Digital Campus Innovation Project: Integration of Building Information Modelling with Building Performance Simulation and Building Diagnostics

Zixiao Shi[1], Aly Abdelalim[1], William O'Brien[1], Ramtin Attar[3], Peter Akiki[2], Katie Graham[2], Barbara Van Waarden[2], Steve Fai[2], Alex Tessier[3], and Azam Khan[3]

[1]Human-Building Interaction Lab
Carleton University
1125 Colonel By Dr
Ottawa, ON K1S 5B6
Canada

[2]Carleton Immersive Media Studio
Carleton University
1125 Colonel By Dr
Ottawa, ON K1S 5B6
Canada

[3]Autodesk Research
210 King St. East
Toronto, ON M5A 1J7
Canada

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ABSTRACT
Building Information Modelling (BIM) has emerged as a powerful technology that creates a central hub for managing building energy and resources at all phases of the building life cycle. Without it, many tools that lack interoperability are used, thus massively under-exploiting the efforts of other building design and management parties; this largely describes the status quo. However, despite the power of BIM, it has not been readily adopted by industry, and especially not at the community and campus scale. Digital Campus Innovation (DCI) is a large multi-year and multidisciplinary project involving development of a methodology for use of BIM for operation and maintenance of a portion of Carleton University's 45 interconnected buildings. Major elements include: (1) development of highly-detailed BIM models for site and buildings; (2) conversion from BIM models to building performance simulation (BPS) models; (3) model validation using measured data; (4) building Fault Detection and Diagnostics (FDD) using advanced algorithms and calibrated modelling; and (5) advanced building performance data visualization on top of 3D BIM model. This paper will describe the methodologies that are being developed while demonstrating the ongoing processes by a case study of Canal Building, a part of DCI project. While the project is only one year old, impactful examples have already demonstrated BIM as an invaluable technology that improves indoor environment quality, reduces energy costs, and has a potential application for asset management.

INTRODUCTION

In Canada, buildings are responsible for about 50% of total electricity use, 35% of total greenhouse gas emissions, and 15% of total water consumption [25]. Canadian Universities have an average energy usage intensity of 2.59 GJ/m^2 per year, 68% more compared to commercial and institutional buildings' average [24]. Carleton University campus has an annual utility cost of $12 million, an average of $30/m^2 or $400/student. Carleton University Facilities Management and Planning Department has suggested that numerous opportunities exist in building operation to significantly reduce energy consumption.

Past research showed that proper commissioning and maintenance can reduce energy use by 20% or more [23], with payback period ranging from several days to years [26]. Although often conducted as a one-time performance assurance activity, the commissioning process can also extend throughout the operation phase to solve operational problems and improve performance [22]. Past projects have shown continuous commissioning can reduce energy cost as much as 25% [22]. Thanks to the development of building sensor network and data storage, building operation data can be used to largely automate the continuous commissioning process. Thus there is a tremendous value to provide better access to building performance data and building information.

An efficient and easy-to-use information infrastructure was not available in the past, but in recent years Building Information Modelling (BIM) is becoming as a powerful technology to establish a comprehensive multi-faceted digital model of physical and functional aspects of buildings that can support data communication, analysis and commissioning activities throughout the building life-cycle [4, 14]. Integrating BIM in building operation and maintenance can decrease operation risk and costs, as well as maintain facility management quality [7], though this application is rarely seen in practice, especially for university campus. Building information from BIM models can feed to the automated continuous commissioning process to improve the information flow and reduce manual input.

Thanks to the interoperability of BIM, Building Performance Simulation (BPS) can also be added to the picture. BPS provides quantifiable analysis to evaluate various aspects of building systems, and over the past 50 years has been developed into a variety of programs performing simulations such as energy consumption, thermal comfort and lighting [10], although it is still rarely used in maintenance and operation due to intensive labour requirements and costs [6]. Integrating

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BIM, BPS and building performance data with proper interoperability could reduce the cost barrier and fully exploit the BPS analysis, but more research is needed for large scale implementations [8].

