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Integrating Wireless Sensor Networks into Industry

Bachelor Thesis

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This is to certify that:

(i) the thesis comprises only my original work towards the bachelor's degree.

(ii) due acknowledgement has been made in the text to all other material used.

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Abstract

Wireless sensor networks (WSNs) play a crucial role in industrial environments for various applications such as monitoring, control, and optimization. The optimal deployment of sensor nodes is vital to ensure maximum area coverage and link quality, which directly impacts the overall performance and efficiency of the network. In this bachelor thesis, we propose a novel approach using a blind predicted Ultra-wide Band (UWB) channel model based on ray tracing to address this deployment optimization problem.

The research begins with a comprehensive literature review, exploring the challenges and requirements of wireless sensor networks in industrial environments. The advantages of UWB technology and the principles of deterministic UWB channel modeling using ray tracing are also discussed, then a system model is developed, considering the 3D industrial environment. A deterministic UWB channel model is formulated based on ray tracing to accurately represent the propagation characteristics in the industrial environment.

To optimize the deployment, an optimization framework is established, considering the coverage requirements, quality metrics, and constraints, the optimization results are validated and evaluated using simulations, considering metrics such as area coverage, link quality, and energy consumption.

The performance of the proposed approach is compared with alternative deployment strategies, highlighting the advantages and improvements achieved using Ray tracing deterministic UWB channel modeling. The results demonstrate the effectiveness of the optimized deployment in maximizing area coverage and quality of communication.

The research findings contribute to the field of wireless sensor networks in industrial environments by providing a practical and efficient solution for optimal deployment. The proposed approach can enhance the performance and reliability of industrial wireless sensor networks, leading to improved monitoring, control, and optimization processes. Future research directions include addressing the limitations of the proposed approach and exploring additional optimization techniques.

Keywords: wireless sensor networks, optimal deployment, UWB channel modeling, ray tracing, industrial environment, area coverage, link quality, optimization.

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List of Acronyms

WSN	Wireless Sensor Networks
BS	Base Station
IWSN	Industrial Wireless Sensor Network
ISM	Industrial Scientific Medical
UWB	Ultra-Wide Band
3D	Three Dimensional
IoT	Internet of Things
RoI	Region of Interest
GPS	Global Positioning System
RSSI	Received Signal Strength Indicator
SNR	Signal to Noise Ratio
LOS	Line of Sight
CCDF	Complementary Cumulative Distribution Function
EMI	Electromagnetic Interference
WLAN	Wireless Local Area Network
DECT	Digital Enhanced Cordless Telecommunications
CCPSO	Cooperative Coevolutionary Particle Swarm Optimization
CLPSO	Comprehensive Learning Particle Swarm Optimizer
GA	Genetic Algorithm
BPSO	Binary Particle Swarm Optimization
WT	Wavelet Transform
MST	Minimum Spanning Tree
FCC	The Federal Communication Commission

WPAN	Wireless Personal Area Network
NLOS	Non-Line of Sight
RMS	Root Mean Squared
PDP	Power Delay Profile
GO	Geometric Optics
UTD	Uniform Theory of Diffraction
FDTD	Frequency Difference in Time Domain
MoM	Methods of Moments
SBR	Shooting and Bouncing Ray
DoD	Direction of Departure
DoA	Direction of Arrival
MPCs	Multi-Path Components
MIMO	Multiple Input Multiple Output
IIot	Industrial Internet of Things
AI	Artificial Intelligence

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List of Symbols

R_s	Sensing disk radius
$\boldsymbol{P}_{s/p}$	Probability of detection of event p by a sensor s
$\|\|sp\|\|$	Euclidean distance between s and p
γ	Path attenuation/Loss exponent
δ	A parameter representing the characteristics of the sensor
R_u	The uncertain range, the range in which detection of the event p is not certain
$RSSI_{s/p}$	The received signal strength transmitted from node p to reach node s
$rssi_{1m}$	The signal strength at the distance of one meter
$snr_{s/p}$	The signal to noise ratio of the signal transmitted from node p to reach nodes
$rssi_{max}$	A value of the received signal strength at the closest point
$\mathbf{P}_p$	The network coverage at point p
R_c	Communication disk radius
$PL(d)$	Path loss at distance d
$P_r(d)$	The received signal strength at a distance d
P_t	Output power of the transmitting antenna
ϵ	A zero-mean Gaussian distributed random variable with standard deviation σ_ϵ (in dB) that represents the shadowing effects
SS_{min}	The minimum acceptable signal strength
$B_{f,3}$	The relative bandwidth of UWB signals defined at -3 dB
C	Shannon's theorem channel capacity
B_w	Bandwidth of the signal
S	Signal power level
N	Noise power level
$e(t)$	Transmitted signal representation in time domain
$s(t)$	Received signal representation in time domain
G_t	Transmitter antenna gain
G_r	Receiver antenna gain
c	Speed of light $\approx 3x10^8$
f	Signal frequency
d	T_x-T_r separating distance

d_f	Far-field distance
D	The largest dimension of the transmitting antenna
λ	Signal wavelength
N_f	Path loss exponent that account for the frequency
N_d	Path loss exponent that account for the distance
$S(f,d)$	A zero-mean Gaussian distributed random variable with standard deviation σ_S (in dB) that represents the shadowing effects
τ_{RMS}	Root mean square delay spread
$\bar{\tau}$	Mean access delay
$\overline{\tau^2}$	Second moment of the PDP
N	Number of multipath components
a_k^2	Power of the k_{th} component
τ_k	Delay of the k_{th} component
B_c	Coherence bandwidth
$R(\Delta f)$	The complex auto-correlation function
$H(f)$	The complex frequency response of the channel
Λ	Cluster arrival rate
λ	Ray arrival rate
$\boldsymbol{A}$	The designated 3D space where the deployment of sensor nodes happens
$\boldsymbol{O}$	Set of obstacles inside the 3D space
$\boldsymbol{A}_m$	Monitoring Area
$\boldsymbol{A}_d$	Deployable Area
$cost(d)$	Cost of deploying a sensor at location d
r_s	Sensing range
r_c	Communication range
$BS.pos$	3D position of the Base Station
S	Set of all sensor nodes
$s.pos$	3D position of sensor s
$RSSI_{threshold}$	Minimum acceptable received signal strength
f_0	Center frequency
$H(f)$	Channel frequency response
M	Set of target points/sensors
D	Set of deployable points
Δ	Grid interval
dc	Ratio between number of points covered to the deployment cost

Chapter 1 Introduction

Wireless communication has become the rapidly expanding sector within the field of communications. Its exponential growth has captivated the attention of the media and the general public alike. In numerous households, businesses, and educational institutions, wireless local area networks are currently either supplementing or replacing wired networks. The realm of wireless technology is witnessing the emergence of various innovative applications, such as wireless sensor networks, automated transportation systems, smart homes and appliances, as well as remote telemedicine. This impressive surge in wireless systems, accompanied by the widespread use of laptop and palmtop computers, indicates a promising future for wireless networks, both as independent entities and as integral components of larger network infrastructures.

Wireless sensor networks (WSNs) are progressively gaining traction across diverse sectors, ranging from residential spaces to industrial settings, from traffic management to environmental and habitat monitoring. The focus of these networks predominantly revolves around monitoring. Moreover, wireless systems also possess the capability to execute control actions, thereby presenting competition to existing process automation systems and conventional home automation solutions.

1.1 Background and motivation

A WSN consists of spatially distributed sensors, and one or more sink nodes (also called base stations) [16]. Sensors monitor, in real-time, physical conditions, such as temperature, vibration, or motion, and produce sensory data. A sensor node could behave both as data originator and data router. A Base Station (BS), on the other hand, collects data from sensors. For example, in an event monitoring application, sensors are required to send data to the BS(s) when they detect the occurrence of events of interest. The BS may communicate with the end-user via direct connections, the Internet, satellite, or any type of wireless links. Figure 1.1 depicts a typical WSN architecture.

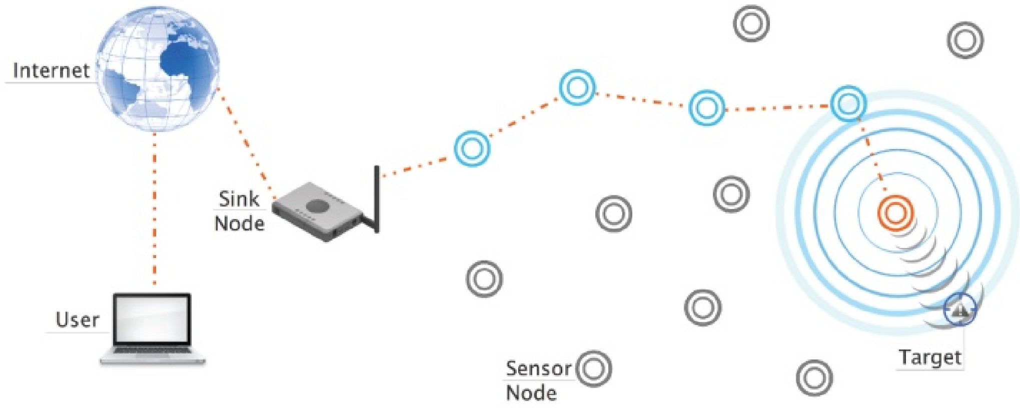


Fig. 1.1 Typical WSN architecture [16]

In practice, special cases of WSNs are encountered such as Wireless Multimedia Sensor Networks (WMSNs), Underwater Wireless Sensor Networks (UWSNs), Wireless Underground Sensor Networks (WUSNs), Wireless Body Sensor Networks (WBSNs), Wireless Sensor Actor Networks (WSANs) and Industrial Wireless Senor Networks (IWSNs).[16]

The use of wireless sensor networks in industrial automation has become a prominent focus. Different technologies, ranging from short-range personal area networks to cellular networks, and sometimes even satellite communications, are being employed. In industrial environments, the coverage area of WSN as well as the reliability of the data may suffer from noise, co-channel interferences, and other interferers [1]. For example, the signal strength may be severely affected by the reflections from the walls (multi-path propagation) [2], interferences from other devices using Industrial Scientific Medical (ISM) bands [1], and by the noise generated from the equipment or heavy machinery [2]. In these conditions, it is important to maintain data integrity for operation-critical data, for example alarms [1]. The complexity of WSN calls for expertise from various disciplines, especially in industrial applications where failure can result in production loss or even endanger lives.

In recent years, Ultra-wide Band (UWB) spread spectrum techniques have gained increasing interest as it has the potential to offer benefits such as wide bandwidth for fast data transfer, low interference with narrowband signals, precise time and location measurements, robustness against multipath fading, and high-precision ranging.

UWB communications are envisioned for at least two types of applications. The first is high-data rate communications, with data rates in excess of 100 Mbit/s. High-definition TV pictures are one typical application for such a high-rate system. The other application concentrates on data rates below 1 Mbit/s, usually in the context of sensor networks, and in conjunction with UWB positioning systems. A considerable part of these systems will be deployed in industrial environments. Interesting applications include machine-to-machine communications in e.g., process control systems, or supervision of storage halls – a fact that also has been recognized by the IEEE 802.15.4a group that will develop a standard for these systems. Furthermore, industrial environments have unique propagation properties (large number of metallic objects, dimensions of halls and objects). Thus, it is vital to understand the behavior of UWB channels in industrial environments.[4]

Since it is mandatory for industrial environment to achieve certain performance standards to be practical, one of the main aspects to enhance WSN performance in Indoor environments such as the industrial one, is the deployment of sensor nodes in the area to be covered.

In the context of industrial networks, it is important to consider the limited energy supply and processing power of sensor nodes. Random deployments in such networks can lead to initial communication gaps and wastage of energy resources [15]. Even structured deployments may not completely eliminate these gaps. Similarly, deploying a large number of sensor nodes can improve connectivity but at the expense of increased overall cost, with no guarantee of enhancing network lifetime. Therefore, achieving optimal connectivity, extended network lifetime, and cost minimization requires a careful deployment strategy. This task becomes even more challenging when nodes are deployed in three-dimensional (3D) space.

In addition, there is often a requirement for real-time data delivery when retrieving information from sensor nodes. Efficient deployment plays a critical role in the operation of sensor networks, greatly affecting performance, management, robustness, and latency in IWSNs. Essentially, the deployment of sensors involves strategically placing sensor nodes in locations where specific monitoring is needed, considering the type of information to be monitored and the specific sensor units being used. For instance, cameras capture data differently than temperature sensors, so the placement of sensors depends on the nature of the information being monitored and the sensor types employed.

Considering the requirements of WSNs, the challenges presented by industrial environments, and the extensive research available, it has been established that UWB technology is highly suitable for sensor network applications. In particular, impulse-radio-based UWB technology possesses inherent properties that align well with the needs of sensor networks. UWB systems exhibit advantages such as low complexity and cost, signal characteristics resembling noise that cause minimal interference to other systems, resilience against multipath effects and jamming, and excellent time domain resolution for precise location and tracking. These qualities make UWB technology an ideal choice for deploying WSNs in industrial environments.

1.2 Problem statement and objectives

In industrial environments, wireless sensor networks play a crucial role in enabling efficient monitoring and control of various processes. However, the deployment of sensor nodes in these environments poses challenges in achieving optimal coverage and ensuring reliable communication links. Existing deployment techniques often lack the ability to consider both area coverage and link quality metrics simultaneously.

Therefore, there is a need to develop an optimized deployment approach that considers both area coverage and quality of communication metrics. By addressing this problem, we can enhance the efficiency, performance, and reliability of wireless sensor networks in industrial environments, leading to improved monitoring and control capabilities and enabling the realization of advanced industrial automation applications.

Through this project, to develop a solution to the aforementioned problem of optimizing WSNs deployment in industrial environments we will incorporate two previously proven technologies to give great results in our context, The first is UWB wireless communications and the second is Ray-tracing technique for blind prediction of the UWB propagation channel.

So, first of all, we will develop a 3D industrial environment model with obstacles using MATLAB to simulate the real-life industrial environments, where the sensor nodes will be deployed.

Second, we will formulate an UWB channel model in the industrial environment using ray-tracing approach between two arbitrary locations inside our environment considering the reflection, diffraction, and scattering effects caused by the objects and surfaces in the environment to properly characterize the propagation in this environment.

Third, develop an algorithm to optimize the deployment of the sensor nodes in our 3D simulated environment based on the area coverage and quality of communication metrics.

At last, once we have optimized the deployment, evaluate its performance using simulations or real-world measurements. Assess metrics such as area coverage, link quality, energy consumption, or network connectivity to validate the effectiveness of your deployment strategy.

1.3 Significance and relevance of the research

This research holds significant importance in the field of wireless sensor networks in industrial environments. By developing an optimized deployment approach that considers both area coverage and link quality metrics, utilizing the deterministic channel model derived from ray tracing between sensor nodes and the base station in an industrial environment using UWB technology, several key contributions are expected.

Firstly, the findings of this research will address the limitations of existing deployment techniques by providing a comprehensive solution that simultaneously optimizes both area coverage and link quality metrics. This will enable more effective monitoring and control of industrial processes, leading to increased efficiency, reduced downtime, and enhanced safety.

Secondly, the utilization of the deterministic channel model based on ray tracing approach will provide a more accurate representation of the propagation characteristics in complex industrial environments. This will facilitate the design of wireless sensor networks that are better tailored to the specific environment, ensuring reliable and robust communication links.

Thirdly, the incorporation of UWB technology in the deployment optimization process will offer high data rates, low power consumption, and improved resistance to multipath interference. This will enable advanced industrial automation applications that rely on real-time, high-bandwidth data exchange, such as industrial Internet of Things (IoT), asset tracking, and predictive maintenance.

Furthermore, the practical implications of this research are significant. Industries across various sectors, including manufacturing, oil and gas, transportation, and utilities, can benefit from the optimized deployment approach proposed in this thesis. The research outcomes will guide industry professionals and researchers in making informed decisions regarding wireless sensor network design and deployment strategies, leading to improved operational efficiency and cost-effectiveness.

In summary, this research will contribute to the advancement of knowledge in the field of wireless sensor networks in industrial environments. By addressing the limitations of existing deployment techniques and leveraging the deterministic channel model and UWB technology, this research has the potential to revolutionize the way wireless sensor networks are deployed and utilized in industrial settings, ultimately driving industrial automation to new levels of productivity and efficiency.

1.4 Thesis organization

This thesis is organized in the following manner, Chapter 2 delves into the fundamentals of wireless sensor networks in industrial settings, highlighting their applications and unique challenges, while also conducting a literature review on existing sensor deployment optimization approaches. Chapter 3 focuses on deterministic UWB channel modeling and ray tracing techniques, explaining their relevance and considerations for accurate modeling in industrial environments. In Chapter 4, the research formulates the problem of optimal sensor deployment and presents the integration of the UWB channel model into the optimization algorithm. The design and development of this algorithm are further explored. Chapter 5 presents the experimental evaluation and results, including a 3D simulation of an industrial environment, implementation of the optimization algorithm, and validation of the results. Comparative analysis with existing deployment approaches is also conducted. Chapter 6 combines the discussion of the interpretation and implications of the results with the identification of limitations of the proposed approach. It also provides suggestions for future research and improvements, then moves to summarizing the research findings, highlighting contributions to the field, and discussing potential applications and benefits of the proposed approach.

