Management Studies, July-Aug. 2023, Vol. 11, No. 4, 185-201
doi: 10.17265/2328-2185/2023.04.001

An Approach to Optimize Multi-family Residence HVAC Systems Using Digitalization

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As mentioned by National Geographic (2017), 70% of world's population is expected to live in large apartment buildings by 2050. Today, buildings in cities generate 30% of world's greenhouse gas emission or GHG (National Geographic, 2017). Major urban centers are committed to reducing greenhouse gases by 80% by 2050 (IEA, 2021). However, achieving such goals in rental properties is not easy. Landlords are hesitant to use high-efficiency technologies because, typically, tenants pay the utilities bill. However, that situation is rapidly changing. For example, New York City like other US cities, is considering a carbon cap on all large buildings (Local Law 97, 2019). That means landlords will pay a carbon penalty if the building's carbon footprint exceeds certain threshold no matter who uses that carbon. The Pacific Northwest National Laboratory (PNNL) has received funds from DOE (US Department of Energy) with the collaboration of a commercial partner to address emerging energy efficiency market opportunity in multi-family or rental housing as discussed above. It has partnered with a large national real estate owner in order to test a novel energy optimization method at a rental property in Tempe, Arizona. By using a seamless-integrated method of acquiring building's operating data, the optimization approach essentially resets setpoints of different energy consuming equipment such as chillers, boilers, pumps, and fans. Data-driven optimization approach is pragmatic and easily transferrable to other buildings. The authors shall share the problem background, technical approach, and preliminary results.

Keywords: HVAC, optimization, IoT, digitalization, multi-family housing, commercial buildings

Introduction

With the rapid home price growth over the past years, more homebuyers are starting to consider the apartment rental market. This trend is highlighted by the National Multi-family Housing Council (NMHC) data, which shows a 35% increase in occupied housing stocks between 2006 and 2016 (NMHC, 2022). According to their report, apartments make up a substantial share of the housing stock, with that share being much higher in metropolitan areas. In fact, many of these large cities are increasing their efforts in reducing carbon or greenhouse gas emissions by 80% before 2050 (IEA, 2021). The NMHC provides an elaborated report where

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they estimate that there are about 17.5 million apartments with a central HVAC system in the U.S. alone. This paper describes a linear piecewise optimization approach for central HVAC systems that serves heating and cooling systems in high-rise multi-family housing or apartment buildings that are found in cities and urban centers.

The objective of this research project is to develop, prototype, and demonstrate low-cost optimization solutions that can lower the carbon footprint of the multi-family residences by simply optimizing the central HVAC System utilizing VOLTTRON (VOLTTRON, 2021) integration platform. Our current approach serves as an example to advance energy-saving technologies that are typically ignored because tenants typically pay for heating, cooling, and other utilities (NMHC, 2022). However, the market is rapidly changing due to a focus on avoiding carbon penalties and the evolving consciousness for decarbonization and sustainability.

The innovation of this approach resides in its pragmatic low-cost solution using real-time data, VOLTTRON as an integrated platform and IoT (internet of things) solution. Moreover, this paper describes the simplicity of the approach based on regression optimization methodologies that can be implemented on a cloud platform.

The implementation of this project can help the multi-family market to achieve decarbonization goals and avoid the carbon penalty. For instance, our commercialization analysis revealed that this proposed solution can roughly help New York City save about $870 million in energy cost and 5 million tons of carbon annually (EIA, 2022). Through data simulation, this linear piecewise regression approach was able to realize an average energy saving of 39% on the chilled water side and 38% on the cooling tower-side.

Nomenclature

ΔT_{chw} = chilled water temperature difference [°F]
ΔT_{ctw} = condenser water temperature difference [°F]
COP = coefficient of performance
$Net\ Refrigeration\ effect$ = heat removed from space [kWT]
P_{total} = total power input [kW]
$P_{ch,des}$ = chiller power design power [kW]
$P_{ct,des}$ = cooling tower design power [kW]
K_{pump} = chiller pump constant dependent on load
K_{Cpump} = condenser pump constant dependent on load
$K_{ctower_{fan}}$ = cooling tower constant dependent on load
$a_0,\ a_1,\ a_2,\ a_3,\ a_4,\ a_5$= chiller empirical coefficients
x = fractional loading of the chiller
y = ratio between measured differential water temperature and design value
z = ratio between calculated chiller power using Equation (2) and design power
P_{comp} = compressor power [kW]
P_{pump} = chiller pump power [kW]
P_{Cpump} = condenser pump power [kW]
P_{comp}= compressor power [kW]
$\Delta T_{chw\ opt}$ = optimal chilled water differential [°F]
$\Delta T_{ctw\ opt}$ = optimal condenser water differential [°F]

K_1, K_2 = load dependent constant coefficient
T_{chwr} = chilled water return temperature [°F]
T_{chws} = chilled water supply temperature [°F]
$T_{chws\,opt}$ = optimal chilled water supply temperature [°F]
$CHW\ Flow$ = valve's authority [%]
C = conversion constant
$Dload$ = design load [kW]

Theoretical Background

Previous literature revealed simple data driven models that are easy to implement and upgradable. Such models have been reported in literature as pragmatic ways to capture the energy performance of various HVAC system components (ASHRAE, 2019; Braun & Diderrich, 1990; Cascia, 2000). Equation (1) depicts the chiller performance equation and Equation (2) represent the total energy consumed by the HVAC system.

$$COP = \frac{NetRefrigerationEffect}{P_{comp} + P_{pump} + P_{Cpump} + P_{ctower_{fan}}} \tag{1}$$

$$\begin{gathered} P_{tatal} = P_{ch,des}(a_0 + a_1 x + a_2 x^2 + a_3 y + a_4 y^2 + a_5 xy) + \\ K_{pump}\left(\frac{1}{\Delta T_{chw}}\right)^3 + K_{fan}\left(\frac{1}{\Delta T_{chw}}\right)^3 \end{gathered} \tag{2}$$

Here, the power consumption characteristic equations of the different HVAC components are commonly expressed heuristically in a quadratic form. Typically, the total power can be represented as a function of two variables, x and y, where both are functions of the ΔT_{chw}.