With the help of BIM technology, BIM-enabled Information Infrastructure (BIM I^2) for fault detection and diagnostics (FDD) proposed by Dong et al. can be adopted [13]. FDD is used to identify problems in building systems for continuous commissioning process. Compared to conventional FDD used in many existing Building Energy Management (BEM) systems, which often focus on controls and mechanical equipment, FDD based on BIM I^2 uses a holistic approach that covers all building system and improves information flow and diagnostic effectiveness [13]. The extra data made available by BIM and BPS also enables more feature extractions and complex model-based diagnostic algorithms. To better visualize the building performance and diagnostics results, tools like Project Dasher [3] makes it possible to generate hierarchical and spatio-temporal representation of the building performance from space level to whole building level by using data from BIM model.

Digital Campus Innovation Project

In early 2014, Digital Campus Innovation (DCI) project started its pilot phase of integrating all the above-mentioned technologies into BIM-enabled information infrastructure on a campus scale. Similar projects on a building scale have been investigated recently by other research teams, such as an office building in Toronto [2] and a two-story recruit barrack in Illinois [13]. The main objective of DCI is to apply an integrated BIM, BPS and the continuous commissioning process on a campus scale, providing a useful platform for building operators and other stakeholders such that they can make informed decisions and efficiently explore operational improvement strategies. The team will also generalize its methodology for widespread implementation in the future. The vision is to have a common model that exists and continuously evolves from design to construction and throughout the operation and maintenance phases, until the reuse or demolition of the buildings. Figure 1 shows the current structure of the DCI project. Besides building models, other campus infrastructure will also be digitized and in the future campus-level analysis and diagnostics will be performed. This paper will focus on the building level of the DCI project. The highlighted parts in Figure 1 will be discussed in the paper with the case study of Canal Building.

The Canal building was one of the first buildings to be modelled in DCI. It is a seven-story mixed-use building with total floor area about 7700 m^2. The building began its operation in 2011 and includes a large variety of functional space such as private offices, open-plan offices, lecture rooms, computer labs, design labs, research labs, conference rooms and other facility rooms. There are two small air-handling units (AHU) designated for the mechanical rooms; the rest of the building is conditioned by two separate air-handling units. The heating system uses campus steam generated at a central plant and the cooling system uses a water glycol loop which also supplies another building. The air distribution system is single-duct

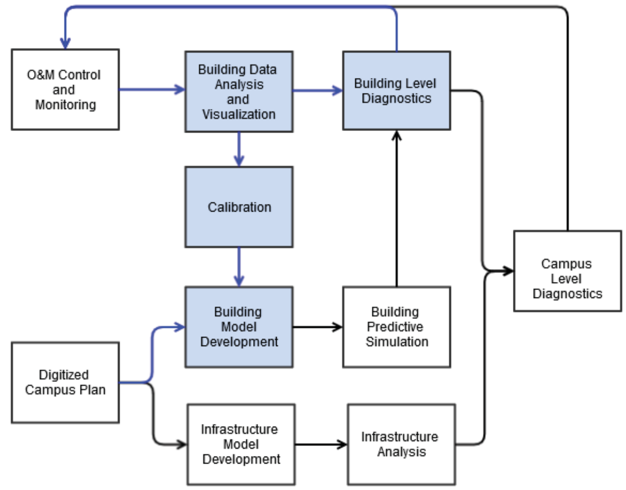

Figure 1. Digital Campus Innovation Project Structure

VAV with reheat and radiant panels to reduce cold surfaces. The windows of this building are double-glazed with air gaps of 13.5mm, and the exterior walls have varied R-values ranging from R-12 to R-24. The building is also equipped with more than 2500 sensors to collect data needed in the DCI project. Since the Canal Building represents typical education buildings on campus with comprehensive documentation and abundant sensor data, it serves as a good starting point for the DCI project and helps to set up a framework for all other buildings on campus.