Chapter 2 Wireless Sensor Networks in Industrial Environments

WSNs offer tremendous possibilities for real-world monitoring and control. This chapter offers a concise introduction to WSNs, beginning with a showing the different architectures of existing WSNs and followed by an overview of common WSN models and applications. Then, we investigate the industrial environments settings and the applications of WSNs in industrial environments, pointing the requirements and challenges of such systems, then we discuss the deployment of IWSNs and review the state-of-the-art of this problem showing different techniques and their respective limitations.

2.1 Introduction to WSNs in industrial settings

Different models and architectures can be utilized for sensor cooperation, depending on the capabilities of the sensors and the requirements of the application. In the following sections, we will present several common models and architectures used in WSNs:

- small, medium, large- and very large-scale WSNs: The size of a WSN can vary based on various factors, including the characteristics of the sensors, the Region of Interest (RoI), and the user’s specific requirements. In real-world scenarios, the number of sensor nodes within a WSN can range from a few tens to hundreds, thousands, or even tens of thousands.
- homogeneous versus heterogeneous WSNs: A WSN can be categorized as either homogeneous or heterogeneous. A homogeneous WSN is one in which all sensors within the network possess identical capabilities in terms of sensing, processing, communication, and other functionalities. On the other hand, a heterogeneous WSN comprises sensors with varying capacities, which can be utilized for different applications. In a heterogeneous WSN, certain sensors may have greater available resources, such as processing power and energy, compared to the remaining sensors in the network.

- Stationary, mobile, and hybrid WSNs: WSNs can be classified into three types based on node mobility. A stationary WSN consists of sensor nodes that are deployed in fixed locations and remain stationary throughout their operation. In contrast, a mobile WSN comprises sensor nodes that can change their positions over time, enabling mobility within the network. Finally, a hybrid WSN combines both stationary and mobile sensor nodes, offering a combination of fixed and movable elements in the network architecture.
- Flat versus hierarchical WSNs: WSNs can also be categorized as either flat or hierarchical based on the organization of sensor nodes. In flat WSNs, all sensor nodes are considered homogeneous and have similar roles and responsibilities within the network. On the other hand, hierarchical WSNs introduce a hierarchical structure where certain sensor nodes are designated for specialized functions. For example, a sensor node may be assigned as a cluster-head responsible for communication with neighboring clusters, thereby enabling efficient data aggregation and management in the network.
- Single-hop versus multi-hop WSNs: WSNs can be classified as either single-hop or multi-hop based on the routing of data. In a single-hop WSN, sensor nodes directly transmit their data to a central sink node. This type of network architecture is suitable for small-scale deployments or when all sensor nodes are within direct communication range of the sink. On the other hand, in a multi-hop WSN, data is relayed through multiple intermediate sensor nodes before reaching the sink. This enables long-range communication and can extend the coverage area of the network. A multi-hop WSN can be organized in a flat or hierarchical manner, depending on the structure and functionality of the sensor nodes.

2.2 Sensor nodes

Typically, a sensor is a device designed to detect and respond to physical quantities like heat, converting them into electrical signals that can be automatically interpreted and processed. A sensor node, often referred to as a sensor or mote, is a self-contained and compact device that not only integrates sensors but also includes additional components to process and transmit sensory data. Therefore, a mote is responsible for generating data by sensing various physical parameters and eventually transmitting this data to a central location.

A typical sensor node consists of some essential units, including a sensor, a communication module, a microcontroller, memory, and power management. Depending on the specific requirements of the application, additional units such as Global Positioning System (GPS) for location tracking, locomotory components for mobility, and energy harvesting mechanisms may be incorporated into the sensor node's design.

First, we will look at the coverage models of sensors, then we will discuss different communication models of sensor nodes.

2.2.1 Senor coverage models

A sensor coverage model is a mathematical function that takes into account parameters such as distances and angles between sensors and a specific point in space. By processing these inputs, the model generates a coverage measure that quantifies the extent to which the sensors effectively cover or monitor the given point. The analysis of sensor coverage models shows the existence of different classifications based on distinct goals [17], senor coverage models are categorized into these three categories: 1. Binary coverage models, 2. Probabilistic coverage models and 3. Evidential coverage models (Fig. 2.1). We will discuss only the first two, as the evidential is too complex and in this project we will be relying on the Probabilistic coverage model.

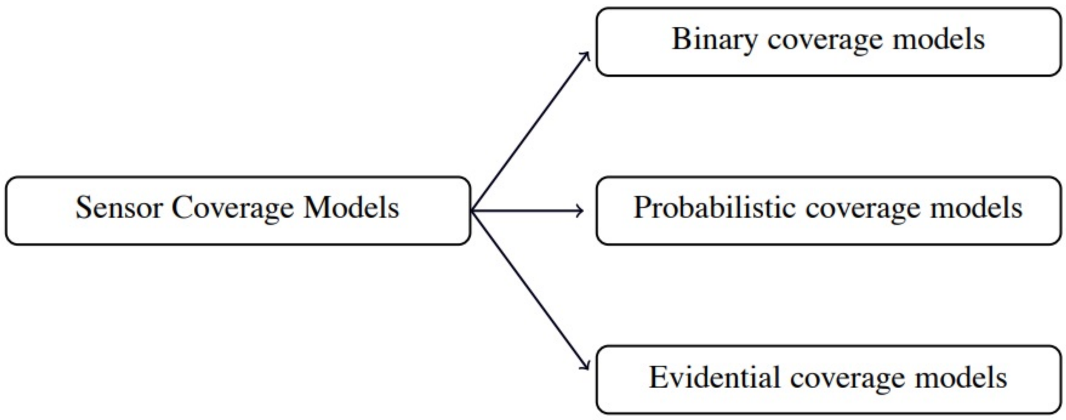


Fig. 2.1 A taxonomy for sensor coverage models [16]

Because of its simplicity, the binary coverage model has been widely used [17]. In this model, sensors are modeled as having a predetermined range of effectiveness. Coverage within the range, which is typically characterized by a disk (but can also be any arbitrary shape or a collection of shapes), is assumed to be effective and coverage outside of the given range is assumed to be non-effective [16]. The disk model is a variant of the binary model where a sensor's sensing area is modeled as a disk with radius $\boldsymbol{R_s}$, centered at the sensor's location. This simplified representation is commonly used to describe a sensor's capabilities. For an event that occurs at p, the following equation calculates the probability of detection of that event by a sensor s:

$$\boldsymbol{P}_{s/p} = \begin{Bmatrix} 1 & if\ \|sp\| \le R_s \\ 0 & otherwise \end{Bmatrix} \qquad [2.1]$$

where $\|sp\|$ is the Euclidean distance between s and p.

The binary model disregards the stochastic nature of sensing, leading to inaccurate system performance estimation. Recent research utilizes probabilistic coverage models to address this issue, considering the inherent uncertainties. An example of a probabilistic coverage model is given by:

$$\boldsymbol{P}_{s/p} = \frac{C}{\|sp\|^{\gamma}} \qquad [2.2]$$

where C is a constant, and γ is the path attenuation exponent.

The coverage measure decreases as the distance between the point and sensor increases. In cases where the distance becomes very large, the coverage measure is often considered to be zero. Truncated probabilistic coverage models, like the following model, adopt this assumption [17]:

$$\boldsymbol{P}_{s/p} = \begin{Bmatrix} Ce^{-\delta\|sp\|} & if\ \|sp\| \le R_s \\ 0 & otherwise \end{Bmatrix} \qquad [2.3]$$

where δ is a parameter representing the characteristics of the sensor.

Another model [17] is defined as follows:

$$\boldsymbol{P}_{s/p} = \begin{cases} 1 & if \ \|sp\| \leq R_s - R_u \\ e^{-\alpha(\|sp\| - (R_s - R_u))^{\beta}} & if \ R_s - R_u < \|sp\| \leq R_s \\ 0 & if \ R_s < \|sp\| \end{cases} \qquad [2.4]$$

where α and β are constants, and R_u is called the uncertain range. Figure 2.2 shows the coverage measure as a function of the sensor-point distance for the above-mentioned coverage models.

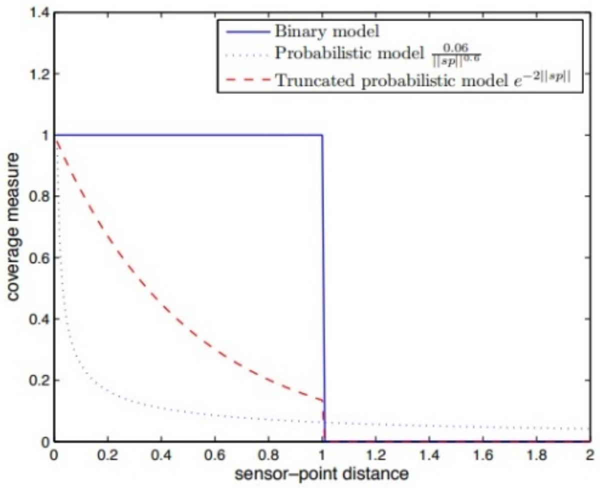


Fig. 2.2 Coverage measure vs. the sensor-point distance for the binary model, probabilistic model, and truncated probabilistic model [16]

In [18], the used probabilistic coverage model for the sensor nodes was based on the Received Signal Strength Indicator (RSSI) and Signal to Noise Ratio (SNR) metrics between the target point and the sensor considering only the Line of Sight (LOS) path between them, not accounting for any wave reflection, diffraction nor scattering. For a target point p and sensor s, RSSI is defines as follows:

$$RSSI_{s/p} = -20\log_{10}(\|sp\|) + rssi_{1m} \qquad [2.5]$$

The received signal strength indicator is a value that depends both on the distance from the sensor as well as the signal strength at the distance of one meter $rssi_{1m}$. The received signal strength indicator value depending on the distance is shown in Figure 2.3.

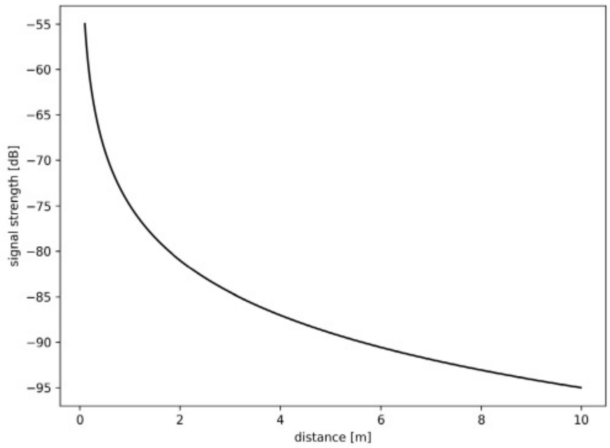


Fig. 2.3 Received signal strength (rssi) depending on the distance between sensor and target point [18]

As received signal strength indicator value drops as the distance increases, the signal strength drops below the strength of the noise signal. As the value of noise represents minimal usable value, SNR is used. The signal-to-noise ratio is the difference between the received signal strength indicator and the noise values in decibels. As any value equal or below the noise level is considered not usable resulting value is set to zero for any signal-to-noise value not bigger than assumed noise value [18]:

$$snr_{s/p} = \begin{cases} RSSI_{s/p} - noise & if\ RSSI_{s/p} > noise \\ 0 & otherwise \end{cases} \qquad [2.6]$$

Since $\boldsymbol{P}_{s/p}$ needs to be between zero and one, to satisfy that requirement a signal-to-noise value is normalized using the $rssi_{max}$ value, a value of the received signal strength at the closest point. This normalized signal-to-noise ratio is the value used as the probability of detection:

$$\boldsymbol{P}_{s/p} = \frac{snr_{s/p}}{rssi_{max} - noise} \qquad [2.7]$$

The sensor coverage model characterizes the observability of physical phenomena by an individual sensor.

On the other hand, **network coverage** can be perceived as a consensus measure delivered by a network of distributed sensors [16]. The network coverage at point p, denoted $\mathbf{P}_p$, is estimated as:

$$\mathbf{P}_p = 1 - \prod_{s \in RoI}(1 - \boldsymbol{P}_{s/p}) \qquad [2.8]$$

2.2.2 Sensor communication models

Wireless sensor nodes establish communication using their radio modules. Direct connectivity between two nodes is established when they can exchange data by transmitting and receiving signals. A sensor communication model, also known as a transmission model, is a mathematical representation that quantifies the direct connectivity between sensor nodes.

The disk connectivity model is a widely used communication model in which a sensor node can establish communication with other nodes located within a disk centered around it, with a radius equal to its communication range $\boldsymbol{R_c}$. In simpler terms, two sensors are considered to have direct communication if they are within one communication hop of each other, meaning they are within the range of each other's transmissions.

This model primarily focuses on network connectivity from a geometric standpoint, simplifying the analysis by considering only the spatial relationships between nodes within the communication range. However, it remains limited and unrealistic. Indeed, empirical studies [19,20] show that there is no clear cut-off boundary between successful and unsuccessful communication.

In practice, the attenuation experienced by a wireless signal at a given distance is described by the path loss, whereas shadowing describes random fluctuations in signal strength at a known path loss. Empirical measurements have indicated that shadowing is a zero-mean normally distributed random variable with standard deviation σ_ϵ [16]. Due to the unique characteristics of each environment, most radio propagation models use a combination of analytical and empirical methods.

One of the most common radio propagation models is the log-normal shadowing path loss model [21] which is given by:

$$PL(d) = PL(d_0) + 10\gamma \log_{10}\left(\frac{d}{d_0}\right) + \epsilon \quad [2.9]$$

where d is the transmitter–receiver distance, d_0 a reference distance, γ the path loss exponent (rate at which signal decays), and ϵ is a zero-mean Gaussian distributed random variable with standard deviation σ_ϵ (in dB) that represents the shadowing effects.

The received signal strength (P_r) at a distance d is the output power of the transmitter minus $PL(d)$. Formally:

$$P_r(d) = P_t - PL(d) = P_t - PL(d_0) - 10\gamma \log_{10}\left(\frac{d}{d_0}\right) - \epsilon \quad [2.10]$$

Figure 2.4 shows an analytical propagation model for $\gamma = 2$, $\sigma_\epsilon = 4$, $PL(d_0) = 55\ dB$, $d_0 = 1$, and an output power $P_t = 0\ dBm$ (e.g., the Chipcon CC2420 IEEE 802.15.4, 2.4 GHz).

From equation [2.10] we have $P_r(d) \sim \mathcal{N}(P_t - PL(d_0) - 10\gamma \log_{10}\left(\frac{d}{d_0}\right), \sigma_\epsilon)$. Since $P_r(d)$ is Gaussian, the probability of successful communication between two sensors s_i and s_j located at distance d from each other is:

$$\mathcal{P}(P_r(d) > SS_{min}) = Q(\frac{SS_{min} - (P_t - PL(d_0) - 10\gamma \log_{10}\left(\frac{d}{d_0}\right))}{\sigma_\epsilon}) \quad [2.11]$$

where SS_{min} represents the minimum acceptable signal strength and Q is the Complementary Cumulative Distribution Function (CCDF) of a standard Gaussian, i.e.

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{+\infty} e^{\frac{-t^2}{2}} dt \quad [2.12]$$

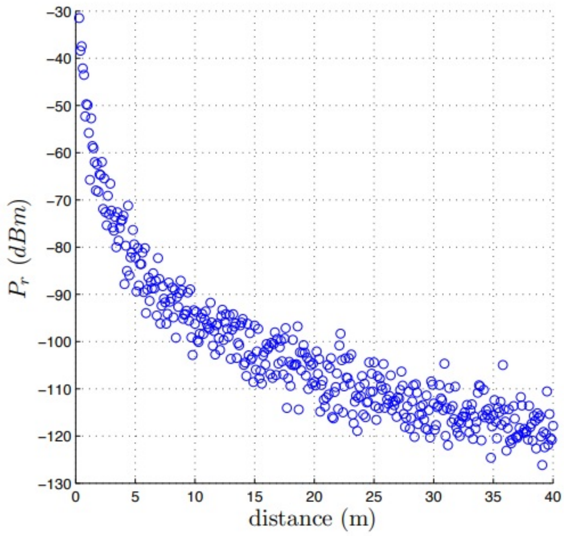


Fig. 2.4 Channel model, γ=2, σ_ϵ=4, P_t=0 dBm [16]

Figure 2.5 shows the connectivity model related to this formulation. We see clearly that some areas within the connectivity range receive power lower than SS_{min}. On the other hand, some areas outside the connectivity range receive power higher than SS_{min}. As mentioned before, this model reflects the fact that there is no clear cut-off boundary between successful and unsuccessful communication.[16]

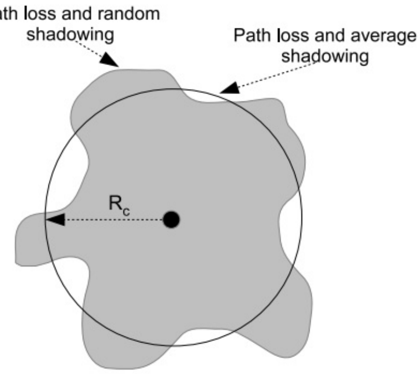


Fig. 2.5 Connectivity model [16]

2.3 Applications and challenges specific to industrial environments

To understand why such focus is given to the problem of deploying WSNs in industrial environments, we need first to investigate the industrial environments and what are the requirements of communication systems deployed in industry and what challenges such environments poses on WSNs.

