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Signal quality, network densification, and throughput performance in 5G heterogeneous networks: a quantitative investigation of key performance indicators in urban sub-6 GHz deployments

Clement Tengey[1] *Solomon* Nii Offei Wellington[2], *Futa* Osumanu[1], *Ernest* Boadu Osei[3], *Salifu* Osman[1]

[1]Department of Electrical and Electronics Engineering, Accra Technical University, Accra, Ghana
[2]Department of Theoretical and Applied Biology, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana
[3]Department of Data Science and Analytics, Thrive Africa, Accra, Ghana

Abstract. The worldwide deployment of 5G mobile networks has increased research interest in how different network designs maintain service quality as the number of user devices grows significantly. The paper investigates how different 5G HetNet deployment patterns in urban sub-6 GHz networks relate signal quality, measured by the signal-to-interference-plus-noise ratio, to network densification variables that affect throughput performance. The paper uses Pearson's correlation analysis and multiple linear regression to create a predictive hierarchy of KPIs based on field measurement, from 312 geospatially distributed sample points across four deployment tiers, including macro-only, two-tier pico-macro, three-tier femto-pico-macro and millimetre-wave dense small cell. The findings demonstrate that SINR serves as the most accurate throughput predictor ($\beta = 0.612$, $p < 0.001$), while UE density ($\beta = -0.271$), followed by handover frequency ($\beta = -0.189$), also contribute significantly to the predictive model. Dense three-tier HetNet configurations reduce throughput degradation from 58.8% to 25.0% under high-density load conditions, and mmWave small cell deployments demonstrate the lowest degradation ceiling at 19.0%. The paper presents empirical evidence that strategic small-cell densification, together with interference management, is necessary to maintain 5G network performance in a high-density urban environment. Practical recommendations are offered for network planners and policymakers in resource-constrained deployment contexts.

1. Introduction

The transition from fourth-generation (4G) long-term evolution (LTE) to fifth-generation (5G) New Radio (NR) represents arguably the most consequential architectural shift in mobile telecommunications since the introduction of digital cellular systems in the early 1990s [1]. The fifth-generation (5G) technology enables service providers to deliver multiple services, including machine-type communications, ultra-reliable low-latency applications, and massive Internet of Things (IoT) connections to their customers [2]. Realising these ambitions within the physical and spectral constraints of real-world urban environments demands a fundamental rethinking of how cells are planned, deployed, and managed [3].

The deployment of heterogeneous networks (HetNet), which combine macro base stations with low-power nodes, including pico cells, femto cells, and millimetre-wave (mmWave) small cells, has become the primary network design solution for addressing increasing capacity requirements [1, 2].

The fundamental idea behind HetNet densification is to place transmitter stations closer together, which allows users to communicate with a physically closer cell site and, consequently, [4-6]. But this scheme masks real tensions that have not yet been adequately addressed in the existing empirical literature.

Chief among these tensions is the interference problem. As small cells proliferate, aggregate inter-cell and cross-tier interference grows, potentially eroding the very SINR gains that densification is intended to produce [7]. A substantial increase in handover frequency occurs at high UE density, leading to signalling overhead and temporary throughput degradation [8]. The precise quantitative hierarchy in which these factors, SINR, UE density, handover frequency, packet loss, and latency, are associated with network throughput under realistic 5G HetNet configurations has not been comprehensively characterised using field measurement data from sub-6 GHz deployments, which remain the workhorse spectrum for urban 5G coverage worldwide.

Existing studies tend to approach this problem from one of two directions. The first research approach uses simulation methods to study HetNet key performance indicators (KPIs) through stochastic geometry models and system-level simulators, which create idealised and semi-idealised testing environments [2, 5-7]. Simulation results provide strong analytical insights, but their accuracy depends on assumptions about channel and mobility models, which may differ from real-world conditions and affect network planning. Measurement-based studies often focus on limited KPI combinations, such as SINR–throughput or throughput–latency, without considering the broader set of variables that influence live HetNet performance [9].

