EFFICIENT RANGE FREE LOCALIZATION SCHEME FOR MOBILE WIRELESS SENSOR NETWORKS

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ABSTRACT

In recent years, wireless sensor networks (WSNs) have been used in several applications to present the reality of operational areas. Owing to the small size and low cost of sensors, they can be efficiently used in mobile objects. However, the location of mobile sensors is a challenging issue because of the need to frequently change location per each time slot. Given this requirement, finding efficient localization method is a significant challenge in mobile objects. This study addresses the impact of localization in mobile WSNs by reviewing the state-of-the-art sequential Monte Carlo method under a range-free scheme.

The localization process in range-free schemes is conducted using network connectivity. Thus, movable sensors require the sharing of locations to estimate new locations. The power requirement for communication between sensors is higher than that for computation. Therefore, reducing the communication cost in WSNs can prolong network life.

The existing range-free schemes use anchor nodes and normal nodes in a neighborhood to estimate the new location of mobile sensors. Using normal nodes in the neighborhood can increase communication cost without improving localization accuracy. An added challenge in mobile WSN localization is the velocity and number of anchor nodes in the neighborhood. Most localization schemes employ the random waypoint mobility model to transmit the location of mobile sensors. The waypoint model produces a large overlap between anchor nodes and identifies more than three anchor nodes in a neighborhood without improving localization accuracy.

In this work, we present a localization framework to solve such problems. The proposed framework solves the first problem by selecting an adjacent normal node in the neighborhood, as in the proposed Low Communication Cost (LCC) scheme. The second problem is solved using the adaptive mobility model (AMM), which selects the

anchor node velocity as a function of the overlap degree and the number of anchor nodes in the neighborhood.

Results show that the proposed LCC scheme can reduce communication costs (the number of messages sent) by a minimum of 0.02 and a maximum of 0.30 with an average of 0.18 for varying node densities of 6 to 20, while nonetheless able to retain similar MSL* localization accuracy rates. Results to solve the second problem on the other hand, show that the proposed AMM improves localization accuracy with an average of 0.05 and a coverage degree of up to 0.50. We evaluate the proposed LCC scheme and AMM through extensive simulation experiments.

ABSTRAK

Pada kebelakangan ini, rangkaian sensor tanpa wayar (WSNs) telah digunakan dalam beberapa aplikasi bagi mencapai kawasan yang jauh dan berbahaya. Oleh kerana sensor adalah bersaiz kecil dan berkos rendah, ia boleh digunakan dalam objek mudah alih dengan berkesan. Walau bagaimanapun, mengenalpasti lokasi sensor mudah alih merupakan suatu isu yang mencabar disebabkan lokasi bertukar pada setiap slot masa. Oleh itu, mencari kaedah penyetempatan yang baru merupakan suatu cabaran yang besar di dalam objek mudah alih. Kajian ini mengkaji kesan penyetempatan WSNs mudah alih dengan meneliti keadah terkini berdasarkan kaedah Monte Carlo di bawah skim jajaran bebas.

Proses penyetempatan bagi skim jajaran bebas boleh dilaksanakan menggunakan rangkaian yang tersambung. Oleh itu, sensor mudah alih memerlukan perkongsian lokasi untuk menganggarkan lokasi baru. Keperluan tenaga kuasa untuk komunikasi antara sensor adalah tinggi berbanding pengiraan. Justeru itu, pengurangan kos komunikasi pada WSNs membolehkan jangka hayat rangkaian dipanjangkan. Skim jajaran bebas yang sedia ada menggunakan nod utama dan nod biasa di kawasan kejiranan untuk menganggar lokasi baru bagi sensor mudah alih. Penggunaan nod biasa di kawasan kejiranan akan meningkatkan kos komunikasi tanpa memperbaiki ketepatan penyetempatan. Cabaran tambahan dalam penyetempatan WSN mudah alih adalah kelajuan dan bilangan nod utama di dalam kejiranan. Kebanyakan skim penyetempatan menggunakan model pergerakan titik laluan secara rawak bagi menghantar lokasi sensor mudah alih. Namun begitu, penggunaan model pergerakan titik laluan secara rawak akan menghasilkan pertindihan yang besar antara nod utama dan mengenal pasti lebih dari tiga nod utama di kawasan kejiranan tanpa memperbaiki ketepatan penyetempatan.

Justeru itu, dalam kajian ini rangka kerja penyetempatan dibentangkan bagi menyelesaikan masalah tersebut. Rangka kerja yang dicadangkan iaitu Komunikasi Kos Rendah (LCC) menyelesaikan cabaran yang pertama dengan memilih nod normal yang berdekatan. Cabaran yang kedua diselesaikan dengan menggunakan Model Mobiliti Mudah Suai (AMM) dimana kelajuan nod utama dipilih sebagai fungsi bagi darjah pertindihan dan bilangan nod utama dalam kejiranan.

Keputusan daripada eksperimen menunjukkan bahawa skim LCC yang dicadangkan dapat mengurangkan kos komunikasi (bilangan mesej yang dihantar) dengan nilai minimum 0.02 dan maksimum 0.30 dimana purata 0.18 bagi kepadatan nod dari 6 hingga 20. Walau bagaimanapun, skim yang dicadangkan gagal mengekalkan kadar ketepatan yang sama seperti yang diperolehi oleh skema yang sedia ada. Keputusan yang diperoleh untuk menyelesaikan masalah kedua seterusnya pula menunjukkan AMM yang dicadangkan. dapat meningkatkan ketepatan penyetempatan dengan purata 0.05 dan darjah liputan sehingga 0.50. Skim LCC dan AMM yang dicadangkan dinilai melalui eksperimen simulasi yang terperinci.

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LIST OF SYMBOLS AND ABBREVIATIONS

AoA	:	Angle of Arrival
BD MCL	:	Binary Detection Monte Carlo localization scheme
GPS	:	Global Positioning System
HMCL	:	Hybrid Scheme Presented In HMCL
IMCL	:	Improved MCL
IoT	:	Internet of thing
MA-MCL	:	Mobile-Assisted Monte Carlo localization
MCB	:	Monte Carlo localization Boxed
MCL	:	Monte Carlo localization
MMCL	:	Multi-hop Version of Monte Carlo Localization
NMCT	:	Novel Monte Carlo-based tracking
OTMCL	:	Oriented tracking-based Monte Carlo localization
Pdf	:	probability distribution function
PIT	:	Point In Triangle
R	:	Radio range
RMCB	:	Range-based Monte Carlo boxed
RMCL	:	The range-based MCL
RSSI	:	Received Signal Strength Indicator
SAMCL	:	Sample Adaptive Monte Carlo Localization
SMC	:	Sequential Monte Carlo
SMCLA	:	Sequential Monte Carlo-Based Localization Algorithm
TDoA	:	Time Difference of Arrival
ToA	:	Time Of Arrival
WMCL	:	Weighted Monte Carlo Localization

WNMCL	:	Wireless node-based Monte Carlo localization
WSN	:	Wireless sensor networks

CHAPTER 1: INTRODUCTION

The development of wireless technologies has maximized the boundaries of the digital world and has increased the application of remote sensing in mobile wireless sensor networks (WSNs). Mobile WSNs overcome the weaknesses of static WSNs and enhance the adaptability of sensor networks to operational environments.

The main features of sensor nodes are their low cost and small size. Sensor nodes can communicate and collaborate to send data to a central point. These features enable sensor nodes to be applied in different domains. A large number of applications that use sensor nodes have been launched in recent years. Some examples of these applications are the sensor nodes used in the military, in firefighting, in zoos, and in the healthcare industry. In addition, the Internet of Things technology has maximized the compatibility of sensor nodes with Internet web sites.

Thin devices such as sensor nodes require lightweight methods for resource conservation. The small size and low cost of sensor nodes cause many limitations, particularly in terms of radio range, CPU speed, memory, and battery size. These limitations give birth to new challenges. One significant challenge is communication cost because sending one message wastes more power than that used in computation. Sensor nodes are highly sensitive to power resources that cause network separation. Signal strength also decreases in low-battery power cases (Gungor & Hancke, 2009).

Sensor nodes can be deployed remotely in outdoor applications, such as the spreading of sensors in far areas via aircraft. Thus, determining the accurate location of these sensors is a significant issue for decision makers. Location problems in outdoor applications are mostly solved using the Global Positioning System (GPS) (Misra &

Enge, 2006). By contrast, GPS technology cannot be applied in indoor application environments, such as for patients in hospitals, because it requires satellites with at least three lines-of-sights; the lines-of-sight in indoor applications are degenerated by many walls and obstacles with large blinding areas.

The location of mobile sensors is a critical issue in indoor applications, for which traditional technologies are not applicable. Locating mobile sensors per time slot necessitate a smart and distributed scheme. The present study addresses the research problem of mobile WSN localization. We begin this thesis, particularly this chapter, with an abridged introduction to the localization of mobile WSNs.

This chapter is organized into six sections. Section 1.1 describes the domain background of mobile sensor localization. Section 1.2 presents the motivation for studying mobile sensor localization. Section 1.3 highlights the research gap, briefly describes the problem of mobile sensor localization in two cases, and explains the communication cost and mobility model. Section 1.4 provides the research objectives. Section 1.5 outlines the layout of the rest of the thesis.

1.1 Domain Background

This section begins with an abridged discussion of WSNs. We then discuss localization categories, namely, range-based and range-free localization. We introduce the problem of mobile sensor localization in terms of communication costs and the mobility model.

1.1.1 WSNs

A sensor is a thin device that can smoothly measure physical phenomena, such as heat, light, sound, pressure, magnetism, a particular motion, or the changing environment, and convert measurement values to digital ones. Moreover, sensor nodes can communicate and collaborate to send data remotely to the sink node. The use of sensor nodes maximizes the boundaries of the digital world and facilitates operations under harsh and distant environments. At present, sensor nodes can communicate with Internet web sites. This interaction has produced a new digital technology called Internet of Things (IoT). Through IoT, we can remotely observe physical phenomena and control an operation area online.

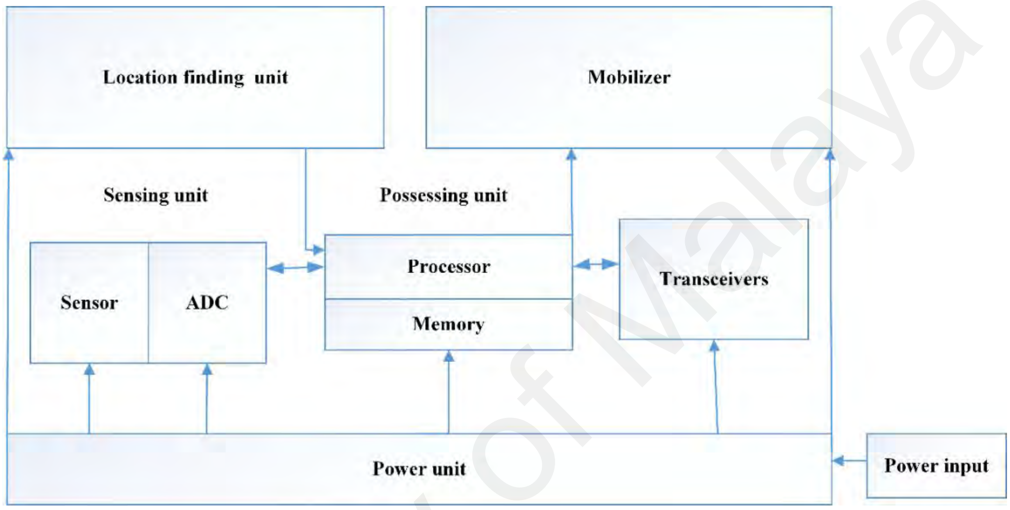

Figure 1.1 : Hardware components of a sensor node

A sensor node constructed with simple and small circuits can sense a changing environment. The analog-to-digital converter (ADC) converts analog data to a digital format. The central processing unit (CPU) evaluates the digital data and records a copy of such data in the memory. The transceiver unit can obtain the data from the CPU and communicate with other sensors in the neighborhood. The sensor node contains a power unit, a localization unit, and a mobilizer unit (Hill et al., 2000). The basic hardware components of sensor nodes are presented in Figure 1.1.

The power of WSNs is affected by sensitivity and accuracy levels. A high level of sensitivity and accuracy can represent the original state of WSNs. Sensitivity can be defined as the ratio between the physical measurement and the output signal. For example, a sensor measures weather temperature as the input and impulse voltage as the output. Nevertheless, the ratio between temperature and voltage is linear. That is, a change in voltage reflects a change in temperature.

Figure 1.2 : Sensor board for firefly environment

For example, a thermometer scale increases by 1 cm when temperature increases by 1 °C. In this sense, sensitivity ratio can be calculated with a linear characteristic of a slope equation (Dy/Dx) at 1 cm/°C. Sensitivity can also be affected by sensor size. For example, a large sensor placed in a hot cup of liquid can be affected by room temperature, whereas a small sensor can measure the original data inside the cup. Figure 1.2 presents an example of a sensor node. In addition to size, sensor nodes are constrained by other factors, such as power, operation in high density, construction cost, and smooth adaptation in an operation area, self-dependence, and unattended function (Jabbar, Aziz, Minhas, & Hussain, 2010).

Real applications use various types of sensors. For example, medical care sensors are used to measure pressure, and weather radars are used to measure humidity, temperature, and wind power. Figure. 1.3 presents a sensor node in different domains. The Figure also shows sensor nodes used in online tracing, object localization, event detection, and others types of applications. A brief example of sensor node applications is also provided.

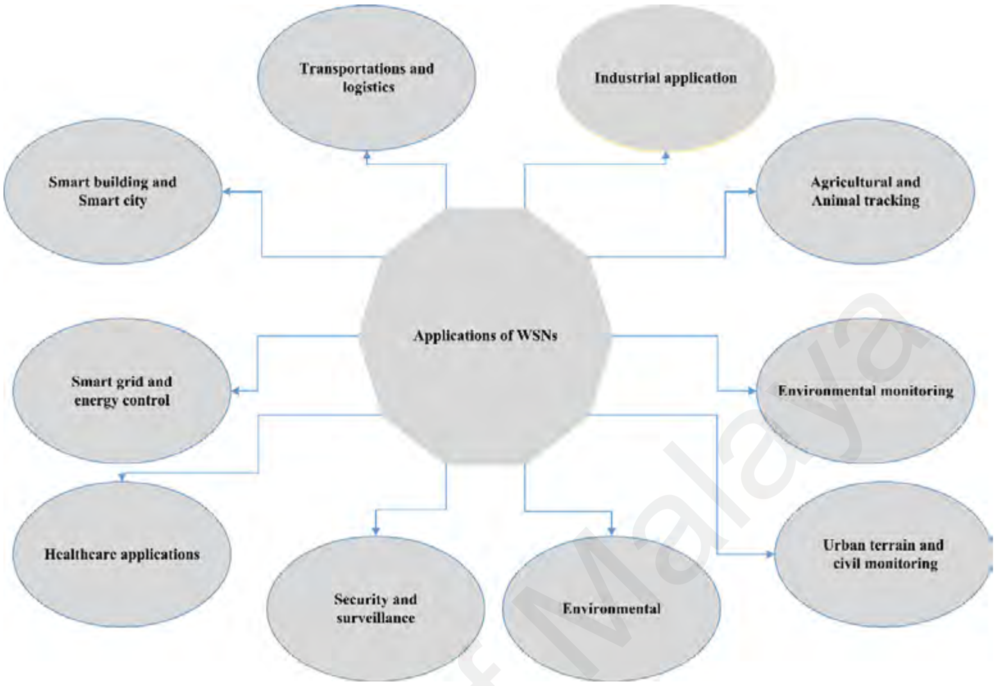

Figure 1.3 : Types of sensor node applications

A WSN comprises a large number of sensor nodes. These nodes can communicate and collaborate to transmit sensing data. Sensor nodes are densely deployed in an operation area or in an area adjacent to the operation area to ensure that each part of the operation is covered by at least one sensor, as shown in Figure 1.4.

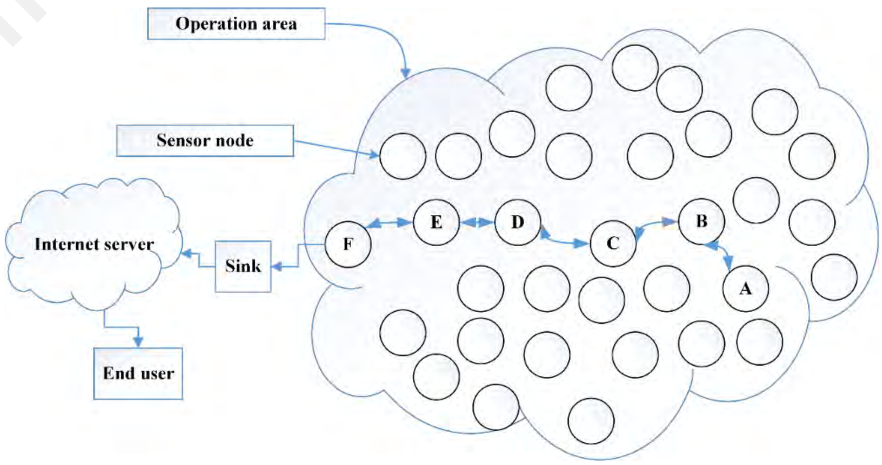

Figure 1.4 : Example of WSN

The characteristics of WSNs facilitate the investigation and control of physical phenomena. These features enable WSNs to become part of our daily lives. The sensor network protocol, which includes task, mobility, and power management phases, can work in each layer, as shown in Figure 1.5.

A comprehensive understanding of WSNs is necessary in the use of wireless ad hoc network techniques. Schemes and protocols proposed for wireless ad hoc networks are not suitable for the special characteristics of sensor nodes and their operation areas. This difference is outlined below (Fox, 2003).

- WSNs comprise a large number of sensor nodes.
- Sensor nodes are deployed densely.
- WSNs are prone to frequent failures.
- The topology of WSNs changes rapidly. Sensor nodes use the broadcasting paradigm from communication, whereas ad hoc networks use point-to-point communication.
- A sensor node is a thin device with limited sources, power, CPU memory, and radio range.
- WSNs cannot easily provide global identification because they distribute a large number of nodes.

The application of sensor networks is plagued with numerous issues that limit their functionality. These issues include fault tolerance, scalability, and cost, adaptability to the environment, changing topology, hardware limitation, radio range, and power depletion (Perkins, 2000).

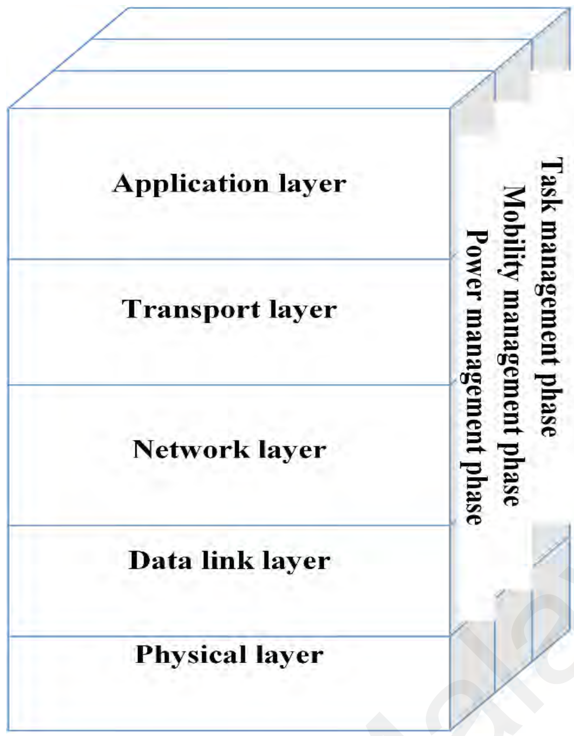

Figure 1.5 : Protocol stack of sensor networks

1.1.2 Mobile WSN localization

Discovering the location of a mobile sensor is an indispensable issue for most applications. For example, in monitoring applications, the location of sensing data is a critical issue when presenting the originality of the data. In routing algorithms, the location of a sensor node can optimize the routing path and reduce the communication cost within the network (Karp & Kung, 2000). Location also benefits other applications, such as coverage, target tracking, and monitoring systems.

A mobile sensor node can discover new areas by changing its location per time slot. This advantage presents challenges in localization. Location changes affect network topology and network connectivity. In the literature, this problem is addressed with localization schemes that are classified into two categories, namely, range-based and range-free localization schemes.

Table 1.1: Comparison of localization categories

	Advantages	Disadvantages
Range-based	High localization accuracy	Hardware limitation Expensive Affected by environmental noise Entails additional power and increases device size Fault tolerant Low scalability Suitable for outdoor applications
Range-free	Autonomy method; minimized dependency on hardware Cost effective Suitable for indoor and outdoor applications Coherent networks High scalability	Low localization accuracy

Using additional hardware, range-based schemes find the location of a blind node by measuring point-to-point distance or angle estimation. Range-based schemes achieve high localization accuracy in ideal environments. However, the use of additional hardware requires increased power, size, and cost. By contrast, range-free category uses network connectivity to estimate the location of a blind node. Connectivity can be used to measure the distance between a sensor node in the radio range or by using received signal strength (RSS). The selection of category depends on application specifications. Table 1.1 presents a brief comparison of the two categories.

1.2 Research Motivation

The development of WSNs expand the boundaries of the digital world and opens new windows of knowledge. At present, WSNs are regarded as a market parameter that covers different applications, such as those in the military, healthcare industry, agriculture, and retail. The advancement of WSNs has resulted in the integration of several types of technologies, such as big data and cloud computing, to meet industry applications, military requirements, and so on (Yick, Mukherjee, & Ghosal, 2008).

The small size, low cost, and capability of small sensors to communicate and collaborate make them an adaptive solution for system monitoring and for applications in hazardous areas. These areas can be efficiently monitored and controlled remotely by design makers. Market reports present the major sectors that use WSNs, which include the mining, food and drinks, healthcare and medicine, and industrial systems sectors. According to this report, the WSN market was worth $401.23 million in 2013 with a projected compound annual growth rate of 12.96% in the coming years. The report predicts that the WSN market will increase to $944.92 million by 2020.

One of the countries that strongly support the development and use of WSNs is the U.S. The Freedonia group report shows that the WSN sales in the U.S. will reach $14.9 billion in 2016, with the military achieving the highest WSN utilization, particularly for monitoring and surveillance applications.

WSNs can be integrated with other technologies, such as the IoT, big data, cloud computing, and smartphone applications. The IoT refers to the use of a large number of sensor nodes on different topics. A considerable number of studies discuss IoT challenges (Gubbi, Buyya, Marusic, & Palaniswami, 2013). WSNs can also be integrated with cloud computing to increase their popularity. A number of service providers can be utilized for WSN integration (Ahmed & Gregory, 2011).

The solution proposed in the present work increases the efficiency of WSNs and improves their application and adaptability in operation areas. Previous localization schemes are not easy to employ in the accurate estimation of blind node locations because of a number of issues. One such issue is the high communication cost arising from the use of all normal nodes in the localization process. Anchor node velocity is another issue in mobile WSNs. Hence, WSN localization is an important issue that should be addressed. One solution is to reduce communication cost, increase the convergence of anchor nodes, and improve localization accuracy. The proposed solution can become a significant part of future mobile WSN applications.

1.3 Statement of the Problem

A number of scholars have proposed localization schemes for mobile WSN localization. For example, range-free schemes are capable of estimating blind node location by utilizing network connectivity without the need for additional hardware. These schemes are based on the idea in which a small number of nodes are aware of their location (anchor node) and can thus assist in the location estimation of other nodes. These schemes focus on enhancing localization accuracy by using the location information of anchor nodes. The pioneer method under the range-free category is the sequential Monte Carlo Localization (MCL) scheme (Hu & Evans, 2004), which enhances localization accuracy in mobile WSNs by employing a sequential Monte Carlo (SMC) method.

Using the location information of anchor nodes in the MCL scheme can enhance localization accuracy and increase dependence on hardware, particularly because anchor nodes use GPS to identify their locations. Alternatively, location can be configured manually. The majority of localization schemes use normal nodes to reduce the dependence on hardware. A normal node is aware of its location in the previous time slot by exchanging messages with anchor nodes.

Normal nodes are used in localization schemes such as MSL* (Rudafshani & Datta, 2007b), WMCL (S. Zhang, Cao, Li-Jun, & Chen, 2010b), and COMCL to enhance localization accuracy and improve the autonomy of mobile WSNs (Z. Wang, Wang, Ma, & Wu, 2013). Using all normal nodes in the neighborhood increases communication cost without improving localization accuracy. Communication cost is a significant parameter in WSNs; for example, sending 1 KB of data at a distance of 100 m is equivalent to executing 3 million instructions by a processor that can execute 100 million instructions per second/W (C. Liu, Wu, & He, 2004).

Another problem in mobile WSN localization is the mobility model. The location of a mobile sensor changes with the function of sensor velocity. A mobile sensor changes its location at each time slot along with a change in network topology. Most previous schemes use a random waypoint mobility model to transmit mobile sensor data. The waypoint model is a simple model that allows a mobile sensor to choose its velocity and direction randomly (Bettstetter, Hartenstein, & Pérez-Costa, 2002). Choosing a random velocity produces an extra overlap area between anchor nodes without improving localization accuracy. With this model, more than three anchor nodes can be found in a neighborhood, thereby minimizing the convergence area of anchor nodes.

These observations indicate that communication cost and the mobility model of anchor nodes in the localization process have not been extensively addressed. This research gap motivates us to explore the existing issues for this thesis.

The proposed framework can solve localization problems by using a smooth and lightweight method. In this framework, we solve the issues in communication cost and dependence on anchor nodes by using the adjacent normal nodes in a neighborhood. The proposed solution can increase anchor node coverage and improve localization accuracy.

1.4 Statement of Objectives

We address the localization problem of mobile WSNs under the range-free scheme and outline specific objectives to achieve the goal of this research.

1. To review the localization schemes in mobile WSNs and thereby acquire insights into this state-of-the-art process with reference to the sequential

Monte Carlo method for issues in range-free localization and the mobility model.

2. To design and implement a new variant of the well-known sequential Monte Carlo localization scheme called LCC to reduce communication cost while achieving localization accuracy that is comparable to that of previous schemes.
3. To investigate the impact of anchor node velocity and implement an efficient coverage on WSNs convergence and localization accuracy.

1.5 Layout of Thesis

This thesis is a structured research addressing the problem of "efficient range-free localization scheme for mobile WSNs." Therefore, this thesis is presented in chapters to ensure the clear comprehension of the problem and proposed solution. For simplicity, we present the organization of the thesis in Table 1.2. This thesis is composed of six chapters and is structured as follows.

In Chapter 2, we present a review of localization schemes for mobile WSNs based on the SMC method and mobility model. Specifically, the critical aspects related to communication cost and the mobility model are investigated. We classify the localization schemes and invent a taxonomy system. We compare the localization schemes on the basis of influencing parameters, localization accuracy, velocity, anchor node density, normal node density, and dependence on anchor nodes, network type, and degree of irregularity (DOI). We also highlight the future direction of the research. The localization issues for reducing communication cost and increasing anchor node convergence are addressed and discussed in the chapter.

Table 1.2 : Chapter organization

What?	Why?	How?
Introduction	Present the motivation of the research Clarify the problem statement and highlight objectives of research Present the thesis layout	Explore the undertaking of the research Write the problem statement and statement of objectives
Literature review	Discover and classify the state-of-the-art process and highlight the advantages and disadvantages of the schemes Address the directions of future research	Provide a critique analysis of existing schemes State the taxonomy and perform an evaluation based on taxonomy parameters
Proposed solution	Explain clearly the proposed solution and increase readability	Present the sequences of execution of the proposed scheme and mobility model and provide a clear explanation through intensive examples
Results and discussion of the first contribution	Identify the performances of the proposed LCC scheme by analysing intensive simulation experiment results	Show the insights acquired from each value from the results Compare the effectiveness of the proposed scheme with that of key benchmark schemes
Results and discussion of the second contribution	Identify the performances of the proposed adaptive mobility model (AMM) by analysing intensive simulation experiment results	Show the insights acquired from each value from the results Compare the effectiveness of the proposed scheme with that of key benchmark schemes
Conclusion	Summarize the research result and identify important solutions Highlight the directions of future research and present limitations	Report the reassessment of research objectives

Chapter 3 presents the localization scheme and mobility model to solve the issue of mobile WSNs localization through range-free schemes using SMC method. It clarifies the proposed solutions called LCC scheme and the mobility model AMM. Moreover, we highlighted and discussed the distinct characteristics of the proposed solutions.

