EVALUATION OF BLUETOOTH LOW ENERGY TECHNOLOGY FOR INDOOR LOCALIZATION IN BUILT ENVIRONMENTS

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ABSTRACT

EVALUATION OF BLUETOOTH LOW ENERGY TECHNOLOGY FOR INDOOR LOCALIZATION IN BUILT ENVIRONMENTS

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Localization in indoor built environments has a considerable importance for architecture, engineering and construction industry. It has a wide scope including building occupancy detection, automated asset tracking in construction sites, supporting facility maintenance and operations, and guiding people in building emergency response operations. Among the uses cases of indoor localization, occupancy detection is shown to be the most critical one, considering the large share of built environments in total energy consumption of the world and the huge potential of automated demand driven building operations, which are based on presence of people, in increasing energy efficiency of buildings. Although there are some existing approaches for detecting the location of occupants in buildings, there is not a widely accepted and reliable solution due to the certain drawbacks of the current approaches including uncertainties in detection, time latency and privacy issues, inability for multiple detection and costly utilization and maintenance requirements. The aim of this research is to assess the possibility of establishing a mobile information technology device integrated framework for building occupancy detection and to investigate the usability of Bluetooth Low Energy (BLE) technology for indoor localization. BLE technology is already embedded in most of the mobile devices and its properties such as ultra-low power consumption, low cost and low latency in data exchange make it a good alternative to currently available technologies. In order to determine the viability of the proposed framework and BLE technology, multiple field experiments carried out in MATPUM Building at Middle East Technical University. Location fingerprinting method was used as the wireless localization technique and k-nearest neighbor algorithm was utilized to assess the feasibility of BLE technology for indoor localization. The results of the field experiments show that, detecting occupancy through a mobile device integrated framework is possible without any complex infrastructure requirement, and BLE technology can be used as a reliable solution for indoor localization as it gives better accuracy and precision results when compared to existing approaches in the industry.

Keywords: Indoor localization, Building occupancy detection, Bluetooth low energy

ÖZ

DÜŞÜK ENERJİLİ BLUETOOTH TEKNOLOJİSİNİN YAPILI ÇEVRE KAPALI ALANLARINDA KONUM BULMA AMAÇLI DEĞERLENDİRİLMESİ

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Kapalı alanlarda konum bulma, mimarlık, mühendislik ve inşaat endüstrisi için dikkate değer bir öneme sahiptir. Konum bulmanın geniş bir kullanım alanı vardır ve bu kullanımlara binada kullanıcı varlığı tespiti, inşaat alanlarında otomatik mal takibi, tesis bakım ve sürdürülmesinin desteklenmesi ve bina acil durum müdahalelerinde insanların yönlendirmesi dâhildir. Kullanım senaryoları arasında, binaların dünyadaki toplam enerji tüketimindeki payı, ve insan varlığına bağlı olarak çalışan, otomatize edilmiş, talebe dayalı bina operasyonlarının bina enerji verimliliğini artırmadaki büyük potansiyeli değerlendirildiğinde, kullanıcı varlığı tespiti en kritik olarak öne çıkmaktadır. Kullanıcıların bina içerisindeki yerini tespit etmek için var olan yaklaşımlar olsa da, bu yaklaşımların tespit etmede belirsizlik, gecikme zamanı, mahremiyet, birden fazla kullanıcıyı tespit edememe ve pahalı kurulum ve bakım masrafları gibi dezavantajlarından dolayı, geniş çapta kabul edilmiş ve güvenilir bir çözüm bulunmamaktadır. Bu araştırmanın amacı, mobil bilgi teknolojisi cihazlarının entegre edildiği bir bina kullanıcı tespiti mekanizmasının uygulanabilirliğini değerlendirmek ve Düşük Enerjili Bluetooth(BLE) teknolojisinin kapalı alanlarda konum bulma için kullanılabilirliğini sorgulamaktır. BLE teknolojisi halihazırda çoğu mobil cihazda bulunmaktadır ve çok düşük enerji tüketimi, düşük maliyeti ve veri alışverişindeki kısa gecikme zamanı gibi özellikleri, bu teknolojiyi mevcut teknolojiler için iyi bir alternatif haline getirmektedir. Önerilen sistemin ve BLE teknolojisinin uygulanabilirliğini saptamak için, Orta Doğu Teknik Üniversitesi'nde bulunan MATPUM binasında birden çok saha deneyleri uygulanmıştır. Kablosuz konum bulma tekniği olarak konum parmak izi metodu kullanılmış ve BLE teknolojisinin kapalı alanlarda konum bulma için elverişliliğini incelemek üzere k-en yakın komşu algoritmasından istifade edilmiştir. Saha deneylerinin sonuçları, mobil bilgi teknolojisi cihazlarının entegre edildiği bir sistemle, kompleks bir altyapı gerektirmeksizin kullanıcı tespitinin mümkün olduğunu, ve BLE teknolojisinin, var olan yaklaşımlardan daha kesin ve hassas sonuçlar vermesi sebebiyle, kapalı alanlarda konum bulma için güvenilir bir çözüm olarak kullanılabileceğini göstermiştir.

Anahtar Kelimeler: Kapalı alanlarda konum bulma, Bina kullanıcı tespiti, Düşük enerjili bluetooth

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TABLE OF CONTENTS

ABSTRACT v
ÖZ vii
ACKNOWLEDGEMENTS ix
TABLE OF CONTENTS x
LIST OF TABLES xiii
LIST OF FIGURES xiv
LIST OF ABBREVIATIONS xvi
CHAPTERS
1. INTRODUCTION 1
1.1 Background Information 1
1.2 Aim and Objectives 3
1.3 Contribution 3
1.4 Disposition 4
2. LITERATURE REVIEW 5
2.1 Indoor Localization Use Cases 5
2.1.1 Building Occupancy Detection 6
2.1.2 Asset Tracking on Construction Sites 9
2.1.3 Facility Maintenance and Operations 11
2.1.4 Building Emergency Response Operations 14
2.1.5 Selected Scope for Indoor Localization 16
2.2 Existing Occupancy Detection Approaches 27
2.2.1 Simulation (prediction algorithm) models 28
2.2.2 Image detection (vision-based) systems 29
2.2.3 Passive infrared (PIR) sensor based systems 30
2.2.4 Carbon-dioxide sensors based systems 32
2.2.5 Radio Frequency (RF) Based (Wireless) Systems 35
2.3 Localization Techniques of Wireless Based Detection Systems 42
2.3.1 Proximity 43

2.3.2 Triangulation 43
2.3.3 Trilateration 44
2.3.4 Scene Analysis (Fingerprinting) 45
2.3.5 Performance Metrics of Wireless Based Location Detection Systems ... 47
2.4 Critical Analysis of Literature Review 49
3. MATERIAL AND METHOD 51
3.1 Bluetooth Low Energy Technology 51
3.2 Material Selection 54
3.2.1 BLE Tag I 55
3.2.2 BLE Tag II 55
3.2.3 BLE Tag III 56
3.2.4 BLE Tag IV 57
3.2.5 Experimental Setup for the Evaluation of the BLE Tags 57
3.3 Research Approach - Location Fingerprinting 62
3.3.1 Offline Phase - Data Collection 65
3.3.2 Online Phase - Data Analysis Approach based on Cases 70
3.4 Parameters of Proposed Framework for Indoor Localization 76
3.4.1 Spatial Accuracy - Precision 77
3.4.2 Number of Real Time RSSI Data Samples 78
3.4.3 Human Body Orientation 78
3.4.4 Number of Data Collection Points 80
3.4.5 Fingerprint Creation Approach 81
4. RESULTS AND DISCUSSION 83
4.1 Field Experiment Results 83
4.1.1 Case I 83
4.1.2 Case II 85
4.1.3 Case III 86
4.1.4 Case IV 88
4.1.5 Case V 90
4.2 Analytical Comparison with Existing Wireless-based Approaches 91
5. CONCLUSION 95
5.1 Summary of the Research 95

5.2 Main Results and Discussion 96
5.3 Limitations of the Study 98
5.4 Recommendations for Further Research 98
REFERENCES 101

LIST OF TABLES

TABLES

Table 1: Core maintenance activities with time data (Lee & Akin, 2009). 12

Table 2: Importance of Indoor Localization 15

Table 3: Comparison of wireless-based localization techniques. 47

Table 4: Cases for Data Analysis – Training Data.. 76

Table 5: Cases for Data Analysis – Test Data.. 76

Table 6: Case I - Localization accuracy results for different precision levels 84

Table 7: Case II - Localization accuracy results for different precision levels.......... 86

Table 8: Case III - Localization accuracy results for different precision levels 87

Table 9: Case IV - Localization accuracy results for different precision levels 89

Table 10: Case V - Localization accuracy results for different precision levels 91

Table 11: Comparison of wireless-based indoor localization approaches based on performance metrics.. 93

LIST OF FIGURES

FIGURES

Figure 1: ASHRAE recommended occupancy profiles by day type 7

Figure 2: Active and passive occupants' effects on building performance. 19

Figure 3: The Intelligent Building Pyramid 21

Figure 4: Functional Domains of Building Automation Systems 23

Figure 5: Breakdown of Building Automation Systems 24

Figure 6: Energy Demand and Supply Model 25

Figure 7: Resolution Framework of Building Occupancy Detection 27

Figure 8: Research setup with PIR sensors by Hauschildt and Kirchhof (2010) 31

Figure 9: CO_2 – Number of Occupant – ACH Relation 33

Figure 10: Main components of RFID based systems 36

Figure 11: Localization concept of SpotON – Experiment setup of LANDMARC .. 37

Figure 12: Radio spectrum of UWB technology 40

Figure 13: Process of location finding with wireless-based detection systems 42

Figure 14: The position of a target node (T) is estimated based on the known positions of beacons (B_i) using (a) triangulation or (b) trilateration-ToA 44

Figure 15: The scene matching method phases 46

Figure 16: Scope of Classic Bluetooth via Scope of Bluetooth Smart 52

Figure 17: Purchased BLE Tags 54

Figure 18: BLE Tag I and LBM313 module 55

Figure 19: BLE Tag II 56

Figure 20: BLE Tag III 56

Figure 21: BLE Tag IV 57

Figure 22: The interface of the research software 58

Figure 23: Experiment environment for Material Selection 58

Figure 24: UML Sequence Diagram of Material Selection Experiment.................... 59

Figure 25: RSSI Logs on Material Selection Experiment.. 60

Figure 26: Number of received signals on Material Selection Experiment 61

Figure 27: IDEF0 diagram demonstrating the research approach 63

Figure 28: Conceptual Framework of Proposed Location Detection System............ 64

Figure 29: Tag Locations on Test Bed Environment, scale: 1/200............................ 67

Figure 30: Fingerprints on Test Bed Environment, scale: 1/200 68

Figure 31: Test Bed Environment - Second Floor of MATPUM Building 69

Figure 32: Placement of BLE Tags on Test Bed Environment.................................. 70

Figure 33: UML Sequence Diagram of Online Phase 71

Figure 34: Flowchart diagram of k-NN algorithm... 72

Figure 35: Location of Fingerprints in Training Data of Case IV, Scale: 1/200 75

Figure 36: An abstract model of the impact of human body orientation 79

LIST OF ABBREVIATIONS

AOA	Angle of Arrival
BAS	Building Automation System
BLE	Bluetooth Low Energy (Bluetooth Smart)
dBm	Decibel-Milliwatt
GPS	Global Positioning System
HVAC	Heating, Ventilation and Air Conditioning
IoT	Internet of Things
K-NN	K- Nearest Neighbor
LOS	Line of Sight
PIR	Passive Infrared
RF	Radio Frequency
RFID	Radio Frequency Identification
RSS	Radio Signal Strength
RSSI	Radio Signal Strength Indicator
TOA	Time of Arrival
TDOA	Time Difference of Arrival
UWB	Ultra-Wide Band
Wi-Fi	Wireless Fidelity
WLAN	Wireless Local Area Network
WPAN	Wireless Personal Area Network

CHAPTER 1

INTRODUCTION

In this chapter, the background information about the outlined problem is presented. Aim and objectives of the research are stated. Contribution of the study is explained and the content organization is outlaid.

1.1 Background Information

With the breakthrough of Global Positioning System (GPS), location-based services has shown a widespread emergence in the world within a wide scope such as on-road navigation, tracking of valuable assets and route monitoring. Although GPS technology is a universally accepted solution for finding position in outdoors, since satellite signals cannot penetrate through structural obstructions (*i.e.,* walls, floors, roofs), it cannot be adapted for localization in indoor built environments. Indoor localization is an important area of research for the construction industry as it is the base for many use cases including detecting occupancy in buildings, tracking assets and on-site personnel in construction sites, supporting facility maintenance and operations, and providing route assistance in building emergency response operations and emerging Internet of Things (IoT) applications (Li, Li, Becerik-Gerber, & Calis, 2012b).

Among the use cases of indoor localization, building occupancy detection is selected as the focus of this research. There are many use cases for building occupancy detection, such as security, emergency, hospitality, commerce, and building operation optimization. In order to satisfy the comfort needs of occupants and ensure energy efficiency in buildings at the same time, it is important to have the knowledge about whether the space is occupied or not, and how many occupants exist in the considered zone. Accurate occupancy information is defined by Li, Calis, and Becerik-Gerber

(2012a) as the number of people in a building space and the resulting activities from occupants being present. It could have a crucial effect in enabling energy savings of buildings as well as providing a comfortable environment for habitants if it is monitored in real-time simultaneously and implicated in building automation systems.

There are some existing technology based approaches for detecting the occupancy and finding the position of people in indoors, such as simulation models, image detection systems, passive infrared (PIR) sensor based systems, CO_2 sensors based systems and radio frequency based (wireless) systems. However, a reliable and precise location detection framework is still missing due to certain shortcomings of the current technologies including uncertainties in detection, time latency and privacy issues, inability for multiple detection and high expense of deployment and maintenance.

The enabling technology in this study is determined as Bluetooth Low Energy (BLE) which is already equipped in most current mobile devices (Scheerens, 2012). Although BLE is not designed specifically for indoor positioning or occupancy detection purposes, its properties such as ability to penetrate through walls, ultra-low power energy consumption, low cost, low latency in data exchange, uniqueness of each BLE tag make it a potentially appropriate technology for utilization in localization frameworks (Lodha, Gupta, Jain, & Narula, 2015). The deployment of BLE for indoor localization is based on the analysis of the radio signal propagation characteristics, such as power, attenuation, and interference.

As mobile devices such as smartphones, tablets or smart watches has became essential objects in people's daily lives and shows a rapid evolvement, there is a potential for using them as an enabler for the integration of BLE in indoor localization systems. These devices have various embedded technologies (*i.e.*, built-in radios, NFC, network connectivity, simple user interfaces, accelerometer, gyroscope, magnetometer, barometer, proximity and light sensors) that has been the subject of indoor localization research (Nick, 2014). According to the research carried out by Smith and Page (2015), 90% of people use a cell phone whereas 64% of them are smartphones in United States. Considering this, establishing a mobile device integrated framework is intended.

Considering the importance of indoor localization for the built environment and the drawbacks of existing approaches in the industry, a new framework, which is accurate, punctual, reasonable in expense and easy to be implemented in current building systems can be developed for location detection using BLE technology and mobile devices.

1.2 Aim and Objectives

The main aim of this study is to develop an indoor localization framework for the use case of occupancy detection through utilizing mobile devices and BLE technology. Research objectives can be listed as:

- Investigating the indoor localization technologies for the built environment and reviewing the different use cases in the sector
- Understanding the rationality of the need for occupancy information and location detection in buildings
- Developing a reliable indoor localization framework for providing the base for accurate occupancy detection in real-time
- Experimenting the applicability of mobile devices and BLE technology in indoor localization
- Investigating the parameters of BLE-based indoor localization

1.3 Contribution

There are various studies in the literature for evaluating the reliability of different technologies for indoor localization and no proposed solution is widely accepted due to their constraints. Yet, there is not a comprehensive framework for BLE based location detection in indoor built environments and the analysis of BLE technology for utilization in such purposes is limited in the literature. The contribution of this research is, therefore, to establish a framework for BLE based indoor localization and to analyze different parameters of BLE technology in a detailed manner. In the light of the analysis of the proposed framework, it is intended to compare BLE technology with the existing approaches through referring the performance metrics of radio signal based localization systems.

1.4 Disposition

This thesis is composed of five chapters, first of which is this Introduction part. The second chapter provides a literature review on indoor localization use cases, building occupancy detection and its emergence in the industry, existing approaches for occupancy detection with their advantages and drawbacks, and localization techniques and performance metrics of wireless based location detection systems. The results of a detailed research on the subjects are given together with discussions and a critical analysis at the end of the chapter.

The third chapter covers the material and method of the study. First, a general overview of Bluetooth Low Energy technology is given. Then, the process of material selection and selected material is presented. Afterwards, location-fingerprinting method, which is composed of two phases, namely offline phase and online phase, is introduced. Finally, five different cases are presented, and the parameters of the proposed framework for indoor localization based on these cases with the guideline of research hypothesis are outlined.

In the fourth chapter, results of the experiments that are clarified in the third chapter are given. Analysis conducted on the gathered data is presented and the results are discussed in terms of usability of the proposed framework for location detection. The chapter is concluded with the demonstration of a table including comparisons between the proposed framework and the existing approaches considering defined performance metrics.

In the final chapter, deductions based on the findings from the conducted experiment are given together with a brief summary of the research. Limitations of the study and further research recommendations are given and the study is concluded.

CHAPTER 2

LITERATURE REVIEW

In this chapter, the related issues on the subject area from the literature are presented under four main sections. The first section covers the importance of indoor localization and its scope in the built environment. In the second section, indoor localization approaches are explained. Following, localization techniques for wireless communication based systems and their performance metrics are presented in detail. This section is concluded with the critical analysis of the literature.

2.1 Indoor Localization Use Cases

Gaining information about the location of a person or an object has become an important issue in the field of built environment (Li *et al.*, 2012b) as well as industries such as logistics, transportation, manufacturing and healthcare (Li & Becerik-Gerber, 2011). Location-based services such as on-road navigation, transportation tracking and route monitoring are the motives for a need towards outdoor location detection. In indoor built environments, the importance of localization arises from its value for construction industry in a various range of applications. Detection of building occupancy for automation systems (Spataru & Gauthier, 2013), tracking personnel and equipment for effective management of facilities, providing assets location in construction sites and determining intended routes in building emergency response operations (Li *et al.*, 2012b) are all within the scope of indoor localization. In outdoors, access to location information is possible via Global Positioning System (GPS) that is adapted universally and is available to public usage since early 1980’s (Lathikumari, 2011). However, since GPS could not be utilized in indoor environments due to the fact that satellite signals are not strong enough to penetrate through the walls (Caron *et al.*, 2007), a convenient and universally accepted solution for sensing locations in indoor built environments still does not exist.

Before going through the existing approaches in the industry, it is beneficial to understand the need for localization in the indoor environments. In this section of the research, a review of literature about the areas of use for indoor localization with their advantages and the selected case will be presented.

2.1.1 Building Occupancy Detection

Reducing CO_2 emissions by 20% compared to 1990, and increasing renewable energy use by 20% by the year 2020 were put as future objectives for '20-20-20 targets' by the European Commission ('Directive 2010/31/EU', 2010). Since buildings use 40% of total energy in the world, Soucek and Zucker (2012) argue that nearly-zero energy buildings should be the only choice for built environments in the future. Benezeth, Laurent, Emile, and Rosenberger (2011) listed three solutions for economizing energy consumption, which are utilizing renewable energy sources, providing passive solutions like insulation and managing the active energy consumption in buildings. It is indicated that reliable building occupancy information is a prerequisite in the third solution. However, a massive part of the large buildings stock in today's world usually operated by energy inefficient building management systems that function based on fixed schedules and do not take crucial factors like presence of people as an input for their operations (Oliveira-Lima, Morais, Martins, Florea, & Lima, 2016). Presence and behaviors of people effects the demands for facility operations and increase the energy consumption in buildings (Page, Robinson, Morel, & Scartezzini, 2008). For example, a space's ventilation and cooling load that represent the amount of fresh air to be supplied to that particular space to maintain good air quality and thermal comfort is affected by the number of occupants in that space zone (Liao & Barooah, 2010). Consequently, developing solutions for operating facility services like heating, cooling, air conditioning and lighting in an occupancy-based demand driven manner has been the topic for many researches in the recent years (Labeodan, Zeiler, Boxem, & Zhao, 2015).

In the current approach of the industry, demand-driven facility services are operated through relying on assumption models and pre-defined occupancy profiles (Labeodan *et al.*, 2015; Li *et al.*, 2012). There are various occupancy assumption models such as the model proposed by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) which includes the definition of several occupancy profiles for office building day types (Duarte, Van Den Wymelenberg, & Rieger, 2013).

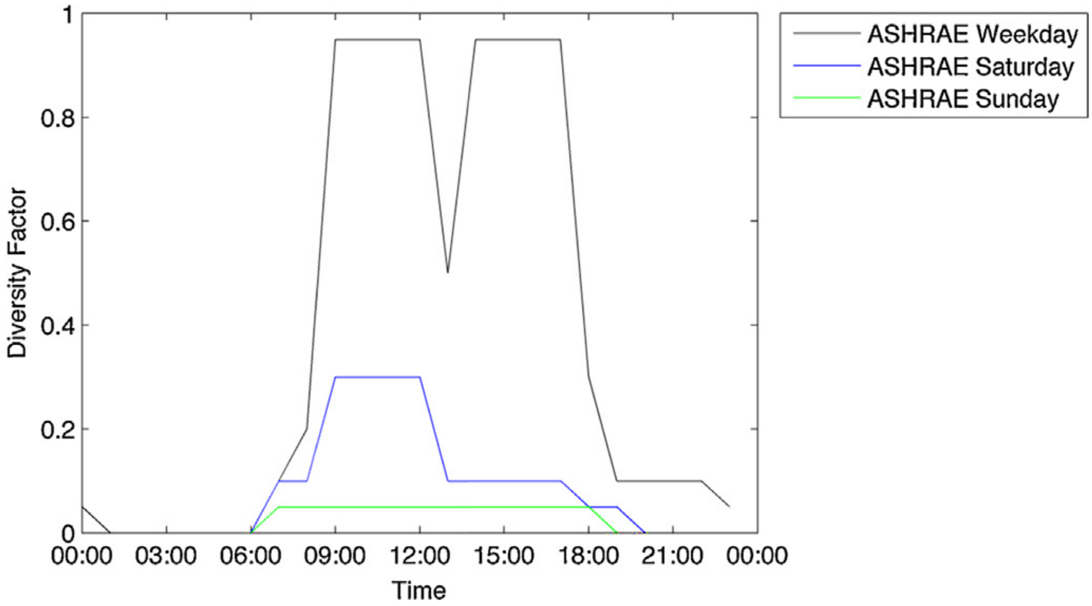


Figure 1: ASHRAE recommended occupancy profiles by day type
(Source: Duarte *et al.*, 2013)

Yet, considering the excessive uncertainty in the nature of occupancy and unpredictable variations over numerous time-scales, it can be deduced that fixed occupancy profiles for buildings are not very reliable and real-time monitoring is necessary to gain instant occupancy information (Liao & Barooah, 2010). Erickson *et al.* (2009) emphasize the inefficiency of relying on maximum occupancy assumptions in their paper and explain the situation in office buildings as:

> In general, the approach used is to assume that all rooms are occupied during working hours and not being used during the night. However, it is obvious that this does not maximize energy savings. Rooms are often left empty during part of the day or perhaps are only used semi regularly, *e.g.* conference rooms. It would be more efficient to only condition rooms

> during the times that are actually occupied. Using an L-HVAC system, various environmental aspects of room can be controlled for energy savings. Thus, knowledge of occupancy is crucial in order to maximize efficiency of a system (p. 19).

In order to understand the influence of dynamic occupancy information on energy usage, Dong and Andrews (2009) simulate energy consumption of an office zone with both static occupancy profiles and dynamic occupancy data. Their research shows that, sensing occupancy in real-time could remarkably reduce the energy consumption to a level of 30%. As using fixed design assumptions are not that efficient in terms of energy consumption, obtaining reliable real-time occupancy information with the combination of raw sensor data and advanced algorithms has become an area of interest for many researchers lately (Ekwevugbe, 2013).

The definition of occupancy information is made by Li *et al.* (2012a) as "the number and identities of occupants in a thermal zone and the resulting activities from occupant being present (*i.e.,* associated plug, lighting and HVAC loads)" (p.89). Considering the fact that one of the main requirements for an economical energy consumption management in buildings is reliable occupancy information, real-time occupancy detection , *i.e.,* instant localization of people in indoor spaces, may be recognized as an effective solution for operating demand driven facility services (Diraco, Leone, & Siciliano, 2015).

Particularly in dynamic environments, having real-time occupancy information, including the number of occupants and their locations in the building, as Li *et al.* (2012a) claim, may be very useful both in building energy management and applications areas including security, safety and emergency response. Yang and Becerik-Gerber (2014) revealed that if occupancy profiles are personalized through real-time location monitoring and used instead of conventional assumption models in HVAC control of a multi-story office building, energy consumption can be reduced by 9%. Likewise, the research of Lo and Novoselac (2010) showed that a reduction of 30% in cooling energy consumption is possible with the utilization of occupancy control in an open plan office, through considering occupied and unoccupied zones separately in providing facility services. Furthermore, as Erickson, Carreira-Perpiñán, and Cerpa (2011) affirm, the energy consumed for air conditioning annually in an office building can be reduced by 42% through sensing the location of people in the buildings while keeping the comfort standards optimum for occupants.

2.1.2 Asset Tracking on Construction Sites

As construction materials and equipment account for almost two-thirds of the total cost in a typical construction project (Kini, 1999), management of assets on the construction site is a critical task for a successful project completion within a constrained budget and targeted project duration (Torrent & Caldas, 2009). Although the cost of construction projects may be reduced with a comprehensive asset management strategy on site (Song, Haas, & Caldas, 2006b), Jang and Skibniewski (2009) explain that, currently, construction materials, equipment and workers are located and tracked manually within the large project sites. Due to the complex nature of project management and uncontrollable system size of built environments, locating and getting spatial information about a construction material manually is a difficult task (Jang & Skibniewski, 2009). As the scale of projects gets larger and become more complex, it becomes even harder to track information related with assets locations and manage supply chain manually. Therefore, providing a real-time localization solution and integrating automation in material management becomes a necessity in construction projects (Jang & Skibniewski, 2008). Bisio, Sciarrone, and Zappatore (2016) revealed that having location information of construction components enhance a considerable efficiency in labor time, on account of the fact that workers waste almost one third of their time on searching the positions of the desired resources (Torrent & Caldas, 2009). Besides, Caron *et al.* (2007) imply that progress state of projects on the site can be monitored in real-time through localization of construction assets.

Considering the fact that countless number of materials and components are going through various stages according to project schedule till the completion of on-site installation in a construction project, there exist a direct relationship between asset management procedure and project performance (Song *et al.*, 2006b). The results of ineffective asset management on construction sites such as lost materials, late detection of additional material needs, material deliveries in incorrect sequences and deficiencies in supply chain (Razavi & Haas, 2011) lead to a reduction of 40% in construction productivity (Nasir, 2008). The primary purpose of asset management is clarified by Song, Haas, Caldas, Ergen, and Akinci (2006a) as to track the availability of construction materials and to provide accurate location information when they are needed by the operation crew. Since manual processes of recording data about the availability and locations of construction components depends on the observations and reporting skills of on-site personnel which is both time-consuming and error prone (Jang & Skibniewski, 2009), there is a huge potential in utilizing identification and localization solutions in construction asset management.

