Classroom Occupancy-based Human Resource Optimization using Sensor- and WiFi-based Location Tracking

by

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ABSTRACT

This thesis presents a framework for dynamic allocation of human resources in operations and maintenance based on occupancy of university classrooms using sensor- and WiFi-based location tracking. It includes case studies where 125 classrooms at the University of Alberta in Edmonton, Canada, are monitored to determine occupancy by using WiFi and heat sensor-based indoor location tracking. The optimal usage of human resources based on a university's classroom occupancy and enablement of coordinated human resource utilization are the main objectives of this research. Humans act as an important central figure in accomplishing numerous operations and maintenance tasks. WiFi and sensor-based indoor location tracking in classrooms enables management systems to identify near real-time classroom occupancy and assists in augmenting workforce allocation based on the observed usage patterns in university classrooms. Furthermore, a comparative analysis is conducted between university schedule-based occupancy models, WiFi-based location tracking systems, and heat sensor occupancy counters to determine the most efficient method of human resource allocation for facility management operations in university classrooms. Based on classroom occupancy density indicators, a rating system is developed to relate classroom usage with human resources allocated for custodial purposes, inspection, and maintenance of classroom facilities for dynamic allocation of human resources. The resulting time and cost savings in facility operations and maintenance services (based on the case study of University of Alberta classrooms) show that dynamic human resource allocation based on real-time classroom occupancy can reduce wastage of human resources.

Keywords: human resource optimization; indoor location tracking; university classroom occupancy; WiFi; heat sensor occupancy counters; cost savings; occupancy density indicators.

PREFACE

This thesis is an original work by Preshit Verma. No part of this thesis has been previously published.

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CHAPTER 1: INTRODUCTION

1.1 Motivation

This research uses university course schedules, heat sensors, and WiFi-based location positioning systems for determining classroom occupancy in real-time for dynamic allocation of human resources in operations and maintenance. The management of supply and demand of resources based on real-time position tracking in indoor environments using WiFi and sensors is becoming increasingly popular as industries seek to optimize resource allocation in order to cut down on resource wastage. The operations and maintenance practices of buildings are critical in enabling efficient functioning throughout the facility. The broad spectrum of services covered under operations and maintenance of facilities includes various day-to-day activities which aid in the functioning of the complete building environment along with its sub-systems and equipment, thereby extending the lifetime of the building infrastructure (Sapp, 2016). O&M is used as the common term for operations and maintenance, as a particular building cannot operate efficiently without timely maintenance, which also increases the lifecycle of the facility and reduces overall lifecycle costs (Sapp, 2016). Operational research conducted during the course of this research focuses on how real-time occupancy behaviours in different indoor facility environments determined using WiFi and sensors can impact the allocation of O&M resources. The occupancy of university classrooms varies greatly and results in over-use of facility resources. Human resource allocation accounts for a large part of the facilities maintenance and operations budget for universities in North America. However, year-round flat allocation of human resources for maintenance of classrooms has led to avoidable expenses for facility management across universities. At Harvard University, for instance, salaries and employee benefits accounted for

49% of the total operational expenditure in 2014 (Finnegan, 2014). For the year 2015, salaries at Yale University, similarly, accounted for 47% of operational expenses (Murphy, 2016). The utility costs at the University of Alberta were $1.18 million and $1.31 million in 2012 and 2013, respectively, following an upward trend for the past 5 years (Facilities & Operations, 2012-13) which are indirectly affected due to excessive O&M resource usage. As human resources at post-secondary institutions are costly and are following an increasing trend in North America, it is important to allocate human resources in an optimal manner for facility operations, thereby reducing lifecycle operational and maintenance costs for different facilities.

The scale of investment in the construction of buildings is a significant portion of the Gross National Product (GNP) for most countries in the global economy. The average annual spending for construction of residential, commercial, industrial, and institutional buildings in the United States alone was approximately $590 billion from 2008 to 2015 (Census Bureau, 2016). For the past year (2015), the value of annual business for construction companies in the development of buildings was estimated at Can$748 billion across North America (Statistic Brain Research Institute, 2015). Figure 1 shows the value of investment in residential and non-residential construction projects.

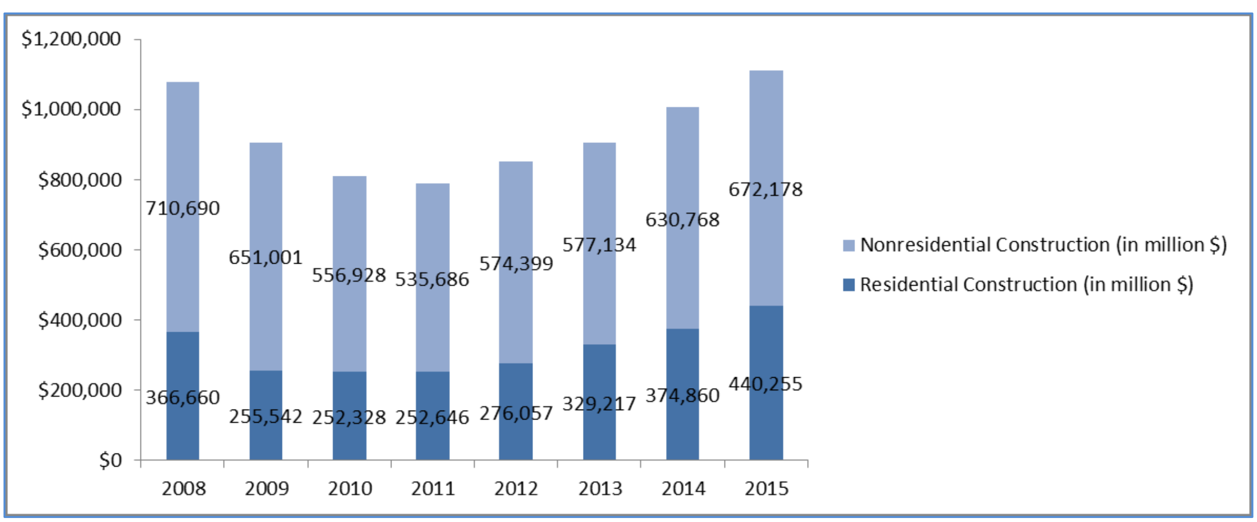


Figure 1: Construction Spending Trend in USA (Census Bureau, 2016)

Although significant, these construction costs only apply to a relatively limited number of buildings in the nascent stages of their lifecycle in any given year. As buildings with a long lifespan are built on limited land resources, the land's utility is constrained for several decades to come, so it is important that the building's utilization is maximized. To achieve the greatest efficiency, lower lifecycle costs, and higher comfort levels, building facilities require proper utilization and management of existing resources.

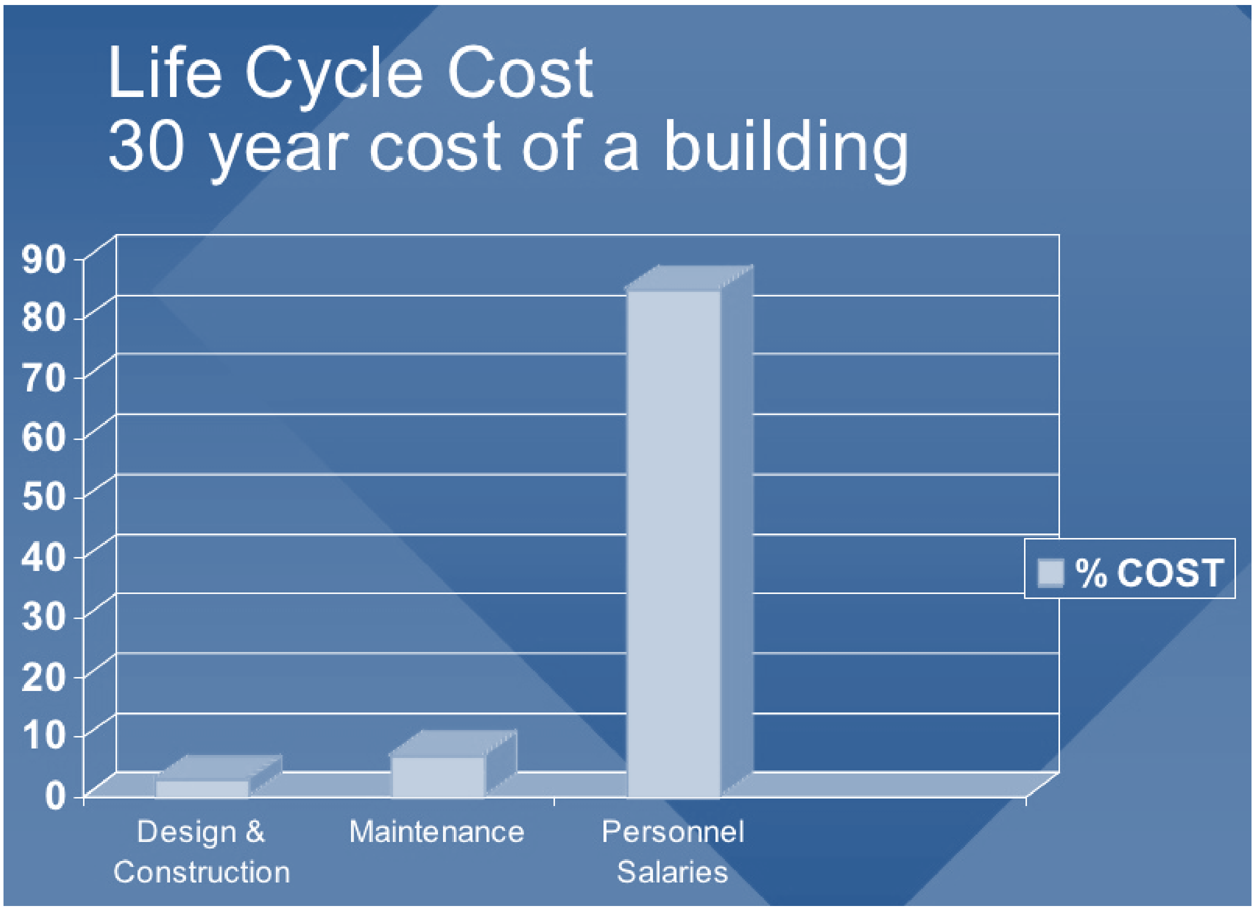
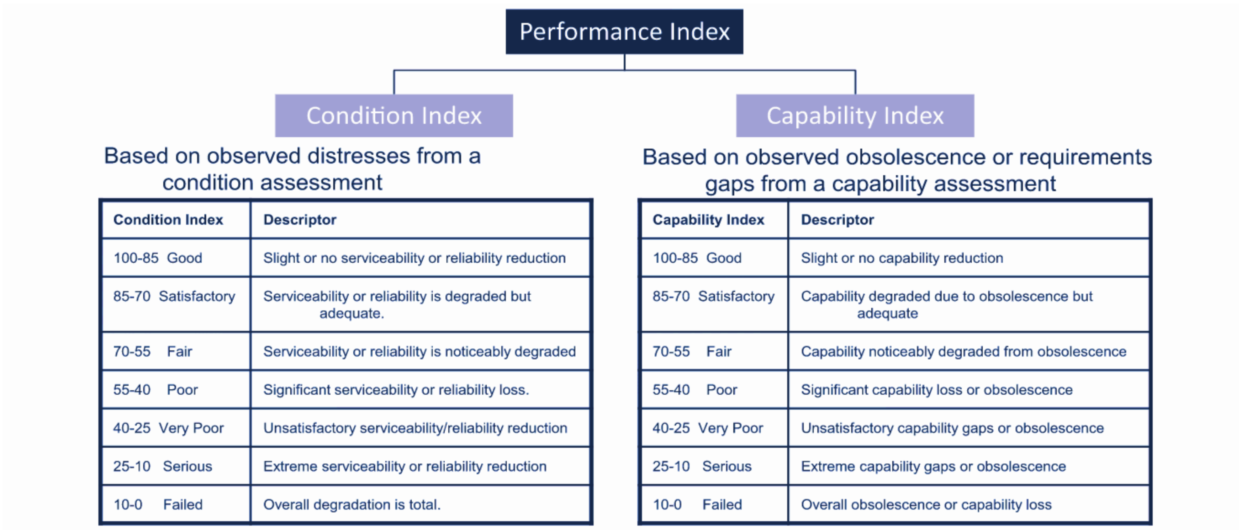


Figure 2: Non-residential Building Lifecycle Costs (Green Design Forum, 2009)

From Figure 2, it is observed that most of the costs incurred during the lifecycle of a non-residential building are during the post construction period, and personnel salaries account for 92% of the overall lifecycle cost. Figure 2 depicts the lifecycle cost analysis for a non-residential building over a period of 30 years. However, as time increases, the proportion of personnel salaries will continue to increase, eventually exceeding 92% of the total lifecycle cost for the building. Therefore, it is important that human resources are used optimally, and over-usage of these resources for O&M must be avoided for effective facility management and cost reduction. Real-time space utilization behaviour in indoor facilities will enable facility management to allocate O&M resources based on the intensity of space usage at different locations throughout the building environment. The monetary savings achieved can be reinvested to improve the facilities and help in extending the lifecycle of the building and its sub-systems, facilitating effective operations and maintenance and enabling a safe and comfortable indoor environment for end users.

A building as a system can be divided into subsystems and components that each perform one or more functions and support one or multiple operations. But these components generally deteriorate over time, having adverse effects on system functions and resulting in deteriorating conditions. Furthermore, due to new discoveries and technologies, building components are also confronted with functional obsolescence due to outdated design and limited capabilities. Thus, an aging building and its constitutive components generally decrease in performance and utility over time. In this context, besides an initial capital investment during construction, buildings also require periodic capital infusions throughout their lifecycle for restoration or modernization in order to slow, halt, or reverse this utility loss. As shown in Figures 3 and 4, buildings require maintenance, repair, and renovation on a periodic basis to keep the Level of Service (LOS) at an acceptable standard or state of condition (Grussing & Liu, 2014). According to RSMeans data repository, the post-construction lifecycle cost of operating, maintaining, renovating, and eventually demolishing a building can far exceed the initial cost (RSMeans, 1996). It is therefore important to wisely plan the allocation of investment in building facilities during their lifespan and to efficiently and reliably transform these investment inputs into service-related outputs.



Condition Index	Descriptor
100-85 Good	Slight or no serviceability or reliability reduction
85-70 Satisfactory	Serviceability or reliability is degraded but adequate.
70-55 Fair	Serviceability or reliability is noticeably degraded
55-40 Poor	Significant serviceability or reliability loss.
40-25 Very Poor	Unsatisfactory serviceability/reliability reduction
25-10 Serious	Extreme serviceability or reliability reduction
10-0 Failed	Overall degradation is total.

Capability Index	Descriptor
100-85 Good	Slight or no capability reduction
85-70 Satisfactory	Capability degraded due to obsolescence but adequate
70-55 Fair	Capability noticeably degraded from obsolescence
55-40 Poor	Significant capability loss or obsolescence
40-25 Very Poor	Unsatisfactory capability gaps or obsolescence
25-10 Serious	Extreme capability gaps or obsolescence
10-0 Failed	Overall obsolescence or capability loss

Figure 3: Condition and Capability Indices for Building Components (Grussing & Liu, 2014)

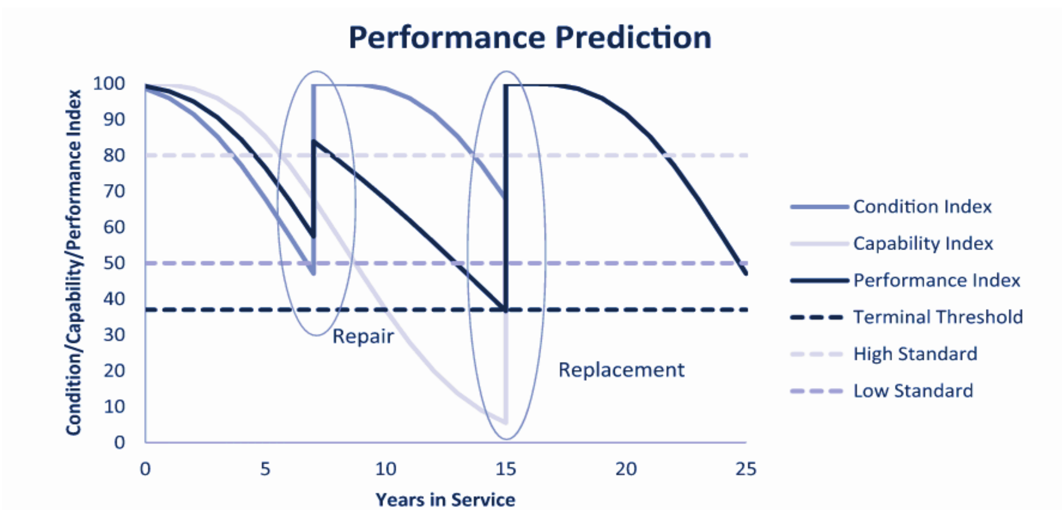


Figure 4: Performance Prediction of Building Components over time (Grussing & Liu, 2014)

The operational condition of a building facility will have a direct influence on physical condition; performance; and the frequency of, options for, and cost of maintenance during the post-construction lifecycle. However, maintenance of buildings is complex and requires careful planning and optimization and high levels of coordination (Das et al., 2010). Improving one individual system (sub-system) may affect the performance of the others (Das, 2007). For instance, incrementing inter-arrival time of one elevator in a low-rise building will increase the utilization rate of stairs. Furthermore, facility operation management is not limited to the subsystems of the facility only, but also focuses on integrating resource utilization systems from a central operation unit. From this viewpoint, efficient management of building operations, which includes human resources, waste management, and security, can reduce lifecycle operational and maintenance costs in addition to improving the level of service. It is thus of vital importance that resources and workforce are allocated in such a manner that the facility repair and maintenance standards are maintained in order to provide the user with a sustainable, safe, and comfortable environment.

Planning lifecycle operational management during the construction phase itself based on occupancy or projected live loads on the structure will result in better designs, reduced long-term living costs, and improved living standards. Although these incentives promote facility usage management and reduce operational costs for the owner, live usage feedback from users is vital and will help to ensure conditions suitable for them. For example, it is important to identify whether a given facility could maintain the same level of service if human resources for building operation are reduced. In a way, facility operation management focuses on facility performance, which in turn is dependent on live usage feedback and smart use of existing resources to reduce lifecycle costs while maintaining or improving living standards.

In this research, informed decision making based on classroom occupancy density indicators is required for optimal allocation of human resources. It has been observed that WiFi location tracking systems can identify indoor occupancy with an accuracy of 94% as indicated by a residential case study presented in Figure 5 (Vasisht et al., 2016), while heat sensor occupancy counters can be installed with a small payback period to obtain highly accurate occupancy data as observed later in this research. Investigation is conducted for the two tracking models to identify the level of accuracy for determining classroom occupancy. The classrooms investigated for classroom occupancy and optimal human resource allocation are located on the University of Alberta's North Campus in Edmonton, Canada. To the author's knowledge, this is the first attempt to utilize real-time classroom occupancy for dynamic human resource allocation in university operations and maintenance.

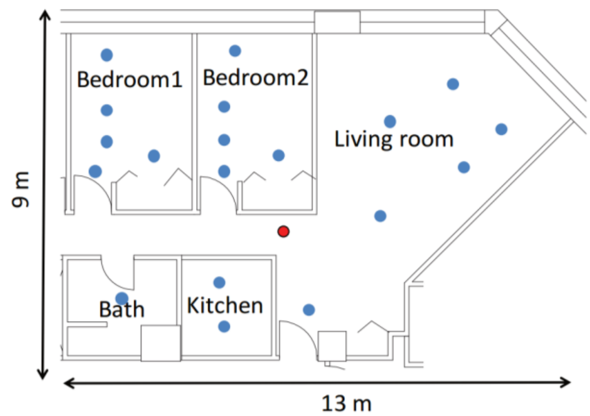


Figure 5: Floorplan with WiFi Access Point (red) and Clients (blue) (Vasisht et al., 2016)

1.2 Research Objectives

The objectives of this research are as follows:

- Determine classroom occupancy using WiFi and sensor-based indoor location tracking.
- Identify intrinsic and extrinsic parameters that influence classroom occupancy behaviour.
- Deduce optimal usage patterns for human resources based on classroom occupancy.
- Determine achievable time and cost savings based on dynamic human resource allocation.
- Equip the management system with an interface to assist in augmenting workforce allocation based on demand.

The operational research presented in this thesis lays the foundation for the utilization in future research of real-time location positioning-based resource optimization in different fields such as inventory management, live demand-based transportation models, and queue management in shopping centres and hospitals, thereby creating smarter cities in addition to achieving optimal facility resource management services.

1.3 Thesis Organization

This thesis consists of five chapters. **Chapter 2** presents a literature review and background. The literature review focuses on post-secondary educational institutions and investments in infrastructural development, educational funding, maintenance and operation of their building facilities throughout the lifecycle. It also provides insight into (1) ways in which the allocation of these investments and lifecycle costs are optimized, and (2) efficiency and impact of different location tracking models used to track indoor occupancy. **Chapter 3** presents the methodology for the conducted research, which consists of three main elements: (1) a comparative study between heat sensor-based occupancy counters and WiFi-based location tracking to identify classroom occupancy behaviour; (2) identification of extrinsic and intrinsic parameters which influence occupancy behaviour; and (3) evaluation of optimal usage patterns for human resources. **Chapter 4** presents case studies which illustrate the methodology described in Chapter 3: (1) the coordinated and dynamic human resource allocation model based on occupancy behaviour observed in Chapter 3, and (2) the usage of occupancy data by the facility management system to augment workforce allocation based on demand while accommodating user comfort. **Chapter 5** offers a general conclusion, academic and industrial research contributions, research limitations, and recommendations for future research.

CHAPTER 2: LITERATURE REVIEW AND BACKGROUND

2.1 Introduction

Given that, to the author's knowledge, this work represents the first attempt to use heat sensors and WiFi-based location positioning systems for determining classroom occupancy and utilizing real-time classroom occupancy for optimal allocation of human resources based on space utilization, a thorough literature review of current practice and recent research advancements is conducted in order to develop a platform for innovation in live demand-based resource optimization. The literature review mainly focuses on (i) O&M in institutional facilities, and monetary investments taking place during the lifespan of these facilities; (ii) resource utilization and facility management practices across various universities; (iii) use of WiFi, GPS, and sensors for location tracking and their practical applications across various industries; and (iv) educational facility maintenance, inspection, monitoring, safety guidelines, and security operations across universities in North America.

2.2 Literature on Institutional Systems and O&M Investment Management

Generally, expenditure on post-secondary institutions can be divided into several parts: (1) construction and infrastructure cost (mostly at the early stages of a facility's lifecycle); (2) academic and administrative staff salaries; (3) scientific research; (4) campus activity costs (educational and community-building activities); and (5) facility management costs (O&M) (Fuller, 2016). Among these, the first four are fixed or imperative costs which can be determined at the early stage as per requirements. However, university facility management systems necessitate long-term resource and expenditure planning for the operational phase. A facility management cost report from Cornell University states that utilities, maintenance, building care, and grounds keeping occupied, respectively, 46%, 34%, 17%, and 3% of facility management and operating costs from 2003 to 2004 (Cornell University, 2005-06). It is also observed that as the personnel salaries increase year-over-year, the O&M proportion also increases linearly relative to the rise in personnel salaries.

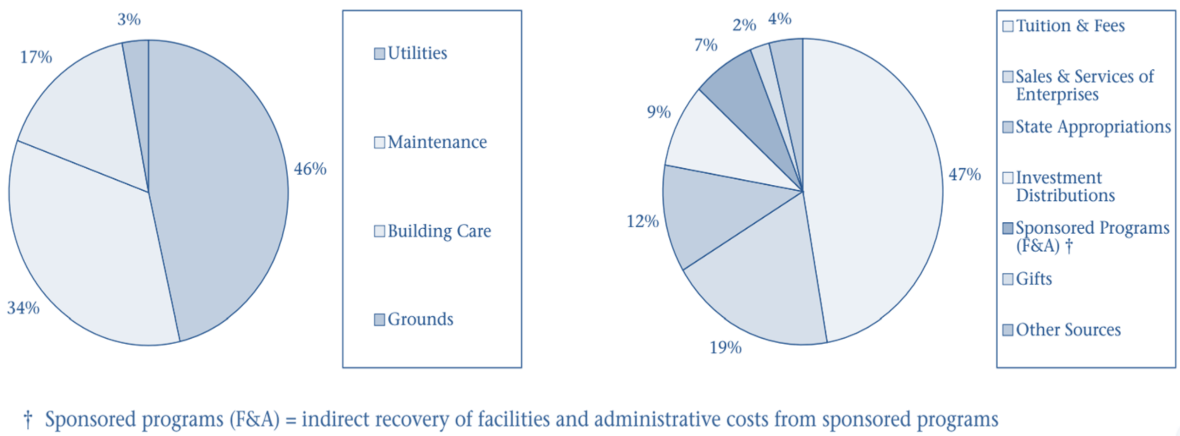


Figure 6: Facilities Management and Operations Cost (Cornell University, 2005-06)

Today, with the rapid growth of the global economy and technological innovation, modes of knowledge delivery and its supporting infrastructure are integral for providing quality education to meet economic and societal demands. UNESCO for instance, with its commitment to the vision of providing quality education worldwide, claims education to be a fundamental right and believes that it plays a critical role in human, social, and economic development (United Nations Educational, 2016). For instance, there are 85.9 million people involved in the education sector (students, instructors, support staff, and administrators) in the United States (Statistic Brain, 2016), and 5.20% of the nation's GDP was spent on education in 2011 (World Bank, 2016). In Canada, government expenditure on education accounted for 5.27% of GDP in the same year (Index Mundi, 2012).

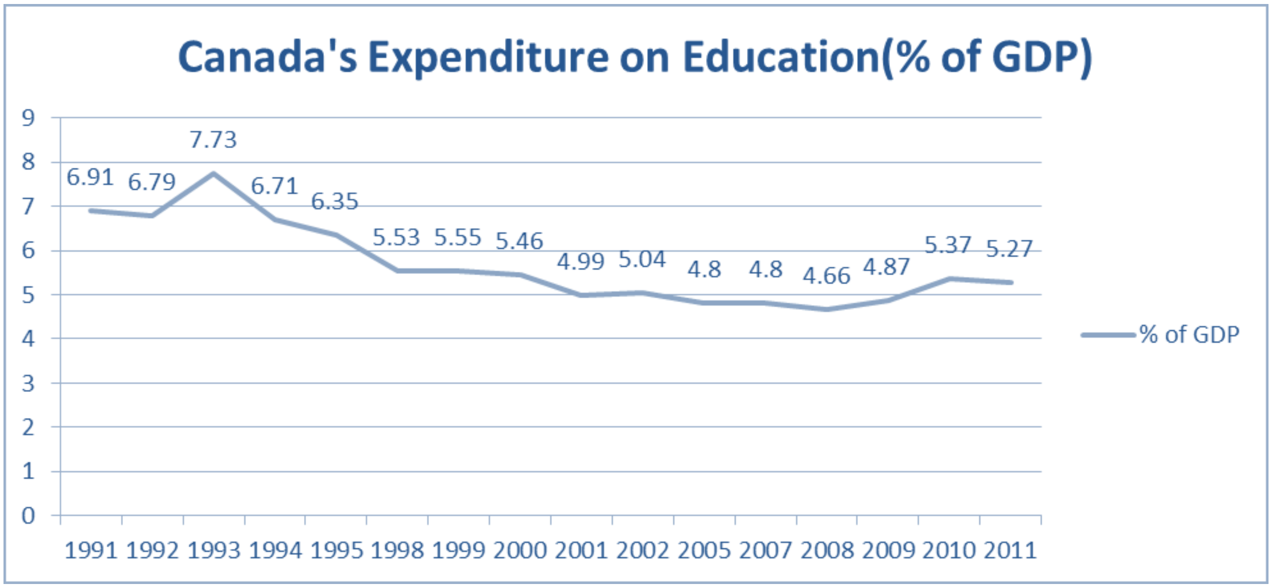


Figure 7: Canada's Expenditure on Education as Percentage of GDP (Index Mundi, 2012)

Among the various types of education, formal education is the most common and widely distributed. Normally, it takes place in a school environment within classrooms where a certified teacher addresses a group of individuals, such as kindergartens and primary schools. Effective management of institutional facilities is critical considering that uninterrupted and high quality education, along with a safe and comfortable instructional environment, play a major role in a country's growth. According to annual data from China, 29.40% of the total educational expenditure is spent on post-secondary education, 28.80% on senior and secondary school, 25.10% on primary school, and 4.26% on kindergarten (National Bureau of Statistics, 2014). In Canada, the government spent 35.60% of the total education expenditure on post-secondary education in 2011, while 26.40% was spent on secondary education (Index Mundi, 2012). From the above information, it is evident that most countries tend to place more emphasis on their post-secondary education and institutional facility expenditure due to its important role in the economy's growth. Post-secondary education places greater emphasis on preparation for professional careers in various disciplines, stimulating creativity and innovation in technology and research. Moreover, the post-secondary school environment is often more complex relative to primary and secondary schools, and the complexity could be reflected by high people density, diversity of research areas, and multi-hierarchical resource management systems.

Efficient management of building operations at universities, which includes human resources, accumulated cost of deferred maintenance, utilities (energy, water, and electricity), waste management, and security, can reduce lifecycle operational and maintenance costs and help to maintain a high facility condition index (Murray, 2016). Along with cost savings it is imperative that the human resources being utilized are not over-loaded with intensive workload and that all personnel involved in facility operations and maintenance are assigned work in a manner which minimizes stress and maximizes output through initial ergonomic analysis. Smarter human resource utilization will enable us to overcome ergonomic challenges and allocate resources in an optimal manner, thereby reducing costs and simultaneously reducing the stress on working personnel (Karwowski & Marras, 2003).

2.3 Literature on University Classroom Resource Usage

To this point, university facilities as a whole have been discussed in the context of utilization of different resources to enhance management systems and optimize cost savings. University classrooms are highly utilized spaces with large occupancy capacity during predefined course schedules. Generally, most classrooms are occupied during lecture time and almost empty during all other intervals, while the human resources allocated for cleaning, inspection, and facility maintenance are scheduled at specific intervals irrespective of identifying whether a particular classroom has been used or not. This over-deployment of resources incurs surplus costs and introduces tedious and unnecessary tasks. This can be mitigated by adjusting the use of resources based on monitoring of classroom occupancy. Such a strategy not only promotes smarter resource utilization, but also reduces expenditure for operations and maintenance.