Chapter 4 presents the proposed LCC scheme by explaining its implementation in the simulation environment. The first part identifies the convergence of the LCC scheme in different networks. The second part discusses the effectiveness of the proposed scheme in reducing communication cost in comparison with the benchmark scheme MSL*. In the third part, key schemes are selected as the benchmark system and then compared with the LCC scheme. The performance of the LCC scheme is evaluated with different parameters, including velocity, anchor node density, normal node density, and degree of irregularity, to realize the objective of reducing communication cost. In the last part, we discuss the evaluated parameters for measuring the performance of the proposed model.

Chapter 5 presents the effectiveness of the proposed mobility model AMM by explaining its implementation in the simulation environment. In the first part, we determine the convergence of the AMM in different networks. A key mobility model is chosen as the benchmark for measuring the convergence performance of the AMM. In the second part, the effectiveness of the proposed scheme in increasing anchor node convergence and enhancing localization accuracy is compared with that of the benchmark schemes, namely, MCL, MSL*, and WMCLB. The performance of the AMM is evaluated with different parameters, including velocity, anchor node density, normal node density, and degree of irregularity, to realize the objectives of increasing anchor node converge and enhancing localization accuracy. In the last part, we discuss the evaluated parameters used to measure the performance of the proposed model.

Chapter 6 concludes the thesis by reassessing the research objectives. This chapter summarizes the research results, clarifies the importance of the proposed solutions, presents the limitation of the research work, and highlights the directions of future research.

CHAPTER 2: SEQUENTIAL MONTE CARLO LOCALIZATION METHODS IN MOBILE WIRELESS SENSOR NETWORKS

We opened the thesis with an introduction to mobile WSNs and an overview of the problem of localization in mobile WSNs. This chapter mainly presents the review of literature on mobile WSN localization. A number of localization schemes that address diverse issues can be found in the literature. We start by reviewing the localization scheme categories and by highlighting their assumptions in mobile WSN localization. We present a thematic taxonomy of the localization schemes with reference to the objective of reducing communication cost in range-free localization schemes, increasing anchor node convergence, and improving localization accuracy. Finally, we discuss the advantages and disadvantages of each scheme to highlight the gaps in the existing schemes presented in this thesis.

The chapter is organized into five sections. In Section 2.1, we present the state-of-the-art mobile WSN localization scheme and their efficiency of estimating mobile WSN localization. Section 2.2 presents classification of the various schemes employed by SMC method to enhance the localization accuracy and save scarce resource, which is a factor affected by the number of messages broadcast in the network and the degree of overlapping between anchor nodes. Section 2.3 presents the state-of-the-art mobility model and their effect on localization accuracy. Section 2.4 highlights the open challenges in mobile WSN location estimation and Section 2.5 summarizes the chapter with conclusive remarks.

2.1 State-of-the-art mobile WSN localization scheme

The digital world is becoming increasingly important in our daily lives with the heavy utilization of numerous small, cheap devices called sensor nodes. These sensor devices can be controlled and can communicate and cooperate remotely to investigate far and hazardous areas (Akyildiz, Su, Sankarasubramaniam, & Cayirci, 2002a, 2002b; Ryu, Irfan, & Reyaz, 2015; Yick et al., 2008). Sensor nodes are utilized in different fields, such as the Internet of Things (Atzori, Iera, & Morabito, 2010; Borgia, 2014), health care (Alemdar & Ersoy, 2010), zoo monitoring (Mainwaring, Culler, Polastre, Szewczyk, & Anderson, 2002), underwater exploration (Akyildiz, Pompili, & Melodia, 2005), intelligent city (Zanella, Bui, Castellani, Vangelista, & Zorzi, 2014), military applications (Đurišić, Tafa, Dimić, & Milutinović, 2012), routing optimization (Mahdi et al.), and dynamic mapping (García-Hernández, Ibarguengoytia-Gonzalez, García-Hernández, & Pérez-Díaz, 2007; Idris, Arof, Noor, Tamil, & Razak, 2012).

The localization schemes in wireless sensor networks (WSNs) can be classified into two types, namely, static and mobile networks (Pal, 2010). A static network is constructed with stationary sensor nodes; the sensors are deployed randomly or on the basis of a previous plan. By contrast, the sensor nodes in a mobile network are flexible to maximize their benefits in improving WSN coverage and power consumption and in discovering other areas with a limited number of sensors (S. Li, Lowe, Kong, & Braun, 2011).

Generally, the localization schemes of a mobile sensor are classified as range-based and range-free schemes (Lai et al., 2013; Singh & Sharma, 2015). However, in this work, we classified the localization schemes into three groups, namely, range-based, range-free, and hybrid schemes. The range-based scheme uses additional hardware such as antenna to estimate the location of a blind node (i.e., a node without location information), whereas the range-free scheme uses network connectivity. The hybrid scheme is a combination of the range-free scheme for noisy cases and the range-based scheme for stabile cases. In all the aforementioned schemes, anchor nodes (i.e., nodes with location information) broadcast their location information per time slot to assist blind nodes in estimating their location.

Range-free localization schemes are classified into four categories, namely, hop count, fingerprint algorithm, Monte Carlo scheme, and hybrid schemes (SMC and hop distance). The hop count estimates the location of a blind node through an average of hop distance. Hence, each node maintains the minimum hop number of the anchor node in the network. In the fingerprint algorithm, the location of a blind node is estimated in two stages. The first stage involves the construction of an offline database by measuring the signal strength in the deployment area, and the second stage involves the real-time estimation of the location of a blind node by matching the signal strength of this blind node with the offline database. The Monte Carlo scheme uses the probability distribution function (pdf) to estimate the location of a blind node (Lai et al., 2013).The hybrid schemes (SMC and hop distance) advances localization accuracy by utilizing the DV-hop technique on MCL.

A majority of range-free schemes use the Sequential Monte Carlo (SMC) technique to estimate the location of blind nodes in dynamic systems within three steps, namely, initial, sample, and filter (Doucet, Godsill, & Andrieu, 2000; Mihaylova, Angelova, & Zvikhachevskaya, 2013). The location of mobile sensors is an important parameter in WSNs. Thus, a high level of localization accuracy can improve the confidence and quality of sensing data. In the presented study, we classified the performance of SMC schemes according to three categories, namely, localization accuracy, computational cost, and communication cost.

Localization accuracy is measured with the variance of the Euclidean distance between the estimated location and the real location. The localization accuracy in SMC schemes is mostly affected by two parameters, namely, the density of anchor nodes and number of samples (Babu & Ramprasad, 2012; Doucet, De Freitas, & Gordon, 2001; Vo, Singh, & Doucet, 2005). Hence, a large number of anchor nodes can improve localization accuracy by broadcasting rich location information in the area. Moreover, a sufficient number of valid samples can improve localization accuracy. However, the performance of SMC schemes is extremely dependent on the distribution function of previous samples.

The computational cost to generate a sufficient valid sample can be measured with the number of iterations required to find a sufficient valid sample. SMC requires a sequential repetition of sample and filter steps until a sufficient valid sample is obtained. The efficiency of the samples is also affected by the bounded sample area and sample evaluation (T. Li, Bolic, & Djuric, 2015).

The communication cost in range-free localization schemes can be determined with the number of messages that are sent during the localization process (Hu & Evans, 2004). Consequently, the accuracy in range-free schemes is highly dependent on the density of anchor nodes and normal nodes, which can increase the number of messages sent. Moreover, the size of messages affects communication cost. The normal node is node which know its location in the last time slot.

2.1.1 Evaluation parameters in SMC localization

The SMC localization in mobile WSNs is mainly evaluated according to localization accuracy, computational cost, and communication cost.

2.1.1.1 Localization accuracy

Localization accuracy is the most important parameter of WSNs. A high level of localization accuracy can help decision makers to identify the precise location and coverage area of data. Localization accuracy can be measured with the variance between a real location and an estimated location, as shown in (Eq 2.1). For simplicity during the simulation test, the SMC technique is employed with the assumption that the anchor nodes know their real locations without error at all times.

$$\text{Localization accuracy} = \frac{1}{n} \sum_{i=1}^{n} \| e_i - l_i \| \qquad \text{(Eq 2.1)}$$

Where n is the number of sensor nodes, e_i is the estimated location, and l_i is the real location. The error in the equation is given in terms of radio range and is thus divided by the sensor radio range.

The localization error in the initial step is reduced quickly when the new observations arrive. In the stability step, the localization error is maintained at around the same mean error (Q. Zhang, Wan, Yi, Bao, & Wang, 2016). Thus, the effects of mobility and connectivity are in equilibrium. The localization accuracy of the SMC technique is mostly affected by sensor node velocity, anchor node density, normal node density, and degree of irregularity.

(a) *2.1.1.1.1 Sensor node velocity*

The mobility of sensor nodes can maximize the benefits of WSNs in various aspects. This mobility allows sensors to communicate with a large number of neighboring anchor nodes. Hence, localization accuracy can be improved with the minimum number of anchor nodes. Mobility also conserves energy and prolongs network lifetime by changing routing paths (Halder & Ghosal, 2016). Static WSNs use the same routing path, through which messages are sent and received frequently even though the sensor is adjacent to the sink node; this frequency exhausts energy and causes network partition (Natalizio & Loscrí, 2013; Silva, Zinonos, Silva, & Vassiliou, 2011; Yang et al., 2015).

In real world applications, the mobility of sensor nodes allows animals to be traced in zoos and patients to be monitored in hospitals, in addition to their other applications. However, this mobility presents an additional challenge in the handshaking case in which the sensor is outside the neighbors' range to transmit and receive data (Deniz, Bagci, Korpeoglu, & Yazıcı, 2016; Y. Wang & Wu, 2006).

The mobility model is classified into three categories, namely, controlled, predefined (map), and random. The details of these categories are explained in (Bai & Helmy, 2004). In most schemes, the SMC technique is used to select a random waypoint model to transmit nodes. The waypoint model is a simple and independent model. Moreover, the sensor node can choose its new direction and velocity randomly without exceeding its maximum velocity (Tracy Camp, Jeff Boleng, & Vanessa Davies, 2002). The pause time is set to 0 in most schemes; this zero pause time allows the sensor to move without stopping (Yoon, Liu, & Noble, 2003b).

The velocity of a sensor node affects localization accuracy differently. A sensor node with a low level velocity achieves the highest localization accuracy because this node is still in the range of the sample from the previous location, which this node reuses to estimate a new location accuracy. A sensor node with a high level velocity can exert a negative effect on localization accuracy if it moves far from the sample in the previous location and becomes unreachable. However, a high-velocity guide sensor explores additional areas per time slot.

(b) *2.1.1.1.2 Anchor node density*

The localization accuracy of all schemes can be enhanced with the increase in anchor node density in the region. A high number of anchor nodes allows the broadcast of many observations throughout the region. However, as the density of anchor nodes increases, the dependence on the global positioning system (GPS) and the extra overlap between anchor nodes increase as well. The extra overlap between anchor nodes is undesirable because it produces a redundant sample without improving localization accuracy. Moreover, the high density of anchor nodes limits the sample area. A narrow sample area requires additional time for blind nodes to generate proper samples. The SMC technique addresses these drawbacks by employing a high number of anchor nodes in the region to maintain a high localization accuracy. In the literature, some schemes such as Monte Carlo localization MCL (Hu & Evans, 2004) and Monte Carlo localization Boxed MCB(Baggio & Langendoen, 2008) are fully dependent on the information of anchor node location, whereas others combine both anchor and normal nodes in the localization process.

(c) *2.1.1.1.3 Normal node density*

The information on normal node location can be used during the positioning process to enhance localization accuracy and reduce the dependence on anchor nodes. The utilization of normal nodes can enhance localization accuracy in two ways. First, normal nodes retransmit the location information of the anchor node to its neighbors. Second, the location information of the normal nodes is used in the localization process; using this information in the sample step narrows the sample area and filters out the invalid samples in the filter step. However, the use of normal node location in the localization process is susceptible to error and significant communication cost in the network. Therefore, this localization process requires a precise and lightweight method.

(d) ***2.1.1.1.4 Degree of irregularity***

The variation of the radio range between sensors leads to communication failure, which degrades the localization accuracy of WSNs (Wu, Tan, & He, 2013; Zhou, He, Krishnamurthy, & Stankovic, 2004). For simplicity, radio range is assumed to be a full circular range in the simulation experiments. However, this assumption does not present the actual radio range in real world applications; in reality, radio range is affected by sensor characteristics, such as antenna direction and sensor power, and by the types of transmission media, such as humidity, temperature, obstacles, and wind speed. These factors can distort radio range at different degrees.

2.1.1.2 Computational cost

Computational cost is quantified from the iteration to generate enough valid samples in each time slot. The main parameters that affect computational cost are the size of the sample area and the number of samples. The sample and filter stages are repeated until enough valid samples are found; this process is costly because it wastes additional power and delays the localization process.

High velocity and high anchor node density negatively affect sample efficiency in the following ways. A high velocity maximizes the sample area. Thus, the sample generation and filtering steps are repeated several times to draw enough valid samples for a large area. A high anchor node density narrows the sample area. Hence, the generation and filtering steps are repeated to generate dissimilar samples.

(a) ***2.1.1.2.1 Sample area size***

In the literature, various strategies are used to draw samples. An example is the random generation of a sample over a previous sample bounded by a circle with a radius equal to the maximum velocity and anchor node bounded box. However, the shape of the sample area in the bounded box is irregular and is mostly affected by the number of anchor nodes in the neighborhood.

(b) ***2.1.1.2.2 Number of samples***

The main idea of the SMC technique is to estimate the location of blind nodes by averaging the weighted samples (or particles). Therefore, the number of valid samples is an important parameter in localization accuracy. A large number of samples can slow down the localization process by repeating the generation and evaluation steps. Thus, a typical maximum number of samples is set to 50 (Hu & Evans, 2004).

The size of the sample area depends on the anchor node density in the first and second hop and on maximum velocity. A large number of anchor nodes in the neighborhood equates to a narrow sample area, and vice versa. Drawing a large number of samples in a narrow region is a critical issue because an additional calculation must be performed to remove redundant and adjacent samples. A large number of samples are required to cover a large sample area. Therefore, a constant number of samples do not represent a sufficient solution for all sizes of sample areas.

The simulation results for different schemes show that 50 samples are enough to estimate an accurate location. Accordingly, most of the studies in the literature used 50 samples as the maximum number of samples, whereas other studies used an adaptive approach based on the sample area to set the number of samples. Nevertheless, the relation between the number of samples and the sample area is a challenging issue in WSNs.

In the SMC method, drawing valid samples involves the following two steps: 1) drawing candidate samples and 2) evaluating candidate samples. Drawing candidate samples is more costly than evaluating them (S. Zhang, Cao, Li-Jun, & Chen, 2010a).

Typically, sample efficiency is affected by the number of valid samples and the bounded area of the samples. Hence, a direct relationship exists between the number of samples and the sample area.

Sample evaluation is a measurement of the distance between two points or a comparison between the distance and its predefined value (the communication radio range R). The operation cost for measuring the distance between two points is approximately 100 times that for comparing distance and its predefined value, as shown in (S. Zhang et al., 2010a) because the sample generation is repeated until the sample overcomes the anchor node constraints.

2.1.1.3 Communication cost

The main purpose of the range-free localization scheme is to reduce the dependency on hardware by utilizing network connectivity during the estimation of blind node location. The estimation process requires network connectivity to broadcast messages from sensor nodes. Therefore, communication cost is computed with the number of messages broadcasted during the localization process (Hu & Evans, 2004). The number of messages is affected by the number of anchor nodes and normal nodes used in the localization process. The size of the message also affects communication cost.

(a) *2.1.1.3.1 Number of messages*

In the SMC method, the anchor nodes broadcast their location information to the first and second hops; the normal nodes forward these messages to their neighbors. The number of messages that are broadcasted is a significant parameter during the localization process because blind nodes need enough location information to estimate their location. However, a large number of messages may include redundant and adjacent samples.

The message of location information is categorized into two types according to its content. The first type of message contains the location coordinate, and the second type contains the sample. The coordinate message commonly defines the exact location of an anchor node on the Cartesian plane; the sample message contains the potential coordinate of the normal node on the Cartesian plane. The sample message can improve localization accuracy, but it increases the communication cost. Nevertheless, the relation between communication cost and localization accuracy is a challenging research area in WSNs.

(b) ***2.1.1.3.2 Message size***

The size of messages transmitted is not fixed in SMC schemes, as presented in (Sheu, Hu, & Lin, 2010). The anchor message contains the IP header, transmitter ID, anchor location, and number of hops. The standard size of an anchor message is 34 bytes in all schemes. By contrast, the size of a normal node message varies between schemes.

2.1.2 Comparison of related survey papers on WSN localization

Localization problems have been studied in various WSN schemes; a survey of these schemes can be found in (Niewiadomska-Szynkiewicz, 2012; Singh & Sharma, 2015; Suo, Wan, Huang, & Zou, 2012; Yang et al., 2015). The present study presents a comprehensive review of the localization problem in mobile WSNs (Znaid, Idris, Abdul Wahab, Khamis Qabajeh, & Adil Mahdi, 2017). However, to highlight and differentiate our contribution from other surveys, we summarized and compared the existing surveys on localization problems in WSNs, as shown in Table 2.1.

In general, previous schemes maintain static networks, whereas current schemes maintain mobile networks. However, the localization schemes in both networks can be classified as range-based and range-free (Alippi & Vanini, 2006b). The survey in (Han, Xu, Duong, Jiang, & Hara, 2013) classified the state of sensors into four types, namely, static landmark node and static node, mobile landmark node and static node, static landmark node and mobile node, and mobile landmark node and mobile node.

The survey of range-free schemes in (Singh & Sharma, 2015) classified these schemes into following categories, namely, APIT, DV-Hop, Multi-hop, centroid, and gradient. Another survey classified range-free localization schemes in emerging applications (cyber-physical systems and cyber transportation systems) into proximity-based localization, one-hop localization, and multi-hop localization. Moreover, range-based schemes were classified in (Pal, 2010) into beacon-based distributed localization, relaxation-based distributed algorithm, coordinate system stitching-based localization, and hybrid localization. Beacon-based distributed localization can be further classified into three categories, namely, diffusion, bounding box, and gradient.

The survey in (Gu, Yue, Maple, Wu, & Liu, 2013) classified mobile sensor networks in disaster scenarios, in which mobile nodes aid in the search for disaster locations. The localization schemes in static networks are classified as range-free and range-based, whereas those in mobile networks are classified as robotic, MCL, and range-based. Another survey on harsh environments (Nazir, Arshad, Shahid, & Raza, 2012) classified localization schemes into range-based and range-free, anchor-based and anchor-free, and distributed and centralized.

The survey of localization classification and technique evaluation (Niewiadomska-Szynkiewicz, 2012) classified localization schemes as geometrical techniques, multidimensional scaling, stochastic proximity embedding, convex and non-convex optimization, and hybrid. An indoor application survey discussed the potential improvement of the human mobility model by utilizing smartphones (Yang et al., 2015).

Moreover, this survey investigated smartphone sensors according to location accuracy, deployment cost, location context, cost, quality, and measurement errors.

In (Cheng et al., 2012), the localization schemes were classified into target localization and self-localization. Additionally, this survey reviewed the localization challenges in non-line-of-sight node selection, optimizing the tradeoff between energy depletion performance, cooperative nodes, and localization in a heterogeneous radio range.

Table 2.1: Previous survey of wireless sensor localization Authors

	Taxonomy	Comparison parameters
(Singh & Sharma, 2015)	APIT, DV-Hop, Multi-Hop, centroid, gradient	Node density, cost, accuracy, overhead, scalability
(Yang et al., 2015)	types of sensors, types of mobility, measurement errors	location accuracy, deployment cost, location context, quality and cost of smartphone, and measurement errors
(Han et al., 2013)	Static landmark and static node, mobile landmark and static node, static landmark and mobile node, mobile landmark and mobile node.	Localization accuracy, coverage, time, landmark density, node density, Energy consumption
(Gu et al., 2013)	Static (range-free, range based) mobile (robotic , MCL, range based)	(Centralized , distributed), Dimensional analysis, simulator, (range-free, range-based), scalability, communication radius
(Nazir et al., 2012)	(range-based, range-free), (anchor based, anchor free), (distributed, centralized)	accuracy, hardware cost, computation cost and communication cost
(Niewiadomska-Szynkiewicz, 2012)	Geometrical techniques, multidimensional scaling, stochastic proximity embedding convex and nonconvex optimization and hybrid	Accuracy, coverage, complexity, scalability, robustness and cost.
(Suo et al., 2012)	proximity based localization, one-hop and multi-hop localization	Without comprehensive comparison
(Cheng et al., 2012)	Target/source localization and node self-localization	Non-line-of-sight, energy-constrained network, trade-off between localization performance and energy consumption, cooperative node localization, and localization in heterogeneous network.
(Pal, 2010)	Beacon based distributed, Relaxation Based Distributed, the Coordinate system stitching based, hybrid	Objective, (centralized, distrusted), description, accuracy, computation cost

Proposed (2017)	Range-based, Range-free and hybrid. Range-free (localization accuracy, communication cost and computation cost).	Velocity, anchor and normal node density, degree of irregularity, size of sample area, number of messages and message size.

The present survey investigates the state-of-the-art localization schemes in mobile WSNs in microscopic classification. The schemes are categorized as range-based, range-free, and hybrid. The range-free scheme is further sub-categorized into fingerprint, Monte Carlo, hop distances, and hybrid (i.e., SMC and hop distance). Furthermore, we classify the SMC scheme according to its main operational parameters, namely, localization accuracy, communication cost, and computation cost, in microscopic classification. The comparison of the localization schemes assists network end users and administrators in tracking and identifying the location of areas under investigation. Thus, appropriate schemes are selected to localize mobile WSNs. Throughout this study, we further discuss the challenges and open issues related to each location parameter (Abu Znaid et al., 2017).

2.1.3 Localization Scheme Classification

Estimating the location of mobile sensors is a challenging task in WSNs because of the frequent changes in the location of mobile nodes per time slot and the whole topology and connectivity of networks. Additionally, the sensor node's hardware limitations, such as limited power sources, memory, processor unit, and communication range, further complicate the estimation process (Römer & Mattern, 2004). Therefore, WSNs need a smart and robust technology to estimate sensor location (Shahra, Sheltami, & Shakshuki, 2017). We classified localization schemes into three categories, namely, range-based, range-free, and hybrid; the SMC in range-free schemes was classified on the basis of localization accuracy, communication cost, and computation cost, as shown in Figure 2.1.

2.1.3.1 Range-based localization

In range-based schemes, the blind node estimates its location using its absolute distance from the anchor nodes. Range-based schemes use different types of hardware to calculate distance, such as time of arrival (ToA). ToA measures the distance between the time of arrival and the time of departure between nodes. Then, light speed is used to calculate the distance between nodes on the basis of a speed equation. However, ToA needs additional hardware to synchronize the transmission times between sensor nodes. The time synchronization increases the traffic in networks and delays the localization process (Patwari et al., 2005).

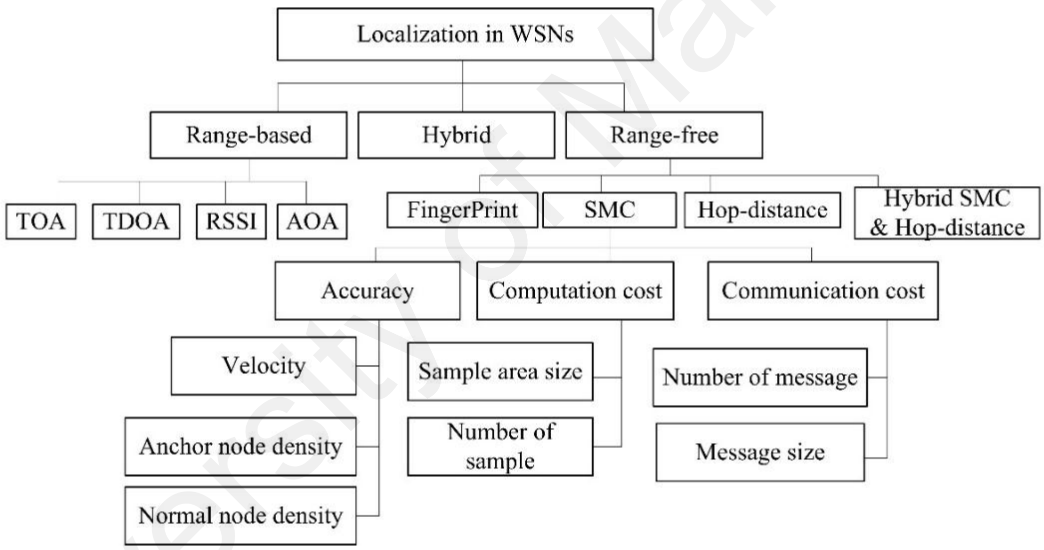

Figure 2.1 : Taxonomy of localization schemes in mobile WSNs, including range-free and sequential Monte Carlo.

The study in (Gustafsson & Gunnarsson, 2003) proposed a time difference of arrival (TDoA) between sound and light to improve ToA. TDoA uses additional acoustic hardware to measure the difference between light and sound signals from the source. The angle of arrival (AoA) and triangle geometry between neighbors are also used to calculate blind node location. In AoA, the sensor node uses antennas to measure the angle between neighbors (Niculescu & Nath, 2003).

The received signal strength indicator (RSSI) measures the distance according to the difference in signal strengths (Shao, Xu, Jia, & Li, 2011). The RSSI assumes that signal strength degrades over distance; this characteristic is used to measure distance without additional hardware. However, signal strength is affected by noise, such as physical phenomena and weather conditions; these distortions reduce the accuracy of distance measurement.

The global positioning system (GPS) is typically used to localize objects in outdoor applications. However, GPS is inapplicable to indoor applications because GPS requires the lines-of-sight of three satellite signals at the same time to determine the location of an object (Hofmann-Wellenhof, Lichtenegger, & Collins, 2012). Moreover, GPS signals are affected by obstacles, walls, and physical phenomena. The other limitations of GPS include high power consumption, high cost, and large size.

2.1.3.2 Range-free localization

Range-free schemes estimate blind node location through network connectivity without additional hardware. Thus, the blind node requires the following: information about nodes that are within its radio range, the location estimation of nodes, and the ideal radio range of each sensor. The anchor nodes in range-free schemes broadcast their locations at each time slot to help the blind node in estimating its location. Generally, the blind node needs at least three anchor node locations in the neighborhood to estimate its location. Range-free schemes are more cost-effective than range-based schemes. Range-free schemes can be classified into the following types: hop distance, fingerprint, SMC, and hybrid schemes utilizing SMC and hop distance.

(a) *2.1.3.2.1 Hop distance*

Hop distance uses the average hop to estimate the distance between anchor nodes. The localization process in DV-hop follows three steps, namely, location broadcast, distance calculation, and location estimation (Safa, 2014). In location broadcast, the anchor node broadcasts its location information and initializes the hop count to zero among its neighbors. The receiver node keeps the minimum hop count for each anchor node and disregards the large hop count from the same anchor nodes. Then, the receiver increases the hop count by one and sends it to the neighbors. Hence, each node has a record of the minimum hop count of all anchor nodes. In distance calculation, the node calculates the average distance with each anchor node over the hop count of all anchor nodes. In location estimation, the blind node calculates its location by interlocking the matrixes of anchor node location and the matrixes of distance with anchor nodes (Perez-Gonzalez, Munoz-Rodriguez, Vargas-Rosales, & Torres-Villegas, 2015). The disadvantage of hop distance is that it requires a uniform distribution of anchor nodes in the whole network to achieve high accuracy. Consequently, DV-hop is limited to specific applications (Das & Ram, 2016).

(b) ***2.1.3.2.2 Fingerprint***

The fingerprint localization approach estimates blind node location in two steps, namely, creation of an offline database and online location estimation. The offline database is constructed from signal characteristics (called fingerprints) and the location recorded from the whole part of the area of interest. Then, location is estimated for the mobile user by matching the signal fingerprint from the user with that in the database server. Once the signal fingerprint matches that in the database server, the estimated location is sent back to the user. The main drawback of the fingerprint localization approach is the creation and updating of the database. Creating the database requires some expert personnel to collect fingerprints from areas of interest; updating the offline database is a time-consuming task when changes, such as the addition or removal of a new access point in the area of interest, are made in the environment. Moreover, mobile sensors can share similar fingerprints that degrade accuracy and promote ambiguity.

