

# Whole-Building Commercial HVAC System Simulation for Use in Energy Consumption Fault Detection

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## ABSTRACT

*Numerous fault detection and diagnostic system techniques have been developed for HVAC systems, but most focus on detecting faults at the component level, for example, air-handling units or variable air volume boxes. This paper examines the use of the ASHRAE simplified energy analysis procedure (SEAP) for fault detection at the whole-building level. In the procedure examined, an implementation of the SEAP is "calibrated" to a period of measured heating and cooling data from a building so the simulated data closely follow the measured data. A small adjustment is added to the simulated data so the total adjusted simulated heating and cooling consumption values exactly match the measured heating and cooling consumption totals for the same period. The adjusted version of the calibrated SEAP simulation is then used to predict future consumption, using future weather data. Visual comparison with future measured data is used to diagnose significant deviations from expected performance. The procedure is applied retrospectively to three years of measured consumption data as a test. It clearly identifies three significant operational changes that occurred during the test period. Three different presentation formats are tested for fault identification—monthly deviations, daily percent deviations, and cumulative deviation plots. All have value, and it is ultimately a user preference as to which is the most informative.*

## INTRODUCTION

Increasing energy costs have led to the need for a simple, reliable, and accurate diagnostic tool to gauge the energy performance of commercial buildings in real time. Historically, the energy efficiency of most buildings depreciates

over time, due to issues ranging from ill-advised operational changes to failed or failing components, such as chilled water (CHW) or hot water (HW) control valves (Claridge et al. 2004; Liu et al. 2002). Fault detection and diagnostic techniques have been developed, but most focus on the component level or subsystem level and detect faults such as those in air-handling units or variable air volume terminal boxes (Norford et al. 2002; Salsbury and Diamond 1999; Xu and Haves, 2002). The focus of this paper is on the development and testing of a whole-building-level fault detection concept. Whole-building-level fault detection and diagnosis is an approach using measured building energy consumption to detect and diagnosis building-level energy consumption problems (Dodier and Kreider 1999; Breekweg et al. 2000a, 2000b). The magnitude of whole-building energy consumption faults using this approach is about five percent (Claridge et al. 1999). The technique described in this paper utilizes calibrated simulations to provide a visual comparison to the measured data. An "on-line" tool that will run in conjunction with the building's EMCS system is the ultimate goal. However, this paper focuses on describing and testing the proposed fault detection approach.

Liu and Kelly (1989) describe a two-step procedure for fault detection and diagnosis. The first step is to predict the system performance under a faultless state using a model and compare these values to measured output data. Significant differences are indicative of a fault. The second step concerns the diagnostic phase of the system, in which possible causes for the faults are constructed using a reasoning logic. This paper is restricted to examination of a whole-building-level fault detection approach.

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## METHODOLOGY

This paper examines the use of a visual comparison of calibrated simulation results and measured consumption data to facilitate detection of significant operational faults in a building. The comparison may also be performed using mathematical criteria to detect faults. This method is compared with the use of a visual inspection of the measured data alone, a time-honored method that can be beneficial in gaining insight into building problems (Claridge et al. 1992, 1999).

To effectively identify faults while minimizing false positives and false negatives, a rigorous methodology was developed. Fault detection studies have utilized a physics-based simulation and measured data to detect performance deviations (Xu and Haves 2002; Haves 1997). The residuals of these two data sets are then subjected to a threshold that is predetermined depending on how stable a system is. Systems that are unstable will require a large threshold range to minimize false positives. Usually three sample standard deviations of the residual under normal operating conditions are used as a threshold value (Montgomery et al. 1994; Rose et al. 1993; Farnum 1992; Fasolo and Seborg 1992).

There are two types of faults: complete (or abrupt failures) and performance degradations (Kelly et al. 1996). Performance degradations are gradually evolving faults. The methodology described in this paper is able to detect both fault types.

Several steps are necessary to ensure that the performance of the fault detection sequence is accurate. This sequence contains three preliminary steps, critical to the accuracy and performance of the system because they are tailored to the specific building's parameters. These steps are described below.

### Step 1: Collect Information

The first step is to collect all the critical building and site data, such as wall composition, building orientation, internal load data, occupancy schedules, equipment data and schedules (including air-handling units and exhaust fans), measured consumption data, and weather data. This step is critical for the construction of a building-specific energy consumption simulation. For the simulation construction, about a month of data is needed. The accuracy of the energy consumption meters should be verified prior to using the measured data for simulation construction.

### Step 2: Calibrate Simulation

The second step is to generate a calibrated baseline energy consumption simulation using the data collected in step 1. First, the measured energy consumption data should be examined to identify erroneous or missing data to enable generation of a clean measured data set.