BUILDING MODEL DEVELOPMENT

Models for several recently constructed buildings, including the Canal Building, are constructed first in Autodesk®Revit 2014 which is the main tool for architectural and analytical model development. Figure 2 illustrates the entire building model development process. EnergyPlus 8.1 was selected as the BPS tool in place of DOE-2 used in Green Building Studio in Revit, due to its versatility and capability of simulating complex building system and its continuous development of new simulation modules [13]. To achieve interoperability between BIM and BPS tools, gbXML was selected as the primary file format for modelling and data storage due to its simplicity and capability for fast prototyping [12].

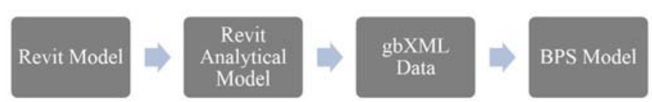

Figure 2. Building Model Development Process

Architectural Model Development

The architectural model created in Revit serves as the foundation of BIM I^2 for DCI project and therefore affects the results of all the analysis in later steps. To achieve good accuracy of the model, the team checked and compared layouts and plans provided by the facility management department of Carleton University. Any discrepancy found across the drawings was resolved through site visits, photography or laser scanning if possible. Figure 3 shows a comparison of the exterior view of Canal Building between a photo of the actual building and and a combined image of Revit model and BPS model.

Figure 3. Real image (left), Revit model (top right) and BPS model (bottom right) of Canal Building

Although Revit is highly capable of developing detailed and complex models, there is a good possibility that high polygon models may not be translated to gbXML format or rejected by BPS tools. The team had to find a balance between the level of detail and the interoperability of the Revit model in order to achieve a smooth transition of the model from Revit to the BPS tool. Strategies used in similar projects for this purpose were reviewed and tested in DCI project [11, 5]. The following major modelling strategies were adopted by the team during the development of architectural model:

1. Simplify complex geometries
Most BPS tools have problems interpreting surfaces (like walls, roofs and floors) or sub-surfaces (like windows, doors) with irregular shapes or round shapes. Therefore building components with irregular or complex surfaces and large number of surfaces were modified in order to simplify geometry, preventing system crashes, errors and long simulation time.

2. Properly define curtain walls
A curtain wall that makes up a whole building façade is usually modelled as a single unit in Revit. However in EnergyPlus, fenestrations can only be represented as sub-surfaces, which means that the curtain wall has to be modelled as a window inside a wall. The team therefore translated the curtain wall elements to windows (with frame) with equivalent thermal and optical properties so that this design can be correctly interpreted by the BPS tool.

3. Properly define non-space bounding elements
Not all elements need to be input into the BPS tool. For example structural elements such as beams and columns in interior spaces often have minimal influence over thermal performance and should not be included to the building energy model. With simulation requirements in mind, the team identified elements that can be neglected and set their properties as non-space bounding.

Analytical Model Development
After the Revit model was properly developed, the team prepared the analytical model in order to output it as a gbXML file that is compatible with the BPS tools. The analytical model translates information of ”rooms” in architectural model to ”spaces and zones”, which are used in the simulation later. To prepare the analytical model properly, the team adopted the following practices:

1. Properly define spaces
In cases where spaces are not bounded by actual structures, such as large open spaces controlled by separate HVAC terminal units, space boundary lines were manually defined to separate the space into appropriate compartments with corresponding thermal interfaces. In some rare cases, where several rooms use the same controller and if the rooms are very different from each other, each room is defined as separate space.

2. Properly define space boundaries
The boundaries of each space were properly defined to ensure the accuracy of the geometric model in BPS. In EnergyPlus, space dimensions are defined from the interior surface, thus the space boundaries in the analytical model were calculated from the interior side of each surface.

3. Space volume computations
A space volume computation method was used for the analytical model to accommodate the varying height of each space.

Model Checking and Conversion
Before exporting the analytical model as a gbXML file, the team performed following checks to ensure the model was interoperable:

1. Proper enclosure of all spaces
If a space is not properly enclosed in the model, most BPS tools will reject it and simulation cannot carry on. If a building space has disjoint surfaces, surface boundary lines must be drawn to enclose the space.

