REAL TIME MODEL-BASED ENERGY DIAGNOSTICS IN BUILDINGS

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ABSTRACT

Building energy systems often consume 20% more energy than is necessary due to system deviation from the design intent. Identifying the root causes of energy waste in buildings can be challenging largely because energy flows are generally invisible. To help address this challenge, we present a model-based, whole building energy diagnostics and performance monitoring system. The proposed system will continuously acquire performance measurements of HVAC, lighting and plug equipment usage and compare these measurements in real time to a reference EnergyPlus model that represents the design intent. A proof-of-concept case study will be discussed in this paper.

INTRODUCTION

The total energy consumption for US commercial buildings was 17.43 quads (2003 CBECS database), approximately 18% of the total U.S. energy consumption. The Department of Energy (DOE), the International Energy Agency (IEA), Intergovernmental Panel on Climate Change (IPCC) and other agencies have declared a need for commercial buildings to become 70-80% more energy efficient. Although energy-efficient building technologies are emerging, a key challenge is how to effectively maintain building energy performance over the evolving lifecycle of the building. It is well known that most buildings lose most of their desired and designed energy efficiency shortly after they are commissioned and recommissioned (Haves 1999, TIAX 2005). Achieving persistent low-energy performance is critical for realizing the energy, environmental, and economic goals expressed in the Energy Policy Act of 2005, Executive Order 13423, and the Energy Independence and Security Act of 2007. Field experience shows that energy savings of five to thirty percent are typically achievable simply by applying fault detection and diagnostics (FDD) in buildings (Liu et al., 2001, Katipamula and Brambley 2005a).

Generally, FDD methods fall into three categories (Katipamula and Brambley 2005b).

- Quantitative model-based methods that include: 1) physical first principles ('textbook') models (Li, 2004) and 2). polynomial curve fits of the components and equipment (e.g., fans, pumps, chillers) (Sreedharan and Haves 2001). Faults are detected as the difference between measurements and the model output. Significant differences indicate the presence of a fault somewhere in the part of the system treated by the model.
- Qualitative model-based methods include rule-based systems and qualitative physics (House et al., 2001).
- In contrast to the other groups, process history-based methods (data driven) assume no a priori knowledge of the process. Most time, these methods are suitable when significant amounts of data are available. The black box models using linear regression models are employed to perform automated fault detection in buildings (Jacob et al., 2010).

Currently, the key barriers/challenges that have prevented energy diagnostics from being pervasively applied are: 1) an integrated whole building energy FDD system does not exist. Major building subsystems are independently controlled with limited, add-on FDD capability. Both control and FDD do not adequately capture the functional and behavioural interactions between subsystems resulting in sub-optimal building energy performance and increased false alarm rates; 2) existing FDD methods are based on available data and simple, ad-hoc rules that do not adequately capture either the component or system functional and behavioural interactions. This limits the scalability and utility of FDD methods; 3) existing FDD methods, which are currently an "after thought" add-on to building control systems, require manual intervention and labor-intensive analysis. This limits the ability of FDD methods to provide real-time actionable recommendations for ensuring pervasive lower energy building performance; and 4) most of existing FDD systems to perform energy diagnostics are not scalable because they rely on manipulation of data by a limited number of experts which makes the scalability of the existing process to the entire industry infeasible.

Haves et al. 2001 explored the idea of model-based performance assessment at the whole building level and pointed out additional measurements are important to provide necessary input data. Lee et al. 2007 used a whole building simulation for energy

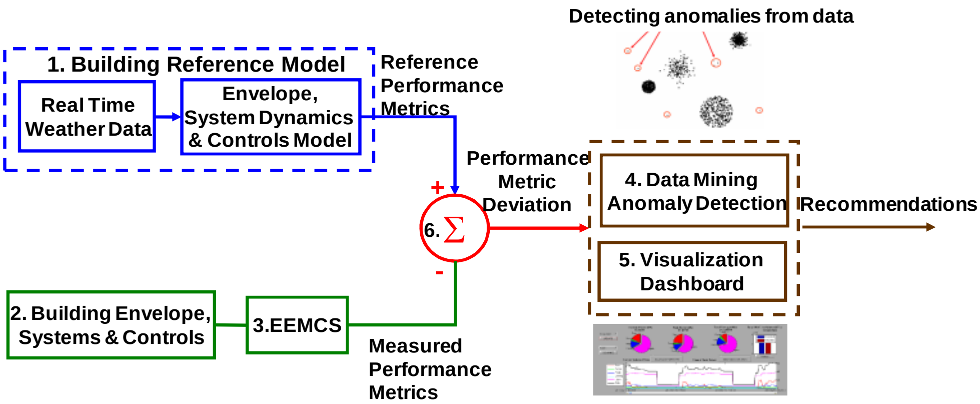

Figure 1 Diagram of real time energy diagnostics System.

