Root Cause Analysis of Cellular Network Throughput Degradations under Vehicular Mobility

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***Abstract*—Despite 5G's promise of enhanced capacity and lower latency, recent measurement studies have shown that users experience significant cellular performance degradation under vehicular mobility. In this paper, we go beyond prior work that merely characterizes 5G performance, by uncovering the underlying mechanisms responsible for throughput degradation episodes during vehicular mobility. Through extensive measurements across 3,687 km of driving routes in the U.S., we collect granular performance and network KPI data from three major carriers across diverse radio access technologies. We introduce a novel KPI-driven clustering methodology that not only quantifies the frequency and duration of performance degradations, but also critically identifies their root causes by analyzing KPIs and their interactions. Our analysis reveals previously unidentified patterns: persistent higher degradation rates in uplink versus downlink, technology-specific vulnerability signatures in LTE and 5G deployments, and the predominance of compound degradation mechanisms where multiple factors interact to create severe throughput reductions. These findings provide essential information for developing mobility-aware resource management strategies to address the unique challenges of vehicular connectivity.**

I. Introduction

Reliable cellular connectivity is fundamental for vehicular applications, particularly connected and autonomous vehicles (CAVs), vehicle-to-cloud machine learning, and real-time cloud services, all of which require sustained throughput. Unlike pedestrian or stationary users, vehicles experience frequent handovers, fluctuating radio conditions, and localized congestion, directly impacting performance stability. These challenges are especially critical for cooperative driving, high-resolution sensor fusion, and remote vehicle control, where uninterrupted high-throughput data exchanges are essential. Even short connectivity degradations can disrupt real-time decision-making and compromise safety [33].

Although 5G networks promise enhanced mobility support, vehicular users continue to experience substantial performance fluctuations. Non-standalone (NSA) 5G deployments, which rely on LTE anchor points for control signaling, introduce performance issues during LTE-to-5G transitions, particularly under frequent handovers [12], [14], [27]. The increasing use of mid-band (e.g., C-band) and mmWave spectrum compounds these issues: mid-band frequencies require denser cell deployments due to their shorter coverage radius, while mmWave suffers from extreme link instability and obstruction sensitivity, necessitating continuous beam realignment. In non-urban environments, where cell density is lower, these factors contribute to prolonged service disruptions and increased throughput variability. Prior studies have examined cellular network performance under mobility, with a focus on operator-specific handover inefficiencies, LTE-to-5G transition delays, and the role of key performance indicators (KPIs) in throughput variations [10], [12], [25], [27]. Other works explore multi-carrier access (MCA) techniques to improve network resilience via dynamic operator switching [5]. Although these studies highlight mobility-related challenges, they do not systematically classify the specific factors responsible for performance degradation.

To address this gap, we performed extensive measurements in 3,687 km of interstate driving in the United States, examining three major carriers (Verizon, AT&T, and T-Mobile) across different radio access technologies. Our methodology quantifies the frequency and duration of the impairment, using degradation thresholds at 5 Mbps (where real-time services deteriorate) and 1 Mbps (where basic connectivity becomes unreliable). To identify underlying impairment mechanisms, we employ unsupervised clustering on a curated set of KPIs, enabling fine-grained characterization beyond aggregate statistical analysis.

Our analysis reveals several critical findings with significant implications for vehicular applications:

- **Persistent directional asymmetry:** Uplink degradations occur 4-5 times more frequently than downlink across all operators, with approximately 20% of uplink measurements with AT&T and Verizon falling below 5 Mbps versus only 10% for downlink. This systemic asymmetry stems from different underlying mechanisms in each direction.
- **Technology-specific vulnerability patterns:** LTE deployments show high susceptibility to interference-related degradations, with interference combined with channel deterioration appearing in 60-70% of degraded measurements. 5G-Low implementations exhibit rate adaptation inefficiencies, where MCS values drop disproportionately relative to SINR changes.
- **Compound degradation factors:** Most severe performance degradations are the result of multiple interacting factors rather than isolated causes. AT&T's 5G-Mid exhibits combined rate adaptation inefficiencies and channel degradation in more than 80% of the degraded samples.
- **Environmental differentiation:** Urban measurements con-

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TABLE I: Dataset statistics.

Measurement dates	May 2023 - August 2023
Network operators	Verizon (V), T-Mobile (T), AT&T (A)
5G deployment types	5G-SA, 5G-NSA
5G frequency bands	V: Low (n5), Mid (n77), High (n260, n261) T: Low (n71), Mid(n41) A: Low (n2, n5), Mid (n66, n77), High (n260)
Total cellular data used	V: 648 GB (Rx), 112 GB (Tx) T: 1328 GB (Rx), 184 GB (Tx) A: 449 GB (Rx), 101 GB (Tx)
Total geographical distance traveled	3687 km

tain higher rates of interference-coupled patterns (55.7% urban vs 38. 7% non-urban), while non-urban data show higher rates of coverage issues and more severe rate adaptation failures, reflecting fundamental differences in network density and deployment constraints.

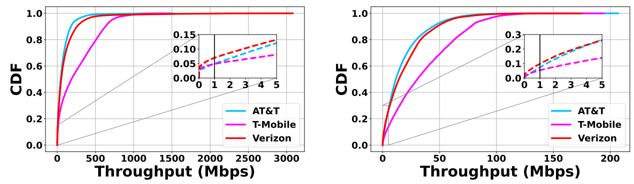
These findings demonstrate that reliable vehicular connectivity requires specialized approaches addressing the multi-dimensional nature of performance degradation during mobility. Current network deployments exhibit systematic vulnerabilities that cannot be addressed through conventional optimization techniques designed for static scenarios.