2. No nested spaces
Current gbXML format does not support nested spaces, i.e. a space wholly contained within another space. If this situation occurs, it was resolved by separating and dividing the surrounding spaces of the nested space using manually defined space boundary lines.

When the analytical model passed all the checks, it was exported as a gbXML file. The gbXML file was checked for its validity before it was input to BPS tool - EnergyPlus in this case. The BPS model was tested for its functionality; error and warnings from EnergyPlus simulation results were used to adjust the analytical model and gbXML file. The process was repeated for several iterations to finalize the BPS model.

The conversion process from the Revit architectural model to the BPS model was largely manual due to the different and even conflicting requirements for these two different types of models. The team has been continuously searching for better practices of model development and model conversion and experimented with different model techniques during pilot phase of DCI project. As more buildings are added to DCI, a standardized guideline for developing and converting Revit models will be developed and refined.

MODEL CALIBRATION

When the BPS model is completely set up and the corresponding weather file is selected, a simulation is performed and results produced. Simulation results can be significantly different from measured building performance [29], which makes model calibration a crucial and effective step to verify and improve the BPS model [21] so that the simulation can produce meaningful results for building analytics, fault detection and predictive simulation. Two calibration methods were proposed for this project: an evidence-based method by Raftery et al. [27] and an analytical optimization method by Sun et al. [28]. Evidence-based method uses a manual input calibration procedure that relies on evidence obtained from design drawings, measurements, sensor readings, etc. [27]. This method proposed a hierarchy of evidence reliability and a version control strategy, but can be time consuming and enough evidence is not always available for all inputs. On the other hand, the analytical optimization method uses a mathematical and statistical procedure to automatically determine the input value, and has better performance than pure stochastic processes. However tweaking high number of unknown parameters can still yield unsatisfactory results, so some form of input parameters calibration before analytical optimization is required [28]. To combine the advantages of both methods, a joined evidence-based and analytical optimization method was developed by Coakley et al. [9] and was adopted in DCI project. The team has decided to conduct an evidence-based calibration with available data and follow up with analytical optimization method to determine input values for variables that cannot be supported by evidence. This paper focuses on the evidence-based part of the calibration that has been carried out for Canal Building at this stage of the project. With each iteration of the calibration process, BIM model and BPS model were updated and version managed.

Weather data calibration is the most important step of evidence-based calibration [27] and should be preformed before building model calibration. Using historical weather data corresponding to the performance data instead of a standard weather file can greatly remove the weather factor from the discrepancy between the simulation results and actual data. Weather data was obtained from a weather station located on the rooftop of the building. It measures weather data at five-minute intervals from four temperature sensors, one humidity sensor, two wind speed/direction sensors and six pyranometers with different tilt angles. Diffuse radiation is not directly measured and was extrapolated from different pyranometers. The weather data was automatically compiled to EnergyPlus weather file format and used in simulation.

The evidence-based calibration method is applicable for most parameters in the building model since this project has a large and growing pool of evidence, lots of effort has been dedicated to this ongoing calibration process. Since each zone has independent schedules and internal load parameters, each zone was calibrated individually first to improve the accuracy of the calibration, and then the overall building-level calibration was performed.

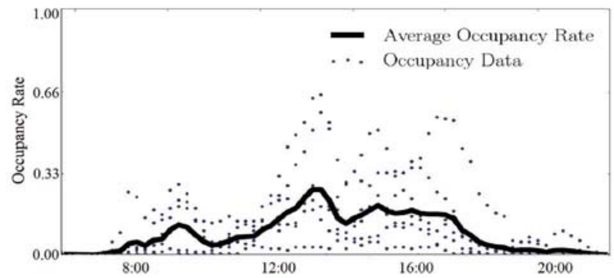

Figure 4. Average faculty office occupancy

One source of evidence for calibration is from design documents. Most of this information, such as architectural, structural, and construction drawings, was already incorporated in the Revit model. Then the model was updated based on newly available as-built document from Facility Management. However, even the as-built documents may be different from actual condition and not all the system information required by BPS were included in those documents. Direct observation through on-site audit, a more reliable evidence source than design and as-built document, was used to update the model so that it reflects the actual condition of the building.