Finding the location of a material, a component or a tool is classified by Li, Li, Calis, and Becerik-Gerber (2013b) as one of the most essential phases of asset management. In reference to Haas, O'Connor, Tucker, Eickmann, and Fagerlund (2000) report, Song *et al.* (2006b) state that popularity in the prefabricated components usage in the last fifteen years has made tracking and locating the construction components on the field even more critical for project management. Ergen, Akinci, and Sacks (2007b) indicate that there is a dense circulation process for prefabricated materials within the construction sites from material delivery to installation. Moreover, since most of the components are uniquely produced according to the precise architectural design decisions, each prefabricated asset is required to be identified, located and tracked separately. Due to the just-in-time delivery requirement of prefabricated precast concrete, for example, Ergen *et al.* (2007b) developed their research on integrating a localization solution with the purpose of gaining the position information of precast concrete components quickly and accurately when requested and minimizing human input in the recorded asset data. Similarly, Song *et al.* (2006a) point out that automated localization and tracking solutions are of utmost importance since lots of unique components of piping activity in construction projects go through a number of phases including fabrication, delivery, storage and installation.

In addition to advantages of localization of assets on construction sites, Cordova and Brilakis (2008) claim that locating on-site personnel in an accurate and precise manner is also critical for various tasks of project management including workers' productivity estimation, activity sequence analysis, early detection of travel path conflicts and providing construction work safety.

2.1.3 Facility Maintenance and Operations

Activities related with operation and maintenance, which form the fundamental part of facility management for ensuring the continuity in efficient building functionality (Taneja, Akcamete, Akinci, Garrett, & Soibelman, 2010), constitute almost 85% of the total lifecycle cost of buildings (Teicholz, 2004). The definition of facility maintenance is made by Cotts, Roper, and Payant (2009) as:

> The work necessary to maintain the original anticipated useful life of a fixed asset. It is the upkeep of property and equipment. Maintenance includes periodic or occasional inspection, adjustment, lubrication, cleaning (non-janitorial), painting, replacement of parts, minor repairs, and other actions to prolong service and prevent unscheduled breakdown, but it does not prolong the life of the property or equipment or add to its value (p. 408).

In their book, Chanter and Swallow (2007) refer to a number of definitions for facility maintenance and conclude the term as "the proper management of a built asset/facility". Consequently, it can be deduced that maintenance of a facility indicates the works that are to be realized by the facility management services for both keeping the living and working built environments comfortable for inhabitants and administrating the performance of equipment and assets of the facilities (Lee & Akin, 2009). Two main category of maintenance activities are sorted by Thomas (2001) as:

- Demand Work: where the client calls in for service, where breakdowns in equipment require repairs and emergency events that affect the facilities department.
- Preventive Maintenance Work: where a scheduled program of work maintains the investment in the physical assets for a corporation. These assets may be equipment assets or facility assets (p. 457).

Considering its huge percentage in the lifecycle cost of buildings, there are many researches that have been conducted for optimization of facility maintenance where the primary subject of most studies is related with utilizing computational support for asset management in built environments (Taneja *et al.*, 2010). In order to ensure an efficient asset management and facility maintenance optimality, indoor localization systems that provide accurate and precise location information of any intended assets or objects in buildings should be integrated into facility management services (Li *et al.*, 2013b).

Table 1: Core maintenance activities with time data (Lee & Akin, 2009).

CMA	Electrician		Plumber		Total	
	Time (min)	Ratio (%)	Time (min)	Ratio (%)	Time (min)	Ratio (%)
Get maintenance requests	7	1	0	0	7	0
Locate equipment	**114**	**10**	**25**	**5**	**139**	**8**
Diagnosis	84	7	15	3	99	6
Get tools	40	3	11	2	51	3
Get materials	**53**	**5**	**8**	**2**	**61**	**4**
Repair	471	40	187	37	658	39
Preventive Maintenance	255	22	161	32	416	25
Project	19	2	0	0	19	1
Contractor Support	30	3	20	4	50	3
Inspection	46	4	43	8	89	5
Request collaboration	10	1	34	7	44	3
Report findings and progress	**16**	**1**	**0**	**0**	**16**	**1**
Document	**0**	**0**	**0**	**0**	**0**	**0**
Others	28	2	7	1	35	2
Total	1173	100	511	100	1684	100

Lee and Akin (2009) listed the core maintenance activities under two categories and demonstrated the time spent for each activity depending on their observations. According to the outcomes of their research, the main inefficiency in the facility maintenance is caused by localization of equipment, which takes approximately 10% of the total maintenance time. It is possible to make an optimization in facility maintenance and save a remarkable amount of time through utilizing accurate localization solutions.

Throughout the activities for providing maintenance in a facility, finding the location of a problematic asset for a demanded work or identification of an equipment for preventive maintenance is always a prerequisite. It is not significant whether the intended asset or equipment is in line of sight or hidden behind a wall or an object, manual visual search is a highly time consuming action on site for facility management service personnel (Taneja *et al.*, 2010). Lee and Akin (2009) indicate that maintenance activities take more time than they should, due to the difficulty in localization of building equipment. It is even harder to locate a building asset or an equipment in more complex and larger buildings and wasting time by searching manually for finding the accurate location may result in more damage in emergencies (Li *et al.*, 2013b). Through referring the research of Leite (2009), Li *et al.* (2013b) explain one of the primary reasons for failure in preventing damage in case of urgent maintenance requirements in buildings as the lack of ability to locate an out of repair component instantly.

For instance, Ergen, Akinci, East, and Kirby (2007a) maintain that, fire valves that are placed in different points in a building, some of which are in non-line of sight and unobservable due to some obstructions, should be checked twice a year by facility management services personnel according to the fire regulations. However, it is not easy for workers to notice each separate fire valve in a building and locating a fire valve takes five to ten minutes for an experienced worker; whereas an inexperienced worker spends thirty to sixty minutes for each one. Even an experienced worker may have difficulties in finding a target location in a complex facility layout (Moeser, 1988). What Ergen *et al.* (2007a) emphasize is that facility management services workers might not be willing to perform this time consuming and troublesome maintenance task properly and verification of a complete maintenance for desired assets is very hard. Consequently, it cannot be assumed as reliable to put a check mark on a prescheduled maintenance activity in the current approach. Ergen *et al.* (2007a) clarify that indoor localization has a crucial significance for optimization of facility management activities, and sticking a sensor tag which would give a unique identification code to each fire valve and make the localization of all desired assets possible can be the solution for overcoming this inefficient workflow on site.

There is a significant potential in location sensing solutions for minimizing the time spent for asset searching in facilities and ensuring a more effective maintenance (Li *et* *al.*, 2013b). In his article, Wing (2006) affirms that the position of water and gas pipes that are either buried under floors or pass through the walls can be determined with localization systems. Motamedi and Hammad (2009) also agree that the information about the locations of building assets is needed in different stages of building lifecycles and indoor localization is a time-saving requirement for maintenance of facilities. In their research, Lee and Akin (2009) demonstrate that it is possible for facility maintenance activities to be performed in a 12% more time-efficient manner through supporting on-site personnel with instant assets-related and location information.

Apart from tracking the locations of assets such as fire valves, pipes or other building assets, indoor localization can also be beneficial for finding the position of hand tools and equipment in a facility. Goodrum, McLaren, and Durfee (2006) state that since availability of tools in a facility effects the productivity of maintenance personnel, it is important to develop some strategies for equipment management. What Goodrum *et al.* (2006) believe is that, contrary to frequent approach of having excessive number of tools in a building for ensuring productivity of workers, which may be described as waste of resources in return, having sufficient number of tools and improving their management on site through indoor localization systems is the right strategy.

2.1.4 Building Emergency Response Operations

Emergencies in buildings such as structural collapse, flooding and especially fire can turn into fatal disasters for occupants in the buildings and first responders (Li, Becerik-Gerber, Krishnamachari, & Soibelman, 2013a). Li, Becerik-Gerber, and Soibelman (2015a) state that real-time localization of people can be remarkably beneficial in minimizing severe injuries and enhancing success rate in first-time response in building emergency operations. A recent study composed of interviews with first responder professionals by Li, Yang, Ghahramani, Becerik-Gerber, and Soibelman (2014b) showed that the location of people were considered as one of the most important information piece that is required in times of fire emergency incidents. Throughout the study, a number of information items were given to responders and a pre-determined procedure was followed in order to reach a classification between all information items. A simplified part of the result drawn was shown in Table 2.

Table 2: Importance of Indoor Localization
(Adapted from Li *et al.* (2014b))

Stage	Importance Sequence for Interview Responders
Before arrival to scene	- Routing information to the building and area map of the neighboorhood of the building - Building occupancy (number and identities of occupants) - Location of water sources nearby
At emergency scene	- Location of fire in the building, size and duration - Presence and location of occupants in the building - Location and condition of smoke
Attack and mitigation	- Location and condition of deployed and standing-by responding units - Required water flow or foam - Location of available areas of refuge, staging areas

According to Li, Becerik-Gerber, Soibelman, and Krishnamachari (2015b), at an emergency scene, detecting presence and position of occupants is not efficient at all with the current process, in which visual inspections are done from a distance to the site, depending on the observations and estimations of incident commanders. It is pointed out that it would be easier to guide the emergency response team only if real time location information was accessible for monitoring.

The inefficiency of current process and need for localization in building emergency response operations is explained by Li, Becerik-Gerber, Krishnamachari, and Soibelman (2014a) as:

> First responders are the first line of defense when building fire emergencies happen, and one of their foremost important tasks is to search and rescue the people trapped in buildings. First responders usually have little knowledge about the location of trapped building occupants, preventing informed decision-making with regard to search route planning

> and task force allocation. Instead, first responders have to perform a complete search of indoor spaces where people may be trapped. Such search is mostly blind and not efficient, increasing the chances of fatalities and injuries of trapped occupants (p. 78).

Considering the current situation, Li *et al.* (2014a) implied that utilization of a real-time location detection system could reduce the time spent for rescuing the trapped people in an incident and prevent possible fatal outcomes. As they are subjected to lots of dangers in emergencies due to the difficulty in being oriented in complicated, unfamiliar built environments (Rueppel & Stuebbe, 2010), the real-time location information of the operation units is also critical (Li *et al.*, 2015b). Although the professionalism and skills of incident commanders are important factors in a good emergency situation management based on available collected information (Martin & Flin, 1997), a successful coordination and decision-making is only possible with real-time location monitoring of on-site units for ensuring their safety and guiding them with the correct routes within the disaster site (Li *et al.*, 2014a). Li *et al.* (2015a) suggested that, those first responder units which are disoriented in dangerous spaces can be noticed and alerted by incident commander through real-time monitoring, and they can be directed to trapped people with navigational directives. In addition, it is asserted in the paper that potential dangers can be better detected and prevented by first response units themselves if they are provided with access to their real-time positions accurately on the field.

2.1.5 Selected Scope for Indoor Localization

Definition of indoor localization is made by Taneja (2013) as ‘the process of determining the semantic location (such as a room number) of a person or an object with respect to a reference coordinate system in an indoor environment’ (p.1). As explained above, location information in indoor built environments have a great value for architecture, engineering and construction industry. In the literature, indoor localization systems are studied for a wide range of purposes with different perspectives. Detection of occupancy for supporting demand-driven building operations and reducing energy consumption, increasing efficiency in construction labor time and supply chain management with automated asset tracking, optimization of facility maintenance and operations through instant localization and identification of building components, and guiding first response units in indoors in time of emergencies are the main causes of interest for indoor localization.

As buildings are responsible for over 40% of total energy consumption in the world (Soucek & Zucker, 2012), possibilities for creating energy efficient built environments are investigated by researchers in many ways. Considering the effects of presence and behavior of people on energy consumption in buildings (Page *et al.*, 2008), information related with presence and location of occupants in indoor built environments is highly valuable. Accordingly, this research focuses on building occupancy detection systems that is thought to be the most critical one among the mentioned scopes of indoor localization.

- **Human Factor in Built Environments**

In definition, what the term ‘human factor’ focuses on is to understand the interactions between people and the elements of a system, as Attaianese (2012) explains, providing hypothetical standards, information and methods to design for optimizing overall system performance and human comfort. In the context of built environment, considering that a large percentage of people’s daily time is spent within their homes or offices, a proper human-centered approach is essential in the design and operation of buildings. A whole set of buildings systems including space, lighting, heating and cooling, ventilation, water supply, and security should be designed with the optimization of daily user activities and to maximize the level of people’s well-being and satisfaction within the built space (Attaianese & Duca, 2010).
In his book, Pallasma (2005) describes buildings as more action-oriented environments and claims that buildings engage with people by uniting, relating and articulating. In order to understand the concept of building occupancy detection, it is beneficial to investigate its theoretical background and the reasons for emergence of a need for sensing people in indoor environments. With this purpose, firstly, the engagement between occupants and built environments will be explored. Secondly, intelligent building approach will be explained with necessary definitions and examples. Following, building automation systems and importance of occupancy information for

automated building operations with possible gaining will be discussed. Finally, the definition for building occupancy detection with related constituted frameworks in the literature will be represented.

- **Occupant – Built Environment Interaction**

Buildings may be described as intricate systems where the collaboration of the discrete components contribute to the interconnected whole. Since the key role for running of the built facilities belongs to its users, as Altomonte, Rutherford, and Wilson (2014) indicate, aspirations and demands of the occupants are essential for the design of built environments and occupants should be engaged directly in a conscientious circle throughout whole design process.

Behaviors of occupants are defined by Klein *et al.* (2012) as the decisions taken and actions of building occupants that influence the energy consumption of buildings. Daily interactions between people and their surrounding built environment requires remarkable attention in the building design and maintenance processes, since they affect both indoor comfort rates and energy usage of buildings (Langevin, Gurian, & Wen, 2015). These interactions are exemplified by Robinson (2006) as:

- Window and door openings: influencing air flow,
- Shading devices / blinds: influencing radiation transmission and glass surface temperature,
- Lighting controls: influencing electricity consumption and casual heat gains,
- Electrical appliances: influencing electricity consumption and casual heat gains,
- Heating, ventilating and cooling system controls: influencing thermal and electrical energy consumption and associated heat injection / rejection,
- Waste is also produced, from which energy may be derived, and for which water is consumed (p. 4).

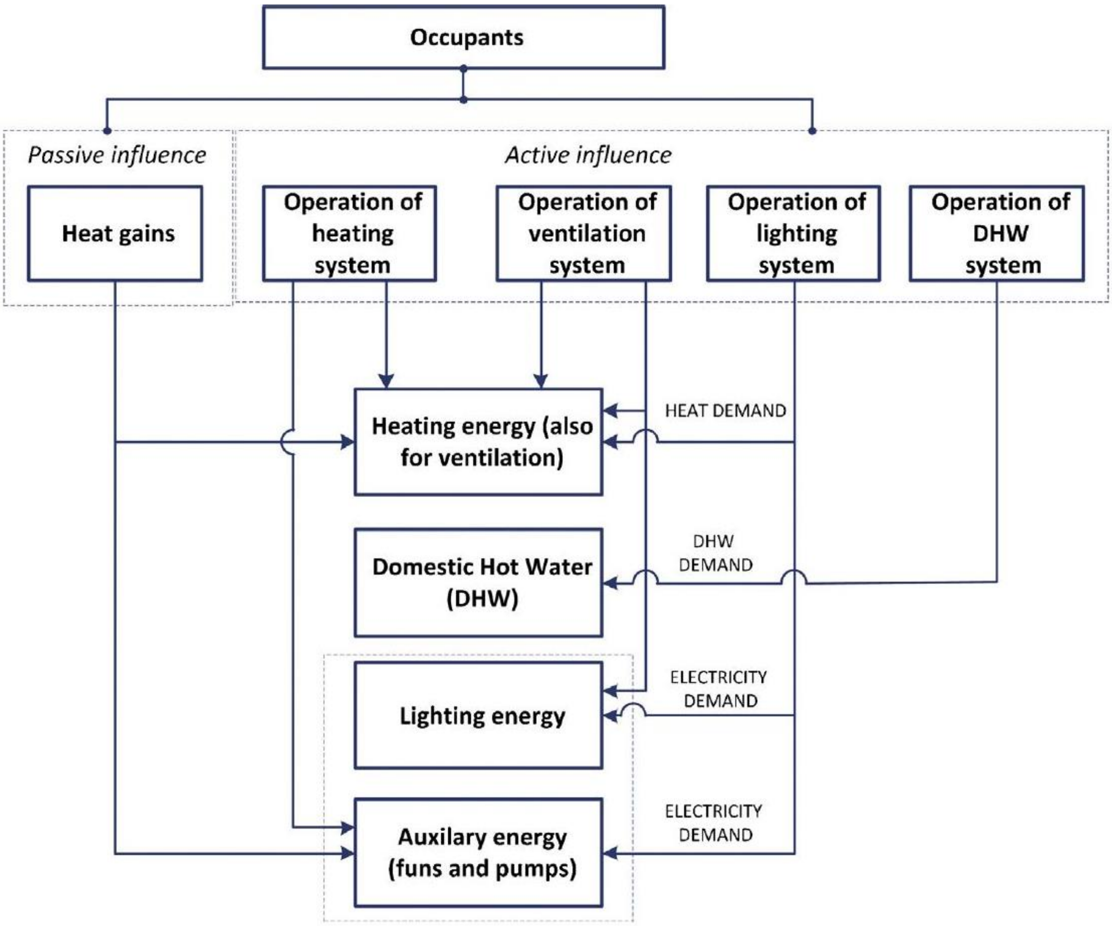


Figure 2: Active and passive occupants' effects on building performance. (Martinaitis *et al.*, 2015)

Supporting Robinson's examples of interaction, Ekwevugbe (2013) argues that, presence and behavior of people has a big impact on energy use of buildings, and through the release of carbon dioxide, water vapor, body heat, sound and odor as a result of their daily activities, they also affect the built environment conditions. Moreover, Martinaitis, Zavadskas, Motuzienė, and Vilutienė (2015) clarify that energy performance of buildings and indoor comfort level are affected both by presence (passive effects) of occupants and their actions (active effects) (Figure 2).

Indoor environments' performance could be analyzed and improved through the overview of two critical parameters, which are occupant comfort and building energy

(Klein *et al.*, 2012). Considering the interrelated effects of people and built environment on each other, it can be said that a two-way interaction between occupants and buildings is critical for achieving success in providing a healthy and energy efficient environment. That is to say, a building should perceive and respond its occupants in its own way, just as occupants experience and affect the buildings (Clements-Croome, 2013).

- **Intelligent Building Approach and Building Automation System**

With the drive towards creating energy efficient, productive and environmentally healthy built environments for occupants, and optimizing the building services, systems and management, the concept of intelligent building was born (Wong, Li, & Wang, 2005). One of the very first definitions of intelligent buildings was done by Clements-Croome (1997) through referring CIB Working Group W98's proceedings as:

> An intelligent building is a dynamic and responsive architecture that provides every occupant with productive, cost effective and environmentally approved conditions through a continuous interaction among its four basic elements: Places (fabric; structure; facilities): Processes (automation, control; systems): People (services; users) and Management (maintenance; performance) and the interrelation between them (p. 396).

What an intelligent building refers to in general is a high technology built environment equipped with computerized and automated building systems whose goal are to meet occupant requirements and to provide appropriate synergy between people and buildings (Harrison, Loe, & Read, 1998). According to Clements-Croome (2013), promoting sustainability (water, energy and waste), creating a healthy environment for occupants, using robotics, embedded sensor technology, and communication and information technology are all included within the key issues for intelligent buildings. On the other hand, Wang (2010) explains, a services-based definition is made by The Japanese Intelligent Building Institute as; an intelligent building is an environment functionalized with building automation systems that ensures satisfaction of its users and rationalize the management of building operations in a cost-effective and healthy manner.

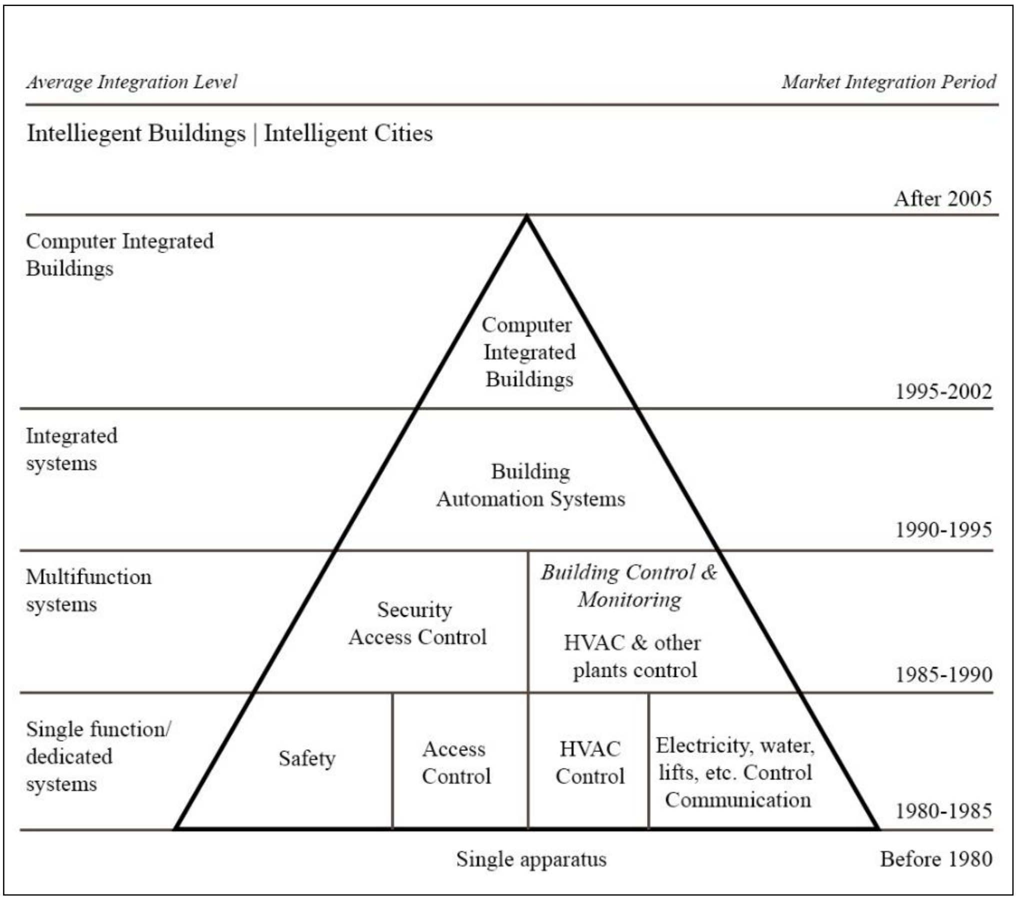


Figure 3: The Intelligent Building Pyramid (Adapted from: Wang, 2010)

Intelligent buildings have a progressive history that improves parallel with the development in intelligent control of building operations after 1980 (Figure 3). Moreover, the integration level is accelerated with the evolution in computer, electronic and information technologies (Wang, 2010).

Visual comfort, thermal comfort and indoor air quality comfort are listed as the three basic factors that determines occupants' life qualities in buildings by Dounis and Caraiscos (2009). Since the overall control of these three factors is made by HVAC system, auxiliary control facilities and lighting system, the management of these systems may be very crucial for improved energy efficiency in buildings and comfort of occupants (Yang & Wang, 2013). The major service of intelligent buildings that deals with the control of building facilities is called Building Automation Systems (Wang, 2010).

Existence of building automation systems industry is predicated on the patent of first temperature control system in 1895 (Clute, 2008). The very first definition of the building automation system is made by Carlson and Giandomenico (1991) as a tool for building operations to provide more efficient and effective control over all building systems. Since then, as Clute (2008) emphasizes, BAS has evolved in many different ways and a new era of machine-to-machine communications, building intelligence and expanded functionality is on the horizon.

Soucek and Zucker (2012) claim that, energy efficient operation of the buildings should be ensured by technological tools like comprehensive building automation systems for achieving the future aim of having zero energy buildings. While energy efficiency requires the building architecture and its systems to be designed accordingly and it starts from the very early stages of construction; operation and maintenance of buildings are the stages where building automation system is responsible for minimizing energy consumption (Soucek & Zucker, 2012).

Commonly, in today's world, what building automation system refers to is the arrangement of computer-based systems to monitor and administrate buildings' physical environments and operations such as heating, ventilation and air conditioning, electricity control, and water systems controls (Yang & Wang, 2012). Vasseur and Dunkels (2010) explain that, HVAC and electricity systems are automatically regulated by BAS for ensuring the comfortable living environments in indoors, while ensuring a more energy efficient built environment. Moreover, utilized security and fire systems can also be controlled and monitored by BAS, which enhances the security and safety of the built environments. Nguyen and Aiello (2013) state in their article that, a wide variety of innovations including building controls and energy administration frameworks, crosswise over local, institutional, industrial and commercial buildings, are incorporated by the course of BAS.

Although the target building size of BAS ranges from 10 K square meter structures (*i.e.*, a five-story office buildings) to 100 K square meter skyscrapers, mid-size buildings (5 K square meter to 10 K square meter) can also be instrumented with automated lighting, HVAC and security solutions (Vasseur & Dunkels, 2010). Improvement in facility management, protection of people and equipment, enhancement in staff productivity, reduced operating costs and increase in the reliability of plant and services are listed as the major benefits and the scope of BAS by Wang (2010). Climate control, visual comfort, personal safety, building security and energy management are all the fields of services within the built environment that can be operated throughout the interface of BAS (Soucek & Zucker, 2012).

