Data-driven evaluations of building operational settings: Lessons learned from the development of a user-focused tool

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Abstract

Building automation systems have created opportunities for energy saving in commercial buildings; however, these systems are typically not well designed for data analysis. To respond to this, tools for continuously monitoring and analysing building data are becoming increasingly popular. This work proposes a data-driven method to estimate the energy associated with equipment schedules; packaged into an interactive tool. We discuss this tool's role in a building operators' workflow, focusing on prioritizing short interaction time, metric transparency, and robust outputs. When applied to a case study office building, we found that even minor adjustments to equipment schedules provide a non-trivial effect on energy. For example, extending the weekday occupied mode operation from 5 pm to 8 pm would lead to an estimated 5% increase in annual energy use compared to current practices. This tool could be rapidly applied to building portfolios to understand how widespread changes to operation affect energy use.

Introduction

Building automation systems (BASs), also commonly referred to as building management systems, are becoming increasingly common in office buildings and have created a significant opportunity for energy-saving techniques. They monitor and control comfort through an array of sensors, including temperature, humidity, and CO_2, while improving energy through automation of energy-saving features and managing sequences of operations (Domingues et al., 2016). In addition, BASs are seen as a promising technology for collecting and analysing building data. Many building automation systems feature historical data logs for analysis and verification. However, the collection and analysis capabilities of the interfaces within BASs are typically limited. In many cases, historical trending needs to be set up manually, and simple features such as adding multiple data streams to a time series graph can be missing. Even when data is collected, there is a lack of integrated data analysis tools that would allow building operators to diagnose faults and optimize building operation (Balaji et al., 2016; Gunay, Shen, et al., 2019).

As a result of the increasing complexity of the technology within buildings and the lack of diagnostic tools, building operators, managers, and facility management companies no longer fully understand the operation of their buildings and are becoming increasingly reliant on controls technicians to operate the buildings they work on (Aune et al., 2009; Goulden & Spence, 2015). It is estimated that systems that are not properly installed, programmed, or operated increase energy use by 20% or more (Mills, 2011; Roth et al., 2004). As such, there is increasing attention to automated fault detections (Kim & Katipamula, 2018; Shi & O'Brien, 2019) and energy monitoring systems (Granderson & Lin, 2016; Piette et al., 2001).

Energy information systems (EISs), fault detection and diagnostics (FDD) systems, and other monitoring-based commissioning (MBCx) analytics are emerging to assist with efficient management and fault detection (Harris et al., 2018; Kramer et al., 2020). Broadly, MBCx refers to an ongoing commissioning process focusing on monitoring and analyzing building data (Kramer et al., 2020). Currently, these systems are separate from BASs and can be custom-built for internal use or contracted out to consulting companies; however, many in the industry have expressed that the features of MBCx should be built-in features of BASs (Balaji et al., 2016; Kramer et al., 2020).

When developing and implementing tools for building operators and facility management, it is important to not only consider the analytical techniques but also usability and human centred aspects. According to (Harris et al., 2018), challenges such as staff time and acceptance are some of the most commonly mentioned barriers to the MBCx implementation phase, along with the effective measurement and verification of energy savings. Researchers and industry should focus on both creating user-friendly apps while simultaneously considering organizational aspects and the individual needs of users. A popular way to address issues of acceptance is by using the technology acceptance model (Lee et al., 2003), which suggests that the use of a tool will depend primarily on perceived usefulness and perceived ease of use. Venkatesh & Bala (2008), expanded this model to understand the primary drivers that lead to technology acceptance, which is

referred to as TAM3. According to their framework, organizational and individual factors such as how a person believes the technology will be easy to use, subjective norms in the workplace, image (how the person believes using the technology will improve their status), and job relevance will affect the perceived usefulness of a tool. In addition, more tangible factors such as output quality and results demonstrability are also drivers of perceived usefulness. Meanwhile, Computer self-efficacy, computer anxiety, computer playfulness, and perceptions of external control inform people's initial impressions of the usability of new technology, while perceived enjoyment and objective usability can adjust the perception of perceived ease of use. The applicability of this framework for the tool discussed in this paper is further explored in the discussion.