Abundant sensors installed in Canal Building provide building operation data, which could also be used as a source of evidence for calibration. For example, the schedules provided by Carleton University were used as inputs for occupancy schedules in classrooms and teaching labs. For faculty offices, due to the variation of schedules from day to day and from person to person, occupancy schedules have to be extrapolated from the building sensor network. With data from occupancy sensors in individual faculty offices, an average occupancy schedule for weekdays was extrapolated (Figure 4) and used in the model. Although sensor data is good evidence as it reflects some actual building usage values, sensor calibration and data noise reduction are necessary steps to take before calibration. For the above example, occupancy durations shorter than 30 minutes were filtered out from the data, since those readings were likely noises caused by sensor error, cleaning staff or other transient occupancy.

In cases where the values of some parameters could neither be obtained from design documents nor sensor data, an onsite audit was required. For instance, equipment power density depends on the number and types of equipment used in each zone; this information is not documented and there is no sub-metering in individual rooms and labs. Therefore a walkthrough of all major rooms in Canal Building was carried out to assess equipment power ratings. For special equipments such as laboratory equipments, specifications were obtained from name plates. Special attention was also given to spaces that hold large amount of equipments (e.g. computer lab) or special equipments (e.g. research lab). For parameters whose values can not be verified through auditing, analytic calibrations will be performed later.

To compare the results from calibrated model and actual energy consumption, it is preferable to have hourly and sub-

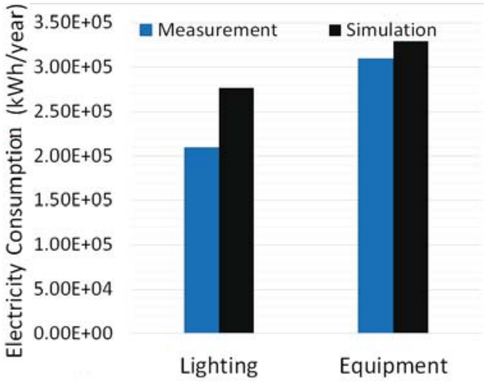

Figure 5. Annual lighting and equipment electricity consumption

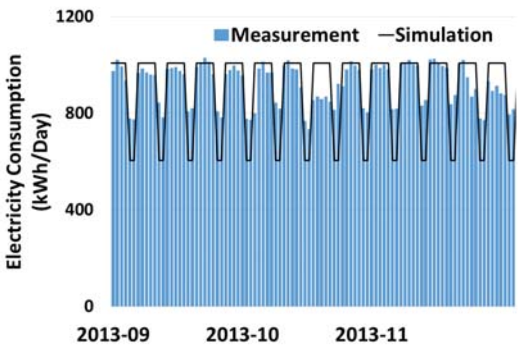

Figure 6. Daily equipment consumption during 2013 Fall Semester

metered utility data [27]. Unfortunately, only part of the utility data was available at this point and the limited number of data points was not enough for fine-tuning the building model input. The utility data available were building plug load (equipment) electricity consumption and building lighting electricity consumption. Other utility data such as cooling energy consumption and heating steam consumption are still in the process of calibration.

Figure 5 compares the measured and simulated results of annual plug load and lighting consumption. The lighting energy consumption calculated based on lighting fixtures design in BIM file and campus schedule produced an over estimation of 32% while the simulated plug load has a better agreement with the measured data with an error of 7%. The plug load inputs were calibrated through audit as mentioned above, while the lighting load inputs were calibrated using document only. This confirmed the importance of selecting more direct and reliable evidence for calibration. Figure 6 compares measured and simulated daily plug load for the Fall Semester in 2013. EnergyPlus uses fixed weekly schedules and the simulation results do not reflect daily variations and small events such as exams that significantly lowers the average occupancy rate. These variations due to stochastic behaviours of occupants could have huge impact on energy use on space level [16] and therefore are important when performing space-level diagnostics using calibrated BPS results. One approach to improve this is to use stochastic occupant schedule [17] and will be investigated in the future.