To achieve a calibrated simulation of the building's energy consumption, known building parameters, acquired in step 1, are input into the simulation software to acquire a first run, or initial simulation of the building, which is then plotted against the baseline screened, measured consumption with outside dry-bulb temperature as the abscissa. The methodol-

ogy chosen to calibrate the simulation presented in this paper used the following approach:

- a. Adjust the cooling energy consumption profile of the simulated output, with very little attention being paid to the magnitude, to closely resemble the measured consumption profile. The profile of the simulated consumption can be adjusted using simulation inputs that are affected by the outdoor environment directly. These include conduction components such as wall compositions, U-values, ratios of glass area to wall area, as well as outside air fraction, CHW temperature schedule, etc.
- b. Once the simulated cooling energy consumption profile closely resembles the measured consumption profile, the magnitude of the simulated consumption can be adjusted using simulation inputs that are not affected by the outdoor environment directly. These variables include the internal gains, occupancy, fraction of interior to exterior floor area, building area, etc.
- c. Once the cooling model profile and order of magnitude closely resemble the measured consumption, repeat the process for the heating consumption. Steps a and b usually require more than one iteration because the cooling and heating consumption are sometimes functions of one another.

### Step 3: "Correct" the Calibrated Simulation

The third step is to adjust the heating and cooling consumption values from the calibrated simulation so the totals of the simulated cooling and heating consumption for the calibration period are identical to the total measured values. This involves the calculation of an appropriate "correction factor" as will be described later. If there is even a small systematic error in the calibrated simulation, it will decrease the sensitivity of the fault detection process.

After the first three setup steps are completed, the following steps become the executable portion of the fault detection process.

### Step 4: Collect Measured Data

The fourth step, or first step of the actual fault detection sequence, collects measured cooling and heating consumption data as well as measured outdoor environmental data (i.e., outside air dry-bulb and wet-bulb temperatures, relative humidity, or dew-point temperatures). These data will typically be hourly average data for a 24-hour period to coincide with the typical simulation time scale.

### Step 5: Compare Measured and Simulated Energy Consumption

The calibrated simulation of step 2 is then run using the appropriate weather input data and other measured input data that may be available (e.g., internal electrical gains, return temperatures, etc.). The output of this simulation is corrected using the procedure developed in step 3. The

corrected simulation output is compared with the measured cooling and heating consumption data.

### **Step 6: Fault Detection**

Any differences between the corrected simulation values and the measured values are evaluated to determine whether they exceed a defined error threshold. The results of the analysis are presented to the user in one or more appropriate forms.

If implemented in an on-line fault detection system, an alarm would be implemented when appropriate and the process would be repeated. Within this paper, we will proceed to define and evaluate this process using an implementation of the ASHRAE simplified energy analysis procedure (Knebel 1983) and will apply the process to a case study building.

## **CASE STUDY BUILDING DESCRIPTION**

A large university food service building is used for testing the fault detection procedure described in the previous section. This building contains 81,936 ft<sup>2</sup> (7612 m<sup>2</sup>) of conditioned floor area according to the plans and includes a basement and first floor, with the basement area about half the first floor area. The building, located in College Station, Texas, was originally built in 1912 but was most recently renovated in 1999, when most air-handling units (AHU) were replaced. The front of the building faces south and the ceiling heights on the first and basement levels are 20 ft (6.1 m) and 10 ft (3.0 m), respectively. The main floor is broken into seven zones with a large majority of the area associated with the kitchen and main dining areas. There is also a small café/coffee bar and some offices located on the main floor. The basement level is broken into five zones with the majority of this level used for storage. The other significant basement uses include a small food court and a convenience store.

Twelve AHUs provide conditioned air to the main floor of the building, eleven of which are single-duct constant-volume systems, with one a single-duct variable air volume system. The first floor is also served by two outside air pretreatment AHUs, which precondition the outside air for the main floor's AHUs. Also located in the first floor kitchen are four hood exhaust fans, which are interlocked with makeup AHUs 8–11. Five single-duct constant-volume AHUs provide conditioned air to the basement level. There is an outside air pretreatment AHU, which preconditions the outside air for the basement AHUs. Also serving the basement level are six exhaust fans, two of which are kitchen hoods. Two CHW pumps with variable-speed drives (VSD) and one constant-speed HW pump with a bypass valve make up the secondary hydronic systems for the building. Heating and cooling for the building are supplied as hot water and chilled water from the campus central system.

Two hundred and twenty-five points with four hundred and ninety-one virtual measured points are monitored or controlled by the energy management and control system (EMCS). These points include flow meters on the CHW and HW secondary hydronic systems, temperature and pressure sensors, and VSD

speeds. One of the major factors that lead to selection of this building for study was the extensive utility metering that is present. Electricity consumption, cooling consumption, and heating consumption are all recorded on the EMCS. Since heating and cooling consumption are recorded by Btu meters on the HW and CHW lines to the building, these values will often be referred to as HW consumption or CHW consumption in the remainder of this paper. In addition, domestic cold water, domestic hot water, and steam use in the kitchen are all metered for this building. The heating, cooling, and electricity consumption are the only quantities directly used in the fault detection analysis to follow, but the presence of the other quantities was considered beneficial for diagnostic purposes.