This paper outlines a prototype of a tool geared to help building operators understand the impact of operational decisions of their buildings. As this is an early prototype, the tool focuses only on the impact of equipment schedules. We analyse this tool in the context of perceived usefulness and perceived ease of use. We demonstrate the technical features of the tool, make observations about the challenges of development, and plan for user testing. We frame this work as a discussion point to forward a conversation about developing robust data-driven models for operation and bringing additional focus to implementation and acceptance in the industry.

Methods

The user interface presented in this paper focuses on the timing of building-level equipment schedules. We targeted these schedules because they can be inferred by high-level building data, meaning that this technique can be easily applied to multiple buildings. Furthermore, equipment schedules are some of the most impactful building-saving measures controlled by the BAS (Fadzli Haniff et al., 2013). In this context, equipment schedules refer to the automated adjustment of settings or switching off building equipment to reduce energy when the building is assumed to be unoccupied. This tool has three main features (1) Based on a prescribed schedule; the tool will train and visualize a simple piecewise function that captures the energy impact of the equipment schedule, (2) if the user is unaware of the equipment schedule, the tool can infer the schedule from the energy use data, and (3) the impact on energy of adjusting the schedule is estimated. A use case for this tool is tested on a case study building in Ottawa, Canada.

As part of a broader project this research fits into, we performed in-depth individual interviews with 11 building management professionals from two facility management companies. One of these companies manages the building used as a case study for this tool. The details of these interviews will be expanded on in a future publication but were also used to inform the development of this tool. In these interviews, we found the energy management tools used by the companies are primarily focused on targeting buildings for major retrofits and for recognizing anomalies in energy, with few tools focused on the effective operation of buildings. Currently, the building technicians who respond to complaints within buildings have no means to understand the energy implications of their control decisions.

Piecewise change point model

Changepoint models are a common method of benchmarking building performance. They are constructed based on piecewise linear regression models correlating building energy and outdoor air temperature (Yin et al., 2019). Their commonplace comes from their robustness and interpretability. While more advanced techniques may achieve higher accuracy (e.g., temporal neural networks), black-box approaches can be challenging to understand by users (Afroz et al., 2021) and, in some cases, may lead to a lack of trust in the outputs of the tools. Changepoint models are defined as the number of slopes and breaks, as shown in Figure 1. For example, a three-parameter change point model has one sloped line (e.g., representing heating) and one breakpoint representing the baseload. A three and four-parameter model is typically used when the building is equipped with only a heating or cooling system, or when the heating and cooling energy can be captured by two data sources (e.g., when natural gas is used for heating and electricity is used for cooling). Finally, a five-parameter change point model captures the effects of both heating and cooling. Benchmarking tools utilize these seasonal trends to quantify energy associated with heating, cooling, and base load energy.

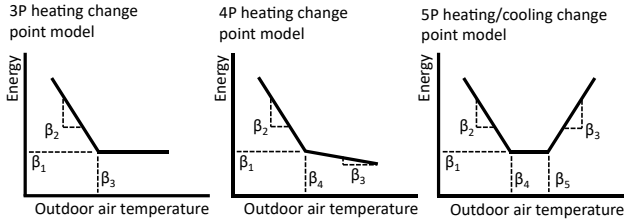

Figure 1- Examples of change point models comparing energy with outdoor air temperature.

To quantify the equipment schedule's effect on energy, energy data is separated into when the equipment can be considered in "occupied mode" compared to "unoccupied mode". While these schedules are often labelled "occupied" and "unoccupied," they are not adaptive to occupancy but instead have prescribed timings within the BAS. Therefore, the times when the building is in each mode can easily be separated using the prescribed schedule. A change-point model was fit to both operation modes, and the differences between the models were used to quantify the energy impact of the equipment schedules.

Fitting of the piecewise linear function used in this research was achieved using the pwlf python package (Jekel & Venter, 2019). This function applies least squares regression

to determine the piecewise linear function and differential evolution for the global optimization to locate the breakpoints.

