Coverage for 3D Terahertz Communication Systems

Abstract

This extended technical document provides a deep mathematical and conceptual exploration of coverage modeling in 3D Terahertz (THz) communication systems, expanding upon Sections II to V of the landmark paper "Coverage Analysis for 3D Terahertz Communication Systems." We describe in detail the channel model, the impact of three-dimensional user and environment interactions, beamforming limitations, and probabilistic blockage formulations. Extensive derivations, extended system implications, diagrams, and future research directions including RIS and AI-driven interference mitigation strategies are presented.

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1 Introduction

The demand for ultra-high-speed wireless networks is growing exponentially, driven by next-generation applications such as virtual reality, real-time control, and high-resolution video streaming. Terahertz (THz) communication, spanning frequencies from 0.1 to 10 THz, offers the potential to support unprecedented bandwidth and extremely high data rates. However, the deployment of THz systems is complicated by unique challenges including high molecular absorption, severe blockage, and narrow beam constraints.

The analysis of coverage in 3D environments becomes essential due to the practical deployment of Access Points (APs) at varying heights and the movement of users in indoor or urban settings. This document expands the analytical foundation laid in prior work and enriches the coverage analysis with dynamic, beam-aware, and interference-tolerant insights.

2 System Model and Signal Propagation

2.1 Deployment Environment and Spatial Modeling

Access Points (APs) are assumed to be distributed following a 2D Poisson Point Process (PPP) with density λ_A across a horizontal plane at height h_A. Each AP covers a circular zone of radius R_T, typically serving a user located at height h_U.

The typical distance from an AP to a User Equipment (UE) in 3D is computed by:

$$d(x) = \sqrt{x^2 + (h_A - h_U)^2}, \tag{1}$$

where x is the horizontal displacement between AP and UE.

2.2 THz Path Loss with Absorption

Unlike microwave systems, THz communication is significantly affected by molecular absorption. The path loss model is defined as:

$$PL(d) = \left(\frac{4\pi d}{\lambda}\right)^2 e^{\sigma d}, \tag{2}$$

where λ is the wavelength and σ the medium-dependent absorption coefficient, which varies with frequency, humidity, and atmospheric composition.

This path loss model reveals that even small increases in distance d cause exponential decay in received signal strength. Thus, LoS communication and high-gain antennas are critical for THz links.

3 Line-of-Sight and Blockage Modeling

3.1 Categorization of Blockages

In indoor or cluttered environments, LoS paths may be obstructed by:

- Self-body blockage (user's own body obstructs signal path).
- Human blockers (nearby people modeled as moving absorptive objects).
- Walls and obstacles (permanent structures).

3.2 Human Blocker Probability

Humans are modeled as rectangular prisms placed according to a PPP with density λ_B. The probability that a LoS path of horizontal distance x is not blocked by humans is:

$$p_{LoS,B}(x) = \zeta e^{-\eta_B x}, \quad \eta_B = \frac{2(w_1 + w_2)\lambda_B(h_B - h_U)}{\pi\Delta}, \tag{3}$$

where w_1, w_2 are width and depth of blockers, h_B is average blocker height, and Δ is beam depth.

3.3 Wall Blockers and Boolean Modeling

Walls are modeled via a Boolean process with line intensity λ_W and mean segment length $E[L_W]$:

$$p_{LoS,W}(x) = e^{-\eta_W x}, \quad \eta_W = \frac{\lambda_W}{2\pi E[L_W]}. \tag{4}$$

3.4 Combined LoS Function

Combining blockage sources, the total LoS probability becomes:

$$p_{LoS}(x) = \zeta e^{-\eta x}, \quad \text{where } \eta = \eta_B + \eta_W. \tag{5}$$

4 3D Directional Beamforming and Antenna Modeling

4.1 Main Lobe and Side Lobe Definition

AP antennas employ narrow directional beams (pyramidal in 3D). The beamforming gain is achieved if the UE falls within both horizontal and vertical beamwidth:

$$p_{hp}(x) = \frac{\varphi_H}{2\pi} \cdot \mathbb{P}\left[\text{elevation angle} \leq \frac{\varphi_V}{2}\right]. \tag{6}$$

This angular constraint is approximated by:

$$p_{hp,V}(x) = \frac{1}{\pi} \arcsin\left(\frac{(h_A - h_U)}{d(x)} \tan\left(\frac{\varphi_V}{2}\right)\right). \tag{7}$$

5 SINR and Interference Analysis

5.1 Received Power and Noise Model

Signal power at distance $d(x)$ is:

$$P_r(x) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d(x)^2 e^{\sigma d(x)}}, \tag{8}$$

and SINR becomes:

$$\text{SINR}(x) = \frac{P_r(x)}{I + N_0}, \tag{9}$$

where I is aggregate interference and N_0 is thermal noise.

