Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 3, July 2026
DOI : https://doi.org/10.33395/sinkron.v10i3.16154
e-ISSN : 2541-2019
p-ISSN : 2541-044X

A Measurement-Driven And Capacity-Aware Framework For 5G NR NSA Deployment

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Submitted :April 29, 2026 | **Accepted** : Jun 1, 2026 | **Published** : July 5, 2026

Abstract: Conventional LTE-to-5G NR Non-Standalone (NSA) planning remains predominantly coverage-oriented and often fails to capture user-experienced throughput degradation under realistic traffic conditions. This limitation is critical in NSA architectures, where LTE acts as the anchor layer for control and mobility while 5G NR provides additional capacity. This study proposes a measurement-driven, throughput-centric spatial framework to identify LTE Capacity Bottleneck Zones (CBZ) as a basis for more realistic LTE-to-5G NR NSA deployment planning. The main novelty is the integration of a KPI-weighted RF Index with Kernel Density Estimation (KDE), DBSCAN spatial clustering, and fuzzy spatial zoning to generate throughput-aware capacity maps rather than purely coverage-based assessments. Drive-test measurements were conducted in Lubuk Alung District, Indonesia, under live LTE network conditions, yielding 8,355 radio KPI samples (RSRP, SINR) and 25,613 HTTP downlink throughput samples with geolocation. Statistical analysis using Pearson/Spearman correlation, polynomial regression, and Random Forest regression reveals consistently weak relationships between RSRP/SINR and throughput, indicating that radio-layer indicators alone provide limited explanatory power for user-experienced performance. The proposed framework classifies the study area into three spatial zones: LTE Stability Zone (28.99%), LTE Degradation Zone (63.02%), and LTE Capacity Bottleneck Zone (7.99%), where CBZs are characterized by acceptable radio conditions but localized throughput degradation. These findings enable a shift from coverage-centric evaluation toward targeted, throughput-aware capacity optimization for LTE-to-5G NR NSA deployment planning.

Keywords: Capacity Bottleneck Zone (CBZ), LTE Drive Test, 5G NR NSA, RSRP, SINR, Spatial Analysis, Throughput

INTRODUCTION

The rapid expansion of mobile broadband services, Internet of Things (IoT), and high–data–rate applications has significantly increased traffic demand in cellular networks (Alhammadi et al., 2024). To meet these requirements, 5G New Radio (NR) has been introduced to enhance throughput, latency, and spectral efficiency compared to LTE systems (Saha et al., 2024). In the early deployment stages, 5G is commonly implemented using a Non-Standalone (NSA) architecture, where LTE serves as the anchor layer, while NR provides additional capacity through dual connectivity (Malik et al., 2024).

Despite this pivotal role, LTE performance remains a key determinant of user experience in NSA deployments (Rochman et al., 2023). LTE throughput is influenced by multiple factors beyond radio conditions, including scheduling mechanisms, traffic load, and resource allocation processes (Sopin et al., 2025). Several studies report that throughput may decrease under traffic and scheduling constraints even when radio indicators such as RSRP and SINR remain favorable, indicating that good coverage conditions do not necessarily translate into high service quality (Pindi et al., 2025), (Polak et al., 2024).

Existing LTE planning approaches predominantly rely on propagation-based models and system-level simulations that emphasize coverage estimation rather than user-experienced service (Xu et al., 2025). Propagation models such as Urban Macro (UMa) assume idealized environments with simplified traffic distributions, leading to optimistic coverage estimations that may not reflect real network dynamics (Carianni et al., 2025). Similarly, system-level simulations often abstract scheduler behavior and congestion, limiting their ability to capture capacity

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JURNAL & PENELITIAN TEKNIK INFORMATIKA
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DOI : https://doi.org/10.33395/sinkron.v10i3.16154
e-ISSN : 2541-2019
p-ISSN : 2541-044X

degradation under realistic load conditions, so they are more suitable for coverage prediction than for identifying performance bottlenecks in operational networks.

Measurement-driven studies based on drive-test data provide more realistic insights through key performance indicators (KPIs) such as RSRP, SINR, and throughput (Hassan et al., 2022). However, most existing works remain signal-centric and implicitly assume a strong relationship between radio quality and throughput, which is often invalid in dense LTE networks where throughput is also affected by scheduler constraints, PRB saturation, and traffic variability (Alam et al., 2023). Many studies focus on performance mapping without explicitly capturing spatial throughput degradation patterns, limiting their usefulness for capacity-oriented optimization. From a methodological perspective, the literature remains constrained by idealized propagation assumptions and simplified simulation models that fail to capture scheduler-level behavior, while spatial throughput degradation patterns are not adequately represented at deployment scale (Wulandari et al., 2026).

A consistent limitation across these approaches is the absence of a unified, throughput-centric spatial representation of LTE capacity bottlenecks, in which spatial analyses rarely identify areas where acceptable radio conditions coexist with localized throughput degradation—regions that are critical for capacity-oriented optimization.