## **IMPLEMENTATION OF FAULT DETECTION PROCEDURE IN THE CASE STUDY BUILDING**

### **Step 1: Collect Information**

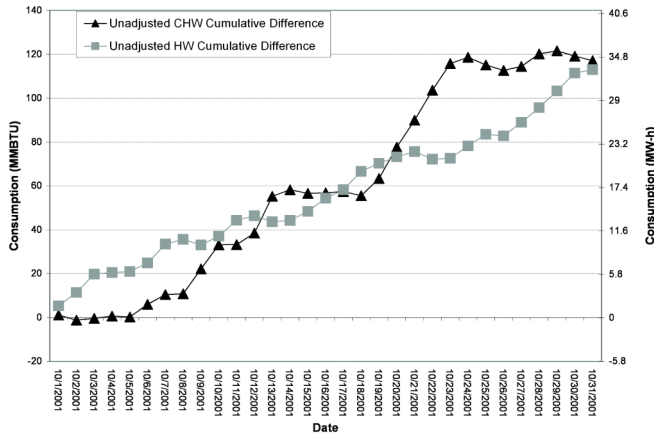
The building construction characteristics and HVAC system information needed for simulation was collected from as-built drawings, from visits to the facility, and from the EMCS. The hourly electricity use (none of which is directly used for heating or cooling) in the building was collected from the EMCS and archived. The building operating schedule was obtained from the university food service.

### **Step 2: Calibrate Simulation**

The second step generated a calibrated baseline energy consumption simulation using the data collected in step 1. The simulation procedure selected for this study was the ASHRAE simplified energy analysis procedure (SEAP) (Knebel 1983). The simulation was performed using an in-house implementation of the SEAP (Liu 1997). Energy use data were available for the building beginning in October 2001. Weather data for the site were available dating back to 1990. The heating and cooling data were examined with time series plots and plotted as functions of ambient temperature. It was observed from the temperature plots that some unusual behavior started in late 2001 or early 2002. Consequently, the October 2001 data were used as the baseline data for the model calibration process. The simulation was calibrated to the measured CHW and HW consumption data using the "Calibration Signature" procedure of Wei et al. (1998). Some model parameters that were used to adjust the simulated CHW and HW consumption profiles included the cold deck schedule, outside air fraction, wall composition, and window and wall areas. Model parameters that were used to adjust the simulated CHW and HW consumption magnitudes included floor area, internal gains (occupant and equipment), and the ratio of interior to exterior zones.

### **Step 3: "Correct" the Calibrated Simulation**

The third step adjusted the CHW and HW consumption values from the calibrated simulation so the totals of the simulated CHW consumption and HW consumption for the calibration period are identical to the total measured values.



**Figure 1** Unadjusted CHW and HW cumulative differences for calibration period (October 2001).

Figure 1 shows the cumulative difference between the simulated and measured CHW and HW consumption for the October 2001 calibration period. At the end of the month, the simulated values for consumption of CHW and HW for the month were 117 MMBtu (34 MW-h) and 113 MMBtu (33 MW-h) more, respectively, than the measured consumption. (Note: 1 MMBtu = 1,000,000 Btu.)

These differences resulted in mean bias errors<sup>1</sup> (MBE) of 3.8 MMBtu/day (1.1 MW-h/day) and 3.6 MMBtu/day (1.1 MW-h/day), or 0.158 MMBtu/h (46 kW) and 0.151 MMBtu/h (44 kW) for CHW and HW, respectively. Since the daily differences did not show any apparent dependence on ambient temperature, the simulated results were “corrected” by simply subtracting the MBE from the simulated values. These “corrected” simulated values will be called the “corrected” values of CHW and HW consumption.

The executable portion of the fault detection process was then implemented.

#### Step 4: Collect Measured Data

The fourth step, or first step of the actual fault detection sequence, collected measured CHW and HW consumption data from the EMCS system. Initially, the dry-bulb and wet-bulb temperature data supplied by the campus energy office were used for this simulation process. However, early in the simulation process, many cases were noted where there were significant differences between measured and simulated energy consumption values without apparent explanations. Eventually, the weather data values were checked, and it was observed that the wet-bulb temperature was frequently almost identical to the dry-bulb temperature for significant periods corresponding to the periods when the simulated consumption

<sup>1</sup>. Defined in the usual manner as  $MBE = \frac{\sum(E_{sim} - E_{meas})}{n}$ , where  $n$  is the number of days in the calibration period.

varied widely from the measured consumption. This indicates that the humidity sensor was out of calibration and was not reading correct wet-bulb temperatures. Consequently, alternative weather data from the National Weather Service at Eastwood Airport in College Station were used.

#### Step 5: Compare Measured and Simulated Energy Consumption

The calibrated simulation of step 2 was executed using the measured dry-bulb and wet-bulb temperature data. The calculated MBE values of Step 3 were used to obtain the “corrected” simulation values. The corrected simulation outputs were then compared with the measured CHW and HW consumption data.

#### Step 6: Fault Detection

Any differences between the corrected simulation values and the measured values were evaluated visually to determine whether they represent true fault status or whether the differences in consumption equate to normal fluctuations in measured consumption.

### RESULTS OF FAULT DETECTION PROCEDURE

Three of the approaches used to compare the “corrected” data from the simulation with the measured energy consumption data are presented, which are monthly comparisons, daily comparisons, and cumulative difference comparison.