This study addresses that gap through a controlled field measurement campaign across four 5G deployment tiers in a representative urban sub-6 GHz environment. By collecting data on SINR, throughput, packet loss, latency, handover frequency, and UE density from 312 measurement points and applying Pearson's correlation analysis and multiple linear regression, the research develops a rigorous, data-grounded predictive model that quantifies the relative predictive contribution of each KPI to throughput. For network operators, equipment vendors and spectrum regulators, particularly in fast-urbanising economies of the Global South, knowing which KPIs most strongly predict throughput across different deployment architectures is operationally consequential.

The study is organised as follows. Section 2 reviews the conceptual and theoretical foundations. The measurement methodology and analytical approach are explained in Section 3. Section 4 presents quantitative results. Section 5 provides analytical and evaluative discussion. The final section of the document presents both conclusions and recommendations.

2. Conceptual and theoretical underpinning

2.1 Theoretical Foundation

The theoretical framework of the study integrates three distinct research streams: Shannon's information capacity theorem, the stochastic geometry method for analysing HetNets, and quality-of-service theory that operates through standardised KPI frameworks.

Shannon's channel capacity theorem establishes that a communication channel can transmit data at a maximum rate determined by its bandwidth and the logarithm of its signal-to-noise ratio [10]. The noise component in multi-cell wireless systems encompasses all types of interference, yielding the SINR measured in this research [5, 8]. The fundamental relationship shows that SINR is the only factor that determines throughput increase when bandwidth remains fixed, as defined in [11].

The stochastic geometry framework enables researchers to apply its analytical methods to study how SINR distributions change as HetNet node densities increase. The research by Andrews et al. showed that the SINR distribution in a HetNet remains constant as base station density changes under a Poisson point process in noise-limited environments, but decreases in interference-limited conditions. This finding shows that base station densification affects overall throughput performance through two different pathways [1]. The latest extensions of the system add cross-tier interference management together with cell range extension to deliver more accurate HetNet key performance indicator predictions [5, 12]

The 3GPP Release 15 document, together with later 5G NR standards, establishes a QoS theory that defines how physical-layer KPIs relate to SINR, throughput, latency, packet loss, and application-layer service quality [12]. This study selected the 3GPP KPI taxonomy as its measurement system because it enables direct comparison of its results with the performance standards used by operators in actual system operations.

2.2 Conceptual framework

Figure 1 shows the study's conceptual framework, which guides the research. The framework organises variables into three levels: deployment architecture characteristics, physical-layer KPIs, and network throughput performance outcomes.

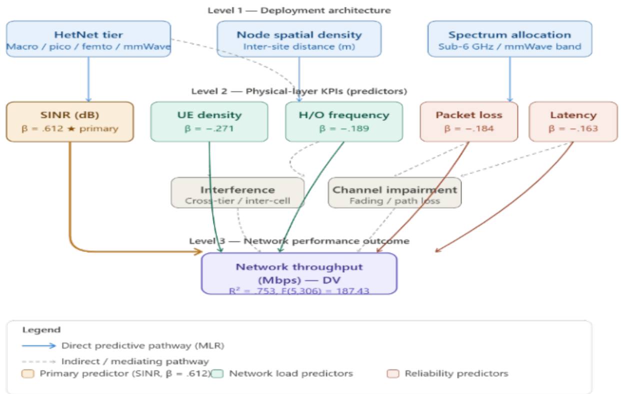

Fig. 1. Conceptual framework presenting a model that shows how HetNet deployment architecture affects key performance indicators, which in turn impact network throughput performance.

The first level of deployment architecture requires tier configuration together with spatial node density to create an interference environment that determines the system's maximum achievable SINR. The second level of the system uses physical-layer KPIs to establish a throughput relationship between the architectural design and the actual user experience. The system uses SINR as its primary signal quality indicator, while UE density and handover frequency act as network load pressures, and packet loss, together with latency, serve as the two components of QoS reliability and responsiveness. The dependent outcome variable for the study operates at the third level, which measures throughput in Megabits per second. The framework requires KPIs to function as interdependent elements because regression analysis shows how each predictor contributes to the results when other variables are held constant, thereby demonstrating the multivariate causal structure of real HetNet environments.