To address these limitations, this study proposes a throughput-centric spatial framework that integrates a KPI-weighted RF Index, KDE–DBSCAN spatial clustering, and fuzzy spatial zoning to identify LTE Capacity Bottleneck Zones (CBZ) from empirical drive-test measurements. Unlike previous KPI-based studies that evaluate radio quality and throughput separately, the proposed framework unifies both aspects into a single spatial bottleneck identification approach for LTE-to-5G NR NSA deployment planning. Unlike conventional coverage-based evaluation, the method combines empirical drive-test data with spatial clustering and weighted KPI modeling to locate regions where acceptable radio conditions coexist with degraded throughput, enabling a shift toward throughput-aware, capacity-oriented planning for 5G NR NSA deployment (Sharmin et al., 2026). In this study, a Capacity Bottleneck Zone (CBZ) is defined as a spatial area where acceptable radio conditions coexist with localized throughput degradation, indicating underlying capacity-related performance limitations within the LTE network (Nsafoa-Yeboah et al., 2022).

LITERATURE REVIEW

Research on LTE-to-5G NR Non-Standalone (NSA) networks can be broadly categorized into four methodological streams: propagation-based modeling, system-level simulation, KPI-driven measurement analysis, and data-driven machine learning approaches. Although each stream contributes to mobile network analysis, a critical review reveals a common limitation in representing spatial throughput degradation patterns in operational NSA environments (Malik et al., 2024). Propagation-based approaches rely on link-budget formulations and standardized channel models such as Urban Macro (UMa) to estimate coverage feasibility (Han et al., 2022). These methods are effective for early-stage planning but assume ideal propagation conditions and simplified traffic distributions (Ray et al., 2025). Consequently, they generate coverage-centric outputs that fail to reflect throughput variability in dense urban environments. In practice, areas with strong RSRP may still experience low throughput due to resource contention and scheduling constraints, indicating a disconnect between coverage prediction and user-perceived performance.

Simulation-based studies extend propagation models by incorporating system-level network behavior, including mobility, scheduling, and traffic modeling (Pedersen et al., 2024). However, these simulations remain limited by simplified assumptions regarding traffic heterogeneity and scheduler realism. In particular, PRB contention and spatial–temporal traffic bursts are often abstracted, resulting in overly optimistic throughput estimates (Sopin et al., 2025). Consequently, throughput degradation is typically treated as an aggregated performance effect rather than a spatially structured phenomenon, limiting its ability to reveal persistent capacity bottlenecks (Baena et al., 2025).

Measurement-based KPI studies using drive-test data provide more realistic network insights through indicators such as RSRP, SINR, and throughput (Shakir et al., 2023). However, most existing approaches remain radio-centric and implicitly assume a strong dependency between signal quality and throughput. In practice, this dependency may be weaker in operational LTE networks, where throughput is also affected by network-layer mechanisms such as scheduler behavior, PRB availability, and dynamic traffic load conditions.

As a result, signal-based evaluation alone is insufficient to identify spatial regions affected by throughput degradation that may arise from multiple network-level factors. Recent advances in data-driven approaches, including clustering methods, machine learning models, and radio environment mapping, have improved spatial analysis of cellular networks (Rekkas et al., 2025). Nevertheless, these methods often lack engineering interpretability and are not consistently grounded in throughput-centric formulations, limiting their applicability for throughput-aware capacity planning.

A consistent limitation across these methodological streams is the absence of a unified throughput-centric spatial representation of LTE capacity bottlenecks for LTE-to-5G NR NSA deployment planning. In NSA architecture,

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LTE serves as the anchor layer for control signaling and mobility management, while NR provides additional capacity through dual connectivity. Despite this dependency, existing studies rarely provide spatially explicit mechanisms to identify LTE capacity bottlenecks for deployment optimization (Alam et al., 2023). Table 1 summarizes the methodological focus and key limitations across LTE-to-5G NR NSA planning approaches.

Table 1. Summary of Methodological Streams in LTE-to-5G NR NSA Planning

Methodological Stream	Representative Studies	Core Method	Key Limitation	Implication
Propagation-based planning	(Yuliana et al., 2022)	Link-budget and 3GPP TR 38.900/38.901 UMa modeling	Assumes ideal propagation and simplified traffic	Cannot reflect real throughput degradation under network load
System-level simulation	(Sliwa et al., 2021)	LTE/5G NSA system-level modeling (mobility, scheduling, traffic)	Simplified scheduler and traffic assumptions	Produces optimistic throughput under congestion
KPI-based drive-test analysis	(Muhammad Rafi et al., 2025)	Empirical RSRP, SINR, throughput measurement (Padang)	Assumes strong KPI–throughput dependency	Misses weak coupling between radio quality and throughput
Spatial clustering data-driven analysis	(Rekkas et al., 2025)	DBSCAN, ML clustering, radio environment mapping	Limited interpretability and weak throughput focus	Hard to directly map results to capacity bottlenecks

METHOD

This study adopts a quantitative, measurement-driven framework to identify LTE Capacity Bottleneck Zones (CBZs) for LTE-to-5G NR Non-Standalone (NSA) deployment planning, as illustrated in Fig. 1. LTE drive-test measurements are collected and preprocessed, followed by statistical analysis and RF Index construction using Multi-Criteria Decision Analysis (MCDA). Spatial clustering is then applied to detect CBZs and classify the study area into deployment-priority zones. Finally, the identified zones are evaluated through system-level LTE-to-5G NR NSA simulations in Atoll to assess deployment feasibility and potential capacity improvements.

