ENHANCING ENERGY EFFICIENCY OF BUILDINGS USING SMART TECHNOLOGIES AND AUTOMATION IN LIGHTING

A Thesis

by

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ABSTRACT

Lighting utilizes a large portion of the energy in commercial and academic buildings. One method of enhancing the energy efficiency of buildings is to implement smart technologies in lighting, such as occupancy sensors. Occupancy-based lighting controls can achieve energy savings, particularly in areas of low and intermittent occupancies, such as library stacks. However, the economic benefits of occupancy-controlled lighting are strongly affected by several parameters such as sensor density, the delay time setting of lighting control, type of lighting, percentage occupancy, etc. University library buildings, which are characterized by their unique occupancy and lighting usage patterns, merit specific focus and additional study. This research presents a long-term case study of occupancy patterns and lighting energy in a university library. A general analysis of the economic feasibility of occupancy-controlled lighting in a library is discussed, including best practices for the deployment of occupancy sensors to maximize energy savings.

One other method of enhancing the energy efficiency of buildings is to conduct lighting energy audits and implement recommended energy saving measures. Automating some elements of the energy assessments would augment the manual auditing process and eliminate simple, time-consuming tasks, and provide additional depth of analysis. This research presents an automated process of identifying the light type. In determining the light type, an optical spectrometer is used to measure the light intensities across the spectrum of wavelengths. The light types are classified using the closest match between the reference and measured optical spectra based on the CVRMS error values. The robustness of the classification algorithm was tested at 10 buildings of

different types, functionalities, and ceiling heights. A total of 260 lamps were tested and the CVRMSE algorithm correctly classified the light type in 95% of the instances. In addition, the algorithm was also used able to identify the lamp type in presence of ambient light.

DEDICATION

I would like to dedicate this thesis to my parents…

ACKNOWLEDGEMENTS

I would like to thank first and foremost my research advisor and committee chair, Dr. Bryan Rasmussen for his continued support over the period of last two years. He is a great advisor and his constant encouragement kept me going even during the most uncertain times of the pandemic. Our weekly review meetings motivated me to work harder and make the best effort possible. There were several challenges in this research, but Dr. Rasmussen made me realize that research is about exploring the unknown path with determination. I would like to express my heartfelt gratitude to him.

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Contributors

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NOMENCLATURE

Symbol	**Nomenclature**	**Unit**
C	Energy consumption constant	kW
N_L	Number of lamps	-
N_S	Number of sensors	-
P_L	Wattage of lamp	W
B	Ballast factor of lamp	-
D	Sensor density	-
$T_{L,T}$	Total time of study	hrs
$T_{L,O}$	Time for which lamps are ON	hrs
$T_{L,D}$	Time for which lamps are dim	hrs
$T_{L,U}$	Time for which lamps are ON but aisle is unoccupied	hrs
E_C	Current energy consumption	kWh
E_S	Current energy savings	kWh
E_T	Total energy consumption	kWh
E_A	Additional energy savings for zero-time delay setting	kWh
S	Number of lamps starts per hour	$\frac{\text{starts}}{\text{hr}}$
L_E	Estimated lifetime	hrs
R	Number of replacements	-
O_T	Operating time	hrs
C_R	Total replacement cost	$
T_P	Payback period	yrs
r	Reference normalized spectrum	-
s	Sample normalized spectrum	-
n	Number of readings	-
C_V	CVRMSE value with respect to reference	-

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1. INTRODUCTION

1.1 Overview of Lighting Energy Consumption by Buildings in the U.S.

Lighting utilizes a large portion of the energy consumed by commercial buildings. According to Energy Information Administration's (EIA) Commercial Buildings Energy Consumption Survey (CBECS) published in 2012, 17% of all the electricity consumed in U.S. commercial buildings is for lighting [1]. As illustrated in Figure 1.1, lighting is one of the largest end usages of electricity in commercial buildings, with the exception of "other" category. Here, the "other" category includes energy consumed by process equipment, motors, air compressors, and miscellaneous electric loads.

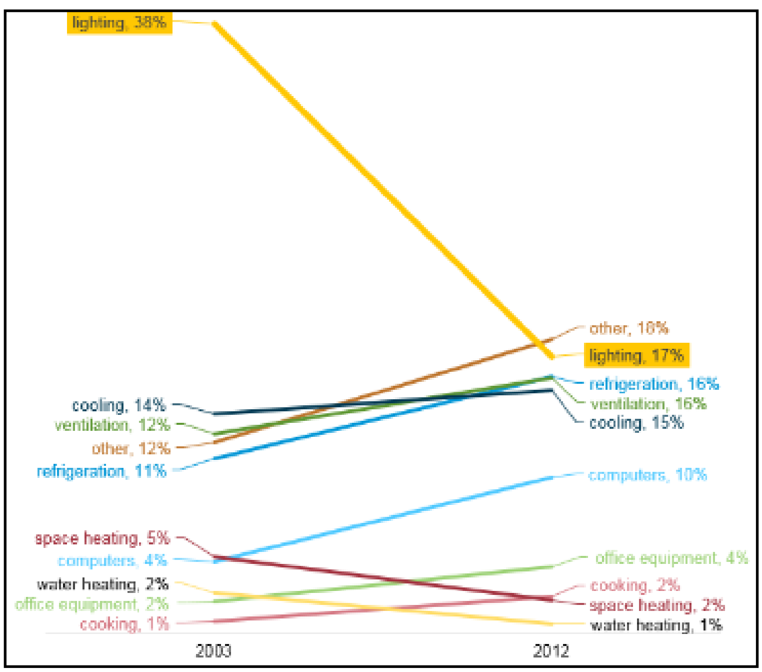


Figure 1.1: Overview of energy consumption of U.S commercial buildings (Reprinted from [1])

As indicated in Figure 1.1, the share of lighting in total energy consumption dropped from 38% to 17%. Apart from lighting upgrades to LED, the advent of smart technologies and upgrades in lighting efficiency standards have contributed to a decrease in the energy consumption of commercial buildings. The EIA survey also collected detailed information about the implementation of lighting controls in buildings: occupancy sensors were used in 16% of all lit buildings and 55% of large lit buildings; scheduled lighting controls were noted in 18% of all lit buildings and 43% of large lit buildings and multi-level dimming devices were installed in 7% of all lit buildings and 23% of large lit buildings. However, there is still a significant potential to save energy in the lighting category.

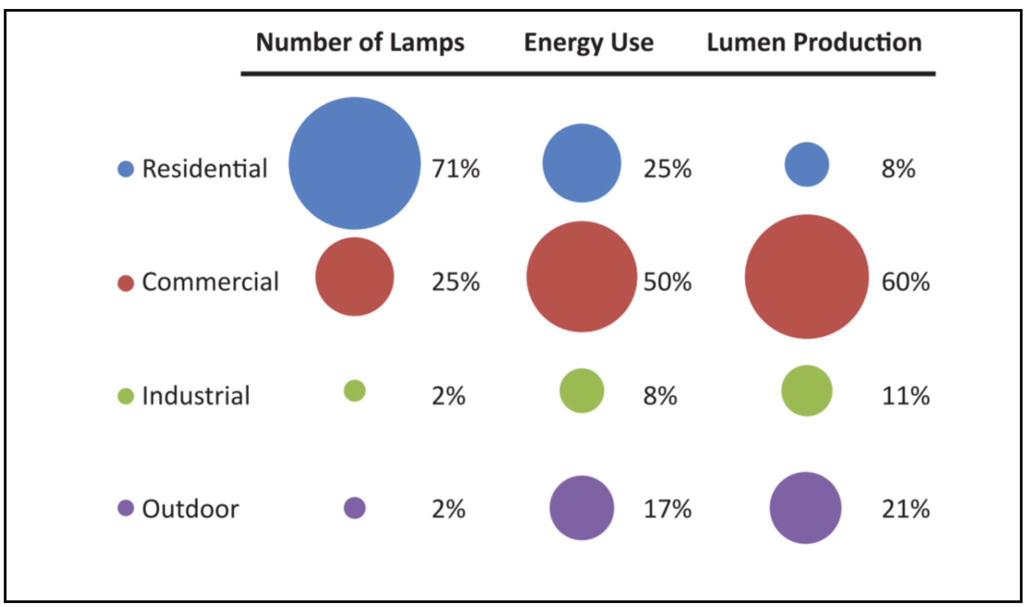


Figure 1.2: Categorization of lighting energy usage as per building type (Reprinted from [2])

To further this notion, the US Department of Energy released a technology review of energy technologies in 2015 [2]. The lighting energy usage is categorized per building type in Figure 1.2. Even though 71% of all the lamps are installed in residential buildings, commercial buildings consume the largest lighting energy of all [2]. An explanation for this might be, commercial buildings heavily use fluorescent lamps, while most of the lighting fixtures in residences are incandescent. Though a fluorescent lamp is more energy-efficient than an incandescent lamp, the energy consumed in commercial buildings is higher than the residences. The study indicates that the lighting usage in commercial buildings is six times more than the residences. Therefore, the lighting energy consumed by commercial buildings is higher than in residences. However, the changing building code requirements and advancements in technologies are changing the current lighting market. Thus, the lighting upgrades to LEDs would change the following distribution of lamps and associated energy consumption.

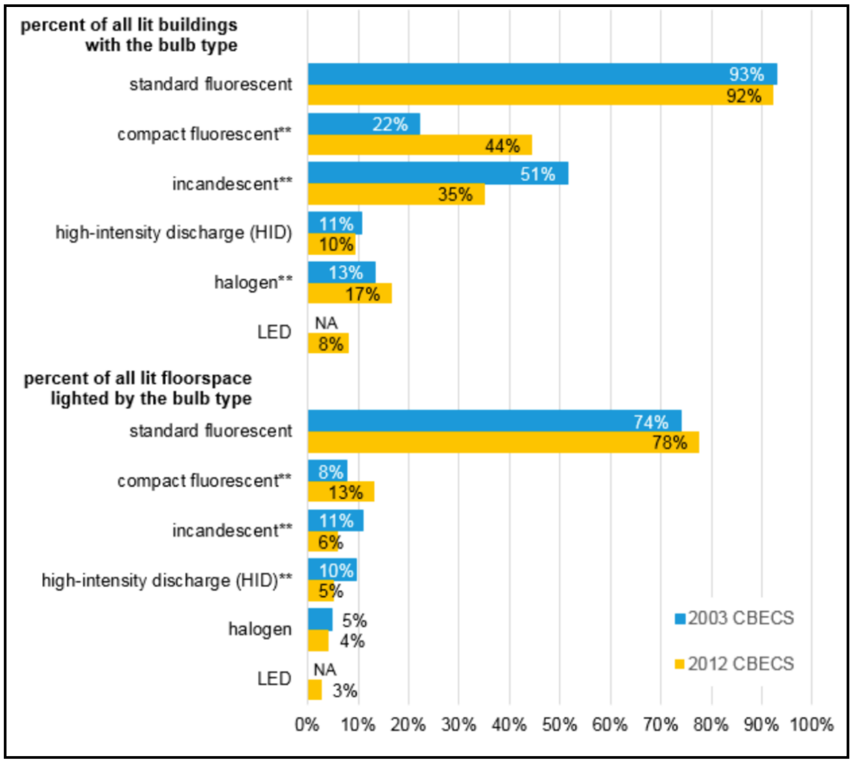


Figure 1.3: Categorization of lighting energy usage per lamp type (Reprinted from [1])

Figure 1.3 categorizes the lighting energy usage per lamp type. According to the CBECS report published in 2012, standard fluorescent lighting is the most used type of lighting in commercial buildings. The higher standards for lighting efficiency have decreased incandescent lighting in commercial buildings [1].

1.2 Background and Motivation

One common method of enhancing the energy efficiency of buildings is to implement smart technologies in the lighting systems. These include installing occupancy sensors, multilevel switches, daylighting control, etc. Installing smart technologies in buildings helps to achieve savings by reducing energy consumption, peak demand charges, HVAC operating costs, and maintenance costs.

Lighting controls reduce energy consumption by turning OFF or dimming lights in cases of unoccupied periods. Previous studies have shown the significant energy saving potential of occupancy sensors in building spaces to range from 10% to 90% savings depending on the use of the space [2]. Specifically, studies indicate that the occupancy-driven lighting controls are effective in building spaces that are used intermittently, like stairwells, breakrooms, and conference rooms. In particular, the occupancy patterns of university buildings are unique. Library stacks are characterized by minimal occupancy with spikes during certain periods of the day. In contrast with most of the commercial buildings, students congregate in particular areas of the library during evenings or weekends. The first part of this research analyzes the impact of occupancy and lighting usage patterns on the energy-saving potential of occupancy sensors in library buildings.

As a case study, the authors selected the Evans library building of Texas A&M University based in College Station. This library has implemented bi-level sensor-controlled lighting, which is a common technology that uses occupancy sensors to control the lighting levels in the library. In such systems, the lamps turn ON when someone walks into the aisle and then dims or switches OFF with a time delay when the occupant leaves the aisle. Extensive data loggers and measurement devices were installed throughout the library to analyze the occupancy and lighting usage patterns over several months. The principal objective of the research is to determine the operating conditions where occupancy-based lighting controls are economically beneficial. The study also identifies and quantifies the impact of critical parameters such as lamp wattage, number of lamps, percentage occupancy, sensor density, etc. on the energy savings and energy economics. Furthermore, the work describes the impact of the delay time setting on the lifetime of lamps and associated replacement costs. Additionally, the research discusses the location of sensors to achieve maximum energy savings in libraries. Finally, the case study concludes with the best practices of implementing occupancy-controlled lighting for university libraries.

One other method to achieve lighting energy savings in buildings is to implement the assessment recommendations given by a comprehensive energy audit of lighting systems. During an energy audit, a trained individual or a team identifies opportunities related to energy efficiency, waste reduction, and process improvement. For lighting systems, a typical energy assessment would include determining the lighting levels and different types of lamps in the facility. This manual audit process is time-consuming and may not provide an in-depth analysis. Also, the cost of an energy audit is dependent on the intensive nature of assessment and training required for the auditors. Automating some elements of lighting energy assessments help reduce the overall cost and enhance the effectiveness of audits. In the second part of this research, the authors propose the automation of lighting and energy assessments. This will be accomplished by using a handheld device consisting of a sensor package: range finder, spectrometer, humidity and temperature sensor, and LiDAR (Light Detection and Ranging). The scope of this research is to automate the repetitive process of identifying the lamp type. The discrete measurement of light intensities across the same set of frequencies of the spectrometer is used to determine the lamp type.

Automating the lighting energy audit of the facility has several other advantages:

a) The device provides detailed maps of measurements in comparison to the single-point measurements taken by an auditor.

b) Automating the repetitive process would essentially reduce the time required for collecting the data resulting in less audit time.

c) The results of lighting scans conducted by the device will be more accurate and consistent if compared to manual auditing.

d) The lighting information collected using the sensor package is used to perform an in-depth analysis of energy consumption and light intensity levels. This could allow determining the areas that have excess lighting and identifying lighting upgrade opportunities.

1.3 Thesis Contribution

The thesis presents an overview of different smart technologies in lighting and the general analysis of occupancy-controlled lighting in university library buildings. The primary objective of this research is to determine the operating conditions when the occupancy-controlled lighting would be cost effective in library buildings. As the occupancy and lighting usage patterns of libraries are unique in nature, the energy savings and payback period are different from the typical commercial buildings. Thus, a set of generalized recommendations specific to the university libraries will be a valuable contribution to the literature. The purpose of the detailed energy study is to evaluate energy savings and provide guidelines to the facility managers on installing occupancy sensors based on the operating conditions. Upon successful completion, the analysis can be extended to different types of facilities and academic buildings.

The thesis describes the concept of autonomous energy audits. These autonomous energy assessments would augment the manual auditing process, eliminate repetitive tasks, and provide more comprehensive analysis. The successful implementation of such automated devices will not only save time and reduce the cost of energy audits but will also increase the number of buildings receiving an energy audit. This translates into significant energy savings which reduces the demand on current electric grids, increased profitability of businesses and decreased carbon emissions.

1.4 Organization of Thesis

The remainder of the thesis is organized as follows: Chapter 2 describes the background information on occupancy-controlled lighting and provides an overview of the lighting energy efficiency studies in different types of buildings. Chapter 3 outlines the example case study of the university library building. Chapter 4 explains the concept of autonomous energy assessments and the functional overview of the sensor package in the handheld device. Chapter 5 demonstrates the methodology for lighting classification based on the optical spectral analysis. Chapter 6 concludes the thesis with final conclusions, and future research directions.

2. OCCUPANCY CONTROLLED LIGHTING

As discussed in Chapter 1, lighting is one of the major end-use categories of energy consumption in U.S. buildings. Installing lighting controls is one method of achieving lighting energy savings in buildings. The total cost savings may come from following categories:

a) Reduced lighting energy consumption
b) Reduced peak demand charges (depending upon the lighting control strategy)
c) Decreased HVAC operating costs
d) Decreased maintenance costs
e) Increased productivity improvement of employees and associated indirect savings

Several types of lighting controls such as occupancy sensors, daylighting control, manual dimmers, and programmable devices are installed to save lighting energy during unoccupied periods. These control devices and smart technologies in lighting are implemented to enhance the lighting quality and maintain or improve occupant satisfaction.

This chapter provides a brief overview of different types of lighting controls and the associated advantages. Then, the chapter outlines the state-of-the-art for occupancy-controlled lighting and its significance in enhancing the energy efficiency of buildings. In addition, this chapter provides an overview on lighting energy efficiency studies in several types of buildings.

2.1 Overview of Selection of Lighting Controls

The following section discusses fundamentals and applications of different types of lighting control strategies that are commonly implemented in buildings. The section also provides guidelines for the selection of lighting control as per the occupancy and lighting usage profile of the buildings.

a) **Occupancy controlled lighting**

Occupancy sensors have shown significant energy saving potential in a variety of lighting applications and achieve energy savings by turning the lamps OFF or DIM during the unoccupied periods. This type of lighting control is also called bi-level controlled lighting or adaptive lighting. These terms are used interchangeably in this thesis.

b) **Scheduling**

The programmable relays, time clock devices, and timers are used to turn OFF the lamps when the building spaces are expected to be unoccupied. Such a type of lighting control may be more attractive for building spaces with predictable occupancy patterns. Scheduling is a lighting control strategy that is implemented typically across the entire building level in large buildings (over 50,000 ft^2).

c) **Daylighting**

In the building spaces with available daylight, photosensors are installed to turn OFF or DIM the lamps based on the light intensity levels and available daylight. The photosensor is used to sense the total lighting level and available daylight in the building space and then a control module is used to switch or dim the lamps. Daylighting controls help reduce the operating conditions of over lighting. Such a type of lighting control may be cost-effective for a building with peak loads during daylight hours.

d) **Tuning**

Tuning refers to reducing power to the lamps depending upon the occupant's needs at the time. This can be achieved by installing dimmers and manual switching devices. The switching systems may be designed to turn OFF one or more lamps in a multi-lamp luminaire for single occupied spaces or building spaces with abundant daylight.

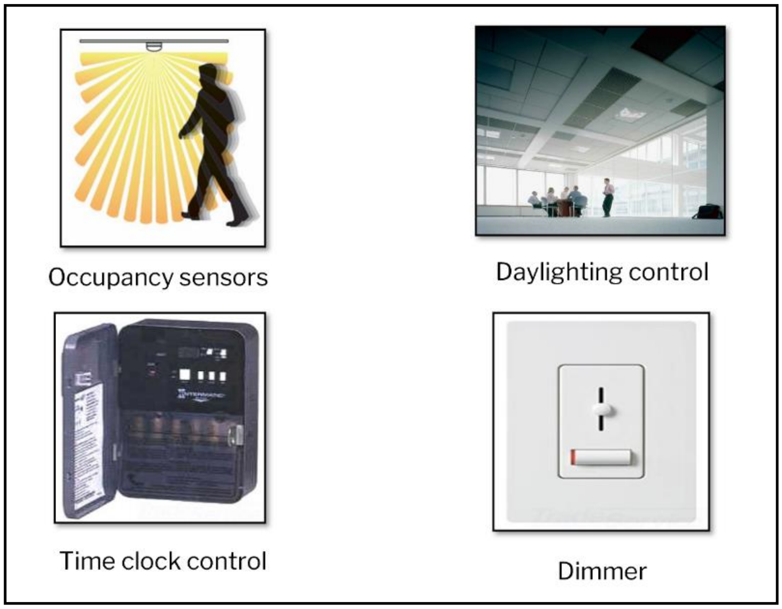
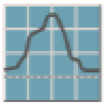
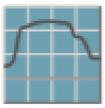
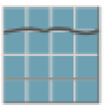
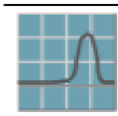


Figure 2.1: Different types of lighting control strategies (Reprinted from [4])

Figure 2.1 refers to different types of lighting control strategies that are typically implemented in the buildings [4]. The selection of control strategy and control devices should take the occupancy and lighting usage profile of a building into account. For example, photosensors may be an attractive choice for a commercial building with a typical weekday occupancy pattern (i.e., regular work hours 9 AM- 5 PM), whereas manual dimmers and switching devices would be more appropriate for a large auditorium exhibiting an event-oriented occupancy pattern.

Table 2.1: Selection of control devices as per lighting usage profile (Reprinted from [3])

Lighting Use Profile		Selection	Devices
	Typical work hours 9 to 5 with limited weekend use	Select controls that reduce peak demand	Occupancy sensors and photosensors for tenant spaces Time clock devices for public areas
	Extended hours	Select controls that reduce unpredictable use	Occupancy sensors Manual dimming/multilevel switching for adaptive compensation
	24-hour	Select controls that reduce lighting day and night	Photosensors Manual dimming/multilevel switching for adaptive compensation
	Event-oriented operation	Manual controls work best	Manual dimming Multilevel switching

The New Buildings Institute, Inc. provides the guidelines for selection of lighting control devices per the lighting usage profile [3]. The remarks are summarized in Table 2.1 [3]. If a building consists of multiple types of spaces, each office space may have its own control needs. For example, occupancy sensors may be more cost effective for restrooms, whereas manual switches and dimmers may be appropriate for large classrooms and auditoriums.

2.2 Occupancy Sensors

This section discusses the fundamentals of how occupancy sensors operate, different types, and associated applications. Occupancy sensors are switching devices that respond to the changes in the occupancy status in the sensor's field of view. The occupancy sensors turn the lamps ON when the space is occupied and turn DIM or OFF when the space is unoccupied for a time delay. This time delay typically varies from 5 minutes to 20 minutes [2].

An occupancy sensor typically consists of two units: a motion detector and a control unit. The motion detector senses changes in the motion of the occupants with the help of ultrasonic sound waves or infrared radiation technologies, whereas the control unit collects the data and determines the occupancy state of the space. The output from this control unit operates the relay, which turns the lamps ON or OFF. The occupancy sensors could be wired or wireless. In a wireless occupancy sensor, the sensor sends a wireless signal to the control unit. Then, the control unit decreases or increases power to a circuit of luminaire based on the collected information.

Following is the summary on operation and applications of the wireless occupancy sensors as discussed in the U.S. Department of Energy Tip sheet [2]:

a) Passive Infrared Radiation (PIR-wireless)

Passive infrared radiation sensors detect the presence of occupants based on the heat energy emitted by them. These sensors have a transducer that converts the infrared heat energy into a voltage signal. Whenever an occupant passes near the sensors, the change in heat energy generates a voltage signal. This signal controls the light output of the fixture. PIR sensors are based on line-of-sight and do not detect occupants if there is any obstruction or partition between the person and the detector. While the sensors are passive and do not actively send out signals, they consume substantially less power in comparison with ultrasonic occupancy sensors. Therefore, PIR sensors are ideal for wireless operations.

b) Ultrasonic (wired)

Ultrasonic sensors emit high-frequency sound signals continuously throughout the room to detect changes in occupancy. The change in position of the occupant corresponds to a change in frequency recorded by the sensor. As the sensor emits continuous signals, they consume more power if compared to PIR sensors. Thus, these types of sensors are generally wired. Additionally, ultrasonic sensors are not line-of-sight based and possess a greater range than PIR sensors. Such types of sensors are more suitable for library buildings, which typically consist of large partitions, book stacks, and tall furniture.

c) Image and microphonic based sensors (wireless)

Microphonic sensors detect the presence of occupants by monitoring sound in the building space. The space is determined to be occupied if sound is detected. The image-based sensors determine whether space is occupied or not based on the real-time images collected. As the sensor is always working, it consumes more power if compared to a PIR sensor.

d) Dual technology-based sensors (wired)

Dual technology-based sensors typically fuse two types of sensing technologies (a combination of one active and one passive type of technology) to detect changes in the motion of the occupants. These sensors increase or decrease the power supply to the lighting fixture if both types of sensors detect a change in the motion of occupants. Dual-technology sensors are advantageous mainly in large building spaces with excessive airflow and are generally more expensive than single-technology sensors.

Though there are many different types of occupancy sensors, this thesis mainly focuses on the energy saving potential of ultrasonic occupancy sensors in university library buildings.

2.3 Discussion on Occupancy Sensor Energy Savings

The previous studies have shown that occupancy sensors save energy from 10% to 90% depending on the functionality of the building space. The U.S. Department of Energy tip sheet provides the expected energy savings for different types of building spaces [2]. Refer to Table 2.2 [3].

Table 2.2: Occupancy sensor energy savings for different building spaces (Reprinted from [3])

Room Type	Lighting Energy Savings
Breakroom	29%
Classroom	40-46%
Conference room	45%
Corridor	30-80%
Private office	13-50%
Open office	10%
Restroom	30-90%
Storage area	45-80%
Warehouse	35-54%

As the occupancy and lighting usage patterns for each of the above building spaces are different, the energy savings realized by installing occupancy sensors also vary. The occupancy sensors may be more cost-effective in building spaces that are used intermittently, like corridors, restrooms, and stairwells.

Table 2.3 specifies the energy savings achieved by occupancy sensors for different lamp types [2].

