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Indoor Localization and Building Occupancy Count Estimation using LTE-A Ultra-Dense Networks

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ABSTRACT
Recent studies have shown that awareness of occupants' presence, location, and count can be used for optimizing building operations and management. We present innovative ideas on how to improve such building sustainability reducing CO_2 emissions and energy consumption, through occupants' localization and tracking, and building occupancy count estimation. We propose to use Long Term Evolution-Advanced Ultra-Dense-Networks to locate users and to estimate the occupancy count. Furthermore, we discuss how awareness of occupants' location and count will be integrated into other parts of our project, namely, Building Information Modeling (BIM), building simulation, design, retrofitting, and studying occupant's behavior.

Author Keywords
LTE-A; Occupancy count estimation; Indoor localization

ACM Classification Keywords
Applied computing → Architecture (buildings) → Computer-aided design.

1 INTRODUCTION
There is an urgent need to improve processes for sustainably managing buildings over its entire lifecycle. Sustainability needs to be considered in building design, construction, and operation. According to [3], buildings consume approximately 40% of the total primary energy use in the U.S. and Europe and 27.3% in China. Total building energy end-use is dominated by *space* and *water heating*. This is translated in approximately 40% of total direct and indirect CO_2 emissions [8]. There is potential to improve energy efficiency although the total floor area is expected to grow by 60% by 2040 (according to the Efficient World Scenario, by 2040, buildings could be around 40% more energy-efficient than today [8]).

To achieve these improvements, buildings should be designed, and run near-optimally to maximize performance and user comfort. Improving building control, operations, and management is low-cost and non-invasive, it can address inefficiencies and improve energy usage. For example, Natural Resources Canada's Office of Energy Efficiency initiatives for existing homes saved 388,000 tons of greenhouse gas emissions and 3.991 PJ of energy [14]. Our research aims to improve building sustainability, investigating new methods that use Building Information Modeling (BIM), exploiting data obtained from different sources such as sensors, network operator elements (such as Base-Stations) and user deployed elements (such as Wi-Fi Access Points). The architecture of the proposed effort is presented in Figure 1.

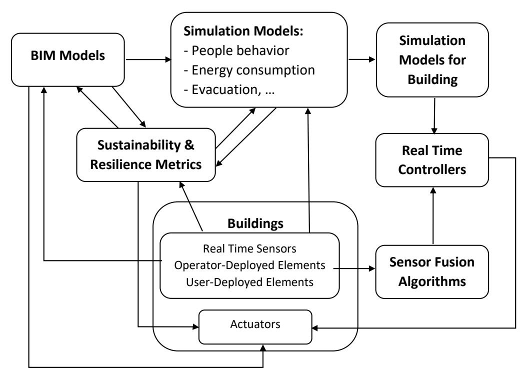

Figure 1. Software Architecture.

As a part of this research, we are investigating standard metrics for evaluating the sustainability and resilience of buildings. These metrics will be used on all the phases of the project: (1) in the design phase, as criteria to select the designs that meet the requirements; (2) in the optimization phase to evaluate the results of building simulations; and (3) during operation to adjust the building controllers.

We use Generative Design to explore building designs (as BIM models) that satisfy all the design requirements. Once we have a set of designs, we run simulations to evaluate energy consumption, evacuation time, etc., including different user's behavior (i.e. movement patterns, preferences, etc.).

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These simulation results are used to select designs or to suggest a reiteration in the design process. They are also used to build the control systems using the Discrete Event Methodology for Embedded Systems (DEMES) [21], which allows transforming models into the actual controllers used in buildings. The raw data from sensors, operator-deployed elements, and user-deployed elements are combined with sensor fusion algorithms to supply fault tolerance. Data extracted from the building is also used to generate Data-Driven Simulation and to populate the BIM models for building management.

