Recent Advances in the Stochastic Geometry for Coverage Probability Prediction with User Mobility

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Abstract

Stochastic geometry (SG), particularly using Poisson Point Process (PPP) models, effectively predicts static wireless network coverage probability. This study assesses SG's application for mobile users. Findings show mobility modeling is sparse; when included, often via handoff analysis, coverage generally decreases with higher handoff rates, though reported impacts are mixed [1]. Critically, integrating varying terrain with mobility is largely absent, typically limited to urban/suburban scenarios. While SG offers simulation-validated theoretical predictions [2], significant gaps remain in modeling realistic dynamic scenarios involving mobile users across diverse terrains.

Ⅰ. Introduction

Predicting coverage probability is fundamental for wireless network design, and Stochastic Geometry (SG) offers powerful tools for modeling the spatial randomness of network components, particularly in static scenarios [3]. However, user mobility introduces significant dynamics, altering interference, necessitating handoffs, and impacting the Signal-to-Interference Ratio (SIR) and thus coverage [1], [4], [5]. This study reviews the use of SG to predict coverage for mobile users, synthesizing findings from existing literature to examine modeling techniques, reported effects, and validation methods, especially the common omission of varying terrain factors.

Ⅱ. Method

A. Stochastic Geometry Frameworks for Coverage Analysis

Stochastic Geometry (SG) provides the mathematical basis for analyzing wireless networks by modeling the spatial arrangement of network elements, like Base Stations (BSs), as random point processes [3]. This approach allows for the derivation of performance metrics influenced by spatial distribution. The most prevalent model identified in the reviewed literature for BS locations is the homogeneous Poisson Point Process (PPP) [1], [4], [5]. Characterized by Complete Spatial Randomness (CSR), the PPP assumes node locations are independent and uniformly distributed, simplifying analysis and yielding tractable expressions for key performance indicators. While the PPP's tractability makes it dominant, it is a simplification of real deployments. Consequently, alternative point processes like the Matérn Hard-Core Process (MHCP) or Poisson Cluster Process (PCP) are sometimes used to capture features like minimum BS separation or clustering, albeit less frequently [2]. While foundational for assessing basic connectivity, the spatial models and analytical tools provided by SG can also serve as a basis for analyzing or setting the context for more complex, dynamic systems. For instance, understanding the spatial distribution and potential connectivity derived from SG could inform the deployment and operation of advanced communication paradigms involving multi-agent reinforcement learning for autonomous systems [6], federated learning in IoT networks [7], spatial-temporal dynamics in metaverse streaming [8], or even influencing channel assumptions in emerging areas like semantic communication [9].

B. Incorporating User Mobility

While foundational SG analyses often assume static users, incorporating mobility is essential for realistic performance evaluation, though less frequently addressed in the reviewed literature. Approaches to capture mobility effects include explicit handoff analysis, which models handoff rates based on speed and density, sometimes incorporating connection failure probabilities [1], [5]; user displacement models, which analyze interference correlation and joint coverage between two spatial points representing movement [4]; and directly linking user velocity to performance or behaviors like tier association. Despite these techniques, the reported overall impact of mobility on coverage probability is mixed and context-dependent. Increased handoff rates due to mobility logically tend to decrease coverage probability [1], yet potential gains have also been reported in specific contexts. Interference correlation reliably decreases with greater spatial separation [4], but a consistent, quantitatively well-understood picture of mobility's broader impact remains limited within current SG frameworks.

Ⅲ. Conclusion

While stochastic geometry effectively predicts static network coverage probability, its application to mobile user scenarios is less developed, showing mixed impacts. Critically, varying terrain considerations are largely absent in these SG frameworks. Although theoretical predictions are often simulation-validated, accurately predicting coverage in dynamic, real-world environments necessitates models that jointly incorporate realistic mobility and diverse terrain features, validated through practical, measurement-based validation.

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