3

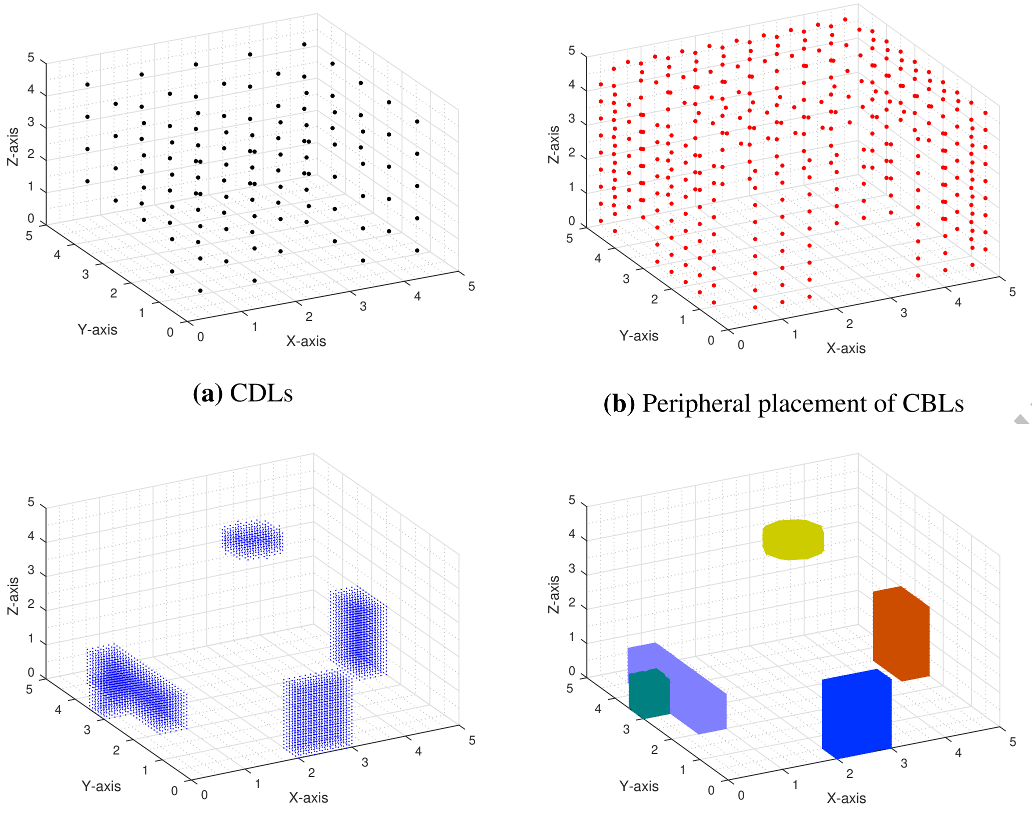
Parameter Selection

3.1 Motivation

Use of three dimensional (3D) modeling for digitization of physical characteristics of objects, indoor maps, monuments etc. has gained wide research and application interest over the last few decades [Adán et al., 2017; Turner et al., 2015]. Use of laser scanning and photogrammetry have proved themselves as prominent measures for creating an immersive 3D coordinate point cloud of any given target structure. Moreover, as mentioned in Chapter 2, the dominant use of 2D simulated designs or floor plans for analyzing BPP, presents the primary source of motivation for adopting a 3D perspective. To the best of our knowledge, the lack of simulated or implemented research work in this direction opens a door for experimenting a novel indoor design paradigm for analyzing BPP. Based on representing each indoor entity as a point cloud of 3D coordinates, we present the *design* elements (for creating basic static indoor structure) and *analytical* (for creating beacon-device sensor network) in the following section.

3.2 Design Elements: *Proposed 3D Classification*

In order to identify Devices, Beacons and Obstacles in simulated indoor designs, we propose a nomenclature that segregates the consolidated coordinate point cloud of an indoor space into corresponding three classes. Figure 4.2 provides a visual representation of aforementioned three classes for a common office room with sitting chair, table, almirahs and ceiling fan which will be detailed in the following:



(a) CDLs **(b)** Peripheral placement of CBLs

(c) OPC **(d)** Convex Hull Visualization of OPC

Figure 3.1: An example point cloud classification of an Indoor Environment

1. **Candidate Device Location (CDL)**: A CDL is essentially the set of 3D coordinates of a location where the device to be sensed can exist. For present implementation, as shown in Figure 3.1a, we assume the volumetric space inside the periphery of an indoor space to contain all CDLs.

