

A Comprehensive Energy Monitoring Environment for District Energy Grid Systems

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By conducting active meter monitoring and performance analysis for the buildings and the plants at the main campus of the Georgia Institute of Technology, it is possible for campus facilities managers to achieve significant efficiency improvements. A key challenge, however, is gathering and making sense of the large volumes of utilities data. In response, a comprehensive web-based building and plant energy-monitoring environment is presented that collects data from multiple energy grids. From the gathered data, particular attention is given to heating, cooling, and ventilation to assess building and ultimately campus energy performance through various analytics. First, techniques for data gathering, organization, and filtering are described, followed by several novel metrics and ways of visualizing them via a comparative method. Data filtering and classification strategies have also been implemented into a framework capable of evaluating a fleet of buildings with respect to a data-driven or model-driven baseline. The resulting monitoring system is shown to reduce the number of variables that campus managers of campus utilities and facilities need to track and make it more obvious where energy efficiency opportunities exist across a large fleet of buildings. Implications and future extensions of the monitoring platform are discussed.

I. Introduction

In 2014, the U.S. consumed 2,224 million tonnes of oil equivalent (TOE) in total, ranking second in energy consumption in the world.¹ Out of the total energy consumption, over 40% was consumed by residential and commercial buildings as end-use sector shares.² Operations of these buildings are often supported by multiple energy grid systems which account for electricity consumption, cooling, heating, and water consumption. Modern grid systems can be better managed with the advance of active monitoring of different forms of energy via computer databases, various types of sensors and meters, user interfaces, and the application of machine learning algorithms. Such examples can be found in large university campuses where there are a large number of buildings with different physical characteristics as well as campus energy plants. This obviously results in a large amount of various data, of which is challenging for campus facilities departments to maximize use while maintaining their campuses in safe and operating conditions.

Maintaining operating conditions, however, does not guarantee an efficient operation. It is not unusual that some buildings degrade and do not satisfy desired efficiency requirements. The degraded behavior of these buildings may go unnoticed because of several reasons. Causes of inefficiency may be difficult to discern during operation unless very carefully monitored. Generally, end users (building occupants) cannot detect anomalies as long as room conditions are within their comfort zone. Therefore, these anomalies are not reported to the operators. Furthermore, changes in the energy consumption profiles due to inefficiencies are easily confounded with effects of operating conditions such as occupants' schedules and changes in weather conditions.

Based upon these issues, there has arisen a strong need to establish a capability for integrated, campus-wide energy management that better accommodates the requirements addressed by associated stakeholders, i.e., minimizing energy consumption, simplifying management/maintenance procedures, etc. This paper addresses the development of a comprehensive web-based building energy-monitoring environment, the precursor to a more advanced district energy-

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efficient management system. The scope covers the buildings of the Georgia Institute of Technology in Atlanta, Georgia and its utilities data, collected from sensors and meters and stored in an internal database. A similar effort is undertaken for the two central chilled water plants on campus, as well as the distribution networks that deliver chilled water to the building loads. The following sections describe the gathering and preparation of data, the definition of metrics for comparative analysis, techniques for identifying and ranking energy efficiency opportunities through indicators of relative performance, and the implementation of data, metrics, and comparative techniques into an integrated software framework.

II. Data Acquisition and Processing

A. Data and Meta-data Structuring

In order to assess the performance of a building, the corresponding energy expenditure of the building must be independently measured. However, out of simplicity and budgetary concerns, a single line often supplies utilities to multiple buildings, and such a building cluster may use a common meter. On the other hand, a single building can have multiple sensors to manage building zones. Furthermore, in a grid of buildings, missing or erroneous readings from the sensors make analysis of building performance hard or even impossible. Hence, there is a need for a systematic, organized data/meta-data handling technique to store and track sensor identity associated with the corresponding building and/or buildings. A solution has been devised where information is stored as elements of two distinct matrices, one for sensor-related quantities and one for building quantities. Operations on these matrices allow single buildings as well as building clusters to be analyzed at the same time. Another advantage of the matrix approach is that if a metering change is made, it can easily be accounted by adjusting the matrix dimensions accordingly.

A sample electrical and chilled water grid is depicted in Figure 1, where the buildings B1 through B6 are served by two networks with different topologies. This is common in any district energy system where each utility has a different structure due to several reasons, including different installation times of infrastructure and the nature of the properties being measured. This problem should be addressed for expanding building clusters and account for meter failures. Quantities regarding a building's energy expenditure are measured using various kinds of sensors and meters. Generally, a building (B) has multiple meters that have their unique meter IDs (mID). In addition, a meter collects various quantities measured by sensors, such as flow rate or water temperature. Each of the measured quantities has a unique quantity ID (qID). Since the meters are installed by different contractors at different times over the years, tracking certain parameters can be quite challenging. Therefore, one must use the combination of $B \rightarrow mID \rightarrow qID$ to track a certain quantity of a certain building in a systematic fashion.

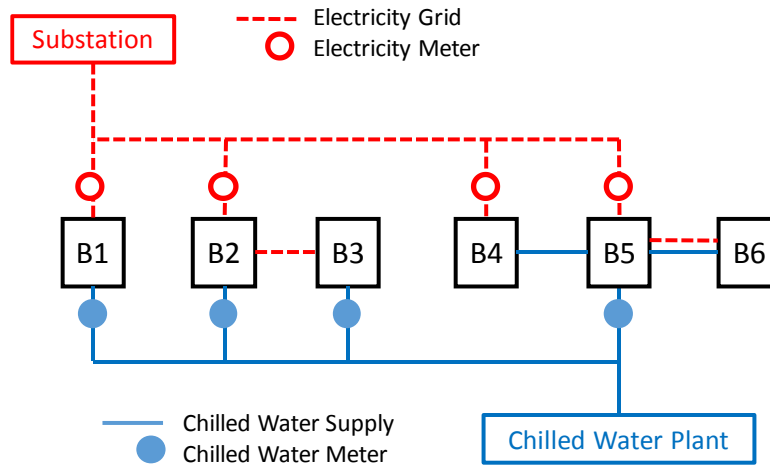


Figure 1. A Sample Grid Structure of a Campus.

B. Filtering Metering Data and Giving It Context via Operating Condition Data

Once the mapping between buildings and metering has been verified, attention can be focused on meter data quality and context. Typically, sensor measurements are affected by various sources of noise such as inherent sensor noise, communication failure, deactivation, sensing wrong properties, lack of calibration, etc. Many filtering techniques exist, but filtering out bad data, instead of data imputation, by a simple 'if-then' condition based on physics is enough if the number of data points is sufficient.