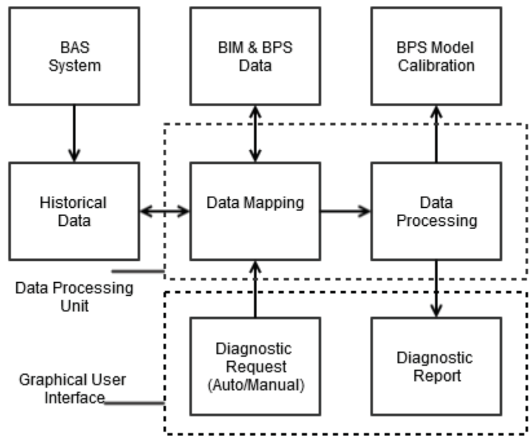

Figure 7. FDD Module Schema

BUILDING DIAGNOSTICS

There are three major types of FDD methods: quantitative model-based, qualitative model-based and process history based [20]. The goal of DCI project is to employ all three methods, but in this phase of the project a combination of qualitative model-based and process history based FDD is used. Qualitative models such as rule based models are qualitative relationships from knowledge of the system. Process history method is purely based on historical data, sensor and BIM model data in our case. The team developed a FDD module that analyses the data from both sensor and BIM model, performed qualitative analysis to extract extra features from the data. A graphical user interface is under development, allowing user to manually generate or to schedule a diagnostic report. Figure 7 shows the structure of the FDD module. FDD in the DCI project is focused on three areas: sensor reliability, energy performance and thermal comfort. In this paper diagnostics of thermal comfort problem in the Canal Building will be presented.

Thermal comfort is an important design goal of the HVAC and control system but can only be verified and studied during the operation and maintenance phase of the building lifecycle. Of all 215 buildings surveyed in U.S., Canada and Finland, only 11% have more than 80% of the occupants satisfied with thermal comfort [18] while the ASHRAE Standard 55-2013 and ISO standard 7730:2005 both require 80% of the occupants to be satisfied with thermal comfort [19, 1]. Some thermal comfort problems are results of over-cooling, over-heating, or malfunctioning HVAC equipment and therefore, accurate and prompt detection of the thermal comfort problem could often detect energy performance issues. Continuous monitoring and maintaining proper thermal comfort could ensure that productivity of the students and faculties are not negatively affected.

Thermally uncomfortable conditions of a building over an operation period should be quantified first in order to perform the diagnostics. One methodology is the degree-hour method proposed in European Standard EN 15251 [15]. This method uses the product of time and temperature difference outside

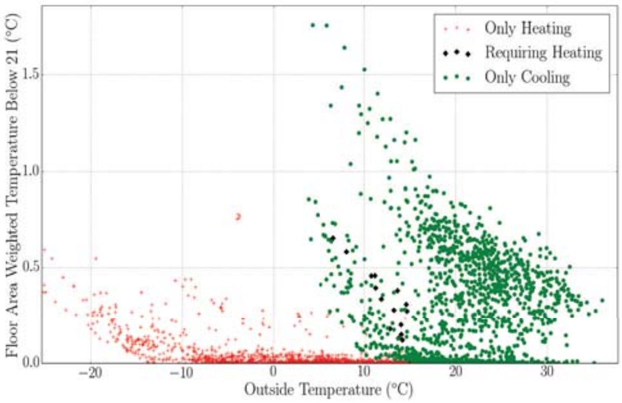

Figure 8. Average hourly building temperature degree lower than 21°C weighted by floor area

comfort range to aggregate the degree of over-cooling and over-heating over time. Another metric used is degree outside comfort range of each room weighted by its area, floor area weighted temperature provides a more accurate representation of the whole building than average of all thermostat data. The data used for the analysis is from Nov 1, 2013 to Oct 31, 2014 on 3-minute intervals. Only reliable sensor measurements within regular office hours were used. The comfort range is assumed to be 21°C – 25°C during office hours.