The decision to select universities for post-secondary education and future research depends upon the facilities and infrastructure available at the universities as they influence global rankings and future employment prospects (Matzdorf et al., 2003). Lavy & Bilbo (2009) in reference to findings from the National Center for Educational Statistics, report that 75% of the post-secondary institutions in the United States need repairs, renovations, and modernizations to make them more user friendly and to enhance the environment. The classrooms across university facilities occupy a large proportion of institutional facility space, with space utilization dependent upon predefined lecture schedules. Therefore, for efficient utilization of resources it is essential that utilization be automated and that resources be utilized based on the specific occupancy demand of the given particular classroom in order to reduce the human effort required for O&M of facilities, to achieve cost savings, and to improve user comfort levels. Important criteria for budgeting of facility maintenance and repair are outlined by Ottoman et al. (1999), as summarized below:

1. The facility's initial cost or the present system replacement cost for classroom units.
2. Lifecycle analysis of the facility's central and sub-systems based on time-based deterioration.
3. Assessment of the classroom facility's current or anticipated physical condition.

There is no better way to assess projected usage and deterioration of facility sub-systems than based on live occupancy of facilities and relative resource allocation. Lavy (2008) emphasizes the importance of health and safety, fire hazard prevention, and online classroom and lab safety courses to increase awareness about public facility usage and risk mitigation practices. Presence of first aid kits, self-cleaning practices of used facilities by students and staff, and safety instructions in all labs and classrooms can increase awareness about health and safety practices among all university facility users, deferring frequent maintenance requirements.

Based on surveys conducted by Karna & Julin (2015), different institutional facility management services such as heating, lighting, and ventilation systems for classrooms and corridors; the design of university classrooms; and cleaning and maintenance of facilities have a strong and direct effect on the quality of education offered. Other factors such as educational building designs, physical appearance of buildings, and historical significance have an indirect influence on the educational process affecting staff and student satisfaction. The design of classrooms, future capital investments in construction of institutional facilities, and allocation of O&M resources depend highly upon the classroom space utilization patterns according to Abdullah et al. (2012). However, the same study reports that the targeted utilization rate for post-secondary classrooms in Virginia is 36%, considering the targeted occupancy of classrooms to be around 60% by Abdullah et al. (2012), where:

$$Space\ Utilization\ Rate = \frac{(Frequency\ rate \times Occupancy\ rate)}{100} \tag{2.1}$$

$$Frequency\ Rate = \frac{(No.\ of\ hours\ used\ during\ week)}{Hours\ allocated\ during\ week} \times 100 \tag{2.2}$$

$$Occupancy\ Rate = \frac{(Total\ no.\ of\ students\ during\ the\ week)}{Room\ capacity\ during\ the\ week} \times 100 \tag{2.3}$$

As shown in Table 1, the classroom occupancy at the Universiti Teknologi Malaysia for different facility buildings is obtained at a frequency of 30 minutes. Each building facility under observation is denoted by ‘Fac. X’ and the occupancy for the total classrooms under observation in a particular facility is summed for the observation period to determine utilization rate, frequency rate, and occupancy rate. The occupancy and capacity specified in Table 1 are cumulative occupancy and capacity values obtained for the observation timeframe. It is observed that the occupancy rate is below the minimum targeted occupancy rate of 60%, so necessary scheduling plans and utilization measures must be undertaken to increase space utility. It is observed later by Abdullah et al. (2012) that the occupancy rate would be on the lower end for Canadian universities. In order to address the problem of low space utilization, the introduction of innovative methods of learning and teaching across campuses and effective lecture schedule management across universities is very important (Abdullah et al., 2012).

Table 1: Occupancy for Facilities at Universiti Teknologi Malaysia (Abdullah et al., 2012)

Faculty	No. of Rooms	Frequency	Meeting Time	Occupancy	Capacity	Utilisation Rate	Frequency Rate	Occupancy Rate
Fac. A	6	183	228	11165	22800	39.30%	80.26%	48.97%
Fac. B	10	173	380	7184	20900	15.65%	45.53%	34.37%
Fac. C	3	81	114	2956	8170	25.71%	71.05%	36.18%
Fac. D	22	532	836	23219	69540	21.25%	63.64%	33.39%
Fac. E	21	568	798	25052	66880	26.66%	71.18%	37.46%
Fac. F	16	455	608	19191	57000	25.20%	74.84%	33.67%
Fac. G	12	368	456	14605	35340	33.35%	80.70%	41.33%
Fac. H	13	309	494	12178	34960	21.79%	62.55%	34.83%
Fac. I	17	311	646	12365	52820	11.27%	48.14%	23.41%
Fac. J	9	328	342	14824	26980	52.70%	95.91%	54.94%
Fac. K	10	317	380	12578	29260	35.86%	83.42%	42.99%
Fac. L	11	234	418	9370	43320	12.11%	55.98%	21.63%
UTM	**150**	**3859**	**5700**	**164687**	**467970**	**23.83%**	**67.70%**	**35.19%**

Karna et al. (2013) observes that students and staff across university campuses consider educational facilities, physical appearance of facilities, cleanliness, and campus security to be important criteria in rating campus facilities. It is vital that quality of education delivery is improved. Such changes which can take place over a long period of time must be considered by the facility management systems to optimally allocate resources while accounting for end-user usage behaviour. It will not only allow the facility management to significantly reduce costs but will allow the surplus capital to be invested for the advancement of educational facilities, creating a healthy and clean campus.

2.4 Literature on Usage of WiFi, GPS, and Sensors for Location Tracking

Positioning using location tracking has emerged as a revolutionary tool in the 21st century and has transformed the navigational industry globally with the introduction of digital maps (e.g., Google Maps), guiding the user to efficiently reach their destination. The advancement in technology and different approaches toward improving the accuracy of a user's position has led to its usage in various industries to identify real-time demand, to estimate requirements for products and services through data analysis, and to make necessary changes to improve the efficiency and user-friendliness of processes.

Various experiments have been conducted using WiFi-GPS combined technique, blue-pass, trilateration, dynamic calibration, and other techniques to determine the best indoor positioning approach and to reduce indoor location detection error (Galvan-Tejada et al., 2013). Galvan-Tejada et al. (2013) propose a propagation model suitable for Bluetooth to obtain a more accurate distance measurement tool, and an algorithm (see Figure 8) to combine it with WiFi in order to improve positioning within the indoor environment of specific dimensions. Galvan-Tejada et al. (2013) also conclude that WiFi and Bluetooth are attractive means of identifying location, as they consume less energy, have global presence, and can track locations with a high level of accuracy. (The research presented in Chapter 3 will address in further detail how sensors and WiFi-based indoor positioning tools help in identifying in real-time the number of people occupying a classroom.) Classroom space utilization and occupancy behaviour enable facility management to allocate human resources effectively for operations and maintenance of university facilities. The objective of the literature on location positioning tools is to identify the most feasible and accurate tool for estimating classroom occupancy and allocating human resources for operations and maintenance of university facilities.

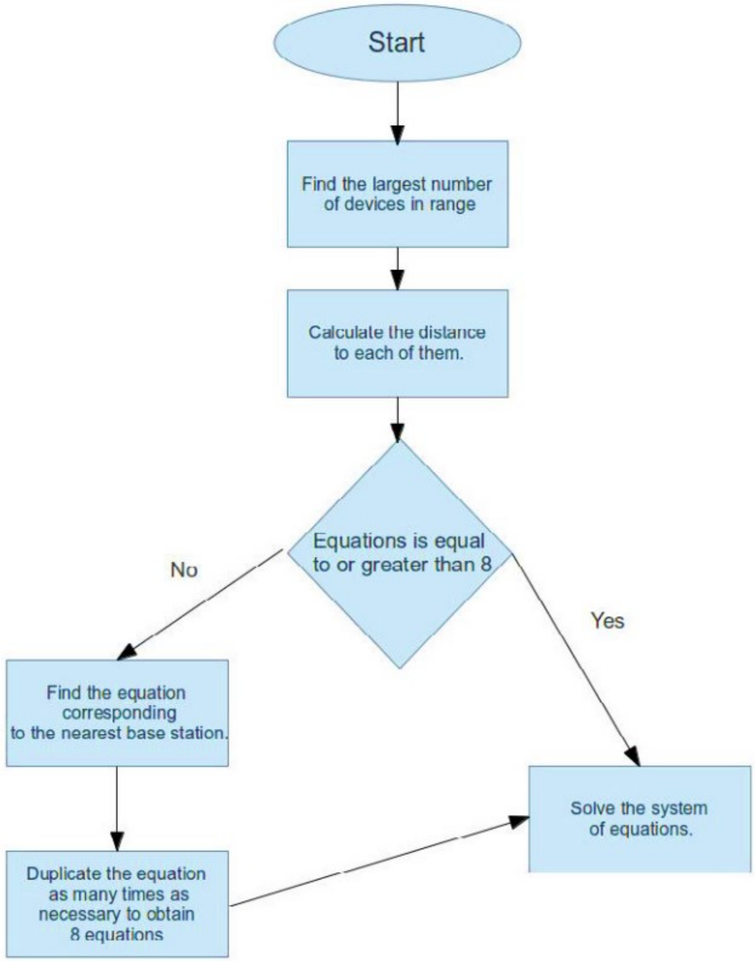


Figure 8: WiFi-Bluetooth based Positioning Algorithm (Galvan-Tejada et al., 2013)

However, high-density occupancy can cause significant local interference of the WiFi signals. This has been resolved though collaborative localization, which refers to the interaction between nearby devices to verify location coordinates with more accuracy due to multiple identifiers in its vicinity (Chan et al., 2006). Lei Zhang (2013) reconstructs the user's trajectory with smartphone sensors, which needs 7% GPS samples using the naive approach, and saves nearly 90% time for which GPS is activated saving battery power while maintaining high accuracy and coverage. Based on this background and combining the advantages of different methods, the research presented in this thesis aims to monitor occupancy based on WiFi-based location trackers and heat sensors in order to accurately identify the utilization of classroom facilities across the University of Alberta.

Zaveri et al. (2011) reports on the deployment of a wireless camera sensor network for collecting data regarding occupancy in a large multi-function building, with the developed system being found to estimate occupancy with an accuracy of 80%. (Skiniewski & Jang, 2009) introduces a novel tracking architecture using wireless sensor modules. It is found to show accurate performance using a numerical simulation approach based on the time-of-flight method, which is used in their study to efficiently track construction assets. In fact various approaches have been developed to improve positioning accuracy. However, the important question is what degree of positioning accuracy is adequate on a macroscopic level to allocate resources in an optimal manner. Accuracy to a certain degree is important to identify the number of people occupying an indoor environment, such as a classroom, as this information in turn allows the facility management to allocate O&M resources accordingly. Beyond the scope of this research, macroscopic level identification (i.e., occupancy head-count) can also be used by different industries to improve inventory planning, supply chain management, facility lifecycle costs, and city-wide transportation networks. The idea of dynamic allocation of resources based on a need-to-need basis can help in reducing the amount of resources required and allow reinvesting of the saved resources to improve functionality.

2.4.1 Evolution of Location Tracking and Its Functionality

Location tracking is a method which can be used for a range of purposes, from locating the position of an individual or vehicle anywhere globally, to identifying an item in the manufacturing plant, to recording and improving production and management activities.

Location tracking is carried out by various positioning techniques and algorithms based on whether the given environment is indoor or outdoor. Various areas of functionality include:

- Heterogeneous and homogenous fleet tracking
- Navigation and personnel tracking
- Inventory and asset management
- Network security and geo-fencing techniques

Location tracking started when Doppler's effect was introduced to track satellites by means of shifts in radio signals in the 1960s. Global positioning systems (GPS) went on to gain popularity as a method for developing navigational systems and tracking. With the increasing popularity of global positioning, the US Department of Defense launched 24 fully operational satellites to improve the navigations and tracking system in 1993 (NASA, 2015). Over the years, with the introduction of search engines like Google, the development of Google Maps, and the increasing ubiquity of smartphones and other mobile devices, localized and indoor positioning systems have been widely adopted. However, although outdoor positioning has become easier and more accurate through technological advances in location tracking techniques, the use of GPS has been more limited in indoor or underground environments. For travel in mines, tunnels, underground parking lots, etc., the use of GPS is difficult as the coordinates estimated result in several errors. Technical advances for indoor positioning systems have thus gained momentum as GPS usage is restricted in indoor environments and unable to provide accurate positioning in such spaces.

As seen in Figure 9, the number of smartphone users grew at an exponential rate from 2010 to 2016 and is forecast to grow at a similar rate for the next 5 years. The idea of using WiFi and sensor technologies for indoor positioning and resource tracking is thus gaining traction.

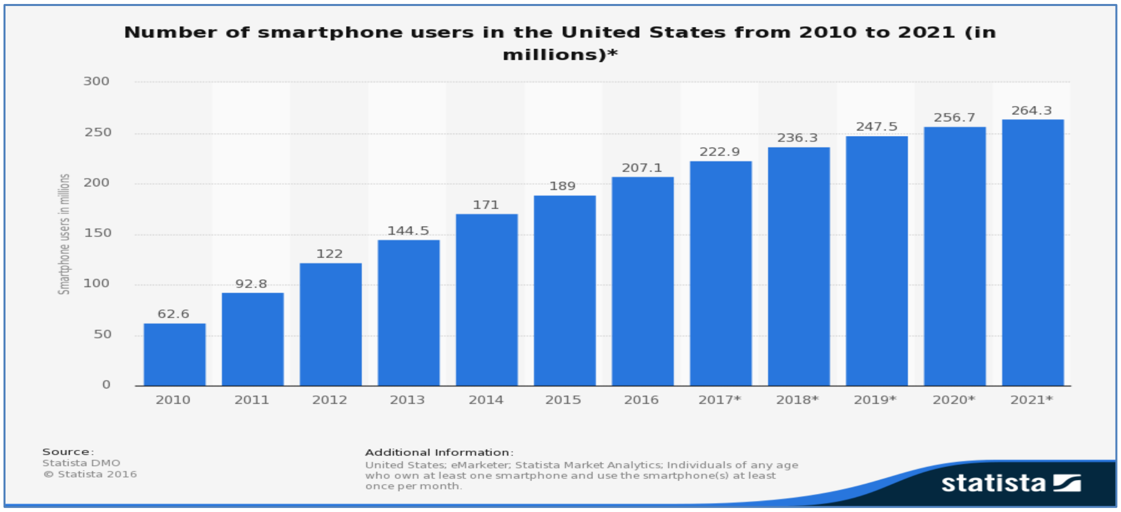
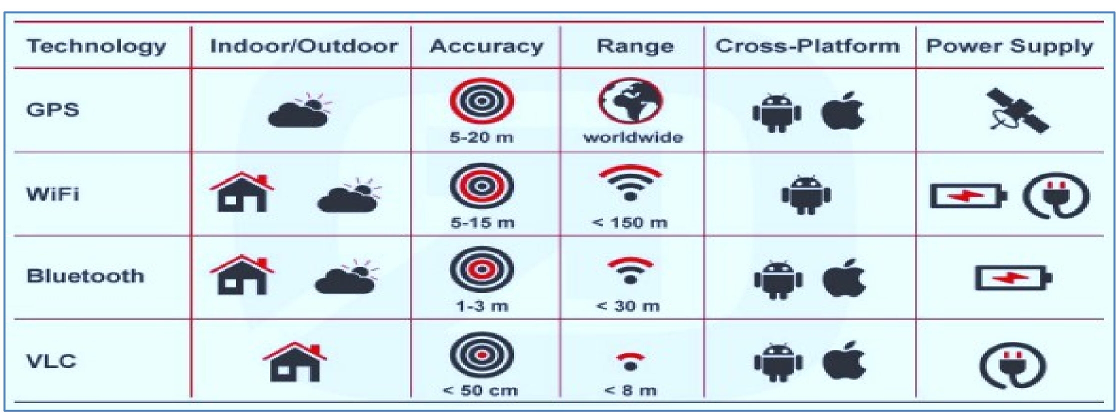


Figure 9: Projected Smartphone Users in the United States (Statista, 2016)

Today, indoor positioning technologies are increasingly utilized due to the various applications for industrial, analytical, and academic purposes. The construction industry is using indoor positioning technology to locate individuals in smart homes at the micro level and identifying facility usage or inventory maintenance at the macroscopic level. Micro level refers to tracking a particular individual in an indoor environment, whereas macro level has to do with viewing the behaviour of a group of individuals in a particular indoor facility. Below is a graphical representation of the features and limitations of different positioning systems used for various purposes:



Technology	Indoor/Outdoor	Accuracy	Range	Cross-Platform	Power Supply
GPS		5-20 m	worldwide		
WiFi		5-15 m	< 150 m		
Bluetooth		1-3 m	< 30 m		
VLC		< 50 cm	< 8 m		

Figure 10: Features and Limitations of Indoor Positioning Techniques (InfSoft, 2016)

2.4.2 Use of GPS in Location Tracking

GPS is based on time and position retrieval of different entities by means of satellites orbiting the Earth and transmitting to the GPS receivers. With the increase in smartphones and advancement in position tracking using GPS over the years with powerful surveying, guidance, and location tracking engines such as Google Maps, outdoor location tracking has become highly accurate. Google Maps today assists the user by acting as a local guide and enabling street view for better graphical representation (Google Maps, 2016).

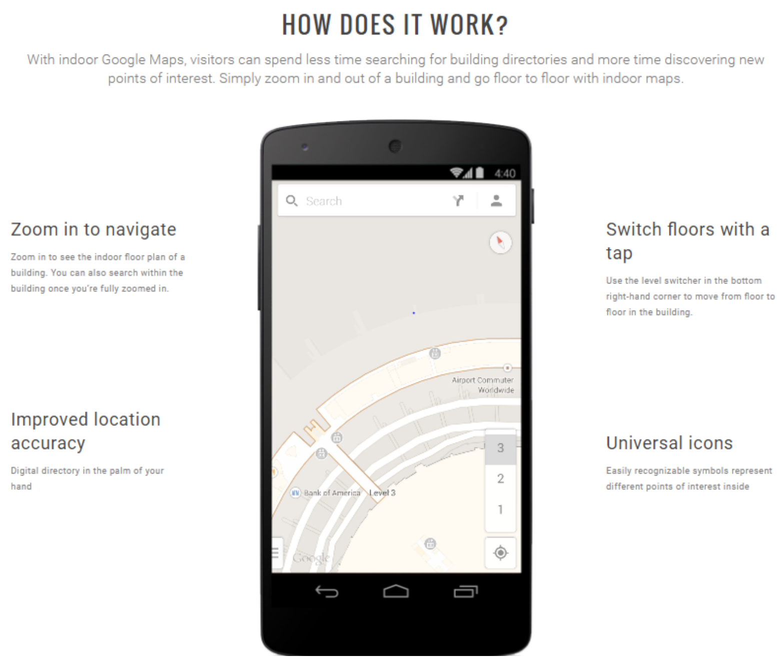


Figure 11: Indoor Google Maps View of San Francisco Airport (Maps, 2016)

However, as previously mentioned, GPS systems produce errors in indoor environments such as underground train stations or underground parking garages (InfSoft, 2016). Google began development of its indoor mapping efforts by targeting transit centres, shopping centres, stadiums, and airports through local mapping workforce. They began incentivizing businesses to increase their outreach to clients and governments in order to improve commuting across cities by making location specifications or floorplans available to users (Maps, 2016). It is difficult to track indoor positions using GPS alone, it should be noted, since the signals in indoor environments are inhibited by walls, tunnels, and other obstacles. As the reach of GPS signals in indoor environments is attenuated due to various signal barriers, it might show a user's position far away from its actual location. Therefore, the approach of Google to map indoor locations by incentivizing indoor layout uploads on their server is a step towards accurate indoor positioning. Moreover, Navizon has created an application by which for businesses to track users using WiFi, cell-ID, and Bluetooth as alternatives for accurate indoor location tracking (Navizon, 2015).

2.4.3 Usage of Sensor Technology in Location Tracking

Since the use of radio technologies is challenging in indoor environments, non-radio positioning techniques such as magnetic positioning (Geospatial World, 2014) determined based on fingerprints made by magnetic interferences caused by steel structures are also being researched as alternatives that provide location accuracy within 1.0 m to 2.0 m with 90% confidence based on local variations in the Earth's magnetic field. The use of sensors has also gained ground in the search for alternatives for accurate position tracking in indoor environments for different sizes varying from a single room to the complete building controlled from a central unit. However, the question of return on investment and payback period for installation of sensor infrastructure must always be considered before installing sensors across the entire facility.

Sensors used to map indoor environments such as rooms, smart homes, commercial buildings, shopping centres, and airports include pseudolites, ultrasonic, microphone, RFIDs, ultra-wideband and light sensors (Khoshelham & Zlatanova, 2016). Gualda et al. (2014) proposes the use of ultrasonic position sensors using several independently referenced local positioning systems (LPS) and a small set of globally referenced LPS to track mobile robots. Their study applies this technology in a case study with high accuracy and average positioning error on sample runs amounting to less than 40 cm. Such sensors can be used within a classroom environment as well. However, the balance between the chosen alternative for accuracy measurement and payback period for cost savings must be considered in the decision analysis.

In an effort to reduce high infrastructure development costs, Galvan-Tejada et al. (2015) develops a user smartphone based infrastructure-less indoor localization methodology using a magnetometer, microphone, and light sensors in a smartphone. Their study shows improved position tracking through sampling, superimposing information obtained through the three sensor types listed above. They observe improved sensitivity of location accuracy by 22% compared to measurements only through the use of magnetometer sensors in a smartphone. Such models provide an advantage of functioning without pre-existing infrastructure, with scaling to cover broader prospects and applications of location tracking.

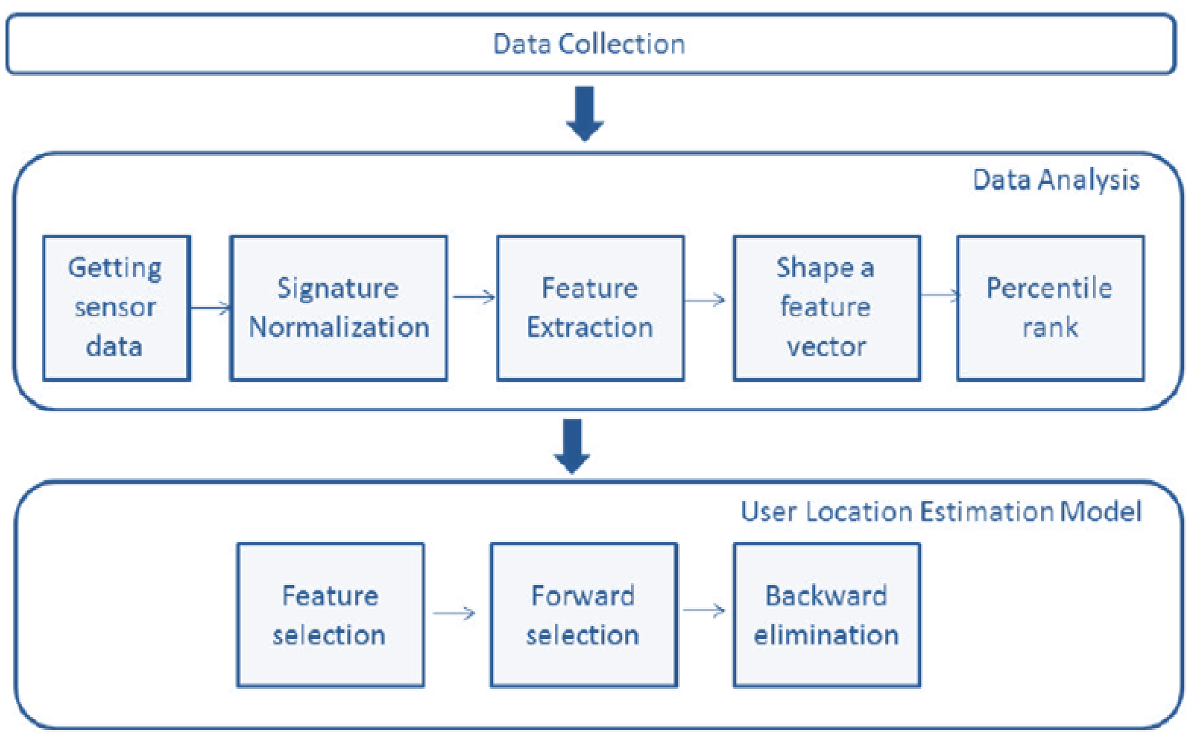


Figure 12: Methodology for Infrastructure-less Location Tracking (Galvan-Tejada et al., 2015)

Pseudolites, or pseudo-satellites, are alternatives to global navigation satellite systems (GNSS) or GPS systems for indoor or on-ground locations where GPS signals are attenuated. They act as ground-based transmitter sensors able to replicate GPS in indoor environments. (Gioia & Borio, 2014) creates a hybrid positioning system using pseudolites for indoor environments where GNSS signals are attenuated by walls. Their system calibrates both horizontal and vertical errors with reference to actual trajectories of users. They observe that using only GPS the horizontal and vertical RMS error is 43 m, whereas using the hybrid system with asynchronous pseudolites reduces the horizontal error to 4.5 m and vertical error to 0.4 m.

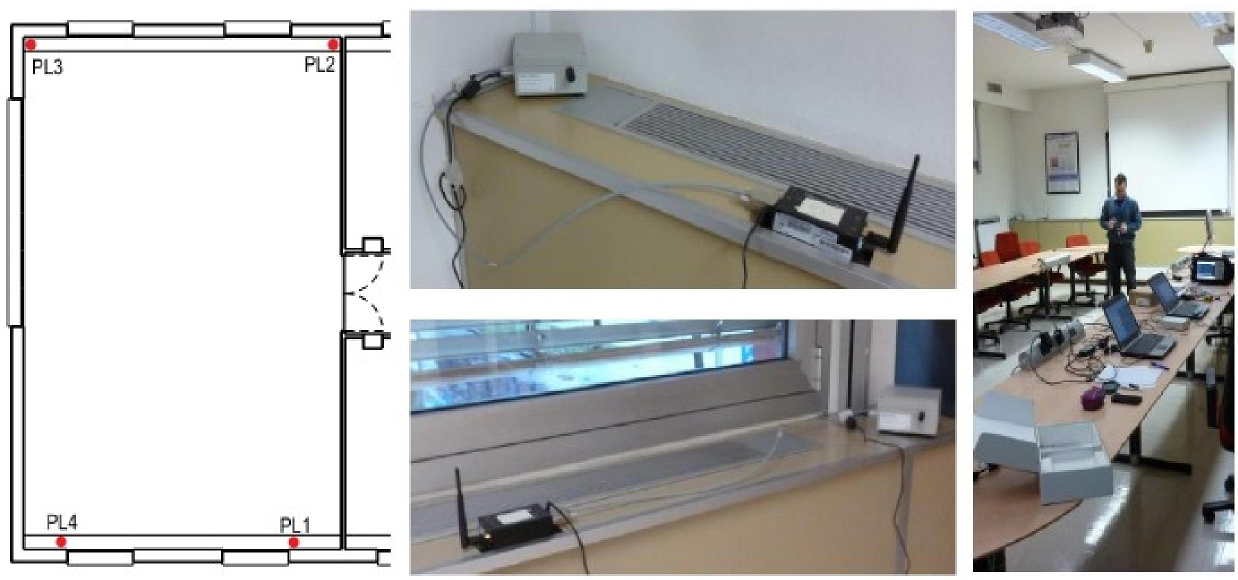


Figure 13: Deep Indoor Pseudolite Transmitter Test in a meeting room (Gioia & Borio, 2014)

Another technique which is being widely used for detecting particular objects, localization, and tracking location in indoor environments is ultra-wide band technology (UWB), this due to its compact size, high range resolution, and lower cost. An experiment conducted by Nguyen & Pyun (2015) uses two impulse radio unified wireless system (UWS) in a confined room to detect the trajectory of personnel movement. The result is an RMSE of 0.2478 m. Such accuracy in tracking of 2D movement within a confined space is suitable for the present research, as it determines location with enough accuracy to allow the user to determine classroom occupancy. However, the pertinent question in this context is how it might behave when multiple users are occupying a confined space.

Martinez-Sala et al. (2015) show how UWB technology, with its high accuracy and lower installation complexity, may help the visually impaired to navigate indoor environments with a higher level of comfort using headphones to provide acoustic signals or voice commands for navigation. The system tests are carried out with the help of the company Life Quality Technology, and they show a precision of up to 15 cm with a confidence level of 95% for the conducted experimentation. For a wide area of 18.0 m × 5.5 m installed with 4 UWB sensors, the error results are as depicted for multi-occupancy scenarios in Figure 14.

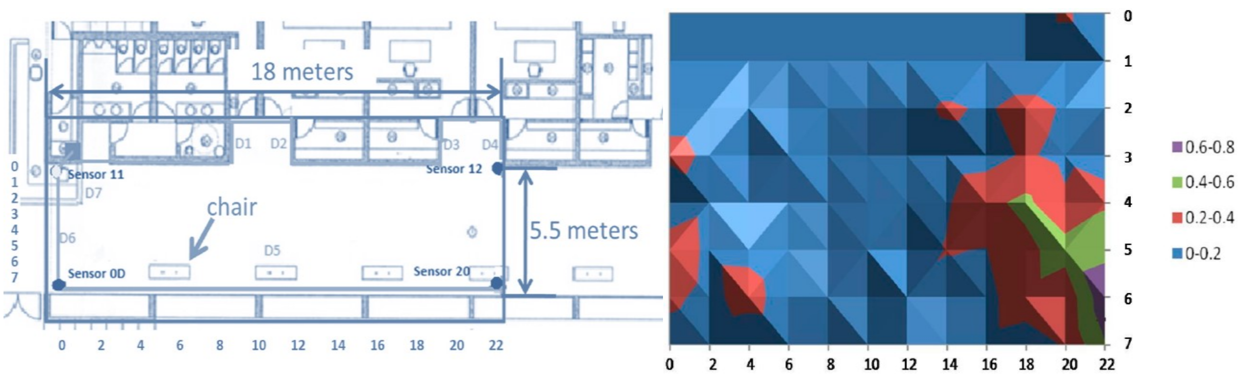


Figure 14: UWS Observation Space and Positioning Error (Martinez-Sala et al., 2015)

Other methods used for indoor location tracking include the use of Light Detection and Ranging (LiDAR) technology. Gao et al. (2015) use a hybrid of GPS and LiDAR to map indoor environments by providing data to Inertial Navigation systems (INS) and the position error for the sample experiment is found to be approximately 0.44 m, which is reasonably accurate.

In addition to those described above, tools such as occupancy sensors have been used for saving energy by turning on/off lights based on the occupancy of a particular space. Neida et al. (2001)

analyzes public and personal spaces using occupancy sensors and infer that people do not occupy spaces for a large period of time, and that the majority of resource wastage occurs during the weekdays rather than weekends. Similar studies are addressed later in this thesis on usage of university classrooms and over-usage of resources. The tendency to assume greater occupancy of facilities during weekdays than on weekends leads to over-usage of facility resources.