Model Performance

The performance of the piecewise linear model was assessed using the coefficient of variation of the root mean squared error (CV(RMSE)), and the normalized mean biased error (NMBE). These metrics are recommended by ASHRAE Guideline 14 (2014), which was designed to develop minimum requirements to assess the impact of retrofits. Based on the *Whole-Building Calibrated Simulation Performance Path*, when calibrating using hourly data, models with a CV(RMSE) of less than 30% and a NMBE of less than 10% is considered to have acceptable predictive capabilities for assessing energy upgrades. These performance guidelines are intended to be used on calibrated energy models and for which the guideline has explicit requirements for the energy models capabilities. Therefore, the applicability of these metrics on the piecewise linear models described in this paper is limited. Nonetheless, they still provide some guidance on acceptable model performance for assessing energy upgrades.

Automatic Schedule Detection

Rather than prescribing a schedule, the schedule can be determined based on the energy data. The purpose of this feature is two-fold (1) the user of this tool may have several buildings in their portfolio and may not know the exact schedule of the building they are modelling, and (2) many buildings function with programming errors, so there may be cases where the true schedule may be different from what a user expects (Gunay, Ouf, et al., 2019; Roth et al., 2004).

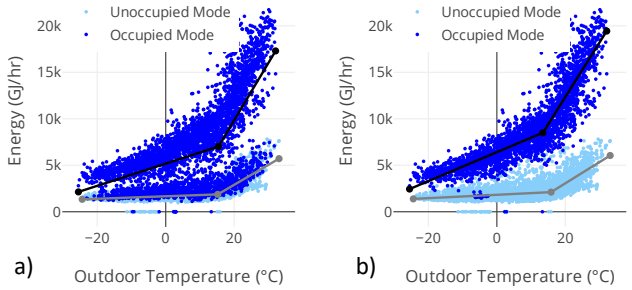

Figure 2 - Examples of piecewise modelling to identify the correct equipment schedule. (a) the occupied and unoccupied modes are incorrectly prescribed, leading to poor separation of data and a higher RMSE. (b) the correct schedule is specified, and the resulting model has a lower RMSE.

To automatically detect the schedule, every possible time series separation of data (e.g., assume the equipment schedule is 6-17, then 6-18, etc.) is tested. A piecewise linear model is generated for both the on-schedule and off-schedule data, and the aggregated root mean squared error (RMSE) is calculated for that model. After iterating through all possible equipment occupied/unoccupied schedules, the model with the lowest RMSE is assumed to be the correct equipment schedule. An example of two separations on the same dataset is shown in Figure 2. In Figure 2b, a schedule of 4 am to 9 pm is being used to separate the data. As shown, many data points where the system seems to be working in unoccupied mode is being categorized as occupied mode. The resulting model is therefore likely to have a larger RMSE than the correct categorization. In Figure 2b, the correct schedule is specified (from 5 am to 5 pm). The RMSE for the correct model is significantly lower, and therefore the program will identify the one on the right as more likely to be the correct equipment schedule.

Energy estimation

The equipment schedules' impact on energy was estimated by applying the occupied model and the unoccupied model at the appropriate hours of the day based on the equipment schedule. The outdoor air temperatures used in the calculation were a typical meteorological year (TMY) collected from the National Renewable Energy Laboratory (NREL) (2020). This calculation is shown in equation (1).

$$\sum f_{occ}(OAT_{occ}) + \sum f_{unocc}(OAT_{unocc}) = Total\ Energy \quad (1)$$

f_{occ} and f_{unocc} represent the trained piecewise functions based on the occupied and unoccupied hours, respectively. While OAT_{occ} and OAT_{unocc} is an array of outdoor air temperatures representing all occupied and unoccupied hours for a typical meteorological year. To estimate the energy impact of any proposed schedule, the outdoor air temperatures are recategorized based on that proposed schedule, and the total energy is calculated using the revised dataset.