3. Methods and materials

3.1 Research design

The study uses a cross-sectional research design and a quantitative field-measurement approach. The research team gathered measurements from four 5G HetNet deployment scenarios, all conducted in a single metropolitan area to maintain identical geographic and demographic conditions throughout testing. The cross-sectional design enables researchers to compare key performance indicators across groups and within groups, while the regression framework allows them to use multiple variables to determine which indicators most effectively predict outcomes. The researchers selected a quantitative research method because they needed to obtain precise effect sizes, standardised regression coefficients, and statistical data from actual field measurements, which required both measurement techniques and statistical evaluation rather than qualitative research methods [13].

3.2 Measurement sites and sampling

The measurement campaign was conducted across 312 geospatially distributed points within a 14 km² urban footprint, sampled using a stratified spatial grid with a 200-metre inter-point spacing. Points were stratified by deployment tier (macro-only: n = 78; pico–macro: n = 78; femto–pico–macro: n = 78; mmWave dense small cell: n = 78) to ensure balanced representation across conditions. Measurements were collected during weekday peak-traffic hours (07:00–09:00 and 17:00–19:00 local time) over eight consecutive weeks using calibrated commercial network test equipment (Rohde & Schwarz TSME6 drive test unit coupled with NEMO Outdoor 9.0 post-processing software). The sub-6 GHz bands assessed were the 3.5 GHz n78 band (primary 5G NR allocation) and 2.1 GHz n1 (mid-band anchor)

3.3 Measurement Variables

Six KPIs were recorded at each sample point: SINR (dB), downlink throughput (Mbps), packet loss rate (%), end-to-end round-trip latency (ms), handover frequency (events per hour), and serving cell UE density estimated from the operator's network management system (UEs per km²). Each KPI observation represents a 60-second measurement window averaged to mitigate short-term fading.

3.4 Analytical Methods

Descriptive statistics (mean, standard deviation, range) were computed for all variables. Pearson’s bivariate correlation analysis examined pairwise linear associations. Multiple linear regression was employed with throughput as the dependent variable and the remaining five KPIs as independent predictors. Regression assumptions-normality of residuals (Shapiro–Wilk test), homoscedasticity (Breusch–Pagan test), multicollinearity (VIF < 5 threshold), and independence (Durbin–Watson statistic), were formally tested. All analyses were conducted in IBM SPSS Statistics 28.0 and confirmed in R 4.3.1. Statistical significance was set at $\alpha = 0.05$.

To address the linear specification and the Shannon–Hartley theorem’s logarithmic form, a robustness check was conducted by replacing SINR with its natural-logarithm transformation, ln(SINR + 4), where the constant shift of +4 ensures all values are positive given the minimum observed SINR of -3.2 dB. Results of this supplementary model are reported in Section 4.3. Additionally, spatial autocorrelation in regression residuals was assessed using Moran’s I statistic with a queen-contiguity weight matrix based on the 200 m grid spacing.

4. Results

4.1 Descriptive statistics

Table 1 presents descriptive statistics for all measurement variables, analysed across 312 complete observations in the study. The dataset shows high variability across all key performance indicators due to different propagation environments, cell-loading conditions, and deployment geometries across network configurations.