2. **Candidate Beacon Locations (CBL)**: A CBL is essentially the 3D coordinates of a location where the observing sensor or beacon can exist. For present implementation, as shown in Figure 3.1b we consider the walls and ceiling of an indoor space to be the placement area for all CBLs.

3. **Obstacle Point Cloud (OPC)**: OPC is a set of 3D coordinates representing an object that can potentially be an obstruction in the LoS of a given CDL-CBL pair. As shown in Figures 3.1c and 3.1d, the set of obstacles for a typical office space i.e. chair, table, almirah and fan are approximated by closest regular solid convex shapes such as cube, cuboid and cylinder.

To elaborate, Figure 3.1c presents the raw coordinate point cloud of obstacles, while Figure 3.1d displays a multi-coloured convex-hull corresponding to differentiate each obstacle.

As the output of a typical 3D modeling objective yields a point cloud with extracted walls, facets and obstacle structures [Turner et al., 2015], the proposed classification stands practical for the basis of our analysis. In the next section, we now define the control parameters required for simulating BPP with respect to available design elements.

3.3 Analytical Elements of BPP: *Control Parameters*

For the present research, we consider regular shaped cubic or cuboid indoor designs as target indoor regions for simulating experimental scenarios. Although, all the concepts explained earlier or upcoming stand equally valid for non-regular objects, given the availability of classified point cloud. The extraction of point cloud features from raw coordinate set is an active field of research but falls out of the scope of present experimentation. With this context, we define the fundamental parameters for simulation as the following

1. **Room Dimension** ($l \times w \times h$): This represents the length, width and height of the target cubic or cuboidal indoor space.

2. **Device Grid Size (DGS)** ($\Delta x_d, \Delta y_d, \Delta z_d$): This defines the dimensions of a 3D grid of coordinates that separates one CDL to another within the volume of indoor region.

3. **Beacon Grid Size (BGS)** ($\Delta x_b, \Delta y_b, \Delta z_b$): This defines the dimensions of a 2D grid of coordinates that separates one CBL to another. This definition is accompanied with the assumption that the surfaces of walls and ceiling used for simulation are 2D planar that a sensor can occupy either on the walls or ceilings of an indoor space.

4. **Obstacle Grid Size (OGS)** ($\Delta x_o, \Delta y_o, \Delta z_o$): This defines the dimensions of a 3D grid of coordinates that represent an obstacle's approximate shape and size by.

5. **Beacon density** (k): As an essential constraint to the BPP optimization, this represents the minimum number of beacons required to be in the LoS of a CDL within R. This is intended

to ensure the availability of significant observational redundancy for multi-lateration based localization methods.

6. **Beacon's threshold sensing range** (R): This defines the threshold of a beacon's proximity. In other words, any device falling within the range R of a beacon can potentially be connected.

Along with this, our methodology assumes that all the surrounding indoor obstacles are either solid convex objects or can be segregated into such sets. This assumption is practically valid for most of the real world objects.

3.4 Qualitative Assessment of Elements

Before proceeding to simulations, it is essential to understand the interplay of *design* and *analytical* elements. In order to do that, we observe the effect of varying the control parameters as mentioned in the previous section over the fundamental optimization problem of minimizing total beacon count for an indoor space. To avoid the effect of design bias we assume a cubic indoor design. Moreover, as the induction of obstacles affects the spatial densities of both CDLs and CBLs, a blank indoor space is assumed to provide an unbiased common ground for comparative analysis. This assessment is intended to explore a suitable set of such parameters that keep optimization computationally tractable and embody practically sufficient 3D features using point cloud paradigm.

3.4.1 Evaluation Basis: *An Optimization Problem*

Finding out a clear set of beacons among all the CBLs requires the optimization problem to conclude an exact i.e. binary status for each CBL. In other words, we attempt to formulate a Mixed Integer Linear Programming (MILP) model that can determine such a minimum beacon count which satisfies underlying constraints. To formulate a standard representation of an optimization problem, we define the following variables that will be used with the same meaning throughout the scope of this thesis, unless otherwise stated:

- We assume the indoor space to have p CDLs and q CBLs with their x, y, z coordinates stored in a $p \times 3$ matrix C and a $q \times 3$ matrix B respectively.