#### Monthly Energy Consumption Differences

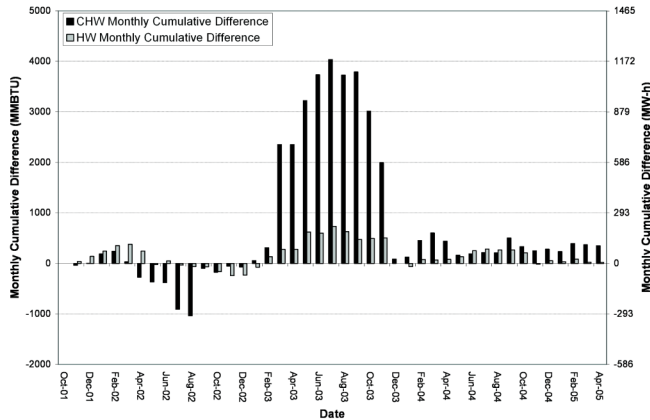
The monthly energy consumption difference is defined as

$$\Delta E_{month\_k} = \sum_j (E_{meas,j,k} - E_{corr,j,k}), \quad (1)$$

where  $\Delta E_{month\_k}$  is the cumulative difference between the measured consumption for a month and the “corrected” consumption simulated for the same month. The values  $E_{j,k}$  are the daily measured and “corrected” simulated totals of CHW or HW consumption for each day of the month. This comparison is presented in Figure 2, where each positive gray bar represents the amount by which measured HW consumption for a month exceeds the expected or simulated consumption, while each negative gray bar represents the amount by which HW consumption is lower than expected. The black bars have the same meanings for CHW consumption.

For October 2001, the difference between measured and simulated energy consumption is zero following the “corrected” calibration process, with total measured consumptions for the month of 1140 MMBtu and 431 MMBtu for CHW and HW respectively.

In November 2001 there were small differences between measured and simulated CHW and HW consumption. From December 2001 through April 2002, there was a dramatic increase in the consumption of HW. CHW consumption was somewhat higher than expected during this period, but the differences were much smaller than for HW consumption.



**Figure 2** Monthly cumulative CHW and HW difference between October 2001 and April 2005.

During May 2002, these trends flipped. CHW use was much lower than expected throughout the summer, and heating was slightly lower than expected during July and August. From September through December, consumption of both HW and CHW was generally a bit lower than expected. During February 2003 through December 2003, another flip occurred, with both CHW and HW consumption again becoming substantially larger than expected, with the excess CHW consumption much larger than the excess HW consumption. During January 2004 the CHW use dropped considerably to a more reasonable number but was still larger than expected. From February 2004 through December 2004, the CHW and HW consumption slowly increased, with spikes in CHW consumption from February through May 2004. From December 2004 through April 2005, the CHW consumption was consistently slightly over the predicted consumption, with the HW consumption accurately predicted.

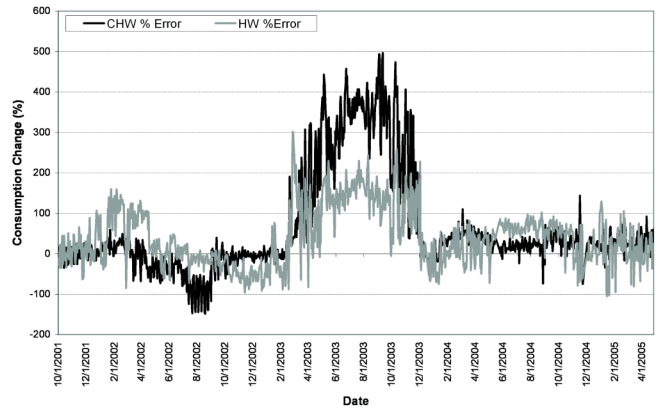
Looking at only this sequence of data might suggest that the simulation is not capable of accurately predicting the consumption of the building. An alternative explanation would be the occurrence of several changes in building operation during the period.

### Daily Energy Consumption Differences

The second visual interpretation of the fault detection data is in the form of a percent change plot. This percent change was calculated for daily consumption differences and was normalized with the respective average daily consumption for the baseline period. This plot is shown as a percent change plot to give a normalized indication of the size of changes observed.

Figure 3 presents the daily energy consumption percent difference as

$$\Delta E_{day} = 100 \cdot \left( \frac{E_{meas} - E_{sim}}{\bar{E}_{meas, cal}} \right), \quad (2)$$



**Figure 3** Daily percent change for CHW and HW consumption between October 2001 and April 2005.

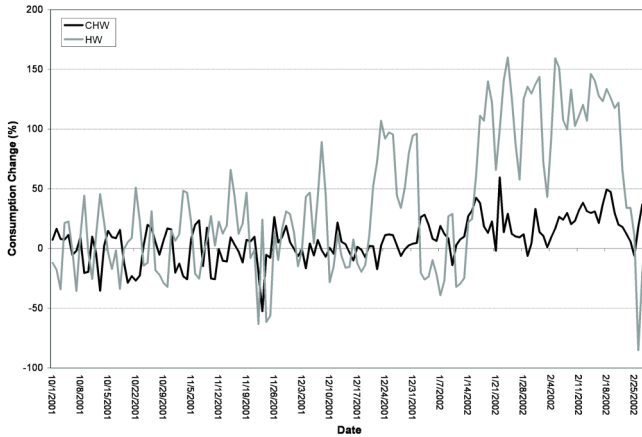
where  $\Delta E_{day}$  is the percent by which measured consumption for a particular day exceeds the “corrected” consumption for that day, as a percent of the average daily measured CHW or HW consumption,  $\bar{E}_{meas, cal}$ , during the baseline calibration period.  $E_{meas}$  is the daily average measured heating or cooling consumption, and  $E_{sim}$  is the “corrected” daily average simulated value of CHW or HW consumption.