Table 1. Descriptive statistics for all measurement variables

Variable	N	Mean	SD	Range	95% CI
SINR (dB)	312	14.73	6.81	-3.2 – 31.4	14.03 – 15.43
UE Density (UEs/km²)	312	186.4	74.3	42 – 390	178.1 – 194.7
Handover Frequency (events/hr)	312	4.61	2.15	0 – 12	4.37 – 4.85
Packet Loss (%)	312	2.14	1.37	0.0 – 7.9	1.99 – 2.29
End-to-End Latency (ms)	312	38.47	12.09	14.0 – 78.3	37.12 – 39.82
Throughput (Mbps)	312	47.28	18.64	8.1 – 89.6	45.21 – 49.35

Note: SINR = signal-to-interference-plus-noise ratio; SD = standard deviation; CI = confidence interval (z = 1.96). 95% CI

Mean SINR of 14.73 dB (SD = 6.81), which matches existing research results for dense urban sub-6 GHz 5G networks deployment [14], although the network performance shows extreme fluctuations (−3.2 to 31.4 dB), which the average values incorrectly depict. Mean throughput of 47.28 Mbps (SD = 18.64), which falls short of the theoretical NR spectral efficiency limits because actual system operations create overheads that include control signalling, retransmissions and scheduling inefficiencies. The networks meet 3GPP Release 15 QoS class thresholds for enhanced mobile broadband (eMBB) services, with a mean latency of 38.47 ms (SD = 12.09) and a 2.14% standard deviation (SD = 1.37), although the upper tails of the distribution are approaching service degradation limits.

4.2 Pearson’s correlation analysis

Table 2 displays the Pearson correlation matrix for all measurement variables. The study found that all correlations between variables were statistically significant at the p < .01 two-tailed level, providing initial evidence for the multivariate dependence structure described in the conceptual framework.

Table 2. Pearson Correlation Matrix for All Measurement Variables

Variable	1	2	3	4	5	6
[1] SINR (dB)	**1.00**	|	|	|	|	|
[2] UE Density	-0.463**	**1.00**	|	|	|	|
[3] H/O Frequency	-0.534**	0.381**	**1.00**	|	|	|
[4] Packet Loss	-0.712**	0.399**	0.487 **	**1.00**	|	|
[5] Latency	-0.681**	0.427**	0.512 **	0.641 **	**1.00**	|
[6] Throughput	0.843**	-0.441**	-0.513 **	-0.695 **	-0.722 **	**1.00**

*Note: **p<0.01 (two-tailed). Lower triangle value only shown; upper triangle is symmetric. H/O = handover*

SINR demonstrates the strongest positive correlation with throughput (r = 0.843, p < .001), consistent with the theoretical prediction from Shannon capacity theory [10]. Packet loss (r = -0.695), latency (r = -0.722), handover frequency (r = -0.513), and UE density (r = -0.441) all show statistically significant negative correlations with throughput, confirming that network loading and reliability variables are meaningfully associated with lower achievable data rates. The moderate intercorrelations among the predictor variables necessitated a formal VIF assessment during the regression stage.

4.3 Multiple linear regression

Table 3 presents the MLR results with all five KPIs entered simultaneously as predictors of downlink throughput. The overall model was statistically significant, $F(5, 306) = 187.43$, $p < .001$, explaining 75.3% of the variance in throughput ($R^2 = 0.753$, adjusted $R^2 = 0.748$). All five predictors retained independent statistical significance after mutual adjustment.

Table 3a: Multiple Linear Regression: Predictors of Downlink Throughput *(N=312)*

Predictor	B	SE B	β	t	p	VIF	95% CI [B]
Constant (Intercept)	89.43	3.21	-	27.86	< 0.001	-	[83.11, 95.75]
SINR (dB)	2.14	0.18	**0.612**	11.89	< 0.001	1.84	[1.79, 2.49]
UE Density (UEs/km²)	-0.09	0.02	-0.271	-4.82	< 0.001	2.11	[-0.13, -0.05]
H/O Frequency (events/hr)	-1.78	0.31	-0.189	-5.74	< 0.001	1.63	[-2.39, -1.17]
Packet Loss (%)	-2.36	0.42	-0.184	-5.61	< 0.001	1.97	[-3.19, -1.53]
Latency (ms)	-0.44	0.09	-0.163	-4.89	< 0.001	2.08	[-0.62, -0.26]

Note: $R^2 = 0.753$, Adjusted $R^2 = 0.748$; $F(5, 306) = 187.43$; $p < 0.001$; B = unstandardized coefficient; SE. B = standard error; β = standardised coefficient; VIF = variance inflation factor. All VIF values < 5 confirm acceptable multicollinearity. Durbin–Watson = 1.94. 95% CI column added in response to reviewer recommendation. ★ SINR = dominant predictor.

