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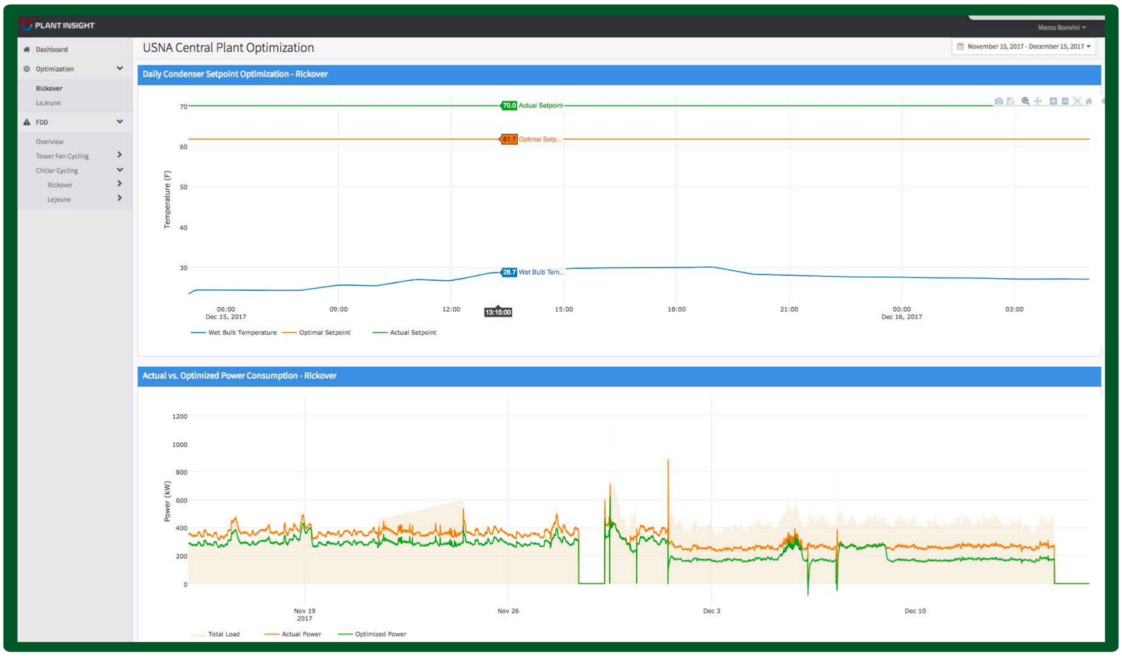

Optimizing Operational Efficiency: Integrating Energy Information Systems and Model-Based Diagnostics

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This report documents findings from a demonstration project to verify the feasibility of employing a model-based approach to central plant operation and diagnostics at U.S. Department of Defense (DoD) facilities, and to quantify the associated benefits. This field demonstration was designed to validate: effectiveness in reducing electricity consumption and associated greenhouse gas (GHG) emissions; user satisfaction; cost-effectiveness and viability of system economics; and validity of model calibration.

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TABLE OF CONTENTS

Page

TABLE OF CONTENTS (Continued)

LIST OF FIGURES

Page

LIST OF TABLES

Page

ACRONYMS AND ABBREVIATIONS

API	application programming interface
ASHRAE	American Society for Heating, Refrigerating, and Air-Conditioning Engineers
BAESA	Building, Asset, and Energy Situational Awareness
BAS	building automation system
BLCC	Building Life-Cycle Cost
Btu	British thermal unit
CDW	condenser water in cooling plant
COP	coefficient of performance
COV	change of value
DIACAP	DoD Information Assurance Certification and Accreditation Process
DoD	U.S. Department of Defense
eGRID	Emissions & Generation Resource Integrated Database
EIS	energy information systems
EISA	Energy Independence and Security Act
EMCS	energy management and control system
EMIS	energy management and information systems
EO	Executive Order
ESTCP	Environmental Security Technology Certification Program
FDD	fault detection and diagnostics
FLA	full load amps
FMI	Functional Mock-up Interface
GHG	greenhouse gas
GUI	graphical user interface
HVAC	heating, ventilation and air conditioning
IT	Information technology
JCI	Johnson Controls International
KPI	key performance indicator
kW	kilowatt(s)
kWh	kilowatt-hour(s)
LBNL	Lawrence Berkeley National Laboratory
NAVFAC	Naval Facilities Engineering Command
NDW	Naval District Washington

NIST	National Institute of Standards and Technology
REST	representational state transfer
RMF	Risk Management Framework
UI	user interface
UKF	Unscented Kalman Filtering
USNA	U.S. Naval Academy
UTC	United Technologies Corporation
VPN	virtual private network
WNY	Washington Navy Yard

DISCLAIMER

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EXECUTIVE SUMMARY

This report documents findings from a demonstration project to verify the feasibility of employing a model-based approach to central plant operation and diagnostics at U.S. Department of Defense (DoD) facilities, and to quantify the associated benefits.

OBJECTIVES OF THE DEMONSTRATION

This field demonstration was designed to validate: effectiveness in reducing electricity consumption and associated greenhouse gas (GHG) emissions; user satisfaction; cost-effectiveness and viability of system economics; and validity of model calibration.

TECHNOLOGY DESCRIPTION

In this demonstration, Lawrence Berkeley National Laboratory (LBNL) developed a hybrid data-driven and physics model-based tool for energy efficiency in central cooling plants. Once developed, the PlantInsight technology was implemented at the U.S. Naval Academy (USNA), and the technology performance objectives were evaluated. PlantInsight 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 simulation 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. Figure ES-1 contains a diagram of the Modelica model used to conduct the cooling optimization and the architecture of the PlantInsight tool, as implemented for the demonstration. Figure ES-2 contains screen shots of the user interface.

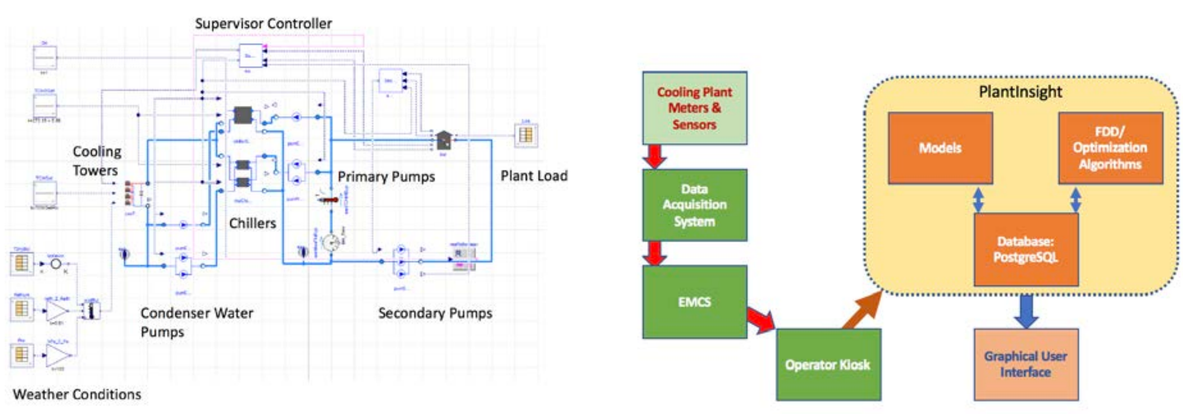

Figure ES-1. Diagram of the System-level Modelica Model Used to Represent the Cooling Plant (left); Architecture (right) of the PlantInsight Operational Tool