Good quality meter data, however, may still be prone to misinterpretations in analysis if its context is not characterized and measured. Buildings in a network undergo various operating conditions over time, such as different weather conditions, inside activities, plant operation settings, etc., but data related to building performance do not explicitly show what those conditions are. Thus, data regarding operating conditions also need to be carefully handled. This study characterizes several important operating conditions for buildings in a chilled water cooling network:

- Cooling Degree Days (CDD) for weather conditions – “Degree days” are commonly used in cooling and heating industries as indicators of energy consumption for space cooling or heating, based on daily temperatures.
- Chilled water supply water temperature for chiller plant operations – Chilled water from a chiller plant is an input to building HVAC systems, and the system behavior is significantly affected by the chilled water temperature. Relatively stable temperature profiles within a pre-designated temperature range need to be verified before assessing a building’s energy performance.
- Day groups, i.e., working or non-working days, for considering the activities inside the buildings.
- Building groups, by inherent intensity of energy consumption – Buildings with laboratories tend to use more energy than office buildings; thus, it is fair to compare buildings only within each group.
- Template matching – Representative hot-day and cold-day profiles are defined in time series, and days having similar trends are collected.

These data, gathered and associated via timestamp with energy consumption measurements, are foundational to the analytics discussed as follows.

C. Development of Metrics

The granularity of an analysis depends on the type of data gathered. This means that a target analysis on a specific inefficiency cause or component degradation requires specific sensors. In reality, existing buildings do not typically have those special sensors, but only have sensors for operational data at the most. Georgia Institute of Technology gathers operational data such as supply chilled water temperatures entering buildings, return water temperatures exiting buildings, and chilled water flow rates in 15-minute intervals. Traditionally, the difference between supply and return water temperatures, ΔT , is used as a measure of building efficiency because a low ΔT potentially implies inefficient heat transfer in air handling units. However, other external factors can affect the ΔT profile over time as described in the preceding sub-section.

Thus, in addition to ΔT , chilled water *flow rates* should also be a key performance metric because flow rate is directly associated with water pump behavior. Electric consumption is proportional to the cube of water flow and thus closely relevant to operational cost and energy consumption. As a means of reducing dimensionality, instead of tracking water flow rates at each time interval, representative quantities are monitored such as: maximum and minimum flow rates; differences between maximum and minimum flow rates; average flow rates; and/or, fluctuations of flow rates for a given time period. This statistical treatment of chilled water flow can also be applied to electric consumption (kilowatts) of each building.

To determine the efficiency of chilled water plant operations, a reasonable figure of merit is the kilowatt per ton metric. This metric quantifies the ratio of the power consumption by all units in the plant (chillers, condenser water pumps, primary and secondary pumps, and cooling towers) to the total tons produced by the plant chillers. While the kilowatt directly represents the power consumption by the plant, it is not sufficient to look at this value in isolation and try to minimize it for energy efficient operations. Rather, the total energy consumption for a given period is proportional to the cooling demand, which dictates the cooling tons required for that period. Weather conditions, thermal characteristics of the buildings receiving chilled water, and the thermal losses encountered in piping strongly affect this cooling demand and thus the plant energy requirements. Consequently, one would expect higher plant energy consumption during summer, as opposed to winter. Since a reasonable comparison of plant efficiency cannot be made merely on the basis of energy consumption, one must normalize this value to account for the cooling demand. The kW/ton metric thus characterizes the power/energy consumption by the plant, per cooling ton produced. This isolates the efficiency of the plant components and operations from the demand, yielding a more accurate assessment of the overall plant efficiency. Lowering the kW/ton value for a given plant thus represents significant cost savings for the operators.

III. Visualization and Analytics Modules of the Comprehensive Energy Monitoring Environment

GT EnergyWatch Portal is a web-based main opening screen that provides a series of general descriptions of each service described in this paper. It introduces different energy analysis/management services and corresponding instructions for users.

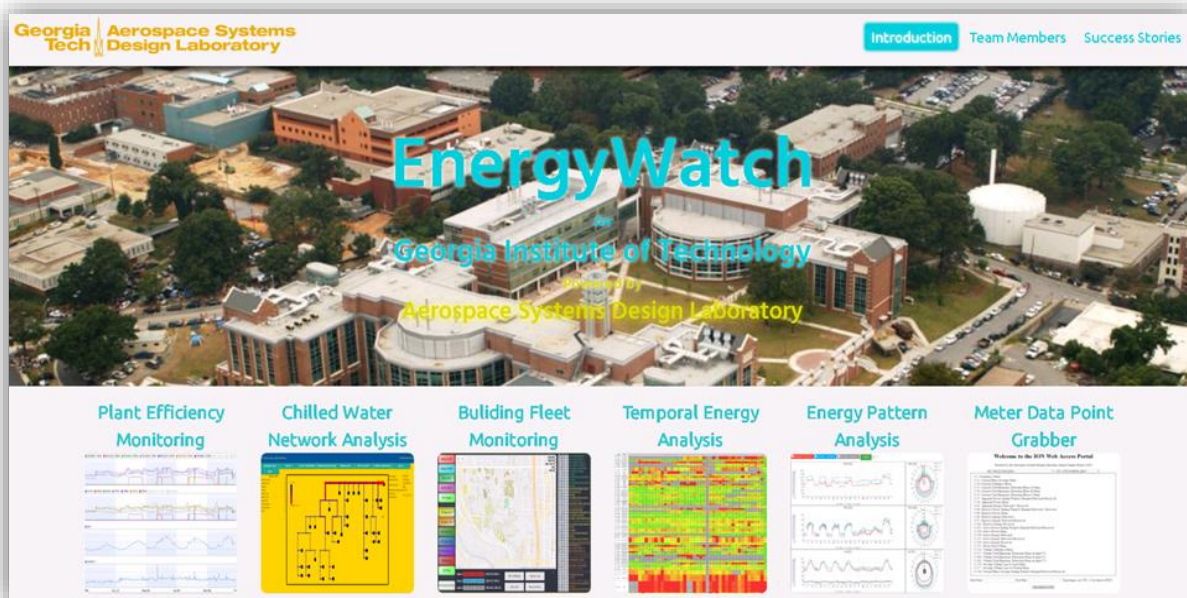


Figure 2. Screenshot of EnergyWatch Portal.

In the portal, methodologies, approaches, and engineering architectures used to establish the suite of services. Specialized capabilities of each services are briefly introduced to not only help one to retrieve a better understanding of each but also give a top-level view as well. The portal is also a repository to collect success stories from use of the tools, i.e., cost avoidance opportunities identified. Selected visualization and analytics modules, to which the portal links, are further described in this section.