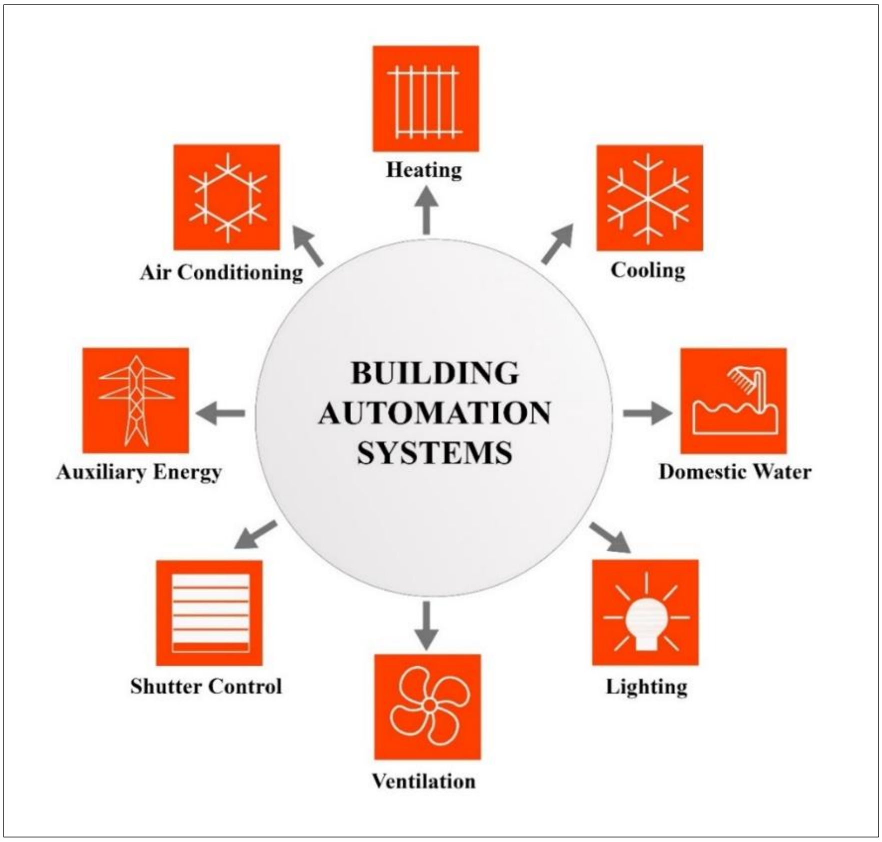


Figure 4: Functional Domains of Building Automation Systems

Apart from building automation system's fragmented operational framework that is pointed out by Prakash (2013), Wang (2010) states that a BAS comprises several subsystems that are joined in various ways to shape a complete system which has to be designed and engineered uniquely around the intended building itself. Six main logical subsystems that compose BAS is shown in Figure 5. As shown in the figure, HVAC, fire, security, lighting, hot water and shutter controls are the major subsystems that are connected logically through application software called building applications. Each subsystem shown in the figure is optional and users may integrate all these subsystems at once or may choose them according to the necessities of the facility (Vasseur & Dunkels, 2010). As it is obvious in the Figure 5, the operation of all major subsystems are based on the occupancy factor within the framework of building automation systems.

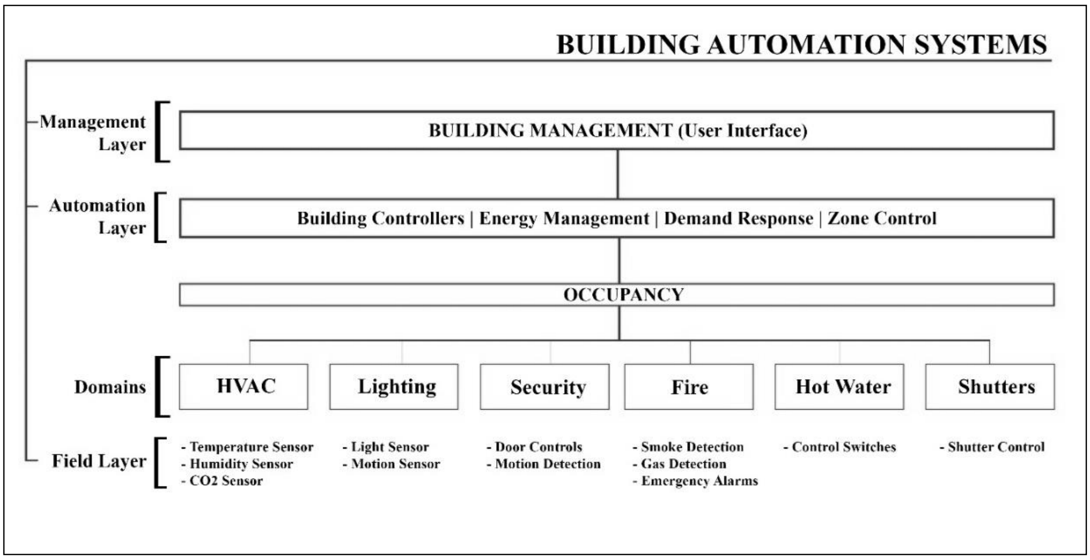


Figure 5: Breakdown of Building Automation Systems
(Adapted from: Vasseur & Dunkels, 2010)

Mohammed (2011) declares that BAS is responsible for the control of these frameworks, monitoring the systems, and recording related data during the life cycle of a given facility. However, although the building systems shown above are typical for most facilities, the whole list is not composed of only these six. Vasseur and Dunkels (2010) argue that the overall objective in the design of building automation systems is to harmonize all typical building functions with the overall system while ensuring a comprehensive adaptability to alter some of the systems and add others according to possible emergent requirements.

- **Importance of Occupancy Detection for Building Automation Systems**

Energy demand and supply model for a building as shown below in Figure 6 is the basis for functionality of BAS (Siemens, 2012). In the figure, rooms represent the source of energy demand that is in return based on occupancy. The goal of providing comfortable living conditions in the building spaces with regards to air quality, humidity, temperature and light for occupants coupled with the desire for reduced energy use can only be achieved through improving this model.

Usual communication model in BAS consist of three layers as field layer, automation layer and management layer from bottom to top (Figure 6). Interface to the physical process in the field layer is composed of sensors which provides information about rooms' requirements in energy demand and supply model (Soucek & Zucker, 2012).

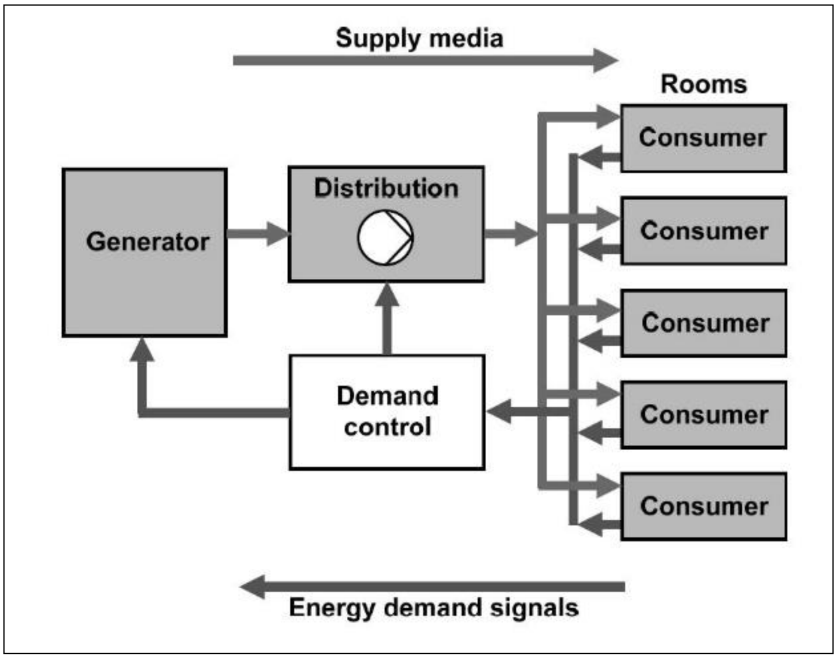


Figure 6: Energy Demand and Supply Model (Siemens, 2012)

Providing indoor comfort, personal safety and a productive environment for the inhabitants is one of the primary objectives of BAS. Yet, as Soucek and Zucker (2012) imply, creating an ideal environment and adapting building services accordingly for all is not possible because of the differences between inhabitants such as age, gender and cultural background and the use of purposes between different spaces in the buildings. Therefore, BAS divides buildings into zones like single office rooms, meeting rooms, open public spaces and service spaces, and behaves according to necessities of spaces and users.

As BAS is responsible for the comfort of occupants within a space, the information about whether the space is occupied or not, or how many occupants do exist in the considered zone has a vital importance. Since the most essential input for BAS is occupancy in the buildings and occupancy rates of spaces may differ based on user calendars, a time-sensitive and logical approach is expected from different sub-systems of BAS (Makarechi, 2007). Yet, Klein *et al.* (2012) state that current building automation systems rely on code defined occupant comfort ranges and they lack real time input of dynamic occupancy that can only be gathered through occupancy detection systems. It is indicated that, consequently, current building automation systems are inefficient in their energy usage for providing occupancy comfort and they cannot adjust themselves according to occupants' comfort needs.

Building occupancy detection is defined along the dimensions of accuracy and resolution by Christensen, Melfi, Nordman, Rosenblum, and Viera (2014). Considering the fact that measurement of occupancy should include information about space, number of occupants and time span, occupancy resolution should be along three dimensions; spatial resolution, occupant resolution and temporal resolution. As shown in Figure 7, while spatial resolution of building occupancy is measured in terms of building structures like floors or rooms and temporal resolutions is measured by time spans, occupant resolution is defined in four levels of detection (Christensen *et al.*, 2014).

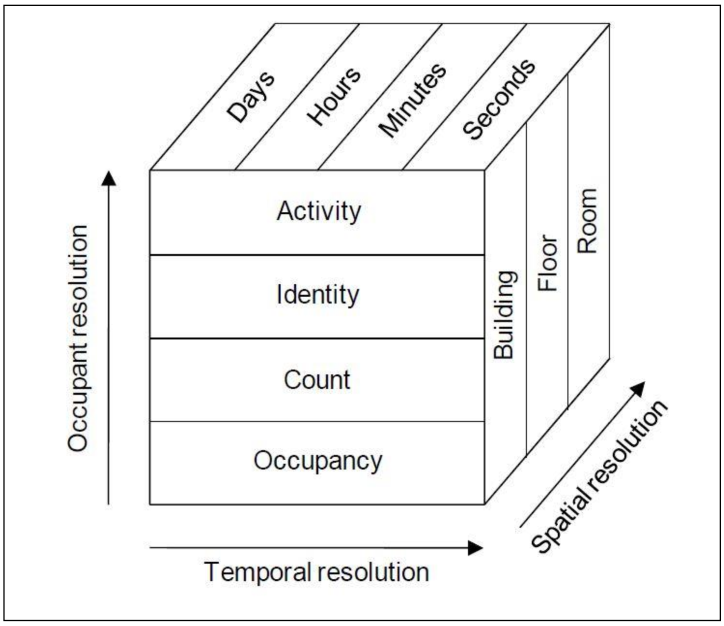


Figure 7: Resolution Framework of Building Occupancy Detection (Christensen *et al.*, 2014)

In minimizing energy consumption by optimizing the intelligence of building automation systems (Breslav, Goldstein, Doherty, Rumery, & Khan, 2013), accurate building occupancy information with the highest resolution possible can be very beneficial. Many researches have been conducted on occupancy detection systems using different methods within the scope of indoor localization, and these works with their benefits and possible drawbacks should be discussed before suggesting a new framework.

2.2 Existing Occupancy Detection Approaches

In this section, it is intended to overview the current approaches for occupancy detection solutions within the framework of indoor localization and explain their benefits and possible shortcomings given in the literature. Prediction algorithm models, image detection systems, passive infrared-based detection systems, carbon-dioxide sensors based detection systems and radio frequency based detection systems will be explained respectively. In radio frequency based detection systems part, different technologies such as radio frequency identification (RFID), Wi-Fi (WLAN) and ultra-wide band (UWB) will be analyzed with their technical frameworks.

2.2.1 Simulation (prediction algorithm) models

In order to characterize the dynamics of building occupancy, mathematical models were utilized in simulation software applications and there are proposed stochastic models in the literature which are created with the purpose of predicting presence of occupants and their interactions with the space they inhabited (Ekwevugbe, 2013). In simulation models, occupancy information is presented using occupant diversity profiles and these profiles are explained by Page *et al.* (2008) as:

> The profiles may depend on the type of building (typical categories being residential and commercial) and sometimes on the type of occupants (size and composition of a family). Weekdays and weekends are usually handled differently, especially in the case of commercial buildings. A daily profile is composed of 24 hourly values; each of these corresponds to a fraction of a given peak load. The weekday and weekend profiles and the peak load are related to a particular category of building and type of heat gain; they may be based on data collected on a large amount of monitored buildings. (p. 84).

For example, in 1999, Degelman (1999) proposed a computer simulation model that was based on recorded experiment data about the usage routines of offices for creating occupancy profiles and lighting schedules for a typical week day. Similarly, an occupancy simulation model was presented by Richardson, Thomson, and Infield (2008) for generating occupancy data of residential buildings in United Kingdom. In their approach, weekdays and weekends are separately evaluated and temporal resolution of occupancy data was specified as 10 minutes. Another occupancy presence simulation method was developed by Page *et al.* (2008) based on a prediction algorithm. In their model that is based on observational data, daily occupancy profiles were generated that reveals the state of absence or presence of individuals on their single-person office spaces.

Although simulated occupancy profiles may match well with ground truth of real-time occupancy information in some cases, it cannot be said that they are effective for occupancy presence prediction in multi-occupant spaces like meeting rooms or libraries, since creating accurate occupant profiles for such spaces are not possible. In general, as Ekwevugbe (2013) argues, simulation models that are created for generating occupancy presence probability data is considered as applicable to single-person spaces like personal offices where dynamics of occupancy is comparatively straightforward. Moreover, rather than providing real-time occupancy information which is also the main purpose of the framework suggested in this research, simulation models can only present the probability of occupancy presence that was labelled as inefficient by Klein *et al.* (2012) for the management of building operations.

2.2.2 Image detection (vision-based) systems

Although vision based devices such as video cameras are usually used for security purposes in buildings, lately their use has also been improved in occupancy detection system (Labeodan *et al.*, 2015). Vision based localization is categorized by Mautz (2012) into two systems with different principles. In the first category, localization target is a mobile vision-based device (*i.e.*, a wireless camera), whereas in the second category, a fixed camera detects moving occupants in the processed images. It is indicated that, all vision-based localization systems rely on detection of people through comparing the perceived image with the buildings' predefined visual database (3D building models, images, recorded coded targets or projected targets) (Mautz, 2012).
A vision based solution in which the static video cameras are used for localizing occupants and identifying objects in indoor environments was developed by İçoğlu and Mahdavi (2007). In their model, every object is coded with a small reference tag image and the visuals derived from cameras are processed with an algorithm for comparing and matching the perceived tag image with the tag images in the deployed database. Information exchange tool in the proposed system is determined as internet, with the intention of ensuring flexible scalability and easy integration for system components in the buildings. Another vision-based position detection system was proposed by Kim and Jun (2008). Contrary to approach of İçoğlu and Mahdavi (2007), they propose a system with wireless cameras for detection of occupant's position. The

wireless cameras are attached to head of the researcher within the experiment, and the locations of occupants are recognized through image data search in the pre-constructed image labelled location model. The researchers report that success rate of this occupancy detection and localization proposal that is tested in an indoor environment is noted as 89% (Kim & Jun, 2008). In the vision-based system proposal of Benezeth *et al.* (2011), presence detection and behavior analysis procedures are reported to be based on processing of videos that are recorded by using static cameras. The video processing system is configured to proceed in three steps, which are detection of change in the environment, tracking of moving objects based on reference points and classification of detected objects (whether it is an occupant or not) respectively. The accuracy of the model is asserted as 93% for personal offices and 83% for public corridors by Benezeth *et al.* (2011). Similarly, Erickson, Achleitner, and Cerpa (2013) deployed static cameras in an office floor whose perspectives cover all entrance points to the separated zones. The purpose of the proposed solution is claimed as detection of occupancy presence in the predefined zones in order to optimize energy management system of the intended building, and presented success rate is noted as above 93% for directional accuracy and above 87% for overall accuracy.

Even though the accuracy rates in the reviewed research papers are quite high, the utilization and deployment of vision-based detection systems cannot get very popular because of number of reasons. Costly requirements for an advanced image processing system and extensive hardware can be listed as the main shortcoming of vision-based systems (Thanayankizil, Ghai, Chakraborty, & Seetharam, 2012). Extreme difficulty of the utilization, testing and system performance verification (Erickson *et al.*, 2013) and privacy concerns of occupants which may arise from being continuously videotaped in living and working spaces (Ekwevugbe, 2013) are the other limitations for implementation of vision based localization systems.

2.2.3 Passive infrared (PIR) sensor based systems

Passive infrared sensors are specifically designed heat energy sensitive tools for detecting infrared radiation waves emitted by human body, which cannot be perceived with the naked eye (Labeodan *et al.*, 2015). Liu, Zhang, and Dasu (2012) state that as a PIR sensor is placed to a zone, it perceives the thermal background of the space and establishes a baseline for itself if it has not already been defined. It is stated that, after the establishment of the baseline, PIR sensors recognize any pattern changes in the infrared energy within the sensor range and presume the room as occupied.

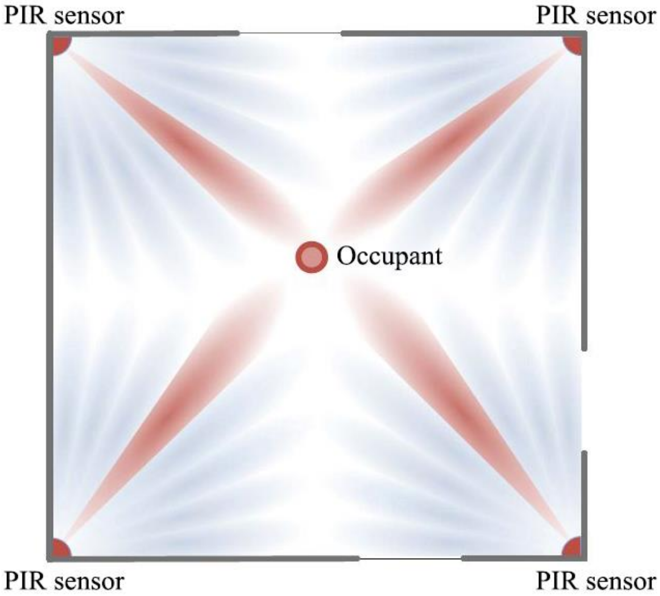


Figure 8: Research setup with PIR sensors by Hauschildt and Kirchhof (2010)

The usage of PIR sensor based systems is largely popular in non-individualized detection of occupancy (Li *et al.*, 2012a) and widely used in lighting control in large office buildings (Delaney, O'Hare, & Ruzzelli, 2009). Yet, there are some researches and proposed systems about detecting occupancy with PIR sensors in the literature. For example, Dodier, Henze, Tiller, and Guo (2006) developed a model composed of three PIR sensors and a phone sensor per zone in a two-room personal office. In the model, each sensor provides an independent detection information to the system and the combination of all measurements reveals whether the room is occupied or not. The reported success rate of occupancy detection is about 98%. A PIR sensor based location detection system was proposed by Hauschildt and Kirchhof (2010) in which utilizes thermopiles, a type of thermal infrared sensors. The research was tested in a room where thermopiles are placed on the four corners and localization of people is done through applying triangulation method (triangulation method is explain in section 2.3 in detail) and angle of arrival principle (Figure 8). The authors concluded that although they achieve high accuracy for position estimation in the test-bed room, the method is applicable only if a prior study is done about the dynamic thermal background of the intended real cases.

Although some PIR sensor based detection systems presented in the literature are claimed to provide real-time information about human presence, due to the number of reasons, they do not have a wide application scope in the real life and their popular use is limited to automated lighting systems (Labeodan *et al.*, 2015). The main downside of this technology is that PIR sensors require unceasing motion and they cannot detect if the state of an occupant is stationary while working or relaxing (Balaji, Xu, Nwokafor, Gupta, & Agarwal, 2013). The other limitations are listed by Kemper and Linde (2008) as sensitiveness to sunshine radiations and airflow movement, ineffectiveness in separating people and pets and inability to penetrate through obstructions like walls. Furthermore, as Liu *et al.* (2012) explain, since the sensor range of PIR is limited, they are not good enough for monitoring large-scale indoor spaces and PIR sensors are useless for multi-occupant detection.

2.2.4 Carbon-dioxide sensors based systems

Carbon dioxide (CO_2) is naturally exhaled by humans on a regular basis and amount of CO_2 varies in spaces throughout time (Fisk, 2008). As occupants are the only source of carbon dioxide (CO_2) in indoor built environments and the amount of CO_2 in a space is proportional to number of people in that space, CO_2 rate can be taken as an indicator of human presence (Kar & Varshney, 2009; Naghiyev, Gillott, & Wilson, 2014). In the light of this assumption, as Labeodan *et al.* (2015) explain through referring the previous literature, occupancy information with a full resolution of presence, count, identity and activity can be provided through the measurement of CO_2 concentration (Labeodan *et al.*, 2015).

CO_2 sensors are widely utilized in demand driven control of ventilation as Emmerich and Persily (2001) presented in their report in detail, and there are also many researches in the literature that employed these sensors for occupancy detection purposes. Wang, Burnett, and Chong (1999) experimented a system in which data from the sensors about the CO_2 rates in an open plan office and a lecture theatre are processed with certain algorithms and used for occupancy estimation. The accuracy of proposed system was tested through comparing the estimated occupancy with the true occupancy information that had been recorded manually. Although it is claimed that the approach is successfully fast, responsive and accurate for occupancy detection, it does not have any potential for localization (Wang *et al.*, 1999). Gruber, Trüschel, and Dalenbäck (2014) investigated the applicability of CO_2 sensors for gaining occupancy information through an on-site experiment in a thirty five meter-square seminar room. Different scenarios were tested through alternating the air exchange per hour (ACH) and number of occupants in the space. CO_2 sensors were placed in the exhaust air ducts to measure the CO_2 concentration in the exhausted air and to relate it with occupancy.

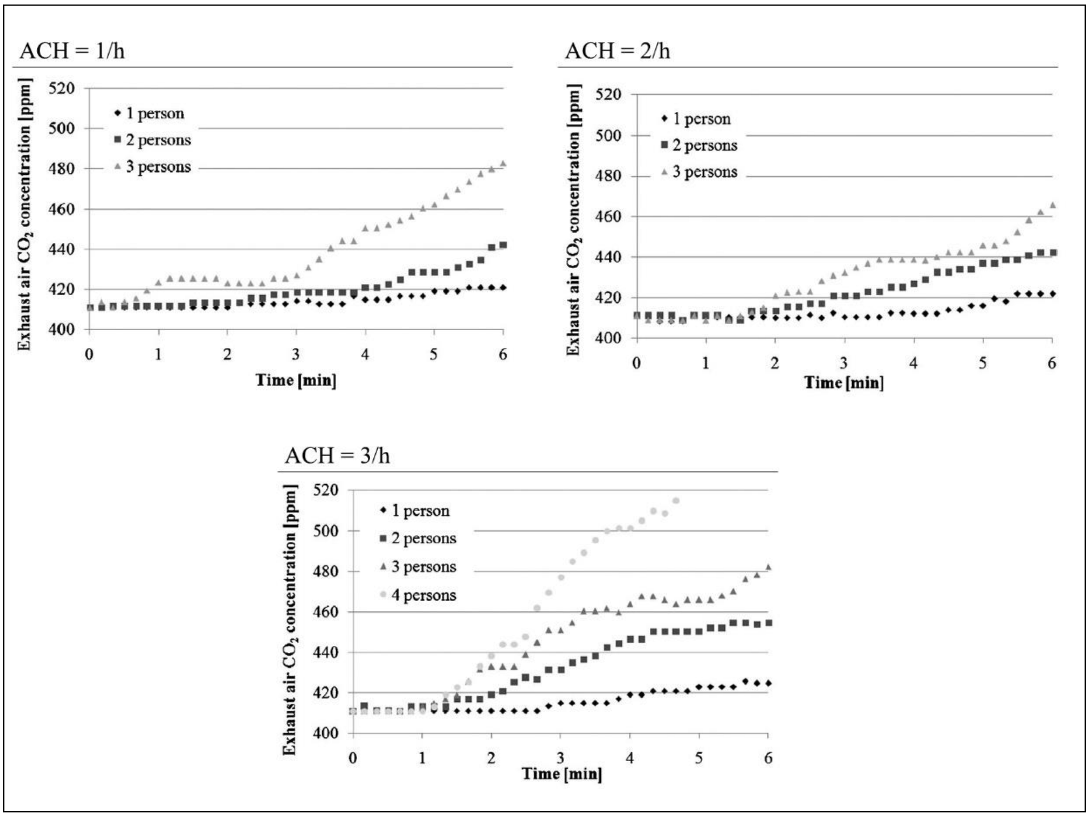


Figure 9: CO_2 – Number of Occupant – ACH Relation (Gruber *et al.*, 2014)

According to their experiment results, as shown in Figure 9, Gruber *et al.* (2014) concluded that, since CO_2 concentration in the experiment field is dependent on both the number of people and ventilation rate, it may have potential for use in automated building systems. It is also reported that there is a time-latency in occupancy detection. These findings are parallel with that of Emmerich and Persily (2001), who indicated that the amount of CO_2 in a space is directly affected by the ventilation rate and the volume of the space. It can be deduced from the research results of Gruber *et al.* (2014) that, even though there is a correlation between the level of CO_2 and presence of people, the effects of uncontrolled ventilation (opening windows or doors) on CO_2 rate may cause inaccuracy in detecting people.

In the literature, there are also some works that investigate the possibility of improving the effectiveness of CO_2 based occupancy detection, through collocating them with some other sensors. For example, Meyn *et al.* (2009) proposed an occupancy sensing system that is composed of CO_2 sensors, PIR detectors and static video cameras. The success rate about detecting the number of occupants is claimed as 89% for the entire building, yet spatial resolution of the system could not reach to room level. Another model in which CO_2, PIR and acoustic sensors are employed to detect the occupancy in an office space with an open-plan layout is demonstrated by Dong *et al.* (2010). Three different algorithms were applied to gathered data and the best occupancy detection accuracy is stated as 73% in the proposed system.

Despite the efforts in the literature for optimizing the accuracy, the utilization of CO_2 sensors in building occupancy detection is still not widely accepted due to some certain limitations. Fisk (2008) argues that, since the natural time latency of sensors in detecting CO_2 level is not fast enough, occupants can already be disturbed by the air concentration and the indoor space can get very uncomfortable for people by the time system get the occupancy information and adjust ventilation level accordingly. Naghiyev *et al.* (2014) also emphasize the problems in the operation of building control systems with fast switching requirements that are caused by the delay in detecting occupancy. Moreover, the level of CO_2 in indoor built environments can be affected by a number of factors including passive ventilation (*i.e.*, air infiltration, open windows) (Ekwevugbe, 2013), wind speed and pressure variations, and sensor orientation (Labeodan *et al.,* 2015). The effects of these factors may mislead occupancy detection, and make it difficult to derive reliable occupancy information using CO_2 sensors based location detection systems.

2.2.5 Radio Frequency (RF) Based (Wireless) Systems

Despite the popularity of GPS for locating people and positioning objects in outdoor environments, it does not work for indoors properly due to the obstructed line of sight between the satellite and receiver tools, which results in attenuation of electromagnetic waves by the walls and obstacles (Farid, Nordin, & Ismail, 2013). Since radio waves has the capability of penetrating walls, obstacles and human bodies, as Vorst *et al.* (2008) demonstrated in their paper, radio frequency based technologies are suitable for indoor localization with their wide coverage area and less hardware necessity. RF based localization systems are generally composed of transmitters and receivers, which interact with each other through radio signals (Boukerche, Oliveira, Nakamura, & Loureiro, 2007). The measurement of radio signal is defined as radio signal strength indication (RSSI) in the literature and explained by Çalış, Becerik-Gerber, Göktepe, Li, and Li (2013) as:

> RSSI is a standard feature in most localization solutions and is defined as the voltage in the received signal strength indicator pin on the radio signal. It is usually expressed in dBm, which is ten times the logarithm of the ratio of power and the reference power. The relationship between power and distance is such that power is inversely proportional to the square of the distance travelled (RSSI α log ($1/\text{distance}^2$)). RSSI is considered as a key parameter to estimate the coordinates of the targets and, thus, is crucial for accurate localization (p. 187).