consumption fault detection and concluded that it is important to have a methodology to define an error threshold to differentiate a true system fault from a false alarm caused by imperfect simulation. We propose an automated, model-based, whole building performance monitoring system. The proposed system will continuously acquire performance measurements of HVAC from the existing Energy Management and Control Systems (EMCS) augmented by additional sensors as required. The system will compare these measurements in real time to a reference simulation model that represents the design intent for the building. The proposed approach mainly aims at large problems, e.g., problems that typically lead to increase of 5% or more in energy use (Claridge et al., 1999).

TECHNOLOGY APPROACH

The proposed technology is a dynamic model-based, whole-building performance monitoring system that compares measured performance metrics to those generated by a physics-based reference model representing "design intent" or ideal performance. The system is depicted in Figure 1. The proposed system integrates and compares the output from a building simulation model to measurements to detect deviations from design intent model that represents the design intent for the building. The comparison will allow for identification and quantification of sub-optimal performance, identification of the conditions under which sub-optimal performance occurs, a means to compare alternative corrective actions using whole building metrics, and finally a means to validate improved performance once corrective actions have been taken.

The six key elements of the system are described as follows:

1. Building Reference Model

A whole-building EnergyPlus simulation model representing the desired performance of the envelope, HVAC, lighting, water, and control systems. EnergyPlus (EnergyPlus 2010) is a whole-building simulation program developed by the Department of Energy. It models heating, cooling, lighting, and ventilating processes in buildings and includes many simulation capabilities such as time steps of less than one hour, modular systems, multizone airflow, thermal comfort, and natural ventilation. The model can also represent "plug" loads including computers and calculates both the direct electrical energy consumption and also the effects of heat gains in the building. The model takes as input a description of the building (e.g., geometry, materials, roof type, window type, shading geometry, location, orientation etc.), its usage and internal heat loads, and the HVAC system description, and then computes the energy flows, zonal temperatures, airflows, and comfort levels on subhourly intervals for periods of days to years.

The design intent baseline model represents the design intent/desired performance of the building. The building descriptions are directly pulled from the design documentation and as-built drawings. In the case where some of the information is not available, an on-site investigation will be used to determine these parameters. The HVAC sequence of operation stands for the initial design intent or the desired performance that the facility management team is attempting to achieve based on the capability of existing equipments. The weather data is collected from the on site weather station if available. The lighting and plug load profile in the design intent baseline model will signify an "ideal" performance that has only minimum lighting and plug loads on during unoccupied hours and lighting and plug loads proportional to the occupancy profile during occupied hours. If the building usage is changed (e.g., conference room is changed to office room), then the internal load profiles will have to be updated with the new intent.

2. Building Envelope and Systems

This represents the physical building, the envelope, HVAC, and lighting systems – the physical plant.

3. Extended Energy Management and Control System (EEMCS)

The building management and control system, together with additional sensors, are used to measure key building performance metrics. Additional sensors will include electrical power submetering, fluid flow meters, and temperature sensors to determine thermal energy flow rates. Measurement of electrical input and thermal output, for example, enables the monitoring of chiller efficiency. Installation of permanent instrumentation connected to the existing EMCS ensures that the benefits of the additional performance monitoring capability are available over the long-term. The existing building EMCS is expanded to provide data acquisition for the additional sensors and to interface to a new personal PC where the proposed system will sit.

4. Data Mining and Anomaly Detection

The proposed algorithms, based on literature from Statistical Process Control, take measured and reference data as inputs and process the deviations of the measured data from model predictions to detect outliers or changes.

The application of statistical theory to monitor processes relies on the assumption that the characteristics of the data variations are relatively unchanged unless a fault occurs in the system. It implies that the properties of data variations, such as the mean and variance, are repeatable for the same operating conditions, although the actual values may not be very predictable. The repeatability of statistical properties allows thresholds for certain measures, effectively defining the out-of-control status, to be determined automatically. This is the essence of the underlying principle used in the FDD module.