Using the tool

The features described above were packaged into a user-focused tool. The purpose of this tool is to allow users to investigate the impacts of making changes to schedules in their buildings. The typical workflow is shown in Figure 3.

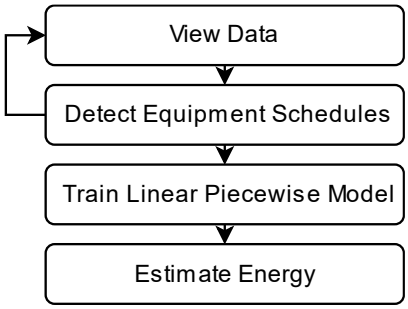

Figure 3 - Workflow of tool use

View Data*:* This is not a core capability of the tool but instead supports users in understanding their input data. By clicking on the *view data* item on the left side navigation menu, users can view hourly time series data for all years in which building data is available. This feature could be useful for users interested in visually inspecting the prevalence of equipment schedules and outliers in data.

Find schedule*:* By going to the *find and model schedule* button on the navigation bar. Users can select the building and year for modelling. Typically, it would be best to use the most recent year; however, the user may be interested in a previous year instead. One example would be if the user was interested in operation before changes were made due to COVID-19. After the year is selected, the user can use the *automatically detect schedules* button to separate the data. The determined equipment schedule will display for the user, and the user can manually fine-tune the schedule based on their knowledge of the building. If the user notices something that looks unusual, they can return to the view data page to access the raw time-series data. An example of this interface is shown in Figure 5.

Train Model: Once the user is satisfied that the schedule, they defined is a good representation of operations, the *accept schedule and train model* button can be used to train the linear piecewise model. Once trained, the model will appear on the graph for the user to inspect.

Estimate energy*:* The user then can navigate to the *estimate energy* tab where they will be presented with three bar charts, one for each utility uses. The user can adjust the proposed building schedule slider to the proposed schedule and view the impacts of this change. A summary is presented to the user below of the effect of this change. An example of this interface is shown in Figure 4.

Usability

Incorporating usability frameworks into the development of MBCx is an important aspect of tool development. Below are some usability considerations we made when developing the tool described in this paper. A more systematic framework combined with user testing will be developed in future iterations.

Robust and visualized modelling: A primary focus of this tool is transparency and interactivity. Users are presented with visual representations of the training data along with the piecewise linear function. Users can also view the time-series data to understand the datasets better. In the TAM3 model, result demonstrability is defined as "The degree to which an individual believes that the results of using a system are tangible, observable, and communicable." Therefore, it affects the perceived usefulness of the tool (Venkatesh & Bala, 2008). The goal of an interactive modelling process is to increase the trust and, therefore, the user's belief in the tangible results of the model.

Speed of use: The modelling process proposed by this tool is intended to be quick – a user can model and investigate the impact of equipment schedules with the clicks of two buttons. According to Harris et al. (2018), staff time was the second most mentioned barrier in the implementation phase of MBCx tools.

Focus on workflows: The TAM3 model suggests that job relevance, "The degree to which an individual believes that the target system is applicable to their job," is important for perceived usefulness. This tool aims to address a particular