The very first RF based occupant localization system was named RADAR that is developed by Bahl and Padmanabhan (2000). The goal of authors was to locate and track occupants in indoor built environments through gathering RSSI data at multiple receiver locations and using collected information for position estimation. In the light of the research of Bahl and Padmanabhan (2000), many studies have been made for establishing a reliable and accurate real-time indoor localization solution based on RF technologies including radio frequency identification (RFID), WLAN, Ultrawideband

(UWB) and Bluetooth. In this part of the research, a review of the literature about the location detection solutions with RFID, WLAN, UWB and Bluetooth technologies will be presented.

- **RFID**

One of the most popular methods studied for indoor localization is RFID sensor based models. A RFID system composed of a number of readers and generally a large number of tags adjusted according to intended building size (Figure 10) (Li & Becerik-Gerber, 2011; Zhen, Jia, Song, & Guan, 2008). What separate RFID from the other sensor technologies are its benefits such as RFID tags' features of having unique identity numbers and light, portable designs (Zou, Xie, Jia, & Wang, 2014), its effectiveness in non-line of sight and longer detection range compared to infrared, ultrasound, and Wi-Fi technologies (Pradhan, Ergen, & Akinci, 2009). A detailed technological review of RFID technology for indoor localization purposes can be found in the research paper of Pradhan *et al.* (2009).

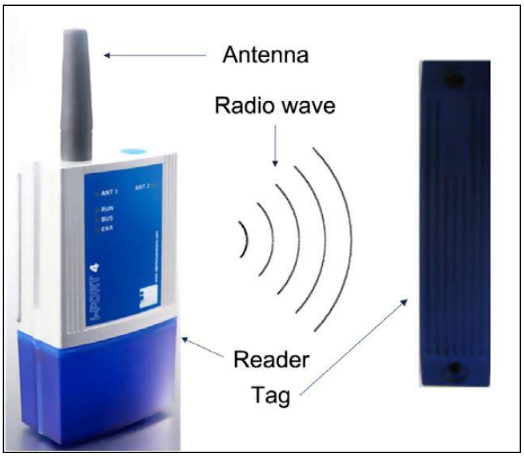


Figure 10: Main components of RFID based systems
(Li & Becerik-Gerber, 2011)

The one of the very first localization system based on RFID sensors was studied by Hightower, Borriello, and Want (2000) with the name SpotON. In the proposed system, randomly placed base stations measure the signal strength transmitted by the target unit and raw data is collected in the main server. The position of target unit then triangulated and detected in three-dimensional indoor environment through analyzing the raw data with an algorithm. Likewise, an RFID sensor based location detection system, LANDMARC, was demonstrated by Ni, Yunhao, Yiu Cho, and Patil (2003) in which, instead of utilizing expensive base stations, a large number of cheap RFID tags were used as reference nodes and four RFID readers were placed in the experiment field. It is indicated that, RFID readers continuously reported the perceived tags within their ranges to the central system. Then, localization of the target object (tracking tag) was done through applying K-nearest neighbor algorithm (k-NN) in which the Euclidian distances in signal strength between reference tags and the target objects are compared. The coordinate of the closest reference tag is determined as the target object’s position. The authors concluded that, although there are several important factors which may affect the accuracy of the system including number of readers, placement of reference nodes and applied algorithm, depending on research analysis, RFID can be demonstrated as a potentially reliable and cost-effective solution for indoor localization (Ni *et al.*, 2003). Yet, authors also noted several limitations for their system including time latency, low accuracy in RSSI reporting and change in tags’ behavior in time.

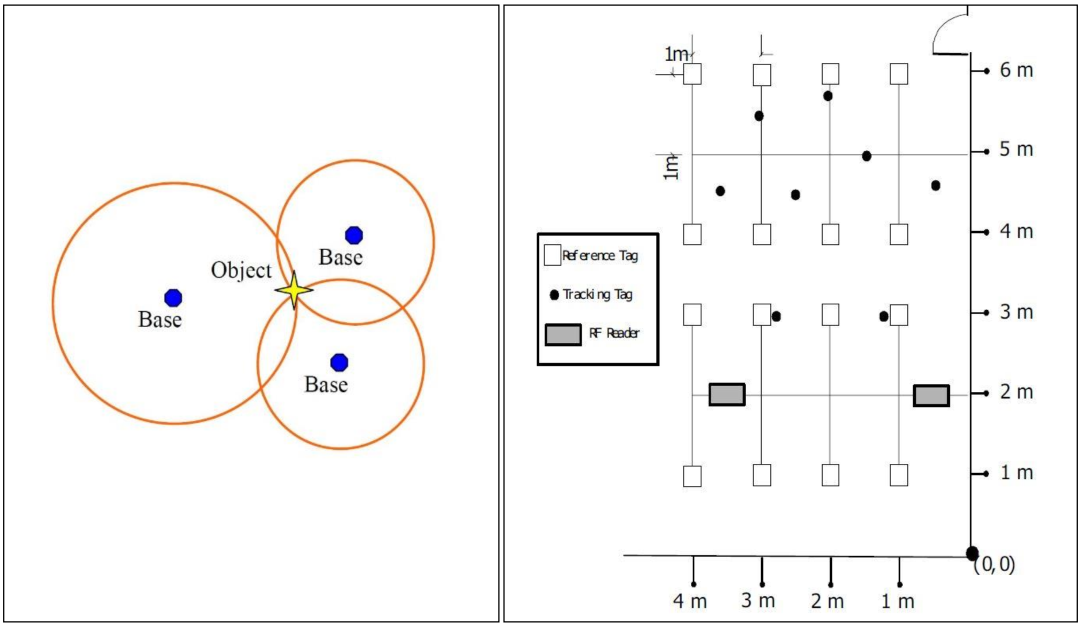


Figure 11: Localization concept of SpotON – Experiment setup of LANDMARC (Hightower *et al.*, 2000; Ni *et al.*, 2003)

Another system with multiple RFID readers and a target unit carrying an RFID tag was presented by Zhen *et al.* (2008) in order to estimate the zone where the occupant is located in a four-room indoor space of 382 meter square. The success rate of zone detection with the application of a logic-based algorithm is claimed as 93%. Li *et al.* (2012a) proposed an occupancy sensing model based on RFID tags for supporting demand-driven operations of building HVAC systems. The scope of the research is stated as dynamic environments where the number of occupancy is very unpredictable and it should be monitored in real time. The proposed system, in which k-NN algorithm was utilized just like the system proposal of Ni *et al.* (2003), is reported to track stationary occupants with an accuracy of 88% , and moving occupants with an accuracy of 62%, and the location errors was indicated as 1.45 meters and 3.24 meters respectively.

Although the capability of RFID sensors based detection systems to provide comprehensive fine-grained information for demand driven applications in buildings (Li *et al.*, 2012a), there are some obstructions. The multipath effect for signal propagation, chancing environments' negative effects on RSSI (Zhen *et al.*, 2008), and unwillingness of occupants to wear RFID tags (Ekwevugbe, 2013) can be listed as the main limitations for the deployment of this technology for indoor localization.

- **WLAN**

As the infrastructure of wireless local area networks (WLAN) is already deployed in many indoor environments including office buildings, educational facilities and public areas, the interest towards using WLAN for indoor localization has become a popular issue for researchers lately (Ismail, Fathi, Boud, Nurdiana, & Ibrahim, 2008). In WLAN based location detection models, position of every Wi-Fi compatible mobile device can be located through using existing Wi-Fi infrastructure through adding a positioning server and line of sight is not required between access points and the target units (Farid *et al.*, 2013). Moreover, the coverage area of a WLAN based localization system is expendable since it can bear additional access points, and any mobile target can be tracked unless it goes out of the covered range (Khoury & Kamat, 2009).

In WLAN based localization systems, as Mautz (2012) explains, empirical fingerprinting and path loss-based positioning (triangulation, trilateration) methods can be utilized, and the former one is claimed to be more effective method in the literature. The very first location detection system was developed by Bahl and Padmanabhan (2000) with the name RADAR, as indicated before, and it is based on wireless LAN technology. Fingerprinting method and kNN algorithm was utilized in the developed model and in the experiment, three base stations as receivers were placed in certain locations on the test bed, which is a 43.5 meters by 22.0 meters office floor. In so-called offline phase, a mobile unit, which transmits RF signals, is placed to a node and at least twenty RSS measurements were recorded at each base station. This procedure was applied for 70 distinct points and in 4 directions, and a radio map of the test bed area is created. Then, in the online phase, signal strength information received in the real time by the base stations is searched in the radio map and the closest match is labelled as the position of the mobile unit. Bahl and Padmanabhan (2000) reported accuracy of the system around 2.5 meters in 50 percentile, and about 6 meters in 90 percentile.

Taneja *et al.* (2012) analyzed three different technologies including RFID, inertial measurement units and WLAN for indoor positioning. In the WLAN-based positioning experiment of the study, the researchers followed a different procedure than that of Bahl and Padmanabhan (2000). Eight Wi-Fi access points are deployed in certain locations and they are used as transmitters instead of being receivers, and RSS data were collected in 55 points by a mobile device. The minimum number for RSS samples was determined as 30 from each access point. With the included high variance in RSS data, the success of localization accuracy was concluded as 70% for 1.52 meters precision and 90% for 4.57 meters precision (Taneja *et al.*, 2012).

Despite its potential for indoor localization, WLAN based systems have their shortcomings and limitations, such as the negative effects of possible changes (*i.e.* moving furniture) in the environments on RSS (Mautz, 2012), high initial deployment cost, variations in Wi-Fi signal strength by time and possible interferences with other appliances (Chen *et al.*, 2015). However, WLAN based location detection solutions are still preferred over PIR based or ultrasound based systems since they need fewer transmitters and provide higher confidence in real-time positioning accuracy (Pradhan *et al.*, 2009).

- **UWB**

Ultra wideband technology is based on data transmission technique through sending and receiving ultra-short radio pulses (Xiao, Liu, Yang, Liu, & Han, 2011). For an UWB based detection system, multiple unique tags for target units, stationary receivers covering signal map of the area, and a location management platform are required (Torrent & Caldas, 2009). UWB system has the capability of high accuracy indoor positioning with low power consumption even in non-line-of-sight conditions (Li, Dehaene, & Gielen, 2007). Since signals transmitted from UWB tags use a wider radio spectrum than the other RF-based tools, it does not effected by the interference of other signals in the environment and it has resistance to multipath effects (Liu, Darabi, Banerjee, & Liu, 2007). In addition, large bandwidth of UWB provides high resolution in both time and location for positioning and tracking, and it is suitable for utilizing positioning techniques including time of arrival and time difference of arrival (Mautz, 2012).

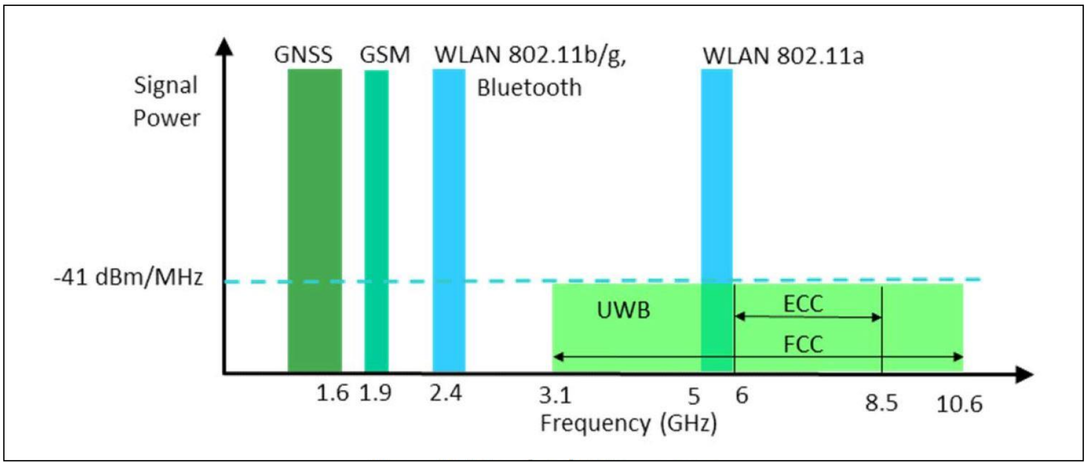


Figure 12: Radio spectrum of UWB technology (Mautz, 2012)

There are several studies in the literature for developing an applicable UWB based localization and tracking system, including the researches of Li *et al.* (2007), Ye, Redfield, and Liu (2010) and (Meissner, Arnitz, Gigl, & Witrisal, 2011), yet there is not a widely accepted solution. Although UWB based location detection models have the highest accuracy and precision (with a location error of 15 cm) among all other indoor localization solutions, a comprehensive receiver-transmitter infrastructure is required (Mautz, 2012) and the necessary initial deployment is so expensive that it is not in wide-scale use (Spataru & Gauthier, 2013).

- **Bluetooth**

Bluetooth is described by Mautz (2012) as “a wireless standard for wireless personal area networks (WPANs)”, which has zero dBm maximum power output. Classic Bluetooth was released as a unification tool for computers and other devices, and the main purposes of usage were connecting headsets and cell phones, and enabling file transfer between devices and printers (Heydon, 2013). However, the latest version of Bluetooth, namely Bluetooth Low Energy, was created by Bluetooth Special Interest Group Incorporation in the year of 2010 with the purpose of providing an extensible opportunity for data exchange with ultra-low energy consumption (SIG, 2016). BLE was widely accepted in the mobile device industry and many companies including Google, Apple and Samsung embedded this technology in all their devices (Townsend, Cufí, Akiba, & Davidson, 2014).

With the breakthrough of these improvements, BLE has become a potential tool for indoor localization and occupancy detection (Ionescu, Osa, & Deriaz, 2014). Low cost, high security, low power, small size and unique ID identification for each Bluetooth tag can be listed as the main advantages that makes Bluetooth technology usable for location detection (Farid *et al.*, 2013). In addition, since an embedded Bluetooth module do exist in almost every mobile device in today’s world, as Iglesias, Barral, and Escudero (2012) maintain, this technology can be used as a location detection tool without any extra infrastructure. A detailed review of literature on appropriateness of BLE for indoor localization is given in Chapter 3.

Even though some researchers investigate the applicability of BLE technology for indoor localization like Pei *et al.* (2010) and Subhan, Hasbullah, Rozyyev, and Bakhsh (2011), a comprehensive analysis and technological assessment of this technology do not exist in the literature.

2.3 Localization Techniques of Wireless Based Detection Systems

Localization with wireless based detection systems is defined as the process of gaining location data of a mobile unit using pre-located reference nodes within a defined space (Farid *et al.*, 2013). Location sensing, geolocation, position location or radiolocation are the different terms that are used describe this process in the literature, and a signal transmitter and a measuring unit can be listed as the minimum hardware requirement for any wireless based localization systems (Liu *et al.*, 2007).

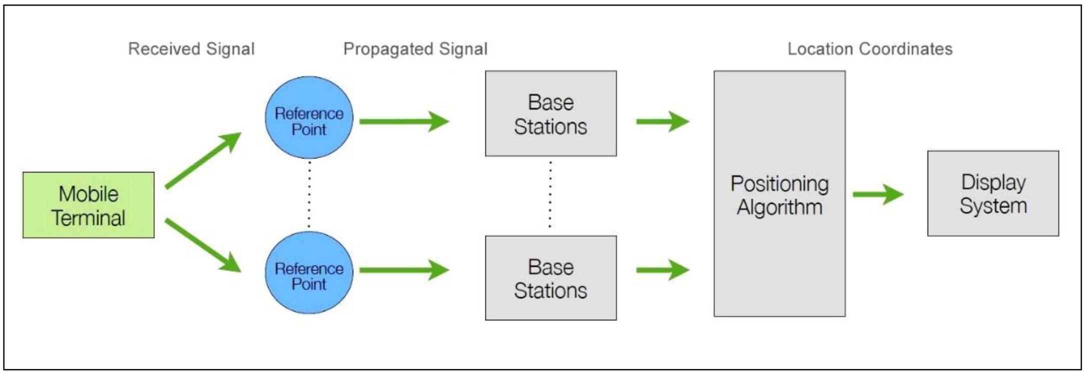


Figure 13: Process of location finding with wireless-based detection systems (Source: Ballazhi & Farkas, 2012)

Localization techniques for wireless systems are explained under four main categories; proximity, triangulation, trilateration and scene analysis (Farid *et al.*, 2013). In this section, in addition to detailed information about these four main techniques deducted from the literature, comparisons of wireless localization techniques properties will be presented in Table 3.

2.3.1 Proximity

Proximity method, which may also be called as connectivity based localization, basically provides relative position information (Farid *et al.*, 2013). This method relies on a dense grid of antennas whose positions are recognized by the system (Ballazhi & Farkas, 2012). If a mobile unit is detected by one simple antenna in the test-bed, its position is assumed to be collocated with that antenna. When more than one antennas detect the mobile unit, the one that receives the strongest signal is considered as collocated with the mobile unit (Liu *et al.*, 2007) .

There are many proposed schemes for proximity method that includes centroid algorithm and DV-hop scheme and area based approximate point-in-triangulation algorithm (Pu, Pu, & Lee, 2011). In centroid algorithm (Bulusu, Heidemann, & Estrin, 2000), which is the most basic one, the location information of $\left(x_{target}, y_{target}\right) = \left(\frac{1}{N}\sum_{i=1}^{N} x_i,\ \frac{1}{N}\sum_{i=1}^{N} y_i\right)$ surrounding reference nodes $\left(x_i, y_i\right)$ is used to estimate the location coordinate of the target unit as ; $\left(x_{target}, y_{target}\right)$ where N is the total number of surrounding reference nodes that is considered in location estimation.

However, proximity method is not robust to noise in radio signal propagation. Pu *et al.* (2011) claim that, since the locations of surrounding sensor nodes can be obtained instead of exact location coordinate of mobile units, this method is not suitable for location tracking applications. Yet, it can be beneficial for location detection in large-scale sensor networks (He, Huang, Blum, Stankovic, & Abdelzaher, 2005).

2.3.2 Triangulation

In triangulation technique, the position of a mobile unit is estimated through computing angles relative to multiple reference nodes (Ballazhi & Farkas, 2012) and angle of arrival (AoA) of wireless signals are taken as the base. Assumed that line of bearings of reference nodes or angular separation between the mobile unit and reference nodes can be obtained, the position of a mobile unit can be determined by using triangulation method (Amundson & Koutsoukos, 2009). Although two reference nodes are enough for location estimation with this method, in most studies, three or more reference nodes are used in order to improve accuracy (Farid *et al.*, 2013).

In the situations where there is a direct line of sight between the mobile unit and reference nodes, AoA method works properly. However, since multipath effect and reflection of signals from interior objects may significantly change the direction of signals arrival and decrease the accuracy, this method becomes barely usable as an indoor positioning system (CiscoSystem, 2008). Moreover, the cost of the system implementation increases with the use of additional antennas with the capacity to measure the angle of arrivals of signals (Farid *et al.*, 2013)

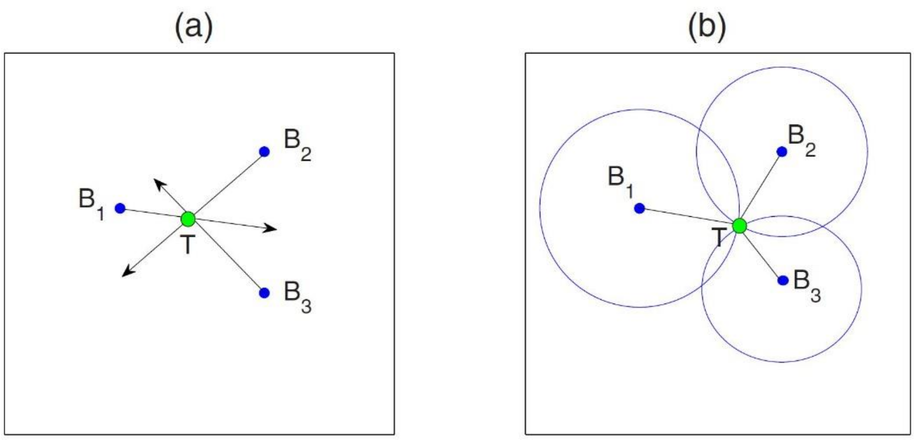


Figure 14: The position of a target node (T) is estimated based on the known positions of beacons (B_i) using (a) triangulation or (b) trilateration-ToA (Source: Amundson and Koutsoukos,2009)

2.3.3 Trilateration

Trilateration is a distance-based method that differs from triangulation in the information provided into the process of location detection. The coordinates of the target unit is estimated by measuring its distances from multiple reference nodes (Pu *et al.*, 2011). In this method, at least three reference nodes are necessary. The distances among the target unit and each reference node, which is computed by multiplying the travel time and radio signal velocity (Ballazhi & Farkas, 2012), may be represented as the radius of circles and the target unit is estimated to be located at the intersection of those three circles (Amundson & Koutsoukos, 2009). Trilateration technique may be reviewed under two sub-headings; time of arrival and time difference of arrival.

In ToA technique, the mobile unit transmits a signal that has a time stamp on it towards reference node beacons. When each beacon receive the signal, the distances between the mobile unit and reference nodes are calculated from velocity of the signal and the transmission time delay (Farid *et al.*, 2013). Since ToA technique needs precise information about the transmission start and signal-receiving times, an accurate synchronization between all devices is an essential requirement and this can be counted as the main drawback of this system. Considering propagation speeds of signals are quite high, very small differences in time synchronization may result in very significant errors in location detection. A time difference as small as 100 nanoseconds, for example, may result in a localization error of 30 meters (CiscoSystem, 2008).

In order to determine the relative position of the mobile unit (transmitter), TDoA technique examines the difference in time at which transmitted signal arrives at multiple reference node beacons (Liu *et al.*, 2007). In TDoA technique, using mathematical concept of hyperbolic lateration, a hyperbole on which the mobile unit is estimated to lie is produced by each difference of arrival time measurement (CiscoSystem, 2008). Both ToA and TDoA techniques are proven to be suitable for localization in large-scale outdoor spaces rather than indoor spaces where high levels of overall obstruction exists.

2.3.4 Scene Analysis (Fingerprinting)

Scene analysis, which is also called fingerprinting in literature, is claimed to be the most accurate and popular method for indoor positioning and object tracking (Subhan *et al.*, 2011). Lin and Lin (2005) explain that since there are lots of obstacles in indoor spaces that may affect the line of sight of receivers and signal propagation, scene matching is the most suitable technique for an indoor environment.

The scene matching technique consist of two phases as off-line phase and online phase. In off-line phase, first reference node beacons are placed providing a complete signal coverage of the intended area. Then the area is divided into grids of suitable ranges and in each grid cell, RSSI fingerprints are collected and labelled on that (x, y) coordinate in order to create a radio map of the area (Bekkelien, 2012).

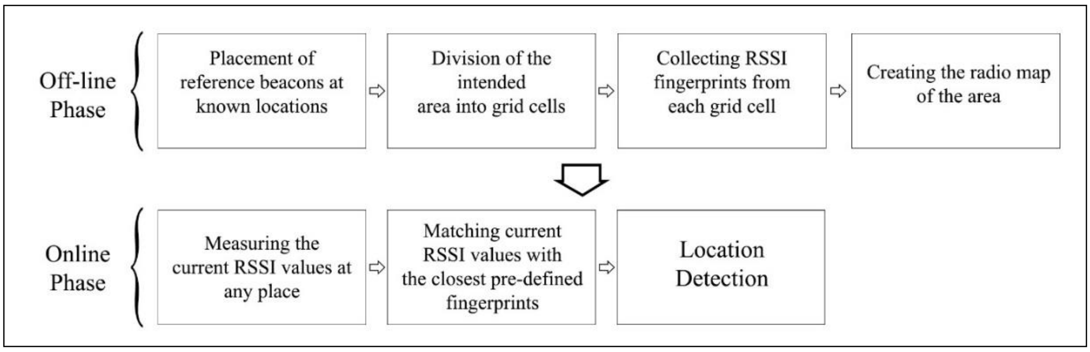


Figure 15: The scene matching method phases

In online phase, where the position of the target estimated, current time RSSI measurement of the mobile unit is matched with the closest pre-defined location fingerprints and the estimation position is detected (Taneja *et al.*, 2012). Although it has serious drawbacks of being highly time-consuming and not tolerable to any possible changes in the indoor environment, as Subhan *et al.* (2011) argue, the accuracy obtained by this method is more than any other RF based positioning techniques.

Table 3: Comparison of wireless-based localization techniques.
(Adapted from: Farid *et al.*, 2013)

Method	Measurement Type	Indoor Accuracy	Coverage	Line of Sight / Non-line of sight	Affected by Multipath	Cost
Proximity	Signal Type	Low to high	Good	Both	No	Low
Triangulation	Angle of arrival (AoA)	Medium	Good (Multipath issues)	LOS	Yes	High
Trilateration	Time of arrival (ToA, TDoA)	High	Good (Multipath issues)	LOS	Yes	High
Scene Matching	RSSI	High	Good	Both	No	Medium

2.3.5 Performance Metrics of Wireless Based Location Detection Systems

In order to provide a suitable location detection system for any particular case, performance parameters should be identified and reviewed whether they matched with the requirements of the intended case or not (Mautz, 2012). In this part, four main performance metrics of wireless based location detection systems that are accuracy and precision, coverage and scalability, complexity and cost are explained.

- **Accuracy and Precision**

Accuracy and precision are the most important features for a location detection system. Usually, the average Euclidean distance between the actual location and the estimated location that is called as location error is defined as the precision, and the statistical probability of detecting a position within a defined location error gives the accuracy (Mao & Fidan, 2009). Although it is claimed that the higher the accuracy is, the better the location detection system is, since there is always a tradeoff between the location error and other characteristics, Liu *et al.* (2007) state, a convincing accuracy and precision with other performance metrics covered is aimed in location detection systems.

- **Complexity**

Software, hardware and operational requirements are considered as the factors for describing the complexity of a localization system (Calderoni, Ferrara, Franco, & Maio, 2015). Usually, it is attributed to the location computation time in the literature. If the localization algorithm is processed in a central server rather than in mobile units, the system is defined as less complex (Liu *et al.*, 2007). In order to make the implementation and evolvement of positioning systems more viable, they should be designed with less requirements and a reduced complexity.

- **Coverage and Scalability**

The term coverage is described by Mautz (2012) as the spatial extension where the performance of the positioning system should be guaranteed. The aimed range of coverage is an essential performance metric for the effectiveness of location detection systems. It is closely related to accuracy and can be categorized as local and scalable coverage. A well-defined, limited area, which is not expendable like a single room or building can be counted as a local coverage, while scalable coverage implies systems with the capacity to increase the range by adding necessary equipment (Farid *et al.*, 2013). The effectiveness of a location detection system in terms of coverage range should be evaluated according to the system's scope and aimed environment.