Based on preliminary analysis, overall temperature of the Canal Building tended to be too low. Over the whole year during occupied hours, over 35% of the time at least one room is below the thermal comfort range, and for every room on average 13% of the time, the temperature is below 21°C. This has been further verified by on-site visit and surveys of occupants. Low indoor air temperatures can be caused by either over-cooling or under-heating. Over-cooling often indicates improper HVAC control and resulting in energy waste; whereas under-heating indicates that the heating system is too small to handle the building heating load. Over-cooling could be possibly fixed by control tweaking; while under-heating might need equipment upgrades.

Figure 8 separates over-cooling and under-heating occurrences of the whole building by plotting the floor area weighted temperature difference under 21°C (y axis) against the outdoor temperature (x axis) for each operating hour of the whole building. Green dots represent data during the cooling period, red crosses during heating period, and black squares for hours when heating is required but not supplied. As shown in the Figure 8, under-heating (red crosses) occurs mostly at very low temperatures (<-15°C) and the average air temperature were above 20°C most of the time, so the under-heating problem is not significant. On the other hand over-cooling (green dots) was significant in the building. Since dehumidification process is handled by the cooling coil and there is no reheat coil in the air handling units, dehumidification may also cause low supply air temperature and result in the over-cooling of the building. A further analysis found that dehumidification process had no meaningful correlation with the over-cooling problem.

To further understand the over-cooling problem observed, the team investigated whether the problem was associated with a specific room parameter in this mixed-use building. Figure 9 shows annual degree-hour over-cooling of each room verses room type, room area, room orientation and window to wall ratio (WWR) with correlation coefficient (r) values plotted in the title section. The room parameters were automatically calculated from the BIM file. No significant correlations have been found between over-cooling and room parameters, except North facing rooms have slightly more over-cooling than other rooms. This may be caused by variations of solar radiation and/or Air Handling Unit One (AHU1) which conditions only the north facing rooms, whereas Air Handling Unit Two (AHU2) conditions all other rooms. Since the over-cooling problem is not likely associated with room properties, it's more likely related to HVAC issues.

Upon further analysis the correlation between the over-cooling and various HVAC sensor data we have found that over-cooling problem was caused by high supply air flow and over-pressurizing of the building. Figure 10 shows some of the selected plot between floor-area weighted building average over-cooling temperature and several HVAC parameters including return air CO_2, outdoor air temperature, fresh air energy flow which is a combined effect of indoor/outdoor air enthalpy difference and damper position, and cooling coil chilled water supply. The building tends to over-cool more when there is higher occupancy indicated by more return air CO_2, and since supply air temperature is constant for the VAV system, the over-cooling is likely caused by high supply air flow. The two AHUs are identical, but AHU1 conditioned 15% less floor area and controls the space where receives less solar radiation, thus showing a stronger correlation (higher r value) with outside air temperature and fresh air energy flow than AHU2. Since AHU1 conditions north facing spaces with lower return air temperature, AHU1 has less need to cool the air with cooling coil, making its over-cooling points shifted towards lower chilled water supply. Upon checking building control, we confirmed this diagnostics: supply air flow controlled by both AHUs were using the same proportional control logic designed for full building occupancy based on supply air CO_2 and temperature, whereas almost half of the building was still unoccupied; the decreased internal heat gain made the building over-cooled and lowered thermal comfort.

BIM I^2 enabled FDD process shows promise and provides in-depth analysis of the building performance, but the process is still not fully automated. In the future, quantitative based models and calibrated BPS models need to be implemented to achieve fully automated diagnostics and improvement suggestions.

FUTURE WORK

During the next phase of the DCI project, the team will complete the following tasks at the building level:

1) Acquire and calibrate sensor data and hourly sub-metered utility data for further evidence-based calibration and analytical optimization calibration.

