Realizing a Smart University Campus: Vision, Architecture, and Implementation

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Abstract—**The revolution in Internet-connected devices like cameras, occupancy detectors and air quality monitors, collectively dubbed as the Internet-of-Things (IoT), is enabling the realization of smart environments ranging from homes and offices to campuses and cities. In this paper, we describe our journey (admittedly still in its early days) towards the realization of a smart campus in a large University with over 50,000 students; 10,000 staff; and nearly 100 acres of real-estate. We begin by charting out the vision of the smart campus, focusing on how IoT technologies can benefit various stakeholders including students, staff, and estate managers. Our second contribution outlines a systematic approach to the architecture of a smart-campus, that horizontally separates the sensing, data storage, and analytics layers. We show that our approach prevents vertical lock-in to any IoT vendor, scales to arbitrary number and type of sensors, and permits analytics across data silos. Lastly, we describe our pilot IoT deployments pertaining to four use-cases on our campus, specifically classroom attendance, student study space usage, parking lot occupancy, and bus-stop wait-times. The data and preliminary insights obtained from these deployments provide quantifiable benefits to stakeholders, such as improved space usage and enhanced user experience.**

I. Introduction

Large university campuses are like mini-cities: they occupy several acres of land; they contain various spaces and facilities such as office buildings, lecture halls, libraries, informal study rooms, retail spaces, car parks, and public transport stops; they are populated with tens of thousands of people; they host a dynamic flow of human activities from students and staff to contractors and general visitors, each with different needs and profiles; and they are under constant pressure to provide better services to stakeholders while reducing costs. Thus, operating a university campus is a complex business.

Recent advances in Internet of Things (IoT) technologies – connected devices such as cameras, screens, motion detectors, ambient environmental sensors – coupled with advances in data analytics tools and platforms, present an opportunity to transform the campus in new ways, prompting many Universities world-wide to develop strategies for a "smart-campus" that not only makes the operation of the campus more efficient [1], but also improves experience for students and staff [2]–[4]. Improved efficiency helps Universities climb up the rankings ladder within tight budgets, while an engaging campus experience helps them distinguish their offerings from online education options – both of these are of paramount importance to Universities in order to attract and retain the best students and staff from around the globe.

Our first contribution in this paper is to articulate the vision that provides the impetus for a smart campus. Our views are informed by discussions with various stakeholders on our University campus. We engaged with various personnel in Estate Management to discuss the ability (or lack thereof) to quantify usage of space assets on campus, specifically lecture halls, study spaces, and parking spots; we engaged with teaching and research staff to identify pain points around meeting room availability and equipment tracking; and we engaged with students to capture the potential of IoT to assist with way-finding, social get-together, transport wait-times, and retail shopping, so as to enhance their campus experience. Documenting these views helps understand the use-cases that motivate a smarter campus.

Our second contribution is to develop a smart campus architecture that is flexible enough to accommodate the diverse use-cases identified above. It is very important for the architecture to have minimum tie-in to any specific vendor or platform, since that can hinder the adoption of new technologies (e.g. sensing devices or analytics tools), and can result in data silos. We therefore propose an architecture that has three layers - the **sensing layer** allows arbitrary sensors with heterogeneous power and communications requirements to be incorporated into the system; the **data layer** stores the collected sensor values in an unstructured manner as type-value pairs that are timed and tagged, so that new sensing data can be included without any format changes; and lastly the **analytics layer** allows arbitrary processing (and visualization) of data by a plethora of open and proprietary tools and platforms. We emphasize the need for the data layer to be as platform agnostic as possible, since it forms the "thin waist" above and below which the sensors and analytics respectively sit.

Our final contribution is the practical realization of some of the identified use-cases via pilot deployments in our campus. We briefly discuss our experiences, highlighting choices we had to make, challenges we faced, and insights we obtained. Our pilot deployments confirm our belief that our architecture is robust enough to handle a wide range of use-cases, while still allowing us to make appropriate trade-off decisions (power, communications, privacy, etc.) suitable to each use-case. The insights obtained from our pilot deployments also highlight the benefits that IoT-based continuous and automated data collection brings to decision making in a University campus, and can be translated to larger smart city-like environments.