The daily percent change plot of Figure 3 shows a more detailed representation of the deviations from expected energy consumption than the monthly totals of Figure 2. When the daily CHW and HW percent change data are examined, the same basic energy consumption deviations are observed as with the monthly cumulative values in Figure 2. The advantage of the percent change method is that the additional detail can more closely identify time of occurrence of changes than can be observed using the monthly difference plot. Figures 4, 5, and 6 show “zoomed-in” areas of Figure 3 for a clearer view of the consumption deviation data. For example, Figure 4 shows that the December 2001 increase in HW consumption occurred entirely during the period right around Christmas when all university offices and buildings were closed. Heat gains from occupants and lighting are lower then and probably account for the increased HW consumption observed.

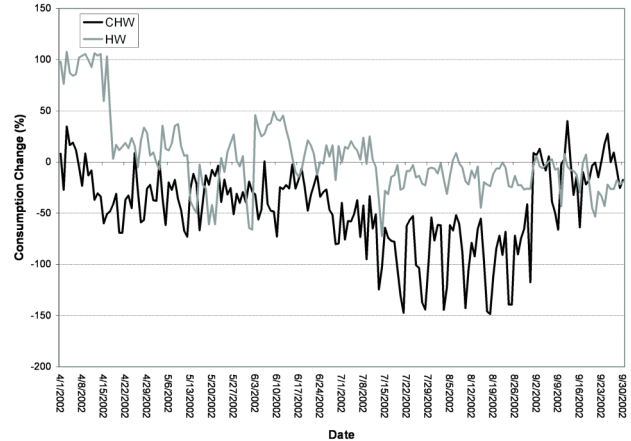
The daily data show that CHW consumption during summer 2002 (Figure 5) was systematically lower, beginning on May 6 or 7, while the HW consumption did not drop until the CHW consumption dropped further in early July. During fall 2002, simulated HW consumption remained slightly lower than predicted, while cooling went back to “normal” in early September. It is further evident that the major increases in HW and CHW consumption evident for March 2003 in the monthly plot of Figure 2 actually started in the second half of February (Figure 6).

### Cumulative Energy Consumption Differences

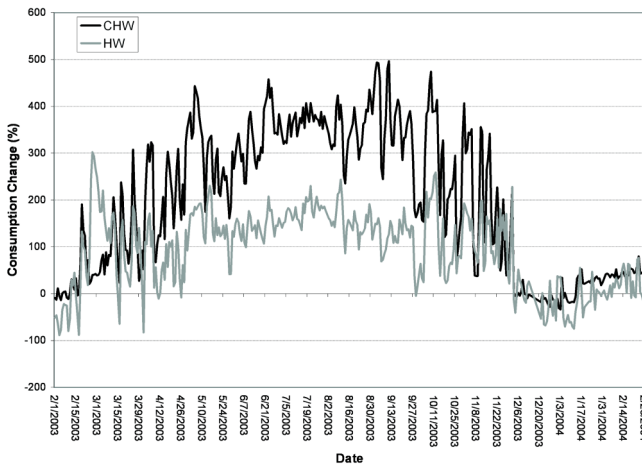
The third visual presentation of the differences between the measured CHW and HW consumption and the “corrected”



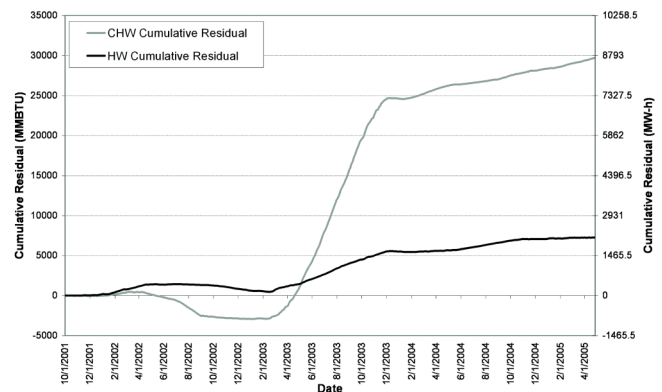
**Figure 4** Daily percent change for CHW and HW consumption between October 2001 and February 25, 2002.



**Figure 5** Daily percent change for CHW and HW consumption between April 1 and September 30, 2002.



**Figure 6** Daily percent change for CHW and HW consumption between February 1, 2003, and February 28, 2004.



**Figure 7** Cumulative CHW and HW consumption differences between October 2001 and April 2005.

simulated consumption values is the cumulative difference plot. These differences are defined as

$$\Delta E_{cum} = \sum_i (E_{meas,i} - E_{sim,i}), \quad (3)$$

where  $\Delta E_{cum}$  is the cumulative difference for the period of the summation and  $E_{meas,i} - E_{sim,i}$  is the daily energy consumption residual.