The remainder of this paper is structured as follows. Section III introduces our clustering-based degradation classification. Section IV analyzes trends in performance degradation across operators and technologies. Section V discusses related work. Finally, Section VI summarizes key insights.

II. Methodology

Measurement Route. We conducted two measurement campaigns spanning a total of over 3687 km of driving across the US. In May 2023 (05/13/2023 - 05/16/2023), we drove from Boston to Chicago, covering major cities along the route, including Rochester, Buffalo, Cleveland, Columbus, and Indianapolis. In August 2023 (08/05/2023 - 08/08/2023), we conducted a second driving trip from Boston to Atlanta, passing through Providence, New Haven, New York City, Richmond, Durham, and Charlotte. All measurement data reported in this study were collected on interstate highways, in suburban areas, and within city limits. Additional measurements were conducted within several major cities encountered along the routes. Our dataset is summarized in table II.

5G Carriers, User Equipment (UE), and Servers. We obtained multiple unlimited data plans from the three major US cellular operators – Verizon, AT&T, and T-Mobile. We used Samsung Galaxy S21 Ultra smartphones as our user equipment (UEs) for data collection. The phones support most of the frequency bands available in the U.S. For server-side infrastructure, we deployed two types of AWS EC2 servers: (1) one cloud server in the Northern Virginia region for most of the tests conducted with all the operators and (2) 5 AWS Wavelength servers in Boston, Chicago, Atlanta, Charlotte, NYC. These servers reside within Verizon's network and are specially designed for edge computing. For measurements over the Verizon network, we used our deployed Wavelength server in each of these five cities and the cloud server in the rest of the driving route. For the other two operators, we only used the cloud server.



(a) Downlink CDF (b) Uplink CDF

Fig. 1: Overall throughput.

Experimental Methodology. We conducted backlogged alternating DL and UL TCP throughput tests on the 3 phones against the 3 mobile networks, respectively, and concurrently, using nuttcp [29] throughout each drive. This parallel testing approach ensured that all networks experienced identical mobility conditions during measurements, allowing for direct performance comparisons. Application-layer throughput was logged at 500 ms intervals. Because commercial off-the-shelf smartphones do not grant access to low-level KPIs, such as handover details or specific 5G frequency bands, we employed Accuver XCAL Solo [1] devices. These devices access the Qualcomm diagnostic interface on the smartphones, allowing us to capture signaling messages between the UE and the base station and to gather low-level KPIs essential for a comprehensive root-cause analysis of network performance degradation during driving. In this work, we extract the following KPIs, which were logged at a granularity of 100-200 ms: RSRP, RSRQ, SINR, MCS, CQI, Tx Power, Block error rate (BLER), and number of resource blocks (RBs).

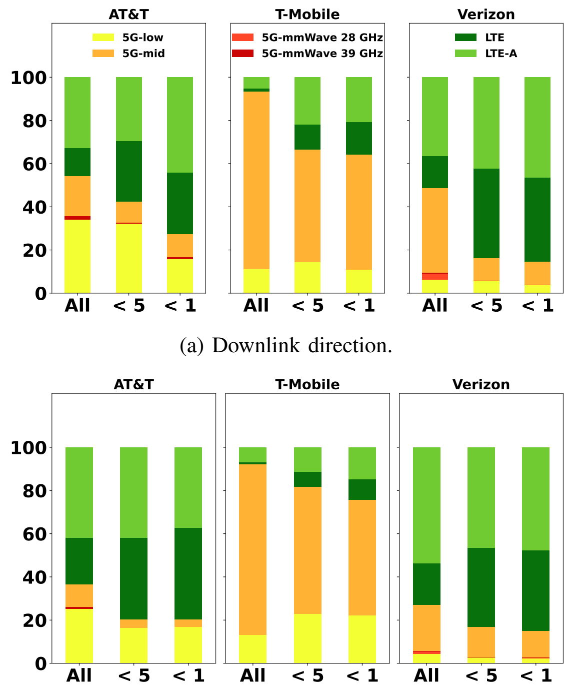
III. Mobility Performance Degradation

This section analyzes cellular performance under large-scale vehicular mobility, identifying key degradation patterns across network operators, radio access technologies, and geographic environments. We quantify throughput impairments using predefined thresholds and evaluate the contribution of different access technologies (LTE, 5G low-band, mid-band, and mmWave) to performance degradation.

A. Throughput Analysis

To quantify the impact of vehicular mobility on service performance, we define degradation thresholds at 5 Mbps and 1 Mbps, which represent critical levels of throughput impairment. Downlink rates below 5 Mbps can disrupt video streaming, cloud-based navigation, and other high-throughput applications, while uplink impairments at this level hinder tele-operated driving and vehicle-to-cloud data offloading. At 1 Mbps, performance degrades to the point where even basic services such as voice-over-IP and background synchronization, become unreliable, increasing the likelihood of service disruptions.

The downlink cumulative distribution function (CDF) in Fig. 1a illustrates that T-Mobile exhibits superior resilience against performance degradation compared to its competitors. In the critical sub-1 Mbps region (shown in the zoomed inset), the T-Mobile curve remains below both AT&T and Verizon, indicating that only approximately 4% of the T-Mobile and AT&T samples experience such severe degradation compared



(a) Downlink direction.

(b) Uplink direction.

Fig. 2: Technology-Bands distribution.

to about 7% for Verizon. This pattern continues at sub-5 Mbps, where T-Mobile maintains its advantage with a lower portion of degraded samples (about 7%), while AT&T surpasses 10% with Verizon reaching a slightly higher value.