2.4.4 WiFi-based Locating Techniques and usage of WiFi-based Location Tracking

WiFi-based location tracking in the indoor environment works most efficiently when multiple small signal strength routers are connected to a central infrastructure. It assists in identifying the user's location through WiFi signal strength, the media access control (MAC) address of devices connected to the central WiFi base, and the distance and direction of the user from a router node based on signals. The MAC address of a device is a unique numeric code assigned to networking hardware components such as adapters and modems. A grid formation of routers set up throughout the floor of a building will enable tracking of the user's location with higher accuracy. Thus, the existing infrastructure can be used to identify space occupancy patterns and allocate resources effectively.

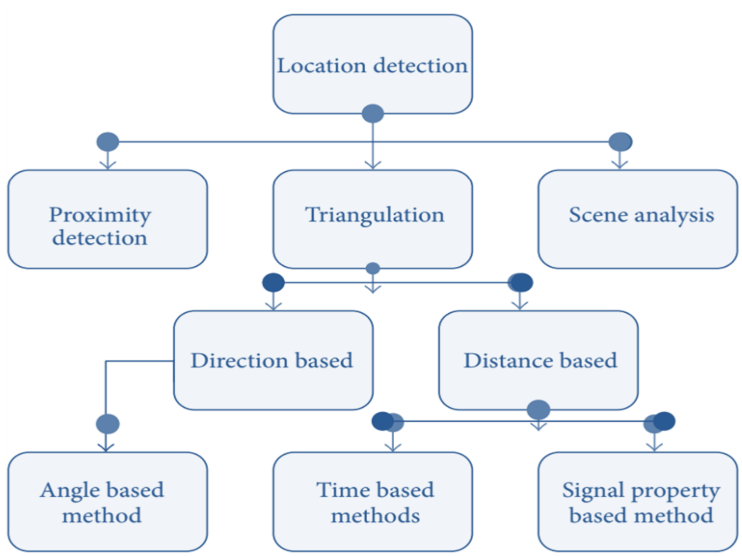


Figure 15: Classification based on Location Positioning Techniques (Farid et al., 2013)

Farid et al. (2013) discusses different algorithms used for indoor position tracking, including proximity algorithm, triangulation algorithm, and scene analysis algorithm. Each of the algorithms is used based on the requirement for indoor location positioning accuracy and its applications. The classification based on location positioning techniques is represented in Figure 15 above.

Proximity algorithm depends upon the retrieval of the strongest signal by a particular access point when multiple access points detect a target device in an indoor environment. The accuracy depends upon the signal range, signal strength detected on multiple access points, and the number of access points around the target device. **Triangulation algorithm** uses the geometric properties of triangles to determine the position of the target device accurately with the help of received signal strength (RSS) from multiple WiFi access points, the time of signal arrival (TOA), and the angle of signal arrival (AOA). Triangulation algorithm requires three or more access points as per the property of triangles to accurately determine the target location.

Scene analysis algorithm is based on initially determining the physical features of the location under the radar for WiFi access points and maps the target device location using RSS-based location fingerprinting or magnetic field attenuations around the target device (Lin & Lin, 2005). Such overlays may be helpful for resource optimization by facility management services, as they can help in identifying the devices in a particular classroom environment, thereby enabling the facility management to alter resource allocation based on occupancy density in classrooms across universities.

Encouraged by the RSS-based location fingerprinting technique for location tracking, Ma et al. (2015) develops a method to overcome its areas of inaccuracy by using the standard deviation in location positioning in an indoor environment to calculate a new Euclidean distance between the access points and target device. The methodology used to remove systematic, gross, and random error based on experimentation in an indoor environment is presented in Figure 16.

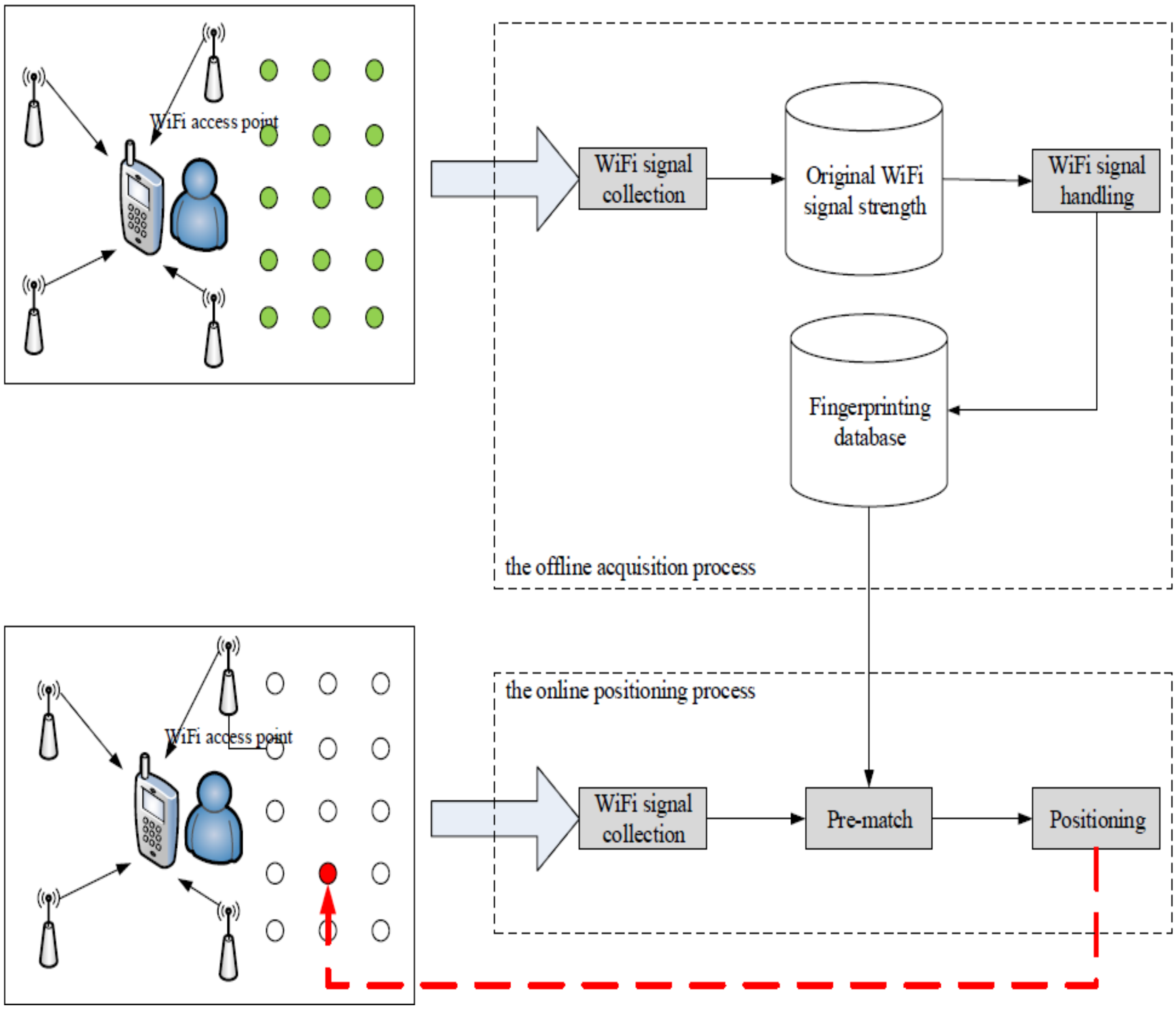


Figure 16: RSS-based Location Fingerprinting Advanced Algorithm (Ma & Xu, 2015)

Ma & Xu (2015) use environmental friendly wireless local area network (WLAN) positioning technology as a continuation of the green product lines of WiFi infrastructure established by Cisco whereby the access points are centrally controlled to power off when they are not required or are in an idle state, saving a surplus of energy resources and thereby minimizing costs for the facility management across various larger indoor facilities such as classrooms, shopping centres, hospitals, commercial offices, and university campuses.

Puga et al. (2015) uses fuzzy logic to create a mobile application to locate devices in an indoor space divided into zones using WiFi signals from pre-defined access points. The author uses subtractive clustering to create zones and determine the confidence level with which a particular target device is located within the zone using the mobile application. Zhou et al. (2015) utilizes WLAN indoor positioning for the mapping of probable motion patterns using gene sequencing method wherein the consequent sources of entry and exit are connected to predict the next probable motion event of a particular person as shown in Figure 17 and 18.

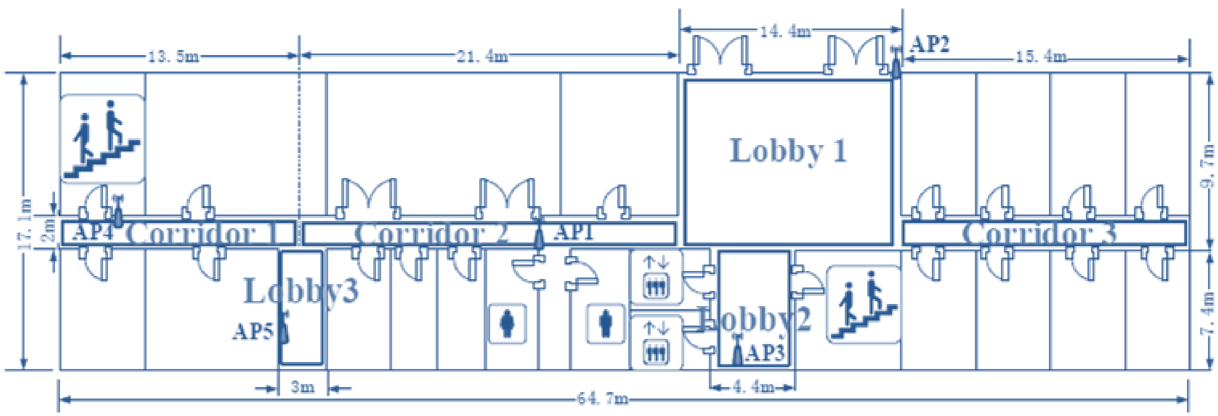


Figure 17: WLAN-based Event Mapping Target Area (Zhou et al., 2015)

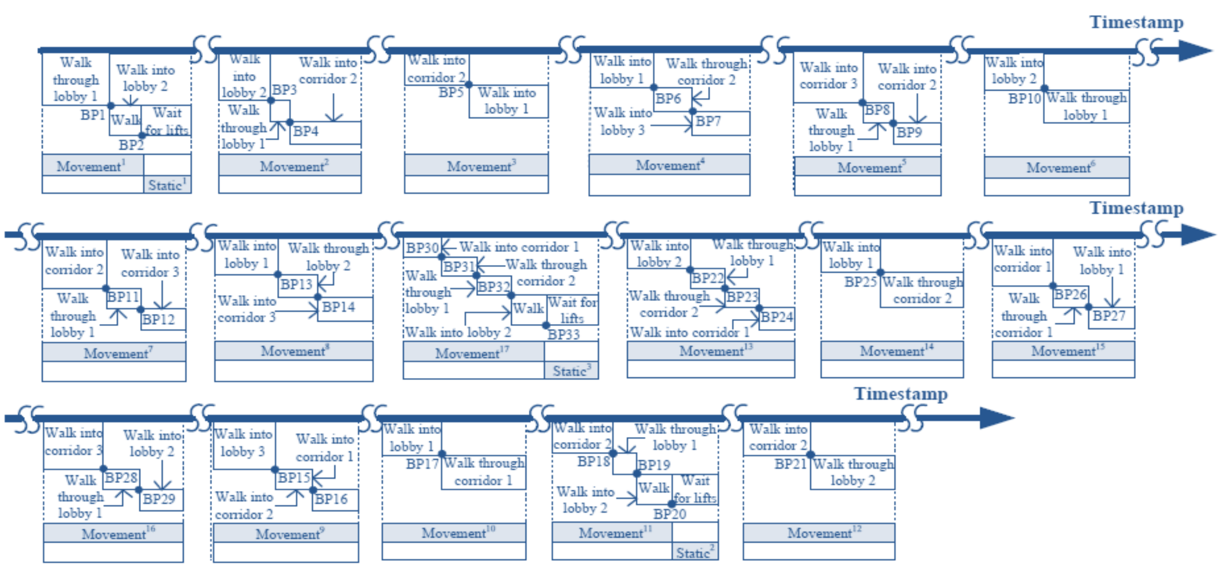


Figure 18: Motion Patterns based Mapping and Localization (Zhou et al., 2015)

For the design of WiFi-based indoor positioning systems using RSS location fingerprinting, weighted k-nearest neighbour algorithm is used for experimentation in a study by Caso et al. (2015) to determine the position of a target device with high accuracy through clustering, coarse localization, and fine localization in two steps by having a trade-off between computational complexity and positioning accuracy.

Zou et al. (2015) develops an online sequential extreme learning machine, which eliminates the hassle of offline site surveys by the WiFi infrastructure management personnel, solves the inflexibility to environmental dynamics that exists in current WiFi-based indoor positioning systems, and maps the location with an accuracy of 2.15 m in different indoor environments.

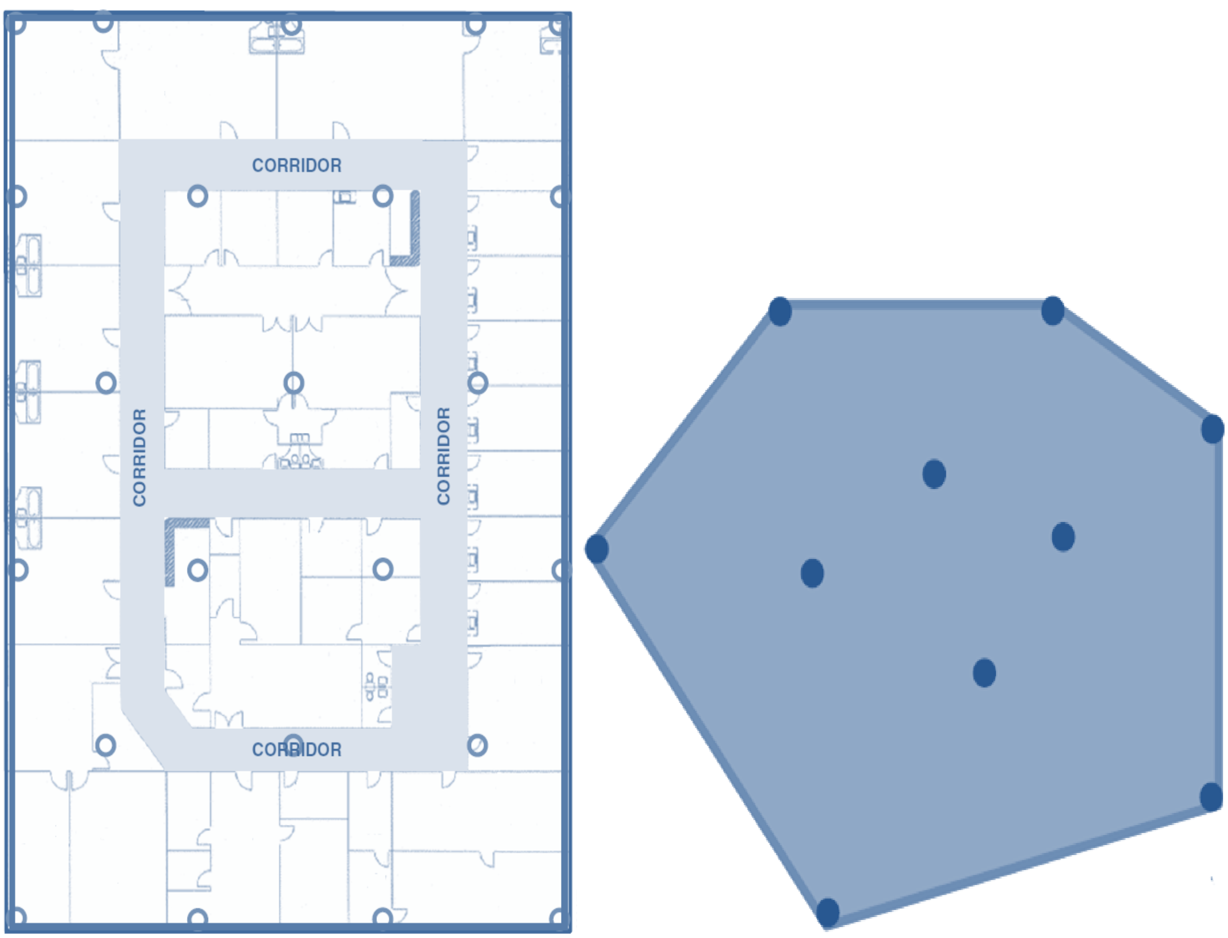


Figure 19: Access point distribution according to Convex Hull method (Cisco, 2008)

Cisco (2008) released its WiFi infrastructure design manual specifying the best practices for infrastructure design and access point installations in an indoor environment for their infrastructure devices capable of target device localization. The placement of access points depends upon the coverage provided by access points, security, cell-to-cell overlap, aesthetics, and distribution feasibility in an indoor environment. It is recommended that the access points are placed at the corner points of the floor and equidistant from each other for access points with equal coverage as per the Convex Hull method as depicted in Figure 19.

Cisco's Wireless Control System Map editor enables the building management team to map irregular floor areas which are not square or rectangular, but irregular in shape. The intensity of signals for the various access points on the floor map can be identified and the differences in signal strength aid in triangulation of the target device location as depicted in Figure 20 (Cisco, 2008).

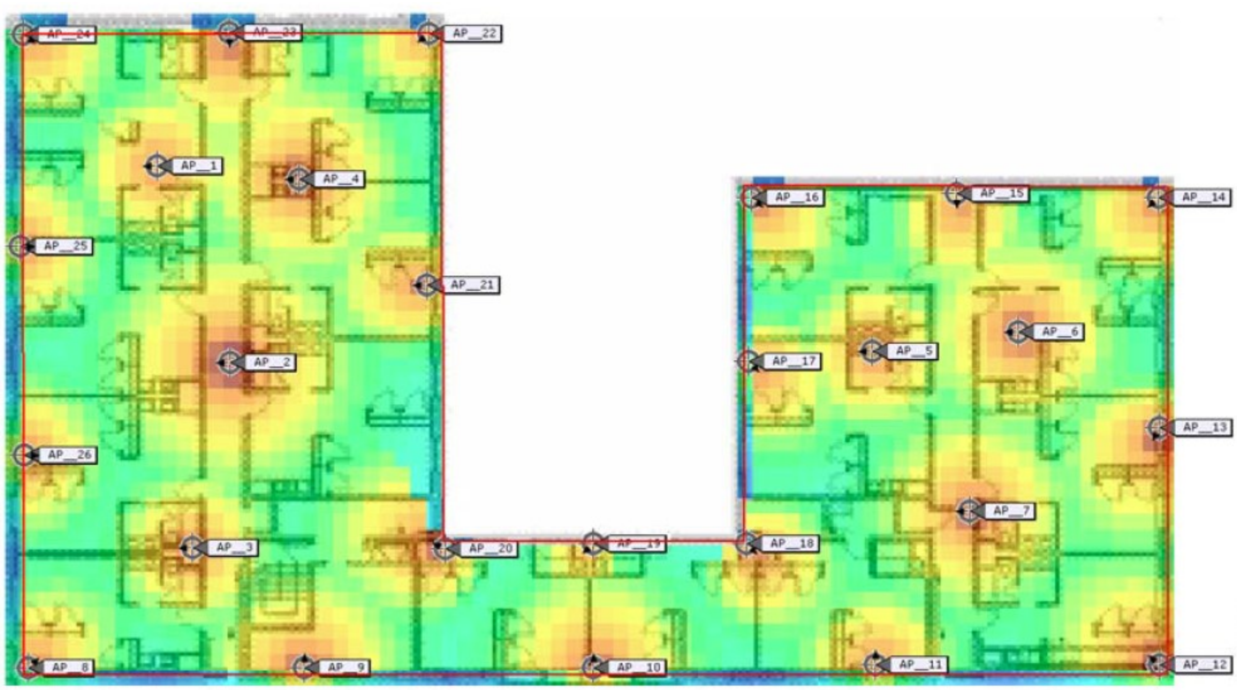


Figure 20: Irregular Floor Access Point Signal Intensity Map (Cisco, 2008)

It is observed that WiFi-based location tracking systems can act as an alternative to the people-counting sensors. A comparative analysis between the two models is conducted in this research to determine the level of accuracy between the obtained results. The WiFi-based location tracking system uses the university WiFi infrastructure networks to obtain locations using various access point signals and helps in obtaining an estimate for the number of people in a particular location indoors. The WiFi location tracking system can be beneficial, as the already-installed WiFi resources are used to obtain the occupancy data and optimize resource allocation in university classrooms, thereby saving the effort and cost of installing sensors to obtain occupancy data. Such experimentation between the two models will help estimate the accuracy of both models, access its range of applicability under different conditions, and help the facility management in making data-driven decisions for resource management.

2.5 Literature on Facility Maintenance, Safety, and Security in Universities

The previous section focuses on the various tools which can be used to track individuals in an indoor environment. However, it is important to realize why the operational research conducted uses positioning tools to identify occupancy and indoor space utilization. For buildings which are used rigorously during their lifecycle, their operational condition has a direct influence on their physical condition, their performance capabilities, the frequency of maintenance resources required and the expenditure to maintain the facilities during its lifecycle. Thus, facility operation management has become a topic of interest for scholars and experts in the construction industry. On the one hand, it is important to wisely plan the allocation of proper investment in building facilities during their lifespan and transform these investments into efficient and reliable service-related outputs. On the other hand, facility operation management focuses on facility performance, which is dependent on live user usage feedback and smart use of existing resources to reduce lifecycle costs and improve space usability standards. The balance between the two helps the facility management to function in an efficient manner. The indoor positioning tools discussed in detail in the previous section enables the O&M facility management to deploy resources based on real-time space utilization feedback. This research considers the O&M resource usage in classrooms as an integral part based on the extensive number of building facilities across all educational campuses. The usage of the educational facilities varies based on parameters defined later in during the research. Based on this, the objectives are to improve human resource utilization and optimize the resource management systems for classrooms based on utilization. Figure 21 shows the percentage distribution of degrees conferred in Canada to relate with the classroom requirements for different faculties.

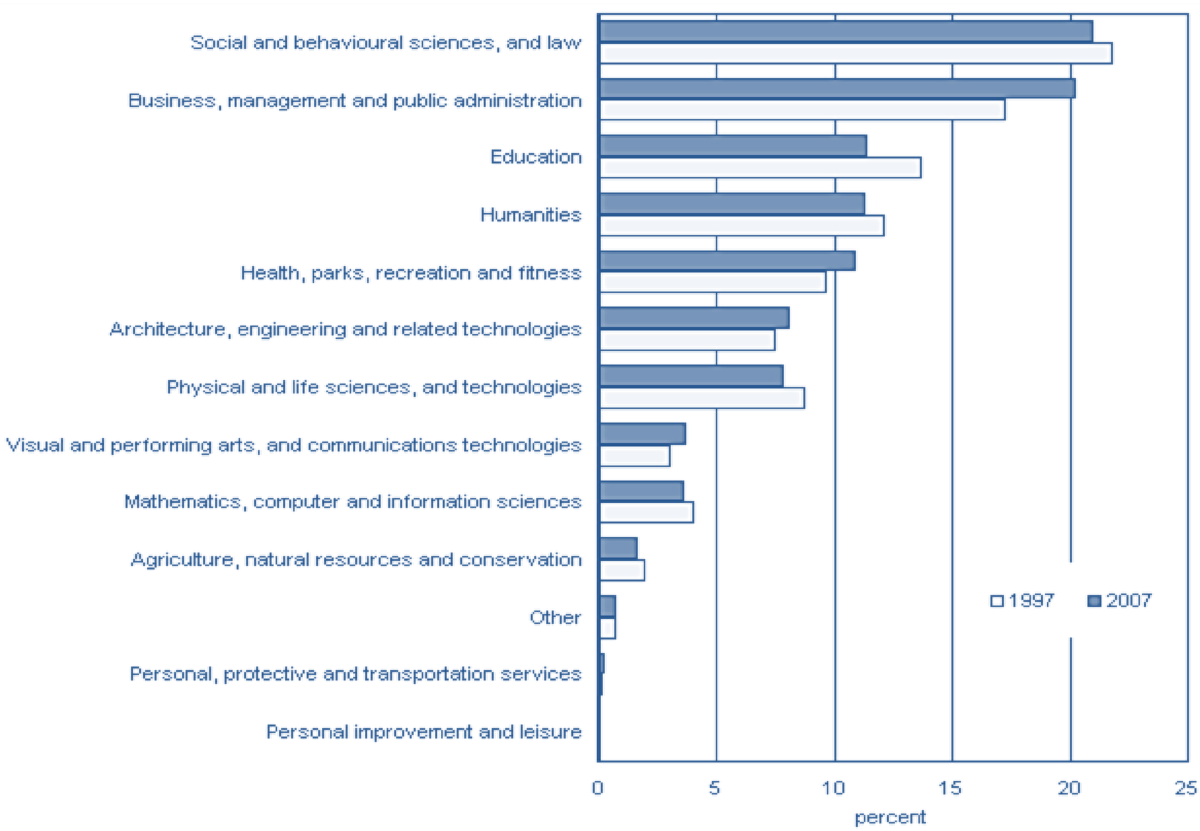


Figure 21: Percentage Distribution of University Degrees in Canada (Council of Ministers of Education, 2009)

The total number of students enrolled in Canadian universities and colleges was 1,996,200 in 2011-12, which grew by 1.9% compared to 2010-11 (Statistics Canada, 2014). The average amount of full-time tuition paid by Canadian undergraduate and graduate students in 2013-14 was $5,772/year and $6,053/year compared to $5586/year and $5916/year, respectively, in 2012-13 (Statistics Canada, 2014). Figure 21 shows a comparison by percentage of university degrees allocated in 1997 and 2007, which can assist the facility management to deploy its resources based on occupancy in different departmental buildings on campuses. For instance, it is evident from Figure 21 that degree programs in the areas of business, management, and public administration have a significant increase in student intake relative to others in Canada, which in turn increases facility usage in these departmental buildings across universities. More O&M resources can be deployed by the facility management to facilitate efficient functioning of these facilities throughout Canada (Statistics Canada, 2014).

Dew & Kulczycki (2016) estimate that the rise in expenses for the University of Alberta does not coincide with the Consumer Price Index (CPI); instead it depends upon the Academic Price index (API), which takes into account the projected compensations and other benefits such as material supplies, utilities, and maintenance expenses. The API for 2017-18 is projected to be 3.02% whereas the CPI for 2017-18 is projected to be 1.5%. The greater increase in academic facility management costs makes it evident that there is a need for optimization of resource usage across academic facilities and reinvestment of saved resources for the betterment of educational buildings. As observed in Figure 22, the incremental rise in salaries and benefits is the main differentiator between the API and CPI. The salaries, benefits, and operational material and services comprise 85% of expenses according to the University of Alberta's 2016-17 operational budget presented in Figure 23.

University's API Calculation for 2017-18

	% Actual Expenditures [1]		Projected Inflation (%)		Weighted (%)
Compensation					
Salary	63%	x	2.48% [2]	=	1.57%
Benefits	14%	x	7.50% [3]	=	1.01%
Sub-Total	**77%**				**2.58%**
Non Salary & Benefits[4]					
Materials Supplies	15%	x	2.00%	=	0.31%
Utilities	4%	x	2.00%	=	0.08%
Maintenance	4%	x	2.00%	=	0.08%
Sub-Total	**23%**				**0.5%**
Total	**100%**		**Projected Inflation**		**3.05%**
			Scholarship Adjustment		-0.03%
			API, 2017-18		**3.02%**

1. Based on three year rolling average of operating expenses per audited 2014, 2015, 2016 financial statements
2. Based on salary expenses weighted between Academic and Support salaries. 2017-18 Academic Settlement of 1.5%. Includes 2016- 17 Support lump-sum payment of 1.5%.
3. Based on 2016-17 Benefits Budget.
4. Projected Inflation based on 2017 forecasted inflation from RBC, BMO, and TD as at Q1 2016.