The cumulative CHW and HW energy consumption differences for the dining hall are shown in Figure 7. The positive values of cumulative difference on the plot indicate that measured consumption exceeds the expected consumption and vice versa. The slope of the curves also has meaning. A positive slope indicates that measured consumption is higher than expected during the time of positive slope and vice versa. The steeper the positive slope, the higher the rate at which

consumption exceeds expected consumption, and vice versa. For example, during summer vacation 2002, CHW consumption was less than predicted by the baseline, and the consumption was even lower during the second half of the summer. Hence, there is a negative slope all summer, but the slope is steeper during the second half of the summer.

All of the differences visible on the other presentations are again readily identifiable on the cumulative difference plots shown in Figure 7. This plot combine some of the features of the monthly plots and the daily plots since they show the amount by which consumption differs from expected consumption during any period and also have enough detail to permit relatively precise identification of the time that a particular period of difference starts or ends. One advantage is that this method produces a much cleaner representation of the data. For example, the CHW consumption decrease during

summer 2002 begins and ends very close to the beginning and end of summer vacation, and the total CHW consumption is about 2300 MMBtu (674 MW-h) less than predicted for this period by the “corrected” simulation.

## REASONS FOR THE DIFFERENCES OBSERVED

### December 2001

Discussions with the personnel responsible for operating and commissioning this building revealed that the control settings were changed while the university was closed during Christmas vacation 2001. Used with the monthly plot (Figure 2), this information would seem to account for the December 2001 differences. On the daily plots (Figures 3, 4), it seems even more apparent that it was due to control changes during Christmas vacation since heating consumption appears to increase sharply just during the period of university closure. A short-term examination of a cumulative difference plot (not shown) reveals the increased HW consumption during the period of closure but also shows that comparable cumulative differences began earlier in the month.

### Spring 2002

The consumption differences during January–April 2002 are attributed to a HW valve problem that was discovered and repaired in April 2002. From the daily plots, the HW valve problem appears to have started a day or so after classes started in mid-January 2002. It appears that the problem was diagnosed and fixed around April 15. This is consistent with information received from the commissioning engineer who was familiar with the operation of the building.

The peak increase in HW energy use during spring semester 2002 is approximately 150% on the daily plot. The cumulative change plots show that the cumulative increase in hot water use for this period was about 1200 MMBtu (352 MW-h), or about \$12,000 at \$10/MMBtu. The increase in CHW consumption was considerably smaller during this period.

This pattern of increased daily HW consumption is relatively constant during a period when outside temperature varies greatly. This implies that the HW waste is occurring at a point independent of outside conditions, such as at the reheat coil or some other place beyond the cooling coil. If this diagnosis is accurate, there should have been a comfort problem since there was not as much CHW waste as HW waste. Review of the call log showed that there was a concentration of hot calls during spring 2002.

### Summer 2002

The lower than expected consumption evident in the monthly plots during the summer of 2002 may be attributed to the closure of the cafeteria from May 15 through August. A weekend HVAC shutdown was also implemented during the latter part of this period. During this time, some HVAC equipment was shut down over the weekend to reduce energy consumption during unoccupied periods.

The daily CHW percent difference plot shows small savings when the cafeteria closed in May with substantially larger savings during July; however, the savings actually start in mid-April. There is evidence of the weekend shutdown in the CHW plot of Figure 5, but this is much smaller than an additional factor that produced savings throughout the week. This factor has not been identified. The peak HW savings were about 75% of average baseline consumption and peak CHW savings were 150% of average baseline consumption on the daily plots.

The cumulative difference plots show the same factors, but the weekend differences are impossible to see here. They do show cumulative CHW savings of about 1800 MMBtu (528 MW-h) during the summer and much smaller HW savings of about 200 MMBtu (59 MW-h).

### Fall 2002

Consumption returned to near expected values in the monthly plots when the cafeteria opened in September, but HW and CHW consumption were both slightly lower than expected through December 2002. This behavior is consistent with a scheduling change that increased the nighttime HVAC shutdown schedule from 4 hours to 6½ hours.

The daily and cumulative difference plots are all consistent with this schedule change. There was a sharp increase in CHW consumption when the fall semester started but very little increase in HW consumption. The change in HW consumption was not visible on the cumulative difference plot. The latter part of the winter vacation in 2003 shows a temporary increase in energy use above expected values.

### Spring 2003

During March 2003, both CHW and HW consumption increased dramatically in all plots, with CHW consumption approximately tripling expected values. Investigation showed the following:

- The CHW differential pressure setpoint was increased from 14 psig (96.5 kPa) to 25 psig (172 kPa) during March in response to hot calls in the leased area and measured supply temperatures of about 60°F (16°C) in this area. It was thought that more CHW pressure was needed to increase the cooling capacity of the cooling coil in AHU-7 that serves the area. There was some thought that a larger cooling coil needed to be installed. Field measurements showed that the existing coil had adequate capacity for the zone served and there was a flow blockage in the supply pipe serving AHU-7. Only 1 psig (6.9 kPa) of the 25 psig (172 kPa) pressure drop was occurring across the cooling coil of AHU-7.
- The AHUs were rescheduled on February 11, 2003, to come on at 4:00 a.m. rather than at 6:00 a.m. as previously.