Table 2.3: Occupancy sensor energy savings for different lamp types (Reprinted from [2])

Considerations	**Incandescent**	**Fluorescent**	**HID**	**LED**
How common as a light source in U.S. commercial buildings?	2%	96%	1%	1%
Effect of switching on lamp life	No	Yes- mitigated with ballast selection	Yes	No
Restrike time	Instant	Quick	Long	Instant
Absolute lighting energy savings	High	Moderate	High	Moderate
Potential issues	None	Dimming ballasts can cost twice as much as standard ballasts	Long warm-up and restriking times	May require a bi-level driver

Occupancy sensors work well with the light sources that are quick starting with less time required to go to the full output from an off state. Thus, the occupancy sensors work well with LEDs, fluorescent and incandescent sources. They may not work well with the metal halides and HIDs due to the long times required to go to the full output from an OFF state.

Additionally, the delay time setting affects the energy savings achieved by occupancy sensors. Significant energy savings could be obtained by minimizing the delay time setting. However, less delay time would mean high switching frequencies of the lamp. This could affect the lamp life of fluorescent and HID lamp types. But these high switching frequencies do not affect the lamp life of incandescent and LED lamps.

2.4 Lighting Controls in Codes and Standards

Building energy codes and standards play a crucial role in reducing the lighting energy consumption of the buildings. These codes and standards mandate lighting controls for new construction and major renovation buildings.

ASHRAE Standard 90.1-2010 and 2013, Energy Standard for Buildings Except Low-Rise Residential Buildings [5] mandates the usage of occupancy sensors in classrooms, conference rooms, breakrooms, restrooms, and building spaces less than 300 ft^2. This standard also requires turning outdoor lighting OFF when daylight is available. The lighting in building spaces such as stairwells and corridors shall be automatically reduced by at least 50% when unoccupied.

U.S. Department of Defense (DOD) Unified Facilities Criteria (UFC) 3-530- 01, Interior and Exterior Lighting Systems and Controls [6], requires the usage of ultrasonic sensors in large spaces with partitions and furniture. U.S. General Services Administration (GSA)'s P-100, Facilities Standards for the Public Buildings Service, guides implementing bi-level lighting in stairwells and hallways [7].

2.5 Best Practices While Installing Occupancy Sensors

The U.S. Department of Energy tip sheet discusses the best practices while installing occupancy sensors in different types of building spaces [2]. Following is the summary:

a) Wall-mounted occupancy sensors may serve better than ceiling-mounted occupancy sensors for smaller building spaces.

b) Ceiling mounted sensors should not be obstructed by the objects that are hung from the ceiling.

c) Shorter delay time settings of occupancy sensors may cause false-offs and occupant dissatisfaction. Thus, finetuning of delay time setting based on the feedback by occupants is recommended for corridors.

d) Multiple occupancy sensors are recommended for the restrooms that are odd-shaped.

Having established a broader understanding of the cost saving potential of occupancy sensors in buildings, this chapter proceeds with outlining the state-of-the-art for occupancy-controlled lighting. The continuously changing technology in lighting and lighting controls causes energy auditors to commonly look at lighting as first among the assessment recommendations. This chapter also presents the advantages of using automated devices and robots in performing lighting energy assessments.

2.6 Energy Efficiency Studies on Commercial Buildings

Several previous case-studies have analyzed the energy-saving potential of installing occupancy sensors in commercial buildings. The case-study conducted by

University of California San Francisco highlighted the fact that occupancy-controlled lighting is economically feasible for the spaces with intermittent and lower occupancy rates [8]. The authors observed that the hallways and corridors of this building consume one-quarter of lighting energy but are typically vacant for at least 75% of the operating hours. Such building spaces are generally a good candidate for installing occupancy sensors. In this case-study, the team installed occupancy sensors and dimming ballasts, which dim the fluorescent lamps during unoccupied periods. Such a demonstration yielded energy savings of 53-68% for the occupancy percentages of 12-16% without compromising safety and comfort of occupants [8]. In addition, the authors compared the energy savings accrued from three control systems having different system architectures. Figure 2.2 depicts the comparison of annual energy savings of 48 lamps for different control strategies and lamp types. The results imply that maximum energy savings could be obtained for LED lamps with delay time setting.

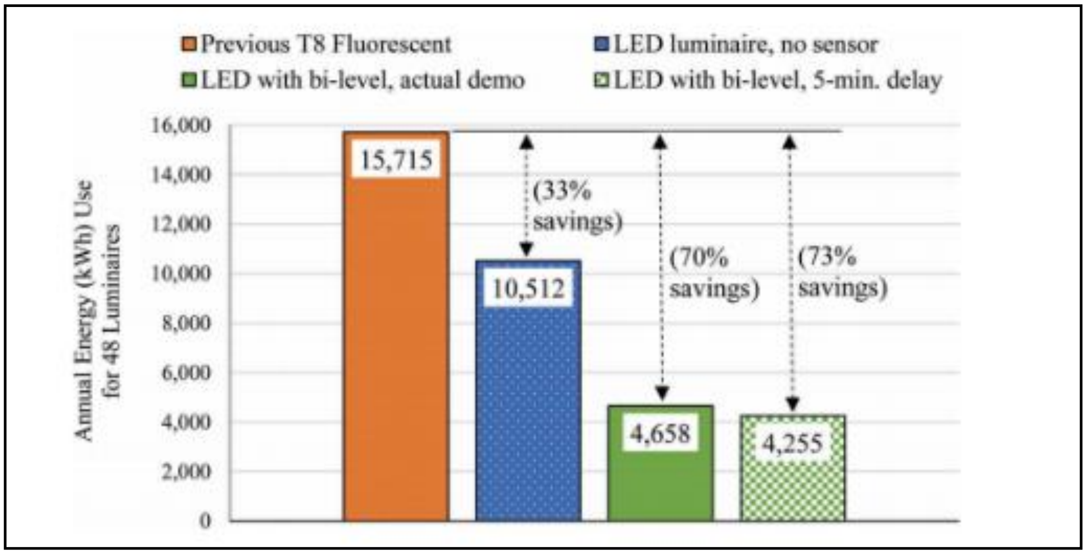


Figure 2.2: Annual energy savings for different lamp types and control strategies (Reprinted from [8])

The researchers at Rensselaer Polytechnic Institute examined the dimming energy savings accrued by installing sensor-controlled lighting in the high-rise residential buildings of New York [9]. The fluorescent luminaries in the corridors were replaced by bi-level LED lighting. During unoccupied periods, the lamps dimmed up to 20% of their output with the help of ultrasonic sensors. The research evaluated the impact of delay time setting of sensors on energy savings and human comfort. The experimental study indicated that in comparison to 15-minute delay setting, the luminaires with 5-minute delay use about 14% less energy annually. Also, the study demonstrated that upgrading existing fluorescent lighting to bi-level LED lighting yields more energy savings compared to mere upgrade to LEDs. The survey results of occupants indicated their acceptance for dimming of lights up to 20%.

The energy efficiency study conducted by the Technical Educational Institute of Greece highlighted that lighting control should also be considered as a solution for reducing energy consumption [10]. In building spaces (such as corridors) which are characterized by low occupancy and abundant daylight, effective control management of lighting could be more cost effective than simply upgrading the lamps. The control scheme can provide energy savings during unoccupied times which LED lighting without control scheme fail to do.

Bill von Neida, Dorene Maniccia and Allan Tweed focused on identifying the factors affecting the performance of occupancy sensors [11]. According to their research, occupancy sensor performance is dependent on the occupancy, lighting control patterns, sensor selection and commissioning. The authors installed occupancy sensors in several types of building spaces of commercial buildings. The results substantiated that the occupancy sensors work best in areas where occupancy is intermittent and unpredictable. For example, the energy savings in restrooms was observed to be greater than that of classroom spaces. The authors concluded that the installation of occupancy sensors may not be a reliable method of achieving peak demand savings.

Numerous case studies have assessed the effect of delay time setting of sensors on the magnitude of energy savings. Though aggressive energy savings can be obtained by minimizing delay time, but this also has significant impact on lamp life. The study performed by Rensselaer Polytechnic Institute strengthened the argument that lamp life decreases after installing occupancy sensors and it further decreases upon reducing the delay time setting [12,13]. The researchers estimated the lifetime of the lamps based on the number of hours per lamp start. The occupancy sensor simulations indicated the increase in re-lamping costs, but despite the increase, it would still significantly reduce the annual energy costs. Furthermore, the research attributed that the shorter delay time settings would increase the likelihood of false offs and the possibility of user dissatisfaction.

2.7 Energy Studies on Religious Buildings

As discussed in this chapter before, there are significant number of energy efficiency studies on various types of buildings. However, very few of them focuses specifically on religious facilities and their unique occupancy patterns. Most religious buildings have one or more large gathering areas which are occupied to the full capacity at certain times. Also, there are typically multiple classrooms or offices in these buildings to accommodate smaller meetings. Thus, religious facilities exhibit unique occupancy patterns compared to other commercial buildings. They are typically characterized with no or minimal occupancy for most of the time, with relatively infrequent periods near maximum occupancy. Trevor Terrill presented the long-term energy analysis of religious facilities in different climates [14,15].

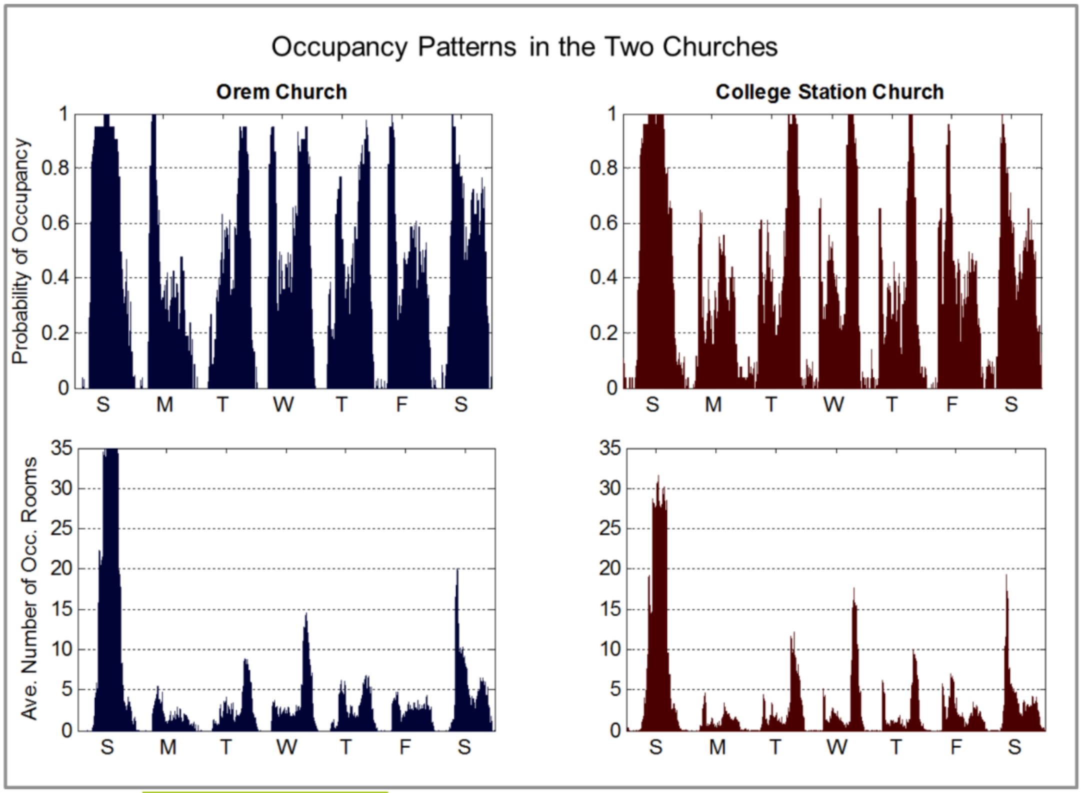


Figure 2.3: Occupancy patterns for the two selected church buildings (Reprinted from [14] and [15])

Figure 2.3 describes the occupancy patterns of the selected two churches on both consistency and intensity of usage. The first figure indicates the probability that someone occupied the building at a particular time of the week. The building is consistently used throughout each week with regularly scheduled activities. However, the largest time of the usage is on Sunday. The second figure shows the average magnitude of the building usage thorough out the study of 40 different rooms. The figure reveals that the dominant usage of the building occurs on Sunday with consistent usage on other days. The research emphasizes the importance of understanding occupancy patterns in determining energy savings of the building. Also, the experimental results of this church study confirm that the functionality of building space affects the occupancy patterns.

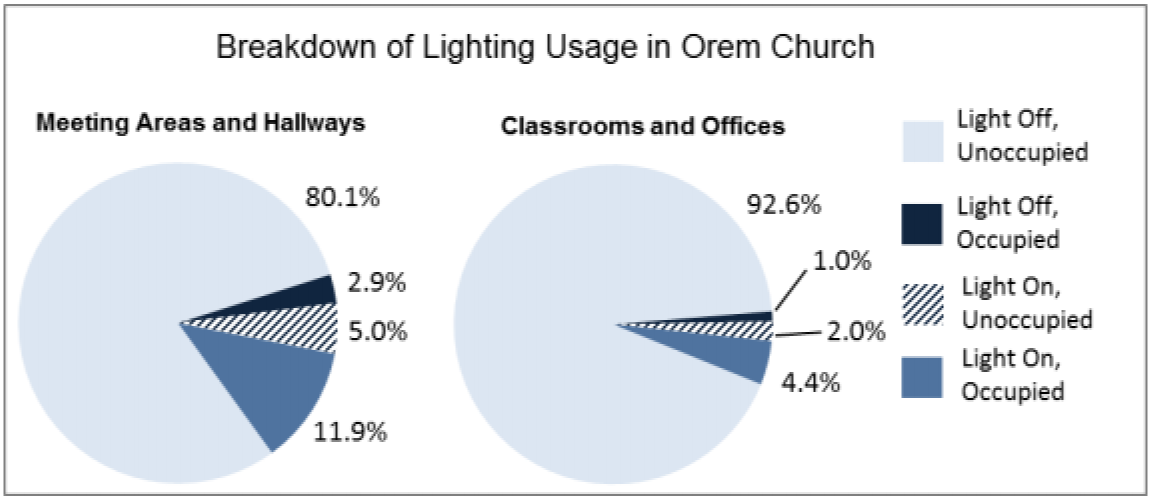


Figure 2.4: Lighting usage patterns of the selected church buildings (Reprinted from [14] and [15])

Figure 2.4 exhibits the lighting usage patterns for the selected church buildings. The overall patterns were observed with similar trends as occupancy profile. As seen in the figure, lamps are in OFF condition and the building space is unoccupied for majority of the times. In general, the buildings have low and intermittent occupancy rates. The category 'Lights ON, Unoccupied' indicates the amount of lighting energy wasted and opportunities for energy savings. The analysis reveals that this portion of lighting energy consumed during periods of no occupancy is found in meeting areas and hallways.

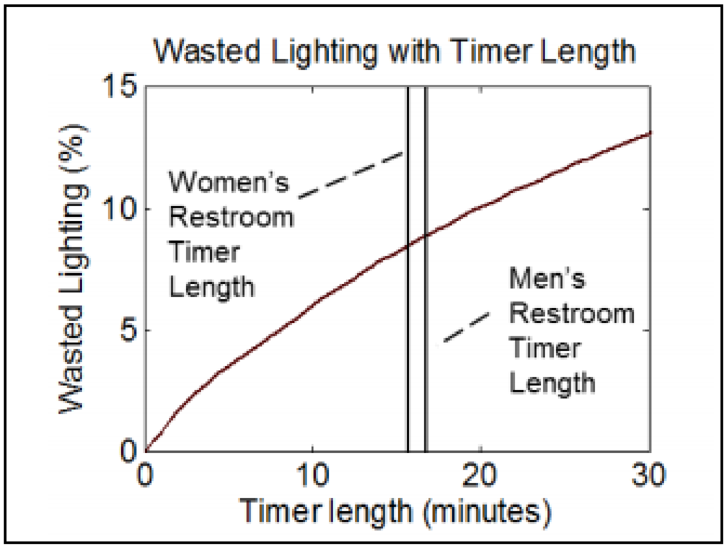


Figure 2.5: Impact of timer length on % wasted lighting (Reprinted from [14] and [15])

Figure 2.5 shows the effect of timer length on the extent of wasted lighting in the restrooms. High timer lengths decrease the energy saving potential of occupancy-based lighting control. The authors recommend installing occupancy sensors with the option to manually turn OFF lighting by occupants, which could improve the cost-effectiveness of occupancy sensors.

2.8 Uniqueness of Energy Studies on Library Buildings

The aforementioned case-studies were conducted to analyze the energy-saving potential of installing occupancy sensors in commercial and religious buildings. However, library buildings merit specific focus and detailed energy efficiency studies. Library buildings exhibit unique occupancy and lighting usage patterns. In particular, the library buildings are frequently comprised of several floors and with aisles of books categorized as per subject matter. Additionally, the occupancy percentage can differ significantly depending upon the aisle and corresponding subject matter. Atypical occupancy patterns, large numbers of lamps, and the associated energy savings potential make the energy efficiency study of library buildings unique.

3. RESULTS: ENERGY ANALYSIS OF OCCUPANCY CONTROLLED LIGHTING IN UNIVERSITY LIBRARY BUILDINGS

Understanding that the occupancy-based lighting controls may be cost effective for building spaces with lower and intermittent usage, such as library buildings, an energy efficiency study of a large university building was conducted. The case study analyzed the Evans Library Building, a primary library building of Texas A&M University campus based at College Station. A detailed discussion on the occupancy and lighting usage patterns and energy analysis is then presented. A general analysis of the economic feasibility of occupancy-controlled lighting in a library is then discussed, including best practices for the deployment of occupancy sensors to maximize energy savings.

3.1 Building Study and Experimental Methodology

The selected building has a total of six floors with library stacks and, from the third floor upwards, library stacks with occupancy-controlled lighting are implemented. A total number of 50 occupancy and lighting sensors were installed throughout the different sections of library stacks to study the occupancy and lighting usage patterns. The occupancy data was collected for a total period of 3~4 months, which included a period of a regular semester and a semester break. In addition, the study was conducted prior to the onset of pandemic. These occupancy sensors used in this study work employ ultrasonic technology to monitor room occupancy and have a detection range of 12 meters.

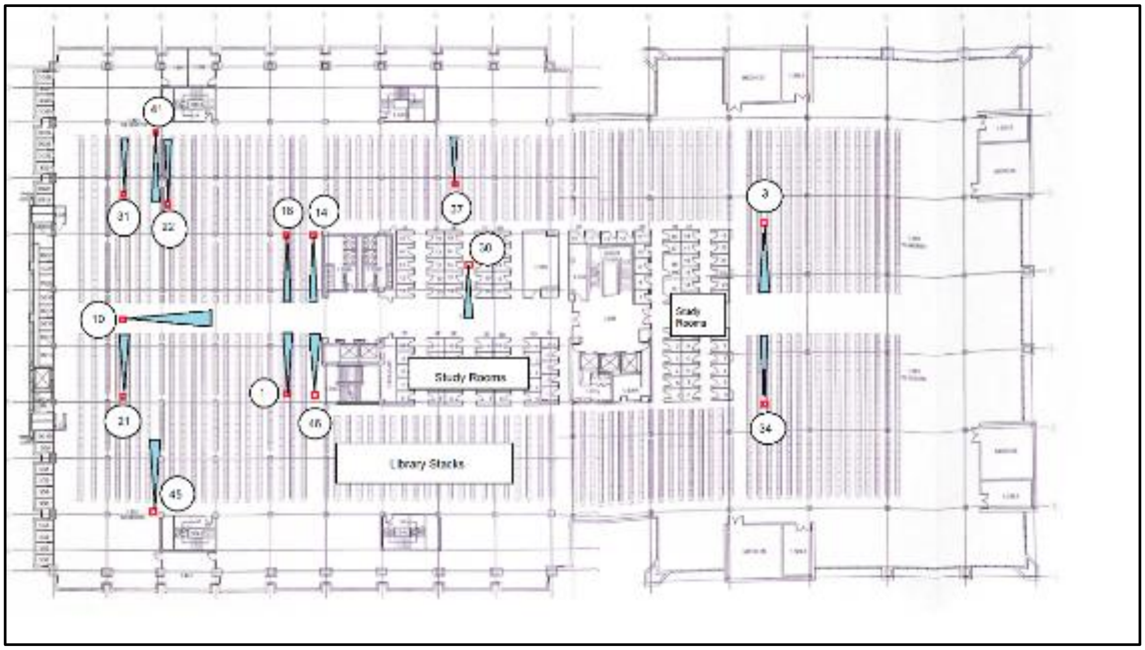


Figure 3.1: Layout of a representative floor of a library building illustrating location of data loggers

Figure 3.1 shows a typical layout of a floor in the library building and the location of the installed sensors. These sensors were installed near the building's occupancy sensors, with locations chosen based on historical library data regarding the book access. Each sensor recorded the time-date stamp and an occupancy state when a change was detected. In the subsequent analysis, the lights are assumed to turn ON when the occupancy sensor detects an occupant. The lighting sensor served as a verification of whether the lights were ON or OFF. The lights remained in the ON condition during the occupied periods and dimmed after a specified time delay. This time delay was typically between 2 minutes to 20 minutes. For this case study, the average time delay setting across the different floors was determined to be 15 minutes. These were used to compute the occupied, unoccupied times and periods for which lamps were in ON and DIM condition. A summary of the parameter values used in the energy and economic analysis is compiled in Table 3.1.

Table 3.1: Summary of parameter values in the energy analysis and payback calculations

Parameter	**Value**
Power of T8 fluorescent lamp	32 W
Ballast factor of T8 fluorescent lamp	0.9
Number of lamps per fixture	2
Rated life of T8 fluorescent lamp	20,000 hours
Power of LED (equivalent to T8-32 W)	18 W
Avoided cost of electric energy	$ 0.1/kWh
Cost of occupancy sensor	$ 130
Cost of replacement T8 fluorescent lamp	$ 2.5
Labor cost	$ 35/hour
Time required for lamp replacement	0.25 hours
Total number of lamps	12,000
Sensor density	9 lamps/sensor

3.2 Results

This section delineates an in-depth analysis of experimental results for the occupancy, lighting, and energy consumption of a large university library building. The section starts with a discussion of unique occupancy and lighting usage patterns of typical library buildings. The energy cost saving potential of occupancy sensors in library buildings is then presented.

3.2.1 Occupancy Patterns

The recorded building occupancy patterns provide key insights related to total energy consumption and the potential for reduction in energy usage. In particular, library buildings exhibit unique occupancy patterns. Library buildings are frequently comprised of several floors and with aisles of books categorized per subject matter and the occupancy percentage can differ significantly depending upon the aisle and corresponding subject matter. Students often visit the library at atypical hours, congregating in particular aisles of the library. At the same time, most of the areas are unoccupied for significant periods. The collected data was categorized on a daily and weekly basis. Also, the data was classified floor wise.

Figure 3.2 shows the floor wise number of occupancy state changes at regular time intervals. Here, the occupancy state change refers to a binary change from occupied to unoccupied state or vice versa. The figure demonstrates that the occupancy profile is similar for all the floors. The average number of occupancy state changes increases sharply in the morning and the evening, typically marking the start and end of a working shift of the library. However, the number of occupancy state changes differ from floor to floor and is at a maximum on the sixth floor. Figure 3.3 illustrates the number of occupancy state changes at a particular day of the week. Importantly, as shown in Figure 3.3, the library is remarkably highly occupied on weekends and sparingly occupied on Mondays. Also, students visit the library on Sundays more frequently. Furthermore, the occupancy pattern is consistent for all the weekdays. Figure 3.4 categorizes the occupancy state changes in two periods: during the semester and spring break. Though the overall occupancy profiles are similar for both the periods, the number of occupancy state changes are low during the typical semester break of one week. The data collected over several months shows that the occupancy percentage across the aisles varies from 1% to 17% with an average occupancy of 5%.