We present a part of this software architecture, namely, the set of methods proposed for occupant localization and tracking, and occupancy estimation. Recent studies showed that this is an important aspect for optimizing building operations and management [18], as awareness of these aspects can help to deliver building services (e.g., lighting) when and where needed. We propose using Long Term Evolution-Advanced (LTE-A) Ultra-Dense-Networks (UDNs) to locate and track occupants and to estimate their count. The advantage of this method over approaches based on sensor data (e.g. measurement of CO_2, camera data, humidity, etc.) is that it does not need to install and set up sensors in the building: LTE-A is already available for cellular communications. Our approach is expected to be accurate for occupancy estimation because LTE-A covers areas where Wi-Fi or Bluetooth devices cannot. Additionally, the geographical area covered by cellular networks can provide valuable data. For example, we can track occupants to understand individuals' movement and extract emergent behavioral patterns.

We also detail how accurate localization and occupancy estimation can benefit other aspects of our software architecture, such as the development of models and simulations of user behavior. We expect that having advanced building controllers will increase comfort while reducing energy consumption and CO_2 emissions. These new methods for localization will also provide accurate data for building retrofitting and additional data for BIM models used for building management. For example, the data about the time slots when the corridors of a business building have minimum occupancy can help to schedule maintenance and cleaning operations. Movement patterns from the students on a University Campus may suggest that the location of the food court is creating traffic on an area initially designed for study (i.e. an area that should not have traffic or noise). This information suggests a change in the location of the study area or the food court, which could be used when retrofitting operations are needed in that area of the Campus.

The data provided by these new localization methods are integrated into BIM models for visualization purposes. BIM models provide Digital Storytelling, i.e., digital techniques to create narratives that transform data into information for end-users. If we want to present our findings to non-specialized users or Architecture, Engineering, Construction, and Operations (AECO) professionals, we need to use a common language to all of them. There are visualization features provided by some BIM platforms that allow users to disseminate data interactively and intuitively. This includes diagrams, adaptive geometry, and interactive parameters, among others. This way of disseminating the data allows to understand and interact with the results of the study.

The rest of the paper is organized as follows. Section 2 discusses indoor localization and building count estimation. Section 3 describes how to use LTE-A UDNs for occupant count estimation, user localization and tracking. Section 4 discusses user behavior on building performance, and occupant count estimation, localization and tracking for the development of user behavior models. Section 5 presents how BIM models benefit with this estimation and vice versa.

2 BACKGROUND AND RELATED WORK

Indoor localization is becoming important for location-based services, for instance, various mobile applications require accurate location of running smart devices, which shows the importance of indoor localization. We propose to use indoor localization for building occupancy count estimation to provide energy efficient buildings. Reducing this significant portion of the world's energy consumption [20] would help with energy shortage and reduce carbon footprints of buildings. In order to deliver building services to occupants in an energy-efficient manner, such services need to be provided in the correct time, location, and amount [4, 18]. This applies for a number of services such as lighting as well as heating, ventilating, and air conditioning (HVAC).

Much work in the literature has been conducted on building occupancy estimation [4, 18]. Most of the existing work is based on data that is extracted from sensors deployed in buildings. This includes passive infrared (PIR) sensors, CO2 sensors, temperature sensors, humidity sensors, pressure sensors, RFID tagging, camera data, keyboard and mouse activities. Other localization and occupancy estimation methods are based on Wi-Fi and Bluetooth signal sniffing. Such methods either use data extracted from Wi-Fi access points or use designated devices to sniff Wi-Fi and Bluetooth signal from surrounding devices to estimate the position of these devices or estimate the number of devices in a building [24].

A cellular network is one where the last link to the end user takes place over a wireless radio link. The coverage area of the network is divided into smaller areas referred to as cells. Each cell is covered by a stationary transceiver that is called the evolved Node B (eNB) [2]. Voice and data communication between the network and User Equipment (UE) take place over radio frequency links between the covering eNB and the UEs. The part of the network that includes the eNB, UEs, and connecting frequency links is called the Radio Access Network (RAN). eNBs are usually connected via a high-speed wired network called the backhaul.