Our goal is to optimize these equations to minimize the power consumption. To implement the equations in real time, we need to find those coefficients of the power equations. Our first approach was to use the multivariate and quadratic approach that was founded in literature. The coefficients are calculated by fitting Equation (2) and the measured data using a multivariate polynomial least-square regression technique. Typically, Equation (2) can be minimized using calculus of variation approach and the optimum set-point can be calculated using the Newton-Raphson method. However, this approach requires a first approximation which can be difficult to implement in real time. Taking Equation (2) first derivative as shown in Equation (3) and equating it to zero results in a fifth-degree polynomial for which the coefficients can be difficult to evaluate in real time. The Python language was used to first put the initial strategy from literature into practice. However, we discovered that when used with the VOLTTRON platform, the Newton-Raphson method requires a significant amount of computational time when applied in real time. Despite our efforts to solve Equation (3) in a computationally efficient manner (3), we took a simpler approach as described in Section 4.

$$\begin{aligned} &\frac{d(P_{total})}{d(\Delta T_{chw})} = \frac{\partial P_{total}}{\partial x}\cdot\frac{dx}{d(\Delta T_{chw})} + \frac{\partial P_{total}}{\partial y}\cdot\frac{dy}{d(\Delta T_{chw})} - 3\cdot\left(K_{pump} + K_{fan}\right) \\ &= P_{ch,des}\left[2a_2\left(\frac{CHWFlow}{C\cdot Dload}\right)^2 + 2a_5\left(\frac{CHWFlow}{C\cdot Dload}\right) + 2a_4\right]\Delta T_{chw}^5 \\ &+P_{ch,des}\left\{\begin{matrix}\left(\frac{CHWFlow}{C\cdot Dload}\right)[a_1 + a_5(T_{cwr} - T_{chwr})]a_3 + \\ 2a_4(T_{cwr} - T_{chwr})\end{matrix}\right\}\Delta T_{chw}^4 - 3\cdot\left(K_{pump} + K_{fan}\right) = 0 \end{aligned} \tag{3}$$

Test Site

The current project's test site is a multi-family housing property that is in Tempe, Arizona, USA. "Tides on South Mill or Solara at South Mill" is a large property owned by the FCP that is split into four quadrants. Each quadrant has roughly 130 apartments (FCP, 2021). The total floor area of each quadrant is about 94,000 sq. ft. The campus of Solara spreads over 27 acres. The mechanical system consists of a two-pipe system that runs chilled or hot water through individual Fan Coil Units depending upon the season. The fully configured and operational HVAC system has two 75 tons water cooled scroll chillers that provide chilled water to the apartments.

The condenser is cooled using a cooling tower where the fan pushes high velocity air and cools the condenser water that is supplied from the chiller. The gas-fired boiler will supply hot water when seasonal change-over will take place. Figure 1 shows the mechanical configuration of the site.

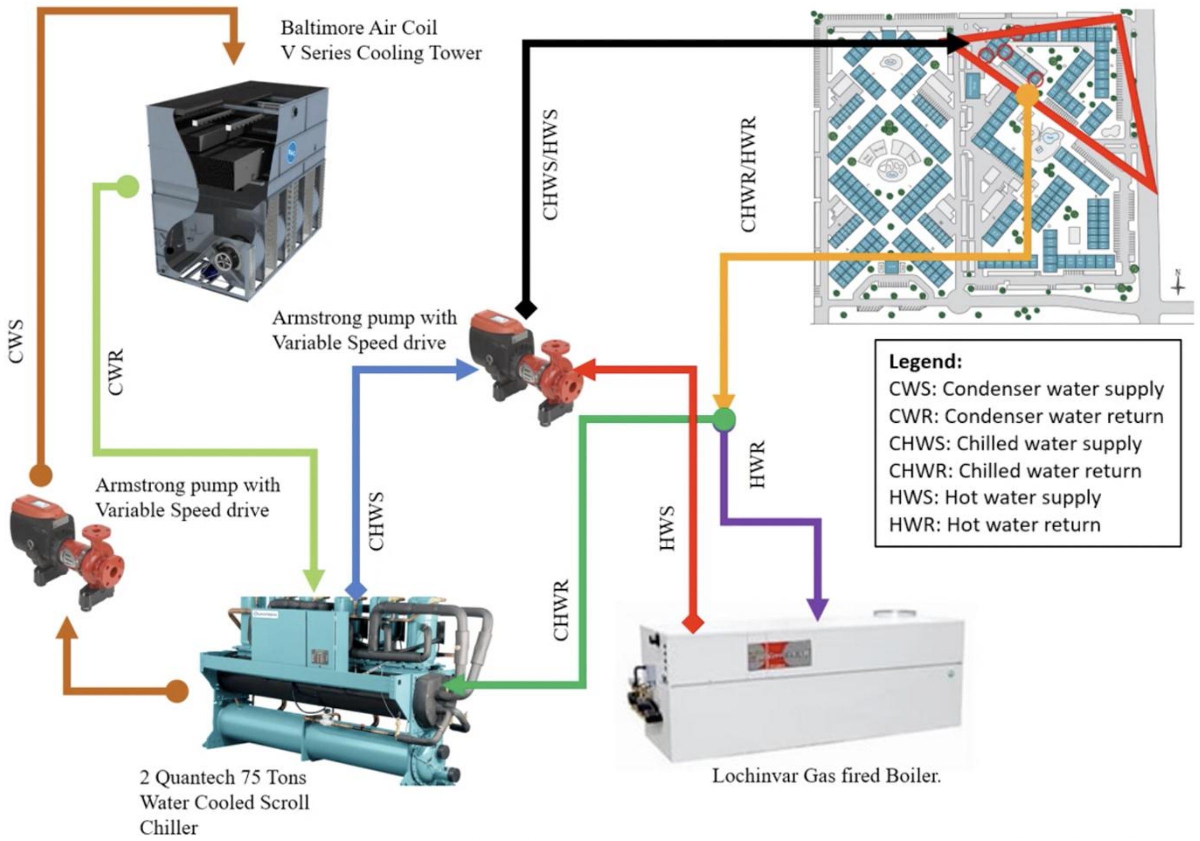

Figure 1. Power plant schematic at tides on South Mill.

Here, the central HVAC system is equipped with the latest equipment available on the market. This retrofit allows for an easy integration of the data pipeline and fast communication between the building management system (BMS) and the cloud.

For the cloud platform, our project utilizes VOLTTRON as a microcontroller to retrieve data from the IoT sensors located on the HVAC equipment. This approach is an improvement from existing products and custom tailored for advanced system optimization. Such optimization does not exist in the target market and is only offered where Building Management System is present in high-end commercial building markets, specialized facilities such as in life science, higher education, and healthcare markets.

VOLTTRON is a flexible, reliable, and scalable patented open-source platform for distributed control and sensing. It is particularly suitable for the industry. Developed at PNNL with funding from DOE, it is freely available for commercial enterprise to use. VOLTTRON uses agents-based architecture to connect devices and run applications. VOLTTRON serves as a single point of contact for interfacing with devices (rooftop units, building systems, meters, etc.), external resources, and platform services such as data archival and retrieval (VOLTTRON, 2021).