Fig. 1 Research Methodology Framework

LTE Drive-Test Data Collection

Drive-test measurements were conducted in Lubuk Alung District, West Sumatera, Indonesia under live network conditions. The dataset consists of 8,355 radio KPI samples and 25,613 HTTP throughput samples with geolocation data. Key variables include RSRP, SINR, and HTTP downlink throughput, representing radio-layer conditions and user-experienced performance collected at different temporal resolutions.

Data Preprocessing

Preprocessing involves duplicate removal, missing-value handling, spatial–temporal synchronization, and Min–Max normalization of RSRP, SINR, and throughput to ensure comparable scaling. The datasets are aligned to maintain consistency between radio KPIs and throughput measurements for subsequent analyses.

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Statistical and Nonlinear Dependency Analysis

Linear and monotonic relationships between KPIs and throughput are evaluated using Pearson and Spearman correlation, while polynomial regression is used to capture potential nonlinear trends. A Random Forest regression model is further applied as an exploratory tool to assess nonlinear dependencies between variables. The model is not used for prediction, but to examine whether nonlinear interactions improve explanatory power of throughput variation. Performance is evaluated using MAE, MSE, RMSE, and R^2.

RF Index Construction

A composite RF Index is developed using a hybrid AHP–Entropy weighting scheme, combining expert judgment and data-driven variability. Normalized indicators (RSRP, SINR, throughput) are aggregated, with higher emphasis on throughput to reflect user-experienced quality. Sensitivity analysis is performed to ensure robustness under different weighting configurations.

Throughput is explicitly included to support throughput-oriented bottleneck identification rather than pure radio-quality assessment. Accordingly, CBZ represents spatial areas where throughput degradation occurs under generally acceptable radio conditions, not direct measurements of network resource utilization. The inclusion of RSRP and SINR enables differentiation between radio-driven and non-radio-driven degradation, making the RF Index a composite performance indicator rather than a single-metric representation.

Spatial Bottleneck Detection

Spatial degradation patterns are identified using Kernel Density Estimation (KDE) and DBSCAN clustering. KDE models spatial density of low-performance regions, while DBSCAN detects non-convex clusters of degraded performance. Spatial distances are computed using the Haversine formula, with ε and minimum samples optimized via k-distance analysis and sensitivity testing. DBSCAN is selected due to its ability to capture irregular, noise-prone spatial structures that cannot be effectively handled by centroid-based methods such as K-Means.

The DBSCAN parameters are determined using a k-distance graph, where ε is selected at the elbow point to balance cluster compactness and noise separation, while MinPts is defined based on dimensionality and empirical sensitivity testing to ensure stable clustering across parameter variations. This iterative tuning ensures that the identified CBZ regions remain robust under minor parameter changes. KDE is selected because it does not assume any predefined spatial distribution, making it suitable for modeling irregular, non-Gaussian, and location-dependent spatial intensity patterns in real-world LTE measurements where performance degradation is spatially heterogeneous.

Spatial Zoning

The study area is classified into three spatial zones — LTE Stability Zone, LTE Degradation Zone, and LTE Capacity Bottleneck Zone (CBZ) — based on RF Index distribution and DBSCAN results. Gaussian fuzzy membership functions are used to model gradual spatial transitions, enabling continuous rather than hard-threshold-based zoning.

5G NR NSA Feasibility Simulation

NSA feasibility is evaluated using Atoll software based on the 3GPP TR 38.901 Urban Macro (UMa) model at 2300 MHz (n40 band) with 50 MHz bandwidth. LTE serves as the anchor layer, while NR operates in dual connectivity mode. The system configuration parameters are summarized in Table 2, which defines the deployment assumptions based on the standardized UMa scenario.

Link budget calculations follow standard propagation formulations, including transmit power, antenna gain, receiver sensitivity, thermal noise, and path loss. The detailed parameters and derived link budget components are presented in Table 3, covering EIRP, receiver sensitivity, propagation margins, and maximum allowable path loss (MAPL) based on conventional NR planning methodology. Penetration and foliage losses follow standardized 3GPP UMa assumptions implemented in Atoll and are not independently optimized in this study.