This drawback of the fingerprint localization approach requires a qualified engineer who would measure signal strength (Kaemarungsi & Krishnamurthy, 2012).

(c) ***2.1.3.2.3 Sequential Monte Carlo (SMC)***

Mobile sensors change their locations frequently over time. Hence, finding their current locations requires re-localization at each time slot. SMC is an efficient method for a dynamic system; SMC employs the pdf in the previous time slot and observes it at the current time to estimate the current location by using a weighted particle filter (Arulampalam, Maskell, Gordon, & Clapp, 2002).

SMC makes the following two assumptions: 1) time is divided into discrete time units, and 2) enough samples are required at each time slot. The SMC scheme estimates blind node location in a distributed manner on the basis of the connectivity information "who is within the communication range of whom" (Shang, Rumi, Zhang, & Fromherz, 2004).

The localization process in SMC involves three stages (as in algorithm 2.1), namely, the initial, sample, and filter stages. In the initial stage, the blind node estimates its location by drawing samples randomly from the whole area. In the sample stage, the blind node draws samples in the current time slot on the basis of the samples from the previous time slot bounded by a maximum velocity. Hence, the node draws samples through the following transition equation (Eq 2.2):

$$p\ (S_t \mid S_{t-1}) = \begin{cases} \frac{1}{\pi {v_{max}}^2} & if\ d\ (S_t \mid S_{t-1}) \leq v_{max} \\ 0 & if\ d\ (S_t \mid S_{t-1}) > v_{max} \end{cases} \qquad \text{(Eq 2.2)}$$

Where V_{max} is the node maximum velocity and $d\ (S_t \mid S_{t-1})$ is the distance of the sample location between the current time and the previous time.

In the filter stage, the samples are weighted according to the anchor node constraint in the current time. Each valid sample must be within one or two hops of the three anchor node constraints. Otherwise, the sample is filtered out. SMC repeats the sample and filter stages sequentially until sufficient valid samples are discovered.

Algorithm 2.1 phase of SMC localization algorithm

Phase one: initial phase

Generate samples S randomly from the whole area.

Phase two: drawing samples

Sample set C_t = ()

For each sample S in previous time (l_{t-1}), draw a new sample according to

Sample $l_t^{(i)} \sim p(l_t | l_{t-1}^{(i)})$

Weight of $l_t^{(i)}$ as $\breve{w}_t^{(i)} = p(o_t | l_t^{(i)})$

$C_t = C_t \cup \{(l_t^{(i)}, \breve{w}_t^{(i)})\}$

Phase three: filtering

$$C_t' = \left\{\left(l_t^{(i)}, \breve{w}_t^{(i)}\right) \middle| \left(l_t^{(i)}, \breve{w}_t^{(i)}\right) \in C_t \, and \, \breve{w}_t^{(i)} > 0\right\}$$

Normalize the weight of valid samples $w_t^i = \frac{\breve{w}_t^i}{\sum_{i=1}^{N} \breve{w}_t^i}$

Set the average of the samples as the blind node location.

The filtration efficiency of the SMC localization scheme is mostly affected by anchor node density in the neighborhood. For example, under low anchor node density, a blind node is not always able to identify three anchor nodes in the first and second hop, especially when the sensor moves with high velocity; this process occurs because the first hop neighbors that communicate with radio range R are unable to identify within its range the second hop sensor that communicates with radio range $2R$.

(d) ***2.1.3.2.4 Hybrid schemes (SMC and hop distance)***

The multi-hop version of Monte Carlo localization (MMCL) (Yi, Yang, & Cha, 2007) improves localization accuracy and reduces the dependence on anchor nodes by utilizing the DV-hop technique on MCL. MMCL measures the average hop distance between anchor nodes and then uses MCL to estimate blind node location. The DV-hop schemes have two drawbacks. First, these schemes need a uniform distribution of anchors to achieve high accuracy. Second, broadcasting the location information of anchor nodes to multiple hops increases the communication cost.

The hybrid scheme presented in HMCL (Chen, Gao, Martins, Huang, & Liang, 2013) utilizes hop distance and the SMC technique to improve localization accuracy. The sample area is constructed over the intersection area between anchor boxes. The anchor boxes are formed over the midpoint between anchor nodes. This scheme can reduce the size of a sample area and improve the localization accuracy through a virtual anchor node. The disadvantage of this scheme is that additional computation is required to estimate the distance and angle between the anchor node and the virtual anchor node.

2.1.3.3 Hybrid localization scheme (range-free and range-based)

The combination of range-based and range-free schemes can improve localization accuracy in WSNs. The RSSI is a simple range-based scheme that measures the distance between two nodes by evaluating the signal strength indicator without additional hardware. Signal strength declines over distance. Hence, the RSSI utilizes this phenomenon to measure distance in the localization process. Consequently, communication and computational costs are reduced in the SMC technique (Bandiera, Coluccia, & Ricci, 2015).

The range-based MCL (RMCL) scheme combines range-based and range-free schemes during the localization process to overcome the high radio measurement error that reduces localization accuracy in range-based schemes. RMCL is a hop distance scheme that maintains the hop count and measurement range at a minimum for each anchor node. However, broadcasting the minimum measurement range for each anchor node increases the communication cost in this hop distance method. Moreover, computing the weights in RMCL is a complex task (Cully, Cotton, & Scanlon, 2012; Dil, Dulman, & Havinga, 2006).

The Monte Carlo box localization algorithm based on RSSI (MCBBR) (Gang, Jingxia, Junjie, & Zhenfeng, 2014) uses a reference genetic algorithm (linear crossing and rectangular crossing) to enhance the localization accuracy of the RMCL scheme and RSSI observation to optimize the sample area. In MCBBR, the localization accuracy is determined with the following four steps, namely, constructing the sampling box, establishing the sample number, optimizing the sample, and estimating the location. The real implementation of RMCL (Al Alawi, 2011; Cully et al., 2012) shows that the RSSI improves the accuracy of personal location inside an operation environment. Another improvement of RMCL (Dil et al., 2006) involves the use of SMC to increase localization accuracy when the range measurement has high variation; this improved scheme also utilizes range measurement to reduce computational costs.

The log-normal statistical model is used in the RSS-based Monte Carlo scheme (RSS-MCL) to improve localization accuracy. The RSS amount is used in the movement model and observation model; in the filter stage, the RSS observation is used to measure the distance between the sample and the anchor nodes. The invalid samples are filtered out without additional calculation. RSS-MCL can reduce the computational and communication costs in the filter stage. However, RSS-MCL suffers from high computational cost in the sample stage because the log-normal model is embedded with complex equations (Cully et al., 2012).

In real world applications, range measurement is affected by path loss, fading, and shadowing phenomena. Hence, radio range can be protected by environmental factors, such as obstacles, rain, wind, and humidity; it can also be affected by the indoor environment (Maneerat, Kaemarungsi, & Prommak, 2016). However, the range noise of the RSSI minimizes localization accuracy. Other studies (Heurtefeux & Valois, 2012; Mihaylova et al., 2013) presented the SMC scheme to enhance the localization accuracy associated with the noise measurement amount.

2.2 State-of-the-art SMC localization schemes

Monte Carlo localization (MCL) is pioneered from the SMC scheme; in MCL, time is divided into discrete time slots, the pause time is set to 0, and all sensors move per time slot. After each movement, the node estimates its new location by utilizing the new observation from the anchor nodes in the neighborhood. Therefore, the sample and filter steps are repeated until the sensor collects enough valid samples. However, MCL is fully dependent on anchor node density and achieves low sampling efficiency. Moreover, the accuracy of MCL declines when the sensor moves with high velocity. Although MCL generates samples randomly over previous samples within the sample area bounded by a circle with a radius of maximum velocity, the sample and filter steps are repeated up to 1,000 times in some cases to find valid samples.

Dual and mixture MCL schemes improve the accuracy of MCL by inverting the probability function in the dual Monte Carlo scheme during the sample and filter steps (Stevens-Navarro, Vivekanandan, & Wong, 2007). The disadvantages of the dual Monte Carlo scheme are high computational cost and low sample efficiency. The authors improved the sample efficiency in the mixture Monte Carlo scheme by mixing dual Monte Carlo samples and MCL samples. However, the mixture Monte Carlo scheme achieves a lower accuracy than the dual Monte Carlo scheme.

The study (Rudafshani & Datta, 2007a) presented MSL* and MSL to improve the accuracy of MCL. The MSL* scheme uses the location information of both anchor and normal nodes from the first and second hop. The location information contains the samples in the current time slot and their weights. However, broadcasting all node samples increases the communication cost. To reduce the communication cost, MSL is used to broadcast only the location coordinates of the anchor and normal nodes. This strategy reduces the communication cost and localization accuracy.

The MSL* scheme adds the additional parameter of maximum velocity ($\alpha = 0.1$ R) in the sample generation to satisfy static networks. Each normal node sample in MSL* has a partial weight in the range of zero to one; the anchor node sample maintains a weight value of 1 at all times. The node keeps its sample on the basis of its weight. Weight is estimated with a power function according to the number of normal nodes in the neighborhood. The node uses the adjacent neighbor's samples to evaluate its samples. Hence, this node is greatly affected by the number of nodes in the neighborhood. Moreover, the power function in MSL* entails a higher computational cost than the distance measurement between two point methods.

The Monte Carlo localization boxed (MCB) scheme uses the bounded box for each anchor node in the first and second hops to improve the sampling efficiency of MCL.

The box is drawn around the node center with radii of R and $2R$ in the first and second hops, respectively (Figure 2.2). The intersection area between the anchor node boxes is used as the valid sample area. Unlike MCL, MCB effectively improves sampling efficiency by minimizing the sample area. Hence, the blind node requires only 100 repetitions to find the valid samples. The number of anchor nodes in the neighborhood and the maximum velocity affect the shape of the sample area. The shape of the sample area is irregular; thus, a complex calculation is needed to determine the bounded area. However, such calculation is impossible in sensor nodes. For simplicity, the box surrounding the sample area is used to assess the shape of the sample area, as shown in Figure 2.2. This implementation improves the sampling efficiency of MCL by 93% and maintains the same accuracy level as that of MCL.

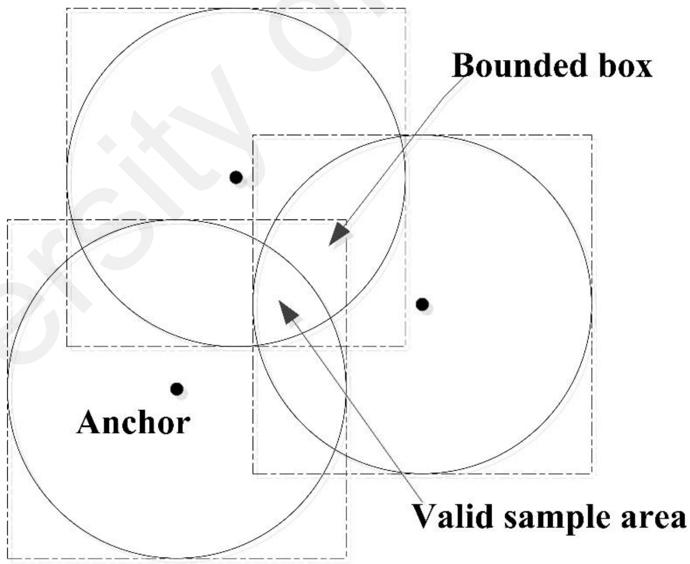

Figure 2.2 : Bounded area of valid sample area.

The weighted Monte Carlo localization scheme (WMCL) improves localization accuracy by utilizing the location information of normal nodes (S. Zhang et al., 2010a), in addition to that of anchor nodes, as in MSL*. The WMCL scheme reduces the size of the sample area and improves the sample efficiency of MCB by employing the two-hop anchor node neighbors' negative effect and normal node location information. The negative effect of the two-hop anchor node neighbors is discussed in Section 2.2.3. The estimated location of the normal node contains a percentage of error. To overcome this challenge, the normal nodes utilize the maximum location error in the x-axis and y-axis to bounding the sample area. Thus, the sample area in WMCL is bounded by the anchor node constraints and normal node location information. The normal nodes estimate the errors in both axes. In filtering out the invalid samples efficiently, the weight for the anchor node samples is set to 1 at all times, and the partial weight for the normal node is set in the range of 0 to 1.

The partial weight for the normal node samples in WMCL is calculated as follows. First, the distance between all sensors samples in the neighborhood are estimated. Second, the intersection of the bounded box is utilized to reduce the communication cost of the first step. Finally, the radio range, maximum velocity, and maximum localization error from the previous time are utilized. These processes filter out the invalid samples more efficiently than MSL* and improve the sampling efficiency. Unlike MCB, WMCL reduces the sample area by 78% and improves the sampling efficiency by up to 95%. Moreover, WMCL uses the normal node location information in the sample and filter steps, whereas MCB utilizes only the anchor node location information in the filter step.

The movement direction of anchor nodes between the previous time slot and the current time slot are used in the constraint rule-optimized Monte Carlo localization scheme (COMCL) (Z. Wang et al., 2013) . COMCL utilizes the locations of anchor nodes in the previous and current time slots to track the movement of these anchor nodes within the upper and lower bounds. COMCL classifies the location of the anchor nodes per time into two types: moving backward and moving forward in time. The location information in COMCL requires the following three steps: 1) construct the anchor node constraint, 2) construct the sample area, and 3) optimize and filter out the invalid samples. Thus, COMCL involves more efficient and faster filtering steps than WMCL.

The range-based Monte Carlo boxed (RMCB) scheme compares and utilizes both range-based and range-free schemes to answer the question “When does range-based localization work better than range-free localization?” RMCB is suitable for both static and mobile WSNs with a heterogeneous radio range (Adnan, Datta, & MacLean, 2014). RMCB improves the sample area and efficiency in WMCL using a positive anchor node effect behind the negative effect used in WMCL. To ensure the efficiency of RMCB, the authors employed the same hardware devices for both RMCB and WMCL. The result shows that RMCB can improve WMCL in different parameters.

In (Sheu et al., 2010), an improved MCL (IMCL) scheme was used to enhance the localization accuracy in MCL by adding constraints of movement direction in the previous schemes to the anchor and normal nodes. IMCL selects the normal nodes in the first hop’s neighbors whose locations are constructed by the anchor node constraint. Moreover, IMCL employs the circular sector in the localization process to filter out the invalid samples. Each normal node divides the circular range into eight sectors; the longest sample sector is used to filter out the invalid samples. However, computing the longest distance of samples and the angle of each sector increases the computational burden in IMCL.

PMCB (Soltaninasab, Sabaei, & Amiri, 2010) uses a time series to forecast the position of a blind node in case no anchor nodes exist in the neighborhood. Otherwise, SMC is used to estimate the location. The time series reduces the dependency on the anchor node. However, a recursive step is required to calculate the linear prediction coefficients in each time slot.

In the PMCB and IMCL schemes, the number of samples is based on the percentage of the sample area with respect to the maximum area of one anchor node in the neighborhood, as represented in (Eq 2.3).However, at least one anchor node is assumed to be in the first hop of the blind node neighbor in most simulations.

$$\text{Sample number} = \left(50 * (\Delta x) * (\Delta y)\right) / 4R^2 \qquad \text{(Eq 2.3)}$$

Where $\Delta x \; and \; \Delta y$ are the height and length of the bounded box (sample area), respectively, 50 is the maximum number of sample and $4R^2$ is the maximum area of one anchor node in the first hop.

The orbit scheme improves localization accuracy by utilizing the characteristics of a star graph. The graph is constructed with one root and five leaves. The orbit coordinates the neighbor's node constraint within the star graph to improve localization accuracy. The orbit scheme is highly affected by node density. However, this scheme may not constantly discover five nodes in the neighborhood (MacLean & Datta, 2014).

In (Jadaliha, Xu, Choi, Johnson, & Li, 2013), a Gaussian process regression was formulated with observations to improve localization accuracy. The observations on noise measurement, localization error, and previous distribution are correlated with the posterior predictive statistics. Hence, the posterior predictive statistics utilize MCL sampling and Laplace's method to improve localization accuracy. However, Laplace's method requires a complex calculation.

In the sequential Monte Carlo-based localization algorithm (SMCLA), each sensor node maintains a table to store the estimated location, velocity, direction, and motion type at the current time slot. The blind node in the initial four steps moves according to the waypoint model. Then, the motion type is estimated by evaluating the velocity, acceleration, and movement direction to generate samples. Hence, the blind node stores the last four pieces of location information in the table with their time stamps. However, utilizing the time stamp requires additional hardware for the time synchronization between sensor nodes (Alaybeyoglu, 2015).

The variation of radio range is evaluated during the localization process in the sequential Monte Carlo localization scheme (SMCL). A perfect circular radio range is used in most schemes. However, the radio range in real world applications is affected by noise, path loss, shadowing, and physical phenomena. Hence, DOI is used to check the variation of the radio range in the SMCL scheme. The updating stage is added to the SMC method to measure the effective factor of each sample in location estimation (W. Wang & Zhu, 2009).

In (Fox, 2003), a sample adaptive Monte Carlo localization (SAMCL) algorithm was employed; in SAMCL, the sample area is divided into small bins, and each valid sample is assigned to one bin. The new samples are selected if they are acquired inside an empty bin. Otherwise, they are ignored. Thus, the number of samples is counted by bin numbers.

The uniform sampling Monte Carlo localization scheme modifies the sampling strategy of SMC by dividing the sample area into small squares; this scheme selects the samples on the basis of their uniform distribution over a small square. The uniform distribution can reduce the time needed to generate random samples over the whole area. However, this uniform distribution does not represent the real state of all systems. Therefore, random generation can improve localization accuracy more efficiently than uniform distribution (Mirebrahim & Dehghan, 2009).

Reduced redundant messages and hop distance overhead using the back off-based broadcasting mechanism. This mechanism uses the following assumption in the RSSI: a node that is far from the sender has a signal strength that is too weak to select messages with a signal strength exceeding a predefined threshold (Chen et al., 2013).

In (L. G. Martins, Nunes, Martins, & de Oliveira, 2013), the location information messages were used to improve failure detection. Generally, sensor nodes in WSNs exchange heartbeat messages to detect neighbors. These messages can be utilized for failure detection during the localization process. Hence, the compound between the localization process and failure detection can reduce the number of exchanged messages in networks.

Localization accuracy can be improved by combining SMC schemes and the genetic algorithm (Luan, Zhang, Zhang, & Cui, 2014). Crossover and mutation can be used to draw samples from a virtual anchor node. Hence, linear crossover and rectangular crossover are used to filter out invalid samples on the basis of the distance between the anchor node and the blind node.

The geometry of the intersection points between sensor nodes is used to bound the polygon shape; the shape is used to filter out the invalid samples (Henderson, Grant, Luthy, Mattos, & Craver, 2005). However, the shape of the sample area is irregular and depends on the number and location of anchor nodes in the neighborhood. Hence, constructing the polygon is not easy in all cases.

2.2.1 Schemes utilizing a single anchor node

A single mobile anchor node (or online localization) is used to save scarce resources of sensor nodes and improve the localization accuracy of MCL. A blind node requests a location estimation from an anchor node. Thus, the anchor node estimates the location of the blind node and sends it back to the blind node.

Mobile-assisted Monte Carlo localization (MA-MCL) uses one anchor node to localize static blind nodes. The anchor node moves randomly to collect arriver and leaver static of blind observation. Then, invalid samples are filtered out. After finding the blind node observation, the anchor node calculates the location and sends it back to the blind node (Teng, Zheng, & Dong, 2011).

Wireless node-based Monte Carlo localization (WNMCL) is another scheme that utilizes a single anchor node in the localization process. WNMCL divides the sample area into separate clusters. The adjacent clusters are merged, and the merging is repeated until the number of separate clusters is found. The center of the separate cluster is used as the estimated location of the blind node (Kurecka, Konecny, Prauzek, & Koziorek, 2014).

A single mobile anchor node with different types of blind node observation, such as connectivity, AoA, ranging, and a mixture of all of these, was utilized to estimate location (Huang & Záruba, 2009). The blind node collects at least the connectivity range of the first neighbor and sends this range to the anchor node when it arrives. The localization process occurs in the anchor node side; the location is sent back to the blind node.

Utilizing a single anchor node in the localization process can save scarce resources in sensor nodes and avoid time synchronization. Moreover, security can be improved by securing a single anchor node. Nevertheless, the use of a single mobile node increases the overhead over the beacon node and maximizes the probability of network congestion. Moreover, the noise of a single anchor node range can degrade the localization accuracy of the whole network.

2.2.2 Schemes utilizing MCL in target tracking

The MCL scheme enhances target tracking by estimating target locations. The novel Monte Carlo-based tracking (NMCT) scheme utilizes the perpendicular bisector zoning technique and triangulation assumption in the point in triangle (PIT) scheme to gather and check the blind nodes within or outside the anchor node triangle (Niu, Huan, & Chen, 2016). The perpendicular line is used to find the bisector area and check the adjacency of the anchor nodes in the neighborhood. Therefore, the possible location of the blind node can be estimated from the anchor node pairs in the PIT and perpendicular bisector line (Girod & Estrin, 2001). Therefore, the valid sample area can be bounded, and the invalid samples can be filtered out efficiently. The weakness of NMCT is that it assumes that anchor nodes are static and that normal nodes are mobile nodes.

Oriented tracking-based Monte Carlo localization (OTMCL) utilizes the movement orientation in the sample step to improve MCL accuracy (M. H. Martins, Chen, & Sezaki, 2009). The angle of the movement sector is calculated on the basis of the elaboration between the location in the previous and current times. The drawback of OTMCL is the need to constantly find enough valid samples. Thus, OTMCL uses the bounded box in MCB to generate samples.

The binary detection Monte Carlo localization scheme (BD MCL) utilizes the binary assumption in MCL to examine the node with the maximum range or outside range (J. Li, You, Xia, & Li, 2012). BD MCL maintains and records the interval time of each mobile sensor in the range. Hence, the mobile sensor with a large time interval has a high weightage sample. The use of the time interval requires the anchor node to synchronize the time between nodes; this synchronization may not be applicable in thin devices.

The movement continuity phenomenon of mobile sensors was used in (Fan, Wen, & Zhou, 2013) to estimate locations and movement directions. The study proposed the use of the linear prediction method and required the normal node to maintain the location information from four previous time slots. In this method, the sample area is divided into separate posterior density function regions on the basis of the movement direction in the previous time slot. However, maintaining four previous locations increases memory usage. Moreover, the network needs a long period to stabilize (Mahdi et al., 2016).

2.2.3 Negative effect: advantages and disadvantages

The negative effect of two-hop anchor nodes in the literature is defined as "node *x* is not within distance *d* of node *y*." Range-free schemes utilize this definition ("node *x* is not within the radio range of *y*") to enhance localization accuracy. The negative effect of two-hop anchor nodes and normal node location information can enhance localization accuracy and sample efficiency by 87% and 95%, respectively, as in WMCL. The shadow area in Figure 2.3 can be ignored without losing any valid samples; this fact can be explained as follows. The *q* is assumed to be the two-hop anchor node for normal node *p*. Thus, the shadow area does not contain *p* because otherwise, *q* is the one-hop neighbor of node *q*. The negative effect of two hops is a critical and precise issue. For example, if the distance between node *p* and *q* is underestimated, then the negative constraints can reduce localization accuracy. On the contrary, if the distance between node *p* and *q* is overestimated, then the practical location may be lost.

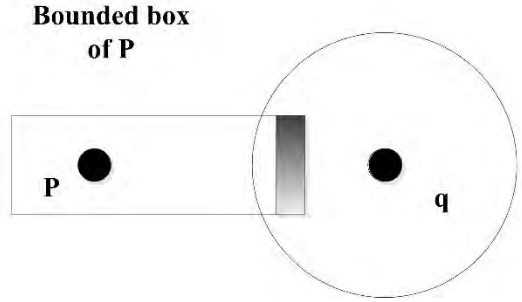

Figure 2.3 : Improve the size of the bounding box: the shadowed area should be cut.

2.2.4 Comparison of range-free SMC localization schemes

Localization is categorized on the basis of additional hardware, scalability, accuracy, noise, operation environment, and cost, as shown in Table 2.2. Among all schemes, the range-based one achieves the highest accuracy despite being fully dependent on special hardware. This scheme is followed by the hybrid scheme that utilizes the network connectivity in noise and the RSSI assumption in the normal case. The range-free scheme achieves the lowest accuracy; location is estimated using network connectivity.

Table 2.2: Summary of localization schemes.

Localization category	Dependent on hardware	Scalability	Accuracy	Noises	Environ ment	Cost
Range-based	Full	Low	High	High	Outdoo r	High
Range-free	Partial	High	Low	Low	Indoor	Low
Hybrid	Partial	High	Medium	Medium	Indoor	Low

SMC locations can be compared in terms of localization accuracy, computational cost, communication cost, number of samples, dependency on anchor nodes, and network type, as shown in Table 2.3.

Table 2.3 : SMC scheme classification.

Studies	Accuracy	Computation cost	Communication cost	Number of samples	Dependent on anchor nodes	Network type
MCL	low	High	Low	constant	Full	mobile
Dual MCL	low	High	Low	constant	Full	mobile
MCB	low	Medium	Low	constant	Full	mobile
MSL*	high	High	High	constant	Partial	mobile/static
LCC	high	High	Low	constant	Partial	mobile/static
WMCL	high	Low	Medium	constant	Partial	mobile/static
COMCL	high	Low	High	constant	Partial	mobile
RMCB	high	Low	Medium	constant	Partial	mobile/static
IMCL	high	Medium	Medium	dynamic	Partial	mobile
Orbit	high	High	High	constant	Partial	mobile
HMCL	medium	Medium	Low	constant	Full	mobile
PMCB	medium	Medium	Low	dynamic	Full	mobile
MCBBR	low	Medium	Low	dynamic	Full	mobile

2.2.4.1 Comparison of communication costs

The communication cost is the most significant parameter in the WSN, sending one message requires power more than computing instruction in CPU as discussed in chapter one. The number of messages sent is the function of anchor node density in the schemes such as MCL, MCB, and dual MCL; and this number is equivalent to the anchor node number (A) in the neighborhood. In MSL* and MSL, the normal node location information is utilized along with the anchor node. The normal node in MSL* broadcasts the samples in each time slot to the first and second hops, whereas the normal node in MSL only broadcasts their coordinates and not all samples. The communication costs of MSL* and MSL are represented by (N*S + A) and (N + A), respectively, where N is the number of normal nodes, S is the number of samples in each time slot (50 samples), and A is the number of anchor nodes in the neighborhood.

Among all schemes, the MSL* scheme achieves the highest communication cost, whereas MCL achieves the lowest communication cost. In our LCC scheme, the communication cost in MSL* is reduced by 18% by selecting the adjacent normal node in the neighborhood.

The assumption in MSL* is adopted in WMCL and RMCL; the normal node broadcasts its sample to the first hop. WMCL and RMCL modify the sample with the information on message size; the location of the maximum error is defined in the x-axis and y-axis. The COMCL scheme embeds the range of the bounded box from the previous time slot in the sample of the normal node. However, the communication cost of COMCL is 1.04 times higher than that of WMCL. The simulation results in WMCL show that the communication cost is more significantly affected by the size of the message than by the densities of the anchor and normal nodes.

MSL* broadcasts the message with information on the IP header, transmitter ID, estimated position, number of hops, and coordinates of 50 valid samples in the previous time unit; this information costs 634 bytes. The normal node messages in WMCL or BB combine the IP header, transmitter ID, estimated position, number of hops, valid samples, and maximum error in the x-axis and y-axis; this information costs only 46 bytes. The normal node message in the IMCL scheme has a size of 66 bytes by combining the IP header, transmitter ID, estimated position, number of hops, valid samples, and eight sectors. The MCL, MCB, and dual MCL schemes yield the lowest communication costs because they only utilize the anchor node location information. The details of bytes sent in each scheme per time slot are listed in (Sheu et al., 2010).