The ability to use low-cost hardware (Raspberry Pi, 2023) and software platform (Python, 2021) using open architecture of VOLTTRON makes the overall solution affordable, expandable, and flexible. Figure 2 shows a simple VOLTTRON architecture that connects many appliances and devices seamlessly.

Figure 2. Innovative approach using VOLTTRON (VOLTTRON, 2023).

Data Driven Analysis

Before we started assessing the performance data of the different power consuming components, we plotted the full range of data collected between 10/01/21 and 11/09/21 representative of the entire cooling season from our test site located in Arizona, Tempe. As seen in Figure 3 below, the data reveal that the power consuming components are operating at a very narrow range.

In fact, system pump, and condenser fan—all were operating at a constant speed although all this equipment has variable speed drives. Additionally, our analysis revealed some variability in power consumption profile of cooling tower fan but in a narrow operating range. Focusing on chiller power consumption data collected between October and November 2022, we found most of the operating values are very close to each other.

As a result, we decided to use a sample of the data to calculate *x*, *y*, and *z* using a python calibration script. Note that *x*, *y*, and *z* are defined in Section 2, Nomenclature. Once the calibration script scans the dataset file, the empirical coefficients from Equation (2) a_0, a_1, a_2, a_3, a_4, a_5, K_{pump}, and K_{fan}, are computed. The following results are obtained as shown in Table 1. As seen in Table 1, the coefficients a_2, a_4 are negative.

Additionally, a weak correlation coefficient $R^2 = 0.0499$ is obtained when the chiller model is a function of both cooling load and water temperature. This result can be explained due to the lack of variance in the water temperature data obtained from the site.

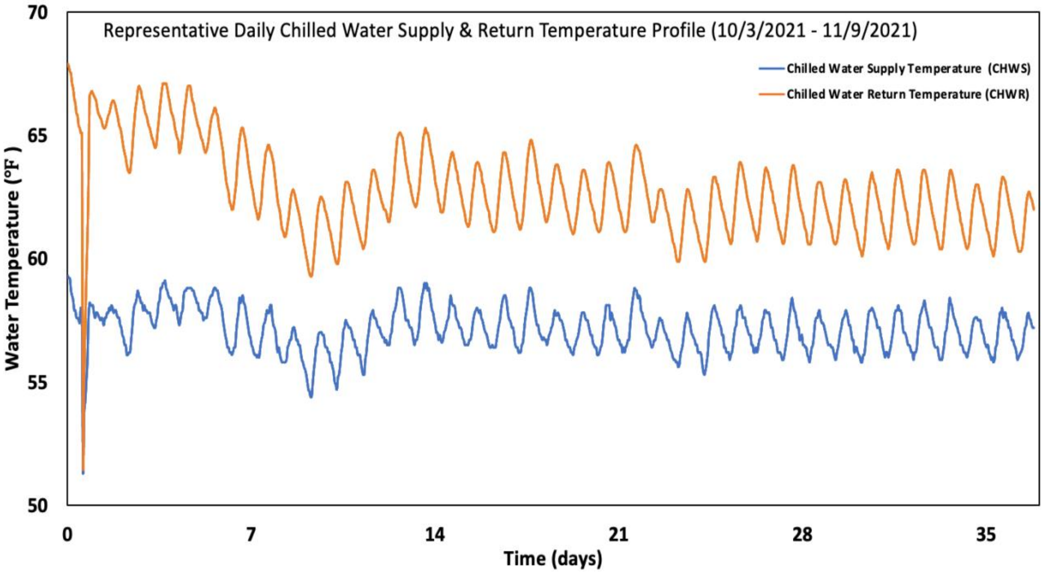

Figure 3. Chilled water temperature profile for chiller.

Table 1

Coefficient of Regression as a Function of Load and Temperature

Coefficient description	Calculated values
a_0	0.12436944
a_1	2.17256312
a_2	-0.4259924
a_3	0.36552359
a_4	-1.9205811
a_5	0.36971378

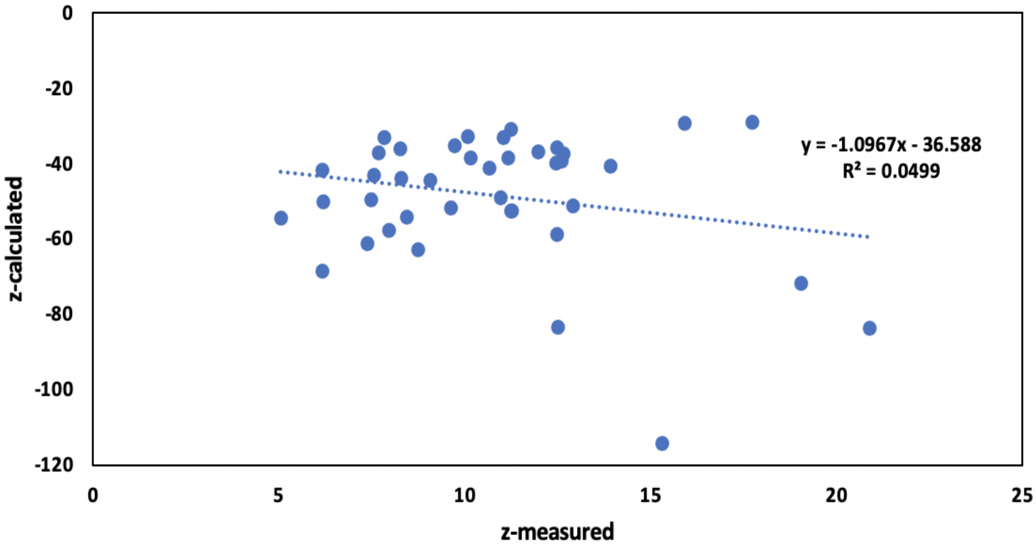

Figure 4. Chiller power calibration as a function of cooling load and water temperature.

Once this observation was made, we decided to check if the model can be improved by forcing the coefficient a_3, a_4, a_5 to zero. Equation (2) was rewritten as a function of cooling load making it a simple 2nd order polynomial where a_0 is the y-intercept, a_1 is multiplied to x and a_2 multiplied with x raised to the second power. Table 2 shows the coefficients calculated after running the calibration script. By modifying the chiller model as a quadratic function of cooling load, the correlation coefficient improved significantly with a value of $R^2 = 0.9117$. With limited data, we decided to use a simpler linear approach. Table 3 depicts the analytical results from the initial linear simulation. Figure 5 shows the daily cyclic variation in outdoor temperature during implementation.