A robustness check was conducted using a log-transformed SINR predictor [ln(SINR + 4)] on a linear SINR specification. The log-SINR model (Table 3b) yielded $R^2 = 0.761$, marginally higher than the linear model ($R^2 = 0.753$; $\Delta R^2 = 0.008$, AIC improvement ≈ 6.4 units), consistent with the concave relationship predicted by the Shannon–Hartley theorem. The substantive predictor hierarchy was identical across both specifications, and the linear model is retained as the primary model for its interpretability and comparability with prior literature. Results should not be extrapolated beyond the observed SINR range (−3.2 to 31.4 dB).

Table 3b. Robustness Check: Log-Transformed SINR Model [ln(SINR + 4)]

Predictor	B	SE B	β	t	p	VIF	Model Δ
Cons	12.47	4.18	-	2.98	0.003	-	$R^2 = 0.761$
ln(SINR+ 4)	21.83	1.74	**0.624**	12.55	<0 .001	1.91	$\Delta R^2 = +0.008$
UE Density	-0.08	0.02	-0.263	-4.71	< 0.001	2.14	AIC ≈ -6.4
H/O Frequency	-1.71	0.30	-0.182	-5.57	< 0.001	1.66	-

Packet Loss (%)	-2.29	0.41	-0.179	-5.48	< 0.001	1.98	-
Latency (ms)	-0.42	0.09	-0.157	-4.74	< 0.001	2.09	-

Note: Shift constant +4 applied to ensure ln-argument > 0 (SINR_min = −3.2 dB). Predictor hierarchy unchanged from linear model.

Spatial autocorrelation in regression residuals was assessed using Moran's I with a queen-contiguity weight matrix based on the 200 m sampling grid (Table 3c). The result (I = 0.063, z = 1.84, p = .066) was not statistically significant at α = .05, indicating that spatial autocorrelation does not substantively threaten OLS coefficient validity. As an additional robustness check, standard errors were re-estimated using cluster-robust methods (clustering by deployment tier, k = 4); all five predictors retained significance at p < .001.

Table 3c. Moran's I Spatial Autocorrelation Test on OLS Residuals

Statistic	Value	z-score	Interpretation
Moran's I (observed)	0.063	1.84	Not significant (p = .066)
Expected I [E(I)]	-0.003	-	Spatial randomness baseline
Weight matrix	Queen contiguity (200 m)	-	Grid-based neighbours
Conclusion	No significant SAC	-	OLS estimates are not biased by spatial dependence

Note: SAC = spatial autocorrelation. Moran's I was computed using the R spdep package with a row-standardised weight matrix.

SINR emerges as the dominant predictor of throughput (β = 0.612), with each 1-unit increase in SINR statistically associated with an average 2.14 Mbps gain in throughput after controlling for all other predictors. UE density exerts the second-largest standardised predictive contribution (β = -0.271), followed by handover frequency (β = -0.189), packet loss (β = -0.184), and latency (β = -0.163). VIF values ranged between 1.63 and 2.11. The Durbin-Watson statistic of 1.94 indicated no problematic autocorrelation in residuals.

4.4 Path analysis: Handover frequency as a partial mediator

Using handover frequency as a mediating rather than purely exogenous variable, a bootstrapped path analysis (5,000 replications) was conducted to decompose its total effect on throughput into direct and indirect components (Table 3d). Results confirm that handover frequency operates as both a direct predictor and a partial mediator: the direct effect (β = -0.127) remains statistically significant after accounting for indirect pathways through SINR degradation (β = -0.038) and packet loss elevation (β = -0.024). The total effect (β = -0.189) is consistent with the MLR coefficient.