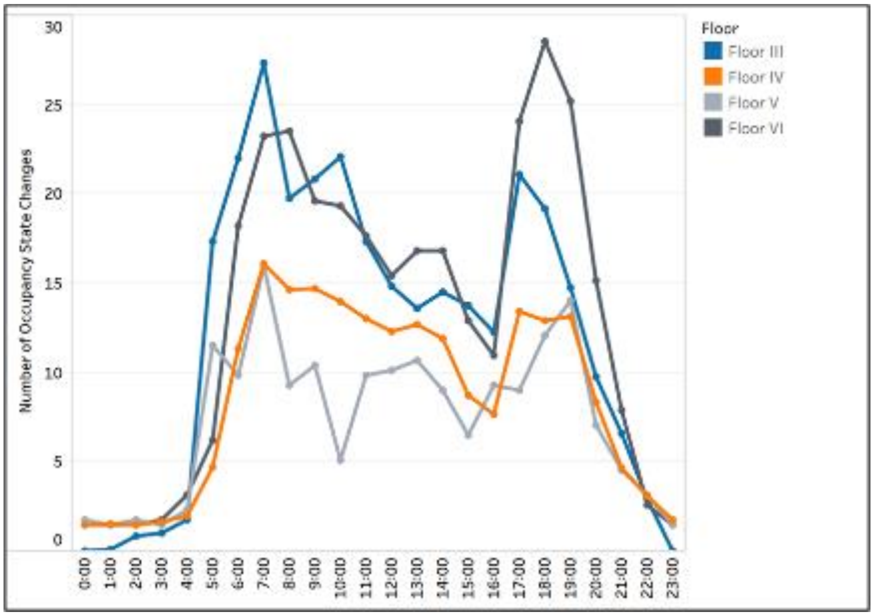


Figure 3.2: Daily occupancy profile

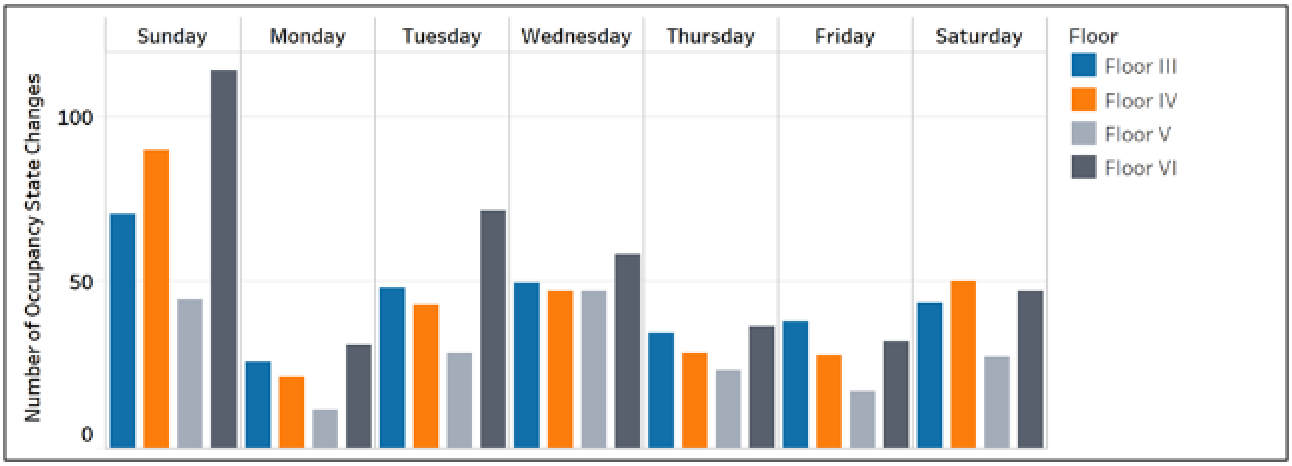


Figure 3.3: Weekly occupancy profile

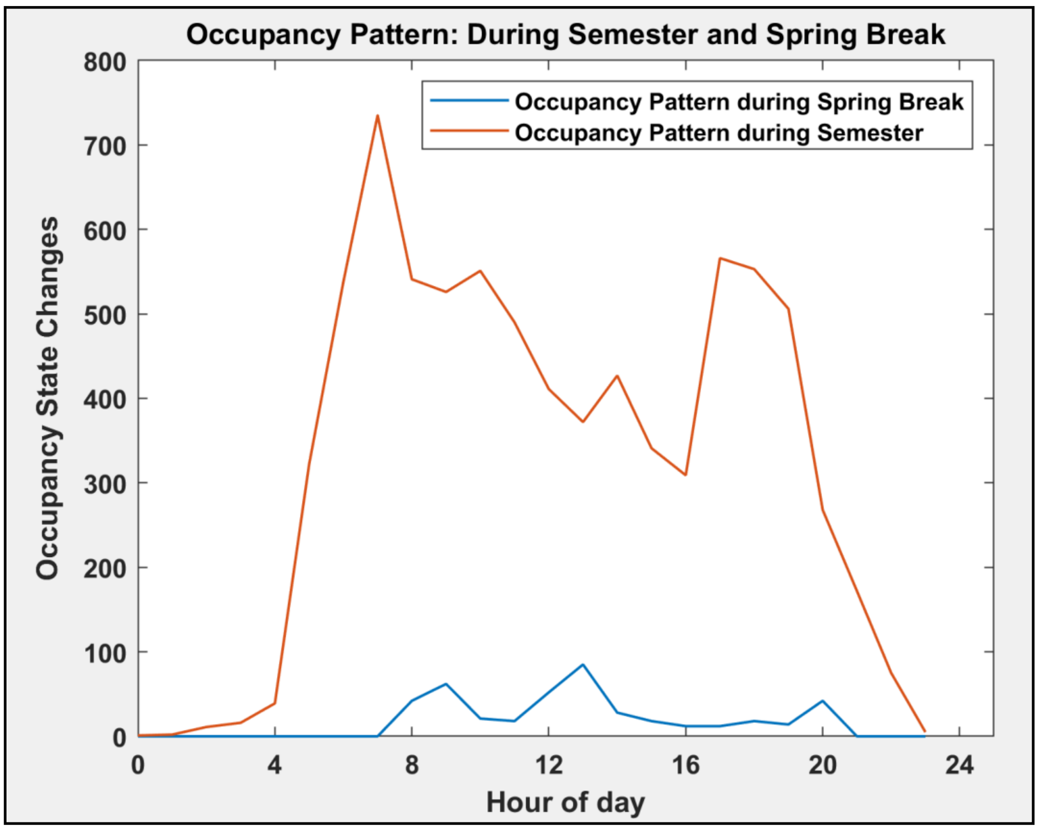


Figure 3.4: Occupancy Patterns During Semester and Semester Break

3.2.2 Lighting Usage

Like occupancy patterns, lighting usage patterns provide insights on energy saving potential of the occupancy-based lighting controls. Normally, the total period is broken into three categories based on occupancy: lights ON during the occupied times, lights ON during the unoccupied times, and lights DIM during the unoccupied times. The first category helps in gathering information about the occupancy and nature of the usage of spaces. The energy saving potential of occupancy sensors can be gauged by the percentage of time the lighting is ON, but the space is unoccupied.

As part of this study, the authors verified that the lights for the library stacks turn ON immediately as the occupant enters the aisle. When the occupant leaves the aisle, the lamps DIM after a specified delay. Based on measurements, the average delay time of the sensors of all floors was 15 minutes. The dimming of the lamps is achieved by turning one of the lamps in the fixture OFF. The equations (1-5) given below are used to calculate lighting energy consumed for each operational mode.

$$\mathrm{C} = \frac{(\mathrm{P_L}).(\mathrm{B}).(\mathrm{D})}{1000} \qquad \text{(Equation 1)}$$

$$\mathrm{E_T} = (\mathrm{C}).(\mathrm{T_{L,T}}) \qquad \text{(Equation 2)}$$

$$\mathrm{E_C} = (\mathrm{C}).\left(\mathrm{T_{L,O}} + \left(\mathrm{T_{L,D}}.(0.5)\right)\right) \qquad \text{(Equation 3)}$$

$$\mathrm{E_S} = \mathrm{E_T} - \mathrm{E_C} \qquad \text{(Equation 4)}$$

$$\mathrm{E_A} = (\mathrm{T_{L,U}}).(\mathrm{C}) \qquad \text{(Equation 5)}$$

The data from individual sensors shows that the percentage of time lamps in the ON condition varies from 1% to 26%, with an average of 10% across all the floors. Figure

3.5 presents the average lighting use for all floors. First, the results show that the lamps are in the dimmed condition the vast majority of the time (i.e., 90% of the total time). This indicates that the lighting controls are responsible for significant energy savings when compared to lights that remain ON during all hours. However, it also represents the potential for additional energy savings if the lights were turned off completely during unoccupied periods, rather than partially dimmed. Second, the results show that the lights remain ON after occupants leave 4% of the time. This is an opportunity for additional energy savings if the delay time setting of the lighting controls is reduced.

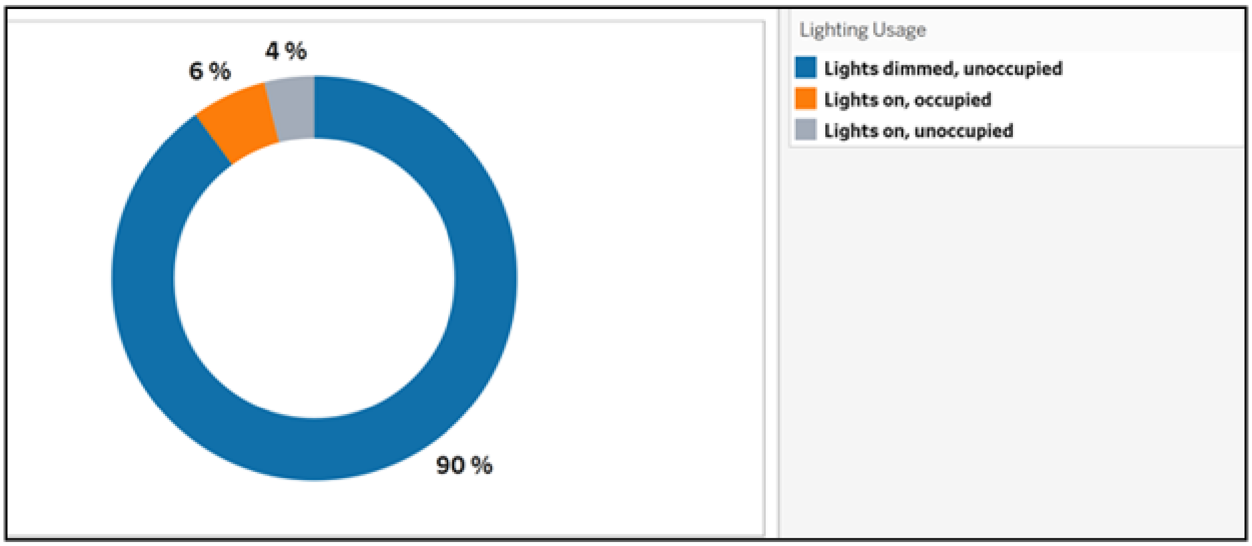


Figure 3.5: Breakdown of lighting usage

3.2.3 Impact of Delay Time Setting on Energy Savings

Advanced occupancy sensing technologies offer several ways for efficient lighting to reduce energy usage during unoccupied periods. One such way could be reducing the delay time: the time between the last detected motion and the instance when the lights DIM. This delay varies from a couple of minutes to 20 minutes for most of the occupancy sensors. This section analyzes the impact of lighting control delay times on energy consumption and energy savings.

The energy usage during unoccupied periods can be minimized by reducing the delay time of the occupancy sensors. Figure 3.6 indicates the variation in daily energy savings of one sensor with different settings of delay time of lighting control, respectively. The data analysis shows that the delay time setting has a significant impact on energy savings. The energy savings are computed using the Equations (1-5) on Page 33. Significant energy savings could be realized by installing sensors with short delay time settings. For instance, the annual energy savings increase by 6% when the delay time setting is reduced from 15 minutes to 0 minutes. Also, the 'Additional energy savings for 0-minute delay' refers to the energy savings that could be achieved by reducing the time delay to zero. That is why these additional savings are zero for no time delay and increase as the time delay increases.

Optimizing the delay timing creates a tradeoff between achieving energy savings, avoiding false offs, and the lifetime of lamps. Though more energy savings are achieved through shorter time delay settings, these are often correlated with false offs and user dissatisfaction. However, to achieve higher energy savings, it is advised to start with a 10-minute delay and then fine-tune as per the feedback from the occupants [2].

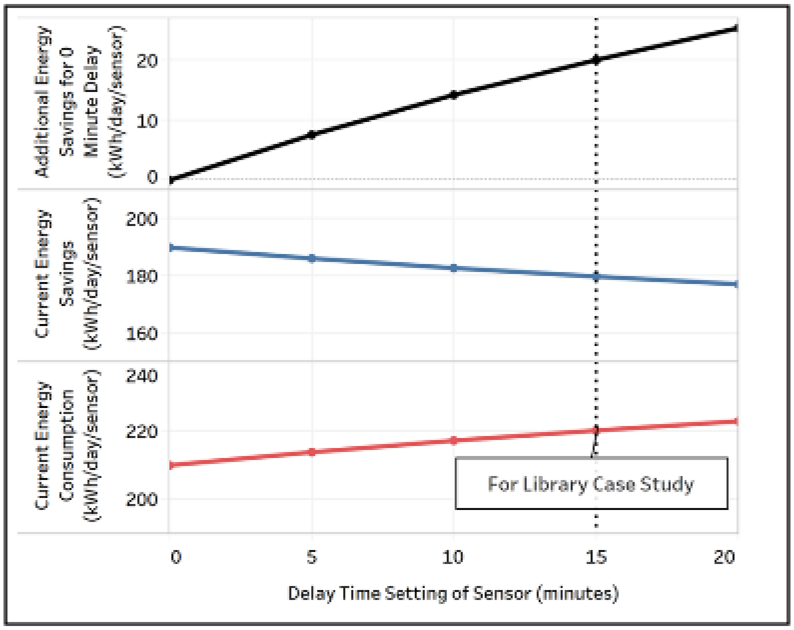


Figure 3.6: Effect of delay time on daily energy savings

3.2.4 Successive Levels of Energy Savings for Fluorescent and LED Lamps

The previous section discussed that the delay time has a significant impact on energy savings. Apart from delay time, the type of lamps as well as whether the lamps are dimmed or in the OFF condition during unoccupied periods also affect the energy savings. This section of the results evaluates successive levels of energy savings for lamps in the dimmed and the OFF condition. Furthermore, the energy savings from the fluorescent as well as LED lamps are compared. Figures 3.7 and 3.8 illustrate the following three successive levels of energy savings for both the lighting types: lamps dimmed with a 15-minute time delay, lamps dimmed with no time delay and lamps turned off with no time delay.

Figures 3.7 and 3.8 indicate average daily energy savings for one sensor. The radial plots demonstrate that the maximum energy savings can be accrued when the lamps are turned OFF rather than dimming for unoccupied periods. The daily energy savings obtained when the lamps are in the OFF condition are about 63% higher than the case when the lamps are in the dimmed condition with a delay time of 15 minutes. Though maximum energy savings are achieved when the lamps are turned off with no delay, this could also cause customer dissatisfaction. Thus, this reiterates the fact that getting feedback from the users is important while optimizing the delay time setting and deciding the state of the lamps in unoccupied states.

Additionally, these plots compare the energy savings achieved by fluorescent and LED lamps. Being energy efficient, LEDs consume less energy if compared to compact fluorescent lamps. Also, the energy consumption is directly proportional to the wattage of a lamp. Therefore, the energy savings for LEDs are lesser than fluorescent lamps by 50% for a 15-minute time delay setting.

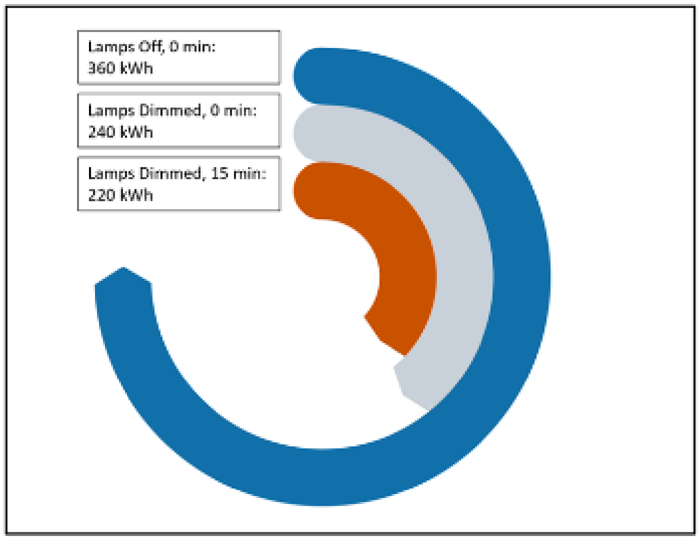


Figure 3.7: Successive levels of energy savings for fluorescent lamps

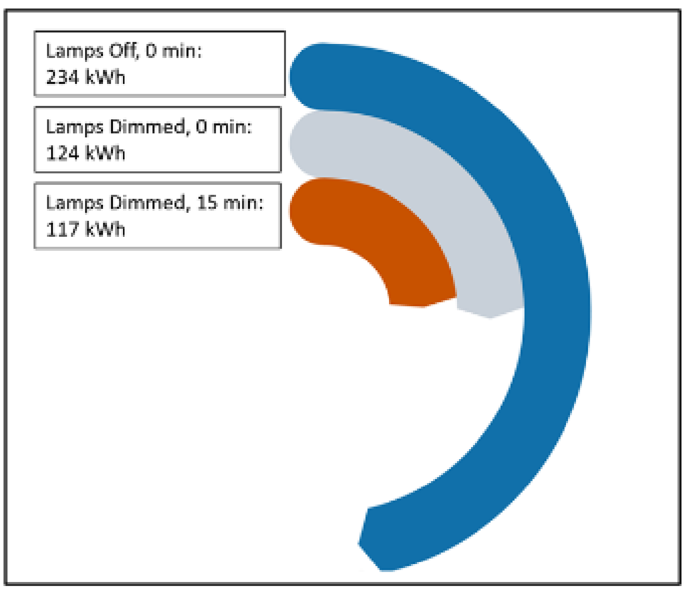


Figure 3.8: Successive levels of energy savings for LED lamps

3.2.5 Effect of Switching on Lifetime and Replacement Costs of Lamps

Though aggressive energy savings can be achieved by minimizing the delay time of sensors, this also has a significant impact on the lifetime of the lamps, particularly fluorescent lamps. Lower delay time settings cause frequent switching of lamps which reduces their lifetime. This section assesses the impact of lowering delay settings on the lifetime and associated replacement costs of lamps.

Previous research demonstrates that the life of lamps decreases if the delay time setting of sensors is reduced. The coating loss of electrodes in fluorescent lamps is a function of the number of starts per hour and total operating hours [12]. Dorene Maniccia et. al. estimated the expected life of lamps as a function of the number of starts per hour using Equation 6. This holds for 32 W, electronic ballast fluorescent lamps [13].

$$\mathrm{L_E} = \frac{\mathrm{S}}{(0.0000314).(\mathrm{S})+(0.0000548)} \qquad \text{(Equation 6)}$$

The percentage of time lamps in the ON condition is calculated from the data collected by the sensors. As described in the earlier section, dimming is caused by turning OFF one of the lamps in the fixture. Therefore, the operating times and replacement frequencies of these two lamps of the same fixture would be different. However, Figure 3.9 indicates that the overall lamp replacement costs increase by reducing the delay time setting. Table B.5 in the Appendix section comprises overall energy savings which are significantly higher than the replacement costs. Even though frequent switching calls for an increase in re-lamping costs and a decrease in lamp life, the occupancy sensors reduce overall costs and provide cost-effective lighting control.

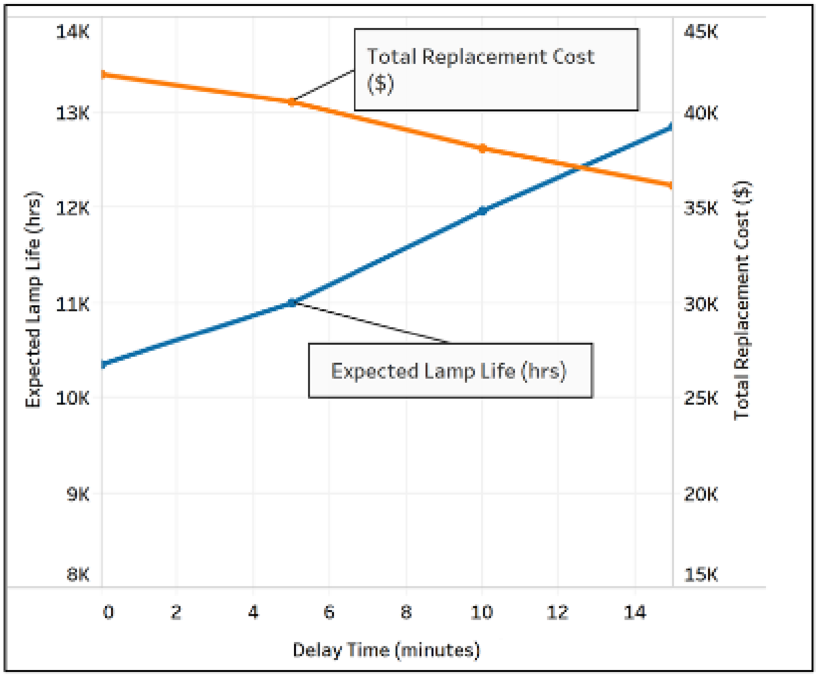


Figure 3.9: Effect of delay time on lifetime of lamps and replacement costs

3.2.6 Effect of Sensor Density on Energy Economics

This section investigates the effect of parameters such as sensor density and the percentage time lamps are in the dimmed condition on the payback period of installing occupancy sensors. It also answers the following questions:

A. Is it worth implementing occupancy-controlled lighting with dimming for LED lamps in libraries?
B. When would this retrofit be economically feasible for fluorescent lamps?

This also increases the investment cost and thereby decreases the payback period. Furthermore, the payback period also depends on the percentage occupancy and the percentage of time lights are ON. The payback period of the project could be estimated if the sensor density and percentage for which the lamps are in the dimmed condition are known. Equations (7-9) were used to study the effect of sensor density on the payback period.

$$\mathrm{R} = \frac{(\mathrm{N_L}).(\mathrm{O_T})}{\mathrm{L_E}} \qquad \text{(Equation 7)}$$

$$\mathrm{C_R} = (\mathrm{R}).(\mathrm{C_P}) + (\mathrm{N_L}).(\mathrm{T_R}).(\mathrm{C_L}) \qquad \text{(Equation 8)}$$

$$\mathrm{T_P} = \frac{(\mathrm{C_S}).(\mathrm{N_S})}{\mathrm{E_S}} \qquad \text{(Equation 9)}$$

Figures 3.10 and 3.11 can be used to estimate the payback period of fluorescent lamps for several combinations of sensor densities and the percentages of lights in dimmed condition. The estimated payback period for the Texas A&M campus library case study is about 2 years, for a sensor density of 10 lamps per sensor and percentage of lights in the dimmed condition equal to 90%. This would make the retrofit economically viable. Also, the increase in the payback period is steep for dimming percentages of less than 50%.

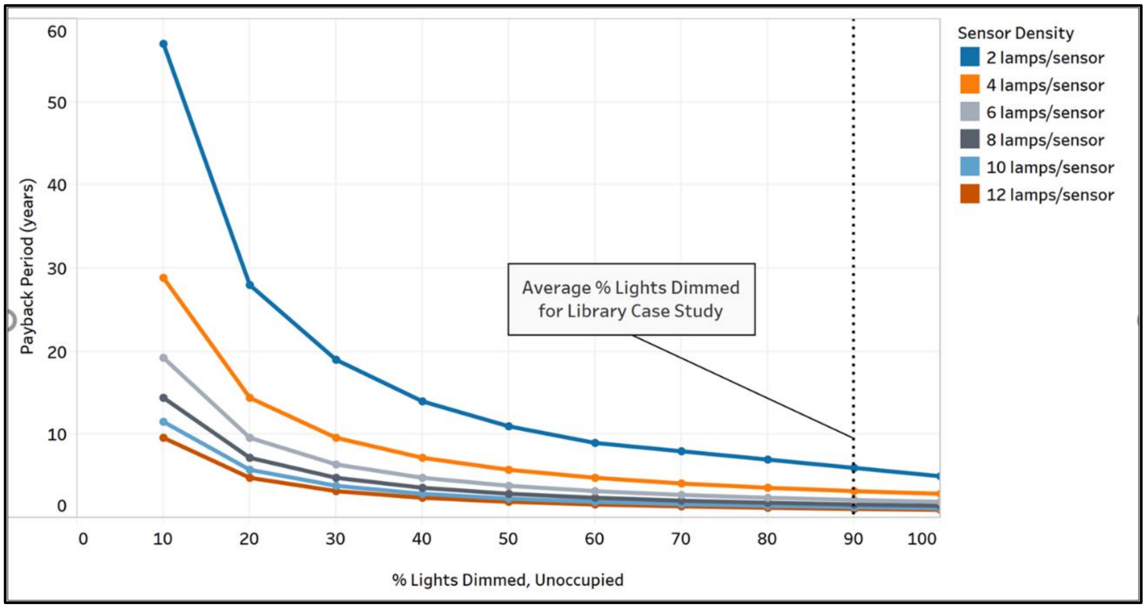


Figure 3.10: Effect of sensor density on the payback period for fluorescent lamps

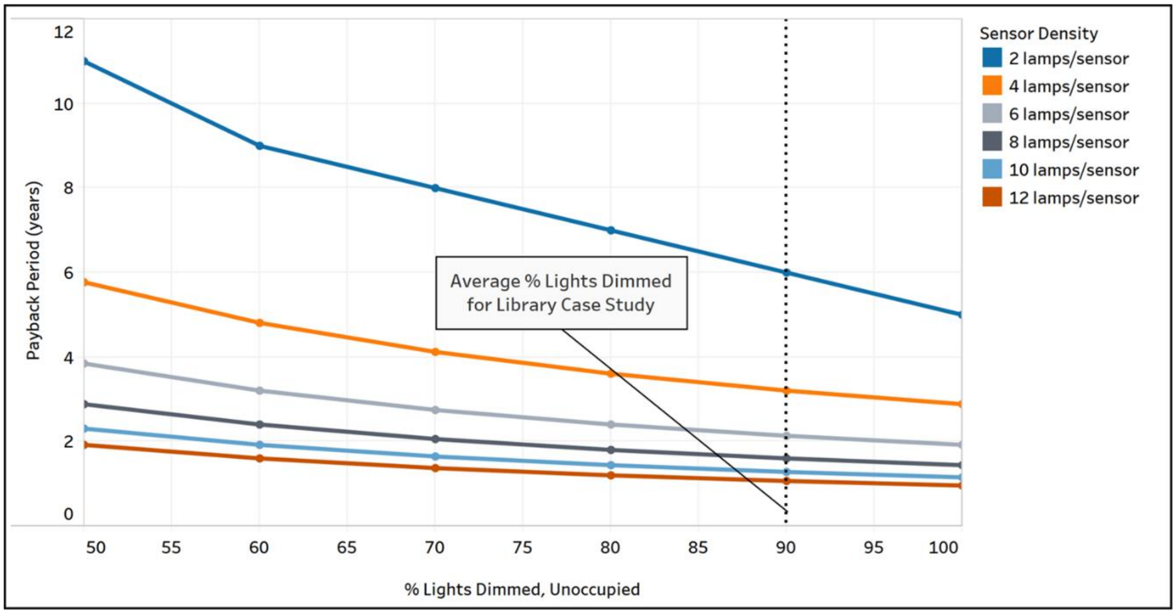


Figure 3.11: Effect of sensor density on the payback period: magnified view

A comparative study of payback periods for fluorescent and LED lamps was carried out. As discussed in the previous sections, LEDs are more energy-efficient and the energy savings are lower; their payback periods are significantly higher than fluorescent lamps.

