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Energy Technology Area

August, 2016

Published in the Proceedings of the 2016 ACEEE Summer Study on Energy Efficiency in Buildings, Pacific Grove, CA, August 2016.

Disclaimer

Acknowledgement

This work was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy, Building Technologies Office, of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231. Development of the PlantInsight tool was conducted under funding from the U.S. Department of Defense’s Environmental Security Technology Certification program, and with the generous participation of the operations staff at the US Naval Academy. The authors thank the following team members who contributed to this research over its duration – Sen Huang, Daniel McQuillen, Oren Schetrit, Michael Sohn, Michael Spears, Michael Wetter, and Wangda Zuo.

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ABSTRACT

Analytics software is increasingly used to improve and maintain operational efficiency in commercial buildings. Energy managers, owners, and operators are using a diversity of commercial offerings often referred to as Energy Information Systems, Fault Detection and Diagnostic (FDD) systems, or more broadly Energy Management and Information Systems, to cost-effectively enable savings on the order of ten to twenty percent. Most of these systems use data from meters and sensors, with rule-based and/or data-driven models to characterize system and building behavior. In contrast, physics-based modeling uses first-principles and engineering models (e.g., efficiency curves) to characterize system and building behavior. Historically, these physics-based approaches have been used in the design phase of the building life cycle or in retrofit analyses. Researchers have begun exploring the benefits of integrating physics-based models with operational data analytics tools, bridging the gap between design and operations. In this paper, we detail the development and operator use of a software tool that uses hybrid data-driven and physics-based approaches to cooling plant FDD and optimization. Specifically, we describe the system architecture, models, and FDD and optimization algorithms; advantages and disadvantages with respect to purely data-driven approaches; and practical implications for scaling and replicating these techniques. We conclude with an evaluation of the future potential for such tools and future research opportunities.

Introduction

This paper presents the development of a hybrid data-driven and physics model-based operational tool for energy efficiency in central cooling plants. The tool, PlantInsight, offers fault detection and diagnostics (FDD) functionality, setpoint optimization, and visualization of key performance parameters. Operational tools that combine analysis of historical data with a representation of the physics of the building and its systems may offer increased diagnostic power. Whereas empirical data-driven analytics permit assessment of operations based on *actual prior* system performance, physics-based approaches also enable assessment relative to *design intent*, and underlying physical principles. While the potential advantages of these hybrid tools are clear, it is less clear whether they can practically be developed and deployed for routine use in today's buildings. In this work, we detail the development of PlantInsight, including its architecture, model creation and calibration, and analysis algorithms. We describe development challenges that were encountered, as well as operator reception of the tool, and savings opportunities identified. Based on this experience we provide discussion of practical implications for scaling and replicating these techniques, and conclude with an evaluation of the future potential for such tools and future research opportunities.

Current State of the Art

Data-driven and rule-based analytics tools, as defined in Katipamula 2005, are increasingly used for operational efficiency in today's commercial buildings. Energy Management and Information Systems (EMIS) span a family of technologies and including energy information systems (EIS), building automation systems, fault detection and diagnostics, and monthly energy analysis tools. These tools have enabled whole-building energy savings of up to 10-20% with rapid paybacks, often under three years (Granderson 2011, 2016). Savings are achieved through multiple strategies such as identification of operational efficiency improvement opportunities, fault and energy anomaly detection, and inducement of behavioral change among occupants and operations personnel. The market for commercial analytics tools has expanded quickly over recent years, marking one of the largest market growth areas in commercial building technologies.

In contrast to data-driven approaches, physics-based modeling tools use first-principles and engineering models (e.g., efficiency curves) to characterize system and building behavior. Historically, these physics-based approaches have been used in the design phase of the building life cycle or in retrofit analyses; EnergyPlus, eQuest, Sefaira, and Integrated Environmental Solutions (IES) VE, are just a few tools that are founded on these physics-based methods. There are also instances of simulation models used for HVAC design, such as Trane Trace. In the commercial market, there are a modest yet growing number of tools that have begun to incorporate physics-based models into applications that target the identification of *operational* efficiency opportunities, such as simuwatt® Energy Auditor and Retroficiency Building Efficiency Intelligence. Those that do are often used to identify capital and operational measures, but are most commonly applied at single points in time for activities such as audits, commissioning, and portfolio opportunity assessment, as opposed to being integrated into continuous tools for operations staff. These examples notwithstanding, the use of hybrid data-driven and model-based approaches for operational tools that conduct continuous fault detection and energy use optimization is largely still the domain of exploratory research. For example, a previous attempt to use EnergyPlus physics-based models to identify whole-building level operational energy waste was proposed by (Pang 2012).