II. Smart Campus Vision

There are three main stakeholders of a smart campus namely estate management, students, and academic staff. These stakeholders may have their own expectations from a smart campus.

Estate Management (EM) of universities want to monitor the real-time utilization of campus-wide facilities: **(a)** our university main campus is located on a 38 hectare site in a city where real-estate is at a premium. With over 50,000 students, the university centrally supports and maintains over 200 classrooms of varying size, ranging from small classroom of less then 50 seats to large lecture hall that can occupy over 400 students. These spaces facilitate a wide variety of learning and teaching styles, from traditional lectures to active, blended and small-group learning. Real-time monitoring of usage of classrooms will not only provide visibility into actual class attendance and how the spaces are being utilized, but will also allow possibility for the university to better allocate classrooms to match the actual student attendance while minimizing the risk of attendance exceeding room capacity; **(b)** we have two major multi-story parking facilities on our campus. Our EM issues various types of physical parking permits (i.e. annual for staff, per-semester for students, weekly/daily for contractors, and casual for visitors). Real-time sensing and visualization would enable Estate Management to accurately quantify parking demands and usage profile thus helping them offer electronic permits and possibly apply dynamic pricing models for each type of users; **(c)** as part of an ongoing development of learning environments, our university continues to heavily invest in different types of spaces including student-led (informal learning) spaces, experimental and innovation spaces, and collaborative classrooms, providing students to study, meet, and collaborate, with an aim to enhance their learning and life experience on campus. In order to evaluate the return on investment, IoT technologies can be brought in to measure occupancy patterns and quantify student experience in these spaces through measuring various ambient conditions such as noise level, air quality, and lighting conditions; **(d)** Anecdotal evidence indicates that the bus stops around our university campus get very crowded during certain times on certain days during session. This not only causes immense frustration to students, who experience large variations in wait time depending on time-of-day and day-of-session, but also creates a challenge for EM in knowing when to request/schedule extra buses. Having continuous data collected on the crowd volume and wait times at these bus stops would thus be highly beneficial.

In our smart campus vision, students and their experience are always at the core. Student experiences can be enhanced through various smart services: **(a)** access to spaces with an optimum lighting, ventilation, and temperature for collaborative group study or social gathering; **(b)** way-finding for classrooms and social events inside large and complex buildings since general positioning services (e.g. Google Map) do not cover indoor spaces on our campus; **(c)** real-visibility into available parking spots or access to the best transport services (e.g. taxi vs. private car sharing vs. public buses) around the campus; **(d)** access to real-time estimated wait times for cafeteria food; and **(e)** access to real-time availability of recreational and fitness facilities.

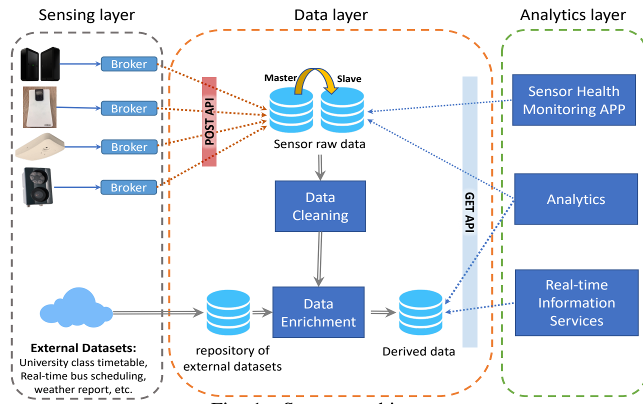

Fig. 1. System architecture.