Figures 3.12 and 3.13 show the similar relationship between payback period, sensor density and percentage lights in the dimmed condition for LEDs. The estimated payback period for a case equivalent to the Texas A&M campus library is 3 years, indicated by a sensor density of 10 lamps per sensor and a percentage of lights in the dimmed condition equal to 90%. Then, in such a scenario, it would be worth implementing occupancy-controlled lighting with dimming for LED lamps.

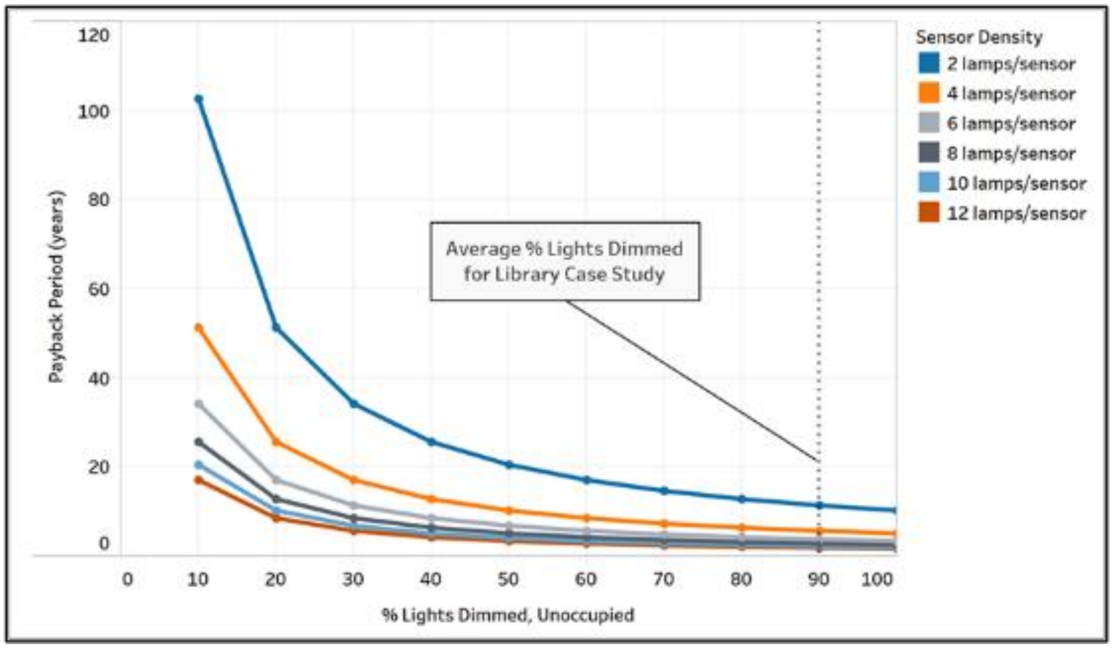


Figure 3.12: Effect of sensor density on the payback period for LED lamps

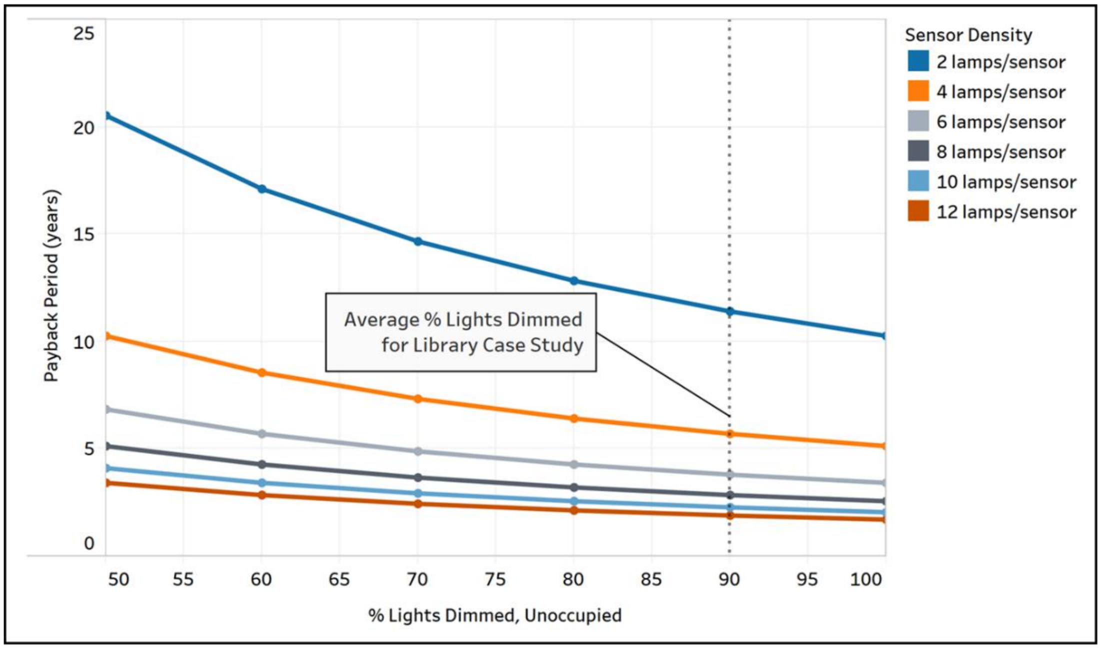


Figure 3.13: Effect of sensor density on the payback period for LED lamps: magnified view

3.2.7 Effect of Lamp Wattage on Annual Energy Savings

The effect of several factors such as delay time setting, occupancy percentage, and sensor density on energy savings was analyzed in the previous sections. This section evaluates the effect of lamp wattage on energy savings.

Figure 3.14 denotes the annual energy savings per sensor, which increases linearly as the lamp wattage increases. Equation 1 on Page 33 demonstrates the linear relationship between the energy consumed by a lamp and its wattage. The dotted reference line highlighted in the figure depicts the present case for 32 W lamps.

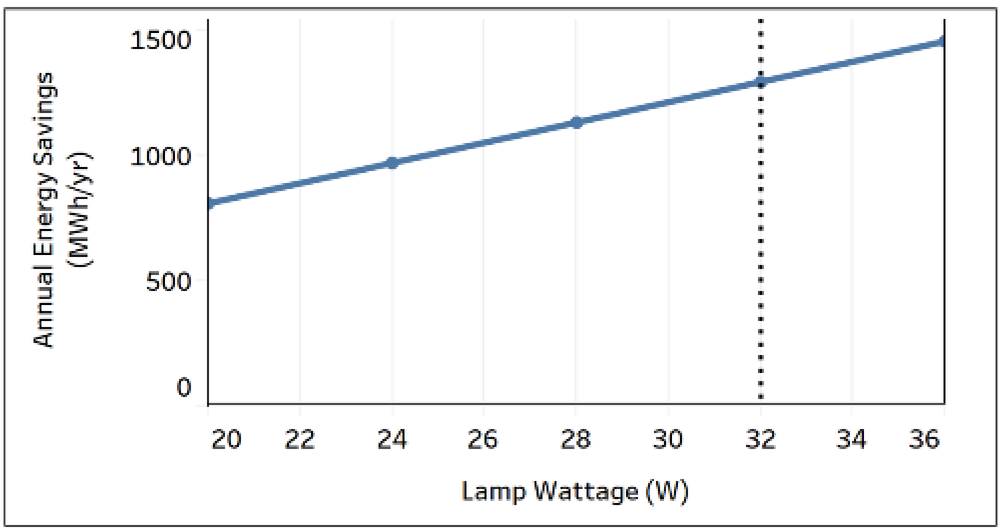


Figure 3.14: Impact of lamp wattage on energy savings

3.2.8 Relationship between Checkout Frequency and Percentage Occupancy

The location of occupancy sensors also affects energy savings. Conducting a preliminary study of occupancy and checkout frequency is important in deciding the locations of sensors. This section validates the relationship between annual checkout frequency of books and the percentage occupancy of corresponding aisles. Here, the checkout frequency denotes the number of instances a book is checked out from the respective library stack.

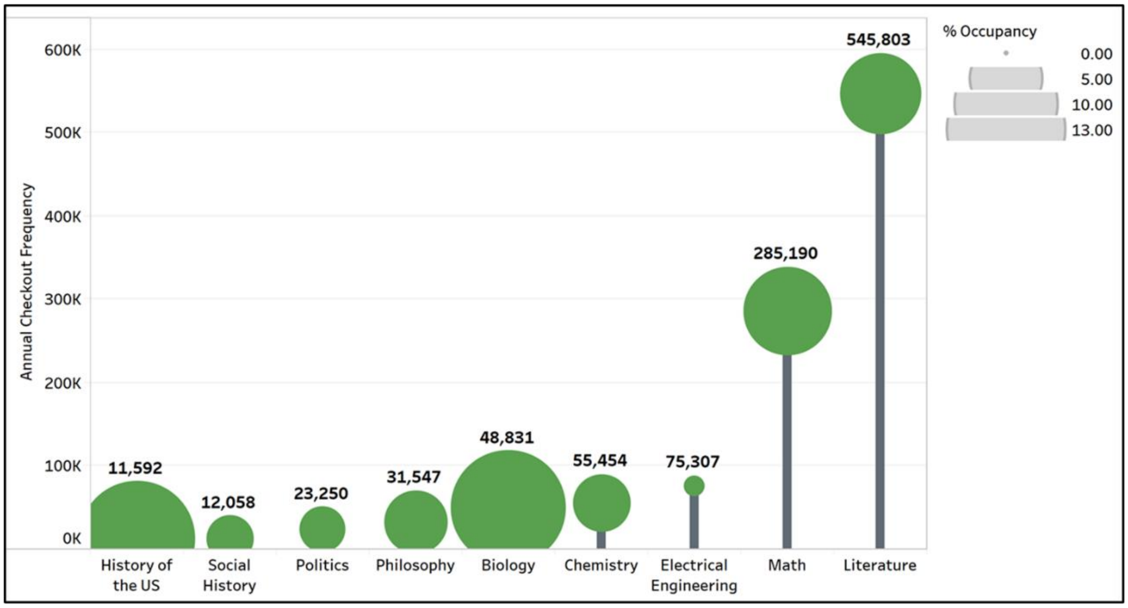


Figure 3.15: Relationship between check out frequency and percentage occupancy

3.3 Conclusions

This research has analyzed the occupancy and lighting usage patterns. The following conclusions and recommendations can be drawn from the analysis of energy cost-saving potential and energy economics of occupancy-controlled lighting.

University library buildings are characterized by their unique occupancy patterns. They are typically characterized by minimal occupancy for most of the time and spikes during the beginning and end of working shifts. The data analysis showed that most areas of the library were unoccupied 95% of the time, and students typically visited the library on weekends.

Lighting in the library were recorded to be in the dimmed condition for 90% of the time. This category of lighting usage helps in garnering information about wasted energy and potential energy savings. The results of this study highlight the fact that understanding the occupancy and lighting usage pattern is important in estimating the energy consumption of the building.

The delay time setting of lamps has a significant impact on energy savings. Significant energy savings could be obtained by minimizing the delay time and turning the lamps off instead of dimming for unoccupied periods.

Optimizing the delay time setting of sensors is correlated with striking a balance between energy savings, occupant satisfaction, and the lifetime of lamps. For achieving greater energy savings, it is advised to start with a 10-minute time delay and adjust depending upon the feedback from the users.

The frequent switching of fluorescent lamps due to lower delay time settings calls for an increase in re-lamping costs and a decrease in lamp life. However, these associated replacement costs are significantly lower than the accrued energy savings. Thus, the occupancy sensors reduce overall costs and provide cost-effective lighting control.

The sensor density, percentage of time for which lamps in the dimmed condition, and the type of lighting affect the energy economics of the retrofit significantly. A comparative study of payback periods illustrates that the installation of occupancy sensors is more economically viable for fluorescent lamps if compared to LEDs. The payback period for the Texas A&M campus library case study is about 2 years, for a sensor density of 10 lamps per sensor and percentage of lights in dimmed condition equal to 90%. The payback period for an equivalent case of LEDs is 3 years. Also, the increase in the payback period is steep for dimming percentages of less than 50%.

The study of checkout frequencies may not be a good idea while deciding about the deployment of sensors in different sections of the library. The sensors can be deployed based on the occupancy percentages of the library stacks or by conducting a preliminary study.

4. LIGHTING ENERGY ASSESSMENTS USING AN AUTOMATED DEVICE

This chapter of the thesis describes the concept and the benefits of autonomous lighting energy assessments. Automated energy assessments would augment the manual auditing process and eliminate simple, time-consuming tasks, and provide additional depth of analysis. This chapter will begin by describing a selected automated device and will focus primarily on the optical spectrometer, a particular sensor on the device which is used for identification of light type.

4.1 Concept and Need of Autonomous Lighting Energy Assessments

Energy saving measures regarding lighting are one of the most common recommendations given in an energy assessment. A typical lighting energy audit in a building consists of counting the number of lights, identifying the lamp type, and analyzing the lighting intensity profile. As the nature of these steps is simple and repetitive, there is a huge scope for automating these tasks. Bay, Terrill and Rasmussen have proposed the concept of autonomous energy assessments to reduce the cost and improve the effectiveness of audits [16,17]. These autonomous audits will be performed using a handheld device, or a robot, consisting of different sensors such as a range finder for measuring the ceiling heights, a spectrometer for capturing the light intensities, a camera for capturing the images of lamps, etc. The data and measurements will be collected in real time as the device or robot navigates the environment. From this data, many of the typical recommendations such as reducing the number of lighting fixtures, upgrading the lighting, and installing the occupancy sensors can be made.

In addition, the quality of analysis and accuracy of the results in conventional audits can vary greatly based on the experience of the auditors. Conversely, automated energy audits can add depth to the analysis by importing the data collected by different sensors into an energy simulation software and using it to create a light intensity profile of the building. Data collected continuously provide greater data resolution and detailed maps of the environment versus single point measurements taken manually by an auditor.

Autonomous audits would also reduce the overall costs mainly due to the savings in labor time achieved by automating the measurement and data collection procedures. The automated audits can also help save the training costs of the personnel as the tasks can be completed using fewer trained individuals.

The benefits associated with automation of energy assessments are enormous. The successful implementation of these assessments will increase the number of buildings receiving an energy audit. This translates into the significant energy and demand savings as well as decreased operating costs of facilities.

4.2 Design and Working of an Automated Device

The handheld automated device performs the functions of localization, data collection and identification of lamp type. Following section discusses the functions of the individual sensors in the package. A LiDAR sensor, which stands for Light Detection and Ranging Systems, is used to compute the distances to surrounding objects with the help of spinning or scanning laser beams. The odometry sensors are used to measure the changes in its own position and acceleration. This sensor is used to navigate the environments in real time. For localization of lighting, the distance to the ceiling plane is also required. The range finder is used to compute this distance from device to the ceiling. The data regarding the thermal conditions of the building space is collected using temperature, humidity, and CO_2 sensors. The spectrometer sensor along with the collimating lens is used to measure the light intensities and wavelengths. Refer Figure 4.1 for a picture of selected automated device.

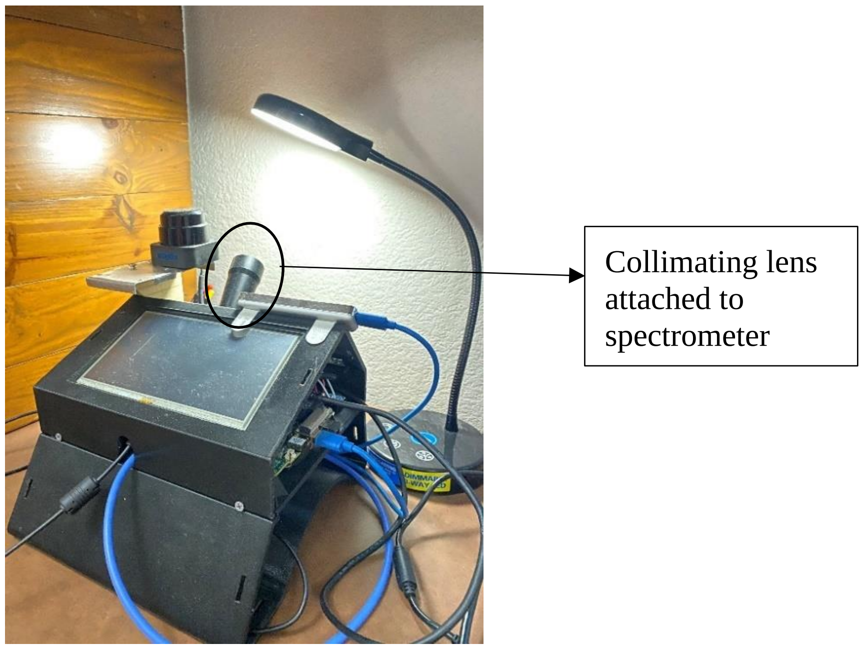


Figure 4.1: Photo of selected automated handheld device
(Designed and manufactured by Marcus Thackeray, 2020)

All the sensors and packages communicate through the Robotic Operating System (ROS) architecture. ROS is a collection of tools, libraries and conventions which aim to simplify the complex tasks. These systems consist of several small programs that connect to one another and continuously exchange messages. Each package or sensor corresponds to a node and the nodes communicate through structures called topics. This is the high-level introduction of ROS and its applications in this automated device.

4.3 Overview of Working and Functions of Optical Spectrometer

Identification of light type is necessary to calculate current energy consumption and make accurate estimations on potential energy savings for different lighting recommendations. In determining the lamp type, an optical spectrometer can be used to measure the light intensities across the spectrum of wavelengths. Each light type is characterized by a distinct spectrum, which can be used for identification and further analysis. For example, a fluorescent tube has a characteristic optical spectrum of sharp spikes at certain wavelengths, whereas a spectrum of an LED is a continuous curve with two peaks.

Optical spectrometers work on the principle of refraction of light, which allow measuring light intensities per wavelength. This can be visualized as a spectral distribution. A typical spectrometer consists of three main components: entrance slit, diffraction grating and detector. The first step in the process is to direct the light through a fiber optic cable into a spectrometer through a narrow aperture known as the entrance slit. The size of the entrance slit determines the amount of light that can be measured by the sensor. The grating acts as a dispersive element which splits the incoming light into its distinct wavelengths. Diffraction gratings of different sizes are used to analyze optical spectra with different wavelength ranges. The detector measures the intensities of light per wavelength and gives a spectral distribution.

Optical spectrometers can be classified by their wavelength ranges. A UV spectrometer measures light in the range between 200 – 400 nm. A VIS spectrometer measures light in the visible region of the spectrometer, i.e. the wavelength range between 400 nm - 700 nm. The wavelength range for an IR spectrometer is from 700 nm to 1 mm. This research focuses on experimentation using a spectrometer in the VIS-IR wavelength range.

4.4 Lighting Identification and Analysis using Spectral Curves

Elvidge, Keith, Tuttle and Baugh described the characteristics of spectra for different lamp types [18]. The results are summarized below.

4.4.1 Spectral Characteristics of the Lamps

a) Incandescent Lamps:

An incandescent lamp has a tungsten filament inside a glass bulb that contains either a vacuum or an inert gas which prevents the oxidation of the hot filament. An electric current passes through the filament, heating it to a temperature that produces light. Figure 4.2 indicates the emission spectrum of a typical incandescent lamp which resembles a blackbody shape. The peak intensities occur at wavelengths between 900 nm to 1,050 nm.

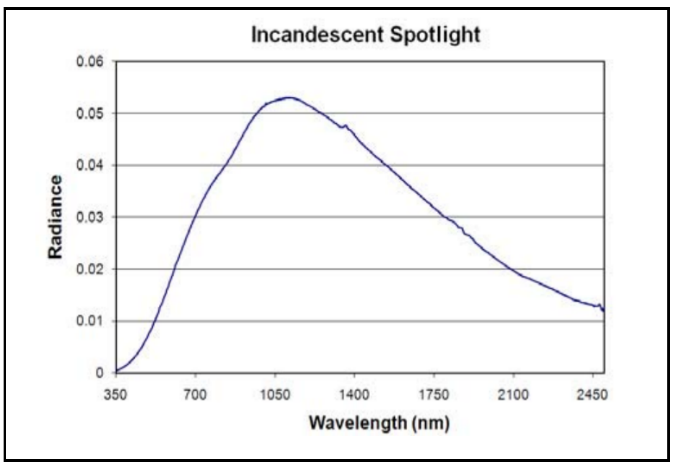


Figure 4.2: Emission spectrum of incandescent light

b) Halogen lamps:

A halogen lamp is an incandescent lamp, which consists of a tungsten filament sealed in a glass enclosure that is filled with a mixture of inert gas and a small amount of halogen. The addition of the halogen promotes a redeposition of tungsten on the filament, which increases the lamp life. Figure 4.3 indicates a spectrum for a typical halogen lamp, which resembles the spectral curve of an incandescent lamp with minimal or low characteristic features that could distinguish between the two lamp types.

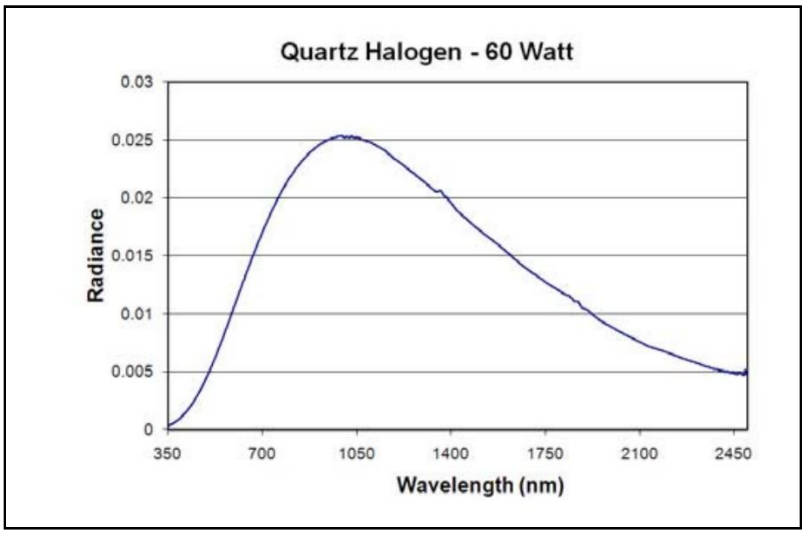


Figure 4.3: Emission spectrum of halogen lamp

c) Compact Fluorescent Lamps:

A compact fluorescent lamp is a low-pressure gas discharge lamp that generates light by phosphors excited by UV emissions. The glass tube is filled with a mixture of low-pressure mercury vapor and inert gases. Figure 4.4 shows the spectral curve for a typical fluorescent lamp. The fluorescent lamp spectra consist of a set of sharp emission lines with two primary peaks at 544 nm and 611 nm. The light intensities decay out after the wavelength of 800 nm. Also, the spectrum for a fluorescent lamp is significantly different from the spectra of halogen and incandescent lamps.

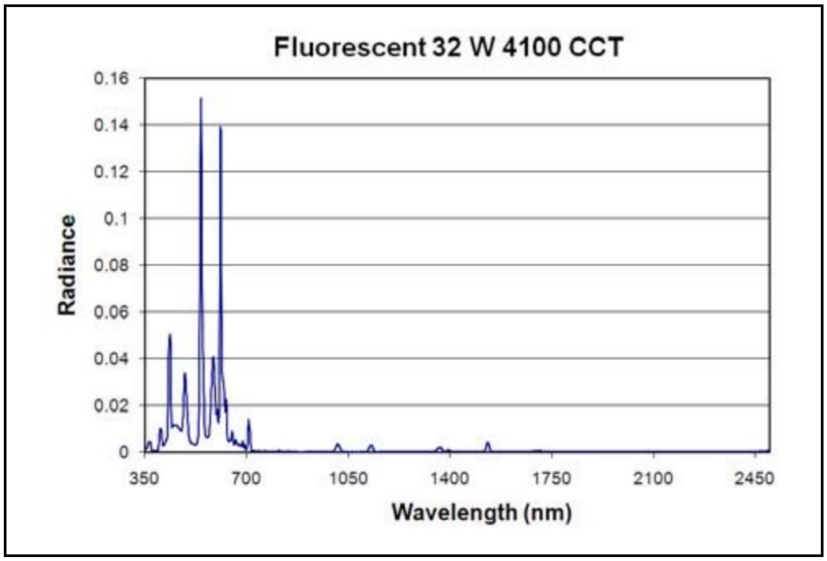


Figure 4.4: Emission spectrum of compact fluorescent lamp

e) Light Emitting Diodes (LEDs):

LEDs are the solid-state light sources that generate light by electroluminescence. The spectrum produced by an LED is a double peak continuous curve with a primary emission line around 450 nm and a second emission line around 600 nm. Unlike incandescent and halogen lamps, LEDs emit light over a very narrow range of wavelengths. All the emission occurs within the visible range, making LEDs the most energy efficient lamp type. Figure 4.5 indicates the spectrum for a typical LED. The location of peaks varies per type of LED, i.e. warm white, cool white and cool daylight.