The scalability character of a location detection system ensures that the system could function normally even the scope of the system gets larger. Liu *et al.* (2007) explain that geography -the area or space covered- and density -number of occupants per space per time- are two axis that location detection systems might scale on. In wireless or radio frequency based location detection systems, since detecting multiple units when it is crowded or covering a wider area may require improvements in the infrastructure, the scalability character of the systems should be considered properly.

- **Cost**

Money, time, space, weight and energy can be counted as the factors for the cost of a location detection system. In order not to let the cost gained from a location detection system exceed the arisen cost from the extra infrastructure, lifetime, weight, or consumed energy of the system, some features like using an existing hardware, equipment or low cost passive sensors can be considered in location detection system approaches (Farid *et al.*, 2013).

2.4 Critical Analysis of Literature Review

Location information in indoor built environments was shown to have a great value for AEC industry in the reviewed literature. There are various use cases for indoor localization including building occupancy detection, automated asset tracking and supply chain management, optimization of facility maintenance and operations, and building emergency response operations. In this research, a detailed investigation on occupancy detection was done among the mentioned scopes.

Throughout the literature, the theoretical background for the emergence of a need for detecting occupants in indoor built environments was studied including the concepts of occupant-built environment interaction, intelligent buildings approach and building automation systems. It was deduced that occupancy constitutes an important part of building automation systems, the aim of which is to satisfy the comfort needs of people in indoors and to administrate main building operations including HVAC, electricity and lighting on a demand-driven manner. Yet, the current operation of BAS was claimed to be inefficient since they lack instant information of occupancy presence input. Considering this gap in the industry, there are quite a large number of researches in the literature for developing a real-time occupancy detection solution.

Existing approaches were organized and presented under five main topics, which are simulation models, image detection systems, PIR sensor based systems, CO_2 detector based systems and RF based systems in the review. It is observed from the literature that, despite the various studies on generating solutions for occupancy detection, a reliable and widely accepted framework is still missing due to the shortcomings of current systems including uncertainties in detection, privacy and time latency issues, inability for multiple detection and high expense of utilization and maintenance. Therefore, the main objective of this study is defined as to investigate a reliable framework for real-time occupancy detection that is punctual, accurate and precise.

In this study, creation of a mobile-device integrated framework is intended considering their extensive usage in today's world, and Bluetooth Low Energy is defined as the enabling technology, which is embedded in almost all current mobile devices including smartphones, tablets, or smart watches. Since BLE is a radio frequency based wireless technology, related literature about the localization techniques of wireless based detection systems and their performance metrics were also presented, and methodology of this research is developed with the derived knowledge.

CHAPTER 3

MATERIAL AND METHOD

In this chapter, the material and methodology that lead this research are explained. In the first section, the selected technology, which is Bluetooth Low Energy (BLE), with its properties and improved advantages are covered. In the second section, the material selection process and the simple experiment for evaluation of different BLE tags with its results are explained. Then, the related information about the methodology including test bed environment and data collection are presented. The location fingerprinting method and k-nearest neighbor algorithm are also explained. After that, the guidelines for analysis of the proposed framework and BLE technology are defined. In order to evaluate the given guidelines and hypothesis, different cases are introduced. This section is concluded with an overview on the relation of given cases and the research hypothesis.

3.1 Bluetooth Low Energy Technology

Bluetooth technology was invented in the year of 1994 with the purpose of replacing data cables with a wireless communication for exchanging data using radio transmissions (SIG, 2016). Bluetooth can be described as a wireless standard for wireless personal area networks (WPANs), which has zero dBm maximum power output (Mautz, 2012). Although the main aim of the creation of Classic Bluetooth was to unite distinct worlds of computing and communications tools, *i.e.*, laptops and cell phones, as Heydon (2013) explains in his book, the technology was used widely and primarily as an audio link between cell phones and headsets. Enabling communication between cars and cell phones, file transfer between devices and wireless printing are some of the uses that were generated as the technology was improved in years.

In 2010, the latest version of the technology, Bluetooth Low Energy (BLE), which is also called as Bluetooth Smart, or Bluetooth 4.0, was created by Bluetooth Special Interest Group Incorporation (SIG, 2016). The core objective of BLE is claimed by Collotta and Pau (2015) as to run with an ultra-low power consumption. While former versions of Bluetooth are mostly used for transmitting huge amount of data such as audio or files, BLE is designed to exchange small data pieces such as humidity readings, which makes this technology convenient for devices requiring long battery life rather than high data rates (Andersson, 2014b). Latencies in connection and data transfer is also much smaller in BLE when it is compared with former technologies. Another feature of BLE is that it enables internet connection for different devices in an efficient way with its server architecture (Collotta & Pau, 2015). In order to connect to the Internet, BLE devices can use other BLE embedded devices such as tablets, smartphones or PCs that have a direct internet connection as a gateway. The primary benefit of this approach, according to Torvmark (2014), is achieving simpler, lower cost and lower power wireless devices.

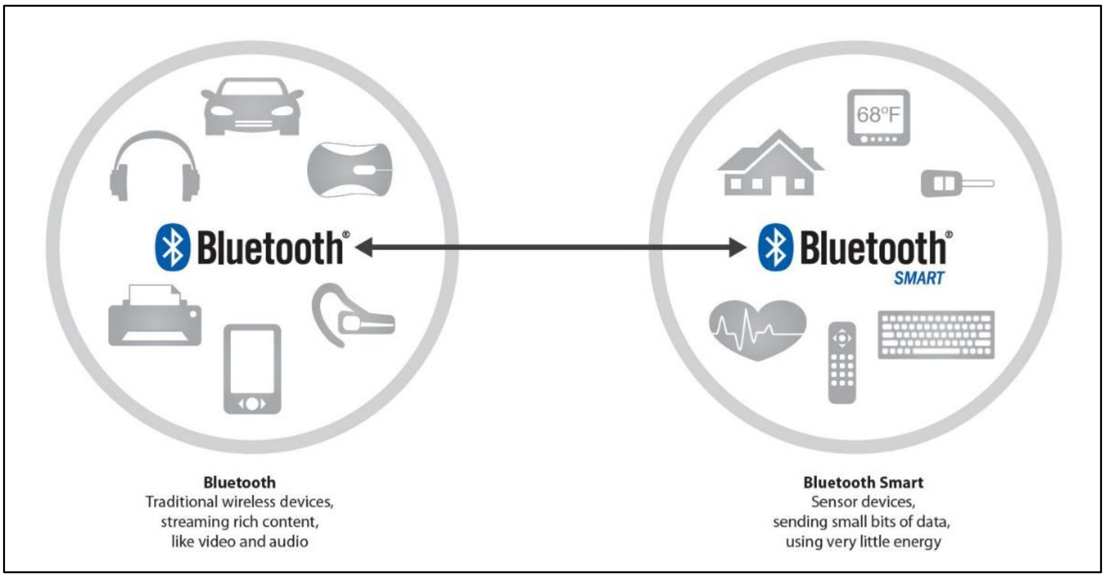


Figure 16: Scope of Classic Bluetooth via Scope of Bluetooth Smart
(Adopted from: SIG, 2016)

BLE has adapted itself into the mobile device industry very rapidly and most of the smart device producer companies, as Townsend *et al.* (2014) observe, including Apple, Samsung and Google are putting significant efforts into embedding this technology into their products and publishing design guidelines around it. The reason behind this uncommonly rapid adoption rate is that it is an extensible framework for exchanging data and it allows little task-specific and innovative devices to talk to smartphones or tablets, which potentially open the gates for new ideas and improvements in the market (Townsend *et al.*, 2014). Another driver for the rapid adoption rate is the concept of Internet of Things (IoT). The visionaries of the IT sector propose a future where every tool, device, component will have the ability to connect to internet and form a network of devices. Easy-to-deploy, cost efficient and low power wireless solutions are the key requirements for the IoT concept, and BLE was shown to be a well-suited technology with its ultra-low power sensors and low-cost deployment needs (Andersson, 2014a).

Although BLE is not specifically designed for indoor positioning and occupancy detection, it has a significant potential (Ionescu *et al.*, 2014). BLE uses tiny chips, widely known as Bluetooth tags, in which radio frequency and microchip technologies are combined for creating a robust system and this system can be used for both identification, monitoring and maintenance of building assets, and indoor positioning of people through communicating with a tag reader (Lodha *et al.*, 2015). As this low energy and low latency data exchange technology is increasingly popular in the device industry (Bronzi, Frank, Castignani, & Engel, 2016), almost all mobile devices such as smartphones, smart watches, tablets or laptops equipped with BLE are able to communicate with Bluetooth tags and can be used as readers. These Bluetooth tags can send small data pieces to the readers, which can be any mobile device, and the distance can reach up to 50 meters (Ionescu *et al.*, 2014). Besides its pervasive availability in mobile devices, relatively low cost of and ultra-low power consumption of BLE tags when compared to other technologies can be claimed as the main advantages for utilizing it for locating people in indoor environments.

Although there are some studies in the literature in which Bluetooth is used for indoor positioning like the researches of Pei *et al.* (2010) and Subhan *et al.* (2011), there is not a comprehensive analysis and framework for BLE based indoor positioning and occupancy detection. In this research therefore, BLE and its potential will be investigated. BLE tags as reference nodes and a mobile device as tag reader will be the materials of this study.

3.2 Material Selection

Before going through the experimental setups to analyze BLE for localization, the available products in the market that are supporting this low energy technology were examined and four different Bluetooth tags were purchased by the researcher. These four different tags, referred as BLE Tag I, II, III and IV, were tested, and the one with the optimal results was selected.

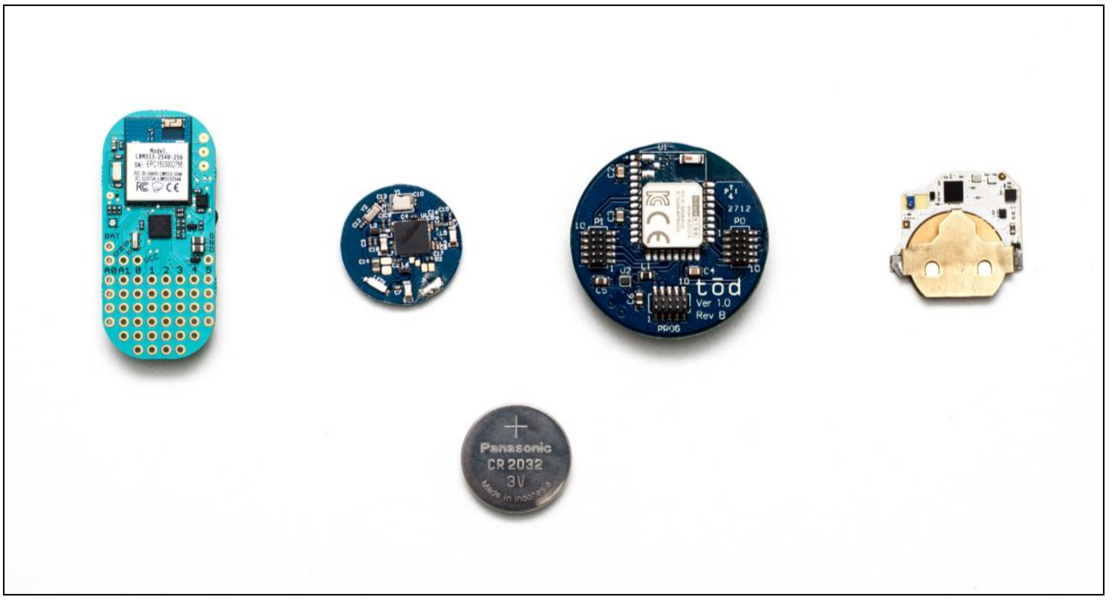


Figure 17: Purchased BLE Tags

3.2.1 BLE Tag I

The product of Vendor I is a 2.4 GHz Bluetooth low energy enabled hardware, designed as suitable for communication and interaction with any static or mobile devices supporting Bluetooth technology. This product is equipped with LBM313 module, which ensures long term usage with 3.3 volts coin-cell batteries and it is ideally suited in low-power wireless applications (PunchThrough, 2016). BLE Tag I has an accelerometer, a temperature sensor and RGB Led on its main board, works with a coin-cell battery and in the dimension of 45mm x 20 mm.

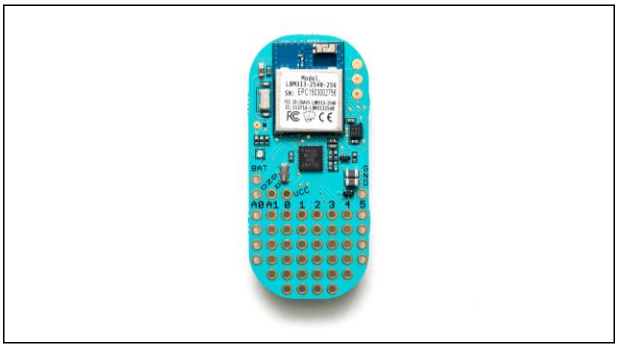


Figure 18: BLE Tag I and LBM313 module

3.2.2 BLE Tag II

BLE Tag II is an ultra-low power tag. It has an N51822 named chip that is optimized for Bluetooth low energy and implementation for 2.4 GHz low-power wireless applications (Nordic, 2016). It is one of the smallest tags available in the market, with 24mm radius and 4mm thickness. SDK (software development kit) is included in the purchase of this tag, which can be downloaded and customized by the clients. This feature of the product is thought to be beneficial for researches and was supplied with the purpose of enabling any researcher to incorporate it into self-developed indoor navigation applications (StickNFind, 2016). Besides supplying SDK demo for clients, it is also compatible with most of the leading platforms including ‘iBeacon’ software of iOS.

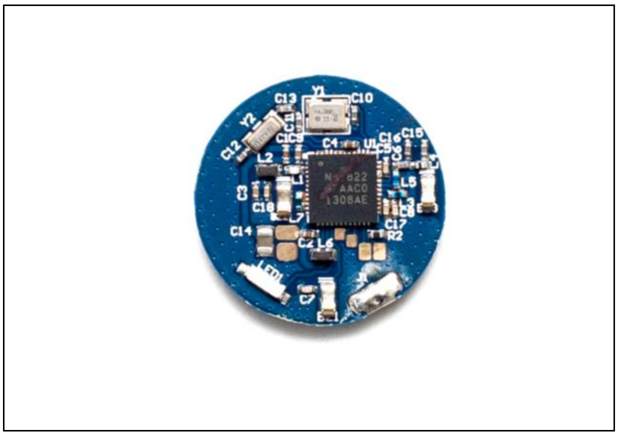


Figure 19: BLE Tag II

3.2.3 BLE Tag III

BLE Tag III is a smart tag with Bluetooth low energy connectivity. It was designed to enable its users connect with their mobile devices for their desired applications (RowdyRobot, 2016). BlueGiga BLE-112A is the Bluetooth Smart module that this hardware equipped with and it is the integration of Bluetooth radio, micro controller and software stack (BlueGiga, 2016). BLE Tag III has a size of 42mm x 19 mm, has a waterproof case and unlike other three tags that are reviewed, development and support from the manufacturer does not continue for this product.

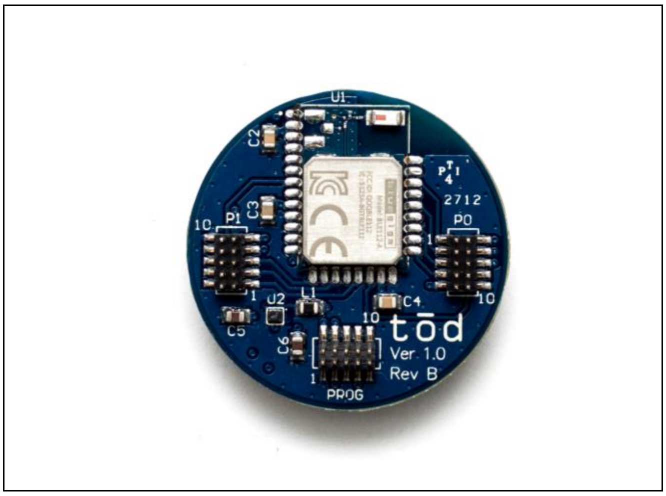


Figure 20: BLE Tag III

3.2.4 BLE Tag IV

BLE Tag IV is a small wireless tag that is attachable to any location, and it is able to communicate with any mobile devices through tiny radio signals. This small object has a Bluetooth Smart module, a powerful processor, temperature sensor and motion sensor on its board and it is powered by 3 volts coin-cell batteries (Estimote, 2015). The chip of BLE Tag IV is the same with that of BLE Tag II, namely N51822, and it is well suited for Bluetooth low energy communication protocol and its supported applications (Nordic, 2016). This product has a size an approximate size of 45mm x 20 mm. While testing this beacon with other three beacons, the silicone case was (destructively) removed in order to ensure the equality of sensors physical conditions.

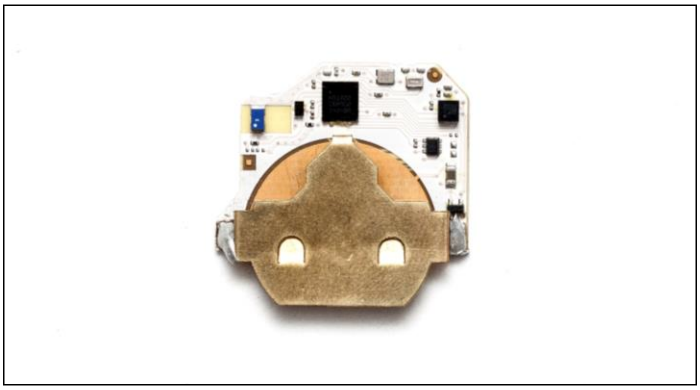


Figure 21: BLE Tag IV

3.2.5 Experimental Setup for the Evaluation of the BLE Tags

After the purchase of the reviewed four tags, a simple experiment was carried out in order to compare the capabilities and convenience of these products for indoor localization. First, a software was developed both for the evaluation of the reviewed BLE tags and for using it in the main experiments of this research. The development of the software was done on a mobile device that runs Android Operating System. Since SDK of BLE Tag II was compatible with all reviewed Bluetooth tags in collecting RSSI values, the demo software SDK of BLE Tag II was customized and modified for the development of the research software.

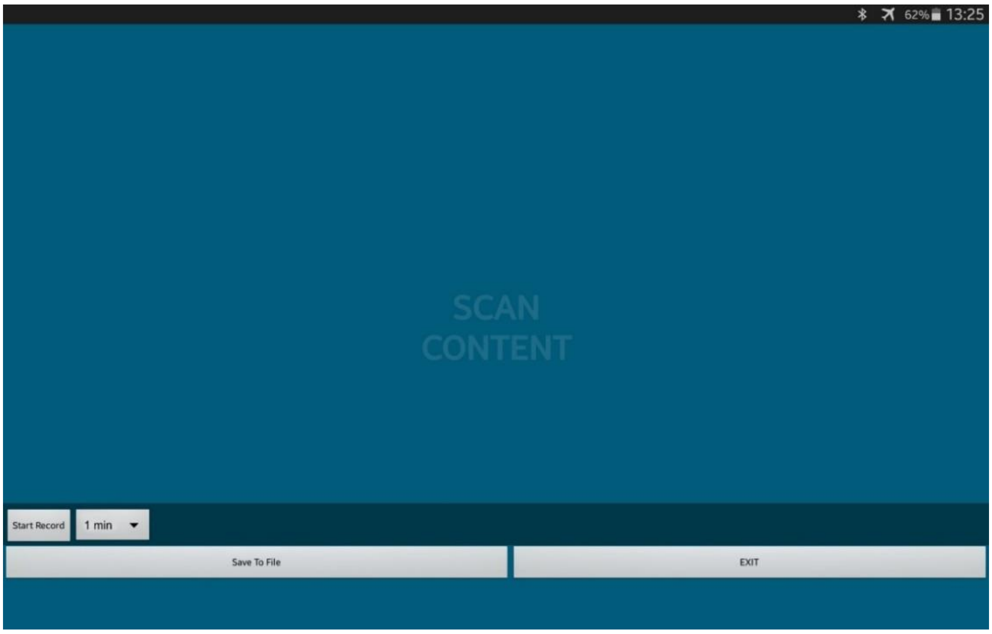


Figure 22: The interface of the research software

Figure 23: Experiment environment for Material Selection

The interface of the developed software has 4 buttons; one for starting the record, one for adjusting the recording time, one is for saving the recorded RSS values to a file and one for exiting the program (Figure 22). In the software, after pressing the start record button, the recording of RSS values starts 10 seconds later and this feature was intentionally added for ensuring more control over the program during the experiments.

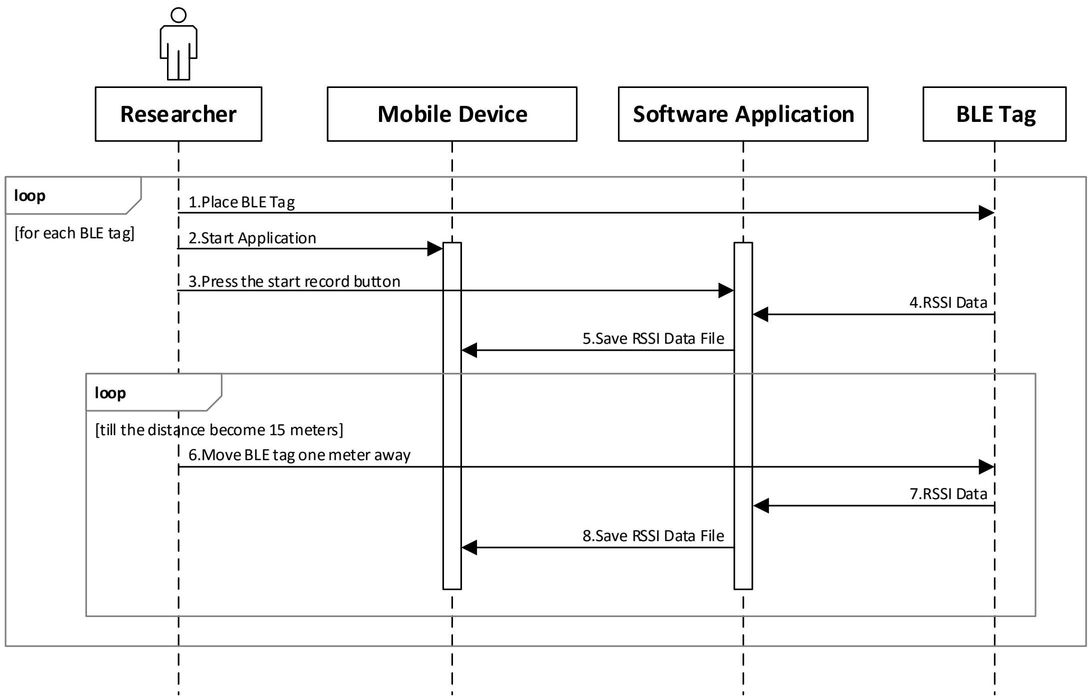


Figure 24: UML Sequence Diagram of Material Selection Experiment

The evaluation of these four BLE tags were performed in a corridor of Annex Building of Faculty of Architecture, at Middle East Technical University. In the corridor, Samsung Galaxy 10.1 Tablet, which is used as the reader throughout all the experiments in this research, was placed on to a box that has a height of 10 centimeters. Then, an identical box was placed one meter away from the reader and BLE tag I was placed on top of it. After this preparation, the localization software was opened on the reader and researcher pushed the start record button for five minutes, and walk away from the setup in order not to effect the radio signals. Five minutes later, the experimenter came near the reader, pushed the 'save to file' button and the record is completed. After this, the distance between the reader and the beacon was adjusted from one meter to two meters and the recording was carried out again. This process was repeated by moving BLE tag away one meter more at each time, until the distance between the reader and the beacon is fifteen meters. The whole process was executed for each BLE tag separately and all the recordings were saved on the reader (Figure24).

The evaluation criteria were identified as the RSSI value and its consistency. RSSI indicates the signal strength received by the reader. RSSI values, which are integer values, that are received from BLE tags changes between -127 to -20 dBM and higher values indicates stronger signals (Dahlgren & Mahmood, 2014).

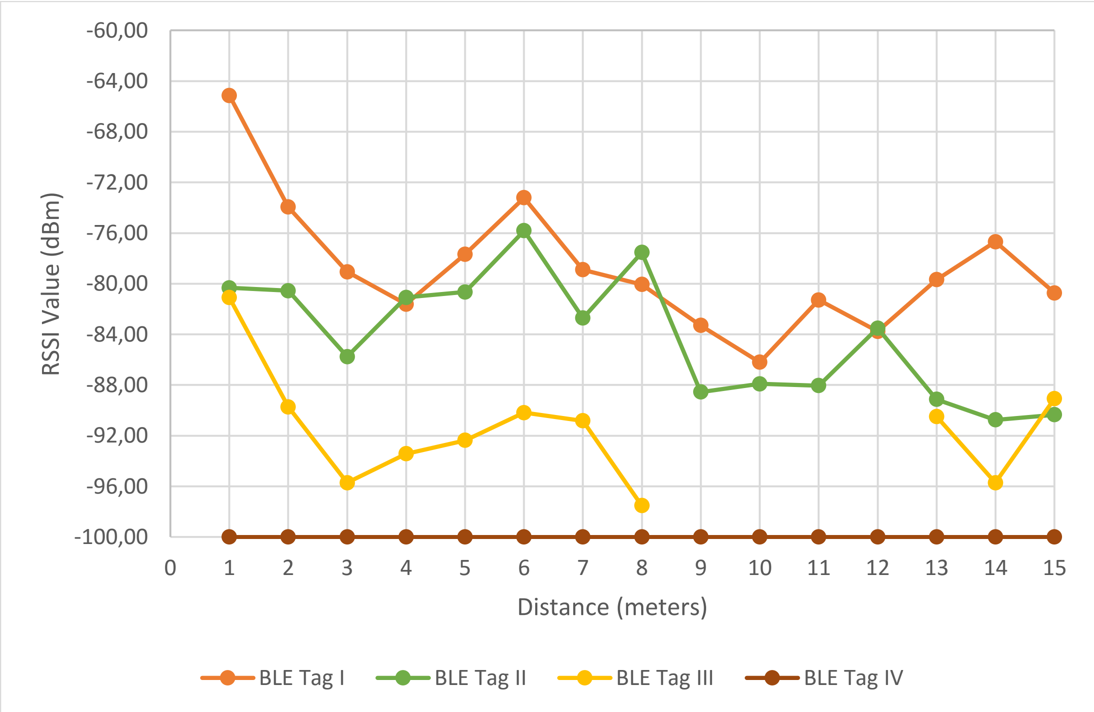


Figure 25: RSSI Logs on Material Selection Experiment

Figure 25 depicts the results of material selection experiment in terms of recorded RSSI data while moving away the BLE tags from the reader. As shown in the table, while RSSI values are fluctuating as the distances between the reader and BLE tags increase for three tags, the reader receives signals consistently from only two tags, which are BLE tag I and BLE tag II. Moreover, the highest RSSI values were recorded for BLE Tag I, demonstrating the strongest signal properties and, only for BLE Tag I, there is an observable change in RSS values that is regarded as a significant feature in creating fingerprints for indoor localization (Bekkelien, 2012). For BLE Tag III, although RSSI values were recorded between one-meter to eight meters distance, no RSS data was received between 8 meters to 12 meters. Unexpectedly, no RSSI data was found for BLE Tag IV in the whole experiment, which is an indication of the fact that it is not an appropriate product for indoor localization purposes. The reason of not getting RSSI data from BLE Tag IV was later identified as its property of sending signals only when it is movement.