LTE-A is standard for the 4th generation (4G) mobile networks introduced by the 3rd generation partnership project (3GPP) to satisfy mobile broadband services with higher data rates and Quality of Service [2]. Cellular and mobile networks witnessed an increasing demand for higher data rates and continuous growth of data traffic and number of subscribers. Furthermore, the number of devices to be connected will continue increasing exponentially due to Internet of Things (IoT) applications that can be deployed over cellular networks (smart cities, autonomous vehicles, etc.). Network densification is a key technology to satisfy these demands; it is achieved by increasing the density of elements in the RAN. This includes operator-deployed and user-deployed elements to increase coverage, frequency reuse, and achieved data rates [10]. Ultra-Dense Networks (UDN) are expected to be widely adopted in the future, to the point where each UE might have its own serving element.

Recent research considered employing the radio signals transmitted by LTE-A cellular networks for localization. The infrastructure of such systems is available for cellular communications. Furthermore, it can provide accurate results due to the wide spread of mobile devices and the ability to detect them, which can provide accurate estimation of occupants' headcount. The advantage of a cellular-based system is its wide availability and ability to cover areas where Wi-Fi access points or Bluetooth devices are not available. The geographical area covered by cellular networks can provide valuable data. With cellular-based localization, occupants can be tracked over the area of interest (e.g., at the building or university campus). This can allow analyzing occupants' movement and understand individual as well as emergent behavioral patterns. For example, the movement of students on campus can be analyzed to find the locations and times to reduce traffic jams. A large number of students on campus might all have to go through a certain corridor to get to a theater. Providing another way or entrance to the theater might improve the situation. As another example, analyzing such movement patterns of occupants might reveal that many occupants must move for a long distance during the day to get to a certain service (e.g., coffeeshop). These findings might help resolving such issue by introducing minor changes to building design.

Several localization systems based on measurements from LTE signals have been proposed. In [16], a localization system that employs Channel State Information (CSI) extracted from LTE signals was proposed. The system uses CSI measurements for signal fingerprinting localization. Experiments in indoor and outdoor environments show that localization based on CSI from LTE signals can be used for both indoor and outdoor localization. The authors in [23] proposed a fingerprinting approach for localization of UE in LTE-A networks mapping multiple radio channel parameters formulated as a fingerprint vector and a geographical location. They employ a feature-extraction algorithm to identify unique channel parameters and use a neural network to build a fingerprinting database of channel parameters and UE locations. Results show that by using only one LTE eNB, the proposed technique provides a median error distance of 6 and 75 meters in indoor and outdoor environments, respectively.

The authors in [15] also considered employing the CSI from LTE signals for fingerprinting-based indoor localization. The authors propose a technique where the fingerprint contains a vector that serves as the shape of the channel frequency response instead of the CSI. The approach uses eNB signaling messages and does not need designated communication between the eNB and the UEs. The approach reduces computation complexity and memory requirements.

In [11], the authors evaluate the accuracy of localization based on radio fingerprinting of LTE signals on 800 MHz, 1800 MHz and 2600 MHz frequency bands. Field measurements are conducted to collect training data that consist of UE locations and the corresponding received signal strength radio measurements from several base stations. Collected data are used to provide a fingerprint of the radio conditions at a specific location. The performance of two systems composed of LTE and LTE+WLAN grid-based RF fingerprint measurements utilizing partial fingerprint matching were studied and compared. Obtained results show that partial fingerprints that consist of LTE and WLAN radio measurements improves localization accuracy by at least a factor of 3.5x while keeping the percentage of discarded samples low.

The work in [6] used Cell-Specific Reference signal measurements from LTE signals for indoor localization to complement outdoors localization systems such as Global Navigation Satellite System. Two algorithms were used for localization. The first one is a Time-Of-Arrival approach called the Threshold-to-Noise Ratio algorithm. The second one is an estimator that is more complex but also robust against multipath fading; it provides more accurate, robust and smooth results indoors, at the cost of increased complexity.

All the research above considers LTE-A networks with macro cells, where a macro eNBs with high power provides the coverage for a wide geographical area and high number of users. In our work, we will studying the performance of localization over LTE-A UDNs. The availability of high number of elements such as femtocells and picocells are supposed to increase the accuracy of localization over mobile networks for indoors environments.

