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Measurement of Packet Loss Patterns in Urban Broadband Networks

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Abstract

Urban broadband networks are crucial for communication, video streaming, and other digital services. However, in today's world, where high-speed connections are a necessity, studying network reliability, in particular, packet loss, has become vital. This urban broadband packet loss is the focus of this measurement-based study. Using urban monitoring probes, we gather packet data from multiple access networks, including fiber, DSL, and wireless broadband. Our goal is to determine the location and time packet loss occurs, its dependence on network traffic, and its response to varying time-of-day conditions. To quantify the loss burst and the distribution burst, a statistical modeling technique is used. We study the effects of packet loss on end-user services like VoIP and video streaming and thus calculate the practical Quality of Experience (QoE). We also propose a classifier for loss patterns in networks, which draws temporal feature vectors and uses supervised learning for validation. Our analysis shows that the majority of packet losses are bursty and linked to certain congested times. This research can help improve construction planning, resource distribution, and flexible network system algorithms.

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Keywords: Packet Loss, Broadband Networks, Urban Connectivity, Network Measurement, Congestion, Quality of Experience (Qoe), Temporal Analysis.

1 Introduction

As people's lives shift towards online learning, working remotely, telemedicine, and entertainment, the demand and need for reliable broadband networks have increased, especially in busy metropolitan areas (Dischinger et al., 2007). Out of all the different network performance criteria, the loss of data packets remains the most critical indicator of service quality (Taleb & Odeh, 2024). Packet loss describes the skipped data in 'packets' that is essential to the real-time applications that make video calls, play games online, and use voice over internet services (Baltrunas et al., 2016).

Urban broadband networks utilize a range of equipment, including fiber optics, coaxial cables, DSL access, and wireless access points (Ma et al., 2023). Due to the high user demand, older network components, and a lot of electromagnetic interference and dynamic routing, urban broadband networks face greater challenges and stress as compared to rural networks (Velliangiri, 2024). Unlike rural areas, urban broadband systems face challenges such as user density, infrastructure restrictions, high-rise interference, and overlapping wireless frequencies.

Understanding packet loss is essential for improving quality of service (Quality of Service) and QoE (Quality of Experience). While most people focus on throughput and latency, it is equally important to focus on packet loss, especially the bursty type (Borella, 2000). Audio degradation, video buffering, data transfer interruptions, and other quality degradations that infuriate end users to no end are caused by bursty packet loss (Baltrūnas et al., 2015).

Previous research on broadband performance has not systematically considered packet loss in urban areas, even with prior works conducted on rural broadband. General studies focus primarily on performance metrics, and packet loss is typically seen as secondary (Tuohy et al., 2016). This leads to an incomplete explanation of packet loss and its various broadband settings. To achieve this goal, we deploy a blend of passive monitoring and active probing to collect packet-level information in diverse urban broadband settings. The goal is to identify various forms of loss, including bursty loss and isolated loss, as well as assess peak hours and congestion levels of network traffic (Fang et al., 2025).

Additionally, we apply statistical algorithms alongside machine learning techniques to classify the diverse forms of loss. This, alongside recognizing recurring trends and anomalies, would provide broadband network providers the ability to predict maintenance, as well as determine dynamic routing ahead of time (Sudhakar et al., 2019). The obtained results can also help in the application of adaptive error correction algorithms as well as congestion control measures (Rahim, 2023). Limitations of this study are that it considers only urban broadband considerations, which restrict its contribution to the field of performance evaluation. This study highlights the need to regard packet loss as a primary area of study rather than as an associated consequence of other performance factors.

Key Contributions:

- In an urban setting, an in-depth, real-time evaluation of packet loss patterns over fiber, DSL, and wireless networks.
- A novel Burstiness factor (BF) and loss behavior classification using machine learning-based feature vectors are proposed.

- More specifically, for congestion-aware urban ISP routing, dynamic QoE provisioning, and urban ISP QoE.

In the other parts of the paper, such as the Introduction, it summarizes two articles about packet loss concerning urban broadband analysis. It will cover the architectural frameworks in Section III and feature extraction in the appropriate parts of the paper. In section IV, it will also detail the visual aspects and self-evaluation metrics of models in terms of their rationality and overall performance. Finally, it will summarize the findings in Section V while discussing research to be finalized in the paper.

