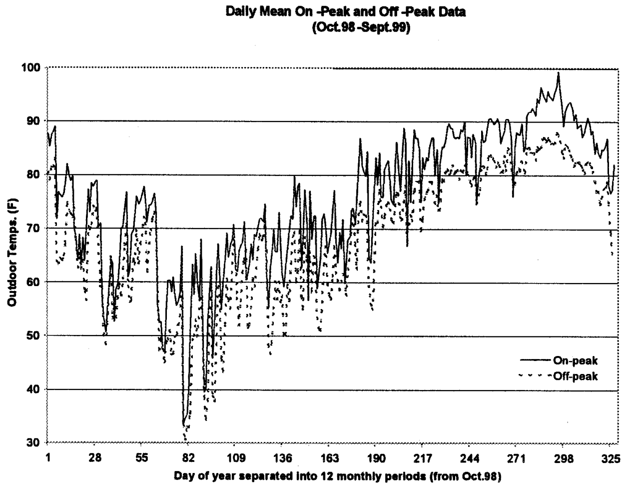

Figure 2a *Time series plots of daily mean data from October 1998 to September 1999 separated into on-peak and off-peak periods: outdoor dry-bulb temperature (ºF)—Case Study #3.*

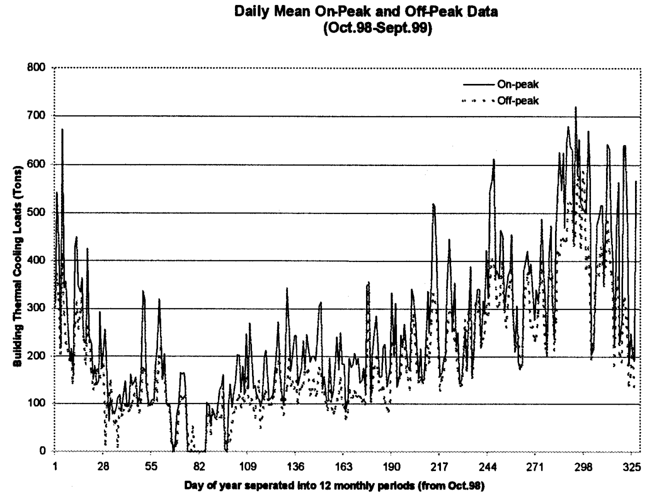

Figure 2b *Time series plots of daily mean data from October 1998 to September 1999 separated into on-peak and off-peak periods: building thermal cooling load (Tons)—Case Study #3.*

closer look at the hourly data revealed that there were specific days during the year when the cooling system was not operated in a diurnal cycle consistent with on-peak rates, that is, there was very high chiller electricity use during on-peak hours. Altogether we were able to identify 26 days that exhibited such behavior during the whole year of data, April and August have a particularly large number of days where such behavior was observed. These days were rejected from the analysis.

To illustrate why we chose to reject these days from our analysis, we have generated load duration curves of hourly cooling plant electricity use during on-peak, off-peak, and baseline hourly values for the months of April and August (Reddy et al. 2001). It was clear that if we were to include these abnormal-operation days in our analysis data set, there would be no demand savings due to the TES, and there would be no opportunity to exercise the methodology for calculating demand savings. Hence, we deemed the cooling plant to be operated intentionally in this manner on such days, in which case we were justified in removing all the 26 days from our analysis.

As discussed earlier, in order to remove the variability in the hourly observations due to the thermal capacity of the cooling loops (which effectively introduce a certain amount of "noise" in the analysis), we have performed daily averages with the above data sets. For example, for a given data set, all hourly observations for the on-peak periods during each day were averaged in order to yield an average daily on-peak value. It is such daily-averaged, hourly values that form the basis of all our subsequent analyses on energy use modeling and energy use savings determination.

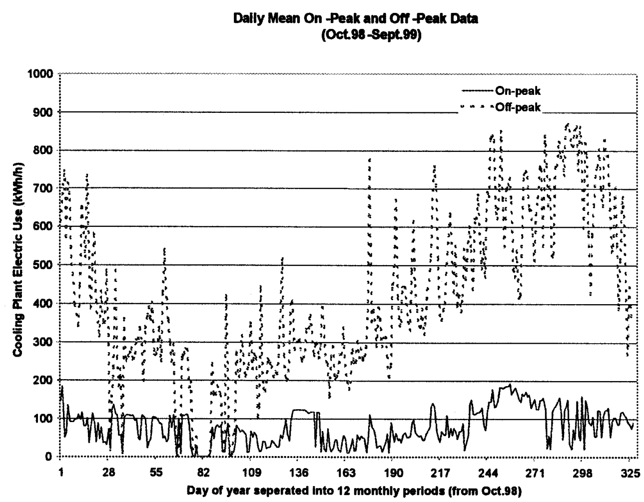

Figure 2c *Time series plots of daily mean data from October 1998 to September 1999 separated into on-peak and off-peak periods: cooling plant electricity use (kWh/h)—Case Study #3.*

Figures 2a-c are time series plots (from Oct. 1998 to Sept. 1999) of outdoor temperature, building cooling thermal loads, and cooling plant electricity use, separated into on-peak and off-peak periods. Generally, building thermal cooling loads and off-peak cooling plant electricity use follow the outdoor temperature trend on a seasonal basis. The on-peak cooling plant electricity use is generally around 100 kWh/h, reaching twice that value during the month of July. Note the large difference in cooling plant electricity use between on-peak and off-peak loads (Figure 2c), despite the fact that the thermal loads and the outdoor dry-bulb temperatures between both periods are very close.