- As a requirement for each CDL, a minimum beacon density of k should be imposed as a constraint to the optimization.

- A decision vector $b = \{b_i \in \{0, 1\}, \forall i = 1..q\}$ is intended to contain a binary entry b_i for each of the q CBLs. Here, each index i corresponds to the respective CBL coordinates in matrix B at row i. A value of $b_i = 1$ concludes the selection of i^{th} CBL as a part of the optimal beacon set, while $b_i = 0$ represents its rejection.

- We define a $q \times p$ matrix Θ, whose rows correspond to q CBLs and columns correspond to p CDLs. Each (i, j) entry i.e. $\theta_{i,j}$ of Θ contains the Euclidean distance between i^{th} CBL and j^{th} CDL.

- Based on the entries in matrix Θ, another $q \times p$ matrix Γ with binary entries $\gamma_{i,j}$ is created. Γ is essentially an adjacency matrix having value 1 at entry (i, j) if corresponding $\theta_{i,j} \leq R$, 0 otherwise. In other words, a CDL at index j falling within the sensing range R of a CBL with index i will have an entry 1 at $\gamma_{i,j}$, while CDLs beyond it receive a value 0.

Based on the above information, the optimization problem for minimizing the total beacon count for localization is formulated as the following:

$$\begin{aligned} \underset{b}{\text{minimize}} \quad & \sum_{i=1}^{q} b_i \\ \text{subject to} \quad & \sum_{j=1}^{q} \gamma_{i,j} b_j \geq k, \; i = 1 \ldots p \end{aligned} \tag{3.1}$$

As can be seen in Equation 3.1, for each j^{th} CDL, the constraint $\sum_{i=1}^{q} \gamma_{i,j} b_i \geq k$ ensures a beacon density of k while $\sum_{i=1}^{q} b_i$ is the objective for total beacon count minimization.

For the modeling and simulation of optimization problems throughout the research, MATLAB environment has been used. Based on the above problem formulation, we investigate the effect of varying the analytical elements using Mixed Integer Linear Programming (MILP) approach for resulting optimal beacon count in the upcoming section.

3.4.2 Analysis-1: Device Grid Size (DGS) and Beacon Grid Size (BGS)

Both DGS and BGS are means of approximating indoor environment. To elaborate, DGS is introduced to control the number of coordinate locations where the devices inside the indoor volume can exist. Similarly, BGS supports the optimization by controlling CBL density on walls and ceilings thus giving a sufficient search domain for calculating optimal configuration. The need for this assessment is due to the contradicting scenarios resulting from choosing a very high or low grid sizes. A higher DGS and/or BGS value results in generating a thin point cloud which can lead to an under-approximation of indoor physical features. On the other hand, a lower value for the two generates a dense coordinate set which can overload computation without significantly improving the result. Intuitively, for configuring practical environments, a lower DGS value can also emphasize unreachable local spaces such as blocked/hidden spaces inside chair/table. These spatial localities stand practically insignificant for optimization yet can force it to choose dedicated CBLs resulting in an overall increase in beacon count. We present the parameter setting for the simulations in the following points:

1. To avoid design induced biases in simulations, an empty i.e. obstacle-less cubic design with dimensions $l = w = h = 5\,units$ is chosen. For the purpose of practical comparison, 1 *unit* distance can be considered equal to 1 *meter*.

2. For the sake of realistic implementation, the placement of CDLs and CBLs is assumed to be starting at a distance of 0.5 unit from the wall and ceiling corners.

3. Both DGS and BGS are considered to be having equal grid sizes in all the three dimensions i.e. $\Delta x_d = \Delta y_d = \Delta z_d = \Delta_d$ and $\Delta x_b = \Delta y_b = \Delta z_b = \Delta_b$.