In Figure 26, number of received signals for each Bluetooth tag are demonstrated. Just like in RSSI values, the consistency is observed for BLE Tag I and BLE Tag II. When these two BLE tags are compared, BLE Tag I is better than BLE Tag II in terms of both RSS values and number of received signals for five minutes.

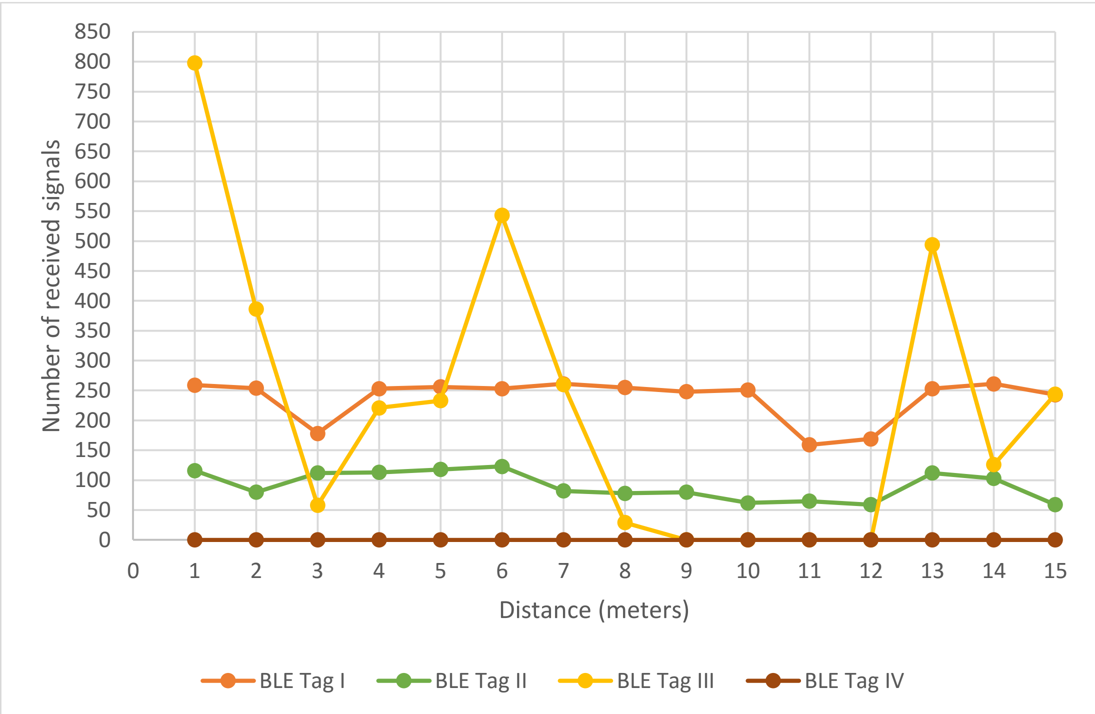


Figure 26: Number of received signals on Material Selection Experiment

The most consistent RSSI values as the distance between the tags and the reader increases were observed for BLE Tag I. Moreover, BLE Tag I was shown to have the highest signals strength values. The number of received signals is also more consistent throughout the experiment for BLE Tag I than the other examined tags. Accordingly, BLE Tag I was selected as the product that will be used as the research material in this study.

3.3 Research Approach - Location Fingerprinting

Rather than testing the occupancy detection system itself, what is intended in this study is to assess the possibility of using mobile devices for locating occupants in indoors and investigating technological applicability of Bluetooth low energy for indoor localization. The scope of the proposed framework in terms of building type is identified as office buildings. The research approach is shown in IDEF0 diagram (Figure 27). Basically, Bluetooth based indoor localization systems are composed of a target unit with Bluetooth support and reference tags providing a complete signal coverage of the intended area (Bekkelien, 2012; Scheerens, 2012). About positioning methods, Cheung, Intille, and Larson (2006) state that standards and protocol characteristics of Bluetooth do not favor conventional signal time-of-flight based positioning methods, and based on the consensus in previous papers, fingerprinting method become prominent in most of the studies in the literature (Bargh & Groote, 2008; Iglesias *et al.*, 2012; Subhan *et al.*, 2011).

Fingerprinting is claimed as the most accurate localization technique for wireless detection systems in an indoor environment (Lin & Lin, 2005). Moreover, signal parameters of Bluetooth are not very convenient for other techniques like triangulation (Hossain & Soh, 2007) in the literature. Considering these facts, location fingerprinting is selected as the indoor positioning technique of this research.

As mentioned earlier in literature review chapter, fingerprinting technique is based on creating a radio map of the experiment field through collecting fingerprints in the offline phase and estimating the position by matching measured RSSI information with pre-defined fingerprints through applying adequate positioning algorithms in the online phase (Bekkelien, 2012). In this research, the defined borderlines of the fingerprinting method in the literature is accepted and a framework, in which mobile devices and Bluetooth Low Energy technology is integrated, is established as shown in Figure 28. Mainly, materials of the proposed system is composed of BLE tags as signal transmitters and a mobile device as reader. In the framework, first, twelve BLE tags are deployed in the test bed environment in a way that all fingerprint data collection points are in the coverage zone. Then, intended area is divided into non-physical grid cells in two dimensions and RSSI data was collected at all defined fingerprint locations. The first phase of the proposed framework is finalized with the creation of a radio map of the area.

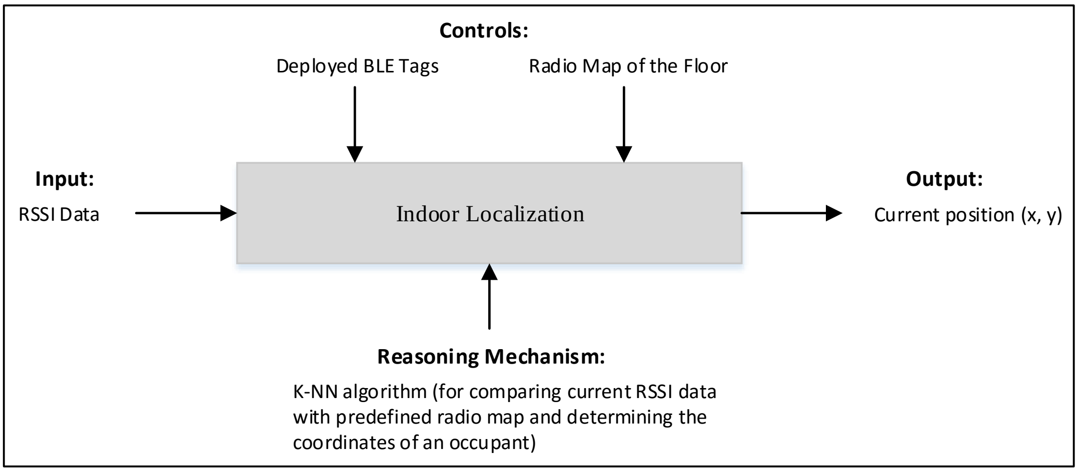


Figure 27: IDEF0 diagram demonstrating the research approach

Afterwards, in real operating conditions of the buildings, when an occupant gets inside the test bed area with his mobile device, it starts to collect RSSI values from the deployed tags. After the mobile device records RSSI values for one minute (as defined in the experiments), it sends the recorded data to the building automation server. Here, it is assumed that the mobile device is equipped with the created application and it starts to record data after occupant gets stationary. When recorded data comes from the occupant to building automation server, the RSSI data is searched in the pre-established radio map with the employment of k-NN algorithm and the positon of the occupant is determined in the predefined coordinates.

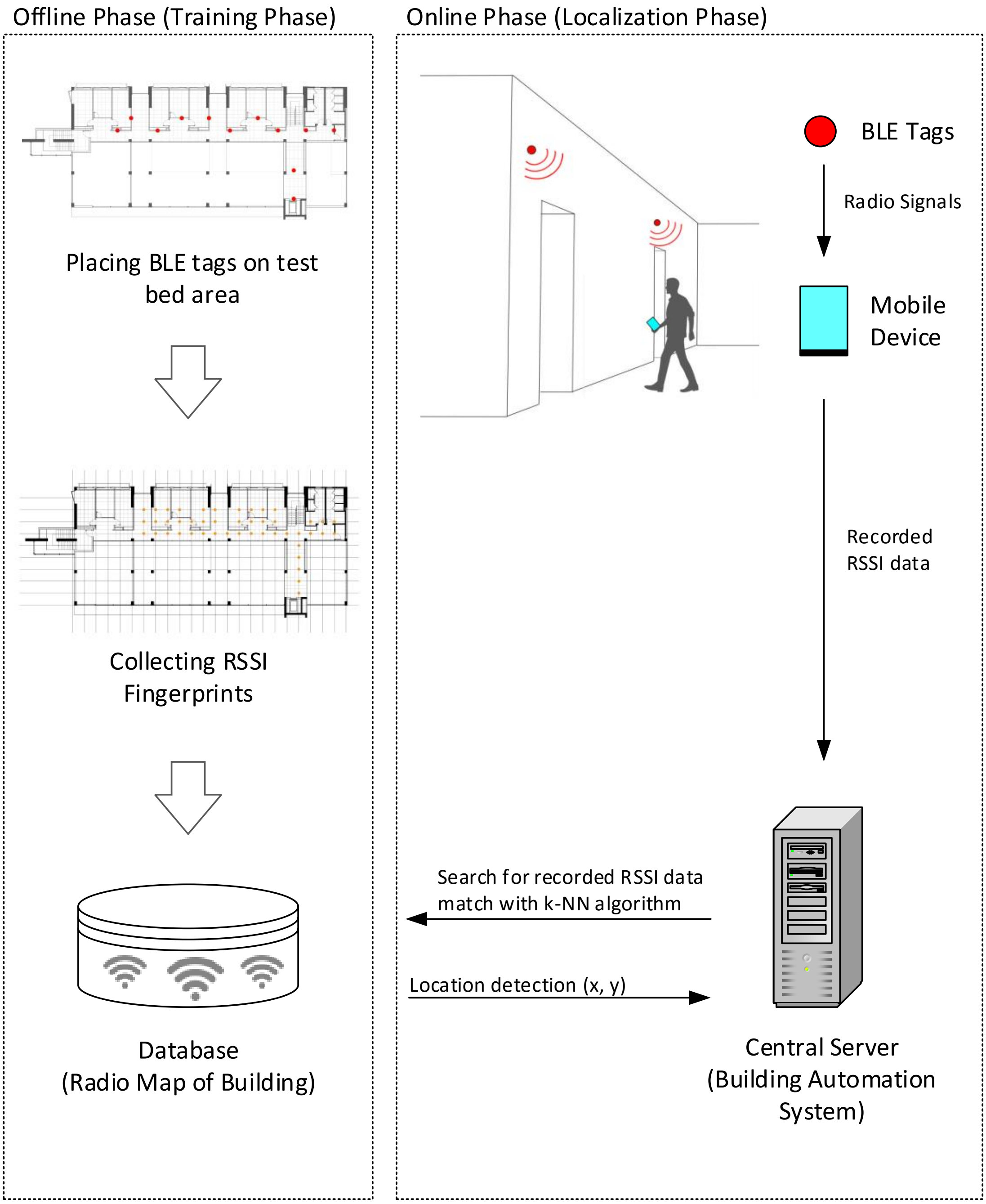


Figure 28: Conceptual Framework of Proposed Location Detection System

In principle, the radio map is supposed to be deployed in the building automation server and RSSI data search process and location detection in the online phase is thought to be automatically done. Yet, due to the lack of infrastructure possibilities in the facility and financial matters, these processes were tested manually in the experiments. Since the only difference between automatic and manual processes is the amount of time spent in the online phase, the reliability of the experiments does not change and the proposed framework is assumed to be tested as it is.

3.3.1 Offline Phase - Data Collection

In order to assess the proposed framework for indoor positioning, field experiments were carried out in MATPUM Building at Middle East Technical University's campus. The second floor of MATPUM building was selected as the test bed, since the floor has a gallery space, metallic structure, many walls and obstructions that may affect the proposed system's performance. The selected area consist of six personal offices, two restrooms and a corridor, and approximate size of the area is 240 m^2 (Figure 29, Figure 31). Twelve BLE tags are placed in certain locations on the floor, considering the actual signal range of the tags and possible signal attenuations. Location of BLE tags are shown in Figure 29 and their placements are shown in Figure 32.

A Samsung Galaxy Note 10.1 2014 tablet was used as the reader and signal data was collected at 46 different points for creating fingerprints and radio map of the floor. Iglesias *et al.* (2012) emphasize that, since variability of signal strength values causes instability in the measurements of particular positions, there should be significant distances between fingerprint points in order to minimize the inaccuracies. Considering this, the distance between two consecutive points is determined as 1.8 meters, and data was collected in all four directions (north, west, south and east) for 46 distinct points (Figure 30). A total number of 184 training data sets are created. Then these data sets are correlated with coordinates on the defined two-dimensional space and radio map is constructed. The signal strength data were collected using the same software application in material selection process and the duration for each record is determined as one minute. Although there are twelve tags deployed in the test bed environment, by the reason of signal attenuation and coverage range of BLE tags, the number of detected BLE tags vary in different data collection points. It is recorded that, at least two BLE tags are detected for every predefined location, whereas the maximum number of detected tags within all data sets is found to be ten. In this research, unless otherwise stated, minimum 30 signal strength data should be received from a tag for assuming that tag as detected at any given points. The number ‘30’ is mentioned by Navidi (2006) as the minimum required number for statistical analysis.

Data collection process was repeated three times with one-month time interval. The first data collection was done right after the Maxell CR2032 Lithium coin cells were placed into BLE tags and the second data collection process was carried out one month later without any change in the cells. The voltages of the coin cells were recorded between 3.10V – 3.20V at the very first placement, which means that they were at full capacity. Around two months later, after the second data collection, the voltages of the coin cells were measured again and some of them were found to be near 0V. This undesired condition was thought to be related with the firmware of some of the BLE tags, since the BLE technology was claimed to have ultra-low power consumption properties (Heydon, 2013). The BLE tags came with a microprocessor to increase the capabilities of the modules, which lead to the fast drain of the batteries.

Considering the possible effects of tags with flat batteries on the reliability of the experiment, the second data collection was not used at all in the analysis. Lessons learned from the previous process, and the third data collection was realized after renewing all the coin cells of BLE tags. After recording RSSI values for 184 discrete positions, the batteries were measured again to confirm their state and they were reported between 3.10V – 3.16 V.

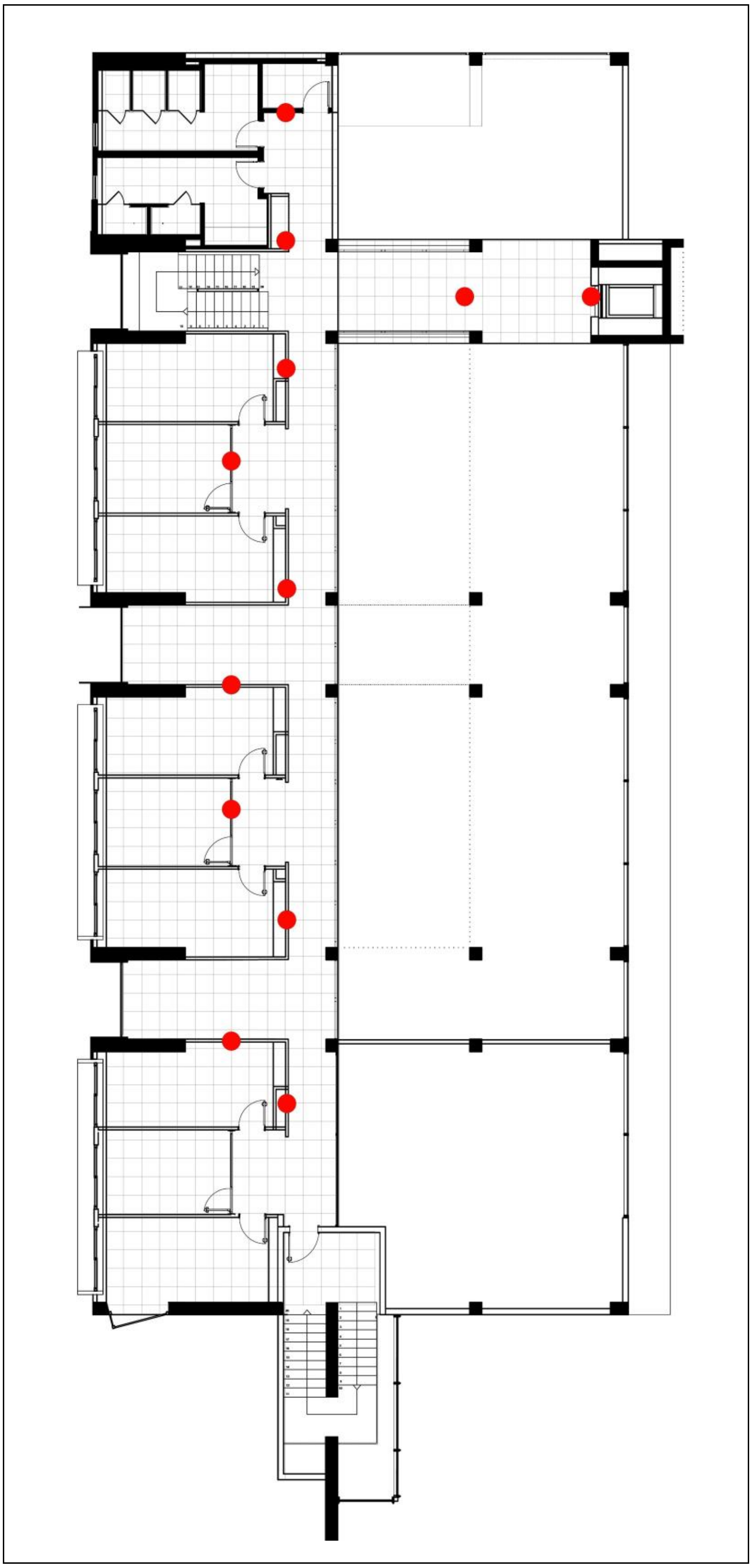


Figure 29: Tag Locations on Test Bed Environment, scale: 1/200

(Second Floor of MATPUM Building)

Figure 30: Fingerprints on Test Bed Environment, scale: 1/200

(Second Floor of MATPUM Building)

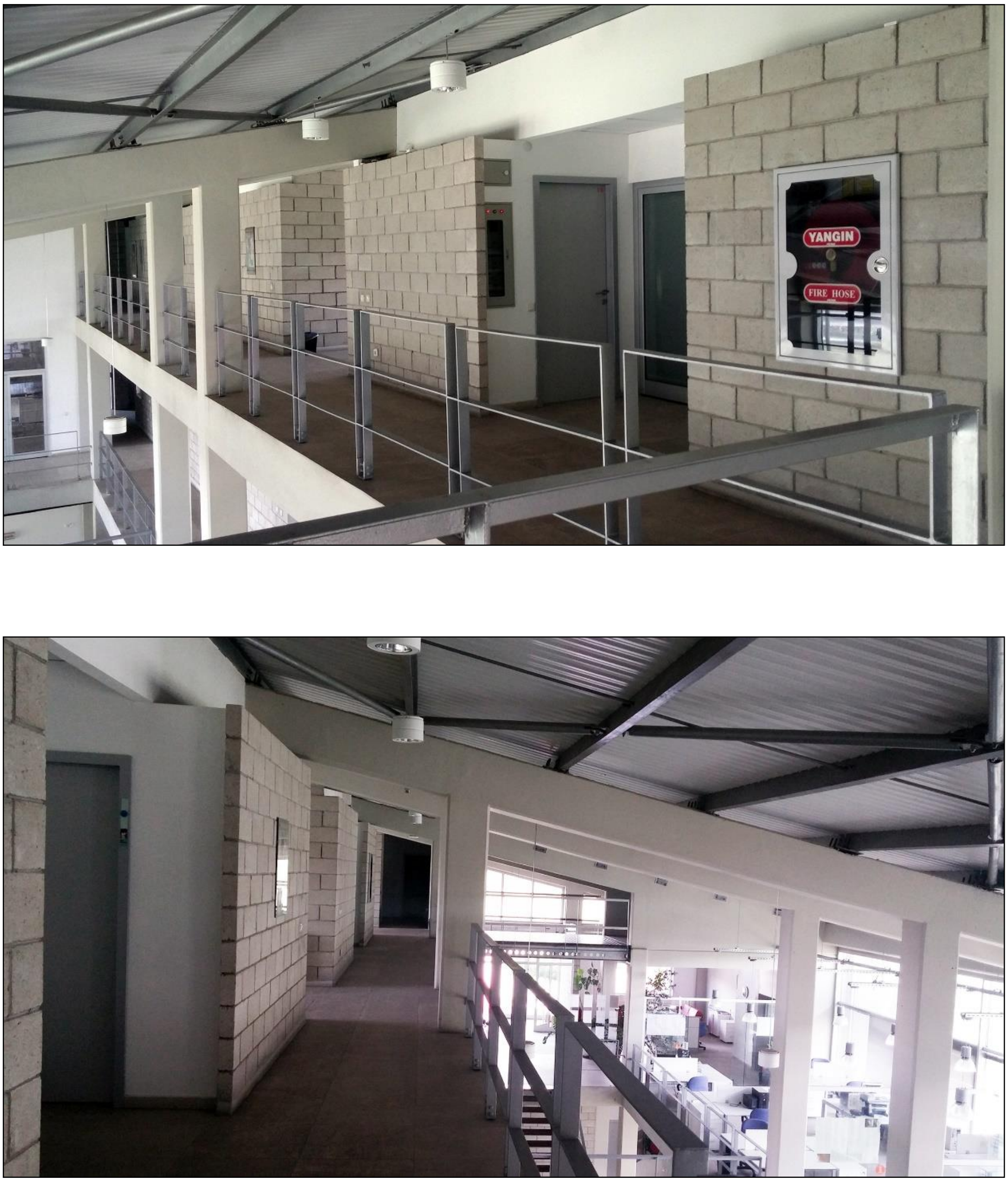


Figure 31: Test Bed Environment - Second Floor of MATPUM Building

Figure 32: Placement of BLE Tags on Test Bed Environment

3.3.2 Online Phase - Data Analysis Approach based on Cases

In this research, online phase was carried out manually due to the lack of infrastructure possibilities. There were 184 test data samples and each of them are processed separately. First, a test data sample is selected and inquired in the pre-established radio map. In the radio map, the closest RSSI data match is derived through using k-NN algorithm. The position of the test data sample is identified as the coordinates of the closest training data sample (Figure 33).

RSSI is taken as the parameter for assessing the technological appropriateness of the BLE for indoor localization. Although signal strength is claimed to be inversely proportional to distance between the transmitter and the reader (Çalış *et al.*, 2013), there is not a regular decrease in RSSI values as the distance increase, due to the attenuation and reflections of the signals in the environment (Ergen *et al.*, 2007a). In order to overcome this nonlinearity, an algorithm to manage this noisy data is needed.

The most commonly used and widely accepted solution is claimed as k-nearest neighbor algorithm by the researchers (Bahl & Padmanabhan, 2000; Pradhan *et al.*, 2009; Taneja *et al.*, 2010). In this study, k-NN algorithm is used as it was asserted to be the most effective classifier for handling large sets of radio signal strength data (Han, Kamber, & Pei, 2012).

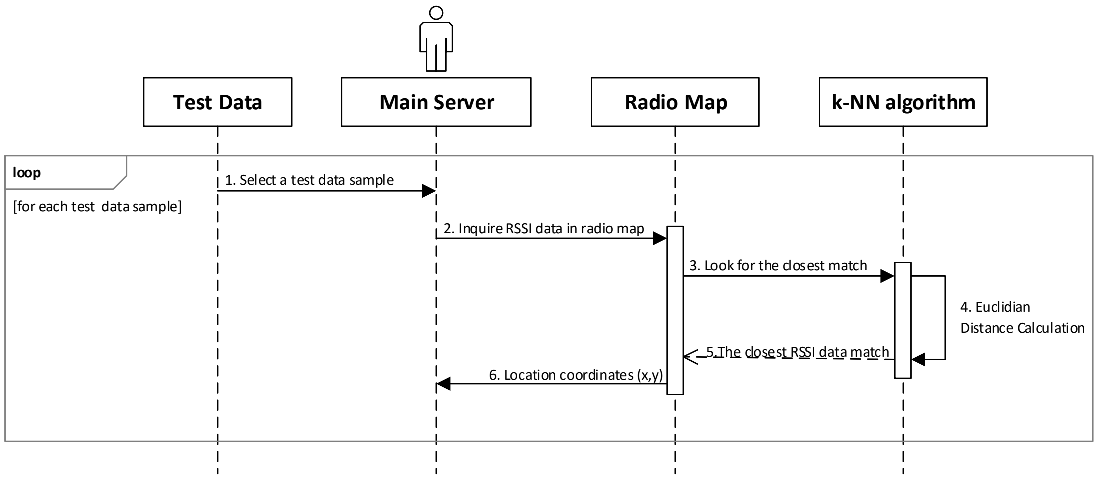


Figure 33: UML Sequence Diagram of Online Phase

K-nearest neighbor (k-NN) is described as a deterministic classifier in which the given input is compared against the entire training data set at a runtime (Bekkelien, 2012), and based on learning by analogy (Han *et al.*, 2012). In an n-dimensional pattern space where each training case represents a point, when given an unknown test case, what k-NN classifier searches is the pattern space for k training cases that are closest to the unknown test case. The found training cases by k-NN algorithm are defined as the k-nearest neighbors of the given unknown test case (Han *et al.*, 2012). In the literature, the closeness of samples is generally measured in terms of Euclidean distance (Bahl & Padmanabhan, 2000; Li *et al.*, 2012a; Pradhan *et al.*, 2009; Taneja *et al.*, 2012).