Overview of PlantInsight: A Physics-based Operational Analytics Tool

PlantInsight is a hybrid data-driven and physics model-based operational tool for energy efficiency in central cooling plants. It provides detection and diagnosis of three types of faults – fan cycling, chiller cycling, and poor chiller efficiency. It also provides analysis of optimal condenser water setpoint temperatures to minimize plant energy consumption. A calibrated Modelica model is used in the algorithms to identify poor chiller efficiency, and optimal condenser water temperature, while the cycling faults are identified using purely data-driven models. In addition, the tool offers visualization for operators to track key parameters such as cooling plant load and chilled water loop temperature. Through provision of these features, PlantInsight targets ten percent plant energy savings, given engaged users who use the tool daily, and are able to take action on the tool's outputs.

Development Methodology

The development of the PlantInsight tool comprised four primary elements: model construction and calibration, creation of FDD and optimization algorithms, architecture definition, and operator feedback. These elements are detailed in the following subsections.

Model Construction and Calibration

The Modelica models that simulate the operation of the central cooling plant were developed using a diversity of information from the cooling plant design specifications, nameplate data, drawings, and trend-log data. Beginning with the design drawings, the plant configuration, components, and equipment were replicated in model form. The Modelica Buildings Library (Wetter 2014) was used to build a representation of a specific central cooling system a large university campus. In this case, the system included 2 interconnected chilled water plants. The first plant contains one 2500-ton York MaxE™ YD Centrifugal Liquid Chiller and two 1250-ton York MaxE™ YK Centrifugal Liquid Chillers, with four cooling towers and five primary pumps. The second plant contains three 2500-ton York MaxE™ YD Centrifugal Liquid Chillers (with space available for an additional 2500 ton chiller), three cooling towers, and four pumps. Typical off-peak operations use the first plant exclusively, while peak summer operations use the second plant either exclusively, or in combination with the first. Once the plant design was represented, manufacturer data including nameplate values, chiller loading curves, and pump curves, were used to quantify key equipment and component-level characteristics. Finally, the specific control sequences that are in use at the plant were embedded into the model. In-person site visits were necessary to compile all of the information needed for model creation, since not all information was readily accessible in digital form.

Once constructed, the models were calibrated to the measured historic data from the cooling plant. The first step in calibration was to filter the historic data to that representing steady state plant operation. From the steady state data, we ensured as large as possible a range in the variation of each variable, for maximum coverage of operational conditions. Next, the GenOpt (Wetter 2001) optimization engine was used to search the (un-calibrated) model parameters to minimize the difference between the model outputs and the associated measured data. The variables involved in the calibration are listed in Table 1. Model parameters are values used in the model that are known a priori, and are specific to the equipment and plant design.

Table 1 Variables used in the model calibration

Plant Components	Model Outputs	Model Inputs	Model Parameters
Chiller model	Coefficient of Performance (COP)	Compressor status (on/off) Chilled water flow rate Condenser water flow rate Chilled water entering temperature Temperature of the condenser water entering the chiller	Coefficients of the chiller operation curve Nominal evaporator temperature Nominal condenser temperature
Cooling tower model	Condenser water leaving temperature Fan energy use	Fan speed ratio of each module Condenser water entering temperature Outside air dry bulb temperature Outside air relative humidity	Nominal approach temperature Nominal wet bulb temperature Coefficient of the fan operation curve

The 'goodness' of calibration for the chiller models was determined based on coefficient of performance (COP), and that of the tower models was based on the temperature of condenser water leaving the tower and fan power consumption. The objective functions are shown in the equations below. Calibration was deemed sufficient when more than 95% of the data points fell within a 10% error band.

$$J_{chiller} = \min\left(\int_{t_0}^{t_0+\Delta t}(COP_{mea}(t) - COP_{sim}(t))^2\right), for\ t \in [t_0, t_0 + \Delta t)$$

$$J_{cooling\ tower} = \min\left(\int_{t_0}^{t_0+\Delta t}(E\_fan_{mea}(t) - E\_fan_{sim}(t))^2 + (T\_lea_{mea}(t) - T\_lea_{sim}(t))^2\right), for\ t \in [t_0, t_0 + \Delta t)$$

In these equations, $COP_{mea}(t)$ and $COP_{sim}(t)$are the measured and simulated COP during the calibration period $[t_0, t_0 + \Delta t)$, $E\_fan_{mea}(t)$; $E\_fan_{sim}(t)$ are the measured and simulated cooling tower fan power consumption during $[t_0, t_0 + \Delta t)$; and $T\_lea_{mea}(t)$ and $T\_lea_{sim}(t)$ are the measured and simulated temperature of condenser water leaving the tower.