Table 2. 5G NR NSA System Configuration Parameters

Parameters	Value	Technical Description
NR Band	n40	Mid-band TDD spectrum for NSA capacity enhancement
Carrier Frequency	2300 MHz	Frequency determining path loss and coverage characteristics
System Bandwidth	50 MHz	Channel bandwidth defining capacity and noise floor
Duplex Mode	TDD	Time-based uplink/downlink separation

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e-ISSN : 2541-2019
p-ISSN : 2541-044X

Parameters	Value	Technical Description
Subcarrier Spacing	30 kHz (μ = 1)	OFDM numerology for balanced latency and robustness
Propagation Model	3GPP TR 38.901 UMa	Standard macro-cell model including shadowing and diffraction

Table 3. 5G NR NSA Link Budget Parameters

Parameters	Symbol / Formula	Value	Technical Description
gNodeB transmit power	P_{tx}	46 dBm	Macro gNB conducted transmit power
gNodeB antenna gain	G_{tx}	8 dBi	Sector antenna gain
Transmitter cable loss	L_{tx}	2 dB	RF chain and feeder losses
Effective Isotropic Radiated Power	$EIRP = P_{tx} + G_{tx} - L_{tx}$	52 dBm	Radiated transmit power
Bandwidth	B	50 MHz	System bandwidth
Thermal noise	$N = -174 + 10\log 10(B)$	−97.01 dBm	Noise floor
UE noise figure	NF_{UE}	9 dB	Receiver noise contribution
Minimum SINR requirement	$SINR_{min}$	−1.1 dB	3GPP UMa decoding threshold
Receiver sensitivity	$P_{rx} = N + NF_{UE} + SINR_{min}$	−89.11 dBm	Minimum required received power
Penetration loss	L_{pen}	26.85 dB	Human body blockage loss
Foliage loss	L_{fol}	19.59 dB	Vegetation attenuation
Body loss	M_{body}	3 dB	Shadow/body loss component
Interference margin	M_{int}	7 dB	System interference margin
Slow fading margin	M_{sf}	7 dB	Macro planning margin
Total margin	L_{margin}	63.44 dB	Combined propagation/system margins
Maximum Allowable Path Loss	$MAPL = EIRP - P_{rx} + L_{margin}$	130.67 dB	Link budget limit

Internal validation using silhouette score analysis indicates acceptable clustering consistency. However, external validation was not feasible due to the absence of independent ground-truth data. Consequently, the results are supported by internal validation only, while external validation and generalizability assessment are left for future multi-region studies.

RESULTS

This section presents the results of LTE drive-test measurements and 5G NR NSA simulation under a measurement-driven analytical framework, covering radio performance, throughput characterization, statistical dependency analysis, feature contribution, spatial classification, and NSA simulation.

LTE Radio Performance Drive Test

The spatial distribution of LTE radio performance derived from 8,355 drive-test samples is presented in Fig. 2, while the corresponding statistical distributions are summarized in Tables 4 and 5. As shown in Fig. 2(a) and summarized in Table 4, 64.90% of the measurements satisfy RSRP ≥ −100 dBm, indicating generally acceptable LTE coverage across the study area. Lower RSRP values are primarily observed in locations farther from the serving base stations, consistent with expected propagation-loss characteristics.

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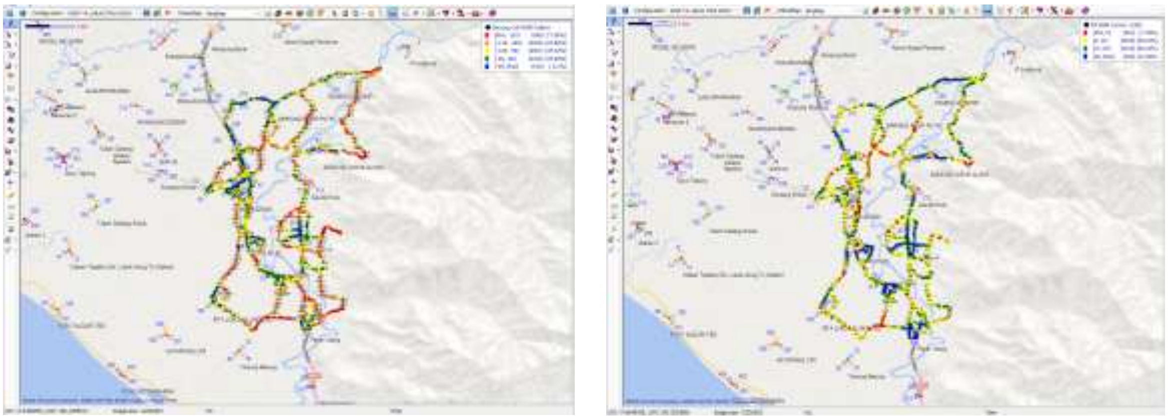
Similarly, Fig. 2(b) and Table 5 indicate that 92.21% of the samples satisfy SINR ≥ 0 dB, suggesting relatively stable interference conditions throughout the network. Despite localized variations, most measurements fall within acceptable RSRP and SINR ranges, indicating that radio-layer performance is generally adequate across the study area. These results establish a baseline for assessing whether throughput degradation can occur independently of coverage and interference limitations.



