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A hierarchical mixed-effects modeling framework with Weibull reliability characterization for spatiotemporal throughput variability in cellular networks

Victor Dela Gordon[1], Amevi Acakpovi[2]
[1]Communications Division, CSIR-Institute for Scientific and Technological Information (CSIR-INSTI), Accra, Ghana
[2]Department of Electrical/Electronic Engineering, Accra Technical University, Accra, Ghana

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ABSTRACT

Reliable cellular throughput is essential for ensuring consistent user experience in modern mobile networks, yet it exhibits significant variability across spatial and operational conditions due to propagation effects, interference, and network congestion. This study proposes a hierarchical mixed-effects modeling framework integrated with Weibull-based reliability analysis to characterize spatiotemporal throughput variability in real-world operating conditions. The analysis is based on a large-scale dataset comprising over 77,000 field measurements collected across multiple university campus locations in Ghana, enabling cross-layer evaluation of network performance using key indicators, including reference signal received power (RSRP), reference signal received quality (RSRQ), and round-trip time (RTT). Analysis results indicate that all modeled predictors significantly influence throughput performance, with signal quality emerging as the dominant factor, alongside notable spatial heterogeneity. The model explains 18.9% of variability using fixed effects and 45.1% when spatial effects are included. Reliability analysis indicates that the probability of achieving 5 Mbps and 10 Mbps is 39.7% and 22.5%, respectively. These findings demonstrate that the proposed framework effectively captures throughput variability, spatial heterogeneity, and probabilistic service reliability in operational cellular environments, providing a practical analytical framework for reliability-aware cellular network optimization and performance evaluation.

Corresponding Author:

Victor Dela Gordon
Communications Division, CSIR-Institute for Scientific and Technological Information (CSIR-INSTI)
Airport Residential, Accra, Ghana
Email: vgordon@csir.org.gh

1. INTRODUCTION

Reliable mobile broadband networks have become a foundational component of modern digital infrastructure, supporting bandwidth-intensive applications such as video streaming, cloud computing, and real-time collaboration [1], [2]. Successive generations of cellular technologies, particularly fifth-generation (5G) systems, promise higher data rates, lower latency, and improved service reliability. However, recent empirical studies still report substantial throughput variability across spatial and operational conditions in practical deployments [3]–[6]. This variability arises from interactions among radio propagation conditions, interference dynamics, and network congestion. Consequently, reliability, defined as the probability of achieving target throughput levels, becomes a critical dimension of network performance evaluation. Accurate characterization of cellular throughput therefore requires models that jointly capture both variability and reliability.

Throughput in cellular systems is governed by tightly coupled cross-layer interactions spanning the physical and transport layers. At the physical layer, signal strength and quality indicators such as the reference signal received power (RSRP) and reference signal received quality (RSRQ) determine achievable modulation and coding schemes, whereas at higher layers, latency metrics such as the round-trip time (RTT) influence transport protocol efficiency through congestion control mechanisms [7]. These effects do not operate independently. Instead, they interact within heterogeneous network environments characterized by spatial clustering and temporal dynamics. Recent studies further emphasize that cross-layer interactions and mobility-aware network dynamics are critical for accurately modeling end-to-end throughput behavior in modern cellular systems [8], [9]. As a result, modeling throughput as an independent and identically distributed process is inadequate for capturing operational network behavior [10].

Conventional approaches to throughput analysis often rely on regression or correlation techniques that assume independence among observations. However, field measurement data inherently exhibit a hierarchical structure, with observations nested within spatial locations and operational contexts. Ignoring this structure can lead to biased parameter estimates and incomplete characterization of performance dynamics [11]. This limitation becomes particularly critical when translating statistical findings into actionable network engineering insights. To address this challenge, hierarchical mixed-effects models have emerged as a principled framework for analyzing complex network datasets. By incorporating random effects, these models enable simultaneous estimation of global performance relationships and location-specific variability, providing a more realistic representation of cellular network behavior [12]. This approach is especially effective for capturing spatial heterogeneity arising from differences in infrastructure configuration, user density, and propagation environments.

In parallel, reliability analysis has gained increasing importance as a complementary framework for evaluating network performance. Unlike average-based metrics, reliability measures quantify the probability that throughput exceeds specified service thresholds, offering a user-centric assessment of quality of service [13]. This perspective is essential in modern cellular systems, where performance variability directly impacts perceived user experience and service-level compliance. Despite these advances, limited work has integrated hierarchical modeling with reliability-based analysis for the joint characterization of throughput variability and performance consistency in operational cellular environments. This gap constrains the development of unified statistical and engineering frameworks capable of supporting both inference and network design.

This study addresses this gap by integrating hierarchical mixed-effects modeling with empirical and parametric reliability analysis using a large-scale field measurement dataset comprising over 77,000 observations. The proposed framework captures cross-layer throughput determinants, accounts for spatial clustering effects, and characterizes reliability behavior through both empirical analysis and Weibull-based parametric modeling. This integrated perspective is particularly relevant for emerging 5G-Advanced and 6G systems, where recent operational studies have shown increasing dependence on reliability-driven optimization, empirical performance analytics, and adaptive resource management under heterogeneous deployment conditions [3], [14]. The proposed framework is further aligned with emerging 6G design objectives emphasizing intelligent network orchestration, AI-assisted optimization, reliability-oriented service provisioning, and context-adaptive resource management across highly heterogeneous wireless environments.

Beyond conventional mobile broadband evaluation, the proposed framework also has broader relevance for emerging ICT ecosystems, including cloud-connected services, edge computing infrastructures, internet-of-things (IoT) deployments, and latency-sensitive digital applications that depend on reliable wireless connectivity. The main contributions of this study are as:

- A hierarchical mixed-effects modeling framework is developed to quantify the cross-layer influence of radio signal indicators, namely, the RSRP and RSRQ, and transport-layer latency on cellular throughput while explicitly capturing spatial heterogeneity through site-level random effects.
- A reliability-based performance evaluation methodology is introduced, which combines empirical throughput reliability analysis with a Weibull parametric model to enable analytical characterization and prediction of service-level performance.
- An integrated statistical-engineering framework is proposed to jointly capture throughput variability, spatial dependence, and nonlinear reliability behavior, providing a practical foundation for data-driven network dimensioning, optimization, and quality-of-service (QoS) forecasting in next-generation cellular systems.

