Leveraging L-Moments to Characterize Traffic Behavior in 4G and 5G Networks

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***Abstract*—While 4G networks have served as the foundation for mobile broadband services, their architecture presents limitations in handling the increasing demand for higher data rates, lower latency, and large-scale connectivity. The transition to 5G addressed these constraints by introducing a more flexible and efficient network design, incorporating key enabling technologies such as virtualization and network slicing. These innovations enhance resource allocation, mobility support, and service differentiation, making 5G a more capable solution for high-demand applications. However, despite these advancements, understanding how traffic behavior differs between 4G and 5G remains a critical challenge, particularly in high-mobility scenarios, where fluctuations in network performance can significantly impact Quality of Service (QoS). To analyze these differences, we examine downlink (DL) bitrate, signal quality, and mobility patterns in both technologies using L-moment ratio diagrams, a robust statistical tool for characterizing traffic behavior. Results reveal that 5G offers a more stable and predictable bitrate distribution, whereas 4G exhibits higher variability, particularly in mobile scenarios, degrading QoS. Additionally, results also show inconsistencies in the dataset mainly due to the presence of traffic from non-declared networks, highlighting the need for more refined and validated datasets for future studies. Understanding these differences is also crucial for identifying current challenges and defining optimization strategies that will guide the development of next generation networks, ensuring more stable and efficient performance in dynamic, high-demand environments.**

***Index Terms*—5G, 4G LTE, traffic analysis, L-moments.**

I. Introduction

The transition from the fourth generation of cellular network technology (4G) to the fifth (5G) has represented a significant leap in mobile network capabilities, enabling the deployment of new high-demand services with unprecedented performance requirements. 5G networks offer significantly higher data rates, drastically reduced latency, and enhanced capacity, accommodating a higher density of connected devices per base station [1], [2]. These advancements are enabled by key architectural innovations, like millimeter-wave spectrum, massive Multiple Input Multiple Output, and Network Function Virtualization, among others [3]. These innovations provide greater flexibility, improved network efficiency, and higher energy performance, meeting the stringent requirements of emerging applications such as augmented reality, autonomous vehicles, and Industry 4.0 [4].

In 4G networks, mainly based on Long Term Evolution (LTE) technology, mobile services were classified into enhanced Mobile Broadband (eMBB) and Machine-Type Communications (MTC), with limited support for ultra-low latency and high-reliability applications. Although LTE-Advanced improved peak data rates and spectral efficiency, its architecture remained constrained by inherent latency limitations and best-effort service provisioning [5]. In contrast, 5G introduces a service-based architecture designed to support three distinct service categories: eMBB, ultra-Reliable Low Latency Communications (URLLC), and massive MTC (mMTC) [6]. These categories address the diverse performance demands of next-generation applications, enabling gigabit-speed connectivity for immersive media, real-time interactivity for industrial automation, and large-scale Internet of Things (IoT) deployments with minimal power consumption [7]. 5G ensures service differentiation by using network slicing and edge computing, delivering tailored QoS levels to meet stringent application requirements beyond the capabilities of LTE networks.

To gain deeper insights into the statistical behavior of different service categories in 4G-LTE and 5G networks, we leverage L-moments, a robust statistical tool to characterize the shape and variability of probability distributions [8]. Unlike conventional moment-based techniques, L-moments provide a more reliable estimation of distributional properties, particularly in scenarios with heavy-tailed or skewed data, which are common in network traffic analysis [9]. L-moments have been employed in a wide range of scientific research domains, including regional frequency [10], stock [11] and network security analysis [12].

To statistically analyze the behavioral differences between 4G-LTE and 5G services, we use L-moments to generate L-

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moment ratio diagrams, enabling a visual representation of the distributional shapes across different service categories. The differences in functionality and performance between 4G and 5G networks have been studied from multiple perspectives, providing valuable insights that contribute to optimizing network deployments and improving QoS [13], [14]. The approach considered in this work allows us to capture variations in key network performance metrics and assess how the transition to 5G affects service differentiation. In particular, we focus on characteristics related to bitrate, signal quality, and user equipment mobility in multimedia traffic scenarios for both 4G-LTE and 5G. Our results reveal significant differences in some of these characteristics between the two technologies, highlighting the impact of 5G's architectural advancements on service performance and network behavior.