(a) (b)

Fig. 2 LTE Radio Performance: (a) RSRP Distribution, (b) SINR Distribution

Table 4. Distribution of LTE RSRP

Range	**Indicator**	**Sample**	**Percentage**
RSRP ≥ -80	Very Good	510	6.10%
-90 ≤ RSRP < -80	Good	2012	24.08%
-100 ≤ RSRP < -90	Normal	2901	34.72%
-110 ≤ RSRP < -100	Poor	2324	27.82%
RSRP < -110	Very Poor	608	7.28%
	Total	8355	100%
RSRP ≥ -100 dBm			64.90%

Table 5. Distribution of LTE SINR

SINR (dB)	**Indicator**	**Sample**	**Percentage**
SINR ≥ 20	Very Good	922	11.04%
13 ≤ SINR < 20	Good	2102	25.16%
0 ≤ SINR < 13	Normal	4679	56.01%
SINR < 0	Poor	651	7.79%
	Total	8355	100%
SINR ≥ 0 dB			92.21%

LTE HTTP Downlink Throughput Drive Test

The spatial distribution of LTE HTTP downlink throughput derived from 25,613 drive-test samples is presented in Fig. 3, while the corresponding statistical distribution is summarized in Table 6. As summarized in Table 6, 91.12% of the measurements achieve throughput ≥ 1500 kbps, with an average throughput of 5250 kbps, indicating generally acceptable service performance.

However, Fig. 3 reveals pronounced spatial variability in throughput distribution. Several localized areas exhibit reduced throughput despite the generally favorable radio conditions observed in Fig. 2. This mismatch between radio quality and user-experienced throughput suggests that throughput performance is influenced by factors beyond coverage and interference alone. Consequently, further statistical and spatial analyses are conducted to examine KPI–throughput relationships and identify potential LTE Capacity Bottleneck Zones (CBZs).

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Fig. 3 Spatial Distribution of LTE Downlink Throughput HTTP

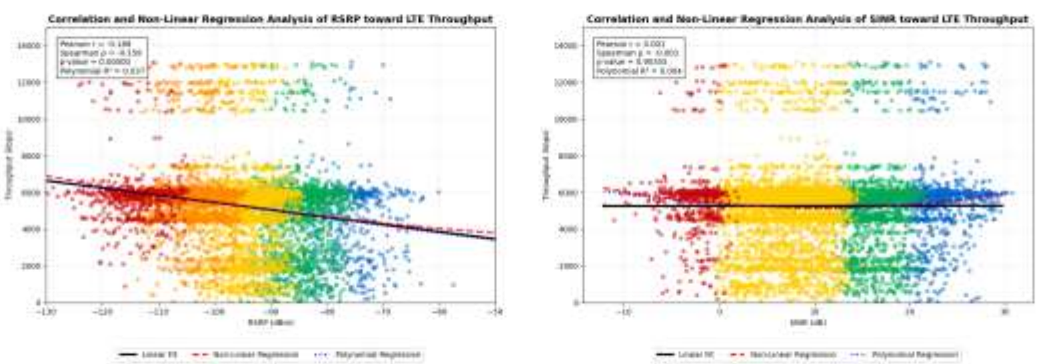
Table 6. Distribution of LTE downlink throughput HTTP

Throughput (kbps)	Indicator	Sample	Percentage
Throughput ≥ 12000	Very Good	62	0.24%
7200 ≤ Throughput < 12000	Good	634	2.48%
1500 ≤ Throughput < 7200	Normal	22642	88.40%
324 ≤ Throughput < 1500	Poor	1741	6.80%
Throughput < 324	Very Poor	534	2.08%
	Total	25613	100%
Throughput ≥ 1500 kbps			91.12%

Statistical Correlation and Regression Analysis

Correlation analysis, as illustrated in Fig. 4, shows consistently weak relationships between radio KPIs and throughput. Figure 4(a) shows that RSRP exhibits a weak negative correlation with throughput (Pearson $r = -0.188$, 95% CI [−0.209, −0.167], $p < 0.001$; Spearman $\rho = -0.158$, $p < 0.001$), although the effect size remains small by conventional standards (Cohen's $|r| = 0.188$). In contrast, Fig. 4(b) indicates that SINR shows an almost zero correlation with throughput (Pearson $r = 0.001$, $p = 0.927$; Spearman $\rho = -0.003$, $p = 0.784$), indicating no statistically significant association.

Regression results further confirm this behavior, where the coefficient of determination remains very low ($R^2 = 0.037$ for RSRP and $R^2 = 0.004$ for SINR), as shown in Fig. 4(a) and Fig. 4(b). These results indicate that radio-layer indicators alone provide limited explanatory power for throughput variation in the observed LTE network. The RSRP correlations, while statistically significant ($p < 0.001$) owing to the large sample size ($n = 8{,}355$), reflect only a small effect size and therefore carry negligible practical significance; the SINR correlations, by contrast, fail to reach statistical significance entirely ($p > 0.05$). Overall, throughput variation is only weakly associated with RSRP and SINR, suggesting the presence of additional influencing factors beyond radio conditions.