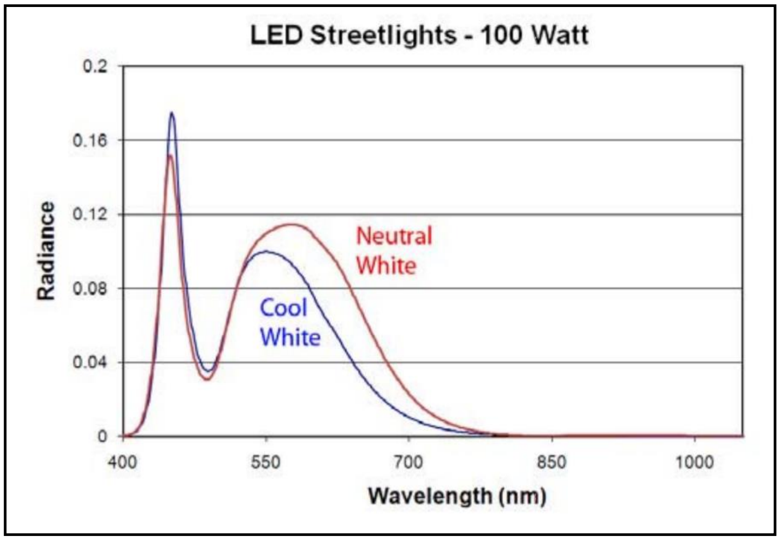


Figure 4.5: Emission spectrum of LED

f) Mercury Vapor Lamps:

The mercury vapor lamps are a type of high intensity discharge lamps which use an electric arc to excite mercury and produce light. This type of lamp produces a substantial quantity of heat, and the emission spectrum is a combination of incandescent and fluorescent spectra. The spectrum resembles a black body shape like the incandescent lamp and has sharp emission lines like the fluorescent lamp. Refer to Figure 4.6.

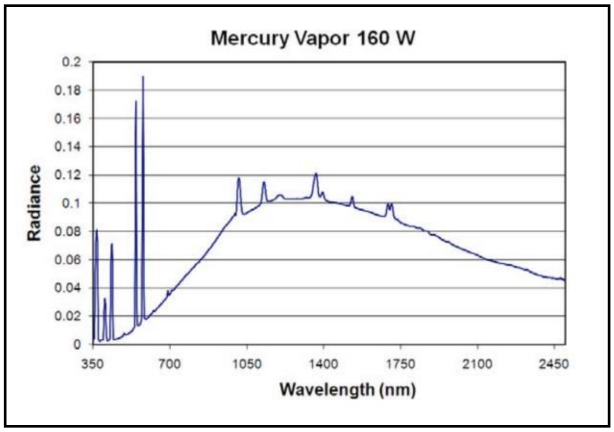


Figure 4.6: Emission spectrum of mercury vapor lamp

d) Metal Halides:

These high intensity discharge lamps (HIDs) are similar to mercury vapor lamps, but the spectra are improved by mixing metal halides into the mercury vapor. Figure 4.7 demonstrates a spectral curve for a typical metal halide, which consists of sharp emission lines at certain wavelengths. The composition of halides present determines the location and intensity of peak emissions.

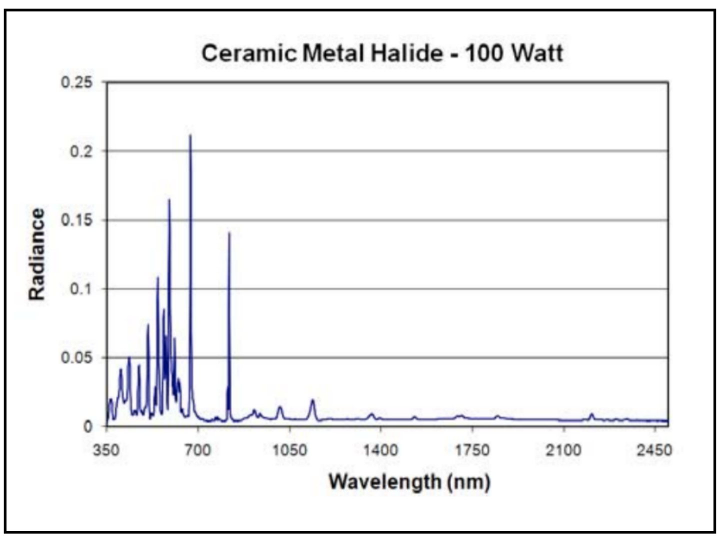


Figure 4.7: Emission spectrum of metal halide

g) High Pressure Sodium Lamps (HPS):

High Intensity Discharge lamps (HIDs) contains a sodium-mercury amalgam and trace quantities of inert gas. These types of high-pressure sodium lamps produce a characteristic golden-orange light. The spectrum has sharp emission lines at certain wavelengths and the strongest emission line of the spectrum is at 819 nm. This emission line is also present in the spectrum produced by the metal halide. Refer to Figure 4.8.

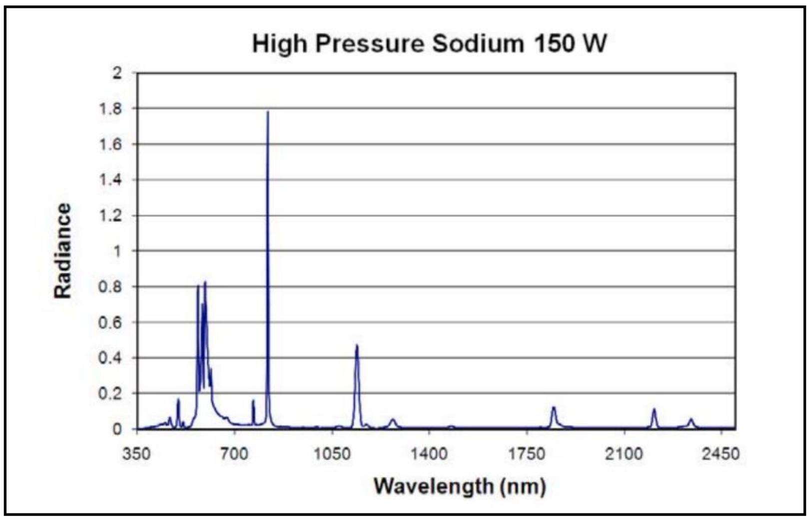


Figure 4.8: Emission spectrum of High-Pressure Sodium lamp (HPS)

4.4.2 Normalization of Spectral Curves

Normalization is a technique used to scale the data of an attribute to a range between 0 to 1. It is an important step before application of any classification algorithm to the data sets as normalizing data brings all the attributes on the same scale. This helps to compare features of the data points and identify trends. As discussed in the earlier section, the magnitude of lighting intensities varies with the lamp types, wattages of lamps and distances of measurements. This highlights the importance of normalizing the spectral data to determine the lighting type accurately.

The different techniques of normalizing data are discussed below.

a) **Peak normalization:**

In this technique, each read in the data is divided by the maximum absolute read of the data. Terrill, Bay and Rasmussen normalized the light spectrum using the peak intensity among all the wavelengths [17]. Following are the example peak normalized spectral curves used for classification by the authors.

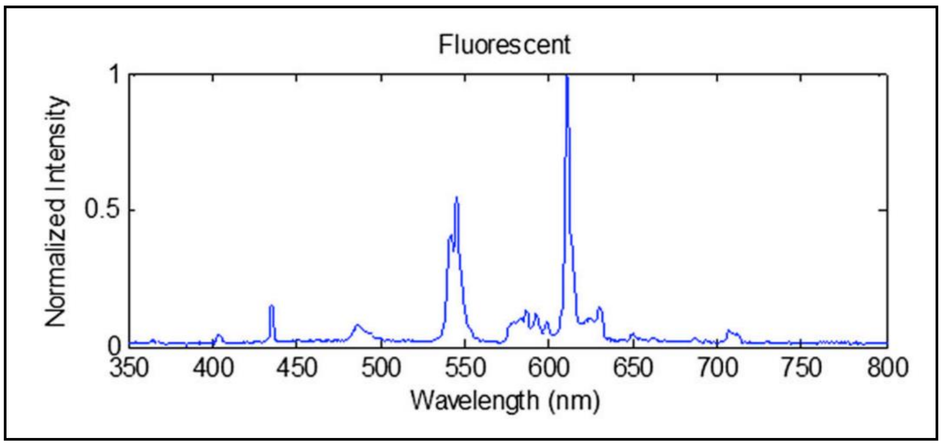


Figure 4.9: Peak normalized spectrum for fluorescent lamp

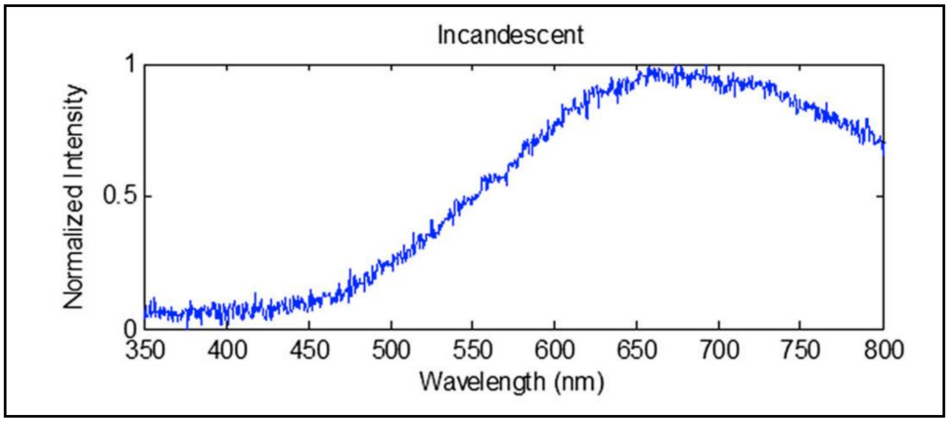


Figure 4.10: Peak normalized spectrum for incandescent lamp

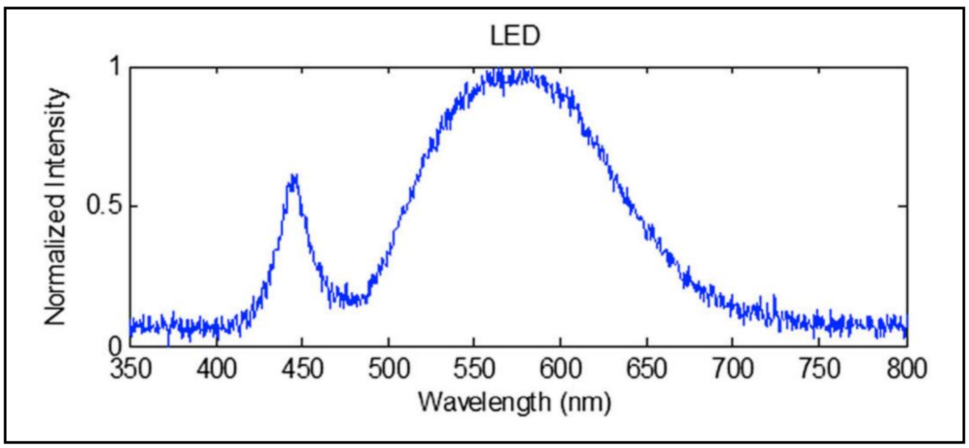


Figure 4.11: Peak normalized spectrum for LED lamp

One of the major drawbacks of using this normalization technique is that there is a possibility of missing the actual peak in cases of a smaller number of reads. This could falsify the reads of normalized intensities and thereby lead to an inaccurate classification of lamp types.

b) Min-max normalization:

In the min-max normalization technique, the minimum value of a feature gets transformed into a value of 0 and the maximum value of a feature gets transformed to a value of 1. Every other value gets transformed into a decimal value between 0 and 1. However, the limitation of using min-max normalization is that it does not handle the outliers in the data sets very well.

c) **Area normalization:**

In the area normalization technique, the reads of the data are divided by the total area under the curve. This is like peak normalization but instead of dividing the reads by peak intensity, one divides by the total area under the curve. The area can be computed by estimating the area of a triangle or by integrating the area under the curve piecewise.

4.4.3 Classification of Spectral Curves

There are multiple ways of comparing the characteristics of spectral curves and classifying them. Elvidge, Keith et. al. analyzed the spectra using the discriminant analysis available in the JMP statistical package [18]. The discriminant analysis technique is used to find a linear combination of features that characterizes the two or more classes. The results indicated that there were zero errors in the analysis of 43 different spectra of several light types.

Bay et. al. classified the spectra using the root-mean-squared (RMS) error approach [17]. The normalized spectrum is compared with the reference spectrum for different lighting types by computing the Euclidean distance between them. The light type is identified using the closest match between the reference and measured spectra based on the RMS error values. The authors conducted a total of 20 tests for each of the lighting types for distances between 1.5 m to 5 m. The results indicated that the classification algorithm correctly classified the lighting in 97% of the instances.

The next chapter discusses the specific classification algorithm that was used for identifying the lamp types in this research.

5. RESULTS: LIGHT TYPE DETECTION USING SPECTROMETER

This chapter of the thesis begins by discussing the specific methodology used for the classification of spectral curves and identification of lamp type. This chapter analyzes the impact of parameters such as distance from lamp, directionality, wattage of lamp and integration time settings of the spectrometer on the light intensity counts. The classification algorithm of identification of lamp type was tested at several types of buildings. A detailed discussion of the test results and remarks is then presented.

5.1 Methodology and Discussion of CVRMSE Algorithm for Classification

The primary goal of this research is to identify the type of lamp based on the spectral curves. Oceanoptics make USB 2000+ spectrometer was used to record the spectral data. A collimating lens and a fiber optic cable was also used along with the spectrometer to collect the spectral data. Initially, testing was done on several different types of lamps using this spectrometer and the reference spectral curves for each type were created. The recorded spectral data was made scale independent using the area normalization technique. Refer to Figures 5.1 and 5.2 for the normalized reference spectra for different types of lamps.

The primary logic behind classification is the comparison of characteristics of reference and measured spectral curves. The light type is identified using the closest match based on cumulative root-mean-squared error values (CVRMSE). This metric is normally used to illustrate how well the simulated or measured data points agree with the baseline. In addition, as this metric normalizes the data, it eliminates the dependency

RMSE has on the scale of the data. The equation 10 is used to compute the CVRMSE values.

$$C_V = \frac{\sqrt{\sum(s-r)^2}}{r/n} \qquad \text{(Equation 10)}$$

In the Robotic Operating Systems (ROS) framework of the selected automated device, two separate nodes were created. One was for recording and normalizing the light intensity counts and the other one was for comparing the measured and reference spectra for classification. Refer to the Appendix for the python scripts of both the ROS nodes.

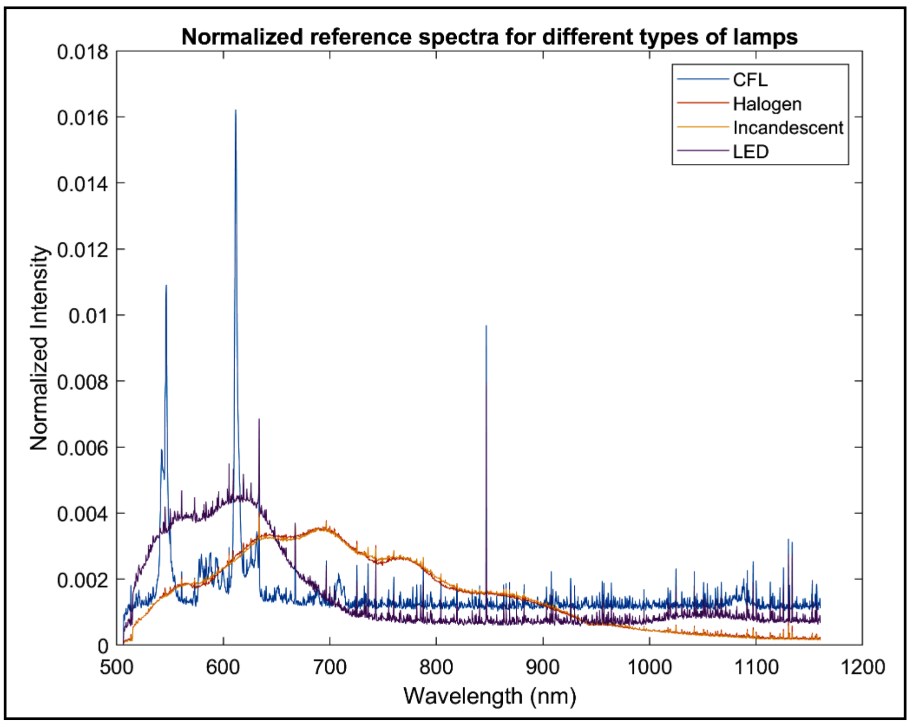


Figure 5.1: Normalized reference spectra for CFL, Halogen, Incandescent and LEDs

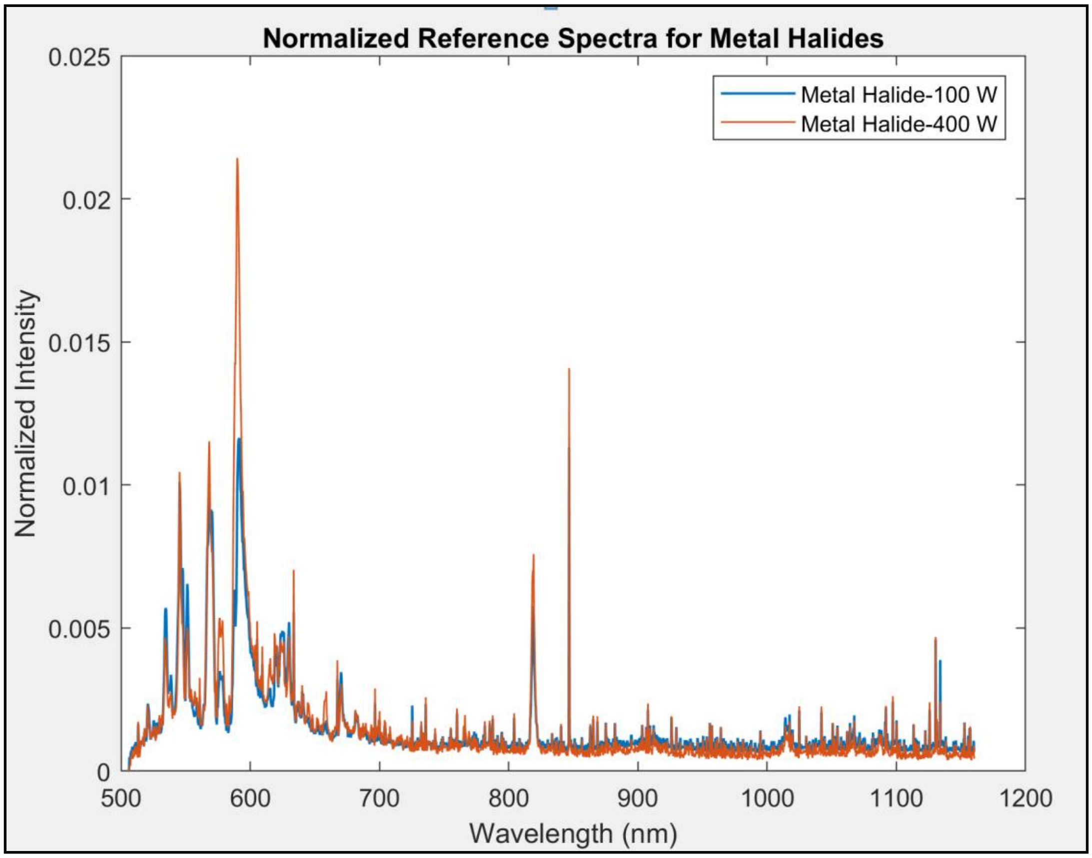


Figure 5.2: Normalized Spectrum for Metal Halides

5.2 Results: Factors Affecting Lighting Intensity and Classification Accuracy

Several parameters such as lamp type, lamp wattage, distance, directionality, and integration time settings of the spectrometer affect the intensity counts. This section of the chapter identifies and quantifies the effect of these parameters on light intensity counts and classification accuracy. The research also describes the impact of ambient light on light intensities and classification accuracy.

5.2.1 Effect of Distance and Directionality

Light intensity is a function of distance from the source and directionality. Here, directionality refers to the orientation of how the sensor is held with respect to the lighting fixture. The inverse square law describes that the intensity of light is inversely proportional to the square of the distances. Testing of the spectrometer was carried out at different distances from the source. The sensor was held at 25, 30, and 35 inches from the compact fluorescent lamps and LEDs. Refer to Figures 5.3 and 5.4. In accordance with the inverse square law, the light intensities were expected to drop significantly with increasing distances. However, as the orientation of the spectrometer is at an angle with respect to the horizontal and not vertical, the intensities do not follow the inverse square law of distances. That is why an increase in the light intensities can be seen despite increasing distances from 25 to 30 inches for an LED. More light enters the sensor if it is directly pointed at the lamp and thus high intensity counts are recorded in that case.

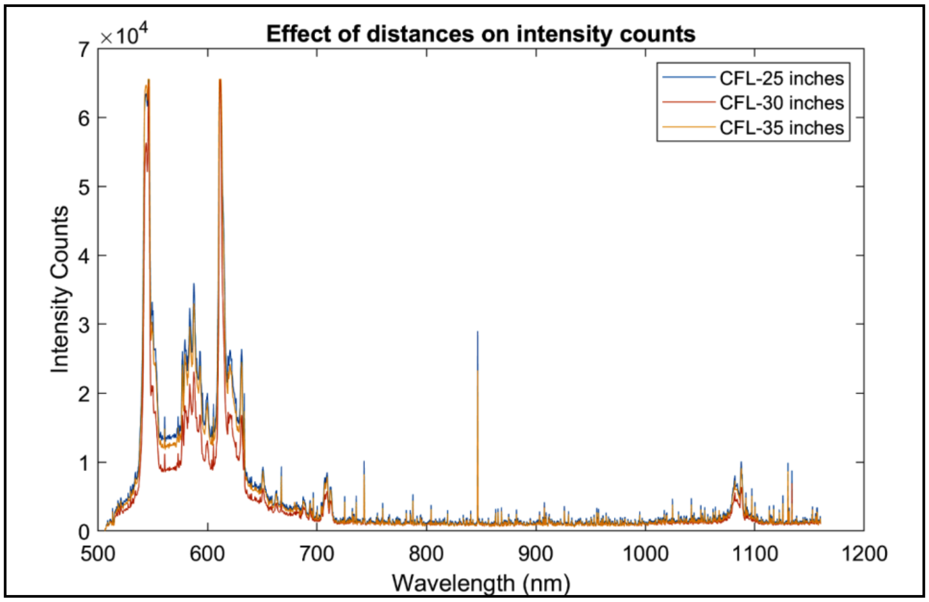


Figure 5.3: Impact of distances from source on intensity counts (CFL)

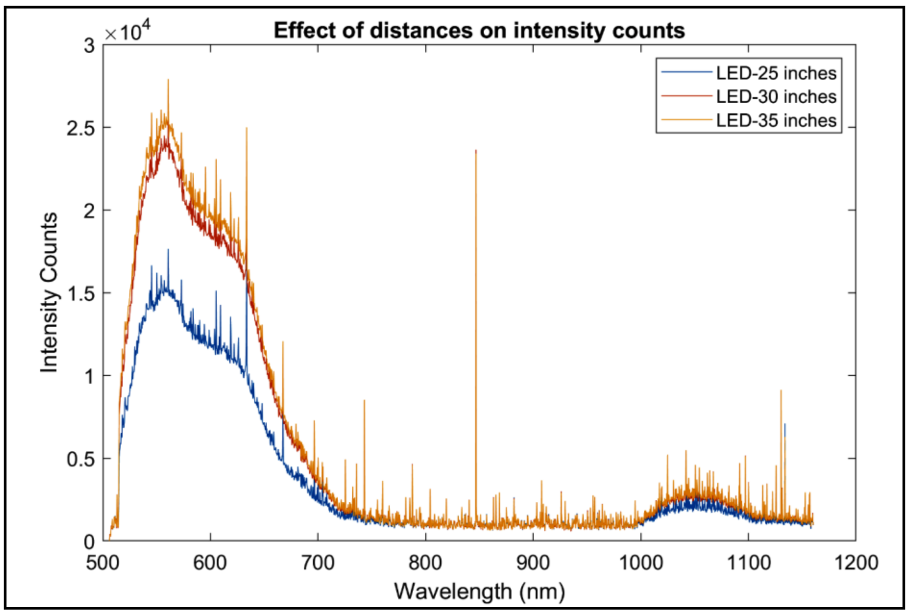


Figure 5.4: Impact of distances from source on intensity counts (LED)

The amount of light that enters the sensor, and thus the light intensities, also depend on the directionality or the orientation. Since the spectrometer is at an angle with respect to the horizontal, the directionality has a significant impact on the readings.

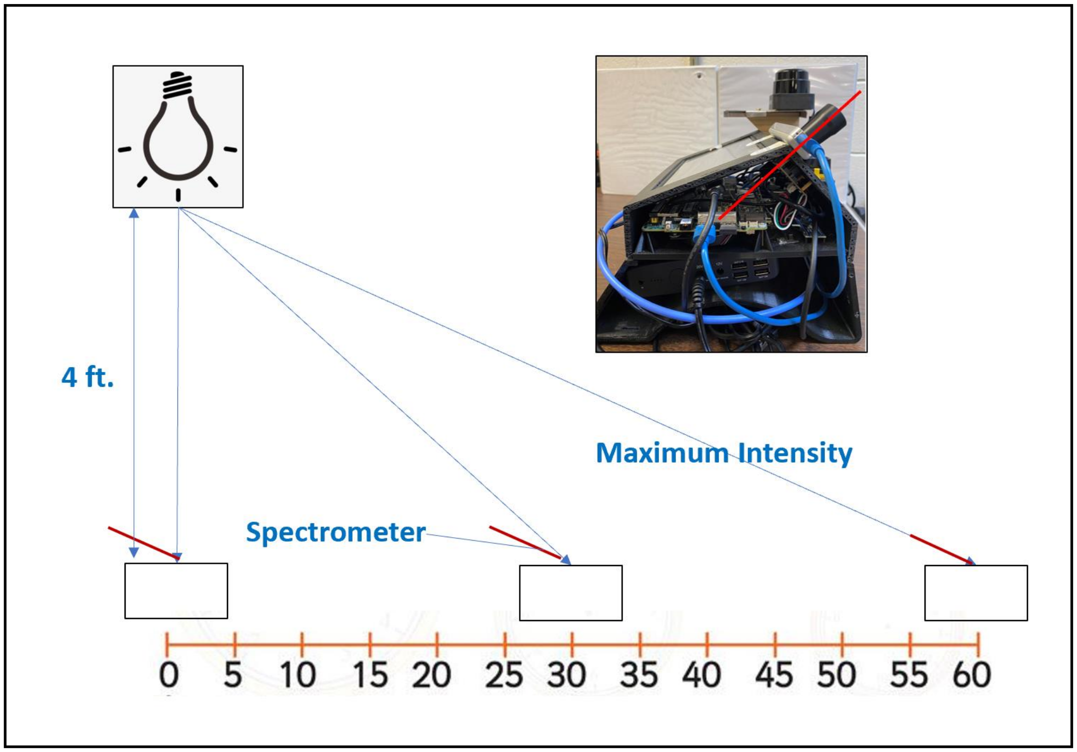


Figure 5.5: Controlled setup for understanding impact of directionality on intensities

Figure 5.5 illustrates the control setup for understanding the impact of directionality on the light intensities. Here, 0, 30 and 60 denote the horizontal distances from the center of the lighting fixture in inches. The testing was carried out at a 4 ft. vertical distance from the source for LED and CFL tubes. The spectral plots for both the lamp types are shown in Figures 5.6 and 5.7. The intensities at the 60-inch distance were recorded the highest. Since the spectrometer is at an angle with respect to the horizontal, more light enters the sensor when the horizontal distance is 60 inches compared to 0 and 30 inches. Thus, while conducting experiments at several types of buildings, the tests were conducted at a horizontal distance of 60 inches.