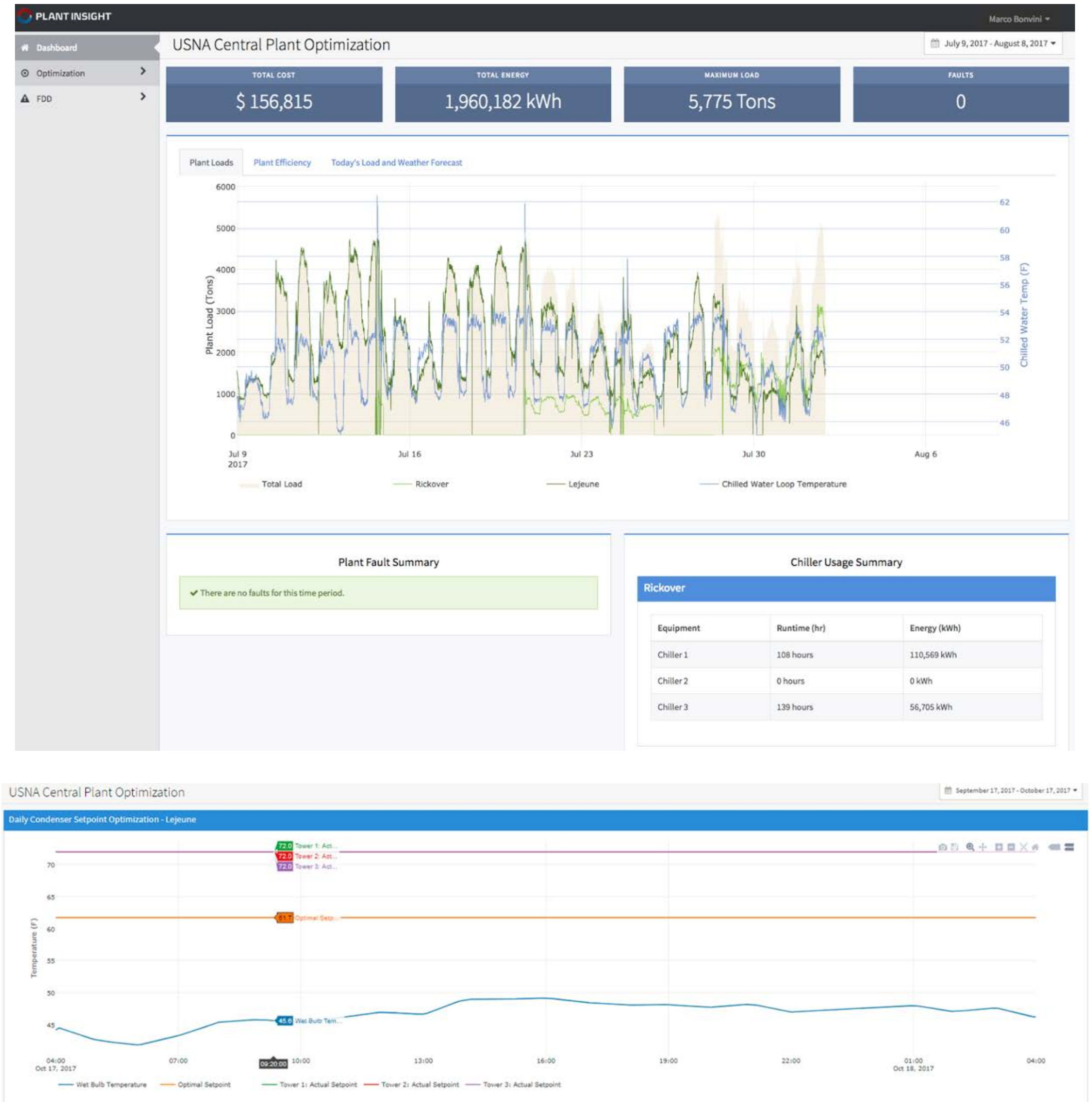

Figure ES-2. Screen Shots from PlantInsight: Visualization and Key Performance Indicator (KPI) Tracking (top); Condenser Water Temperature Setpoint Optimization (bottom)

DEMONSTRATION RESULTS

Model calibration: To ensure that the models developed to simulate the central plant were representative of the central plant's actual physical performance, the chiller and tower models were calibrated to measured data from the site. The calibration goal targeted a difference between model-predicted and measured parameters of less than 10% for 90% of data points. This was achieved for ten of ten tower cells for which data were available, and for three of six chillers. The soundness of the calibration process was confirmed; however, calibration was challenged by the limited volume of data representing full-capacity chiller operation, and perhaps by inaccurate water temperature sensor data, or faulty operations underlying the data.

User satisfaction: The demonstration technology was evaluated to determine whether PlantInsight offered equal or improved satisfaction relative to existing operational tools. Survey responses indicated that satisfaction with the capabilities of PlantInsight was equal to or better than that with the preexisting Johnson Controls International (JCI) Metasys system that is used for plant operations. Table ES-1 summarizes operational staff's feedback on the user interface (UI), outputs of the fault detection and diagnostics (FDD) and optimization analytics, and the tool overall, on a scale of one to five.

Table ES-1. User Feedback on the PlantInsight UI, FDD, and Optimization Outputs, and Overall Tool

Characteristic	Not Satisfied		Neutral		Highly Satisfied
	1	2	3	4	5
User interface				X	
FDD and optimization outputs				X	
Tool overall				X	

Energy and GHG emissions savings: The demonstration targeted 10% annual reductions in electricity consumption and associated GHG emissions at the central cooling plant. The results of the savings analysis indicated that daily energy savings greater than 10% are obtainable for approximately six months of the year, mainly during the winter season. However, for the year as a whole, energy savings of approximately 1.5% are obtainable. Since savings were driven by wet bulb temperature (lower), which occur in winter, when total plant consumption is lowest, larger annual savings are possible in drier climates. GHG emissions were quantified using a conversion factor based on references published by the U.S. Environmental Protection Agency. Since the conversion factor was represented as a single constant for the region, the emissions reduction results are the same as those for energy, in terms of percent savings.

System economics: Assessment of system economics based on standard capital budgeting metrics provides a gauge for determining financial feasibility of the demonstration technology. The analysis showed that simple and discounted payback can be met in 1.4 years, well within the five-year target that was established.

IMPLEMENTATION ISSUES

Future implementation of the technology will require attention to three areas: information technology (IT) security, maintenance and evolution, and scale-up and transition.

IT security: The PlantInsight technology requires unidirectional transfer of cooling plant operational data *from* the site *to* the application's database. The application is hosted on a web server. In the USNA demonstration, port 443 was used for secure communication from the building automation system (BAS) kiosk to PlantInsight. To satisfy DoD IT security requirements, future installations can consider several options. PlantInsight can be integrated within existing accredited applications or could be put through the accreditation process itself. Another option that was explored was to push plant operational data from the installation to a server farm on a secure DoD network, with PlantInsight accessing the data through a virtual private network (VPN) application.

Technology maintenance and evolution: As the demonstration comes to a conclusion, LBNL will work with UNSA IT and Naval District Washington (NDW) to identify options to transfer the tool to a server and location that will comply with security requirements. Although it is not yet used universally throughout the industry, companies such as HOK, JCI, and United Technologies Corporation (UTC) have staff that are familiar with the modeling language (Modelica) upon which the tool is built. They could potentially be contracted to support future model modification and calibration.

Technology scale-up and transition: To make the PlantInsight Tool available to other DoD installations, it will be released through an open source software license. This will enable stand-alone use according to its current design, or adaptation for use within existing installation energy management facility and information systems as described in the considerations of IT security. Several types of documentation have been developed to support these future transition activities, and to support ongoing use at USNA.

CONCLUSIONS

Future implementations of the technology will benefit from awareness of the following higher-level lessons that were learned throughout the course of the demonstration. First, operators place strong value on access to tools that provide visibility into how controls impact energy use and cost. This is not as a rule available in today's commercial analytics technologies that span BASs, meter analytics tools, or equipment-specific FDD tools. As such, heating, ventilation and air conditioning (HVAC) optimization technologies represent advances in the state of today's available technology, and this is even more true of optimization tools that incorporate physics-based modeling approaches. Environmental Security Technology Certification Program (ESTCP) and USNA have acted as a leader in the demonstration of these cutting-edge solutions, and future implementations will continue to contribute to the state of knowledge of their development and application.

Model-predictive optimization combined with FDD is recognized as a critical aspect of realizing the dynamic low-energy buildings of tomorrow; it can deliver even more impact by expanding the set of parameters included in the optimization, and the number of end-uses that are considered. Although these technologies represent advanced applications, the external infrastructure to support their delivery is mature; cloud hosting and computational scalability are well supported through modern IT solutions. The most significant practical implementation barrier is brittle building data acquisition and communication systems that present chronic challenges to applications that interface with controls data. Finally, we note that the creation and calibration of physics-based models for use in the operational phase of the building life-cycle is highly dependent upon the specific algorithms with which they will be paired. The open, reference implementations that are delivered with PlantInsight are important contributions to the industry's continued success in leveraging these promising approaches for next-generation building energy efficiency.

1.0 INTRODUCTION

1.1 BACKGROUND

It is estimated that 5% to 30% of the energy used in commercial buildings is wasted due to faults and errors in the operation of the control system, including suboptimal setpoints, operational sequences, and control problems (Fernandez et al. 2017; Katipamula and Brambley 2005; Mills 2011; Roth et al. 2005). Energy managers, owners, and operators are using a diversity of commercial offerings often referred to as energy information systems (EIS), fault detection and diagnostics (FDD) systems, or more broadly energy management and information systems (EMIS) to cost-effectively enable savings on the order of 10% to 20% (Granderson and Lin 2016; Granderson et al. 2017; Kramer et al. 2017; Henderson and Waltner 2013; Lane and Epperson 2013). Most of these EMIS analytic technologies use data from meters and sensors, with rule-based and/or data-driven models to characterize system and building behavior. Within the family of EMIS technologies, automated heating, ventilation and air conditioning (HVAC) system optimization offerings are beginning to emerge. Newer to the market than meter analytics and FDD technologies, these tools use physics-based, or more commonly data-driven, models to predict optimal supervisory system control settings. These are then automatically implemented through bi-directional connectivity and communication with the building automation system (BAS).

In contrast to data-driven approaches, 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. 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. Physics-based models can be used to automate the detection of system or component faults, and to identify optimal control strategies to minimize system energy use. 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 (Pang et al. 2012) to use EnergyPlus physics-based models to identify whole-building level operational energy waste was proposed and demonstrated (Adetola et al. 2014).

In this demonstration, Lawrence Berkeley National Laboratory (LBNL) developed a hybrid data-driven and physics model-based operational tool for energy efficiency in central cooling plants. The tool, PlantInsight, offers FDD functionality, setpoint optimization, and visualization of key performance parameters, targeting 10% energy savings and associated reductions in greenhouse gas (GHG) emissions. With annual U.S. Department of Defense (DoD) expenditures of $3.7 billion on facility energy consumption (DoD 2016), and HVAC comprising over 40% of commercial building site energy usage (US EIA 2012), the savings potential reaches hundreds of millions of dollars if the technology is successful and applied across all DoD facilities and HVAC end uses. The key targets for this specific demonstration are facilities with central cooling plants. This represents a smaller, but more energy intensive, fraction of DoD facilities.

1.2 OBJECTIVE OF THE DEMONSTRATION

The overarching goal of the demonstration project was to verify the feasibility of employing a model-based approach to central plant operation and diagnostics at DoD facilities, and to quantify the associated benefit. Although the tools developed under this project can be applicable to both buildings and central plants, the primary focus is on central plant energy efficiency.

Specific objectives that the field demonstration was designed to validate include:

- Effectiveness in reducing electricity consumption and associated GHG emissions
- Ease of use and user acceptability
- Cost-effectiveness and viability of system economics
- Validity of model calibration
- Acceptable latency in data transfer between software components

It was originally planned that the demonstration would be conducted at the U.S. Navy Yard in Washington D.C., and that the technology would be integrated with Naval District Washington's (NDW's) Building, Asset, and Energy Situational Awareness (BAESA) and IBM monitoring systems. Due to disruptions at the Navy Yard that affected the central plant operations and ability to host a demonstration, the project was moved to the U.S. Naval Academy (USNA) in Annapolis, Maryland (site points of contact are provided in Appendix A). Over the course of the project the NDW discontinued its use of the IBM system, so the PlantInsight tool was deployed as a stand-alone tool.