2 Literature Survey

The issue of packet loss has been a hot topic for years in the field of broadband network research. As with many other technologies, the internet has become an indispensable part of life (Samizadeh, 2019). This has made the study of broadband network packet loss phenomena increasingly crucial in urban areas (Rahman, 2024). In studying the network functions, a range of features like delay, throughput, and jitter have been studied, but packet loss has always been put in the background and never treated as the main factor (Tobagi, 2002). The earlier network measurement studies concentrated exclusively on the so-called end-to-end performance measurements (Rischke et al., 2021). These studies helped to understand the problem of how packets are transmitted through the network, what causes congestion, how routing changes affect the drop of packets, and how the evolution of networks in time changes this behavior (Klavin, 2024). Nonetheless, most studies have been conducted on backbone or wide area networks, and little research has been done on urban broadband access networks, which geographically and topologically, as well as functionally, differ significantly (Brik et al., 2008).

With the advent of high-speed internet services, intensive performance measurement programs were initiated to monitor the quality of services provided in broadband (Maier et al., 2009; Yang, 2022). These included the installation of household probes for measuring specified latency, throughput, and packet loss metrics (Alay et al., 2022). While these attempts collected useful information, they failed to distinguish between urban, suburban, and rural places, instead treating entire regions as one. Because of that, Apple and other companies overlooked the prevailing issues in the metropolitan areas (Zadobrischi et al., 2025). There is considerable literature discussing the effect of packet loss on video streaming, VoIP, and online gaming (Fida et al., 2019). These studies pointed out that even a small percentage of packet loss could disrupt the user experience (Zhang et al., 2019). Especially, if the packet loss is in bursts, resulting in jitter, buffering, or audio glitches. In these cases, packet loss versus Quality of Experience (QoE) has become one of the most discussed issues.

About population density, electromagnetic interference, and varying types of infrastructure, urban broadband networks are more challenging (Afanasyev et al., 2008). These issues cause unpredictable and bursty packet loss. Unlike simpler topologies present in rural regions, metropolitan networks include overlapping access technologies like fiber optics, DSL, broadband, and mesh networks (Al-Shehri et al., 2017). These interfaces worsen packet routing and create more congestion and data loss (Beyene et al., 2023). New research in data-driven network analysis has revealed new approaches to studying packet loss (Won-Bum et al., 2004). Machine learning and statistical analysis are currently being used to identify and classify patterns of movement and cycles in data flow. Yet, the majority of these models focus on predicting network outages, anticipating congestion, and anomaly detection (Romaniak & Janowski, 2010). In addition, the majority of these models are built on unrealistic frameworks of urban environments, like static or evenly distributed loads (Eltahir, 2007).

Another complicated issue in current research is the lack of detailed, multidimensional, and temporal analysis. Existing research, for instance, seems to overlook short-term spikes in packet loss during peak

traffic times, averaging outburst packet loss over more extended periods. Even though these bursts are short, they greatly diminish the quality of service and are masked by long-term averages. Without a multidimensional analysis, critical factors that affect the end-user experience may be ignored by service providers. The issue of spatial variability has also received little attention. Packet loss rates in most urban areas, for example, differ significantly from neighborhood to neighborhood because of differences in infrastructure, aging equipment, interference, and localized disruption.

To truly grasp the dynamics of urban broadband networks, the study of packet loss patterns must integrate both temporal and spatial dimensions (El-Saleh et al., 2023; Mishra et al., 2025). Having reviewed a great deal of the literature, I can conclude that the performance of broadband networks has been comprehensively researched, but the study of packet loss patterns specifically in urban areas is lacking (Sindhu, 2024). Most of these studies have either ignored the unique features of cities or have not actively focused on packet loss. I intend to conduct a modern, detailed, and high-precision measurement of packet loss in broadband networks of urban areas using advanced techniques and sophisticated pattern recognition to bridge the gap identified in the literature (Doniyorov et al., 2024).