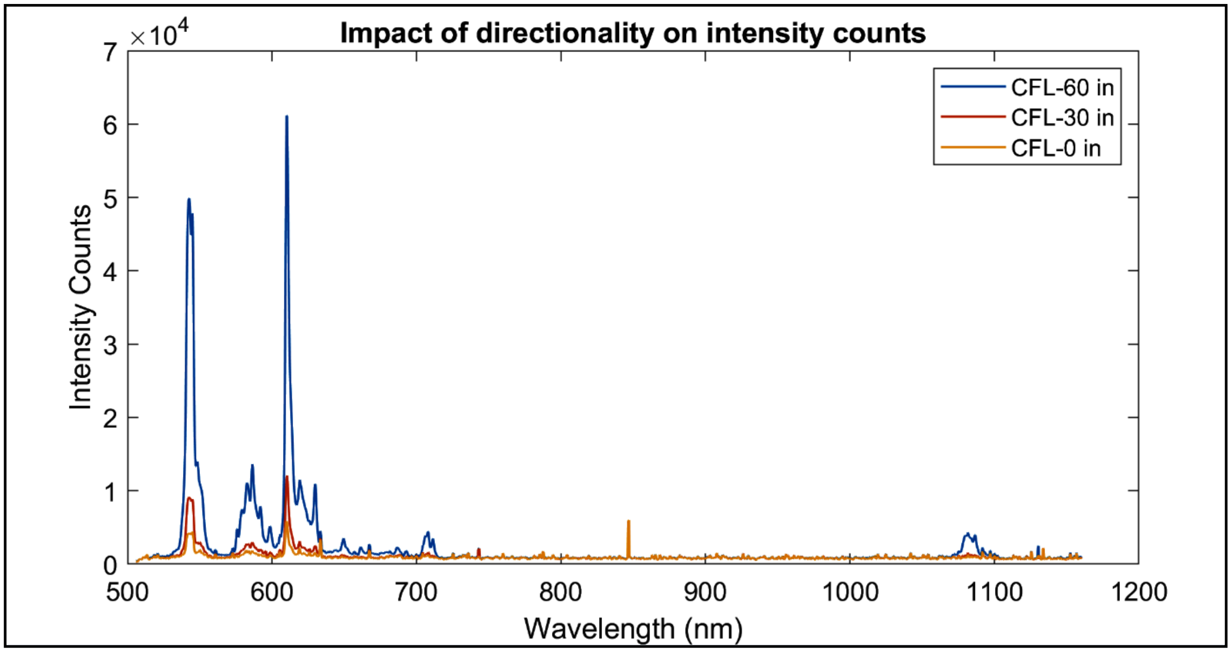


Figure 5.6: Effect of directionality on intensity counts and spectra: CFL

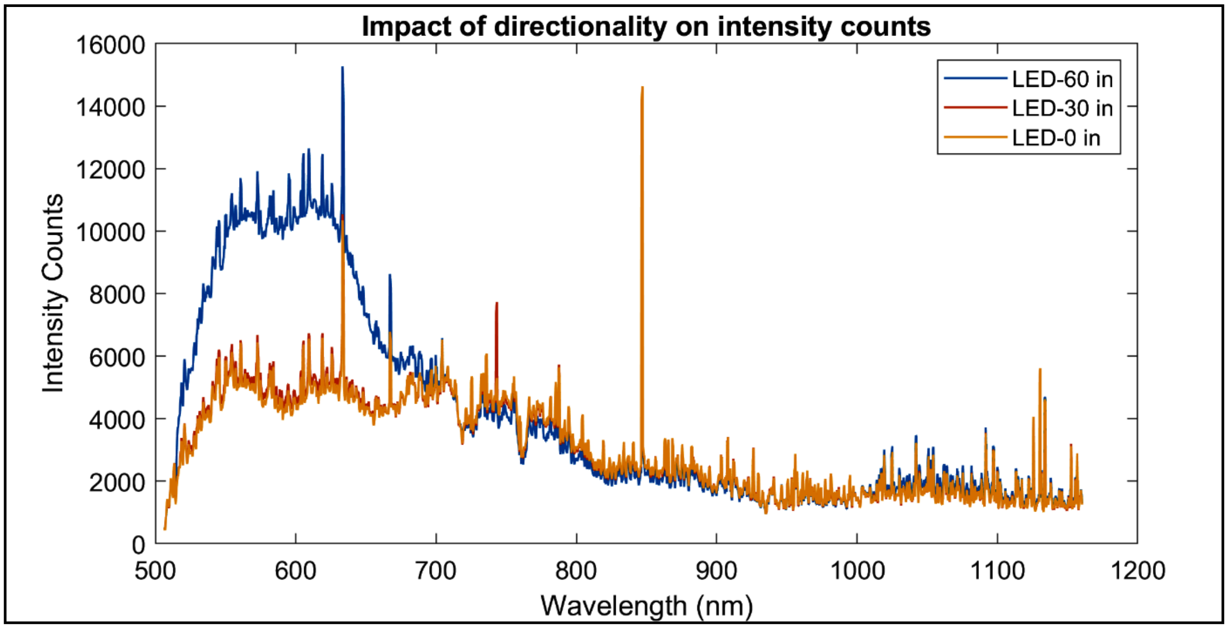


Figure 5.7: Effect of directionality on intensity counts: LEDs

5.2.2 Impact of Integration time

The integration time, or exposure time, is the amount of time that the detector is exposed to light. This is analogous to the shutter speed of a camera. The integration time setting for the Oceanoptics make USB 2000+ spectrometer ranges between 10 micro-seconds to 65 seconds [19]. A higher integration time setting would mean more light entering the aperture of sensor. However, using a high integration time causes the intensity readings to become jumpy and oversaturated. If the reads exceed the ‘saturated’ value of 65,334 intensity counts, analyzing the spectral curves and classifying them would become difficult. Thus, the selection of optimum integration time is important in recording the light intensities and accurate classification of light type.

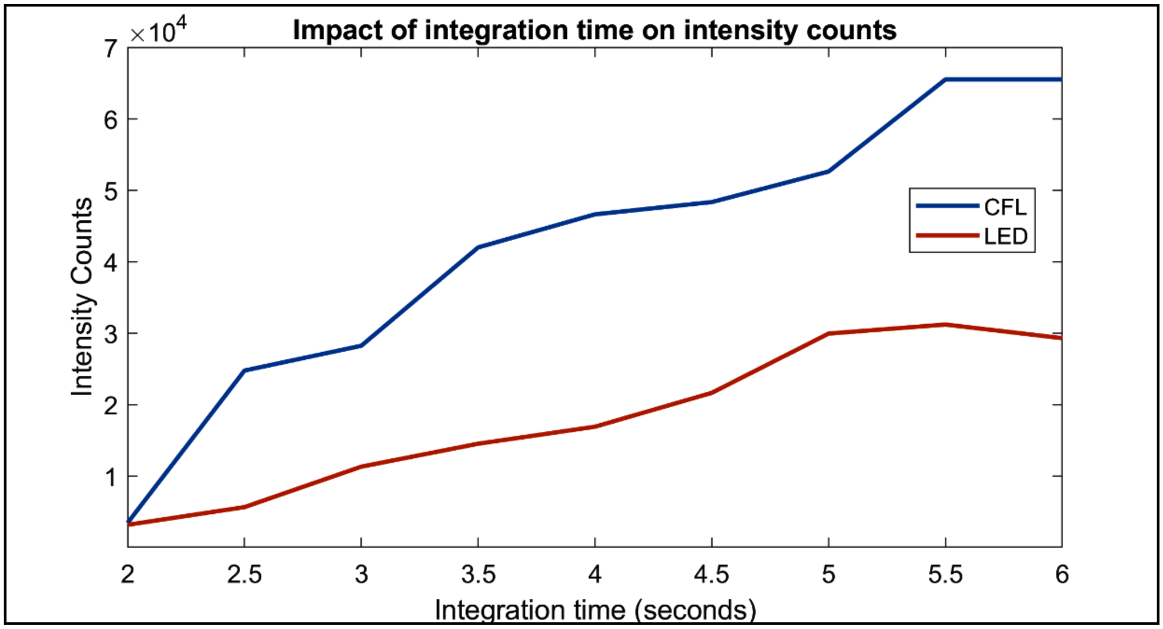


Figure 5.8: Impact of integration time on intensities of LED and CFL

Figure 5.8 illustrates the impact of the integration time setting on the intensities of LED and CFL. The intensity counts increase up to a certain value with an increase in the integration time setting for both the lamp types. The rate of increase in the intensity counts is lower for an LED than compared to a CFL. As illustrated in the figure above, the intensities saturate for an integration time of 5.5 seconds for CFL. Thus, an optimum integration time of 5 seconds was selected for the experimentation.

5.2.3 Effect of Wattage

The wattage of a lamp is the amount of energy it takes to produce a certain amount of light. The higher the wattage, the brighter the light. The effect of lamp wattage on the light intensity counts was studied. Refer to Figures 5.9 and 5.10. The intensity counts increase with increasing lamp wattage. The overall characteristics of the spectral curves remain the same. However, the spectral curves become identical after area normalizing the raw intensity counts. This also highlights the significance of normalizing the data before comparison and analysis.

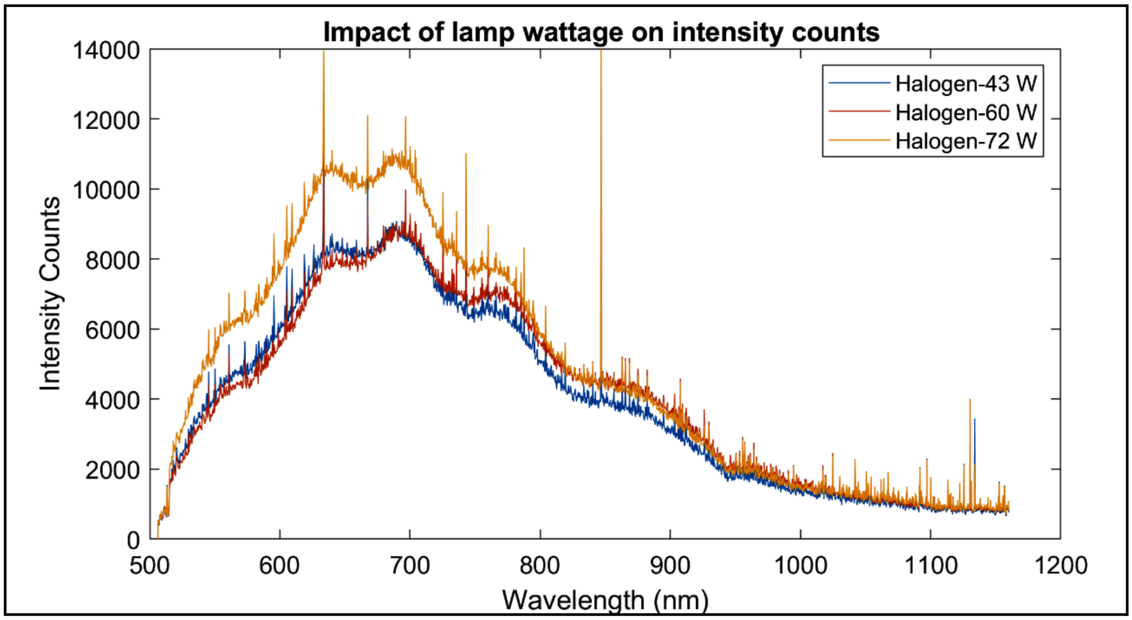


Figure 5.9: Impact of wattage on intensity counts (Halogen lamps)

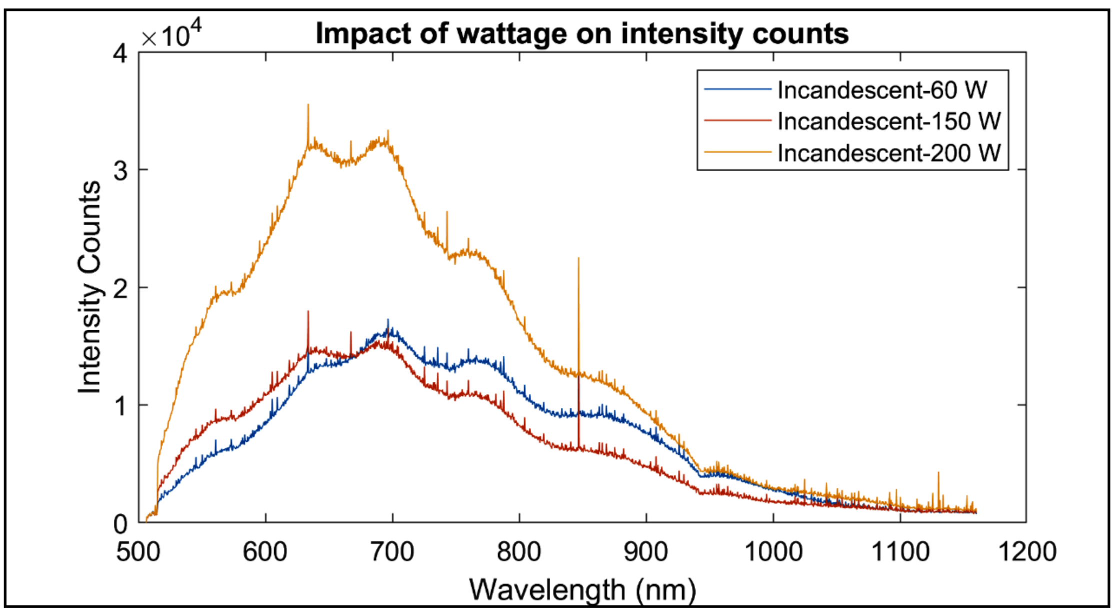


Figure 5.10: Impact of wattage on intensity counts (Incandescent lamps)

5.2.4 Effect of Ambient Light

One of the major challenges in the experimentation is to determine the lighting type accurately in the presence of ambient light. The ambient light could potentially interfere with the characteristic spectra of lights and thereby affect the classification accuracy. To understand the impact on light intensity and classification accuracy, the tests were carried in presence and absence of ambient light. Figure 5.11 indicates the spectral plots obtained at Fuzzy Tacos restaurant in College Station. Though the intensities drop in presence of ambient light, the classification algorithm can determine the lamp type correctly.

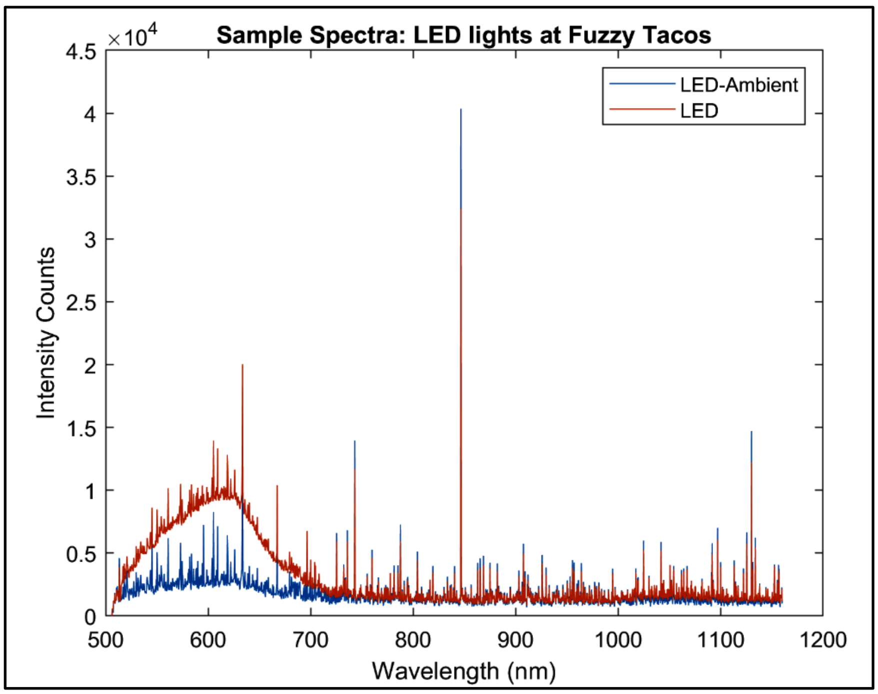


Figure 5.11: Effect of ambient light on classification accuracy

Figure 5.12: Testing in presence of ambient light from window

5.3 Results: Testing at Different Types of Buildings

The robustness of the classification algorithm was evaluated by conducting tests at several types of buildings such as academic, residential, and commercial buildings. The detailed discussion and remarks are presented below.

5.3.1 Testing at Blocker Building, Texas A&M University

- Location: Blocker Building, Department of Mathematics, Texas A&M University
- Type of building (Academic/Commercial/Residential/Religious): Academic
- Date and time of testing: 30th June, evening
- Presence of daylight (Yes/No): No
- Does the building have lighting of heterogeneous nature? (Yes/No): Yes

(LEDs on first floor, fluorescent tubes on second floor)

- Type of lighting: LED and Fluorescent
- Number of lamps tested: 20
- Classification accuracy: 19 out of 20 (The sensor was not able to detect signals from the high bay LED light which was at a 20 ft. distance)

- Photographs:

Figure 5.13: Representative LED tube (first floor)

Figure 5.14: Representative fluorescent tube (second floor)

Figure 5.15: Fluorescent lights (5 ft. height)

Figure 5.16: LED lights (5 ft. height)

- Sample Reference Spectra:

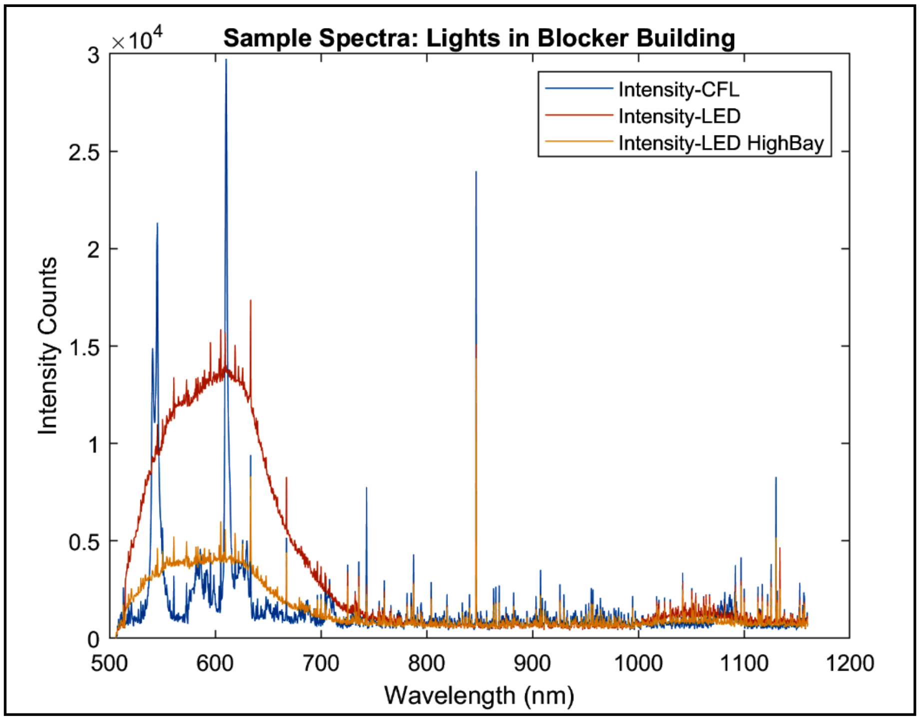


Figure 5.17: Fluorescent and LED lighting- Blocker Building

5.3.2 Testing at Evans Library, Texas A&M University

- Location: Evans library, Texas A&M University
- Type of building (Academic/Commercial/Residential/Religious/Other): Library
- Date and time of testing: 9th July, morning
- Presence of daylight (Yes/No): Yes
- Does the building have lighting of heterogeneous nature? (Yes/No): Yes
- Type of lighting: Fluorescent and LED
- Number of lamps tested: 40
- Classification accuracy: 40 out of 40
- Photographs:

Figure 5.18: Fluorescent lighting on first floor (presence of ambient light)

Figure 5.19: LED lighting on second floor: 5 ft. height

Figure 5.20: Fluorescent lighting on first floor: 12 ft. height

Figure 5.21: LED lighting in the aisles of third floor: 5 ft. height

Figure 5.22: Fluorescent lighting: 5 ft. height (presence of ambient light)

- Sample Reference Spectra:

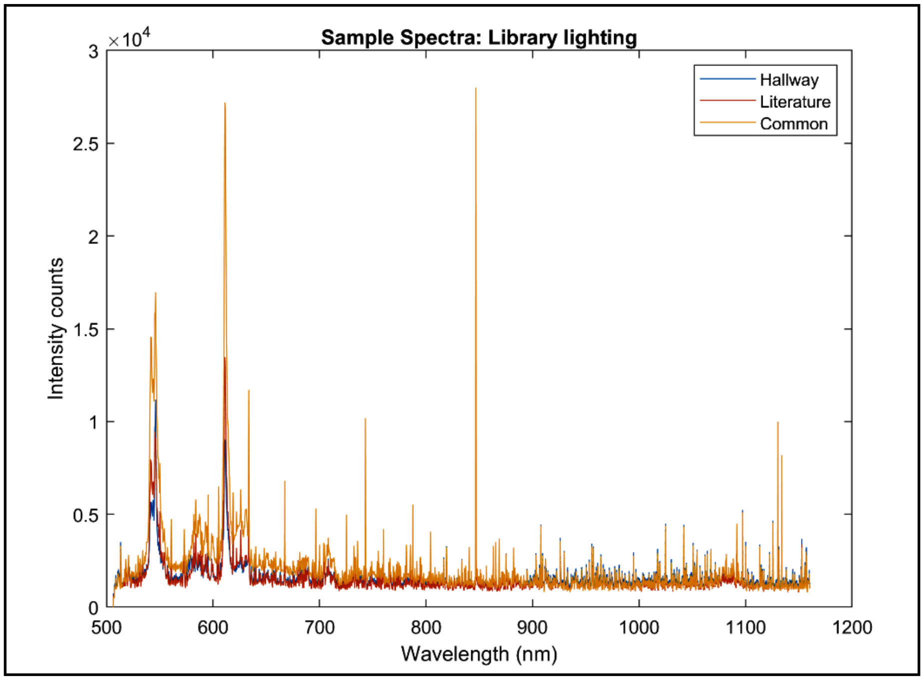


Figure 5.23: Fluorescent lighting on first floor

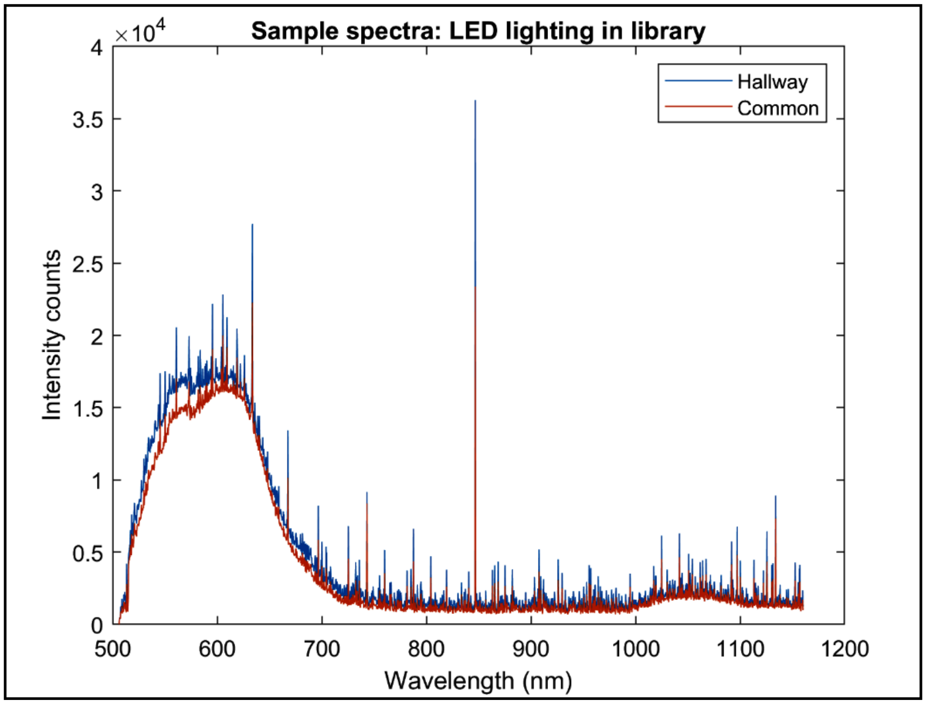


Figure 5.24: LED lighting on second floor

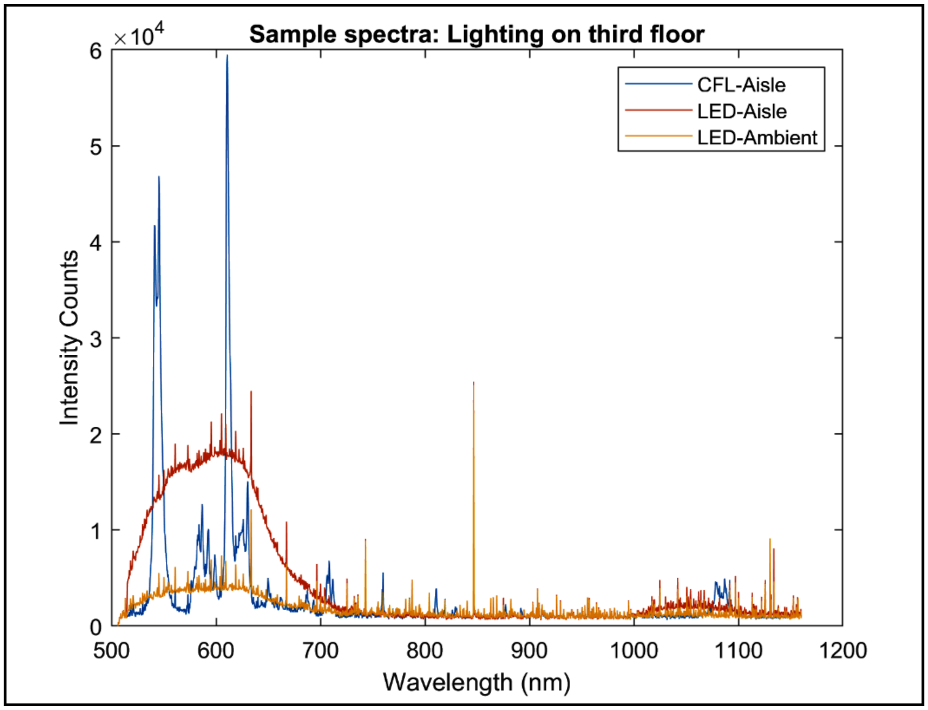


Figure 5.25: Fluorescent and LED lighting on third floor

5.3.3 Testing at HEB store, Bryan

- Location: HEB store, Bryan
- Type of building (Academic/Commercial/Residential/Religious): Commercial
- Date and time of testing: 18th July, late night
- Presence of daylight (Yes/No): No
- Does the building have lighting of heterogeneous nature? (Yes/No): No
- Type of lighting: Fluorescent
- Number of lamps tested: 60
- Classification accuracy: 60 out of 60
- Photographs:

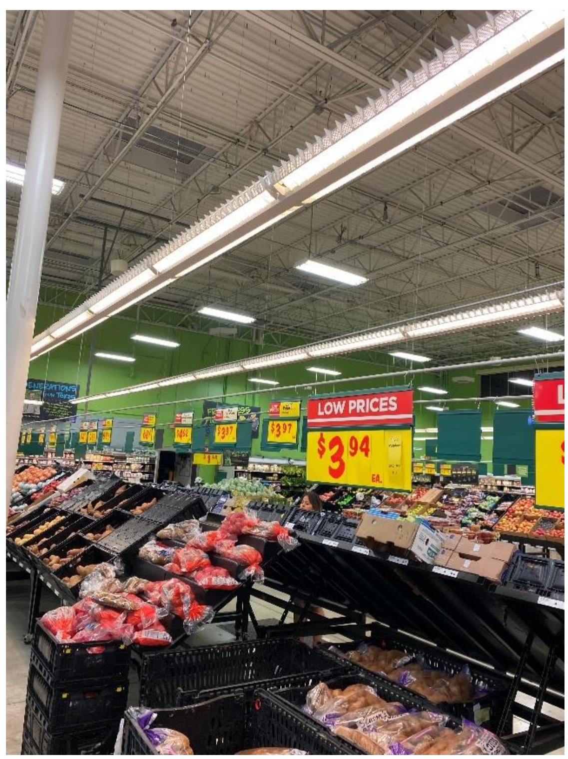


Figure 5.26: T5 and T8 Fluorescent tubes

(T5 tubes at 5 ft; T8 tubes at 12 ft. distance)

Figure 5.27: T8 Fluorescent tubes

Figure 5.28: T5 and T8 fluorescent tubes

- Sample Reference Spectra:

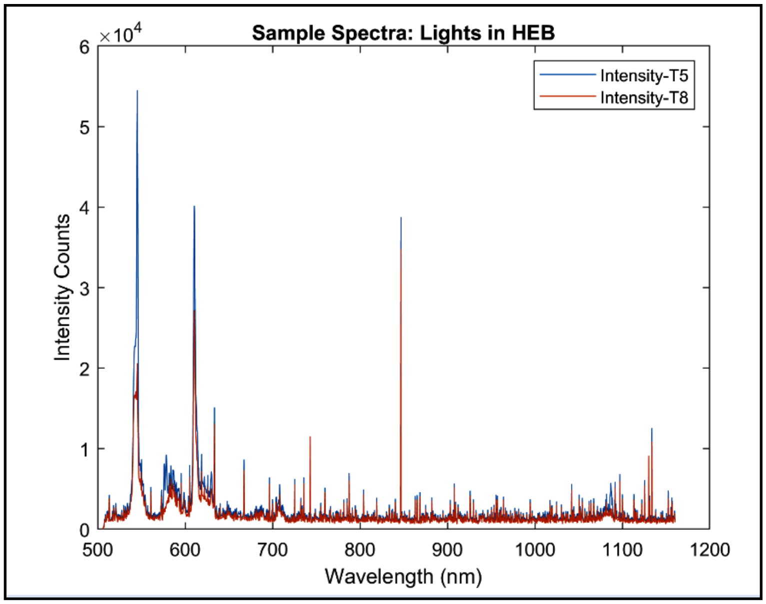


Figure 5.29: Spectra of Fluorescent lights in HEB

5.3.4 Testing at Memorial Student Center and Texas A&M Hotel

- Location: Memorial Student Center & Hotel, Texas A&M University
- Type of building (Academic/Commercial/Residential/Religious/Other): Other
- Date and time of testing: 19th July, evening
- Presence of daylight (Yes/No): Yes
- Does the building have lighting of heterogeneous nature? (Yes/No): Yes
- Type of lighting: Fluorescent and LED
- Number of lamps tested: 30
- Classification accuracy: 24 out of 30 (The sensor was not able to detect signals from the up lights and the LEDs that are deep inside the fixtures.)
- Photographs:

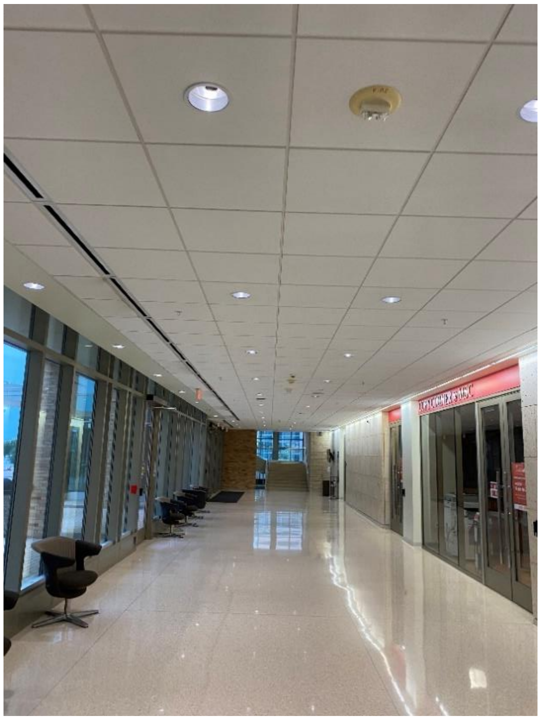


Figure 5.30: LEDs in the common area of Memorial Student Center

Figure 5.31: Up lights in the Texas A&M hotel

Figure 5.32: LEDs in the common passage of Texas A&M Hotel

- Sample spectra:

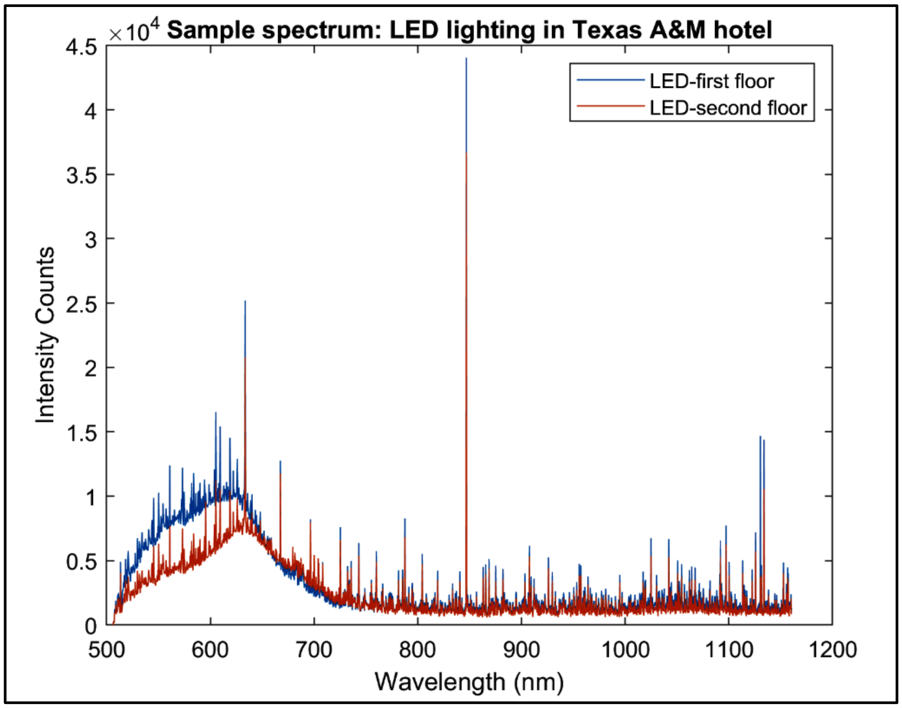


Figure 5.33: LEDs in the common passage of Texas A&M Hotel

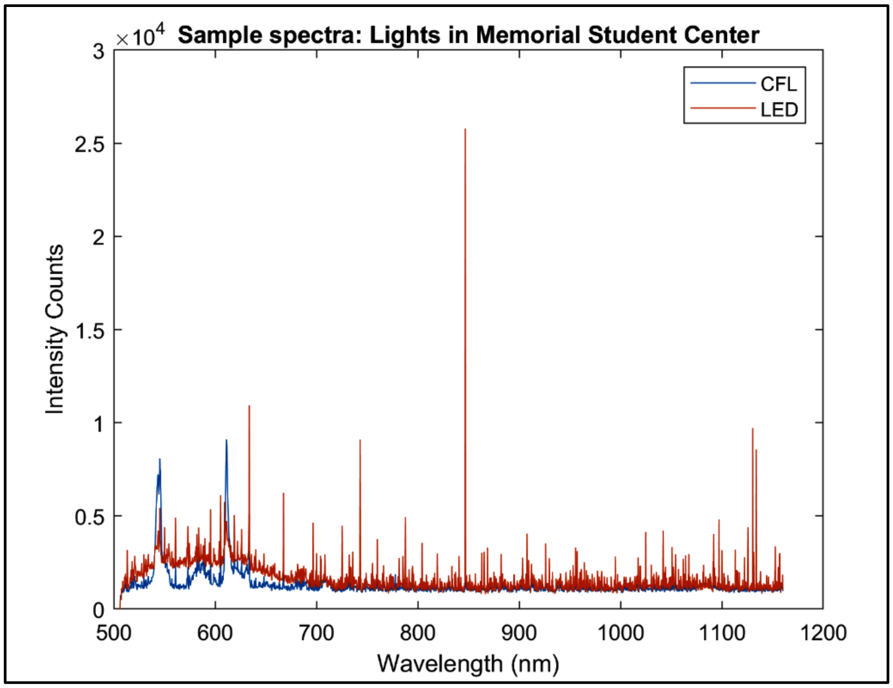


Figure 5.34: Lights in Memorial Student Center

5.3.5 Testing at Recreation Center, Texas A&M University

- Location: Recreation center, Texas A&M University
- Type of building (Academic/Commercial/Residential/Religious/Other): Other-Sports
- Date and time of testing: 18th July, late night
- Presence of daylight (Yes/No): No
- Does the building have lighting of heterogeneous nature? (Yes/No): Yes
- Type of lighting: Fluorescent and LED
- Number of lamps tested: 36
- Classification accuracy: 36 out of 40 (The sensor was not able to sense the signals from some of the high bay LEDs at 12 ft. distance)
- Photographs:

Figure 5.35: Fluorescent tubes in common area (at 5 ft. distance)

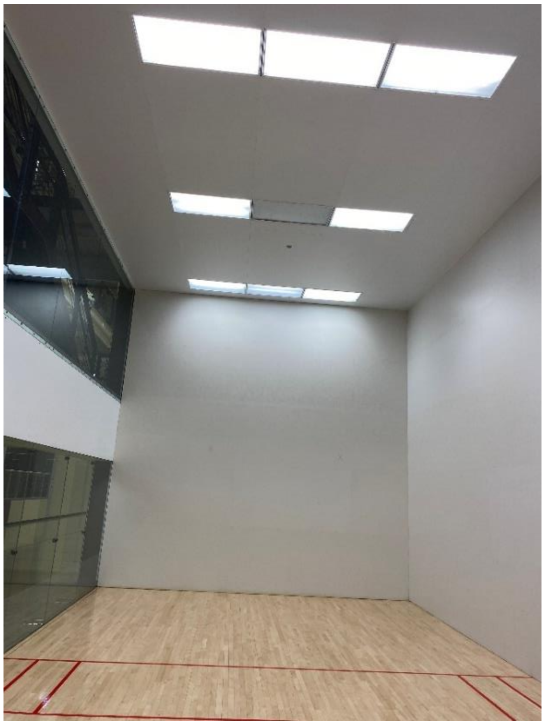


Figure 5.36: Fluorescent tubes in racket ball room (at 15 ft. distance)

Figure 5.37: LED tubes in dance room (at 15 ft. distance)

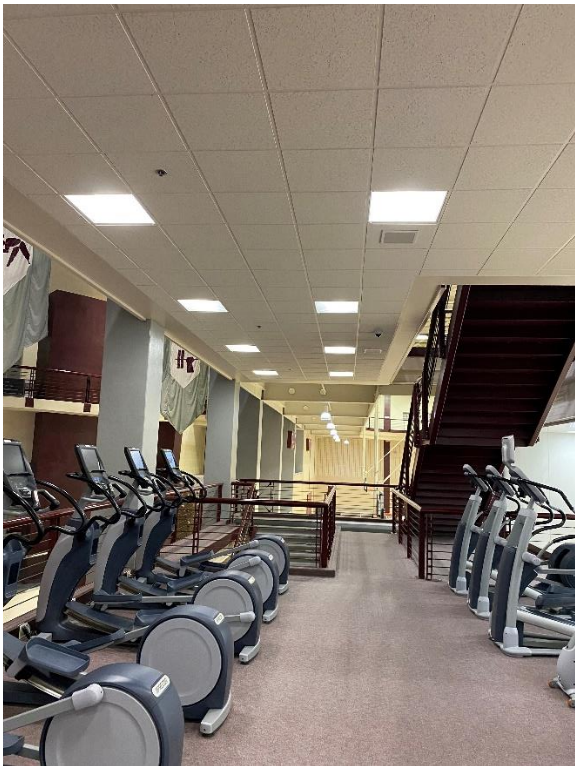


Figure 5.38: Fluorescent tubes in gym (at 7 ft. distance)

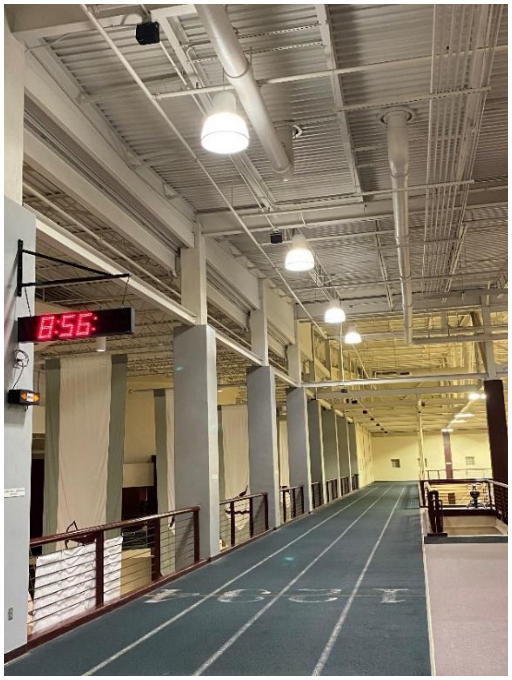


Figure 5.39: High Bay LEDs on running track (at 12 ft. distance)

- Sample Spectra:

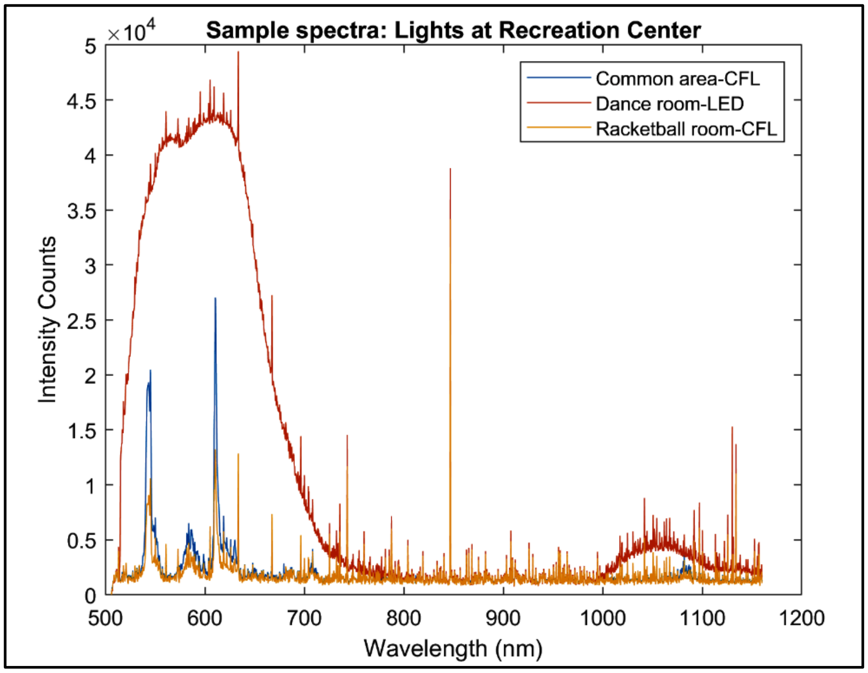


Figure 5.40: Spectra of lights on first floor of Recreation center

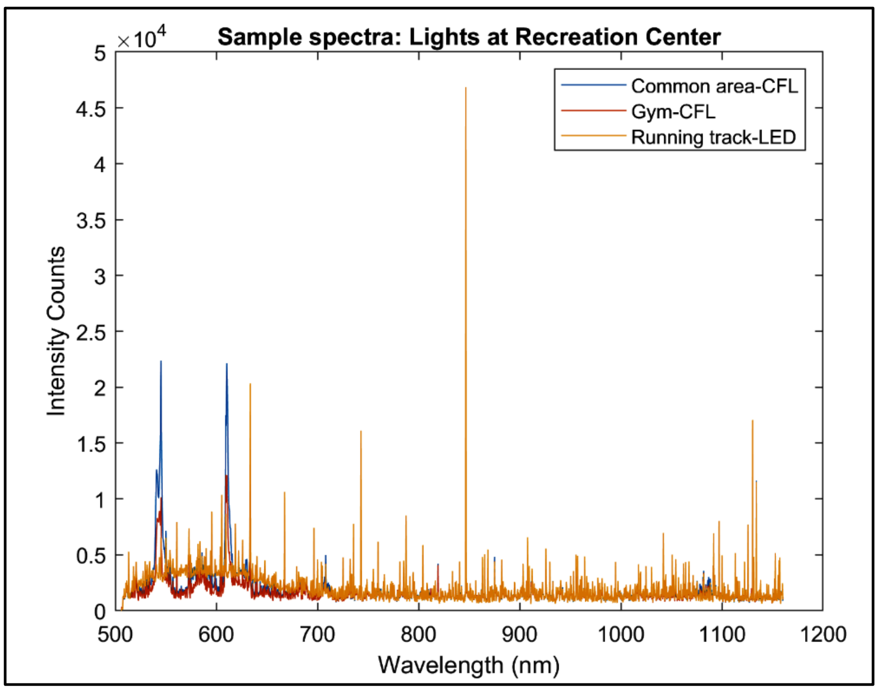


Figure 5.41: Spectra of lights on second floor of Recreation center

5.3.6 Testing at Fuzzy Tacos Restaurant, College Station

- Location: Fuzzy Tacos Restaurant, College Station
- Type of building (Academic/Commercial/Residential): Commercial- Restaurant
- Date and time of testing: 10th July, morning
- Presence of daylight (Yes/No): Yes
- Does the building have lighting of heterogeneous nature? (Yes/No): Yes
- Type of lighting: LED and Fluorescent
- Number of lamps tested: 8
- Classification accuracy: 8 of 8
- Photographs:

Figure 5.42: Fluorescent tube near restroom (3 ft. distance)

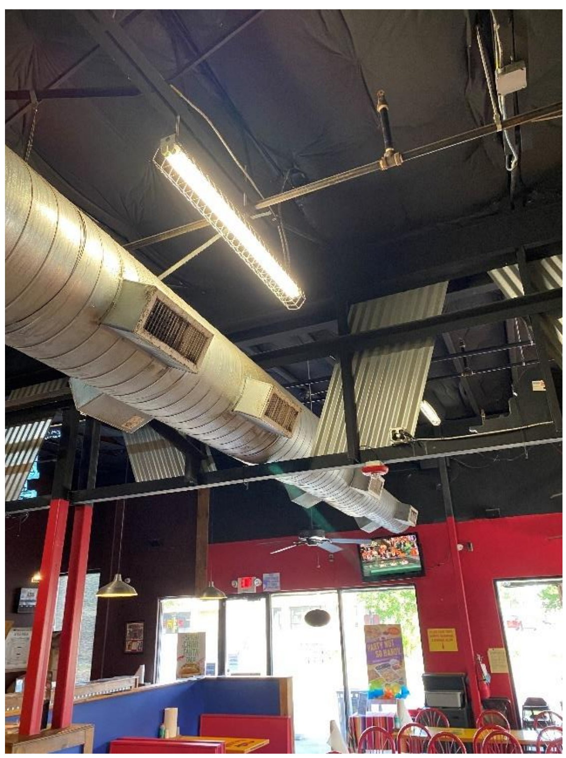


Figure 5.43: Fluorescent tube (10 ft. distance) and LED lamps (3 ft. distance)

- Sample spectra:

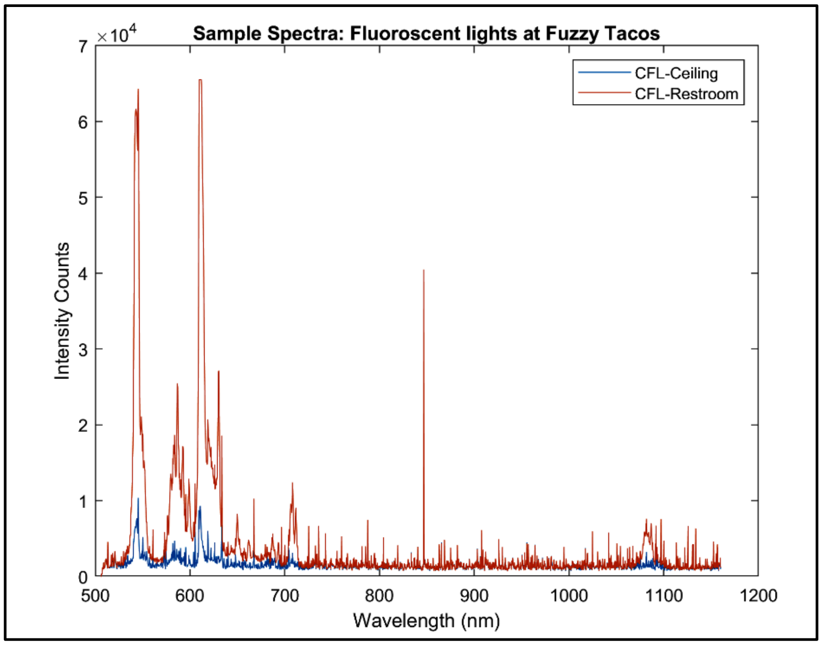


Figure 5.44: Spectra of CFLs of ceiling and restroom at Fuzzy Tacos

5.3.7 Testing at Los Cucos Restaurant, College Station

- Location: Los Cucos Restaurant, College Station
- Type of building (Academic/Commercial/Residential): Commercial- Restaurant
- Date and time of testing: 10th July, morning
- Presence of daylight (Yes/No): Yes
- Does the building have lighting of heterogeneous nature? (Yes/No): No
- Type of lighting: LED
- Number of lamps tested: 10
- Classification accuracy: 8 out of 10 (Dim LEDs which are fixed deep inside the fixtures were not able to be detected by the sensor)

- Photographs:

Figure 5.45: LED lamp (warm yellow)

Figure 5.46: Testing of LED in presence of ambient light (2 ft. from sensor)