1.3 REGULATORY DRIVERS

This technology demonstration leverages and supports compliance with several regulatory drivers. Advanced metering was required at federal buildings beginning in 2012 (Energy Policy Act of 2005, section 103, codified in 42 USC 8253(e)), providing a foundation of metering and monitoring infrastructure that the demonstration builds upon. Analytics technologies such as those demonstrated in this project support the automation of baselining and performance reporting, which are required in the Energy Independence and Security Act (EISA) 2007. Finally, the advanced diagnostic capabilities that will be integrated with EIS in this demonstration will further enable compliance with the 30% energy reduction and associated carbon reduction goals in Executive Orders (EOs) 13423 and 13514, and EISA 2007. Most recently, EO 13693, signed in March 2015 and effective the beginning of fiscal year 2016, calls for the promotion of building energy conservation, efficiency, and management by reducing agency building energy intensity (measured in British thermal units [Btu] per gross square foot) by 2.5% annually through the end of fiscal year 2025, relative to the baseline of the agency's building energy use in fiscal year 2015 and taking into account agency progress to date.

2.0 TECHNOLOGY DESCRIPTION

2.1 TECHNOLOGY/METHODOLOGY OVERVIEW

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 simulation 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.

Figure 1 shows the landing page of the tool. The period of time for which data are shown and faults are summarized is user-selected and shown in the upper right date summary. In the plot, the total load on both plants (tons) is overlaid with the load from each plant individually. The landing page plots can be toggled to plant efficiency (kilowatts [kW]/ton) as well as the load and weather forecast for the next 24 hours. Above the plot, the total cost of operations, total consumption, maximum load, and number of current faults are summarized in key performance indicator (KPI) tiles. The landing page also shows runtime summaries and fault summaries. The menu options on the left side of the page allow the user to access drill-down information associated with the optimization and fault detection capabilities.

Development of PlantInsight comprised four primary elements: model construction and calibration, creation of FDD and optimization algorithms, architecture definition, and graphical user interface (GUI) development. The architecture of the Tool is shown in Figure 2 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 (energy management and control system, or EMCS), which is accessed through an operator kiosk. Data from the site is pushed to a remote PostgreSQL database that is used to store data for access by the PlantInsight tool. The user accesses the tool through a browser-based JavaScript graphical front-end application that interacts with the back-end via a representational state transfer (REST) application programming interface (API).

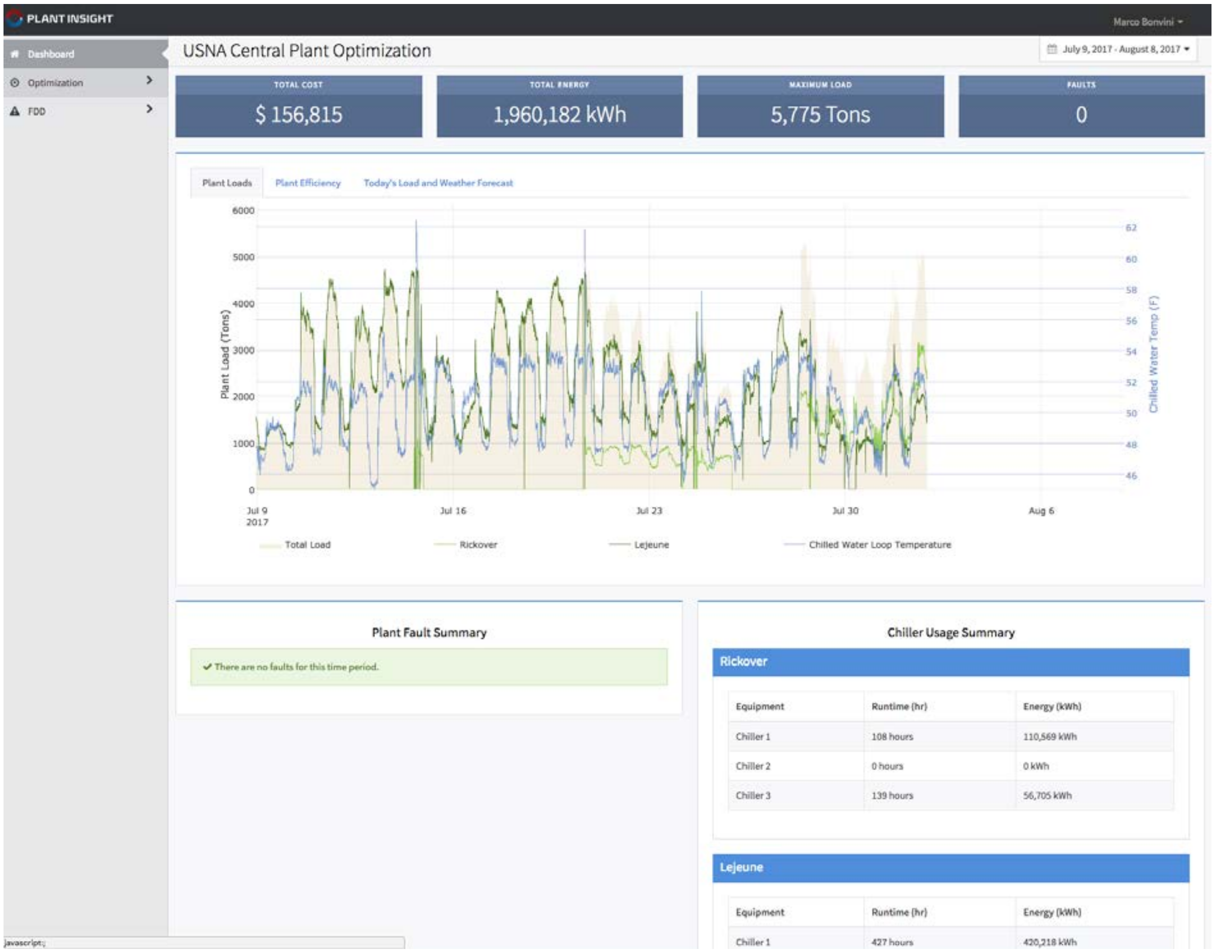

Figure 1. Screen Shot of the Landing Page of the PlantInsight Tool

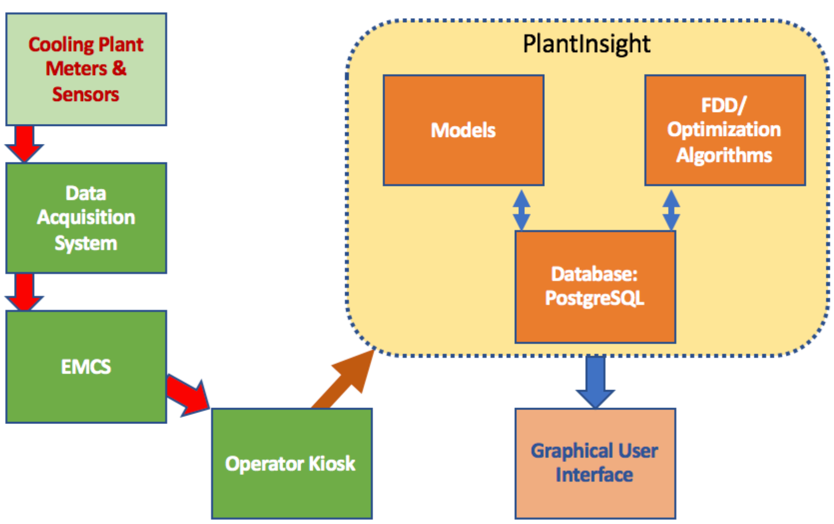

Figure 2. Architecture of the PlantInsight Tool for Hybrid Model-based and Data-Driven Central Plant Diagnostics and Optimization

2.1.1 Model Construction and Calibration

The physics-based modeling approaches that underlie PlantInsight's optimization and efficiency diagnostics are built using the Modelica language specification (Wetter et al. 2014) and Functional Mock-up Interface (FMI) standard (Blochwitz et al. 2011), each of which are open standards. Modelica is an equation-based, object-oriented programming language for the modeling and simulation of physical systems, for which there is a Modelica Buildings Library (Wetter et al., 2014). FMI is a standard way of packaging and interfacing physical models to enable exchange and co-simulation among different tools.

The Modelica models that simulate the operation of the central cooling plant were developed using information from design specifications, nameplate data, drawings, and trend-log data. Component models for chillers, pumps, and cooling towers were taken from the Modelica Buildings Library and parameterized using specification and nameplate data. These component models were combined to form plant-level models of the two central plants. Finally, control sequence models were embedded into each plant model. Figure 3 illustrates the Rickover plant model, where solid blue lines represent the water pipes and the dashed lines are the paths for control signals and other inputs for the model, such as weather data and plant cooling load.