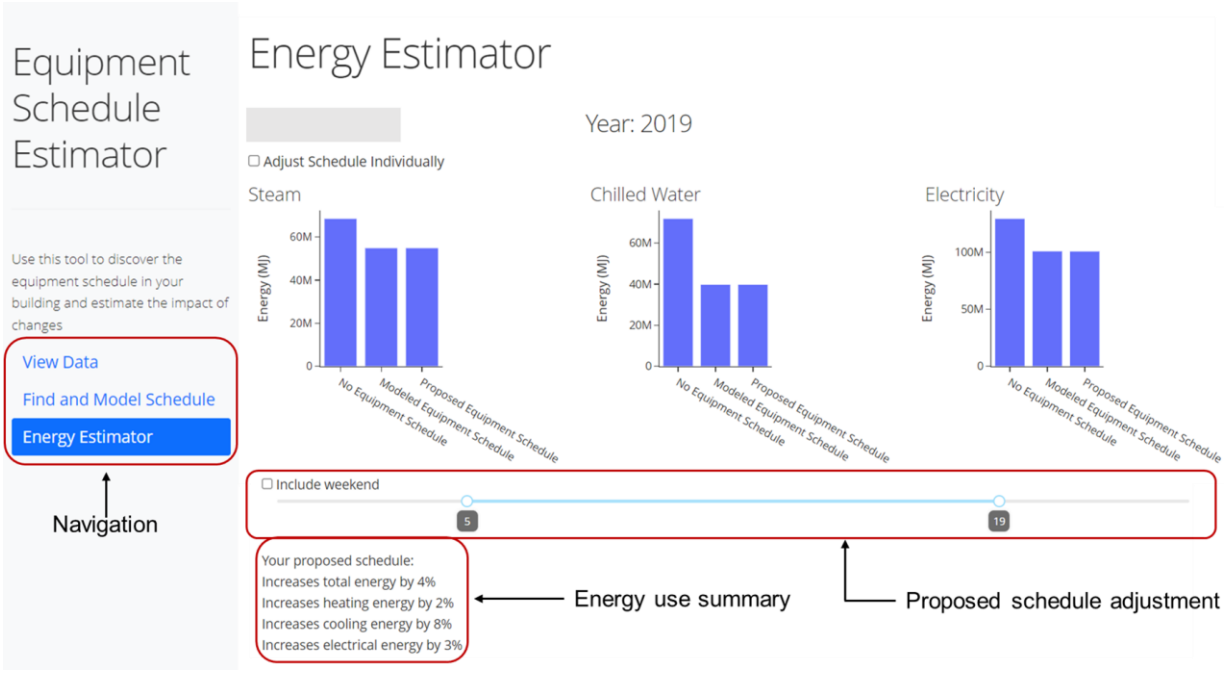

Figure 4 - Dashboard for interactively adjusting schedules

workflow. That is, if an operator is interested in changing a schedule, they can use this tool to understand the impact of that change. This conceptual workflow was developed by the authors of this project to design this prototype. However, A better understanding of the roles within FM companies is vital for designing future tools for specific workflows.

Interactivity and usability: The TAM3 model suggests that individual factors such as computer self-efficacy, computer anxiety, and computer playfulness can be relieved by perceived enjoyment and objective usability (Venkatesh & Bala, 2008). This tool was designed to be easy to use and interactive for the user, allowing for the real-time manipulation and data visualization. As mentioned with the focus on workflows, these aspects of design were considered on a conceptual level by the authors of this paper. In general, interface design should incorporate user testing and rapid prototyping of different methods to measure objective usability.

Case study building

The results presented in this paper are based on a case study building located in Ottawa, Ontario. The floor area of the building is approximately 150,000 square meters and primarily functions as an office building, but also contains ground level commercial space, a small data centre, and underground parking. Because it is primarily an office building, schedules observed in the energy data represent typical weekday office hours.

This case study building was connected to a district heating system that supplied both steam and chilled water as a service. The utility data for steam energy, chilled water energy, and electricity usage was recorded by meters and available over several years of building operation; between January 2017 and September 2020.

All three utilities were modeled individually. A four-point (two-line segment) change-point model was used for cooling and heating energy, while a three-line segment model was used for electricity. Using the standard naming convention described above, this would be considered a six-point change point model; however, this model is not considered standard in the literature. This three-line segment model was chosen due to the discontinuity observed in electricity use. Since electricity is not strictly dependent on outdoor air temperature and, in some cases, changes throughout the year, a two-line segment change-point model can capture discontinuities in dependency on outdoor air temperature. This will be discussed further in the results section.

Results

Detected schedules

The automatically detected schedules and their impact on energy is shown in Table 1. Equipment schedules have a significant impact on energy in this building. The savings were calculated by comparing the energy consumed assuming the current schedule with the energy consumed if no schedule was applied (using the TMY weather file). In all cases, the schedules are assumed to be Monday to Friday, with no occupancy on weekends. This building operates in unoccupied mode over the weekend; however, to increase the generalizability of this tool, detecting weekend equipment schedules will be a future implementation.