Industrial environments are typically characterized by their large dimensions and the presence of numerous metallic elements, which can amplify the multi-path propagation of signals. Additionally, these environments often contain a variety of electric machinery, transportation equipment, and repair activities, which contribute to Electromagnetic Interference (EMI).

Industrial environment is a term used to describe environments under harsher conditions than typical office environments. The different conditions that can be found in industry can degrade the performance of wireless systems. Depending on the characteristics of the environment, such as dimensions, materials and the presence of electronic equipment, the propagation channel will be subject to different types of degradations.[22]

An example of indoor industrial environments are Metal works, which are usually buildings with large dimensions and metallic objects present (Figure 2.6). This typical environment can be found in a large percentage of the industry. Many wireless systems working in different ISM bands, such as WLAN, DECT, Bluetooth and ZigBee are used in this type of environment.

Fig. 2.6 Large industrial halls at metal works [22]

There are other examples of indoor industrial environments that are also widely found like the bark furnace, paper warehouse, outdoor industrial environments, laboratory/office, and rail yards, etc. With each of those examples exhibiting different effects on the propagation channel but I chose to review this example of industrial environment as it will simplify the 3D simulation of the environment part later in the thesis based on the model in Figure 2.7.

Fig. 2.7 3D model of factory indoor hall

WSNs have been recognized as valuable resources for implementing robust process monitoring and control functions within industrial environments. In recent years, many works have proposed promising contributions aimed at higher performance of such networks, addressing different particularities such as routing, energy efficiency, fault tolerance and availability [23-25]. The spread of sensing technologies for applications in industry has created new possibilities for monitoring and control, but some challenges still require proper attention when deploying such networks [26].

In the context of IWSNs, applications must exhibit a high level of robustness, ensuring a minimum acceptable level of dependability and data retrieval quality. This is crucial because even a single failure in a deployed wireless sensor network for industrial automation can result in financial losses or pose a risk to people's safety.

Prior to deploying WSNs in industrial applications, it is essential to be aware of the potential challenges in terms of coverage areas and data reliability within the industrial environment. Factors such as noise, co-channel interferences, multipath effects, and other sources of interference can adversely impact the coverage and reliability of data in industrial settings.

Signal strength can be significantly affected in factory environments due to reflections from walls and floors, interferences from ISM bands, as well as noise generated by equipment and heavy machinery. These factors should be taken into consideration to ensure the successful deployment and operation of WSNs in industrial environments.

Maintaining data integrity is crucial, particularly for mission-critical data such as alarms, even in the presence of noise and interference. To ensure the reliable delivery of messages from sensors to the application host, changes in signal level and radio connectivity need to be carefully addressed.

Proper strategies should be implemented to mitigate the impact of noise and interference on the communication between sensors and the application host. This may involve techniques such as signal level monitoring, adaptive modulation schemes, error detection and correction mechanisms, and robust routing protocols. By carefully managing signal level changes and radio connectivity, the reliable delivery of messages can be ensured, thereby preserving data integrity in industrial applications.

The Interference signal can be classified as narrowband and broadband. Broadband interferences are signals with a constant energy spectrum over all frequencies and have high energy. They are usually unintentional radiating sources whereas narrowband interferences are intentional noise sources with lower energy. Table 1 shows the narrowband and broadband interference sources that are generally found in the industries. Both interferences have varying degradation effects on wireless link reliability.[1]

Table 2.1 Interferences sources in industrial environments [1]

Broadband interferences	Narrowband interferences
Motors	Cellular telephones
Inverters	Radio and TV transmitters
Computers	Signal generators
Ignition systems	Local oscillator, UPS system
Voltage regulators	Test equipment
Lightning electromagnetic pulses	Microwave & Ultrasonic equipment
Pulse generators	Medical equipment
Thermostats	Microprocessor systems
Welding apparatus	Pager transmitters
Frequency converters	High-frequency generators

WSNs provide numerous advantages in industrial environments. They offer cost-effectiveness by eliminating the need for extensive cabling infrastructure. WSNs provide flexibility and scalability, allowing sensors to be easily deployed, relocated, and scaled to accommodate changing requirements. With remote monitoring and control capabilities, WSNs enable real-time data collection and decision-making without physical presence.

They cover large areas, facilitating comprehensive monitoring, and can be rapidly deployed and reconfigured as needed. WSNs contribute to reduced downtime, enhanced efficiency, and improved safety by detecting anomalies and optimizing processes in real-time. Additionally, WSNs enable environmental monitoring, data integration, and advanced analytics, facilitating informed decision-making. Their energy efficiency is crucial in environments with limited power sources. Overall, WSNs in industrial environments deliver cost savings, operational improvements, and safer workspaces.

2.4 Literature review on existing approaches for sensors deployment optimization

In this section, we will review previous works on the problem of optimizing the deployment of WSNs in indoor environments preferably an industrial environment.

One of the key design considerations in WSNs is determining the optimal placement of sensors within the RoI. The positioning of sensors can significantly impact the system's requirements and various performance metrics of the network. Hence, careful sensor placement becomes a crucial optimization strategy to achieve desired design objectives.

For instance, the coverage objective focuses on ensuring that all target points within the RoI are adequately covered by the WSN. To achieve this, sensors should be positioned in a manner that optimally utilizes the sensing capabilities of the network. It is important to strike a balance between placing sensors too close to each other, which can lead to redundancy, and placing them too far apart, which can result in coverage gaps or holes. An optimal sensor deployment facilitates efficient information gathering and communication, thereby enhancing overall network performance.

In the RoI, sensors can be placed using either deterministic or random deployment schemes. The selection of the deployment scheme depends heavily on factors such as the type of sensors being used, the specific application requirements, and the characteristics of the operating environment.

Deterministic deployment involves carefully planning and strategically placing sensors in predetermined locations within the RoI. This approach is often employed when precise coverage or specific monitoring objectives need to be achieved.

Deterministic deployment can be advantageous in scenarios where the RoI has known characteristics or where certain areas require targeted coverage.

On the other hand, random deployment involves placing sensors in the RoI without following a predetermined pattern. Random deployment is often used when the RoI is large or complex, or when the specific coverage requirements are not well-defined. This approach can provide a more flexible and adaptable sensor placement, particularly in dynamic or uncertain environments.

Indeed, all WSN deployment strategies, including deterministic and random placement, should consider the optimization of one or more objectives that align with the specific application requirements. These objectives can include factors such as maximizing coverage, minimizing energy consumption, optimizing network connectivity, improving data accuracy, or enhancing system lifetime.

Furthermore, these deployment strategies need to operate within certain constraints. Constraints may involve limited resources such as energy, memory, or computational capabilities of the sensors. They could also include constraints related to communication range, data latency, or environmental considerations.

Indoor environments are often well-characterized and studied, making deterministic deployment schemes more suitable for indoor WSNs. Therefore, this section focuses on reviewing the works specifically related to deterministic deployment schemes in indoor WSNs.

Deterministic deployment involves precomputing sensor locations prior to WSN start-up, often used in indoor applications or when sensor cost and position impact their operation. Unlike random deployment, it offers optimum network configuration, strategically positioning sensors in advance to meet design goals like coverage, connectivity, and cost reduction. Maximizing coverage while minimizing sensor usage has been a key focus in the literature, optimizing the deployment for efficient sensor utilization and meeting application requirements.

Different approaches have been suggested in the literature, mainly falling in one or more of these categories (Figure 2.8):

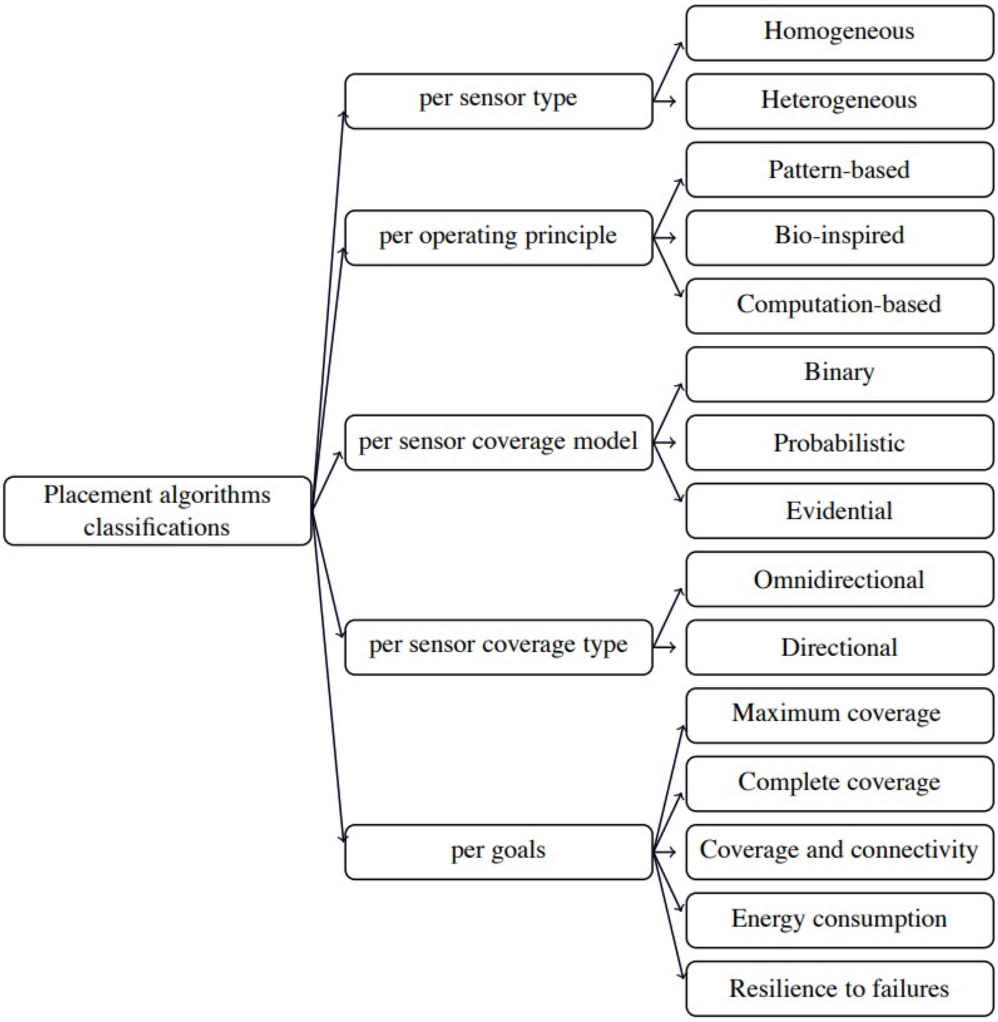


Fig. 2.8 A taxonomy of deterministic WSNs deployment schemes in the literature [16]

In our review, we will categorize the works based on the type of sensor model used, wether it is a binary or probabilistic coverage model. So let's first look at the binary coverage models suggested approaches in the literature.

In [27], researchers utilized a regular hexagonal cell architecture to construct a two-tier WSN consisting of regular sensors and relay nodes. Their focus was on minimizing the number of sensors while ensuring adequate coverage and connectivity. [28] explored regular polyhedron patterns like octahedron, cube, and tetrahedron, which find applications in three-dimensional WSNs. Investigating the optimal placement pattern in terms of sensor density, [29] determined that among all placement patterns composed of regular polygons, the regular triangular lattice exhibited the most optimal configuration. In [30], cost minimization was a key consideration while achieving coverage for all target points.

[31] delved into the underwater WSN domain, addressing the challenge of achieving maximum coverage with the fewest sensors by proposing a triangular grid topology. An incremental deployment process was introduced in [32], involving the placement of new sensors at locations without existing sensors within their sensing range. Researchers in [33] introduced a novel system based on the Archimedes' spiral pattern, aimed at prolonging the lifetime of WSNs. [34] proposed a deployment process resulting in a hexagon-structured topology, demonstrating superior performance in terms of minimal sensor requirement compared to triangular and square topologies. [35] presented a range of deployment patterns for achieving full area coverage and k-connectivity, with k being less than or equal to six. [36] introduced a grid topology for sensor deployment. Finally, in 1939, Kershner [37] mathematically established the regular triangular lattice as the optimal placement pattern for complete coverage of an unbounded plane.

The problem of sensor placement on grids In two and three dimensions has been extensively studied, and it has been shown to be a challenging combinatorial optimization problem with NP-complete complexity [38]. However, this approach has certain limitations. Firstly, the computational complexity associated with the grid-based approach makes it impractical for large-scale problems. Secondly, the grid coverage method assumes perfect sensor detection, where sensors are expected to provide a binary detection outcome consistently. Despite these drawbacks, researchers have proposed various techniques to address the grid-based WSNs deployment problem. These include integer linear programming [39], local search algorithms [40], simulated annealing [41], genetic algorithms [42, 43], and ant colony optimization [44].

It should be emphasized that there exists a correlation between connectivity and coverage in binary deployment strategies. Wang et al. [45] and Zhang et al. [46] were among the first researchers to independently demonstrate this relationship. They concluded that if a convex RoI is entirely covered by a set of sensors, the communication graph formed by these sensors will be connected when the communication range (R_c) is equal to or greater than twice the sensing range (R_s). In simpler terms, as long as R_c is at least 2 times R_s, ensuring coverage in a wireless sensor network configuration is sufficient to guarantee both coverage and connectivity. Consequently, if the transmission range (R_c) of a sensor greatly exceeds its sensing range (R_s), achieving connectivity becomes less of a concern. This finding has also been extended to the concept of k-coverage, indicating that k-coverage implies k-connectivity when $R_c \geq 2R_s$ [47]. In summary, when $R_c \geq 2R_s$, satisfying k-coverage requirements in a WSN inherently ensures k-connectivity.

Moving to the more practical direction of WSNs deployment strategies, which are the ones based on the probabilistic sensor coverage models, In [48], the authors study the problem of optimizing WSN deployment in a 3D industrial region with obstacles included, his proposed solution is based on the heterogonous directional sensor and relay nodes structure, with the objective of maximizing coverage using two particle swarm optimizers, the Cooperative Coevolutionary Particle Swarm Optimization (CCPSO2) and the Comprehensive Learning Particle Swarm Optimizer (CLPSO), finding that CCPSO2 performs much better than 803 CLPSO. CCPSO2 guarantees 90% coverage degree by 804 using at least 180 sensor nodes, while CLPSO could 805 only reach ca. 81% coverage using 210 sensor nodes. In [15], A multi-objective deployment strategy for 3D wireless sensor networks is proposed in this study, utilizing heuristic optimization approaches such as Genetic Algorithm (GA) and Binary Particle Swarm Optimization (BPSO). The WSN architecture incorporates a two-layer hierarchy consisting of sensor nodes, cluster heads, and a base station. The objective is to achieve an optimal or nearly optimal placement of cluster heads to fulfill the desired objectives. The results indicate that in most scenarios, the deployment based on GA and BPSO achieve similar lifetimes. However, when all three objectives (lifetime, connectivity, and cost) are given equal importance, the GA-based deployment outperforms the BPSO-based deployment in terms of overall performance. It demonstrates better results in terms of lifetime, connectivity, and cost. In [49], the authors primarily focused on deploying sensors on 3D terrains, utilizing a multi-objective genetic algorithm combined with a novel Wavelet Transform (WT) based mutation operator. They also calculated the minimum path-loss values and maximum coverage gain of the network by constructing the Minimum Spanning Tree (MST). Through simulation studies conducted on various types of terrains, their approach demonstrated robustness and efficiency in sensor deployment on 3D fields. The performance results indicate that Their algorithm is effective and reliable for sensor deployment in real-world 3D environments.

In the studies conducted by Dhillon et al. [50,51], a probabilistic coverage model was considered, assuming a two-dimensional n × n grid as the Region of Interest. In [50], the authors formulated sensor placement as an optimization problem and proposed a greedy heuristic called ***PLACE_SENSORS***. This heuristic aims to minimize the number of sensors while ensuring full coverage of the RoI. The computational complexity of ***PLACE_SENSORS*** is $O(n^4)$.

In [51], the same authors presented two additional placement heuristics. The first heuristic, ***Max-Avg-Cov***, focuses on maximizing the mean coverage of the grid points. The second heuristic, ***Max-Min-Cov***, aims to maximize the coverage of the grid points that are the least effectively covered. Both algorithms have a computational complexity of $O(n^4)$.These studies provide different heuristics to address the sensor placement problem under the probabilistic coverage model, with the goal of optimizing coverage while minimizing the number of sensors required.

Dhillon et al. [50,51] introduced several key variables to address the sensor placement problem. The sensor detection matrix D, denoted as $D = [P_{i/j}]$, represents the pairwise sensor detection probabilities between grid points in the RoI. With an n × n RoI, the matrix D has n^2 rows, n^2 columns, and a total of n^4 elements.

The miss probability matrix M, denoted as $M = m_{ij} = 1 - P_{i/j}$, captures the probability of missing detection between grid points. The vector $M^* = (M_1, M_2, \dots, M_N)$ represents the set of miss probabilities for the $N = n^2$ grid points in the RoI. Initially, when no sensors are deployed, M^* is initialized as the all-1 vector (i.e., $M^* = (1, 1, \dots, 1)$). As sensors are placed in the RoI, one or more entries in this vector are decreased accordingly. Furthermore, M_{min} denotes the maximum allowable miss probability for any grid point.