Figure 22: Projected Academic Price Index, University of Alberta (Dew & Kulczycki, 2016)

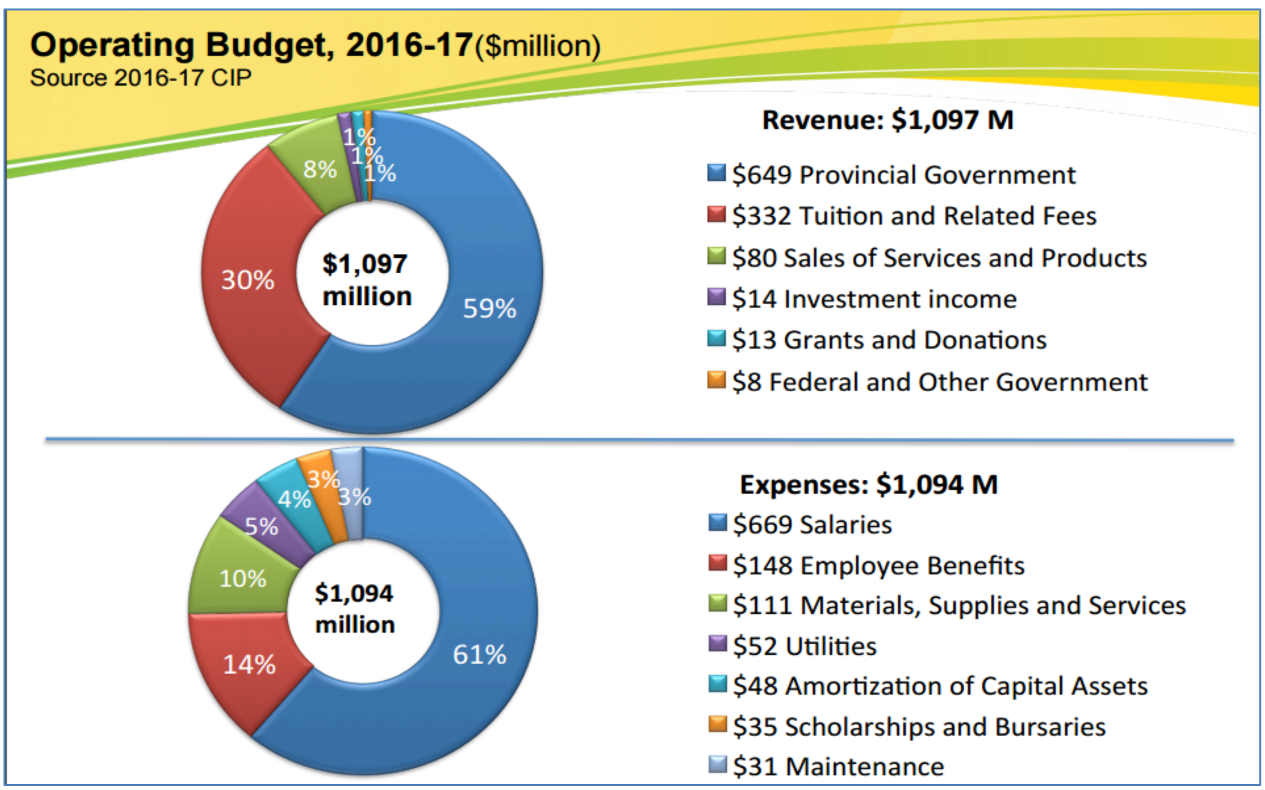


Figure 23: Operational Budget 2016-17, University of Alberta (Dew & Kulczycki, 2016)

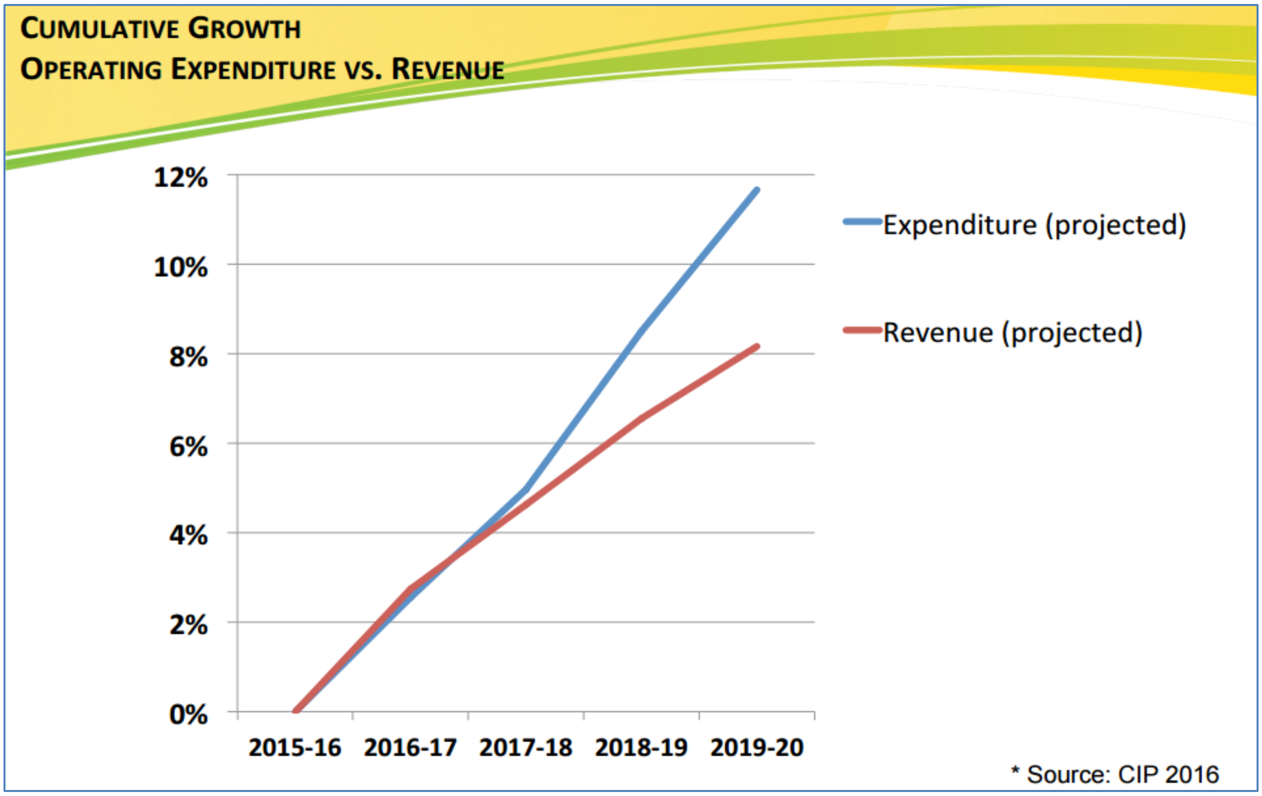


Figure 24: Operational Expenditure versus Revenue, University of Alberta (Dew & Kulczycki, 2016)

As observed in Figure 24, the projected expenditure is increasing relative to the yearly revenue at a rapid rate, thus there may be two action scenarios which the University may consider moving forward. First, they may increase the revenue by increasing the tuition fees for students, and second, as an alternative, they may research methods through which they can reduce incurred additional costs. Therefore, it is apparent that wastage of resources in terms of salaries, benefits, and operational material and services, which accounts for the majority of the incurred costs in universities across North America, is clearly observed, and that the utilization of resources is optimized.

Wantrup & Bishop (1975) discuss the tendencies of over-usage of natural resources when they are defined as common property as people tend to waste public resources. The African government estimated resource utilization and allocated specific quotas of resource usage. In the case of university facilities, the ideology of “common property” can affect the usage of facilities; however, the creation of resource usage awareness in the educational community can help facility management across universities to cut down on over-usage through a unified effort of all facility users.

Another important aspect that must be considered is the level of comfort for facility users along with their safety and security on campus premises. As communication through digital media such as smartphones and tablets has evolved rapidly in the past five years, different modes of peer-to-peer interactions and messaging systems have risen. This has enabled students and staff members in universities to interact with one another. Gow et al. (2008) discusses the emergency messaging systems in place at the University of Alberta which create a sense of safety in the minds of University facility users and provide the freedom to explore different facilities across the University for academic and social purposes based on their survey. Cutting et al. (2006) emphasizes the advantages of implicit peer-to-peer messaging and networking, thereby increasing connectivity between individuals having a common interest. Similar peer-to-peer messaging networks may help in increasing the awareness for facility usage among students and staff members at universities and help facility management to optimize resources as per live feedback.

Figure 25 presents a photograph captured during daytime for a University of Alberta classroom which is inspected, cleaned, and maintained on a daily basis by O&M staff for a period of 30 minutes irrespective of whether the space is used during the day or not. This practice on inspecting, cleaning and maintaining classrooms is the same for all 3,050 classrooms on the North Campus (Campus Maps, 2017). As the majority of the University’s expenses are linked to efficient human resource management and salary allocation, it is important that the over-usage of resources is monitored and resource allocation is linked with space occupancy for university facilities.

Figure 25: Rarely used Classroom Cleaned and Inspected Daily at the University of Alberta

The research focusses on utilizing the existing tools to assist facility management in making more informed decisions pertaining to allocation of human resources, reducing associated surplus costs, and providing the necessary services at the University to serve academic, research, and operational purposes. The next chapter describes how the use of real-time position tracking tools, such as installed heat sensors as well as existing university-wide WiFi infrastructure to identify classroom occupancy and modulate human resource allocation based on dynamic demand, can help reduce yearly expenditures for universities.

CHAPTER 3: METHODOLOGY

3.1 Introduction

This chapter highlights the research methodology based on the following research hypothesis:

"Dynamic human resource allocation based on requirement determined by accurate real-time classroom occupancy identification in universities can save over-usage of human resources".

The integral components of this research are as follows: (1) Determine the intensity of occupancy in sample classrooms across the University of Alberta collected through different methods of location tracking: (a) WiFi-based tracking; (b) thermal sensor-based tracking. (2) Identify intrinsic and extrinsic parameters which influence occupancy. (3) Develop a dynamic and coordinated human resource allocation model based on use of university facilities and assist facility management in the decision-making process by optimal allocation of human resources. Figure 26 illustrates the methodological research flowchart depicting the inputs, analysis, and outputs for the conducted research.

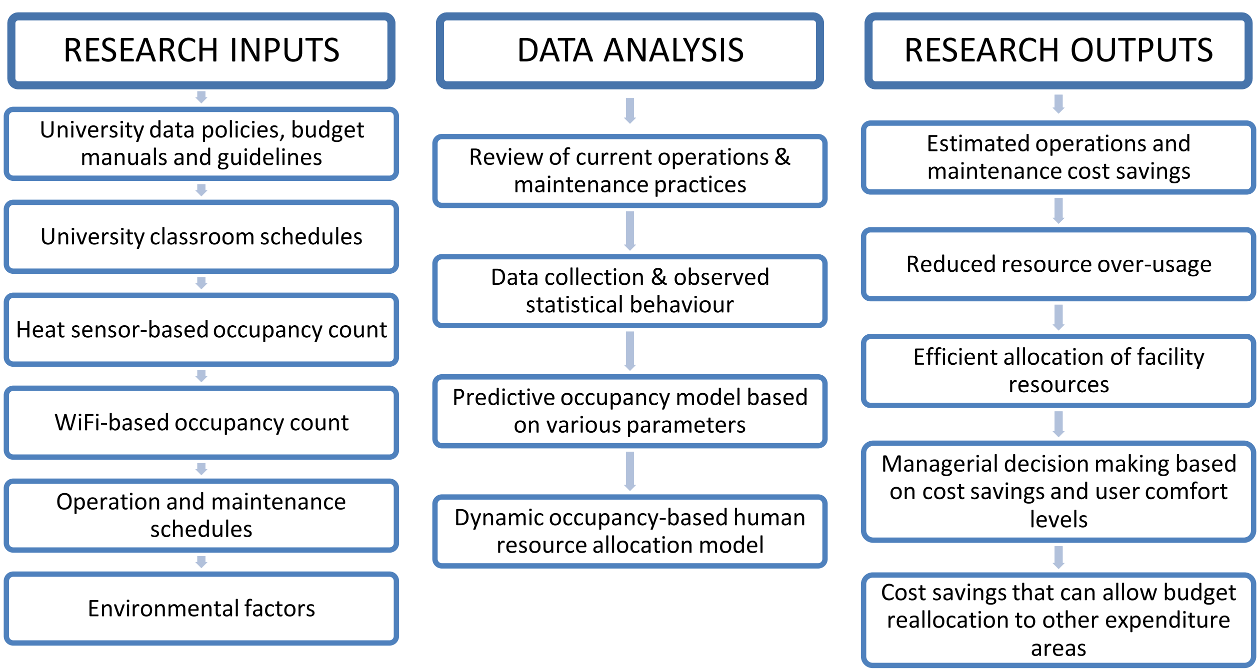


Figure 26: Research Methodology

The initial step in the methodology is to conduct a detailed study of the University data policies, guidelines, and the current O&M practices by the facility management at the University of Alberta. It will be followed by classroom occupancy data collection and observed statistical behaviour analysis using installed heat sensors and existing WiFi-based infrastructure. The next step includes development of a predictive occupancy model based on observed data and stochastic simulations. Finally, dynamic occupancy intensity based human resource allocation model, which will enable the facility management to allocate resources efficiently, is proposed.

3.2 Review of University Policy Guidelines and Current Operations Practices

Facility management at the University of Alberta abides by the standards put forth by the Association of Physical Plant Administrators, APPA (2014) which is a non-profit organization comprising over 1,500 higher educational institutions across North America. The research in this thesis specifically focuses on the custodial O&M services sub-section in the facility management operations at the University of Alberta. The codes for custodial services across academic institutions emphasize that all necessary custodial service level requirements, the quality of service, and the health and safety standards of any facility occupant across the universities, take priority over any custodial cleaning or inspection task undertaken by the respective facility management across universities. The priorities depend upon multiple factors including building design and architecture, scheduled use of facilities, facility occupancy type, climate, etc. According to APPA, all educational administrators and their facility management are the individuals responsible to determine appropriate best practices and guidelines required for custodial cleaning and inspection requirements within their facilities (APPA, 2014). APPA determined the need for individual guidelines as a universal guideline might not apply under various conditions and restrict the facility management across academic institutions to provide innovative solutions to improve the level of services offered.

According to APPA (2014) cleaning and inspection tasks across institutional facilities are performed using a "team approach" to ensure that repetitive work does not erode the worker's willingness to perform the task. Generally, a team is assigned to a larger area rather than assigning individuals to perform specific tasks, which ensures uniformity in the level of work carried out and services offered. However, if a particular area is unusually dirty or requires special inspection, facility management can be contacted for on-spot immediate inspection and cleaning by request. Encouraging users to notify the facility administrators about such events will help the management deploy resources effectively and maintain an acceptable level of service throughout its facilities.

Currently, the classrooms at the University of Alberta are inspected every night, necessitating approximately 30 minutes, irrespective of whether they were used during the day or not. The dynamic scheduling model based on occupancy intensity during the day will enable the facility management to craft strategies to deploy its resources more efficiently, saving manpower and decreasing resource usage costs. Additionally, the equipment costs incurred due to over-usage of resources will also be curtailed through dynamic scheduling.

3.3 Data Collection and Observed Statistical Behaviour

APPA guidelines provide the facility maintenance and operations management at the University of Alberta with the liberty to innovate, reduce surplus costs, and improve its offered services. Occupant presence and behaviour in buildings has been shown to have large impacts on space utilization. Therefore, accessibility of occupancy data is crucial to maximize efficiency of an

O&M facility management system and prevent over-usage of existing human resources. It is essential to determine the initial functionality of the utilization-based scheduling in order to facilitate effective management through the provision of adequate information to improve resource allocation.

Data collection based on reviews of existing literature, as well as information from industry experts and end users, is important to comprehend and plan the collection process accordingly. For example, collecting information from facility managers or workers regarding their day-to-day work schedules, factors affecting their work-loads, recommended improvements in allocation, and introduction of alternative collaborative approaches which make their tasks easier will enable the collection of the correct input parameters for effective dynamic scheduling. As types and availability of database management systems vary across different universities, this chapter will provide an overview of the general data requirements for the development of an occupancy-based dynamic human resource allocation model. The next chapter will include case studies for the occupancy observed in the classrooms at the University of Alberta based on university lecture schedules, heat sensor-based classroom occupancy, and WiFi-based classroom occupancy.

Figure 27 represents the 4 types of databases and the parameters drawn from each to conduct the research study. The classroom schedules databases provided by the University's Office of the Registrar offer information about the course allotments for different classrooms and at different time periods throughout a given semester, the capacity of classrooms, and the enrollment count for different courses. The facility management O&M schedules provide information about the workforce and time allocated for inspection, monitoring, and performing custodial services for classrooms. Determining the classroom occupancy based on heat sensor counters provides information about the number of people occupying a particular classroom. The WiFi-based location tracking database draws inputs about the number of individuals connected to the access point in a particular classroom and assists in making a comparison with the heat sensor counter occupancy data to determine the efficiency of the models, equipping the facility management with alternatives to minimize initial investments and make long-term productive resource management decisions.

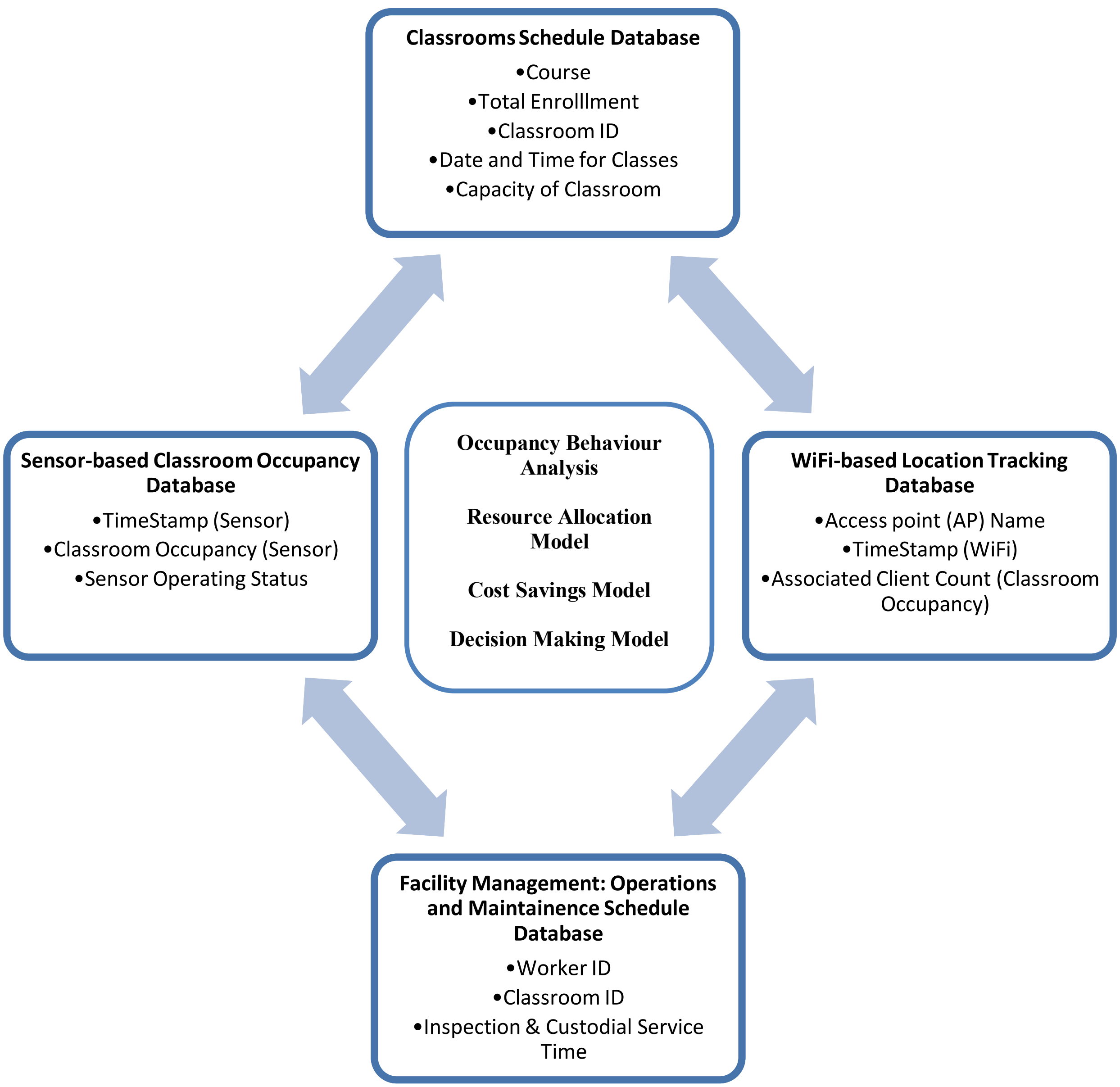


Figure 27: Data Collection Schematic

3.3.1 University Course Schedule-based Human Resource Allocation Concept

The main purpose for conducting research using a university course schedule-based model is to identify classroom usage frequency and occupancy patterns for different classrooms and to enable the central management and users with a smart, automated, and informative interface. It is apparent that the classrooms are utilized the most during lecture hours in universities across North America; however, the intensity of occupancy may vary due to the number of enrolled students actually attending the lectures. This research focuses on determining the scheduling and occupancy behaviours in universities as per obtained usage patterns and will implement a dynamically evolving scheduled mechanism to estimate the requirement for resource usage. Given that human resources are costly in North America, the focus is to optimize the process, achieve maximum operational savings, and create a sustainable environment while simultaneously maintaining high comfort levels. Surveys conducted for the purpose of this research and expert opinion from facility management services at the University of Alberta assisted in the creation of a basic equation which helps to identify the parameters influencing classroom occupancy intensity and resource usage. The density function expressed in Eq. 3.1 acts as an indicator of general classroom occupancy:

$$\text{Classroom Occupancy Density}_{\text{i}} = \frac{\text{Classroom Occupancy}_{\text{i}}}{\text{Frequency of Time Occupied}_{\text{i}} \times \text{Capacity of Classroom}_{\text{i}}} \tag{3.1}$$

where

Classroom Occupancy$_i$ = Daily average number of people occupying classroom i in person/minute

Frequency of Time Occupied$_i$ = Daily average frequency of time classroom *i* is occupied in minute^{-1}

Capacity of Classroom$_i$ = Maximum number of people who can occupy classroom *i*

It is observed that, as the number of people occupying a classroom increases, the density increases proportionately, and that, as the time occupied increases, the density function decreases in inverse proportion. The same comparison is true for the capacity of a particular classroom. As the capacity of a classroom increases the density function decreases in inverse proportion. For example, if a classroom with a capacity of 200 people is occupied in one day for (i) 50 minutes by 100 people, and (ii) 60 minutes by 200 people, then the classroom occupancy density for the first case is (100 x 60 x 24) / (50 x 200) = 14.4, and for the second case is (200 x 60 x 24) / (60 x 200) = 24 for that classroom on that particular day. The classroom density is estimated as it functions as a parameter to identify how indoor spaces across the university facilities are utilized and allocates resources based on space usage insights. Alternatively, variables such as classroom capacity and classroom occupancy count could have been independently used for resource allocation, but they would not act as standard indicators for allocating O&M resources across the university facilities. Finally, a centrally controlled interface can be developed to assist the university O&M personnel to keep track of resource requirements, enabling them to make informed decisions.

Table 2 presents a rating scheme developed in collaboration with the facility management experts at the University of Alberta to conduct experimental alterations in the maintenance, operations, and custodial service schedules based on the intensity of work and time required to accomplish it. The classroom occupancy density can be calculated for university classrooms and resources can be allocated based on the distribution of density function and equal segmentation of the distribution based on rating as displayed in a sample graph in Figure 28.

Table 2: Rating Scheme based Service Time Allocation Model

Rating	Service Requirement	Cleanliness	Current Service Time [C] in minutes	Optimized Service Time [O] in minutes	Savings [C – O] in minutes
1	No Inspection	Most Clean	30	0	30
2	No Inspection	Most Clean	30	0	30
3	Basic Inspection	Moderately	30	5	25
4	Detailed Inspection	Moderately	30	10	20
5	Detailed Inspection	Less Clean	30	10	20
6	Basic Clean-up	Less Clean	30	15	15
7	Basic Clean-up	Less Dirty	30	15	15
8	Detailed Clean-up	Less Dirty	30	20	10
9	Detailed Clean-up	Moderately	30	25	5
10	Complete Clean-up	Most Dirty	30	30	0

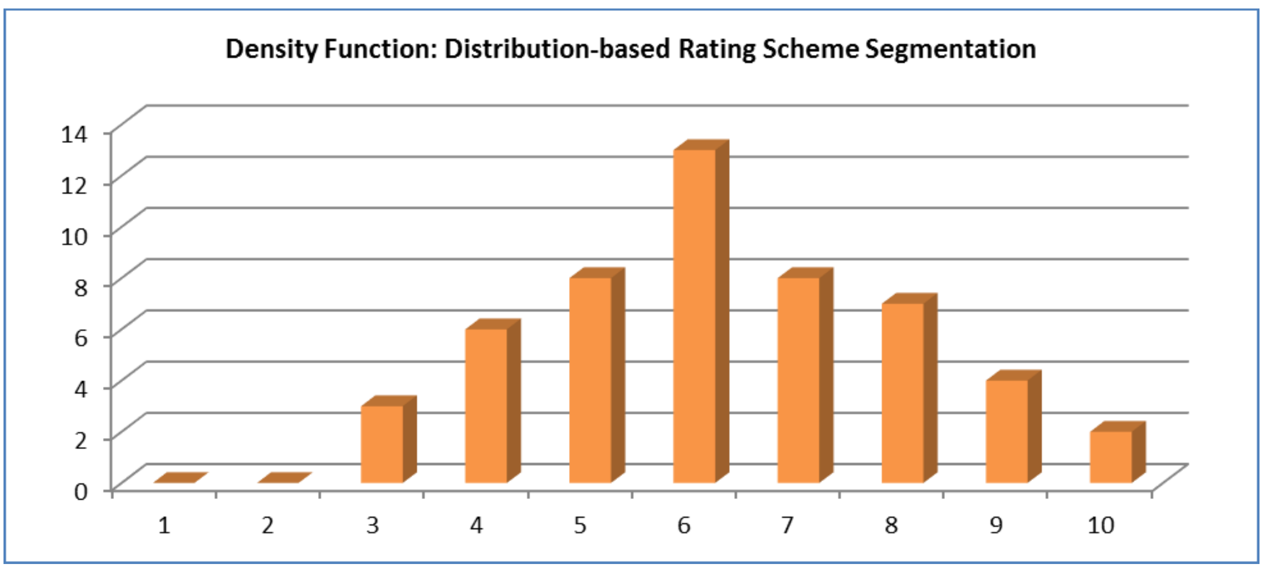


Figure 28: Distribution-based Rating Scheme Segmentation of Density Function

A detailed analysis of classrooms at the University of Alberta is presented in Chapter 4, which includes case studies based on university course schedule-based resource optimization as a subchapter. The classroom occupancy also depends on various extrinsic and intrinsic factors. Future behaviour statistics may help to identify the extent to which frequency of classroom usage depends on intrinsic parameters such as university classroom schedules, classroom capacity, and aesthetic classroom features, as well as extrinsic factors such as environmental factors: temperature and humidity; highly occupied landmarks in close proximity to classrooms; seasonal behaviour; time during a semester; or variations in winter and summer occupancy, etc. The above attributes can enable the management system to make an informed decision with regards to efficient resource usage and are covered in detail in Chapter 4.

3.3.2 Thermal Occupancy Sensor-based Human Resource Allocation Concept

Students at schools and universities are the primary users of classrooms and their academic achievement has been the core evaluation criteria for institutional reputation in current society. Thermal occupancy sensors play a vital role in the determination of occupancy in environments where smartphones or laptops are underutilized, such as school environments where the use of smart devices is restricted. As a result, WiFi-based location positioning may provide an incorrect evaluation of occupancy in such conditions. Thermal occupancy sensors installed at the entrance and exit of a particular classroom assist in identifying the number of people entering or exiting the classroom at any given time based on human body heat signatures.

The research study conducted in Chapter 4 indicates that classrooms are not utilized at all times. For efficient management of indoor facilities, it is important to identify how and when they are being utilized. Installation of thermal sensor counters at access points of different classrooms is one method of identifying classroom occupancy. Figure 29 demonstrates the layout for the first floor of the Education North Building at the University of Alberta where this experimentation (installation of thermal occupancy sensor counters) to identify occupancy demand is conducted in order to monitor centrally scheduled classrooms and manage them effectively. The case study is discussed in detail in Chapter 4.

Figure 29: 1st Floor Indoor Layout for Education North Building, University of Alberta

Thermal counters are used primarily in smart buildings, in retail for people-counting in shopping centres and supermarkets, and for queue management in department stores, ticket counters, hospitals, etc. With current sensor counters having a high degree of resolution array, supported ibeacons, such as Bluetooth and WiFi, which are able to aggregate count data and offer a wide field of view (FOV) of approximately 50 m, make installation of sensors a compelling choice in locations where occupancy count is required and smart devices are not consistently present (IRISYS, 2016). IRISYS (2016) determined based on customer surveys that the thermal sensors installed at various locations project an accuracy of 98%, which is precise in terms of calculating the number of individuals occupying classrooms in universities and schools.

Figure 30: IRISYS Thermal People-counter Concept (InfraRed Integrated Systems, 2016)

Thermal people-counters are based on the concept depicted in Figure 30. When a thermal sensor is installed on the ceiling, wall, or door at an entry point, it detects people entering or exiting as indicated by the black lines in the graph in Figure 30. After they cross the red line in the middle of the graph (intersecting the black lines) at the door entrance as shown in Figure 30, the count is incremented by 1 for people entering and decremented by 1 for people exiting the space. This allows the management to keep track of the number of people occupying a certain room or space at a particular time. The challenge is that continually retrieving data from the sensors can consume a significant amount of energy and increase the cost of utilities for the facility. Therefore, the occupancy-count data is retrieved from the sensors at specific time intervals, which in turn saves some utility resources.

However, it is important to focus on how the determined occupancy at a particular interval can enable effective allocation of human resources given that the most significant savings would be achieved through its management. Initially, the university-based schedule model provided the classroom occupancy density function as described in Eq. 3.1. Therefore, a combination of live classroom-occupancy data aggregated to identify the necessary parameters of daily average of classroom occupancy and daily average of time a classroom is occupied will enable the researcher to obtain the occupancy density in a particular classroom, and its distribution range will enable the researcher to allocate resources much more effectively. More accurate identification of occupancy density will help in determining behaviours and predictive allocation of resources.

Above we discussed the positive aspects of sensor installations, other major factors to consider in the installation of precise sensors are the incurred installation costs; infrastructure maintenance costs; and the possible payback period from achieved savings. Such drawbacks can be resolved using the existing university-wide WiFi infrastructures which are present in most universities across North America. The abundant usage of smart devices connected to the central WiFi infrastructure is evident from the survey results conducted across the University of Alberta, which will be discussed in the WiFi-based case study in Chapter 4.

3.3.3 WiFi-based Location Tracking-based Human Resource Allocation Concept

WiFi-based location tracking systems can act as an alternative to people-counting sensors. The aim is to utilize existing infrastructure for university-wide WiFi systems to track users connected to WiFi services across universities. As discussed earlier in Chapter 2, extensive experimentation and research has been conducted on WiFi-based indoor location tracking models due to their varied range of applications for indoor facilities. In addition to occupancy-based resource usage across universities, WiFi-based indoor location tracking services can assist in different smart home services, geo-fencing services for security management, targeted customer acquisition in shopping centres, and various demand-based services such as transit management, hospital queue management, and inventory management, as depicted in Figure 31.

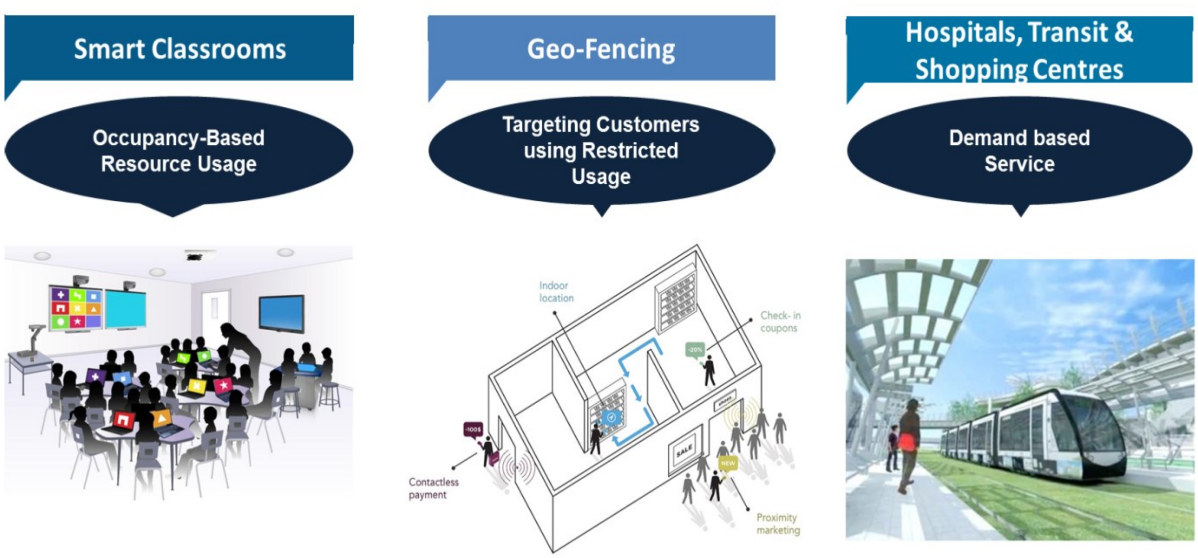


Figure 31: Varied Application for WiFi-based Indoor Location Tracking

Due to its wide range of indoor applications, aggressive and extensive research is being conducted to improve the accuracy of WiFi-based indoor services. WiFi-based location tracking infrastructure at universities enables the management to retrieve information about the number of people connected to a particular access point (AP) in a large building environment. Accurate position of an individual can be tracked through the triangulation method based on the received signal strength from the connected device, angle of signal receivable, etc.