Lastly, our university is increasingly embracing new modes of education delivery including flipped classrooms, work-based learning, blended learning, or student-led learning to enhance students education experience on campus. Having classrooms and labs instrumented by various IoT devices which can count room occupancy, detect movement patterns and measure ambient conditions such as air quality, would enable academic staff to: **(a)** quantify students attention and engagement during classes; **(b)** measure the effectiveness of learning delivery and lab resources; and **(c)** track specialized portable lab equipments.

III. System Architecture and Challenges

In this section, we describe our system architecture built to accommodate the realization of our smart campus as well as highlight practical considerations and challenges involved during the deployment.

A. *System architecture*

The main purpose of our system architecture is to support the collection of data generated from a variety of smart sensing devices and the retrieval of these data for applications to consume. Our architecture comprises the following elements: (i) the sensing layer that contains multiple IoT devices. Not only these devices are used for different purposes, they also have heterogeneous requirements in terms of power, communications, and installation; (ii) the data layer which is platform agnostic and is responsible for storage of data collected from the sensing layer; and (iii) the analytics layer where raw sensing data is transformed into insights and actionable intelligence for applications use, enabling various services offering in a smart campus.

Fig. 1 shows a high-level system architecture representing the flow of data from the sensors in the sensing layer (on the left) to the applications in the analytics layer (on the

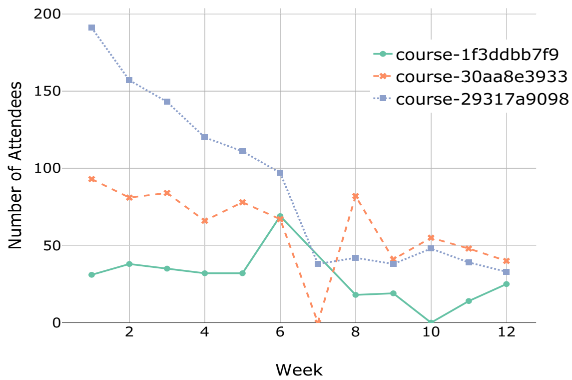

Fig. 2. Attendance pattern of three anonymized courses.

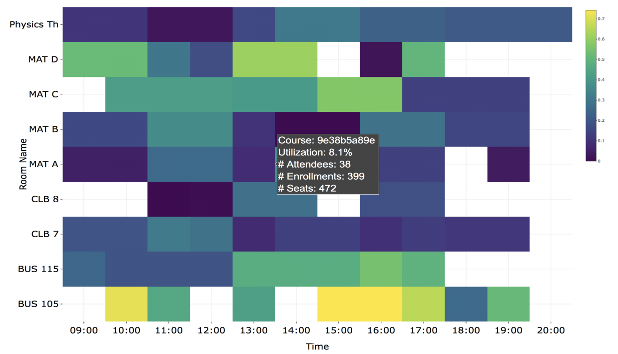

Fig. 3. Heatmap of classrooms occupancy across campus.

right). The sensors first communicate with a corresponding message broker where sensing data from a variety of format is unified into a common format accepted by the database (i.e. type-value pair that is timed and tagged). Each sensing record comprises of three main fields namely "sensor identifier", "measurement" and "time-stamp". The measurement field is a JSON array of elements, providing flexibility for different types of sensors to embed various metrics each as a separate key/value pair. For example, {`"temperature":20`, `"humidity":25`, `"CO2":24`} is a the measurement of an air quality sensor. This unified data is then transferred to our raw sensor database via a HTTP POST API (i.e. RESTful).

The raw sensor data is next fed to another processing engine to get first cleaned (for example any outliers in data will be removed in this stage) and then enriched with external datasets such as class-timetable, enrollment list, weather report, or real-time public transport schedule. The resulting output of these processes will be stored in a "derived database" (e.g. the total number of people in a classroom), ready to be consumed directly by various applications in the analytics layer.