In the ***Max-Avg-Cov*** heuristic, a sensor is deployed at a grid point i where the summation $\sum_j M_{ij}$ is minimal. On the other hand, in the ***Max-Min-Cov*** heuristic, a sensor is deployed at the grid point with the minimum coverage in the RoI. The placement algorithms terminate either when the generated detection probabilities surpass the desired detection probabilities or when the number of deployed sensors exceeds the allocated sensor budget.

The pseudo code for the ***Max-Avg-Cov*** and ***Max-Min-Cov*** algorithms outlined in [51] presents the pseudo code for the algorithms. These algorithms provide a systematic approach for sensor placement, considering either the average coverage or the minimum coverage requirements, while adhering to specified detection probability thresholds and sensor budget constraints.

Most of the reviewed works proved to contribute to the field in some manner, but none of them investigated the effect of the indoor environment surfaces material on the propagation model of the channel and thus affect the WSN links quality metric, and those of them who investigated this point, did not consider UWB channel model in their study, all of them dealt with the narrowband propagation models of the indoor environment channels. Also, another aspect they did not investigate is how the BS architecture would affect the deployment scheme.

Chapter 3 Deterministic UWB Channel Modeling and Ray Tracing

In the planning of wireless systems, channel measurements and modeling play a crucial role. It has been widely recognized through both theoretical analysis and practical experiments that the UWB channel exhibits properties that are fundamentally distinct from those of narrowband channels. As a result, the extensive body of literature on "conventional" narrowband channel modeling cannot be directly applied to UWB channels. Instead, it is necessary to conduct new measurements and develop specific models tailored to UWB characteristics. By doing so, a comprehensive understanding of the UWB channel can be achieved, enabling accurate predictions and effective planning for UWB-based wireless systems.

In this chapter, we will delve into the foundational aspects of UWB technology and its application in industrial environments. The chapter begins with an introduction to UWB, providing an overview of its characteristics and capabilities. Following this, the focus shifts to channel modeling, where different types of models are explored to capture the intricacies of wireless communication. The subsequent section introduces the Ray Tracing Approach, a powerful methodology for simulating wave propagation and interactions in complex environments. The chapter then delves into the specifics of deterministic UWB channel modeling using the Ray Tracing technique, explaining the process of generating accurate and realistic channel models for UWB communication systems. Special considerations for achieving fidelity in UWB channel modeling within industrial environments are discussed, accounting for factors such as multipath propagation, obstacles, and material properties, then a blind predicted UWB channel model is derived using the Band-divided Ray Tracing technique. To provide a comprehensive perspective, the chapter concludes with a literature review, examining existing studies that have explored UWB in industrial environments. This review offers insights into the current state of knowledge, highlighting relevant findings and gaps in research that the present study aims to address. Overall, this chapter establishes the necessary foundation for understanding UWB channel modeling and the role of Ray Tracing in capturing the intricacies of wireless communication in industrial environments.

3.1 Introduction to UWB

The term "UWB" encompasses various names for a radio technique, including impulse radio, carrier-free radio, baseband radio, time domain radio, non-sinusoid radio, orthogonal function radio, and large relative bandwidth radio [53]. The relative bandwidth is defined by [52]:

$$B_{f,3}\,dB = 2.\frac{f_H - f_L}{f_H + f_L} \qquad [3.1]$$

where f_H and f_L represent the upper and lower cut-off frequencies respectively of the frequency band defined at −3 dB.

UWB signals were initially defined as having a relative bandwidth of 25% or more [54]. In 2002, the Federal Communication Commission (FCC) expanded the definition to include a wider range of signals, encompassing those with a relative bandwidth B_f defined at 10 dB greater than 20% or a frequency band exceeding 500 MHz [55]. The typical bandwidth of UWB signals ranges from 500 MHz to several GHz. Therefore, the term UWB encompasses not only impulse techniques but also any modulations that exhibit an instantaneous bandwidth equal to or greater than 500 MHz.

The exploration of electromagnetism in the time domain began four decades ago. Initially, the research was primarily focused on radar applications due to the wide frequency range of the signals, which offered significant time domain resolution capabilities.

In 1960, impulse radars were developed by the American and Soviet armies, taking advantage of the space resolution properties of impulse systems. The bandwidth of an impulse signal determines its spectrum width and, inversely, the resolution in distance of the system.

In the 1970s, Bennett and Ross conducted comprehensive research on UWB technology, providing foundational insights [56]. Two decades later, Taylor further described the application of UWB technology to radar systems [54]. Progress in this field has been consistently made since the mid-1960s, as documented in the historical bibliography published by Barrett [53]. However, it was not until the late 20th century that the use of UWB signals for radio communication started gaining attention. In 1990, the US Department of Defense published its evaluation of UWB technology, which primarily focused on radar systems, with limited consideration for communication systems at that time [57].

In 1998, the FCC initiated its first study on UWB technology. This marked a significant milestone in the regulatory exploration of UWB. In February 2002, the FCC published its initial regulatory report, which introduced provisions for the transmission of signals in the 3.1–10.6 GHz frequency band specifically for wireless communications. The report also imposed stringent constraints on the power spectral density of UWB signals [55]. Following the publication of this report, extensive research efforts were undertaken by both academic and industrial communities with the objective of developing robust and efficient communication systems utilizing UWB technology. The availability of regulatory guidelines provided a framework for further exploration and advancement in the field.

UWB technology is well-suited for future wireless communication systems due to its wide frequency band. With appropriate coding, UWB signals can achieve low error rates and transmit data at rates below the channel capacity defined by Shannon's theorem.

$$C = B_w . \log_2(1 + \frac{S}{N}) \qquad [3.2]$$

where C is the channel capacity (bit/s), B_w is the signal bandwidth (Hz), S is the signal power level (W), and N is the noise power level (W).

UWB technology, characterized by a broad frequency band reaching several GHz, offers high data rates and various advantages. It provides high temporal resolution for accurate localization, robustness against fading in multipath environments, low power spectral density for coexistence with existing systems, less vulnerability to jamming, secure communications with low detection and interception probabilities, simplified system design without carrier modulation, and good obstacle penetration properties. It is particularly suitable for short-range, high data rate applications in residential, office, ad hoc, and other network types.

The telecommunications industry has witnessed a growing demand for wireless applications, driven by both industrial and public needs for connectivity anytime and anywhere. This has led to the development of various wireless standards, such as Bluetooth, Wi-Fi, Zigbee, and IEEE 802.15.3. While these technologies operate in limited bandwidths of around 10 MHz, UWB stands out with its significantly lower emission levels and higher transmission data rates. UWB primarily focuses on short-range Wireless Personal Area Networks (WPANs) but offers superior performance compared to existing WLAN and WPAN standards in terms of data rate and range (Figure 3.1).

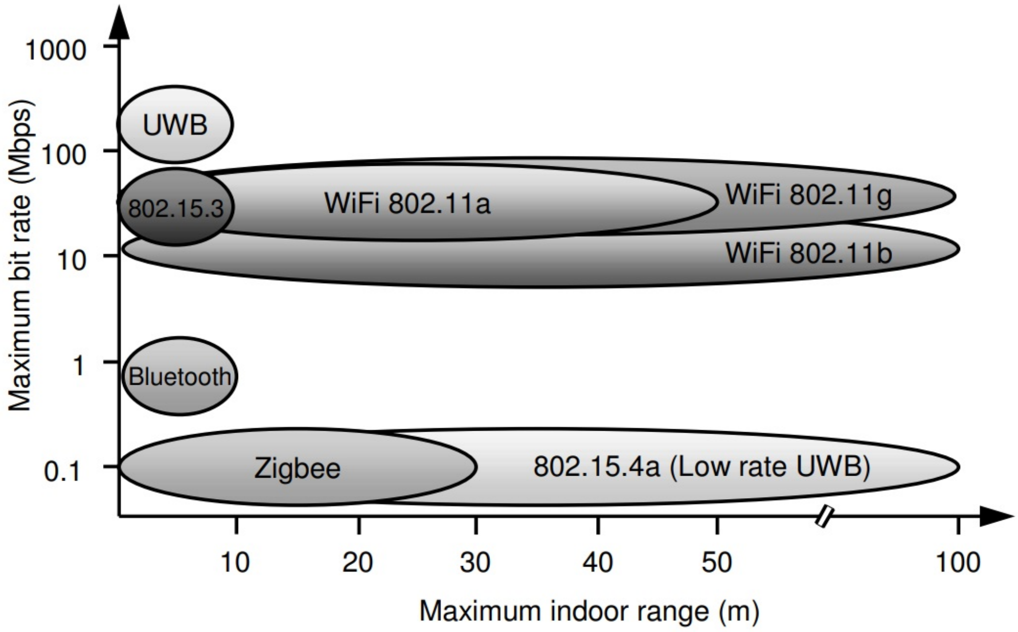


Fig. 3.1 WLAN and WPAN main standards: rate and maximum ranges [52]

Electromagnetic waves were predicted by Maxwell in 1855, and Hertz conducted the first radio propagation experiments in 1886, using a short-duration pulse that can be considered as an ultra-wideband signal. Research has since been conducted to understand electromagnetic wave propagation, initially focusing on narrow frequency bands, and later extending to wideband signals.

In a radio transmission system, the emitted electrical signal $e(t)$ is transformed into a received electrical signal $s(t)$ through the transformation to and from electromagnetic waves. The propagation channel represents the process by which the signal $e(t)$ is converted into the signal $s(t)$, taking into account the interactions between the electromagnetic waves and the surrounding environment (Figure 3.2).

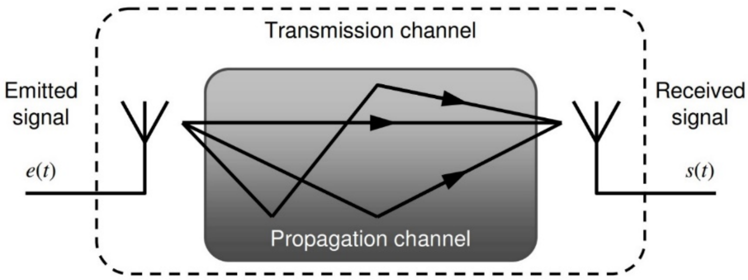


Fig. 3.2 Propagation channel and transmission channel [52]

Let us first consider an ideal case where the transmission system is placed in free space, i.e., in an environment where no obstruction is present. Friis formula states that the signal attenuation in free space is given by [52]:

$$\frac{P_r}{P_t} = \frac{G_t G_r c^2}{(4\pi f d)^2} \qquad [3.3]$$

Where P_r is the power collected at the receiving antenna, P_t is the power of the signal outputted by the transmitting antenna, G_t is the transmitter gain, G_r is the receiver gain, c is the speed of light, f is the signal frequency and d is the T_x-T_r separating distance.

For Eq. 3.3 to hold, the receiving antenna should be in the far-field region in relation to the transmitting antenna.

$$d > d_f = \frac{2D^2}{\lambda} \qquad [3.4]$$

Where D is the largest dimension of the transmitting antenna, λ is the wavelength.

In real-world environments, signal transmission involves not only the direct path but also multiple propagation paths. These paths are influenced by various interactions between the waves and the surrounding objects. At the receiving antenna, the observed signal is a combination of different waves with varying attenuation and phase rotation. Each wave arrives at the receiver with a different delay, corresponding to the length of its propagation path. Multipath propagation can cause significant distortion of the received signal.

Additionally, in certain situations, such as indoor settings, the LOS path may not be available, requiring the use of Non-Line of Sight (NLOS) for effective radio communication. Figure 3.3 provides an illustration of multipath propagation and the main propagation phenomena involved.

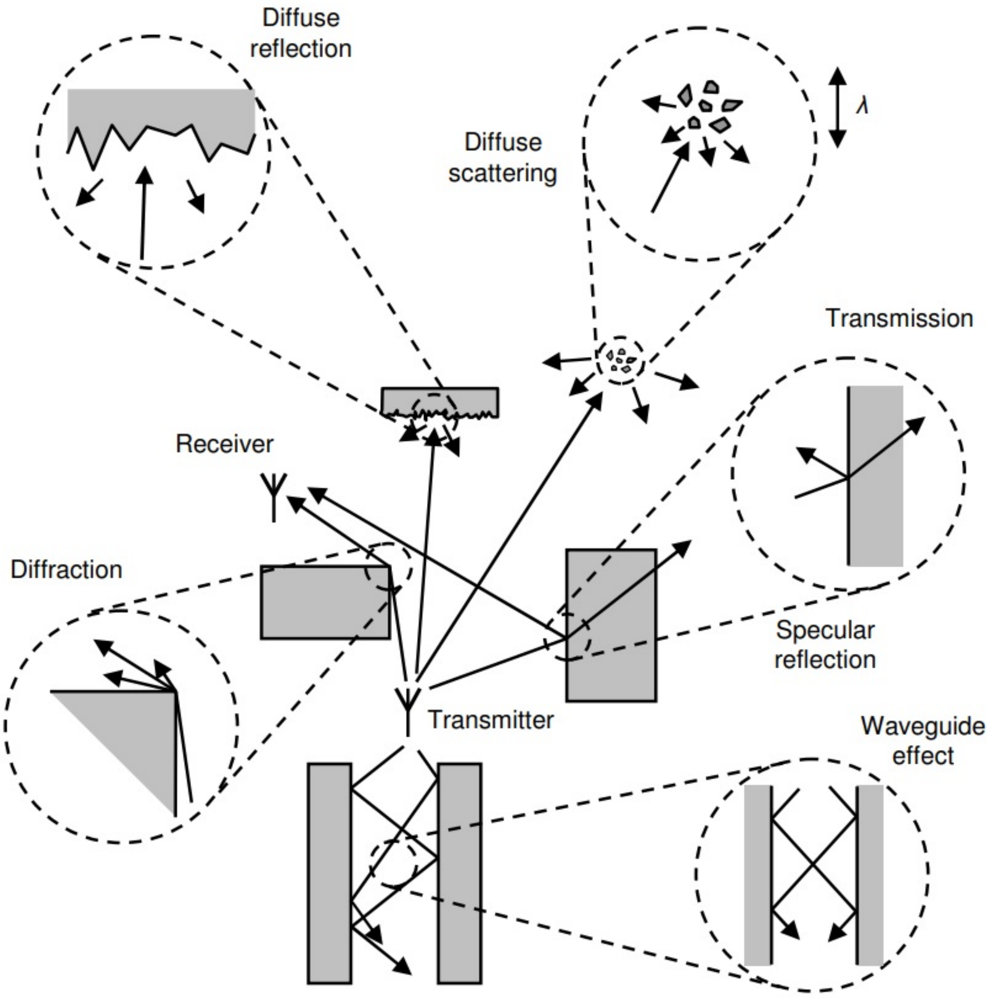


Fig. 3.3 Main propagation mechanisms [52]

- Reflection: Occurs when waves encounter large obstacles and bounce off them. Specular reflection follows predictable laws, while diffuse reflection occurs when the surface has random rough spots, scattering energy in various directions.
- Transmission: When waves pass through a material that is not fully radio-opaque, a portion of the incident wave is transmitted. Building materials in indoor environments attenuate the transmitted wave, and the attenuation and direction depend on the material's properties and the wavelength.
- Diffraction: Takes place at the edges of large obstacles relative to the wavelength. The electromagnetic field extends beyond the line of sight, and diffraction occurs based on Huygens' principle, treating each point on a wavefront as a secondary source.
- Diffusion: When waves encounter small obstacles, such as foliage or small objects, multiple random diffractions occur, resulting in a statistical distribution of the wave in various directions with variable attenuation.

- Waveguide Effect: Occurs in indoor and urban environments when waves undergo successive reflections between parallel obstacles, leading to a wave motion along the guiding direction. This phenomenon can be observed, for example, between corridor walls or buildings in a narrow street.

In wireless communication, the channel characteristics vary at different scales. Large-scale variations are influenced by obstacles and multiple paths, causing additional attenuation. The pathloss exponent N_d determines the rate of signal power decrease with distance. N_d is 2 in free space, 2-5 in NLOS, and <2 in LOS with waveguide effects. Small-scale fluctuations result from multipath propagation, where multiple signal versions combine with varying attenuations and phase delays, leading to rapid power fluctuations of 10-20 dB.

In realistic scenarios, signals spread over a frequency bandwidth can experience different types of fading. For narrow frequency bands, the fading is constant across the entire band, known as flat fading. However, in wider frequency bands, different frequencies can be affected differently, causing frequency selective fading. The coherence bandwidth is the range of frequencies affected similarly. In the delay domain, frequency selectivity corresponds to delays between different signal versions, resulting in echoes that can interfere and cause fades. Wideband signals, like UWB, have high time domain resolution and experience less pronounced fading. Frequency selectivity also leads to time domain spreading, which needs to be characterized for system calibration and mitigating inter symbol interference.

In order to evaluate the characteristics of a propagation channel, a set of measured impulse responses need to be analyzed.