Once constructed, the chiller and cooling tower models were calibrated to 16 months of historic steady-state plant operational data (May 13, 2014–September 22, 2015). The GenOpt (Wetter 2001) optimization engine was used to find model parameters that minimized the difference between the model outputs and the associated measured data. Calibration was deemed sufficient when more than 90% of the data points fell within a 10% error band. The calibration results are described in detail in Section 6.4

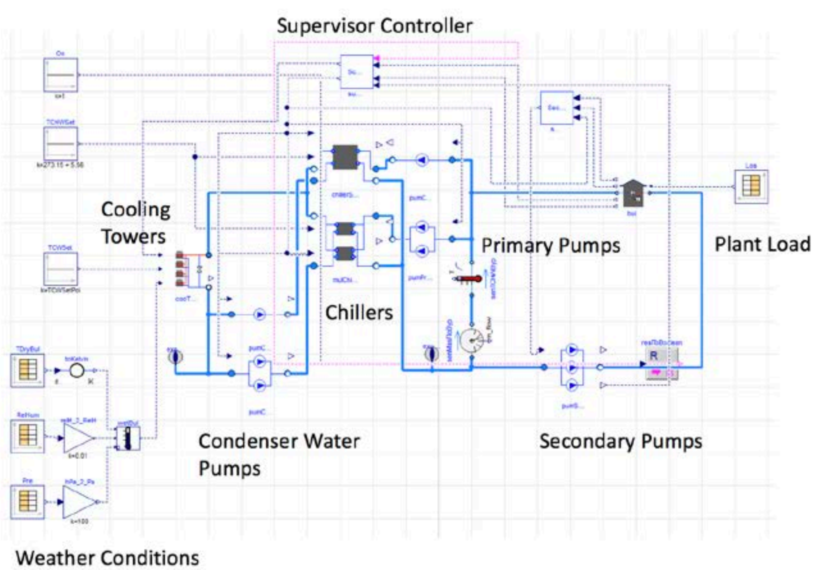

Figure 3. Diagram of the System-level Modelica Model for the Rickover Cooling Plant

2.1.2 Optimization and FDD Algorithms

The optimization algorithm determines the most effective cooling tower condenser water temperature setpoint for the next day at which the total energy consumption of the chillers and the cooling towers is minimized. First, the plant load was predicted using a linear model of minute, hour, forecast outside air temperature, day of week, and constant bias. The outside air temperature forecasts were downloaded from Weather Underground (www.wunderground.com). The coefficients of the linear model was trained by linear least squares on the previous year's data. Second, the predicted plant load was split among the two plants with a separate model that was created based on previous measurements of the load split ratio. Third, the optimal condenser water setpoint was determined for the given plant load running GenOpt and plant models. The minimum and maximum condenser water setpoints were defined based on plant operators' recommendation and equipment capacity. The conventional setpoint is 22.22°C.

Two types of FDD algorithms are implemented in the tool. The first is the detection of cycling faults in the cooling tower fans and chiller compressors. The second is identifying efficiency faults in the chiller. The detection and diagnosis of chiller efficiency faults was developed and implemented in the development version of the tool, but was not included in the "live" version of the tool that was released to the site for day-to-day use in operations.

<u>*Cycling Faults*</u>

Tower fan cycling faults are detected using cooling tower variable frequency drive speed data while chiller cycling faults are detected using chiller compressor current data. For each five-minute time interval being analyzed during the period of interest, the algorithm counts the number of fan or chiller transitions from on to off, or off to on, that occur in the hour surrounding the time interval. If the number of transitions is excessive, a fault is flagged for that five-minute time interval.

Figure 4 illustrates that flagged faults are then aggregated into *faulty intervals* if they persist for at least 90 minutes. Multiple faulty intervals are aggregated into a *faulty period* if they occur within two hours of each other.

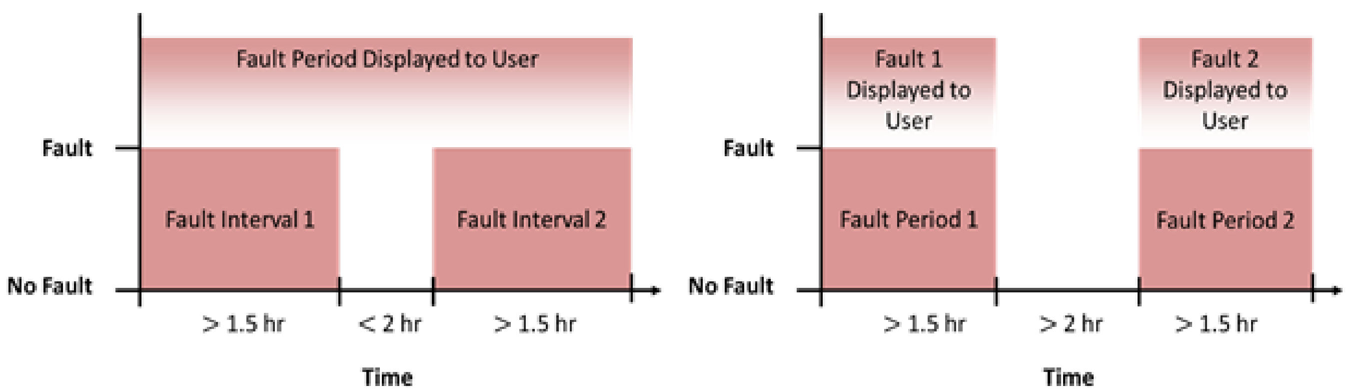

Figure 4. Fault Aggregation Algorithm.

A single faulty period is displayed to the user if two faulty intervals are within two hours (left). If the time interval is greater than two hours (right), two faulty periods are displayed.

Chiller Efficiency Faults

Poor chiller efficiency is determined by comparing model-predicted coefficient of performance (COP) with that estimated from measured data. Described in detail in Bonvini et al. (2014a and 2014b), the FDD algorithm is based on an advanced Bayesian nonlinear state estimation technique called Unscented Kalman Filtering (UKF) that estimates system states and parameters based on measured data and a model of the system (Julier and Uhlmann 1996). Detecting poor chiller efficiency for a given time period occurs by first identifying steady-state operating periods, then estimating a COP based on the data using the UKF, comparing the estimated value with the expected value from the model and flagging if faulty, and aggregating faulty intervals into faulty periods as described previously.

In the future, a clustering and decision tree analysis procedure could be implemented to provide further diagnostic insight. A procedure was developed to group detected faults based on the similarity of conditions under which they occur using k-means clustering. Once the clusters are identified, a human readable diagnostic message must be assigned, using a decision tree to determine the boundaries in the feature space that distinguish between regular and faulty data, and thus identify them. 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.

2.1.3 Architecture Definition

PlantInsight is written in Python 2.7, and consists of three main components: the Django web framework, the model simulation and optimization EstimationPy Python packages, and a PostgreSQL relational database. The Django web framework serves the web pages and API calls, runs the data update routines to calculate derived data points, runs the models, and runs the FDD/optimization algorithms. Within these algorithms, model simulations are run by Dymola dymosim files, optimizations are run by GenOpt, and FDD use EstimationPy. Dymola is a Modelica development, compiling, and simulation program; GenOpt, developed by LBNL, is an optimization tool for building energy simulation programs; and EstimationPy is a Python package, developed by LBNL and used for state and parameter estimation of dynamic systems that conform to the FMI standard.

The PlantInsight data originates from a Johnson Controls International (JCI) Historian database running Microsoft SQL Server located at the USNA site. A program was written in Java 8 to copy the data from the USNA SQL Server database to the PlantInsight PostgreSQL database, located at LBNL. The program was installed on an operator kiosk at USNA and scheduled to run daily at 8:00 AM PT. Automated routines on the PlantInsight system read in the new data, update its derived data points, run the models, run the FDD/optimization algorithms, then update the results on GUI.

2.1.4 GUI Development

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 integrated into the tool design and functionality is summarized in the following:

- *Add KPIs*: Primary chilled water loop temperature, and weather forecast are critical parameters tracked by the operations staff. Staff also requested that the tool-predicted plant load forecast be added to the interface.
- *Convert energy units to dollars*: While campus energy managers regularly track kilowatt-hours (kWh) and Btu, tons and dollars resonate more strongly with plant operations staff.
- *Limit the frequency of optimization*: The operations staff were not comfortable implementing changes more than once a day. In addition, if the savings are not significant (>1%), the conventional setpoint temperature is recommended.

Figure 5 shows the condenser water temperature setpoint optimization features in the tool. In the upper plot, the model-determined optimal setpoint is shown along with the (constant) conventional actual setpoint for the upcoming day. The forecasted wet bulb temperature is also plotted. In the lower plot, the actual measured power (orange) and the predicted power that would have been consumed under the model-determined optimal condenser water temperature setpoint (green) is shown.

Figure 6 contains a summary overview of tower fan and chiller cycling fault detection results during the time period of April 24–27, 2016. The red box indicates that tower fan cycling fault was detected in Rickover Tower 1 Cell A.

Figure 5. Screen Shots of the Condenser Water Temperature Setpoint Optimization Features in PlantInsight

(Top) Optimal and conventional condenser water setpoints with predicted wet bulb temperature. (Bottom) Measured and predicted optimal power.

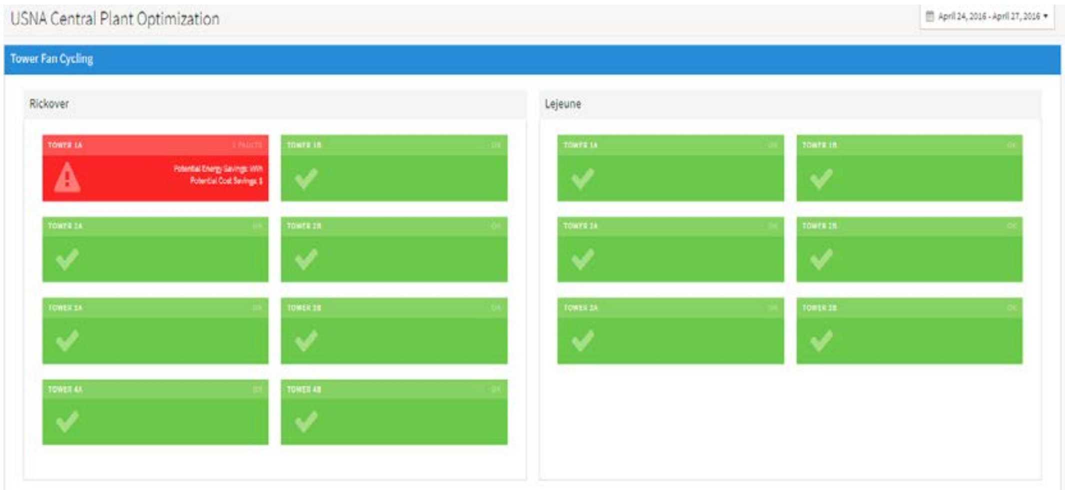

Figure 6. Screen Shot of the Cycling Fault Detection Results Overview in the PlantInsight Tool for a Time Period during which a Tower Fan Cycling Fault Was Detected

2.2 ADVANTAGES AND LIMITATIONS OF THE TECHNOLOGY/ METHODOLOGY

In assessing the advantages and limitations of the technology, we considered diagnostic and optimized control power, scalability, required expertise, maintainability, and contrast with approaches based purely on rule-based and data-driven techniques.