The remainder of this paper is organized as follows. Section II presents the datasets and methodologies considered in this study. The analysis and results of the experiments carried out using the described methodology are presented in Section III. Section IV contains our concluding remarks and points to some future work directions.

II. Datasets and Methodology

This section contains the datasets and the analysis methods used. Specifically, it describes both the 4G-LTE and 5G datasets, together with a brief review of the L-moments statistical theory and the L-moment ratio diagram (LmomRD).

A. Datasets

Two different but quite related datasets are used in this work: a 4G LTE [15] and a 5G one [16]. The main difference lies in the specific technology used during the experiments, while they share similarities in terms of the database structure and the variables collected. These two databases are commonly used for comparisons between 4G-LTE and 5G technologies; however, the methodology employed in this study introduces a novel approach based on the usage of the LmomRD. In the following sections, both databases are briefly described.

1) 4G-LTE dataset: The 4G-LTE dataset includes traffic traces collected through experiments conducted in Ireland [15]. It contains a wide range of features, including performance, data rates and contextual information for five different mobility patterns. The mobility patterns are: (i) static, experiments conducted indoors with the user remaining in a fixed location; (ii) pedestrian, in which the user walked through the city of Cork, Ireland; (iii) bus, experiments conducted on public transport in urban and suburban scenarios; (iv) car, where the user drove through urban and suburban environments; and (v) train, experiments performed on the Cork-Dublin and Cork-Farranfore railway lines. The car mobility pattern has the highest number of experiments (53 trials), while the static and bus mobility patterns have the lowest counts (15 and 16 trials, respectively). Additionally, as highlighted in [15], the train mobility pattern includes traces from multiple network standards, not just 4G, due to the limited 4G coverage outside urban areas at the time of data collection. The database comprises a total of 135 experiments, amounting to more than 2,900 minutes of recorded data.

2) 5G dataset: The 5G dataset was collected in scenarios comparable to those of the previous study [16]. In this case, only the static and car mobility patterns are included: (i) static, experiments performed indoors and in static car scenarios; and (ii) car, trials included urban and suburban scenarios. Three applications were considered: the download of a large file (>200MB), and Netflix and Amazon Prime video streaming services. The database includes a total of 83 experiments, with a total duration of more than 3,100 minutes.

Readers are referred to the primary references such as [15] and [16], and subsequent works for further details regarding the datasets generation and specific characteristics.

The specific variables considered in this work are:

- `DL_bitrate` feature measured at the application layer;
- `CQI` for the channel state metrics;
- the velocity in km/h of the mobile device `Speed`;
- the `State` of the download process, idle or active entries;
- the specific technology for each sample `NetworkMode`.

The selection of `DL_bitrate` is based on its impact on resource allocation and critical role in determining the perceived QoS for users. `CQI` is relevant to understand the performance of the technology. `Speed`, `State`, and `NetworkMode` are included for verification purposes.

B. L-moments and LmomRD

The statistical framework for our analysis is the L-moments statistical theory [8], an approach that has already shown advantages in the analysis of network flow data [12], [17]. It is particularly beneficial in scenarios where classical approaches reach their limitations, such as in the presence of high skew, heavy tails, or outliers [18], [19].

L-moments, λ_i for $i \in \mathbb{N}$, are computed as linear combinations of expected values of order statistics. One advantage is that all L-moments exist for any variable with finite mean. Also, interpretation of λ_i is analogous to that of classical statistical moments. That is, λ_1 is also known as *L-location* and is the average value of the dataset; λ_2 is known as *L-scale* and describes the scale of dispersion. Standardized L-moments, $\tau_i = {}^{\lambda_i}/_{\lambda_2}$ for $i \in 3, 4, \ldots$, are bounded to $-1 \leq \tau_i \leq 1$ for $i \geq 3$, facilitating comparison between distributions with different locations and scales. The τ_3 and τ_4 are known as *L-skew* and *L-kurtosis*, respectively. In addition, $\tau_2 = {}^{\lambda_2}/_{\lambda_1}$ is know as *Coefficient of L-Variation* or *L-CV* and it is also bounded by $0 \leq \tau_2 \leq 1$. For non-negative variables, L-CV is equivalent to the Gini index [20]. When analyzing actual datasets, like in this work, a key advantage of L-moment theory is its highly accurate and precise estimators, which are unbiased, robust to outliers, and exhibit low sampling variability [8], [19], even for small sample sizes [8].

