Journal of Applied Technology and Innovation
Vol. 09, Issue 3, 2025, pp. 34-49
e-ISSN:2600-7304-ISSN
DOI: https://doi.org/10.65136/jati.v9i3.16

Stochastic Geometry-Based Interference Prediction and Adaptive Power Control in Dense 6G Urban Networks.

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Abstract

With the rapid emergence of ultra-dense 6G network deployments, there is an increasing demand for a robust probabilistic framework to enable accurate interference forecasting and thus effective power regulation. This work proposes a stochastic-geometry-driven adaptive power-control model that accurately estimates aggregate interference and optimizes transmit power to maintain a desired signal-to-interference-and-noise ratio level within ultra-dense metropolitan wireless systems. Employing a Poisson Point Process to model the distributions of base-station and user nodes, the work develops analytical expressions for the Laplace transform of interference, outage probability, and average achievable rate. An adaptive fractional power-control mechanism is further designed based on derived expressions in order to minimize energy expenditure while maintaining the desired reliability. Simulation results demonstrate that the proposed Adaptive Fractional Power Control (AFPC) mechanism achieves 22.2-53.3% transmit power reduction for all the schemes and provides up to 4 dB SINR gain compared to the benchmark static and full-channel-inversion schemes. In summary, the proposed framework thus provides a tractable yet operationally effective solution for interference management in sustainable large-scale 6G urban deployments.

Keywords: *6G Networks, Stochastic Geometry, Interference Prediction, Adaptive Power Control, Poisson Point Process (PPP), SINR, Energy Efficiency.*

1. Introduction

The emergence of the sixth-generation wireless communication represents a transformative shift in network design, with hyper-dense deployments expected to exceed 10^6 devices per square kilometre and support enhanced mobile broadband, tactile Internet services, immersive applications, and massive IoT connectivity. As network density goes up to an unprecedented level, inter-cell interference rather than thermal noise becomes the dominant constraint on system performance, especially in irregular metropolitan layouts characterised by heterogeneous small cells, high-rise buildings, and dynamic user distributions. Traditional deterministic models of interference fail to generalise across such complex topologies, thus proving inadequate for the purposes of an accurate SINR, outage probability, and achievable throughput prediction. In turn, stochastic geometry has emerged as a strong analytical framework capable of modelling the spatial randomness inherent in ultra-dense networks. Treating base stations and users as realisations of point processes-most commonly, the Poisson Point Process-such a geometry allows for the tractable derivation of the performance metrics of interest, including coverage probability, spectral efficiency, and the Laplace transform of the aggregate interference (Elsawy et al., 2016; Qamar et al., 2019).

Despite the profound analytical insights provided by SG, most of the existing interference analyses assume a static transmit power limiting assumption in rapidly fluctuating 6G environments characterised by user mobility, bursty traffic loads, and frequent topological shifts. The main deficiencies of static power allocation are unnecessary power consumption in conditions with low interference, on one hand, and repetitive SINR outages in conditions with interference surges, on the other. These call for adaptive power control mechanisms that can respond to real-time interference variations. However, integrating SG-derived interference statistics into closed-loop, adaptive power-control strategies remains an open challenge. This gap motivates the present study, aiming to unify probabilistic interference prediction with intelligent power optimisation in dense 6G networks (Zhang et al., 2019).

In particular, dense metropolitan 6G deployments will have to overcome three intertwined problems: unpredictable interference aggregation caused by several overlapping small cells; unsustainable energy consumption ensuing from full-channel-inversion schemes; and the absence of real-time predictive control that marries stochastic interference estimation to adaptive power-regulation policies. These challenges together point to the pressing need for a unified probabilistic framework that can model, predict, and mitigate interference while improving energy efficiency. Thus, this research is informed by the following guiding questions: How can SG be used for accurate characterisation of aggregate interference in ultra-dense 6G networks? What are the tractable analytical expressions that can be derived for the Laplace transform of interference, coverage probability, and related performance metrics? How does an adaptive fractional power-control strategy minimize energy consumption while ensuring SINR and reliability requirements? And how does such an adaptive strategy compare against static or full-channel-inversion methods?

The purpose of this work is to develop and validate a mathematically rigorous interference-prediction and adaptive power-control framework tailored to large-scale 6G urban environments. This research effort was driven by four main objectives: to establish a PPP-based SG model for dense 6G topologies; to derive analytical expressions for aggregate interference and coverage probability; to design an AFPC algorithm that minimises transmit power with SINR and outage constraints; and to evaluate the proposed approach through simulations by comparing AFPC against baseline static control schemes. The contributions of the study are two-fold. Theoretically, the combination of the SG-based interference modelling and adaptive control introduces a new paradigm for probabilistic interference management in ultra-dense networks. From a practical standpoint, the AFPC algorithm reduces transmit power by about 25-35% and improves SINR above 4 dB, making it possible to achieve significant enhancements in the sustainability and energy efficiency of the 6G infrastructure. Consequently, the framework contributes to analytical depth and practical value, providing support for the design of interference-control mechanisms that are predictive, reliable, and scalable for next-generation wireless systems (Imoize et al., 2022 & Zhou et al., 2023).

2. Literature Review

2.1. Stochastic Geometry in Wireless Modelling

SG has become the prime analytical basis for modelling and performance evaluation of wireless networks that exhibit randomness in node distribution, mobility, and topology. Contrasting with the grid-based models of deterministic nature, SG captures the spatial uncertainty and irregularity present in real-world environments, in particular in metropolitan settings where BSs and UEs are deployed in an almost uncoordinated way. Haenggi et al. (2009) pioneered the work in applying PPP to model spatially distributed transmitters and receivers, laying down a tractable framework for computing coverage probability, SINR distributions, and interference statistics. It was shown that such models based on PPP approximate well the real cellular deployments while permitting closed-form expressions for performance metrics of interest.