The basic approach is to monitor a variable for out-of-control behaviour by obtaining upper and lower thresholds (either statistically or from domain-expertise) that define boundaries for in-control operation. A violation of these limits would indicate a fault. However, analyzing each variable this way when we have multivariate data will fail to capture correlations between variables. We use Principal Components Analysis (PCA) to account for such correlations. PCA is an optimal dimensionality reduction technique in terms of capturing the variance of data and is widely used in monitoring industrial systems. The lower dimensional representations of data produced by PCA are used to generate the Hotelling T^2 statistic and the Q-statistic (Chiang et al., 2000) which serve as "anomaly scores" – indicators of in-control and out-of-control behaviour.

The T^2 statistic is a scaled squared 2-norm of an observation vector from its mean. The scaling on the observation vector is in the direction of eigenvectors obtained by PCA. Given a level of significance, appropriate threshold values for the T^2 Statistic can be determined automatically (See Chiang et al., 2000 for details).

The Q-statistic is a similar measure and indicates the squared 2-norm of an observation vector from its mean in directions orthogonal to the eigenvectors retained from the PCA decomposition. In other words, it is a 2-norm of the residues. T^2 and Q statistics thus are complementary and together, give a good indication of the statistical process going out of the normal operating range.

The FDD module utilizes operational data from the BMS such as temperature, airflows and electricity consumption as well as output data from EnergyPlus simulations. T^2 and Q statistics are computed on the deviations of the measured data-points from model predictions for the purpose of fault detection and fault identification. PCA, which underlies T^2 and Q statistics, models the multivariate data as multivariate Gaussian distributions but this assumption may not be true in the cases of the measured data from BMS or data from EnergyPlus simulations. However, it is more reasonable to assume that the differences between measured points and corresponding predictions from EnergyPlus can be approximated as a multivariate Gaussian distribution. This is the motivation for computing the anomaly scores on the deviations rather than the measured data or model predictions directly.

5. Energy Performance Visualization Dashboard

The current state-of-the-art building management systems (BMS) provide facility managers with a rich set of building data. This building data includes system and equipment performance (temperature, pressure, energy consumption, etc.), controller status, and equipment fault status. However, the interconnected complexity and shear volume of this building data often make facility manager building operation decision-making difficult. Today, facility managers rely on their personal intuition and experience to perform building operation decision-making. We are developing an interactive, visual interface for facility managers to more effectively exploit available building data to improve building operation decision-making. The energy performance visualization dashboard aims to enable: 1) visualization of energy-related metrics at different building and HVAC systems levels; 2) comparisons between measured quantities and data derived from the integration of both data mining and physics-based modeling methods; 3) energy fault diagnostics and classification to aid in decision support targeting of root cause analysis; and 4) identifying persistent trends in energy usage.

6. Integrated Software Environment

Represented by the ∑ symbol in Figure 1, a software environment and supporting signal processing integrated with the EEMCS and Reference

EnergyPlus Model such that the Reference Model outputs can be automatically assimilated with and compared to measurements. This software system is built upon the Building Control Virtual Test Bed (BCVTB) (Wetter 2011) an open source software platform for integration of EEMCS data and a range of energy modeling software tools including EnergyPlus. The BCVTB makes use of Ptolemy II (Eker et al., 2003), an open source software environment for combining heterogeneous modeling and simulation tools. Figure 2 shows a screen shot of BCVTB.

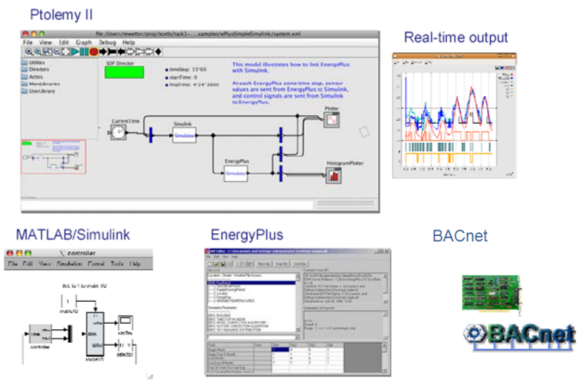

Figure 2 Diagram of the Building Control Virtual Test Bed.