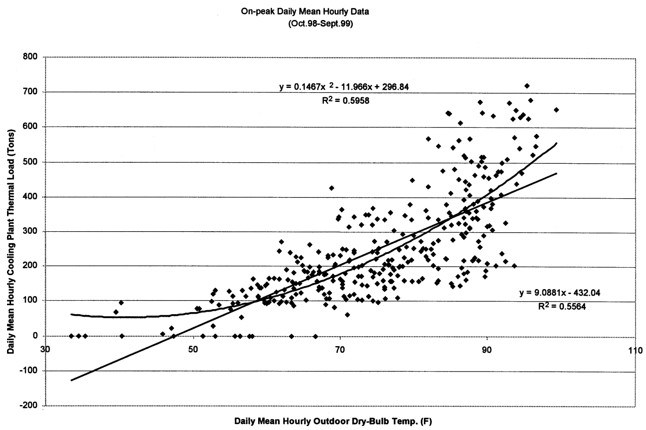

Figure 3a *Scatter plot of daily mean hourly thermal cooling load vs. outdoor temperature during on-peak period for the whole year—Case Study #3.*

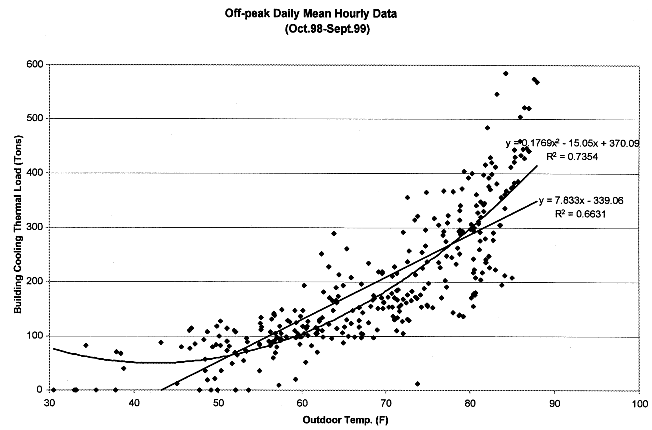

Figure 4a *Scatter plot of daily mean hourly thermal cooling load vs. outdoor air temperature during off-peak period for the whole year—Case Study #3.*

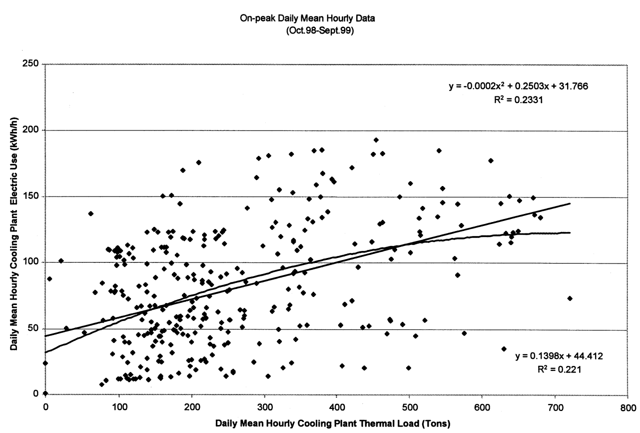

Figure 3b *Scatter plot of daily mean hourly cooling plant electricity use vs. thermal cooling load during on-peak period for the whole year—Case Study #3.*

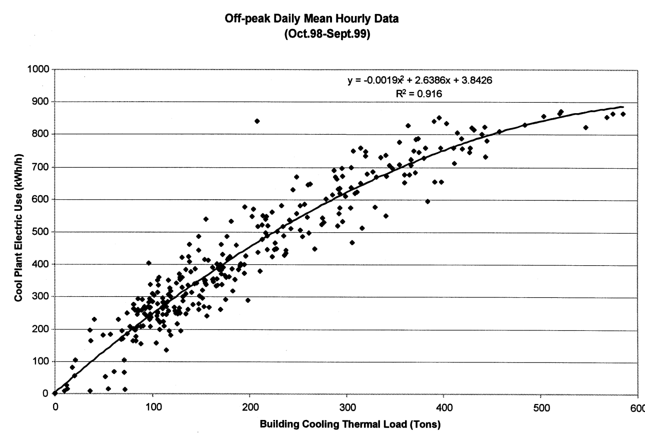

Figure 4b *Scatter plot of daily mean hourly cooling plant electricity use vs. thermal cooling load during off-peak period for the whole year—Case Study #3.*

Figures 3a and 3b are scatter plots of the daily mean hourly values of building thermal cooling load versus outdoor temperature and of the cooling plant electricity use versus building thermal cooling load for the whole year. Linear and second order polynomial trend lines (with corresponding R^2 values) are also indicated. While there is a certain amount of data scatter in Figure 3a, which is to be expected during on-peak periods from a real facility, there is nevertheless a clear and generally well-behaved linear (or even change-point linear; see ASHRAE 2001 or Kissock et al. 1998) pattern in the former. Unfortunately, the correlation between E_{Plant} and Q_{Bldg} is very poor and is not improved by fitting a second order polynomial model (refer to the R^2 values shown in Figure 3b). Unlike the other two case studies investigated during this research, case study Site #3 is a convention center. Therefore, for this site, we would expect the building thermal load (Q_{Bldg}) to be heavily influenced by the building internal loads (E_{lr}). Consequently, we included the building internal lights and equipment channel (E_{lr}) as an additional regressor variable (along with T_0), and though the model improved ($R^2 = 0.77$ and CV = 29.9%), it is still poor.

Figures 4a and 4b are scatter plots of the same quantities as Figures 3a and 3b, but for the off-peak period. The data scatters fairly well around the trend lines, indicating that the cooling plant is operated fairly consistently during this period. Similar behavior was also noted for the baseline period (see Reddy et al. 2001 for more details).

The demand models had to be based on 12 data points only. Figures 5a and 5b are scatter plots of the peak values of building thermal cooling load versus outdoor temperature and of the cooling plant electricity use versus building thermal cooling load for each of the 12 months of the whole year. A clear and generally well-behaved linear relationship is noted, although outliers reduce the R^2 value.