B. Practical Considerations

This subsection describes key practical considerations one may need to consider for the realization of smart campus. Several methods and technologies are available to measure various parameters, from counts of people and vehicles to indoor and outdoor environmental metrics. Each method has its own pros and cons in various aspects such as cost, power (AC or battery), Comms (WiFi, LoRaWAN, 3G/4G, or Ethernet), calibration, ease of deployment and operations, privacy, security, accuracy, sustainability and scalability [5], and more importantly interoperability and cloud computing integration [6]. Sensors requirements for power and Comms become crucial when it comes to deployment of IoTs for each use-case. For example, AC power sockets or Ethernet ports may not be easily available for outdoor installations.

For our campus, we investigated several commercial sensors and straightaway eliminated those that send data to the vendor's cloud servers, since we wanted to: (a) keep the data entirely on-premises and not risk it leaving our campus infrastructure; and (b) not be beholden to a vendor to access our own data, hence freeing us from ongoing service costs. In other words, we wanted a "sale" model of the device so we could have unfettered access to our data without any ongoing "service" fees. Further, this model allows us to integrate data into a centralized repository to facilitate better analytics across the many data feeds we have on campus.

The wide variety of smart sensors creates the next challenge namely heterogeneity of generated data sources and formats. Multiple data sources from different types of sensors produce different formats of data leading to inconsistency in data structure, for instance some sensors produce data in a csv format while the other in a JSON format, some off-the-shelf sensor posts data to their own proprietary database with a specific data structure, creating further diversity in data characteristics. This poses a challenge in the data collection process as the data will need to be unified through message brokers into the same structure prior to being stored into our centralized database.

Furthermore, the collected data from IoT devices may contain private or sensitive information (e.g. cars license pate captured by License-Plate-Recognition cameras, or individuals' enterprise id captured by campus WiFi logs) that can not be shared across different entities. This creates a challenge in design of data accessibility.

IV. Pilot Execution of Smart Campus Use-cases

To achieve our smart campus vision mentioned in section II, we execute four use cases of different domains as a pilot execution of our smart campus initiative. We obtained appropriate ethics clearances for this study (UNSW Human Research Ethics Advisory Panel approval numbers: HC17140, HC171044, and HC180359). For each use case, we outline our motivations, implementation methods, and applications of smart services enabled by IoT technologies.

A. Classroom Occupancy

1) Motivation: An increase in availability and accessibility of online courses and video recordings has led class attendance to well below the enrollment number. Furthermore, due to a lack of occupancy monitoring, the university has no visibility into how classrooms are being utilized. The result is a wastage of classroom spaces which is one of the university's most expensive assets especially in the area where land price is at a premium. Providing visibility into actual class attendance is essential to inform better decision for classroom allocation,

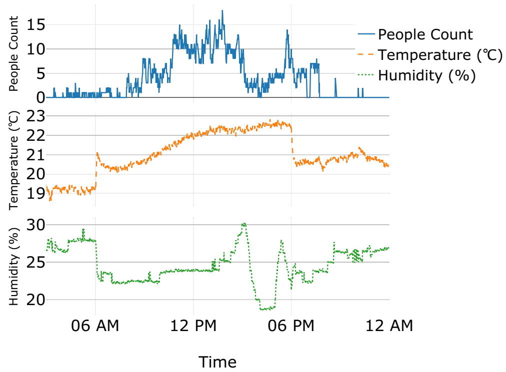

Fig. 4. Real-time monitoring of occupancy and air quality measures for informal learning space.

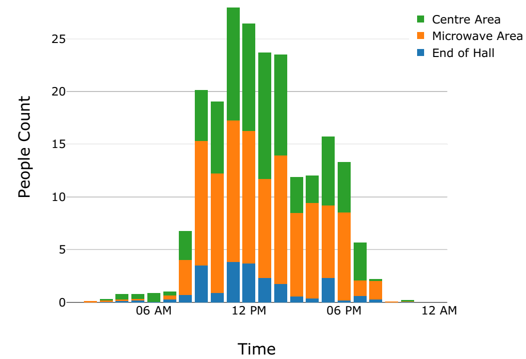

Fig. 5. Temporal variation of usage for various parts of informal learning space.