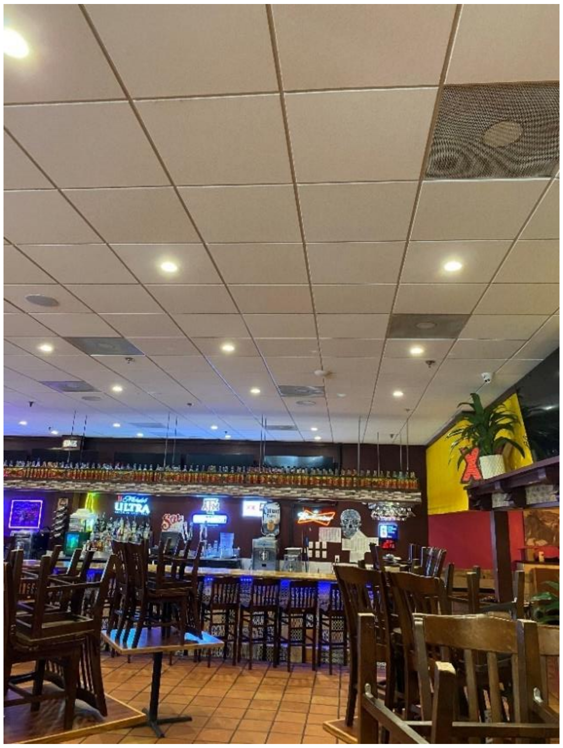


Figure 5.47: LED lighting at restaurant (8 ft. from sensor)

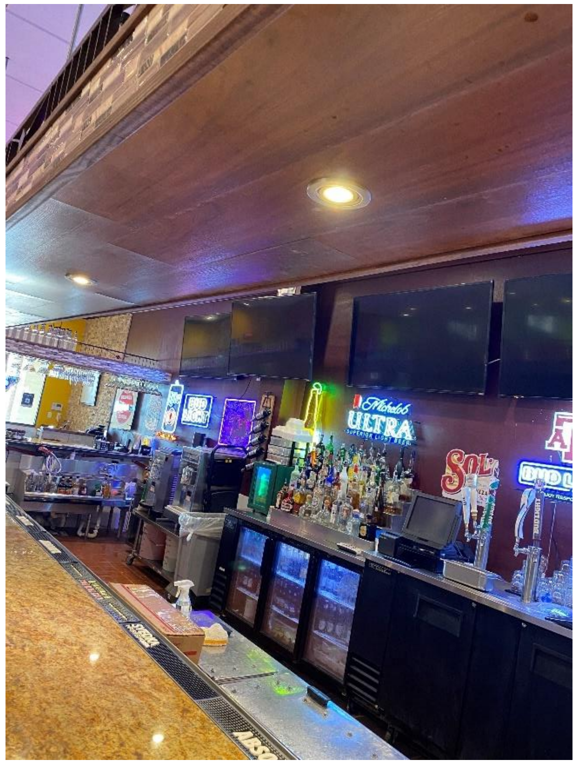


Figure 5.48: Dim LEDs on the bar table (2 ft. from sensor)

- Sample spectra:

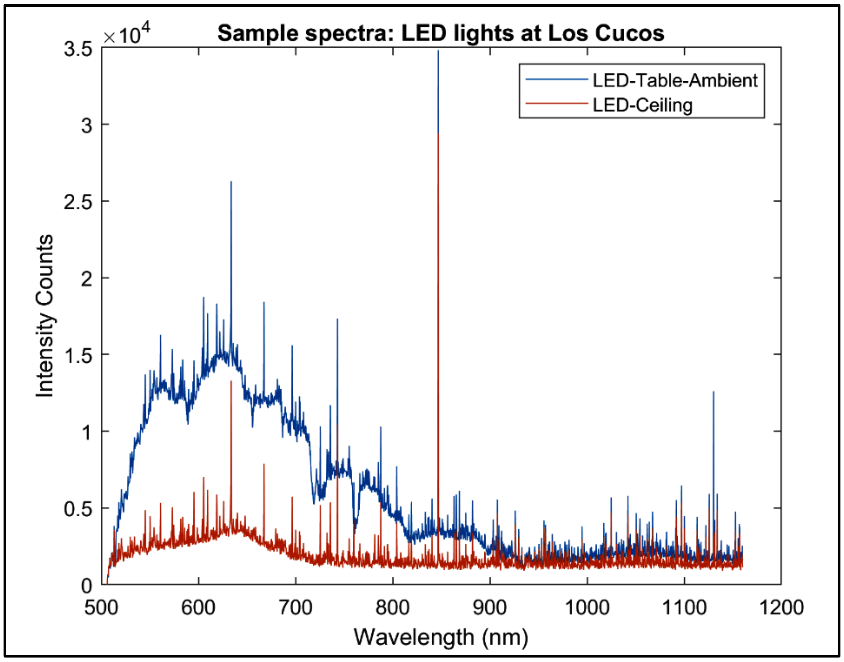


Figure 5.49: Table and ceiling LEDs at Los Cucos Restaurant

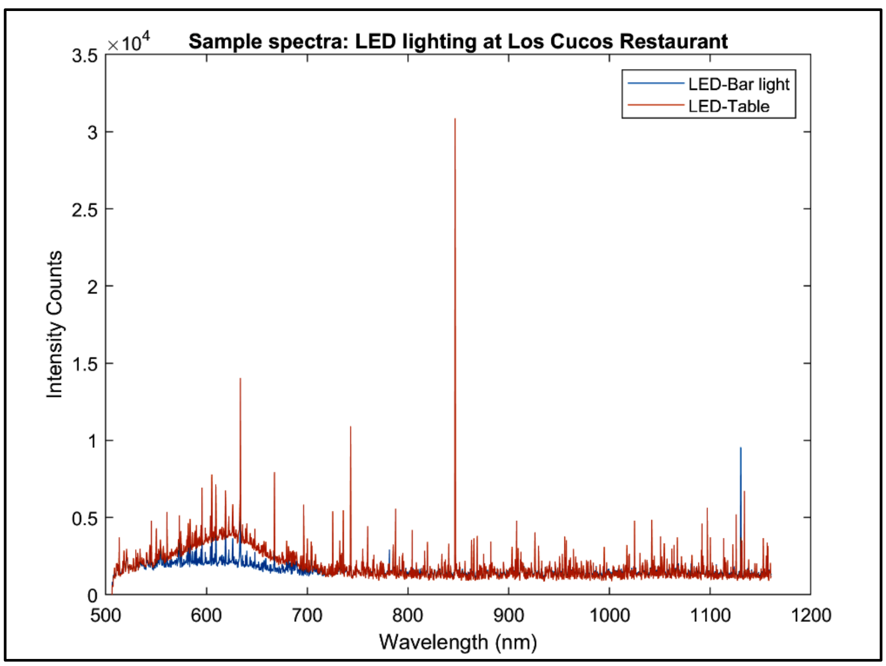


Figure 5.50: Bar and table LEDs at Los Cucos Restaurant

5.3.8 Testing at Target Mall, College Station

- Location: Target Mall, College Station
- Type of building (Academic/Commercial/Residential): Commercial
- Date and time of testing: 10th July, morning
- Presence of daylight (Yes/No): Yes
- Does the building have lighting of heterogeneous nature? (Yes/No): No
- Type of lighting: LED
- Number of lamps tested: 4
- Classification accuracy: 4 out of 4
- Photographs:

Figure 5.51:LED lights at Target Mall (at 4 ft.)

Figure 5.52: LED lights at Target Mall (at 12 ft.)

- Sample spectrum:

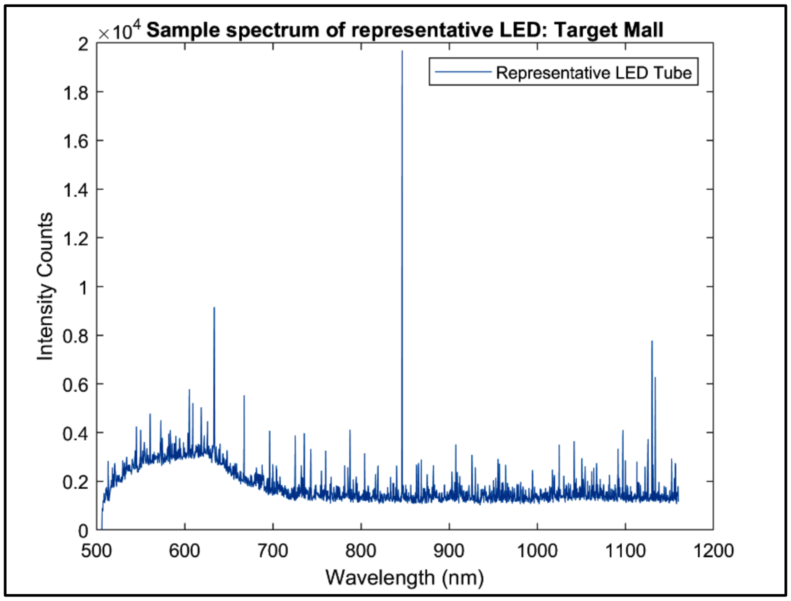


Figure 5.53: Sample spectrum of LED at Target Mall

5.3.9 Testing of Exterior Lights in Parking Garage

- Location: Parking Garage- West Campus, Texas A&M University
- Type of building (Academic/Commercial/Residential/Other): Other
- Date and time of testing: 18th July, evening
- Presence of daylight (Yes/No): No
- Does the building have lighting of heterogeneous nature? (Yes/No): No
- Type of lighting: LED
- Number of lamps tested: 10
- Classification accuracy: 10 out of 10
- Photographs:

- Sample spectrum:

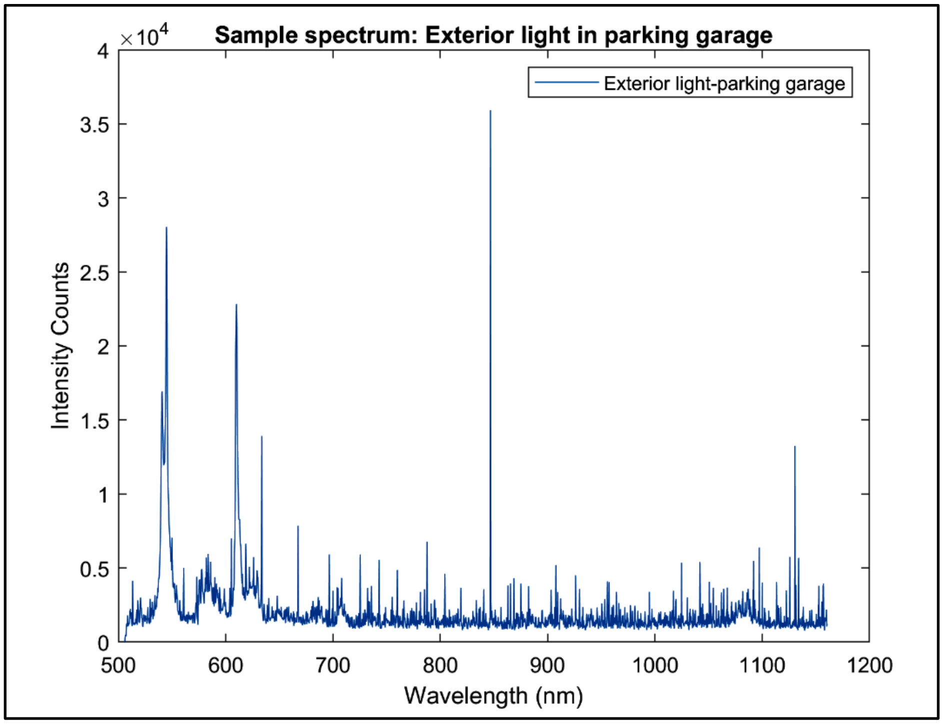


Figure 5.54: Spectrum of LED Exterior light in parking garage

5.4 Final Results

The testing was conducted at 10 buildings of different types and functionalities. The results are summarized in Table 5.1. Measurements were taken from distances ranging from 3 ft. to 15 ft., which encompasses the range of expected distances in the field. A total of 260 different lamps were tested and the CVRMSE algorithm correctly classified the lighting type in 95% of the instances. In addition, the algorithm was also able to identify the lamp type accurately in presence of ambient light.

Table 5.1: Results table of experimentation

Location	Type of Building	Type of Lighting	Number of lamps tested	Classification Accuracy
TAMU Blocker Building	Academic	LED and Fluorescent	20	95%
TAMU Evans Library	Library	LED and Fluorescent	40	100%
HEB Store	Commercial	Fluorescent	60	100%
TAMU Memorial Student Center	Other	LED and Fluorescent	30	80%
TAMU Mechanical Engineering-JCain	Academic	LED and Fluorescent	20	100%
TAMU Recreation Center	Other- Sports	LED and Fluorescent	40	90%
Fuzzy Tacos Restaurant	Restaurant	LED and Fluorescent	8	100%
Los Cucos Restaurant	Restaurant	LED	10	80%
Target Mall	Commercial	LED	4	100%
Parking Garage	Other-Exterior	LED	10	100%
Reveille Ranch	Residential	Halogen, LED, and Fluorescent	15	100%

6. CONCLUSIONS AND FUTURE WORK

One common method of enhancing the energy efficiency of buildings is to implement smart technologies in their lighting systems. The first half of the thesis presents a long-term energy analysis of occupancy-controlled lighting in the large university library buildings. Library buildings are characterized by their unique occupancy and lighting usage patterns. The research highlights the importance of determining the occupancy and lighting usage patterns to estimate the energy consumption and savings accurately. The impact of several critical parameters such as sensor density, wattage of lamp, type of lamp, delay time setting of lighting control on energy savings and the payback period is discussed. This research can be extended, and the learnings can be horizontally deployed to other large public library buildings. In addition, future work will analyze the energy savings achieved from occupancy sensors with adaptable delay time settings.

The other method of enhancing the lighting energy efficiency of buildings is to conduct energy assessments and improve the way in which they are conducted. Automating elements of energy audits have several advantages such as decreased auditing time, improved depth of analysis and less requirement of trained professional. Identification of lamp type is an important step in a typical lighting energy audit. The second half of this research demonstrated an automated analysis which can determine the light types based on the spectral curves using a spectrometer. The impact of parameters such as lamp wattage, presence of ambient light, integration time setting of spectrometer, distance, and directionality on the classification accuracy and intensity spectra was studied. The light types are identified by comparing the measured spectra with the reference spectra using the CVRMSE values. This classification algorithm has been tested at 10 different buildings each of different type, functionalities, and ceiling heights. However, this device won’t work for industrial settings at this moment due to the following limitations. First, the spectrometer is not sensitive to heights greater than 12 ft. Also, the signal to noise ratio of current spectrometer is very low.

Future work will integrate the output results of other sensors (such as range finder and Light Detection and Ranging sensor) in the selected automated device and provide an in-depth energy analysis. Future work will also explore the usage of intensity measurement sensors in creating lighting intensity maps of buildings. An algorithm for predicting the wattage of lamp based on the lighting spectra could be created and evaluated.

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APPENDIX A

SUMMARY TABLES: LIBRARY CASE STUDY

Tables A.1 and A.2 indicate daily and annual energy savings for different delay time settings of sensor.

Table A.1: Effect of delay time on daily energy savings

Delay time (mins)	**Energy consumption (kWh)**	**Potential energy savings (kWh)**	**Additional energy savings for 0-minute delay (kWh)**
0	210	190	0
5	214	186	8
10	217	183	14
15	220	180	20
20	223	177	25

Table A.2: Effect of delay time setting on annual energy savings

Delay time (mins)	**Energy consumption (kWh)**	**Potential energy savings (kWh)**	**Additional energy savings for 0-minute delay setting (kWh)**
0	1,512	1,368	0
5	1,539	1,340	55
10	1,563	1,316	103
15	1,584	1,295	145
20	1,604	1,275	183

Tables A.3 and A.4 indicate the payback periods for different percentages of lights in dimmed condition.

Table A.3: Impact of sensor density on payback period (yrs.): Fluorescent lamps

% Lights dimmed, unoccupied	D=2	D=4	D=6	D=8	D=10	D=12
10	58	29	19	14	12	10
20	29	14	10	7	6	5
30	19	10	6	5	4	3
40	14	7	5	4	3	2
50	12	6	4	3	2	2
60	10	5	3	2	2	2
70	8	4	3	2	2	1
80	7	4	2	2	1	1
90	6	3	2	2	1	1
100	6	3	2	1	1	1

Table A.4: Impact of sensor density on payback period (yrs.)- LED lamps

% Lights dimmed, unoccupied	D=2	D=4	D=6	D=8	D=10	D=12
10	103	51	34	26	21	17
20	51	26	17	13	10	9
30	34	17	11	9	7	6
40	26	13	9	6	5	4
50	21	10	7	5	4	3
60	17	9	6	4	3	3
70	15	7	5	4	3	2
80	13	6	4	3	3	2
90	11	6	4	3	2	2
100	10	5	3	3	2	2

Table A.5 denotes the expected life, total replacement costs and energy savings for different delay time settings.

Table A.5: Effect of delay time setting on lifetime of fluorescent lamps

Delay time (mins)	Expected lamp life (hrs)	Total replacement cost ($)	Energy savings ($)
0	10,348	41,996	146,046
5	10,998	40,534	143,111
10	11,963	38,090	140,529
15	12,847	36,147	138,270

The successive levels of energy savings for fluorescent and LED lamps are tabulated in Tables A.6 and A.7.

Table A.6: Successive levels of energy savings: fluorescent lamps

Delay time setting (mins)	**Energy savings (kWh)**
15-minute delay, lights dim	220
0-minute delay, lights dim	240
0-minute delay, lights off	360

Table A.7: Successive levels of energy savings: LED lamps

Delay time setting (mins)	**Energy savings (kWh)**
15-minute delay, lights dim	117
0-minute delay, lights dim	124
0-minute delay, lights off	234

Table A.8 denotes the relationship between annual checkout frequency and % occupancy of corresponding aisle.

Table A.8: Relationship between checkout frequency and occupancy

Section	Annual checkout frequency	% Occupancy of corresponding aisle
Politics	23,250	2.0
Electrical Engineering	75,307	0.4
Philosophy	31,547	3.7
Literature	545,803	6.1
Chemistry	55,454	3.1
History of the US	11,592	12.4
Biology	48,831	12.3
Social History	12,058	2.1
Mathematics	285,190	7.3

APPENDIX C

SPECTROMETRY PYTHON CODE SNIPPETS

Below ROS node is created for collecting optical spectral data from spectrometer.

C1. ROS Node for Spectral Data Collection

```
import time
import rospy
import numpy
import usb
import seabreeze
seabreeze.use("pyseabreeze")
import seabreeze.spectrometers as sb
import csv
import numpy as np
from std_msgs.msg import Float64MultiArray
from std_msgs.msg import MultiArrayLayout
from std_msgs.msg import MultiArrayDimension

class rosGeneral:
        def __init__(self):
                self.msg = []

        def sub(self, rosTopic, rosType):
                rospy.Subscriber(rosTopic, rosType, self.callback)

     def pubInit(self, rosTopic, rosType, qs):
          self.pubInit = rospy.Publisher(rosTopic, rosType, queue_size=qs)

     def pub(self):
          self.pubInit.publish(self.msg)

        def callback(self, msg):
                self.msg = msg

        def setarray(self):
                self.msg=Float64MultiArray ()
                self.msg.data=[1,2]
```

```
                self.msg.layout.dim=[MultiArrayDimension(),MultiArrayDimension()]

if __name__ =='__main__':
        rospy.init_node('array_pub', anonymous=False)
        rate = rospy.Rate(0.5)
    wave_topic = "/wavelength_pub"
        inten_topic = "/intensity_pub"
    wave_msg = rosGeneral()
        wave_msg.pubInit(wave_topic, Float64MultiArray,10)
        wave_msg.setarray ()
    inten_msg = rosGeneral()
        inten_msg.pubInit(inten_topic, Float64MultiArray,10)
        inten_msg.setarray ()
        spec = sb.Spectrometer.from_serial_number()
        spec.integration_time_micros(500000)
        array_copy=[]
        array_copy2=[]

        count=0
        sum=0
        while not rospy.is_shutdown():
                if count < 2:
                        array=spec.wavelengths()
                        array2=spec.intensities()
                        for i in array:
                                array_copy.append(float(i))
                        for j in array2:
                                array_copy2.append(float(j))
                        wave_msg.msg.data = array_copy
                        inten_msg.msg.data= array_copy2
                        wave_msg.pub()
                        inten_msg.pub()
                        rate.sleep()
                        count=count+1
                        array3=np.array([array,array2])
                        sum=sum + array3
                        print(array3)
                        print(sum)
                else:   pass

        newarray=(sum)*(0.5)
```

```
        print(newarray)
        with open('Desktop/data.csv', 'w') as file:
                        mywriter = csv.writer(file,delimiter=',')
                        mywriter.writerows(newarray)
        rospy.spin()
```

Below ROS node is created for classifying light type based on collected spectral data.

C2. ROS Node for Light Type Classification

```
import time
import rospy
import numpy
import usb
import seabreeze
seabreeze.use("pyseabreeze")
import seabreeze.spectrometers as sb
import csv
import numpy as np
import numpy
import math
from numpy import trapz
import pandas as pd
import seabreeze.spectrometers as sb
from std_msgs.msg import Float64MultiArray
from std_msgs.msg import MultiArrayLayout
from std_msgs.msg import MultiArrayDimension
from std_msgs.msg import String

class rosGeneral:
  def __init__(self):
    self.msg = []

  def sub(self, rosTopic, rosType):
    rospy.Subscriber(rosTopic, rosType, self.callback)

    def pubInit(self, rosTopic, rosType, qs):
        self.pubInit = rospy.Publisher(rosTopic, rosType, queue_size=qs)

    def pub(self):
        self.pubInit.publish(self.msg)
```

```
    def callback(self, msg):
        self.msg = msg

    def setarray(self):
        self.msg=Float64MultiArray ()
        self.msg.data=[1,2]
        self.msg.layout.dim=[MultiArrayDimension(),MultiArrayDimension()]
    def setstring(self):
        self.msg=String ()

if __name__ =='__main__':
    rospy.init_node('array_pub', anonymous=False)
    rate = rospy.Rate(0.5)
        wave_topic = "/wavelength_pub"
    inten_topic = "/intensity_pub"
    type_topic = "/type_topic"
    type_msg = rosGeneral ()
    type_msg.pubInit(type_topic, String, 10)
    type_msg.setstring ()
        wave_msg = rosGeneral ()
    wave_msg.pubInit(wave_topic, Float64MultiArray,10)
    wave_msg.setarray ()
        inten_msg = rosGeneral()
    inten_msg.pubInit(inten_topic, Float64MultiArray,10)
    inten_msg.setarray ()
    spec = sb.Spectrometer.from_serial_number()
    spec.integration_time_micros(1500000)
    array_copy=[]
    array_copy2=[]

#Importing normalized reference spectra-training set
data=pd.read_csv('/home/tfcl/Downloads/Normalized_ref_spectra.csv')
wavelength=data['w']
cfl_reference=data['cfl_r']
hal_reference=data['hal_r']
inc_reference=data['inc_r']
led_reference=data['led_r']

count=0
sum=0
```

```
n=1024
while not rospy.is_shutdown():
    if count < 2:
        array=spec.wavelengths()
        array2=spec.intensities()
        count=count+1
        sum=sum + array2
        tarray=(sum)*(0.5) #Average intensity array
        sample_area=np.array([tarray])
        sample_area[0,0]=0
        sample_area[0,1]=0
        print(sample_area)

#Defining the columns of reference data as arrays
        cfl_area=np.array([cfl_reference])
        hal_area=np.array([hal_reference])
        inc_area=np.array([inc_reference])
        led_area=np.array([led_reference])
        wavelength_area=np.array([wavelength])

#Normalization of collected sample
        normalized_s=trapz(sample_area,wavelength_area)
        sample_normalized=sample_area/normalized_s

#CVRMSE Calculations
        cvrms_row_cfl_1=(sample_normalized-cfl_area)*(sample_normalized-cfl_area)
        cvrms_row_cfl=np.array([cvrms_row_cfl_1])
        s=np.sum(cvrms_row_cfl) #Sum of elements
        cvrms_sum_cfl=math.sqrt(s)
        s1=np.sum(cfl_area)
        mean_cfl=s1/n
        cvrms_cfl=cvrms_sum_cfl*100/mean_cfl
        print(cvrms_cfl)

        cvrms_row_hal_1=(sample_normalized-hal_area)*(sample_normalized-hal_area)
        cvrms_row_hal=np.array([cvrms_row_hal_1])
        s=np.sum(cvrms_row_hal) #Sum of elements
        cvrms_sum_hal=math.sqrt(s)
        s1=np.sum(hal_area)
        mean_hal=s1/n
        cvrms_hal=cvrms_sum_hal*100/mean_hal
```

```
        print(cvrms_hal)

        cvrms_row_inc_1=(sample_normalized-inc_area)*(sample_normalized-inc_area)
        cvrms_row_inc=np.array([cvrms_row_inc_1])
        s=np.sum(cvrms_row_inc) #Sum of elements
        cvrms_sum_inc=math.sqrt(s)
        s1=np.sum(inc_area)
        mean_inc=s1/n
        cvrms_inc=cvrms_sum_inc*100/mean_inc
        print(cvrms_inc)

        cvrms_row_led_1=(sample_normalized-led_area)*(sample_normalized-led_area)
        cvrms_row_led=np.array([cvrms_row_led_1])
        s=np.sum(cvrms_row_led) #Sum of elements
        cvrms_sum_led=math.sqrt(s)
        s1=np.sum(led_area)
        mean_led=s1/n
        cvrms_led=cvrms_sum_led*100/mean_led
        print(cvrms_led)

        cvrms_min=min(cvrms_cfl,cvrms_hal,cvrms_inc,cvrms_led)
        print(cvrms_min)

        if cvrms_min==cvrms_cfl:
            print('Compact Fluoroscent')
        if cvrms_min==cvrms_hal:
            print('Halogen')
        if cvrms_min==cvrms_inc:
            print('Incandescent')
        if cvrms_min==cvrms_led:
            print('LED')
        wave_msg.msg.data = array_copy
        inten_msg.msg.data= array_copy2
        array_copy=[]
        array_copy2=[]
        type_msg.pub()
        wave_msg.pub()
        inten_msg.pub()
        rate.sleep()
    else: pass
rospy.spin()
```