The performance of cellular networks has been extensively investigated across both theoretical and empirical domains. Early foundational work focused on the theoretical limits of communication systems, with Shannon [15] capacity theorem establishing the maximum achievable data rates under idealized conditions. Building on this foundation, subsequent studies extended the analysis to wireless environments, emphasizing the role of propagation effects, fading, and interference in shaping achievable throughput [7].

With the evolution of modern cellular systems, particularly the transition toward 5G networks, research has increasingly focused on performance under realistic deployment conditions. As noted in Andrews *et al*. [4], while significant architectural and technological advancements have been achieved in 5G systems, ensuring consistently high data rates in heterogeneous and interference-limited environments remains a major challenge. Empirical measurement studies further confirm that observed throughput often deviates from theoretical predictions. Significant variability is observed across spatial locations and temporal conditions because of dynamic traffic loads, radio propagation effects, and variations in user density [3], [5], [6], [9], [14], [16], [17].

Recent studies highlight the importance of cross-layer interactions and mobility-aware performance analysis in accurately modeling end-to-end throughput behavior in modern cellular systems [8], [9]. A substantial body of work has examined the influence of radio-layer indicators on throughput performance, with metrics such as RSRP and RSRQ widely recognized as key determinants of link quality. These parameters directly affect the modulation and coding scheme selection, thereby influencing the spectral efficiency and achievable data rates. In parallel, transport-layer metrics such as the RTT have been shown to affect throughput through their impact on congestion control mechanisms, particularly in TCP-based communications, where latency constrains acknowledgments and retransmission processes [7]. Although these studies provide valuable insights into cross-layer dynamics, many analyze predictors in isolation or within simplified frameworks. This limits their ability to capture the complexity of practical network dynamics.

A key limitation in much of the literature is the assumption of independence among observations. In practice, field measurement datasets exhibit inherent hierarchical structures, with observations clustered across spatial locations and temporal intervals. Ignoring this structure can obscure important sources of variability and lead to biased or incomplete inference. Hierarchical mixed-effects models have been proposed as an effective approach to address this challenge, enabling the decomposition of variability into within-cluster and between-cluster components while simultaneously estimating global performance relationships [11], [12]. This approach is particularly well suited for analyzing large-scale network measurement data characterized by spatial heterogeneity. The increasing availability of large-scale operational cellular datasets has further enabled more realistic spatial and performance analytics for next-generation wireless systems [17].

In parallel, reliability analysis has emerged as an important framework for evaluating network performance from a user-centric perspective. Rather than focusing solely on average throughput, reliability-based metrics quantify the probability that the network satisfies specified performance thresholds, thereby capturing variability in the user experience. These metrics are widely used in network benchmarking and QoS evaluation and are emphasized in standardization and performance assessment guidelines [13]. Reliability formulations, including survival-type functions, QoS-aware reliability provisioning, and percentile-based metrics, provide a more comprehensive characterization of network behavior under realistic operating conditions [18], [19].

Despite these advances, existing studies have largely treated hierarchical modeling and reliability analysis as separate analytical approaches. While prior hierarchical modeling studies have focused primarily on explaining spatial or temporal throughput variability, they generally do not incorporate probabilistic service reliability characterization within the same analytical framework. In contrast, the proposed approach jointly models cross-layer throughput determinants, spatial heterogeneity, and throughput exceedance reliability using an integrated mixed-effects and Weibull reliability framework, thereby enabling simultaneous statistical inference and reliability-oriented network evaluation.

Consequently, there remains a lack of unified frameworks that simultaneously capture spatiotemporal variability and quantify performance reliability in a consistent and analytically tractable manner. This limitation constrains the ability to translate statistical findings into actionable engineering insights for network planning and optimization. Although recent empirical studies have provided detailed evaluations of 5G throughput, latency, and deployment performance [3], [5], [6], [14], integrated frameworks that jointly model hierarchical variability and reliability behavior remain limited.

This study addresses this gap by integrating hierarchical mixed-effects modeling with both empirical and parametric reliability analysis within a unified framework. By combining cross-layer performance modeling, spatial variability characterization, and reliability-based evaluation using a large-scale field measurement dataset, the proposed approach provides a comprehensive and practically relevant understanding of cellular throughput behavior.

2. METHOD

2.1. Measurement dataset

The empirical analysis in this study is based on a large-scale field measurement dataset comprising 77,075 valid cellular network observations collected across multiple university campus environments in

Ghana. The dataset spans four spatial clusters (measurement sites), namely the University of Ghana (UG), Accra Technical University (ATU), University of Cape Coast (UCC), and Kwame Nkrumah University of Science and Technology (KNUST), capturing heterogeneous propagation conditions, user densities, and network load characteristics.

Data were collected using the NEMO Invex II drive test platform configured on mobile telephone network (MTN) Ghana's commercial fourth-generation (4G long-term evolution or LTE) network, consistent with contemporary large-scale cellular measurement methodologies employed in recent wireless network assessment studies [20]. The system synchronously logs geolocation (global positioning system or GPS), timestamps, RSRP, RSRQ, RTT measured via internet control message protocol (ICMP) ping, and downlink throughput obtained through file transfer protocol (FTP)-based testing. All the measurement sessions were conducted under stationary conditions, with each session lasting approximately one hour per site. A standardized measurement configuration was enforced by the National Communications Authority (NCA) across all sites to ensure consistency and comparability.

Only parameters available in the recorded logs were used for analysis. Consequently, metrics such as the signal-to-interference-plus-noise ratio (SINR), uplink throughput, packet loss, and call drop rates were not included. In addition, physical layer attributes, including carrier frequency, channel bandwidth, and antenna configuration, were not available in the operator profile. Nevertheless, RSRQ serves as a practical proxy for interference and channel quality, enabling meaningful inference under radio conditions despite the absence of explicit SINR measurements.

Although measurements were collected continuously within each session, the present analysis focused on spatial variability across sites. Temporal fluctuations are therefore implicitly captured within the residual variation rather than explicitly modeled as a separate hierarchical component. Each observation includes the following key performance indicators: RSRP (dBm), RSRQ (dB), RTT (ms), and measured downlink throughput (converted from kbps to Mbps for interpretability). Collectively, these measurements provide a coherent cross-layer dataset that captures the interaction between radio conditions and transport-layer dynamics under operational network conditions, forming a robust empirical basis for analyzing throughput variability and reliability.