The BCVTB enables the integration to the EEMCS and also scripting and signal processing within the Ptolemy II environment. The BACnet module in BCVTB allows the user to interface with any BACnet (A Data Communication Protocol for Building Automation and Control Networks) compatible building management system so as to collect the real time building operation data. To real time run EnergyPlus in BCVTB, the external interface objects are used to exchange data between EnergyPlus and BCVTB. Details about this implementation can be found from (Wetter 2011).

CASE STUDY

The implementation of the proposed system greatly depends on the existing building control system communication capability. It is desirable that the existing EMCS should support open communication protocols such as BACnet, LonWorks, or Modbus. The building used in this case study is the Atlantic Fleet Drill Hall, at Naval Station Great Lakes, Great Lakes, IL.

Building Facts

Drill Hall is a two-story facility with a gymnasium-like drill deck, office, classroom, and administrative rooms. The gross area of this building is 69,218 ft2 (6,431 m2). The construction was finished in October 2007. This building is LEED® Gold certificated. Figure 3 shows the exterior and drill deck interior views for this building.

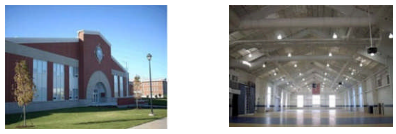

Figure 3 Drill Hall building at Great Lakes Naval Station

The Drill Hall HVAC system consists of four airside subsystems and two separate waterside subsystems. The drill deck is served by two variable-air volume (VAV) air handling units (AHU) with heating and cooling capability. A classroom on the second floor is served by one VAV air handling unit. Unit operation depends on the occupancy of the drill deck space. Double-walled sheet metal ductwork with a perforated liner and drum louvers distribute the air throughout the space. The office and administrative area is served by one VAV air handling unit with VAV terminal units (with hot water reheat). The chilled water system consists of two 110-ton (386.85 kW) air-cooled rotary-screw type chillers with fixed-speed primary pumping and variable-speed secondary pumping. Heating is supplied from the existing campus-wide steam system through a steam-to-water heat exchanger. The hot water serves unit heaters, VAV box reheating coils, and air handling unit heating coils. There is an instantaneous steam-to-domestic hot water generator for domestic hot water service. The server room and communication service room are served by dedicated duct free split systems. A distributed Direct Digital Control (DDC) control system is installed in this building to monitor all major environmental systems. Building electric and water meters are also read by the DDC system. Operator workstations provide graphics with real-time status for all DDC input and output connections.

Additional meters and sensors are required to calibrate models and accurately measure energy consumption to validate results. An on-site weather station, including a pyranometer, aspirated wet and dry bulb temperature sensors, and wind speed and direction sensors, is installed on the roof. BTU meters (a matched pair of supply and return water temperature sensors, water flow meters) are installed for the chillers, secondary chilled water loop, and hot water loop. Lighting load power, plug load power and individual chiller power are also monitored through sub meters. These sensors and meters are integrated into the existing building Energy Management and Control System (EMCS).

EnergyPlus Reference Model

The EnergyPlus model used in this study is version 5.0 (build 5.0.0.035.). The structure of the HVAC system in the EnergyPlus model is a series of modules connected by air and water fluid loops that are divided into a supply and a demand side. In order to keep the size of the model and computation time manageable, zoning simplifications were made when entering the building geometry. All the rooms serving by the same VAV box were integrated into one thermal zone. The building model consists of 30 conditioned zones (12, 12, and 6 zones for the drill deck, first, and second floors respectively). Some zones represent a physical room in the building while other zones represent adjacent multiple rooms operating under similar energy usage/requirements. Each zone includes an "internal mass" that represents the thermal storage capacity of the room(s) (e.g., interior walls, furnishings, books, etc.).

Both an extensive sensitivity analysis and an uncertainty analysis were performed to understand the EnergyPlus model behaviours (Eisenhower et al., 2011). The top three input parameters, which influence the facility annual total electricity consumption most, are the AHUs (serving the drill deck) supply air temperature setpoint, chiller reference COP (Coefficient of Performance) and drill deck lighting schedule. The top three input parameters with significant impact on facility electricity peak demand are chiller optimum part load ratio, chiller reference COP and the AHUs supply air temperature setpoint.