A. Chilled Water Plant Energy Watch

The Plant Energy Watch tool provides an easy way to assess the efficiency of the two chilled water plants at Georgia Institute of Technology. Its fundamental function is to provide a visual representation of the total kilowatt consumption by the plant, the total ton production, and the kilowatt per ton efficiency metric, as a function of time, for a specified period. Additionally, with access to real-time energy pricing rates from the power company, the tool is also able to provide real-time energy expenditure by the power plants. Figure 3 displays some of these outputs for a five-day period, collected at 15-minute intervals using FIN Stack[®] framework. The first two plots in particular depict contributions by the chillers to the plant power consumption and ton production. Chiller staging based on the cooling demand is evident from these plots, with chiller 2 staged on or off through the week as required. Plots like this provide insight into the coupling between plant operation control and cooling demand management, something which is unique to each plant.

The tool has access to data from sensors attached to the plant equipment, facilitated by Haystack data-tagging standards.^{3,4} Data from sensors reading the chiller flow rates, and supply/return temperatures is used to compute the ton production. Data from sensors reading the kW values for every component in the plant can be combined to obtain the total kW consumption. The total kW value and the electric power company's price (\$/kWh) together are used to calculate the real-time energy cost.

Quality of the raw data used by the tool is of concern, as any erroneous values, possibly due to faults in the sensors and/or communication links, can impact the accuracy of the kW/ton metric. While rare, it is still necessary to account for such scenarios. For example, faulty flow rate sensors may record a flow value of near zero gallons per minute through the chiller. Assessing the validity of this value requires checking the temperature difference between the supply and return flows, as well as checking the sensor stream indicating whether that specific chiller is on or off. If the temperature difference is as expected, and the sensors indicate that the chiller is running, then the fault is likely in the flow rate sensor. In such scenarios, either these data points need to be filtered out, or, imputed based on other streams of information. Having access to this large set of data from the plant facilitates development of imputation based raw data error checking and replacement schemes.

The chilled water plants at Georgia Tech recently underwent significant equipment and operation management upgrades. These plants are now automated through optimized control logic that adjusts operations based on the cooling demand and outside temperature/humidity. The developed Plant Energy Watch tool allows operators to assess the impact of their upgraded and automated operation process on the overall plant efficiency. As stated before, there is a cost savings incentive to lowering the kW/ton metric. With data on pre-upgrade plant energy performance available, operators can now use real time data processed by the Plant Energy Watch tool to compare current operation efficiency with the past, and translate it to real cost savings. With such a capability, operators can quantify the reduction in expenditure that is achieved.

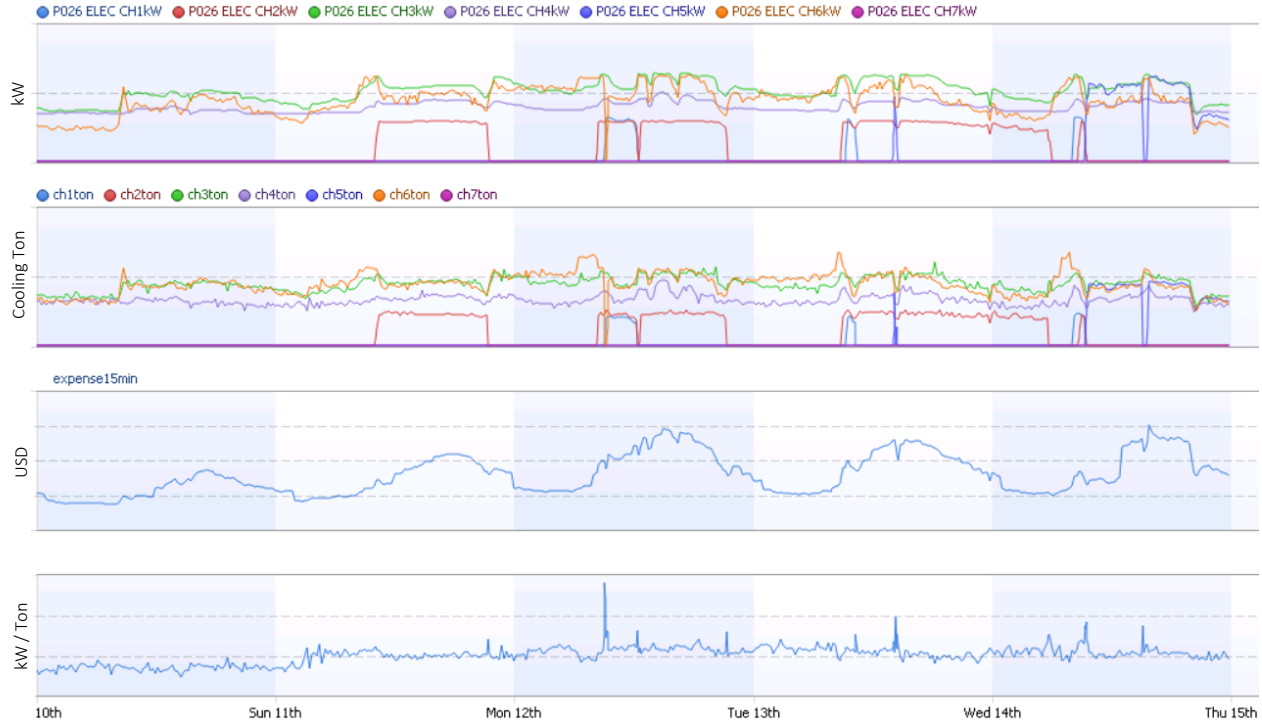


Figure 3: Five-day Performance Tracking of a Plant

B. Chilled Water Piping Network Monitoring

In a chilled water network, a central plant supplies chilled water to buildings through pipes that are buried underground. A large amount of data is needed to understand and identify problems in a network, which include abnormal flow velocity, abnormal line pressure and its distribution, leaks, etc. The chilled water network monitoring tool was developed to assist in the visualization and analysis of chilled water networks by using estimation algorithms that can quickly determine flow properties throughout a chilled water network. This allows operators of the network to perform fast network diagnostics and predictive problem identification. Currently, the tool can provide information on mass flow rate, temperature, and velocity distributions for two campus chilled water networks. Combined, these networks cover more than 100 buildings in the main campus.

The tool contains its own definitions for the topology of a network. The tool splits each network into nodes and pipe segments. A pipe is a connection between two nodes, and the tool calculates the flow properties of any element in the chilled water network. A node can either be a building or a branching node. A building is an entity that takes water from the plant, uses it, and returns the water back into the network. Usually, meters are installed at the buildings in the network, so flow properties are generally known at the buildings. A branching node is a node that allows water to pass through it and redirects water into two directions.