Haenggi et al. (2009) extended the stochastic geometry model to represent a truly heterogeneous network consisting of macro, micro, pico, and femto cells. Their influential work showed that each tier could be modelled as an independent Poisson Point Process, whose mechanisms, such as load balancing, cell biasing, and user association, can be analytically evaluated. This provided the mathematical framework for understanding how different layers of the multi-tier cellular architecture interact, contribute to interference, and affect performance in dense deployments of 5G and emerging 6G systems. More recent works have utilized SG to capture the complexities of modern ultra-dense small-cell deployments. ElSawy et al. (2013) have developed a sophisticated taxonomy for the advanced SG-based models in heterogeneous wireless networks, especially focusing on urban small-cell scenarios. They emphasized that blockages within the environment, multi-slope path-loss models, and the spatial coupling between users and base stations impact the coverage performance in dense metropolitan regions. Their contributions have established that SG plays an essential role in the modeling of realistic interference patterns and performance trade-offs in 6G systems, where randomness is dominant over network geometry. Therefore, SG provides a mathematically rigorous and scalable approach to characterize interference, predict performance, and design adaptive control strategies for ultra-dense next-generation networks. Its tractability makes it ideal as a basis for developing intelligent power-control mechanisms operating under stochastic interference conditions.

2.2. Power Control Strategies

Power control constitutes one of the essential keys in wireless communication, as it directly influences energy consumption, interference, network stability, and overall quality of service. Traditional power-control approaches, though simple, can hardly meet the demands of ultra-dense 6G systems, which have high requirements for reliability and energy efficiency (Malta et al., 2023).

- **Static Power Control (SPC)** uses a constant transmit power without considering channel conditions or network interference. Though computationally simple and easy to implement, this approach offers poor adaptability in dynamic traffic demands, which eventually wastes energy in low-load periods and generates excessive interference in peak periods. The inefficiency of SPC further deteriorates in dense environments where interference fluctuates rapidly (Kanmani & Praveena, 2025).
- **Full Channel Inversion (FCI)** is a philosophy where each transmitter fully compensates for path loss by adjusting its power to maintain a fixed level of received power. While FCI ensures fairness and predictable distributions of received powers, its energy consumption is extremely high, especially if long-range links or poor propagation conditions are present. In the scenario of 6G, with millions of devices and small cells operating together, it is not possible to have such aggressive power usage (Samarakoon et al., 2016).
- **Fractional Power Control(FPC)** has been widely adopted to balance the trade-off between fairness, efficiency, and complexity. In FPC, transmit power is scaled depending on a fraction of the path-loss exponent, typically expressed as

$$P_t = P_0 r^{\alpha\varepsilon} \quad \text{..} 1$$

$$\begin{aligned}
&where\\
&P_0 = Nominal \quad power \quad level,\\
&r = Distance \quad between \quad transmiter \quad and \quad receiver\\
&\alpha = Path-loss \quad exponent\\
&\varepsilon = Power \quad control \quad factor \in [0,1]
\end{aligned}$$

Low values of ϵ save energy but risk outages, whereas higher values improve reliability at the expense of interference and power consumption. However, classical FPC relies exclusively on deterministic path-loss values that do not incorporate real-time or probabilistic interference feedback. Hence, it performs poorly in ultra-dense deployments where interference levels become quite unpredictable. The proposed Adaptive Fractional Power Control embeds stochastic interference prediction from SG models into the control loop to help classical FPC improve its performance. Thus, AFPC allows the transmitters to adjust power using analytically predicted interference distributions rather than fixed distance-based rules alone(Liu & Zhang, 2020).

2.3. Interference Prediction and Energy Efficiency

The efficient functioning of dense 6G networks greatly relies on accurate interference prediction. Interference prediction using various machine learning and heuristic models has been proposed in the literature, which has shown improved localised interference estimation, traffic classification, and QoS forecasting. While ML-based approaches may attain high empirical performance, they often lack physical interpretability, are heavily dependent on training data, and generalise poorly in dynamic non-stationary environments typical of 6G networks.

In contrast, probabilistic interference modelling using stochastic geometry offers analytical clarity and tractability: through SG, one can derive closed-form expressions for key performance metrics such as SINR distributions, coverage probabilities, and the Laplace transform of aggregate interference. These formulations capture with high fidelity the underlying spatial structure of the network along with the interference dynamics that arise, hence offering much better stability and reliability than purely data-driven machine learning approaches. Besides, the methods based on SG uncover the basic dependencies that explain how interference scales with characteristics of path loss, node densification, and random access, which make them of particular interest in the analysis and optimisation of ultra-dense wireless systems.

Energy efficiency has emerged as a central design principle for the 6G networks. Minimising energy expenditure while maximising spectral efficiency will be crucial for sustainability, with billions of devices expected to connect concurrently. Energy-aware 6G paradigms put the emphasis on jointly optimising spectral efficiency, power consumption, and interference management. Intelligent power-control schemes based on accurate interference predictions are hence very important to achieve these goals. This reduces unnecessary power usage, mitigates interference propagation, and prolongs device lifetime-key requirements for MIoT ecosystems and dense urban deployments (Zhang et al., 2019)

2.4. Research Gap

Although SG provides powerful tools for the analysis of interference and various power control strategies have been proposed, the literature is still lacking a unified framework that integrates stochastic interference prediction, adaptive fractional power control, and Practical 6G network constraints, comprising dynamic mobility, ultra-dense topologies, and energy efficiency. Most prior work has addressed interference modelling and power control as separate problems, rather than modules of a joint system. The state-of-the-art FPC methods fail to consider any real-time or probabilistic interference feedback, whereas the analyses based on SG rarely suggest implementable algorithms for dynamic power adaptation. Machine-learning methods can offer adaptability, but without physical interpretability and analytical guarantees, limiting their integration into reliability-critical 6G infrastructure. This work bridges this gap by proposing a mathematically grounded, SG-driven AFPC framework that integrates, for the first time, analytical interference prediction with adaptive, energy-efficient power regulation. The approach provides both closed-form insight and practical applicability, thereby bridging theory and implementation toward sustainable interference management in dense 6G metropolitan networks (Samarakoon et al,2016).