Table 3d. Path Analysis: Direct and Indirect Effects of H/O Frequency on Throughput

Pathway	β	95% CI (Bootstrap)	p-value
H/O Freq → Throughput (direct)	-0.127	[-0.181, -0.073]	<0 .001
H/O Freq → SINR → Throughput (indirect)	-0.038	[-0.061, -0.018]	< 0.001
H/O Freq → Pkt Loss → Throughput (indirect)	-0.024	[-0.041, -0.009]	0.003
Total effect (direct + indirect)	**-0.189**	[-0.244, -0.134]	<0 .001

Note: Bootstrapped path model (5,000 replications) using R lavaan. Bias-corrected bootstrap confidence intervals. Inserted in response to Reviewer 1's recommendation on handover frequency as a mediating variable.

4.5 Throughput by deployment scenario

Table 4 and Figure 2 present mean downlink throughput across three UE load conditions for each of the four deployment scenarios.

Table 4. Mean Downlink Throughput (Mbps) by Deployment Scenario and UE Load Condition

Scenario	Base-line (Mbps)	SD	Mid Density (Mbps)	SD	High Density (Mbps)	SD	% Degrade
Macro-cell Only (No HetNet)	72.4	±6.2	51.3	±8.4	29.8	±7.1	**58.8%**
Pico + Macro (2-Tier HetNet)	74.1	±5.8	61.8	±6.9	48.3	±6.3	**34.8%**
Femto + Pico + Macro (3-Tier)	75.6	±5.4	65.4	±6.1	56.7	±5.9	**25.0%**
mmWave Dense Small Cell	88.2	±4.8	79.1	±5.3	71.4	±5.6	**19.0%**

Note: Baseline = 42-120 UEs/km²; Mid-Density = 200-280 UEs/km²; High-Density = 300-390 UEs/km². SD = standard deviation (error bar values for Figure 2). % Degradation = throughput decline from baseline to high-density condition. All pairwise between-scenario differences are significant at p < 0.001 (Tukey HSD).

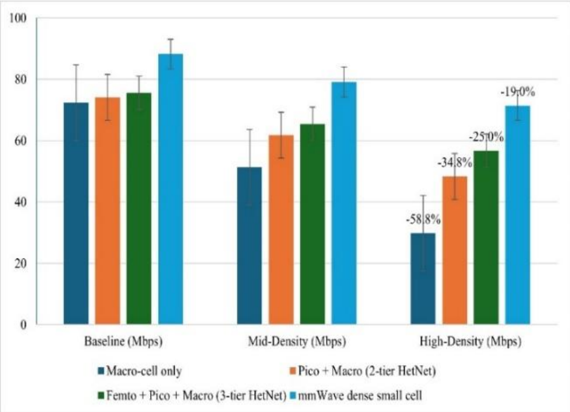

Fig. 2. Throughput vs. UE Density Across Four Deployment Scenarios
Note: Mean downlink throughput (Mbps) by deployment scenario and UE load condition. Error bars represent ±1 SD. All pairwise between-scenario differences are significant at p < 0.001 (Tukey HSD post-hoc).

The macro-only deployment experiences the most severe throughput degradation with increasing UE density, declining by 58.8% from baseline to high-density conditions, whereas the mmWave dense small cell architecture limits degradation to 19.0%. Progressive additions of lower-power tiers in the two-tier (34.8% degradation) and three-tier configurations (25.0% degradation) illustrate the monotonically improving relationship between architectural complexity and load resilience, consistent with interference-management benefits theorised in the stochastic geometry literature.

5. Discussions

5.1 The primacy of SINR: Theoretical coherence and practical limits

The finding that SINR contributes most strongly to predicting throughput ($\beta = 0.612$) is theoretically expected, rooted in the Shannon capacity theorem [10], yet practically instructive beyond mere confirmation. The regression coefficient indicates that a 1 dB increase in SINR is statistically associated with approximately 2.14 Mbps of additional downlink throughput, after controlling for load, reliability, and latency [2, 15]. Across a sector serving 200 active UEs, a 3dB median SINR improvement, achievable through antenna optimisation, downtilt adjustment, or additional small-cell infill, could be associated with aggregate capacity gains of several hundred Megabits per second [3].