3 Methodology

Different factors, such as congestion, interference, and the quality of infrastructure ecosystems, lead to broadband urban networks experiencing diverse packet loss and varying patterns. To analyze and understand these urban broadband loss patterns, both passive monitoring and active probing techniques were integrated to develop a more extensive approach. These monitoring devices were set up in urban locations with diverse access technologies, including but not limited to fiber optics, DSL, and broadband wireless. These devices were capturing real-time traffic for weeks, including peak and off-peak periods. Using the methods described in the previous paragraph, raw collected data can be cleaned, in which relevant data is separated from irrelevant data. Once irrelevant data is removed, the collection can be cleaned more and normalized to make the data mathematically usable. With this information, loss frequency, loss duration, and burstiness can be measured using statistical models. At the same time, machine learning was utilized to generate feature vectors from streams of data packets to enable classification of different behaviors associated with packet loss. By doing this, the goal is to recognize repetitive patterns data, correlations with the time of the day, and one of the most critical objectives, consistency across different networks. The impetus behind this approach is to determine not only how prevalent packet loss is, but to reveal the context of why it happens in urban broadband environments.

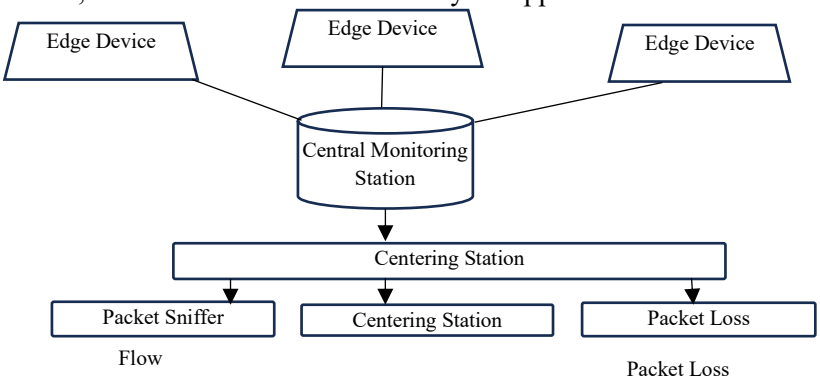

Figure 1: Urban broadband packet loss detection architecture

In urban broadband networks, Figure 1 shows the architecture for detecting packet loss. The system is built around a distributed model comprising edge devices, central monitoring systems, and machine

learning powered detection engines. Edge devices are positioned throughout the network to capture real-time traffic data, including packet sequences and transmission anomalies. These devices interface with a Central Monitoring Station, which consolidates data and applies advanced algorithms to identify missing, delayed, and loss patterns of packets.

The architecture includes an Anomaly Detection Engine that classifies loss types using intelligent learning algorithms, triggering alerts. This data is still sent to the Centering Station, which performs more complex analysis. This station contains a Packet Sniffer monitoring flow metrics, a Learning Integration Unit that merges real-time with historical data, and a Packet Loss Identifier that detects and classifies dropped packets. The learning engine adapts to refine detection models, allowing the detection system to respond adaptively to the degradation of the network.

This complex urban broadband architecture, comprising various network types such as fiber, DSL, and wireless, significantly enhances the accuracy and reliability of loss detection, offering valuable insights into network congestion, infrastructure inefficiencies, and performance delays.

Mathematical Model:

To measure and explain the packet loss behavior in an urban broadband network, a set of equations is derived. These equations account for basic packet loss data along with the intricate time-based patterns crucial for understanding data traffic in saturated urban regions.

Packet Loss Rate (PLR):

The fundamental metric for packet loss is defined as:

$$PLR = \left(\frac{N_s - N_r}{N_s}\right) \times 100 \qquad (1)$$

Where:

- N_s = Total Number of packets sent
- N_r = Total Number of packets received

Equation (1) shows the percentage of packets that failed to reach their destination. It is used to evaluate the overall reliability of the broadband network. A PLR above 1% in real-time applications is often deemed critical.