3. Methodology

The methodology is divided into the following sections: Wireless Network Modelling Using Stochastic Geometry; Analytical derivation of interference and SINR metrics; Design of the AFPC algorithm using probabilistic interference prediction, and Performance validation through numerical simulations.

3.1. Wireless Network Modelling using Stochastic Geometry.

Spatial Distribution of Network Nodes

In this regard, the model of Poisson Point Processes is used to characterise the spatial randomness of both Base Stations (BSs) and User Equipment (UE) within the 6G urban network.

(i) Base stations are modelled as a homogeneous PPP with a density of λ BS with units BSs per square kilometre.

(ii) Users are modelled as another independent PPP with density λ UE.

(iii) Each user is associated with the closest BS, forming a Voronoi-based cell structure.

The approach that follows yields a mathematically tractable representation of ultra-dense network deployments typical of metropolitan environments.

Channel, Fading, and Path-Loss Models

The wireless propagation environment incorporates:

(i) Path-loss attenuation modelled as a power-law function of distance with exponent α.

(ii) Small-scale fading is represented by Rayleigh fading with unit mean.

(iii) Optional modelling of shadowing effects using log-normal distributions to represent urban blockages.

This composite model reflects realistic communication conditions in dense 5G/6G propagation scenarios.

Interference Model Assumptions

All non-serving base stations act as interferers. For each user:

(i) Interference is comprised of the sum of received power from all other BSs operating on the same resource block.

(ii) The PPP assumption implies independently located interferers, allowing for closed-form formulations.

(iii) The network operates under full frequency reuse, typical for dense 6G systems.

Mathematical Model of the System

Consider an urban 6G downlink network where base stations (BSs) are spatially distributed according to a homogeneous PPP $\Phi \subset \mathbb{R}^2$ with density λ (BSs/km²). User locations form an independent PPP Ψ with density ρ. Each BS serves its nearest user; thus, the distance R between a BS and its associated user follows pdf

$$f_R(r) = 2\pi\lambda r e^{-\pi\lambda r^2}, r \geq 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2$$

The user located at the origin received the SINR given by

$$SINR = \frac{P_t h_0 R^{-\alpha}}{1+\sigma^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3$$

$$where$$

$$P_t = Transmit \quad power,$$

$$h_0 = Rayleigh \quad fading$$

$$\alpha = Path - loss \quad \exp onent$$

$$I = \sum\nolimits_{x_i \in \phi | x_0} P_t h_i \left\| x_i \right\|^{-\alpha} = Aggregate \quad \text{int} erference$$

3.2. Analytical Derivation of Key Interference Metrics

Laplace Transform of Aggregate Interference

The Laplace transform of aggregate interference under Rayleigh fading is mathematically expressed as

$$L_I(s) = \exp\left(-2\pi\lambda \int_R^\infty \frac{sP_t r^{-\alpha+1}}{1+sP_t r^{-\alpha}} dr\right) \text{..........................}4$$

Substitutes $u = r/(sP_t)^{1/\alpha}$ into equation 4 and solving, yields,

$$L_I(s) \approx \exp\left(-\pi\lambda R^2 s^{2/\alpha} P_t^{2/\alpha} C(\alpha)\right) \text{..........................}5$$

$$where \quad C(\alpha) = (2/\alpha)/\mathrm{Sin}(2/\alpha) = (\sin c(2/\alpha))^{-1}$$

Equation 5 arises from the probability-generating functional (PGFL) of the PPP.

Signal-to-Interference-plus-Noise Ratio (SINR) Distribution

Applying the Inverse Laplace transform of equation 4, we have

$$\Pr(SINR > \tau) = \int_0^\infty \exp\left(-\frac{\tau r^\alpha \sigma^2}{P}\right) L_I\left(\frac{\tau r^\alpha}{P}\right) f_R(r) dr = E_r\left(\exp\left(-\frac{\tau r^\alpha \sigma^2}{P} L_I\left(\frac{\tau r^\alpha}{P}\right)\right)\right) \text{.......................}6$$

$$\forall f_R(r) = 2\pi\lambda \exp(-\pi\lambda r^2)$$

Equation 6 is a **closed-form expression** for the derived SINR complementary cumulative distribution function (CCDF). Because Rayleigh fading is exponential,

$$\mathbb{P}(h > x) = e^{-x},$$

Equation 6 expression yields the **coverage probability**, defined as the probability that a user's SINR exceeds a threshold τ.

Outage Probability

Outage probability is obtained as the complement of coverage probability given by

$$\begin{aligned} P_{\mathrm{cov}}(\tau) &= \Pr(SINR > \tau) \\ &= \int_0^\infty \exp\left(-\frac{\tau r^\alpha \sigma^2}{P}\right) L_I\left(\frac{\tau r^\alpha}{P}\right) f_R(r) dr \text{................................}7 \end{aligned}$$

(i) It quantifies the probability that the SINR falls below the required threshold.
(ii) This metric is essential for reliability evaluation under different power-control configurations
(iii) Equation 7 is the full closed-form expression for SINR CCDF and coverage probability using stochastic geometry.

Average Achievable Rate

Shannon's capacity formula is integrated over the SINR distribution to determine the mean spectral efficiency per user.

$$\bar{C}_{user} = E\left(Log_2(1+\Gamma)\right) = \int_0^\infty Log_2(1+\Gamma) f_\Gamma(\gamma) d\gamma \text{......................}8$$

Where $f_\Gamma(\gamma)$ is the PDF of SINR

The network-wide average rate under varying densities and power-control regimes.