Table 2

Coefficient of Regression as a Function of Load and Temperature Modified

Coefficient description	Calculated values
a_0	0.00478467
a_1	1.34861066
a_2	-2.3436457

Table 3

Error Between Calculated Power vs. Measured Power for Data in Figures

Analytical description	Initial linear model simulation	
	Chiller-side linear model	Condenser side linear model
% Error	0.1832129	0.40538974
RMSE	1.94279075	2.24660928
R-squared	0.9993	0.9977
Equation	$y = 1.355x - 5.6936$	$y = 1.6844x - 6.0443$

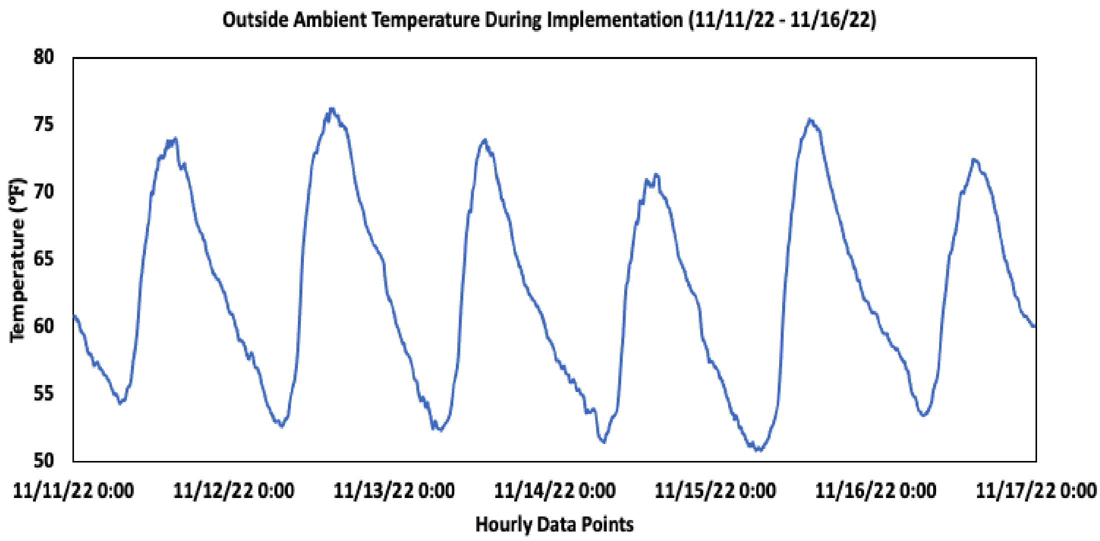

Figure 5. Outside temperature during implementation.

Grafana Cloud is the modular observability platform that integrates the HVAC system data (Grafana, 2023). Using this tool helps us access the best open-source observability software, such as Prometheus, Loki, and Tempo, without the hassle of installing, maintaining, and scaling our observability stack. Figure 6 depicts the dashboard of sample data collected.

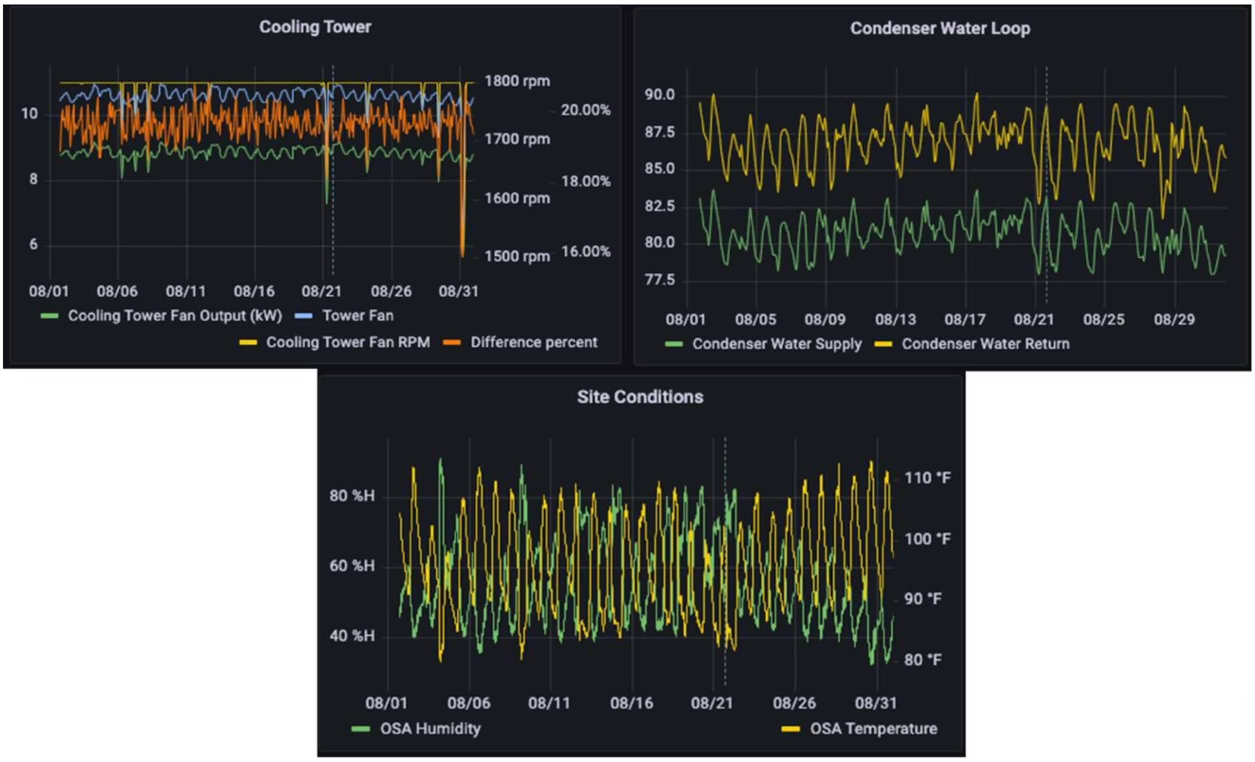

Figure 6. IoT software for data visualization (Graphana, 2021).