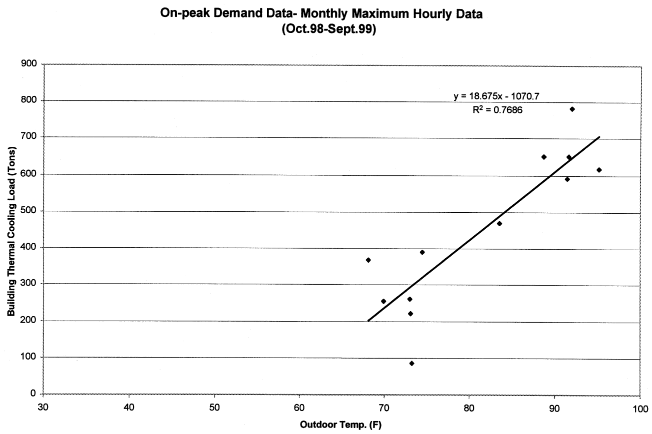

Figure 5a *Scatter plot of monthly peak hourly building cooling thermal load vs. outdoor temperature during on-peak period—Case Study #3.*

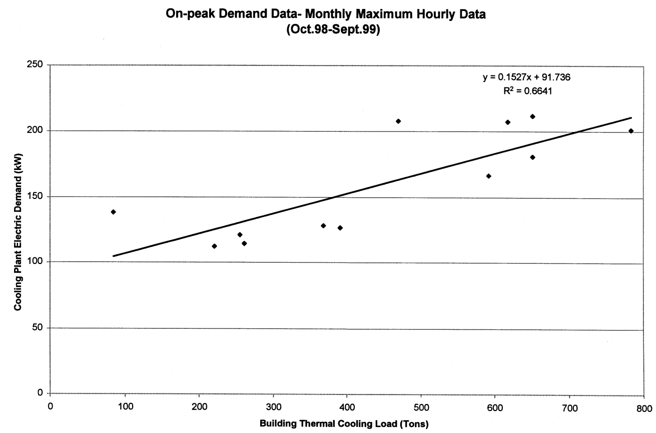

Figure 5b *Scatter plot of monthly peak hourly cooling plant electricity use vs. building cooling thermal load during on-peak periods—Case Study #3.*

Figure 6 is a scatter plot of the monthly maximum total building and cooling plant electric use ($E_{Bldg+Plant}$) (which is similar to what is available in the utility bills) versus building cooling load for Case Study #3. A fairly good trend is observed, and using a regression model identified with this data would be the best choice in such a case, namely, when year-long data are available. As discussed above, such an approach cannot be adopted with short-term data, and an alternative approach was proposed involving the use of the variable “Ratio.”

(b) *Model Development*

As stated earlier, energy use of the cooling system should be modeled based on daily averaged hourly data separated into weekday on-peak, weekday off-peak, and weekend/holiday periods. For each of the three periods, two sets of energy use models are developed:

- one for building cooling load Q_{Bldg} as a function of outdoor dry-bulb temperature T_0 and
- one for cooling plant electric E_{Plant} as a function of Q_{Bldg}.

Furthermore, performance data corresponding to those hours when the TES is idle (i.e., neither being discharged nor charged) are used to develop the baseline model for E_{Plant} as a function of Q_{Bldg}.

The summary statistics of the mean energy use regression models for all three sites are shown in Table 3. We note the following:

- The Type 1 models for Site #2 are generally good (CV values about 8%). Those for Site #1 are poorer (CV about 15%) but still acceptable. Unfortunately, those for Site #3 are very poor (CV about 28%) even though an additional variable E_{Ir} (the building internal electricity load) was included in the model because this is a convention center with highly variable and irregular internal loads.

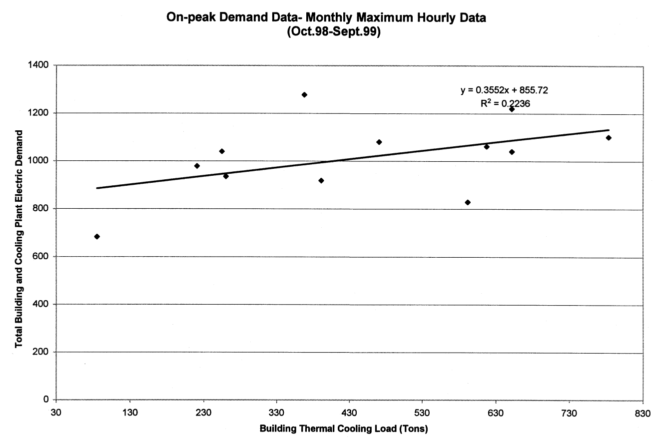

Figure 6 *Scatter plot of monthly peak facility (building plus cooling plant) electric demand vs. building thermal cooling load during on-peak period—Case Study #3.*

- Generally, the weekday off-peak and weekend/holiday models are good for all three sites, while those for weekday on-peak are poor as one would expect (CV values of 35% and 52% for Site #1 and Site #3). Site #2 seems to be an exception (CV about 10%). The fact that Site #1 is a hotel and Site #3 a convention center, both with highly variable and irregular operating schedules, may partly explain why these models are poor. In the case of these two sites, the poor CV may be improved by including additional variables or investigating other types of models, issues that could be studied in the future.