FDD and Optimization Algorithms

To-date PlantInsight addresses three faults. Poor chiller efficiency is determined by comparing the model-predicted versus the metered coefficient of performance. Described in detail in Bonvini 2014a, 2014b, and briefly summarized here, the FDD algorithm is based on an advanced Bayesian nonlinear state estimation technique called Unscented Kalman Filtering (Julier 1996) that quickly reconciles model predictions with measured data. A back smoothing method is added to reduce the likelihood of false positives from operational variability and data uncertainties. A clustering and decision tree analysis procedure was developed to group detected faults based on the similarity of conditions under which they occur; similar instances are grouped, and summarized in the tool interface to support root cause diagnostics by the operator. First, a k-means clustering algorithm divides the observed faults into distinct operational conditions under which the faults can be characterized. Each k cluster corresponds to a diagnostic message for the operator (see Figure 4). Once the clusters are identified, a human readable diagnostic message must be assigned. A decision tree is used to determine the boundaries in the feature space that distinguish between regular and faulty data, and thus identify them. The variables used in the decision tree, i.e. the feature space, are condenser and evaporator water temperatures, cooling load, electric power, time of the day, outside air temperature and the condenser and evaporator mass flow rates. The results of the decision tree are then sorted in order of importance to find the set that best describes the majority of the faulty conditions. This algorithm will be evaluated in field testing to assess the effectiveness of the clustering and decision tree analysis, as well as the thresholds used in the probabilistic identification of faults.

Excessive chiller cycling and excessive cooling tower fan cycling are detected using data-driven algorithms that rely upon chiller motor current data and fan speed data. The data is collected every 5 minutes and interpolated to 10 seconds, using cubic interpolation (linear and quadratic interpolation created spurious high frequencies, and large oscillations respectively). Interpolation was needed to increase the number of data points in order to use Fourier transformation. The time series data is transformed into the frequency domain using a Fourier transform on a rolling two-hour window. The area under the amplitude versus frequency curve of the Fourier transform is calculated using trapezoid integration, for the area between a frequency of 4 cycles per hour to a frequency of 6 cycles per hour. Due to the data sampling frequency of every 5 minutes, the shortest cycling frequency (the Nyquist frequency) that can be detected is 6 cycles per hour. Higher frequency of data collection is desirable to avoid aliasing problems but was unfortunately not available. If the area under the curve is higher than a reference value, then an excessive cycling fault is identified.

The optimization algorithm determines the most effective condenser water temperature setpoint.The chillers' efficiency increases when the temperature of condenser water entering the chillers ($T_{cw,ent}$) decreases. On the other hand, reducing $T_{cw,ent}$ may increase the energy consumption of cooling towers. Therefore, there is an optimum condenser water temperature setpoint for cooling towers that the total energy consumption of the chillers and the cooling towers is minimized. To determine the optimal condenser water temperature setpoint, the component models of multiple chillers, cooling towers and pumps were packaged into a system model. The system model was run to predict the energy consumption under different condenser water set points. Optimization constraints, such as the desired cooling load, were also incorporated into the model. As with the calibration activity, GenOpt was used as the optimization engine. The optimization period can be set to any desired value, in the case of this work, ranging from one hour to one day. Specifically, the optimal condenser water set point is determined by solving the optimization problem defined in the equation below, and documented in Huang, 2014.

$$\min\left(E|_{t_0}^{t_0+\Delta t}\right) = \min\left(\int_{t_0}^{t_0+\Delta t} f\left(T_{cw,set}(t_0), \dot{Q}^P(t), T_{wb}^P(t), \vec{S}(t_0)\right)\right), \text{for } t \in [t_0, t_0+\Delta t)$$

$$\text{such that} \qquad T_{cw,set,L} \leq T_{cw,set}(t_0) \leq T_{cw,set,H},$$

In these equations, $E|_{t_0}^{t_0+\Delta t}$ is the total energy consumption of the chillers and cooling towers during the optimization period $[t_0, t_0+\Delta t)$, $T_{cw,set}$ is the condenser water set point, $\dot{Q}^P$ is the predicted cooling load, T_{wb}^P is the predicted wet bulb temperature from a weather forecast, $\vec{S}$ is the state vector of the system (e.g. equipment operating status, water temperature in chiller condenser and evaporator), and $T_{cw,set,L}$ and $T_{cw,set,H}$ are the low and high limits of the condenser water set point during $[t_0, t_0+\Delta t)$.