The tool functions by first collecting data about the network from an online database. This database contains data for the properties of the flow at the buildings in the network where a sensor is present. Then, by using these known values, the mass flow across the entire network for each pipe is calculated using a recursive algorithm that works backwards from the buildings to the plant. Also, the tool reads the supply temperature and return temperature at the buildings, and does calculations for the supply temperature, the return temperature, and the velocity of each pipe segment despite there being some missing information at the building level. The tool identifies where there is missing

information in the network by highlighting pipe segments red or yellow, depending on whether the database value is missing or undefined. Also, it can indicate where data anomalies such as reverse flows are located. The user of the application can click on these segments and change the value of the mass flow rate in this segment by providing a guess based on the history of the building to which the segment is connected. This allows the user to have a better understanding of the current state of the network despite missing information. The user can also input mass flow values in building segments where the current value is unusually high or low, resulting from sensor/communication failures, allowing for the correction of bad values. The tool also calculates diagnostic values for each pipe segment: delta T, velocity buffer, and temperature “watchdog”. Delta T represents the difference between the supply and return temperature values for each segment. Velocity buffer returns if the velocity in a pipe over its rated velocity limit. Temperature watchdog uses a reference building to calculate whether temperature measurements at building in the network are physically possible. This is important, because temperature values tend to be incorrect, and this calculation makes it easy for a user of the tool to determine which temperature readings are incorrect.

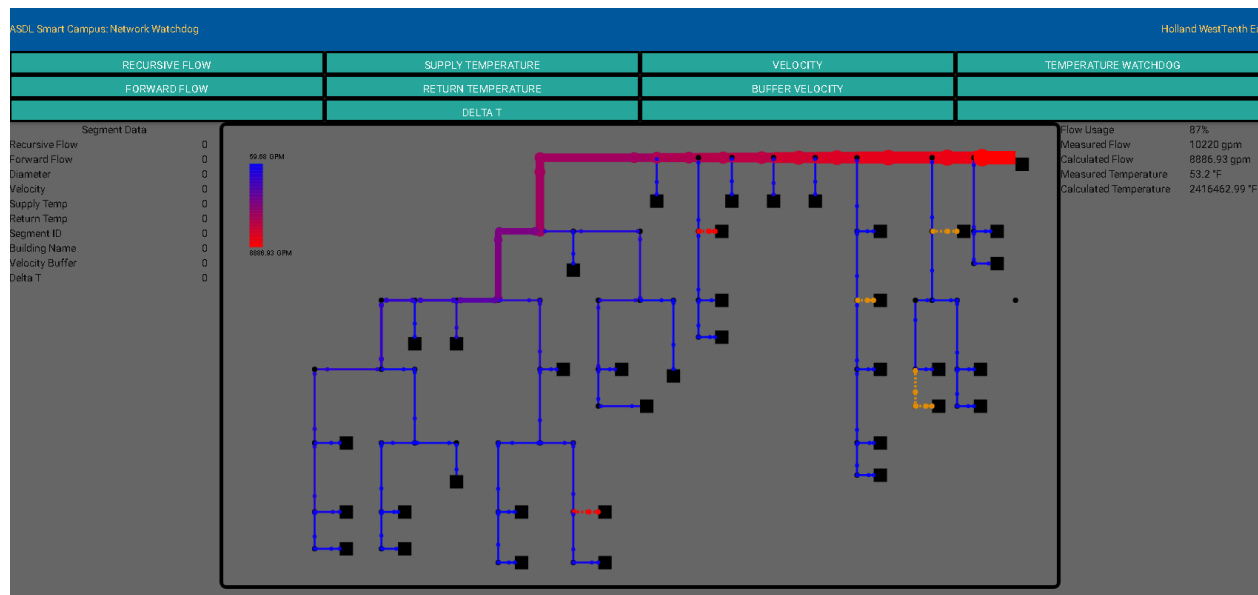


Figure 4. Screenshot of the Chilled Water Network Monitoring Tool.

C. Building Fleet Energy Watch

The Building Fleet Monitoring Tool (BFMT) is a web-based GUI platform to visualize data and to provide user with a capability to perform data analytics. It is the starting point for a comprehensive user experience framework for monitoring and analyzing the trends and correlations of energy metrics. For this goal, BFMT is designed to visualize data for metrics, including time-series, for groups or individual buildings, facilitating the identification, by users, of signatures of inefficiencies that lead to cost avoidance when corrected. Metrics BFMT currently investigates are data associated with cooling, heating, and electricity. The usage of water and gas will be included in the future. Data included at 15-minute intervals is:

- for cooling: cooling flow (Gallons Per Minute: GPM), supply- and return- water temperature
- for steam heating: the amount of water condensed every 15 minutes
- for electricity: kilowatt (kW) consumption

BFMT also creates more in-depth metrics out of these raw data.

BFMT consists of two individual dashboards: primary (Figure 5) and secondary (Figure 6). The primary dashboard is used to define all settings for building fleet energy monitoring. More specifically, the user can customize buildings, areas, dates ranges, metrics, etc. to query from the ION metering database. Once the user chooses buildings, corresponding geographical information is populated into the map at the center of the dashboard to provide the user with better understanding of the layout of the energy network system. Up to three different date ranges (required to have equal length) can be queried and superimposed to understand seasonal differences. The Cooling Degree Days (CDD) and Heating Degree Days (HDD) are calculated for these ranges to determine the comparability of how weather drives the thermal loads over each period.

Once the user finishes defining the settings and click the ‘Fetch ION data’ button, BFMT applies a pre-filter algorithm for refining data depending on the metrics’ probable errors due to equipment malfunctions, etc. Once it finishes querying all requested data, it allows the user to:

1. Download both raw and summarized data. This data can then either be used offline for studying or become input data of other tools for further analysis.
2. View all metrics and associated analyzed data in a series of charts. These are summarized in Table 1.
 - a. Different date periods with similar CDD or HDD are overlapped to be easily compared and studied
 - b. Consumption rates and accumulated totals are simultaneously shown.
3. View summarized statistical information of each building.

On the left side of the secondary dashboard (i.e., the results screen, Figure 6), there is a list of selected buildings. Once the user clicks any buildings of interest, corresponding information is updated. In the section in the middle, an aerial view of the building is presented with the summarized statistical results of the building in the selected date period underneath the map view. In the right half of the pane are charts visualizing the temporal data associated with each selected metric. The user can navigate through the tabs to see the corresponding charts by clicking each tab. The initially appearing tab is a summary showing GPM and kW, since they are highly correlated major energy metrics. Figure 6-b shows results from the ‘Cooling’ tab, superimposing a week of data in August of 2016, 2015, and 2014.

Table 1. Metrics of interest in BFMT.