(a) (b)

Fig. 4 Correlation and Regression Analysis between LTE Signal Parameters and Throughput Performance: (a) RSRP versus Throughput, (b) SINR versus Throughput

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Volume 10, Number 3, July 2026 e-ISSN : 2541-2019
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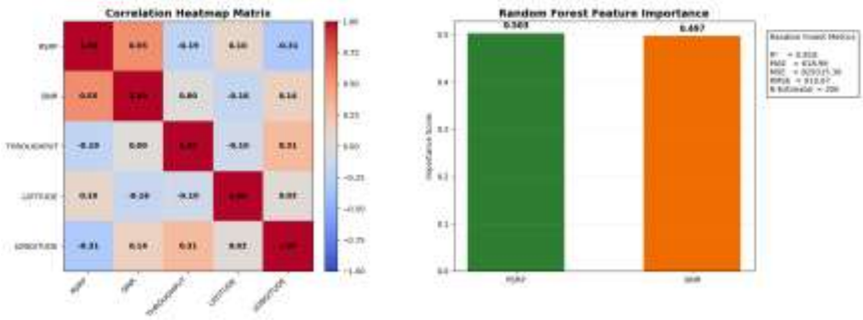
Multivariate Feature Contribution

The correlation structure presented in Fig. 5(a) indicates a moderate relationship between RSRP and SINR ($r = 0.55$), reflecting the expected coupling between signal strength and interference conditions. The heatmap also shows weak correlations between throughput and both RSRP ($r = -0.19$) and SINR ($r = 0.00$), confirming limited linear dependency of throughput on radio KPIs.

The Random Forest analysis, shown in Fig. 5(b), produces nearly balanced feature importance scores for RSRP (0.503) and SINR (0.497). However, the overall model performance remains low ($R^2 = 0.018$), indicating limited predictive capability. Since only two radio KPIs are included as inputs, these importance values should be interpreted cautiously and do not imply equal physical influence on throughput behavior.

The weak KPI–throughput relationships observed in Fig. 5(a), together with the low Random Forest performance shown in Fig. 5(b), constitute empirical evidence that throughput variability in real LTE networks is substantially governed by latent higher-layer mechanisms—including scheduler behavior, physical resource block (PRB) utilization patterns, and user density dynamics—which are not captured by radio-layer KPIs alone. This finding directly justifies the adoption of a spatial clustering-based framework (KDE-DBSCAN) as a more appropriate analytical paradigm than feature-based regression: when radio KPI predictors are demonstrably insufficient, the locus of analysis must shift from feature-space modeling to spatial density characterization of degradation zones.



(a) (b)

Fig. 5 Correlation Heatmap Matrix and Exploratory Feature Contribution Analysis: (a) LTE KPI Correlation Matrix, (b) Random Forest Feature Contribution

Spatial Capacity Bottleneck Identification for LTE-to-5G NR NSA Transition

The present analysis refines the methodological approach from a rule-based multi-criteria overlay to a hybrid MCDA framework integrating kernel density estimation (KDE) and DBSCAN-based spatial clustering, which yields a revised LTE Capacity Bottleneck Zone (CBZ) coverage of 7.99% of the study area. This result reflects the improved sensitivity of the data-driven approach to spatial density variations, rather than inconsistencies in the underlying network conditions, and represents a methodological refinement that enhances the spatial precision of bottleneck delineation. The proposed hybrid Spatial MCDA framework classifies LTE drive-test data into three spatial zones: LTE Stability Zone (28.99%), LTE Degradation Zone (63.02%), and LTE Capacity Bottleneck Zone (CBZ) (7.99%), as illustrated in Fig. 6.

The LTE Stability Zone is characterized by high RF Index values, indicating stable coverage, low interference, and sufficient throughput, forming compact clusters in strong-signal areas. The LTE Degradation Zone dominates the study area, with moderate RF Index values and fluctuating SINR and throughput, acting as a transitional zone between stable and poor performance conditions. The LTE Capacity Bottleneck Zone (CBZ), although the smallest, marks locations where degradation is driven primarily by capacity-related limitations rather than signal strength.

The RF Index is constructed using a hybrid AHP–Entropy weighting method with a consistency ratio (CR) of 0.0032. The derived weights are RSRP = 0.0807, SINR = 0.3310, and Throughput = 0.5883, confirming throughput as the dominant contributor. Spatial clustering using DBSCAN ($\varepsilon = 0.00001$ km, MinPts = 8) identifies 68 clusters and 1,480 noise points, with a silhouette score of 0.0411, indicating irregular but spatially coherent degradation patterns. Gaussian fuzzy membership functions were then applied to the RF Index distribution to model gradual transitions between the three zones, producing continuous spatial boundaries rather than hard thresholds and thereby reducing abrupt misclassification at zone edges.

The relatively low silhouette score is expected and scientifically acceptable in this context, as silhouette-based metrics assume convex, well-separated clusters and are known to underperform when applied to geospatial datasets characterized by non-convex cluster geometries, heterogeneous spatial density, and overlapping performance zones — all of which are inherent properties of real LTE measurement distributions.

DBSCAN was selected precisely for its capacity to detect arbitrarily shaped clusters and explicitly identify noise points, making it particularly suited to the non-uniform spatial distribution of throughput degradation observed in

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the studied network. The hyperparameters ε and MinPts were determined through k-distance plot analysis, following established practice for data-driven DBSCAN parameterization, ensuring that cluster boundaries reflect genuine spatial density gradients rather than arbitrary geometric thresholds. Overall, the results presented in Fig. 6 demonstrate that LTE-to-5G NR NSA performance limitations are primarily driven by spatially clustered capacity bottlenecks rather than uniform coverage degradation. The integration of MCDA and DBSCAN effectively reveals hidden spatial heterogeneity in network performance.