A visual inspection of Figures 3 and 6 shows a maximum CHW consumption change of approximately 500% and a

maximum HW consumption change of 300%. The problem seems to be dependent on outside air temperature since the excess CHW use increases and excess HW use decreases near the end of the semester. After further investigation into the unusual behavior of the building, it was discovered that an incorrect proportionality coefficient was input into the metering software for this time period. This was a major cause for the extremely high CHW and HW consumption recorded.

### Spring 2004–Spring 2005

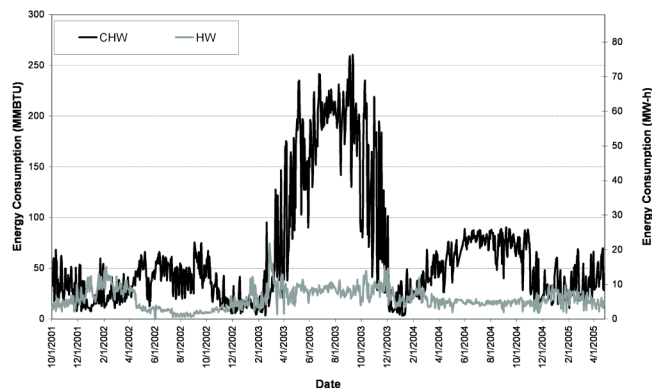
From spring 2004 through spring 2005, the CHW use was slightly above normal, consistently increasing, with the exception of spikes in February through May 2004. The HW monthly residuals increased steadily until December 2004. At this point the HW consumption residuals decrease to almost zero. The causes for these consumption changes remain unknown.

### VISUAL INSPECTION VERSUS TESTED FAULT DETECTION PROCEDURE

Visual inspection of measured data has been used for some time to detect building operational problems (Claridge et al. 1992, 1999). One of the most commonly used presentations of the data has been time series plots of heating and cooling consumption as shown in Figure 8. The other has been plots of HW and CHW consumption data plotted as functions of ambient temperature, shown in Figures 9 and 10.

### Visual Interpretation of Measured Time Series Energy Consumption

The CHW consumption shown in Figure 8 shows evidence to an experienced eye of most of the consumption changes observed and discussed using the plots of Figures 2–7. For the HW consumption, the highest consumption during the winter of 2001–2002 appears in February; however, it remains high throughout March and April, which would be unusual. There is a very abrupt drop in mid-April, but this occurs during a time when you would expect consumption to drop due to rising ambient temperatures, especially when consumption has been



**Figure 8** Time series plot of measured CHW and HW consumption from October 2001 to April 2005.

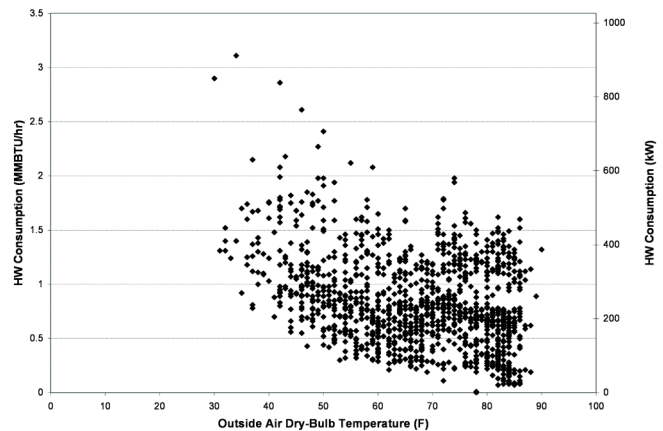
high. The weekend shutdowns during the last half of summer 2002 are visible, as is the sharp increase in consumption during February 2003. The CHW consumption shows the summer 2002 shutdown of the cafeteria and also shows the late summer weekend shutdown of HVAC. There is a sharp drop in CHW consumption in early May, but this would not seem surprising for a campus facility that has the major part of its operation closed down during the summer. The February 2003 increase in CHW use is evident and exceeds the peak consumption of the previous summer.

The problem with this kind of representation of building performance is that there is no aid to help the user know what level of consumption is normal and what is abnormal. This gap in identifying a faulty building leads to higher degrees of error. If an operator or building manager does not or cannot determine if the building is operating normally, than how can abnormal operation be determined? By establishing a gauge to determine normal energy consumption, abnormal energy consumption can more readily be identified. This is the real advantage of utilizing the calibrated simulation approach for fault detection.

### Visual Interpretation of Measured Energy Consumption as a Function of Outdoor Air Dry-Bulb Temperature

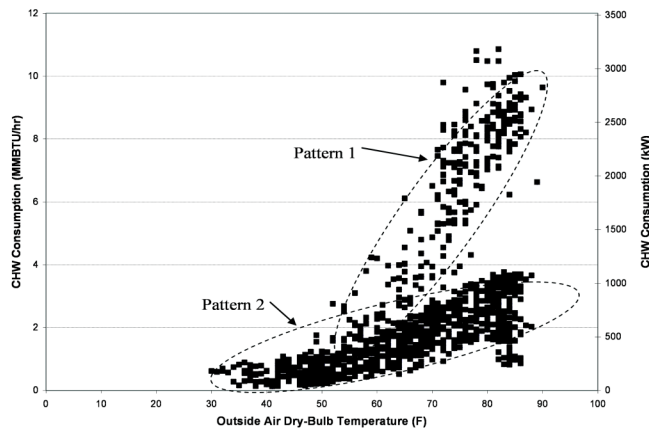
The CHW and HW consumption data are plotted as a function of outdoor temperature as shown in Figures 9 and 10.