3 LTE-A UDN FOR OCCUPANCY ESTIMATION

3.1 LTE-A UDN Scenarios

New network architectures such as UDNs and Ultra-Dense Heterogeneous Networks (UDHetNets) are enabling technologies to meet increasing demands and achieve the required performance of 5G cellular networks [10]. With UDNs, the density of the operator-deployed and user-deployed elements is reduced, improving coverage, frequency reuse, and achieving higher data rates. In UDHetNets, several types of wireless access nodes are employed, and hence, macrocells are overlaid with low-power nodes such as Remote Radio Head, Pico eNB (PeNB) and Home eNB. These smaller cells can be used to offload traffic, which improves the network coverage at the cell edge and increase data rates.

The LTE-A Pro standard [1] proposes different scenarios for implementation of UDNs and UDHetNets. These include scenarios for UDNs where similar elements are employed, such as PeNBs, as well as heterogeneous scenarios where distinct types of cells coexist such as eNBs and PeNBs.

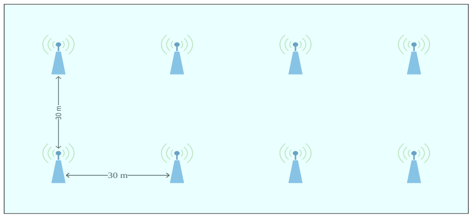

Figure 2. LTE-A UDN scenario A.

Following, we list the possible scenarios considered in the LTE-A Pro standard [1]:

- Scenario A-Indoor small cell deployment: this scenario consists of a single layer of small cells in an indoor environment. This scenario is shown in Figure 2.
- Scenario B-macro cell deployment: this scenario consists of a single layer of macro cells.
- Scenarios C and D-Heterogeneous network of urban macro and outdoor small cell deployment: these contain macro cells coexisting with small cells. The two differ in the method of channel allocation for the two layers.

Table 1. Transmission parameters for scenario A.

Parameters	Scenario A
Type	Indoor Hotspot (Figure 2)
Layout	Single layer Indoor TP: Number of TPs: N=8, N=12 (optional) per 120m x 50m
ISD (inter-site distance)	20m, 30m
Carrier frequency	3.5GHz
Coordination cluster size for ideal backhaul	All sites
System Bandwidth	10MHz (50RBs)
Channel model	Channel model available in document TR 36.814

We are interested in scenario A because our work is focused on indoor localization and building occupancy count estimation. The transmission parameters for such scenario is provide by the LTE-A standard and presented in Table 1. These parameters will be adopted in our study.

3.2 Methodology and localization approach

We propose using the Channel Quality Indicator (CQI) or Received Signal Strength Indicator (RSSI) values sent from the UEs to the eNBs for localization. A fingerprinting-based method will be used where a database of pairs of locations inside the building and corresponding CQI or RSSI values will be first built. During the localization phase, we will estimate location from the built database.

We propose simulating indoor LTE-A UDN scenarios. First, we will run simulation scenarios involving simple prototype floor plans. Afterwards, real building designs will be obtained from existing BIMs to generate simulation scenarios automatically. Various BIMs developed to produce a digital campus at Carleton University contain various attributes (spatial, areas, volumes, and uses of the rooms), which can be used to create real simulation scenarios.

As discussed in the next section, we will include occupants' behavior and their personas. This can result in developing models for the movement of occupants. Such realistic movement models can be used to create more precise simulation scenarios to study localization and count estimation. For instance, a study of occupants may reveal that many occupants tend to sit close to windows during the summer. In such case, occupants will stay close to the edge of the building, which means that an accurate localization algorithm would be needed to produce an accurate count estimation.

From these simulations, we will extract various data sets for the UEs locations and corresponding RSSI values as per the approach presented in the previous section. From the collected data, we will build a fingerprinting database, and evaluate the performance of indoor fingerprinting localization in LTE-A UDNs. The localization accuracy as well as building occupancy estimation accuracy will be considered as the performance metrics. Additionally, the performance of such scenarios will be studied and compared to those achieved in the case of a macro cell architecture.