The number of messages is also affected by the number of hops used in the localization process. Normally, SMC utilizes the sensor in the first and second hops. However, the sensor node in the second hop can maximize the communication, especially when normal node samples are used. For example, MSL* uses the normal node samples of the first and second hops; each anchor node and normal node broadcast their respective samples in each time slot to the first and second hop neighbors. Therefore, MSL* requires a high communication cost.

2.2.5 Security issue in localization process

A secure localization mechanism is an aspect of WSNs that is worth exploring. However, the available literature on the subject is limited and has yet to be explored. Generally, SMC schemes estimate position without considering security issues. In reality, localization schemes are susceptible to attacks; these attacks can decrease the reliability and availability of SMC schemes. Without a proper authorization policy, the probability of false node injection is high. A false node broadcasts invalid location information to the whole WSN (Bartariya & Rastogi, 2016; Fan et al., 2013; Miao, Dai, Chen, Jin, & Chen, 2016; Yick et al., 2008).

The localization process in WSNs may suffer attacks through an exposed sensor or interruptions in the localization result. An aggressive sensor can broadcast misleading location information to the blind node. In most SMC schemes, the localization process depends on anchor node observations; other schemes, such as MSL* and WMCL, utilize both normal and anchor node location information. SMC schemes are highly dependent on anchor nodes; if these anchor nodes are attacked, then the localization accuracy of all nodes in the neighborhood is affected. However, an attack on normal nodes may have little effect on localization accuracy.

SMC's characteristics, such as the movement of mobile sensors, filtration steps, and weighted samples, can help to secure the position scheme. The movement of a mobile sensor can be a defense mechanism for aggressive nodes. A mobile sensor changes its location and neighbors over time; the new neighbors can limit the effect of aggressive nodes. Moreover, the SMC scheme can be further secured during the filtering step when all of the samples are filtered in each time slot. The filtering step can easily detect invalid samples upon the arrival of new anchor node observations. Furthermore, SMC estimates the blind node location by averaging a sufficient weighted valid sample; this process limits the effect of invalid samples on localization accuracy.

The probability of attacks differs among schemes. Here, we discuss the effect of security in sampling methods. Sampling methods can be classified into two types, namely, the bounded box and distance methods. The bounded box method is more susceptible to attacks given that the size of the bounded box is maintained by the anchor node location information. Attacks on anchor nodes may increase or minimize the size of the sample area; these effects on the sample area subsequently reduce the sample efficiency and localization accuracy.

Attacks on normal nodes can reduce sample efficiency and localization accuracy particularly for schemes that utilize normal node location information in the localization process; MSL* and WMCL are such schemes. In the distance method, the distance between the blind node and anchor nodes in the neighborhood is measured to satisfy the anchor node constraints. Thus, an attacker in the neighborhood insufficiently affects localization accuracy, especially in a dense network.

The SecMCL scheme improves localization security by checking the sample number. The blind node is assumed to be able to generate enough valid samples in the stable state unless the neighbors are under attack. SecMCL uses a public key technique to authenticate the transmitted messages. However, SecMCL assumes that only the anchor node can be attacked; in fact, the normal node is also susceptible to attacks (Zeng, Cao, Hong, Zhang, & Xie, 2009).

Limited research has discussed the security issues in the localization process (Lai et al., 2013). Security in localization schemes is a challenging research area; the traditional security technique is incompatible with WSNs because of various limitations. Public key autographs can broadcast false node location information. Hence, anchor nodes can broadcast public keys consisting of private keys before the deployment to each node. The disadvantages of public key encryption are its high computational cost and the increase in the size of messages.

Symmetric cryptography techniques secure WSNs by utilizing alternative key establishment mechanisms with a random key. However, symmetric cryptography techniques involve bidirectional messages, which are incompatible with WSNs because of the limitation of WSNs. In this case, anchor nodes need to send the location information directly to all normal nodes (Zeng, Cao, Hong, Zhang, & Xie, 2013).

Localization results can also be interrupted by an attacker to confuse the sensor nodes and reduce localization accuracy. Moreover, an attacker can hide messages or change their destination without tampering the content of the message. In general, a network with a limited number of anchor nodes is more susceptible to attacks than other networks.

A wormhole attacker can interrupt messages and change the destination without tampering the content of messages. Although a wormhole attacker is difficult to detect, the nodes in the current time can help to detect this attacker in the neighborhood. Additional hardware, such as clock synchronization or directional antennas, can also aid in detecting wormhole attackers.

2.3 State-of-the-art mobility models

The performance of localization schemes is highly affected by mobility patterns. A mobile sensor can change its location, velocity, and acceleration frequently. Changes in sensor location in mobile WSNs can affect network connectivity and the distribution of neighbors in an operation area. The mobility model should thus resemble movement patterns in real-life systems. Simulation results can be ambiguous and fail to explain observations and derive effective conclusions. Thus, the evaluation of mobile WSN schemes should involve the selection of an accurate and suitable mobility model.

The mobile nodes in previous research mostly use a random waypoint model to simulate the movement pattern, where the velocity, direction, and neighbors' velocity are not dependent on previous values (Jardosh, Belding-Royer, Almeroth, & Suri, 2003). By contrast, the nodes in a group mobility model should request for velocity and direction from the reference node (leader) (Hong, Gerla, Pei, & Chiang, 1999). Thus, the mobility model should match real application requirements to ensure an effective performance (Le Boudec & Vojnovic, 2005).

Mobility patterns have been studied in previous research at a macroscopic level. Most existing studies in a particular area, such as cellular networks, concentrate on cell change rate, traffic handover, and blocking probability (Hyytiä & Virtamo, 2007). Mobile WSNs face the special challenge of finding movement patterns at the microscopic level, such as individual sensor movement, velocity, and number of nodes in the neighborhood. WSNs use the broadcasting method as a mode of communication.

Mobile WSNs facilitate the dense deployment of sensors in operation areas, with the sensors performing self-organized location estimation. Network topology changes frequently in such a dynamic network (Santi, 2005). Thus, a smart mobility model should be integrated with WSN features.

2.3.1 Types of Mobility Models

A number of mobility models can be found in the literature. This section provides brief descriptions of these models. Additional details can be found in (Tracy Camp et al., 2002). Mobility models have been classified into two categories, namely, trace mobility model and synthetic mobility model (Musolesi & Mascolo, 2006) . In the trace mobility model, the patterns of mobility are obtained from real experiments. However, collecting these patterns from real experiments is not an easy task. By contrast, in the synthetic mobility model, movement patterns are obtained from a mathematical model.

The synthetic mobility model can be divided into two types: entity mobility model and group mobility model, as presented in Figure 2.4. In the first type, the sensor node moves in an individual style without coloration with the neighbors. This characteristic is similar to that of the random waypoint model, random walk model, and Gauss–Markov model. Mobile sensors belong to the group mobility model, which is fully dependent on the nodes in the neighborhood. This characteristic is similar to the reference point group pursue mobility model and column model.

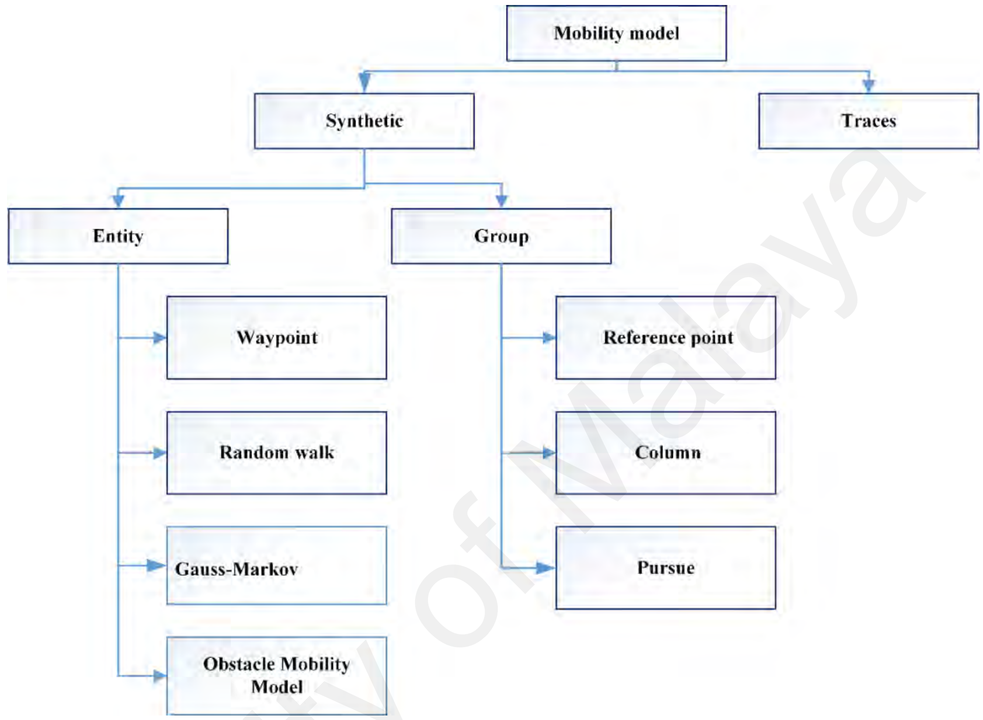

Figure 2.4 : Mobility model types

Random Waypoint Model: The waypoint model is simple and is widely used in previous studies. In this model, the velocity and direction of the mobile sensor can be chosen randomly without any dependency on previous values. The main issue in the waypoint model is pause time, wherein the mobile node can be stopped between time slots (Yoon, Liu, & Noble, 2003a).

Random Walk Model: The movement behavior in a dynamic system is an unpredictable motion, which is referred to as Brownian motion (Jahromi, Zignani, Gaito, & Rossi, 2016).The random walk model is employed in dynamic systems to mimic movement behavior (Rogers, 2016). It is a special case of the random waypoint model, in which the pause time is set to zero. The lack of memory is the main feature of the random walk model; in such a case, mobile sensors move freely without any dependency. However, in this model, the mobile node selects the direction and velocity randomly and uniformly for each time slot. The weakness of the random waypoint and random walk models is the boundary effect (Bettstetter & Wagner, 2002).

Manhattan Grid Model: The movement pattern in the Manhattan grid model is likened to that in an urban area, with a viable route path represented by a street map. The routing path of this model is constructed as horizontal and vertical streets (or grids). Thus, the permissible movement of a mobile sensor is limited by grid map constraints and horizontal and vertical streets (Hou, Li, Jin, Wu, & Chen, 2016).

Gauss–Markov Mobility Model: The study conducted in (Liang & Haas, 1999) presented the Gauss–Markov mobility model, which has been used in many types of research (Tracy Camp et al., 2002) . In this mobility model, the mobile node chooses constant values for direction and velocity at the beginning of each period. Time is constant for each time slot. However, in this mobility model, the α parameter presents a degree of dependency between the current velocity and the direction with previous values. The parameter α is the tuning parameter in interval [0,1]; various levels of randomness or degree of dependency exist when α is zero, and this condition means that the sensor nodes move with maximum velocity and the direction follow Brownian motion without dependency on previous values (full random) (Uhlenbeck & Ornstein, 1930). When the value is 1, the sensor node moves with minimum velocity and linear motion. When α is between 0 and 1, dependency exists based on the α value. Equations 2.4 and 2. 5 formulate the direction and velocity of this mobility model.

$$v_n = \alpha\, v_{n-1} + (1 - \alpha)v^{-} + (1 - \alpha^{2})\sqrt{v_{x_{n-1}}} \qquad \text{(Eq 2.4)}$$

$$d_n = \alpha\, d_{n-1} + (1 - \alpha^{2})\sqrt{v_{x_{n-1}}}, \qquad \text{(Eq 2.5)}$$

where α is the tuning parameter, v_n is the current velocity, $v_{x_{n-1}}$ is the velocity in the previous time slot, d_n is the direction on the current time, and d_{n-1} is the direction in the previous time slot.

Reference Point Group Mobility Model (RPGM): The RPGM mobility model is used in military battlefield applications, in which soldiers move in a group unit. Each group has a group leader that correlates member motion. Consequently, every node in the group requests for direction and velocity from the leader at each time slot (Hong et al., 1999).

Column Mobility Model: The column mobility model uses a fixed direction to reach a destination. It is used to track objects or scanning areas in military applications, such as exploring mines using special robots (Tracy Camp et al., 2002).

Pursue Mobility Model: The pursue mobility model is used in various applications, in which a number of mobile nodes move to arrest one object node. This mobility model is mainly used in target tracking and law enforcement. In this model, the mobile node moves according to the random waypoint model (Tracy Camp et al., 2002).

Obstacle Mobility Model: In real applications, the mobile node is intercepted by geographical constraints, such as obstacles on the road. The mobile node should change trajectory to avoid obstacles and thereby reach its destination. Thus, the existence of obstacles affects movement behavior and the direction of movement (Amirshahi, Fathy, Romoozi, & Assarian, 2015; Jardosh et al., 2003).

The main drawback of the existing mobility models in mobile WSNs is their effect on the performance and connectivity of the entire network. Thus, mobile WSNs require an efficient mobility model (Bai, Sadagopan, & Helmy, 2003; Campos, Otero, & de Moraes, 2004; Mousavi, Rabiee, Moshref, & Dabirmoghaddam, 2007).

2.3.2 Taxonomy of Mobility Models

The synthetic model emulates the physical law of motion using a mathematical model (equations) in the mobility model. A hierarchical classification of the synthetic mobility model is presented in this study.

This study divided mobility models into four categories: entity model, group model, social model, and vehicular model, as shown in Figure 2.5. Entity mobility models are classified into four categories: random model, model with temporal dependency, model with special dependency, and model with geographic restrictions, as shown in Figure 2.6.

The combination of the entity mobility model and group mobility model can emulate a real mobility model. Hence, the motion behavior of a single node and group motion behavior can be considered to present a smooth mobility model. Under this model, the motion of pedestrians can be moved individually or with group correlation. Vehicular motion can be considered correlated motion. Another study classified mobility model into six categories: pedestrians, vehicles, aerial, dynamic media, robotics, and outer space motion (Schindelhauer, 2006) .

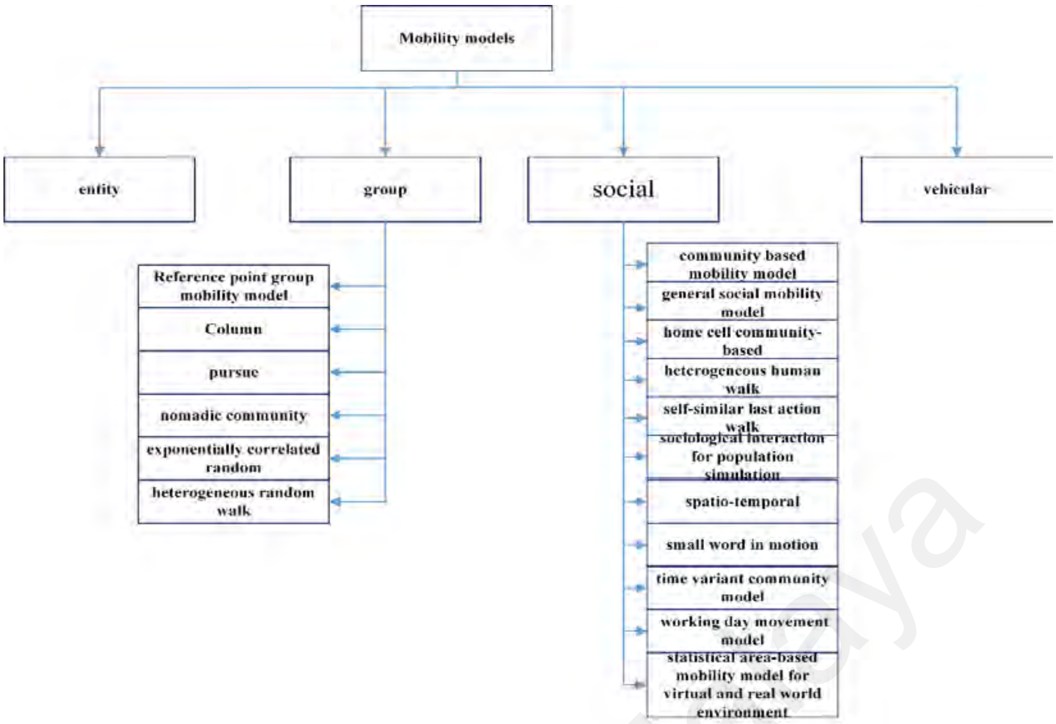

Figure 2.5 : Mobility model classification

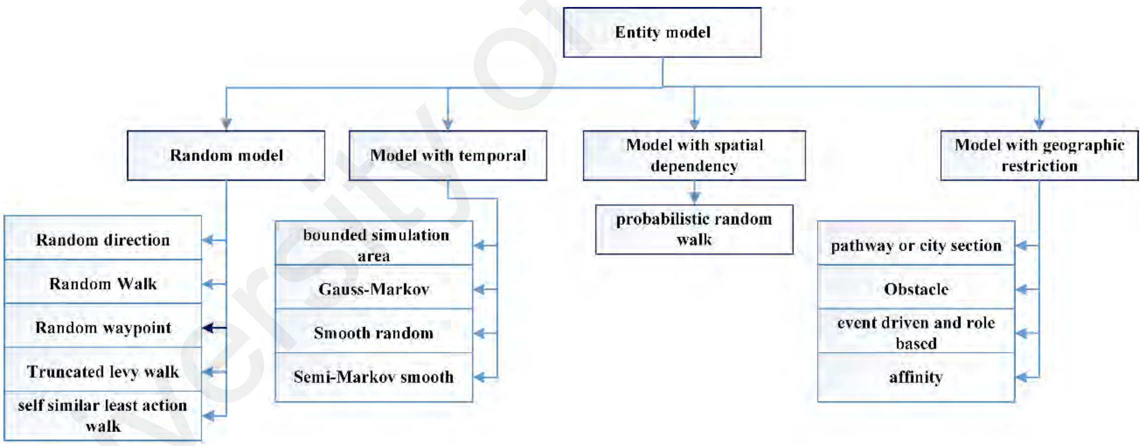

Figure 2.6 : Entity mobility model classification

The main direction of future research on mobility models and classification of existing mobility models is discussed in (Bettstetter & Wagner, 2002; Campos et al., 2004). The classification of mobility models follows this sequence: entity mobility model, group model, autoregressive model, no-recurrent model, virtual game-driven model, flock and swarm model, and social model (Batabyal & Bhaumik, 2015; C. Zhao, Sichitiu, & Rhee, 2015).

2.3.3 Features of realistic movement patterns

The existing mobility models fail to present some significant features of mobile WSNs (Tracy Camp et al., 2002), such as dependency on velocity, sudden change, and physical constraints (obstacles in the trajectory) (Harri, Filali, & Bonnet, 2009).

The velocity of a mobile node is normally associated with a time slot. For example, the acceleration of vehicles and pedestrians changes incrementally, and the direction changes smoothly. Hence, the new velocity is dependent on the last velocity. Entity mobility models require some mobility behaviors to be memorized, such as unexpected stop, unexpected acceleration, and squeaky turn. In the group mobility model, dependency exists between current time motion behavior and that of previous motion (T.-y. Liu, Chang, & Gu, 2009). In this model, the group leader can correlate the velocity and direction of group members.

Physical constraint is another challenge faced by existing mobility models. Most mobility models assume an ideal environment in the simulation test. However, in real applications, limitations and obstacles exist in the trajectory; these obstacles include buildings, trees, and road jams. Thus, the mobility model should address these issues (Harri et al., 2009) .

2.4 Discussion of future works and localization issues

Range-based schemes achieve a higher localization accuracy than range-free schemes. However, range-based schemes are highly dependent on additional hardware that consume a large amount of power and increase the size and cost of sensor nodes, especially in a dense deployment. The battery replacement of sensor nodes is difficult, particularly when nodes are in remote and hazardous areas. Moreover, communication range and hardware signals are affected by noise and obstacles. Therefore, range-based schemes are unsuitable for certain types of applications.

By contrast, range-free schemes estimate locations using network connectivity and without any additional hardware. A range-free scheme is a challenging area. The obstacle of SMC is its dependency on anchor node density and a high number of valid samples to estimate an accurate location. Repeating the sample and filtering stages several times is a time-consuming process. Furthermore, hop distance schemes require a uniform distribution of anchor nodes, and fingerprint schemes are time consuming because expert personnel is required to create the offline database and update the database every time the environment changes.

Connectivity information may remain unchanged when sensor nodes move a small distance without establishing a new connection or disestablishing the previous connection. Therefore, we can defend the lower bounds in range-free schemes as the average distance in which the sensor node can move with the same connectivity information between the previous time and the current time. In this case, localization accuracy degenerates for range-free schemes (Chan & Soong, 2011).

The localization accuracy of range-free schemes is a challenging research area. The localization error in SMC increases rapidly when the velocity of mobile nodes increases. A high velocity can change the topology of WSNs quickly. Therefore, WSNs require an adaptive mobility model to transmit sensor nodes efficiently. Another issue in the SMC localization process is the accuracy highly affected by anchor node density and number of samples.

Sample efficiency is a significant parameter in the SMC method. However, the repetition of the sample and filter steps for several times delays the localization process. Other significant parameters are the number of samples and sample area channeling. The shape of the sample area is irregular, and the bounded area is difficult to find. The number of samples of this area requires the highlight method, whereas the use of the bounded box is embedded with a high percentage of error.

Messages in WSNs consume scarce resources and waste sensor battery life. Hence, localization schemes require a lightweight algorithm to avoid additional, redundant messages.

2.5 Conclusion

The localization of mobile sensors is a key issue in WSNs. Specifically, an accurate location can maximize the benefits of WSNs. A high localization accuracy can be achieved through an efficient and lightweight scheme that is adaptable to sensor characteristics. Constructing an efficient scheme on the basis of the SMC method can improve the localization accuracy in dynamic systems, such as mobile sensors. In this study, we introduced a thematic taxonomy to classify the current SMC localization schemes. Moreover, we presented a comprehensive survey of state-of-the-art SMC schemes and classified them according to their localization requirements. The critical aspects of existing SMC localization schemes were analyzed to identify the advantages and disadvantages of each scheme. Furthermore, the similarities and differences of each scheme were investigated on the basis of important parameters, such as localization accuracy, computational cost, communications cost, and number of samples. We also discussed the challenges and open research issues related to the parameters.

CHAPTER 3: FRAMEWORK FOR LOCALIZING MOBILE WSNS

This chapter presents in detail the strategy phase of the developed framework for achieving our main goal, which is to design a framework that solves localization problems in mobile WSNs. In other words, the proposed framework can solve the communications cost and anchor node convergence problem to enhance localization accuracy and thereby prolong the life of WSNs.

The formal analysis in the previous chapter shows that WSNs involve various challenges in their applications. One significant problem is communication cost in the localization process. In the face of such issue, the mobility model of sensors emerges as a substantial problem. The purpose of this chapter is to present a framework for clarifying the aforementioned challenges.

The first contribution of this thesis is a solution for significantly reducing the communication cost in the mobile WSN localization process via our proposed Low Communication Cost (LCC) scheme. To this end, we present WSNs in an adjacency matrix and use the intersection in set theory as a solution to the communication cost problem in mobile WSN localization. The second contribution of this thesis is a mobility model Adaptive Mobility Model (AMM) to expressively improve anchor nodes' convergence and enhance localization accuracy by adapting the velocity of anchor nodes with the overlapping degree and number of anchor nodes in the neighborhood.

The mathematical analysis of the problems in this chapter and the simulation results in the next chapters show that the proposed framework can efficiently reduce the communication cost while achieving localization accuracy that is comparable to that of previous schemes. It can also increase anchor nodes' coverage and further enhance the localization accuracy achieved by previous models.

The following is the sequence of this chapter. Section 3.1 (Methodology) solves the localization problem. Section 3.2 presents our framework to solve the significant challenges in mobile WSNs. Section 3.3 presents our proposed method for resolving the communication cost problem in three subsections: 3.3.1 – the adjacency matrix, 3.3.2 – set theory, and 3.3.3 – an example of the proposed framework of the LCC scheme. Section 3.4 presents an AMM. Finally, we discuss the issues on communication cost and anchor nodes' coverage in section 3.5.

3.1 Methodology

We construct our methodology using four main steps to achieve the objective of this thesis, as discussed in Section 1.4.

Literature review: In this step, a summary and critical analysis are performed on the key schemes and research associated with the mobile WSN localization problem, particularly those that use the SMC method and mobility model to solve such problem. Range-free schemes are classified on the basis of thematic taxonomy. Furthermore, the advantages and disadvantages of these schemes are highlighted in exploring the existing gaps in mobile WSN localization schemes, particularly in the SMC method.

Modeling: After the existing research is reviewed and the literature review is analyzed, the mandatory features and challenges of mobile WSN localization are identified and categorized in Section 3.2. The proposed framework considers the major weaknesses of localization schemes, such as communication cost, anchor node convergence, and localization accuracy. In this step, all the required components of the proposed framework are discussed in detail.

Development: The proposed framework is developed to simulate real-time localization in mobile WSNs. All data are generated via intensive simulation to present the characteristics of mobile WSNs. The special characteristics of mobile WSNs include dense deployment, high velocity, and large experiment area requirement in some cases. Therefore, the experiments on the effectiveness of the proposed framework can be implemented through a simulation tool. However, the real testing for any mobile WSN scenario is costly.

Testing and Evaluation: In this step, the performance of the proposed framework is evaluated and validated through various extensive simulation tests, and the experiment results are compared with key benchmarks to ensure the effectiveness of the proposed model. In addition, the paramount values for the proposed framework are obtained through the simulation test.

Various simulation scenarios with different mobile WSNs are measured to achieve an effective comparison of the proposed framework and existing schemes. The number of samples, velocity, anchor node density, normal node density, and degree of irregularity are used as comparison parameters. The result of the LCC scheme is presented in Chapter 4, and that of the AMM is presented in Chapter 5.

3.2 Framework for the Efficient Localization of Mobile WSNs

This section presents the main component of the proposed framework for localizing mobile WSNs efficiently. The proposed model can solve the most significant problems in mobile WSNs by reducing the communication cost, increasing the anchor node coverage, and enhancing localization accuracy simultaneously. Figure 3.1 shows the main component of the proposed framework.

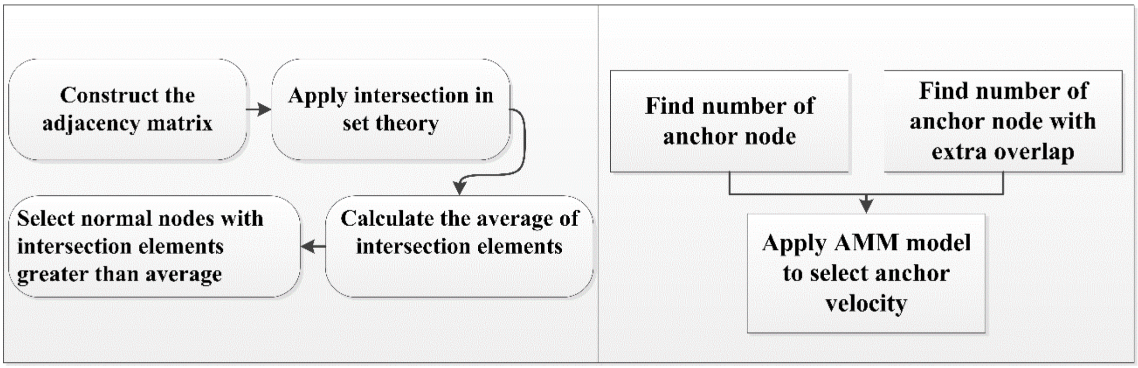

Fig 3.1.a

Fig 3.1.b

Figure 3.1 : Framework for the efficient localization of mobile WSNs.

3.3 Reducing Communication Cost in WSNs (LCC)

The network connectivity used in range-free schemes is highly affected by the number of sensor nodes used in the localization process. Thus, the use of all pieces of normal node location information maximizes the number of messages sent in the network. In such a case, each normal node needs to broadcast its location information frequently for each time slot. However, when all normal nodes of the neighborhood are used in the localization process, many messages are sent without the localization accuracy being enhanced.

To address this problem, we present in this thesis a scheme to select a number of normal nodes adjacent to the blind node with simple and smooth methods that do not necessitate the addition of complex calculations. Consequently, the proposed scheme can reduce the communication cost for the same localization accuracy as that of previous schemes. The proposed framework selects adjacent normal nodes in four steps, as presented in Figure 3.1.A.