4. For both Δ_d and Δ_b a set of values ranging from 0.1 to 1 with a step size of 0.1 is chosen i.e. $\Delta_d, \Delta_b = \{0.1x : x \in \mathbb{N}, x \leq 10\}$. Thus, as an example, for $l = w = h = 5\,units$, a value of $\Delta_d = \Delta_b = 0.1$, will provide 97,336 CDLs and 4,232 CBLs while with $\Delta_d = \Delta_b = 1$, the scenario will have 125 CDLs and 50 CBLs. As explained earlier in this subsection,

a step size of 0.1 is chosen to gradually observe and conclude such sufficient density values, for both DGS and BGS, which neither unnecessarily overload computation by over-approximation nor loose information by under-approximation of the indoor design.

5. For each configuration formed with all the combinations of Δ_d and Δ_b, a minimum range value of R_{min} is calculated that ensures $k = \{3, 4, 5\}$ coverage for all CDLs. In order to do this, starting from a range value of $R_0 = \lceil \frac{max(l,w,h)}{2} \rceil$, incrementing with step size of 0.5, we formulate the matrix Γ and identify such R_{min} that ensures $\sum_{i=1}^{q} \gamma_{i,j} \geq k,\ j = 1 \ldots p$.

6. Choosing a starting value of 3 for k is due to the minimum requirement of three observations for calculating location in 3D by multi-lateration.

As shown in Figure 3.2, for all the k values, as we move towards low values of Δ_d and Δ_b, the over-approximation results in either an infeasible beacon configuration or imposes a relatively higher beacon count. For example, with $(\Delta_d = 0.1, \Delta_b = 0.2)$ and all the three k values, the resulting beacon count is 0 which signifies the unavailability of any optimal beacon configuration due to over-approximation. Moreover, for combinations such as $(\Delta_d = 0.2, \Delta_b = 0.2, k = 3, 4)$ and $(\Delta_d = 0.1, \Delta_b = 0.1, k = 4)$ a substantial jump in the output beacon count reaching values beyond 40 demonstrate the lack of reliability in choosing low grid sizes. Thus, we tend to discard grid sizes that are below 0.5 as they can be spotted varying abruptly for all the three cases. Keeping in the mind the exponential change in the number coordinates with density, values $\Delta_d = 1, \Delta_b = 0.5$ are chosen that also supports perfect division of room dimensions. Although the logical flow of this thesis is independent of these values, they will be used invariably throughout the research, for designing indoor point clouds, unless otherwise stated.

3.4.3 Analysis-2: k and R

Beacon's Threshold Sensing Range R is a significant element for maximizing coverage in a given indoor environment. While choosing a higher range value decreases the number of total beacons required, it also increases the energy consumption as well as observational noise due to signal propagation anomalies. On the other hand, favouring a lower value for R can reduce the concerns of energy and noise at the cost of requiring a higher beacon count to maximize coverage