Architecture

The architecture of the PlantInsight Tool is shown in Figure 1 as a block diagram schematic. The green blocks indicate portions of the system that are located at the site, while the orange blocks represent remote components. Data from the meters and sensors at each cooling plant is transferred to the on-premise automation system (EMCS), which is accessed through an operator kiosk. Data from the site is pushed to a remote set of databases (Cassandra storing the long term persistent data and Redis for faster access to the most recent data as well as a cache for results) that are used to store data for access by the PlantInsight tool. The models, FDD and optimization algorithms, and code to generate output and represent findings to the user are hosted in a platform on the cloud. The user access to the tool through a browser-based Javascript graphical front-end application that interacts with the back-end via a REST API.

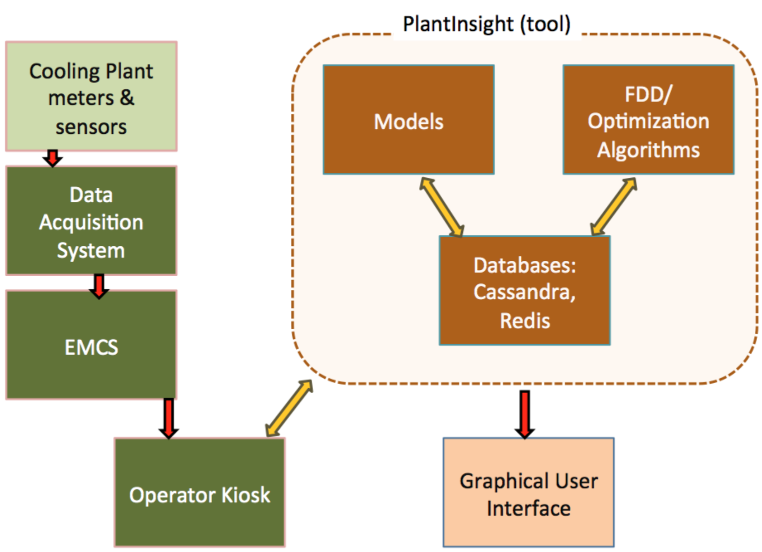

Figure 1. Architecture of the PlantInsight tool for hybrid model-based and data-driven central plant diagnostics and optimization

Operator Feedback and Tool Reception

To ensure that the tool would be of maximum utility to plant operators, design feedback was obtained iteratively, throughout development. The most important feedback that was (and is being) integrated into the tool design and functionality is summarized in the following:

- *Add key performance indicators*: Primary chilled water loop temperature, and weather forecast are critical parameters that are tracked by the operations staff. In addition, staff also requested that the tool-predicted plant load forecast be added to the interface. Since these variable are tracked on a continual basis under existing operations, it was important that they be included in the PlantInsight tool. If excluded the tool would be less likely to be integrated into daily management processes because it would lack the most valuable monitoring features are included in the current EMCS.
- *Convert energy units to dollars*: while campus energy managers regularly track kWh and Btus, tons and dollars resonate more strongly with plant operations staff. Therefore, the impact of faults and optimal setpoints are represented in terms of utility costs. Operators and energy management staff were interested in two cost scenarios – savings gained from changes that are implemented (to communicate the value of the team's contributions to others in the organization), and the cost of not addressing changes (to facilitate approval of remedial actions and associated expenditures).
- *Limit the frequency of optimization*: Although the tool was initially configured to generate optimal setpoints each hour, the operations staff were not comfortable implementing changes more than once a day. More frequent changes were deemed impractical, and risky. Over time, twice-daily changes may be integrated into operational routines to address overnight conditions.

Both the alpha and beta versions of the tool were well received by the plant operations staff. The site has plans to develop standard operating procedures to formalize action taking based on findings from use of the tool. This is an important aspect of maximizing value - if there is no process to authorize changes required to modify setpoints and to eliminate faults, energy saving benefits cannot be achieved.