Real Time Performance Monitoring and Energy Diagnostics System

The overall system schematic diagram is shown in Figure 4. The personal computer (PC) server running the proposed system is located in the same building location as the PC running the EMCS. The required building performance data is collected through the existing EMCS and then made accessible to the energy diagnostics system through a BACnet gateway.

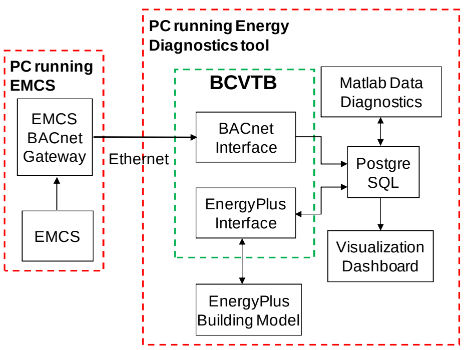

Figure 4 Energy diagnostics system schematic diagrams

Within the BCVTB, there are two modules necessary to achieve the proposed functional requirements. The BACnet module is used to acquire the relevant building performance data from the EMCS BACnet interface through an Ethernet connection. The sampling interval is 5 minutes. The data then is transferred to the PostgreSQL database. The EnergyPlus module establishes the communication between the BCVTB and an external pre-built EnergyPlus model that represents the design/optimal building performance. The EnergyPlus simulation timestep is 15 minutes. The EnergyPlus module receives the relevant real time data (e.g., weather data) and execute the external EnergyPlus reference model. The EnergyPlus output results then are passed back to the PostgreSQL database.

The Matlab Data Diagnostic tool applies data mining and anomaly detection methods to identify building faults using building measurements and building EnergyPlus reference model predictions data stored in the PostgreSQL database.

The Visualization dashboard is the user interface to demonstrate the results as well as to display the real-time building performance data. It should be noticed that the BCVTB, EnergyPlus building model, the Matlab Data Diagnostic and database software are all running in the background and not be visible to the user.

Energy Diagnostics Results

The proposed energy diagnostic tool was installed in the drill hall since April 2010. The facility was well maintained and so many things were done right from an energy perspective. However, the tool did indentify a series of improvements that include changes to lighting, controls and other further optimizations in the drill hall. Currently, anomaly scores and thresholds are computed by analyzing data form the previous 30 days. In other words, data used for analysis comes from a 30-day sliding window and thus the thresholds can vary with time.

Potential sensor bias

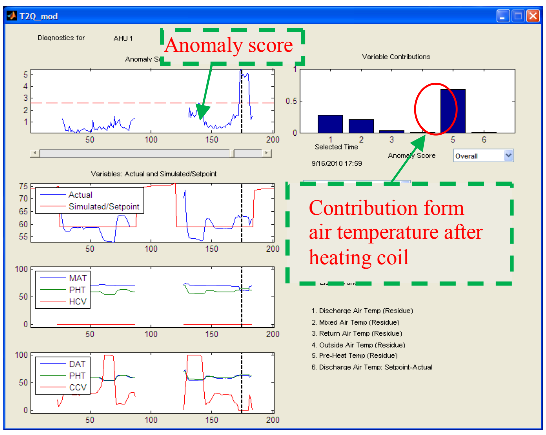

Figure 5 Potential sensor bias diagnostics

Figure 5 shows an anomaly in an AHU displayed in the visualization dashboard (discussed in the next section). The biggest contribution to this anomaly comes from a difference between the simulated and measured air temperature exiting the heating coil. The anomaly corresponds to potential sensor bias for the temperature sensor located right after heating coil. It was confirmed with other data analysis that this temperature sensor was drifting.