Table 4 assembles the summary statistics of the demand models for all three sites. Here instead of using daily mean hourly data, the models are identified based on monthly maximum hourly values of Q_{Bldg} versus T_0 (model 4) and the corresponding monthly maximum hourly values of E_{Plant} versus Q_{Bldg} (model 5). Models 4 and 5 are based on one data point for each month corresponding to peak or maximum weekday

TABLE 3
Summary Statistics of Mean Energy Use Regression Models for all Three Sites
(Based on Daily Averages of Hourly or 15-minute Data—See Figure 1 for Description of Model Numbering)

Model No.	Period	Model Type	Site #1 No. of points	Site #1 R^2	Site #1 CV (%)	Site #2 No. of points	Site #2 R^2	Site #2 CV (%)	Site #3 No. of points	Site #3 R^2	Site #3 CV (%)
1a	WD on-peak	$Q_{Bldg} = a + b \cdot T_0$	216	0.83	16.1	86	0.28	8.6	327	0.77*	29.9*
1b	WD off-peak	$Q_{Bldg} = a + b \cdot T_0$	216	0.87	14.0	88	0.35	6.1	327	0.82*	26.7*
1c	WE/holidays	$Q_{Bldg} = a + b \cdot T_0$	92	0.88	14.6	32	0.65	12.0	—	—	—
2a	WD on-peak	$E_{Plant} = a + b \cdot Q_{Bldg}$	234	0.50	35.4	86	0.00	10.3	327	0.22	52.0
2b	WD off-peak	$E_{Plant} = a + b \cdot Q_{Bldg}$	234	0.91	9.6	88	0.48	5.4	327	0.89	17.4
2c	WE/holidays	$E_{Plant} = a + b \cdot Q_{Bldg}$	100	0.79	14.6	32	0.81	6.2	—	—	—
3	Baseline+	$E_{Plant} = a + b \cdot Q_{Bldg}$	214	0.97	5.9	88	0.92	2.3	309	0.96	10.4

*Models were of the type $Q_{Bldg} = a + b \cdot T_0 + c \cdot_{Elr}$

+ Based on periods when the TES is idle (i.e., neither being charged nor discharged)

TABLE 4
Summary Statistics of Electric Demand Regression Models for all Three Sites
(Based on Monthly Maximum On-Peak Hourly or 15-Minute Data—See Figure 1 for Description of Model Numbering)

Model No.	Model Type	Site #1 No. of points	Site #1 R^2	Site #1 CV (%)	Site #2 No. of points	Site #2 R^2	Site #2 CV (%)	Site #3 No. of points	Site #3 R^2	Site #3 CV (%)
4	$Q_{Bldg} = \min(a + b \cdot T_0, Q_{max})$	12	0.96	6.2	4	0.03	20.8	12	0.77	24.4
5	$E_{Plant} = \min(a + b \cdot Q_{Bldg}, E_{max})$	12	0.70	12.6	4	0.17	11.5	12	0.66	15.3
6	Baseline $E_{Plant} = \min(a + b \cdot Q_{Bldg}, E_{max})$	12	0.95	5.6	4	0.78	1.6	12	0.76	15.1

on-peak periods (i.e., during the period when on-peak electric rates are in effect). For Sites #1 and #3 these models are based on 12 data points, while for Site #2 they are based on 4 points corresponding to the 4 months of TES operation. Models for Sites #1 and #2 are generally satisfactory while those of Site #3 are poorer due to the variable and irregular operating schedules. The baseline demand models for Sites #1 and #2 are very good (CV values of 5.6% and 1.6% respectively), but poorer for Site #3 (CV = 15%), which is consistent with our earlier observation.

(c) *Energy and Demand Savings Results*

The results of the savings calculation are shown in Table 5 for the three sites based on one year of monitored data. The top half of the table relates to savings while the bottom half to the uncertainty in the calculated savings values. We note that, as expected, demand savings are the major determinant of the total savings. For Site #1, demand savings account for over 90% of the total savings. Sites #2 and #3 experienced increases in energy costs due to increased energy use for operating the TES, which partially offset the savings due to demand shifting.

Note that all of the energy use and demand models are linear. There was not much improvement in the model fits when quadratic terms were included. This allowed us to use the energy use models 1, 2, and 3 for an average day of each month in order to predict monthly mean daily values of Q_{Bldg} and E_{Plant}. Monthly mean outdoor temperature values (which are known beforehand) are used to drive the energy use models, while the maximum hourly T_0 values for each month are used to drive the demand models 4, 5, and 6. Since the calculations are performed on a month-by-month basis, only once for each period (on-peak, off-peak, and WD/holidays) for the energy use, and only once for demand, the whole analysis procedure is conveniently done on a spreadsheet program with limited effort, although the handling of the hourly data is best accomplished with a relational data base. Table 6 illustrates how a sample spreadsheet table can be set up to facilitate the entire savings calculation. This table pertains to Case Study #1 when one year of data are available. In Table 6, we note that there are three tables for energy use (for on-peak, off-peak, holidays/weekends), one for demand, and, finally, one for the total. The calculations are set up for monthly calculations and the inputs (such as hours of operation, electric rates, model coefficients, mean and maximum monthly values of T_0) are clearly indicated.

TABLE 5
Summary of Savings Results Based on Whole-Year (or Whole-Season) Data for all Three Sites

	Site #1 (Whole Year)		Site #2 (4 Months)		Site #3 (Whole Year)	
Energy use	**Fractional electricity use savings**	**Dollar savings ($/year)**	**Fractional electricity use savings**	**Dollar savings ($/year)**	**Fractional electricity use savings**	**Dollar savings ($/year)**
WD on-peak	0.43	$22,078	0.43	$6500	0.79	$19,680
WD off-peak	–0.21	–$12,834	–0.18	–$6911	–0.32	–$24,788
WE/Holidays	–0.15	–$5347	–0.15	–$3364	—	—
Demand	0.48	$49,775	0.70	$16,240	0.77	$60,062
Total	—	$53,672	—	$12,465	—	$54,955
Fractional uncertainty (at 68% confidence level)						
In energy use	18%		10%		30%	
In demand	15%		20%		26%	
In energy dollar savings	170%		300%		very large	
In demand dollar savings	40%		40%		40%	