Figure 32: Access Point based mapping of 5th Floor of GSB, University of Alberta

Figure 32 presents a snapshot of a floorplan indicating where people are positioned at an instance on the 5th floor of the General Services Building (GSB) at the University of Alberta. This information is obtained by the positioning of connected smart devices using mounted access point devices (from Cisco Wireless Infrastructure) managed by the Information Services and Technology unit. Cisco Unified Wireless network is reported to have an accuracy of 90% when the access points are within the convex hull and a distance less than 10 m from one another (Cisco, 2008).

The WiFi-based location tracking system uses the University WiFi networks to obtain the location of end-users using modem signals and assists in estimating the number of people in a particular location indoors. The WiFi location tracking system can be beneficial given that the already installed WiFi resources are used to obtain the data and optimize resource allocation in University classrooms, thereby eliminating the need to install sensors and saving significant installation costs. A comparative analysis between occupancy determined from the sensor-based model and WiFi-based model can be conducted to determine the level of accuracy for the models and enable the facility management to make more informed decisions pertaining to human resource allocation. Such experimentation between the two models will help to estimate the accuracy of both models and help the facility management in making data-driven decisions for resource management. Additionally, the WiFi networks possess the ability to be scaled beyond the classroom environment and can assist in the study of the complete building infrastructure and facility usage for future research since the infrastructure is already established and will not incur surplus costs in the case of sensors.

The correlations between the classroom occupancy obtained from both the Sensor and WiFi infrastructure can help in the development of a hybrid model for classroom occupancy and more effective calculation of the occupancy density function. The developed models can be tested to observe occupancy behaviour changes based on various intrinsic factors such as pre-defined classroom schedules and extrinsic factors such as outside temperature, humidity, and time period during a semester.

3.4 Summary of Methodology

The basic concepts and frameworks used in this research are presented in this chapter. They include (1) the facility management policies and guidelines followed by universities for custodial services and resource planning; and (2) the description of three interlinked models, including university schedule-based human resource allocation, thermal occupancy sensor-based human resource allocation, and WiFi-based location tracking-based human resource allocation. The next chapter emphasizes the comparison between (i) schedule-based resource model versus occupancy-based resource model, and (ii) thermal sensor-based resource model versus WiFi-location tracking-based resource model. A more analytical observation has been made to implement the above methodology at the University of Alberta in the case studies presented in Chapter 4.

CHAPTER 4: CASE STUDY

4.1 Introduction

The concepts and frameworks described in Chapter 3 are applied to a case study conducted in Edmonton, Canada, for classrooms at the University of Alberta's main campus. Along with the results produced for the classrooms at the University of Alberta based on the university schedule-based human resource allocation model, thermal occupancy sensor-based human resource allocation model, and WiFi-based location tracking-based human resource allocation model, this chapter includes a decision-making model for facility management at the University of Alberta for effective resource allocation. The research in this case study focuses on determining occupancy patterns, the intensity of occupancy, and consequential decisions to be made by facility management for effective resource dispersion in the indoor classroom environment at the University of Alberta.

4.2 University Course Schedule-based Resource Allocation at University of Alberta

As discussed in Chapter 3, the university classroom occupancy depends highly on the courses scheduled for these classrooms. The enrollment for these courses during a particular semester acts as an occupancy cap during the lecture time frames for the classrooms at the University of Alberta. The usage of classrooms differs based on the decrement in occupancy due to lesser attendance of students compared to the enrolled strength and occupancy of these classrooms in non-scheduled hours of usage by students for self-study, group-study activities for projects, assignments, and other social and professional meetings. A sample case study is conducted for the classrooms in the Natural Resources Engineering Facility (NREF) building at the University of Alberta based on university courses scheduled in the facility during the Fall 2016 semester.

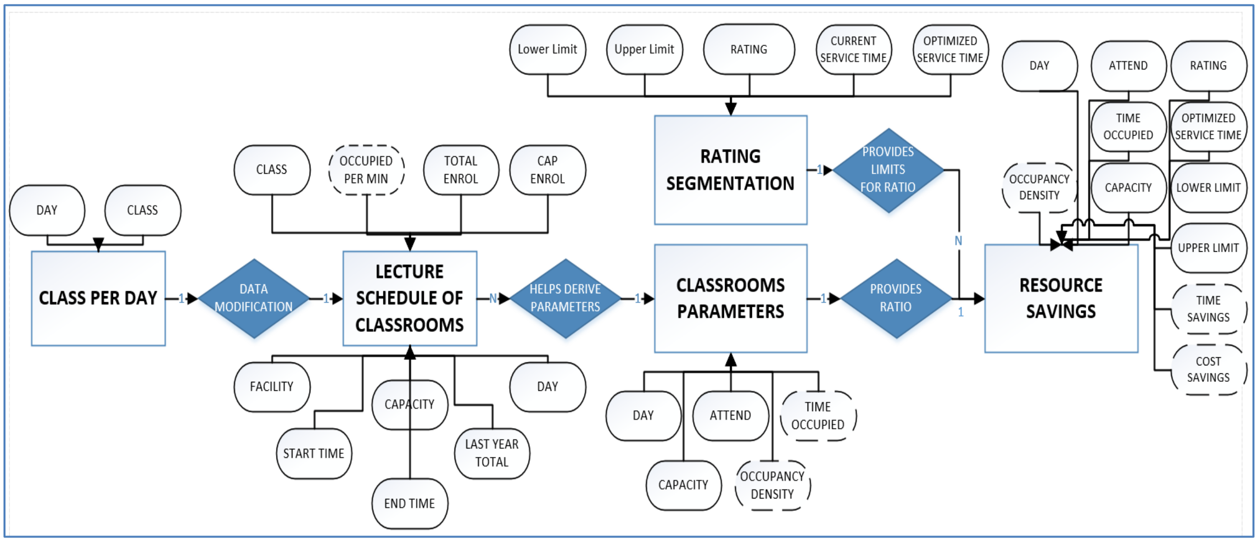


Figure 33: Entity Relationship (ER) Diagram for Classroom Custodial Resource Savings

Figure 33 presents an ER Diagram for the classroom custodial resource savings model developed for classrooms at the University of Alberta based on university course schedules. The above model represents a basic framework adopted to determine the occupancy density function and allocates custodial resources dynamically as per the rating scheme presented in Table 2 in Chapter 3. The raw data obtained from facility management for the scheduled courses has been cleaned and modified to structure the database as per the requirement of the model in the data modification stage. The next stage involves the classroom occupancy density determination based on the assumption that classrooms are occupied by an average of 90% of the enrolled students for the duration of the semester as identified through visual inspection during tutorial and lecture sessions at the University of Alberta. The occupancy density function obtained for classrooms is matched with the rating scheme which is segmented based on the distribution of the density function. The final stage involves the time and cost savings estimation based on the usage of the demand-based resource allocation model for different classrooms in NREF at the University of Alberta during the semester period in survey.

As specified above in the university schedule-based model, the University classroom occupancy has been determined based on visual inspection during lectures and tutorials. The number of assignments submitted and tutorial lectures attended for a particular semester can be classified with a decent accuracy due to in-class submissions provided by students. Figure 34 depicts the sample in-class submissions graph for the CIVE 395 course during the Fall 2016 semester, denoting the occupancy patterns during different stages of the semester.

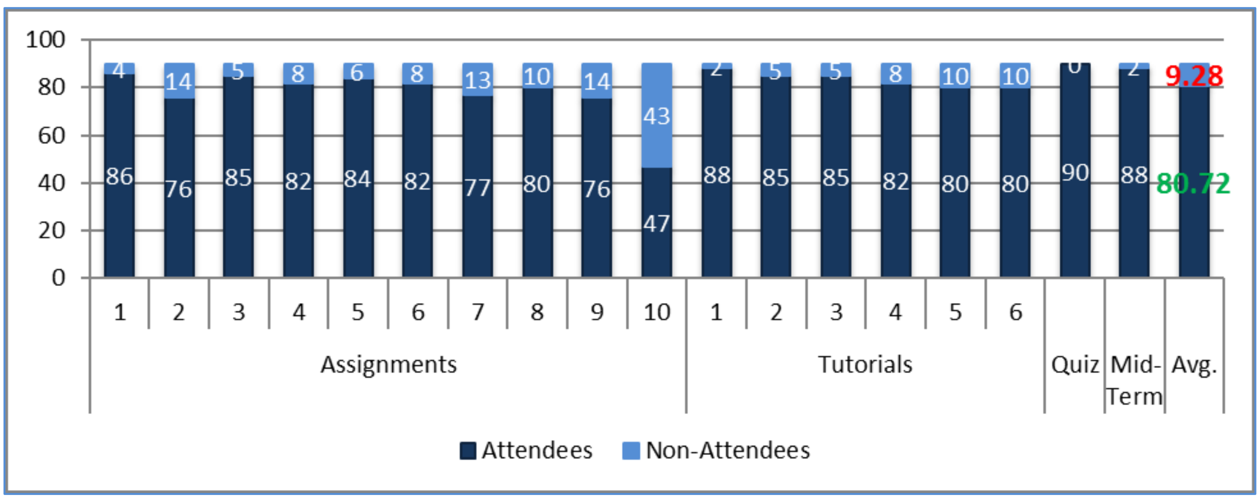


Figure 34: CIVE 395 In-class Submissions, University of Alberta

The above sample indicates that, in most cases, not all the students enrolled in the class were in attendance for in-class assignments and tutorials. The attendance gradually decreased as the semester progressed and the last few submissions showed a rapid decline due to preparations for final exams, of which most students attended. The average attendance for in-class submissions was 80.92 out of 90 students with an average percentage of attendees of 89.69%. Thus, based on the observed phenomenon, an assumption of 90% average attendance is considered for the university schedule-based human resource allocation model. A similar model can be developed for other classes to improve the accuracy of the course schedule-based model.

Table 3 presents a sample from the structured database generated based on SQL queries to retrieve course schedules and classroom characteristics required for NRE at the University of Alberta for estimation of classroom occupancy density. It is used to observe the percentage of un-occupied space in classrooms at the University of Alberta and develops insights for facility management to optimize O&M resource allocation and increase space utilization.

Table 3: Sample NRE Classroom Schedule for Fall 2016, University of Alberta

Class	Tot Enrl (TE)	Cap Enrl (CE)	Last Year Total	Facility	Cap (C)	Day	Start Time	End Time	Occupied in Min	% Not Occupied
AFNS 601	17	50	21	NRE 2 090	53	Thursday	11:00	11:50	50	**67.92**
AREC 313	50	56	50	NRE 1 143	56	Monday	13:00	13:50	50	**10.71**
AREC 313	50	56	50	NRE 1 143	56	Wednesday	13:00	13:50	50	**10.71**
AREC 313	50	56	50	NRE 1 143	56	Friday	13:00	13:50	50	**10.71**
BME 320	52	95	50	NRE 2 003	126	Thursday	11:00	12:20	80	**58.73**
CH E 358	44	80	50	NRE 1 003	126	Thursday	12:30	13:50	80	**65.08**
CIV E 331	87	90	81	NRE 1 003	126	Thursday	09:30	10:50	80	**30.95**
CIV E 374	104	111	103	NRE 2 001	126	Monday	09:00	09:50	50	**17.46**
CIV E 374	104	111	103	NRE 2 001	126	Wednesday	09:00	09:50	50	**17.46**
CIV E 374	104	111	103	NRE 2 001	126	Friday	09:00	09:50	50	**17.46**
CIV E 411	36	40	35	NRE 2 127	53	Thursday	08:00	09:20	80	**32.08**
CIV E 431	40	70	70	NRE 1 001	126	Thursday	09:30	10:50	80	**68.25**
CIV E 474	81	90	67	NRE 1 003	126	Wednesday	11:00	11:50	50	**35.71**
CIV E 474	81	90	67	NRE 1 003	126	Friday	11:00	11:50	50	**35.71**
									Average	**48.43**

It can be observed from the above retrieved sample database that classrooms enrollment is far below the maximum classroom capacity for most courses held in NRE. The average minimum percentage for unoccupied NRE classrooms in Fall 2016 for the duration of the course period is 48.43% based on classroom enrollment and capacity. This value increases with each enrolled student that does not attend lectures. The research indicates that there is under-utilization of classroom space solely based on the observed enrollment, classroom allocation for courses, and classroom capacity. The under-utilization of classrooms and uninformed custodial resource utilization implies that there is significant over-usage of custodial resources for under-utilized classroom spaces, emphasizing the need for effective space usage management and allocation of custodial resources as per its requirement.

Based on Eq. 3.1 and the required parameters obtained from the retrieved database represented in Table 3, the classroom occupancy density is estimated for NRE classrooms as shown for the sample classroom presented in Table 4. Occupancy density values are obtained for each day based on classroom attendance, time classrooms are occupied throughout the day and capacity of particular classroom under survey.

Table 4: NRE 2 090 Occupancy Density Estimation for Fall 2016, University of Alberta

Facility	Day	Attendance (person)	Time Occupied (minutes)	Capacity (person)	Occupancy Density
NRE 2 090	Friday	126	320	53	20.869
NRE 2 090	Monday	128	330	53	20.525
NRE 2 090	Tuesday	40	170	53	12.626
NRE 2 090	Wednesday	109	150	53	38.478
NRE 2 090	Thursday	105	470	53	11.874
NRE 2 090	Saturday	126	1,920	53	3.478

Similarly, the classroom occupancy density is obtained for 14 other classrooms throughout NREF based on university course schedules. The distribution behaviour for the range of occupancy density values is observed for the various classrooms under survey.

The descriptive statistics for classroom occupancy density function and correlation between attendances, time occupied and capacity for the NREF classrooms are depicted in Table 5.

Table 5: Descriptive Statistics for Occupancy Density and Correlation between Classroom characteristics

Descriptive Statistics: Occupancy Density	
Mean	60.1565188
Standard Error	11.05557625
Median	17.595
Mode	136.08
Standard Deviation	78.95260652
Sample Variance	6,233.514077
Kurtosis	0.418754781
Skewness	1.310854965
Range	258.132
Minimum	0.42
Maximum	258.552
Sum	3,067.982459
Count	51
Largest(1)	258.552
Smallest(1)	0.42
Confidence Level (95.0%)	22.20577842

Correlation	Attendance	Time Occupied	Capacity
Attendance	1		
Time Occupied	-0.009153439	1	
Capacity	0.85680251	-0.152803522	1

The statistical behaviour of occupancy density depicted for the 14 classrooms in NREF indicates that for most classrooms on most days of the week the occupancy density is quite low—the mean is 60.150 and median is 17.595—and skewness depicts positive asymmetry even though the maximum density value is 258.552. This demonstrates that the majority of the classroom spaces at this facility are under-utilized and there is over-usage of man-hours for inspection and performance of custodial services as there is flat allocation of custodial man-hours. Thus, it is imperative that the facility management allocates resources based on the observed demand and promotes higher space utilization for classrooms in coordination with the Registrar’s Office.

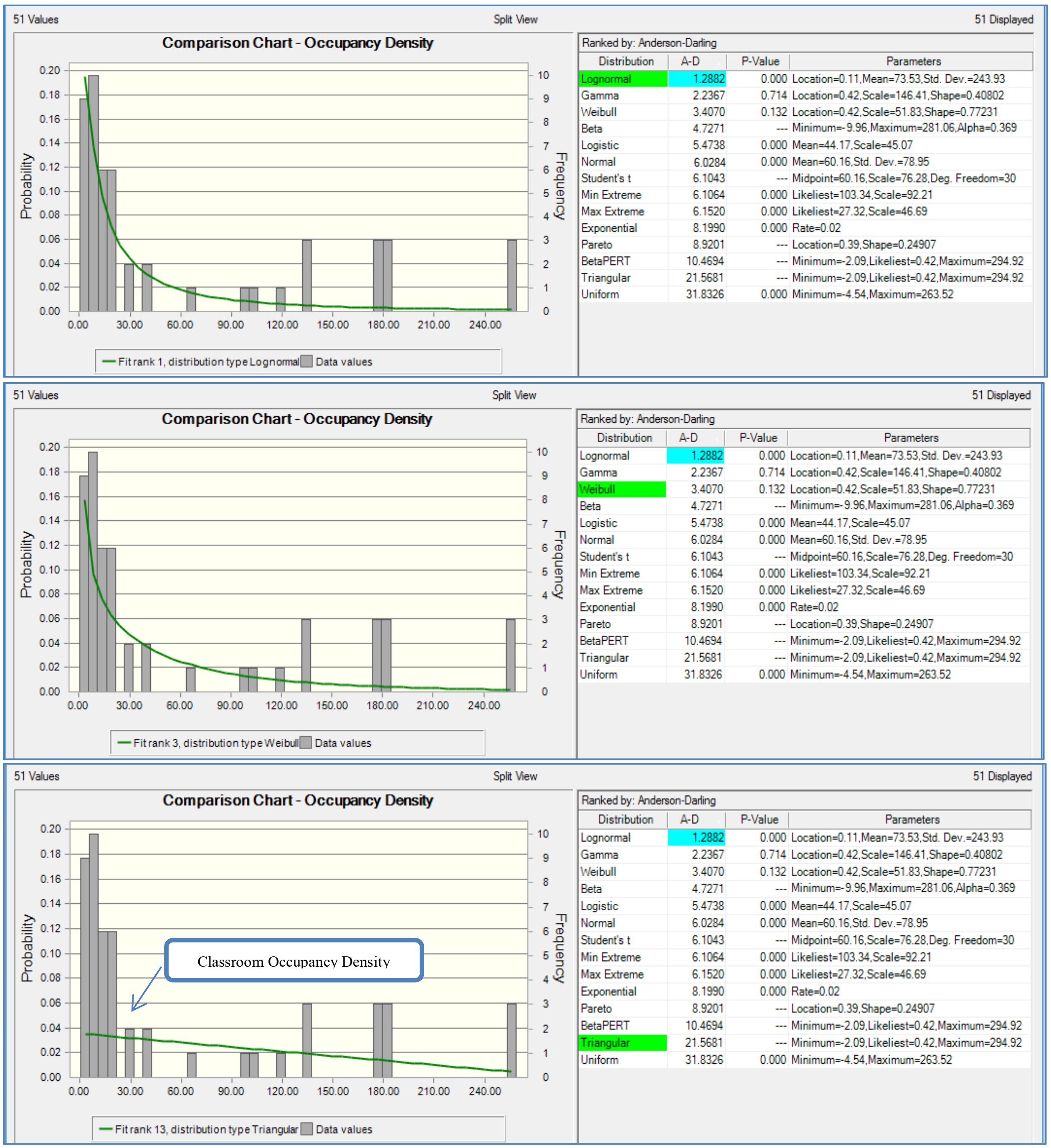


Figure 35: Classroom Occupancy Density Distribution for NREF classrooms

Using the Oracle Crystal Ball software for distribution fitting of classroom occupancy density, which is obtained using university schedules, it is observed that log-normal distribution has the best goodness-of-fit based on the Anderson-Darling value of 1.2882 and mean of 73.53. The distribution is then segmented using percentile values for the log-normal distribution and synchronized with the rating scheme for time allocation obtained from Table 2. The segmentation rating range values used based on the log-normal distribution of occupancy density for NREF are presented in Table 6.

Table 6: Log-normal Distribution Percentiles based Resource Allocation Rating Scheme

Percentiles	Log-normal Distribution	Rating	Lower Limit	Upper Limit
0th	0.11			
10th	2.92	1	0.11	2.92
20th	5.72	2	2.92	5.72
30th	9.37	3	5.72	9.37
40th	14.30	4	9.37	14.30
50th	21.27	5	14.30	21.27
60th	31.67	6	21.27	31.67
70th	48.51	7	31.67	48.51
80th	79.93	8	48.51	79.93
90th	159.87	9	79.93	159.87
100th	∞	10	159.87	∞

Table 6 allows the allocation of lower and upper limits to the occupancy density values for the designation of ratings as established in Table 2 for O&M service time optimization and enables the dynamic allocation of human resources for inspection and custodial services at the University of Alberta. The percentile values provide the population of occupancy density values below the "*x* percentile" value, which enables orderly distribution of the rating scheme for classroom occupancy density. The rating scheme obtained based on the log-normal distribution will assist in the estimation of achievable cost and time savings for performance of custodial, maintenance, and inspection services at the University of Alberta. Based on SQL query as depicted in Figure

36, the time and cost savings are estimated based on university classroom schedule-based resource allocation. The cost savings are based on the differential time savings achieved through demand-based allocation of resources and assuming an average pay rate of Can$18.00/hr for custodial, maintenance, and inspection services based on feedback from facility management at the University of Alberta.

NRE090#Rating

OccupancyDensit	Day	Attend	TimeOccupied	CAP	Rating	LowerLimit	UpperLimit	SavingTime	CostSaving
20.86875	Friday	126	320	53	5	14.3	21.27	20	6
20.5254545454545	Monday	127.8	330	53	5	14.3	21.27	20	6
3.478125	Saturday	126	1920	53	2	2.92	5.72	30	9
11.8742553191489	Thursday	105.3	470	53	4	9.37	14.3	20	6
12.6264705882353	Tuesday	40.5	170	53	4	9.37	14.3	20	6
38.478	Wednesday	108.9	150	53	7	31.67	48.51	15	4.5

NRE090#Rating

```
SELECT NRE090A.OccupancyDensity, NRE090A.Day, NRE090A.Attend, NRE090A.TimeOccupied, NRE090A.CAP, RatingSegmentation.Rating, RatingSegmentation.LowerLimit,
RatingSegmentation.UpperLimit, (RatingSegmentation.CurrentServiceTime-RatingSegmentation.OptimizedServiceTime) AS SavingTime, SavingTime*(18/60) AS CostSaving
FROM RatingSegmentation, NRE090A
WHERE NRE090A.OccupancyDensity> RatingSegmentation.LowerLimit AND NRE090A.OccupancyDensity< RatingSegmentation.UpperLimit;
```

Figure 36: NRE 2 090, University of Alberta Time and Cost Savings using SQL Queries

It is observed from Table 7 below that there is a total yearly time savings of 44,720 minutes and a total yearly cost savings of Cad$13,416.00 for all 14 classrooms under survey based on the university schedule-based dynamic resource allocation. The University of Alberta comprises more than 500 buildings with similar resource usage and allocation patterns. The above model can be extended to all classrooms across the University in order to save physical as well as monetary resources which can be reinvested for the improvement of facility management services and educational facilities. The university schedule-based model relies on the criteria that the majority of the classrooms are occupied during the scheduled lecture times to provide a reasonably effective model for dynamic allocation of resources based of the occupancy density. As this initial model has been developed based on a small sample distribution of data, the accuracy of the model will improve as a larger set of data points are considered, resulting in better allocation of human resources by the facility management.

Table 7: Projected Yearly Resource Savings for NRE Classrooms, University of Alberta

Facility	Occupancy Density	Day	Rating	Lower Limit	Upper Limit	Time Savings (min)	Cost Savings (CAD)	Yearly Time Savings (min)	Yearly Cost Savings (CAD)
NRE 2 090	20.869	Friday	5	14.303	21.274	20	6.0	1,040	CAD 312.00
NRE 2 090	3.478	Saturday	2	2.916	5.724	30	9.0	1,560	CAD 468.00
NRE 2 090	11.874	Thursday	4	9.367	14.303	20	6.0	1,040	CAD 312.00
NRE 2 090	12.626	Tuesday	4	9.367	14.303	20	6.0	1,040	CAD 312.00
NRE 2 090	38.478	Wednesday	7	31.670	48.506	15	4.5	780	CAD 234.00
NRE 2 020	7.051	Thursday	3	5.724	9.367	25	7.5	1,300	CAD 390.00
NRE 2 020	4.874	Wednesday	2	2.916	5.724	30	9.0	1,560	CAD 468.00
NRE 2 043	28.080	Thursday	6	21.274	31.670	15	4.5	780	CAD 234.00
NRE 2 080	3.261	Wednesday	2	2.916	5.724	30	9.0	1,560	CAD 468.00
NRE 2 118	17.595	Friday	5	14.303	21.274	20	6.0	1,040	CAD 312.00
NRE 2 122	6.210	Monday	3	5.724	9.367	25	7.5	1,300	CAD 390.00
NRE 2 122	6.210	Friday	3	5.724	9.367	25	7.5	1,300	CAD 390.00
NRE 2 122	6.480	Thursday	3	5.724	9.367	25	7.5	1,300	CAD 390.00
NRE 2 122	6.210	Wednesday	3	5.724	9.367	25	7.5	1,300	CAD 390.00
NRE 2 127	11.687	Friday	4	9.367	14.303	20	6.0	1,040	CAD 312.00
NRE 2 127	11.687	Monday	4	9.367	14.303	20	6.0	1,040	CAD 312.00
NRE 2 127	14.894	Thursday	5	14.303	21.274	20	6.0	1,040	CAD 312.00
NRE 2 127	5.830	Tuesday	3	5.724	9.367	25	7.5	1,300	CAD 390.00
NRE L2 020	5.760	Wednesday	3	5.724	9.367	25	7.5	1,300	CAD 390.00
							Total	**44,720 min**	**CAD 13,416.00**

As it may be necessary to edit university schedules during the semester, an interface is proposed in which schedules can be edited, and allowing facility management to make resource allocation decisions based on the changes in the lecture schedules in the university schedule-based model. A graphical interface makes it easier for management to observe the occupancy behaviours and space utilization patterns based on lecture schedules, which affects the way in which decisions are made regarding human resource allocation and maintenance of facilities across the university.

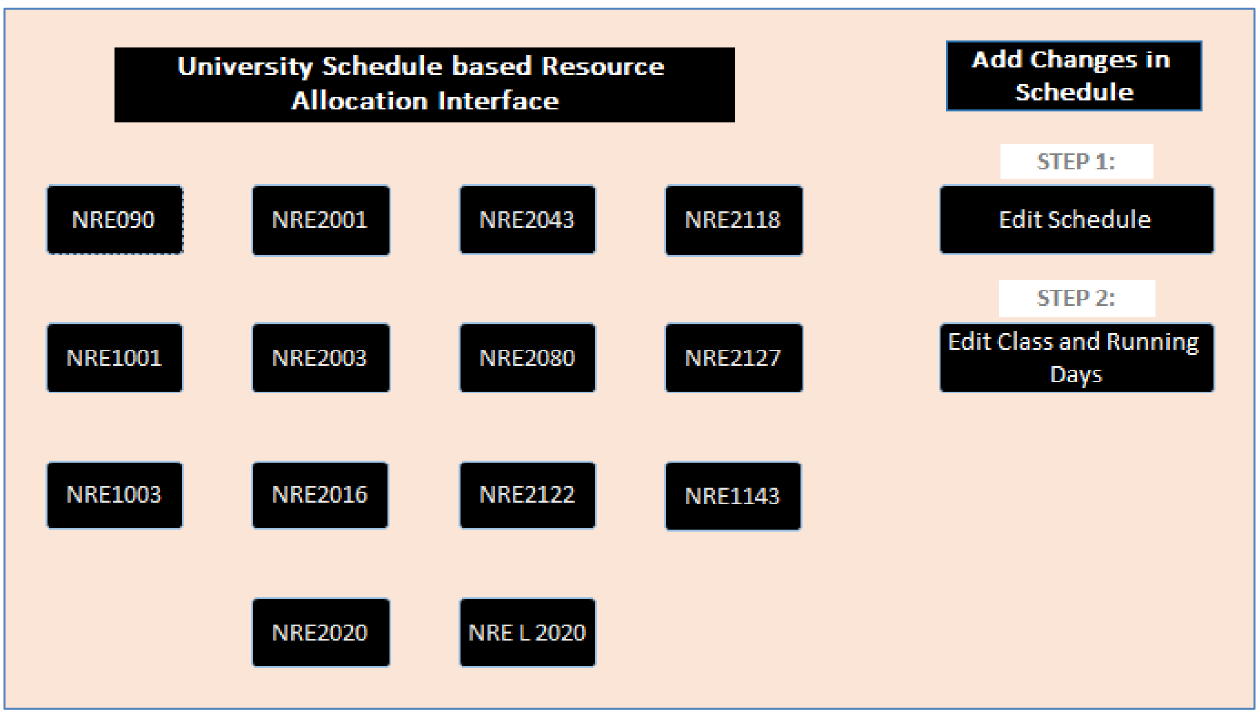
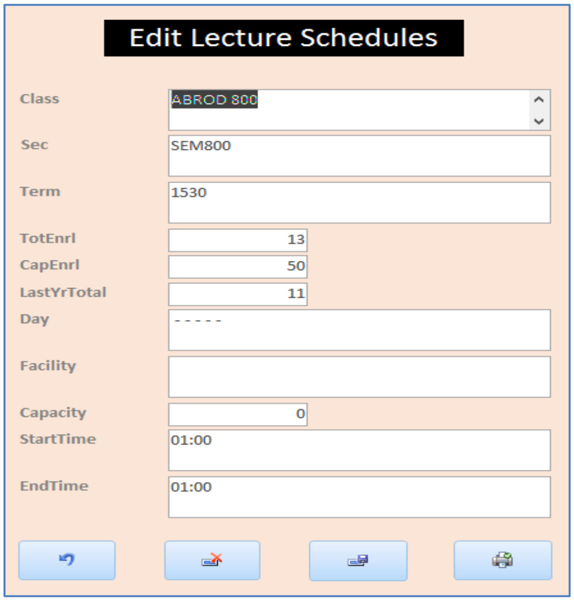


Figure 37: University Schedule-based Resource Allocation Interface, University of Alberta

The service time and cost savings estimated based on the university schedule-based model can be obtained by clicking on any of the classroom icons as shown in Figure 37. The semester schedules can be altered by following two steps which lead to two different forms where new entries can be added, current entries can be edited, and non-existent entries can be deleted from the database system as depicted in Figure 38.



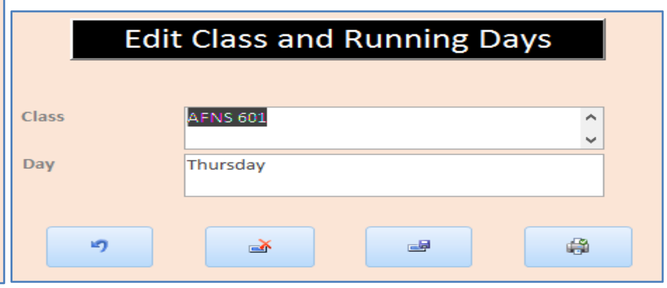


Figure 38: Graphical User Interface to Edit Lecture Schedules, University of Alberta

4.3 Thermal Occupancy Sensor-based Resource Allocation at University of Alberta

As discussed in Chapter 3, thermal occupancy sensors help in the determination of live occupancy demand in indoor environments where the use of smart devices is restricted, and solve the efficiency problem of non-scheduled lecture hour usage of facilities confronted in the university schedule-based model. The occupancy of classrooms is detected at a frequency of 15 minutes using thermal sensor counters installed at the point of entry and exit for the University of Alberta classrooms, thereby facilitating a more dynamic allocation of human resources by the facility management. In the university schedule-based model, the resource allocation is based on the estimates developed for classroom occupancy based on the semester lecture schedules;

however, thermal sensors help to obtain accurate occupancy with 98% efficiency. The case study involves 110 centrally scheduled classrooms at the University of Alberta.