For uplink performance in Fig. 1b, the degradation patterns become more pronounced between carriers, with T-Mobile again showing superior characteristics. The sub-1 Mbps region in the zoomed inset shows approximately 10% of AT&T and 8% of Verizon samples compared to only about 5% for T-Mobile. At sub-5 Mbps, the disparity further widens, with the above 20% of AT&T and Verizon measurements experiencing degradation versus approximately 12% for T-Mobile.

The above comparative analysis shows that *there exists distinct asymmetry between uplink and downlink degradation patterns between carriers*. While T-Mobile consistently demonstrates superior resilience in both transmission directions, performance degradation is substantially more pronounced in uplink scenarios for all carriers. This disparity becomes even more significant at the 5 Mbps threshold, highlighting that uplink transmission presents a more challenging technical domain with greater performance variability and more substantial inter-carrier differentiation than downlink performance.

B. Technology breakdown

Figure 2 presents the technology distribution breakdown between carriers in the downlink (a) and uplink (b) transmissions with particular emphasis on performance degradation patterns.

Regarding downlink, AT&T's 5G-low constitutes approximately 35% of all samples and maintains a similar representation in sub-5 Mbps groupings before decreasing to approximately 15% in severely degraded measurements (sub-1 Mbps). Concurrently, LTE's and LTE-A's combined representation increases substantially in degraded performance groups, rising from approximately 45% overall to nearly 70% in sub-1 Mbps measurements. The T-Mobile distribution shows the dominance of 5G-mid technology in all performance categories, comprising more than 80% of total samples and maintaining a significant presence even in degraded throughput groups. Verizon's measurement distribution demonstrates LTE and LTE-A as predominant technologies (50% combined), which increase to approximately 85% in sub-1 Mbps measurements, while its 5G-mid representation decreases from 40% overall to merely 15% in the most degraded group.

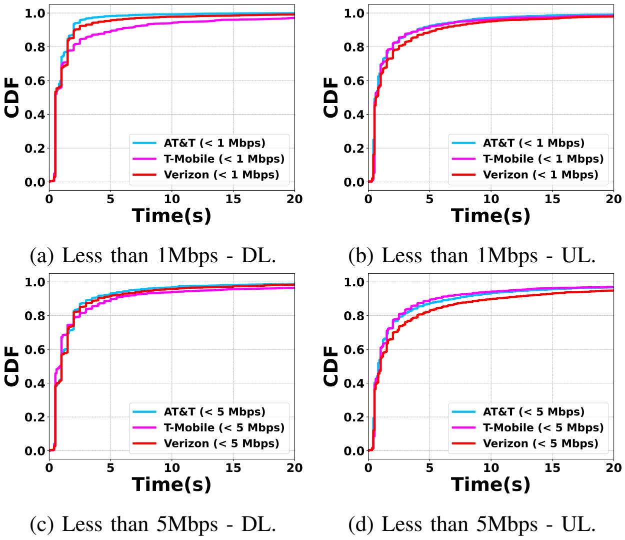
The uplink performance (Fig. 2 (b)) demonstrates similar patterns with greater extremes. AT&T shows even a stronger prevalence of LTE/LTE-A in degraded measurements (increasing from 65% to 80% in sub-5 Mbps and sub-1 Mbps groups). T-Mobile maintains 5G mid-dominance (85% overall), although this decreases to approximately 55% in severely degraded measurements, with a slight increase in the low 5G representation from 15% to about 25%. Verizon's uplink distribution parallels its downlink pattern, with combined LTE technologies increasing from 70% to 85% in degraded measurements, while the 5G-mid representation decreases from 25% to 15%.

In summary, LTE technologies consistently show a higher representation in measured degraded throughput of both directions of transmission for AT&T and Verizon, indicating inherent performance limitations in these older network technologies. T-Mobile's distinctive persistence of 5G-mid deployment even among degraded measurements differentiates its network architecture from competitors.

C. Analysis of Consecutive Degradations

The CDF of performance degradation durations including episodes as short as 500 ms is presented in Figure 3.

For severe degradations in downlink (Fig. 3(a)), the issues are generally short across all operators, with over 80% of episodes lasting under 3 seconds. T-Mobile connections experiencing severe degradation tend to remain problematic for longer periods than those of competitors, as shown by the more gradual slope of their performance curve throughout the measurement period. This suggests that when T-Mobile service quality drops significantly, customers can expect these issues to persist for extended durations. By the 20-second mark, approximately 95% of the degraded T-Mobile samples have resolved, leaving about 5% of the cases with persistence beyond that value. In contrast, AT&T exhibits the steepest CDF curve in the initial 2-3 seconds, indicating that approximately 80% of AT&T's degraded connections experience short-duration issues. Verizon shows an intermediate profile, with its CDF curve positioned between the other carriers, suggesting moderate issue duration distribution. The initial steep rise in all three curves indicates that a substantial portion of degraded connections across all carriers experience short-duration performance issues



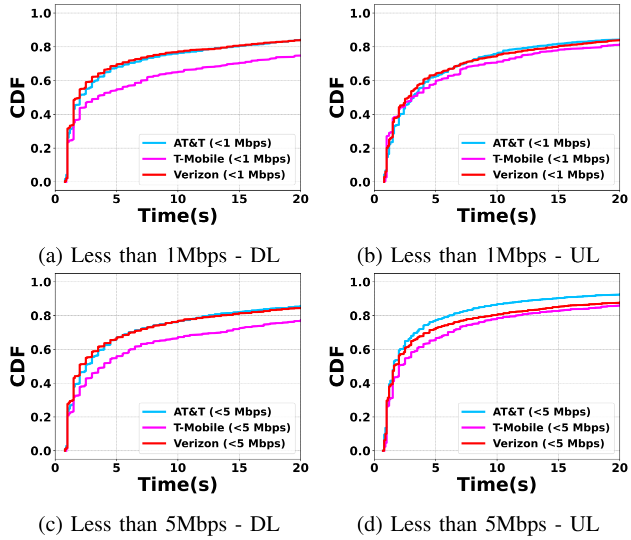
(a) Less than 1Mbps - DL.