Within this framework it is common to include a graphical tool to perform the exploratory analysis as well as for the distribution selection. This tool is the LmomRD and it plots tuples (usually pairs) of L-moment ratios [8], [18]. Readers

TABLE I
SUMMARY OF THE COMMON FEATURES OF THE CONSIDERED DATABASES

	Mobility pattern			Application pattern		
4G LTE	Static	Car		File Download		
5G	Static	Car	Bus	File Download	Netflix	Amazon Prime

are referred to the primary references like [8] and subsequent works for further details regarding the L-moments theory.

In this work, we estimate the τ_2, τ_3 and τ_4 for selected dataset features and used them to analyze and compare the behavior and performance of 4G-LTE and 5G networks. Furthermore, we use the LmomRD tool for the result presentation in different versions: using $\{\tau_2, \tau_3, \tau_4\}$ tuple and the respective 2D projections.

These tools from the L-moments statistical theory have been widely used in state of the art works, in a wide variety of research fields. Some examples include the regional frequency analysis [19], [21], stock analysis [11], [22], mechanical processes modeling [23], among others. L-moment-based studies can also be found for network data analysis, where works such as [12], [17], and [24] have shown the potential of this framework for gaining deeper insights into specific application behavior and serving as input for Machine Learning (ML) algorithms in Distributed Denial-of-Service (DDoS) attack classification. The results in [17] are a preliminary and limited version of this study. In this work, we extend the analysis by providing a direct comparison between two network standards and incorporating a broader set of features.

III. ANALYSIS AND RESULTS

First, in this section we analyze database features to establish a common ground for fair comparisons. Next, we detail data preprocessing, including sample discarding criteria. Finally, we examine results for `Speed`, `DF_bitrate`, and `CQI` features.

A. Common features in the 4G-LTE and 5G datasets

Although the experimental setup for both databases is similar, a fair comparative analysis requires identifying the exact common features. The first part of the analysis is dedicated to identifying this common ground, while the rest of the study focuses exclusively on these shared aspects of the data.

First, the 4G-LTE dataset includes data from two operators, while the 5G dataset is limited to one. By examining network usage conditions in the 4G-LTE dataset [15] and the applications described in the 5G dataset [16], we identify the common operator and the subsequent analysis uses exclusively traces collected from it.

Then, mobility patterns also differ between the datasets, with only the static and car categories being shared. Additionally, we consider the car and bus patterns in the 5G dataset as a group, given their similarities in terms of urban mobility. The usage of this subset of mobility patterns also eliminates the issue with the train pattern that includes traces with mixed 3G and 4G technologies [15]. Finally, regarding the application patterns in the 5G dataset and their equivalence to the 4G-LTE case, the only strictly comparable experimental setting is the file download scenario. However, to provide a broader comparison, all three scenarios are included in the analysis. In conclusion, Table I provides a summary of the features considered in the following analysis.

B. Datasets preprocessing

Data preprocessing starts with data exploration to detect any missing values or erroneous outliers. This exploration revealed several issues, which were discarded, as follows:

- entries with a `State` different from `'D'` are removed to only consider active data transfers.
- entries with absurd velocities, such as $> 2km/h$ in a static scenario, are also removed.
- entries with a `NetworkMode` different from the one stated in the corresponding database are also removed. This includes, entries with `NetworkMode` of EDGE, HSPA+, HSUPA and UMTS in the 4G-LTE database and of HSPA+, HSUPA, UMTS, LTE and HSDPA in the 5G database.

Table II provides a summary of the number of entries at the beginning of the preprocessing stage and after each step. Regarding the removal of entries with absurd velocities from the database, only 253 samples fell into this category. Finally, other missing data, for example, an '`-`' instead of a number in a given entry, were simply excluded from the specific analysis of that variable. These cases total less than 200 instances.