When represented in decibels (dB), equation [3.3], which relates to the Friis formula for the propagation of signals in free space, can be expressed as follows:

$$PL(f,d) = 20\log\left(\frac{4\pi f d}{c}\right) - G_t(f) - G_r(f) \qquad [3.5]$$

The slow variations of the propagation channel are primarily caused by propagation loss and shadowing effects. To characterize the path loss with respect to frequency and distance, the parameter $PL(f,d)$ is approximated using the following formula:

$$PL(f,d) = PL(f_0,d_0) + 10N_f \log\left(\frac{f}{f_0}\right) + 10N_d \log\left(\frac{d}{d_0}\right) + S(f,d) \qquad [3.6]$$

The parameters $f_0$and d_0 represent an arbitrary frequency and distance, respectively. N_f and N_d are path loss exponents that account for the frequency and distance dependence of the propagation channel. N_d reflects the interactions between the radio wave and the environment and can significantly differ from the theoretical value $N_d = 2$, while N_f captures the frequency dependence of propagation phenomena and variations in the effective area of an ideal isotropic antenna, in a LOS situation where the antenna is not included in the propagation channel, we can assume $N_f = 2$. The term $S(f,d)$ represents the slow variations of the propagation channel and has a zero average. In dB, $S(f,d)$is typically assumed to follow a Gaussian distribution with a standard deviation of σ_S.

The Root Mean Squared (RMS) delay spread, denoted as τ_{RMS}, is a measure of the dispersion or spread of delays in the channel's impulse response. It is computed as the standard deviation of the Power Delay Profile (PDP), which is given by [58]:

$$\tau_{RMS} = \sqrt{\overline{\tau^2} - (\bar{\tau})^2} \qquad [3.7]$$

Where $\bar{\tau}$ is the mean access delay of the PDP and is given by:

$$\bar{\tau} = \frac{\sum_{k=0}^{N-1} a_k^2 \tau_k}{\sum_{k=0}^{N-1} a_k^2} \qquad [3.8]$$

Where N is the number of multipath components, and for the k_{th} component $a_k^2 = P(\tau_k)$ is the power and τ_k is the delay.

$\overline{\tau^2}$ is the second moment of the given PDP and is given by:

$$\overline{\tau^2} = \frac{\sum_{k=0}^{N-1} a_k^2 \tau_k^2}{\sum_{k=0}^{N-1} a_k^2} \qquad [3.9]$$

The coherence bandwidth, denoted as B_c, is the frequency range over which the wireless channel remains relatively constant or varies insignificantly. If the signal bandwidth (B_w) is equal to or smaller than the coherence bandwidth (B_c), the transmitted signal does not experience frequency selective fading, meaning that fading effects are similar across the entire frequency range. However, if the signal bandwidth is greater than the coherence bandwidth, the signal will experience frequency selective fading, indicating that different frequency components of the signal are affected differently by fading.

In the case of UWB, $B_w > B_c$.

The coherence bandwidth (B_c.) at -3 dB is determined by calculating the complex auto-correlation function [59], as follows:

$$R(\Delta f) = \int_{-\infty}^{+\infty} H(f) H^*(f + \Delta f)\ df \qquad [3.10]$$

Where $H(f)$ is the complex frequency response of the channel, Δf is the frequency shift and $*$ denotes the complex conjugate. The absolute value of $R(\Delta f)$ corresponds to the magnitude of correlation between the channel response at two spaced frequencies.

$$B_c = \begin{cases} \frac{1}{50\tau_{RMS}}, & if\ corr > 0.9 \\ \frac{1}{5\tau_{RMS}}, & if\ corr > 0.5 \end{cases} \qquad [3.11]$$

In the absence of detailed environmental information, it is commonly assumed that the arrivals of rays or clusters follow a Poisson process. In the Saleh and Valenzuela formalism, the probability of a new cluster or ray arrival is modeled as an exponential distribution with arrival rates Λ and λ, respectively.

The values 1/Λ and 1/λ represent the mean duration between successive clusters or rays. These parameters are estimated by analyzing the distributions of inter-cluster and inter-ray durations [52].

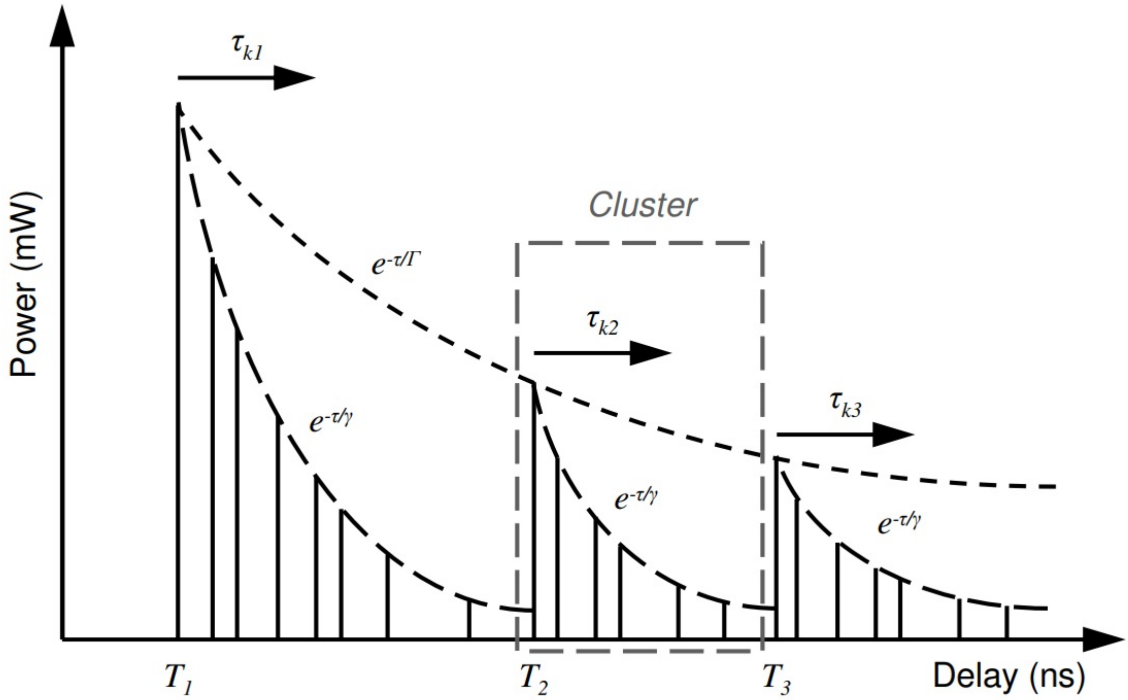


Fig. 3.4 Power delay profile following the Saleh and Valenzuela formalism [52]

3.2 Channel modeling

A channel model is a mathematical representation of the effects of a communication channel through which wireless signals are propagated. The channel model can represent the power loss incurred by the signal as it travels through the wireless medium. In a more general case, the channel model is the impulse response of the channel medium in the time domain, or its Fourier transform in the frequency domain. The channel impulse response of a wireless communication system typically varies randomly over time.

Empirical models are utilized to model radio propagation via measurements and statistics. They represent fast and easy facilities to quantify the wave propagation. However, they are less susceptible to the surrounding geometry and hence result in relatively lower accuracy [60], [61].

On the other hand, deterministic models depend on physical laws and thus necessitate the availability of an enormous amount of geometrical data. According to Geometric Optics (GO) and the Uniform Theory of Diffraction (UTD), the ray-based approach is convenient for radio propagation investigation since it simplifies the physical processes involved and accelerates complex calculations while maintaining a reasonable accuracy [62 - 64], [65], [66], [67], [68]–[70]. Therefore, the deterministic prediction models provide realistic precision but require comparatively higher computational complexity.

Deterministic propagation models are derived from simulations conducted in simplified propagation environments and are based on electromagnetic wave propagation theory. These models require a good understanding of the specific propagation environment and enable precise and accurate predictions of signal propagation in that environment. While theoretically, wave propagation characteristics can be calculated by solving Maxwell's equations, this approach involves complex mathematical operations and computationally intensive numerical calculations. Therefore, commonly used methods include Frequency Difference in Time Domain (FDTD) techniques, Methods of Moments (MoM), and ray techniques to approximate the propagation behavior.

3.3 Ray tracing approach

The ray-based approach, which combines geometric optics with the uniform theory of diffraction, is well-suited for studying radio wave propagation. In this approach, energy is assumed to be radiated along infinite tubes called rays, which define the propagation directions. These rays can undergo reflection or refraction at surfaces they encounter. The UTD complements the GO by introducing diffracted rays and ensuring field continuity in regions where the GO predicts no field existence.

Before determining the propagated field, the rays need to be identified using ray finding techniques. There are two main techniques: ray launching, which is a forward technique, and ray tracing, which is a backward technique. Once the rays are determined, the propagated field can be calculated from the transmission to the reception side.

Compared to other methods like FDTD and MoM, the ray-based approach requires fewer numerical resources for wave propagation prediction. Therefore, it is commonly used for deterministic propagation modeling. However, it is not suitable for low frequencies (typically below 100 MHz) when the size of objects interacting with the rays becomes small or comparable to the wavelength.

To improve the accuracy of propagation prediction, the ray-based approach can be combined with exact methods such as FDTD or MoM. This hybrid approach leverages the strengths of both techniques to enhance the accuracy and efficiency of propagation modeling.

Ray tracing is an approach used for modeling radio wave propagation, and it is characterized as a backward technique. It involves applying the image principle from the transmitter and receiver positions to determine the reflected rays. The complexity of the environment affects the number of potential image combinations, resulting in longer ray calculation times. In ray tracing, rays are traced backward from the receiver to the transmitter, taking into account reflections and diffractions encountered along the path. However, the computational complexity of ray tracing increases with the complexity of the environment, making it a time-consuming process, especially in scenarios with numerous reflecting surfaces and intricate geometries.

The Fermat's principle or the principle of least time has been demonstrated in [71] using the ray concept where the optical length of an actual ray between two arbitrary points $P1$ and $P2$ is shorter than the optical length of any other curve which joins these points and which lies in a certain regular neighborhood of it.

$$\int_{P_1}^{P_2} n\, ds = c(t_1 - t_2) \qquad [3.12]$$

As in Fig. 18, when the source T_x and field R_x positions are known, the path of a ray reflected from a planar surface Σ is determined by the image method where the image R_i, of the target field location R_x, is positioned with respect to the reflection surface Σ. Then, the line segment, connecting the transmitter T_x and the image R_i, intersects the surface Σ at a point Q. Eventually, the reflected ray trajectory is determined by the three points (T_x, Q, R_x). It is to be mentioned here that the image method can be extended to specify ray paths with multiple reflections where the process is recursive and can be conveniently realized using a computer-based program.

In this concern, the authors in [66] developed an efficient field prediction procedure, which utilizes a single ray-based simulation, at a specified spatial point at a single frequency, to evaluate the field in the neighboring region and extended the results to span a given range of frequencies.

Particularly, they developed a two-step process which first operates over the field contributions at the studied point to find a suitable set of field contributions for each new reception point followed by an extrapolation procedure to obtain the electric field throughout the given frequency range. Nevertheless, in an urban environment, applying the image method may not be efficient because of the large number of reflection surfaces resulting in slow computational speed.

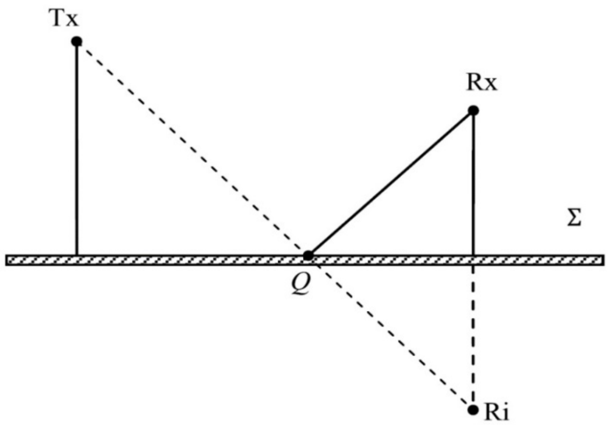


Fig. 3.5 Illustration of the image method [77]

To overcome the computational speed problems of the image method, the Shooting and Bouncing Ray (SBR), whose basic idea is to trace the rays launched from the source and specify whether they reached a given target point, offers a more convenient means for field prediction in more complex situations. The SBR comprises the launching of rays, ray tracing, and reception of rays. Concerning the launching of rays, it is necessary that the rays originating from the source be uniformly-distributed such that each ray carries the same power for an isotropic radiator. This implies dividing the surrounding spherical surface uniformly. The next step is the ray tracing where it is required to determine for each ray whether it intersects an object in the surrounding environment or not since a given ray, emanating from the source, may directly travel to the target point or it may undergo reflection, transmission, and/or diffraction before reaching the prediction point. This is because if the ray hits an object, a reflected or diffracted ray will be produced. The last step is to determine, for each ray, if the ray tube, associated with the ray, illuminates the reception point or not. When the reception point is hit, the ray is received, and the corresponding field can be evaluated.

As an application for this method, the authors in [72] simulated an outdoor scene where the receiver is equipped with a vertical rectangular array. Through the analysis of the propagation paths, they verified the validity of the SBR method by studying the propagation characteristics, which include the power angle profile, power delay profile, and delay spread in both LOS and NLOS circumstances. In spite of the fact that the SBR scheme has the advantage of simple implementation, the ray paths may not be exactly specified as compared with the image method. In this concern, the authors in [73] proposed a hybrid method that takes the benefits of the SBR scheme, which has a faster computational speed, and the image method, with precise determination for the ray paths. This scheme first utilizes the SBR technique to determine the rays received by the receiver then applies the image method to regulate the ray trajectory. Since all the reflecting surfaces accompanying a given ray are known, the aim of the image method is only to determine the images of the transmitters or receivers with respect to those reflecting surfaces in a definite sequence. Consequently, as the number of rays received is smaller than that of rays launched, there is a negligible overhead of using the image method to improve the precision of ray trajectories.

3.4 Deterministic UWB channel modeling using ray tracing

Deterministic models are commonly employed as site-specific models to accurately predict signal propagation in a specific environment through simulation software. However, there is currently a limited availability of simulation software specifically designed for UWB systems compared to narrowband systems, where such software is widely used for radio system deployment planning.

When applying classical deterministic modeling software to UWB, certain adjustments are necessary to account for the wide frequency band of impulse signals. In addition to considering the amplitude of power loss in the overall calculation, it is crucial to incorporate phase information. This enables the reconstruction of the received signal in the time domain, corresponding to the modeled UWB link. By capturing both amplitude and phase characteristics, the deterministic modeling software can provide a comprehensive representation of UWB signal propagation.

In narrowband transmission techniques, deterministic software emphasizes the power loss of the transmitted signal. This enables the creation of radio coverage maps for any given environment at a specific central frequency corresponding to the narrowband signal.

The propagation study in narrowband systems typically focuses on this central frequency, assuming that the bandwidth is narrow enough.

However, in the case of UWB systems, the transmitted signal encompasses a significantly broader frequency range, often reaching up to 7.5 GHz. Therefore, simulations for UWB must consider all the phenomena occurring across the entire bandwidth, rather than focusing solely on the central frequency. This necessitates incorporating the effects of antennas and material properties across the entire frequency band in the synthesized link.

Moreover, UWB deterministic modeling requires the inclusion of phase information related to propagation, along with considering the combined effects of antennas and material properties. The phase information is vital for identifying potential distortions, such as attenuation and dispersion, experienced by the received signal during transmission. Deterministic modeling in UWB allows for studying the effects of physical phenomena observed in channel propagation measurement campaigns, thereby enhancing the understanding of these effects in specific environmental configurations.

By utilizing site-specific tools for deterministic modeling, researchers can investigate wave propagation in various environments and specific configurations. This approach not only aids in comprehending the observed effects in measurements but also provides valuable insights into the physical aspects of UWB signal propagation.

There are four principal deterministic models which appear in the literature, Qiu model, Yao model, Attiya model and the Uguen and Tchoffo Talom model. We will only look at the last one which pretty much is the most accurate of all the previous.

In the model proposed by Uguen and Tchoffo Talom. In their initial contribution, they focused on synthesizing the received signal using a formalism that considers the channel ray by ray. However, this initial model did not account for important elements such as indoor multi-layered materials and antennas. Subsequently, they made a more comprehensive description of the model, addressing these shortcomings and providing a better representation of each channel element [74, 75].

This model shares similarities with the one proposed by Attiya [76]. However, Uguen and Tchoffo Talom's model offers an improved treatment of antennas within the model. Additionally, they construct each ray contribution separately, enabling easy access to the Direction of Departure (DoD) and Direction of Arrival (DoA) information. Consequently, each ray in the model is influenced by the antenna functions corresponding to its actual DoD and DoA, as defined in the frequency domain.

In this thesis, we used another approach to model the propagation channel over UWB which is called Band-Divided Ray Tracing invented in [85], In which they proposed to characterize the UWB propagation, we divide the bandwidth into multiple sub-bands, ensuring that each sub-band has a narrow width to assume flat frequency characteristics within it. We employ a standard ray tracing method to obtain delay profiles for each sub-band, considering the analysis frequency at the center of each sub-band. Due to the frequency-dependent nature of materials, the delay profiles may vary, even for the same propagation path.

To obtain more accurate results, we convert these delay profiles into frequency responses that are precise around each analysis frequency. We then extract the accurate portions from each frequency response and combine them to create a new frequency response. Finally, we convert the combined frequency response back into the time domain, resulting in a delay profile that is valid and applicable over the entire UWB bandwidth. This process allows us to obtain a comprehensive characterization of UWB propagation taking into account the frequency-dependent effects of materials (Figure 3.6).