(b) Less than 1Mbps - UL.

(c) Less than 5Mbps - DL.

(d) Less than 5Mbps - UL.

Fig. 3: CDF of the time length of sustained performance degradation.



(a) Less than 1Mbps - DL

(b) Less than 1Mbps - UL

(c) Less than 5Mbps - DL

(d) Less than 5Mbps - UL

Fig. 4: CDF of inter-degradation time

(resolving within 2-5 seconds), while the flattening of all curves after approximately 10 seconds demonstrates that each carrier maintains a small percentage of persistent performance issues extending beyond the presented time window.

In the uplink (Fig. 3(b), AT&T and T-Mobile demonstrate similar performance characteristics throughout most of the measurement period. Both carriers show approximately 80-85% of their severely degraded uplink connections experiencing issues lasting less than 2 seconds, with nearly identical slopes in this critical region. Verizon remains distinctly separated its CDF curve positioned consistently below. This indicates that Verizon's severely degraded uplink connections persist longer.

For moderate degradations below 5 Mbps (Fig. 3(c)-(d)) the operators exhibit distinct performance patterns across transmission directions. In the downlink AT&T demonstrates the most favorable resolution pattern with its CDF curve rising most rapidly among competitors. By the 5-second mark, approximately 90% of AT&T's moderately degraded connections have resolved, establishing it as the leader in downlink recovery. Verizon follows with a resolution of 93% in the same interval, showing comparable initial behavior to AT&T in the 0-2 second range, but diverging with a less steep increase in the critical period of 2-5 seconds. T-Mobile consistently performs poorly in downlink scenarios, with only 90% of the issues resolved in 5 seconds and its CDF reaching merely 0.95 at the 20-second mark, indicating that 5% of T-Mobile's moderately degraded downlink connections persist beyond the measurement window.

For uplink performance, the carrier hierarchy is reversed. T-Mobile exhibits superior characteristics, with its CDF rising more rapidly than competitors and maintaining this advantage throughout the measurement window. Approximately 90% of T-Mobile's moderately degraded uplink connections resolve within 5 seconds. AT&T occupies the intermediate position with performance metrics between its competitors, particularly evident in the 2-10 second range. Verizon demonstrates the poorest uplink recovery with only 85% of its moderately degraded connections resolving within 5 seconds, and its CDF curve positioned consistently below the others throughout the measurement period.

This directional asymmetry in performance between operators exposes fundamental differences in network resource allocation strategies across transmission paths. The complete inversion of performance rankings between uplink and downlink scenarios suggests that each carrier implements distinctly different prioritization mechanisms for traffic flows in each direction, likely reflecting divergent architectural trade-offs in their respective radio access network implementations and spectrum utilization approaches.

D. Inter-degradation time

Figures 4(a)-(b) reveal distinctive carrier patterns in inter-degradation intervals. In downlink measurements, T-Mobile exhibits substantially longer intervals between events, with a median inter-degradation time of 4 seconds versus 2-3 seconds for both AT&T and Verizon. By the 20-second mark, T-Mobile's CDF reaches only 0.75, indicating that 25% of its inter-degradation periods exceed the measurement window. For uplink severe degradation, carrier differentiation diminishes somewhat, with T-Mobile showing a 60 percentile of 5 seconds compared to 3 seconds for competitors. The CDFs of all three carriers reach approximately 0.8-0.85 by the 20-second mark, suggesting more uniform temporal patterns in severe uplink degradation.

For moderate degradation events (below 5 Mbps), Figures 4(c)-(d) demonstrate more pronounced performance stratification. In downlink scenarios, T-Mobile maintains longer intervals with a 60 percentile of 6 seconds while AT&T and Verizon remain at 3-4 seconds. Uplink measurements reveal the most differentiated carrier behavior, with AT&T exhibiting the shortest intervals, Verizon occupying an intermediate position, and T-Mobile maintaining the longest intervals. This clear stratification indicates carrier-specific optimization approaches for moderate degradation management.

Uplink degradations consistently occur more frequently than downlink in all operators, highlighting inherent challenges in resource management. These patterns expose a fundamental trade-off for carriers: The T-Mobile approach results in fewer but longer-lasting degradations, while AT&T and Verizon experience more frequent but shorter issues. Mid-band 5G provides consistent coverage but sustained congestion limitations, whereas heterogeneous deployments lead to shorter but more frequent degradations due to technology transitions.

IV. Analysis of Degradation Patterns

A. Methodology

To systematically classify performance degradation causes, we employ an unsupervised clustering approach after segmenting the dataset by operator and technology band. This ensures that each clustering process is performed on homogeneous network conditions, avoiding distortions due to inter-operator or inter-band differences. The analysis is based on a curated set of key performance indicators (KPIs) that capture critical aspects of signal quality, resource allocation, power control, and rate adaptation. These KPIs, listed in Table II, are selected based on their established relevance in characterizing cellular network impairments.

Filtering and Clustering Process: After filtering the dataset by operator and technology band, we determine the optimal number of clusters using the Elbow Method [20], which evaluates the trade-off between within-cluster variance and segmentation granularity. Typically, the optimal number of clusters falls between two and three (Tables IV and V). Once the number of clusters is determined, we apply the K-Means algorithm to group the samples based on the selected KPIs, ensuring that each cluster represents a distinct degradation pattern.