Although the dataset provides large-scale empirical insight into operational network dynamics, several limitations should be acknowledged. Measurements were collected under stationary user conditions within university campus environments, which may not fully capture mobility-driven dynamics present in dense urban or highway scenarios. Furthermore, the dataset primarily reflects MTN Ghana's operational deployment characteristics during the measurement period and may therefore exhibit operator-specific bias.

In addition, some lower-layer parameters, including SINR, uplink throughput, packet retransmission statistics, and scheduler-level information, were unavailable in the operator measurement profile. Their absence limits direct characterization of interference coupling and bidirectional traffic dynamics. Nevertheless, RSRQ was retained as a practical proxy for radio quality and interference behavior, enabling meaningful cross-layer inference despite these constraints.

2.2. Conceptual framework

Figure 1 shows the conceptual framework adopted in this study, highlighting the cross-layer interactions between radio conditions and transport-layer performance. The radio signal strength and signal quality determine the achievable modulation and coding schemes at the physical layer. The transport latency influences the efficiency of higher-layer protocols, particularly congestion control mechanisms. These combined effects ultimately determine the end-to-end throughput performance. This study extends the framework by incorporating throughput reliability analysis, where performance is evaluated not only in terms of average throughput but also in terms of the probability of achieving predefined service thresholds.

2.3. Hierarchical model specification

To account for spatial clustering inherent in the dataset, a hierarchical mixed-effects model was employed. The model is specified as:

$$T_{ij} = \beta_0 + \beta_1 \, RSRP_{ij} + \beta_2 RSRQ_{ij} + \beta_3 RTT_{ij} + u_j + \epsilon_{ij} \tag{1}$$

where T_{ij} denotes the throughput (Mbps) for observation i at site j and where RSRPij, $RSRQ_{ij}$, and RTT_{ij} represent the RSRP, RSRQ, and RTT, respectively. The term u_j is a site-specific random effect capturing unobserved spatial heterogeneity, whereas ϵ_{ij} represents the residual error term. The random intercept u_j accounts for site-level variations caused by differences in infrastructure configuration, interference conditions, and geographic characteristics.

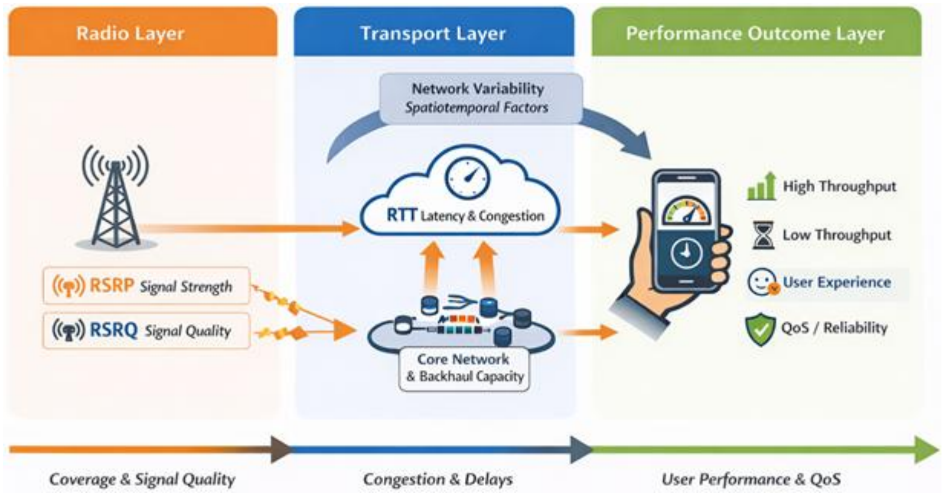

Figure 1. Conceptual framework linking radio-layer indicators, transport latency, and throughput performance

The hierarchical mixed-effects framework assumes that observations collected within the same spatial cluster are statistically correlated because of shared environmental and operational conditions. In this formulation, β_0 represents the fixed intercept, whereas β_1, β_2, *and* β_3 denote the fixed-effect coefficients associated with RSRP, RSRQ, and RTT, respectively. The random effect is modeled as $u_j \sim N(0.\sigma^2_u)$, where σ^2_u denotes the between-site variance component, while the residual term is modeled as $\epsilon_{ij} \sim N(0.\sigma^2)$. The model therefore assumes conditional independence of residuals given the random effects, homoscedastic residual variance, and normally distributed random intercepts.

Parameter estimation was performed using the restricted maximum likelihood (REML) approach, which provides unbiased estimates of variance components in hierarchical models and is widely recommended for mixed-effects modeling. Parameter estimation using REML enables robust inference for both fixed and random effects in clustered datasets and aligns with recent spatially aware network performance modeling approaches [21]. Model adequacy was further evaluated using residual diagnostics, intraclass correlation analysis, and marginal and conditional R^2 statistics to assess both fixed-effect explanatory power and overall hierarchical model performance. REML estimation was preferred over ordinary maximum likelihood estimation (MLE) because it provides less biased variance component estimates in hierarchical datasets with clustered observations and unequal group sizes, conditions commonly encountered in real-world wireless measurement campaigns. The hierarchical structure of the dataset is shown in Figure 2.

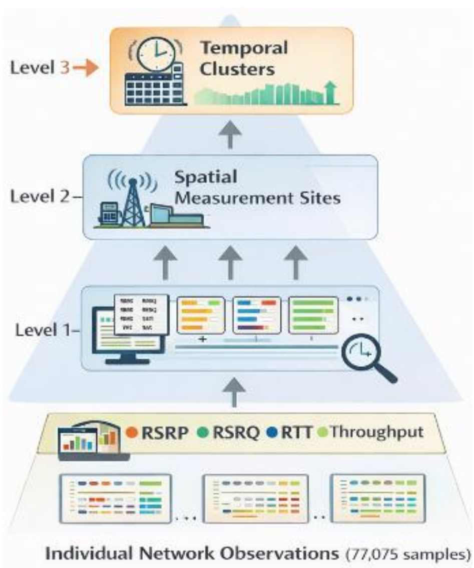

Figure 2. Hierarchical structure of the measurement dataset showing nested observations within spatial clusters. Individual network observations are nested within spatial measurement sites and temporal clusters, forming a multilevel data structure suitable for hierarchical mixed-effects modeling

2.4. Throughput reliability modeling

To extend the analysis toward network engineering applications, throughput reliability was modeled as a survival-type function defined as:

$$R(T) = P(Throughput \geq T) \tag{2}$$

where *R(T)* denotes the probability that the network achieves at least a specified throughput threshold *T*. This formulation is widely used in network dimensioning and QoS evaluation, as it directly captures service availability from a user-centric perspective.