The start and end of the equipment schedule remained constant throughout the four years, except a one-hour change from 6 am to 5 am for steam energy. On average, the equipment schedules in this building saved 38% for chilled water, 20% for steam, and 22% for electricity. Notably, chilled water savings decrease significantly in 2020, likely as a result of changes to operational strategies due to COVID-19. However, the same changes were not observed in heating as the work from home order occurred in March of 2020, after the heating season, and data is only available until September of 2020.

Table 1: Detected schedule, model performance, and schedule impact between 2017 and 2020. 2020 Data is only available to September 2020. Equipment schedules are assumed to be Monday-Friday.

Year	Schedule Start	Schedule End	CV(RMSE) (%)	Savings* (%)
Steam				
2017	6 am	5 pm	31%	18%
2018	6 am	5 pm	28%	19%
2019	5 am	5 pm	28%	20%
2020	5 am	5 pm	39%	23%
Chilled Water				
2017	5 am	5 pm	27%	42%
2018	5 am	5 pm	28%	42%
2019	5 am	5 pm	25%	45%
2020	5 am	5 pm	23%	23%
Electricity				
2017	6 am	6 pm	9%	24%
2018	6 am	6 pm	30%	25%
2019	6 am	6 pm	17%	21%
2020	6 am	6 pm	15%	19%

** Savings are measured compared to if no schedule was in place*

The 2019 equipment schedules and fitted models are shown as they would appear on the dashboard in Figure 5. Comparing the steam and chilled water, the chilled water energy has a more apparent separation of data than steam energy. Nonetheless, both graphs demonstrate a high level of interpretability to a well-trained user.

Because this model simplifies the building energy use to only a function of outdoor air temperature and equipment schedule, the model will not fully capture building performance. Nonetheless, the NMBE was less than 1% for

all the trained models and in nearly all cases, the CV(RMSE) was close to, or less than 30%. The only notable exception is the model trained on the 2020 steam data, which has a CV(RMSE) of 39%. It is possible that this poorer performance may be attributed to the limited data available for the year, or changes to occupancy as a result of COVID-19. These results marginally meet the standards of ASHRAE Guideline 14 (2014) and provide reasonable credibility to the predictive capabilities of these models.

There is an observable discontinuity of electricity usage, which is somewhat correlated with outdoor temperature. For this reason, a three-line segment piecewise function was used to model electricity energy, as it models a continuous interpretation of this discontinuity. The reason for this sudden change of energy is related to a seasonal change in electricity usage – with a discrete jump in usage increasing in the cooling season and decreasing in the heating season. This trend, however, was not reflected in every year. The reason for this is unknown, and a follow-up with the building operator is planned to clarify this intricacy of the building's performance.

Energy Impact of schedule adjustments

The final step of using the tool allows users to scenario test adjustments made to the equipment schedule. The data presented in this section is for 2019, the most recent year in which a full year of data is available and before the strategy shifted significantly due to COVID-19. Figure 6 shows the impact of adjusting the equipment schedule from unoccupied to occupied at the end of the day. The change in energy is zero at 17h for heating and cooling and 18h for electricity based on the current schedule. If the user is proposing the schedule be extended to 8 pm, this would lead to an 11.5% increase in energy associated with chilled water, 3% for steam, and 2.5% for electricity (5% total energy). As a building total, each hour added to the weekday schedule amounts to 1.8% increase in total energy with similar impacts observed when adjusting the morning schedule.