K-NN algorithm is used to locate a test sample, in 184 (46 points x 4 directions) training data sets of signal strength values that were created in the offline phase of location fingerprinting. Accordingly, the Euclidian distance in signal space between the given test sample (ss_1, ss_2, $ss_3 \ldots ss_{12}$) and the each training data sample (ss'_1, ss'_2, $ss'_3 \ldots ss'_{12}$), where ss_i represents the signal strength value of tracked BLE tag i ($i \in 1{,}12$), is calculated. The formula for calculating Euclidian distance is:

$$\rightarrow \quad \text{Euclidian Distance}(p_1, p_2): \sqrt{\sum_{i=1}^{n=12} (ss_i - ss'_i)^2} \qquad (1)$$

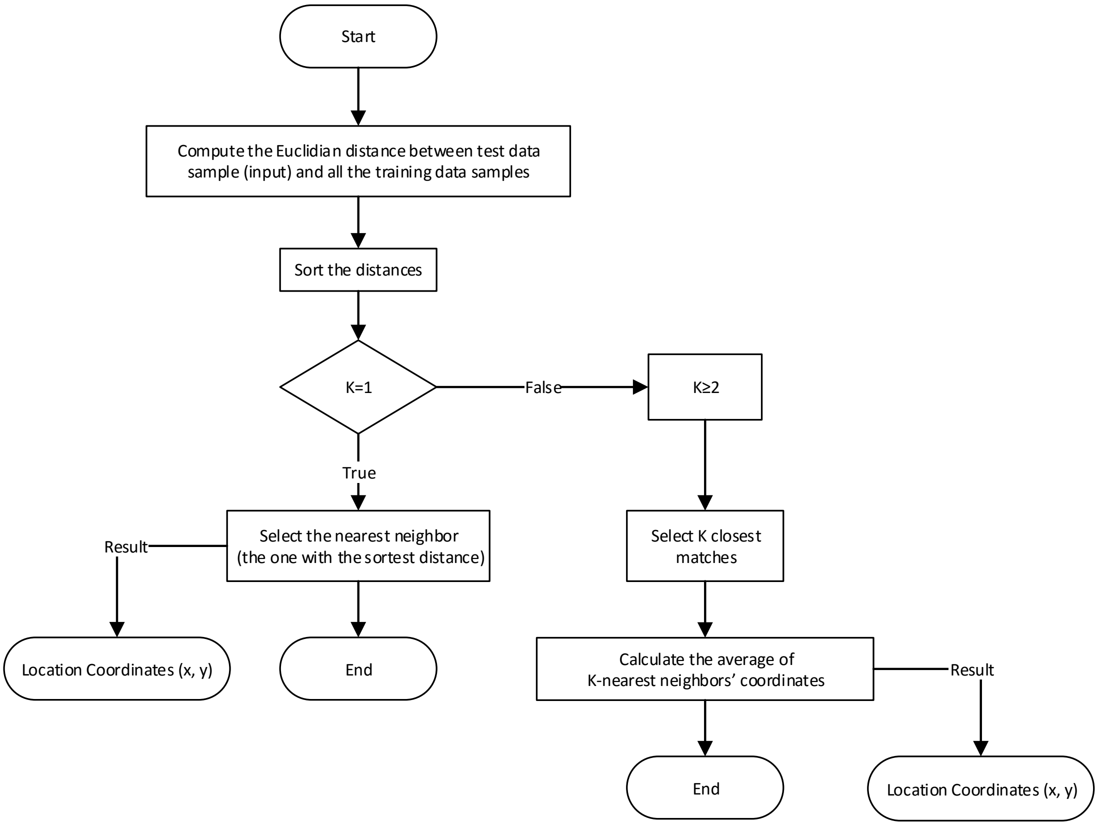


Figure 34: Flowchart diagram of k-NN algorithm

After the calculation of the Euclidian distance between the test sample and each training data sample, calculation results are sorted from the smallest to the largest, and the coordinates of the closest match is identified as the position of the test sample, in the case that k=1. If k is set as 2 or 3, or even higher, the location of the test sample is calculated through determining closest k-number of training data sets, and calculating the average of their coordinates. Han *et al.* (2012) state that, the most effective value for k, in which give the minimum error rate is achieved, can only be determined through experimental trials. Similar to what Bahl and Padmanabhan (2000) propose in their study and the preference of Taneja *et al.* (2012), the error distance for the estimated location in this research is defined as the Euclidian distance between the location coordinates identified by k-NN algorithm and the true location coordinates of the test sample (Figure 34).

As it is explained earlier, a training data set was prepared in the offline phase and a test data set is required both for analyzing the proposed system and the utilization of k-NN algorithm. Since the second data collection was decided to be ignored, and not used for its unreliability due to the flat batteries of some coin-cells, the very first set of data collection is taken as the training data set and the third data collection set is taken as the test data set. Test and training data sets are collected with a time interval of two months in real operating conditions of the test bed building, which familiarize the experiment to the real-case usage of the proposed framework.

For data analysis, the approaches of Bahl and Padmanabhan (2000), Pradhan *et al.* (2009) and Taneja *et al.* (2012) are taken as the main guidelines in this study, and the cases defined by Pradhan *et al.* (2009) are modified and developed for assessing different properties of Bluetooth Low Energy technology for indoor localization. Accordingly, the researcher of this study created the following cases for experiments and the aim of establishing each case is explained in the next section (Table 4, Table 5):

- Case I – Training data is composed of data collection at 46 points and four directions (N, W, S and E). Minimum required number of data samples for each tag is set as 30, and fingerprinting is done through averaging RSSI Values. Test data is also consist of data collection at 46 points and four directions (N, W, S and E), and the minimum required number of data samples for each tag and fingerprinting approach is similar to training data.

- Case II – Training data is kept same as in Case I, with a total number of 184 fingerprints are created through data collection at 46 points and four directions (N, W, S and E). In the test data, in order to analyze the effect of number of data samples, the duration of RSSI recording for each position is reduced to 30 seconds, and the minimum required number of data samples is set as 15 for each tag, while keeping the number of fingerprints same as in training data.

- Case III – With the purpose of understanding user orientation factor and directional invariance, training data is composed of 46 points and limited to only one random direction (it is taken as West in analysis). The number of fingerprints, therefore is determined as 46. The test data is taken same as in test data of Case I, and a total number of 184 test data sets are searched in 46 training data sets through applying k-NN algorithm.

- Case IV – Training data is reduced to 88 fingerprints; data is collected at 22 points in four directions (N, W, S and E), as shown in Figure 35. The distance between two consecutive data collection points is set as 3.6 meters. The minimum required number of data samples is kept as 30, and fingerprinting is done through averaging RSSI Values. Test data is kept same as in Case I and Case III, and the change in the accuracy with this reduction in the number of data collection points is investigated through experimenting this case.

- Case V – While keeping the number of fingerprints same as in Case I in both training and test data, the fingerprinting approach is changed from averaging the RSSI values to taking the highest value within the received signal strengths for each tag.

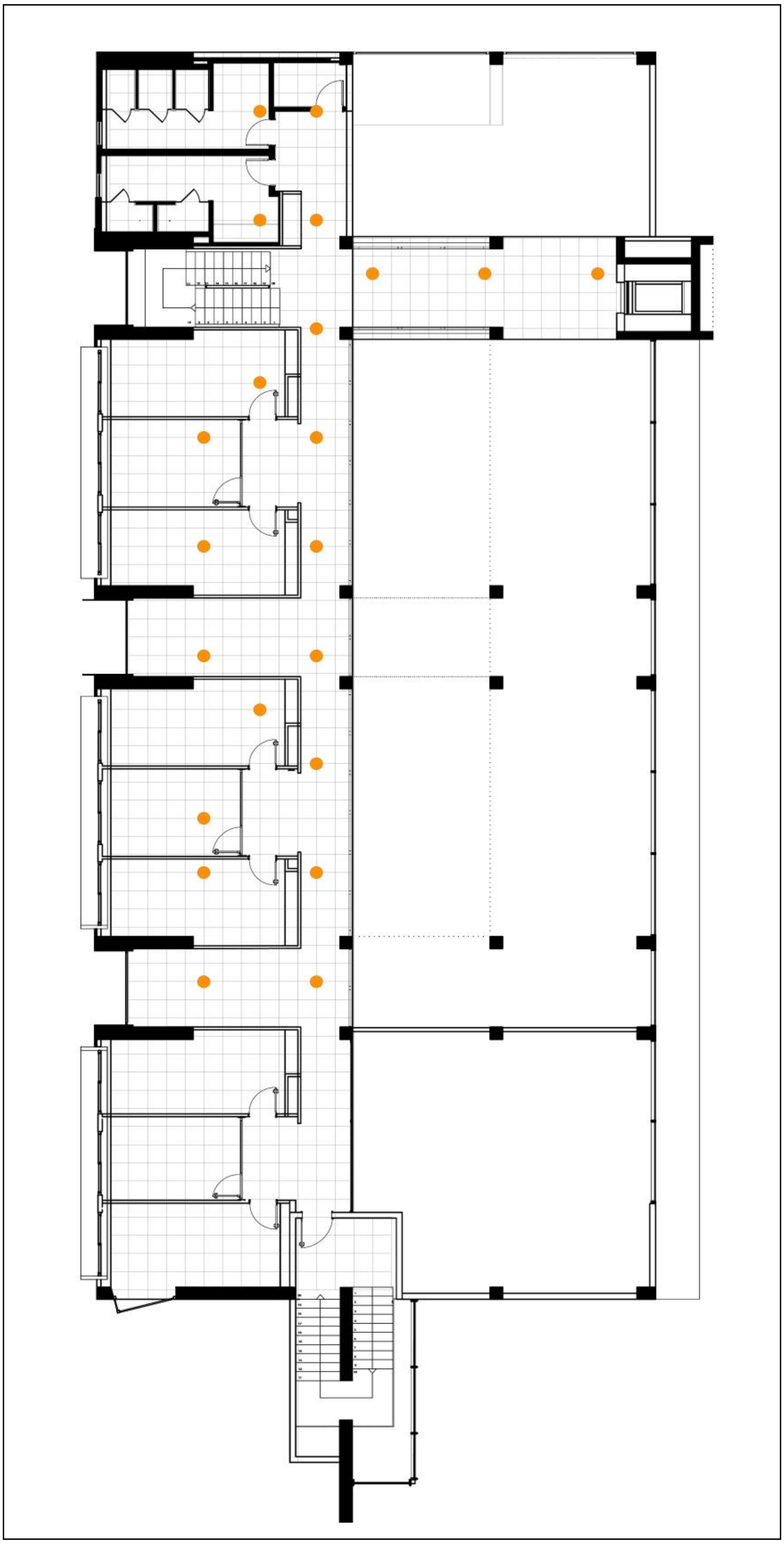


Figure 35: Location of Fingerprints in Training Data of Case IV, Scale: 1/200

Table 4: Cases for Data Analysis – Training Data

Training Data					
Case	**# of Fingerprints**			**Approach**	**# of Data Samples**
	# of Points	**Direction**	**Total #**		
CASE I	46	4 directions (N,W,S,E)	184	Average of RSSI Values	Min. 30 for each tag
CASE II	46	4 directions (N,W,S,E)	184	Average of RSSI Values	Min. 30 for each tag
CASE III	46	Random Direction (West)	46	Average of RSSI Values	Min. 30 for each tag
CASE IV	22	4 directions (N,W,S,E)	88	Average of RSSI Values	Min. 30 for each tag
CASE V	46	4 directions (N,W,S,E)	184	Highest of RSSI Values	Min. 30 for each tag

Table 5: Cases for Data Analysis – Test Data

Test Data					
Case	**# of Fingerprints**			**Approach**	**# of Data Samples**
	# of Points	**Direction**	**Total #**		
CASE I	46	4 directions (N,W,S,E)	184	Average of RSSI Values	Min. 30 for each tag
CASE II	46	4 directions (N,W,S,E)	184	Average of RSSI Values	Min. 15 for each tag
CASE III	46	Random Direction (Any)	184	Average of RSSI Values	Min. 30 for each tag
CASE IV	46	4 directions (N,W,S,E)	184	Average of RSSI Values	Min. 30 for each tag
CASE V	46	4 directions (N,W,S,E)	184	Highest of RSSI Values	Min. 30 for each tag

3.4 Parameters of Proposed Framework for Indoor Localization

In order to analyze the appropriateness of the proposed framework for locating an occupant within an indoor built environment, multiple field experiments were conducted and the cases given above are organized. In determination of the case contents, certain localization metrics are taken as the basis, which are derived from the previous researches of Bahl and Padmanabhan (2000), Elnahrawy (2006) and Pradhan *et al.* (2009), for evaluating the different parameters of BLE-based localization. Localization metrics are defined under five sub-headings namely spatial accuracy-precision, number of real time data samples, human body orientation, number of data collection points, and fingerprint creation approach.

3.4.1 Spatial Accuracy - Precision

The main parameters for location detection systems are clearly described in the literature as spatial accuracy and precision (Bahl & Padmanabhan, 2000; Elnahrawy, Li, & Martin, 2004). Spatial accuracy and precision are interdependent localization metrics and they are used to define the effectiveness of any location detection solution. In their book, Mao and Fidan (2009) explain the relation between accuracy and precision as:

> The accuracy is a generalization of localization error to areas. Location error is the distance between the true position of the unit and the returned area. Precision describes the size of the area. A point is hence infinitely precise, but may not be very accurate. On the other hand, the area containing the entire scope of the localization system (e.g. a whole building) would have a high accuracy but poor precision. Accuracy and precision are useful utilities to quantitatively describe the performance of different localization approaches by observing the impact of increased precision (*i.e.*, less area) on accuracy (p. 309).

The accuracy metric in this research is given in percentage, which reveals the probability of locating the intended unit within a defined range. Division of the number of successful location detection attempts for a determined precision to the all localization trials, when multiplied with 100, gives the percentage of the accuracy. The interpretation of localization precision is defined in meters and it is calculated as the location error. If it is assumed that P_t (x_t, y_t) be the true location of a unit and P_e (x_e, y_e) be the estimated location, the precision is defined as the Euclidian distance between these two points. It can be shown as:

$$\rightarrow \text{Precision} = \sqrt{(x_t - x_e)^2 + (y_t - y_e)^2} \qquad (2)$$

Referring to the fingerprinting grid size in the field experiments, four values, namely 1.8 meters, 3.6 meters, 5.4 meters and 7.2 meters are taken as the precision levels to analyze the accuracy of the proposed location detection framework.

3.4.2 Number of Real Time RSSI Data Samples

In the field experiments of this research, duration of RSSI data measurements were defined as one minute and the number of RSSI data samples is determined to be at least 30 for each BLE tag. As Bahl and Padmanabhan (2000) claim in their paper, although it is understandable to specify a minimum number for RSSI samples from each tag for constructing training data set as it is only done once, it may be problematic to collect certain number of RSSI samples in the real case for locating the occupant. Considering this, the researcher of this study investigated whether the number of real time data samples has an impact on localization accuracy, or not. With this purpose, in Case II that is explained previously, data collection duration is decreased to 30 seconds and minimum number of RSSI samples is limited to 15 in the test data set, while keeping the same offline data set same as in the beginning. It should be noted that, if there is not a considerable change in localization accuracy in Case II when compared with Case I, BLE-based localization can be instant without requiring the occupant to be stationary.

Hypothesis I:
Null Hypothesis: There is no relationship between number of real time RSSI data samples and the spatial accuracy and precision of BLE based indoor localization.
Alternative Hypothesis: Number of real time RSSI data samples affects the spatial accuracy and precision of BLE based indoor localization.

3.4.3 Human Body Orientation

As 70% of human body is composed of water and it acts like an absorber for radio signals, the orientation of human body can have effects on RSSI data communication between signal transmitters (BLE tags) and the readers (Samsung Galaxy Note 10.1 2014 Tablet). User orientation is an important parameter that should be considered in the proposed framework since people hold and keep their mobile devices in different orientations throughout the daily life. Cinefra (2013) asserts that, different orientations of human body may change the state of line-of-sight between the wireless transmitters and the reader. His experimental results showed that this affects RSSI values up to 5dB according to the change in user direction. Zhang *et al.* (2011) clarified the impacts of human body orientation on wireless radio signals and described human body as an obstruction for blocking the signals. In Figure 36 which is illustrated by Zhang *et al.* (2011), it is indicated that, when an occupant's direction is in between d_1 and d_2, line of sight between the mobile device and the transmitter is obstructed this creates fluctuations in RSSI data.

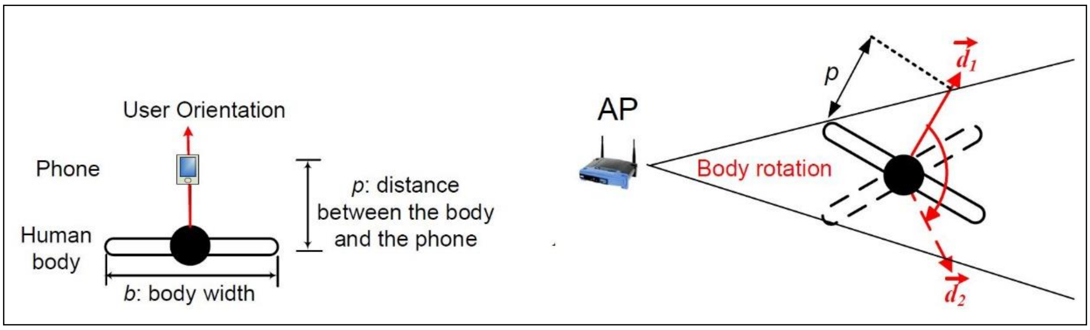


Figure 36: An abstract model of the impact of human body orientation (Zhang *et al.*, 2011)

Bahl and Padmanabhan (2000) also tested the effects of user direction on signal strength and observed an important decrease in the localization accuracy. Accordingly, the impact of the directions that occupants are facing on the accuracy of BLE-based localization is investigated in this research. In Case III, as explained in Section 3.3.2, training data set contains RSSI data of 46 points in only one random direction (it is taken as west in analysis), while test data set has RSSI data corresponding to all directions.

Hypothesis II:

Null Hypothesis: There is no impact of human body orientation on RSSI data communication, and spatial accuracy and precision of BLE based indoor localization.

Alternative Hypothesis: Human body orientation has an impact on RSSI data communication, spatial accuracy and precision of BLE based indoor localization.

3.4.4 Number of Data Collection Points

Due to the nature of location fingerprinting method, real time RSSI samples collected by the mobile unit are searched within the offline radio map of the defined indoor area, and location is determined by deducing the closest matching training sample. It may be possible to obtain higher precision as the minimum distance between two consecutive data collection points decreases and therefore more fingerprints are deployed in the offline phase. The accuracy may also be affected by the variation in number of data collection points. In their research, Bahl and Padmanabhan (2000) studied the impact of variations in data collection points quantity, and it is revealed that, the more data collection points deployed in the offline phase, the more precise the localization system is achieved.

In order to understand the effects of number of data collection points in this research, Case IV is created. In the training data set of Case IV, the data collection points' quantity is reduced to 22 points in such a way that the distance between two data collection points is minimum 3.6 meters. There are 88 fingerprints deployed in the radio map, and the position of 184 test data samples are inquired within this narrowed offline data set.

Hypothesis III:

Null Hypothesis: There is no relationship between number of data collection points and the spatial accuracy and precision of BLE based indoor localization.

Alternative Hypothesis: Number of data collection points affects the spatial accuracy and precision of BLE based indoor localization.

3.4.5 Fingerprint Creation Approach

In all four cases mentioned above are all processed through averaging RSSI values collected from the deployed BLE tags. Instead of using the average value, utilizing the maximum RSSI values for each tag is suggested as an alternative in the literature (Bahl & Padmanabhan, 2000; Pradhan *et al.*, 2009; Taneja *et al.*, 2012). Keeping the base of requiring at least 30 RSSI values for assuming a tag as detected, the highest RSSI value for each tag is identified and both training and data sets are created with this approach in Case V. Since the number detected tags for a predefined fingerprint point would not change with this approach due to the assigned limitation of minimum required RSSI values, it is expected that, there will only be minor changes in localization accuracy and precision between Case I and Case V.

Hypothesis IV:

Null Hypothesis: There is no difference between creating fingerprints through averaging RSSI values and creating fingerprints through taking maximum RSSI values for the accuracy levels of BLE based location estimation.

Alternative Hypothesis: Creating fingerprints through taking maximum RSSI values gives considerably different accuracy and precision results than creating fingerprints through averaging RSSI values for the accuracy levels of BLE based location estimation.

CHAPTER 4

RESULTS AND DISCUSSION

In this chapter, results of the field experiments are presented according to the given cases and specified deterministic algorithm. K-NN algorithm was applied manually in Microsoft Excel software by the researcher. The achieved accuracy levels at each case for different precision levels, and for different values of k (k=1, k=2, k=3 or k=4) are shown respectively. Results of different cases are compared, and on the basis of these comparisons, the parameters of the proposed framework are discussed. The inferences derived from the comparative analysis of the cases are demonstrated. Various metrics of BLE-based localization is compared with those of existing approaches in the literature and a general evaluation of BLE-based indoor localization is deduced.

4.1 Field Experiment Results

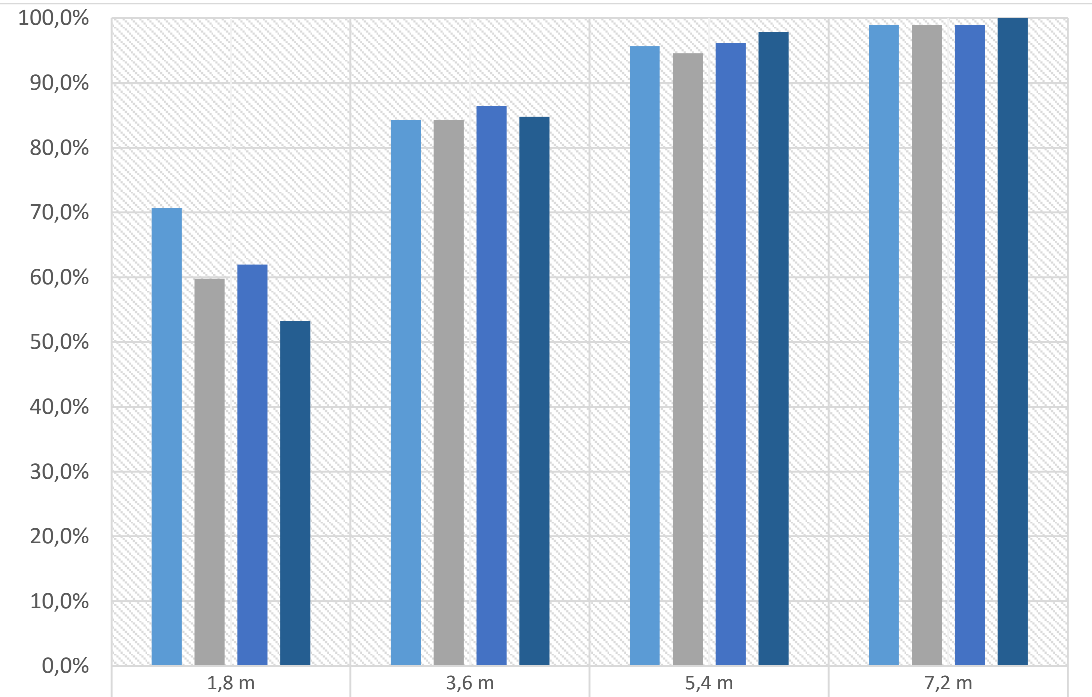
In this section, the results of field experiments are analyzed based on the defined cases. Variations on spatial accuracy levels according to the changes in parameters of BLE based localization are presented together with the interpretations of the researcher.

As explained earlier, referring to the fingerprinting grid size in the field experiments, four values, namely 1.8 meters, 3.6 meters, 5.4 meters and 7.2 meters are taken as the precision levels to analyze the accuracy of the proposed location detection framework.

4.1.1 Case I

Table 6 shows the accuracy and precision results of Case I. According to the results, at the highest specified precision, which is 1.8 meters, an accuracy of 70.7% is achieved at k=1. There is not a regular variation in the accuracy level as the k value gets higher, yet the worst accuracy level for 1.8 meters precision is achieved in the case where k=4, with a percentage of 53.3. For a precision of 3.6 meters, the spatial accuracy levels for different k values are almost the same, ranging between 84.2% and 86.4%. Since room level precision, which is claimed as meaningful for many indoor localization based applications in the literature, is defined as about 5 meters (Bargh & Groote, 2008; Dahlgren & Mahmood, 2014; Li *et al.*, 2015b), the indoor localization solution proposed in this research can be claimed as successful considering the results for a precision of 5.4 meters. Accordingly, at k=4, an accuracy of 97.8% is achieved for room level location detection. In this research, the lowest precision level is determined as 7.2 meters, for which full accuracy (100.0%) is gained. It can also be inferred from the results that, as the precision level gets low, the change in the k value does not affect the accuracy results in a considerable manner. The results obtained in Case I is used as a base for comparison of various parameters of BLE-based indoor localization. In the following cases, some metrics are changed while keeping the other attributes same as in Case I, as explained in Sections 3.3 and 3.4.

Table 6: Case I - Localization accuracy results for different precision levels



	1,8 m	3,6 m	5,4 m	7,2 m
k=1	70,7%	84,2%	95,7%	98,9%
k=2	59,8%	84,2%	94,6%	98,9%
k=3	62,0%	86,4%	96,2%	98,9%
k=4	53,3%	84,8%	97,8%	100,0%

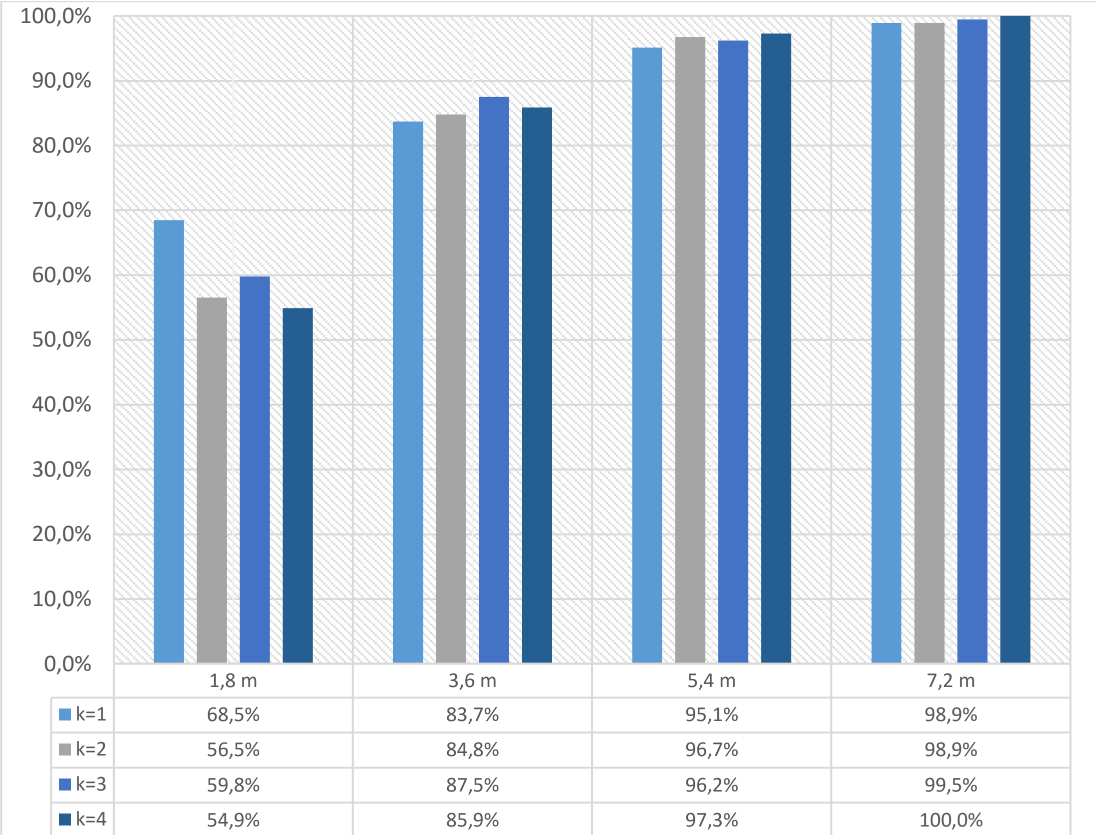
4.1.2 Case II

The localization accuracy and the precision results of Case II are presented in Table 7. The achieved accuracy levels for 1.8 meters precision are very close to those of Case I, and the maximum accuracy rate for the highest precision was founded to be 68.5% at k=1. The accuracy decreases when k is set as 2, 3 or 4 and it is gained as 56.5%, 59.8% and 54.9% respectively. This condition is also identical with Case I, which demonstrates the fact that, averaging the coordinates of multiple nearest neighbors does not give as accurate results as deducing the location of an occupant as the coordinates of the nearest neighbor for the highest precision. Yet, it is not the case when the precision is 3.6 meters. When k=1 for a precision of 3.6 meters, the accuracy is the worst when compared to other values of k. The best accuracy is gained by 87.5% for 3.6 meters precision, in the case where k=3. The diagram outlines that there is a slight difference between the achieved accuracy levels with 5.4 meters and 7.2 meters precisions, for different k values. Room level accuracy levels range between 95.1% and 97.3%, whereas the full accuracy (100.0%) is gained for 7.2 meters precision as in Case I.