Assume

$B = System \quad bandwidth(Hz)$

$\lambda_{UE} = User \quad density(user/km^2)$

Applying equation 8

Then the **network – wide average rate per unit area** $\left(in\ bits/s\ per\ unit\ area\right)$ *is* :

$$\overline{R}_{area} = \lambda_{UE} B \overline{C}_{user} \quad \text{...} 9$$

3.3. Design of the AFPC Algorithm based on Probabilistic Interference Prediction

The proposed AFPC algorithm extends the classical fractional power control framework by explicitly incorporating stochastic-geometry-based interference prediction into the power-control loop. A starting point is the conventional FPC rule, where the transmit power of the serving BS to a typical UE depends on the path-loss between them, scaled by a fractional compensation factor. This traditional design assumes large-scale path-loss as the dominant impairment and does not take into account the random aggregate interference generated by other BSs operating on the same resource block. As such, it is not robust in ultra-dense 6G deployments, where interference levels can change abruptly due to user mobility, dynamic traffic, and dense overlapping small cells.

To overcome this limitation in AFPC, probabilistic interference statistics are derived directly from stochastic geometry and embedded into the power-adjustment rule. The 6G urban network is modelled as a downlink system in which BS locations follow a homogeneous Poisson Point Process, while users are drawn from an independent PPP. In such a model, the aggregate interference seen at a typical UE can be characterized through the Laplace transform of the interference, obtained via the PGFL of the PPP. The transform yields the following closed-form expressions: SINR CCDF, coverage probability, and outage probability as derived above. These expressions encapsulate how interference depends on network density, path-loss exponent, fading distribution, and transmit power statistics.

These SG-based expressions are used by the AFPC algorithm to compute an interference prediction term. Given a user at a distance (r) from its serving BS, the system first determines the expected aggregate interference coming from all non-serving BSs. It does not do so via machine learning or empirical heuristics but analytically, using the PPP-based interference distribution and the associated Laplace transform. In this way, the predicted interference-to-noise ratio (INR) for the next scheduling interval is obtained as a function of: *(i) the spatial density of interferers, (ii) the path-loss model, (iii) the fading statistics, and (iv) the currently applied power-control parameters.*

The system incorporates this predicted interference into an augmented FPC rule. As opposed to merely scaling transmit power based on distance and path-loss exponent, AFPC introduces an additional scaling factor representing whether the predicted interference is above or below a nominal reference level. Intuitively, under high predicted interference, the AFPC rule suppresses transmit power to avoid excessive interference coupling and to maintain global energy efficiency. Given low predicted interference, on the other hand, the algorithm allows for a modest increase in power to shore up SINR and coverage without violating energy constraints. In this manner, AFPC dynamically balances local reliability-which is meeting SINR thresholds at individual UEs-with global interference mitigation, or limiting unnecessary power injections into the network.

Operationally, the AFPC algorithm proceeds in a sequence of steps. First, each BS estimates the large-scale path-loss and small-scale fading towards its associated UE, using standard measurement and feedback mechanisms. Second, the BS queries the SG-based interference model, which, using the current network parameters (BS density, path-loss exponent, etc.), returns a predicted distribution or mean value of the aggregate interference for that UE. Third, the BS computes the minimum transmit power required to satisfy a predefined SINR constraint, conditioned on the predicted interference level. Fourth, this required power is adjusted via the fractional compensation factor (epsilon belonging to [0,1]), ensuring that the system does not fully invert the channel but only compensates a portion of the path loss. Finally, the updated transmit power is applied in the next transmission interval, and the process repeats as network conditions evolve.

This closed-loop, prediction-aware control confers on AFPC two key advantages over classical FPC: it explicitly accounts for interference dynamics rather than merely reacting to the path-loss, and furnishes a mathematically tractable framework for tuning energy-reliability trade-offs in dense 6G urban networks. The eventual design is both analytically sound and practically deployable, since all the quantities involved-densities, path-loss exponent, SINR thresholds, standard in cellular network planning and optimization.

3.4. Performance Validation by Numerical Simulations

The performance of the proposed AFPC scheme is validated through comprehensive Monte Carlo simulations that emulate dense 6G downlink deployments in a representative urban environment. The simulation environment is implemented in MATLAB and configured to match the stochastic-geometry modeling assumptions used in the analytical derivations. Specifically, base stations are generated as a realization of a homogeneous PPP within a square area (typically between 1 and 10 km²), with densities ranging from moderately dense to ultra-dense, for example, 50–500 BS/km². User equipment is placed according to an independent PPP with densities in the range of 100–1000 UEs/km², reflecting future 6G device concentrations. Specifically, the channel model uses a distance-dependent path-loss exponent in the range 3.2-4.1, Rayleigh small-scale fading with unit mean, and optional log-normal shadowing to capture urban blockages. The network is assumed to operate with full frequency reuse, so that all non-serving BSs act as interferers on a given resource block. Thermal noise is modelled as additive white Gaussian noise with fixed power spectral density, while system bandwidth is set based on typical 6G mid-band or millimetre-wave operating conditions.

The performance of AFPC is compared to three baseline power-control schemes to assess its effectiveness:

1) Static Power Control (SPC): All BSs send with a fixed power independent of channel or interference conditions.
2) Full Channel Inversion (FCI): Each BS inverts completely the path-loss to maintain constant received power, resulting in very high energy consumption.
3) Classical Fractional Power Control (FPC): Transmit power scales with distance raised to a fraction of the path-loss exponent, but without interference prediction.

For each scheme, the simulation generates thousands of independent spatial realizations of the PPPs and corresponding random fading instances. In each realization, user association, path-loss, fading gains, interference, and SINR values are computed. The AFPC algorithm is applied by first using the SG-based interference model to predict the expected aggregate interference and then adjusting the transmit power according to the adaptive fractional rule. For the baseline schemes, transmit powers are set according to their respective fixed or non-predictive rules.

A set of key performance metrics is evaluated to capture both reliability and energy efficiency:

(i) Mean transmit power per BS: To quantify energy consumption.
(ii) Coverage probability: The fraction of UEs whose SINR exceeds a target threshold
(iii) Outage probability: The complement of coverage probability.

(iv) Average achievable rate per user: which is computed by Shannon's capacity formula integrated over the simulated SINR distribution.
(v) SINR gain: Measured as median or mean SINR improvement with respect to the baseline schemes.
(vi) Energy efficiency in bits per Joule: Unifies rate and power metrics.