Two key service thresholds were considered in this study. A minimum broadband threshold of T_{min}=5Mbps was adopted to represent baseline service availability, whereas a higher threshold of T_{QoS}=10 Mbps was used to characterize a satisfactory user experience for typical mobile broadband applications. These thresholds are consistent with practical performance benchmarks used in cellular network evaluation.

2.5. Parametric throughput reliability modeling

To enable an analytical characterization of network performance, the empirical throughput reliability function introduced in the previous section was further modeled using a parametric distribution. A Weibull model was adopted because of its flexibility in capturing skewed and heavy-tailed network performance distributions common in cellular systems. Weibull-based models have been widely applied in reliability engineering and network performance analysis because of their ability to capture nonlinear failure and variability behavior [22]. The Weibull distribution is particularly suitable for modeling positively skewed throughput distributions commonly observed in wireless communication systems, where throughput variability exhibits asymmetric and threshold-dependent behavior. The Weibull reliability function is expressed as:

$$R(T) = \exp\left[-\left(\frac{T}{\lambda}\right)^{k}\right] \tag{3}$$

where λ>0 is the scale parameter and k>0 is the shape parameter of the distribution. The corresponding cumulative distribution function (CDF) is given by:

$$F(T) = 1 - \exp\left[-\left(\frac{T}{\lambda}\right)^{k}\right] \tag{4}$$

In this formulation, the shape parameter k governs the variability behavior and tail characteristics of the throughput distribution, whereas the scale parameter λ determines the characteristic throughput level of the network. The parameters were estimated using MLE, which enables statistically efficient estimation of reliability characteristics from large-scale empirical observations and provides robust fitting performance for positively skewed throughput data.

To validate model robustness, alternative positively skewed distributions including the lognormal and gamma distributions were preliminarily examined during exploratory analysis. Although all three distributions captured the general shape of the throughput distribution, the Weibull model provided superior tail flexibility and more stable reliability estimation across higher throughput thresholds. This behavior is particularly important for reliability-oriented characterization of cellular service performance. A comparative summary of exploratory distribution fitting characteristics is presented in Table 1.

Table 1. Exploratory comparison of candidate parametric distributions for throughput reliability modeling

Distribution	Strength	Limitation
Weibull	Flexible tail modeling and stable reliability estimation	Moderate parameter sensitivity
Lognormal	Good fit for central throughput values	Less stable tail reliability behavior
Gamma	Captures positive skewness effectively	Reduced flexibility at high throughput extremes

Goodness-of-fit evaluation was additionally performed through visual comparison between empirical and fitted reliability curves, where the Weibull formulation demonstrated close agreement across both central and tail throughput regions. The resulting model enables probabilistic characterization of throughput exceedance levels for reliability-oriented network evaluation and service-level assessment. Furthermore, the parametric formulation provides a compact analytical framework for throughput prediction at arbitrary service thresholds, supports network dimensioning, and facilitates QoS-aware performance forecasting in cellular networks.

3. RESULTS AND DISCUSSION

3.1. Spatiotemporal variability

Figure 3 shows the spatiotemporal variability of throughput across measurement locations and time intervals. The heatmap reveals substantial throughput variability across spatial locations and temporal intervals. This observation provides strong justification for hierarchical modeling.

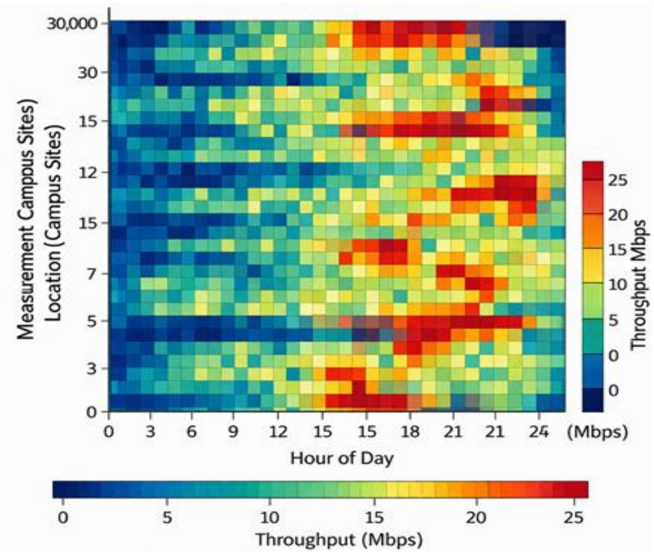

Figure 3. Heatmap showing throughput variability across locations and time periods

3.2. Hierarchical model results

The hierarchical mixed-effects model results are presented in Table 2. This subsection presents the statistical findings associated with the hierarchical mixed-effects framework, focusing on the influence of radio-layer and transport-layer predictors on throughput variability across spatial clusters. The estimated coefficients shown in Table 2 indicate that both signal strength and signal quality have statistically significant positive effects on throughput, whereas latency has a statistically significant negative effect. The random-effects results presented in Table 3 reveal non-negligible site-level variance, confirming the presence of spatial heterogeneity in throughput performance across measurement locations.