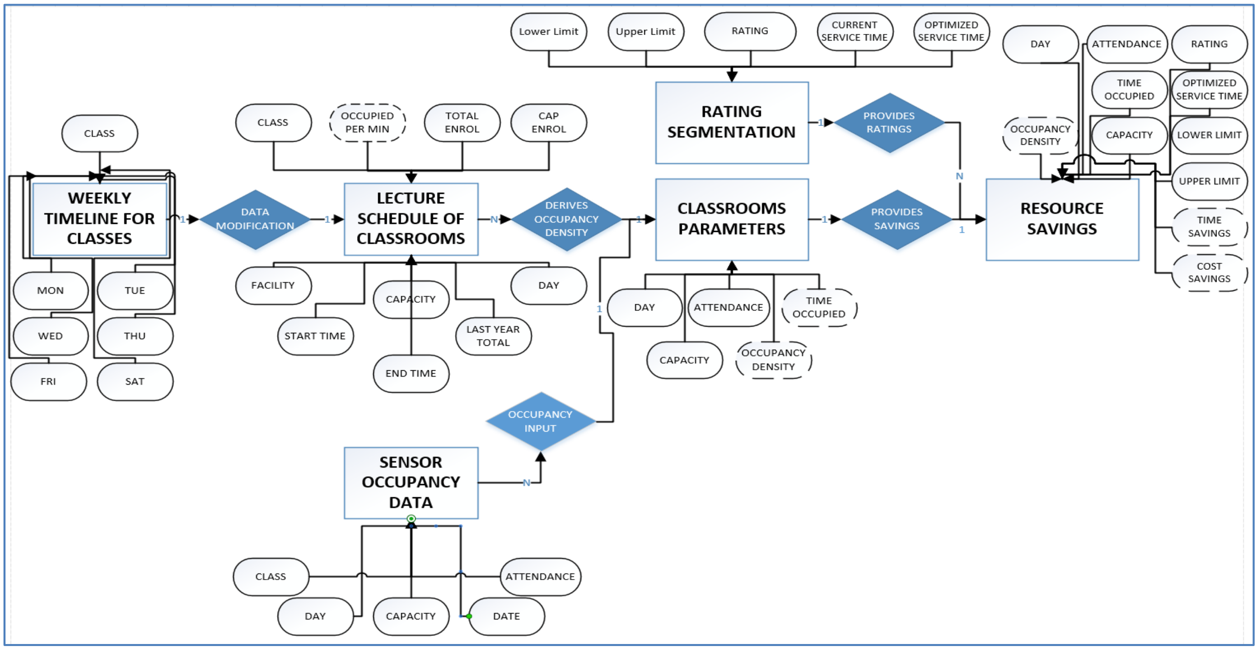


Figure 39: Entity Relationship Diagram for Occupancy Sensor-based Resource Allocation

Figure 39 represents an entity relationship (ER) diagram for the occupancy thermal sensor-based human resource allocation model and acts as a framework for facility management at the University of Alberta for effective and dynamic allocation of workforce. The initial stage involves structuring and cleaning of sensor occupancy data collected for centrally scheduled classrooms at a frequency of 15 minutes by the Information Services and Technology unit at the University of Alberta. The daily average time of classroom occupancy, class ID, day and date of occupancy, and daily average occupancy count obtained from sensors acts as the occupancy input parameters for the determination of classroom density at the next stage for centrally scheduled classrooms across the University of Alberta. The newly obtained average occupancy density for each day provides facility management with the tools to dynamically change schedules in real-time. As numerous data points for occupancy density are gathered, a more accurate distribution model can be used to create the rating segmentation limits and help the management to make decisions with precision involving the allocation of its workforce based on attainable savings. The schedule-based model facilitates the management to alter resource allocation schedules on a semester-to-semester basis based on the patterns in which course schedules are drafted. However, the sensor-based live occupancy data will help management to make alterations in real-time and allocate resources more effectively.

IRSYS people-counting thermal sensors collect occupancy data at a frequency of 15 minutes at the access points for the centrally scheduled classrooms at the University of Alberta. 110 classrooms at the University of Alberta are monitored to determine the occupancy behaviour in classrooms throughout the year. It is evident through occupancy data obtained for the 2015-2016 school year as presented in Figure 40 that classrooms in close proximity to one another or classrooms which are on the same floor of a building have a tendency to have similar occupancy patterns through the course of the semester. A year-long occupancy analysis for these classrooms depicts that classroom schedules play an important role in occupancy. The occupancy patterns for Spring, Summer, Fall, and Winter semesters tend to follow similar trends of a gradual initial rise until the mid-semester point and a gradual decline in occupancy in the latter half of the semester for the majority of classrooms. Classrooms are mostly unoccupied during the buffer period between the end of one semester and start of a new semester. It is also evident that the space utilization is far less than the classroom capacity for these classrooms, which results in over-usage of custodial workforce by facility management. As classrooms follow similar occupancy patterns for those in close proximity it becomes easier for facility management to provide similar servicing instructions to the workforce for these classrooms and distribute its workforce team more effectively based on their ability to work for short or long periods.

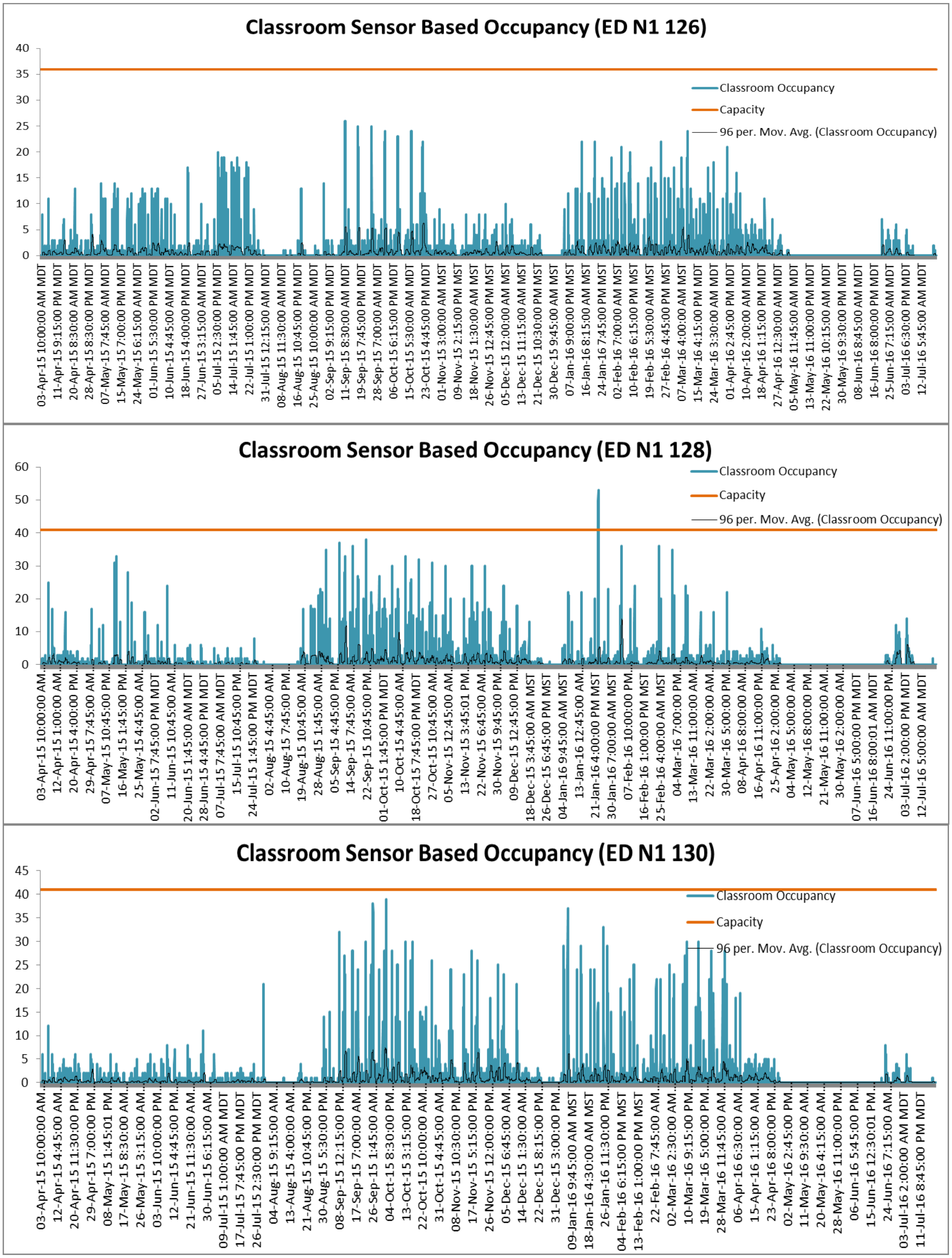


Figure 40: Thermal Sensor-based Classroom Occupancy Patterns, University of Alberta

The moving average for 96 occupancy data points collected at a 15-minute frequency for University of Alberta classrooms presented in Figure 40 helps to obtain the average daily occupancy count: (60/15) × 24 = 96 counts/day. The daily average occupancy trend-line in Figure 40 indicates that the majorities of the classrooms are occupied for a short period of time during the day and are not used in the remaining period, making under-utilization of space more evident. For effective utilization of space and resources, it is important that required steps such as efficient course scheduling are undertaken. Effective space utilization will result in lesser dispersion of workforce by facility management, thus saving monetary resources and manpower. The saved resources will enable facility management to provide better services and allocate funds to improve educational infrastructure.

Table 8: 15-minute Frequency-based Occupancy Sensor Data, Education South Building

Date	Time	Day	ED B 77	ED 651A	ED 734	ED 751	ED 833	ED 933	:	ED 934	ED 1030B
03-04-2015	10:00:00 AM	F	0	0	0	0	0	0	:	0	0
03-04-2015	10:15:00 AM	F	0	0	0	0	0	0	:	0	0
03-04-2015	10:30:00 AM	F	0	0	0	0	0	0	:	0	0
03-04-2015	10:45:00 AM	F	0	0	0	0	0	0	:	0	0
03-04-2015	11:00:00 AM	F	0	0	0	0	0	0	:	0	0
03-04-2015	11:15:00 AM	F	1	1	1	1	0	0	:	0	0
03-04-2015	11:30:00 AM	F	1	0	0	1	0	1	:	0	0
03-04-2015	11:45:00 AM	F	1	0	1	0	0	0	:	2	0
03-04-2015	12:00:00 PM	F	0	0	0	0	0	0	:	2	0
:	:	:	:	:	:	:	:	:	:	:	:
20-07-2016	08:15:00 AM	W	0	0	0	0	1	0	:	0	0
20-07-2016	08:30:00 AM	W	0	0	0	0	0	0	:	0	0

The cleaned database, presented in Table 8 for occupancy obtained at a 15-minute frequency created for 110 classrooms in the Education North, Education South, GSB, and V-Wing buildings at the University of Alberta, is used to determine occupancy density for classrooms on different days throughout the year and observe behavioural patterns. It is observed that the estimated occupancy density values are quite low. As such, to obtain a better batch fitting using Oracle Crystal Ball software and to create a better rating schematic, a modified classroom occupancy density equation is used for its estimation, as depicted in Eq. 4.1,

$$\text{Modified Classroom Occupancy Density}_{\text{i}} = \frac{\text{Classroom Occupancy}_{\text{ i}}}{\text{Frequency of Time Occupied}_{\text{ i}} \times \text{Capacity of Classroom}_{\text{ i}}} \, x\, 10^5 \qquad (4.1)$$

where,

Classroom Occupancy$_{\text{i}}$ = Daily average number of people occupying classroom *i* in person/minute

Frequency of Time Occupied$_{\text{i}}$ = Daily average frequency of time classroom *i* is occupied in minute^{-1}

Capacity of Classroom$_{\text{i}}$ = Maximum number of people who can occupy classroom *i*

The modified classroom occupancy density helps to increase the spread of the density function which was confined to a lower value in past estimates and restricted complete behaviour analysis. Better batch fitting of classroom occupancy density data will enable the creation of a more accurate resource allocation model resembling the resource usage with higher precision.

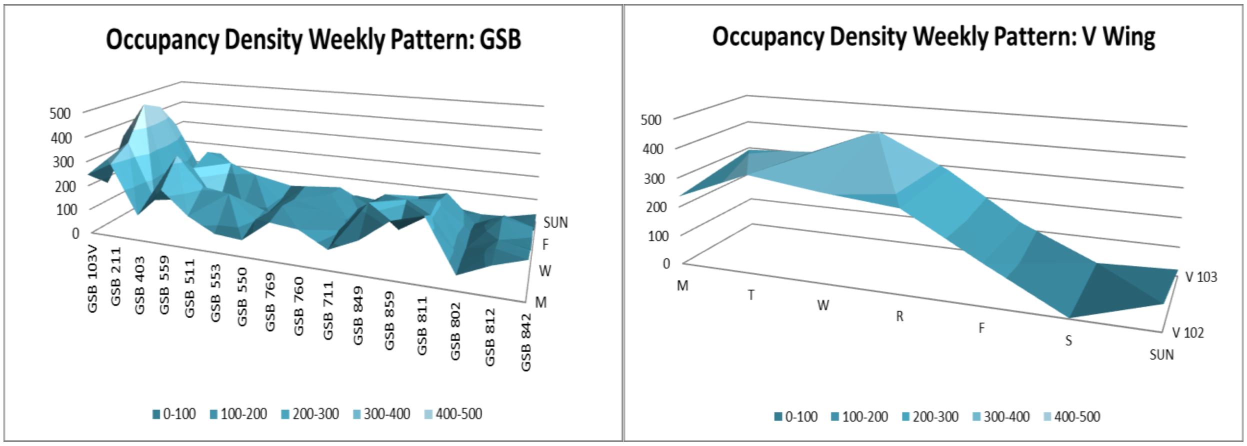


Figure 41: Weekly Patterns for Classroom Occupancy Density, GSB and V-Wing

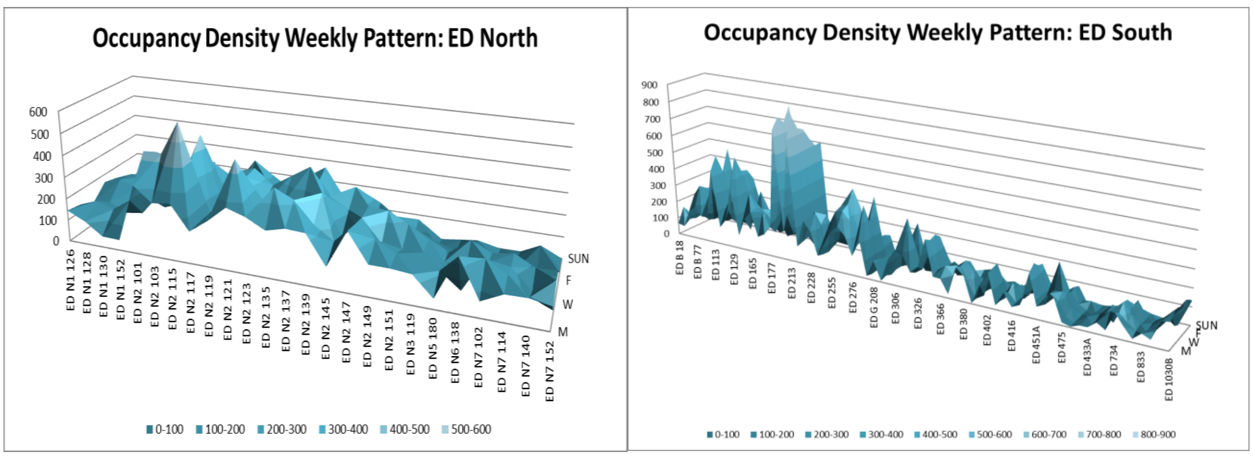


Figure 42: Weekly Patterns for Classroom Occupancy Density, Education North and South

The weekly classroom occupancy density patterns for 110 classrooms across the University of Alberta's North Campus are depicted in Figure 41 and Figure 42. It is observed that the highest classroom occupancy occurs on Wednesdays. There is a gradual increase in classroom occupancy from Monday to Wednesday and a gradual decrease in occupancy from Wednesday onward. One cause for this may be due to the high intensity of scheduled courses on Wednesdays. It is also observed that classrooms are occupied on weekends irrespective of courses being conducted during those periods. Most of the occupancy on weekends during non-course hours may be due to student group meet-ups, different scheduled events, peer-to-peer weekend study, and other activities. An important insight observed through the occupancy density patterns is that classrooms are occupied during non-lecture hours. It is thus important to move beyond the university course schedule-based model and obtain occupancy patterns using sensor counters and other modes of indoor location tracking, which will enable facility management to develop the correct human resource allocation model. For instance, maintenance, inspection, and custodial service allocation on Wednesdays require more resources than other days. The time and human resource allocation can increase gradually from Monday to Wednesday and decrease gradually from Wednesday to Sunday, creating the first level of dynamic resource allocation at the macroscopic level. More detailing in resource allocation can be conducted based on micro-level study for classrooms as it will be observed later in this chapter.

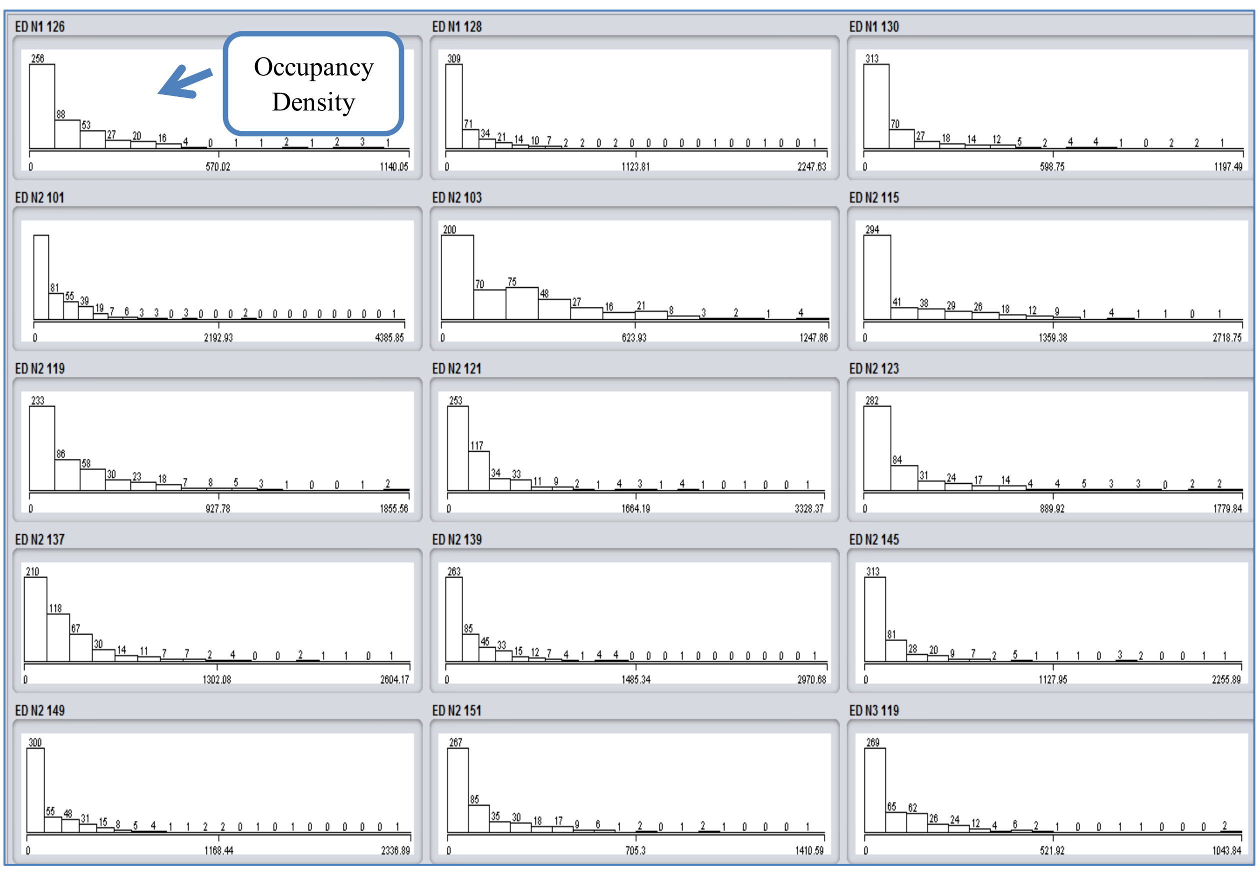


Figure 43: Occupancy Density Histogram for Individual Classrooms in Education North Building

It can be observed in Figure 43 through estimated occupancy density, based on Eq. 4.1 for individual classrooms that most classrooms are under-utilized and they all follow similar occupancy density distribution patterns. Similar patterns have been observed for Education South, GSB, and V-Wing classrooms. Therefore, it is safe to consider the occupancy density distribution batch fitting model for all 110 observed classrooms at the macroscopic level to distinguish between the labour-effort required to maintain different classrooms. The daily occupancy density based on Eq. 4.1 is estimated for all 110 classrooms across the University of Alberta for the period from 3rd April 2015 to 20th July 2016 using SQL queries. The estimated occupancy density for all 110 classrooms can be used to determine a distribution using batch fitting and to segment the batch in equal parts based on percentiles to develop the rating scheme as carried out earlier in the university course schedule-based model.

EDSouth_OccupancyDensity

```sql
SELECT Date, AVG(EDB18)*100000/(60*15) AS OccupancyDensityEDB18, AVG(EDB19)*100000/(69*15) AS OccupancyDensityEDB19,
AVG(EDB76)*100000/(24*15) AS OccupancyDensityEDB76, AVG(EDB77)*100000/(23*15) AS OccupancyDensityEDB77,
AVG(ED106)*100000/(60*15) AS OccupancyDensityED106, AVG(ED107)*100000/(60*15) AS OccupancyDensityED107,
AVG(ED113)*100000/(59*15) AS OccupancyDensityED113, AVG(ED122)*100000/(60*15) AS OccupancyDensityED122,
AVG(ED128)*100000/(60*15) AS OccupancyDensityED128, AVG(ED129)*100000/(145*15) AS OccupancyDensityED129,
AVG(ED158)*100000/(60*15) AS OccupancyDensityED158, AVG(ED164)*100000/(60*15) AS OccupancyDensityED164,
AVG(ED165)*100000/(92*15) AS OccupancyDensityED165, AVG(ED170)*100000/(55*15) AS OccupancyDensityED170,
AVG(ED176)*100000/(60*15) AS OccupancyDensityED176, AVG(ED177)*100000/(36*15) AS OccupancyDensityED177,
AVG(ED203)*100000/(36*15) AS OccupancyDensityED203, AVG(ED206)*100000/(60*15) AS OccupancyDensityED206,
AVG(ED213)*100000/(32*15) AS OccupancyDensityED213, AVG(ED218)*100000/(32*15) AS OccupancyDensityED218,
AVG(ED221)*100000/(40*15) AS OccupancyDensityED221, AVG(ED228)*100000/(60*15) AS OccupancyDensityED228,
AVG(ED229)*100000/(23*15) AS OccupancyDensityED229, AVG(ED254)*100000/(92*15) AS OccupancyDensityED254,
AVG(ED255)*100000/(42*15) AS OccupancyDensityED255, AVG(ED262)*100000/(48*15) AS OccupancyDensityED262,
AVG(ED265)*100000/(48*15) AS OccupancyDensityED265, AVG(ED276)*100000/(60*15) AS OccupancyDensityED276,
AVG(ED277)*100000/(36*15) AS OccupancyDensityED277, AVG(ED282)*100000/(23*15) AS OccupancyDensityED282,
AVG(EDG208)*100000/(30*15) AS OccupancyDensityEDG208, AVG(ED301)*100000/(17*15) AS OccupancyDensityED301,
AVG(ED303)*100000/(60*15) AS OccupancyDensityED303, AVG(ED306)*100000/(30*15) AS OccupancyDensityED306,
AVG(ED314)*100000/(36*15) AS OccupancyDensityED314, AVG(ED315)*100000/(56*15) AS OccupancyDensityED315,
AVG(ED326)*100000/(40*15) AS OccupancyDensityED326, AVG(ED327)*100000/(52*15) AS OccupancyDensityED327,
AVG(ED358)*100000/(65*15) AS OccupancyDensityED358, AVG(ED366)*100000/(48*15) AS OccupancyDensityED366,
AVG(ED367)*100000/(36*15) AS OccupancyDensityED367, AVG(ED377)*100000/(76*15) AS OccupancyDensityED377,
AVG(ED380)*100000/(60*15) AS OccupancyDensityED380, AVG(ED333A)*100000/(11*15) AS OccupancyDensityED333A,
AVG(ED401)*100000/(25*15) AS OccupancyDensityED401, AVG(ED402)*100000/(36*15) AS OccupancyDensityED402,
AVG(ED403)*100000/(36*15) AS OccupancyDensityED403, AVG(ED413)*100000/(48*15) AS OccupancyDensityED413,
AVG(ED416)*100000/(23*15) AS OccupancyDensityED416, AVG(ED423)*100000/(48*15) AS OccupancyDensityED423,
AVG(ED428)*100000/(40*15) AS OccupancyDensityED428, AVG(ED451A)*100000/(78*15) AS OccupancyDensityED451A,
AVG(ED456)*100000/(60*15) AS OccupancyDensityED456, AVG(ED465)*100000/(30*15) AS OccupancyDensityED465,
AVG(ED475)*100000/(48*15) AS OccupancyDensityED475, AVG(ED476)*100000/(26*15) AS OccupancyDensityED476,
AVG(ED482)*100000/(32*15) AS OccupancyDensityED482, AVG(ED433A)*100000/(150*15) AS OccupancyDensityED433A,
AVG(ED533A)*100000/(48*15) AS OccupancyDensityED533A, AVG(ED651A)*100000/(23*15) AS OccupancyDensityED651A,
AVG(ED734)*100000/(36*15) AS OccupancyDensityED734, AVG(ED743)*100000/(23*15) AS OccupancyDensityED743,
AVG(ED751)*100000/(14*15) AS OccupancyDensityED751, AVG(ED833)*100000/(40*15) AS OccupancyDensityED833,
AVG(ED933)*100000/(17*15) AS OccupancyDensityED933, AVG(ED934)*100000/(40*15) AS OccupancyDensityED934,
AVG(ED1030B)*100000/(30*15) AS OccupancyDensityED1030B
FROM EDSouth_SensorOccupancy
GROUP BY Date;
```

Figure 44: SQL Query for Estimated Occupancy Density for Classrooms in Education South Building

Table 9: Estimated Daily Occupancy Density for Classrooms in Education South Building

Date	ED B 18	ED B 19	ED B 76	ED B 77	ED 106	ED 107	:	ED 933	ED 934	ED 1030B
2015-04-03	0	0	0	0	13.88889	11.90476	:	0	0	0
2015-04-04	49.76852	0	0	217.3913	10.41667	100.6944	:	0	0	0
2015-04-05	26.62037	0	17.36111	45.28986	15.0463	20.83333	:	0	0	0
2015-04-06	19.67593	0	410.8796	39.25121	280.0926	0	:	0	0	0
2015-04-07	237.2685	19.12238	101.2731	75.48309	359.9537	285.8796	:	0	326.3889	85.64815
2015-04-08	188.6574	44.28341	188.0787	241.5459	211.8056	229.1667	:	85.78431	147.5694	0
2015-04-09	288.1944	28.18035	193.8657	247.5845	129.6296	86.80556	:	81.69935	197.9167	0
2015-04-10	167.8241	26.16747	8.680556	69.44444	229.1667	151.6204	:	0	17.36111	2.314815
2015-04-11	64.81481	18.11594	141.7824	368.3575	65.97222	24.30556	:	0	0	541.6667
2015-04-12	156.25	27.17391	72.33796	181.1594	64.81481	34.72222	:	0	0	0
2015-04-13	130.787	35.22544	477.4306	120.7729	24.30556	32.40741	:	0	175.3472	92.59259
2015-04-14	130.787037	27.17391	847.8009	489.1304	46.2963	136.5741	:	0	27.77778	0
2015-04-15	178.2407407	39.25121	477.4306	585.7488	423.6111	200.2315	:	0	1.736111	0
2015-04-16	268.5185185	33.21256	416.6667	172.1014	125	189.8148	:	0	8.680556	321.7593
:	:	:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:	:	:
2016-07-18	0	0	0	0	111.1111	0	:	0	0	888.8889
2016-07-19	0	0	0	0	83.33333	0	:	0	0	851.8519
2016-07-20	0	0	0	0	0	0	:	0	0	0

Figure 44 depicts the SQL query used to estimate daily occupancy density for various classrooms. The average daily occupancy count for individual classrooms, average time of classroom occupancy, and capacity for the classrooms are the parameters which influence the occupancy density values calculated in Table 9. Oracle Crystal Ball software is used to obtain the best batch fit for the occupancy density values obtained for all 110 classrooms from April 2015-July 2016.