Cluster Validation: We validate each cluster through statistical analysis of KPI distributions across samples. For each potential cluster, we compute mean values and standard deviations of all relevant KPIs, then assess whether the separation between normal and degraded clusters meets domain-specific significance thresholds for that particular degradation type. A cluster is considered valid when its KPI deviation patterns align with expected characteristics and demonstrate clear statistical separation (exceeding one standard deviation) from non-degraded samples. This validation process ensures that our classification captures meaningful impairment patterns rather than statistical anomalies.

Resulting Degradation Categories: The clustering analysis identifies multiple degradation patterns, which are summarized in Table III. Impairment categories are defined by specific KPI deviations. Bad channel conditions occur with decreased RSRP and SINR, lowering MCS. Congestion is evident when RB allocation is much lower than in non-degraded settings, despite acceptable SINR, showing network resource contention.

TABLE II: Selected KPI Features. Note that CQI is not available for LTE and Tx Power is available only on the UE side.

KPI	Unit
RSRP	[dB]
RSRQ	[dB]
CQI (5G only)	-
UE Tx Power[a]	[dBm]
SINR	[dB]
MCS	-
BLER	[%]
number of RBs	-

[a] Uplink only

TABLE III: KPI-Driven Degradation Characterization

Root Cause	Observed KPI Impact
Bad Channel	Low RSRP (<-110 dBm) and SINR (<0 dB) force lower MCS levels, increased retransmissions and reduced spectral efficiency, despite available RBs [10], [20].
Congestion	The UE receives fewer RBs (< 30) despite good SINR, indicating network-wide resource contention limiting data rates [10].
Interference	Low SINR (<0 dB) with stable RSRP suggests co-channel interference, increasing HARQ retransmissions and throughput variability [10], [32].
Low Tx Power	UE transmit power constraints (<23 dBm) lead to high BLER (>10%) and uplink degradation due to insufficient link budget [16].
Bad Rate Adaptation	Suboptimal MCS selection: fallback to low MCS despite SINR (>15 dB) or aggressive MCS (>20) causing high BLER (>15%) [2], [10].

Interference arises when SINR declines while RSRP stays stable. Low power uplink occurs when the UE transmission power drops, often with a BLER over 10%. Bad rate adaptation arises from the suboptimal MCS choice, either too reduced despite good SINR or too increased, raising BLER.

The methodology ensures that the identified patterns are statistically robust and generalizable across different operators and technologies. The identified degradation causes are consistent with empirical observations and previous studies on impairments of cellular performance, confirming that the clustering methodology effectively distinguishes between different mechanisms [2], [10], [16], [20], [32].

B. Degradation Patterns

Tables IV, V summarize key throughput degradation patterns observed across different cellular technologies and deployment environments. The percentage column indicates the relative frequency of each degradation pattern within its specific network/technology segment, representing what proportion of all degraded samples for that particular operator and technology combination falls into each pattern category.

1) Bad Channel Conditions

Bad channel conditions represent one of the most fundamental degradation patterns in cellular networks, characterized by poor received signal strength.

The clearest representative case is observed in AT&T LTE UL (BC1), where RSRP deteriorates dramatically from -86.6 dBm to -109.2 dBm with a proportional reduction in SINR from 13.0 dB to 3.5 dB. This clean deterioration pattern leads

TABLE IV: Degradation Patterns with Critical KPI Values Across Operators and Technologies (Downlink)