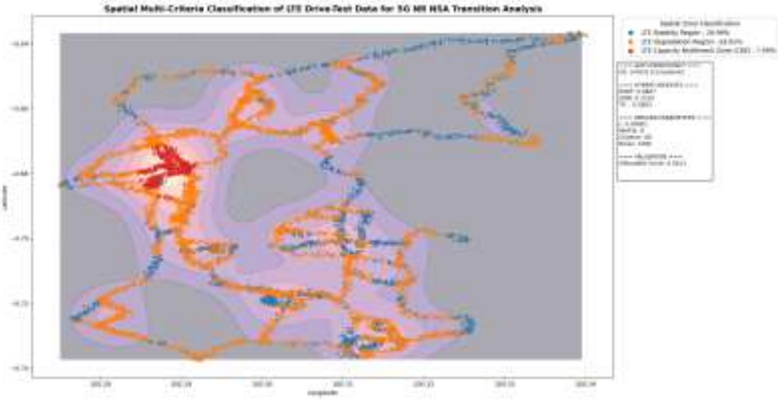

Fig. 6 Spatial Multi-Criteria Classification of LTE Drive-Test Data

5G NR NSA Throughput Simulation

The 5G NR NSA simulation results indicate that 97.40% of the evaluated area achieves throughput ≥ 250000 kbps, while 2.60% remains below 25000 kbps, as shown in Fig. 7 and summarized in Table 7. The results are obtained using the Urban Macro (UMa) propagation model with a standardized mid-band deployment configuration. The simulation is based on deterministic propagation and link-budget modeling and therefore represents an upper-bound capacity estimate rather than actual user-experienced performance.

Dynamic traffic behavior, mobility, interference variability, and radio resource allocation are not explicitly modeled. As a result, the outputs reflect theoretical capacity under idealized conditions rather than field performance. The throughput values are generated by the Atoll planning tool using standardized 3GPP TR 38.901 UMa assumptions and spectral-efficiency configurations. Overall, the results presented in Fig. 7 and Table 7 confirm that the simulation reflects theoretical capacity limits rather than operational network performance.

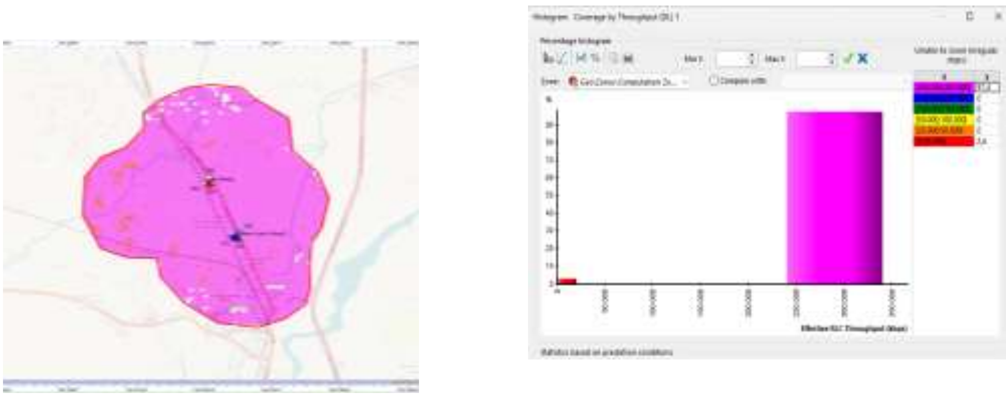

Fig. 7 Effective Downlink RLC Throughput Distribution of 5G NR NSA

Table 7. Distribution of 5G NR NSA Effective Downlink RLC Throughput

Range (kbps)	Legend	Indicator	Percentage
Throughput ≥ 250000		Very Good	97.40%
150000 ≤ Throughput < 250000		Good	0%
100000 ≤ Throughput < 150000		Normal	0%
50000 ≤ Throughput < 100000		Bad	0%
25000 ≤ Throughput < 50000		Pretty Poor	0%
Throughput < 25000		Very Poor	2.60%

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p-ISSN : 2541-044X

DISCUSSION

The results confirm that LTE network performance in the studied NSA environment cannot be fully explained by radio coverage indicators alone (Shakir et al., 2023). Although most RSRP and SINR measurements satisfy conventional LTE performance thresholds, throughput exhibits pronounced spatial heterogeneity across the study area, indicating that acceptable radio conditions do not necessarily guarantee consistent user-experienced service quality. The weak correlations and low regression performance between RSRP/SINR and throughput further show that radio-layer KPIs provide limited explanatory power for throughput variation (Alvarez-Merino et al., 2026), suggesting that additional network-level factors such as scheduler behavior, physical resource block (PRB) allocation, and traffic load conditions play a dominant role (Chmieliauskas et al., 2025). This observation is consistent with prior drive-test studies that also report a weak coupling between radio-layer KPIs and user-experienced throughput in operational LTE networks (Shakir et al., 2023), reinforcing that the near-zero RSRP/SINR–throughput correlations found here ($R^2 = 0.037$ and 0.004, respectively) are not isolated to this dataset but reflect a broader characteristic of capacity-constrained deployments. These findings motivate the use of the proposed measurement-driven, throughput-centric spatial framework to reveal LTE Capacity Bottleneck Zones (CBZ), where localized throughput degradation occurs despite generally favorable radio conditions.