TABLE I
SENSORS COMPARISON.

	Installation	Calibration	Power	Comms	Accuracy	Cost	Privacy
Beam counter	easy	easy	battery	wireless	high	medium	✓
Thermal camera	hard	medium/hard	AC power	wireless	low	high	✓
HPD camera	medium	hard	PoE	Ethernet	medium	medium	✓
PIR sensor	hard	easy	AC power	wireless	binary	medium	✓
WiFi	existing	existing	existing	existing	low	0	✗

where expected attendance can be taken into account during the allocation process in order to achieve a higher utilization of resources.

2) Methods and Deployment: As note in Section III-B, we evaluated several sensing devices including beam counter [7], people counting camera [8], overhead thermal sensor [9], and WiFi data, along the different dimensions including cost, ease of installation, power and communication requirement, accuracy, and privacy as shown in Table I. We therefore decided on a larger-scale deployment of the beam counter, based on its relatively low cost, ease of installation, acceptable accuracy, and good protection of privacy. The deployment has been completed across 9 lecture halls of varying sizes ranging from 35-seat room to 497-seat lecture theater.

3) Applications: We developed a web application tool to provide an intuitive interface into the visualization of real-time and historical class attendance. The tool allows us to see occupancy pattern for each of the deployed classroom, where large gaps between the actual attendance and the enrollment number are often observed. We are able to quantify attendance rate which in general, is seen to vary widely between 10-90% across courses. Fig. 2 shows an example of attendance patterns for 3 courses across the 12 weeks of a semester. The plot allows us to spot interesting trends such as a general decline of attendance over weeks (blue line), class cancellation (orange line), and mid-session test (green line) where a spike can be seen during the middle of the semester. Our tool also provides visualization of the utilization "heatmap" of the classrooms on a chosen day (Fig. 3), where bright yellow cells represent high utilization of classroom spaces while dark blue cells represent poor utilization of classrooms.

We observe that course attendance varies over the weeks which leads to under-utilization of classrooms. This presents an opportunity for campus managers to employ a dynamic allocation scheme to save cost. A practical implementation could use historical attendance data (say from the previous year) to develop a dynamic schedule for a course using an optimization algorithm, while leaving some margin for error arising from the use of retrospective rather than prospective attendance counts.

B. Occupancy of Informal Learning Space

1) Motivation: Informal learning spaces are described as non-discipline specific spaces used by students and staff for self directed learning activities which can be within and outside library spaces [10]. These spaces have a major impact on students engagement outside the classroom by helping the creation of a shared, supportive learning community [11]. However, the university does not have any insight into how these spaces are used or what are students' experience toward the spaces, thus unable to quantify the effectiveness of these spaces being constructed across the university.

2) Methods and Deployment: As in Section IV-A2, people counting methods are necessary to quantify occupancy of these spaces. The approach adopted therein, however cannot be replicated for informal spaces as they are not completely enclosed – no doorways. For informal learning spaces, we used human presence detection camera which has a built-in image processing unit to count the number of people present within a configurable area of interest [8]. The camera required a special PoE switch to provide Ethernet for both power and communications and the installation of the camera can be done by a certified tradesman as it needs to be mounted on the ceiling. In terms of privacy, the camera employs an on-board processing and does not store any image or personal information, hence it can be deemed to preserve privacy.

Students experience can be measured using traditional methods such as conducting a survey or interviews – these methods require significant human resources and the data will be limited to specific period of time when the survey is being conducted. Researchers [10] have identified a number of environmental factors such as noise level, CO2 measure, and ambient light that indicate students preference to learning spaces. Therefore, we use IoT technology to continuously measure various environmental factors to infer experience of occupants.