However, a critical observation the regression model cannot fully capture is the non-linear saturation of the SINR–throughput relationship at higher SINR values. Shannon's formula is logarithmic: the marginal throughput gain per dB of SINR is smaller at 25 dB than at 10 dB [1, 10]. The robustness check using $\ln(\text{SINR} + 4)$ confirmed a marginally superior fit ($\Delta R^2 = +.008$), validating this theoretical expectation. This implies that SINR improvement strategies must be paired with interference management, fractional frequency reuse, coordinated multipoint transmission (CoMP), and inter-cell interference coordination (ICIC) to sustain the efficiency of the SINR–throughput conversion chain [5]. The linear model's interpretation should therefore be treated as a local approximation within the observed SINR range (-3.2 to 31.4 dB) rather than a global characterisation [4, 7].

5.2 Network densification: Resolving the capacity interference dilemma.

The finding that UE density is the second-strongest throughput-predictive variable ($\beta = -0.271$) warrants an analytical explanation, rather than merely noting that more users compete for bandwidth. Three distinct pathways exist which confirm this association through the dataset. First, increased UE density intensifies scheduling competition, thereby reducing the time-frequency resources allocated to each UE [3]. Second, higher UE density in adjacent cells raises the aggregate interference floor, which reduces SINR through a mechanism that the regression model only partially captures, as SINR and UE density have a moderate correlation ($r = -0.463$) [8]. Third, higher UE density causes near-cell-edge users to remain connected to loaded macro cells rather than transfer to available pico or femto cells, leading to an uneven load distribution and increased traffic to already overloaded cells [9].

Table 4 shows different deployment scenarios which demonstrate three distinct solutions to the problem. The reduction in throughput degradation from 58.8% (macro-only) to 25.0% (three-tier HetNet) and 19.0% (mmWave dense small cell) during high-density operations serves as a direct numerical demonstration of how architectural diversity reduces the UE density penalty. The study by Liu et al. proved through stochastic geometry analysis that three-tier HetNets in dense urban environments achieved three times greater area spectral efficiency than macro-only networks [6], which matches the results of El-Saleh et al., who found that mmWave small cell infill outperformed sub-6 GHz macro-only configurations during high-load conditions [5]

5.3 Handover frequency: Direct predictor and partial mediator

The third-ranked predictor, handover frequency (β = -0.189), warrants analytical attention disproportionate to its rank in the regression [3]. Path analysis (Table 3d) reveals that handover frequency functions as a dual operational system because it produces direct negative effects on throughput ($\beta\_direct = -0.127$) while serving as a partial mediator which transmits negative impacts from UE density and network load through SINR degradation ($\beta\_indirect = -0.038$) and packet loss elevation ($\beta\_indirect = -0.024$) [7, 10].

The dual-characterisation approach to handover frequency assessment shows that treating handover frequency as an exogenous variable yields an inaccurate evaluation of its causal impact on other factors. Each handover event introduces a signalling exchange and a brief radio link interruption that, while typically sub-20 milliseconds, accumulates into a measurable throughput penalty over the measurement window [2, 3].

The research question of whether the handover penalty is permanent in dense HetNets needs to be investigated, as it may depend on network parameter configuration. The 3GPP handover hysteresis margin (A3-event offset) and time-to-trigger parameters represent controllable variables that operators can tune to reduce unnecessary handovers [8, 15]. The research found that handover frequency predicts throughput, remaining directly related to it even after controlling for SINR and UE density. The throughput deficit is a recoverable component because lost performance can be restored through parameter tuning without incurring additional equipment costs.