Energy	Metric	Unit	Description
Cooling	Flow rate	Gal/min	Amount of cooling flow used per minute
	ΔT	$^{\circ}F$	Return flow temperature – supply flow temperature
	Cumulated Gallons (Daily)	Gal	Daily cumulated usage of water for cooling
	Flow rate fluctuation	Gal/min	Current GPM – Previous GPM (1 hour interval)
Heating	Condensation	Gal	Amount of condensed water per minute by heating
	Condensation Gallons (Daily)	KGal	Daily cumulated condensed water by heating
	Cumulative Gallons (Total)	KGal	Total cumulated condensed water in the period
Electricity	Wattage	KW	Amount of electricity power usage
	Cumulated Wattage (Daily)	KWH	Daily cumulated amount of electricity usage
	Cumulated Wattage (Total)	KWH	Total cumulated amount of electricity in the period
	Wattage fluctuation	KW	Current KW – Previous KW (1 hour interval)

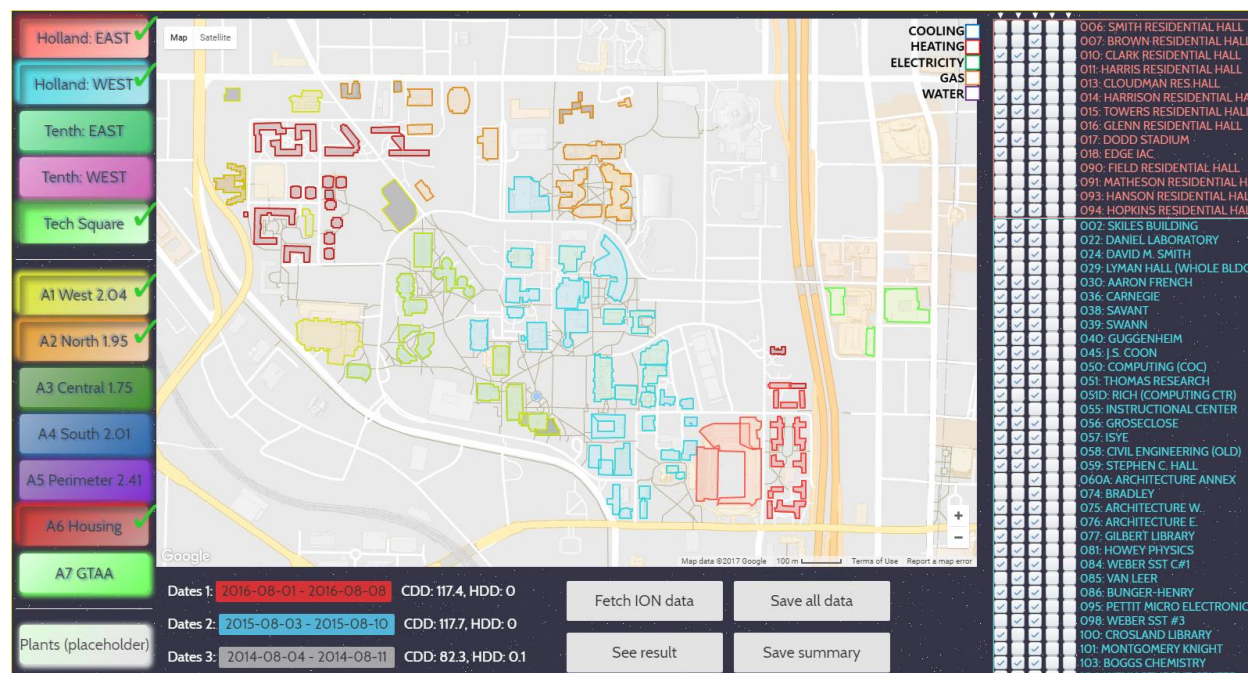


Figure 5. Building Fleet Monitoring Tool: Primary dashboard, for selecting what to view.

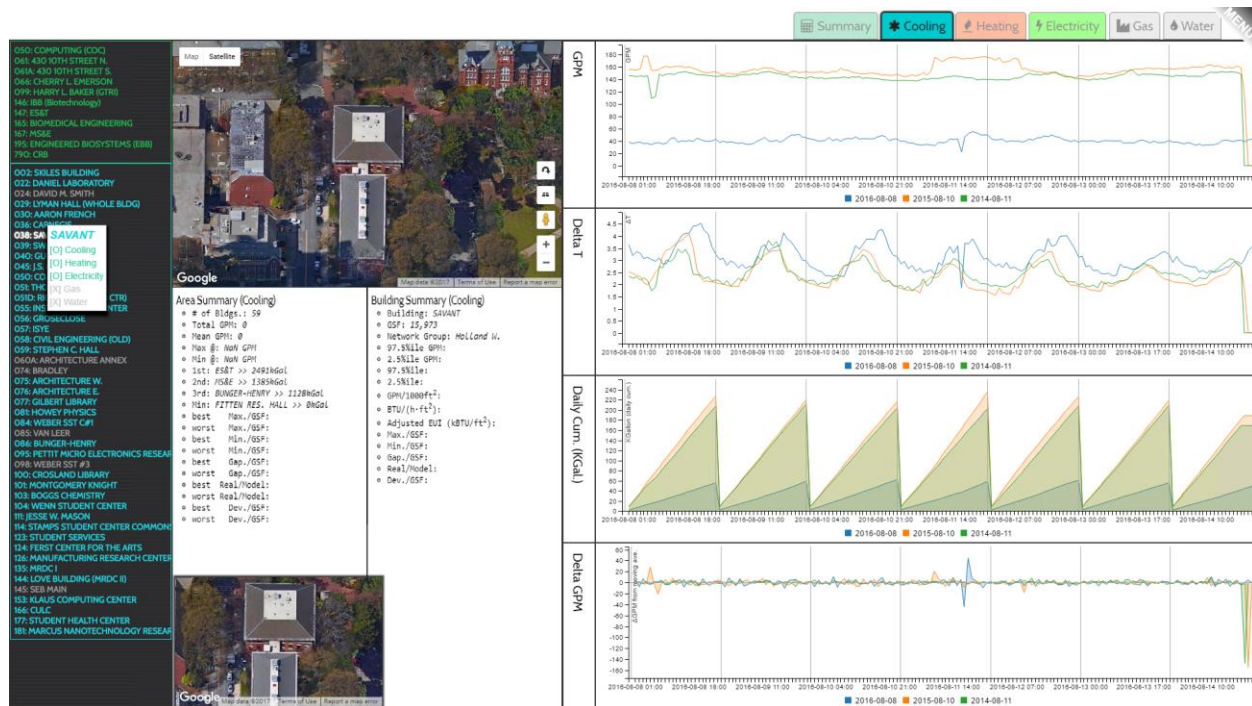


Figure 6. Building Fleet Monitoring Tool: Secondary dashboard, for viewing results.

D. Temporal Building Energy Consumption Analysis

In a district energy system, which has multiple buildings in a central heating or cooling network system, it is challenging to distinguish an actual load from avoidable energy waste because it is difficult to directly measure an actual or waste load. A traditional measure, ΔT , over time does not provide a clear situational awareness. A thermal load model may be able to show a reference cooling or heating power required at a given operating condition, but having those models for each and every building causes another challenge because all buildings are unique.