The total amount of data available for 4G-LTE and 5G technologies is considerably lower than originally expected, as even as much as 40% of the samples were discarded in some cases. In both cases, this is mainly because the `NetworkMode` does not match the expected value. This fact is not mentioned in any of the works describing these datasets, except for the train mobility pattern. However, it could have a significant impact on the interpretation and discussion of the results, especially in analyses where the specific technology plays a central role.

C. `Speed` feature

The mobile device's `Speed` feature is relevant for both data and results validation, specially for non-static patterns. We compute the empirical values of τ_2, τ_3, and τ_4 for car and bus patterns. The hypothesis is that these statistics should be similar, as experiments were conducted in similar conditions, where comparable urban mobility patterns are expected.

Figure 1 shows the obtained results[1], revealing that the hypothesis is not fully satisfied. The main difference is for τ_2, dividing the results in three groups: (a) 4G-LTE car and bus; (b) 5G car and File download and Amazon Prime applications; and (c) 5G car and Netflix application. These groups are distinguished by the three computed variables showing significant differences in their statistical behavior.

Considering that urban mobility is constantly evolving, particularly over the two years between the construction of each database, it is understandable that the speed statistics differ between them. However, the differences between groups (b) and (c) are quite unexpected. These can only be explained by inconsistencies between consecutive trials during the database

[1] Interactive versions of the 3D subplot are available upon request.

TABLE II

NUMBER OF ENTRIES IN THE DATABASES AFTER EACH PREPROCESSING. BOLD INDICATES THE FINAL COUNT OF AVAILABLE DATA FOR THE ANALYSIS.

			Initial samples	Samples with `State='D'`	Samples from common Operator	Samples with proper technology	% of entries removed due to technology	Samples with reasonable `Speed`
4G LTE	Static		15261	15157	12859	12859	0%	**12859**
	Bus		10783	10366	6482	**3875**	40.21%	
	Car		75874	75721	58625	**37240**	38.08%	
5G	Static	File download	15617	15552		15552	0%	**15552**
		Netflix	34608	11569		11213	3.07%	**10960**
		Amazon Prime	34941	28373		23602	16.81%	**23602**
	Car	File download	27591	26751		**13880**	48.11%	
		Netflix	38224	16023		**10714**	33.13%	
		Amazon Prime	37730	29400		**13590**	53.77%	