4 LOCALIZATION AND BUILDING DESIGN

4.1 Occupant Behavior and Building Operation

Occupants are one of the leading causes for the difference in predicted and actual energy usage in buildings [5, 22]. The knowledge of how occupants behave and interact within a context is not available to them. Such behavior is usually more complex than the assumptions made by the modelers. The modeling and simulation (M&S) community does not have access to the ‘lived experience' of the people, therefore they need to assume the possible set of occupants' behavior in the buildings. Furthermore, factors like socioeconomic conditions, available technology, environmental conditions, and temporal adaptations influence the occupant’s behavior. The context decides the interaction possibilities. Privacy limits the possibility of understanding user behavior in buildings. Hence, measured data in buildings plays a crucial role in understanding occupancy behavior though it lacks qualitative interpretation. Various technologies are integrated in new buildings (e.g., sensors), and this makes various data (e.g., CO2 levels) available to designers. IoT allows us to have access to certain information without invading occupants' privacy (e.g., their current activities). Though there is a limitation in assumptions for occupants' behavior from measured data (like their perception or personal comfort), it could be used to improve design decisions. Our proposal focuses on creating and generating personas from measured data and build a model that optimizes the design based on the criteria [12]. The research goal is to use personas at the design stage and during building operation and automation. Using the personas at building operations will help the buildings to adapt sustainably. Likewise, the automation system could suggest efficient interactions based on the occupants' location. Additionally, it enables the building systems (like blinds, thermostat) to make dynamic changes to improve occupancy comfort and building performance.

4.2 The use of personas

During the design stage, building simulation can be used to analyze lux levels or temperature in a room, and the behavior of occupants for those conditions. However, during building operation more precise parameters can be defined through LTE-A. A qualitative questionnaire or inputs can collect the occupants' preferences. The measurable and qualitative information can enable automation to fine-tune comfort level during building operation. Persona gives flexibility: the same personas used at the initial stages of design could be used with finer granularity in real-time to improve building performance. The attributes are individual characteristics (age, clothing, activity, and role), comfort preferences (thermal comfort, visual comfort, and views), interactive behavior (blind, door, windows, equipment states), eco-behavior (active or passive decisions made to save energy), and social behavior (socio-economic conditions and group dynamics).

During operation, the occupants' location enables us to make the spatial relationship with other measurable data like available interactions, room temperature, and lux levels. The automation can use the information to make effective dynamic changes. Further, occupancy count and tracking enable us to understand group dynamics like preferred location, most likely used space as a group and as an individual. All these pieces of information may help in refining building operation. The following section explains how the personas help in understanding the user behavior at the design stage.

4.3 Personas for Occupancy

Figure 3 illustrates the integration of personas to the model of a typical generative design (we limit the discussion to the parameters of the personas and not the whole generative design components). We propose defining the geometry using Dynamo [7] and Autodesk Refinery for Generative Design. The model runs energy simulation with the initial geometry, and then evaluates the output for occupant behavior.

The personas are generated randomly using two main parameters: the number of occupants and the building type (see Figure 4). It creates different persona types for simulation and evaluation. Once the simulation is completed, the system runs fitness criteria for sustainable behavior goals.

Fitness evaluation is performed using Discrete Event Simulation. Once the performance data is updated, the model runs a fitness check on how the different personas will behave on those conditions. If their interactions with building elements and systems (like windows or thermostats) lead to more energy usage than the defined goal, the system modifies the geometry and reruns the process to produce an optimal design. Personas may be a solution to minimize the discrepancy between predictive and actual scenarios of use for energy use and comfort. Understanding the behavior of the occupants will affect the design decisions. Personas could be used in automated building to control thermostat, blinds, or lighting.

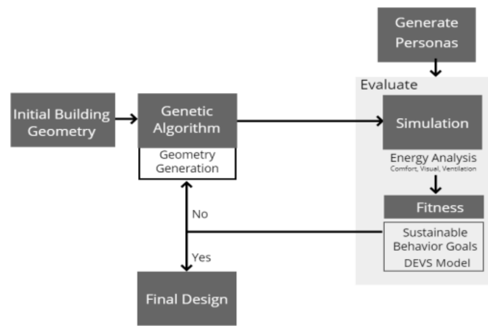

Figure 3. Integration of personas to a typical generative design model using Revit/Dynamo/Refinery/DEVS.