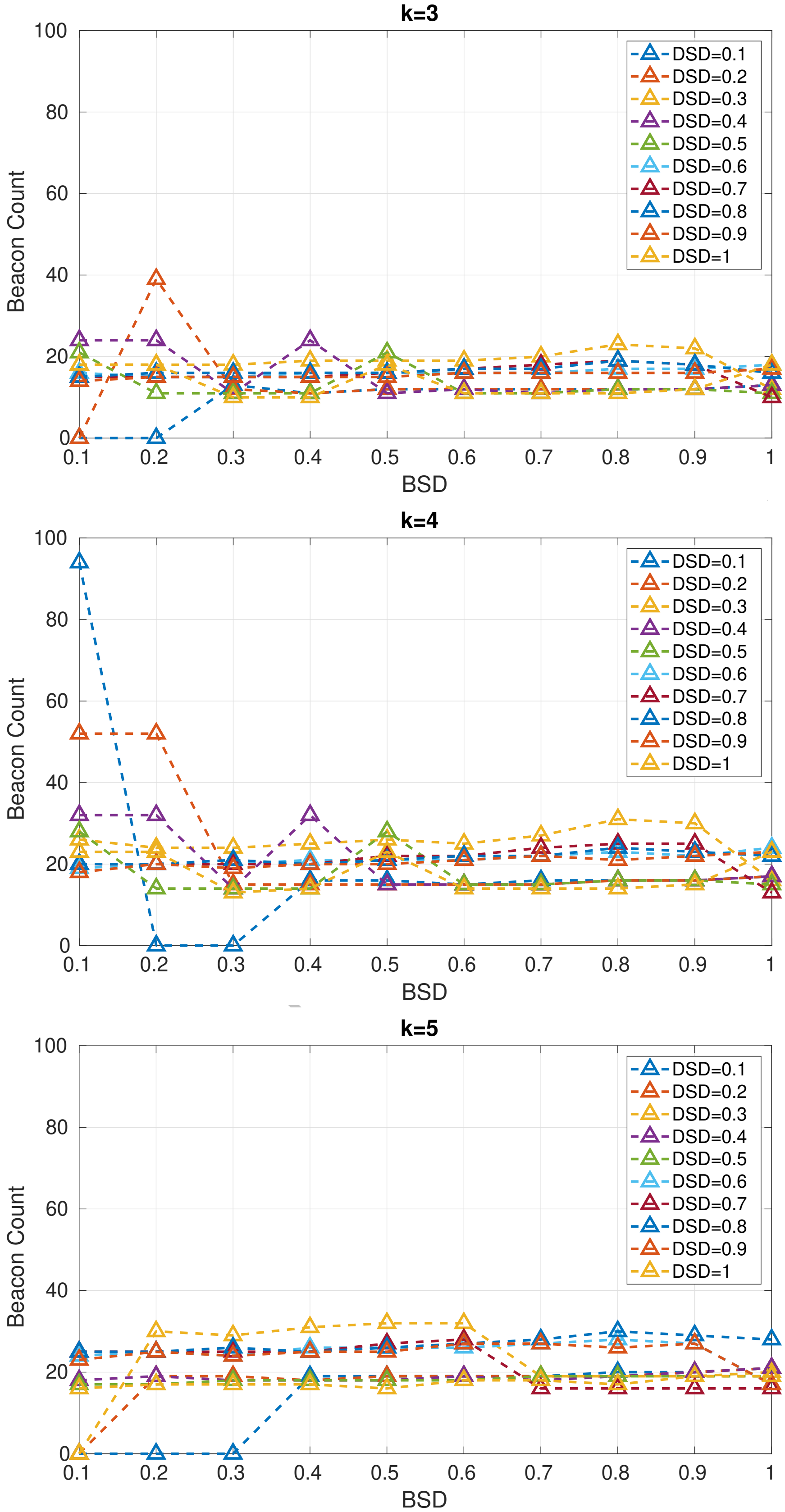


Figure 3.2: Variation of minimum total beacon count required for the respective variation of k, DSD and BSD. The respective variations are presented for all the combinations of DSD and BSD values, ranging from 0.1 to 1 with a step size of 0.1, with k value of 3, 4 and 5 from top to bottom.

and accuracy when compared to a higher value. To understand this trade-off, we analyze the variance in R along with the variance in beacon density k using the optimization problem as mentioned in Equation 3.1. For simulations, as concluded in previous subsection, an obstacle-less indoor design with dimensions $l = w = h = 5\,units$ using DGS and BGS values of $\Delta_d = \Delta_d = 0.5$ is configured.

The trade-off is observed by considering integer values for R and k both varying from 3 to 10. A lower bound of 3 for R is chosen due to the fact that no feasible solution was concluded by the optimization below it. Also, a lower bound of 3 for k represents the practical requirement of minimum three range observation for each localization in 3D.