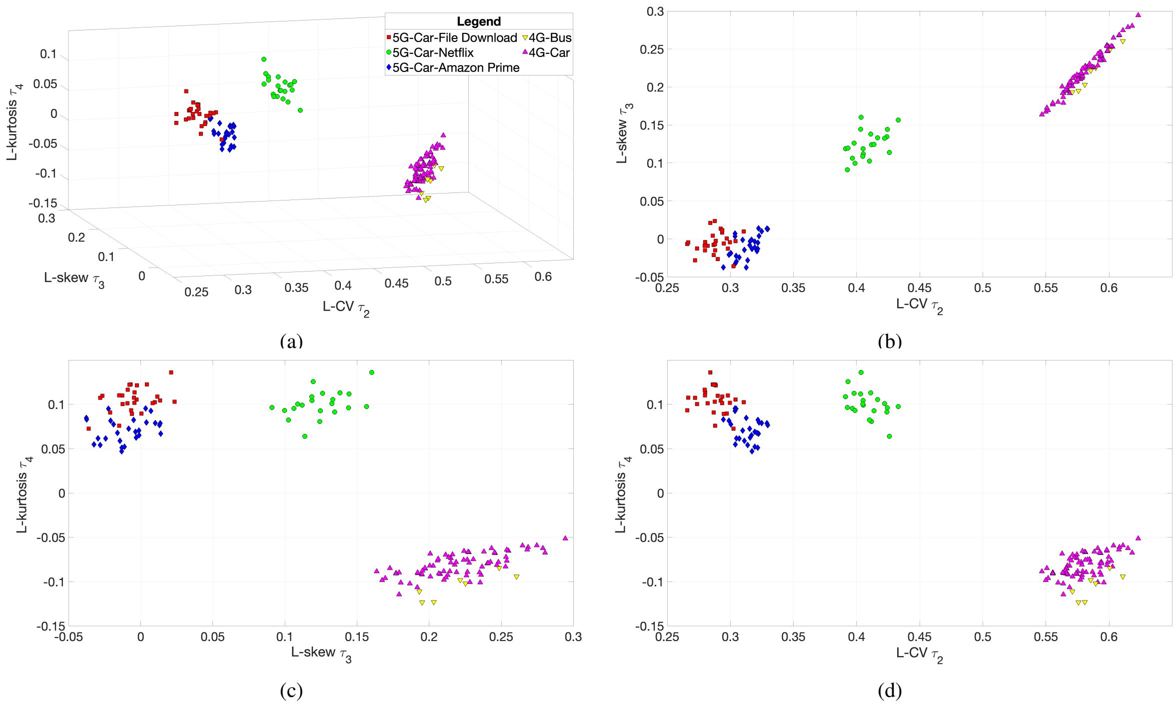


Fig. 1. L-moment ratio diagram including the estimation for L-CV τ_2, the L-skew τ_3 and the L-kurtosis τ_4 of the `Speed` feature. Both 3D representations along with the 2D projections for each pair of axes are plotted in subfigures. All subfigures share the legend.

construction, such as trials conducted at different times of the day or in different areas of the city. As the relative movement between the mobile device and the base station affects the communication's quality – primarily at the physical level due to the Doppler effect [25] – the presence of these distinct groups in the 5G database should be considered in the subsequent analysis of channel quality metrics.

D. `DL_bitrate` feature

The `DL_bitrate` is likely the most relevant factor for the user's perceived QoS, particularly in streaming services, as well as in download wait times and overall network usage. This analysis allows a better understanding of the statistical behavior of this feature and, in line with the objective of this study, allows a comparison of the two considered technologies. Figure 2 presents the obtained results for this feature[1].

These results are consistent with previous findings [17], indicating, for example, that the 5G File Download and Amazon Prime scenarios share significant similarities regarding the τ_3 and τ_4 values, while the Netflix scenario is markedly different. The inclusion of τ_2 provides a significant added value. The `DL_bitrate` for Netflix has already shown high L-skew and high L-kurtosis [17], however it also has high values for L-CV, revealing a highly unpredictable statistical behavior for this feature. Also, τ_2 is the metric that enables even the differentiation between File Download and Amazon Prime cases: although they share similar τ_3 and τ_4 values, results show a higher range or τ_2 for the Amazon Prime case. This fact shows higher dispersion in the `DL_bitrate`, likely caused by a non-uniform download rate for the streamed video.

The values of τ_2 are also relevant to distinguish features in the 4G-LTE network, as observed in the static pattern. The smallest τ_2 values are for the 4G-LTE car pattern. The group of estimated τ_i for this specific case is located around the $(0.47, 0.25, 0.11)$ centroid, revealing high L-CV – being 0.5 the case of maximum entropy among the values of the feature [20] – along with a slightly positive L-skew and with an L-kurtosis similar to a normal distribution.

This behavior suggests that users in the 4G-LTE car pattern experience highly variable DL bitrates, likely due to frequent handovers and fluctuating signal quality while moving through different cells. These variations can negatively impact