Table 2. Hierarchical mixed-effects model results

Predictor	Coefficient	Std. Error	z-value	p-value	Interpretation
Intercept	42.556	2.298	18.520	<0.001	Baseline throughput
RSRP	0.231	0.004	53.640	<0.001	Strong positive effect
RSRQ	0.960	0.013	75.180	<0.001	Strong positive effect
RTT	-0.005	0.000	-29.790	<0.001	Latency reduces throughput

Table 3. Random effects

Component	Variance
Site variance	20.550
Residual variance	43.080

3.3. Model explanatory power

The model explanatory power was evaluated using the Nakagawa and Schielzeth [12] framework for hierarchical models. The marginal coefficient of determination, representing the variance explained by fixed effects only, was R^2_m=0.189. The conditional coefficient of determination, representing the variance explained by both fixed and random effects, was R^2c=0.451. The substantial increase between marginal and conditional explanatory power confirms that spatial clustering contributes significantly to throughput variability, reinforcing the importance of hierarchical modeling for realistic network performance characterization.

3.4. Residual diagnostics

Residual diagnostics were used to evaluate model adequacy. The root mean square error (RMSE) of the fitted model was 6.56 Mbps, providing an overall measure of prediction accuracy. The residual distribution characteristics were assessed using higher-order statistics. The residuals exhibited a skewness of 0.64 and kurtosis of 0.63, indicating mild positive skewness and near-normal tail behavior. Given the large sample size, these deviations are unlikely to materially affect inference, supporting the validity of the fitted model.

3.5. Elasticity interpretation of predictors

The estimated coefficients provide quantitative insight into the sensitivity of throughput to key radio- and transport-layer indicators. A 1 dBm increase in signal strength is associated with an increase of 0.231 Mbps, confirming that improved coverage enhances throughput performance. Similarly, a 1 dB improvement in signal quality results in an increase of 0.96 Mbps, making it the strongest predictor and underscoring the critical role of interference conditions in determining achievable data rates. In contrast, a 1 ms increase in RTT reduces throughput by 0.005 Mbps, reflecting the impact of transport-layer latency on protocol efficiency. Overall, these results indicate that although both coverage and latency influence throughput performance, signal quality remains the dominant factor, emphasizing the importance of interference management in cellular network optimization. Collectively, these statistical findings demonstrate that throughput behavior in operational cellular environments is governed by coupled cross-layer interactions and location-dependent network conditions.

3.6. Throughput reliability analysis

The following subsection presents a reliability-oriented evaluation of network performance, extending beyond average throughput analysis toward probabilistic characterization of service consistency under varying throughput thresholds. Throughput reliability was evaluated using a survival-type formulation that quantifies the probability of achieving a minimum throughput threshold. The resulting reliability curve, shown in Figure 4, illustrates how the probability of achieving a given throughput level decreases as the required data rate increases. Key reliability values:

– R (1 Mbps)≈0.746
– R (2 Mbps)≈0.612
– R (5 Mbps)≈0.397
– R (10 Mbps)≈0.225
– R (15 Mbps)≈0.154
– R (20 Mbps)≈0.108

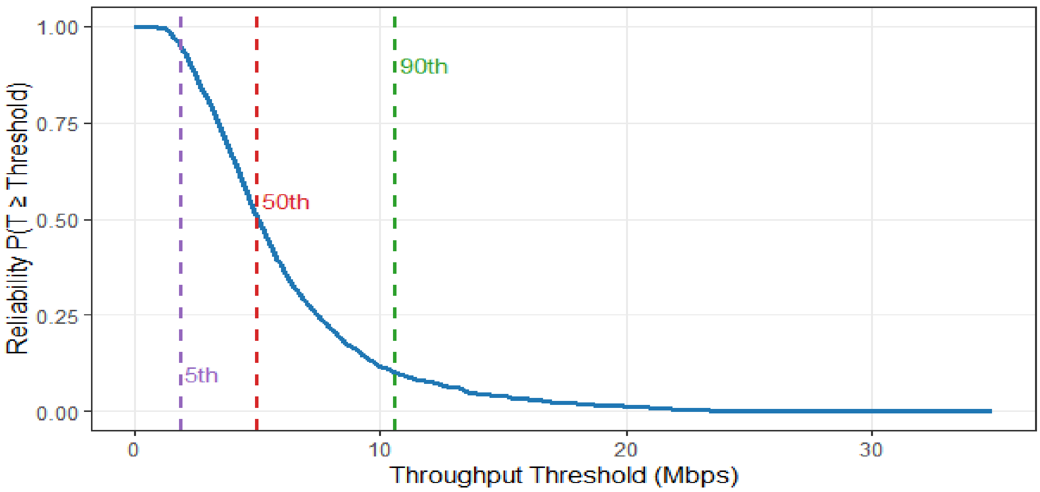

Figure 4. Throughput reliability curve showing empirical reliability measurements (blue line), representing the probability that measured cellular throughput exceeds specified thresholds under real operational conditions. The curve demonstrates a rapid decline in reliability as higher throughput requirements are imposed, reflecting the impact of radio variability and network congestion on service performance

The additional reliability thresholds further demonstrate the nonlinear decline in service consistency as throughput demand increases. In particular, the network maintains relatively high reliability at moderate throughput levels but exhibits substantially reduced reliability under higher service-rate requirements, reflecting the influence of dynamic interference conditions and shared radio resources. These results indicate that while basic connectivity is generally reliable, higher throughput levels are achieved less consistently, reflecting moderate network reliability under realistic operating conditions.

3.7. Throughput distribution and percentile performance

The empirical CDF of throughput is shown in Figure 5, providing a comprehensive view of achievable data rates across the measurement campaign. Percentile statistics:

- 5th: 0.083 Mbps
- 10th: 0.221 Mbps
- Median: 4.89 Mbps
- 90th: 21.19 Mbps
- 95th: 26.84 Mbps

The median throughput remains below 5 Mbps, confirming moderate typical performance, whereas higher percentiles indicate the presence of strong peak capacity. The widespread distribution highlights substantial variability in the user experience across the network.