TABLE 6
Sample of Spreadsheets to Illustrate the Various Tables and Their Specific Layout Used to Estimate Energy and Demand Data for TES

The Numerical Values Correspond to Case Study #1

	WD On-Peak (12:00 - 19:00 h)								WD Off-Peak (19:00 - 12:00 h)						
					Electric Use (kWh/mo)		Electric Use Savings					Electric Use (kWh/mo)		Electric Use Savings	
					Baseline	Actual						Baseline	Actual		
Month	**Energy Electric Rate $/kWh**	**No. of Days**	**Mean T_0 (°F)**	**Q_{Bldg} (ton) Model 1a**	**Model 3**	**Model 2a**	**kWh/mo**	**$/mo**	**Energy Electric Rate $/kWh**	**T_0 (°F)**	**Q_{Bldg} (ton) Model 1b**	**Model 3**	**Model 2b**	**kWh/mo**	**$/mo**
Jan.	0.08	21	56.75	137.66	26,125	12,686	13,439	$1075	0.05	56.62	130.85	61,673	70,474	–8801	–$440
Feb.	0.08	17	62.30	261.14	31,876	17,450	14,426	$1154	0.05	60.06	214.93	67,662	80,254	–12,591	–$630
Mar.	0.08	20	65.16	324.64	43,990	24,872	19,118	$1529	0.05	60.90	235.41	84,687	101,067	–16,380	–$819
Apr.	0.08	21	64.58	311.71	44,802	25,187	19,615	$1569	0.05	61.68	254.57	93,914	112,652	–18,738	–$937
May	0.1	21	68.63	401.75	54,465	31,654	22,810	$2281	0.05	65.27	342.15	116,738	142,511	–25,773	–$1289
June	0.1	21	67.00	365.44	50,569	29,047	21,522	$2152	0.05	64.68	327.86	113,014	137,639	–24,625	–$1231
July	0.1	22	66.84	361.97	52,586	30,169	22,418	$2242	0.05	64.86	332.09	119,550	145,704	–26,154	–$1308
Aug.	0.1	21	71.03	455.02	60,181	35,480	24,700	$2470	0.05	68.40	418.65	136,676	168,595	–31,918	–$1596
Sept.	0.1	21	74.09	523.09	67,486	40,370	27,116	$2712	0.05	70.13	460.87	147,678	182,987	–35,309	–$1765
Oct.	0.1	22	68.67	402.64	57,158	33,228	23,929	$2393	0.05	65.77	354.47	125,660	153,697	–28,037	–$1402
Nov.	0.08	17	64.67	313.78	36,449	20,510	15,938	$1275	0.05	62.96	285.70	82,593	99,787	–17,193	–$860
Dec.	0.08	20	60.10	212.05	32,484	17,171	15,313	$1225	0.05	58.10	167.09	67,730	78,884	–11,154	–$558
Annual		244			558,170	317,825	240,345	**$22,078**				1,217,577	1,474,250	–256,674	**–$12,834**

TABLE 6 (Continued)
Sample of Spreadsheets to Illustrate the Various Tables and Their Specific Layout Used to Estimate Energy and Demand Data for TES
The Numerical Values Correspond to Case Study #1

Month	WE								WD						
					Electric Use (kWh/mo)		Electric Use Savings					Electric Demand (kWh)		Electric Demand Savings	
	Energy Electric Rate $/kWh	No. of Days	T_0 (°F)	Q_{Bldg} (ton) Model 1c	Baseline Model 3	Actual Model 2c	kWh/mo	$/mo	Demand Rate $/kWh	Max T_0 (°F)	Q_{Bldg} (ton) Model 4	Baseline Model 6	Actual Model 5	kWh	$/mo
Jan.	0.05	10	57.05	129.28	41,186	50,052	–8866	–$355	14	65.16	476.50	425	237	188	$2630
Feb.	0.05	11	63.46	289.06	76,096	88,042	–11,946	–$478	14	67.32	535.60	468	256	212	$2967
Mar.	0.05	11	61.02	228.18	64,364	75,474	–11,111	–$444	14	77.01	800.47	662	342	320	$4476
Apr.	0.05	9	62.49	264.99	58,465	67,969	–9504	–$380	14	76.37	782.96	649	336	313	$4376
May	0.05	10	67.01	377.46	84,666	96,629	–11,963	–$479	14	88.47	900.00	734	374	360	$5043
June	0.05	9	65.49	399.70	70,245	80,588	–10,343	–$414	14	75.49	758.88	631	328	303	$4239
July	0.05	9	64.56	316.51	66,589	76,671	–10,083	–$403	14	76.13	776.40	644	334	310	$4339
Aug.	0.05	10	69.12	430.15	93,897	106,518	–12,621	–$505	14	77.41	811.42	670	345	324	$4538
Sept.	0.05	9	71.33	485.28	93,201	105,179	–11,978	–$479	14	87.11	900.00	734	374	360	$5043
Oct.	0.05	9	66.42	362.84	73,894	84,497	–10,603	–$424	14	82.86	900.00	734	374	360	$5043
Nov.	0.05	13	64.56	316.53	96,189	110,753	–14,564	–$583	14	77.25	807.04	666	344	322	$4513
Dec.	0.05	11	58.04	153.99	50,065	60,157	–10,092	–$404	14	64.75	465.55	417	234	183	$2568
Annual		121			868,855	1,002,529	–133,674	**–$5347**				7435	3879	3555	**$49,775**