Ref	Network	Link type	%	Critical KPIs (Normal vs. Degraded)	Big City / Non-Big-City
			Downlink		
D1	LTE, AT&T	Interference + Bad Channel	49.4	SINR: 14.3±6.8 vs. -0.27±3.9 dB RSRP: -90.7±11.5 vs. -110.7±9.2 dBm	32.3% / 52.7%
		Low Power	50.6	Tx Power: -4.2±12.2 vs. -8.5±15.0 dBm	67.7% / 47.2%
D2	LTE, T-Mobile	Interference + Bad Channel (IBC)*	69.6	SINR: 14.9±6.0 vs. -1.2±3.4 dB RSRP: -90.4±10.0 vs. -115.5±8.7 dBm	40.0% / 70.0%
		Low Power	30.4	Tx Power: -9.6±10.1 vs. 11.1±9.0 dBm	60.0% / 30.0%
D3	LTE, Verizon	Interference + Bad Channel	60.6	SINR: 14.7±6.9 vs. -0.01±3.8 dB RSRP: -87.8±11.8 vs. -108.6±7.3 dBm	49.4% / 58.8%
		Low Power + Rate Limiting	39.4	Tx Power: -6.9±12.9 vs. -2.4±12.1 dBm RBs: 55.3±24.4 vs. 21.3±18.0	50.6% / 41.2%
D4	5G-Low, AT&T	Interference + Bad Channel	36.4	SINR: 10.5±8.4 vs. -1.0±6.0 dB RSRP: -87.7±12.0 vs. -101.7±10.1 dBm	15.8% / 40.5%
		Interference + Rate Limiting (IRL)*	41.8	SINR: 10.5±8.4 vs. 0.9±6.5 dB RBs: 40.2±13.4 vs. 6.5±5.1	55.7% / 38.7%
		Interference (I1)*	21.8	SINR: 10.5±8.4 vs. -3.3±7.6 dB BLER: 10.4±10.5 vs. 56.5±20.7%	28.5% / 20.9%
D5	5G-Low, T-Mobile	Interference + Bad Channel	24.1	SINR: 7.0±6.7 vs. -0.4±5.3 dB RSRP: -93.2±11.8 vs. -106.8±7.6 dBm	6.5% / 24.8%
		Bad Channel (BC2)*	32.4	RSRP: -93.2±11.8 vs. -105.0±7.4 dBm MCS: 14.4±5.8 vs. 9.4±4.5	38.7% / 32.1%
		Bad Channel + Rate Limiting (BCRL)*	43.5	RSRP: -93.2±11.8 vs. -100.5±9.2 dBm RBs: 80.9±24.4 vs. 11.2±6.1	54.8% / 43.0%
D6	5G-Low, Verizon	Bad Rate Adaptation (RA1)*	100.0	MCS: 11.4±6.3 vs. 6.7±5.6 SINR: 12.3±7.3 vs. 8.3±7.9 dB	100.0% / 100.0%
D7	5G-mid, AT&T	Interference + Bad Channel	19.3	SINR: 12.3±8.6 vs. -0.3±7.8 dB RSRP: -90.3±11.5 vs. -102.8±12.3 dBm	22.3% / 19.6%
		Combined Rate + Bad Channel (CR1)*	80.7	MCS: 13.7±5.3 vs. 5.2±4.8 RSRP: -90.3±11.5 vs. -102.9±9.8 dBm SINR: 12.3±8.6 vs. 3.8±7.8 dB	77.7% / 80.4%
D8	5G-mid, T-Mobile	Bad Rate Adaptation (RA2)*	67.1	MCS: 14.4±5.3 vs. 4.8±6.0 SINR: 10.3±9.0 vs. 6.1±8.8 dB BLER: 10.7±9.3 vs. 3.8±10.4%	59.2% / 71.4%
		Interference + Bad Channel	21.6	SINR: 10.3±9.0 vs. 0.5±8.3 dB RSRP: -87.2±12.3 vs. -101.3±14.6 dBm	24.7% / 19.5%
		Bad Channel	11.3	RSRP: -87.2±12.3 vs. -100.0±11.8 dBm MCS: 14.4±5.3 vs. 4.4±5.2	16.1% / 9.2%
D9	5G-mid, Verizon	Combined Rate + Bad Channel (CR1)	60.8	MCS: 13.7±5.4 vs. 5.8±6.3 RSRP: -97.3±11.3 vs. -103.4±9.7 dBm SINR: 8.2±8.0 vs. 2.8±7.5 dB	53.5% / 64.2%
		Interference + Bad Channel	39.2	SINR: 8.2±8.0 vs. -1.6±6.9 dB RSRP: -97.3±11.3 vs. -109.1±9.4 dBm	46.5% / 35.8%

*Representative cases that clearly demonstrate the pattern
† Cases with significant spatial distribution differences (urban vs. rural)
Single-cause patterns: BC (Bad Channel), I (Interference), RA (Rate Adaptation), LP (Low Power), RL (Rate Limiting)
Combined patterns: IBC (Interference + Bad Channel), IRL (Interference + Rate Limiting), BCRL (Bad Channel + Rate Limiting)
Combined rate adaptation: CR1 (Rate Adaptation + Bad Channel), CR2 (Rate Adaptation + Resource Limiting), CR3 (Rate Adaptation + Resource Limiting + High BLER)

to substantial MCS decrease (16.5 to 4.4) without significant changes in other metrics, making it an ideal example of isolated channel degradation.

T-Mobile 5G-Low DL (BC2) presents another unambiguous bad channel example, with RSRP values shifting from -93.2 dBm to -105.0 dBm in degraded scenarios while maintaining proportional reduction in MCS (14.4 to 9.4), indicating path loss as the primary issue without significant interference effects.

2) Congestion

Network congestion becomes evident through constraints in resource allocation, even when signal quality metrics are satisfactory, as reflected in the allocation characteristics of resource blocks (RBs).

AT&T LTE UL (RL1) provides the clearest illustration of pure congestion, with the allocation of resource blocks markedly decreasing from 50.7 to 16.1 RBs despite minimal changes in signal quality metrics (SINR: 13.0 dB vs. 12.4 dB). This pattern demonstrates administrative rate limiting rather than channel-based restrictions.

3) Interference

Interference presents as degraded signal quality ratios (SINR, RSRQ) despite adequate signal strength, with characteristic disproportionate degradation compared to RSRP changes.

AT&T 5G-Low DL (I1) provides the clearest interference signature, with SINR degrading substantially from 10.5 dB to -3.3 dB with BLER increasing from 10.4% to 56.5% despite moderate RSRP changes. This pattern demonstrates how interference directly impacts error rates and throughput, regardless of signal strength.

4) Low Power

Low transmit power scenarios represent distinct degradation patterns where device or network power constraints drive performance reductions. T-Mobile LTE UL (LP1) presents the most pronounced low-power degradation pattern, with Tx Power dropping sharply from 6.8 dBm to -9.9 dBm in degraded scenarios. Counterintuitively, SINR rises (17.4 dB vs 10.8

TABLE V: Degradation Patterns with Critical KPI Values Across Operators and Technologies (Uplink)