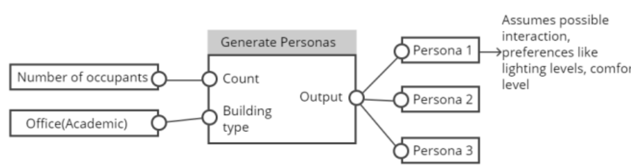

Figure 4. Conceptual model for generating personas

4.4 Personas and localization

The novelty of the idea is to use the personas with occupants' location, count, and tracking for building operation (see Section 3). In this section, we discuss the use of persona with the localization concept at a small geographical and quantitative scale (i.e., room or building, and individuals). Figure 5 shows the parameters considered to develop personas for automation purposes.

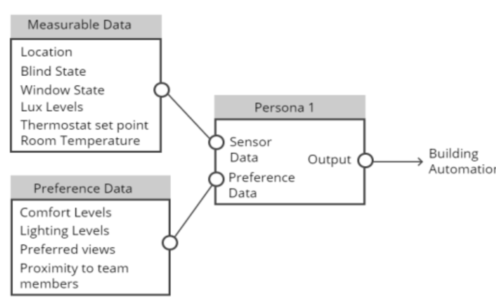

Figure 5. Personas for building automation

There are two categories for the collected parameters. First, the measured data (like blind state, room temperature) and second occupant's preference data (like preferred light settings). Based on occupant location, the automation system collects other corresponding data like room temperature, lux levels, and blind state. It compares the information with the preferences of the occupants to automate the blinds or thermostat or any automated system. The automation can consider the decisions at the individual level or collective level. It depends on the influence on its surrounding. For example, at a collective level, a person sitting close to windows may have more daylight compared to the person sitting on the far end. Hence, a person sitting at the far end may need more artificial light than the person sitting closest to the windows. Likewise, a person sitting closest to the window may feel colder during winter compared to the person sitting at the far end. Hence, considering the location and corresponding measurable data will help in refining occupant comfort.

The comfort of an occupant needs to be considered at an individual level and a group level.

5 BIM AND BUILDING OCCUPANCY SIMULATION

We use BIM models as a host where to produce simulations, to apply building retrofitting concepts (using data extracted from the occupancy count estimation as a parameter in the model to inform future designs); and as a tool for digitally assisted storytelling (which refers to graphical dissemination of data and visual communication of the simulation results).

Figure 6. Render of InfraWorks of the Digital Campus model.

We built a BIM model of Carleton University campus, consisting of a federated digital assembly of more than 50 buildings, roads, tunnels, landscape, etc. (Figure 6). The model includes many different layers of data received from various parties, some of which are anticipated to be beneficial for the three applications mentioned above [19].

5.1 Using BIM models for prediction

To produce simulations, an architectural setting is needed; however, in some cases, it is not necessary to have a model that reflects an actual physical place. If one has an accurate virtual representation of a real building that contains all the attributes required for occupancy count estimation and tracking, one can replace the need for a physical one. For this reason, a digital model was a more feasible alternative. The digital campus has all the essential elements required to run the simulations and has the potential of holding more parameters if it is required in the future. The campus BIM model contains rooms with parameters for spatial attributes, such as their area, volume, uses, etc. It also contains walls, ceilings, floors and all the architectural elements needed to understand the space, as well as location and all the attributes of the eNBs. With these components, it is possible to simulate scenarios as accurate and as close to reality as possible. The virtual representation of physical spaces and architectural elements creates a good environment for hosting both the simulation and the personas.

The model can be used at different scales. At building scale, it is possible to understand the characteristics of the indoor environment. For example, one can simulate the impact on new buildings over existing buildings to predict the consequences this new relationship is going to have over the occupants of the existing space. Additionally, at campus scale, it is possible to visualize occupancy in relation to groups of buildings, circulation, services, shared areas, landscape, etc. This could be beneficial to larger scale planning strategies by producing a better understanding of campus use.