Diagnostic and optimized controls power: Physics-based techniques remain a compelling direction for the continuous commissioning, optimization, and FDD systems of the future. Users can compare how the system *should operate* to how it has operated in the past. Accordingly, knowledge of the underlying physics holds potential to enhance diagnostic power. Model-based approaches are critical in the delivery of *holistic* strategies for advanced, efficient building controls. The buildings industry is only beginning to deliver dynamic, anytime optimization. These capabilities will be needed in the buildings and energy supply systems of the future, and will require model-based representations of the underlying physics in the system.

Required expertise: 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. If components change, retrofits are made, or controls are modified, physical models may also require modification. It is possible to leverage reference models that provide a coarser 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 preexisting libraries. However, the models must then be adapted for use with specific diagnostic algorithms. Model calibration requires a specialized expertise in building modeling, and building science. In general, however, it can largely be conducted with data that are commonly available from building control systems.

Scalability and maintainability: Cost-effective integration of control system data into analytics tools remains a significant challenge whether model-based or data-driven approaches are employed. In practice, the cost and complexity often outweigh the benefits of the advanced analytics. Once the data are obtained, care must be taken to ensure that the models are being calibrated in a physically meaningful way. Auto-calibration routines are being developed and are beginning to be offered to the industry (Sanyal et al. 2014; Sun et al. 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. The questions of when to recalibrate and how to account for faults present in the calibration data are the subjects of ongoing research. Finally, one can consider the infrastructural aspects of delivering model-based approaches for use in 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 they provide.

3.0 PERFORMANCE OBJECTIVES

Table 1 below provides a summary of the demonstration performance objectives, metrics, data requirements, success criteria, and results.

Table 1. Performance Objectives

Performance Objective	Metric	Data Requirements	Success Criteria	Results
Quantitative Performance Objectives				
(1) Reduce Central Plant Electricity Use	Annual energy use, normalized for weather (kWh/year)	Plant energy data, and independent variables such as outside air temperature and relative humidity	At least 10% reduction compared to baseline cooling plant energy use	Objective achievable for ~6 months of the year
(2) Reduce Central Cooling Plant GHG Emissions	Equivalent carbon dioxide emissions (metric tons)	Metered energy use before and after the demonstration, and emissions factors	10% reduction compared to cooling plant baseline	Objective achievable for ~6 months of the year
(3) System Economics	Simple and discounted payback for technology use	Costs: sensor hardware, installation, model creation and calibration, electricity use, software maintenance, training, and time to use tool	Simple and discounted payback in less than 5 years	Objective met with simple and discounted paybacks of 1.4 years
(4) Central Plant Model Calibration	Difference between model prediction and measurement	Plant operational parameters, e.g., compressor status, flow rates, temperatures, weather, fan speed, etc.	Difference between model-predicted and measured parameters less than 10% for 90% of data points	Objective met for 3 of 6 chillers and 10 of 10 cooling tower cells
(5) Latency in Data Transfer Between Database and GUI	Latency (milliseconds)	Measured time to transfer data between the tool's components	Near-zero latency, in data transfer between GUI and database, i.e., <500 milliseconds	Objective superseded by Performance Objective 6
Qualitative Performance Objectives				
(6) User Satisfaction	Qualitative measures of satisfaction	Pre- and post-installation interviews with operators	Equal or improved satisfaction relative to existing operational tools	Objective met

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4.0 SITE DESCRIPTION

The technology demonstration was conducted at the USNA. The technology was implemented across the two central plants, Rickover and Lejeune, that serve the campus-wide chilled water loop.

4.1 FACILITY/SITE LOCATION AND OPERATIONS

The USNA is located in Annapolis Maryland, and therefore operates within mixed-humid American Society for Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) Climate Zone 4A. The cooling plant is split into two separate buildings, and serves a diverse set of buildings, including traditional office spaces, classrooms, libraries, gymnasiums, laboratories, a small data center, and other university buildings.

The plant is relatively new (constructed in 2006) and represents the current state of efficient design practice. The plant management staff uses the BAS to trend the standard operational parameters that are leveraged by the PlantInsight tool, and it contains a good degree of monitoring and measurement. USNA shares many common characteristics with other DoD installations.

4.2 FACILITY/SITE CONDITIONS

The Rickover plant, which is used for the majority of the year, contains two 1,250-ton chillers, one 2500-ton chiller, and four two-cell cooling towers. The Lejeune plant contains three 2,500-ton chillers, and three two-cell cooling towers.

Figure 7 shows images of the Lejeune cooling towers and one of the chillers. The 2,500-ton chillers at the plant have two compressors, while the 1,250-ton chillers have one compressor each. The central chilled water loop is operated in a primary/secondary pumping arrangement with each plant. Variable frequency drives are outfitted on each cooling tower fan and secondary chilled water loop pump. The plants use a JCI Metasys® BAS. USNA energy management staff report that the campus HVAC operates during typical “campus” operating hours but can run long hours to accommodate students during exam weeks or other high-activity times.

The primary loop pumps are operated as follows. Each pump is associated to a specific chiller and operates at nominal speed if the chiller is designated to turn on. One backup pump is available for chiller during operation. The pumps are staged based on minimum runtime. The secondary loop pumps each have variable frequency drives and are controlled to maintain the prescribed differential pressure setpoint across the campus loop. The condenser pumps are operated similarly to the primary pumps.

Figure 7. Lejeune Plant Cooling Towers (left), Chillers and Pump (right)

The cooling plant is operated to provide campus loop chilled water at 42°F ±2°F. Each plant is operated in a seasonal configuration. During winter months, only the Rickover plant provides cooling to the campus by running one of the two 1,250-ton chillers at a time, with one cooling tower. In non-winter mode, the two plants (Rickover and Lejeune) are operated to satisfy the cooling load requests. Once the load surpasses the capacity of the single 1,250-ton chiller, the Rickover 2,500-ton chiller begins to operate. When the load rises above the capacity of the 2,500-ton chiller, the 1,250-ton chiller with the lowest runtime commences operation. Upon continued rise of the cooling load above 3,750 tons, the operation is switched to the Lejeune plant. Personnel may decide to operate both plants simultaneously under certain circumstances. Finally, cooling towers are staged on/off according to minimum runtime and to maintain a nominal condenser water temperature of 72°F ±2°F (adjustable). Cooling tower fan speeds are modulated to maintain fine control of the setpoint. Note that this condenser water setpoint is the optimization variable of interest, as described in Section 2.

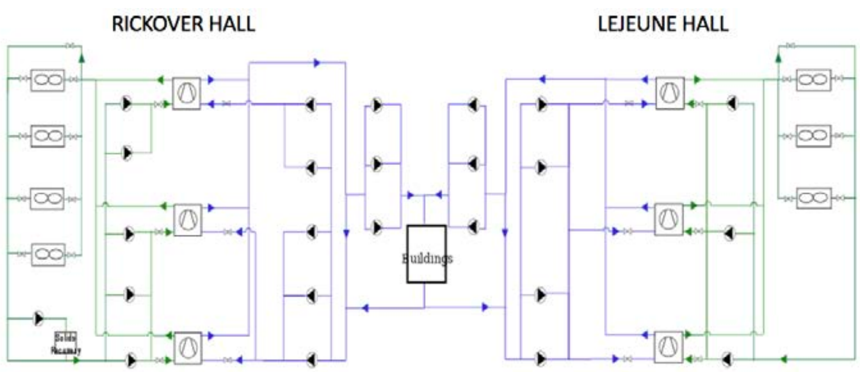

Figure 8. Configuration of the USNA Cooling Plants and the Chilled Water Loop

5.0 TEST DESIGN

5.1 CONCEPTUAL TEST DESIGN

The technology demonstration was conducted in three phases. First, design wireframes and an alpha version of the PlantInsight optimization and diagnostic tool was developed to obtain early design feedback. This alpha version interfaced with a static database of historical operational data. In the second phase, we connected operational data with a beta version of the tool and conducted troubleshooting and refinement. We vetted the diagnostic and optimization algorithms. In the third phase, we released the first version (v1) of the tool for operator use and began tracking its performance.

5.2 BASELINE CHARACTERIZATION

The technology demonstration evaluated three categories of performance objectives:

1. *System economics, energy and GHG reductions,* which require a rigorous quantitative baseline characterization.
2. *Model calibration* and *system latency,* which are absolute measures that do not require comparison relative to a baseline.
3. *User satisfaction,* which is a qualitative measure that was assessed relative to a baseline comprising the existing technologies used in by the operations staff, using a survey and interview instrument.

Baseline energy use and GHG emissions were characterized using measured cooling load at each plant, measured weather conditions at the site, and the conventional condenser water setpoint temperature of 22.2°C as inputs in the plant simulation models. The simulated electricity consumption of each plant includes chiller compressors and cooling tower fans. Baseline conditions for the evaluation of system economics are detailed in Section 7.