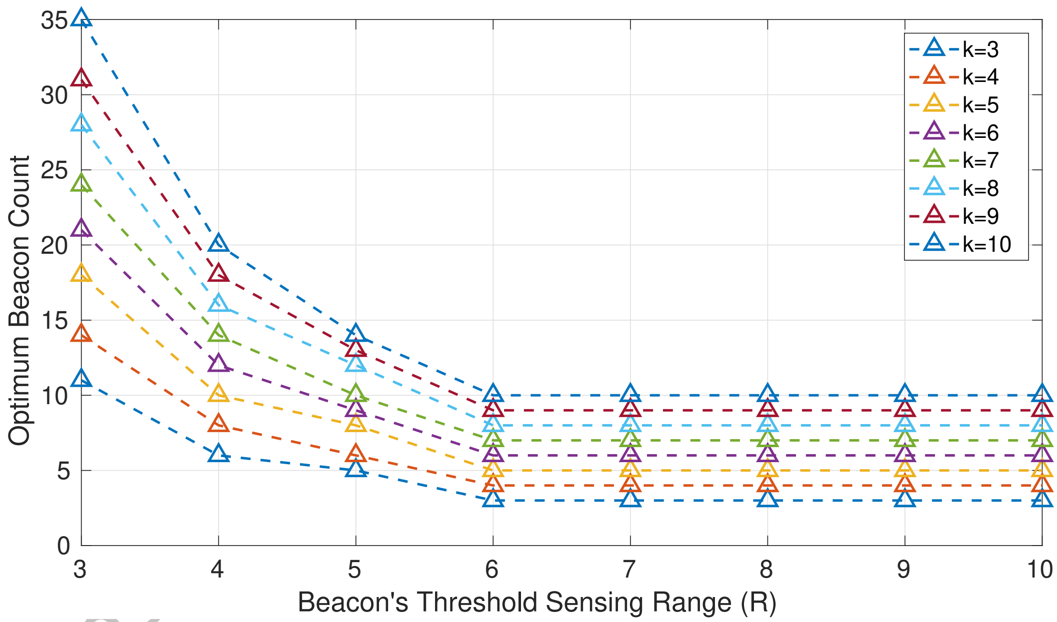


Figure 3.3: Effect of varying R with k for Optimum Beacon Count

As intuitively suggested earlier, Figure 3.3 demonstrates the idea that, for all the k values, the resulting optimum count of beacons decreases with an increase in R from 3 to 6 and becomes constant thereafter. From $R = 6$ as we move to the lower values of R, the increase in minimum required beacon count becomes critical with an increase in the k value. This difference, over successive decreases in R, increases substantially with the successive increase in k. For example, with $k = 3$, the difference of beacons required for $R = 6$ and 3 is 6, while with $k = 10$, this difference exceeds to 25.

As shown in Equation 3.2, beacon density k is used as a lower bound constraint on the connectivity of each CDL. A value of $k = 3$ will be used, satisfying minimum observational requirement for range based localization, invariably throughout the scope of this thesis.

To finalize an optimal value for Beacon's Sensing Range, it is essential to analyse the degradation of signal's strength for short range indoor propagations. In order to do that, we simulate the Free Space Propagation model derived from Friis transmission formula [Friis, 1946] as shown in Equation 3.2 over the common wireless frequencies of 0.9 GHz, 2.4 GHz and 5 GHz.

$$P(dB) = 20\, log_{10} \left(\frac{4\pi r f}{c} \right) \tag{3.2}$$

Here, P is the signal propagation loss measured in decibels (dB) for the beacon's transmission range of r in meters. Also, f represents the frequency of signal propagation in Hz and c is the speed of light i.e. 3×10^8 meters/second. Both the transmitting and receiving antennas are assumed to be isotropic with no directivity. Based on the above context, Figure 3.4, presents the resulting variance of propagation loss with respect to sensing range over the selected wireless frequencies. As can be see in Figure 3.4, the major drawback of choosing a higher frequency signal is that

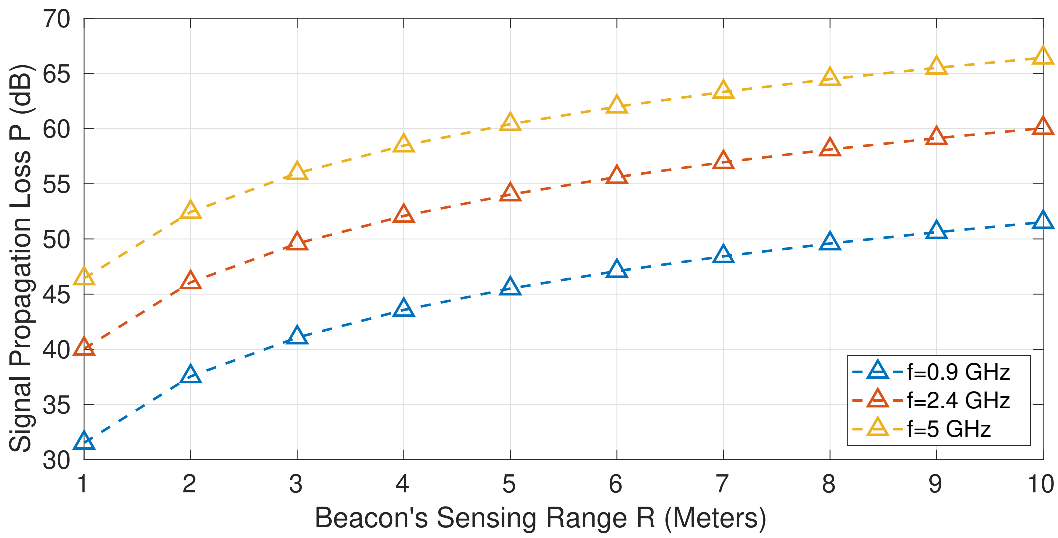


Figure 3.4: Variance in path loss in decibels against Beacon's Sensing Range (R) over different wireless frequencies