To overcome those challenges, this paper proposes a data-driven relative building energy consumption analysis using chilled water flow rate-based metrics in a novel way. The basic idea is to compare the energy consumption of one building to the other buildings of the same kind within the network. Then, it can be extended into time-oriented analysis by repeating them over multiple, successive time intervals to reveal trends. This provides not only relative assessment within a specific time period, but also an assessment along a series of time periods for each building. To do so, as a baseline, reference cooling degree day (CDD) vs. evaluation metrics for each building group are defined first. These data can come from historical data or a thermal load model. In a data-driven approach, metric values for all buildings are plotted against corresponding CDD, and choose the best CDD vs. metric profile out of them. This approach has an advantage in that it does not need a full understanding of system dynamics. A downside, though, is that one baseline does not represent all buildings in a network since every building is unique in general. Also, quality of data varies due to outliers, degrees of noise, and/or possible temporary changes in operating conditions. Figure 7 shows several examples of cooling tons vs. CDD charts. Buildings share the general tendency: the higher CDD, the greater cooling tons. However, certain buildings have a clear trend, others do not. Building 2 has large variations. Building 3, specifically, shows two separate trends. Also, Building 2 spends more specific energy than the other two, which also supports that each building requires their own baselines.

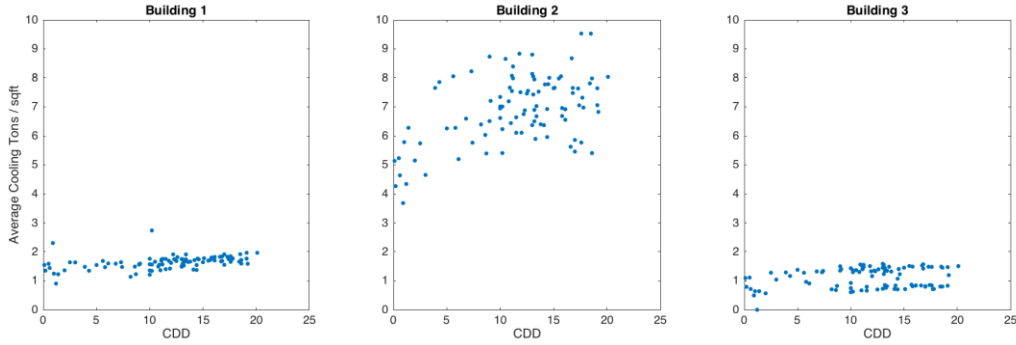


Figure 7. Examples of Cooling Tons/ft² vs. Cooling Degree Days.

These observations lead the need of automatic and robust baseline generation capability for each building. To achieve the goal and satisfy the requirements, Gaussian Mixture Modeling (GMM) technique has been introduced. GMM is a probabilistic modeling method by the mixture of a finite number of Gaussian distributions.⁵ It is also used as a clustering technique like the k-means clustering method. Like the k-means method, GMM requires specification of the number of distributions (groups). Since the number of groups in a data set is generally unknown, Bayes Information Criterion can be used to determine the number of groups preferred.⁶ It is a measure of a maximized likelihood function of a model penalized by the number of groups. Difference from the k-means method is that groups clustered by GMM can overlap with each other. Figure 8 depicts the snapshots of online GMM for Building 3. It shows how a baseline can change as more data are collected. The first half data points were gathered as one group. After that, the building performance slightly changed (in a good way); at the end, they were grouped into two.

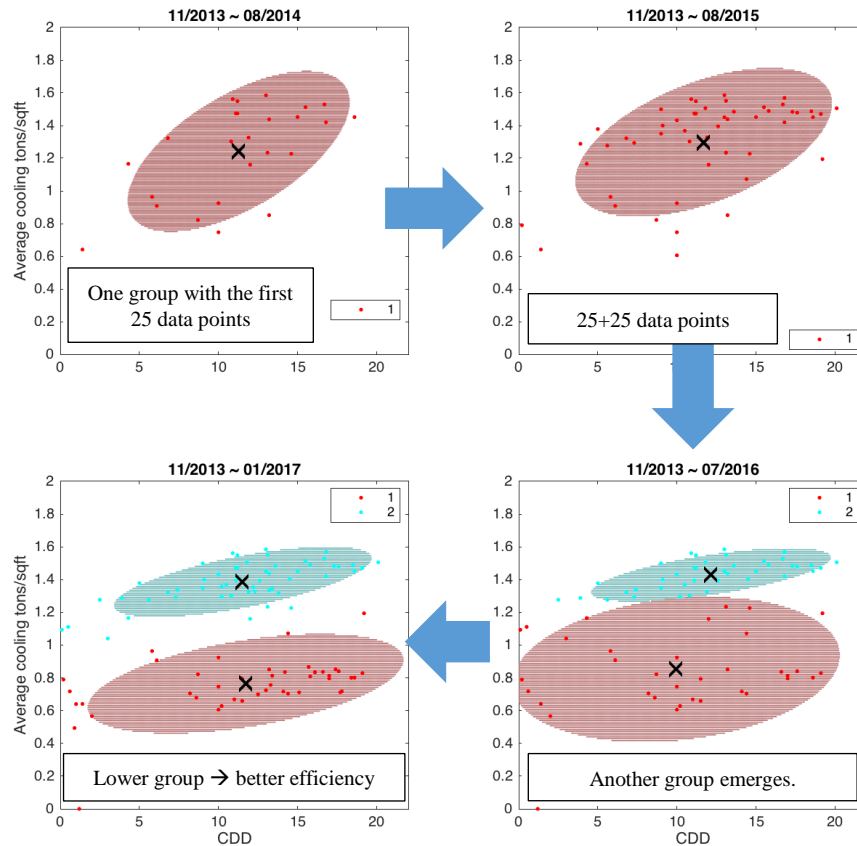


Figure 8. Online Gaussian Mixture Model.

Then, each group can be regressed by a linear function. Since we know that the lower energy consumption implies better efficiency, the least values of their regressions are chosen as baseline energy consumption rates as a function of CDD.

$$V_{\text{ref}}^i = \min[f(CDD)]$$

where V_{ref}^i is a reference metric for a building i , and $f(CDD)$ represents linear functions from each group of GMM clusters. This reference metric is a normalizer of relative building assessment values of each building for each different time period.

$$V_{\text{temporal}}^{t_k} = V_{\text{relative}}^{t_k} / V_{\text{ref}}^i$$

V^{t_k} is a metric value at time t_k , $V_{\text{temporal}}^{t_k}$ is a temporal metric value, and $V_{\text{relative}}^{t_k}$ is a relative metric value. The created regressions can then be used to evaluate the performance of each building within their own group, assigning different grades based on their performance with respect to the baseline. If the analysis carries on with the time period, it will be apparent which buildings improve and which buildings worsen.