Screen shots of the beta version of PlantInsight are provided in Figures 2-4. Figure 2 shows the landing page of the tool. Since the text size in the images is small the contents are described in detail in the following. The period of time for which data is shown, and faults are summarized is user-selected and shown in the upper right hand date summary. In the plot, the total load on both plants (tons) is overlaid with the load from each plant individually. Above the plot, the total cost of operations, total consumption, maximum load, and number of current faults are summarized in KPI tiles.

Figure 3 shows the condenser water temperature setpoint optimization features in the tool. In the upper plot, the total load on the plant (tons) is overlaid with the actual measured power, and that power that would be consumed under the model-determined optimal condenser water temperature setpoint. In the lower plot, the actual setpoint (degrees F) is plotted; as reflected in the horizontal trend, this is an annual constant under current operational strategies. The model-determined hourly optimal setpoint is also shown, along with the wet bulb temperature. The model-determined optimal generally follows the trend of the wet bulb temperature, suggesting that an automated solution could be implemented to remove the need for operators to manual adjust this control parameter.

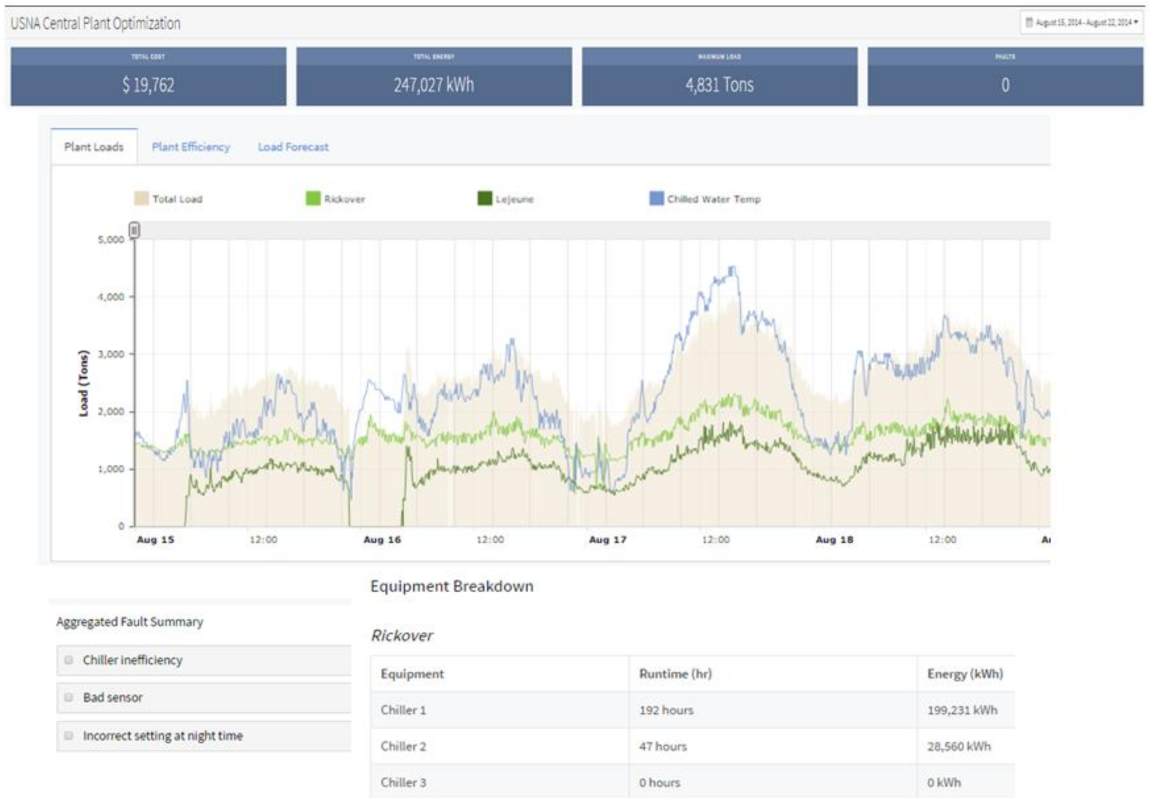

Figure 2. Screen shot of the landing page of the PlantInsight tool.