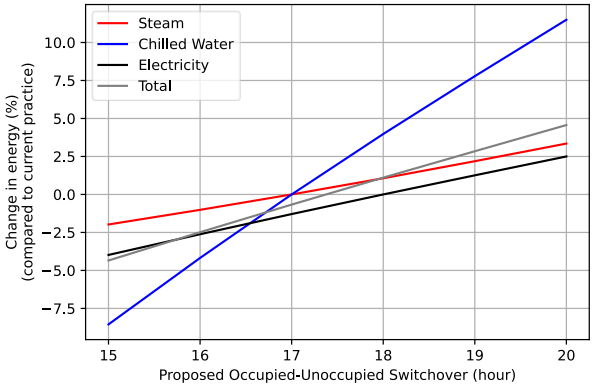

Figure 6 - Change in energy compared to adjusting the end of day equipment schedule using the 2019 piecewise function model.

To consider another scenario, if a user wanted to extend the schedule to 5 am – 5 pm over the weekend, this would increase steam energy by 5%, chilled water by 21%, electricity by 7%, and total energy by 9%. These impacts are far from trivial and demonstrate the importance of the use case for this tool.

Discussion

The results of this case study support the literature that adjustment to equipment schedules significantly impacts total building energy use. To the best of our knowledge, there are currently no tools that specifically allow building operators to understand the impact of their operational decisions. It is likely that adjustments to the building schedule would be made in response to a complaint; however, this tool would allow them to understand the impact of a whole building change to the schedule. If the impact is large enough, they may want to consider a more

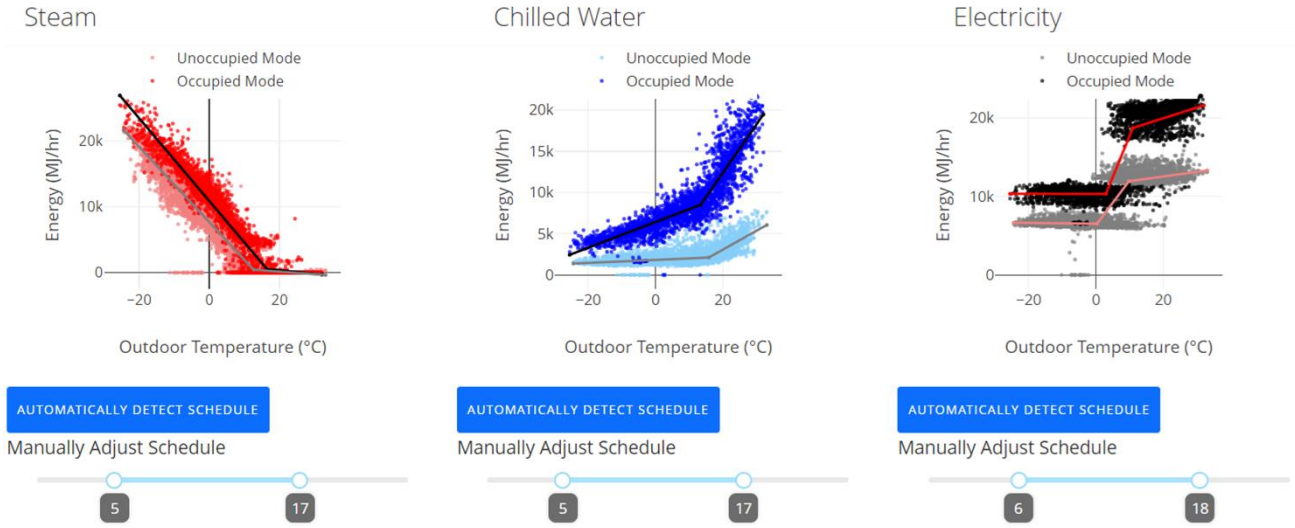

Figure 5 - Dashboard of change point models for 2019

local solution, such as the installation of occupancy-based ventilation control.

Usability and technology acceptance analysis

The development of this tool allows for a discussion of usability. As described in the methods section, this tool was designed with several aspects that aim to increase acceptance and use; however, many aspects were not addressed. According to the TAM3 model of technology acceptance, the determinants of technology acceptance are perceived usefulness and perceived ease of use. While this model is intended to be a framework for user testing and implementation, we use the major factors as a theoretical consideration to discuss potential limitations to the current development of the tool described in this paper.