it results in higher propagation loss for small range values. For example, at $R = 1$ meters with $f = 5$ GHz the power loss is $P = 46.42$ dB, which is approximately 1.5 times greater than the

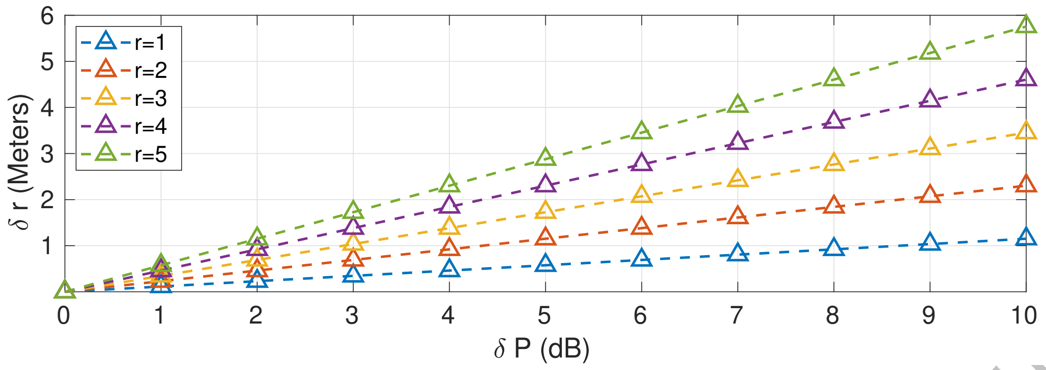


Figure 3.5: Error propagation in range (δr) due to noise in path loss estimation (δP) for different range values

power loss of $P = 31.53$ dB with $f = 0.9$ GHz. To overcome this higher propagation loss with higher frequencies, provisioning a higher transmission power in-turn increases input power consumption resulting in shortened working life of battery operated stand alone systems. Moreover, with practical situations contributing as hardware and environmental noises, the corresponding propagation of error in range observations increases uncertainty in accurate location estimation. To understand this, a partial derivation of Equation 3.2 as shown in Equation 4.1 relates the noise in path loss estimation δP to its propagated effect as deviation in range measurement δr.

$$\delta r = \left[\frac{rln10}{20}\right] \delta P \tag{3.3}$$

The aforementioned effect is demonstrated in Figure 3.5 as, even with a nominal noise of $\delta P = 5$ dB, for $r = 1$ meters, the resulting range measurement noise is $\delta r = 0.5756$ meters while with a higher range value of $r = 5$ meters it increases to $\delta r = 2.8782$ meters. This issue becomes severe with a higher noise in path loss measurements such as $\delta P = 10$ dB and reaches range measurement error of $\delta r = 5.7565$ meters for $r = 5$ meters.

Hence, considering the orientation of present research for short range indoor applications that require less power consumption and are highly prone to noise, we finalize a sensing threshold of $R = \{3, 4, 5\}$ for future simulations.

3.4.4 Analysis-3: Obstacle Grid Size (OGS)

The knowledge of obstacle point cloud is essential in maximizing the direct visibility between devices and beacons. The variation in OGS doesn't have a direct relevance to optimization as OPCs are used in designing adjacency matrix between CDLs and CBLs. This process is termed as the LoS detection and will be detailed with an indigenous algorithm developed for the same in the next Chapter. Although, we incorporate a high density point cloud i.e. $\Delta x_o = \Delta y_o = \Delta z_o = 0.1$, for obstacle approximation invariably through out the thesis.

3.5 Summary

This chapter presented our choice of necessary parameter elements for designing or approximating an indoor environment. Additionally, by the help of an example optimization problem, the interplay of relevant parameters was observed, and a resultant set of suitable values was selected for further usage in this thesis.