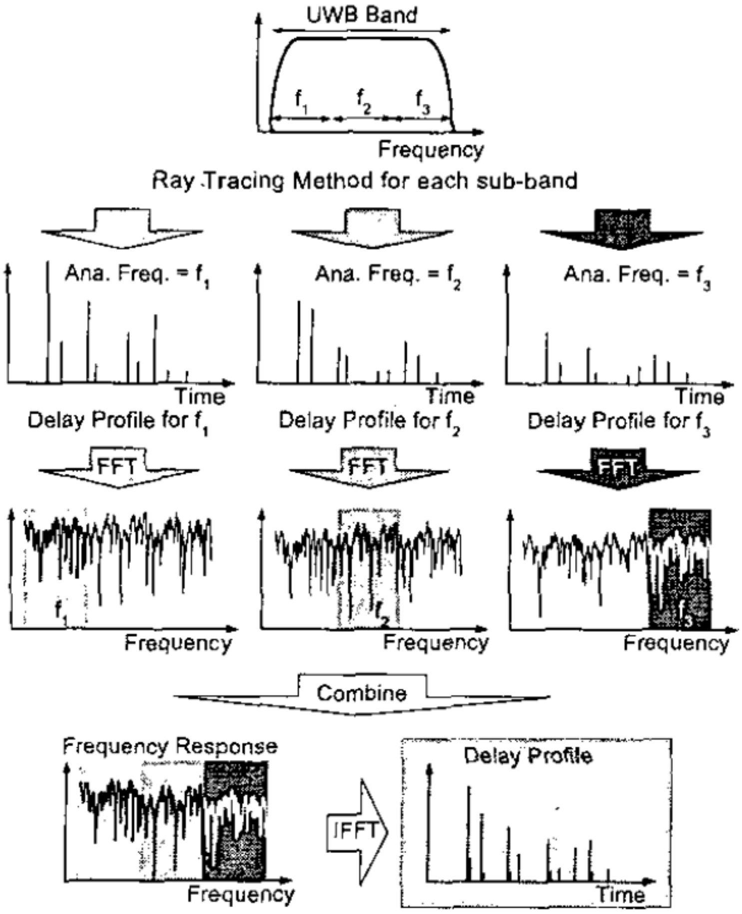


Fig. 3.6 Flowchart of band-divided ray tracing method [85]

3.5 Considerations for accurate and realistic UWB channel modeling in industrial environments

To properly describe the UWB channel in industrial environments we need to consider certain environmental induced parameters for the model to be approximately realistic.

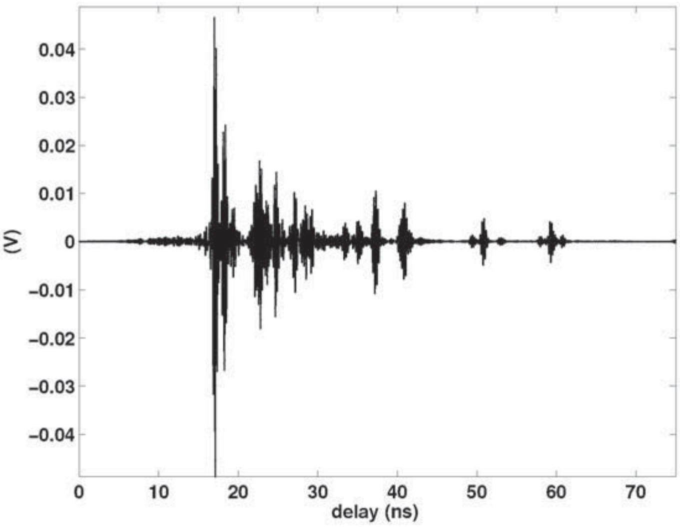
In industrial environments, the communication performance is significantly impacted by reflections from metallic structures such as machinery and pipes. These reflections often give rise to specular reflections and dense multipath phenomena. The presence of these reflections can have a detrimental effect on the overall communication performance.

Experimental studies conducted to characterize UWB propagation in industrial environments have revealed deviations from the widely accepted Saleh-Valenzuela model [81]. In typical indoor environments, LOS communication primarily exhibits a dominant multipath component corresponding to the first signal path, with subsequent Multi-Path Components (MPCs) decreasing in strength. However, in industrial scenarios, propagation characteristics differ from indoor office or residential environments due to the presence of numerous scatterers and reflections from metallic surfaces.

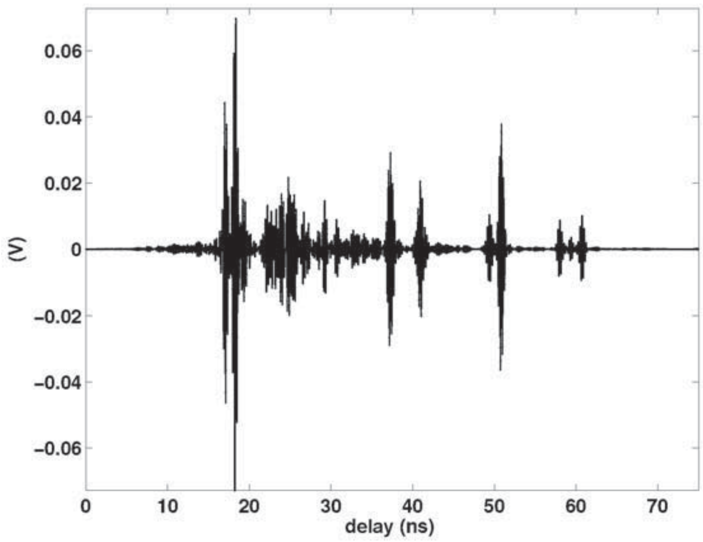
A channel model specifically designed for industrial environments [81], based on measurement campaigns conducted in industrial halls, demonstrated that although MPC clusters were observed, they did not follow a single exponential delay profile. The decay time constants of the clusters varied for each cluster, indicating non-exponential behavior. Consequently, it was concluded that neither the decay of cluster power nor the power distribution of individual rays within the clusters can be accurately modeled using pure exponential functions.

So, it is mandatory to include the environment materials in the channel model to consider these effects.

In [52], the authors investigated the effects of the building materials on the received signal finding that materials with higher conductivity increases density of MPCs giving rise to rays arriving after the direct path which shows a higher level. In figure 3.7, the two PDPs for the receiving antenna before and after introducing new materials with higher conductivity. [52]



(a)



(b)

Fig. 3.7 Received signal obtained for two configurations of building material properties: a) low conductivity materials, b) higher conductivity materials [52]

Changes in material properties have a substantial impact on the shape of the received signal. To enhance the accuracy and realism of waveforms generated through deterministic modeling tools, it is crucial to incorporate the appropriate material properties of building materials specific to the environment being modeled. This ensures that the modeling accurately represents the characteristics of the environment in the link modeling process.

Chapter 4 Optimal Sensors Deployment Framework

In this chapter, we will formulate our problem of optimizing the sensor nodes deployment in a simulated industrial environment in this flow, we will start by showing our WSN proposed architecture and what assumptions were used, then we will define our design variables and constraints, then investigate our coverage requirements and how to optimize them in our context and finally we will describe the optimization algorithm used.

4.1 Problem formulation for optimal sensors deployment in indoor environments

This section outlines the assumptions made in our proposed method and presents the formulation of the problem related to the deployment of sensor nodes in a 3D indoor environment.

The designated 3D space where the deployment of sensor nodes takes place is referred to as $\boldsymbol{A}$. Within this space, there exist certain objects known as obstacles, which have the potential to impede communication and/or sensing capabilities of the sensor nodes. The set containing these obstacles is denoted as $\boldsymbol{O}$.

The specific region within $\boldsymbol{A}$ that require monitoring is referred to as *the monitoring area* and is denoted as $\boldsymbol{A}_m$. On the other hand, the subarea(s) of $\boldsymbol{A}$ where the installation of sensor nodes is feasible is referred to as *the deployable area* and is denoted as $\boldsymbol{A}_d$. It's important to note that the cost associated with installing a sensor node can vary depending on its location within $\boldsymbol{A}_d$. The cost for installing a sensor node at a given location d in $\boldsymbol{A}_d$ is represented by $cost(d)$.

We only consider stationary sensor nodes in our 3D area $\boldsymbol{A}$. These nodes cannot move once they are placed in their locations. Each sensor node can communicate wirelessly and has a range for sensing r_s and another range for communication r_c . The sensing range represents the sphere centered at the sensor with radius r_s, in which the node can detect and gather information. The communication range is also represented by a sphere of radius r_c within which the node can directly communicate with other sensor nodes. However, both the sensing and communication ranges can be blocked by obstacles present in the environment.

In our method, we assume that the target points to be covered are sensors that directly read the desired information and send it to one of the relay nodes covering it. So, for the relay sensor nodes, the target points/sensors must be in its sensing range.

In the presence of obstacles, certain areas within the sensing range of a sensor node are obstructed, and the node cannot gather information from these blocked regions (Figure 4.1). We assume that for two sensor nodes to communicate with each other, there must be a direct LOS between them without any obstacles obstructing the straight path.

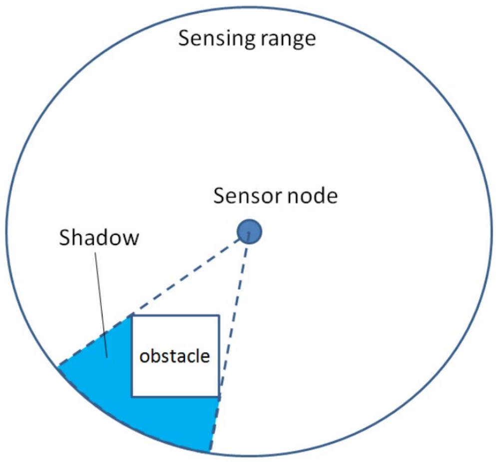


Fig. 4.1 Shadow area generated by obstacle in sensing range [83]

Our objective is to address the following problem in a three-dimensional indoor area $\boldsymbol{A}$: Given a set of obstacles $\boldsymbol{O}$ within $\boldsymbol{A}$, a deployable area for sensor nodes ($\boldsymbol{A}_d \subseteq \boldsymbol{A}$) with a cost function $cost(d)$, a monitoring area ($\boldsymbol{A}_m \subseteq \boldsymbol{A}$), a BS node with its position ($BS.pos$), we aim to determine the optimal number of sensor nodes and their respective positions. The goal is to achieve k-coverage of $\boldsymbol{A}_m$ and ensure connectivity and quality of communication between all sensor nodes and the BS, while minimizing the total deployment cost and ensuring a minimum level of quality for the links.

Let's denote the set of sensor nodes for deployment as S. Each sensor node $s \in S$ must be deployed within the deployable area $\boldsymbol{A}_d$. We can represent the deployed position of sensor node s as $s.pos$. The following equation holds:

$$\forall s \in S, s.pos \in \boldsymbol{A}_d \quad [4.1]$$

To ensure coverage of the monitoring area $\boldsymbol{A}_m$, we define coverage criteria based on the sensing range r_s of sensor nodes. We consider a monitoring point m ($m \in \boldsymbol{A}_m$) to be covered by a sensor node s only if it falls within the sensing range r_s and is not obstructed by any shadow area.

For k-coverage of the monitoring area $\boldsymbol{A}_m$, we require that each monitoring point m is covered by at least k sensor nodes. We denote this as m being "k-covered". To achieve k-coverage of $\boldsymbol{A}_m$, the following equation must hold:

$$\forall m \in \boldsymbol{A}_m, | \{s | s \in S \ \wedge \ m \in r_s \setminus LOS(s,m) \ \wedge RSSI(R_x) \geq RSSI_{threshold}\}| \geq k \qquad [4.2]$$

Where $LOS(s,m)$ means there exists a direct LOS between the sensor and the target point and $RSSI(R_x) \geq RSSI_{threshold}$ means that the received signal strength at the receiving end is bigger than a threshold value.

To ensure the connectivity of the entire WSN, we define connectivity based on the presence of a connected path between a sensor node s and the BS.

A sensor node s is considered connected if it has a path, either direct or indirect to the BS, to achieve overall connectivity, the following equation must hold:

$$\forall s \in S, connected(s, BS) = true \qquad [4.3]$$

Using the above constraints, the objective function of our target problem is given by the following equation:

$$\boldsymbol{minimize} \ \sum_{s \in S} cost(s.pos) \qquad [4.4]$$
$$subject\ to\ constraints\ (4.1) - (4.3)$$

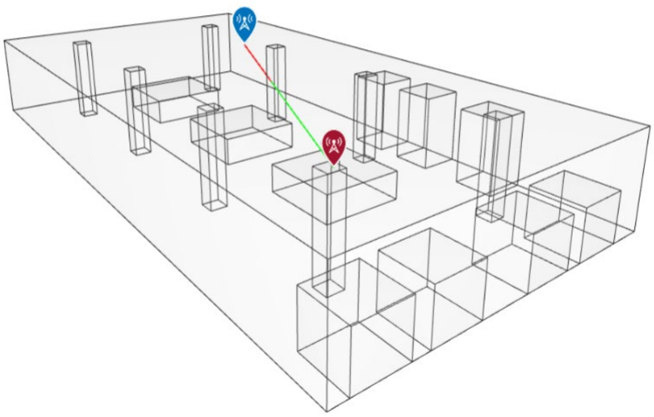
4.2 Integration of the UWB channel model

In the optimization of sensor placement, the seamless integration of the UWB channel model derived from the band-divided ray tracing approach assumes paramount significance. This integration enables us to leverage the comprehensive understanding of the wireless channel by accurately calculating the RSSI for each pair of sensor and monitoring point/sensor within the industrial environment.

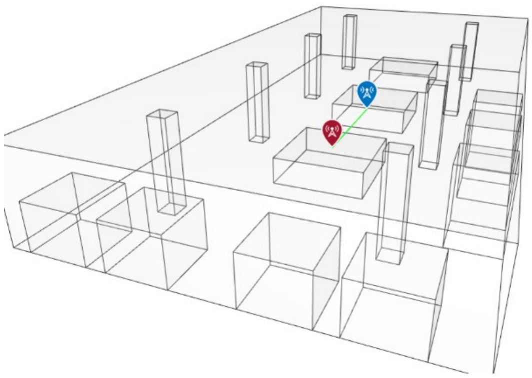
By harnessing the rich propagation characteristics offered by the channel model, we gain insights into the signal strength and quality at diverse locations, which becomes instrumental in determining the most optimal deployment of sensors. The UWB channel model accounts for intricate electromagnetic wave interactions encompassing reflections, diffractions, and multipath effects. Incorporating this model into our optimization algorithm ensures meticulous consideration of the channel's characteristics, thereby facilitating the creation of a deployment plan that guarantees dependable and robust wireless communication across the entirety of the industrial setting. Precisely calculating RSSI values based on the UWB channel model serves as a pivotal metric for evaluating the performance and feasibility of distinct sensor placement configurations, consequently enabling us to identify optimal solutions that fulfill the desired coverage and communication requirements in a reliable manner.

To ensure coverage and quality of communication, a metric representing the covered area per deployment cost was used, where for each deployable location $d \in \boldsymbol{A}_d$, this metric is calculated as the ratio of the number of monitoring points/sensors covered by this location to the deployment cost of this sensor. The notion of whether the sensor sees the target point or not was derived using ray tracing approach and UWB channel model to calculate the RSSI at the receiving end.

For each sensor and monitoring point pair, a ray tracing algorithm was applied to detect the existence of a LOS propagation path or not (Figure 4.2), if there is, then the RSSI value is calculated using the UWB channel model derived from the band-divided ray tracing technique, where we make sure that the RSSI value is greater than a certain threshold to ensure quality of communication.



(a)



(b)

Fig. 4.2 LOS Ray tracing between relay sensor node and target point, a) No LOS, b) LOS

After the detection of target points which exhibits a LOS link with the relay sensor, we need to make sure that the RSSI is higher that a threshold value to ensure the connection quality, so we apply a band-divided ray tracing approach between arbitrary transmitter and receiver in our environment, so we can model the UWB channel and blind predict the RSSI.