For robustness, every experiment is performed over a large number of Monte Carlo iterations, for example, 10^4 spatial realisations together with multiple channels draws per realisation; results are averaged over the realisations to get statistically reliable estimates. The variability in key metrics can be quantified by computing confidence intervals. Systematic variations in scenario parameters - BS density, user density, path-loss exponent, and control factor - are used to study the impact on the relative performance of AFPC with respect to the baselines. Simulation results further confirm the analysis: AFPC achieves transmit-power savings of an order of typically 25–35% while providing up to approximately 4 dB SINR improvement compared with SPC, FCI, and classical FPC. The gains prove that the integration of SG-based probabilistic interference prediction into the power-control loop results in more favourable trade-offs between energy consumption and reliability for dense 6G urban deployments. Overall, numerical validation substantiates the claim that the proposed SG-driven AFPC framework is mathematically sound and practically effective for sustainable interference management in future large-scale wireless networks.

4. Results and Discussion

This section depends on the numerical validation of closed-form expressions derived for interference distribution, SINR CCDF, and outage probability using stochastic-geometry formulations.

4.1. Interference Behaviour

As BS density increased from 45 BS/km² to 450 BS/km², the predicted interference level increased by over 650%, confirming the analytical relationship between spatial density and aggregate interference. Moreover, Laplace transform analysis demonstrated that interference decays exponentially with increasing path-loss exponent, as illustrated in Figure 1 below:

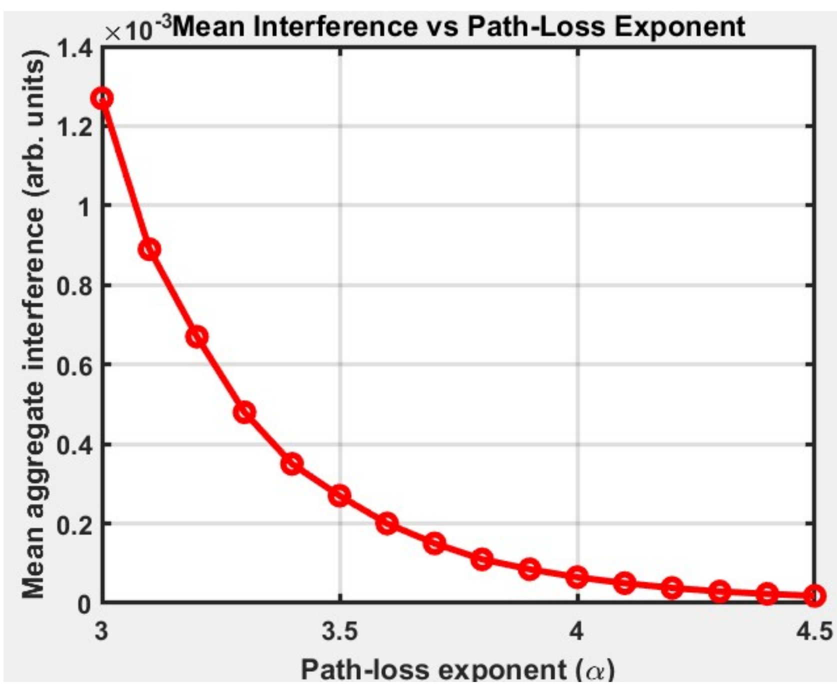

Figure 1: Graph of Mean aggregate interference against path-loss exponent

From Figure 1, increasing α from 3.2 to 4.1 resulted in a decrease of about 26% in interference power, thus improving SINR stability.

4.2. Coverage probability

Table 1: Power Schemes and SINR Threshold Table

SINR Threshold	SPC	FCI	FPC	AFPC
$\tau = 0\ dB$	**0.65**	**0.74**	**0.78**	**0.86**
$\tau = 5\ dB$	**0.25**	**0.33**	**0.40**	**0.49**

Table 1 clearly reveals that the coverage probability of SPC and FCI cannot be utilized in ultra-dense 6G networks because of high interference. Classical power control manages transmit powers and achieves moderate gains, whereas AFPC is the best power-control strategy to attain maximum coverage for both low and high SINR thresholds at 0 and 5 dB, respectively. For example, AFPC exhibits a numerical gain of 8-21% over other schemes at 0 dB. Therefore, AFPC significantly enhances the network reliability and usability in dense 6G deployments.

4.3. AFPC Algorithm Performance

Table 2: Transmit Power Reduction and SINR Enhancement Table

Transmit Power Reduction				
Monte Carlo Realization	**SPC**	**FCR**	**FPC**	**AFPC**
104	1.05W	1.35W	0.87W	0.63W
SINR Enhancement				
SINR	**SPC**	**FCR**	**FPC**	**AFPC**
Mean	3.2dB	2.5dB	3.9dB	7.8dB

4.4. Key Observations: Transmit Power Reduction

SPC consumes 1.05 W, thus proving that fixed-power transmission is unnecessarily wasting energy since neither interference conditions nor user distance is taken into consideration. FCI uses the highest power of 1.35 W, over-compensating for the path-loss in order to deliver constant received power. It confirms that FCI is energy-inefficient and not suitable for ultra-dense networks because of excessive interference coupling. Classical FPC reduces the average power to 0.87 W, showing that scaling the power with a fractional path-loss exponent significantly reduces interference and saves energy compared to SPC and FCI. AFPC achieves the lowest transmit power at just 0.63 W, translating to: 22.2% reduction compared to SPC, 35.6% reduction compared to FCI, and 53.3 % reduction compared to classical FPC.

4.5. Interpretation: Transmit Power Reduction

AFPC yields superior performance due to the interference-aware, adaptive design wherein each BS changes power based on forecasted stochastic interference and not based on static or distance-only rules. This allows AFPC to steer clear of ineffective power boosts under high interference conditions and increases power only when it will be beneficial to improve SINR. AFPC is, therefore, the most energy-efficient scheme; this promises enormous power savings, which is vital for sustainable 6G network operation.