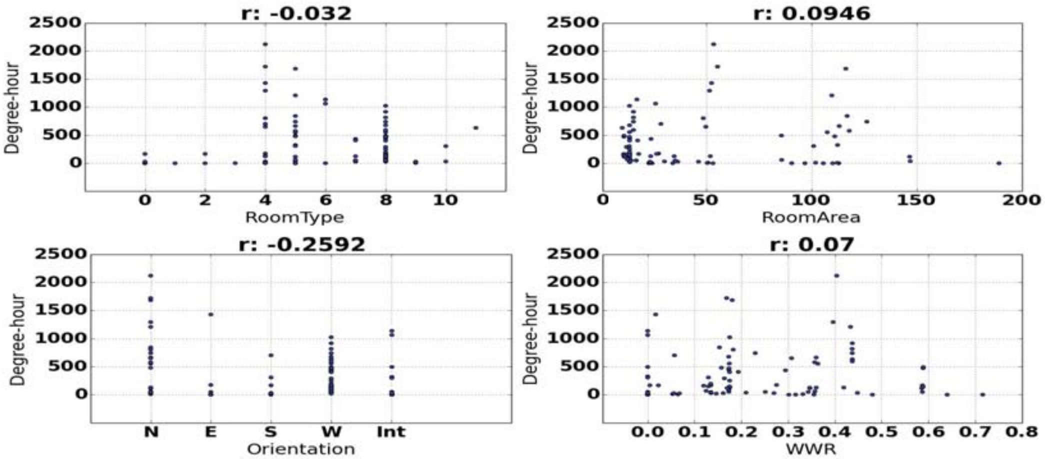

Figure 9. Annual degree-hour over-cooling verses room parameters

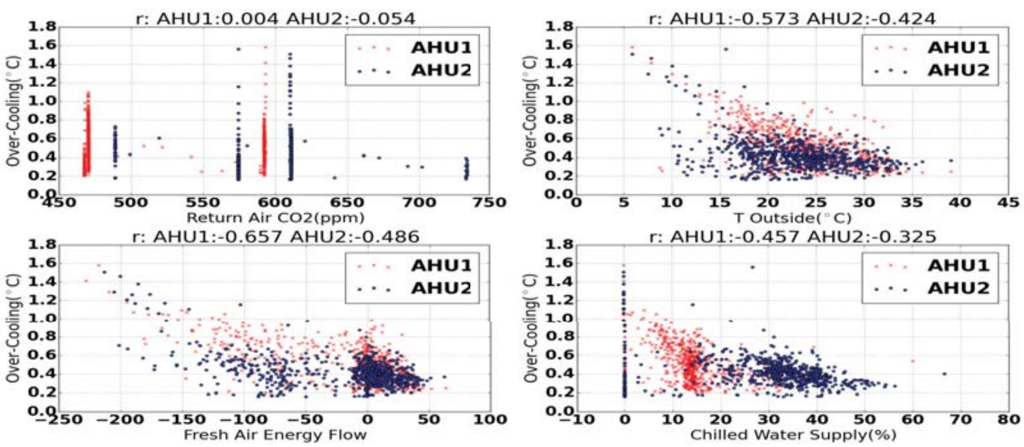

Figure 10. Floor area weighted over-cooling verses HVAC variables

2) Develop diagnostics algorithms for sensor data mining, quantitative FDD, and predictive simulation for performance improvement.

3) Apply model based FDD techniques.

4) Standardize the procedures and add other buildings in DCI to BIM platform.

5) Perform advanced building performance visualization using Project Dasher.

CONCLUSION

One year into the DCI project, the team has set up the framework with BIM technology. The impact of integrating BIM and BPS into the operation and maintenance of building was promising. The BPS model development and calibration process and sensor data exploiting processes benefited from BIM tools like Revit. The process of model development, conversion and calibration reported in this paper could be implemented for other buildings in the DCI project. Thermal comfort diagnostics using BIM and BAS data already discovered over-cooling problems in the Canal Building; solving this problem can improve both thermal comfort and energy performance of the building. In the future, DCI project will focus on acquiring more reliable data and provide quantitative results of evaluating improvement options by using a calibrated building model. Next, the methodology will be generalized from the pilot building and be applied to more buildings on Carleton University campus.

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