The identified CBZs further confirm this pattern at the spatial level. This highlights the limitation of traditional coverage-based planning approaches, which primarily rely on signal strength indicators without adequately capturing capacity-related constraints. A clear distinction must be made between drive-test measurements and simulation results. Drive-test data reflect real-world network behavior under operational conditions, while 5G NR NSA simulation outputs represent theoretical upper-bound capacity derived from deterministic propagation and link-budget assumptions. Consequently, simulation results should be interpreted as planning-level capacity estimates rather than actual user-experienced throughput.

From a network engineering perspective, these findings suggest that coverage-oriented optimization is insufficient for evaluating service quality in dense LTE deployments. A more comprehensive evaluation must also consider traffic distribution and other system-level mechanisms, particularly in LTE-to-5G NR NSA architectures where LTE serves as the anchor layer for mobility and control signaling. The spatial identification of CBZ demonstrates that localized throughput degradation can occur even in areas with acceptable radio conditions. Although this study does not explicitly model scheduler behavior, PRB utilization, or traffic load, the presence of CBZ zones indicates that such factors play a significant role in shaping spatial throughput performance.

However, capacity-oriented optimization introduces practical trade-offs. Enhancing network capacity may require infrastructure densification, advanced resource management strategies, and tighter LTE–NR coordination. These improvements can increase deployment cost and operational complexity, requiring more adaptive and intelligent traffic management strategies. The identified LTE Capacity Bottleneck Zones (CBZ), covering approximately 7.99% of the study area, provide a practical basis for targeted optimization strategies. Rather than applying uniform upgrades across the entire network, operators may prioritize these localized regions to improve investment efficiency and user experience. In the LTE-to-5G NR NSA context, these CBZs directly indicate where NR small-cell placement or capacity densification should be prioritized, since they mark locations where LTE—acting as the NSA anchor layer—reaches its capacity limits despite adequate coverage, making them the most effective candidates for NR offloading. Despite these contributions, several limitations remain. The analysis is based on a single-region dataset, which limits generalization to other geographic or traffic environments.

In addition, drive-test measurements represent snapshot conditions and may not fully capture temporal traffic variation, mobility dynamics, or user density fluctuations. Furthermore, the 5G NR NSA evaluation is based on deterministic link-budget modeling and does not incorporate dynamic network behavior such as traffic load or inter-cell coordination. Overall, the results support a broader interpretation of LTE performance beyond conventional coverage metrics. The findings highlight the importance of throughput-oriented spatial analysis for identifying hidden capacity bottlenecks and supporting more efficient LTE-to-5G NR NSA deployment planning. Importantly, the observed weak negative correlation between RSRP and throughput should not be interpreted as a causal relationship (Eyceyurt et al., 2022). Instead, it reflects the dominance of non-radio factors in determining throughput variability under real network conditions.

CONCLUSION

This study demonstrates that acceptable LTE radio conditions do not necessarily guarantee uniform user-experienced throughput. Using a measurement-driven spatial framework that integrates KPI weighting, statistical dependency analysis, and spatial clustering, the study successfully identifies LTE Capacity Bottleneck Zones (CBZ) that represent approximately 7.99% of the total study area. The proposed framework shifts LTE performance evaluation from a traditional coverage-centric perspective toward a throughput-centric spatial

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bottleneck identification approach. This enables more realistic assessment of network performance and supports more efficient LTE-to-5G NR NSA deployment planning.

The main contribution of this work is the development of an integrated framework combining a KPI-weighted RF Index, KDE–DBSCAN spatial clustering, and fuzzy spatial zoning to identify localized performance degradation areas in LTE networks. Nevertheless, several limitations remain. The study is restricted to a single-region dataset, limiting broader applicability across different network deployments. In addition, the use of snapshot drive-test data limits the ability to capture temporal variations in traffic and mobility patterns. Furthermore, the NSA simulation relies on deterministic propagation assumptions and represents theoretical capacity rather than real-world throughput. Future work should extend this study by incorporating multi-region datasets, temporal traffic dynamics, real network load indicators, and live 5G NR NSA measurements to improve robustness, scalability, and practical applicability.

ACKNOWLEDGMENT

This research was conducted independently without external funding. The authors would like to express their sincere gratitude to the Padang State Polytechnic for its institutional support and the research facilities provided. Special thanks are extended to the telecommunications operator for granting access to the network performance data used in this study, as well as to the field testing team for their dedication during the field data collection. The authors would also like to thank Muhammad Khoiruddin Harahap for his valuable pre-review feedback, which significantly contributed to enhancing the quality and scientific depth of this manuscript.

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Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 3, July 2026
DOI : https://doi.org/10.33395/sinkron.v10i3.16154
e-ISSN : 2541-2019
p-ISSN : 2541-044X

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