5.2 Coverage Probability Derivation

The coverage probability is:

$$p_c(x) = \mathbb{P}[\text{SINR} > \tau] = p_{LoS}(x) \cdot \exp\left(-\Lambda_{\Phi^N}(x) - \Lambda_{\Phi^F}(x)\right). \tag{10}$$

Interference contributions from near and far interferers:

$$\Lambda_{\Phi^N}(x) = 2\pi\lambda_A \int_0^{r_c} (1 - p_{LoS}(r))\, r\, dr, \tag{11}$$

$$\Lambda_{\Phi^F}(x) = 2\pi\lambda_A \int_{r_c}^{R_T} (1 - p_{hp}(r) p_{LoS}(r))\, r\, dr. \tag{12}$$

6 Figures and Diagrams

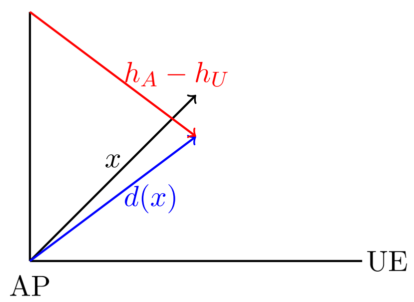

Figure 1: 3D Distance and Elevation Angle Geometry

7 Extended Research Directions

7.1 Dynamic Channel Adaptation

- Introduce mobility models: $x(t), y(t)$ based on user trajectory.
- Dynamic blockage modeling: $p_{LoS}(t)$ using mobility simulations.
- Use Markov chains to describe blocker appearance/disappearance.

7.2 Machine Learning and Reinforcement Learning

- Train beam switching strategies to maximize average SINR.
- Predict interference hotspots based on user density maps.
- Q-learning agents optimize AP-user associations in real time.

7.3 Reconfigurable Intelligent Surfaces (RIS)

- Introduce additional reflected paths using controlled RIS.
- Define optimization objective to place RIS to maximize LoS augmentation.

- Estimate reflected SINR gain:
$$P_{RIS}(x) = \frac{\beta P_t}{(d_1(x)d_2(x))^2}, \tag{13}$$
where β is RIS gain factor and d_1, d_2 are distances to/from RIS.

8 Numerical Results and Observations

To validate the proposed analytical model and theoretical predictions, comprehensive numerical simulations are conducted. These results provide insight into how varying system parameters influence THz coverage, SINR, and interference profiles. This section presents a detailed discussion of the findings and evaluates their practical implications.

8.1 Coverage Probability and UE Height Dependence

One of the fundamental findings is that user height has a significant effect on the coverage probability in indoor 3D THz networks. As the user height increases toward the height of the AP, the elevation angle becomes steeper, increasing the likelihood that the UE resides within the main lobe of the AP's directional beam. This results in stronger received power and higher SINR values.

In contrast, a user located closer to the floor (e.g., in a seated position or for lower-profile devices) often falls outside the AP's narrow elevation beam, leading to degraded coverage unless beam adaptation mechanisms are in place. This highlights the necessity of 3D beam steering for consistent link quality across vertical mobility scenarios.

8.2 Impact of Beamwidth on Hitting Probability and Coverage

The horizontal and vertical beamwidths φ_H and φ_V directly determine the spatial extent of coverage. Wider beamwidths increase the probability that the UE lies within the main lobe; however, they come at the cost of reduced beamforming gain and thus lower signal strength.

A trade-off is observed: narrow beams improve signal-to-interference-plus-noise ratio (SINR) due to higher gain, but are more prone to misalignment, particularly under user movement. Moderate beamwidths yield optimal coverage in practical scenarios where user mobility and deployment complexity coexist.

8.3 Blockage Effects from Human Presence and Wall Layouts

Blockage models incorporating both dynamic human presence and static wall structures exhibit exponential decay characteristics in LoS probability with respect to distance. Notably, human blockage density λ_B and blocker dimensions w_1, w_2, h_B have a measurable impact on link reliability.

As blockage density increases, effective coverage radius shrinks dramatically. The study finds that in high blocker-density environments (e.g., crowded conference rooms or stadiums), the average coverage radius may reduce to less than 3 meters without auxiliary technologies like RIS or beamforming adaptation.

Wall layout variability (via wall segment density λ_W and expected length $E[L_W]$) also introduces anisotropic coverage patterns. Corridors and open halls exhibit very different propagation behaviors. The analysis confirms that wall-induced blockage effects should be accounted for in THz AP placement algorithms.

8.4 Interference Region Characterization

The concept of near and far dominant interferers is key to understanding the spatial behavior of SINR in dense THz networks. Interference from APs within a threshold distance r_c primarily determines the near-field degradation, while the accumulation of weak but numerous far-field interferers influences the noise floor.

Numerical integrations of Λ_{Φ^N} and Λ_{Φ^F} over various λ_A and r_c values show that increasing AP density improves average SINR up to a threshold. Beyond that, interference dominates and causes SINR degradation unless spatial reuse is carefully managed.