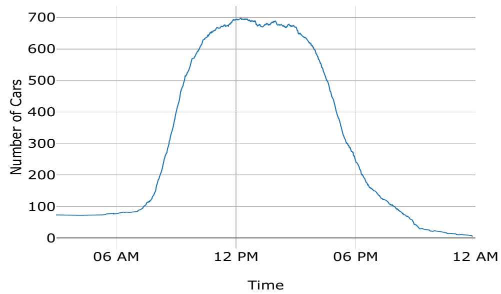

Fig. 6. Daily usage profile of carpark (for a weekday).

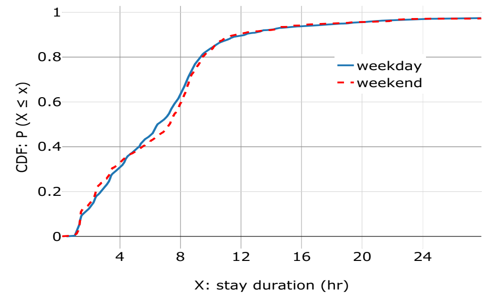

Fig. 7. CDF of stay duration of cars in carpark during weekday and weekend.

3) Applications: We have deployed three units of people counting cameras in a large informal learning space close to our campus library that is typically used by students. Each camera is configured to monitor a non-overlapping zone of interest. Fig. 4 shows the time-trace for the aggregate number of people present at the space along with the temperature and humidity of the environment. This allows the EM to quantify the usage of the space as well as to monitor if the environmental condition is within the comfort zone of occupants.

Fig. 5 shows the time trace of people count for each zone (in the space). It is seen that the "microwave area" (shown by orange bars) is utilized more compared to the "centre area" and "end of hall", highlighting the facility of interest for students in this space.

C. Car park monitoring

1) Motivation: A lack of real-time visibility into campus parking space usage and availability has led many students and staff members to spend a frustrating amount of time searching for a parking space. This not only causes poor user experience but also worsen traffic congestion around the campus. In addition, our university EM needs to have access to accurately quantified data on how campus car parks are utilized in order to make informed decisions on pricing policy or shared-transport space renting.

2) Methods and Deployment: There are various technologies used for parking management system worldwide including parking guidance information system (PGIS) where users are informed on the availability and location of parking spaces; smart payment system; E-parking which provides users with reservation services; and automated parking [12]. Due to budget constraints, we decided not to employ parking disks (affixed to parking bays that detect presence/absence of a car) for occupancy monitoring of hundreds of parking bays – disks would be a preferred solution for usage monitoring of a handful of bays dedicated to car-sharing vehicles. One may choose to deploy RFID tags (incorporated into parking permits) that can be scanned whenever a car enters/exits the parking lot. This sensing method was not appropriate for our case since it required changes into parking permits that get renewed annually for staff. For our pilot deployment, we installed 2 units of License Plate Recognition (LPR) cameras at the entrance and exit to one of our campus car parks.

3) Applications: Our preliminary results allow us to gain insights into real-time usage and availability of the car park, Fig. 6 shows a daily usage profile of our campus car park. Unsurprisingly, the car park is fairly utilized between 7:30am and 6pm during staff working hours. This real-time usage profile enables the EM to plan for the number of bays they can rent to car sharing service providers.

Fig. 7 shows a cumulative density function (CDF) plot for stay duration of cars at the car park, allowing us to quantify the parking behavior of users. We can see that over 90% of users are using the car park for less than 12 hours at a time while a minor fraction (i.e. 2%) of cars stay longer than a day.

D. Passenger queue at bus stops

1) Motivation: Bus stops around campus, especially those serving express buses to the central station, can get very crowded during certain times. Currently there is no data available to inform passengers on how long they are expected to wait once they join the queue at a bus stop. This not only causes immense frustration to students who experience large variations in wait time, but also creates challenges for the university EM and the transport authority in knowing when to schedule extra buses.