3.3.1.1 Adjacency matrices

In general, a graph that contains many vertices is a complex graph. To cover this complexity, we employ the adjacency matrix to represent the relation between vertices in such a graph, in which adjacent vertices share a common edge and non-adjacent vertices do not. Different synonyms of adjacency matrices exist in the literature (connectivity matrix and reachability matrix).

The relation between vertices in a finite graph can be represented effortlessly in the adjacency matrix. In the adjacency matrix, the connected vertices can be assigned with the value of 1, and those that are out of range (not connected) are assigned with the value of 0. Thus, each node comprises a row that contains a full record of connected neighbors and out-of-range neighbors.

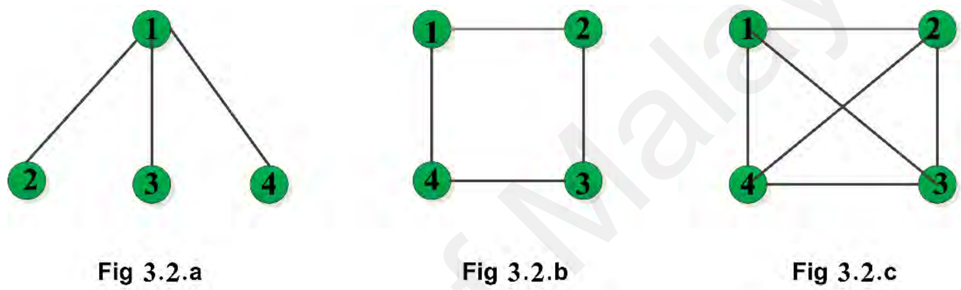

Figure 3.2 : Examples of adjacency matrices.

For simplicity, if the finite graph G has vertices n, then accordingly, we need a square adjacency matrix A with (n × n) cells, where each vertex of G is represented in a column and row. Thus, the cell Aij of such matrix contains the number of edges between vertex i and vertex j. For example, the networks in Figure 3.2 can be represented in the adjacency matrices shown in Figure 3.3. The node number 1 in the first graph in figure 3.2 has no connection with itself and has one connection with other nodes thus the value of its matrix record is (0 1 1 1).

$$\begin{bmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix} \qquad \begin{bmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{bmatrix} \qquad \begin{bmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{bmatrix}$$

Figure 3.3: Adjacency matrix for graphs presented in Figures 3.2.a, 3.2.b and 3.2.c, respectively

3.3.1.2 Set Theory

A set is a container of unordered objects sharing some common features or following the same rule; an example is a finger set = {thumb, pointer, middle, fourth, pinky}. The objects in a set are labeled as elements. The elements of a set are bounded by curly braces and separated by a comma, thus representing the main characteristics of a set. Each element is distinct; the number of elements can be finite or infinite, and elements can be arranged in any order.

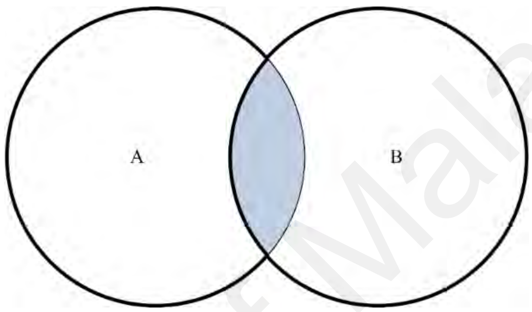

Figure 3.4 : Intersection between two shapes

In general, the intersection operation between two sets produces elements that are common in both sets. The gray area in Figure 3.4 presents the common area between shape A and shape B. In mathematics, the intersection formula between two sets is represented as $A \cap B = \{x : x \in A \text{ and } x \in B\}$. For example, if A = {e1, e2, e3, e4, e5, e6} and B = {e0, e2, e4, e6, e8}, then $A \cap B$ = {e2, e4, e6}

3.3.2 Example of the LCC scheme

As outlined in Section 3.3.1, the proposed scheme (LCC) follows this sequence of steps. First, it presents the normal nodes in an adjacency matrix. Second, it finds the intersection elements between the blind node set and the normal node set of neighbors. Third, it obtains the average of the intersection elements. Fourth, it selects the normal node with intersection elements greater than the average.

In the proposed method, the relations among normal nodes can be classified into three types, namely, out-of-range, neighbor in the first hop, and neighbor in the second hop, whose values are 0, 1, and 2, respectively. For simplicity, in the proposed scheme, we assign 1 for both types of normal nodes in the first and second hops. In the adjacency matrices, each normal node comprises a row containing its neighbors. We label this row as a considered set. After finding a set for each neighbor, we employ the intersection between the blind node set and its neighbors' sets to determine the number of intersection elements (common neighbors). Thereafter, we calculate the average of the intersecting elements. Finally, we select a normal node that shares more common neighbors with the blind node set than others. The neighbors with less than the average intersecting elements are considered to be out of range in the adjacency matrix.

Figure 3.5 presents an example of the LCC scheme. The nodes are labeled with an identity number (id). The blind node comprises a set of neighbors, B = {0, 1, 6, 7, 8, 9}, and the numbers of the intersecting elements between the blind node set and its neighbor sets are 2, 4, 2, 3, 4, and 4, respectively for id0, id1, id6, id7, id8 and id9 while node id2, id3, id4 and id5 are neighbors of neighbors of blind node B. For example, the number of intersecting elements between the blind node set, B = {0, 1, 6, 7, 8, 9}, and the neighbor set, (with id = 0) = {1, 3, 4, 5, 8}, is two: B ∩ (id = 0) = {1, 8}.

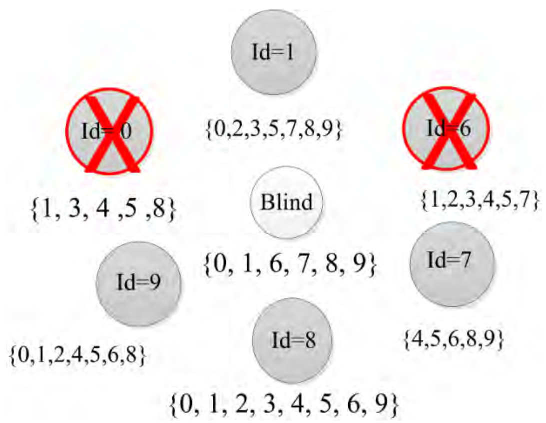

Figure 3.5 : Example of normal node selection based on the LCC scheme

The average number of intersecting elements between the blind node and its neighbors equal to three (sum of intersection element 19 / numbers of neighbors 6) = 3. Thus, nodes (id = 0, 6) have intersecting elements that are less than the average. Consequently, the relations of both nodes with the blind node are considered to be out of range. A low number of intersecting elements indicates that the two nodes are distant from each other.

For example, Figure 3.6 presents a square adjacency matrix of a network in Figure 3.5 that containing ten nodes. For more clarification, Figure 3.5 presents a network with one time slot; in this network, the blind node comprises a set of neighbor B = {0, 1, 6, 7, 8, 9}, and each neighbor comprises its own set of neighbors.

$$\begin{bmatrix} 0 & 1 & 0 & 1 & 1 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & 1 & 1 \\ 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 & 1 & 1 & 1 & 0 & 1 & 0 \end{bmatrix}$$

Figure 3.6 : Adjacency matrix of a network in Figure 3.5 with 10 × 10 cells

3.4 AMM for mobile WSN localization

Accuracy in range-free schemes is highly affected by the number of anchor nodes in the neighborhood. An anchor node broadcasts its location information for each time slot to aid blind node location estimation. However, mobile anchor nodes change their location frequently; thus, network connectivity becomes highly affected. In previous mobility models, the anchor node chooses its direction and velocity randomly that increase the overlap degree between anchor nodes and reduce anchor nodes' coverage without improving localization accuracy. To solve such problem, we propose a mobility model that adapts the anchor node velocity to the number of anchor nodes in the neighborhood and the overlap degree between anchor nodes.

3.4.1 AMM

The mobility models in WSNs can be classified into three categories, namely, random, predictable, and controlled, as presented in the previous chapter (Sahoo & Sheu, 2011) **.** Most previous schemes use the random waypoint model to transfer mobile sensor data. The waypoint model is a simple model in which a node can choose its velocity and direction randomly without any dependency. As we observed from the results of the intensive simulation experiments, the random waypoint model produces a large overlap between anchor nodes without improving localization accuracy. Moreover, we can find more than three anchor nodes in the neighborhood. Conversely, a minimum overlap is a significant issue in WSNs. A sensor node requires this overlap to maintain the coherence and rigidity of the network. Thus, two sensor nodes require 1.73R overlap as the minimum value (H. Zhang & Hou, 2005). Where R is the radio range of sensor node.

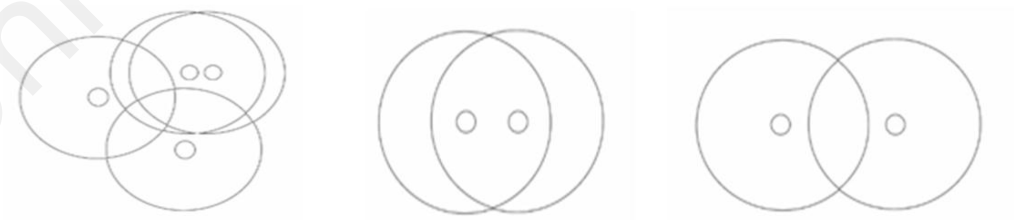

Fig.3.7.a **Fig.3.7.b** **Fig.3.7.c**

Figure 3.5 : More than three anchor nodes in the neighborhood. Figure 3.7.b Two anchor nodes with extra overlap. Figure 3.7.c Two anchor nodes with normal overlap.

Figure 3.7 presents examples of overlaps between anchor nodes in the waypoint model. To solve such a problem, we propose the AMM to adapt the anchor node velocity to the number of anchor nodes in the neighborhood and the overlap degree. The AMM first determines the number of anchor nodes in the neighborhood, the location estimation of free node requires at least three anchor node constraints in a two-dimensional and four anchor nodes in a 3-dimensional plane(Wu et al., 2013) ; if the number is greater than three, then the anchor node moves with maximum velocity. Second, the AMM determines the overlap degree between anchor nodes and then selects a velocity as a function of overlap degree. Algorithm 3.1 presents the steps of the AMM.

Algorithm 3.1. Framework of AMM localization algorithm

Initial phase:

1. Find the number of anchor node in the neighbor (NA)
2. Calculate the distance between anchor nodes in the neighbors (The overlap degree (OD))

Velocity calculation phase:

If NA >= 3 or OD <=0.25R then velocity= max_v;

Else if OD > 0.25R and OD <= 0.50R then velocity= max_v * 0.75;

Else if OD > 0.50R and OD <= 0.75 R then velocity= max_v * 0. 50;

Else if OD > 0.75R and OD <= R then velocity= max_v* 0.25;

Else if OD > R and od < =1.75 R then velocity= min_v;

If OD < 1.75R then velocity= selected randomly;

Where R is the communication range, max_ is maximum velocity and min_v is minimum velocity.

3.5 Conclusion and discussion the issues on communication cost and anchor nodes' coverage

In this chapter, a distributed framework is proposed to reduce the communication cost in the mobile WSN localization process and maximize anchor node coverage. As the first contribution of this work, the proposed scheme can select the adjacent normal nodes effectively with a simple and smooth method that does not necessitate the addition of complex calculations. The normal node selection follows these steps. First, we present WSNs in the adjacency matrix to simplify the search for neighbors. Second, we use the intersection in set theory to determine the adjacent neighbors, and we calculate the average number of intersecting elements. The normal node in the neighborhood intersecting with the blind node greater than the average is selected, and the other normal nodes are set out of range.

Previous schemes use all normal nodes in the neighborhood. Most of these schemes use the normal node in the first hop, whereas others use the normal node in the first and second hops. The use of normal nodes can enhance localization accuracy and reduce the dependency on anchor nodes. However, the use of all normal nodes in the neighborhood can increase communication cost without improving localization accuracy.

The reduction of communication cost can improve WSNs from a different aspect. The most important challenge for WSNs is the energy issue; thus, the proposed scheme prolongs network lifetime by reducing the number of messages sent in the network. Moreover, the proposed scheme can help to resolve the congestion problem in networks. In addition, it can reduce the dependency on additional hardware (GPS), including anchor nodes.

As the second contribution of this thesis, the proposed AMM can maximize anchor node coverage and increase the localization accuracy in mobile WSNs by adapting the anchor node velocity to the number of anchor nodes in the neighborhood and the overlap degree. However, anchor node coverage can improve WSNs separately. The proposed AMM can improve localization accuracy and distribute anchor nodes' location information over the whole area.

In the subsequent chapters, the results of the simulation experiments are presented in detail to verify the reliability of the proposed framework. The efficiency of the proposed scheme is improved in a mathematical analysis, and an effective parameter is tested with various values in each experiment.

CHAPTER 4: LOW COMMUNICATION COST (LCC) SCHEME FOR LOCALIZING MOBILE WIRELESS SENSOR NETWORKS

The localization problem in mobile WSNs is an interesting and a significant issue. In this chapter, a distributed range-free scheme is proposed for localizing mobile WSNs with low communication cost. We evaluate the performance of the proposed scheme (LCC) and provide insights into the performance of the proposed scheme by varying the parameter values.

The chapter discusses the data collection method for the evaluation of the proposed scheme in the simulation experiments. The purpose of this chapter is to explain the experimental setup used for testing the performance of the proposed scheme, the evaluation of parameters, the data collection, and the experiment results. Moreover, the chapter emphasizes the verification of the proposed scheme in various scenarios and the comparison of its results with those of three conventional benchmark schemes in mobile WSNs, namely, MCL, MCB, MSL*. According to the simulation results, our proposed scheme is superior to state-of-the-art localization schemes for mobile WSNs.

The sections of this chapter are arranged in this sequence. Section 4.1 introduces the chapter. Section 4.2 briefly describes the benchmark schemes. Section 4.3 presents the experiment setup. Section 4.4 presents the simulation result. Subsection 4.4.1 presents the convergence of the proposed LCC scheme. Subsection 4.4.2 presents the effect of the number of samples. Subsection 4.4.3 presents the effect of velocity. Subsection 4.4.4 presents the effect of normal nodes. Subsection 4.4.5 presents the effect of anchor nodes. Subsection 4.4.6 presents the effect of DOI. Subsection 4.4.7 presents the communication cost measurement and shows the manner in which our proposed scheme can reduce the communication cost. Finally, Section 4.5 presents the discussion.

4.1 Introduction

The LCC scheme is constructed to assist the mobile WSN framework in reducing communication cost while achieving localization accuracies that are comparable to those of previous schemes. The significance of the LCC scheme lies in the selection of adjacent normal nodes in the localization process to solve the communication cost problem in mobile WSNs. The performance of the LCC scheme is evaluated by varying the effective parameters in different networks.

The results of the simulation experiment are tested in various values to measure the effect of each parameter. The effective parameters in mobile WSNs include the number of samples, velocity, anchor node density, normal node density, and degree of irregularity. However, these parameters can directly affect localization accuracy, computation cost, and communication cost in mobile WSNs.

The performance of the LCC scheme is evaluated with respect to localization accuracy. The LCC scheme can achieve a localization accuracy that is comparable to those of the previous schemes in all experiment results. Moreover, the LCC scheme can prolong the life of WSNs by reducing the number of messages sent in the network.

4.2 Brief description of benchmark schemes

In this thesis, the range-free schemes are studied as they are more energy conserving and realistic for real-world implementation as it is unaffected by the environments. In range-free schemes a blind node can estimate location through message exchanges between nodes within an overlap area and without additional hardware.

The most prominent range-free schemes that effectively approximate the location of blind node are sequential Monte Carlo (Doucet et al., 2000) approaches such as Monte

Carlo localization (MCL) (Hu & Evans, 2004) , Monte Carlo localization boxed (MCB) (Baggio & Langendoen, 2008) and MSL* (Rudafshani & Datta, 2007b).

Generally, the location of a blind node can be estimated either from anchor node or from a combination of anchor and normal nodes. For example, MCL estimates the location of blind node using its anchor nodes in neighbors. However, the accuracy of the scheme depends on the density of anchor nodes; thus, the error of location estimation increases as the density of anchor nodes decreases. The process of MCL is described in three steps as we present in chapter two: the initial step, the prediction step, and the filtering step. Overall, the MCL improves the localization accuracy but suffer from high density of anchor node and low sampling efficiency.

To improve the sampling efficiency in MCL, MCB (Baggio & Langendoen, 2008) uses anchor boxes, which are square boundaries drawn around the anchors. The estimated location sets are constructed using random samples from the rectangle intersection area between the current time (t) and the previous time slot ($t - 1$). The anchor location information set is used in both prediction and filtering steps. Although MCB effectively minimizes probability of selecting inappropriate samples, it still experiences the same localization error as in MCL and apply the same filtering constraint.

The dependency on the anchor nodes in both previous schemes in estimating blind node location can be reduced with utilization of both anchor and normal nodes as in MSL*. As a result, size of sample sets and number of parameters are adapted, and energy and cost are saved. Nevertheless, MSL* approach increases the communication cost in the existing WSNs.

Therefore, Low Communication Cost (LCC) scheme for localizing mobile WSNs is proposed to reduce communication cost but maintain a localization accuracy comparable to MSL*. In the proposed LCC scheme, neighbor nodes are selected based on the number of the intersecting elements between the neighbor nodes and the blind node instead of using all the neighbor nodes as in MSL*.

4.2.1 MSL* scheme

MSL* estimates a blind node location through a set of weighted samples drawn from neighboring anchor and normal nodes in the first and second hops. The quality of a sample is based on its weight. The samples with high weights are chosen to estimate a blind node location. Anchor node samples always have high weights, whereas normal nodes have partial weights ranging from 0 to 1. MSL* location estimation is divided into three stages.

Initial stage: In this stage, sensor nodes are distributed randomly in the area and the sample set is constructed randomly from the whole area. The samples are then weighted according to the anchor node samples within their range. The localization accuracy in this stage is lower than in staple stage where the blind node can find enough location information from anchor nodes and normal nodes in the staple stage.

Sampling stage: In this stage, the blind node constructs a set of new samples by drawing new samples based on pervious sample bounded by maximum velocity. The movement of the mobile nodes per each time slot is function of velocity, consequently, the sensor node moves based on the following transition equation (Eq 4.1):

$$p(S_t|S_{t-1}) = \begin{cases} \frac{1}{\pi(Vmax + \alpha)^2} & if\ d(S_t, S_{t-1}) \leq Vmax \\ 0 & if\ d(S_t, S_{t-1}) \geq Vmax \end{cases} \quad \text{(Eq 4.1)}$$

where (V_{max}) represents the maximum speed of the node from point to point and $d(S_t, S_{t-1})$ represents the distance between nodes at time (t) and the previous time ($t - 1$). In each time slot, a new sample set is constructed randomly within a circle radius ($V_{max} + \alpha$) centered at the coordinates of a previous sample. For a static case, parameter α with a value of $\alpha = 0.1R$, where R is the circle radius of the transmission range, is used.

Resampling stage: In this stage, the elements of the current sample set are reconstructed based on the sample weight. Samples with high weights are retained, whereas samples with low weights are removed.

The weight of a node sample is based on the location estimation of its neighbors. A node selects neighbors according to their adjacency values as in the equation (Eq 4.2). Adjacency is the average of the distances between all valid samples and the estimated blind node location. The adjacency value for the anchor node is always 0, and the adjacency values of the normal nodes are between 0 and 1.

$$adjacency_p = \frac{\sum_{i=1}^{N} W_i \sqrt{(x_i - x)^2 + (y_i - y)^2}}{N} \qquad \text{(Eq 4.2)}$$

Where N is sample number of node p, (x_i, y_i) are the i-th sample coordinates (i = 1, ..., N), (W_i) is sample weight, and (x, y) is estimated location of node p at the current time.

4.2.2 Differences between proposed scheme LCC and MSL*

The main idea of MSL* (Rudafshani & Datta, 2007a) is to estimate the location of blind nodes by drawing samples from the anchor nodes and all normal nodes among the first-hop and second-hop neighbors. Normal nodes are used to improve localization accuracy and reduce dependency on the anchor nodes. The use of all normal nodes in MSL* highly increases communication cost without improving location estimation accuracy due to redundant and low-weight samples as we explain in the previous chapter.

In the filtering stage, MSL* uses a adjacency value to weight samples. A low adjacency value indicates that the node has a low localization error. Thus, the blind node can use the adjacency value to weight its samples. The use of adjacency values can minimally reduce communication cost in the filtering stage when high-weight samples are selected. The LCC scheme can reduce communication costs by selecting normal nodes that share a more common neighbors with a blind node before the location estimation process, which starts by redefining the relation between a blind node and its neighboring normal nodes.

LCC improves MSL* by drawing an estimated location set from both anchor and normal nodes. It selects a number of normal nodes within the first- and second-hop neighbors. LCC selects a number of normal nodes in neighbors to achieve localization accuracy with minimum dependency on anchor nodes and lower communication cost. The selection is based on the common elements between the blind node set and its neighbor sets and unlike in MSL* which considered all neighboring normal nodes.

The proposed approach is expected to have a localization accuracy comparable with that of MSL*. Additionally, LCC has a major advantage over MSL*, that is, lower communication costs across different parameter ranges. Moreover, LCC approach present a distributed framework to find the adjacent neighbors in the simple and lightweight method.

4.3 Experimental Setup

This section present the methodology used from evaluation of LCC scheme. The general performance of LCC scheme was achieved through intensive simulation. We discuss the experimental setup, convergence of LCC, communication cost of LCC. The localization accuracy is measured in effective parameters, number of samples, velocity, an anchor node density, a normal node density, and the degree of irregularity.

In this study, MCL, MCB and MSL* are simulated using the simulator code obtained from Hu and Evans (Hu & Evans, 2004), Aline Baggio and Rudafshani (Rudafshani & Datta, 2007a), respectively. The proposed LCC is implemented in MSL*, and the original parameters are retained.

4.3.1 Experimental parameters

The proposed scheme is tested in a simulation executed 50 times. The location estimations of all sensors were reset to the same values in each simulation. The parameters in LCC were set to the same values as those parameters in MSL*. Sensor nodes were randomly distributed in a bounded square of 500 units × 500 units. The radio transmission range for all nodes was set as a perfect circle with a radius (R) of 50 units. The node density (N_d) is the mean density of the normal nodes and the anchor nodes in the neighborhood of a node, whereas the anchor node density (A_d) is the mean density of the anchor nodes in the neighborhood of a node. In our experiment, we use default values for anchor node density (A_d = 1), normal node density (N_d = 10) and velocity (V_{max} = 0.20R), and the number of sample sets was 50 unless otherwise specified. Sensors move according to a modified *waypoint* model (Tracy Camp et al., 2002) in which the time paused is 0 (Hu & Evans, 2004; Yoon et al., 2003b).

4.3.2 Node communication

WSN location is constructed from a set of nodes N, which are distributed randomly in a two-dimensional *Euclidean* space (E2). The space is presented as a bounded flat surface area in E2 if any boundary exists. When nodes overlap with each other, the Euclidean distance d (node g, node h) between each pair of nodes can be derived by applying RSSI (Alippi & Vanini, 2006a; C. Liu et al., 2004). The node coordinates are a pair of dimension axes using the values x and y. Each sensor has a full circle of radio range with a radius R. However, a sensor can also use a heterogeneous radio range.

In the initial stage, sensor nodes are spread randomly throughout the network region E2. The node movements per time slot according to the modified random waypoint mobility model (T. Camp, J. Boleng, & V. Davies, 2002) are used in MCL and MSL*. In a waypoint model, the movement direction and speed of a node in a time slot are considered. Time is divided into static slots and has the maximum speed (V_{max}); speed varies from 0 to V_{max}.

4.4 Simulation results

In this section, LCC, MSL*, MCB and MCL are compared at various network settings. The simulation results are presented in the following sequence to show convergence time of LCC, communication costs and accuracy.

4.4.1 Convergence time of LCC scheme

The variation in the convergence of LCC at various speeds and anchor node densities is presented in Figure 4.1 and 4.2. The location estimation error decreases in initial state until the error converges where the error slightly changes around a constant value in the stable state. In the stable stage, the variation of network connectivity caused by movement of sensor can be dominated by large number of observation in the network. The error under a static condition rapidly converges because the node has the same location when it receives a new observation. In contrast, in the high velocity mobile sensors change locations per time unit, and new observations can be drawn from each of these locations.

Generally, a new observation can improve localization accuracy and reduce localization error. This concept is suitable for low- and medium-speed observations with an exception for high-speed observation. The localization accuracy in low velocity can be enriched by using high number of previous sample in last time slot. While, the observation in the previous time slot does not improve the localization of high-speed moving sensors.

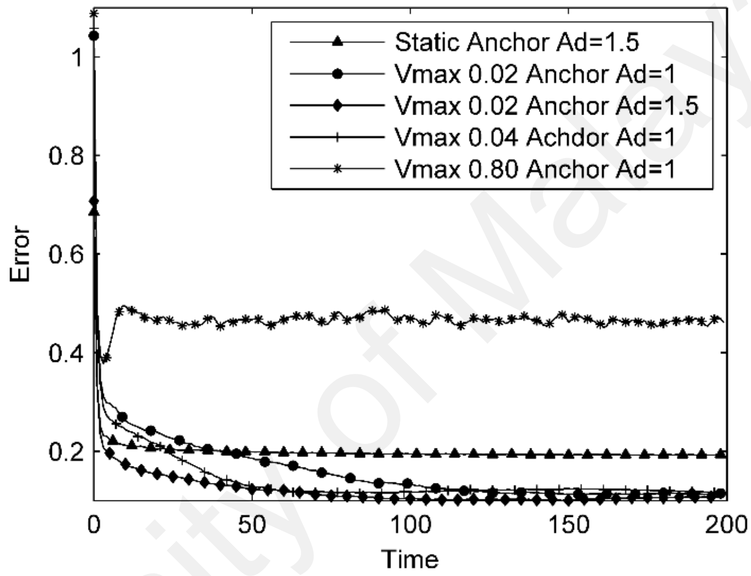

Figure 4.1 : Localization error and speed values of LCC in different mobility cases

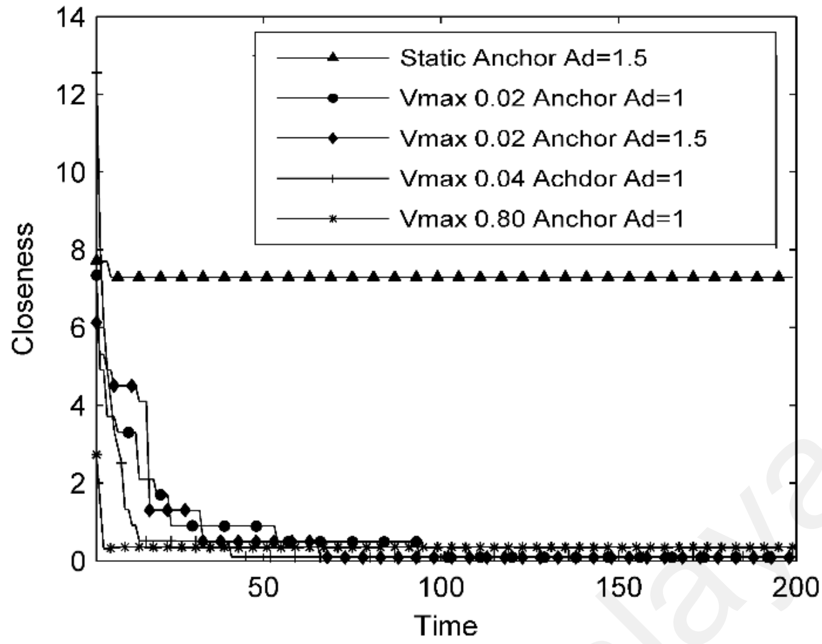

Figure 4.2 : Relation between adjacency and speed of LCC in different mobility cases

In our experiment, the localization error and the value of adjacency have quickly converged because the LCC scheme received samples from normal nodes with more common neighbors the same as those of a blind node. The low value of the adjacency indicates high quality and the high value indicate low quality of samples. The adjacency value is calculated according to the equation (Eq 4.2). This result validates the concept presented in previous chapter, that is, selecting normal nodes that share more common neighbors with a blind node reduces localization error and communication costs.