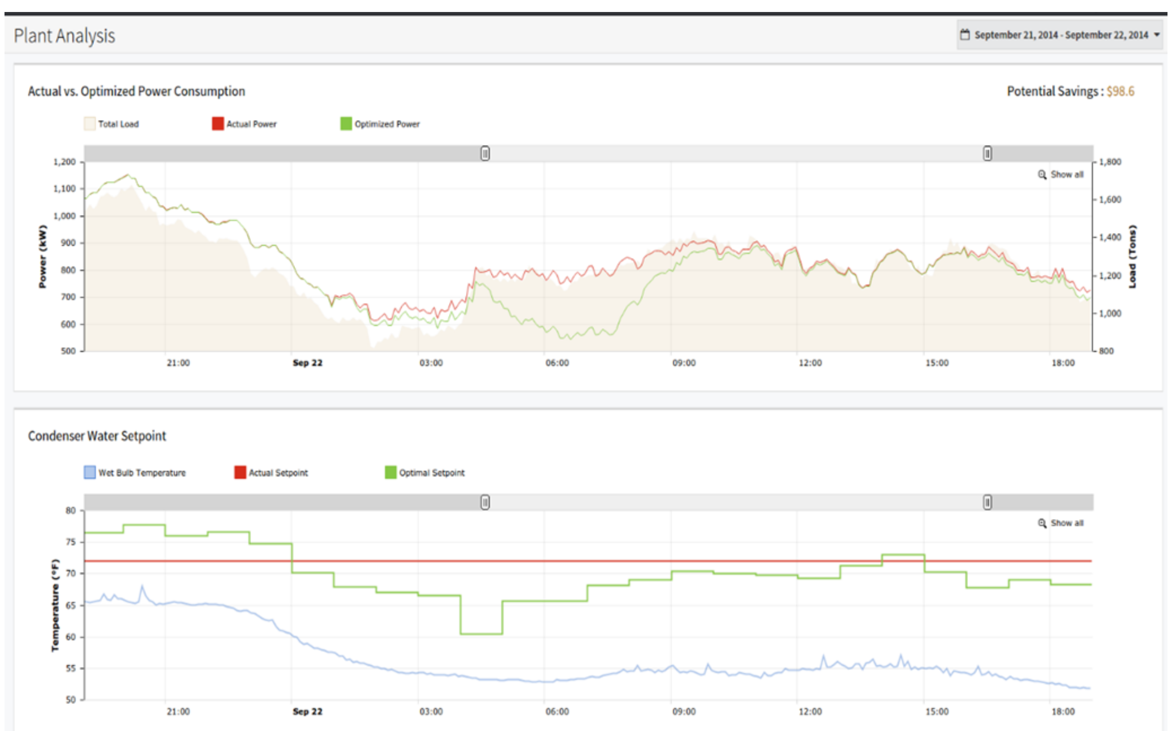

Figure 3. Screen shot of the condenser water temperature setpoint optimization features in the PlantInsight tool.

Figure 4 shows the fault detection and diagnostic features in the tool. In the upper plot, the chiller efficiency curve is plotted with kW/ton on the y-axis, and cooling tons on the x-axis. In the bottom plot, a time series of detected efficiency faults is provided. A time series of the measured coefficient of performance (COP) is overlaid with the model-predicted COP; when the two values diverge beyond a threshold size and probability, a fault is detected. Diagnostic fault aggregation to group faults instances based similarity of conditions is summarized in the lower right hand portion of the plot. Please refer to the section FDD and Optimization Algorithms for further description on how faults are detected and grouped for diagnosis.

Figure 4. Screen shot of the fault detection and diagnostic features in the PlantInsight tool.

Evaluation of Model-based Analytics Approach

To evaluate the research question of whether physics-based models can be practically brought into operational tools, we consider scalability, required expertise, and maintainability and contrast with approaches based purely on rule-based and data-driven techniques. Admittedly, these approaches are diverse and quite varied, as are physics-based models, and the use cases for which they may be deployed. Therefore, we present a general discussion, based on the current state of today's most readily available solutions. From the experiences and prior work that ground this discussion, we develop conclusions for future work.

Given the modeling tools available today, physics-based model construction is more labor intensive and less scalable than rule-based and data-driven models. While non physics-based approaches typically require tuning of key parameters, they are less likely to require customization or rebuilding for each new building or system encountered. Moreover, if components change, retrofits are made, or control sequences are modified, physical models may require modification. It is possible to leverage whole-building reference models that provide a more coarse representation of the building and its systems, however it is not clear that these offer sufficient resolution for reliable fault diagnostics and optimization. Depending on the specific modeling environment used, 'stock' components may be available from pre-existing libraries.