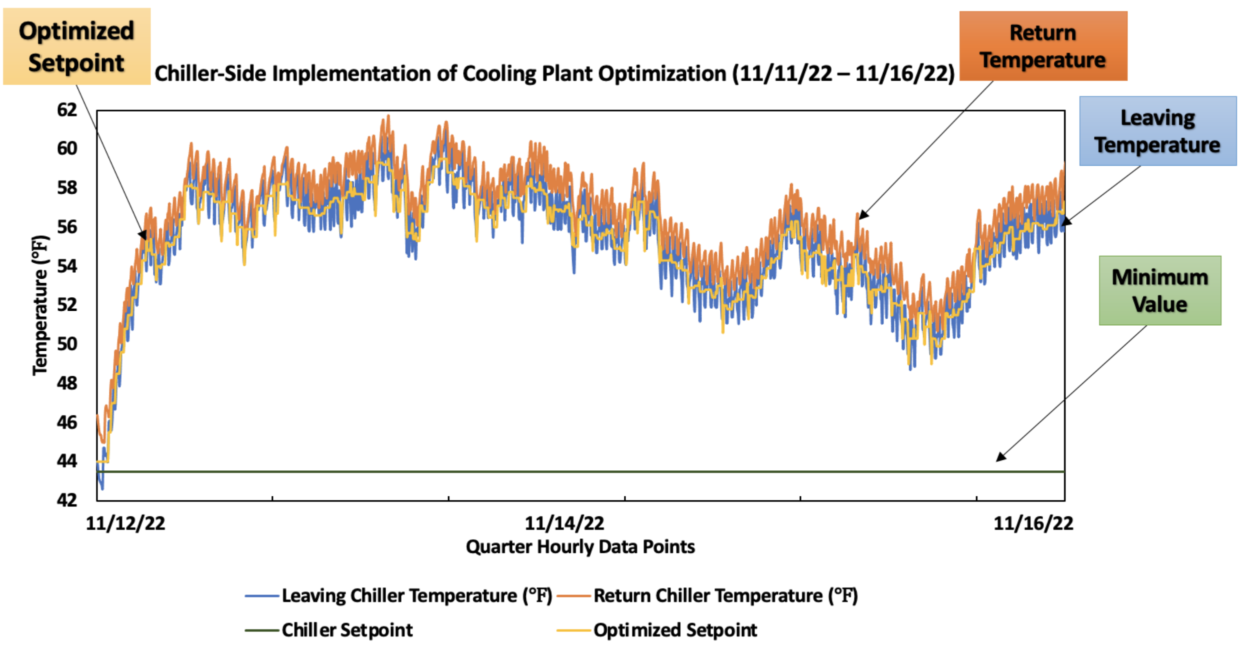

Figure 7. Implementation of cooling plant optimization on the chilled water side.

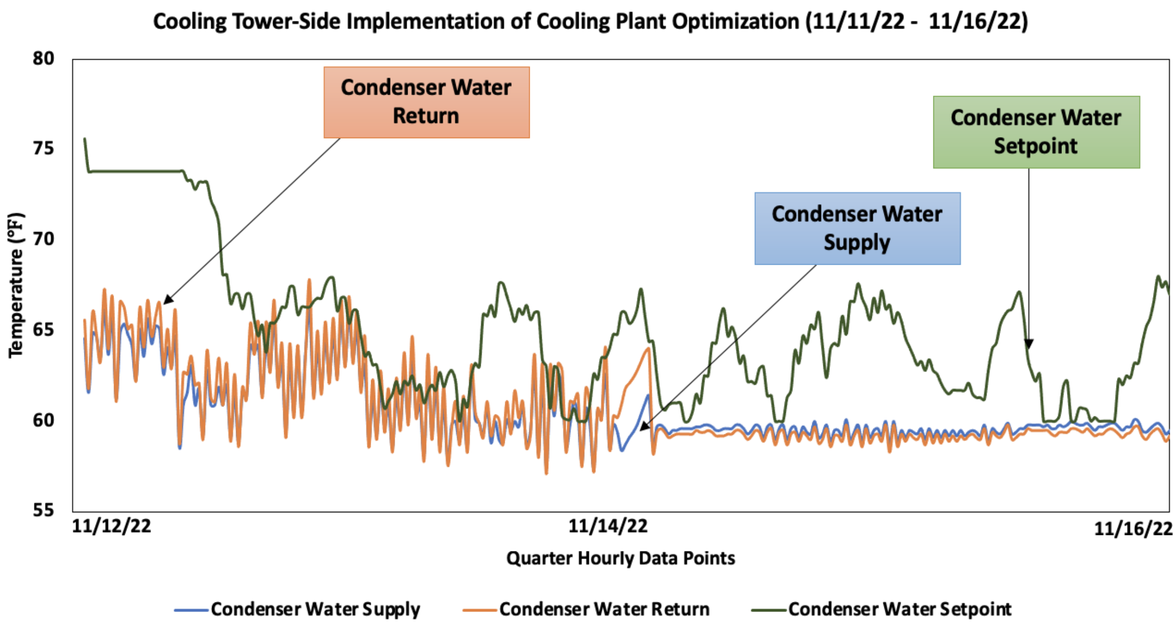

Figure 8. Implementation of cooling plant optimization on the cooling tower-side.

Figure 7 shows that cooling plant operates and tracks optimized setpoints well using linear regression. The optimized setpoints were successfully deployed at the test site from November 12th till November 16th.

In Figure 7, we can see that our optimized set points stayed well above the operational limits, as denoted by the green line. During this preliminary test, the optimization script was able to reset the setpoint every 15-20 minutes following the logic of our optimization algorithm. Based on a discussion with the plant operators, we have decided not to go below a minimum allowable value of 43.5 ℉. This observation is consistent with the leaving water setpoint in blue that is following closely the optimized setpoint determined by the BMS on the yellow line.

Similarly, Figure 8 shows that the condenser water supply or leaving water temperature is below the optimized setpoint. The differential between the optimized setpoint and the actual condenser water supply can be explained by the uncertainty factor of the sensors.

Further data analysis reveals that the data can be collected in different batches to ensure the power equations are properly calibrated. Thus, this approach can be implemented using weekly, monthly, and yearly data.

Methodology

Equations (4)-(12) show the derivation of our general linear regression model. The proposed linear optimization approach is based on the use of simple piecewise functions that can easily be applied in an algorithm to calculate and control the near optimal chilled water set points to minimize the cooling plant power consumption while satisfying cooling loads in the facility. This proposed approach allows the optimization script to re-calculate all coefficients used to characterize the HVAC system component models every 15 minutes. This piecewise linear optimization approach calculates the optimized chilled water temperature while assuming that the time constant for chilled water temperature is on the order of 15-20 minutes for quasi-steady load state. Additionally, it is assumed that the water's temperature is constant during the calculation of the optimal chilled water temperature due to loop control. This implies that to calculate the optimal set point, both the flow rate of chilled water through the cooling coil and the flow rate of air across the cooling coil must be constant over 15 minutes.

Mathematical Formulation

Two Python functions are developed implementing the linear model of the optimization approach. The mathematical formulation is shown in Equations (4)-(12). The optimal water setpoint is determined using Equation (8) on the water loop and Equation (12) on the condenser water loop.

Chilled water loop implementation. The first function implements the linear optimization algorithm on the chilled water side loop. Equations (4) and (5) show the linear power models used for this python function. The python code scans the measurement input data every 15-20 minutes to evaluate K_{comp} and K_{pump}.