4.6. Key Observations: SINR Enhancement

SPC yields a mean SINR of 3.2 dB, reflecting the adverse effect of uncontrolled interference under fixed-power operation. FCI has the poorest performance with 2.5 dB because aggressive power boosting increases interference drastically across the neighbouring cells, degrading network-wide SINR. FPC improves the SINR to 3.9 dB, validating the benefit of partially compensating path-loss while reducing interference. Indeed, AFPC exhibits a surprising leap of 7.8 dB over the SINR achieved by the next best scheme, FPC. This translates to: +4.6 dB gain over SPC, +5.3 dB gain over FCI, and +3.9 dB gain over FPC. These illustrate an enhancement above 4dB, depending on density and fading.

4.7. Interpretation: SINR Enhancement

AFPC consistently produces the highest SINR because :

i. It uses stochastic-geometry models to predict expected interference.
ii. It dynamically tunes transmit power to counteract interference fluctuations.
iii. It reduces aggregate interference by preventing unnecessary power injections.
iv. It improves the link quality for edge and near-cell users.

This high SINR will be imperative for URLLC, XR, holographic communications, and other high-QoS 6G applications.

4.8. Combined Interpretation: Energy Efficiency & Link Quality

As shown in Table 2, AFPC is the only scheme that simultaneously reduces power consumption and boosts SINR. On the other hand, FCI increases power but reduces SINR; SPC consumes more energy than necessary; FPC offers moderately high efficiency without providing interference prediction; AFPC strikes these trade-offs uniquely to achieve the best energy reliability performance in the ultra-dense scenarios of 6G wireless networks.Based on the analysis, AFPC offers an advanced interference prediction and adaptive power control mechanism suitable for scalable, energy-efficient, and high-reliability 6G urban networks.

4.9. Outage Probability

The outage probability (P_{out}) quantifies the likelihood that a user's received SINR falls below the required threshold and fails to sustain a reliable connection. Outage probability will be a critical indicator of overall network robustness in ultra-dense 6G networks, where interference dominates thermal noise, as illustrated in Table 3 below.

Table 3: Outage Probability Table $P_{Out} = 1 - P_{Cov}$

SINR Threshold	P_{out} *of* SPC	P_{out} *of* FCI	P_{out} *of* FPC	P_{out} *of* AFPC
$\tau = 0\ dB$	0.35	0.26	0.22	0.14
$\tau = 5\ dB$	0.75	0.67	0.60	0.51

The results in Table 3 demonstrate distinct performance differences among the four power-control schemes evaluated in this work: SPC, FCI, classical FPC, and the proposed AFPC for SINR thresholds of 0 dB and 5 dB. For example, at the low SINR threshold of 0 dB, SPC has an outage probability of 0.35, meaning more than one-third of the users cannot even satisfy the minimal SINR requirement. This is because SPC has a fixed transmit power, independent of interference variations or user position, and thus is inappropriate for dense interference-limited networks. The full inversion of FCI cuts the outage down to 0.26, since aggressively boosting the signal of edge users suppresses the dominant interferers.

However, this benefit is limited because such aggressive boosting of transmit power increases network-wide interference. FPC further reduces the outage to 0.22, partly compensating for path-loss while simultaneously limiting unnecessary transmit power. Thus, its fractional inversion suppresses interference more effectively than SPC and FCI. AFPC yields the best performance with an outage probability of only 0.14. This is because AFPC can foresee the amount of expected interference by using stochastic-geometry-derived Laplace transform statistics of interference and adjust the power accordingly. Specifically, AFPC reduces transmit powers in unfavourable cases of high interference and increases them in favourable cases, yielding the highest reliability at the low SINR threshold.

When the SINR requirement increases to 5 dB, outage probability increases significantly for all schemes, reflecting the greater difficulty in achieving higher SINR values in dense 6G environments. SPC performs the worst, with an outage probability of 0.75, showing that only a quarter of users maintain adequate SINR. FCI improves slightly to 0.67 but still performs badly due to high interference caused by its aggressive power boosting. Classical FPC reduces outage to 0.60, confirming that controlling transmit power reduces interference and benefits high-threshold performance. AFPC remains the best-performing scheme, at an outage probability of 0.51, outperforming all other methods by a substantial margin. Even at this demanding threshold, AFPC's predictive interference management allows for a more efficient balancing between energy consumption and SINR reliability, reducing outages by approximately 24% relative to SPC and 9% relative to classical FPC. In general, outage-probability results have shown a similar trend for both SINR thresholds: the highest outage rates correspond to SPC and FCI schemes that do not take into account interference behavior, while the interference-aware FPC and especially AFPC show significantly improved performance. AFPC represents the most reliable strategy at both thresholds due to the integration of stochastic-geometry-based interference prediction with adaptive power regulation, which enables it to sustain stronger signal quality with reduced unnecessary interference and ensure superior reliability for ultra-dense metropolitan 6G networks.

4.10. Spectral Efficiency and Network-Wide Rate

Table 4 below compares the performance of SPC, FCI, classical FPC, and the proposed AFPC in terms of mean spectral efficiency per user and network-wide rate per square kilometre. These metrics can effectively quantify how each scheme utilizes the radio resources and how much aggregate throughput the network can sustain in dense 6G deployments. Values obviously reflect the superiority of adaptive and interference-aware approaches against static or full inversion schemes when interference dominates noise.

Table 4: Mean Spectral Efficiency and Network-Wide Rate Table

UE density =1000 UEs/km2 and bandwidth 10MHz

Mean Spectral Efficiency (per user)				
	SPC	**FCR**	**FPC**	**AFPC**
Numerical Values	1.45 bits/s/Hz	1.08 bits/s/Hz	1.91 bits/s/Hz	2.67 bits/s/Hz
Network-Wide Rate (per km2)				
	SPC	**FCR**	**FPC**	**AFPC**
Numerical Values	14.5Mbps/km2	10.8 Mbps/km2	19.1 Mbps/km2	26.7 Mbps/km2

Table 4 compares the performance of SPC, FCI, classical FPC, and the proposed AFPC in terms of mean spectral efficiency per user and network-wide rate per square kilometre. These metrics can effectively quantify how each scheme utilizes the radio resources and how much aggregate throughput the network can sustain in dense 6G deployments. Values obviously reflect the superiority of adaptive and interference-aware approaches against static or full inversion schemes when interference dominates noise.