5.3 DESIGN AND LAYOUT OF TECHNOLOGY COMPONENTS

The primary components of the demonstration technology, PlantInsight, were described in Section 2 and illustrated in Figure 2. Data from meters and sensors at the USNA's two central cooling plants is stored locally in the JCI Microsoft SQL server. These data are accessed by operational staff through the "operator kiosk." The kiosk is located in a different facility on the USNA campus than either cooling plant. The PlantInsight tool is located on a server at LBNL, and accessible to USNA via web browser. Site data required for PlantInsight is pushed to LBNL using secure port 443 and a data transfer program installed on the kiosk.

5.4 OPERATIONAL TESTING

The phases and dates of development and operational testing are summarized below:

2012: Project launch at Washington Navy Yard (WNY); central plant information and data acquisition; Demonstration Plan development and approval.

2013: Early model development; integration plan to deliver PlantInsight through NDW's EnergyICT analytics system; demonstration site relocation due to WNY shooting incident.

2014: Update of Demonstration Plan to reflect new location; information and data gathering for new site; NDW recommendation to deliver PlantInsight through the IBM operational platform; wireframe mockups of PlantInsight delivered for early design testing and feedback.

2015–2016: NDW recommendation to untether PlantInsight from IBM platform; reassignment of GUI implementation and tool hosting to LBNL.

2016–2017: Alpha version released; troubleshooting to establish continuous data access from USNA to LBNL database; features update based on user feedback. Beta released with live data updates; iterative hardening and enhancement. Full-fledged in-situ operational testing including implementation of optimized setpoints recommended by the tool.

5.5 SAMPLING PROTOCOL

The data that were used for the development and operation of PlantInsight are summarized in Table 2.

Table 2. Summary of Data and Monitoring Points Used for Technology Development and Operation

Data Point	Sampling Frequency	Quantity	Data Source	Use of Data
Chiller compressor status	COV[1]	10	Metasys	Model calibration Fault detection and diagnosis
Chiller chilled water leaving temperature	5 min	6	Metasys	Model calibration Fault detection and diagnosis
Chiller chilled water entering temperature	5 min	6	Metasys	Model calibration Fault detection and diagnosis
Chiller chilled water leaving temperature setpoint	COV	6	Metasys	Model calibration
Chiller FLA[2] motor current	5 min	10	Metasys	Energy calculation Model calibration Fault detection and diagnosis
Chiller chilled water pressure difference	5 min	6	Metasys	Calculate chilled water flowrate for model calibration Fault detection and diagnosis
Chiller condenser water pressure difference	5 min	6	Metasys	Calculate chilled water flowrate for model calibration Fault detection and diagnosis
Cooling tower module status	COV	14	Metasys	Model calibration Fault detection and diagnosis
Cooling tower condenser water leaving temperature	5 min	14	Metasys	Model calibration Data quality check
Cooling tower condenser water entering temperature	5 min	14	Metasys	Model calibration Data quality check

Table 2. Summary of Data and Monitoring Points Used for Technology Development and Operation (Continued)

Data Point	Sampling Frequency	Quantity	Data Source	Use of Data
Cooling tower condenser water leaving temperature setpoint	5 min	2	Metasys	Model calibration CDW[3] setpoint optimization
Cooling tower module fan speed	5 min	14	Metasys	Model calibration
Cooling tower module electric power	5 min	14	Metasys	Energy calculation Model calibration Fault detection and diagnosis
Outside air dry bulb temperature	5 min	1	Metasys	Model calibration
Outside air relative humidity	5 min	1	Metasys	Model calibration
Primary loop chilled water leaving temperature	5 min	1	Metasys	Data quality check
Primary loop chilled water entering temperature	5 min	1	Metasys	Data quality check
Secondary loop chilled water leaving temperature	5 min	1	Metasys	Data quality check
Secondary loop chilled water entering temperature	5 min	1	Metasys	Data quality check
Forecasted outside air dry bulb temperature	Hourly	1	Weather underground	Load forecast CDW setpoint optimization
Forecasted outside air relative humidity	Hourly	1	Weather underground	Load forecast CDW[3] setpoint optimization

1 COV: change of value

2 FLA: full load amps

3 CDW: condenser water in cooling plant

The demonstration did not require addition of meters or sensors other than those already in place at the site. As such, demonstration-specific calibration beyond the site's standard calibration procedures was not conducted, except for the plant temperature sensors (which are critical to the models that underlie the PlantInsight tool). Data were cleaned using standard logic to remove outlier spikes and discard data for periods when values that should have been variable were observed to be constant, or "pinned." Quality assurance checks showed that among the twelve temperature sensors for six chillers, four temperature sensors had biased readings. The biases were corrected through a calculation within the PlantInsight tool. Analyses for the cooling tower condenser water leaving and entering temperature indicated that the cooling tower temperature sensors were producing accurate readings.

5.6 SAMPLING RESULTS

The figures in this section contain data plots for some of the most critical points used in operational testing. In Figures 9 and 10, operational data for Rickover Chiller 3 and Tower 4, respectively, are shown over a five-day period in spring. Figure 11 shows the implementation of the optimal condenser water setpoint, which was 10°F lower than the typical static setpoint otherwise used.

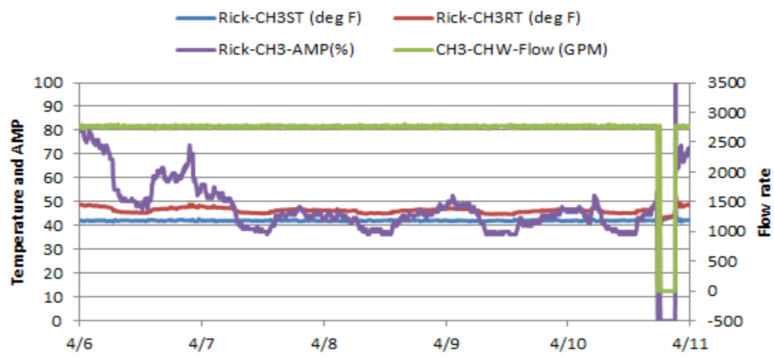

Figure 9. Operational Data for Rickover Chiller 3: April 6–10, 2017

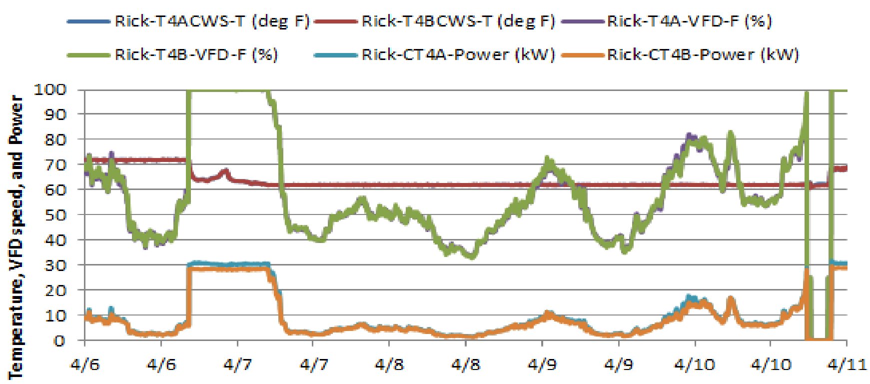

Figure 10. Operational Data for Rickover Tower 4: April 6–10, 2017

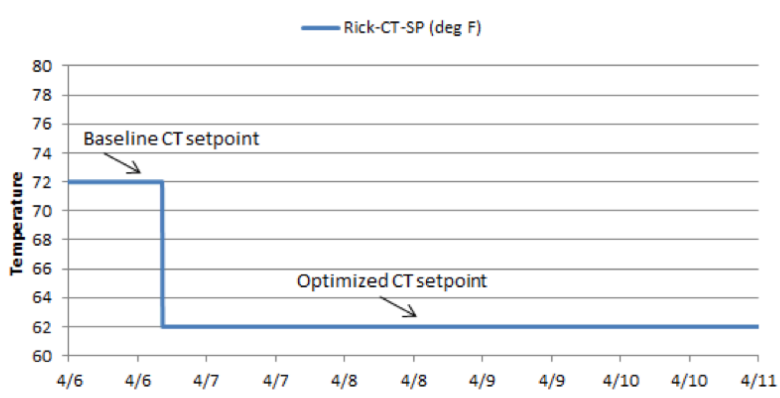

Figure 11. Rickover Cooling Tower Leaving Temperature Setpoint Changing Due to the Implementation of an Optimized Setpoint from April 6–10, 2017

6.0 PERFORMANCE ASSESSMENT

6.1 REDUCE CENTRAL PLANT ELECTRICITY USE

6.1.1 Procedure

To determine whether the 10% energy savings objective was met, a simulation analysis was conducted. For each plant, measured cooling load data and observed weather conditions were used by the optimization algorithm to determine the optimal condenser water setpoint for a given day. Once this setpoint was determined, the operation of each plant for the given day was simulated using the developed models twice—once with the optimized setpoint and once with the conventional setpoint. The conventional setpoint represents the baseline operation, while the optimized setpoint represents operation with the tool in use. This procedure was repeated every day for one year. The savings were taken as the difference between the total annual energy consumption simulated with baseline operation and that with optimized operation.

In addition to assessment of yearly energy savings with a simulation, real energy savings were analyzed using measured data from the site during the period during which plant operators implemented setpoints suggested by the PlantInsight tool.

6.1.2 Annual Simulation Results

The analysis indicated that daily energy savings of greater than 10% can be obtained for approximately six months of the year, mainly during the winter season. However, on an annual basis, across all 12 months of the year, obtainable annual energy savings were 1.38% (434,785 kWh, $30,435). Figure 12 (left) shows the absolute savings for the two plants as a total, for each day over the course of the year.

Figure 12 (right) shows the relative savings as a percentage of the baseline operation for each day. In total, the Rickover plant achieves greater than 10% energy savings 48% of the days of the year, while Lejeune does not achieve greater than 10% energy savings for any portion of the year. While relative savings during the winter can be as high as 30%, the total power consumption is low, and therefore the contribution to annual savings is too low to meet the annual 10% target.