4.4.2 Effect of sample size

Generally, a *Monte Carlo* localization technique use the average of valid samples to estimate the locations of blind sensors. A considerable number of valid samples require more memory and computation time; however, a low number of samples are inadequate to estimate the blind sensor location. Therefore, the optimum number of samples should be obtained to estimate the blind sensor location (Doucet et al., 2000). Through simulation, LCC is implemented using various numbers of samples, as shown in Figure

4.3, From the LCC simulation results and the results of MCL, MCB and MSL*, 50 samples are considered adequate in estimating a blind node location in LCC, MCL, MCB and MSL*.

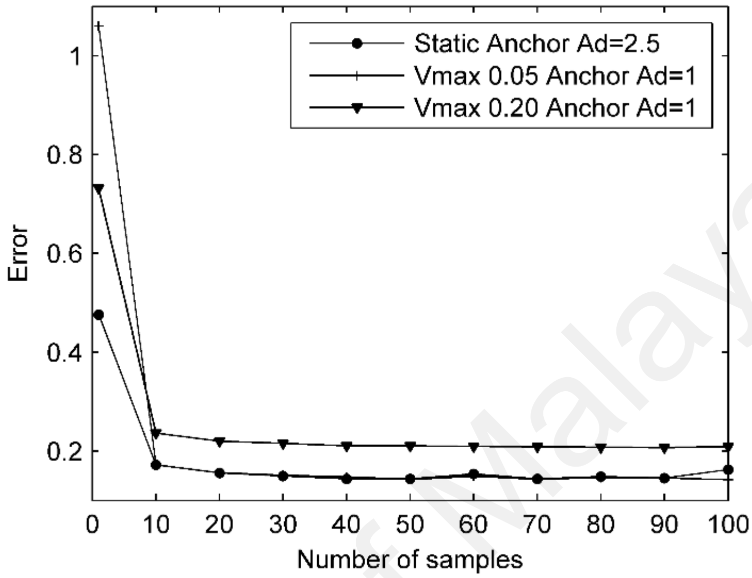

Figure 4.3 : Effect of sample size in LCC

4.4.3 Impact of sensor node velocity

Figure 4.4 shows the simulation results of LCC, MSL*, MCL and MCB at various sensor node velocities. The movement of the sensors can improve localization accuracy by visiting more areas, increasing observations number, and obtaining new samples. However, when sensors move at a high speed, the location information at the previous time is no longer applicable. Thus, the localization error increases.

Figure 4.4 shows that the optimum maximum speed for LCC, MSL*, MCL and MCB schemes is 0.20*R,* where R is the radio range. Thus, this value is used as the default setting in the present experiment unless another value is assigned.

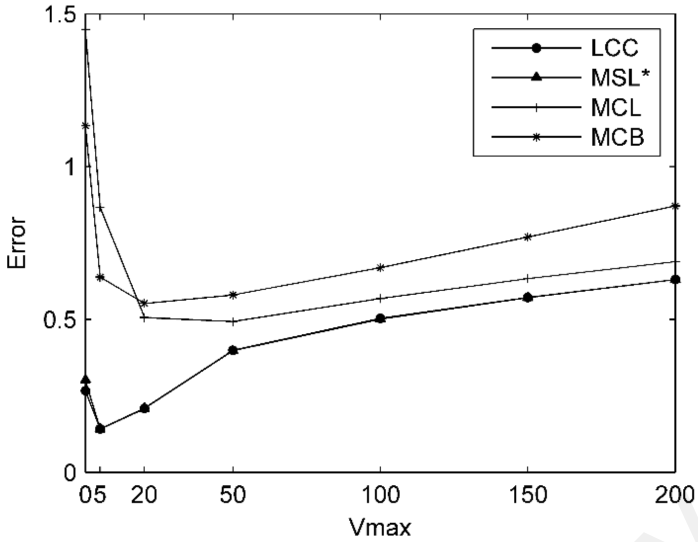

Figure 4.4 : Effect of the sensor node speed on localization

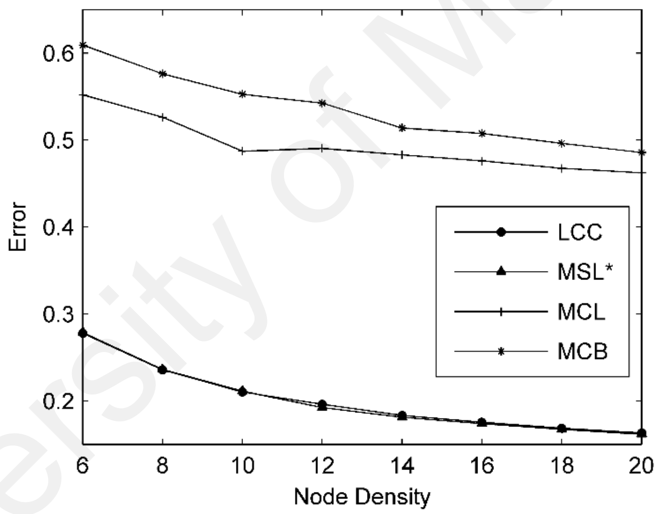

Figure 4.5 : Effect of normal node density

4.4.4 Impact of normal nodes density

The simulation results presented in Figure 4.5 are obtained when the normal node density varies whereas the anchor node density is fixed, the node density (N_d) is the mean of the normal nodes and anchor node in the one hop. The location estimation error in MCL and MCB decreases slightly with an increase in normal node density because the normal node can communicate with more anchor nodes in the first and second hop (He, Huang, Blum, Stankovic, & Abdelzaher, 2003; Nagpal, Shrobe, & Bachrach, 2003). This reduction in location estimation error is twofold in LCC and MSL* with an increment in normal node density. Each blind node in LCC and MSL* has more neighboring normal nodes in their first and second neighborhoods. Thus, a blind node obtains more location information; consequently, the location estimation error is reduced. The use of normal nodes in the localization process beside it can improve the localization accuracy it can also reduce the dependency of anchor nodes by broadcasting its location information to neighbors. Thus the mobile WSNs can conserve the power and become self-dependent.

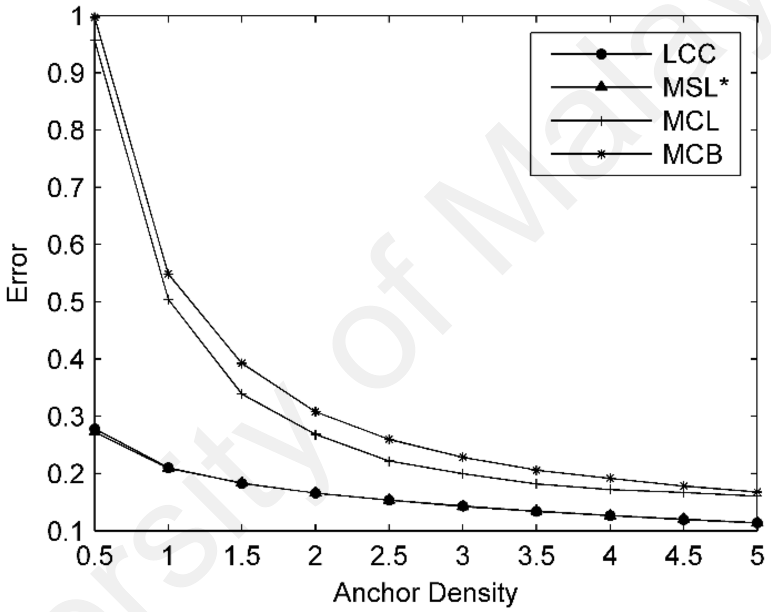

Figure 4.6 : Effect of anchor node density

4.4.5 Impact of anchor node density

In Figure. 4.6, the anchor node density increases, whereas the normal node density is constant, the anchor node density (A_d) is the mean of the anchor nodes in the neighborhood of a node. Increasing anchor node density per time slot has impacted the performance of all schemes. MCL and MCB benefits the most from this increment because both MCL and MCB only uses anchor location information to determine a blind node location. LCC and MSL* are less affected by anchor node density than MCL and MCB because they both normal and anchor nodes are used in LCC and MSL* to estimate a blind node location. As shown in Figure 4.6, the simulation results demonstrate that using a small number of anchor nodes in the LCC is sufficient to estimate a blind node location. However, the dependency of anchor nodes increases the cost and wasted power in networks.

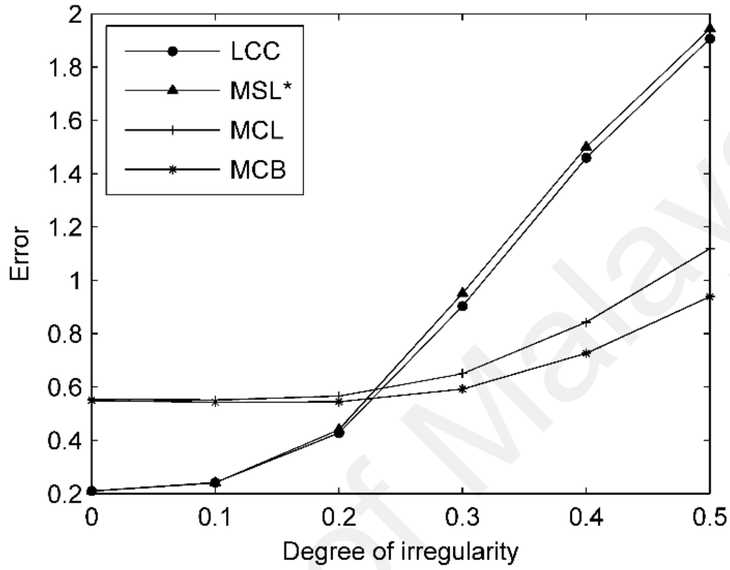

Figure 4.7 : Effect of degree of irregularity

4.4.6 Impact of irregularity in radio range:

Using perfect circles denoted by R in radio transmission during the simulation cannot express the actual value of radio transmission. Therefore, the degree of irregularity (DOI) is applied to measure the variation in the range and direction of radio transmission. For example, the actual range and direction of radio transmission can randomly vary within the range [$0.7R$, $1.3R$] when DOI = $0.03R$. The variation in DOI obtained in the simulation is depicted in Figure. 4.7, which indicates that a high variation in the range and direction of radio transmission can increase localization errors. The simulation results show that all schemes are negatively affected as DOI increases. Thus, in the real-world implementation of WSN, DOI is more critical than other obstacles due to environmental conditions and antenna irregularities.

4.4.7 Communication cost of LCC

Communication overhead is measured according to the number of messages sent by a sensor in each step of location estimation (Hu & Evans, 2004). The number of messages varies across location estimation schemes. The number of messages sent in both MCL and MCB is equal to the number of anchor nodes while in MSL* is equal to the number of anchor and normal nodes multiplied by the sample number, which is by default 50 samples in this study. The number of messages sent in LCC is set to the total number of anchor and normal nodes that have more common neighbors with a blind node. Thus, the number of messages sensor nodes should send is reduced in LCC.

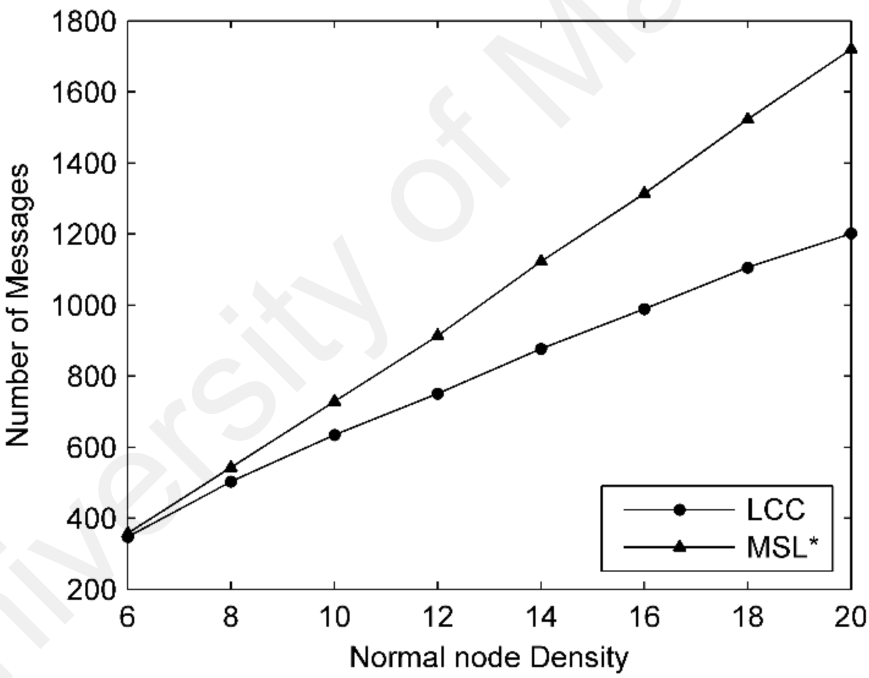

Figure 4.8 : Effect of normal node density on the number of exchanged messages in the LCC and MSL* schemes.

Figure 4.8 shows the correlation between the normal node density and the number of messages sent. The LCC scheme has a lower number of messages sent than MSL* as the node density increases. As Figure 4.8 shows LCC have low number of messages send when increased normal node density while the number of messages in MSL* highly affected by increasing normal nodes density.

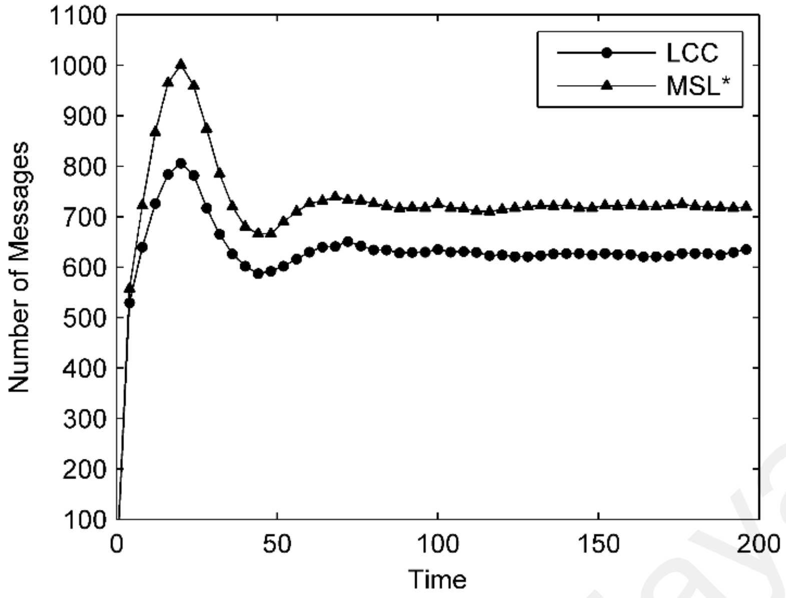

Figure 4.9 : Number of exchanged message sent in speed 0.2R.

In the total, LCC sends a lower number of messages at a time than MSL*, as shown in Figure 4.9. In both Figure 4.8 and 4.9, both MCL and MCB are excluded in the analysis of number of messages sent because of an inaccurate comparison. As the number of messages sent by MCL is equal to the number of anchor nodes only, MCL and MCB will always generate the smallest number of messages sent at all times.

Resources, memory, and processing time are required each time a message is sent in the networks. The computation and communication costs are low if the number of messages is minimal. According to the results, a small number of messages are sent over time in LCC. Therefore, LCC is expected to reduce communication costs, save energy, and work with manageable resources.

4.5 Discussion

We presented a distributed localization scheme to reduce the communication cost in mobile WSNs. Our proposal is scalable, self-adaptive and robust to dynamic WSNs. Our proposed scheme can reduce the communication cost by utilizing simple and lightweight method. The extensive simulation results of LCC scheme show that the proposed scheme is superior state-of-art scheme in reducing the communication cost.

The main concept of the LCC scheme is to use a normal node instead of relying solely on anchor nodes to improve location estimation. This scheme works by discovering more overlapping areas to improve localization accuracy. Therefore, a blind node can construct its location estimation set from both anchor and normal nodes within the overlap area. A large overlap area will negatively affect the location estimation accuracy. This condition is particularly observed when all normal nodes are used in localizing a blind node position. When a small number of normal nodes are employed, the small overlap area is insufficient for drawing samples.

In this study, we used normal nodes to estimate a blind node location beside a limited number of anchor nodes as in the MSL* scheme. However, MSL* requires high communication cost. Therefore, we improved the MSL* by selecting a number of normal nodes that is adjacent to a blind node. Then, we find their adjacency value through the number of common neighbors between a blind node and its neighboring normal nodes.

In all simulation scenarios, the accuracies of LCC and MSL* in locating the blind node are comparable. However, LCC entails lower communication costs because a lower number of messages are sent over time. The sample size, velocity, anchor node density, normal node density, and degree of irregularity mainly affect localization accuracy in mobile WSNs.

Drawing a sufficient number of valid samples is critical for the Monte Carlo scheme. However, drawing a high number of samples requires more energy without improving the accuracy. Therefore, a simulation is performed to find the optimum number of valid samples. The simulation results show that a sample size of 50 samples is the optimum; thus, it was the default value used in MCL, MCB, MSL*, and LCC. Moreover, the simulated results show that even a limited number of samples are sufficient in LCC to estimate a blind node location accurately.

Mobile sensors can receive more observations; thus, localization accuracy can be increased by visiting new areas. However, this mechanism holds true only if the mobility of the node is at low and medium speeds. Therefore, improving the accuracy of LCC in high-speed cases can be explored in future studies.

The variation in anchor node density has minimal effect on MSL* and LCC because both used normal and anchor nodes to estimate a blind node location. By contrast, MCL and MCB are significantly affected as the density of the anchor nodes decreases because of the high dependency on anchor nodes when estimating a blind node location.

Increasing normal node density has improved localization accuracy of blind nodes and reduced dependency on anchor nodes. In MSL*, each normal node needs to send its samples in each time slot. Therefore, the number of samples sent is highly affected when normal node density increases. The number of samples sent is reduced by selecting the adjacent normal nodes to estimate a blind node location. The selection reduces communication costs but maintains the same localization accuracy in all cases. Communication cost (i.e., the number of messages sent) is reduced by a minimum of 0.02, a maximum of 0.30, and an average of 0.18 at different normal node densities ranging from 6 to 20.

The degree of irregularity affects all schemes. A slight irregularity in the range and direction of radio transmission can easily increase localization error. By contrast, more controlled increments in errors are observed in MSL* and LCC. Both schemes increase the number of overlapping areas and the size of the overlap area to accommodate the variation in the range and direction of radio transmission.

In the next chapter, we will present a mobility model to increase the converge area of anchor nodes and enhance the localization accuracy as will.

CHAPTER 5: ADAPTIVE MOBILITY MODEL (AMM) FOR ACCURATE LOCALIZATION IN MOBILE WIRELESS SENSOR NETWORKS

The mobility model problem for mobile WSNs is an interesting and a significant issue in the localization process. This chapter proposes a distributed mobility model for localizing mobile WSNs with high accuracy. We evaluate the performance of the proposed AMM and provide insights into the performance of the model by varying the parameter values in various networks.

The chapter discusses the data collection method for the evaluation of the proposed model in intensive simulation experiments. The purpose of this chapter is to explain the experimental setup used for testing the performance of the proposed model, the evaluation parameters, the data collection, and the experiment results. Moreover, the chapter emphasizes the verification of the proposed model in various scenarios and the comparison of the results of the proposed model with those of conventional benchmark models in mobile WSNs, namely, the random waypoint model and the RPGM model. According to the simulation results, our proposed model is superior to the state-of-the-art localization schemes for mobile WSNs.

The chapter is arranged as follows. Section 5.1 introduces the chapter. Section 5.2 brief description of mobility model benchmark. Section 5.3 performance evaluation. Subsection 5.3.1 experimental setup. Subsection 5.3.2 experimental parameters. Section 5.4 Experimental Results. Subsection 5.4.1 presents the Coverage of AMM model. Subsection 5.4.2 Localization Accuracy. Subsection 5.4.2.1 presents the effect of anchor nodes. Subsection 5.4.2.2 presents the effect of normal nodes. Subsection 5.4.2.3 presents the effect of velocity. Subsection 5.4.2.4 presents the effect of DOI. Finally, section 5.5 present the discussion.

5.1 Introduction

The AMM is constructed to assist the mobile WSN framework in increasing the coverage area of anchor nodes while achieving localization accuracies that are comparable to those of previous schemes. The significance of the AMM lies in its capacity to adapt anchor node velocity to the overlap degree and the number anchor nodes in the neighborhood to solve the coverage problem of anchor nodes and improve localization accuracy. The performance of the AMM is evaluated by varying the effective parameters in different networks.

The results of the simulation experiment are tested in various values to measure the effect of each parameter. The effective parameters in mobile WSNs include velocity, anchor node density, normal node density, and degree of irregularity. However, these parameters can directly affect the localization anchor nodes' converge, localization accuracy, computation cost, and communication cost in mobile WSNs.

The performance of the AMM is evaluated with respect to localization accuracy and anchor node coverage. The AMM can maximize anchor node coverage and improve localization accuracy in all experiment results.

5.2 Brief description of mobility model benchmark

The high-speed movement of sensor nodes rapidly changes the topology in mobile WSNs (M. Li, Li, & Vasilakos, 2013). Therefore, the mobility model highly affects the coverage and connectivity, as well as prolongs the life of WSNs (Tracy Camp et al., 2002). Generally, mobility models can be categorized as random, predictable, and controlled. The detailed comparisons, strengths, and challenges of the mobility models in the literature are discussed in (Cortes, Martinez, Karatas, & Bullo, 2002; Natalizio & Loscrí, 2013).

An adequate coverage area with at least one sensor node is a critical issue in WSNs. This issue is mainly because of the movement of sensors that affect the coverage area in two ways. The optimistic way transfers the mobile sensor to more discovered areas, communicates with the isolated sensor, and extends network life (Akkaya, Senel, Thimmapuram, & Uludag, 2010). However, nodes in static networks use the same routing path to communicate with the sink, which consumes more power of sink neighbors and causes a split between the network and isolated sink node (Anisi, Abdul-Salaam, Idris, Wahab, & Ahmedy, 2015). The negative approach of the movement originates from the data lost in the handover process when the network disjoints into two parts. Moreover, sensors with high-speed movement can frequently disconnect and decrease network performance and stability.

The waypoint model permits the mobile sensor to move forward independently from its neighbors and its previous position. Hence, the movable sensor chooses its direction and velocity randomly without any correlation to its neighbors (Han et al., 2013). Such flexibility fails to represent the real situation of the system in various applications, such as speed of vehicles, disaster relief, battlefield, and other applications. A reason is that a level of dependency occurs between the velocity of the nodes in the neighbors (Pong & Moors, 2006; M. Zhao & Wang, 2009). Another drawback of the waypoint model is the convergence of nodes adjacent to the center of the simulation area (Hong et al., 1999), which decays the velocity of the respective nodes (Bettstetter, Hartenstein, & Pérez-Costa, 2004; Nunes & Obraczka, 2014).

In the previous literature, the waypoint model was typically used in range-free localization schemes (Tracy Camp et al., 2002). In the waypoint model, the sensor node just knows the maximum and minimum velocities; hence, it has a weak memory, and this simplicity led to its use in most of the previous studies. Pause time is an important parameter in the waypoint model (Yoon et al., 2003b). In the AMM and waypoint model, the pause time is set to zero, in which the sensor nodes move continuously without pausing time.

The sensor node moves with high dependency on the reference point or as a leader in the reference point group mobility model (RPGM). However, the election of the leader requires a long process, and the loss of the leader will affect the robustness and stability of the networks. Another issue in the RPGM is that each sensor node must request the leader for direction and velocity of movement in each time slot (Han et al., 2013), which causes an increase in communication cost in the networks and overhead for the leader. Therefore, RPGM is appropriate for specific applications, such as museum visitors and conference members.

The unbalanced distribution of sensor nodes in the random waypoint mobility model and RPGM increase the overlap between anchor nodes without improving localization accuracy. Based on this observation, we proposed an adaptive mobility model to control the movement of the anchor nodes based on the number of anchors in the neighbors and the degree of overlap between the anchor nodes (Imran, Younis, Said, & Hasbullah, 2012) as presented in chapter 3.

5.2.1 Differences between AMM and previous model waypoint and RPGM models

In most range-free models, the movement of the mobile sensor is inspired by the waypoint model because of its simplicity, but this simplicity causes a large overlap between anchor nodes without improving the localization, as observed in the simulation results. The AMM model can improve the localization accuracy and maximize the coverage area with the same number of anchor nodes in the waypoint model. Moreover, the AMM model can work in a distributed manner, whereas RPGM requires following the leader direction and velocity, which restricts its functionality for specific applications.

The simulation results show that the AMM model can improve the localization accuracy by 5%, reduce the extra overlap between the anchor nodes to 50%, and maximize the coverage area with the same number of anchor nodes in distributed manner.

5.3 Performance Evaluation

This section present the methodology used from evaluation of AMM model. The general performance of AMM model was achieved through intensive simulation. We discuss the experimental setup, convergence of AMM. The localization accuracy is measured in effective parameters, velocity, an anchor node density, a normal node density and the degree of irregularity.

5.3.1 Experimental Setup

In this study, MCL, MCB and MSL* are simulated using the simulator code obtained from Hu and Evans (Hu & Evans, 2004), Aline Baggio (Baggio & Langendoen, 2008) and Rudafshani (Rudafshani & Datta, 2007a), respectively. The proposed AMM is implemented in MCB, and the original parameters are retained.

In these experiments, the MCB scheme was selected to measure the performance of AMM because this scheme uses only anchor nodes observation in the localization process. The MCB scheme also has an advantage over MCL in sample efficiency. Other schemes use both anchor and normal nodes to improve localization accuracy. However, the use of normal nodes can increase communication costs in the networks and the overhead because of frequent location changes. For these reasons, MCB was selected to measure the coverage of AMM.

5.3.2 Experimental parameters

We test the AMM model in MCL, MCB, MSL*, WMCL, and WMCLB schemes with various simulation parameters to verify its efficiency. The simulation of MCL, MCB, and MSL* are received from the original authors, whereas WMCL and WMCLB are implemented in the Java-based simulator. The normal nodes were set to move randomly based on the waypoint model and the anchor nodes were set to move based on the AMM model. Anchor node density (Ad) is the number of anchor nodes in the first and second hops, whereas normal node density (Nd) is the number of anchor and normal nodes in the first hop.

The performance of AMM model measured within three significant parameters: the degree of overlap between anchor nodes, the density of anchor nodes, and the velocity of the anchor node. The impact of each parameter is measured in localization accuracy by several simulation tests. The appropriate parameter values are selected and applied in the simulation. We evaluate the distance between anchor nodes in five periods as presented in chapter 3.

In this experiment, the value of each parameter is calculated by executing 30 networks randomly. We simulated 1,000 time units in each network, and then the time unit was averaged between 600 and 1,000 to assess each value. Each data point presented in this study was averaged by 30 independent experiment results. Other important parameters used during the simulation were the boundary of simulation area, which was set as 500 unit*500 unit, and the communication range (R) for anchor and normal nodes at 50 units. Time is a discrete time unit. In the initial setup, all sensors were distributed randomly over the simulation area. The pause time is set to zero, max_v is 0.2R, the number of samples is 50, Ad = 1 and Nd =10, and the minimum overlap is 1.73R.

5.4 Experimental Results

The experimental results are described in two sub-sections. The first sub-section describes the coverage of the AMM model in different overlap degrees and different anchor node densities. The second sub-section explains the measurement value of location accuracy in different velocity values, anchor nodes, normal nodes densities, and degrees of irregularity.

5.4.1 Coverage of AMM model

The degree of overlap is measured by Euclidean distance, in which the small value of this similarity measure implies a large overlap between the anchor nodes and vice versa. For example, a distance value lower than 0.1R indicates a substantial overlap, whereas a distance value small than 1.73R indicates the smallest overlaps (H. Zhang & Hou, 2005).

The threshold value of the overlap degree is a fundamental issue in WSNs because communicates and maintains network stability. In this study, the threshold value of the overlap was set as in previous research 1.73R (H. Zhang & Hou, 2005).