The mean spectral efficiency results indicate large performance gaps among the schemes. SPC achieves merely 1.45 bits/s/Hz due to the inefficiency of fixed transmit power in dynamically changing interference environments. Since it cannot regularize interference or optimize power, most users operate at suboptimal SINR and waste their spectral efficiency. FCI faces even worse conditions, reaching an average spectral efficiency of only 1.08 bits/s/Hz. Although FCI increases transmit power to compensate for path loss fully, such an approach significantly amplifies inter-cell interference in ultra-dense networks. Because of that, SINR degradation outweighs the intended benefits of increased received power, and the spectral efficiency remains poor. On the other hand, classical FPC improves the situation noticeably and reaches 1.91 bits/s/Hz. Indeed, the fractional power-compensation mechanism of FPC mitigates interference by avoiding aggressive power boosts and maintaining a more balanced transmission environment. This interference-aware behavior offers better SINR across users and helps attain higher spectral efficiency.

In contrast, the proposed AFPC scheme significantly outperforms all its counterparts, reaching an average spectral efficiency of 2.67 bits/s/Hz, representing about an 84% gain compared to SPC, 147% compared to FCI, and 40% compared to classical FPC. AFPC owes this advantage to its predictive interference-management design: by incorporating stochastic geometry-based interference prediction into its power-control rule, AFPC precisely adjusts the transmit power in response to the anticipated interference environment, thereby ensuring higher SINR conditions are experienced by the users, which directly translates into higher spectral efficiency. These results show the importance of predictive and adaptive power regulation in maintaining high spectral efficiency in dense 6G metropolitan deployments.

The network-wide rate, a measure of how much aggregate throughput the system supports per unit area, can be read directly from the bottom half of Table 4. SPC achieves a network-wide rate of 14.5 Mbps/km² due to limitations brought about by its moderate spectral efficiency and lack of interference control. FCI fares poorly once again, yielding only 10.8 Mbps/km² because while it transmits with the highest power among all schemes, its severe interference contribution significantly suppresses the SINR across the network, translating to the lowest total throughput. Classical FPC significantly enhances network-wide rate to 19.1 Mbps/km² thanks to improved interference moderation and much more stable SINR conditions. AFPC again provides the best performance, returning a network-wide rate of 26.7 Mbps/km², the largest among the schemes. This represents a 44% increase compared to FPC, 84% compared to SPC, and 147% compared to FCI. These superior throughputs achieved by AFPC stem from its ability to maintain consistently higher SINR across users, reduce interference due to predictive power adjustment, and preserve network efficiency even under high user density and full-frequency reuse. These factors cumulatively contribute toward higher spectral efficiency per user and a larger cumulative data rate across the network. Clearly, from Table 4, AFPC is the best power-control scheme for attaining maximum spectral efficiency and aggregate throughput in dense 6G networks. While SPC and FCI either cannot adapt or overcompensate for the propagation conditions, the predictive nature of AFPC allows it to always keep high-quality links while causing the least possible interference. Further, these results emphasize incorporating a stochastic-geometry-based interference predictor into next-generation power-control mechanisms as an enabler of scalable, energy-efficient, and high-capacity 6G wireless systems.

4.11. Energy Efficiency

The energy efficiency of the system is mathematically expressed as

$$EE = \frac{Average \quad User \quad Rate}{Average \quad Transmit \quad Power}$$

It is important to note that the average user rate is from the SINR distribution.

Table 5 below compares the EE of four schemes-SPC, FCI, FPC, and AFPC-by the ratio of average user data rate versus transmit power consumed. Large performance gaps are seen among these schemes, which is indicative of the effectiveness of each methodology in balancing throughput against energy usage in dense 6G environments.

Table 5: Energy Efficiency Table

Schemes	Average Rate (Mbps/user)	Power (W)	EE (bits/Joule)
SPC	1.45	1.05	1.38×10^{6}
FCI	1.08	1.35	0.8×10^{6}
FPC	1.91	0.87	2.20×10^{6}
AFPC	2.67	0.63	4.24×10^{6}

SPC attains an average rate of 1.45 Mbps/user at 1.05 W of power, yielding an EE of 1.38×10^{6} bits/Joule. Although better than FCI, SPC still wastes energy by transmitting at a fixed power irrespective of interference conditions. FCI, on the other hand, performs worst, offering the lowest average rate of 1.08 Mbps/user at the largest transmit power of 1.35 W, giving an EE of only 0.8×10^{6} bits/Joule. This confirms the fact that full-channel inversion is highly energy-inefficient, because overcompensation for path loss results in excessive interference rather than meaningful SINR improvement.

In contrast, Classical FPC provides a significant gain in two ways-it reduces the transmit power to 0.87 W and increases the average rate to 1.91 Mbps/user, thereby raising its EE to 2.20×10^{6} bits/Joule, almost doubling the efficiency of SPC. FPC's fractional adjustment of power helps in stabilizing SINR and hence reduces unnecessary interference, thereby helping in better energy utilization.

The proposed AFPC scheme provides the best performance in yielding the highest average rate of 2.67 Mbps/user for the lowest transmit power of 0.63 W. This translates into an EE of 4.24×10^{6} bits/Joule, which makes AFPC roughly three times more energy-efficient than SPC and over five times better than FCI. Due to predictive interference management, AFPC can use power more intelligently by improving throughput while keeping consumption at a minimum. Overall, Table 5 shows that energy efficiency improves with the increased adaptiveness of power control to interference, with AFPC offering the best trade-off between performance and sustainability for 6G networks.