5.2 Using collected data to inform design

The second BIM application for this study refers to the use of data collected from the occupancy count estimation, as well as the behavior of people and their location in space to inform future designs. For example, every few years, the university produces a campus master plans to set the parameters, policies and directions for the physical development of its campus. This master plan aim to set the basis for future developments, guiding them to be in harmony with the university's principles. Having a better understanding of the occupancy, behavior and location of people on campus could help designers to generate better and more accurate master plans. For instance, the campus that we used to run the simulation in this study has tunnels to connect different buildings during the winter months. Should the collected occupancy data reveal one tunnel having more intensive use than another, the designers can respond to this information, potentially widening tunnels, reducing others, or even building new ones to reduce congestion in future master plans. Another application could be to define the dimensions of new spaces. For example, if a space demonstrates a greater occupancy than expected, a similar typology in a new building could be designed taking into consideration the results of the simulation. Additionally, it could help to make decisions regarding materiality: designers could pick stronger tiles for a floor that proves to be used more intensely than another do, or to reduce the dimensions of beams supporting a space that is not as frequently occupied. In both cases, the process may result in using materials and elements that are better fitted for their use, thus making them more durable and cost-effective in the construction of new buildings. The collected occupancy data, treated as a parameter in the BIM model, could become additional information for HVAC system designers (see Figure 7). Here, optimal systems and equipment for the ventilation of a new building can be developed, taking into consideration the potential use of its spaces. Finally, the data could be used through the BIM model for operation and maintenance (O&M). It is becoming increasingly common for Facility

Managers (FMs) to use BIM models to operate buildings. Integrating real time collection of occupancy data such as location and behavior into a BIM model, could help FMs better understand the use of different spaces, enabling a higher efficiency of O&M management [17].

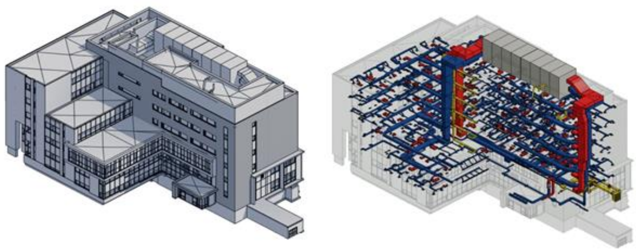

Figure 7. Mechanical, Electrical and Plumbing model (MEP) of the Health Science Building (digital campus model).

5.3 Digital Assisted Storytelling

Digital Assisted Storytelling refers to the use of digital techniques to create narratives that disseminate information and ideas. BIM platforms, such as Revit, provide powerful visualization features that allow users, through two or tri-dimensional geometry, to display data in intuitive and interactive ways. This includes diagrams, adaptive geometry and interactive parameters, among others. This way of disseminating the data obtained through simulation could help non-specialized users or those without any AECO background to understand and interact with the results of the study in real-time.

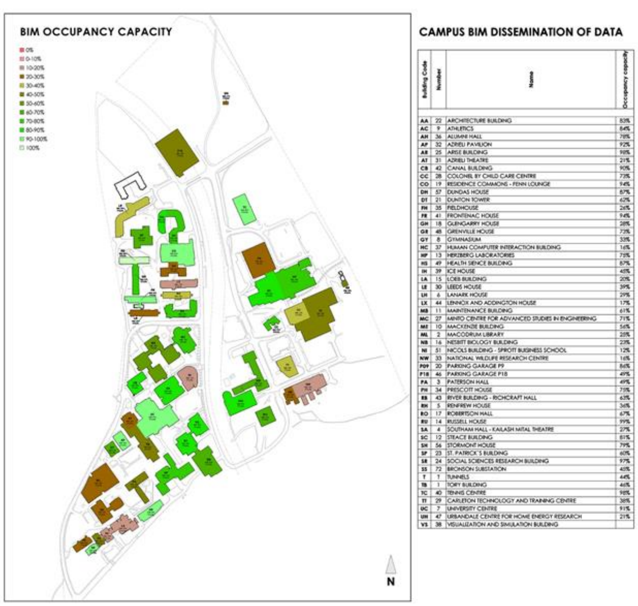

Figure 8. Simulated occupancy diagram.