Economizer fault

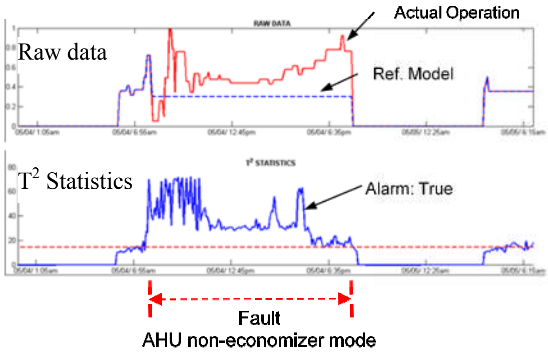

Figure 6 Economizer fault

The upper plot in Figure 6 compares the outside air fraction for an AHU on May 4th, 2010 in the actual operation with that calculated from the reference EnergyPlus model. The anomaly scores (blue line) based on T^2 statistics are plotted in the lower part. Whenever the anomaly score is above the threshold (red dash line), a potential fault is indicated. Since only one variable (outside air fraction) was used to compute anomaly score, there is no contribution weights plot. In non-economizer mode, the outside air intake is up to around 50% of total supply airflow, which is around 8,000 CFM (3.775 m^3/s). According to the design intent, the building needs about 6,000 CFM (2.831 m^3/s). to make up the exhaust and ensure a slightly positive building pressure. Therefore, there is a potential to further reduce the outside air intake under non-economizer mode, which will save both cooling and heating energy. The annual steam consumption in heating season will be reduced by about 30% based on reference EnergyPlus model prediction.

Lighting fault

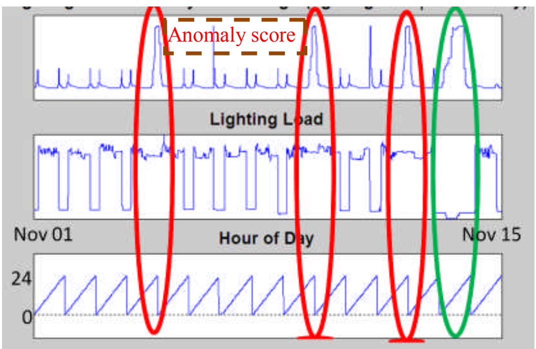

Figure 7 Lighting fault

Figure 7 shows the identified faults due to lights on during unoccupied hours from November 1st to November 15th, 2010. Lighting submetering data from June 2010 was used as training data. The top plot shows the anomaly score. The middle plot shows the actual lighting electricity consumption. The periods marked with red line correspond to the hour when lights on during unoccupied hours. While, the periods that lights were off when supposed to be on is marked with green line.

Visualization Dashboard

Figure 8 shows a snapshot of the interactive user-interface. The interface is divided in three panes – (a) loading data (shown in red box in figure below); (b) energy usage (shown in green box); and (c) system health – anomalies (shown in blue box).

The top part of the user interface is for visualizing energy usage data. There are five visualizations that display various aspects of how energy usage is distributed across different modalities (lights, plug loads, cooling, fans etc.) in the selected time period.

- The first pie-chart displays energy breakdown at any given time instant,
- The second pie-chart displays energy breakdown at the time-step corresponding to peak overall power consumption during the selected time period,
- The third pie-chart displays energy breakdown of the total energy usage over the selected time period,
- The line plot describes the power breakdown over the entire history of the selected time-period.
- The bar chart displays total energy consumed on the HVAC Hot Water side for the selected time period.

There are two kinds of data that can be explored: (a) real time data from BMS and (b) data from the EnergyPlus simulation model. There is a pull-down menu from which user can select either the BMS data or the model data to visualize. User also can select a modality (lights, plug loads, cooling, fans, total) and visualize comparison between the model data and measured data from BMS. Once the selection is made, a new plot opens up that displays the comparison for the selected attribute (shown in Figure 9).

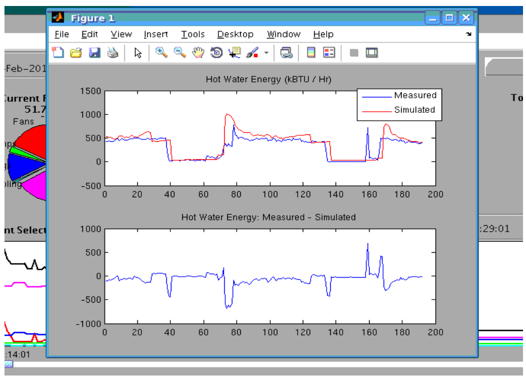

Figure 9 User interface showing hot water consumption comparisons between the model predictions and measurements (noon February 14, 2011 to noon February 16, 2011)