Overall, when the accuracy and precision results in Table 7 is compared with those of Table 6, very slight differences are observed. This similarity reveals that, the number of real time RSSI data samples does not have a crucial impact on location estimation accuracy in BLE based indoor localization. Therefore, it is possible to locate an occupant within an indoor environment with small number of RSSI samples in real time, and this enables instant localization. The result is very much in line with the findings of Bahl and Padmanabhan (2000), who indicated that constraints in obtained number of RSSI samples in the online phase does not considerably effect the performance of the radio frequency based localization systems.

Although there is not a dramatic change in percentages, there is a difference between spatial accuracy results of Case I and Case II. Therefore, it can be said that number of real time RSSI data samples has an impact on the spatial accuracy and precision in BLE based indoor localization, and null hypothesis in Hypothesis I is not accepted.

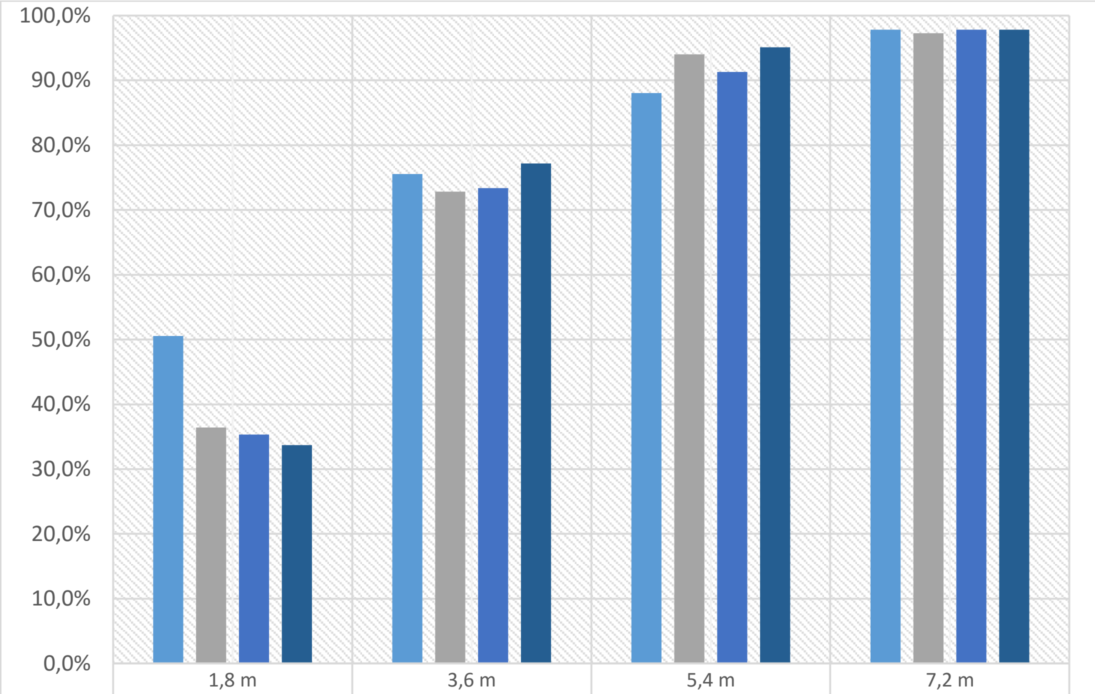
Table 7: Case II - Localization accuracy results for different precision levels



4.1.3 Case III

In Case III, training data set is composed of RSSI data that is collected at 46 points and from only one random direction (it is taken as west in the analysis). In order to understand the impact of human body orientation, training data is constructed with measurements from all four directions for each point. For example, the location of an occupant facing north direction at point A is tried to be estimated in the radio map in which the only fingerprint data of point A is corresponding to west orientation. In Table 8, the accuracy results of Case III with different precision levels are depicted. For 1.8 meters precision, there is a substantial decrease in the spatial accuracy for all values of k when compared with Case I. An accuracy 50.5% is achieved where k=1 for the highest precision. The results for other values of k with 1.8 meters precision do not display very high levels of accuracy for an indoor localization solution with a range between 33.7% and 36.4%. The spatial accuracy also fall off for 3.6 meters of precision and it fluctuates between 72.8% and 77.2% for different k values. Although a vast change in accuracy is monitored for 1.8 meter and 3.6 meters precision, the accuracy of location detection remain very close to that of Case I for room level precision. The best accuracy observed for room level precision is 95.1% where k=4. The results of Case III analysis for 7.2 meters precision represent that, almost full spatial accuracy can be gained regardless of impact of human body orientation with the proposed framework. The achieved accuracy for 7.2 meters precision is about 97%.

Table 8: Case III - Localization accuracy results for different precision levels



	1,8 m	3,6 m	5,4 m	7,2 m
k=1	50,5%	75,5%	88,0%	97,8%
k=2	36,4%	72,8%	94,0%	97,3%
k=3	35,3%	73,4%	91,3%	97,8%
k=4	33,7%	77,2%	95,1%	97,8%

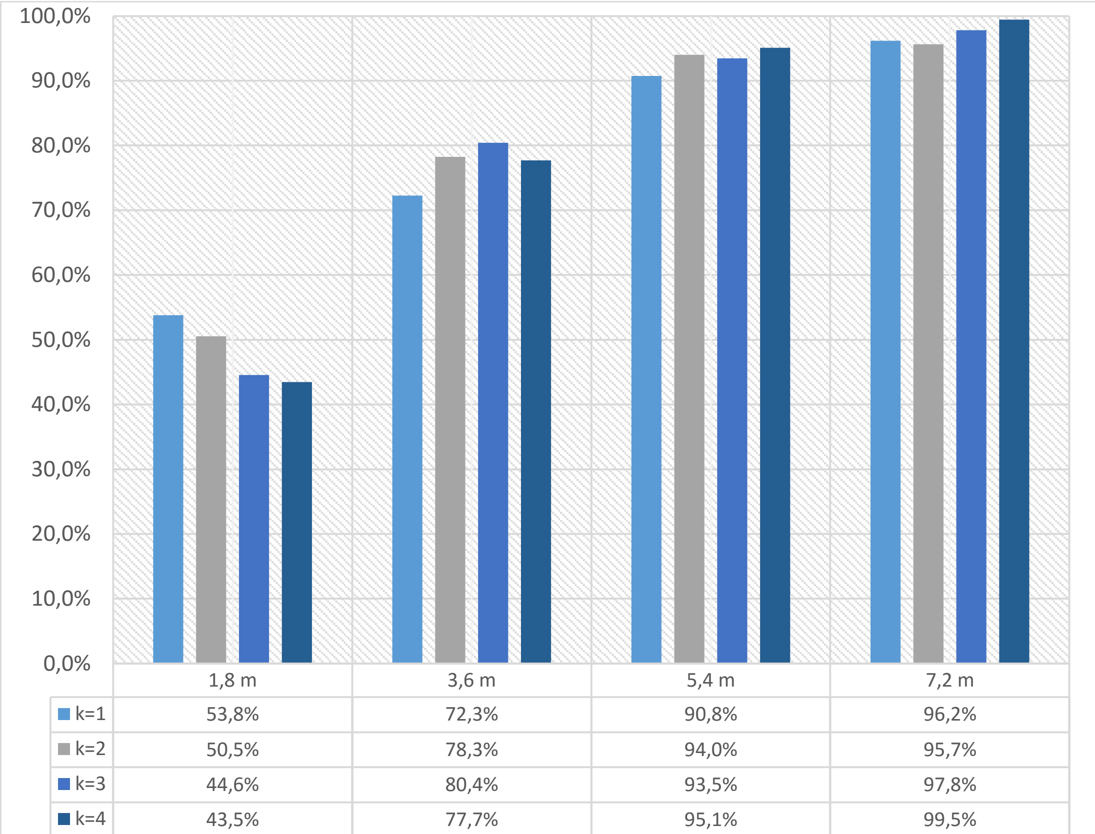
It can be inferred from the comparison of spatial accuracy - precision results of Case I and Case III that, human body orientation has a huge impact on accuracy of BLE based indoor localization for higher precision levels, whereas if the intended precision is at room level or lower, it does not have considerable effects. By the reason of the fact that the position of mobile devices may be in various orientations throughout the daily life, in order to achieve good accuracy levels with higher precisions, it is important to regard directional variance as significant and to collect RSSI data in different directions for a given location in location fingerprinting. Considering the inconsistency of the impact of body orientation in spatial accuracy with different precisions, it can also be deduced that BLE-based localization may not be very reliable in instant route monitoring with the proposed framework and further improvements are needed for such purposes.

Similar to the observations of Bahl and Padmanabhan (2000), in which the impact of user orientation on the accuracy of wireless based localization systems was indicated to be fairly significant, human body orientation can be interpreted as an essential input for BLE-based location detection. Accordingly, since human body orientation is demonstrated to affect spatial accuracy - precision of BLE based indoor localization and thereby on RSSI data communication, null hypothesis in Hypothesis II is not accepted.

4.1.4 Case IV

Table 9 represents the spatial accuracy - precision results of location detection in Case IV. The purpose in analyzing Case IV is to evaluate the variations in accuracy and precision levels in the condition where training data set is composed of fewer fingerprints. Therefore, the number of fingerprints is decreased from 46 points to 22 points, while keeping the same test data set as in Case I. The results in Table 9 reveals that, at k=1, success rate of location estimation in Case IV is lower than Case I, for 1.8 meters of precision, with a percentage of 53.8. The accuracy rates vary between 43.5% and 50.5% for other values of k, with the highest precision. For 3.6 meters of precision, a moderate reduction in the localization accuracy is observe. The success in location detection for 3.6 meters precision is worst at k=1, by 72.3%, and best results is achieved at k=3, by 80.4%. The bar chart outlines that, number of data collection points do not have considerable effects on spatial accuracy of BLE-based localization framework with room level precision. A success rate of 95.1% is achieved in location estimation for 5.4 meters precision, at k=4. The quantity of fingerprints is also presented to have slight effects for 7.2 meters of precision, yet an high accuracy is gained by 99.5% for k=4. It can be concluded that, the number of data collection points has substantial effects on localization accuracy for higher precisions, whereas the changes in the success rate of location estimation for lower precision levels are not necessarily significant.

Table 9: Case IV - Localization accuracy results for different precision levels



As the distance between two consecutive data collection points is set as 3.6 meters instead of 1.8 meters in Case IV, it is understandable that the change in number of fingerprints on localization accuracy have higher impacts on precision levels of 1.8 meters and 3.6 meters than lower precision levels. Since further increase in the distance between data collection points would not give reliable results due to the coverage zone dimensions of the test bed environment in this research, the quantity of fingerprints was not reduced any more. Yet, it is estimated that, if the distance between two points of data collection was further increased (*i.e.* if it was set as 5.4 meters or more) in a bigger test bed area, the same impact as in the highest precision level would be observed for precision levels of 5.4 meters and 7.2 meters.

Considering the change in the accuracy rates of location estimation with the change in the number of fingerprints, the null hypothesis in Hypothesis III is not accepted.

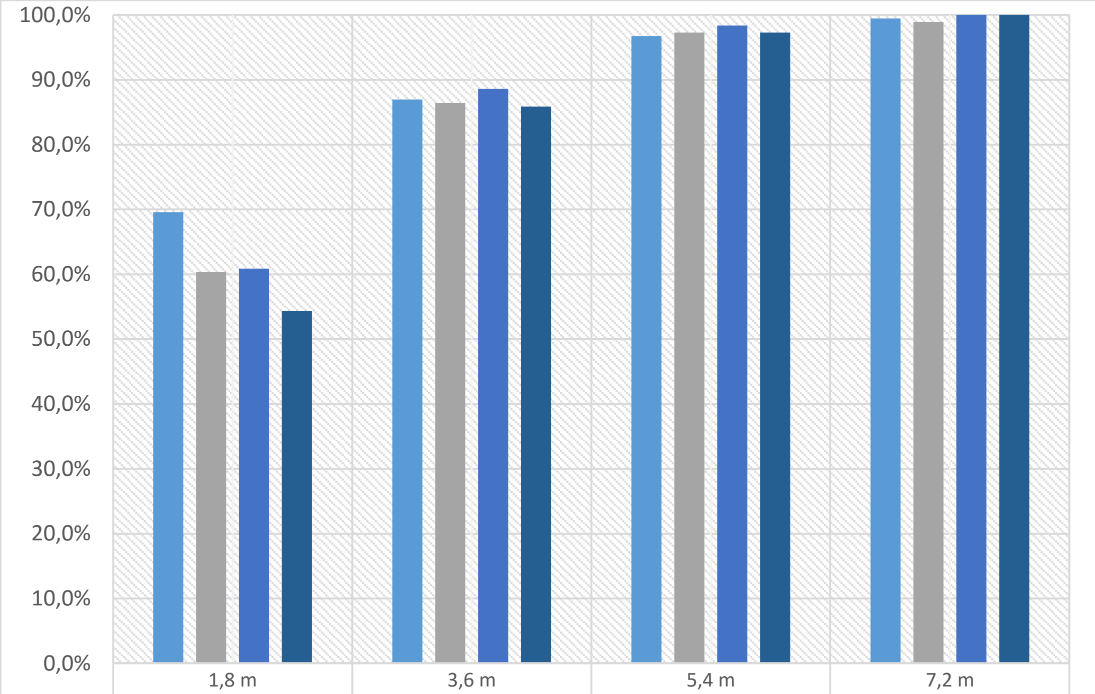
4.1.5 Case V

The spatial accuracy – precision results of Case V is presented in Table 10. Both training and test data sets are composed of fingerprints that are created by taking the highest signal strength values received from each tag for a given position. The primary intention in this approach is to investigate whether using maximum RSSI values can be a good alternative to averaging the collected RSSI data for location fingerprinting. For the highest precision, 1.8 meters, the accuracy in location estimation is almost the same as in Case I for all k values. The best accuracy result with 1.8 meters precision was found to be 69.6% at k=1, as it was observed as 70.7% in Case I. For 3.6 meters of precision, the achieved accuracies are slightly better than those of Case I and it varies between 85.9% and 88.6%. The most accurate location estimation with room level precision among all cases is observed in Case V, by 98.4% at k=3. The analysis give the highest accuracy results with 7.2 meters of precision, as in all cases, and full accuracy is achieved at k=3 and k=4.

Similar to the findings of Pradhan *et al.* (2009) about using maximum RSSI values for location fingerprinting, difference in the accuracy percentage between Case I and Case V is only about 4% for all values of k and with all precision levels. These results prove that, using maximum RSSI values may be considered as an alternative to taking the mean of collected RSSI data.

Since creating fingerprints through taking maximum RSSI values gives almost the same accuracy and precision results (4% different at most) than creating fingerprints through averaging RSSI values, the null hypothesis in Hypothesis IV is not rejected.

Table 10: Case V - Localization accuracy results for different precision levels



	1,8 m	3,6 m	5,4 m	7,2 m
k=1	69,6%	87,0%	96,7%	99,5%
k=2	60,3%	86,4%	97,3%	98,9%
k=3	60,9%	88,6%	98,4%	100,0%
k=4	54,3%	85,9%	97,3%	100,0%

4.2 Analytical Comparison with Existing Wireless-based Approaches

In order to compare the proposed framework in this research with the existing approaches in the literature, performance parameters for wireless based localization systems are determined through referring to Tekinay, Chao, and Richton (1998) and Liu *et al.* (2007), as explained in Section 2.3.5. The intention in establishing these guidelines is to check whether the developed solutions are covering the requirements of a reliable and sustainable location detection framework or not. Accuracy-precision, complexity, scalability and cost are identified as the main evaluation metrics. The most important feature of a localization system can be claimed as spatial accuracy-precision. In almost all the existing wireless-based reviewed approaches in the literature, a tradeoff between localization accuracy and other defined parameters is observed. For example, if the achieved spatial accuracy and precision is very high, like the UWB based framework of Steggles and Gschwind (2005), the deployment cost can be very high or the system may be too complex.

In order to establish a viable indoor localization solution, considering the optimization of defined parameters is crucial. Although the main aim of the location detection systems is to detect the position of the intended unit with the highest precision and accuracy, it will be unserviceable unless the system is simple enough for easy deployment, scalable in case of a need for widening the coverage area or cost effective for initial deployment and maintenance.

In the BLE-based framework of this research, a competitive accuracy and precision is achieved when compared to the existing approaches. As explained in the previous section, an accuracy of 70% is observed for the highest precision, 1.8 meters. For room level precision, which has been the objective of many approaches in the literature, 98% accuracy is achieved. These results show that, Bluetooth low energy could be assessed as a strong alternative to RFID or WLAN, which are extensively studied in the literature, for location detection in indoor built environments.

Complexity of the proposed localization system is defined as low, considering and comparing the different requirements of the current frameworks in the literature. In the most simplified approaches, the system is usually composed of readers as the signal receivers and sensors or tags as the transmitters (Bahl & Padmanabhan, 2000; Ni *et al.*, 2003; Pradhan *et al.*, 2009). However, as the system in this research is based on a mobile-device integrated framework, the only requirement for the implementation is the deployed BLE tags. Moreover, since the localization algorithm is to be processed in the main building automation system, and not in mobile devices, the position computation duration will be very short.

Table 11: Comparison of wireless-based indoor localization approaches based on performance metrics

Researchers	Wireless Technology (System)	Localization Algorithm	Accuracy - Precision	Complexity	Scalability	Cost
Bahl & Padmanabhan (2000)	WLAN RSS (RADAR)	k-NN	50% w/ 2.5 m 90% w/ 5.9 m	Medium	Good	Medium
Bekkelien (2012)	Bluetooth RSS	k-NN	50% w/ 1.7 m 95% w/ 5.1 m	Low	Good	Low
Calderoni *et al.* (2015)	RFID RSS	Random Forest Classifiers	83% w/ room level	High	Moderate	Moderate
Dodier *et al.* (2006)	PIR	Probabilistic Method	76% w/ presence detection	Medium	Poor	Moderate
Hightower *et al.* (2000)	RFID RSS (SpotON)	Ad-Hoc lateration	Not Specified	Medium	Good	Low
Ismail *et al.* (2008)	WLAN RSS	Not Specified	80% w/ 2.5 m	Medium	Good	Medium
Li *et al.* (2012)	RFID RSS	k-NN	88% w/ room level	Medium	Good	Moderate
Lim *et al.* (2007)	WLAN AOA	Not Specified	75% w/ 0.85 m	Medium	Poor	High
Ni *et al.* (2003)	RFID RSS (Landmarc)	k-NN	50% w/ 1-2 m	Medium	Dense node placement required	Medium
Pradhan *et al.* (2009)	RFID RSS	k-NN	40% w/ 1.52 m 93% w/ 10.7 m	Medium	Good	Medium
Steggles & Gschwind (2005)	UWB AOA (Ubisense)	Least Square	99% w/ 0.3 m	High	4 sensor per cell (1m) required	High
Taneja *et al.* (2012)	WLAN RSS	k-NN	70% w/ 1.52 m 94% w/ 6.1 m	Medium	Good	Medium
Topak (2016)	BLE RSS	k-NN	70% w/ 1.8 m 98% w/ 5.4 m	Low	Good	Low
Zhen *et al.* (2008)	RFID RSS	Support Vector Machine	93% w/ room level	Medium	Good	Medium

As described in Chapter 2, the test bed environment, *i.e*. the coverage zone of the proposed framework, is 240 m^2 and full signal coverage is provided with the placement of twelve BLE tags with certain intervals. If an expansion in the coverage area is needed or desired, the only required action to be taken is to deploy more tags for full signal coverage and widen the radio map. Therefore, the scalability of BLE based localization is outlined as good in the table. Although there are some exceptions, wireless sensor based location detection systems are generally scalable for changing needs.

Cost is an important metric for indoor localization systems. If the profit gained through the utilization of the system is exceeded by the cost of the required infrastructure or maintenance operations, the total effort becomes redundant (Farid *et al.,* 2013). In this research, the cost of the utilized BLE tags is 30$ per tag, and the only maintenance requirement is to replace coin pills as they run out of batteries. As BLE technology has ultra-low power consumption, the maintenance circle can be claimed as about two years, depending on the coin pill type. Considering this, BLE-based localization is labelled as low-cost in Table 11.

CHAPTER 5

CONCLUSION

Summary of the research is initially presented in this chapter. Then, the main results and discussions are outlined and limitations of the study are stated. The chapter is concluded with the recommendations about how further researches can be handled based on the proposed indoor localization framework.

5.1 Summary of the Research

With its various use cases, indoor localization is shown to have a great value for the construction industry. The wide scope of researches about finding the location of an object or a person includes building occupancy detection, asset tracking in construction sites, assistance to facility maintenance and operations and supporting building emergency response operations. Among the described use cases, the emergence of the need for building occupancy detection was reviewed, through establishing a breakdown including interaction between people and buildings, intelligent buildings approach and building automation systems.

There are many studies in the literature with the intention of creating a reliable framework for indoor localization. The proposed systems are composed of prediction algorithms, vision-based scenarios, PIR or CO_2 sensors based solutions and radio frequency based frameworks, in which different sensor technologies such as RFID, WLAN, UWB and Bluetooth are utilized. Nevertheless, there are some drawbacks for all the existing approaches, including uncertainty in detection, privacy concerns, time delays in detection, inability for multiple detection and high deployment and maintenance costs.

Considering the need for a reliable indoor localization approach, the aim in this research was to propose an efficient framework for location detection in indoor environments and to analyze its applicability. As the mobile devices became an inseparable part of people in the last decade, a mobile device integrated framework was designed. Bluetooth Low Energy, which is a novel release in the wireless industry, was determined as the enabling technology. BLE is a low cost and ultra-low power consumer technology, signals of which can penetrate through any obstructions like walls or objects. Although it is not developed for localization purposes, such properties make it a potentially appropriate technology for indoor localization.

In order to investigate the applicability of the proposed framework and BLE technology for location finding, several field test were conducted within MATPUM Building at Middle East Technical University. Before the main field experiments, a material selection experiment was carried out and the most appropriate BLE tag was selected according to the result. The main experiments were examined through employing location-fingerprinting method that is composed of offline and online phases. A radio map of the defined zone was created in the offline phase through collecting fingerprints, and location is estimated in the online phase by matching the real time data with the closest fingerprint. RSSI was taken as the measurement type and k-nearest neighbor algorithm was used as the classifier.

Five different cases were presented for assessing different parameters of BLE technology, based on the guidelines outlined by Bahl and Padmanabhan (2000) and Pradhan *et al.* (2009). Results of defined cases are compared for the evaluation of BLE based indoor localization and a table demonstrating the performance metrics of the proposed framework with the existing approaches was given together with the comparative discussions.

5.2 Main Results and Discussion

The main objective of this research was to determine the applicability of utilizing Bluetooth Low Energy in indoor localization and experimenting the different parameters of this radio frequency based technology. The results of the experiments outlined an accuracy of 70% with 1.8 meters precision and 98% with room level precision that is 5.4 meters. The achieved accuracy and precision levels show that BLE technology can be taken as an alternative to current approaches with its low complexity, good scalability and low cost properties. Considering the extensiveness of BLE adoption in mobile devices, it can be deduced that a mobile device integrated indoor localization framework is technologically feasible. The main results and relative discussions can be listed as:

- The achieved accuracy through a BLE based localization system is comparatively better than the existing approaches (Table 13), by 70% for 1.8 meters precision, 88% for 3.6 meters precision, 98% for 5.4 meters precision and full accuracy for 7.2 meters precision.

- Number of real time RSSI data samples does not have considerable effects on location detection accuracy and precision results, which reveals that instant localization with smaller numbers of RSSI data samples in the online phase is possible with BLE based localization approach.

- Since human body acts as a signal blocker and absorber, human body orientation has huge impacts on the accuracy percentages of the proposed framework. Accordingly, directional variance between BLE tags and mobile devices should be considered as a significant input while establishing a BLE based location detection solution.

- Number of data collection points in the creation of radio map effects the localization accuracy. As the distance between two consecutive fingerprint positions is increased from 1.8 meters to 3.6 meters, the achieved accuracy with 1.8 meters precision decreased considerably. The same impact is estimated to be observed in other precision levels, if the distance between data collection points is further increased.

- Creating fingerprints through taking maximum RSSI values can be considered as an alternative fingerprint creation approach to creating fingerprints through averaging RSSI values. Almost the same location detection accuracy results are achieved in both approaches.

5.3 Limitations of the Study

This research has a number of limitations on the field experiments and system analysis. Firstly, the method in this study was determined as location fingerprinting and the main limitation of the selected method is the significant effort for constructing the radio map of each intended floor. In addition, it may be required to refresh radio map in certain intervals according to the changes in the environment (*i.e*. furniture layout change). Yet, there are some current studies in the literature like the research of Gu *et al.* (2016) for overcoming this limitation and shortening the data collection processes. Secondly, the evaluation of the proposed framework was done through experiments in two dimensions on a single floor, and a three dimensional assessment was not pursued for multi-story buildings cases. Lastly, BLE based indoor localization was tested for the use case of occupancy detection, and other mentioned use cases were not considered due to the defined borderlines of the research.

5.4 Recommendations for Further Research

The main outcome of this study is that BLE technology can be used for detecting the position of occupants in indoor built environments. Based on what this study provides, the proposed occupancy detection system can be established in real operating conditions of the test bed building. In order to test the reliability of the proposed occupancy detection framework, the achieved occupancy detection results can be compared with the ground truth about real-time occupancy information. The question, 'how the energy consumption would decrease if the building operations were driven based on the achieved occupancy detection data?' could be answered through comparing the current energy consumption of the test bed and the energy simulation results that are based on the established occupancy detection system.

This study provides a base for assessing the utilization of BLE for detecting the location of occupants in indoor environments. However, the location information alone may not be enough for creating an energy efficient and comfortable built environment, and further information related with the type of occupants (young or old, man or woman, etc.), their behavior patterns and daily activities may be needed. For that purpose, a further research can be carried out for investigating the semantic data collection from both built environments and people using BLE technology to enhance intelligence and efficiency in the management and maintenance of facilities.

Considering the research limitations, the reliability of this low energy technology may be further assessed with experiments in three-dimensional space. BLE based indoor localization can be tested for other use cases such as asset tracking in construction sites, route guiding in building emergency response operations, and supporting facility maintenance activities.

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