So, after applying the band divided ray tracing approach on sample frequencies $f_c = [3.25e9, 3.75e9, 4.25e9, 4.75e9, 5.25e9, 5.75e9]$, for a total bandwidth of 3Ghz with central frequency $f_0 = 4.24e9$, we obtained the Channel frequency response $H(f)$.(Figure 4.3)

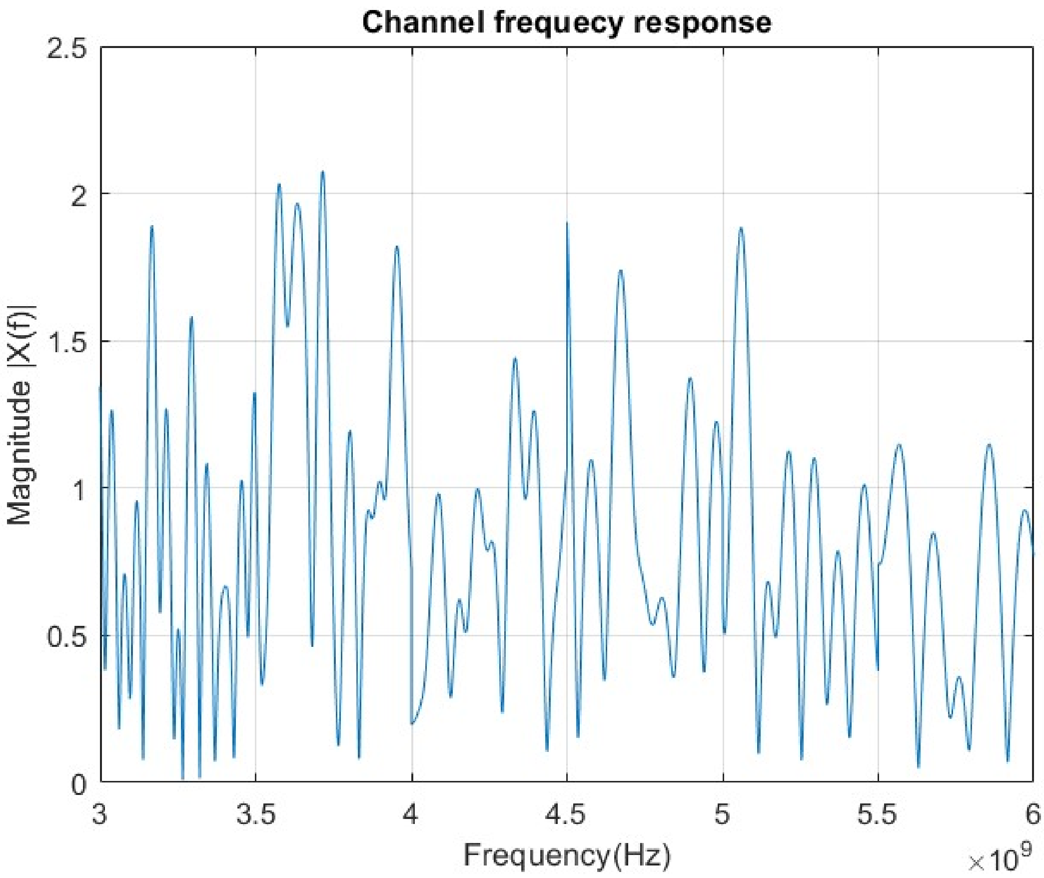


Fig. 4.3 UWB channel frequency response H(f)

We then apply a signal x(t) to the channel and calculate the RSSI from the output received signal after the channel, denoted as y(t).

4.3 Design and development of the optimization algorithm

To make the computation more manageable in the proposed algorithm, we adopt a discretization approach for both the monitoring area and the deployable area. We divide the monitoring area $\boldsymbol{A}_m$ and the deployable area $\boldsymbol{A}_d$ into a set of grid points, respectively.

The set of monitoring points M comprises the points that need to be covered by the wireless sensor network. These monitoring points are represented by a collection of target points placed within the monitoring area $\boldsymbol{A}_m$.

The set of deployable points D consists of the points where sensor nodes can be placed. These points correspond to the grid points located within the deployable area $\boldsymbol{A}_d$.

In our assumption, we consider the target 3D space to be adequately covered when all the monitoring points M are adequately covered. This means that each monitoring point is covered by a sufficient number of sensor nodes, ensuring that the desired level of coverage is achieved throughout the entire space. By ensuring the sufficient coverage of all monitoring points, we can ensure the overall coverage of the target 3D space.

The algorithm we propose comprises two phases: initial deployment and node selection. Also, we assume that the sensing radius of a sensor node is not greater than half of its communication radius, i.e., $r_s \leq \frac{1}{2} r_c$. The pseudo code for the algorithm is presented below as Algorithm 1:

- Initial deployment
  As depicted in lines 1-3 of Algorithm 1, the algorithm starts by creating the 3D indoor model then, the algorithm calculates the 3D Euclidean coordinates of the monitoring points M and the deployable points D, based on the given monitoring area $\boldsymbol{A}_m$, deployable area $\boldsymbol{A}_d$, and the grid interval Δ . It is important to note that the grid interval Δ should not exceed the communication range r_c of the sensor nodes ($\Delta \leq r_c$). Selecting a smaller Δ value will lead to a more precise deployment, although it may also increase the computational cost of the algorithm.
- Node selection
  In the subsequent step, the algorithm chooses the deployable point d with the highest dc ratio. The dc ratio is computed using the following function:

$$dc = \frac{|\{m | m \in M \wedge m \in Sphere(d, r_s) \wedge LOS(d, m) \wedge RSSI(d, m) \geq RSSI_{threshold}\}}{cost(d)} \qquad [4.5]$$

Here, d refers to a specific deployable point, and the dc ratio represents the ratio between the number of monitoring points covered by d and its associated cost. $sphere(d, r_s)$ means the sphere with radius r_s centered at d. The algorithm selects the deployable point with the highest dc ratio, indicating that it provides the best coverage-to-cost ratio among the available options.

Initially, the dc ratio is calculated for each deployable point $d \in D$, and the algorithm selects the deployable point with the highest dc ratio. This process is described in loop 7.1 of Algorithm 1. The algorithm iterates through each deployable point d in the set D and computes the dc ratio for each point using the formula mentioned earlier. Then, it identifies the $index$ of the deployable point d with the highest dc ratio as the one that provides the best coverage-to-cost ratio among all available deployable points.

A sensor node s is then placed on index (line 7.2), Then the used deployable location d is removed from the available deployable locations $\boldsymbol{A}_d$. The coverage level of all the newly covered target points/sensors are updated. After this, the algorithm loops over the coverage levels of all the target points, removing any sufficiently k-covered ones. The algorithm keeps repeating until all the target points are sufficiently covered.

Finally, after obtaining the deployment of the WSN sensor nodes, the algorithm make sure that each deployed sensor is connected to the BS by detecting the connected and unconnected sensors.

Algorithm 1 IWSN 3D nodes deployment optimizing target coverage, cost, connectivity, and communication quality.

---

1. Construct the 3D industrial environment model $\boldsymbol{A}$.
2. $DeployableLocations = computeDeployableLocations(\boldsymbol{A}, \Delta)$
3. $targetPoints = computeTargetPoints/sensors(\boldsymbol{A})$
4. $UWBmodel = uwbBandDividedRayTracing(Ptx, f_c, BW)$
5. $k = input$
6. $coverageLevels(targetPoints) = 0$
7. $maxDC = 0$
8. $While(\ minimum(coverageLevels) < k)$
    - 7.1. $for\ each\ deployable\ location\ d\ \in D$
        - I. $computeDC(d, targetPoints, RSSI_{threshold})$
        - II. $if\ dc > maxDC$
            - $maxDC = dc$
            - $Index = d$
    - 7.2. $Deployed(index)$
    - 7.3. $removeDeployableLocation(d)$
    - 7.4. $updateCoverageoftargetPoints(targetPoints)$
    - 7.5. $removeSuffcientlyCovered(targetPoints)$
9. $detectConnectedAndUnconnected(deployed)$

Chapter 5 Experimental Evaluation and Results

In this chapter we show the details of our simulation settings and the implementation of the optimization framework using MATLAB, First we construct our 3D industrial environment and show how it was designed to mimic the real life industrial environments, then we look at the MATLAB implementation of our optimization algorithm, we then set our simulation settings and provide the results obtained, lastly we compare our obtained results with WSNs deployment algorithms from various aspects.

5.1 3D Industrial environment simulation

Based on our decision to model the metal works type of industrial environments previously discussed in Chapter 2, we choose the model represented in Figure 2.7 to try and create a simplified 3D model that mimics it with the integration of obstacles in the form of metallic columns that extend to the ceiling , also to increase the reality of the model we created square obstacles inside the model to represent the existence of different dimension machinery inside the environment.

There are different programs available to create a 3D model to be used for simulations like AutoCAD, 3Dsmax, etc. but for the sake of our simple simulation, we choose to model the environment by creating a triangulation object in MATLAB to define the vertices and the construct the surfaces between those vertices as shown in Figure 5.1.

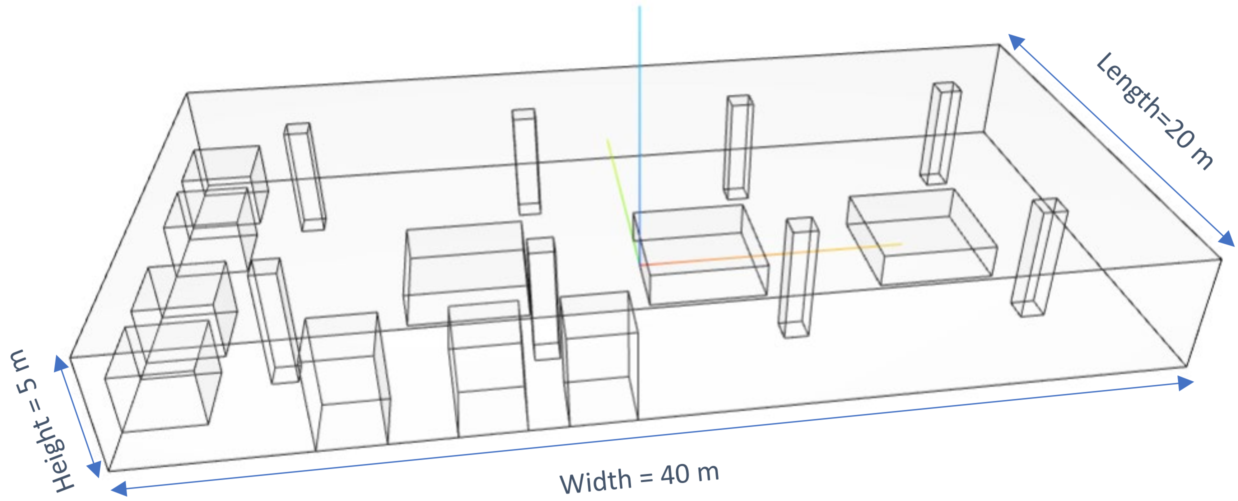


Fig. 5.1 3D industrial environment model

The dimensions of the environment are 40x20x5 meters, with every obstacle is a square with various heights.

Furthermore, to capture the true nature of industrial environments and the abundance of reflecting surfaces in the environment, In the UWB channel model derived using band-divided ray tracing, the surfaces material was inputted as metals to accommodate for the dense multipaths propagation effects on the RSSI.

```
pm = propagationModel("raytracing", ...
    "CoordinateSystem","cartesian", ...
    "Method","sbr", ...
    "AngularSeparation","low", ...
    "MaxNumReflections",3, ...
    "MaxNumDiffractions",1,...
    "SurfaceMaterial","metal");
```

Fig. 5.2 Propagation model initialization for ray tracing in MATLAB

5.2 Implementation and execution of the optimization algorithm

Given the 3D industrial environment model we constructed earlier, the implemented code on MATLAB according to Algorithm 1 will deploy the relay sensors accordingly in our environment achieving the k-coverage of the target points.

So for the initial deployment phase, we first discretize the deployable locations using a step distance, while for the target points to be covered, we hard coded the 3D positions of the target points to simulate the presence of sensors embedded inside the machinery that have communication range equals to the sensing range of the relay nodes, so in order for them to relay the sensed information to the BS, they need to be in the sensing range of 1 or more relay nodes (Figure 5.3).

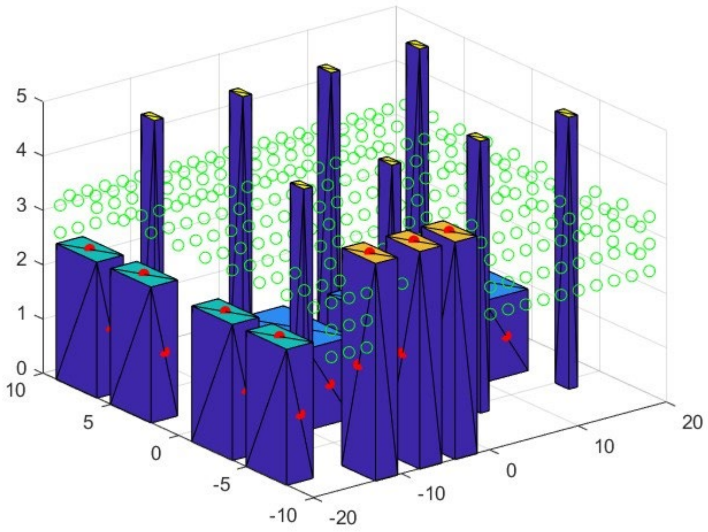


Fig. 5.3 Monitoring points and deployable points in industrial environment

In our context, we used the height of the deployable location as the determining factor of the cost of deployment of the sensors, with sensors deploying high enough has lower cost than sensors deployed at lower heights.

There are 3 levels for deployable locations, at a height of 3.5 meters a grid of deployable locations that simulates a mesh of relay nodes deployed at a lower level from the ceiling, and at heights of 3 and 2.5 meters, two vertical rows of deployable locations on the empty walls of the environment as shown in Figure 5.4.

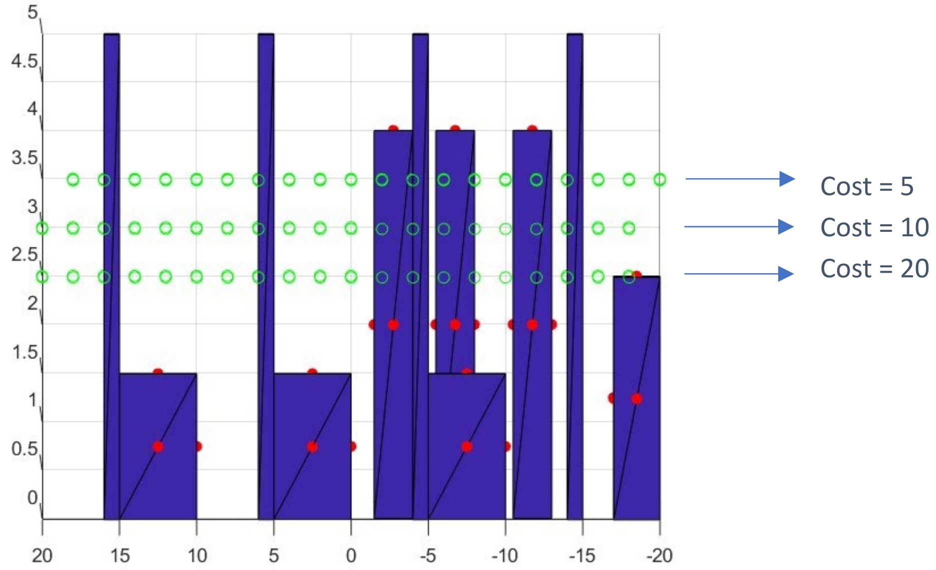


Fig. 5.4 Deployable location at different heights with different costs

Then for the next phase, which is node selection, the implemented code will run a series of loops and computations to calculate the near-optimal locations of the relay sensors to deploy.

5.3 Simulation results

For this simulation all the values that were used are stated in Table 5.1.

Table 5.1 Simulation configuration parameters

Target space	40m x 20m x 5m
k-coverage	3
Sensing rang r_s	5 m
Communication range r_c	10m
$RSSI_{threshold}$	-80 dBm
BS location	(0, 0, 5)
Δ	2 m
P_{tx}	10 dBW
f_c	4.25 GHz
BW	3 Ghz

After running the optimization algorithm with this configuration.

The algorithm took 67 iterations to finish the deployment of the 46 relay nodes to sufficiently cover all the target points totally as shown in Figure 5.5.

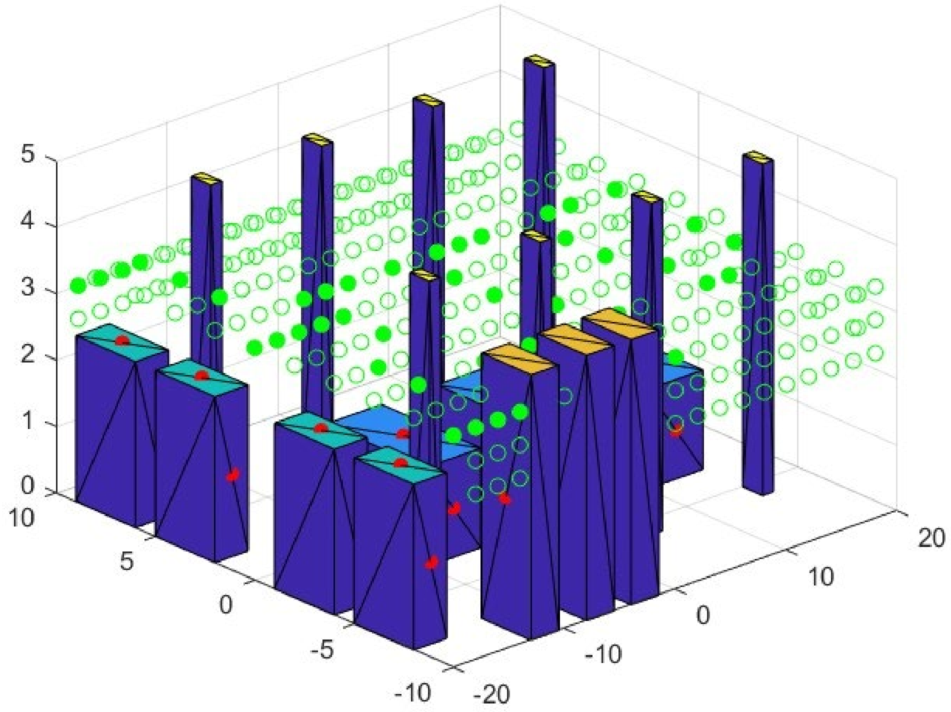


Fig. 5.5 WSN deployment result

The coverage levels for the 32 target points are shown in Figure 5.6.

```
Columns 1 through 17

   5     3     3     5     3     4     5     3     3     5     3     5     3     3     3     3     3

Columns 18 through 32

   3     3     4     3     5     3     3     3     3     6     3     3     3     3     6
```

Fig. 5.6 Coverage levels

To ensure the connectivity of the relay nodes to the BS, another check is run based on the notion of calculating the edges of the WSN, where each two connected relay nodes construct an edge if they are in each other's communication range r_c and there exists LOS between them and the RSSI is bigger than the threshold value, plotted in Figure 5.7, the edges between each two deployed sensors, also we added the BS to the deployed sensors to show which sensor are directly connected to the BS.