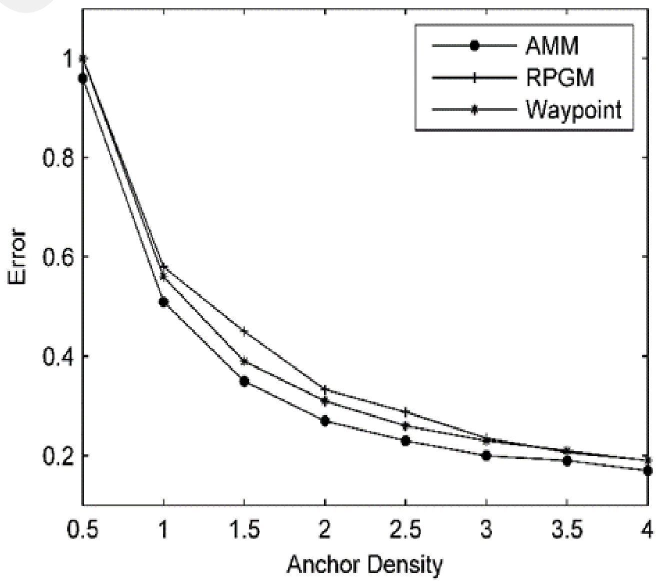

Figure 5.1 : Anchor node density and localization error.

Figure 5.1 shows that AMM is capable of improving localization accuracy in all cases by minimizing the overlap between the anchor nodes. The large overlap between anchor nodes means there are more than three anchor node in the neighbors or there is small distance between two anchor nodes, thus the large overlap between anchors minimize the coverage area and waste more energy without increasing the localization accuracy. Hence, the anchor nodes are distributed equitably to cover additional areas with the same number of anchor nodes. Moreover, the increment of anchor node density improves the localization accuracy of all mobility models.

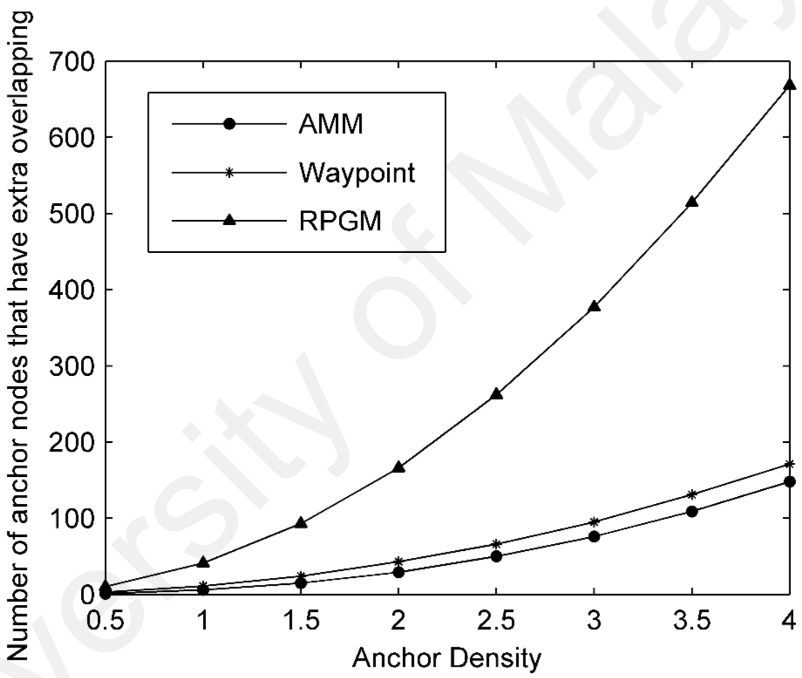

Figure 5.2 : Relationship between anchor density and a number of anchor nodes with extra overlap.

The possibility of occurrence of a large overlap between the anchor nodes increases when the density of anchor nodes increases, as shown in Figure 5.2. However, AMM uses adaptive velocity with the overlapping degree to minimize these overlaps and maximizes the coverage area with the same number of anchor nodes when compared with the waypoint model. The unbalanced distribution of anchor nodes in the waypoint model maximizes the number of anchor nodes that have extra overlap. The RPGM model is also highly affected by the increased anchor node density because the velocity and direction of the nodes are maintained based on the leader decision. This effect causes a large overlap between the anchor nodes.

Table 5.1 : Localization accuracy in different schemes.

Mobility Model	Localization scheme				
	MCL	**MCB**	**MSL***	**WMCL**	**WMCLB**
RPGM	0.55	0.5	0.4	0.48	0.39
Waypoint	0.56	0.5	0.3	0.38	0.40
AMM	0.51	0.5	0.2	0.34	0.35

Table 5.2 : Number of anchor nodes with extra overlap.

Mobility Model	**Localization scheme**				
	MCL	**MCB**	**MSL***	**WMCL**	**WMCLB**
RPGM	41	41	42	42	41
Waypoint	10	11	10	10	10
AMM	6	6	6	5	6

Different schemes (MCL, MCB, MSL*, WMCL, WMCLB) are used to examine the efficiency of the AMM model. The performances of these schemes are listed in Table 5.1. The performance of the AMM model attained the highest localization accuracy among the tested schemes, with an overall improvement of 5%.

Table 5.2 presents the number of anchor nodes with extra overlap degree, in which AMM reduced the number of anchor node with extra overlap degree in each time slot by 50% while maximizing the coverage area as compared to the waypoint model. The RPGM model has the highest number of extra overlap degree in all cases.

5.4.2 Localization Accuracy

Localization accuracy is measured in localization schemes: WMCLB, MSL*, MCB and MCBAMM based on the following parameters: anchor node density, normal node density, velocity, and degree of irregularity. The MCBAMM evaluate MCB scheme based on AMM model.

5.4.2.1 Anchor node density

In Figure 5.3, the localization accuracy of MCBAMM and MCB improved quickly by increasing anchor nodes density because they draw observations primarily from the anchor nodes. Other schemes that draw observations from the anchor and normal nodes, such as MSL* and WMCLB, are less affected by the increment of anchor node density. Nevertheless, the increment of anchor node density can be reflected negatively in the power consumption and dependency on hardware such as GPS.

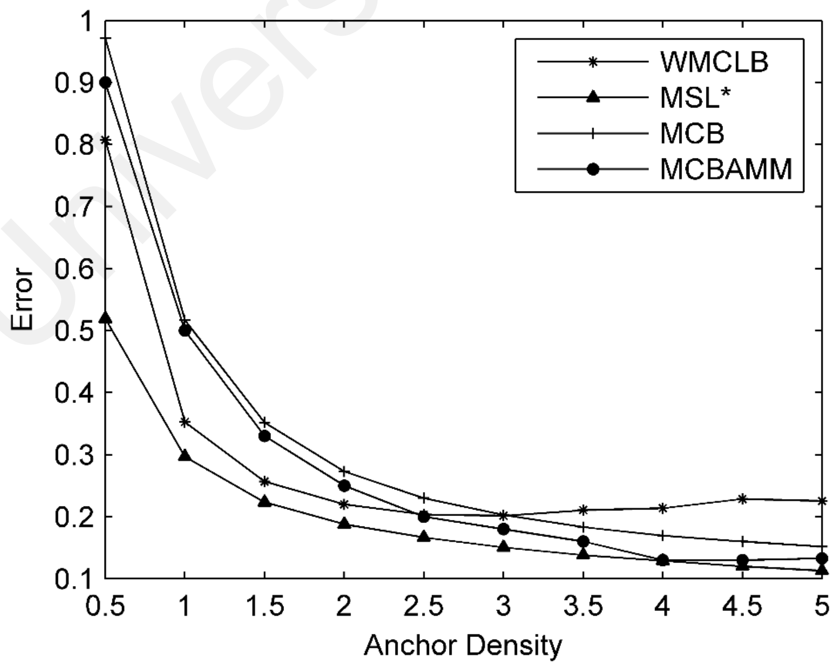

Figure 5.3 : Accuracy and anchor node density.

5.4.2.2 Normal node density

Localization accuracy improved with the increment of normal node density with various percentages, as shown in Figure 5.4, MCBAMM and MCB improved with the low percentage by broadcasting the location information of anchor nodes to the first and second hop sensors in the neighbor. However, MSL* and WMCLB are the most affected because they draw observations from both anchor and normal nodes in the neighbors. MSL* is more effective because it uses all normal nodes in the first and second hops to draw observations with high communication costs. WMCLB uses normal node location information to improve sampling efficiency and filter out the invalid samples, and is more sensitive to changes in normal node density.

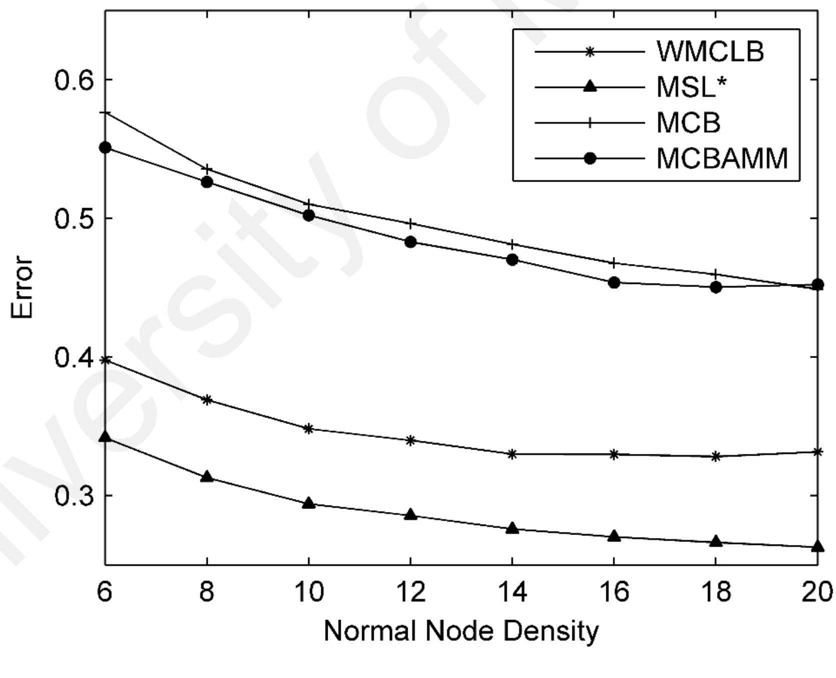

Figure 5.4 : Accuracy and normal node density.

5.4.2.3 Velocity of nodes

Results in Figure 5.5 show that sensor nodes movement can improve the localization accuracy by receiving new anchor nodes and finding more observations. Movement with limited velocity can improve the localization accuracy as presented in Figure 5.5. A high-velocity sensor can move to a farther distance from the previous location, thereby reducing localization accuracy. Figure 5.5 shows that all schemes have high accuracy at velocity 0.20R. This value is used throughout this study.

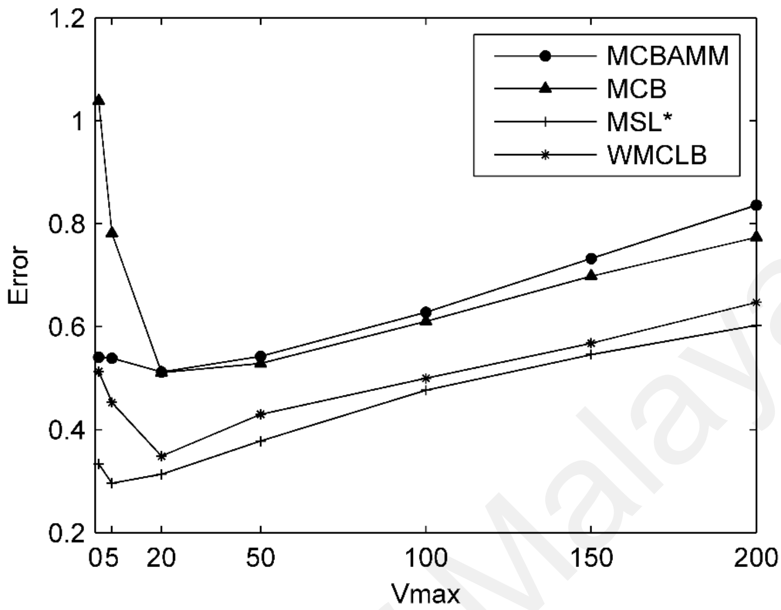

Figure 5.5 : Accuracy and velocity of sensor nodes.

5.4.2.4 Degree of Irregularity (DOI)

Results in Figure 5.6 show the effects of DOI on localization accuracy, and indicated that an increase in DOI minimizes localization accuracy in all schemes. However, in real-world applications, the signals are interrupted by noise and affected by antenna direction and natural phenomena such as humidity and walls. In some cases, the distance between two sensor nodes is nearly half of the radio range; they cannot communicate because they share a large variation of radio range. A full circle in AMM was used during the experiments to present the communication range of the sensor nodes.

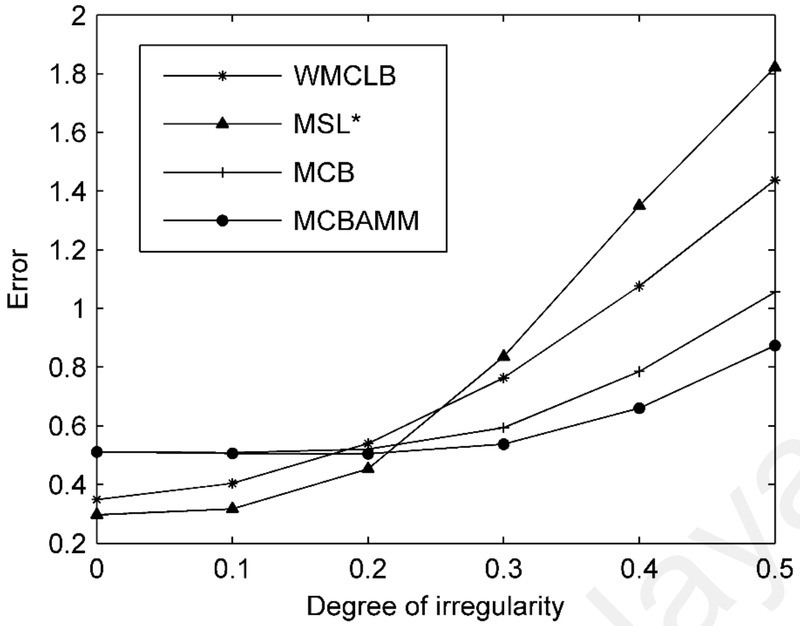

Figure 5.6 : Accuracy and degree of irregularity.

5.5 Discussion

The random mobility models used in previous schemes, especially the waypoint model, generates a large overlap between anchor nodes, thereby consuming high power and reducing the coverage area without improving localization accuracy. The proposed AMM can distribute anchor nodes efficiently by using the adaptive velocity and overlapping degree between anchor nodes in the neighborhood.

We present in this thesis a distributed mobility model to distribute anchor nodes efficiently and thereby increase anchor node coverage while enhancing localization accuracy in mobile WSNs. Our proposed scheme is scalable, self-adaptive, and robust to dynamic WSNs. Our proposed scheme can also distribute anchor nodes by using a simple and lightweight method. The extensive simulation results of the AMM show that the proposed scheme is superior to the state-of-art schemes in terms of distributing anchor nodes and maximizing their coverage.

The main concept of the AMM is to adapt anchor node velocity to the overlap degree and the number of anchor nodes in the neighborhood. This model works through the discovery of more overlapping areas that improve localization accuracy. Therefore, a blind node can construct its location estimation set from anchor and normal nodes within the overlap area. A large overlap area negatively affects the location estimation accuracy and produces a large number of redundant messages. This condition is particularly observed when the waypoint model is used to localize a blind node position. When anchor nodes move with adaptive velocity with a number of anchor nodes and anchor nodes with large overlap, a small number of anchor nodes can cover a large area. The optimized overlap area between anchor nodes is insufficient for communication and conserving network rigidity.

In this thesis, the AMM is presented to select anchor node velocity as a function of overlap degree and the number of anchor nodes in the neighborhood. In contrast, the waypoint model produces a large overlap between anchor nodes without improving localization accuracy. Therefore, we improve the coverage of the waypoint model and the localization accuracy using a simple method.

In all simulation scenarios, the coverage and accuracy of the AMM are improved, unlike those of the waypoint and RPGM models. The AMM entails high coverage and localization accuracy because the velocity of anchor nodes adapts to the overlap degree. The velocity, anchor node density, normal node density, and degree of irregularity mainly affect localization accuracy in mobile WSNs.

Mobile sensors can receive more observations. Thus, localization accuracy can be increased by visiting new areas. However, this mechanism holds true only if the mobility of a node is at low and medium speeds and the accuracy in high velocity declines.

The variation in anchor node density exerts a minimal effect on the coverage of the waypoint and RPGM models because in the waypoint model, the anchor node chooses its velocity randomly without any dependency on the previous velocity or overlap degree. By contrast, the velocity and direction of movement in the RPGM model is fully dependent on the reference point. Nevertheless, the coverage of the proposed AMM can be maximized through an increase in anchor node density. Moreover, the AMM can improve localization accuracy by equally distributing the anchor nodes observed.

Increasing normal node density improves the localization accuracy of blind nodes and reduces the dependency on anchor nodes. In MSL* and WMCLB, the normal node location information is used in addition to the anchor nodes to improve localization accuracy. The MCB scheme and the proposed model are fully dependent on anchor nodes. Thus, they are not greatly affected by an increase in normal node density.

The degree of irregularity affects all schemes. A slight irregularity in the range and direction of radio transmission can easily increase localization error. By contrast, more controlled increments in errors are observed in the AMM. In the AMM, the overlap degree is optimized. Thus, changes in radio range minimally affect localization accuracy.

Coverage is increased by selecting adaptive velocity with overlap degree and the number of anchor nodes in the neighborhood. The AMM increases the coverage by 50% in comparison with the waypoint model and the localization accuracy by 5% in comparison with the MCB scheme, which uses the same strategy.

CHAPTER 6: CONCLUSIONS

The conclusion of this thesis reflects the set of objectives presented in Section 1.4. This chapter summarizes the outcomes of the research and discusses the open research direction to assist future researchers.

This chapter follows this sequence: 6.1 – Re-examination of thesis objectives, 6.2 – Research contributions, 6.3 – Research scope and limitations, and 6.4 – Future work direction.

6.1 Re-examination of thesis objectives.

The problem of localizing mobile WSNs is explored in this thesis. We review the four objectives presented in Section 1.4 and explain the manner in which the throughput of the study encountered the objectives.

The first objective is to review the localization schemes and mobility models through the SMC method and thereby acquire insights into state-of-the-art schemes with reference to reducing communication cost, increasing anchor node coverage, and improving localization accuracy during the localization process in mobile WSNs.

The literature review was classified according to the thematic taxonomy to achieve the objective. We conducted the literature review using various resources, including web resources and online digital libraries such as IEEE, ACM, Springer, and Elsevier. We combined and comprehensively studied 170 papers in the expansive field of mobile WSN localization and mobility models.

A number of characteristics of range-free localization schemes were investigated to improve localization accuracy in mobile WSNs. The qualitative analysis of the critical aspects of state-of-the-art range-free schemes highlighted the open research area for improving localization accuracy and reducing communication cost.

The second objective is to reduce the communication cost in mobile WSNs while achieving a localization accuracy that is comparable to that of previous schemes. Hence, we presented WSNs in an adjacency matrix to identify the normal neighboring nodes. The intersection in set theory was used to select the adjacent normal nodes. The relation in the adjacency matrix was updated as a function of adjacent normal nodes. The intensive simulation result showed that the proposed LCC scheme can reduce the communication cost by an average of 18% while maintaining a localization accuracy that is comparable to that of previous localization schemes. Moreover, the proposed scheme can achieve this objective with a simple and lightweight expression. The result of the mathematical analysis and simulation showed that selecting adjacent normal nodes insignificantly affects the reduction of communication cost.

The third objective is to construct and develop a mobility model to improve localization accuracy by maximizing the coverage area while minimizing the anchor node deployment. The AMM was proposed to address the coverage problem in the waypoint model (Bettstetter et al., 2004; Mitsche, Resta, & Santi, 2014). The proposed AMM can distribute anchor nodes to increase the coverage area, improve localization accuracy with the same number of anchor nodes used in previous mobility models and save network robustness by adapting the anchor node velocity to the overlapping degree and the number of anchor nodes in the neighborhood. The performance of the proposed model was measured through extension in various networks. The results showed that the AMM can maximize anchor node coverage and improve localization accuracy simultaneously in a simple manner without additional calculations. Moreover, the proposed model can improve anchor node coverage by 50% and localization accuracy by 5%.

6.2 Research Contributions

This research makes a number of contributions to the existing body of knowledge.

• Thematic taxonomy: The critical aspect of mobile WSN localization was analyzed in the taxonomy and compared with previous schemes on the basis of significant parameters. The literature review addressed an open research area and highlighted the unsolved problem.

• LCC scheme: We proposed a scheme to reduce the communication cost in mobile WSNs. The MSL* scheme improves localization accuracy by using all normal nodes in the neighborhood. However, the use of all normal nodes in the neighborhood broadcasts a large number of messages without improving localization accuracy. We solved this problem by selecting adjacent normal nodes. To this end, we presented WSNs in the adjacency matrix and applied the intersection in set theory to select adjacent neighbors. The proposed scheme presents a solution to neighbor selection, which can be used in numerous schemes.

• AMM: We proposed the AMM to increase the coverage area of anchor nodes and improve localization accuracy. This model addresses the coverage problem in previous mobility models. Most of the previous schemes use the waypoint model to transmit mobile sensor data; in these schemes, a sensor chooses its velocity and direction randomly. The problem is observed in random movement in the waypoint model; it increases the overlap degree between anchor nodes without improving localization accuracy. To solve such problem, we presented the AMM, which selects anchor node velocity as a function of overlap degree and the number of anchor nodes in the neighborhood. The proposed model can increase the coverage area of anchor nodes by 50% and enhance localization accuracy by up to 5% simultaneously.

6.3 Research Scope and Limitations

The proposed solution is constructed to localize mobile WSNs in an indoor application. The LCC scheme and the AMM are effective for localizing mobile WSNs in a distributed manner. The sensor nodes in these solutions use network connectivity (range-free) to estimate blind node location without the need for additional hardware. The proposed solutions can solve the localization accuracy problem effectively in indoor applications, in which the line-of-sight of GPS declines. The proposed solutions can also be used in outdoor applications.

For simplicity and to avoid loss of generality, we used the static radio range in the proposed solution. We assigned a 50 unit range for the anchor nodes and normal nodes. The proposed solutions can function under a heterogeneous radio range, but we chose a static radio range for simplicity. Moreover, we used a static number of samples, i.e., 50.

In the proposed solutions, we assumed that the signal strength is ideal (full circle). However, in real applications, signal strength is affected by experimental environments. The variation of radio ranges was measured with the proposed solution in terms of the degree of irregularity (DOI) to test the effect of the variations of radio range.

6.4 Future studies

Many PhD studies have been performed to improve the use of mobile sensors in our daily lives. However, overlaying all boundaries of any research subject is never sufficient for a single PhD study. Thus, we highlight insights into a number of possible guidelines on which supplementary research can be performed on the basis of the output of the current research. This research only focused on localizing mobile WSNs in indoor applications. Localization accuracy was achieved through intensive simulation on various networks. The effect of significant parameters was measured, and the result was presented in graphs to simplify the addressing of the gaps between comparable schemes.

The motivation of this research is to improve the two-way localization accuracy in mobile WSNs, reduce communication cost, and increase anchor node coverage for the AMM. Hence, the future direction of this research includes extending the scope of this research to identify localization issues, such as accuracy in high velocity, handshake problem, mobility models, dependence on anchor nodes, security in the localization process, and effect of the environment.

6.4.1 The direction of future research.

• Localization accuracy declines in all schemes when sensors move with high velocity. Sensor nodes travel far from the last location. Thus, the samples in the last time slot are not sustainable to support the localization in the current time.

• The topology of mobile WSNs changes frequently when sensors move around. The handshake problem emerges when sensors go out of range during message transmission.

• Most of the mobility models in previous research lack a simplified model of mobility pattern calculations, such as the random waypoint model. Hence, each sensor is assumed as an individual point in the operation area and in an ideal environment without obstacles.

• The weakness of the SMC method is that it is highly dependent on anchor node density, and it requires a certain number of samples in each time slot.

• Research on the security issue in localization accuracy is lacking. A secure localization is a significant issue for decision makers. Traditional security techniques do not correspond to thin devices, such as sensor nodes.

• The variations of radio range and the impact of the environment highly affect localization accuracy. The accuracy in real applications is affected by noise, antenna direction, weather, and battery life.

• The use of RSSI technology in the localization process can reduce the computation cost for determining the distance between two sensor nodes. Thus, a few studies use RSSI in range-free localization schemes.

• The combination of range-free and range-based schemes can produce an accurate scheme. The margining between the high localization accuracy in range-based schemes and the low cost and autonomous features in range-free schemes can solve the problem of localization accuracy in critical applications.

The significant challenges faced by most of the existing mobility models in mobile WSNs are the effects of the performance and connectivity of the whole network based on mobility model assumption. Thus, mobile WSNs require an efficient mobility model.

Many research directions can still be uncovered in this phase regardless of the completion of the current research study and the solution to life's problems. Inquisitive minds can constantly find different ways to solve problems and upgrade the state-of-the-art schemes to facilitate and satisfy human needs.

LIST OF PUBLICATIONS AND PAPERS PRESENTED

We published our research output in reputable journals.

1. **Accepted manuscript on research topic:**

Ammar M.A Abu Znaid, Idris, M.Y.I., et al., Low communication cost (LCC) scheme for localizing mobile wireless sensor networks. Wireless Networks: p. 1–11.

2. **Article under Review on Research Topic:**

Adaptive Mobility Model (AMM) for accurate localization in mobile wireless sensor networks (journal of wireless networks)

Sequential Monte Carlo localization methods in mobile wireless sensor networks: A review (journal of Sensors)

3. **Articles in Collaboration with Group Members:**

WDARS: A Weighted Data Aggregation Routing Strategy with Minimum Link Cost in Event-Driven WSNs. (Hindawi).

ESAM: Endocrine Inspired Sensor Activation Mechanism for Multi-Target Tracking in WSN.

REFERENCES

Abu Znaid, A., Idris, M. Y. I., Abdul Wahab, A. W., Khamis Qabajeh, L., & Adil Mahdi, O. (2017). Sequential Monte Carlo Localization Methods in Mobile Wireless Sensor Networks: A Review. *Journal of Sensors, 2017*.

Adnan, T., Datta, S., & MacLean, S. (2014). Efficient and accurate sensor network localization. *Personal and Ubiquitous Computing, 18*(4), 821-833. doi:10.1007/s00779-013-0692-9

Ahmed, K., & Gregory, M. (2011). *Integrating wireless sensor networks with cloud computing.* Paper presented at the Mobile Ad-hoc and Sensor Networks (MSN), 2011 Seventh International Conference on.

Akkaya, K., Senel, F., Thimmapuram, A., & Uludag, S. (2010). Distributed recovery from network partitioning in movable sensor/actor networks via controlled mobility. *Ieee Transactions on Computers, 59*(2), 258-271.

Akyildiz, I. F., Pompili, D., & Melodia, T. (2005). Underwater acoustic sensor networks: research challenges. *Ad Hoc Networks, 3*(3), 257-279.

Akyildiz, I. F., Su, W., Sankarasubramaniam, Y., & Cayirci, E. (2002a). A survey on sensor networks. *Communications magazine, IEEE, 40*(8), 102-114.

Akyildiz, I. F., Su, W., Sankarasubramaniam, Y., & Cayirci, E. (2002b). Wireless sensor networks: a survey. *Computer Networks, 38*(4), 393-422.

Al Alawi, R. (2011). *RSSI based location estimation in wireless sensors networks.* Paper presented at the Networks (ICON), 2011 17th IEEE International Conference on.

Alaybeyoglu, A. (2015). An Efficient Monte Carlo-Based Localization Algorithm for Mobile Wireless Sensor Networks. *Arabian Journal for Science and Engineering, 40*(5), 1375-1384.

Alemdar, H., & Ersoy, C. (2010). Wireless sensor networks for healthcare: A survey. *Computer Networks, 54*(15), 2688-2710.

Alippi, C., & Vanini, G. (2006a). *A RSSI-based and calibrated centralized localization technique for Wireless Sensor Networks.* Paper presented at the Proc. IEEE Int. Conference on Pervasive Computing and Communications Workshops (PERCOMW).