Ref	Network	Link type	%	Critical KPIs (Normal vs. Degraded)	Big City / Non-Big-City
			Uplink		
U1	LTE, AT&T	Bad Channel (BC1)*	64.9	RSRP: -86.6±9.7 vs. -109.2±6.7 dBm SINR: 13.0 ±7.5 vs. 3.5±5.1 dB MCS: 16.5±4.6 vs. 4.4±3.0	40.5% / 69.7%
		Rate Limiting (RL1)*	35.1	RBs: 50.7±20.0 vs. 16.1±8.6 SINR: 13.0±7.5 vs. 12.4±6.3 dB	59.5% / 30.3%
U2	LTE, T-Mobile	Interference + Bad Channel	42.7	SINR: 10.7±7.5 vs. -0.6±3.2 dB RSRP: -86.8±10.9 vs. -116.6±5.0 dBm	36.4% / 43.1%
		Bad Channel	43.2	RSRP: -86.8±10.9 vs. -107.2±6.9 dBm	62.5% / 42.1%
		Low Power (LP1)*†	14.1	Tx Power: 6.8±6.9 vs. -9.9±10.8 dBm BLER: 5.1±4.4 vs. 10.1±11.1 SINR: 10.8±7.5 vs. 17.4±8.0 dB	1.1% / 14.8%
U3	LTE, Verizon	Interference + Bad Channel	41.1	SINR: 13.6±7.4 vs. -0.4±3.2 dB RSRP: -84.9±10.5 vs. -109.6±5.9 dBm	41.5% / 40.6%
		Rate Limiting	19.4	RBs: 49.8±20.1 vs. 11.6±7.2 SINR: 13.6±7.4 vs. 12.0±5.9 dB	22.0% / 19.4%
		Bad Channel	39.5	RSRP: -84.9±10.5 vs. -104.7±6.1 dBm SINR: 13.6±7.4 vs. 7.7±4.0 dB MCS: 21.8±5.2 vs. 6.7±4.1	36.5% / 40.0%
U4	5G-Low, AT&T	Interference + Bad Channel	22.9	SINR: 7.7±8.8 vs. -1.9±6.2 RSRP: -86.5±12.3 vs. -106.7±5.8 dBm	19.2% / 24.1%
		Bad Rate Adaptation	25.1	MCS: 10.8±7.5 vs. 2.8±3.9 dBm SINR: 7.7±8.8 vs. 4.4±5.5 dB BLER:10.4±9.7 vs. 10.9±6.6	23.3% / 24.2%
		Combined Rate + Resource (CR2)*	52.0	MCS: 10.8±7.5 vs. 3.0±5.1 RBs: 36.8±12.9 vs. 6.1±4.4 SINR: 7.7±8.8 vs. 1.3±6.3 dB	57.5% / 51.7%
U5	5G-Low, T-Mobile	Bad Channel	47.7	RSRP: -91.2±9.9 vs. -107.0±5.1 dBm	100.0% / 47.8%
		Bad Channel + Rate Lim (BCRL)†	52.3	RSRP: -91.2±9.9 vs. -105.1±7.4 dBm RBs: 84.6±22.6 vs. 4.3±3.8	0.0% / 52.2%
U6	5G-Low, Verizon	Combined Rate + Resource (CR2)	79.2	MCS: 13.7±7.6 vs. 4.4±4.5 RBs: 32.5±15.8 vs. 9.1±8.7 SINR: 10.6±8.2 vs. 4.8±7.1 dB	100.0% / 78.5%
		Combined Rate + Resource + Errors (CR3)*†	20.8	MCS: 13.7±7.6 vs. 4.5±4.8 BLER: 8.8±5.8 vs. 33.7±12.9% RBs: 32.5±15.8 vs. 7.1±6.1	0.0% / 21.5%
U7	5G-Mid, AT&T	Bad Channel	100.0	RSRP: -89.2±10.1 vs. -107.1±8.7 dBm SINR:10.8±9.7vs. 3.0±7.1 dB MCS: 13.4±7.5 vs. 3.4±5.5	100.0% / 100.0%
U8	5G-Mid, T-Mobile	Bad Rate Adaptation	19.6	MCS: 19.8±7.6 vs. 6.5±6.5 dBm SINR: 10.5±9.3 vs. 5.5±7.7 dB BLER: 7.4±7.0 vs. 10.9±12.8	38.1% / 16.9%
		Bad Channel	80.4	RSRP: -85.3±11.1 vs. -103.0±11.0 dBm SINR: 10.5±9.3 vs. 4.5±8.1 dB MCS: 19.8±7.6 vs. 4.8±6.5 dBm	61.9% / 83.1%
U9	5G-Low, Verizon	Bad Channel	100.0	RSRP: -94.9±11.2 vs. -109.6±6.9 dBm SINR: 8.2±8.4 vs. 2.7±6.0 dB MCS: 10.1±7.9 vs. 2.6±3.4	100.0% / 100.0%

See signs in Table III

dB), indicating that the device power constraint is the primary limiting factor rather than the RF conditions.

5) Bad Rate Adaptation

Rate adaptation issues occur when modulation and coding schemes are not optimally aligned with channel conditions, leading to suboptimal throughput given the RF environment. Verizon 5G-Low DL (RA1) provides a textbook example of pure rate adaptation issues, where all degradations (100% of cases) stem from non-optimal MCS selection. The MCS values drop from 11.4 to 6.7 despite relatively modest reduction in SINR (12.3 to 8.3 dB), indicating unnecessarily conservative modulation choices.

T-Mobile 5G-Mid DL (RA2) shows another clear pattern of rate adaptation, with MCS values dropping precipitously from 14.4 to 4.8 despite moderate SINR reduction (10.3 dB to 6.1 dB). Interestingly, BLER actually decreases (10.7% to 3.8%), may suggest excessive conservatism in the adaptation algorithm.

6) Combined Degradations

Our analysis identified several compound degradation mechanisms that occur during vehicular mobility. These patterns represent more complex interactions between multiple network factors that collectively degrade throughput. The first category involves interference-coupled patterns. When interference combines with channel deterioration (IBC), as observed in T-Mobile LTE DL (SINR: 14.9→-1.2 dB, RSRP: -90.4→-115.5 dBm), the multiplicative effect creates more severe degradation than either mechanism alone. Similarly, when interference triggers restrictive resource allocation (IRL) in AT&T 5G-Low DL deployments, the network responds by significantly reducing available resource blocks (40.2→6.5 RBs) despite only moderate SINR degradation.