The concepts of subjective norm, image, and job relevance are driving factors of perceived usefulness (Venkatesh & Bala, 2008). Subjective norm refers to a person's belief that most people in their position are using a specific type of technology, while the term image refers to if they believe that using that technology would enhance how they are viewed in the context of their job. These factors likely need to be driven by the organization and should be considered in tandem with other aspects discussed here.

We touched on the idea of job relevance in the development, but this was only done in a conceptual manner. To tailor a tool for job relevance, more research must be done to understand the workflow and positions of expertise within FM companies. It may be the case that the positions which have the expertise to generate the models are different than those making the decisions to adjust the schedule. In this case, a hand-off system may be necessary. For example, an energy expert ensures the trained models are accurate, while a building technician uses the tool to ensure their changes do not exceed a certain threshold. The need for improved reporting among stakeholders appears to be a challenge with both BASs and MBCx systems (Balaji et al., 2016; Harris et al., 2018) and should be addressed as a workflow element in the development of operational tools. Supporting this finding in the literature, we found that BAS management is nearly entirely contracted out to external controls companies within the two companies we interviewed. Therefore, tools such as this could play a role in providing communication and verification between the FM companies and the controls contractors.

Output quality and result demonstrability is another important aspect of perceived usefulness. This tool focuses significant effort on ensuring users understand and trust results, which, along with extensive user testing, should be factors in future tools. A current limitation to the tool presented in this paper is the presentation of results. For example, energy impact is indicated in both absolute energy and a percent of total energy; however, it is unclear if either of these would have significant meaning to those using the tool. Through our interviews we found that buildings owners are the ones that approve, finance, and ultimately benefit from upgrades to building systems. Therefore, the FM companies in charge of changing and upgrading the BAS systems need robust estimations that relate to the client's energy or GHG reduction targets. This challenge of output quality and results demonstrability is also reflected in the literature (Goulden & Spence, 2015; Harris et al., 2018). Outputs such as the effect on GHG emissions, utility costs, or other benchmarking metrics should be considered. Robust metrics and clear targets should be implemented and built into future iterations of tools.

Aspects such as computer self-efficacy, computer anxiety, computer playfulness, and perceptions of support all play a role in acceptance. These factors drive initial impressions of technology and can be alleviated by perceived enjoyment and objective usability (discussed next). Still, it's important to consider the expertise and computer efficiency of the user. This is particularly relevant given that building technicians' job descriptions can range anywhere from attending to the basic operational requirements of a building to highly specialized technicians (ECO Canada, 2011). While the modelling assisted by the tool described in this paper is designed to be easily interpretable, there is still a significant amount of expertise required to be confident in the models and spot issues. This factor should be considered in tandem with job relevance to target workflows with users that have the expertise to use them.

Finally, perceived ease of use, perceived enjoyment, and objective usability are essential factors in tool design. While we aimed to design a user-friendly tool, interface development should not be left up to the perceptions of the designers. Instead, it should undergo extensive user testing. Techniques including rapid prototyping, thinking aloud, and other commonplace techniques in human factors need to be employed to ensure tools are useful to those who will be using them.

Conclusion

This paper outlines the development of a user focused tool that targets understanding the energy impact of equipment schedules. Through a case study, we found equipment schedules to have a significant impact on energy and indicates a relevant workflow for this type of tool. Increasing the weekly schedule in which the system operates in occupied mode increases annual energy use by ~2% per hour. To the best of our knowledge, a tool that dynamically captures building operational techniques does not exist in industry.

This tool provides users with a rapid way to create robust energy models which captures the impact of equipment schedules and allows them to interactively investigate the impact of adjustments. This tool was designed with usability in mind; however, further efforts in understanding FM organizations, determining effective workflows, and performing user testing is required for the successful adoption of these types of tools.

This tool only explores one aspect of building operation: equipment schedules. We plan to expand this feature to be part of a suite of MBCx tools the allows for the rapid modeling and assessment of several other building settings and faults. Future work includes the development of a suite of operational focused tools coupled with further attention to technology acceptance and usability.

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