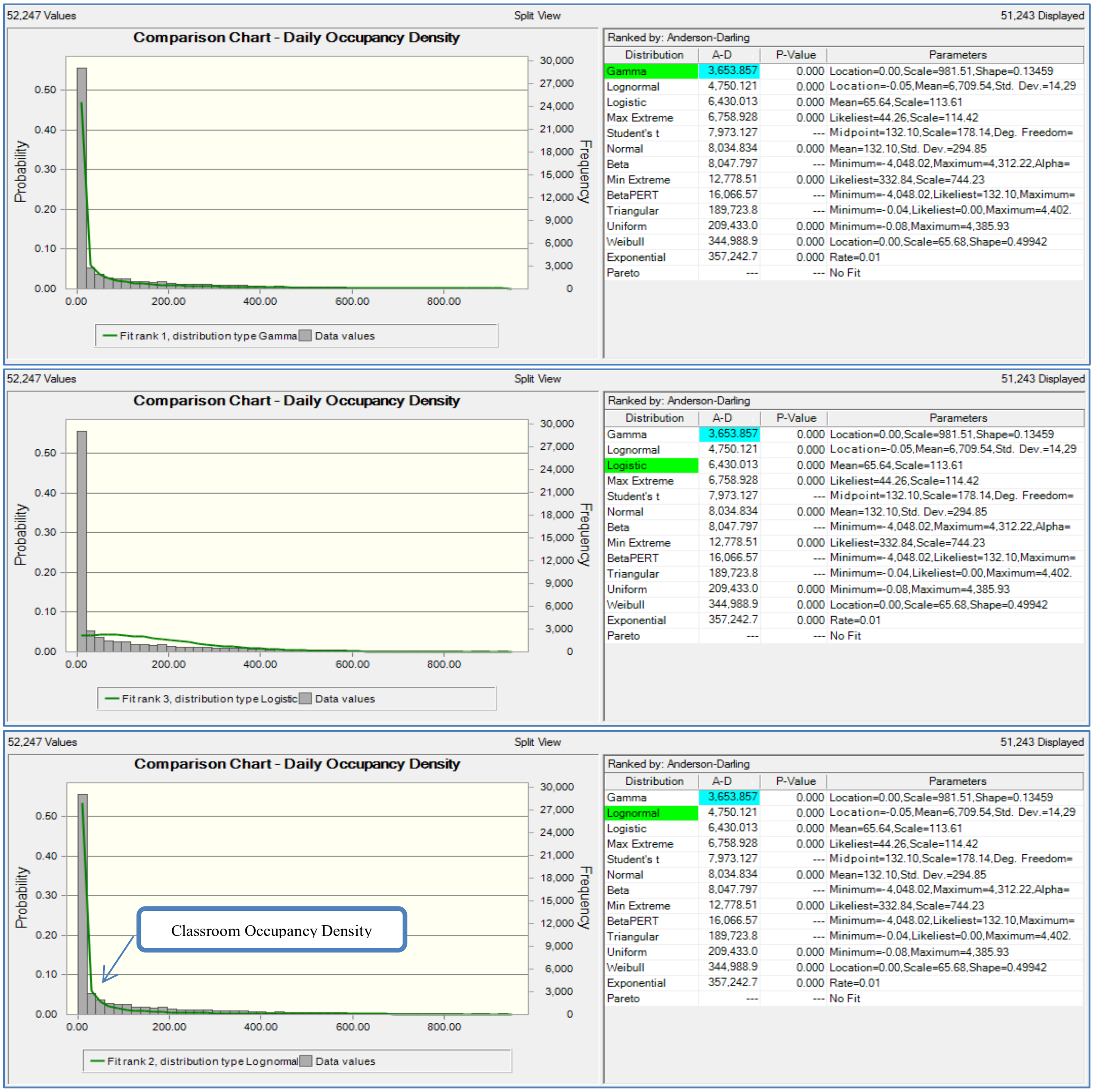


Figure 45: Daily Occupancy Density Distribution Batch Fit, Sensor-based Model

$$Gamma\ PDF: f(x; k, \theta) = \frac{x^{k-1} e^{-\frac{x}{\theta}}}{\theta^{k}\Gamma(k)}\ for\ x > 0\ and\ k, \theta > 0 \tag{4.2}$$

The batch fitting results presented in Figure 45 depict that the gamma distribution function, as specified in Eq. 4.2, is the best fit for the daily classroom occupancy densities obtained using thermal sensor counters for 110 classrooms at the University of Alberta with shape parameter k =

0.13459 and scale parameter θ = 981.50932. The high value of scale parameter implies that the distribution has a wide spread, and a very low k-value emphasizes the fact that most values that are present are close to zero, replicating very low occupancy. It is evident that the occupancy patterns are quite similar for the classroom level-based analysis and the university level-based analysis through Figure 43, 44 and Figure 45. The similarity in occupancy patterns enables facility management to allocate the workforce more effectively with similar task allocations in terms of work hours and effort required.

Table 10: Gamma Distribution Percentiles based Resource Allocation Rating (Sensors)

Percentages	Gamma Distribution	Rating	Lower Limit	Upper Limit	Current Service Time (min)	Optimized Service Time (min)
0^{th}	0	1	--	--	--	--
10^{th}	0	1	0	0	30	0
20^{th}	0	2	0	0	30	0
30^{th}	0.08	3	0	0.08	30	5
40^{th}	0.68	4	0.08	0.68	30	10
50^{th}	3.56	5	0.68	3.56	30	10
60^{th}	13.91	6	3.56	13.91	30	15
70^{th}	44.96	7	13.91	44.96	30	15
80^{th}	130.59	8	44.96	130.59	30	20
90^{th}	384.61	9	130.59	384.61	30	25
100^{th}	∞	10	384.61	∞	30	30

The batch fitting-based gamma distribution is divided into equal segments based on percentiles to create a 10-point rating scheme for resource allocation. The rating scheme enables dynamic allocation of resources as depicted in the university schedule-based model in the previous case study. An analogous model is created based on daily occupancy density estimated using thermal sensors to determine time and cost savings attainable for all 110 classrooms. The attainable time and cost savings between the period of 3rd April 2015 to 20th July 2016 for individual classrooms is depicted in Figure 46.

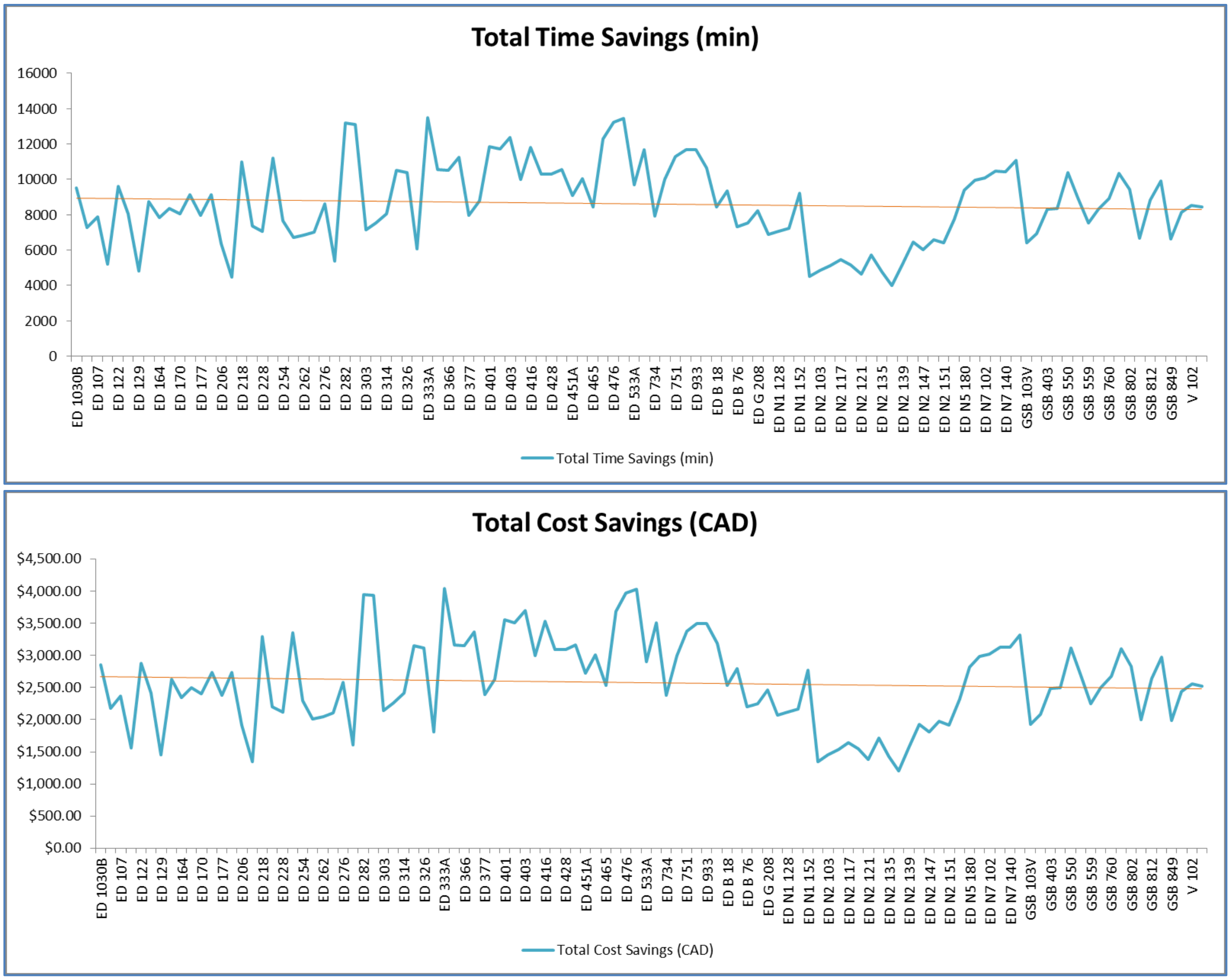


Figure 46: Total Time and Cost Saving based on Sensor-based Dynamic Resource Scheduling

The dynamic occupancy-based resource allocation determined based on occupancy of university classrooms offers an average cost savings of Can$2,578.39 per classroom and 2,895/60 = 48.25 hours of time savings on average per classroom for the selected span of 15 months. The total attainable cost and time savings are Can$283,623.00 and 945410/60 = 15,756.83 hours, respectively, for 110 classrooms. Dynamic resource allocation based on usage patterns saves significant resources which can be allocated for the betterment of facility management services and educational facilities across universities. Such models can be expanded to all schools where the usage of smart devices for indoor person tracking is limited.

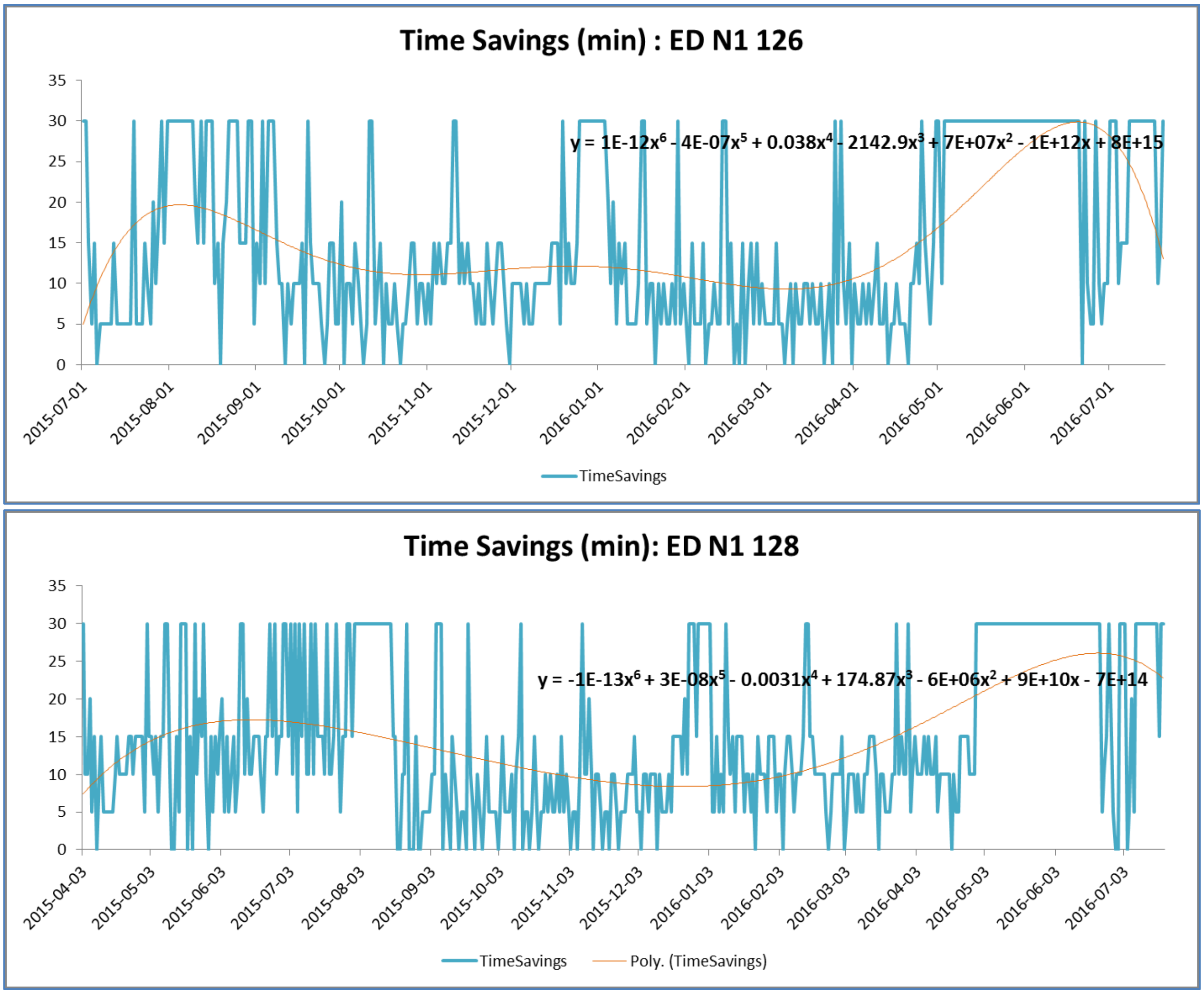


Figure 47: Savings in Service Time for Individual Classrooms, Sensor-based Model

Figure 47 shows the savings patterns in terms of service time for the 15-month sample duration for which sensor occupancy data is obtained. The polynomial fitting for attained time and cost savings shows that the classrooms are less occupied during the Spring and Summer semesters as the savings are the highest during that period, whereas the occupancy during the Fall and Winter semesters is high, leading to lower resource savings.

IRSYS people-counting thermal sensors have been installed in centrally scheduled classrooms across the University of Alberta as depicted in Chapter 3. Additionally, Can$2.642 million has been budgeted to install 627 sensors in 343 centrally scheduled classrooms by the facility management at the University of Alberta. Thus, on average, an installation cost of Can$2.642 million/627 = Can$4,214.00 per sensor is incurred by the management to install these thermal sensors and regulate the automated people-counting mechanism for obtaining occupancy data for classrooms. The compelling question is whether investment in sensors is the best course of action, or if alternative low-cost approaches such as the university schedule-based model or WiFi-based location tracking model can be adopted for occupancy determination and effective resource management. Based on current strategic plans drafted by facility management at the University of Alberta, the model can be extended to all 343 classrooms. The total yearly attainable cost and time savings based on the current model developed using thermal sensor counters for 343 classrooms are Can$673,460.06 and 2,244,867/60 = 37414 hours as depicted in Table 11.

Table 11: Yearly Time and Cost Savings for 343 sensor classrooms, University of Alberta

	110 classrooms		343 Classrooms	
Period	**Time Savings (min)**	**Cost Savings (CAD)**	**Time Savings (min)**	**Cost Savings (CAD)**
15 months	945,410	$283,623.00	2,921,402	$876,420.62
Yearly	726,473	$217,941.88	2,244,867	$673,460.06

Considering the estimated yearly cost savings of Can$673,460.06 and installation costs for all installable sensors of Can$2.642 million, the model will have a payback period of 3.92 years based on the assumption that 100% of costs are recovered upfront. However, using the same sensors to save other energy and utility resources can lower the payback period significantly. Furthermore, to avoid these initial installation costs for all classrooms, existing university WiFi infrastructure can be used to track people in indoor environments and save over-usage of human resources.

4.4 WiFi-based Location Tracking for Resource Allocation at University of Alberta

As discussed in Chapter 3, WiFi-based indoor location tracking has numerous applications and the WiFi infrastructure is present throughout most universities in North America. In order to save the installation cost involved in the sensor-based model and avoid the inaccuracies of the university schedule-based model, the WiFi-based indoor location tracking model facilitates the usage of indoor location tracking access points which track smart devices transmitting radio signals to obtain the coordinates of people in indoor environments based on triangulation using signal strength, angle of received signal, etc. Given that the infrastructure is already installed throughout the universities, the occupancy in classrooms can be determined at a particular frequency as presented earlier in the sensor-based model using active-user smart devices.

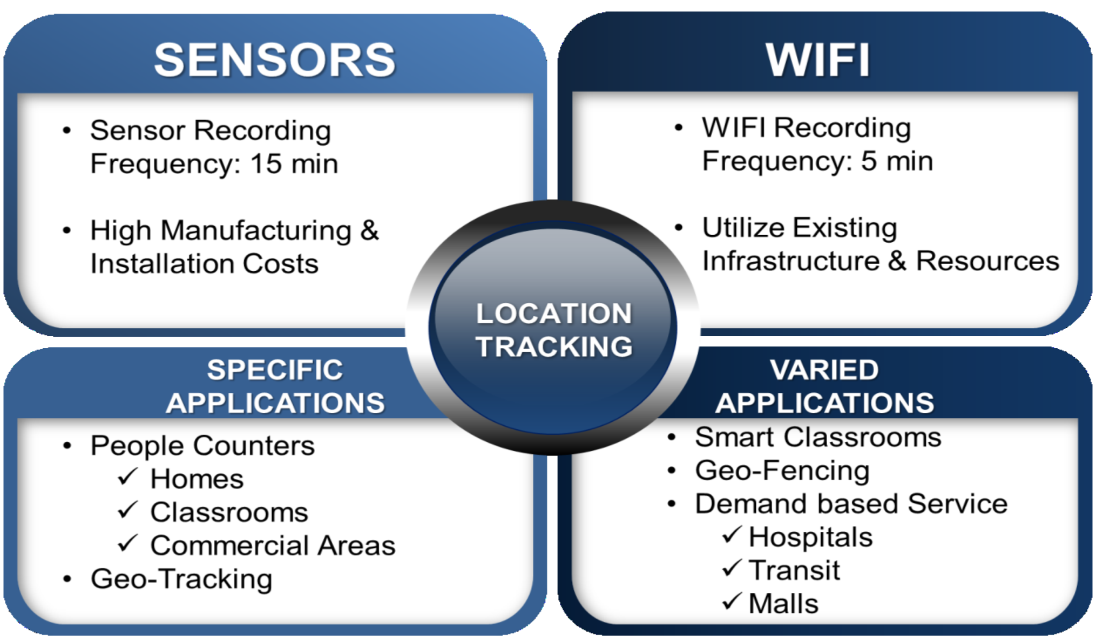


Figure 48: Comparison between Sensors and WiFi Tracking Systems, University of Alberta

Figure 48 shows the comparison between thermal sensor- and WiFi-based indoor location tracking infrastructure existing at the University of Alberta and their varied applications.

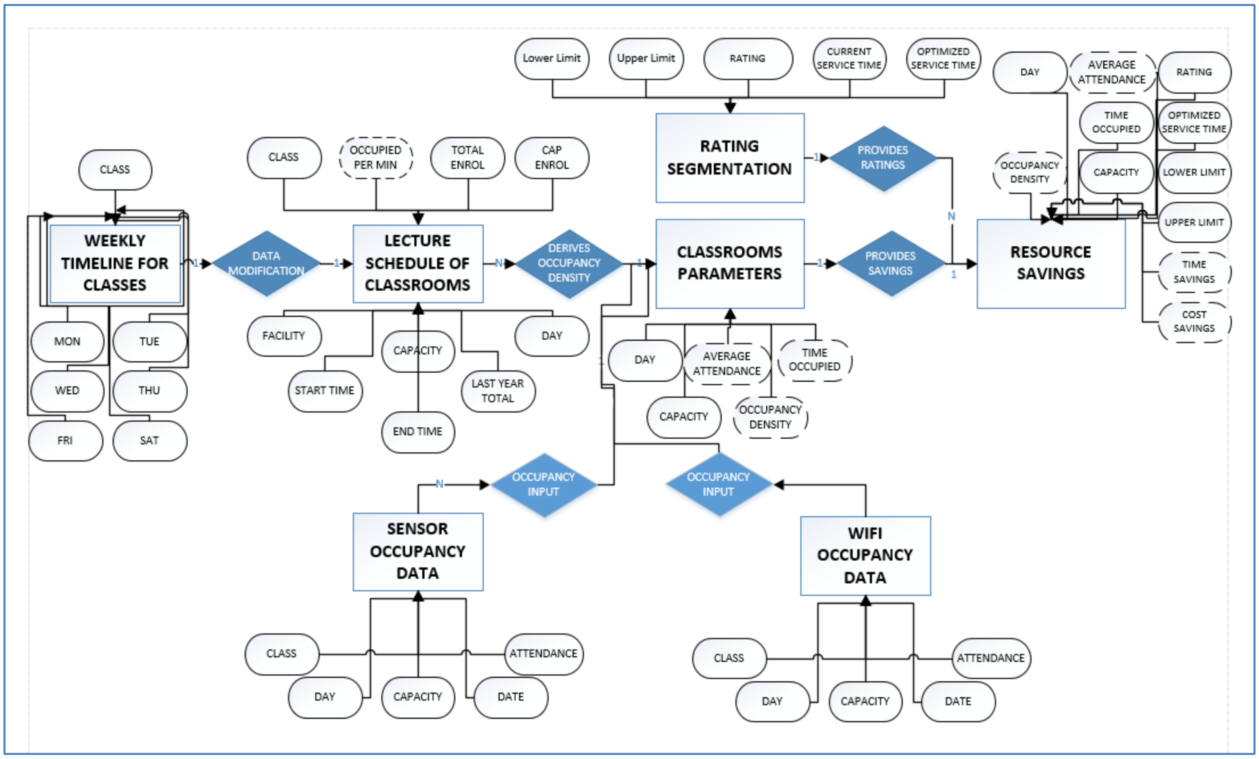


Figure 49: Entity Relationship (ER) Diagram for WiFi Occupancy-based Resource Allocation

Figure 49 represents an entity relationship (ER) diagram for a hybrid WiFi location tracking for an indoor environment-based resource allocation model. The hybrid acts as a framework for facility management at the University of Alberta to verify the coherence in collected occupancy data and optimize the allocation of its workforce for custodial services, daily inspection, maintenance, and other activities. As the database infrastructure of the university schedules and sensor occupancy-based resource model already exists, the first step now is to clean and structure the WiFi-based indoor positioning-based classroom occupancy data at the University of Alberta. The WiFi-based indoor classroom occupancy data is obtained using pre-existing Unified Wireless System (UWS) access points collected at a frequency of 5 minutes by the Information Services and Technology unit at the University of Alberta. The daily average classroom occupancy count, daily average time of classroom occupancy, class ID, day and date of occupancy data act as the input parameters along with the sensor parameters to obtain an average occupancy density at the next stage. After the average occupancy density based on both data models is obtained the facility management can observe the occupancy patterns and allocate their workforce in an optimal manner. The usage of a WiFi-based indoor positioning model allows the management to increase their scope beyond the pre-defined 343 classroom spaces in the sensor-based model and sequentially equip management with a pre-existing infrastructure which incurs no initial costs. The initial installation costs of Can$2.642 million for thermal sensors can be avoided using this model. The WiFi-based indoor positioning model can be scaled easily to cover all spaces across the University of Alberta and later implemented by other universities across North America having similar occupancy and space utilization patterns.

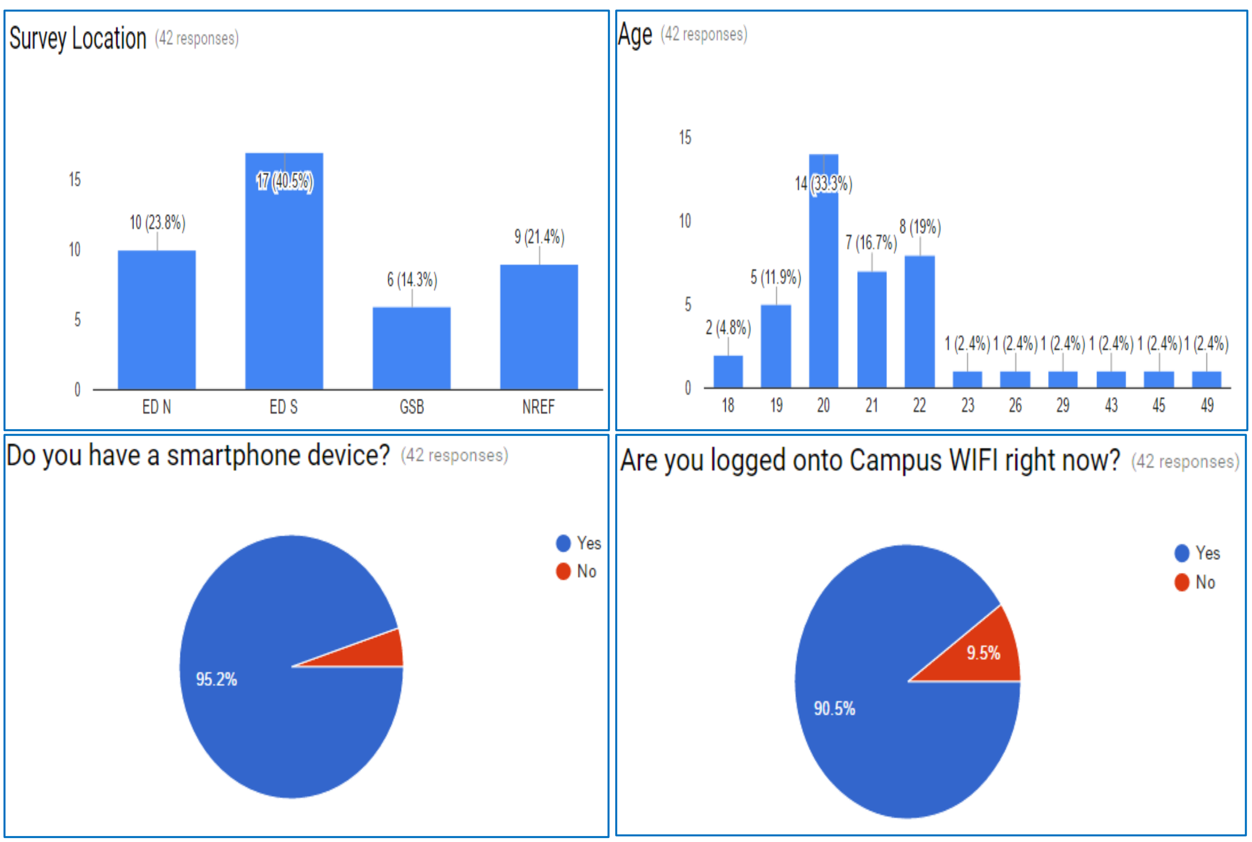


Figure 50: Campus WiFi Usage Survey-Part 1, University of Alberta

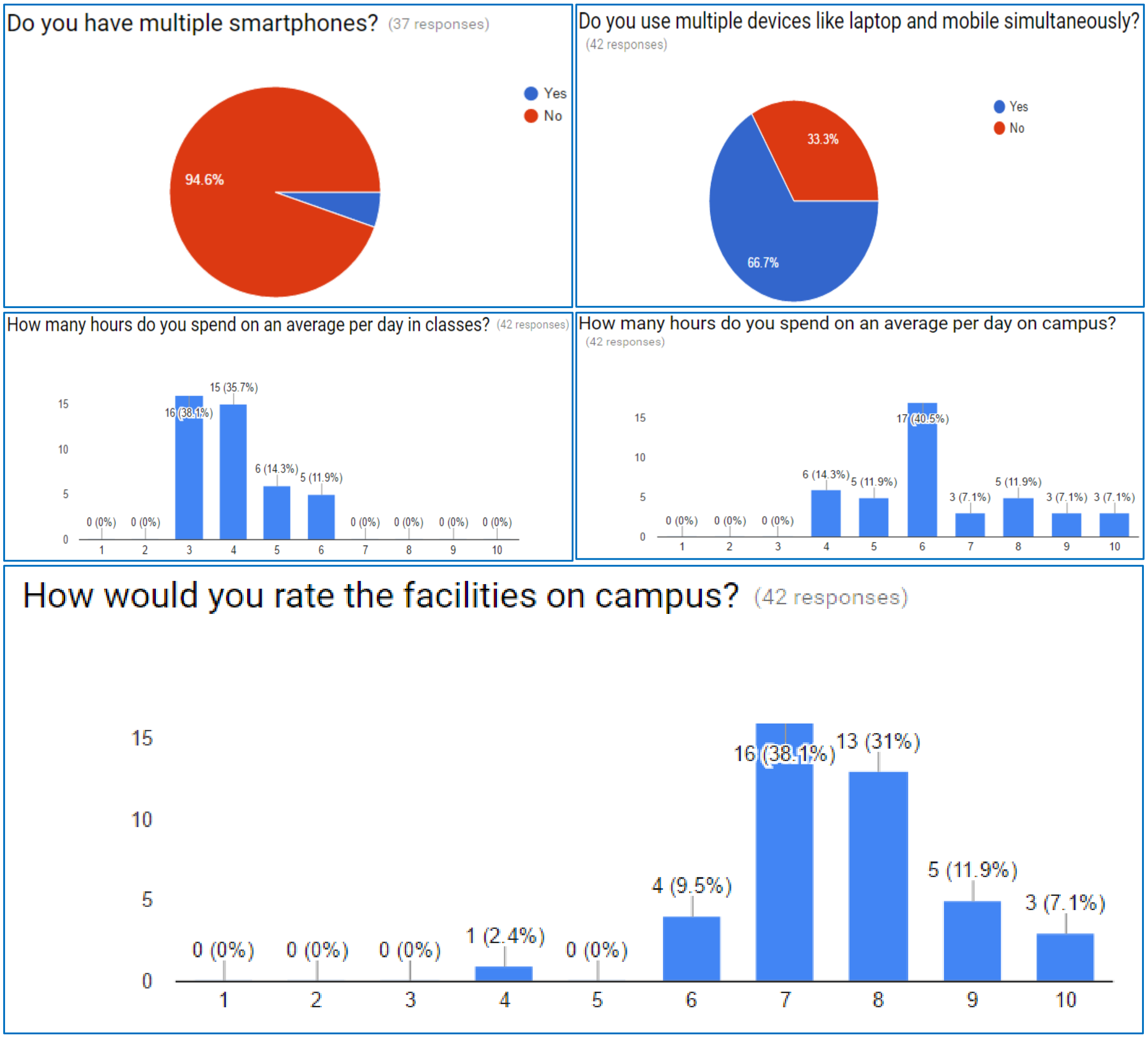


Figure 51: Campus WiFi Survey-Part 2, University of Alberta

However, the WiFi-based indoor positioning model is useful only when the majority of the people present on campus make use of campus WiFi services. Figure 50 and Figure 51 show results of the survey conducted across the University of Alberta campus to identify the percentage of WiFi users across campus. It was observed from the survey that 95.2% of campus facility users have smartphones and 90.5% are logged on to campus WiFi whenever they are present on campus premises. 94.6% of the campus survey group mentioned that they do not use multiple smartphone devices on campus. As most of the facility users at the University of Alberta campus use smart-devices and are connected to the central campus WiFi infrastructure, it is safe to move forward and create a WiFi-based resource allocation model. The survey also focuses on the amount of time people spend in classrooms and on campus daily to understand classroom and campus occupancy behaviour. It is observed from the survey that the majority from the survey group spend 3-6 hours per day in classrooms for lectures and spend 4-10 hours per day on campus per day in total, inferring that most students spend additional time on campus apart from the scheduled lecture period for academic and non-academic activities. The majority from the survey group rated the facilities from 6-10 on a rating scale of 10 and suggested that more interaction between the O&M staff and end users can help improve university facilities.