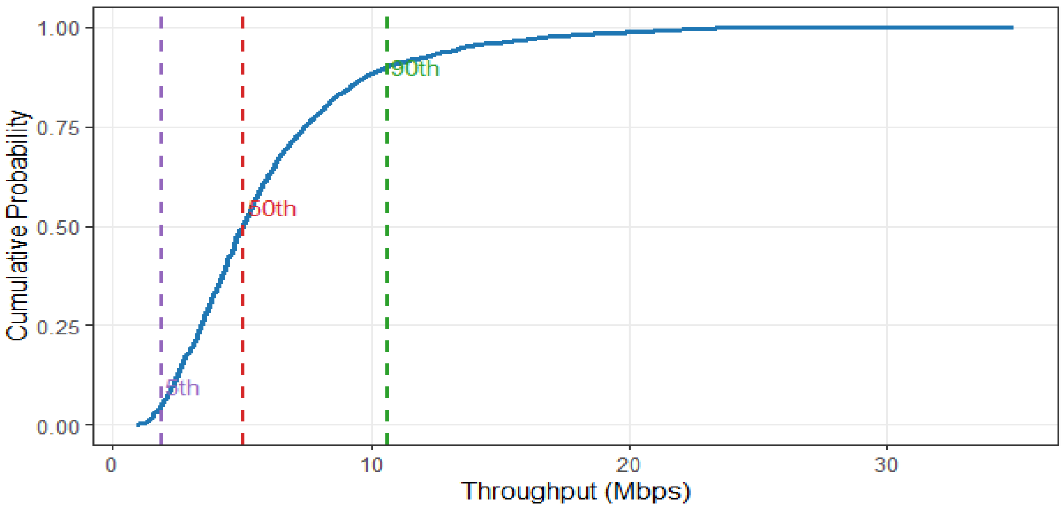

Figure 5. Empirical CDF of the measured cellular throughput. The curve illustrates the distribution of achievable data rates, highlighting median performances as well as the upper tail behavior associated with peak throughput conditions

3.8. Reliability curve interpretation

The throughput reliability function, $R(T) = P(Throughput \geq T)$, captures network performance across different service thresholds. The empirical results indicate high reliability at low-throughput thresholds, followed by a rapid decline as throughput demand increases. This pattern reflects the inherent variability of cellular network performance under realistic operating conditions.

The observed decline in reliability at higher throughput thresholds suggests that although the network is capable of delivering high data rates, such performance is not consistently sustained across all observations. This behavior reflects the impact of dynamic radio conditions and shared network resources on achievable throughput. It also reinforces the importance of reliability-based performance evaluation. From a service engineering perspective, these results demonstrate that user experience consistency cannot be adequately represented using average throughput metrics alone, particularly in heterogeneous and interference-sensitive network environments.

3.9. Parametric reliability model results

To obtain a compact analytical representation of throughput reliability, the empirical data were fitted using a Weibull distribution. The estimated parameters are as follows: λ=8.12 Mbps, k=0.87. The estimated shape parameter (k=0.87) provides important insight into network performance dynamics. In reliability theory, values of $k<1$ indicate a decreasing hazard rate, which in this context reflects high variability and instability in throughput performance. From a network engineering perspective, this implies that the probability of achieving higher throughput levels decreases rapidly as the service demand increases, which is consistent with fluctuating interference conditions, dynamic user loads, and shared resource constraints in cellular systems.

The scale parameter represents the characteristic throughput level of the network. The fitted model closely matches the empirical reliability curve, as shown in Figure 6. This agreement confirms the suitability of the Weibull model for representing throughput variability and enables the analytical prediction of QoS performance. This behavior confirms that throughput reliability declines rapidly as service thresholds increase, reflecting the high-variability regime captured by the estimated Weibull parameters. The close agreement between empirical and parametric reliability behavior further supports the suitability of the proposed framework for predictive QoS assessment and reliability-aware network dimensioning.

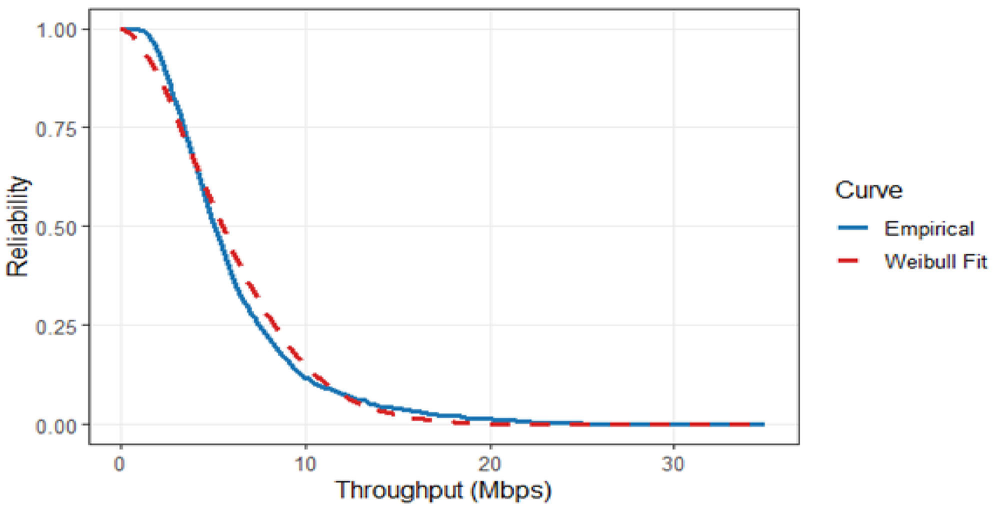

Figure 6. Comparison between empirical throughput reliability measurements (blue line) and the fitted Weibull reliability model (red dashed line). The close alignment between the empirical curve and the Weibull model demonstrates the suitability of the parametric approach for representing throughput variability and enables analytical prediction of QoS performance across different throughput thresholds

3.10. Engineering insights and contributions

The integration of hierarchical mixed-effects modeling with probabilistic reliability analysis enables this study to bridge statistical inference, reliability-oriented QoS evaluation, and practical network engineering applications within a unified analytical framework. The results demonstrate that average throughput alone is insufficient for characterizing network performance, as it does not capture variability in the user experience. Instead, reliability-based metrics provide a more realistic and application-relevant assessment of network behavior. Additionally, the findings highlight the dominant role of signal quality and the importance of spatial heterogeneity in network planning and optimization. These findings further demonstrate the relevance of large-scale empirical analytics and data-driven modeling approaches for intelligent network management, adaptive optimization, and future machine learning-assisted cellular performance forecasting. These results show that radio and latency indicators explain only part of throughput variability, while a substantial portion arises from site-level heterogeneity. This reinforces the importance of location-aware and reliability-driven optimization strategies in next-generation cellular networks.