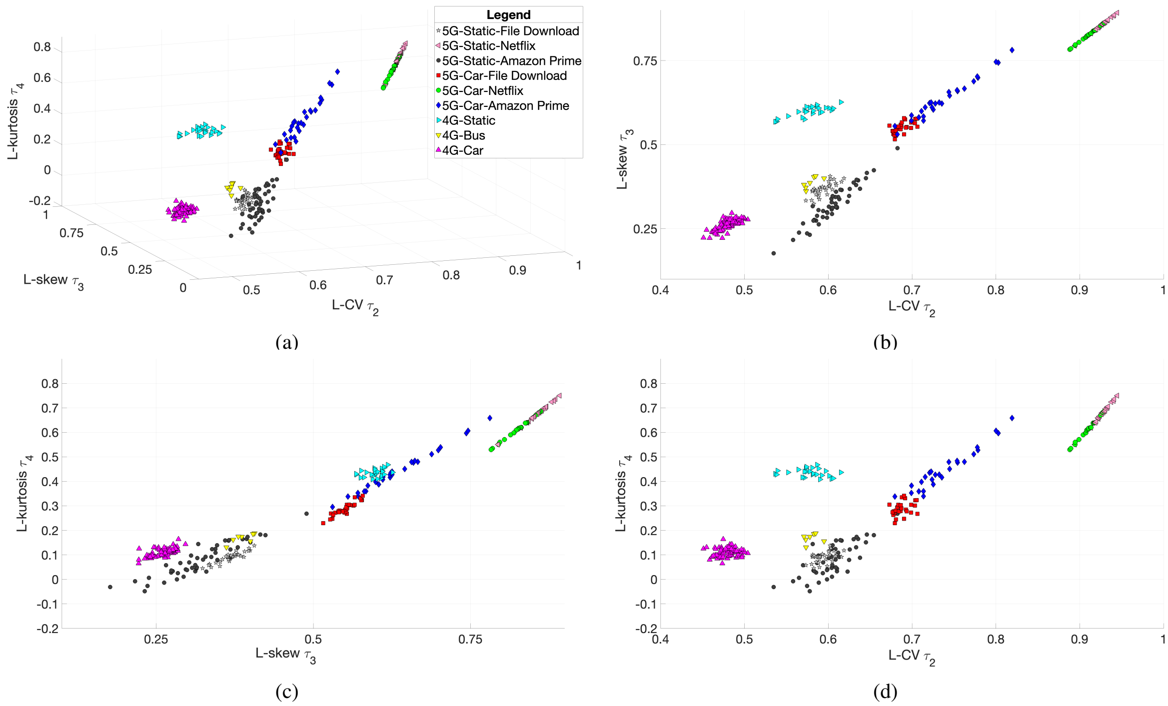


Fig. 2. L-moment ratio diagram including the estimation for L-CV τ_2, the L-skew τ_3 and the L-kurtosis τ_4 of the `DL_bitrate` feature. Both 3D representations along with the 2D projections for each pair of axes are plotted in subfigures. All subfigures share the legend.

streaming services and downloads, leading to buffering or quality degradation due to bitrate adaptation. The slightly positive L-skew indicates that, while low bitrates occur, users still experience occasional high-bitrate periods, though not consistently. The lack of extreme peaks or drops – due to normal-like L-kurtosis – suggests a moderately stable network performance, rather than abrupt degradation.

E. `CQI` feature

The CQI is computed by the mobile device and utilized by the network to dynamically adjust the transmission parameters. It is an indicator of radio channel quality based on multiple factors like SNR, interference, signal quality, etc. Therefore, understanding its statistical behavior could provide valuable insights to improve network management and optimize transmission parameters. Figure 3 presents the obtained results[1].

It is observed low value (< 0.22) for τ_2 across all patterns, indicating significantly lower data variance for this feature compared to other analyzed features. These values indicate uniformity in the measured CQI values, which we consider beneficial from a network management perspective.