Burst Loss Ratio (BLR):

To capture the nature of bursty losses, we define:

$$BLR = \frac{B}{L} \qquad (2)$$

Where:

- B = Number of burst loss events
- L = Total Number of loss events

Equation (2) shows the ratio of clustered (bursty) losses to total losses. A higher BLR indicates a strong presence of congestion or interference that causes back-to-back packet drops.

Inter-Loss Time Interval (ILTI):

Temporal gaps between losses are measured as:

$$ILTI = \frac{T}{L - 1} \qquad (3)$$

Where:

- T = Total time duration of observation
- L = Total Number of packet loss events

Equation (3) shows the average time interval between two consecutive loss events, giving insight into whether packet loss is randomly distributed or occurs in tight clusters.

Burstiness Factor (BF):

Combining temporal and volume characteristics:

$$BF = \left(\frac{N_b . D_b}{T}\right) . \left(\frac{P_l}{P_t}\right) \qquad (4)$$

Where:

- N_b = Number of burst loss periods
- D_b = Average duration of each burst (seconds)
- T = Total observation time (seconds)
- P_l = Number of packets lost in bursts
- P_t = Total packets lost

Equation (4) shows the *Burstiness Factor*, which reflects the intensity and dominance of burst losses in a given interval. It helps differentiate between sporadic and congestion-driven packet loss behavior.

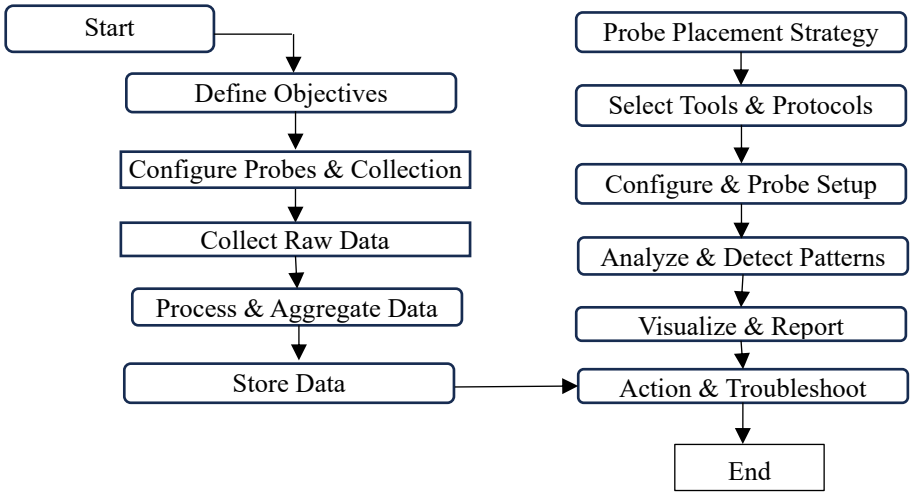

Figure 2: Flowchart of packet loss measurement in urban broadband networks

In Figure 2, the step-by-step flowchart exemplifies how to measure packet loss in urban broadband networks. The entire workflow begins with setting the objectives of the measurement campaign, followed by setting up data probes and collecting raw network traffic data. Along with data collection, there is also a strategic design of the probe placement, and the necessary monitoring tools and protocols are chosen for broadband heterogeneity. After raw data collection, the monitoring architecture is built, which involves data collection and a series of processing steps such as aggregation and cleaning. The monitor-clean model builds are constructed sequentially to generate a model-free dataset. This dataset is retained until behavioral loss is identified, at which point data is processed through pattern analysis, utilizing various anomaly detection and statistical inference techniques.

After analysis, the data is summarized and presented visually, including reports and graphs to aid in data interpretation. The study presented assists in network optimization through fine-tuning network functionality and corrective measures. The final step is to store raw data for analysis of trends and changes in data over time. The flowchart is clear for urban broadband packet loss to aid researchers and network engineers, providing a clear model to follow.

Dataset Description

The dataset used in this study was collected over 4 weeks from urban broadband deployments in four metropolitan districts. Data probes were installed at 12 endpoints representing diverse access types (fiber, DSL, and wireless). Each probe recorded real-time packet traces, including timestamps, packet sizes, inter-arrival times, and sequence numbers. Data was logged during peak and non-peak hours, generating approximately 200 GB of raw traffic logs. All packet traces were anonymized to ensure user privacy. This diverse and high-volume dataset provided the foundation for the statistical modeling and pattern classification described in the subsequent subsections.