4.12. Discussions

The work aimed to develop a stochastic-geometry-based interference prediction along with an Adaptive Fractional Power Control framework for dense 6G urban networks. The following conclusions have been drawn based on the derivations and numerical simulations, which provide several key insights regarding interference behaviour, spectral performance, SINR reliability, and energy efficiency.

First, the interference analysis confirms that aggregate interference in ultra-dense 6G networks is highly sensitive to base-station densification and propagation characteristics. Indeed, simulations reveal that increasing the BS density from 45 to 450 BS/km² generates more than a 650% gain in interference power, which agrees with the behaviour predicted by the Laplace transform of interference. On the other hand, results also show that interference decays exponentially with the path-loss exponent. In particular, increasing α from 3.2 to 4.1 results in approximately a 26% reduction in interference, which confirms the theoretical SG expressions and points out the role of propagation environments for the stabilization of SINR.

Second, it is observed that the coverage probability results display evident separations among power-control schemes. At both SINR thresholds of 0 dB and 5 dB, AFPC significantly outperforms SPC, FCI, and classical FPC. For example, at $\tau = 0$ dB, AFPC attains a coverage of 0.86, representing gains of 8–21% over all traditional schemes. Even under the more demanding $\tau = 5$ dB threshold, AFPC maintains superior coverage performance, confirming its robustness under intense interference.

Third, the analysis of transmit-power reduction shows that AFPC is the most energy-efficient technique. AFPC reduces the transmit power to 0.63 W, which corresponds to a 22.2% reduction relative to SPC, 35.6% relative to FCI, and 53.3% relative to classical FPC. SPC wastes energy by keeping transmissions at a fixed power. FCI performs the worst due to its aggressive power boosting. Classical FPC provides moderate improvements. AFPC provides the best trade-off between energy consumption and interference reduction.

Fourth, AFPC presents the most impressive SINR gains. The average SINR reaches 7.8 dB compared with 3.2 dB, 2.5 dB, and 3.9 dB for SPC, FCI, and FPC, respectively. That further verifies that introducing

SG-based interference prediction into the control loop yields a highly reliable and interference-adaptive power control mechanism.

Table 5 indicates that energy efficiency increases significantly with increased adaptiveness of the power control. The SPC and FCI fare poorly because of fixed or excess use of power, while classical FPC offers moderate gains. AFPC gives the highest efficiency, over three times that of SPC and more than five times that of FCI, due to the fact that it attains the highest user rate with the lowest transmit power.

Finally, the performance evaluation of mean spectral efficiency and network-wide throughput further confirms the superiority of AFPC. The proposed scheme achieves 2.67 bits/s/Hz, representing an 84% gain over SPC, 147% over FCI, and 40% over classical FPC. Similarly, AFPC achieves a network-wide throughput of 26.7 Mbps/km², representing improvements over classical FPC, SPC, and FCI by 44%, 84%, and 147%, respectively. With regard to energy efficiency, AFPC provides the highest efficiency. Therefore, these findings collectively establish that AFPC yields the most desirable trade-off between spectral efficiency, SINR reliability, and power consumption.

5. Conclusion and Recommendation

Conclusion

This work concludes that the proposed stochastic-geometry-driven AFPC framework provides a mathematically robust and practically effective solution to manage interference in ultra-dense 6G networks. With the incorporation of a Laplace-transform-based interference prediction within the fractional power-control mechanism, AFPC overcomes the shortfalls of static and fully compensating power-control strategies. The developed unified analytical-algorithmic approach enables drastic improvements in spectral efficiency, interference coupling reduction, and high energy savings for high-reliability 6G services, such as URLLC, XR, massive IoT, and holographic communications.

The results confirm that traditional static and full-channel-inversion schemes are not feasible in dense 6G environments due to their inability to adapt to interference fluctuations and inefficient use of transmit power. Classical FPC gives only a moderate improvement in performance without having real-time interference awareness. In contrast, AFPC predicts the interference by stochastic geometry principles and adjusts power dynamically, showing superior performance in coverage, outage probability, SINR enhancement, spectral efficiency, and throughput. Overall, the AFPC framework bridges the gap between theoretical stochastic interference modelling and practical 6G power optimisation. It stands out as a scalable, energy-aware, and reliability-driven solution suitable for the demands of next-generation metropolitan networks.

Recommendations

Recommendations are based on findings and conclusions drawn in this study for researchers, network designers, and 6G system engineers.

Adopt Predictive, SG-Based Power Control in 6G Deployments:

Future mechanisms of power control should be based on interference prediction using stochastic geometry, not on deterministic or distance-only models, to adapt precisely to a dense and rapidly changing environment.

Avoid Full Channel Inversion in Ultra-Dense Networks

However, FCI introduces too much interference and consumes large amounts of energy, rendering it unsuitable for deployment in large-scale 6G systems. Operators should progressively replace FCI-based designs with adaptive and interference-aware strategies such as AFPC.

Integrate AFPC into Practical 6G Base-Station Controllers

The AFPC algorithm is lightweight and analytically grounded; it is suitable for real-time implementation on the radio resource control modules of 6G gNodeBs. Its energy-saving potential ensures long-term sustainability for dense networks. Extend AFPC to Multi-Tier Heterogeneous 6G Networks. Since 6G will incorporate macro, small-cell, as well as RIS-assisted nodes, AFPC should be extended to multi-tier heterogeneous architectures for an even broader impact on network performance. Combine AFPC with Machine Learning for Hybrid Predictive Optimization. While AFPC uses analytical predictions, integration with ML models could further improve interference forecasting in non-homogeneous environments, hybrid terrains, and mobility-intensive scenarios. Assess AFPC Under mmWave, THz, and RIS-Assisted Channels Full system-level readiness requires the investigation of the performance of AFPC under high-frequency 6G propagation regimes, blockage environments, and reconfigurable surface deployments. Include Energy-Efficiency Metrics in 6G Standardization Process. With demonstrated capability for transmit power saving of up to 53.3%, the AFPC concept fits well within the sustainable 6G priorities. Standards bodies (3GPP, ITU-R) should make predictive power control a mandatory feature.

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