The HW consumption shown in Figure 9 does not yield any obvious abnormalities. It is possible to find evidence of the abnormal heating consumption discussed earlier if multiple plots are provided for appropriately chosen time periods, but this plot alone is not very helpful in originally identifying the occurrence of problems that occurred during this period. This can be attributed to the nature of the systems being used in the case study building. Single-duct constant-volume systems using reheat will use HW more frequently and not necessarily



**Figure 9** Measured daily average HW consumption versus mean daily outside air dry-bulb temperature.





**Figure 10** Measured daily average CHW consumption versus mean daily outside air dry-bulb temperature.

as a direct function of outside air temperature. This is why using outside air dry-bulb temperature as the abscissa is not a very effective representation to aid in fault detection for HW consumption.

When the CHW consumption data are plotted versus ambient outdoor air temperature for October 2001 to April 2005, two distinct consumption patterns reveal themselves, as shown in Figure 10. This plot alone does not yield any indication of what is occurring to cause such wide variations in CHW consumption for the same outside air dry-bulb temperature. Since CHW consumption is not solely related to the outside air dry-bulb temperature, one would not want to gauge the performance of their building using this plot.

These traditional techniques can be used to uncover most of the abnormal consumption when used together; however, it requires a much higher level of experience and skill, as well as considerably more time and effort, than is the case using the calibrated simulation approach.

## CONCLUSIONS

A calibrated version of the ASHRAE simplified energy analysis procedure (SEAP) has been tested for use in identifying significant deviations from expected building energy consumption and fault detection at the whole-building level. Retrospective application of the calibrated simulation to three years of measured consumption data showed that the simulation closely tracked normal operation and clearly identified three significant operational changes that occurred during the test period. Three different presentation formats are tested for fault identification: monthly deviations, daily percent deviations, and cumulative deviation plots. All have value and it is ultimately a user preference as to which is the most informative.

An on-line version of this fault detection technique is being developed and implemented to test the technique in real time. The SEAP is an incomplete representation of any building, so it is important that a methodology be developed that can

clearly and accurately define an error threshold to differentiate a true system fault from normal deviations between simulated and measured consumption caused by the imperfect simulation model. This problem will be addressed in a future paper. However, the off-line test reported here shows the methodology capable of clearly detecting faults and shows promise for future on-line implementation.

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## DISCUSSION

**T. Agami Reddy, Professor, Drexel University, Philadelphia, PA:** (1) How confident are you of the accuracy of your calibrated simulation program, since you used only one month of data (October) to calibrate the model?

(2) What are your thoughts about how a simple (and faster-to-develop) baseline regression model would compare in terms of fault-detection accuracy to a calibrated simulation model?

**Frank L. Painter:** (1) When we compared the uncorrected calibrated simulation cumulative residuals during the calibration period, we achieved a somewhat linear profile. This would indicate to me that the error was not heavily a function of outdoor air conditions; therefore, the mean bias error correction factor was used. With this correction factor incorporated into the model, I am as confident as I can be in this simulation.

(2) I think that a baseline regression model would work fine as long as the correct inputs are used, such as outside air wet- and dry-bulb temperatures, as well as parameters such as solar gain.

**K. Subbarao, Texas A&M University, College Station, TX:** Would you get the best of both worlds by using longer-term data to calibrate a simulation rather than a regression model?

**Painter:** A regression model was not used. We did use the calibrated simulation approach; however, we used a short period of calibration data. Yes, a longer period of calibration data would enhance the accuracy of the model. The idea was to use a relatively short period of data, which might be more attainable than a long period of historical consumption data.

**Reinhard Seidl, Principal, Taylor Engineering, Alameda, CA:** Does the proposed method envision a bad calculation running in parallel with the building meter on a real-time basis to provide a calculated target for building energy use?

**Painter:** The method proposed is intended for future “real-time” FDD; however, the idea would be to run an energy consumption prediction model calibrated to “normal” consumption data and then compare the output of that model to the building consumption meter. This calibrated energy simulation is intended to provide the target to which you refer.

**Bill Mohs, Research and Development Engineer, Thermo King, Minneapolis, MN:** What model would be best to use as a prediction measure?

**Painter:** The model that was tested was based on ASHRAE’s simplified energy analysis procedure (SEAP). We did not test any other model types; however, there is extensive research regarding prediction models. Refer to “The Great Energy Predictor Shootout,” *ASHRAE Transactions*, Vol. 100, Part 2, for a great compilation of prediction models.

**Andreas Wagner, Professor, University of Karlsruhe, Karlsruhe, Germany:** Does the fluctuation of occupancy influence the method of calibration?

**Painter:** Not necessarily. The model utilizes daily average data, which I would expect to mask any normal occupancy fluctuations. Obviously, if there were some major occupancy fluctuations, it might be a parameter to adjust during the calibration process; however, I did not feel it was appropriate in our particular case.

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