- Input: chilled water supply, chilled water return, chiller power, system pump power.
- Output: optimal chilled water set-point or none when the setpoint is not optimal.

$$P_{comp} = K_{comp} \cdot \Delta T_{chw} \tag{4}$$

$$P_{pump} = K_{pump} \cdot \left(\frac{1}{\Delta T_{chw}}\right)^3 \tag{5}$$

$$P_{tot}(\Delta T_{chw}) = P_{comp} + P_{pump} \tag{6}$$

$$P_{tot}(\Delta T_{chw}) = K_{comp} \cdot \Delta T_{chw} + K_{pump} \cdot \left(\frac{1}{\Delta T_{chw}}\right)^3 \tag{7}$$

$$\frac{d(P_{tot})}{d(\Delta T_{chw})} = K_{comp} - \frac{3 \cdot K_{pump}}{\Delta T_{chw}{}^4} = 0$$

$$\therefore \Delta T_{chw\,opt} = \sqrt[4]{\frac{3 \cdot K_{pump}}{K_{comp}}} \tag{8}$$

$$T_{chwsopt} = T_{chwr} - \Delta T_{chwsopt} \tag{9}$$

Condenser water loop implementation. The second function implements the linear optimization algorithm on the cooling-tower water side loop which is a similar approach from the previous function.

- Input: condenser water supply, condenser water return, cooling tower fan power, condenser pump power.
- Output: optimal chilled water set-point or none when the setpoint is not optimal.

$$P_{tot}(\Delta T_{chw}) = P_{ctower\_fan} + P_{Cpump} \tag{10}$$

$$P_{tot}(\Delta T_{ctw}) = K_{ctower\_fan} \cdot \Delta T_{ctw} + K_{Cpump} \cdot \left(\frac{1}{\Delta T_{ctw}}\right)^3 \tag{11}$$

$$\frac{d(P_{tot})}{d(\Delta T_{ctw})} = K_{ctower\_fan} - \frac{3 \cdot K_{Cpump}}{\Delta T_{ctw}{}^4} = 0$$

$$\therefore \Delta T_{ctw\,opt} = \sqrt[4]{\frac{3 \cdot K_{Cpump}}{K_{ctower\_fan}}} \tag{12}$$

Open-source Python libraries such as NumPy, Scikit-learn, and Panda can be used to facilitate the data manipulation and computation (PNNL VOLTTRON, 2023). These tools, for instance, are open-source data manipulation and analysis tools that are quick, powerful, flexible, and simple to use on python. In this project, the library Matplotlib is utilized for further data visualization in collaboration with AceIoT engineers.

Integration Approach

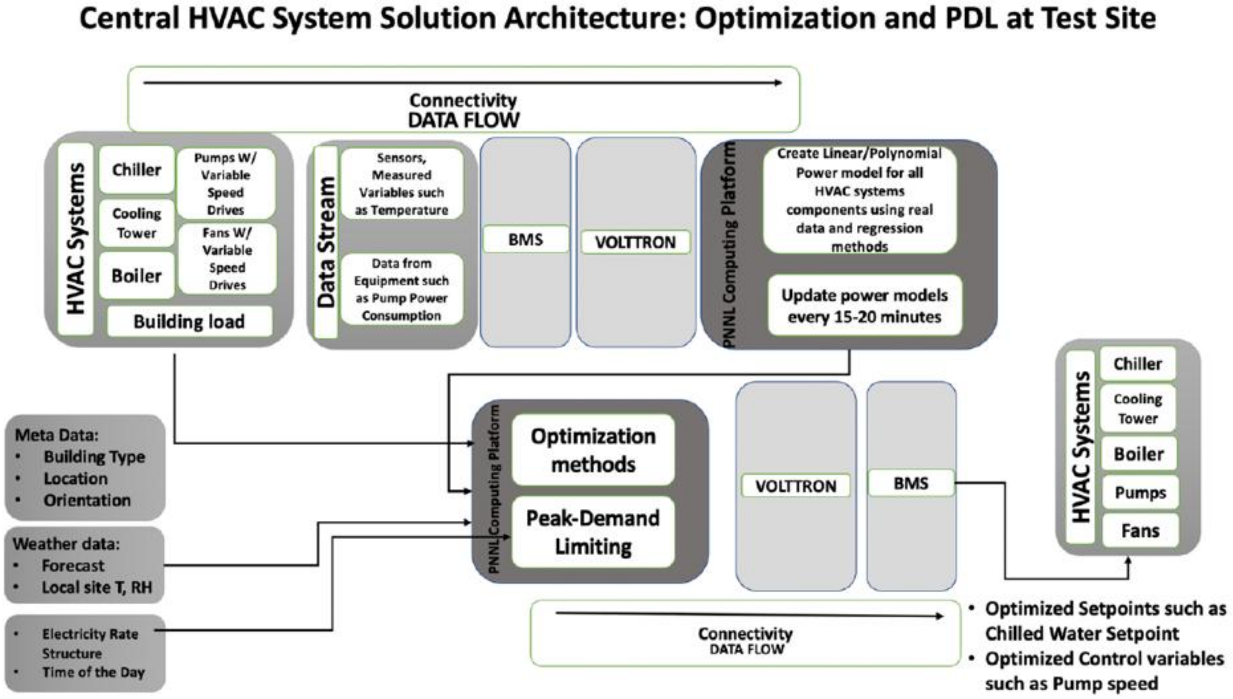

Figure 9. Solution architecture for central HVAC system configuration.

Figure 9 shows an overall solution architecture for optimization. The data from the central HVAC system are acquired by the Building Management System (BMS). It is then passed onto VOLTTRON that is connected to the PNNL computing platform. Once the optimization is done, the optimized set-points are then sent to mechanical system via VOLTTRON and BMS. This is only possible in real-time due to the availability of IoT platform and all the elements—from sensing to cloud platform—that seamlessly integrate using open and interoperable hardware, software, and communication protocols.

The data are then retrieved on a cloud platform for further processing to update power models. After the processing, the total system power is modeled mathematically as a sum of the cooling and heating plant component models. The mathematical models are re-evaluated every 15 to 20 minutes as load varies. Once the setpoints are determined, the results are then dispatched to VOLTTRON and ultimately, fed to the HVAC systems via BMS.

Figure 10 shows an overall network using Digitalization, where data flows using Ethernet5 and BACnet6 communications networks (VOLTTRON, 2023). This hybrid network essentially enables data communication among BAS, VOLTTRON, Energy Meter (EMON), and BMS front end. The BACnet network shows data flows across all the physical devices. For deployment in the target control system, the algorithm previously described was encapsulated in an Eclipse VOLTTRON agent and connected to the VOLTTRON System message bus.

As depicted by Figure 10, the VOLTTRON platform driver framework collects data from the process equipment and publishes it to the message bus every 5 minutes. The agent subscribes to the data topics necessary to calculate the optimal setpoint, collects data as it is published to the bus, ensures it has the correct, synchronized values from the equipment then calculates the optimal setpoint.