Regression Models:		$Y = \min(a + b \cdot X, Y\max)$				
Energy-WD (on-peak)	Model 1a	Q_{bldg}	**–1123.2**	**22.219**	T_0	
Energy-WD (off-peak)	Model 1b	Q_{bldg}	**–1252**	**24.425**	T_0	
Energy-WE	Model 1c	Q_{bldg}	**–1293**	**24.93**	T_0	
Energy-WD (on-peak)	Model 2a	E_{plant}	**19.041**	**0.4886**	Q_{bldg}	
Energy-WD (off-peak)	Model 2b	E_{plant}	**72.44**	**0.955**	Q_{bldg}	
Energy-WE/Holidays	Model 2c	E_{plant}	**107.45**	**0.782**	Q_{bldg}	
Energy-Baseline	Model 3	$E_{chiller+aux}$	**77.23**	**0.73**	Q_{bldg}	
Demand-WD (on-peak)	Model 4	Q_{bldg}	**–1303.55**	**27.32**	T_0	**900**
Demand-WD (off-peak)	Model 5	E_{plant}	**83.31**	**0.323**	Q_{bldg}	**1200**
Demand-WD (Q_{hx} = 0)	Model 6	$E_{chiller+aux}$	**77.23**	**0.73**	Q_{bldg}	**1200**

Savings Summary ($/mo)						
Month	WD On-Peak	WD Off-Peak	WE	Energy	Demand	Total
Jan.	$1075	–$440	–$355	$280	$2630	$2910
Feb.	$1154	–$630	–$478	$47	$2967	$3013
Mar.	$1529	–$819	–$444	$266	$4476	$4742
Apr.	$1569	–$937	–$380	$252	$4376	$4628
May	$2281	–$1, 289	–$479	$514	$5043	$5557
June	$2152	–$1, 231	–$414	$507	$4239	$4746
July	$2242	–$1, 308	–$403	$531	$4339	$4870
Aug.	$2470	–$1, 596	–$505	$369	$4538	$4908
Sept.	$2712	–$1, 765	–$479	$467	$5043	$5510
Oct.	$2393	–$1, 402	–$424	$567	$5043	$5610
Nov.	$1275	–$860	–$583	$167	$4513	$4346
Dec.	$1225	–$558	–$404	$264	$2568	$2831
Annual	$22, 078	–$12, 834	–$5, 347	$3, 897	$49, 775	$53, 672

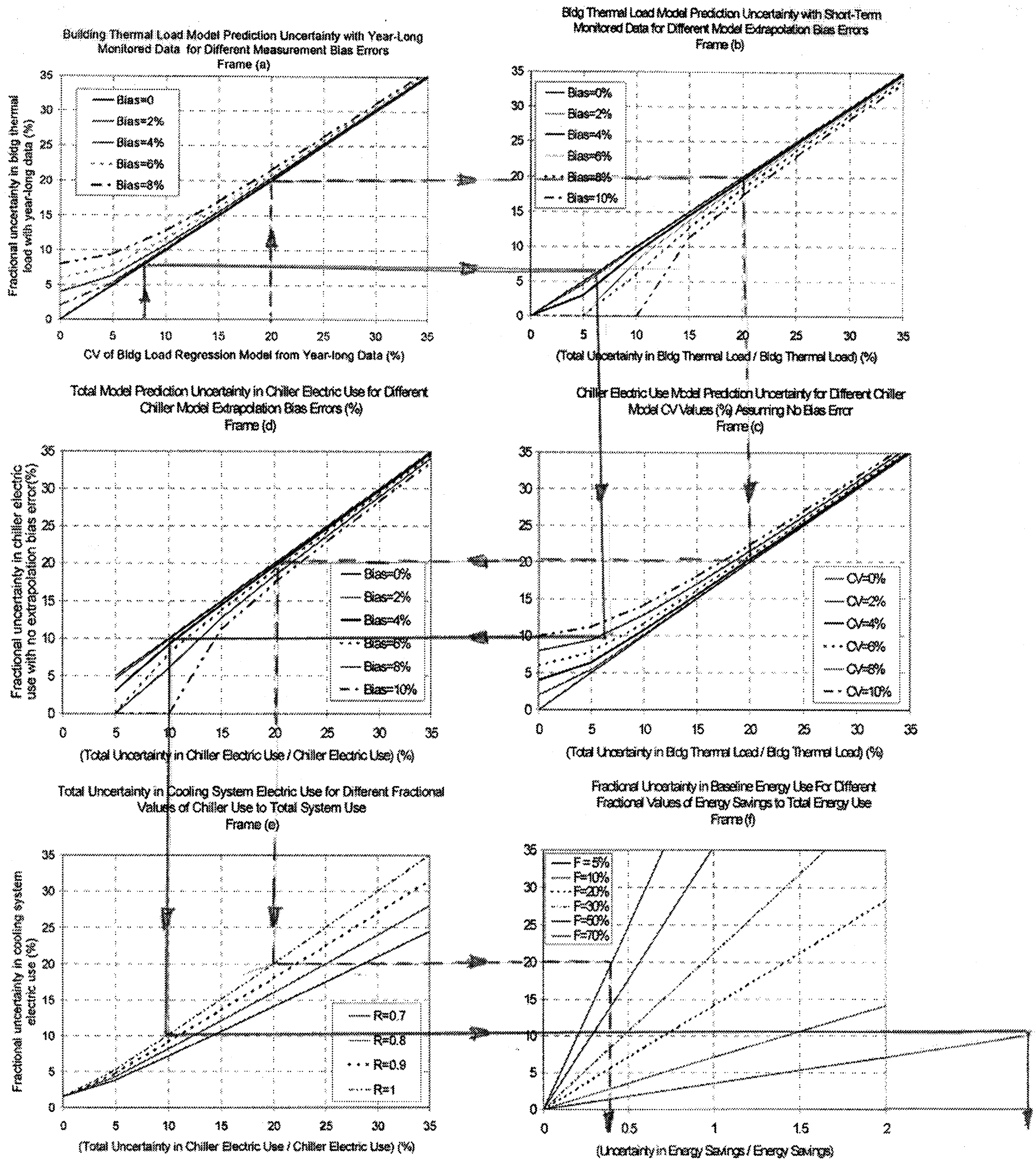

Figure 7 *Nomograph to determine uncertainty in the estimated energy (continuous line) and demand (dashed line) savings due to the TES system. The values pertain to Case Study #2.*