Further analysis shows that savings potential is driven by outside wet bulb temperature in addition to the trade-off between cooling power and chiller power consumption. For Rickover, during the winter when savings potential is high, the optimal condenser water setpoint temperature is low due to low wet bulb temperatures, indicating that working the fans harder to achieve a lower condenser water temperature is worth the increase in chiller efficiency and lower chiller energy consumption. Meanwhile, in the summer, high wet bulb temperatures limit the ability for the cooling towers to lower the condensing temperature and provide any energy savings. For Lejeune, on days that provide a higher savings potential, the optimal condenser water setpoint temperature is high, indicating that working the fans less on those days is worth a slight loss in chiller efficiency. However, the savings in tower fan energy is relatively small compared to chiller power, and so the savings on the system is small.

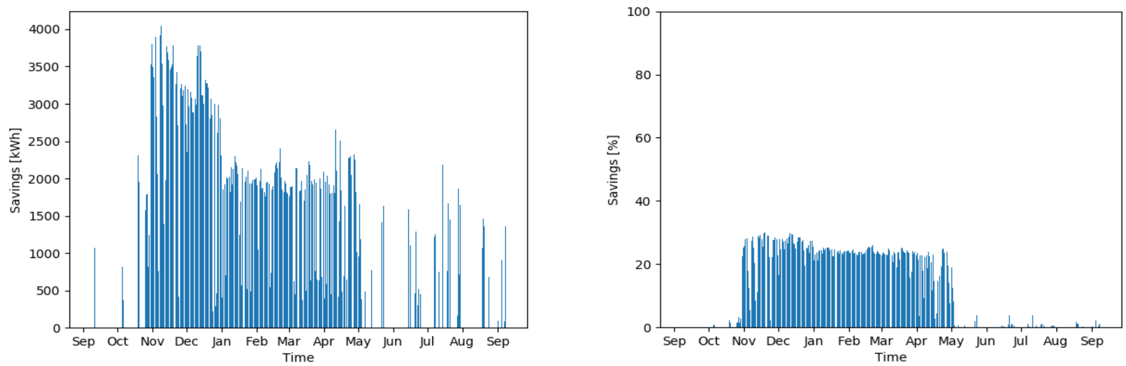

Figure 12. Simulated Daily Energy Savings from September 2014 through September 2015 (left: absolute value; right: relative)

6.1.3 Performance Assessment with Field Data

In addition to simulation, energy savings were evaluated using field testing data from before and after the implementation of optimal setpoints from April 7–10, 2017. Energy savings were determined by creating a baseline model of plant electricity consumption as a function of cooling load. The linear regression showed good fitness to the data, with an R^2 of 0.8, normalized mean bias error of 0.04%, and coefficient of variation of the root mean square error of 6%.

Although these results correspond to a short-term period of implementation, they serve to validate the simulation findings, which indicate comparable savings potential. Taken together, these analyses provide confidence in the assessment of demonstration performance objectives.

We also note that there is some flexibility in the overall system so that even imperfectly calibrated models for some chillers and towers can be used to strong effect to obtain savings relative to baseline practices. Figure 13 shows the savings results from projecting the baseline model to estimate the energy use that would have occurred during the test period had the optimized setpoints not been implemented. 17% savings were achieved over this four-day period, for a total of 5,436 kWh.

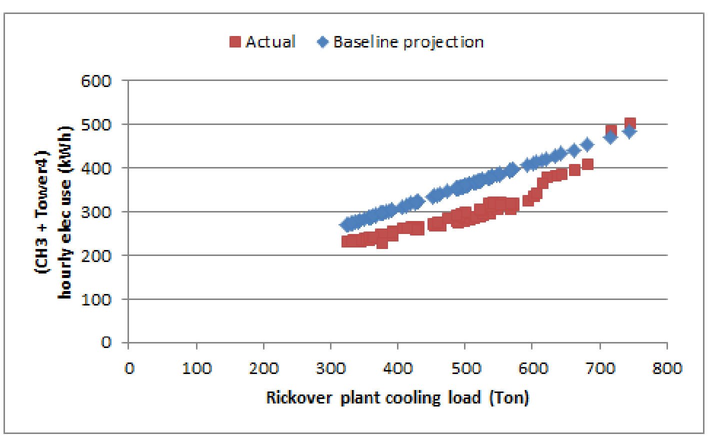

Figure 13. Actual vs. Baseline-predicted Energy Use (test period: April 7–10, 2017) during which 17% Energy Savings Were Quantified

6.2 REDUCE CENTRAL COOLING PLANT GREENHOUSE GAS EMISSIONS

The goal of this performance objective was to reduce the equivalent carbon dioxide emissions associated with the electricity used to run the central cooling plant over the course of one year (metric tons) by 10% with respect to baseline operations. Therefore, to analyze this performance objective, the procedure and findings in Section 6.1 were used with a conversion factor applied to estimate GHG emissions attributable to plant electricity consumption. With a single conversion factor applied (using Energy Star and eGRID [Emissions & Generation Resource Integrated Database]), the results of the analysis were the same as performance objective 6.1 in terms of percent savings. That is, greater than 10% daily savings were achieved for approximately six months of the year for the two-plant combined total. However, on an annual basis, achievable annual savings of 1.38% were achieved. This savings potential translates to 181,403 tons of cooling for the combined plant total.

6.3 SYSTEM ECONOMICS

The life-cycle cost analysis that was conducted to evaluate system economics is described in detail in Section 7.0. The analysis confirms that the demonstration technology can meet simple and discounted paybacks of 1.4 years, satisfying the five-year performance objective.

6.4 CENTRAL PLANT MODEL CALIBRATION

The performance objective associated with plant model calibration stipulated that the difference between model-predicted and measured parameters be less than 10% for 90% of data points. This objective was satisfied for three of six chillers, and for each of the ten cooling towers for which there was sufficient data.

For the three chillers that could not be calibrated to the performance objective, it is suspected that the causes were either a limited volume of data representing full-capacity operation, erroneous data, or faulted operations underlying the data. In the case of the cooling towers, four cells could not be calibrated because the necessary calibration parameters were not available or were erroneous from the measured data history at the site. Since the model structure for each of the cooling towers were equivalent, the calibration parameters for towers that were well-calibrated were applied to those for which calibration data were not available. The calibration parameters for chillers that were less well-calibrated were used in the chiller models, even though they were less than ideal with respect to the performance objective. Although measured data required to calibrate these three chillers was limited, we were able to leverage information from identical equipment on site that was calibrated, and thereby provide sufficient calibration across the board to meet the project objectives sufficiently to develop a credible tool whose predictions were consistent with user expectations.

Figures 14 and 15 contain selected examples of the calibration results for the chiller and cooling tower models. Figure 14 shows model-simulated versus measured COP for a case in which the performance objective was met, and for a case in which it was not met.

Figure 15 shows model-simulated versus measured cooling tower fan power and cooling tower leaving temperature, for one of the ten towers for which the performance objective was met.

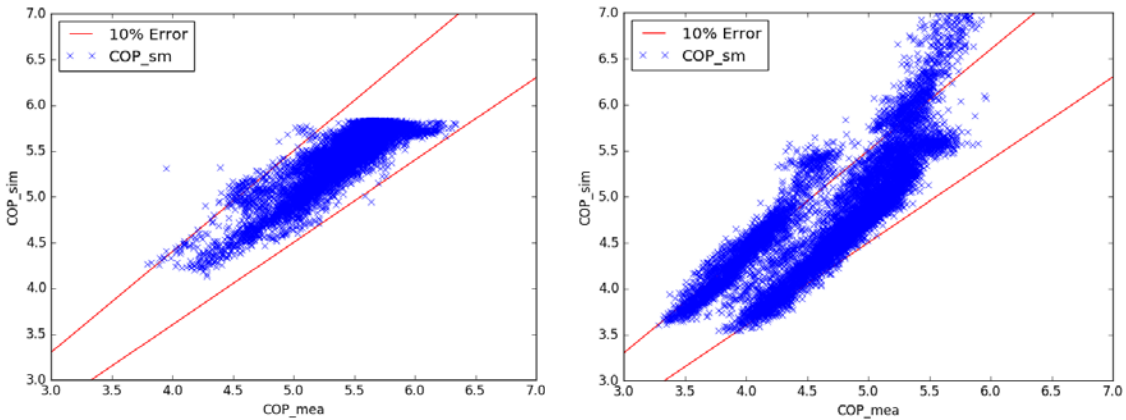

Figure 14. Comparison of Simulated and Measured Chiller COP for Chiller Lej-CH2, for which the Model Calibration Performance Objective Was Met (left,) and for Chiller Lej-CH3, for Which It Was Not Met (right)

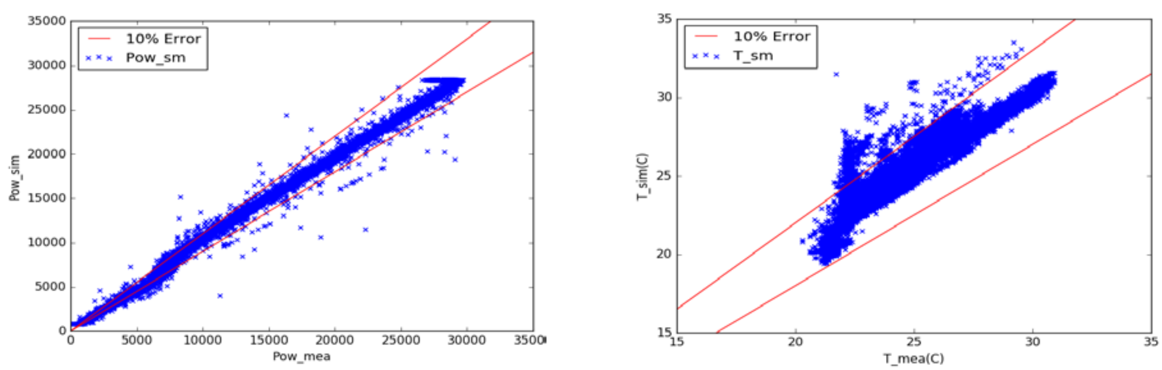

Figure 15. Comparison of Simulated (left) and Measured (right) Cooling Tower Fan Power and Cooling Tower Leaving Temperature for Tower Rick-T3A.