Alippi, C., & Vanini, G. (2006b). A RSSI-based and calibrated centralized localization technique forWireless Sensor Networks.

Amirshahi, A., Fathy, M., Romoozi, M., & Assarian, M. (2015). A Fuzzy Realistic Mobility Model for Ad hoc Networks. *Journal of Advances in Computer Engineering and Technology, 1*(1), 9-18.

Anisi, M. H., Abdul-Salaam, G., Idris, M. Y. I., Wahab, A. W. A., & Ahmedy, I. (2015). Energy harvesting and battery power based routing in wireless sensor networks. *Wireless Networks*, 1-18.

Arulampalam, M. S., Maskell, S., Gordon, N., & Clapp, T. (2002). A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking. *Signal Processing, IEEE Transactions on, 50*(2), 174-188.

Atzori, L., Iera, A., & Morabito, G. (2010). The internet of things: A survey. *Computer Networks, 54*(15), 2787-2805.

Babu, M. V., & Ramprasad, A. (2012). *Discrete antithetic Markov Monte Carlo based power mapping localization algorithm for WSN.* Paper presented at the Advanced Communication Control and Computing Technologies (ICACCCT), 2012 IEEE International Conference on.

Baggio, A., & Langendoen, K. (2008). Monte Carlo localization for mobile wireless sensor networks. *Ad Hoc Networks, 6*(5), 718-733. doi:10.1016/j.adhoc.2007.06.004

Bai, F., & Helmy, A. (2004). A survey of mobility models. *Wireless Adhoc Networks. University of Southern California, USA, 206*.

Bai, F., Sadagopan, N., & Helmy, A. (2003). The IMPORTANT framework for analyzing the Impact of Mobility on Performance Of RouTing protocols for Adhoc NeTworks. *Ad Hoc Networks, 1*(4), 383-403.

Bandiera, F., Coluccia, A., & Ricci, G. (2015). A Cognitive Algorithm for Received Signal Strength Based Localization. *Signal Processing, IEEE Transactions on, 63*(7), 1726-1736.

Bartariya, S., & Rastogi, A. (2016). Security in Wireless Sensor Networks: Attacks and Solutions. *environment, 5*(3).

Batabyal, S., & Bhaumik, P. (2015). Mobility models, traces and impact of mobility on opportunistic routing algorithms: A survey. *IEEE Communications Surveys & Tutorials, 17*(3), 1679-1707.

Bettstetter, C., Hartenstein, H., & Pérez-Costa, X. (2002). *Stochastic properties of the random waypoint mobility model: epoch length, direction distribution, and cell change rate.* Paper presented at the Proceedings of the 5th ACM international workshop on Modeling analysis and simulation of wireless and mobile systems.

Bettstetter, C., Hartenstein, H., & Pérez-Costa, X. (2004). Stochastic properties of the random waypoint mobility model. *Wireless Networks, 10*(5), 555-567.

Bettstetter, C., & Wagner, C. (2002). The Spatial Node Distribution of the Random Waypoint Mobility Model. *WMAN, 11*, 41-58.

Borgia, E. (2014). The Internet of Things vision: Key features, applications and open issues. *Computer Communications, 54*, 1-31.

Camp, T., Boleng, J., & Davies, V. (2002). A survey of mobility models for ad hoc network research. *Wireless Communications & Mobile Computing, 2*(5), 483-502. doi:DOI 10.1002/wcm.72

Camp, T., Boleng, J., & Davies, V. (2002). A survey of mobility models for ad hoc network research. *Wireless communications and mobile computing, 2*(5), 483-502.

Campos, C. A. V., Otero, D. C., & de Moraes, L. F. M. (2004). *Realistic individual mobility markovian models for mobile ad hoc networks.* Paper presented at the Wireless Communications and Networking Conference, 2004. WCNC. 2004 IEEE.

Chan, Y. W. E., & Soong, B. H. (2011). A new lower bound on range-free localization algorithms in wireless sensor networks. *Communications Letters, IEEE, 15*(1), 16-18.

Chen, H., Gao, F., Martins, M., Huang, P., & Liang, J. (2013). Accurate and efficient node localization for mobile sensor networks. *Mobile Networks and Applications, 18*(1), 141-147.

Cheng, L., Wu, C., Zhang, Y., Wu, H., Li, M., & Maple, C. (2012). A survey of localization in wireless sensor network. *International Journal of Distributed Sensor Networks, 2012*.

Cortes, J., Martinez, S., Karatas, T., & Bullo, F. (2002). *Coverage control for mobile sensing networks.* Paper presented at the Robotics and Automation, 2002. Proceedings. ICRA'02. IEEE International Conference on.

Cully, W. P., Cotton, S. L., & Scanlon, W. G. (2012). Empirical performance of rssi-based monte carlo localisation for active rfid patient tracking systems. *International Journal of Wireless Information Networks, 19*(3), 173-184.

Das, B. B., & Ram, S. K. (2016). *Localization using beacon in wireless sensor networks to detect faulty nodes and accuracy improvement through DV-Hop algorithm.* Paper presented at the Inventive Computation Technologies (ICICT), International Conference on.

Deniz, F., Bagci, H., Korpeoglu, I., & Yazıcı, A. (2016). An adaptive, energy-aware and distributed fault-tolerant topology-control algorithm for heterogeneous wireless sensor networks. *Ad Hoc Networks, 44*, 104-117.

Dil, B., Dulman, S., & Havinga, P. (2006). Range-based localization in mobile sensor networks *Wireless Sensor Networks* (pp. 164-179): Springer.

Doucet, A., De Freitas, N., & Gordon, N. (2001). An introduction to sequential Monte Carlo methods *Sequential Monte Carlo methods in practice* (pp. 3-14): Springer.

Doucet, A., Godsill, S., & Andrieu, C. (2000). On sequential Monte Carlo sampling methods for Bayesian filtering. *Statistics and computing, 10*(3), 197-208.

Đurišić, M. P., Tafa, Z., Dimić, G., & Milutinović, V. (2012). *A survey of military applications of wireless sensor networks.* Paper presented at the Embedded Computing (MECO), 2012 Mediterranean Conference on.

Fan, S. P., Wen, Y. J., & Zhou, L. (2013). *An Enhanced Monte Carlo Localization Algorithm for Mobile Node in Wireless Sensor Networks.* Paper presented at the Applied Mechanics and Materials.

Fox, D. (2003). Adapting the sample size in particle filters through KLD-sampling. *The international Journal of robotics research, 22*(12), 985-1003.

Gang, L., Jingxia, Z., Junjie, C., & Zhenfeng, X. (2014). *A Monte Carlo box localization algorithm based on RSSI.* Paper presented at the Control Conference (CCC), 2014 33rd Chinese.

García-Hernández, C. F., Ibarguengoytia-Gonzalez, P. H., García-Hernández, J., & Pérez-Díaz, J. A. (2007). Wireless sensor networks and applications: a survey. *IJCSNS International Journal of Computer Science and Network Security, 7*(3), 264-273.

Girod, L., & Estrin, D. (2001). *Robust range estimation using acoustic and multimodal sensing.* Paper presented at the Intelligent Robots and Systems, 2001. Proceedings. 2001 IEEE/RSJ International Conference on.

Gu, S., Yue, Y., Maple, C., Wu, C., & Liu, B. (2013). *Challenges in mobile localisation in wireless sensor networks for disaster scenarios.* Paper presented at the Automation and Computing (ICAC), 2013 19th International Conference on.

Gubbi, J., Buyya, R., Marusic, S., & Palaniswami, M. (2013). Internet of Things (IoT): A vision, architectural elements, and future directions. *Future Generation Computer Systems, 29*(7), 1645-1660.

Gungor, V. C., & Hancke, G. P. (2009). Industrial wireless sensor networks: Challenges, design principles, and technical approaches. *Ieee Transactions on Industrial Electronics, 56*(10), 4258-4265.

Gustafsson, F., & Gunnarsson, F. (2003). *Positioning using time-difference of arrival measurements.* Paper presented at the Acoustics, Speech, and Signal Processing, 2003. Proceedings.(ICASSP'03). 2003 IEEE International Conference on.

Halder, S., & Ghosal, A. (2016). A survey on mobility-assisted localization techniques in wireless sensor networks. *Journal of Network and Computer Applications, 60*, 82-94.

Han, G., Xu, H., Duong, T. Q., Jiang, J., & Hara, T. (2013). Localization algorithms of wireless sensor networks: a survey. *Telecommunication Systems, 52*(4), 2419-2436.

Harri, J., Filali, F., & Bonnet, C. (2009). Mobility models for vehicular ad hoc networks: a survey and taxonomy. *IEEE Communications Surveys & Tutorials, 11*(4), 19-41.

He, T., Huang, C., Blum, B. M., Stankovic, J. A., & Abdelzaher, T. (2003). *Range-free localization schemes for large scale sensor networks.* Paper presented at the Proceedings of the 9th annual international conference on Mobile computing and networking.

Henderson, T. C., Grant, E., Luthy, K., Mattos, L., & Craver, M. (2005). *Precision Localization in Monte Carlo Sensor Networks.* Paper presented at the CAINE.

Heurtefeux, K., & Valois, F. (2012). *Is RSSI a good choice for localization in wireless sensor network?* Paper presented at the Advanced Information Networking and Applications (AINA), 2012 IEEE 26th International Conference on.

Hill, J., Szewczyk, R., Woo, A., Hollar, S., Culler, D., & Pister, K. (2000). System architecture directions for networked sensors. *ACM SIGOPS operating systems review, 34*(5), 93-104.

Hofmann-Wellenhof, B., Lichtenegger, H., & Collins, J. (2012). *Global positioning system: theory and practice*: Springer Science & Business Media.

Hong, X., Gerla, M., Pei, G., & Chiang, C.-C. (1999). *A group mobility model for ad hoc wireless networks.* Paper presented at the Proceedings of the 2nd ACM international workshop on Modeling, analysis and simulation of wireless and mobile systems.

Hou, X., Li, Y., Jin, D., Wu, D. O., & Chen, S. (2016). Modeling the Impact of Mobility on the Connectivity of Vehicular Networks in Large-Scale Urban Environments. *Ieee Transactions on Vehicular Technology, 65*(4), 2753-2758.

Hu, L., & Evans, D. (2004). *Localization for mobile sensor networks.* Paper presented at the Proceedings of the 10th annual international conference on Mobile computing and networking.

Huang, R., & Záruba, G. V. (2009). Monte Carlo localization of wireless sensor networks with a single mobile beacon. *Wireless Networks, 15*(8), 978-990.

Hyytiä, E., & Virtamo, J. (2007). Random waypoint mobility model in cellular networks. *Wireless Networks, 13*(2), 177-188.

Idris, M. Y. I., Arof, H., Noor, N. M., Tamil, E. M., & Razak, Z. (2012). A co-processor design to accelerate sequential monocular SLAM EKF process. *Measurement, 45*(8), 2141-2152.

Imran, M., Younis, M., Said, A. M., & Hasbullah, H. (2012). Localized motion-based connectivity restoration algorithms for wireless sensor and actor networks. *Journal of Network and Computer Applications, 35*(2), 844-856.

Jabbar, S., Aziz, M. Z., Minhas, A. A., & Hussain, D. (2010). *A Novel Power Tuning Anchors Localization Algorithm for Mobile Wireless Sensor Nodes.* Paper presented at the Computer and Information Technology (CIT), 2010 IEEE 10th International Conference on.

Jadaliha, M., Xu, Y., Choi, J., Johnson, N. S., & Li, W. (2013). Gaussian process regression for sensor networks under localization uncertainty. *Signal Processing, IEEE Transactions on, 61*(2), 223-237.

Jahromi, K. K., Zignani, M., Gaito, S., & Rossi, G. P. (2016). Simulating human mobility patterns in urban areas. *Simulation Modelling Practice and Theory, 62*, 137-156.

Jardosh, A., Belding-Royer, E. M., Almeroth, K. C., & Suri, S. (2003). *Towards realistic mobility models for mobile ad hoc networks.* Paper presented at the Proceedings of the 9th annual international conference on Mobile computing and networking.

Kaemarungsi, K., & Krishnamurthy, P. (2012). Analysis of WLAN's received signal strength indication for indoor location fingerprinting. *Pervasive and Mobile Computing, 8*(2), 292-316.

Karp, B., & Kung, H.-T. (2000). *GPSR: Greedy perimeter stateless routing for wireless networks.* Paper presented at the Proceedings of the 6th annual international conference on Mobile computing and networking.

Kurecka, A., Konecny, J., Prauzek, M., & Koziorek, J. (2014). Monte Carlo Based Wireless Node Localization. *Elektronika Ir Elektrotechnika, 20*(6), 12-16.

Lai, W.-C., Su, Y.-Y., Lee, C.-M., Fang, S.-H., Lin, W.-J., He, X.-P., & Feng, K.-C. (2013). *A survey of secure fingerprinting localization in wireless local area networks.* Paper presented at the Machine Learning and Cybernetics (ICMLC), 2013 International Conference on.

Le Boudec, J.-Y., & Vojnovic, M. (2005). *Perfect simulation and stationarity of a class of mobility models.* Paper presented at the Proceedings IEEE 24th Annual Joint Conference of the IEEE Computer and Communications Societies.

Li, J., You, X., Xia, J., & Li, H. (2012). A MCL-Based Localization Algorithm for Target Binary-Detection of Mobile Nodes *Advances in Future Computer and Control Systems* (pp. 567-572): Springer.

Li, M., Li, Z., & Vasilakos, A. V. (2013). A survey on topology control in wireless sensor networks: Taxonomy, comparative study, and open issues. *Proceedings of the Ieee, 101*(12), 2538-2557.

Li, S., Lowe, D., Kong, X., & Braun, R. (2011). *Wireless sensor network localization algorithm using dynamic path of mobile beacon.* Paper presented at the Communications (APCC), 2011 17th Asia-Pacific Conference on.

Li, T., Bolic, M., & Djuric, P. M. (2015). Resampling methods for particle filtering: classification, implementation, and strategies. *Signal Processing Magazine, IEEE, 32*(3), 70-86.

Liang, B., & Haas, Z. J. (1999). *Predictive distance-based mobility management for PCS networks.* Paper presented at the INFOCOM'99. Eighteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE.

Liu, C., Wu, K., & He, T. (2004). *Sensor localization with ring overlapping based on comparison of received signal strength indicator.* Paper presented at the Mobile Ad-hoc and Sensor Systems, 2004 IEEE International Conference on.

Liu, T.-y., Chang, L., & Gu, T.-l. (2009). *Analyzing the impact of entity mobility models on the performance of routing protocols in the MANET.* Paper presented at the Genetic and Evolutionary Computing, 2009. WGEC'09. 3rd International Conference on.

Luan, J., Zhang, R., Zhang, B., & Cui, L. (2014). *An Improved Monte Carlo Localization Algorithm for Mobile Wireless Sensor Networks.* Paper presented at the Computational Intelligence and Design (ISCID), 2014 Seventh International Symposium on.

MacLean, S., & Datta, S. (2014). Reducing the positional error of connectivity-based positioning algorithms through cooperation between neighbors. *Mobile Computing, IEEE Transactions on, 13*(8), 1868-1882.

Mahdi, O. A., Wahab, A. W. A., Idris, M. Y. I., Znaid, A. A., Al-Mayouf, Y. R. B., & Khan, S. WDARS: A Weighted Data Aggregation Routing Strategy with Minimum Link Cost in Event-Driven WSNs.

Mahdi, O. A., Wahab, A. W. A., Idris, M. Y. I., Znaid, A. A., Khan, S., & Al-Mayouf, Y. R. B. (2016). *ESAM: Endocrine inspired Sensor Activation Mechanism for multi-target tracking in WSNs.* Paper presented at the Fourth International Conference on Wireless and Optical Communications.

Mainwaring, A., Culler, D., Polastre, J., Szewczyk, R., & Anderson, J. (2002). *Wireless sensor networks for habitat monitoring.* Paper presented at the Proceedings of the 1st ACM international workshop on Wireless sensor networks and applications.

Maneerat, K., Kaemarungsi, K., & Prommak, C. (2016). Robust Floor Determination Algorithm for Indoor Wireless Localization Systems under Reference Node Failure. *Mobile Information Systems, 2016*.

Martins, L. G., Nunes, R. C., Martins, J., & de Oliveira, L. L. (2013). *A hybrid method to detecting failures in mobile sensor networks using localization algorithms.* Paper presented at the New Circuits and Systems Conference (NEWCAS), 2013 IEEE 11th International.

Martins, M. H., Chen, H., & Sezaki, K. (2009). *OTMCL: Orientation tracking-based Monte Carlo localization for mobile sensor networks.* Paper presented at the Networked Sensing Systems (INSS), 2009 Sixth International Conference on.

Miao, C., Dai, G., Chen, L., Jin, H., & Chen, Q. (2016). *A Node Localization Verification Model for WSN.* Paper presented at the International Conference on Human Centered Computing.

Mihaylova, L., Angelova, D., & Zvikhachevskaya, A. (2013). Sequential Monte Carlo Methods for Localization in Wireless Networks *Advances in Intelligent Signal Processing and Data Mining* (pp. 89-118): Springer.

Mirebrahim, H., & Dehghan, M. (2009). Monte Carlo localization of mobile sensor networks using the position information of neighbor nodes *Ad-Hoc, Mobile and Wireless Networks* (pp. 270-283): Springer.

Misra, P., & Enge, P. (2006). *Global Positioning System: Signals, Measurements and Performance Second Edition*: Lincoln, MA: Ganga-Jamuna Press.

Mitsche, D., Resta, G., & Santi, P. (2014). The random waypoint mobility model with uniform node spatial distribution. *Wireless Networks, 20*(5), 1053-1066.

Mousavi, S. M., Rabiee, H. R., Moshref, M., & Dabirmoghaddam, A. (2007). *Mobisim: A framework for simulation of mobility models in mobile ad-hoc networks.* Paper presented at the Third IEEE International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob 2007).

Musolesi, M., & Mascolo, C. (2006). *A community based mobility model for ad hoc network research.* Paper presented at the Proceedings of the 2nd international workshop on Multi-hop ad hoc networks: from theory to reality.

Nagpal, R., Shrobe, H., & Bachrach, J. (2003). *Organizing a global coordinate system from local information on an ad hoc sensor network.* Paper presented at the Information Processing in Sensor Networks.

Natalizio, E., & Loscrí, V. (2013). Controlled mobility in mobile sensor networks: advantages, issues and challenges. *Telecommunication Systems, 52*(4), 2411-2418.

Nazir, U., Arshad, M., Shahid, N., & Raza, S. H. (2012). *Classification of localization algorithms for wireless sensor network: A survey.* Paper presented at the Open source systems and technologies (ICOSST), 2012 international conference on.

Niculescu, D., & Nath, B. (2003). *Ad hoc positioning system (APS) using AOA.* Paper presented at the INFOCOM 2003. Twenty-Second Annual Joint Conference of the IEEE Computer and Communications. IEEE Societies.

Niewiadomska-Szynkiewicz, E. (2012). Localization in wireless sensor networks: Classification and evaluation of techniques. *International Journal of Applied Mathematics and Computer Science, 22*(2), 281-297.

Niu, Q., Huan, T., & Chen, P. (2016). NMCT: a novel Monte Carlo-based Tracking algorithm using potential proximity information. *International Journal of Distributed Sensor Networks, 2016*, 4.

Nunes, B. A. A., & Obraczka, K. (2014). A framework for modeling spatial node density in waypoint-based mobility. *Wireless Networks, 20*(4), 775-786.

Pal, A. (2010). Localization algorithms in wireless sensor networks: Current approaches and future challenges. *Network protocols and algorithms, 2*(1), 45-73.
Patwari, N., Ash, J. N., Kyperountas, S., Hero III, A. O., Moses, R. L., & Correal, N. S. (2005). Locating the nodes: cooperative localization in wireless sensor networks. *Signal Processing Magazine, IEEE, 22*(4), 54-69.
Perez-Gonzalez, V. H., Munoz-Rodriguez, D., Vargas-Rosales, C., & Torres-Villegas, R. (2015). Relational position location in Ad-hoc networks. *Ad Hoc Networks, 24*, 20-28.
Perkins, C. (2000). Ad hoc networks: Addison-Wesley, Reading, MA.
Pong, D., & Moors, T. (2006). The impact of random waypoint mobility on infrastructure wireless networks. *International Journal of Wireless Information Networks, 13*(2), 99-114.
Rogers, G. (2016). Random walk analysis for reflection and transmission of turbid media. *Color Research & Application*.
Römer, K., & Mattern, F. (2004). The design space of wireless sensor networks. *Wireless Communications, IEEE, 11*(6), 54-61.
Rudafshani, M., & Datta, S. (2007a). *Localization in wireless sensor networks.* Paper presented at the Information Processing in Sensor Networks, 2007. IPSN 2007. 6th International Symposium on.
Rudafshani, M., & Datta, S. (2007b). *Localization in wireless sensor networks.* Paper presented at the 2007 6th International Symposium on Information Processing in Sensor Networks.
Ryu, J. H., Irfan, M., & Reyaz, A. (2015). A Review on Sensor Network Issues and Robotics. *Journal of Sensors*.
Safa, H. (2014). A novel localization algorithm for large scale wireless sensor networks. *Computer Communications, 45*, 32-46.
Sahoo, P. K., & Sheu, J.-P. (2011). Limited mobility coverage and connectivity maintenance protocols for wireless sensor networks. *Computer Networks, 55*(13), 2856-2872.
Santi, P. (2005). Topology control in wireless ad hoc and sensor networks. *ACM Computing Surveys (CSUR), 37*(2), 164-194.
Schindelhauer, C. (2006). *Mobility in wireless networks.* Paper presented at the International Conference on Current Trends in Theory and Practice of Computer Science.
Shahra, E. Q., Sheltami, T. R., & Shakshuki, E. M. (2017). A Comparative Study of Range-Free and Range-Based Localization Protocols for Wireless Sensor Network: Using COOJA Simulator. *International Journal of Distributed Systems and Technologies (IJDST), 8*(1), 1-16.
Shang, Y., Rumi, W., Zhang, Y., & Fromherz, M. (2004). Localization from connectivity in sensor networks. *Parallel and Distributed Systems, IEEE Transactions on, 15*(11), 961-974.
Shao, Q., Xu, H., Jia, L., & Li, P. (2011). *The research of Monte Carlo localization algorithm based on received signal strength.* Paper presented at the Wireless Communications, Networking and Mobile Computing (WiCOM), 2011 7th International Conference on.
Sheu, J.-P., Hu, W.-K., & Lin, J.-C. (2010). Distributed localization scheme for mobile sensor networks. *Mobile Computing, IEEE Transactions on, 9*(4), 516-526.
Silva, R., Zinonos, Z., Silva, J. S., & Vassiliou, V. (2011). *Mobility in WSNs for critical applications.* Paper presented at the Computers and Communications (ISCC), 2011 IEEE Symposium on.
Singh, S. P., & Sharma, S. (2015). Range Free Localization Techniques in Wireless Sensor Networks: A Review. *Procedia Computer Science, 57*, 7-16.

Soltaninasab, B., Sabaei, M., & Amiri, J. (2010). *Improving Monte Carlo localization algorithm using time series forecasting method and dynamic sampling in mobile WSNs.* Paper presented at the Communication Systems, Networks and Applications (ICCSNA), 2010 Second International Conference on.

Stevens-Navarro, E., Vivekanandan, V., & Wong, V. W. (2007). *Dual and mixture Monte Carlo localization algorithms for mobile wireless sensor networks.* Paper presented at the 2007 IEEE Wireless Communications and Networking Conference.

Suo, H., Wan, J., Huang, L., & Zou, C. (2012). *Issues and challenges of wireless sensor networks localization in emerging applications.* Paper presented at the Computer Science and Electronics Engineering (ICCSEE), 2012 International Conference on.

Teng, G., Zheng, K., & Dong, W. (2011). MA-MCL: Mobile-Assisted Monte Carlo Localization for Wireless Sensor Networks. *International Journal of Distributed Sensor Networks, 2011*.

Uhlenbeck, G. E., & Ornstein, L. S. (1930). On the theory of the Brownian motion. *Physical review, 36*(5), 823.

Vo, B.-N., Singh, S., & Doucet, A. (2005). Sequential Monte Carlo methods for multitarget filtering with random finite sets. *Aerospace and Electronic Systems, IEEE Transactions on, 41*(4), 1224-1245.

Wang, W., & Zhu, Q. (2009). Sequential Monte Carlo localization in mobile sensor networks. *Wireless Networks, 15*(4), 481-495.

Wang, Y., & Wu, H. (2006). *DFT-MSN: The Delay/Fault-Tolerant Mobile Sensor Network for Pervasive Information Gathering.* Paper presented at the INFOCOM.

Wang, Z., Wang, Y., Ma, M., & Wu, J. (2013). Efficient localization for mobile sensor networks based on constraint rules optimized Monte Carlo method. *Computer Networks, 57*(14), 2788-2801.

Wu, X., Tan, S., & He, Y. (2013). Effective error control of iterative localization for wireless sensor networks. *Aeu-International Journal of Electronics and Communications, 67*(5), 397-405.

Yang, Z., Wu, C., Zhou, Z., Zhang, X., Wang, X., & Liu, Y. (2015). Mobility increases localizability: A survey on wireless indoor localization using inertial sensors. *ACM Computing Surveys (CSUR), 47*(3), 54.

Yi, J., Yang, S., & Cha, H. (2007). *Multi-hop-based monte carlo localization for mobile sensor networks.* Paper presented at the Sensor, Mesh and Ad Hoc Communications and Networks, 2007. SECON'07. 4th Annual IEEE Communications Society Conference on.

Yick, J., Mukherjee, B., & Ghosal, D. (2008). Wireless sensor network survey. *Computer Networks, 52*(12), 2292-2330.

Yoon, J., Liu, M., & Noble, B. (2003a). *Random waypoint considered harmful.* Paper presented at the INFOCOM 2003. twenty-second annual joint conference of the IEEE computer and communications. IEEE societies.

Yoon, J., Liu, M., & Noble, B. (2003b). *Sound mobility models.* Paper presented at the Proceedings of the 9th annual international conference on Mobile computing and networking.

Zanella, A., Bui, N., Castellani, A., Vangelista, L., & Zorzi, M. (2014). Internet of things for smart cities. *Internet of Things Journal, IEEE, 1*(1), 22-32.

Zeng, Y., Cao, J., Hong, J., Zhang, S., & Xie, L. (2009). *SecMCL: A secure monte carlo localization algorithm for mobile sensor networks.* Paper presented at the Mobile Adhoc and Sensor Systems, 2009. MASS'09. IEEE 6th International Conference on.

Zeng, Y., Cao, J., Hong, J., Zhang, S., & Xie, L. (2013). Secure localization and location verification in wireless sensor networks: a survey. *the Journal of Supercomputing, 64*(3), 685-701.

Zhang, H., & Hou, J. C. (2005). Maintaining sensing coverage and connectivity in large sensor networks. *Ad Hoc & Sensor Wireless Networks, 1*(1-2), 89-124.

Zhang, Q., Wan, J., Yi, K., Bao, T., & Wang, D. (2016). Efficient and Accurate Localization for Mobile Wireless Sensor Networks Based on Compressive Sensing. *Adhoc & Sensor Wireless Networks, 34*.

Zhang, S., Cao, J., Li-Jun, C., & Chen, D. (2010a). Accurate and energy-efficient range-free localization for mobile sensor networks. *Mobile Computing, IEEE Transactions on, 9*(6), 897-910.

Zhang, S., Cao, J., Li-Jun, C., & Chen, D. (2010b). Accurate and energy-efficient range-free localization for mobile sensor networks. *Ieee Transactions on Mobile Computing, 9*(6), 897-910.

Zhao, C., Sichitiu, M. L., & Rhee, I. (2015). N-body: A social mobility model with support for larger populations. *Ad Hoc Networks, 25*, 185-196.

Zhao, M., & Wang, W. (2009). A unified mobility model for analysis and simulation of mobile wireless networks. *Wireless Networks, 15*(3), 365-389.

Zhou, G., He, T., Krishnamurthy, S., & Stankovic, J. A. (2004). *Impact of radio irregularity on wireless sensor networks.* Paper presented at the Proceedings of the 2nd international conference on Mobile systems, applications, and services.