However the models must then be adapted for use with specific diagnostic algorithms. For example, in this work, the chiller model from the Modelica Buildings Library was adapted and modified for use in the state/parameter estimation phase of the fault detection algorithm.

Model calibration requires a significant degree of specialized expertise in building modeling, operations, and building science. In general however, it can largely be conducted with data that is commonly available from building control systems. As in the case of rule-based and data-driven models, the required data often needs to be cleansed to fill gaps and filter extreme or erroneous values. Cost effective integration of control system data into analytics tools remains one of the most significant challenges to advancing the state of today's technology, whether model-based or data-driven approaches are employed. In principle it is possible, but in practice the associated cost and complexity often outweigh the benefits of the advanced analytics that require the data integration. Once the data is obtained, care must be taken to ensure that the models are being calibrated in a physically meaningful way. Auto-calibration routines that codify some of the expertise that is needed for successful calibration are being developed by researchers, and are beginning to be offered to the industry (Sanyal 2014; Sun 2016). However, calibration approaches must be matched to the application. For example, calibration of a model used for a chiller fault detection as it operates through dynamic and steady state regimes may be quite different from that of a whole-building model that is used to determine faults in centralized HVAC systems. Finally, the questions of when to recalibrate and how to account for faults present in the calibration data are the subjects of ongoing research.

As described in the Introduction, in theory, model-based approaches offer the potential for enhanced diagnostic power. PlantInsight permits detection of periods of low chiller efficiency that may be difficult to detect purely with data-driven approaches that are limited only to historic data. In general however, more research is needed to validate whether model-based fault detection, in *practice*, is more or equally effective than data-driven techniques. Finally, one can consider the infrastructural aspects of practically delivering model-based approaches for use in continuous operational analytics. The infrastructural requirements for such systems do not present a practical challenge for scaled delivery. Cloud-based software services dominate today's solutions for operational analytics tools, precisely because of the cost-efficient, scalable, computational and hosting flexibility that they provide.

Conclusions, Future Work

This paper presented the development of a physical model-based FDD and optimization tool for a cooling plant. One conclusion on this work is that this approach is still cumbersome given all of the steps to build and calibrate the model for ongoing operational use. With further research to automatically calibrate and construct models, these types of tools could be made more ready for production use. These physics-based techniques remain a compelling direction for the continuous commissioning, optimization and FDD systems of the future. One major advantage of a physics based models over data-driven models is the ability to extend them for retrofit analysis as well as those that focus on operational efficiency analysis. One can drop in new chillers, towers, or pumps and use the model for further analysis beyond the realm of prior historic operations. In addition, how the system *should operate* can be compared to how it has operated in the past.

Scaled delivery of these approaches will require a change in industry capacity and expertise, as well as continued research and development to lower the bar of expertise that is required. Today's building energy analytics providers tend to have in-house data scientists, rather than the building scientists who are currently needed to work with these complex models. We also need to demonstrate the costs and benefits of these tools, and their advantages, to build market demand. Ideally, physics-based models will be used throughout the building life cycle – from design, to initial commissioning, to ongoing operations, valuation of proper maintenance, and retrofit exploration. Even if these approaches are costly and complex if used solely for identifying and diagnosing waste and efficiency opportunities, there is certainly a role for model-based approaches in *holistic* strategies for advanced, efficient building operation. The building energy analysis community is only beginning to have tools to deliver energy-aware transactive controls and dynamic, anytime optimization – capabilities that will surely be needed in the buildings and energy supply systems of the future.

Future research will explore auto-calibration techniques for diverse types and applications of system and whole-building-level physical models. Solutions to automate and simplify the creation of physics-based models based on existing specifications, drawings, and building information models (BIM) are also needed for practical scalability. If the BIM vision were successful, and coupled with information on sequences of operations, one could generate digital specifications in a format that was interoperable with energy analysis tools. The next stage for greater tool interoperability would be the capability to automatically import trend log data to a model calibration routine. The development of standard, open FDD algorithms could ensure that algorithms, models, and calibration routines can be seamlessly integrated. Finally, there is a need for auto-correction and auto-tuning of controls based on the outputs of FDD algorithms. Most of today's systems either optimize controls or perform FDD, but it is rare to close the loop by connecting the two. While not yet practical for deployment in today's buildings, these model-based systems are important for the eventual delivery of truly optimal building performance.

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