2) Methods and Deployment: One of the methods we have started using to measure passenger queue at the bus stop is to install miniature ultrasonic sensors along the fence bordering the queue, in the direction in which the queue grows. The sensors measure the distance between itself and the closest object, allowing us to determine whether someone is in front of the fence and thus helping us to infer the estimated length of the queue in real-time. Since these sensors will be located outdoor where no power and communications point is available, the device has to be battery-powered and needs to communicate wirelessly. We chose LoRaWAN [13] as the communications method due to its low power requirement which leads to a long battery life, and its wide range communication as the bus stop of our interest is located in an area where the campus WiFi signal is not available.

To complement the data collected from the sensors, we will also receive a CSV file of daily WiFi connection logs for the access points located close to the bus stop of interest from our University IT department. Analysis of this data will be performed to determine if the connected user is joining the passenger queue in order to approximate the demands at the

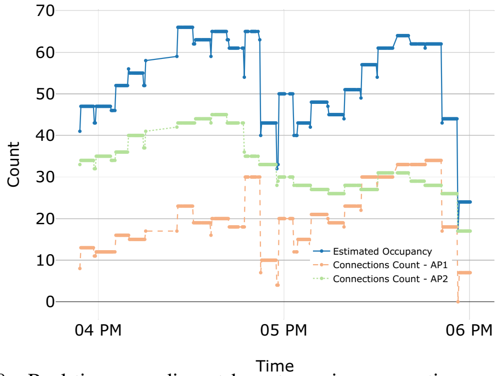

Fig. 8. Real-time crowding at bus stop using connections count of campus WiFi access-points.

Fig. 9. Placards with unique QR codes regularly spaced along the bus-stop queue.

bus stop. Fig. 8 shows an example of WiFi connections count from 2 access points (green and orange lines) close to the bus stop during a 2-hour period – the sum of these two counts (blue line) is an estimate for the number of people waiting at the bus stop.

Additionally, we will employ a method that involves users contributing data. In this method, we will install placards with unique QR codes regularly spaced along the bus-stop queue (possibly co-located with the sensors mentioned above), as shown in Fig. 9. A person joining the queue can (if they wish to volunteer data to this project) scan the QR code nearest them using their mobile phone. This will trigger two actions: (a) they will be directed to our website, and our server will assign a "cookie" (unique id) to their phone; and (b) we will record in our database the position of the cookie (individual) in terms of distance (meters) from the head of the queue (based on the known location of the QR code placard), along with the time-stamp. As users keep advancing in queue and scan subsequent QR codes placed along the queue, our algorithms will be able to estimate the rate at which the queue is moving, and wait-times incurred by users at the bus-stop. In order to incentivize students to contribute their data on queue progression and wait-times by scanning the QR codes at the bus-stop, we intend to give them "points" that are accumulated with each scan, and these points can be redeemed for a cash/voucher reward.

3) Applications: Data associated with crowding at bus stops collected from the methods mentioned above can be used to derive estimated waiting time at bus stops across campus. Availability of this information in real-time allows users to make informed decisions about their departure time and which bus stop they will be heading to, based not only on the existing real-time bus schedule but also the expected wait time incurred at each bus stop [14]. The data will also encourage peak spreading of public transport services where demand for travel can be broaden over time and space, for example if there is a long queue of passengers at a certain bus stop, a fraction of those passengers can be encouraged to walk to the next nearest bus stop or take another route, thus reducing the crowd and waiting time for all passengers. Furthermore, real-time data on actual transport service demand will allow a development of new methods to dynamically optimize bus schedules based on bus stop crowding information, minimizing the mismatch between demand and supply.

V. Conclusion

In this paper, we have outlined our journey towards the realization of smart campus in a large university. We engaged with various stakeholders to articulate the vision of a smart campus using IoT technologies. We then developed our three-layer system architecture comprising separate layers of sensing, data, and analytics that prevents vertical lock-in and scales easily. Lastly, we executed four pilot use-cases in our campus and revealed insights we obtained, highlighting the benefits that IoT-based continuous and automated data collection brings to decision making in a University campus.

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