(d) *Uncertainty in Savings*

To best understand the uncertainty calculations, it is useful to illustrate the use of the nomograph (Figure 7) to estimate the uncertainty in our savings estimate using the numerical values corresponding to the case of one year of data available for Case Study #2. We start the analysis with the model CV values between the building loads and the outdoor temperature (from Tables 3 and 4, model 1 has a CV = 8% and model 4 has a CV = 20%) in Frame (a) as shown in Figure 7. The dotted line through the various frames corresponds to the propagation of uncertainty in the demand savings, while the continuous line corresponds to that in the energy savings. Since complete seasonal data are used, there is no model extrapolation error in predicting annual building loads due to short-term monitored data, and we therefore assume prediction bias to be zero. We then move down vertically to Frame (c), as shown. Model 2, which is the model between plant electric use and building loads, has a CV of about 7%, while the associated demand model 5 also has a CV of about 10%. Again because year-long monitored data are used, there is no extrapolation bias error in the chiller (or plant) electricity use prediction, and therefore the corresponding extrapolation CV is taken as zero.

This allows us to plot the uncertainty propagation lines for energy and demand savings as shown in Frame (d). The fraction of electricity consumed by the chillers compared to the total plant electricity use is taken to be 100% in this case because we have included the auxiliary energy use with that of the “lumped” chiller at the onset of our analysis. This allows us to descend vertically into Frame (e) and then move horizontally into Frame (f) as shown. The fraction (F), i.e., the savings fraction, is about 70% for demand and slightly less than 5% for the energy savings if all three periods (WD on-peak, WD off-peak, and WE) are combined together (see Table 5). From Frame (f), these correspond to about 40% and 300%, respectively in the fractional savings uncertainty values. Thus, the demand savings, which is about 75% of the total savings, has an uncertainty that is acceptable for M&V projects (about 40% at a confidence level of 68%) largely because of the large savings fraction. Since TES systems are primarily meant to lower demand charges, such savings fractions are likely to be large in general, an aspect that lends credibility to M&V programs and reduces the risk involved in such projects.

Looking at the lower half of Table 5, we note that the prediction uncertainties in electricity use and demand values by themselves are acceptable for M&V projects (10-30% for energy use and 15-26% for demand). Unfortunately, uncertainty in the estimated savings is larger. This is not surprising since savings is estimated as the difference between two large numbers, namely, the difference between the demand (or energy use) of the actual system and that of the baseline system. The propagation of errors formula results in savings having more uncertainty than either one by itself. This is further exacerbated, especially in the case of energy use, by the fact that the savings are a very small fraction of the baseline energy use. We notice that the uncertainties in energy use savings are so large that little or no confidence can be placed in their estimation (170% for #1, 300% for #2, and even larger for #3). However, those for demand savings are acceptable, about 40% in all three cases, partly because the demand reduction is large. This feature essentially justifies the money and effort spend on the entire M&V process itself.

(e) *Results with Different Short-Term Monitoring Periods*

One of the two main objectives of this study was to investigate the effect of using short-term monitored data to predict the annual energy and demand savings of the actual cooling plant with TES. If monitoring during part of the year could yield acceptable prediction accuracy, the effort and cost of the M&V program are reduced. We have investigated the effect of different lengths of monitoring periods coupled with the effect of doing so during different seasons of the year. The results of our investigation are summarized in Table 7. More elaborate discussion and detailed results are documented in the reports by Reddy et al. (2000, 2001). The values listed in Table 7 are shown as fractional differences between the savings calculated with short-term monitoring, and those determined from year-long monitoring. A negative value indicates under-

TABLE 7
Summary of Savings Results Determined from Different Short-Term Monitoring Periods for all Three Sites

	Site #1		Site #2		Site #3	
	Analysis Period	**Percentage difference**	**Analysis Period**	**Percentage difference**	**Analysis Period**	**Percentage difference**
Entire cooling season	May-Oct. (6 months)	–25.2%	—	—	Apr-Sept (6 months)	36.1%
Spring season	Mar. – May (3 months)	13.5%	—	—	Mar-May (3 months)	3.3%
Late spring-early summer	May-July (3 months)	–27.2%	June-July (2 month)	–13.1%	—	—
Summer season	Aug. – Oct. (3 months)	–16.1%	Aug-Sept (2 month)	–1.7%	July-Sept (3 months)	30.8%
Fall season	—	—	—	—	Oct-Dec (3 months)	–19.3%
Late spring month	May (1 month)	38.5%	June (1 month)	–36.6%	—	—
Late summer month	Sept. (1 month)	52.1%	Sept (1 month)	–11.1%	—	—

prediction in savings when a short-term monitoring M&V scheme is adopted, while a positive value indicates an over-prediction. Thus a value of –25% implies that a short-term monitoring scheme underpredicts annual savings due to TES by 25% as compared to annual savings determined from year-long monitoring.

Let us first study the results of Sites #1 and #3, which are operated year-round. Clearly, using only the six months of the cooling season is unacceptable since there is more than a 25% difference. In Site #1, using only one month of monitoring also seems to result in unstable estimation. From a practical point of view, a monitoring period lasting three months would be an attractive solution. Hence, several three-month options were evaluated as shown in the table. Using a three-month monitoring period from March-May (spring season) seems to yield the best results (13.5% difference for #1 and 3.3% for #3). This conclusion should be verified by performing other case study analyses. However, this conclusion seems to be in general agreement with previous studies performed with similar objectives, although the previous studies were limited to building thermal load predictions rather than cooling plant energy use (Katipamula et al. 1995; Kissock et al. 1998; Reddy et al. 1998).