To better visualize the building performance evaluation results, allowing comparisons by buildings and by time, a “heat map” visual was devised: buildings in rows and ordered time periods in columns. Figure 9 illustrates the evaluation results by the proposed temporal building energy consumption analysis. Red, green, and blue cells mean more expenditure than a baseline, as much as a baseline, and lower than a baseline, respectively. Heights of rows represents the relative amount of cooling tons consumed: the greater heights, the more energy consumptions. This chart easily implies which buildings are all-time culprits, degrade over time or have seasonal effects as well as which buildings are relatively inefficient or consume more energy than others.

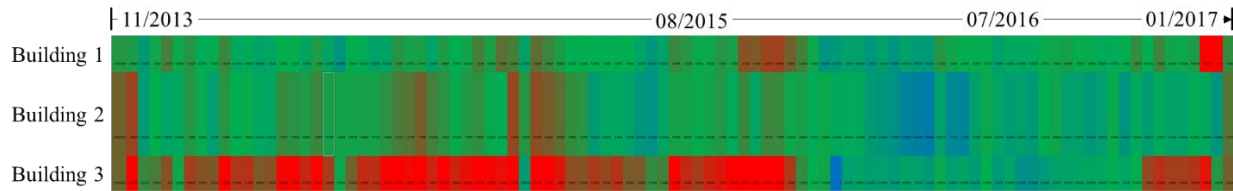


Figure 9. Temporal Building Energy Consumption Analysis by a Heat Map.

E. Energy Usage Pattern Analysis (Fingerprint Analysis)

Sometimes, data filtering and visualization can reveal important information hidden by noise and uncertainty. Given the knowledge that the HVAC system behavior is dependent on weather conditions, which have daily periodicity, daily patterns of historical energy expenditure of each building were collected and compared in radial charts: 24-hour, from 12am to 12am of the next day. Figure 10 shows a cooling ton per square footage profile of a sample building: a) before, and b) after filtering – excluding outliers, choosing weekdays, and selecting days having typical hot (orange) and cold (blue) weather by a template matching method. Not surprisingly, a pattern before filtering was a mixture of various operating conditions; thus, it was not enough to determine how the building worked. After data filtering, the usages of cooling tons were distinguished between hot and cold working days. This specific example represents that the sample building spends more cooling tons during summer seasons than winter seasons, which is reasonable. However, there is not much difference between days and nights, which may not be a good trend unless there exist heating sources and activities during nighttime.

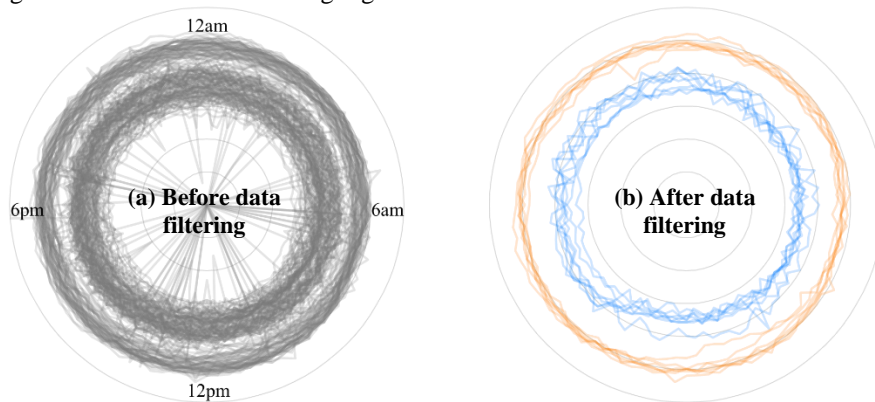


Figure 10. A Daily Energy Consumption Pattern for a Building by a Radial Chart.

Collecting and comparing daily patterns for multiple buildings tells two other stories: patterns and magnitude. Figure 11 depicts pattern and magnitude comparisons of multiple buildings. The first row is a cooling ton per square footage profile and the second row is kW consumption per square footage. First, as mentioned above, the shape of the patterns represents how a HVAC system reacts to daily cooling demands of hot and cold seasons. In terms of a cooling ton consumption, Building A spent more energy during daytime than nighttime, and the usage difference between seasons was clear. Building B had a spiky pattern in cold seasons. Likewise, Building D also had a spiky pattern in cold seasons, but often the building consumed even more energy in cold seasons than hot seasons. Building C spent almost the same cooling energy between days and nights. In kW consumption, Building B and C had inverse patterns: more energy consumption in cold seasons than hot seasons.

Second, the magnitude of the expenditure has potential to render building energy efficiency since the metrics used in this exercise were normalized by the effective area of each building. Figure 11 also illustrates the magnitude by the sizes of the profiles: the smaller rings, the less energy consumptions. Of course, the bigger rings do not always imply the bad efficiency, though, because of the inherent differences in energy usage tendencies between lab-oriented and office-oriented buildings. However, it can be the first cut indicating which buildings could be more efficient.

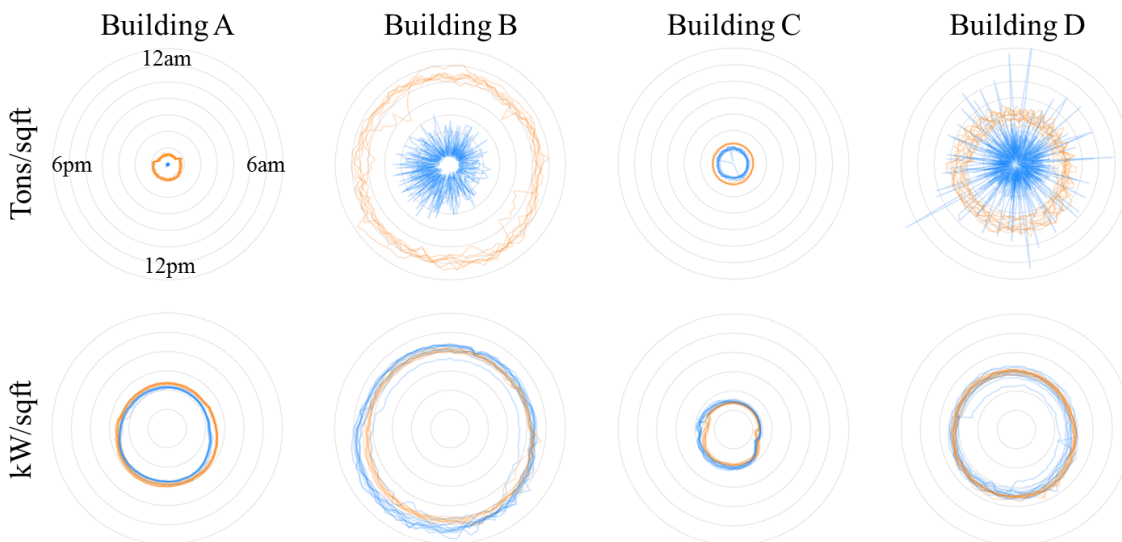


Figure 11. Daily Energy Consumption Pattern Comparisons for Multiple Buildings.