The optimal setpoint is then published back to a new topic on the VOLTTRON message bus, collected by the platform historian and forwarded to the cloud data system. Raw data collected from the process equipment are similarly collected and forwarded to the cloud platform, enabling correlation of actual process state with the optimized output.

If the *write_to_equip* configuration flag to the agent is set, on successful calculation of a new optimal setpoint, the agent will write the setpoint to the appropriate process controller. This setpoint is written through the VOLTTRON platform driver framework that includes controls that will revert the setpoint in the instance of a software issue, or a timeout of the setpoint.

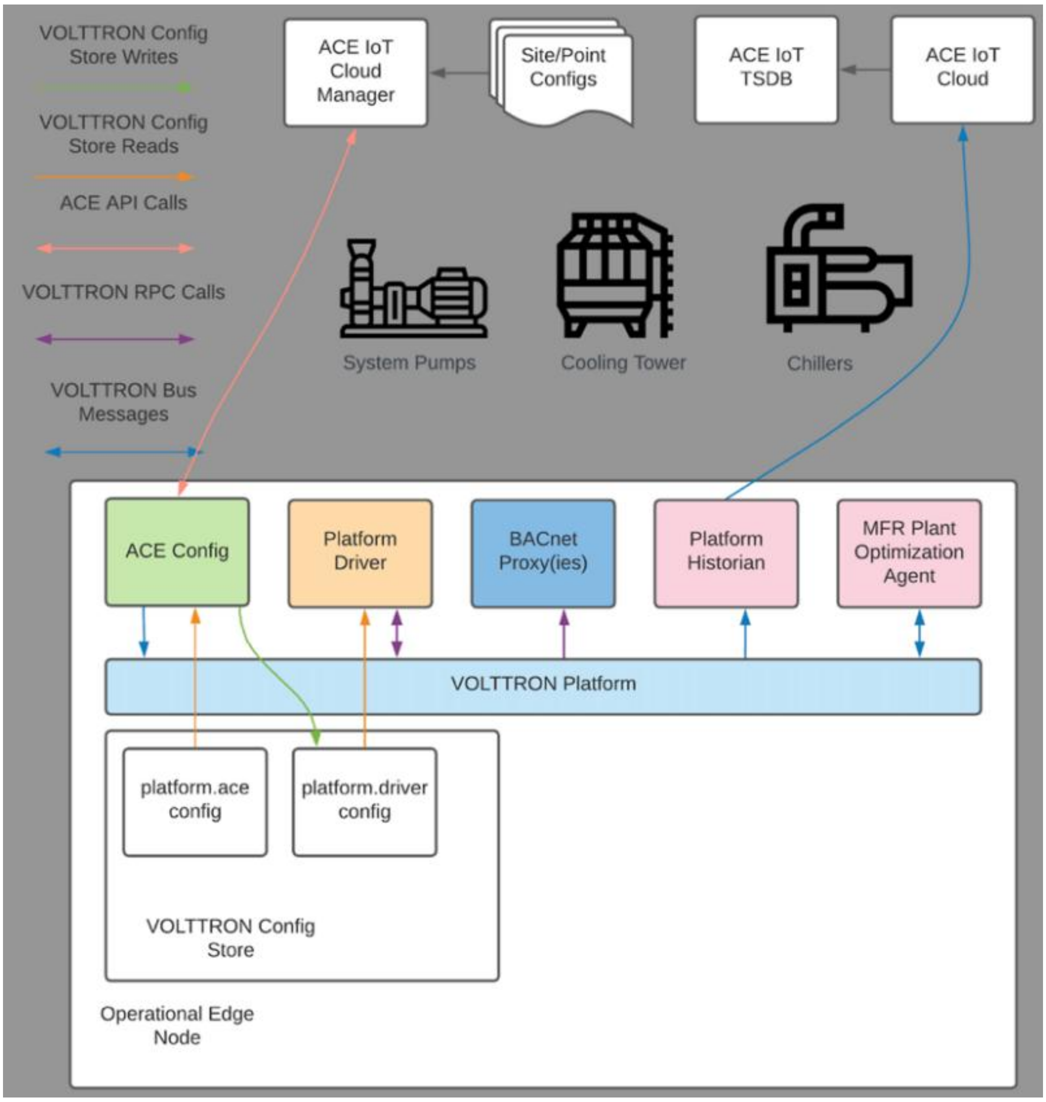

Figure 10. Implementation of VOLTTRON at test site.

Results and Discussions

First, we took a deeper look at the issue of data size that can be used for our regression approach. We could use short-term data, say daily or weekly or monthly or even the entire range of data collected during 2022 cooling season (May till October) and October of 2021. The data fit improved as more data are used. However, use of entire cooling season data did not increase computational time at all. Therefore, we decided to use entire seven-month data—from May till October in 2022 and October 2022—for linear regression. Tables 4 and 5 show the regression equations evaluated during our investigation using seven-month data.

Throughout the data monitoring phase of the project, various tests were conducted to validate the quality of the data. Moreover, the database history is constantly being monitored by the AceIoT with the help of PNNL scientists and engineers. This collaboration is important as it ensures that the sensors are well calibrated, and they can capture good data to calibrate the power models in real time. The next step of this project is to focus on the boiler power models during the winter season in Arizona.

Table 4

Chiller Side Regression Analysis

HVAC component	Regression analysis equation	Coefficient of determination
Chiller 1	$y = 6.2929x$	0.9325
Chiller 2	$y = 6.4475x$	0.7418
System pump	$y = 263.95x$	0.1933

Table 5

Cooling Tower Side Regression Analysis

HVAC component	Regression analysis equation	Coefficient of determination
Cooling tower fan	$y = 1.1933x$	0.1063
Condenser pump	$y = 38.241x$	0.1933

Table 4 shows that the correlation coefficient for Chiller 1 is the highest. We have maximum number of operating points available for this chiller. The operating points available for Chiller 2 is low and as a result, the correlation coefficient value reduced to about 0.75.

The coefficient values are even lower for the system pump, condenser fan, and condenser pump because all these equipment is running at constant speed and as a result, a very few diverse points are available for this equipment.

Using seven-month data, the linear regression approach, in calculating constants in Equations (7) and (11); was able to realize an average energy saving of 39% on the chilled water side and 38% on the cooling tower-side, respectively. These energy savings were calculated using the collected data from the months mentioned in Tables 6 and 7.