3.11. Discussion

This study set out to address the challenge of jointly characterizing throughput variability and reliability in large-scale cellular networks using an integrated hierarchical and reliability-based analytical framework. The results show that cellular throughput performance is influenced not only by average behavior but also by structured variability and probabilistic service reliability. These effects arise from interactions among radio conditions, transport-layer dynamics, and spatial heterogeneity.

The hierarchical modeling framework shows that signal strength and signal quality positively influence throughput. In contrast, latency reduces throughput. These findings confirm the critical role of cross-layer interactions in shaping end-to-end network performance, extending beyond traditional single-layer analyses.

Importantly, RSRQ emerges as the dominant predictor of throughput performance. This finding indicates that interference conditions and radio resource utilization influence achievable data rates more strongly than signal strength alone. This result has direct implications for network optimization, suggesting that strategies focused on interference mitigation, scheduling efficiency, and resource allocation may yield greater performance gains than coverage enhancement in already served areas. Consequently, interference coordination, scheduling optimization, and load balancing may yield greater throughput improvements than increasing transmit power alone, particularly in already well-covered areas.

The hierarchical model further demonstrates that a substantial proportion of throughput variability is attributable to site-level heterogeneity, as reflected in the difference between marginal and conditional explanatory power. The comparatively modest marginal explanatory power of the fixed effects indicates that throughput behavior in operational cellular systems is influenced by additional latent factors not explicitly captured in the present dataset. These factors may include dynamic interference variation, user mobility, scheduling policies, traffic load fluctuations, carrier aggregation behavior, and unobserved radio-layer characteristics such as SINR. The substantial increase from marginal to conditional explanatory power further confirms the importance of spatial clustering effects and suggests that future predictive models could achieve improved performance through the incorporation of richer contextual and spatiotemporal network descriptors.

Although temporal dynamics were not explicitly modeled as a separate hierarchical component, short-term temporal fluctuations are inherently captured within the residual variation, and their influence is therefore reflected indirectly in the reported variability estimates. This highlights the importance of incorporating spatial context into network performance analysis, as local factors such as base station configuration, user density, and environmental propagation characteristics can significantly influence the observed throughput. From an engineering perspective, this finding underscores the limitations of models that assume spatial independence and reinforces the need for location-aware network planning approaches.

From a reliability perspective, the analysis provides a more application-oriented view of network performance. It quantifies the probability of achieving specified throughput thresholds. The results indicate that while the network can achieve high peak throughput values, the likelihood of consistently delivering high data rates remains limited, reflecting substantial variability in real-world operating conditions. This highlights a critical gap between peak capacity and experienced user performance, which cannot be captured using average-based metrics alone.

A central contribution of this study is the integration of reliability analysis with hierarchical modeling. This approach jointly characterizes mean throughput, performance variability, and service-level consistency within a unified framework. This dual perspective is increasingly important for next-generation cellular systems, where performance guarantees and service-level agreements are progressively defined using probabilistic reliability measures [23]. Recent beyond-5G studies further emphasize the role of QoS-aware service prediction, intelligent orchestration, and cloud-network integration in supporting reliability-sensitive applications and adaptive network management [24].

Furthermore, the parametric reliability modeling results demonstrate that throughput behavior can be effectively approximated using a Weibull distribution, providing a compact analytical representation of network reliability characteristics. Such models support predictive analysis and can be applied to network dimensioning, capacity planning, and service-level agreement design, thereby linking empirical network measurement with practical engineering applications.

Nevertheless, although the Weibull distribution demonstrated strong fitting performance for the observed throughput data, its ability to fully characterize extremely heavy-tailed or multimodal network behavior may be limited under highly heterogeneous operating conditions. Future studies may therefore investigate hybrid reliability formulations, mixture distributions, or machine learning-assisted probabilistic modeling approaches to further improve reliability characterization in 5G-Advanced and emerging 6G environments.

From an operational perspective, the proposed framework can assist mobile network operators in identifying reliability bottlenecks, support regulators in establishing evidence-based QoS benchmarks, and enable service providers to develop robustness-oriented optimization and performance assurance strategies under heterogeneous deployment conditions. In contrast to the literature, which often treats cross-layer effects, spatial variability, or reliability analysis in isolation, this study provides a unified statistical-engineering framework that integrates these dimensions into a single coherent methodology. These findings are consistent with prior empirical studies that identify signal quality and interference conditions as primary determinants of achievable throughput in LTE and 5G systems [4]. However, the present study extends this understanding by quantitatively demonstrating the magnitude of spatial heterogeneity and integrating reliability-based performance evaluation, which is often overlooked in conventional analyses. Such analytical fragmentation has been identified as a key limitation in recent network performance studies, motivating the development of integrated analytical frameworks [8]. Such integrated analytical frameworks enable a more comprehensive understanding of cellular network performance under realistic operating conditions and enhances the interpretability and applicability of the results.

Despite these contributions, several limitations should be acknowledged. The dataset is restricted to university campus environments, which may not fully capture the diversity of large-scale urban or rural deployments. Future research should extend the analysis to broader geographic regions and incorporate additional contextual variables such as traffic load indicators, user mobility patterns, and environmental features. Additionally, the incorporation of explicit temporal dynamics through spatiotemporal or time-series modeling represents a promising direction for future work, enabling improved predictive capability and deeper insight into the evolution of network performance over time. Future work should also incorporate additional radio-layer indicators such as SINR, carrier aggregation metrics, mobility states, and uplink throughput measurements to further strengthen predictive modeling and enable deeper characterization of bidirectional QoS behavior in 5G-Advanced and emerging 6G environments.

From a network engineering perspective, the findings of this study suggest that effective cellular network optimization should prioritize interference management and resource allocation strategies over purely coverage-driven enhancements, particularly in environments where the baseline signal strength is already sufficient [25]. Furthermore, reliability-based performance metrics should be explicitly incorporated into network dimensioning and service-level agreement design, as they provide a more realistic representation of the user experience under variable operating conditions. The proposed probabilistic modeling framework can support adaptive resource allocation, edge-service orchestration, IoT reliability management, and cloud-assisted network optimization where throughput consistency and latency stability are critical operational requirements. The integration of spatially aware modeling and probabilistic reliability analysis provides a practical foundation for developing data-driven and location-sensitive optimization strategies in next-generation cellular networks. These capabilities are particularly relevant to emerging 5G-Advanced and 6G systems, where intelligent orchestration, reliability-driven optimization, and adaptive service management are expected to operate under highly heterogeneous and ultra-dense deployment conditions.