F. Building Thermal Load Model

Evaluating and monitoring HVAC system efficiency of buildings is of utmost importance to increase overall efficiency. Especially in a district energy system, simplicity and scalability are two key attributes so that multiple buildings can be rigorously modeled and analyzed. A framework that models the thermal properties of a building with an electrical RC circuit analogy has been previously proposed.⁷

The resulting model is an enhanced one-dimensional heat load model where ambient temperature, relative humidity and solar energy profiles are treated as external conditions. The electrical energy expenditure profile of the considered building is also fed into the model as a proxy of internal activities. The model was validated for different types of buildings and successfully predicts the cooling-ton profiles over time. The model can analyze a building over multiple days and by comparing the model predictions versus the actual data the user can monitor the building for faults in thermal balancing behavior. The model went through some upgrades that boosted the capabilities, allowing it to handle more realistic conditions for different building sizes and space types (offices, laboratories, etc.).

The previous model used an analysis result of the effects from both external and internal conditions in an aggregate fashion. This approach could ignore the subtle changes that could happen during the day, which might trigger responses on the cooling system. Regression analysis was performed based on 15-minute intervals, while removing non-existent data periods and outliers, so that user can have a more granular perspective to better understand dynamics from the variables of interest. For example, the regression includes differences in the AHU system that relate to the amount of recycled air that is used. The percentage of outside air is related to the spatial composition of the building and tables of required air recirculation in different types of spaces.^{8,9} The new data gathering mechanism accommodates any number of cooling or electrical power inputs to consider a large building and/or a building cluster that has multiple AHUs and electricity meters. In the first version of the model, the AHU was assumed to only switch

between two cooling states, occupied and unoccupied. The new model added a standby mode that actual buildings usually have. The capability of handling the intermediate loading condition is important to improve the simulation of the heat exchange behavior during inactive periods.

In Figure 12, the GUI for the Building Load Model is presented. The GUI is created by using MATLAB. The left part of the GUI consists of building and simulation parameters. The simulation results and the temperature profiles are demonstrated on the right side for a sample building.

In order to perform a simulation, the user has to select a previously saved building or enter the meter / sensor information manually. The GUI will address the cached weather and energy data and start the simulation. If the building is not energy efficient, the user may have to tweak some internal parameters such as threshold and heat capacitance. When the dry bulb temperature (light blue line) is below the predetermined cutoff value (horizontal red line), the cooling rate needed is set to zero. In the previous iteration, the model was able to model only hot summer days successfully. The new model overcomes this limitation. As shown in Figure 12, the results of the simulation match quite well with the actual cooling-ton values for a 10-day during the fall even when there was a large fluctuation in temperature.

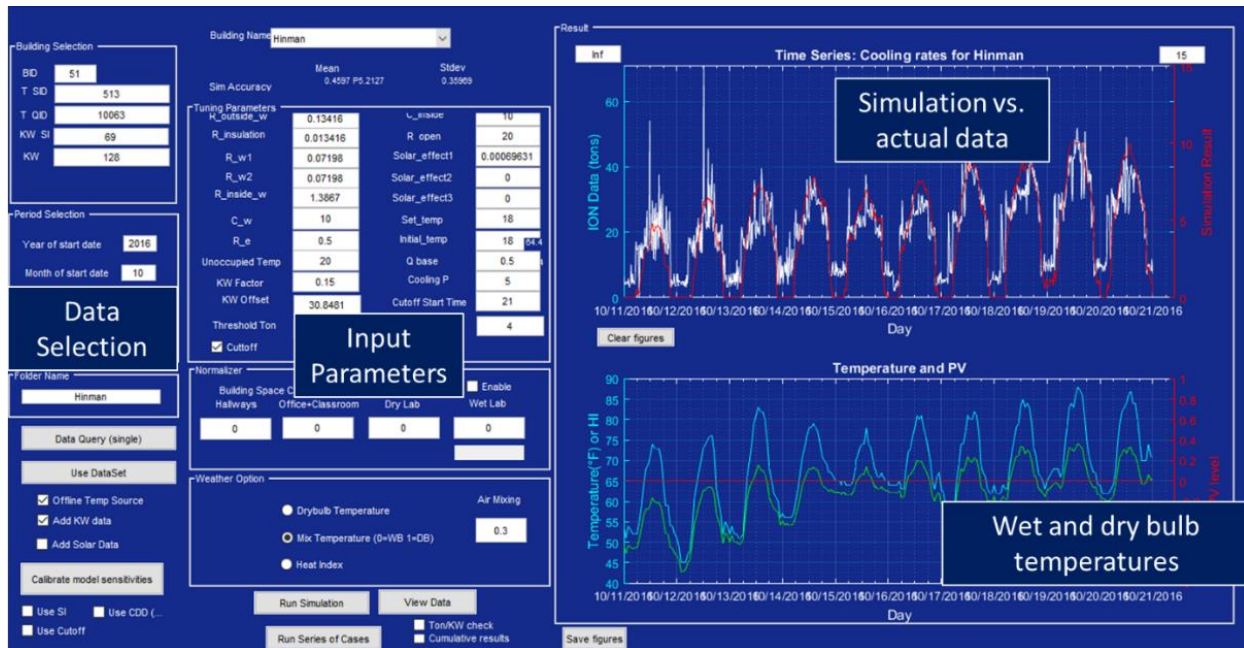


Figure 12. The User Interface of the Building Thermal Load Model.

IV. Closure

In this paper, a data visualization and analytics modules are presented, along with introductions to the technical concepts enabling them. Prior to reviewing the modules, tactics for meter data cleaning, mapping, and association with operating conditions were highlighted, since they are critical to the accuracy of analytics and their interpretation. Then, trending and metrics-based analysis were reviewed for the chilled water district energy cooling system, including central chiller plants, the distribution piping network, and the fleet of buildings. Further analytics were presented for buildings, at individual and fleet-wide levels (i.e., via “heat map”). Technical enablers for advanced baselining, including GMM-based classification of building efficiency behaviors; visual examination of operating energy profiles (i.e., radial plots); and a hybrid building load model. Many of these tools have been deployed and are in use by Georgia Tech Facilities Management engineers, leading to significant cost savings. This overview has been presented with the hopes that other campuses can implement some version of these services and can use the lessons learned presented in this paper to accelerate adoption.

In the future, the goal is to progress into follow-on applications useful to managing campus utilities, including: more automated baselining and fault detection; operational performance prediction and situational forecasting; optimization across the system-of-systems of supply (central thermal plants), distribution, and loads (buildings); technology analysis for planning campus infrastructure upgrades. The enablers to these capabilities, besides the

foundational work in this paper, includes machine learning, physics-based modeling, and model-based systems engineering, to be investigated by the research group.

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