Site #2 is only operated four months of the year and so the recommendations for the best short-term monitoring period differ from those of sites operated yearlong. At Site #2, only one-month and two-month monitoring periods were evaluated. Monitoring over the summer season (Aug. - Sept.) seems to yield very accurate results (difference of 1.7% only). While this finding is supported by intuitive reasoning, it would be judicious to investigate other cooling plants with seasonal TES operation to confirm this preliminary recommendation.

REPORTING

The reporting of the electricity energy savings (or increases in electricity use) and electric demand savings for a thermal storage site should be such that the information contained in the report could be independently verified by a third party. This would, therefore, require the following information:

1. Complete description of the TES site, including the information described in the companion paper (Elleson et al. 2002).
2. Complete description of the monitoring plan.
3. Document data quality checks performed, and any data reconstituted.
4. Make a copy of the complete data set used for the calculations. This should include a copy of the 15-minute or hourly data in columnar ASCII format with a description of each data channel, as well as the data used for model identification (period averaged data).
5. Complete description of calculation methodology. This should include equations and sample values so that someone could trace through the calculations. If spreadsheets are used, copies of the spreadsheet formulas are also helpful.
6. Calculated baseline (i.e., without TES) electricity use and electric demand. This should be presented in tabular format using monthly values corresponding to the normal utility billing periods.
7. Calculated TES electricity use and electric demand. This should be presented in tabular format using monthly values corresponding to the normal utility billing periods.
8. Calculated savings in demand and energy use. This should be presented in tabular format using monthly values corresponding to the normal utility billing periods.
9. Determine uncertainty in energy use and demand savings at the annual time scale (using the nomograph proposed).
10. Prepare an executive summary of the overall findings of the M&V effort.

RECOMMENDATIONS FOR FUTURE RESEARCH

This research project has defined a methodology for determining the performance of cool storage systems from short-term tests. In the course of this research, we have identified several issues and questions that deserve further exploration. We recommend that this performance evaluation methodology be applied to additional cooling systems with a wide range of characteristics and that the results be used to recommend refinements to the methodology:

In particular, the following issues need to be explored further:

- How general are the findings of this research vis-a-vis the selection of the best short-term monitoring period?
- How can the uncertainty in the prediction of energy use and demand savings be reduced?
- What simplifications in the analysis procedure are possible to make it even more usable for practitioners?
- What extensions of the analysis procedure are required to allow it to be used to diagnose cool storage system performance and to identify improvements in operation?
- Can the use of more sophisticated analysis procedures such a day-typing and component modeling improve the results of the methodology?
- What other practical improvements can be recommended by practitioners who use the methodology?

SUMMARY

This paper described an analysis methodology intended to allow reliable and low-cost evaluation of the long-term performance of cool storage systems to be determined. It also presented the results of applying the methodology to three case study sites.

Since electric utilities generally bill their clients monthly with utility rates likely to change seasonally, the analysis methodology recommends that savings be calculated on a month-by-month basis. Further, instead of an analysis approach using characteristic or prototypical day-types for summer and winter, a monthly mean daily computational approach is advocated. Finally, it was suggested that energy use savings be inferred from the monthly mean daily data (separated of course into on-peak and off-peak periods during the day). Analysis at the hourly or 15-minute level for energy use modeling is not recommended since unacceptable, unknown statistical noise is introduced into the data because of such factors as the relatively large thermal capacity of the chilled water in the water loop, control dynamics, and other factors such as part-hour usage (i.e., when one period contains part of an on-cycle and part of an off-cycle). However, 15-minute data monitoring intervals are recommended since this improves the data quality associated with system dynamics.

A component modeling approach, using in-situ performance-based models of plant components such as chillers, storage tanks, pumps, etc., may provide higher accuracy but requires substantially more analytical effort and statistical knowledge perhaps beyond the capabilities of many practitioners. A nested, lumped regression model approach that aggregates or lumps all cooling plant electricity use (i.e., building chillers, auxiliary, TES chiller, and TES pump electricity use) into a total electricity use is suggested. The distinctive manner in which the particular cooling plant is operated and controlled during different times of the day is implicitly captured in the lumped methodology. It is felt that such an approach, while yielding adequate accuracy, offers the necessary convenience appropriate for practitioners.

There is some element of unpredictability in the operation of many thermal storage systems. Each of the three case study sites showed some variability in their strategies for scheduling and limiting chiller operation. Site #1, which operated under a real-time pricing electric rate, had the most variability since chiller operation was scheduled manually in response to changes in electricity pricing. Site #3 had significant variability, since it was operated to provide additional capacity for the municipal utility but was not subject to time-of-use electric rates. Site #2 also showed some variability, although it was operated under a fairly typical time-of-use rate schedule. Many systems are subject to unintentional or uninformed chiller operation during on-peak periods, or to the use of chillers during on-peak periods to meet abnormal load conditions. Such occurrences are difficult to predict, and they often determine the peak demand in a given month.

Our analyses revealed that despite this variability, the nested lumped model approach has merit in that the models identified were statistically acceptable and yielded uncertainty in the demand savings which were about 40%. Though this may seem excessive, other studies related to M&V of retrofit energy savings have estimated similar uncertainties and were deemed acceptable by the professional M&V community (ASHRAE 2001). However, we recommend that monitoring of actual peak demand over an extended period (we suggest an absolute minimum of three months and that in the right season, namely, spring, for TES operated year-round) be adopted in order to predict demand based on short-term data.

This methodology will simplify the evaluation of cool storage system performance and enhance the application of cool storage technology. It will also provide a basis for the development of evaluation methodologies for other technologies, for example, thermal heating storage systems used in areas where expensive electrical energy is used for heating.

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