Beyond conventional cellular optimization, the framework is also applicable to IoT service management, cloud-assisted orchestration, edge-computing evaluation, and distributed intelligent communication systems requiring stable throughput and latency-aware operation. Collectively, these capabilities position the framework as a scalable analytical foundation for future data-driven wireless and ICT infrastructures. The framework also provides a statistical foundation for future integration with machine learning and big-data analytics methods. Potential applications include QoS prediction, anomaly detection, adaptive resource optimization, and intelligent network orchestration in 5G-Advanced and 6G systems.

3.11.1. Forward-looking analytical extensions

The results of this study establish a foundation for advanced analytical applications in cellular network engineering. The throughput reliability function, $R(T) = P(Throughput \geq T)$, provides a practical framework for network dimensioning and service-level agreement design by enabling the evaluation of performance guarantees across throughput thresholds. Furthermore, the hierarchical modeling framework supports predictive throughput analysis under varying radio and network conditions, enabling QoS forecasting and data-driven network optimization.

3.11.2. Practical implications for network operators and regulators

The findings of this study have direct implications for cellular network operators and regulators, particularly within emerging market contexts such as Ghana and the broader ECOWAS region. The dominance of signal quality over signal strength suggests that network optimization strategies should prioritize interference management techniques, including intercell interference coordination, spectrum reuse optimization, and adaptive scheduling. Furthermore, the observed moderate reliability levels indicate that traditional coverage-based performance metrics are insufficient for regulatory assessment. Instead, reliability-based metrics, such as the probability of achieving minimum throughput thresholds, should be incorporated into QoS benchmarks and service-level agreements. For policymakers, these results highlight the need to promote performance evaluation frameworks that account for spatial variability and user-experienced reliability rather than relying solely on average throughput indicators. Such approaches can support more effective spectrum management policies and infrastructure investment strategies aimed at improving consistent user experiences across diverse deployment environments.

4. CONCLUSION

This study investigated the spatiotemporal variability and reliability of cellular throughput using a large-scale field measurement dataset comprising over 77,000 observations. By integrating hierarchical mixed-effects modeling with empirical and parametric reliability analysis, this study provides a comprehensive framework for understanding and quantifying cellular network performance under heterogeneous deployment conditions. The results demonstrate that throughput performance is significantly influenced by radio signal strength, signal quality, and transport latency, with signal quality emerging as the most dominant factor. In addition, spatial clustering effects account for a substantial portion of the observed variability, highlighting the critical role of site-specific characteristics in network performance.

The reliability analysis shows that although high-throughput levels can be achieved under favorable conditions, the probability of consistently attaining such performance remains limited owing to strong spatiotemporal variability. This finding underscores the importance of reliability-based metrics for evaluating network performance beyond traditional average-based measures. From a network engineering perspective, this study establishes that effective network planning and optimization must incorporate cross-layer indicators, spatial heterogeneity, and reliability considerations. The proposed analytical framework provides a practical foundation for data-driven decision-making in next-generation wireless systems. The framework is also well aligned with emerging 6G research directions emphasizing intelligent network automation, context-aware resource management, and reliability-oriented service delivery across highly dynamic wireless environments.

For network operators and policymakers, these findings provide actionable guidance by emphasizing reliability-driven and interference-aware optimization strategies, including interference management and adaptive resource allocation, over conventional coverage-centric approaches for delivering consistent quality of service in operational cellular deployments. Future research can extend this work by incorporating additional contextual variables such as traffic load, user mobility patterns, and environmental propagation characteristics, as well as by applying the framework to emerging network architectures, including 5G-Advanced and beyond-5G systems.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Victor Gordon	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓		✓	
Amevi Acakpovi					✓	✓		✓		✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state that they have no conflicts of interest.

DATA AVAILABILITY

The dataset supporting the findings of this study was collected from operational measurements conducted across four university campuses on a commercial cellular network in Ghana. Owing to network confidentiality and operator privacy constraints, the raw data are not publicly available. However, anonymized and aggregated data supporting the reported results may be made available by the corresponding author upon reasonable request and subject to approval by the network operator.

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BIOGRAPHIES OF AUTHORS

Victor Dela Gordon is a final year Ph.D. candidate in Computer Science at the University of Cape Coast, Ghana, researching mmWave and wireless communication systems. He holds an M.Sc. degree in Telecommunications and Internet Technologies from the University of Applied Sciences Technikum-Wien, Austria and B.Sc. Computer Engineering from the Kwame Nkrumah University of Science and Technology (KNUST), Kumasi, Ghana. He is a Research Scientist at CSIR-INSTI, Accra, Ghana and a member of the Institution of Engineering and Technology (IET-Ghana). He can be contacted at email: vgordon.insti@gmail.com or vgordon@csir.org.gh.

Amevi Acakpovi is a professor of Electrical and Electronic Engineering and Vice-Chancellor of Accra Technical University, Ghana. He holds a B.Sc. in Computer and Electrical Engineering, an M.Sc. in Electrical Engineering, and a Ph.D. in Energy Systems Engineering. He is a Fellow of the Institution of Engineering and Technology (IET-Ghana) and a Senior Member of IEEE. His research interests include wireless communications, smart grid systems, hybrid renewable energy systems, microgrid optimization, artificial intelligence applications in engineering, and network performance modeling. Prof. Acakpovi has authored over 120 peer-reviewed journal articles and conference papers published in IEEE and other internationally indexed outlets. His academic contributions span teaching, postgraduate supervision, engineering research, and international collaborative projects. In this study, he contributed to the technical supervision and critical revision of the manuscript. He has received several professional distinctions and research awards, including the Best Paper Award at the IEEE International Conference on Adaptive Science and Technology, the Decade Researcher Award at the Applied Research Conference in Africa, and the Distinguished Professor Award in Electrical Engineering. He has also led multiple funded engineering and sustainability projects, including smart energy and technical education initiatives, and currently serves in several leadership roles within IEEE, IEC Ghana, and African electrotechnical standardization committees. He can be contacted at email: acakpovia@gmail.com.