Resource management patterns reveal how network algorithms respond to changing RF conditions. The BCRL pattern in T-Mobile's networks demonstrates particularly aggressive resource conservation when channel quality deteriorates, with allocations reduced from 84.6 to merely 4.3 RBs. Rate adaptation failures manifest through three progressive mechanisms of increasing severity. The base pattern (CR1) involves excessive MCS reduction in response to moderate channel degradation, as seen in AT&T 5G-Mid deployments where MCS drops from 13.7 to 5.2 despite manageable decrease in SINR. More complex is the CR2 pattern, where rate adaptation coincides with resource limitations, as observed in AT&T 5G-Low UL scenarios. The most severe manifestation (CR3) combines the reduction of MCS and resource limitation with substantially higher error rates (BLER: 8.8→33.7%), indicating failures of the fundamental adaptation algorithm in the Verizon 5G-Low implementation.

These compound patterns highlight the multidimensional nature of mobile network performance degradation during vehicular mobility, where often single-cause frameworks are insufficient to characterize the observed behavior.

C. Spatial Analysis

We classify big cities as locations within 3 miles of major metropolitan centers, based on a curated dataset of U.S. cities of interest. Using geodesic distance calculations, measurement points within this radius are labeled big city (urban), while those beyond 6 miles are classified as not-big city (non-urban). Points in the intermediate range (3 to 6 miles) remain unclassified to avoid ambiguity in transition areas. The degraded clusters have a radius of gyration[1] of approximately 400 km. This size makes them unsuitable for highly localized analysis. However, clustering-based classification highlights clear trends between urban and non-urban deployments.

Urban environments exhibit distinctly different degradation profiles compared to their rural counterparts. Interference-related patterns (I, IBC, IRL) show significantly higher prevalence in urban deployments, particularly for interference combined with resource limitations (IRL: 55. 7% urban vs 38. 7% nonurban). This aligns with the higher cell density and resulting co-channel interference in metropolitan areas. Conversely, pure bad channel conditions (BC) and low power (LP) cases dominate non-urban scenarios, where the extended inter-site distances create coverage challenges. Resource management behaviors also demonstrate environment-specific optimization strategies. The extreme resource limitation observed in BCRL patterns occurs almost exclusively in non-urban deployments (52.2% non-urban vs. 0% urban), suggesting carriers implement more aggressive resource conservation in coverage-limited rural scenarios. Similarly, the most severe rate adaptation failure (CR3) appears limited to non-urban environments (21.5% non-urban vs. 0% urban), indicating management limitations in handling the more variable RF conditions outside big city areas.

V. Related Work

A. 5G measurement studies under limited mobility

A large number of measurement studies have evaluated various aspects of 5G including performance [4], [8], [12], [13], [18], [21]–[23], [28], [30], [31], [34], [35], latency [7], handovers [11], [15], [17], carrier aggregation [36], resource allocation [6], power consumption [28], impact on application QoE [19], [28], beamforming [26], roaming [9], multi-carrier access [5], and throughput prediction [3], [24], [36]. Most of these works have limited geographic coverage conducting measurements in one or a few cities. The only exceptions are the works in [17], [30], which use country-wide datasets collected by an operator, the work in [18], which uses a crowd-sourced dataset from 8 cities, and the works in [3], [5], [12], [15], which analyze datasets obtained from one or multiple cross-country drives, similar to this work.

Several of these works highlight suboptimal 5G performance under driving [4], [5], [8], [8], [12], [13], [18], [22]–[24], [30], [31], [34], [36], often worse than LTE, and some of them have identified a variety of factors that affect performance, including but not limited to suboptimal scheduling, rate adaptation, carrier aggregation, beam misalignments (in the case of 5G mmWave), etc. Nonetheless, none of these works has focused specifically on analyzing the root causes of performance degradation under driving.

To our best knowledge, this is the first systematic analysis of cellular performance degradation under driving conditions across multiple operators and technologies over thousands of kilometers. Our work advances beyond previous studies by: (1) providing high-resolution spatial and temporal breakdown of performance impairments; (2) systematically classifying root causes through unsupervised clustering; and (3) establishing a structured taxonomy distinguishing between radio link impairments, congestion limitations, rate adaptation failures, and power control issues. These insights reveal operator-specific and technology-specific patterns critical for improving network resilience in high-mobility environments.

VI. Conclusion

Our large-scale measurement study across major US interstate routes reveals fundamental challenges for cellular networks supporting vehicular applications. The systematic analysis of degradation factors through our KPI-driven clustering methodology demonstrates that mobile connectivity issues stem from complex interactions between network architectures, deployment environments, and mobility patterns. The pronounced directional asymmetry in degradation frequency, technology-specific vulnerability patterns, and prevalence of compound impairment fctors indicate that current network designs have not fully addressed vehicular mobility requirements. The significant environmental differences between urban and rural degradation profiles further complicate optimization approaches. Looking forward, these findings point to several critical research directions: developing direction-aware resource allocation strategies that specifically address uplink vulnerability, creating environment-adaptive scheduling algorithms that respond to local interference or coverage conditions, and implementing multi-factor adaptation mechanisms capable of mitigating compound degradation scenarios. As vehicular applications

[1]The radius of gyration quantifies the spread of measurement points around their centroid, representing the root-mean-square distance of all sample locations from their center of mass.

increasingly rely on uninterrupted connectivity for safety-critical functions, addressing these identified challenges will be essential for enabling the next generation of connected vehicle services.

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