BIM helps to graphically disseminate the results of a simulation in multiple ways; since the BIM model contains all the architectural and geometrical information of each building in the campus, the data could be displayed as floor plans, sections, elevations, axonometric views, renderings, etc. In Revit, through Visibility Graphic Display, it is possible to pre-set the expected visualization to update according to the changes in the data (Figure 8). One can also create View Templates that can adjust the properties of multiple views at the same time, making the process more efficient while also providing visual consistency. Furthermore, through Revit, one can use Dynamo, a visual programming tool, to manipulate large amounts of data and complex geometry with great precision. With Dynamo, it is possible to manipulate the data and produce real time diagrams and graphs. This way of visualizing data helps us to better communicate the results of our simulation, making the information available to more people, and allowing better feedback and collaboration.

Using a BIM model allows us to generate a bridge between complex technical language—which was required for the simulation—and the common designer or user. This communication enriches the process of Storytelling. As the architect and scholar, Marco Frascari wrote: “Buildings are not experienced as data ‘fed to passive spectators’ but, instead, are experienced culturally through the stories found embodied in buildings and retold by architects… the real architectural craftsmanship is the crafting of a good story” [13]. Data, on its own, has no real power to generate an impact on people, or to have a deep implication towards their experience; the real power is in the story that one is able to tell or to graphically display. We are facilitating the understanding of complex processes in a simplistic and didactic way.

When working on multidisciplinary projects, it is important to maximize the diverse capabilities of each team member. Indeed, for a group composed by professionals and academics with diverse backgrounds, BIM becomes an ideal tool to congregate technical analysis and qualitative results with a rich and intuitive visualization. “BIM has the untapped potential to unhinge the link between instrumentality and architectural representation. For example, the capacity to simultaneously incorporate large and diverse sources and types of information, represent it in multiple formats, and react to input in real time present an opportunity to develop modes of architectural representation that are in flux and responsive to the people, history, materials, and environment that contribute to the making of architecture.” [9]. BIM promotes collaboration and communication among professionals of the AECO industry and it has the capability to transmit the produced information massively and in elemental ways.

6 CONCLUSION

We propose the use of LTE-A UDNs to provide estimates for occupancy count and user location and tracking in buildings. We specifically proposed to use CQI or RSSI values from the UEs to the eNBs. To use this data, we are building a database of pairs of locations inside the building and corresponding CQI or RSSI values. We will use different algorithms for the localization phase. We will also evaluate the performance of those algorithms and provide a comparison. We will evaluate them on different simulation scenarios created from the information stored in BIM models.

The advantage of using LTE-A UDNs over other approaches based on data collected over a network of sensors (e.g. CO_2 levels, camera data, humidity, etc.) is that it eliminates the need to install and set up sensors in the building. We reuse the LTE-A infrastructure that is already deployed for cellular communications. Because we do not need to deploy specific sensors for occupancy and user location, we expect that this approach will reduce the cost of the building equipment and its maintenance. Additionally, the LTE-A UDNs are maintained by the cellular service provider. We also expect that this method will provide better results than other methods that also use already deployed infrastructure for communications (e.g. Wi-Fi AP). As future work, we will validate this assumption comparing our proposed method with others based on Wi-Fi APs and Bluetooth.

Having accurate occupancy count estimation, and user location and tracking can have an impact in optimizing building Operation and Management. Employing occupancy detection and localization (using LTE-A UDNs) is being investigated. We propose using occupancy data to optimize the operation of the building through actuators and controllers (e.g., controlling HVAC systems). We also propose using both sensor data as well as occupants' locations and count estimation to study occupants' behavior and generate personas (e.g., movement patterns, preferred locations within offices, etc.) that are also used in the process of analysis and design of the building and its controllers through simulation. Furthermore, occupants tracking, and count estimation will be included as parameters in BIM models and visualized. Such data will be used to design future buildings with the same purpose as the current building, or to generate designs during expansion or retrofitting of the same building.

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