As discussed earlier in Chapter 3, WiFi-based location tracking in the indoor environment is conducted by tracking radio signals from smart devices in the vicinity of access points. The obtained classroom occupancy count for 31 days during the semester transition period from Fall 2016 to Winter 2017 at the University of Alberta is displayed for sample classrooms in Figure 52. It indicates that the utilization of classrooms is significantly low during this period and is also coherent with the occupancy data obtained using the sensor-based model. The calibration of occupancy at an interval of 5 minutes provides more occupancy information and avoids the missing data points lost in the discrete 15-minute data obtained using sensors. Limited space usage in the transition period between semesters can allow facility management to close certain classrooms that are rarely used during this time, which can allow for significant savings in terms of workforce hours and other resources used for servicing these classrooms. Management can then make use of complete resources at the start of the next semester as attendance is near complete capacity on day 1 of the new semester.

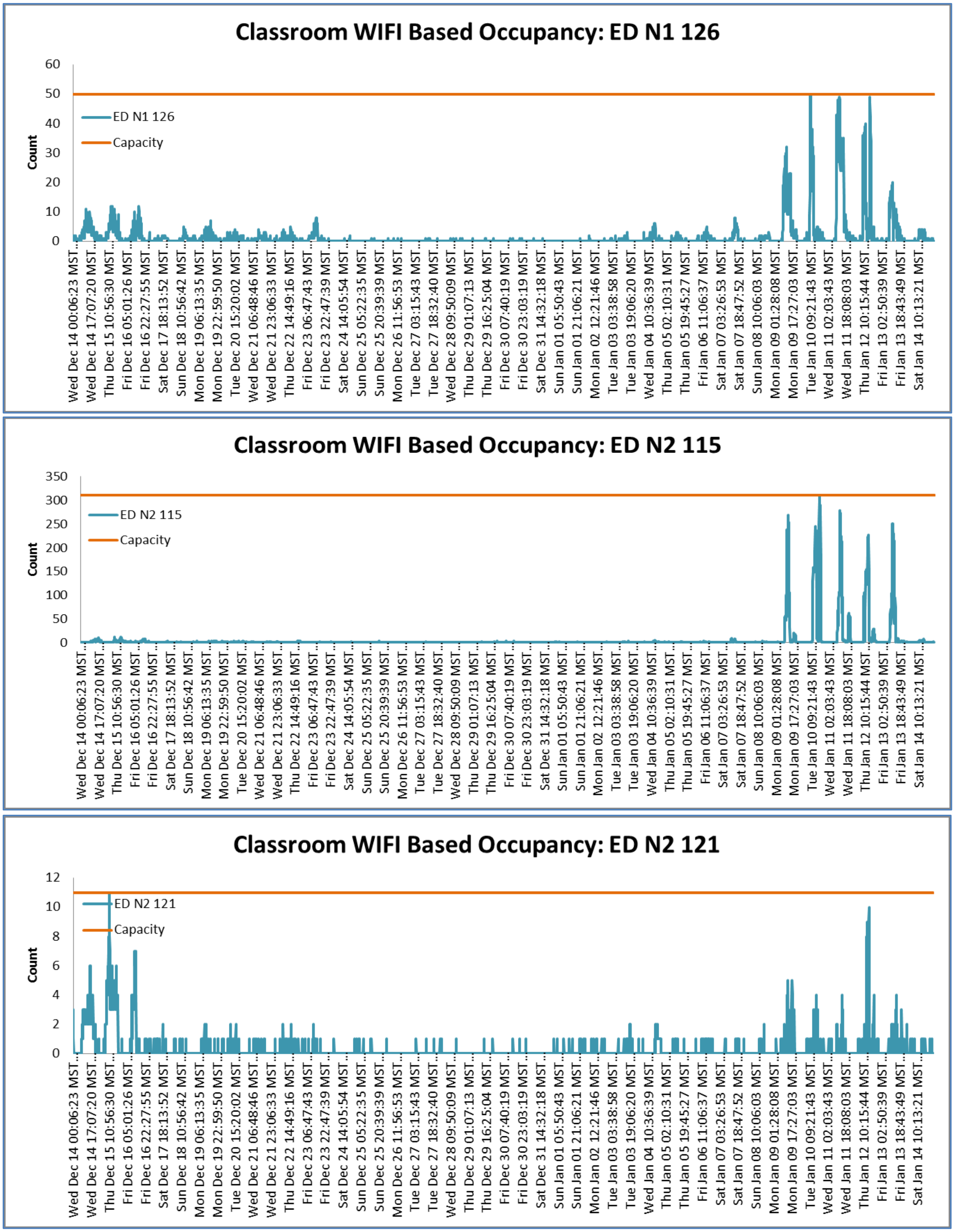


Figure 52: WiFi-based Location Tracking-based Classroom Occupancy Patterns

The cleaned and structured occupancy count obtained for classrooms at a 5-minute frequency is used to estimate daily occupancy density values using Eq. 4.1 for the period of 31 days, which is analogous to the estimations in the sensor-based model. The average weekly classroom occupancy density patterns for sample classrooms under WiFi-based occupancy survey are depicted in Figure 53. It is observed that the occupancy density increases gradually from Monday to Wednesday and then decreases gradually from Wednesday to Sunday even for the transition period between semesters. The verification that the sensor model and WiFi model work accurately can be observed due to the analogous behaviour patterns observed and occupancy density results obtained for both models. Additionally, the literature review in Chapter 2 and methodology in Chapter 3 suggest that both models have an accuracy of more than 95%, which is sufficient for developing resource allocation models. The first layer in dynamic allocation of resources from facility management must involve allocation of more resources on Wednesdays for classroom custodial services, inspection, and maintenance, followed by decreased allocation as per occupancy density patterns for other days of the week. The second layer can involve allocation based on live occupancy density values estimated on a day-to-day basis.

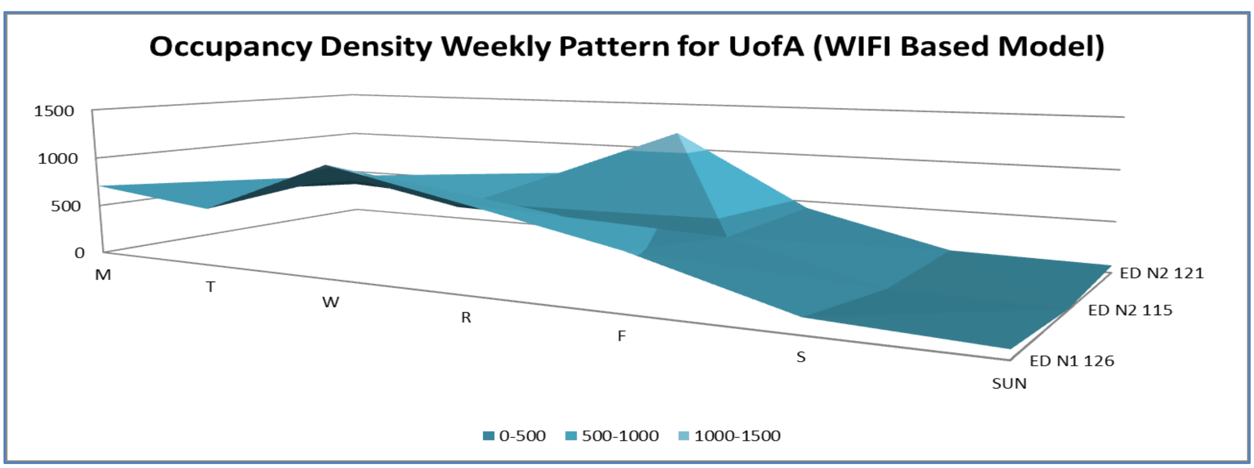
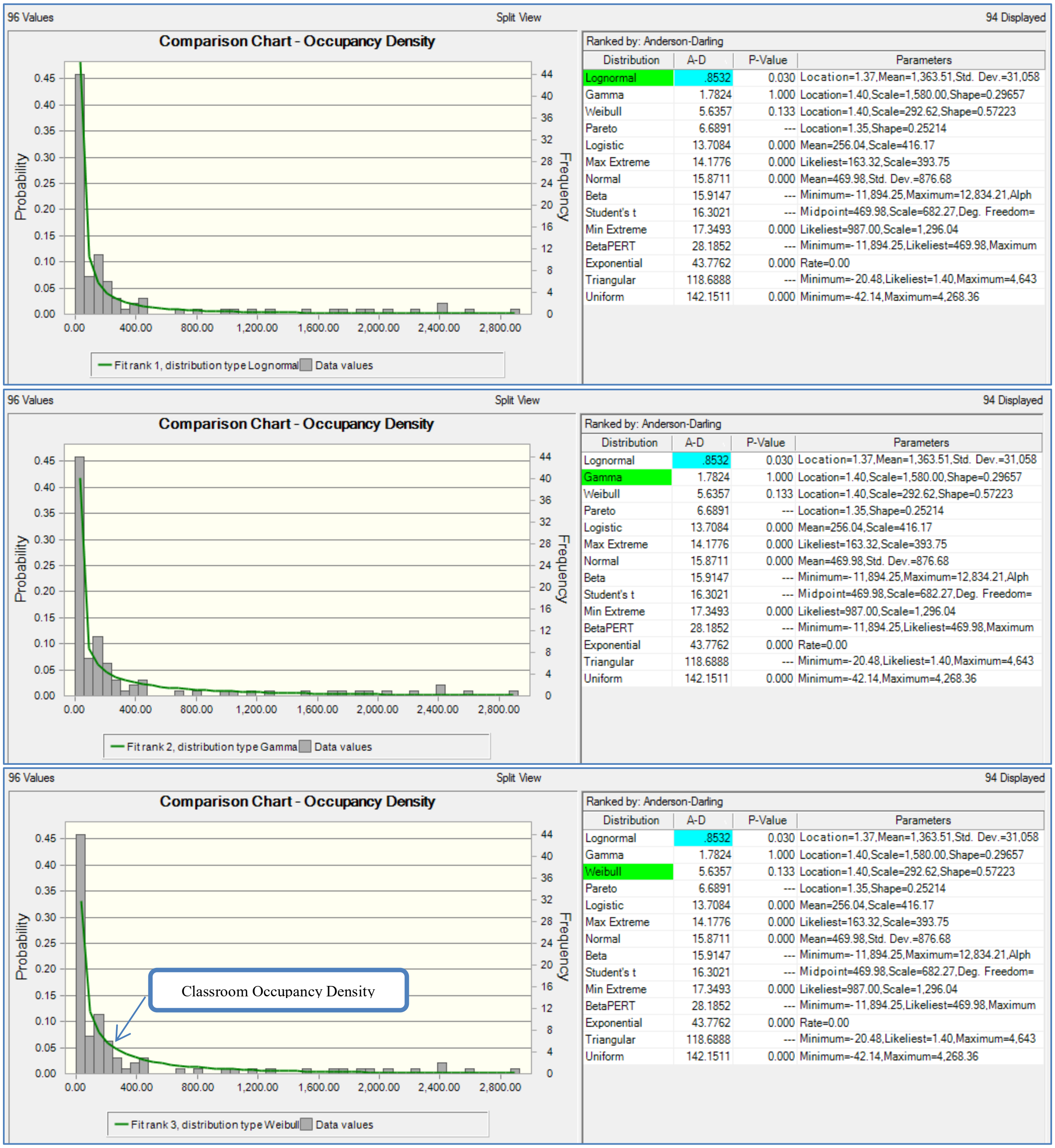


Figure 53: Weekly Patterns for Classroom Occupancy Density, WiFi-based Model



Distribution	A-D	P-Value	Parameters
Lognormal	.8532	0.030	Location=1.37,Mean=1,363.51,Std. Dev.=31,058
Gamma	1.7824	1.000	Location=1.40,Scale=1,580.00,Shape=0.29657
Weibull	5.6357	0.133	Location=1.40,Scale=292.62,Shape=0.57223
Pareto	6.6891	---	Location=1.35,Shape=0.25214
Logistic	13.7084	0.000	Mean=256.04,Scale=416.17
Max Extreme	14.1776	0.000	Likeliest=163.32,Scale=393.75
Normal	15.8711	0.000	Mean=469.98,Std. Dev.=876.68
Beta	15.9147	---	Minimum=-11,894.25,Maximum=12,834.21,Alph
Student's t	16.3021	---	Midpoint=469.98,Scale=682.27,Deg. Freedom=
Min Extreme	17.3493	0.000	Likeliest=987.00,Scale=1,296.04
BetaPERT	28.1852	---	Minimum=-11,894.25,Likeliest=469.98,Maximum
Exponential	43.7762	0.000	Rate=0.00
Triangular	118.6888	---	Minimum=-20.48,Likeliest=1.40,Maximum=4,643
Uniform	142.1511	0.000	Minimum=-42.14,Maximum=4,268.36

Figure 54: Daily Occupancy Density Distribution Batch Fit, WiFi-based Occupancy

The estimated occupancy density values from WiFi-based location tracking data are used for distribution fitting using the batch fit tool in Oracle Crystal Ball. It is observed that the distribution is similar to that obtained in the university schedule-based model and sensor-based model. The log-normal distribution provides the best fit for the occupancy density values obtained using the WiFi-based occupancy density values during the semester transition phase. The percentile values for the log-normal distribution are used to develop the rating schematic for the transition phase analogous to the rating schematic in the sensor-based model. Table 12 presents the 10-point rating segmentation scheme for the WiFi-based resource allocation model which enables occupancy-based dynamic resource allocation.

Table 12: Log-normal Distribution Percentages based Resource Allocation Rating (WiFi)

Percentiles	Distribution	Rating	Lower Limit	Upper Limit	Current Service Time	Optimized Service Time
0^{th}	1.37	0				
10^{th}	3.79	1	1.37	3.79	30	0
20^{th}	8.64	2	3.79	8.64	30	0
30^{th}	17.45	3	8.64	17.45	30	5
40^{th}	33.04	4	17.45	33.04	30	10
50^{th}	61.05	5	33.04	61.05	30	10
60^{th}	113.84	6	61.05	113.84	30	15
70^{th}	222.91	7	113.84	222.91	30	15
80^{th}	491.18	8	222.91	491.18	30	20
90^{th}	1,473.31	9	491.18	1,473.31	30	25
100^{th}	∞	10	1,473.31	∞	30	30

The rating scheme developed based on occupancy density values using the WiFi-based classroom occupancy determination model assists facility management in the dynamic allocation of resources similar to the sensor-based model. It can be observed that during the transition phase the rating scheme is altered from the sensor-based model as the classrooms are occupied less during the transition period between semesters. Therefore, it is important to allocate resources as per the occurring changes in occupancy patterns during the semester transition period for effective workforce management and resource allocation. Figure 55 indicates the service time savings which can be achieved for individual classrooms during the semester transition period.

The least usage of facilities is during the middle of the transition period between semesters. The usage increases drastically as soon as the next semester begins.

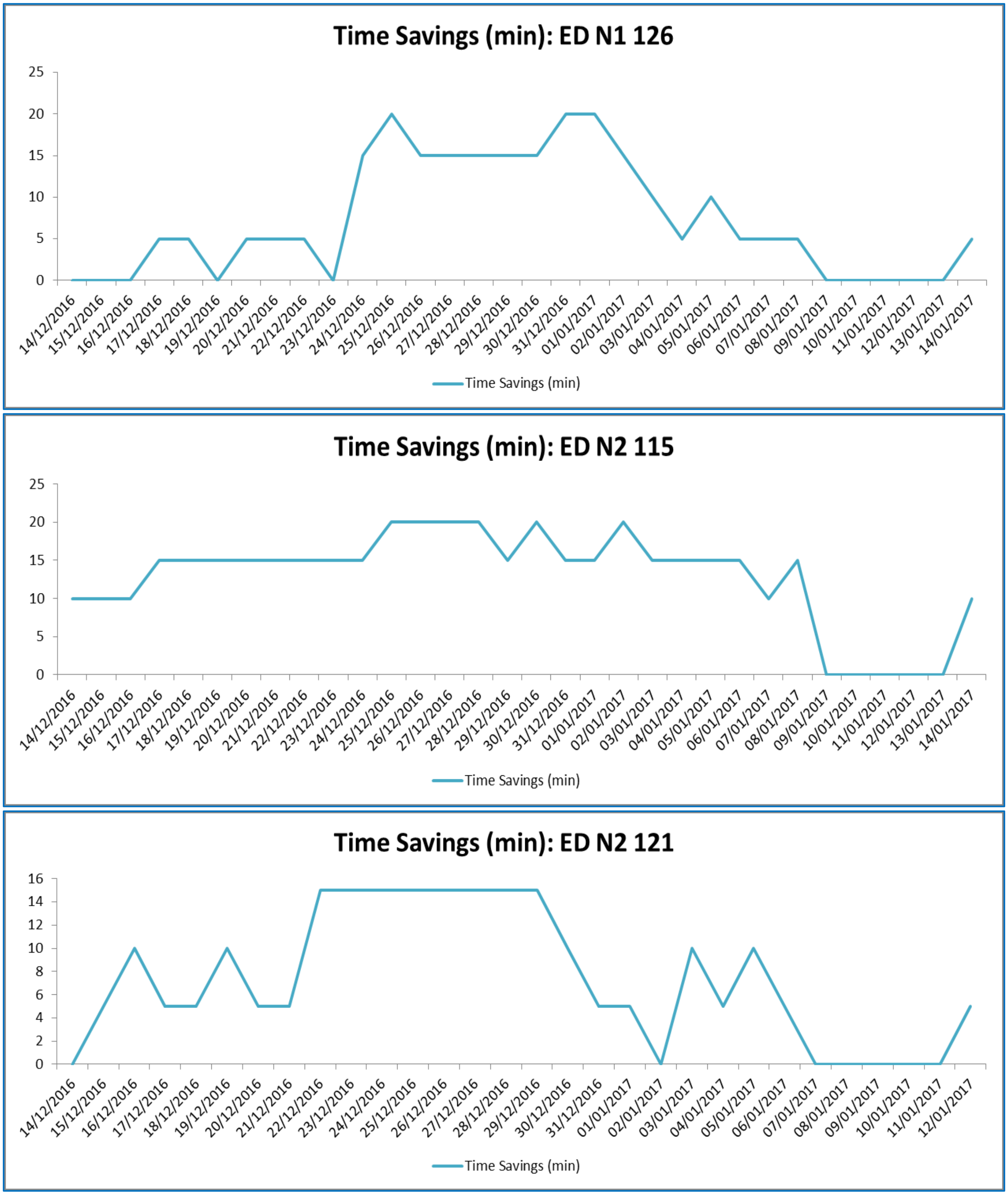


Figure 55: Savings in Service Time for Individual Classrooms, WiFi Model

The total time and cost savings for the three classrooms under WiFi-based model survey is 710 minutes and Can$213/month during the transition phase between semesters. Due to the easy access of WiFi-based facilities throughout the university campus, the model can be enlarged to cover the complete campus. The total number of classrooms at the University of Alberta has been estimated using the interior campus maps for different indoor building environments on the University of Alberta website (Campus Maps, 2017). Using the occupancy patterns developed in the sensor- and WiFi-based model, under the assumption that similar service time and cost savings can be achieved for other classrooms across the University of Alberta, the dynamic resource allocation model can be scaled throughout the campus. The estimated time and cost saving patterns across all 3,050 classrooms on the University of Alberta's North Campus are depicted in Figure 56.

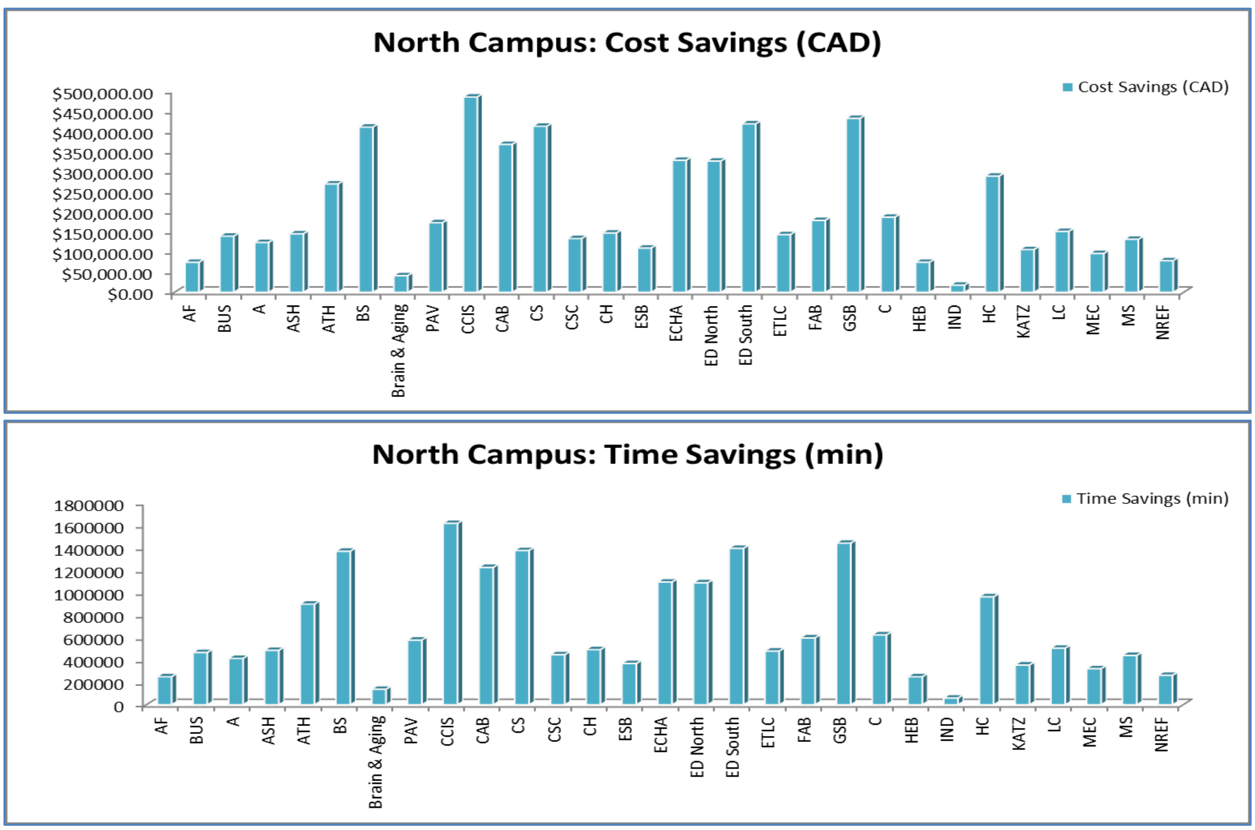


Figure 56: Service Time and Cost Savings for North Campus, University of Alberta

It is estimated that yearly, an average of Can$206,500.00 per building and 688,333/60 = 11,473 service hours per building can be saved based on dynamic occupancy-based resource allocation throughout the University of Alberta's North Campus. The estimations have been developed based on the assumption that the occupancy patterns in the other buildings throughout campus will behave similarly to those developed in the Sensor- and WiFi-based model classrooms. Classroom occupancy-based workforce allocation across the North Campus will enable the University of Alberta's facility management to save Can$6 million/year as estimated in Table 13. The high amount of time and cost savings depict that there is surplus usage of existing resources. The curtailment of allocated resources based on requirement can help the University to allocate its funds to the improvement of educational facilities across campus.

Table 13: Total Savings based on Occupancy-based Resource Allocation, North Campus

	WiFi-based Model		Sensor-based Model				North Campus classrooms	
No. of Classrooms	3		111		343		3050	
Period	Time Savings (min)	Cost Savings (CAD)	Time Savings (min)	Cost Savings (CAD)	Time Savings (min)	Cost Savings (CAD)	Time Savings (min)	Cost Savings (CAD)
Yearly	-	-	726,473	$217,942	2,244,867	$673,460	19,961,645	$5,988,493
1 month	710	$213	60,539	$18,162	187,072	$56,122	1,663,470	$499,041

4.5 Summary of Case Study

This chapter has presented three different case studies to facilitate dynamic allocation of human resources for custodial services, maintenance, and inspection of university classrooms. In total 125 classrooms at the University of Alberta are monitored using all 3 models to determine year-long classroom occupancy patterns. The three models used to develop the occupancy-based dynamic resource allocation model are: (1) university course schedule-based model, (2) thermal occupancy sensor-based model, and (3) WiFi-based location tracking-based model. It is observed that there is a large amount of over-usage of facility resources and many classroom spaces are under-utilized throughout the year. The estimated cost savings through occupancy-based dynamic human resource allocation across the University of Alberta's North Campus is Can$6million/year. Therefore, optimization of allocated human resources for classroom facility management based on determined classroom occupancy can reduce the over-usage of resources, thereby validating the hypothesis proposed in Chapter 3.

CHAPTER 5: CONCLUSION

The research presented in this thesis has developed a framework for dynamic allocation of human resources for the purpose of custodial, maintenance, and inspection services for university classrooms based on classroom occupancy patterns observed throughout the year. The rendered daily services are controlled by the facility management at the University of Alberta; however, a standard service time based on space size had been previously allocated by facility management for custodial, maintenance, and inspection services. In order to prevent the over-usage of human resources, the importance of space utilization-based workforce allocation is presented in this research. Overcoming the challenge of obtaining live classroom occupancy data for all classrooms across the University was one of the most integral parts of this research. The three different models used to estimate classroom occupancy patterns and allocate human resources in a dynamic manner based on occupancy are university course schedule-based model, thermal heat sensor-based model, and WiFi-based indoor location tracking model. Each model has its own advantages and disadvantages which have been discussed in the previous chapters. A rating scheme developed based on the occupancy patterns and classroom space utilization based on all three models assists in the dynamic allocation of human resources, since not all spaces require the same level of human effort for various rendered services.

Through this research it is identified that the classroom spaces are under-utilized, which results in over-usage of human resources and a surplus of operational effort for the classrooms at the University of Alberta. After careful observation of the statistical classroom occupancy behaviours and development of dynamic occupancy-based resource allocation rating schematic, the estimated yearly service cost savings amounted to Can$5.988 million/year for the University of Alberta's North Campus.

5.1 Research Summary

The stated research hypothesis, "*Dynamic human resource allocation based on requirement determined by live classroom occupancy identification in universities can save over-usage of resources*", has been proven using the three different resource allocation models. Due to the varied methods of determining classroom occupancy in all three models, the inaccuracies and benefits of all models complement each other to provide useful insights to the facility management for human resource allocation. The university course schedule-based model relies on the fact that the majority of classrooms are occupied during the period of conducted university lectures to obtain classroom occupancy. The thermal sensor-based model relies on the classroom occupancy count calibrated using IRISYS thermal sensors installed at the point of entry and exit with an accuracy of 98%. It is estimated that achieved savings will enable the University to attain return on installation investments on thermal sensors with a payback period of 3.92 years. The WiFi-based indoor location tracking model focuses on determining the number of people in indoor environments by triangulation of indoor coordinates of usable smart devices emitting radio signals through the pre-existing unified wireless service (UWS) infrastructure. The WiFi model enables facility management to obtain the classroom occupancy data with an accuracy of 90% as described in the methodology chapter. Additionally, since the infrastructure is already developed there are no initial costs incurred for classroom occupancy determination, thereby saving the costs incurred for sensors and enabling the management to scale the classroom occupancy-based resource allocation model throughout the University campus with little human effort required to scale the model.

As the University of Alberta's North Campus estimated service cost savings are Can$5.988 million/year, the rising maintenance and operation costs for the next 5 years at the University of

Alberta can be controlled. This will reduce the burden on facility management in terms of institutional facility maintenance as well as the university students in terms of tuition expenses, enabling them to focus more on educational and research endeavors. As the APPA standards provide freedom in service management methods if the quality of services remains intact, this research will act as a platform to scale the dynamic resource allocation to all universities across North America. This research also lays the foundation for indoor location positioning-based resource optimization in other diverse fields such as inventory management, live-demand based transportation, service management in shopping centres and hospitals, and the creation of smarter cities using live occupancy-based service time models.

5.2 Research Contributions

The dynamic resource allocation framework described in this thesis can be extended to all classroom environments across all schools and universities in North America. The process involves the determination of daily classroom occupancy density using Eq. 4.1, observation of occupancy patterns, and drawing of conclusions pertaining to resource allocation. This research makes the following academic contributions:

1. It describes and formulates occupancy density indicators necessary for creating an occupancy density distribution segmentation-based rating scheme for dynamic service time determination and human resource allocation.
2. It identifies intrinsic parameters such as pre-defined classroom schedules and classroom capacity, and extrinsic factors, such as seasonal usage patterns based on

time lapse during a semester, that influence classroom space utilization and occupancy behaviours.

3. It creates a platform for further academic research in live indoor space utilization-based service time optimization and dynamic resource allocation models using WiFi infrastructures and thermal sensors for diverse sectors.

In addition, this research makes the following contributions to industry practice:

1. Occupancy-based service time optimization and dynamic resource allocation improves work productivity, saving monetary resources and involved human effort.
2. It equips the facility management across the industry with the tool to identify real-time space utilization and amend the resource allocation process using service time rating schematic by making data-driven decisions.
3. It provides the industry with standardized guidelines and processes for developing rating scheme-based dynamic resource optimization models.

5.3 Research Limitations and Challenges

This research study has the following limitations and challenges:

1. As the occupancy values obtained using all the models involve discrete occupancy value collection at specified time intervals, there is a possibility of missing data points collected at a larger time interval.
2. As the positioning coordinates obtained using WiFi-based indoor tracking involves tracking individual smart devices, the challenge of widening the scope of research is limited due to granted access of the unified wireless infrastructure (UWS).

3. The high cost of installing sensors for data collection limits the use of thermal sensors and hinders future scalability of the model.
4. The optimization models have been verified by statistical distributions, simulation, and industry expert opinions, but not through actual field operations.
5. This research study focuses on the attainable workforce service time and cost optimizations for rendered facility management services, but not on optimization in usage of other classroom resources such as energy resources, aesthetic features, and classroom infrastructure.

5.4 Recommendations for Future Research

Based on the observed findings and limitations of this research, the recommendations for future work are as follows:

1. There is a great need to expand the WiFi-based location positioning model to other classrooms where there are pre-installed sensors across the University of Alberta to compare the two models and determine the influence of occupancy data collection at different frequencies of time interval for efficient allocation of resources.
2. The dynamic human resource allocation model can be modified based on real-time monitoring of operational performances by the facility management.
3. The standardized processes developed in the research can be expanded to accommodate other universities across North America to observe varied space utilization and occupancy patterns. The standardized process can also be expanded to other sectors that involve inventory management, live-demand based transportation,

and service and queue management in facilities such as shopping centres and hospitals.

4. Another important aspect to be considered in future research involves reinvesting the yearly saved monetary resources for the betterment of educational facilities and improving the educational standards at the universities.

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