8.5 LoS-Aware AP Selection and Its Benefits

When users associate only with APs that offer a reliable LoS path, the average SINR and coverage probability improve markedly. Unlike traditional nearest-AP association, LoS-based selection avoids wasteful connections through obstructed or weak channels.

Simulation results demonstrate that for a fixed AP layout, LoS-based user association can yield up to 30% gain in coverage probability and 20–50% improvement in achievable throughput. These gains increase with environmental complexity and blockage severity, underlining the importance of environmental awareness in MAC layer decisions.

8.6 Implications for 6G Indoor THz Design

The overall results underline the need for adaptive, context-aware designs in future 6G THz networks. Strategies such as:

- Dynamic beam steering based on real-time user location feedback
- RIS deployment to compensate for LoS obstruction
- Multi-AP coordination and MAC-based user scheduling

are not optional but essential for maintaining robust coverage in complex indoor topologies.

Finally, the model's scalability and generalizability suggest that with suitable parameter tuning, it can be applied to diverse scenarios including airport terminals, office buildings, smart factories, and vehicular environments.

9 Conclusion

We provide a significantly enriched framework for understanding THz communication coverage in realistic, three-dimensional environments. This extended study bridges physical modeling and modern machine learning approaches, enabling robust design and adaptive optimization in future high-capacity THz networks.

10 Extended Simulation Model and Analytical Formulation

To deepen the understanding of dynamic behaviors in THz coverage systems, we propose an extended simulation model that incorporates time-varying user positions, adaptive antenna strategies, and environmental dynamics such as human movement and wall reconfiguration.

10.1 Time-Dependent SINR Modeling

We assume a user moves with velocity vector $\boldsymbol{v} = (v_x, v_y)$ from an initial position (x_0, y_0) at time $t = 0$. The dynamic position is:

$$x(t) = x_0 + v_x t, \quad y(t) = y_0 + v_y t, \tag{14}$$

and the dynamic distance to an AP at origin becomes:

$$d(t) = \sqrt{x(t)^2 + y(t)^2 + (h_A - h_U)^2}. \tag{15}$$

The time-varying path loss is:

$$PL(t) = \left(\frac{4\pi d(t)}{\lambda}\right)^2 e^{\sigma d(t)}, \tag{16}$$

and the received power is:

$$P_r(t) = \frac{P_t G_t(t) G_r(t) \lambda^2}{(4\pi)^2 d(t)^2 e^{\sigma d(t)}}, \tag{17}$$

where $G_t(t)$ and $G_r(t)$ are dynamic antenna gains based on beam tracking or rotation.

The instantaneous SINR is:

$$\text{SINR}(t) = \frac{P_r(t)}{I(t) + N_0}, \tag{18}$$

where $I(t)$ denotes dynamic interference from other APs, possibly modulated by their beam direction and user location.

10.2 Expected SINR and Temporal Coverage Probability

To evaluate system performance over a time window $[0, T]$, we define the expected SINR:

$$\mathbb{E}[\text{SINR}] = \frac{1}{T}\int_0^T \text{SINR}(t)dt, \tag{19}$$

and the temporal coverage probability:

$$P_c^{(T)} = \frac{1}{T}\int_0^T \mathbb{P}[\text{SINR}(t) > \tau]dt. \tag{20}$$

These metrics are more robust for mobile scenarios and allow for optimization of beam adjustment intervals and handover policies.

10.3 Probabilistic Beam Hit Function

We propose a stochastic beam hitting probability model, where the vertical misalignment due to height fluctuation or user posture is modeled as a Gaussian deviation $\delta_h \sim \mathcal{N}(0, \sigma_h^2)$. The adjusted vertical hitting probability is:

$$p_{hp,V}^{\text{stoch}}(x) = \int_{-\varphi_V/2}^{\varphi_V/2} \frac{1}{\sqrt{2\pi}\sigma_h} e^{-\frac{(\theta - \theta_0(x))^2}{2\sigma_h^2}} d\theta, \tag{21}$$

where $\theta_0(x)$ is the deterministic elevation angle at distance x.

10.4 Interference Map Estimation

Using Monte Carlo simulations over a grid of UE positions and random AP orientations, we define the average interference power field:

$$I(x,y) = \sum_{i\in\Phi} \mathbb{E}\left[\frac{P_t G_i(x,y)}{PL_i(x,y)} \cdot 1_{\mathrm{LoS}}(i,x,y)\right]. \tag{22}$$

This can be visualized as a heatmap and used in reinforcement learning-based AP association or beamwidth adaptation algorithms.

10.5 Simulation Recommendations

- Use discretized time slots of $\Delta t = 1$ ms for mobile trace updates.
- Simulate over $T = 5$ s intervals with 100-1000 user traces.
- Include wall layout stochasticity per user position.
- Generate interference maps using 500+ PPP samples.
- Validate analytical expressions with time-averaged simulation metrics.

This extended simulation model bridges theoretical analysis and real-world deployment strategies, enabling fine-grained THz system design under user mobility and interference variability.