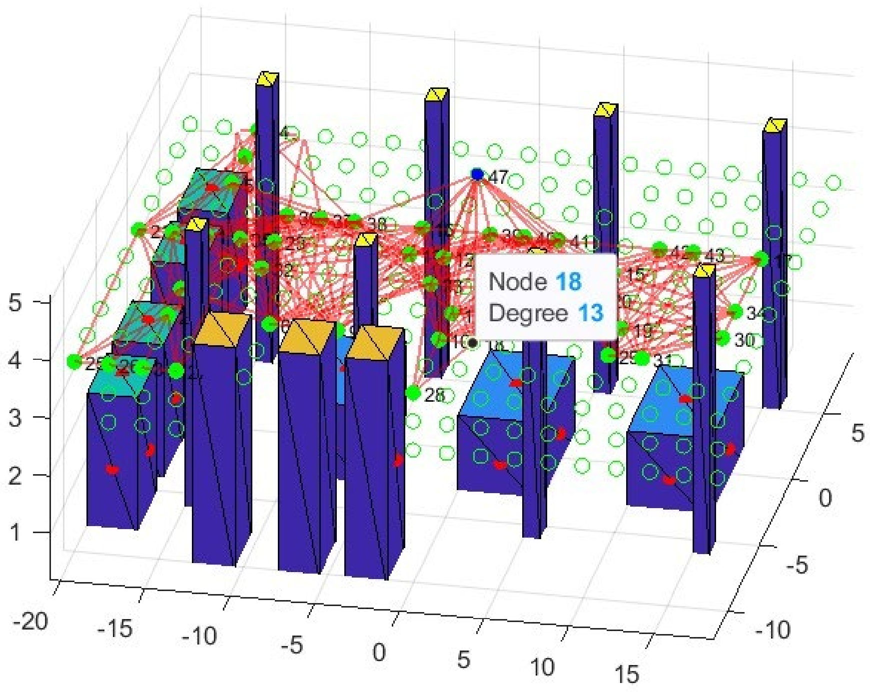


Fig. 5.7 Connectivity plot of the deployed Sensors with the BS

Using the function $conncomp(Graph)$ which calculates what group each element is connected to directly or indirectly, shows that each one of our 46 deployed sensors together with the BS all belong to the same group as shown in Figure 5.8.

```
ans =

  Columns 1 through 17

     1     1     1     1     1     1     1     1     1     1     1     1     1     1     1     1     1

  Columns 18 through 34

     1     1     1     1     1     1     1     1     1     1     1     1     1     1     1     1     1

  Columns 35 through 47

     1     1     1     1     1     1     1     1     1     1     1     1     1
```

Fig. 5.8 Conncomp(graph) output

5.4 Comparison with existing deployment approaches

To evaluate the performance of our proposed algorithm, it is done by comparing it to existing deployment approaches in the same simulation settings, we selected the *LowCost* algorithm proposed by Kouakou et al. (2010) in [83], which uses the same dc ratio parameter used in our proposed algorithm to deploy the nodes one by one to fulfill k-coverage and connectivity, but it's deployment was based only on the existence of LOS between the sensor node and the covered point with the covered point lying in the sphere of radius r_s centered at the sensor node.

The key performance metrics we are evaluating are the number of deployed nodes, execution time, k-coverage percentage, connectivity to the BS and the Mean RSSI for every target point.

For the k-coverage KPI, it is calculated as the summation of the number of target points which are k-covered divided by the total number of target points, as shown in equation 4.6.

$$K - coverage = \frac{\sum_{i=1}^{M} m \mid \forall m \in A_m, \left| \{ s \middle| s \in S \ \wedge \ m \in r_s \setminus LOS(s,m) \ \wedge RSSI(R_x) \geq RSSI_{threshold} \} \right| \geq k}{M} \qquad [5.1]$$

The mean RSSI for every target point is calculated for every target point m as the summation of every RSSI at every deployed sensor covering this point m over the number of the deployed sensors covering it, then it's summed over all the target points M divided by the number of target points.

$$MeanRSSI_{m_i} = \frac{\sum_{j=1}^{deployed} RSSI_{i,j} \mid deployed(j) \ is \ covering \ m_i}{\sum_{j=1}^{deployed} deployed(j) \ is \ covering \ m_i} \qquad [5.2]$$

$$MeanRSSI = \frac{\sum_{i=1}^{M} MeanRSSI_{m_i}}{M} \qquad [5.3]$$

As a reference for the RSSI values, check Figure 5.9.

-30 dBm: This is the maximum signal strength. If you have this measurement, you are likely standing right next to the access point.

-50 dBm: This is considered an excellent signal strength.

-60 dBm: This is a good signal strength.

-67 dBm: This is a reliable signal strength. This is the minimum for any online services that require a reliable connection and Wi-Fi signal strength.

-70 dBm: This is not a strong signal strength. You may be able to check your email.

-80 dBm: This is an unreliable signal strength. You may be able to connect to your network, but you will not support most online activity.

-90 dBm: This is a bad signal strength. You are not likely to connect to internet at this level.

Fig. 5.9 RSSI dBm values indication [84]

The obtained results for both algorithms are showed in table 5.2.

Table 5.2 KPIs comparison of proposed algorithm and LowCost algorithm

Algorithm	Number of deployed nodes	Execution time (sec)	K-coverage percentage (%)	Connectivity (Sensor node to BS)	Mean RSSI (dBm)
Proposed	67	3116	100	Yes	-61
LowCost	85	162	78	Yes	-71.9

Also, according to literature the LowCost algorithm presented in [84] showed great results compared to other algorithms using multi-objective optimization in the case of optimizing the coverage and connectivity of deployed sensors while minimizing the cost and exhibiting much less execution time compared to other algorithms.

Chapter 6 Discussion and Conclusion

In this chapter, we present a comprehensive discussion of the research findings, their interpretation, and their implications for the field of wireless sensor networks in industrial environments. We also address the limitations encountered during the study and propose suggestions for future research and improvements.

6.1 Interpretation and implications of the results

Moreover, the interpretation of the results underscores the potential for significant economic and environmental benefits. The optimized sensor deployment approach leads to more efficient resource utilization, reducing energy consumption and minimizing waste. By precisely monitoring and controlling various industrial processes, companies can identify areas of inefficiency, optimize workflows, and implement sustainable practices. This, in turn, contributes to cost savings and a reduced environmental footprint.

The implications of the research findings extend beyond individual industries. The advancement of wireless sensor networks in industrial environments can have broader societal impacts. For instance, in the context of smart cities, the deployment of sensor networks can enable the monitoring of critical infrastructure, such as transportation systems, utilities, and public spaces. This facilitates proactive maintenance, enhances public safety, and improves the overall quality of urban life.

Additionally, the research outcomes stimulate further research and development in the field of wireless sensor networks. The proposed approach opens avenues for exploring advanced optimization algorithms, novel wireless technologies, and integration with other emerging technologies like artificial intelligence and edge computing. By continuing to refine and expand upon this research, future studies can further optimize sensor deployment strategies, overcome existing limitations, and tackle new challenges that arise in industrial environments.

In conclusion, the interpretation of the research results reveals the transformative potential of the optimized sensor deployment approach based on the integration of the UWB channel model and RSSI calculations. The implications encompass improved industrial processes, economic benefits, environmental sustainability, and broader societal impacts.

The research findings not only contribute to the field of wireless sensor networks in industrial environments but also serve as a catalyst for innovation, inspiring further advancements in this rapidly evolving domain.

6.2 Limitations of the proposed approach

While the proposed approach for optimized sensor deployment in industrial environments offers significant advantages, it is essential to acknowledge its limitations. These limitations provide insights into areas that require further investigation and potential improvements:

1. Model Assumptions: The proposed approach relies on certain assumptions regarding the environment, sensor characteristics, and network dynamics. While these assumptions facilitate the development of the optimization algorithm and UWB channel model, it is important to acknowledge that they may not fully capture the complexities of real-world industrial scenarios. Further research is needed to refine these assumptions and assess their impact on the accuracy and reliability of the results.
2. Scalability: The scalability of the proposed approach should be carefully considered. As the size of the industrial environment or the number of sensors increases, the computational complexity and resource requirements of the optimization algorithm may also grow significantly. This can pose challenges in terms of execution time and memory utilization. Exploring strategies for handling scalability issues is crucial to ensure practical applicability in larger-scale industrial settings.
3. Dynamic Environments: Industrial environments are often dynamic, with changing conditions, moving objects, and varying interference sources. The proposed approach may not fully account for these dynamic factors, potentially leading to suboptimal sensor placement solutions. Incorporating real-time adaptation mechanisms and considering dynamic environments in the optimization algorithm are areas that require further investigation.
4. Practical Implementation Challenges: Implementing the optimized sensor deployment approach in real-world industrial environments may face practical challenges. These challenges could include physical obstructions, environmental constraints, and limitations in sensor deployment options. Addressing these practical implementation challenges through field tests, prototyping, and validation studies is essential to ensure the feasibility and effectiveness of the proposed approach.

By recognizing these limitations, future research endeavors can focus on refining the proposed approach, addressing the identified challenges, and developing more robust and practical solutions for optimized sensor deployment in industrial environments.

6.3 Suggestions for future research and improvements

The research study on optimized sensor deployment in industrial environments opens up several avenues for future research and improvements. Building upon the findings and limitations identified during the study, the following suggestions can guide further investigations and advancements in this field.

Firstly, one area for future research is the refinement and extension of the optimization algorithm. While the proposed approach has demonstrated promising results, there is room for enhancing its efficiency, scalability, and adaptability. Researchers can explore advanced optimization techniques, such as genetic algorithms, particle swarm optimization, or machine learning-based approaches, to overcome the computational complexity and resource limitations. Additionally, incorporating real-time adaptation mechanisms to account for dynamic environments and evolving industrial processes can further improve the flexibility and robustness of the algorithm.

Secondly, further research is needed to investigate the integration of additional wireless technologies and protocols with the proposed approach. While the use of UWB technology has shown significant potential, exploring the synergies and benefits of combining UWB with other wireless technologies, such as Bluetooth Low Energy (BLE), Zigbee, or LoRa, can provide more comprehensive solutions for diverse industrial applications. The integration of multiple wireless technologies can enable hybrid communication strategies, where each technology is utilized based on its strengths and suitability for specific monitoring or control tasks. This hybrid approach can enhance the overall performance, reliability, and energy efficiency of the wireless sensor network.

Moreover, researchers can focus on expanding the scope of the UWB channel model and improving its accuracy. The proposed approach leverages a band-divided ray tracing method for channel modeling, but there is potential for further advancements. Exploring advanced propagation models, considering complex multipath effects, and incorporating materials with specific electromagnetic properties encountered in industrial environments can lead to more realistic channel models. Additionally, capturing the impact of dynamic objects, such as moving machinery or vehicles, on the wireless channel can enhance the accuracy of the model.

By refining the UWB channel model, researchers can better understand the wireless propagation characteristics in industrial settings and develop more precise guidelines for optimized sensor deployment.

Furthermore, the practical implementation of the proposed approach warrants further investigation. Field tests, prototyping, and validation studies in real industrial environments are essential to evaluate the performance and feasibility of the optimized sensor deployment. Researchers can collaborate with industrial partners to conduct extensive field trials, where the proposed approach can be tested and validated under different operating conditions, environmental constraints, and interference scenarios. These practical implementation studies will provide valuable insights into the challenges, limitations, and potential optimizations required for successful deployment in real-world industrial applications.

In addition to the above, future research should also consider the downlink channel and the integration of massive Multiple-Input Multiple-Output (MIMO) base stations. While the proposed approach primarily focuses on optimizing the uplink communication from the sensors to the base station, considering the downlink channel can provide a more holistic approach to wireless communication in industrial environments. By analyzing and optimizing the downlink channel, researchers can ensure efficient and reliable transmission of control signals, commands, and feedback from the base station to the sensors. Furthermore, integrating massive MIMO techniques, which employ a large number of antennas at the base station, can improve the capacity, coverage, and interference management capabilities of the wireless sensor network. Investigating the integration of massive MIMO base stations and optimizing their deployment can enhance the overall performance and robustness of the network.

Lastly, considering the evolving landscape of Industry 4.0 and the Industrial Internet of Things (IIoT), future research should explore the integration of the optimized sensor deployment with other emerging technologies. This includes leveraging Artificial Intelligence (AI) and machine learning algorithms for real-time decision-making, edge computing for distributed data processing and analytics, and blockchain for secure and transparent data sharing. Integrating these technologies with optimized sensor deployment can enable advanced functionalities, such as predictive maintenance, anomaly detection, and intelligent resource allocation, leading to more efficient and autonomous industrial systems.

In conclusion, the research study provides a foundation for future research and improvements in the field of optimized sensor deployment in industrial environments. By refining the optimization algorithm, exploring the integration of multiple wireless technologies, improving the accuracy of the UWB channel model, conducting practical implementation studies, considering the downlink channel and massive MIMO base stations, and incorporating emerging technologies, researchers can further advance the state-of-the-art in this domain. These suggested areas of research aim to address the identified limitations, enhance the applicability and scalability of the proposed approach, and pave the way for more efficient, reliable, and intelligent wireless sensor networks in industrial settings.

6.4 Summary of the research findings

This research study aimed to investigate optimized sensor deployment in industrial environments using a band-divided ray tracing approach for UWB channel modeling. The study focused on developing an optimization algorithm that considers the UWB channel model derived from ray tracing to determine the optimal placement of sensors in industrial settings. The research findings shed light on the effectiveness of the proposed approach and its implications for improving the performance of wireless sensor networks in industrial applications.

The research began with a comprehensive review of wireless sensor networks in industrial environments. It highlighted the unique challenges faced in such settings, including harsh operating conditions, complex interference scenarios, and the need for reliable and energy-efficient communication. The literature review emphasized the importance of optimized sensor deployment to maximize coverage, minimize communication costs, and ensure seamless data transmission in industrial environments.

Based on the problem statement and objectives, the research proposed an optimization algorithm that integrates the UWB channel model derived from band-divided ray tracing. The algorithm aimed to determine the optimal placement of sensors by calculating the Received Signal Strength Indicator for the sensors and monitoring points. The algorithm considered the specific requirements and constraints of industrial environments, such as coverage area, transmission range, and interference mitigation.

The experimental evaluation and results section presented a 3D industrial environment simulation to validate the effectiveness of the proposed optimization algorithm. The algorithm was implemented and executed, and simulation results were obtained for various scenarios.

The results demonstrated the superiority of the proposed approach compared to existing deployment approaches in terms of coverage, communication reliability, and energy efficiency.

Furthermore, the research findings provided insights into the interpretation and implications of the results. The optimized sensor deployment approach achieved improved coverage and communication performance in industrial environments, leading to enhanced monitoring and control capabilities. By strategically placing sensors based on the UWB channel model, the proposed approach mitigated interference and signal attenuation, resulting in reliable and accurate data collection.

The limitations of the proposed approach were also acknowledged in the research findings. The study identified model assumptions, scalability concerns, dynamic environment considerations, and practical implementation challenges as areas requiring further attention. Future research should focus on refining the assumptions, addressing scalability issues, incorporating real-time adaptation mechanisms, and conducting practical implementation studies to ensure the feasibility and effectiveness of the proposed approach in real-world industrial applications.

The research findings have significant implications for the field of wireless sensor networks in industrial environments. The optimized sensor deployment approach presented in this study offers a valuable framework for enhancing the performance and reliability of industrial monitoring and control systems. By strategically placing sensors based on accurate UWB channel modeling, industrial processes can be monitored more effectively, leading to improved operational efficiency, reduced downtime, and enhanced safety measures.

The proposed approach also contributes to the advancement of wireless communication technologies in industrial settings. By considering the specific challenges and requirements of industrial environments, the research findings highlight the potential of UWB technology for robust and reliable communication. The integration of the UWB channel model derived from ray tracing provides a more realistic representation of the wireless propagation characteristics in industrial environments, enabling more accurate optimization of sensor deployment.

The research findings also emphasize the potential for further improvements and future research directions. Suggestions include refining the optimization algorithm, integrating additional wireless technologies, enhancing the accuracy of the UWB channel model, and conducting practical implementation studies. These recommendations aim to address the identified limitations, enhance the scalability and applicability of the proposed approach, and pave the way for more efficient, reliable, and intelligent wireless sensor networks in industrial settings.

In conclusion, the research findings demonstrate the effectiveness of the proposed optimized sensor deployment approach in industrial environments. The integration of the UWB channel model derived from ray tracing and the development of an optimization algorithm provide a valuable framework for maximizing coverage, improving communication performance, and enhancing monitoring and control capabilities in industrial settings. The implications of the research findings extend to various industrial sectors, offering opportunities for improved operational efficiency, enhanced safety measures, and reduced downtime. The recommendations for future research and improvements provide valuable guidance for advancing the state-of-the-art in this domain and ensuring the practical implementation of optimized sensor deployment in real-world industrial applications.

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