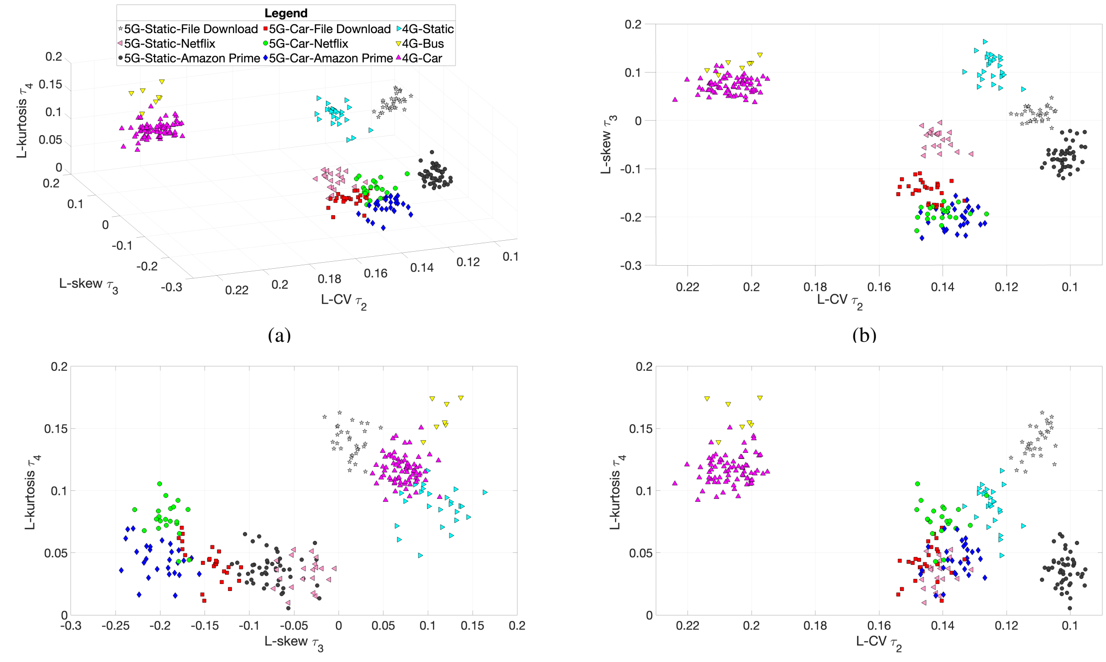
Regarding the τ_3 and τ_4 metrics, three groups can be observed: the complete 4G-LTE dataset, the static pattern in 5G, and the car pattern in 5G. First, the L-skew is approximately 0.09 indicating a higher probability of lower `CQI` values and that the dataset's median is lower than its average, while the L-kurtosis is close to 0.11 – close to the Gaussian distribution value of 0.1226. Second, the L-skew is concentrated around 0, while the L-kurtosis is around 0.14, closely matching the logistic distribution, where $\tau_3 = 0$ and $\tau_4 = 1/6$. The third group exhibits a negative L-skew ranging approximately between -0.25 and -0.1, along with a very low L-kurtosis between 0 and 0.07. Data from 5G show a null or negative L-skew, suggesting a higher probability of higher `CQI` values and that the median is greater than the average. These results indicate that the `CQI` for 4G-LTE is lower than that measured in the 5G experiments.

At this stage, it would be ideal to determine whether this difference is directly attributable to the communication standard. However, it is crucial to consider multiple confounding factors and avoid the fallacy of equating correlation with causation. First, the experiments for the two datasets were conducted at different points in time, likely several years apart [15], [16]. Additionally, there are no guarantees that the experimental conditions were perfectly comparable. For instance, the routes followed in the car mobility pattern may have differed due to changes in the urban mobility infrastructure of Cork.

IV. Conclusions and Future Work

This work has provided a comparative analysis of 4G-LTE and 5G networks using L-moment ratio diagrams, offering new insights into their statistical behavior across different mobility and service categories. Our results highlight significant differences in DL bitrate, signal quality, and mobility patterns, demonstrating the impact of 5G's architectural advancements on network performance.

Key findings indicate that 5G offers a more stable and predictable bitrate distribution, particularly for high-mobility users, while 4G-LTE networks show higher variability and less consistent QoS. The L-CV and L-skew further confirm that 4G-LTE users in mobile scenarios experience more frequent fluctuations in bitrate and a degraded QoS due to higher CQI variability. Additionally, one of the challenges encountered in this study was the presence of traffic in the dataset from



(a) (b) (c) (d)

Fig. 3. L-moment ratio diagram including the estimation for L-CV τ_2, the L-skew τ_3 and the L-kurtosis τ_4 of the `CQI` feature. Both 3D representations along with the 2D projections for each pair of axes are plotted in subfigures. All subfigures share the legend.

network standards other than the declared one, which could introduce inconsistencies in the comparative analysis. This highlights the difficulty of ensuring dataset homogeneity in real-world network measurements and underscores the need for the development of new datasets with stricter validation and collection methodologies.

Future work could expand this analysis by incorporating more mobility patterns and service types to gain a broader perspective on network behavior. Adding QoS metrics such as packet loss, jitter, and end-to-end latency would provide a clearer understanding of how network conditions impact user experience. Additionally, studying network performance over time, particularly during peak and off-peak hours, could help uncover relevant traffic trends. Finally, combining the statistical insights from L-moments with ML techniques to develop predictive models for traffic optimization could lead to smarter, more adaptive network management strategies.

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