In both cases the model calibration performance objective was met.

Given that the majority of the models used in PlantInsight were able to be closely calibrated to the measured data from the site, the demonstration team was comfortable to incorporate the models into the PlantInsight tool. The assessment of the energy-savings performance objective confirmed that for key seasonal conditions (low wet bulb temperature), the model-derived optimized setpoints were indeed more efficient than the heuristic static setpoint typically used to operate the plant.

6.5 USER SATISFACTION

The criterion to provide equal or improved satisfaction relative to existing operational tools was satisfied. The two primary users of PlantInsight—the USNA central chilled water plant manager and the lead central plant operator—were interviewed and surveyed following release of the v1 version of the tool to USNA.

Overall, users reported that satisfaction with the capabilities of PlantInsight was equal to or better than that with the preexisting JCI Metasys system that is used for plant operations. Although PlantInsight is intended to complement (not replace) the Metasys system, from a user satisfaction standpoint, it provides a meaningful benchmark.

The capabilities of PlantInsight that were deemed most valuable are summarized in Table 3. Users were asked to select three to five capabilities from a list of eleven options. On the whole, users stated that the technology improved their ability to operate the plant more efficiently by identifying the load and energy impacts associated with changes in setpoints and equipment operations.

Table 3. User Feedback on the Three to Five Most Valuable Capabilities of PlantInsight

PlantInsight Capabilities	Highest Value to Plant Manager	Highest Value to Plant Operator
Visualization and plotting of plant load data	X	X
Visualization and plotting of efficiency curves (kw per ton vs. tons)	X	X
Quantification of plant energy consumption	X	
Quantification of plant utility/operational costs	X	
Weather forecasting	X	
Chiller runtime and energy use summary statistics		X
Optimization of central plant setpoints		X
Fan cycling fault detection		
Chiller cycling fault detection		
Quantification of cost of faults		
Central plant load forecasting		

On a scale of 1–5, with 3 being neutral and 5 being highly satisfied, the plant manager and lead operator rated the PlantInsight user interface, FDD and optimization outputs, and tool overall at a level 4.

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7.0 COST ASSESSMENT

7.1 COST MODEL

A cost model for PlantInsight is presented in Table 4. This cost model reflects estimated cost that would be required to implement the technology anew at a real site. All estimates are based on observations of team and partner experiences throughout the course of the demonstration.

Table 4. Summary of Demonstration Technology Cost Elements and Estimates

Cost Element	Description of Cost Element	Estimated Costs
Hardware Capital Costs	Cost of metering required to calibrate models and execute optimization and FDD algorithms	$18,000
Installation Costs	Labor to install and configure PlantInsight	$897
	Labor required to implement data export from BAS to PlantInsight	$897
	Labor to install flow meters	$6,435
	Labor to create and calibrate models	$8,372
Consumables	N/A	N/A
Facility Operational Costs	Annual plant energy used with PlantInsight optimized setpoints	$2,170,535/year
	Labor time to use the tool	$4,126/year
Maintenance	Labor to conduct software information technology (IT) maintenance	$1,077/year
	Labor to calibrate flow meters	$423 every five years
	Labor to update and recalibrate models	$8,416 every five years
Hardware Lifetime	Natural degradation flow meters over time	10 years
Operator Training	Staff time to learn how to use the software and become familiar with the interface	$423 every five years

7.2 COST DRIVERS

The most significant cost drivers for the demonstration technology are hardware capital and installation costs, engineering costs to create and calibrate models, and operators' time to use the tool. USNA has a modern well-instrumented central cooling plant that did not require the addition of supplementary hardware to monitor plant operational parameters. This may not be the case in other facilities. The cost model assumed that installation of chiller flow meters would be required; however, depending on the specific site, additional instrumentation could be required, introducing higher hardware and installation costs. Over time, as equipment and operations evolve, or for new installations, the models that underlie the tool's algorithms may require modification and calibration.

7.3 COST ANALYSIS AND COMPARISON

To model and run the cost analysis, we assume implementation of the technology in a large facility approximately equivalent to that of the USNA, which is served by multiple chillers, which may be split across several individual cooling plants. Hardware costs assume that, on average, six chiller flow meters may need to be added to provide the required data for the tool, and that those meters would need periodic calibration. Similarly, models may require periodic updating by an engineer. The National Institute of Standards and Technology (NIST) Building Life-Cycle Cost (BLCC) tool was used to conduct a comparative analysis between the demonstrated technology and the current approach. Since the energy savings potential is driven by climate (wet bulb temperatures), cost-effectiveness could increase in drier climates.

The following are the other assumptions used in the model:

- Project Life: 10 years (assuming the software has a shelf life of only 10 years and needs major overhaul after that time period)
- Salvage Value: $0
- Escalation Rates:
  - Assumed BLCC recommended rates for the energy rates
  - Assumed an inflation rate of 2% for operations and maintenance, repair, and other labor costs
- Assumed a discount rate of 3%, with a mid-year discounting
- The project will start performing from April 1, 2018. The period between April 1, 2017, and March 3, 2018, is considered to be the baseline period.

The following are the results of the cost-comparison analysis between the two options ("do nothing" and maintain current operations versus operate with PlantInsight):

- Savings-to-Investment Ratio: 7.21
- Adjusted Internal Rate of Return: 23.26%
- Simple Payback: 1.37 year
- Discounted Payback: 1.42 year

8.0 IMPLEMENTATION ISSUES

Future implementation of the technology concerns three pertinent areas: IT security, maintenance and evolution, and scale-up and transition. There are no regulations that apply to use of the technology. The only equipment that may be required for implementation may comprise additional off-the-shelf sensors or meters, as discussed in Section 7.

1. IT Security

The PlantInsight technology requires unidirectional transfer of cooling plant operational data *from* the site *to* the application's database. The application is hosted on a web server and is accessible via a web browser. In the USNA demonstration, port 443 was used to establish secure communications from the Metasys BAS Kiosk to the PlantInsight application; for ongoing use at USNA, PlantInsight could be ported to a USNA server.

To satisfy DoD IT security requirements, future installations can consider several options that surfaced over the duration of the demonstration. PlantInsight can be integrated within existing accredited applications, as was the original intent when the demonstration was first initiated at the WNY. Specifically, accreditation refers to compliance with the Risk Management Framework (RMF) for DoD IT, which has replaced DIACAP (DoD Information Assurance Certification and Accreditation Process). Alternatively, PlantInsight could be put through the accreditation process itself. Another option that was explored was to push plant operational data from USNA to a server farm on a secure Navy network, with PlantInsight accessing the data through a virtual private network (VPN). The third option that was explored was to leverage the "Enabler" data transport system that was under development by NDW at the time that the demonstration was being transferred from WNY to UNSA. The Enabler is no longer available for use, and if NDW decides to pursue implementation of the technology at additional installations, viable cyber security solutions will need to be identified.

2. Technology Maintenance and Evolution

As the demonstration comes to a conclusion, LBNL will work with UNSA IT to transfer the tool from LBNL's server to a server and location that will comply with IT security requirements. This is a key step in ensuring that the technology can continue to provide efficiency improvements to the chiller plant operations. Similarly, as the campus grows and cooling load is added, as plant equipment is updated, and as operations evolve over time, it will be necessary to update and recalibrate the models used in PlantInsight. Although it is not yet used universally throughout the industry, companies such as HOK, JCI, and United Technologies Corporation (UTC) have staff that are familiar with the modeling language (Modelica) upon which the tool is built. They could potentially be contracted to support future model modification and calibration.

3. Technology Scale-up and Transition

To make the PlantInsight Tool available to other DoD installations, it will be released through an open source software license. This will enable stand-alone use according to its current design, or adaptation for use within existing installation energy management facility and information systems as described in the considerations of IT security. Several types of documentation (for developers and implementers and for installation users) have been developed to support these future transition activities, and to support ongoing use at USNA.

In conclusion, future implementations of the technology will benefit from awareness of the following higher-level lessons that were learned throughout the course of the demonstration. First, operators place strong value on access to tools that provide visibility into how controls impact energy use and cost. This is not as a rule available in today's commercial analytics technologies that span BASs, meter analytics tools, or equipment-specific fault detection and diagnostics tools. As such, HVAC optimization technologies represent advances in the state of today's available technology, and this is even more true of optimization tools that incorporate physics-based modeling approaches. The Environmental Security Technology Certification Program (ESTCP) technology demonstration program has acted as a leader in the demonstration of these leading-edge solutions, and future implementations will continue to contribute to the state of knowledge of their development and application.

Model-predictive optimization, combined with fault detection and diagnostics, is recognized as a critical aspect of realizing the dynamic low-energy buildings of tomorrow, and today's applications can deliver even more impact from expanding the set of parameters that are included in the optimization, as well as the number of end uses that are considered. Although these technologies represent advanced forward-looking applications, the external infrastructure to support their delivery at scale is mature; cloud hosting and computational scalability are well supported through modern IT solutions. In contrast, the most significant practical implementation barriers are the brittle building data acquisition and communication systems that present chronic challenges to analytics applications that need to interface with controls data. Finally, we note that the creation and calibration of physics-based models that are intended to be used in the operational phase of the building life-cycle is highly dependent upon the specific algorithms with which they will be paired. The open, reference implementations that are delivered with PlantInsight are important contributions to industry's continued success in leveraging these promising approaches for next-generation building energy efficiency.

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