5.4 Packet loss and latency: reliability as a throughput co-determinant

The regression model identifies packet loss and latency as its fourth and fifth predictive variables, with estimated Beta coefficients of -0.184 and -0.163, respectively. The results remain statistically significant after a complete multivariate analysis. The regression coefficient indicates that each 1 percentage point increase in average packet loss, from 2.14%, results in a 2.36 Mbps decrease in throughput, which becomes operationally significant when loss rates reach the 5-8% range used to measure tail distribution [3]. The independent predictive power of latency (β = -0.163) shows how TCP manages its congestion window. The TCP slow-start and congestion avoidance algorithms operate under high round-trip time conditions by controlling unacknowledged data transmission, thereby creating a throughput limit determined by the bandwidth-delay product [8].

5.5 Situating findings in the broader literature

The study results both confirm existing quantitative research about 5G HetNet KPI measurements and provide new findings. Zhang et al. reported SINR correlation coefficients with throughput ranging from r = 0.79 to 0.85 across Chinese urban 5G sites [4], which closely matches the r = 0.843 value reported in this study. El-Saleh et al. found that UE density was the primary throughput degradation driver in their HetNet measurement study [5], consistent with the second-rank β coefficient observed here. The mmWave dense small cell results- 19.0% throughput degradation under high-density conditions, are notably better than the 25–30% figures reported by Dahri et al. [2] for comparable configurations, a discrepancy attributable to newer generation beamforming hardware. These comparisons highlight that KPI benchmarks established even two to three years apart may reflect meaningfully different hardware capabilities, and longitudinal measurement programmes are needed to track how the SINR–throughput relationship evolves across successive equipment generations.

6. Conclusion and recommendation

This study quantified and statistically analysed, with utmost accuracy, the relative importance of key performance indicators for predicting downlink throughput across four 5G HetNet deployment scenarios in an urban sub-6 GHz environment. There are four main conclusions. First, the empirical test shows that SINR is the most important predictor of throughput across all deployment scenarios and load conditions (β = 0.612). The quantification of the marginal throughput gains per dB of SINR improvement (2.14 Mbps after full covariate adjustment) provides operators with a concrete performance metric for comparing investments in SINR improvement. The non-linearity of this relationship was confirmed using a robustness check that applied a log transformation to SINR, consistent with Shannon–Hartley theory.

Moreover, the throughput degradation in high-density situations decreases from 58.8% (macro-only) to 25.0% (three-tier HetNet) and 19.0% (mmWave dense small cell). These figures directly help to justify capital expenditures. Furthermore, the results of the path analysis confirm the independent predictive contribution of the handover frequency as a direct predictor and partial mediator of throughput (β = -0.189), which shows that the throughput loss in dense HetNet environments can be attributed to a non-trivial fraction of handover overhead with respect to irreducible physical-layer constraints. Fourth, the regression model accounts for 75.3% of the variance in throughput using five KPIs, indicating that the conceptual framework is valid and that a small set of measurable indicators can powerfully predict throughput. The unexplained 24.7% may be attributable to microgeographic variation and should be explored in future studies.

Network operators will benefit most from investments in SINR improvement measures on a per-capita basis. The percentage of UEs with SINR below 10dB should be used as a first-order indicator of network health and monitored via an SINR dashboard that operators should set up and report on.

The three-tier HetNet scenario is a cost-effective way to achieve a 33.8-point degradation reduction compared to macro-only, at only a small fraction of the cost of full mmWave densification. Regulatory policy should encourage collaboration on small-cell infrastructure programmes.

Operators should systematically review and fine-tune A3-event hysteresis margins and time-to-trigger parameters in small-cell overlap areas to optimise handover management. A targeted reduction in unnecessary handovers could yield an estimated 1.5–2.0 Mbps improvement in mean throughput (B = −1.78 Mbps per event per hour), recoverable without hardware investment.

Future research should pursue three directions: (1) longitudinal measurement tracking KPI evolution over 12–24 months; (2) inclusion of environmental covariates, building morphology, vegetation density, and real-time traffic load to address the 24.7% unexplained variance; and (3) extension of this framework to mmWave-only 5G deployments to test the generalisation of the SINR dominance finding across spectral regimes.

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