Table 6

Energy Savings on Chilled Water Loop

Months	Percentage energy savings (%)
October (2021)	17.0583614
May (2022)	36.54871076
June (2022)	32.21703369
July (2022)	36.5291076
August (2022)	39.34518858
September (2022)	53.9218332
October (2022)	28.97849067
Average	34.94262754

Table 7

Energy Savings on Tower-Side Water Loop

Months	Percentage energy savings (%)
October (2021)	4.08093406
May (2022)	13.23112433
June (2022)	50.4269472
July (2022)	58.90011747
August (2022)	66.73209178
September (2022)	55.40931465
October (2022)	17.85015101
Average	38.09009722

As seen from the data, this optimization approach has the potential to create great energy savings in the multi-family housing market where HVAC systems often run sub-optimally. It is important to note that this approach requires close collaboration with the owner and operator to monitor and validate the quality of the data.

Innovation Management for Commercialization

McKinsey and Company (2020) after spending much with energy companies who were engaged in digitalization transformation, suggested a framework that can get success. The framework is shown in Table 8. According to McKinsey, "After much experience in the trenches, we have developed a digital transformation journey that breaks the inertia, unlocks large-scale value, and lasts" (McKinsey, 2020). The optimization solution presented in this paper heavily relies on data and simple analytics but executed in real-time. Since digitalization broadly depends on data and analytics (Gartner, HBR), it is appropriate to use digitalization framework that is presented by McKinsey for the commercialization of optimization solution.

Three core elements or requirements of digitalization commercialization process are mentioned in the *y*-axis as value unlock, data and technology, and culture and capabilities or capacity. On the *x*-axis, six core elements of digitalization process are highlighted as roadmap, vision, MVP or minimum value product, industrialization or commercialization, scale and expansion, and platform. Table 8 shows various elements within digitalization requirements vs. process matrix that are self-explanatory. For example, McKinsey selected inventory technologies as a key ingredient as a vision for data and technology requirements.

Following McKinsey's example, a similar matrix was developed for commercialization of optimization solution. Here again, most of the matrix elements are self-explanatory but a few of them require elaboration as highlighted in Table 9.

Open Collaboration and Innovation

Intense collaboration is suggested with different potential real-estate companies, technology providers, investors, and even marketing companies, who can all work in a team environment with the sole focus on offering affordable decarbonization solutions in multi-family housing or large private apartments complex. Collaboration with public housing sectors at federal, state, and local government agencies is also highly recommended. The overall workflow shall create an eco-system through synergistic partnership and collaboration by adding values over the entire project life-cycle.

Table 8

Digitalization Framework for Commercialization

	Road map	Vision (by workflow)	MVP[1]	Industrialize	Scale and expand	Platform
Value unlock	**Define the end-to-end workflows** that drive the most value in the business ("needle movers")	**Reimagine future workflows** to get the most value	**Rapidly deploy initial products** to users to deliver value fast, generate learnings, and create a springboard	**Harden the MVPs** to make sure they will work in live operation at scale	**Realize full vision** by expanding beyond MVPs, reusing across business units, and building new products	**Establish a sustained digital factory** that is an engine of enabling digital for the enterprise
Data and technology	**Conduct rapid gap analysis** of tools and infrastructure	**Inventory key systems** of record and field, pilot, or planned technologies	**Institute basic best practices,** including API-first approach, rationalized tech stack across business units, automated security approvals	**Clean the code,** enabling scale-up **Institutionalize tech enablers** (eg, site reliability engineering)	**Create code libraries** for common needs, and instrument the code to enable performance analytics	**Create an API marketplace** that makes the reusable building blocks available to all for continuous innovation
Culture and capabilities	**Conduct rapid gap analysis** of digital and nondigital capabilities	**Engage** the most courageous, informed, creative leaders to own and shape the vision	**Catalyze frontline buy-in** from business units and create a forcing mechanism to simplify IT policies	**Establish user support** process and capabilities to ensure manageable scale-up	**Demonstrate the value** of sharing, standardization, and scale **Expand in-house talent** base	**Formalize the digital factory's** operating model and replicate it

Open Platform

An open platform for data and technology is recommended for cost-effective deployment, easy operation, and providing flexibility. The core of this platform is to deploy optimization algorithm in Python code and creating object models for all heating and cooling system and its components using standard Building Information Modeling (BIM) technologies. The open platform shall also use user-friendly graphical user interface where system can be configured, and object models will be created. The optimization application, written in Python Code, will be wrapped in a package with proper API. That way the optimization has easy plug-n-play feature and can be easily integrated with an external plug-in such as data curation software. In essence, the open platform shall provide interoperability and plug-n-play features that will have significant advantage of transferability of optimization solution from one site to the others.

Use of AI and Transfer Learning

An autonomous optimization can be envisioned that shall dramatically reduce the cost of deployment and operation and simplify the overall engineering process. For that, AI process needs to be developed. Data Driven Machine Learning Algorithm will essentially learn the pattern between the input variables such as outdoor temperature, cooling load, and output variable such as chilled water supply temperature setpoint. Once the pattern is learnt, another ML algorithm can be deployed for optimization. Since the entire approach is data-driven, the algorithm can be transferable from one site to another with some minor adaptation necessary to reflect change in system parameters such as capacity, types, location, etc.

Table 9

Digitalization Framework for Optimization Solution

Core elements	Roadmap	Vision	MVP	Industrialize	Scale & expand	Platform
Value	Open Collaboration & Innovation	Best value in optimization service	Low cost roof top units	Product durability	Expand to adjacent markets	End-2-end cloud process
Data & technology	Open platform	Use AI and transfer learning	Agility and value proposition	Clean code	Code libraries	API marketplace
Culture & capacity	Rapid development	Collaborative	Online service	User community group	Demonstrate value	Formalize process

Conclusions

This paper presents a novel approach for using digitalization to develop affordable and open-source intellectual property that will help building owners realize savings and lower carbon emission in the building sector.

The algorithm can be used to calculate near optimal setpoint for chilled water and condenser water setpoints temperature with a strategy that allows the BMS to actuate the HVAC components. Our experience tells that most critical component of our optimization approach is “Good Quality Data”. We found that overall IoT and VOLTTRON platforms have matured well and cost-effective but data must be monitored closely. In that respect, all sensors require annual calibration and even mechanical and electrical systems require a good “on-demand” service or maintenance plan. What is also important is a well-developed and documented technical document that qualifies a site, identifies the requirements, and assesses a site for its qualification for optimization. We also recommend for developing and implementing a simple configuration and commissioning plan. The range of savings generated in this “Proof of Concept” project is in the range of 25%-35% considering both heating and cooling plant optimizations. Although there is no guarantee that such savings can be achieved in general, the potential of such savings does exist in multi-family housing because the heating and cooling plants and distribution systems are not typically optimized. At the end, a brief commercialization framework plan has been discussed that can be implemented with special emphasis on collaborating with a diverse external companies and organization in order to create a valuable eco-system.

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