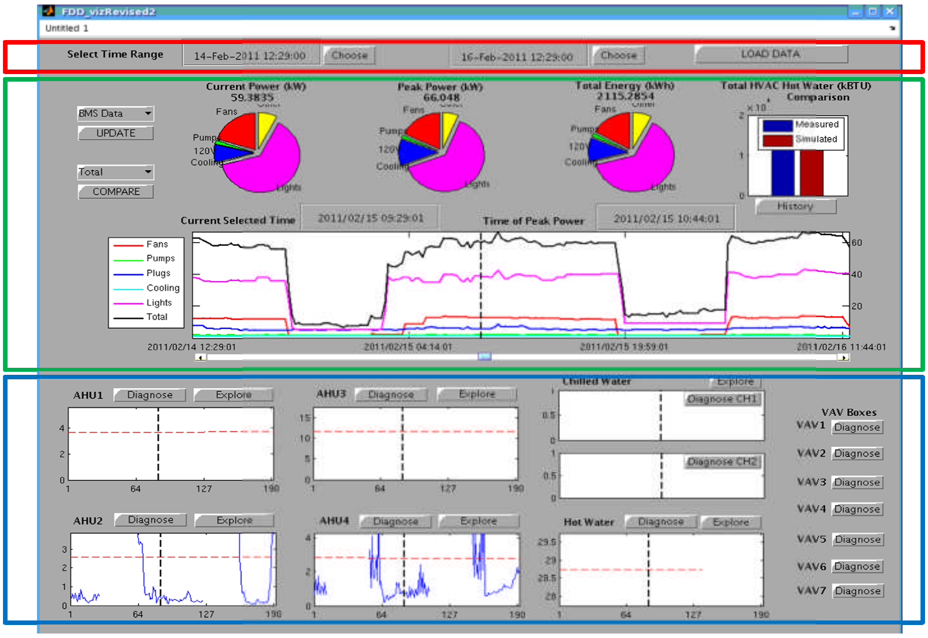

Figure 8 Visualization dashboard energy usage and performance monitoring

System Health–Anomaly Scores

The bottom part of the user interface (Figure 8) is dedicated to Anomaly Scores and monitoring the health of each subsystem (Chilled Water System, Hot Water System, Air Handling Units and Variable Air Volume Boxes). Each subsystem (AHU, Chillers, and the Hot Water System) has a graph associated with it indicating the anomaly score (in blue) corresponding to the system health. Also shown in red is a threshold calculated mathematically. If the anomaly score exceeds the threshold at any time instant, it indicates an anomalous event. The anomaly score is computed only when the system is in operation and no anomaly score is displayed when the system is not running.

Subsystem Drilldown – Diagnose

The user interface displays the anomaly score and the threshold. In addition, the display also plots the "contributions" of individual variables that were used in computing the anomaly score (see an example in Figure 6). This gives the user an idea of the significance of different variables in causing an anomaly. A slider functionality is provided where the user can explore a time-instant of his/her choice to understand the variable contributions. The user interface also allows the user to select any of the variables via a pull-down menu and view time-history of the BMS data corresponding to that sensor, data from the model and the difference between the raw data and model simulation.

CONCLUSIONS AND LESSONS LEARNED

A proof-of-concept real time whole building energy and diagnostics tool is developed and demonstrated in a real building. There are a few lessons and observations from the case study.

- A real-time whole building performance monitoring and energy diagnostics tool using EnergyPlus has been developed and demonstrated in proof-of-concept form. The EnergyPlus model is a dynamic representation of expected building performance, and it does not represent the real conditions in buildings. Real buildings often don't perform as expected by their designers due to 1) faulty construction, 2) malfunctioning equipment, 3) incorrectly configured control systems, and 4) inappropriate operating procedures, etc.
- A framework of whole building simulation-based FDD has been established. FDD algorithms based on statistical process control method such as T^2 and Q statistics have been tested.
  - The quality and availability for both nominal and faulty data are very important to establish ground truth to test and validate FDD algorithms.
  - Variable contributions to the anomaly scores provide a good insight into probable causes of a detected change and/or fault.
  - Transient periods including system start-up and shut-off need to be excluded to avoid some false alarms.
- A visualization dashboard for building performance energy monitoring and energy diagnostics has been developed and deployed in a real building. This dashboard provides an effective way for building facility manager to perform building performance decision-making.
- Real-time weather data are essential to real-time whole building performance monitoring and energy diagnostics.
- Electrical submeters and thermal energy meters (BTU meters) are important for FDD.

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