Data Segmentation and Preprocessing

The raw packet-level information retrieved from various urban broadband sources undergoes segmentation into uniform time windows ranging from 5 to 10 seconds. Each time segment functions as a snapshot of a continuous traffic stream, enabling focused examination of packet loss during the period. The dataset undergoes critical steps, including the removal of duplicates, incomplete logs, and non-IP frames, to improve accuracy. Additionally, it is time-aligned to adjust timestamps across probes with many edge nodes, enabling proper time alignment. There are also custom filters which are used to disregard irrelevant control traffic to focus on the user-level data which yields a controllable dataset which is consistent in time and structured for statistical analysis and machine learning. The entire system is automated to enable faster, wide-area implementations and minimize manual error when dealing with packet traces.

Feature Vector Construction

Once the data is divided, important statistical characteristics from each time frame are used to build multidimensional feature vectors. Features that are extracted include the statistics of inter-arrival time, the distribution of packet size, packet retransmission indicators, and gaps in the sequence numbers. Also calculated are temporal properties such as the duration of bursts, the counts of loss clusters over time, and the variability in the time between packets. As behavioral indicators, each vector corresponds to a network state within that time frame. Feature vectors encode quantitative characteristics which permit classification models to distinguish between normal network traffic, sporadic loss, bursty loss, and persistent degradation. These vectors are also assigned labels based on known ground truth or statistical thresholds, which allows for supervised learning and frameworks for detecting anomalies.

Temporal Pattern Detection

Identifying loss trends over time comes after feature construction. The observation period can be split into intervals morning, afternoon, evening peak, and night based on user activity. Different time intervals are assigned PLR, ILTI, and BF metrics. Spikes and other anomalies, such as periodic bursts and sustained high-loss periods, are detected using time-series analysis. Significant anomalies are also detected using moving average and peak detection algorithms, which refine packet transmission. This form of profiling helps researchers correlate packet loss with actual network activity, such as congestion during business hours, maintenance during the night, or heavy infrastructure loads. The derived knowledge is useful for network providers focused on adapting bandwidth or applying congestion control dynamically.

Pattern Classification Using Machine Learning

The last part of the methodology is focused on the trainable model of the observed packet loss patterns. Classifying observed packet loss patterns can be accomplished via machine learning. For the models of the decision trees and the random forests models they were both selected due to their robustness in dealing with noisy network data. The model employs labeled feature vectors and assesses model validation with stratified k-fold cross-validation. The categories of the output are normal (no loss), sporadic loss, bursty loss, and persistent loss. The model is evaluated on its precision, recall, and F1-score. The verifiable data is also extracted to shed the light of certain metrics loss of inter-arrival variance or loss frequency that most affects the decisions on losses. The automated detection of the loss conditions can be done in real time systems, and in turn can enable automated alerts or mitigation actions.

4 Results and Discussion

Urban broadband networks have unique behaviors of data loss depending on network types, locations, and temporal usage patterns (Al Jahdhami et al., 2024). The packet-level data collected from various urban parts were sliced, scrutinized, and structured into classes through both statistical and machine learning models. The earliest analysis revealed considerable changes in loss rates, particularly, bursty loss events during the peak hours. This was especially observed in shared bandwidth technologies, like wireless broadband, as opposed to dedicated fiber optic lines, which exhibited consistent performance.

From the dataset, two distinct packet loss behaviors were identified: the sporadic loss could be episodic and occurs randomly at some point during the day, and burst loss which occurs clustered in clusters within peak and high-traffic period. The temporal analysis suggested a strong attribution of bursty losses to higher downstream demand. Some geographic variation was also notable, with older infrastructure zones having a higher loss rate compared to newly upgraded zones. In addition, machine learning-based pattern classifiers were highly accurate in distinguishing loss types, confirming the relevance of the feature vectors that were extracted. The presented findings are essential for the development of traffic responsive measures and policies for proactive infrastructure change.

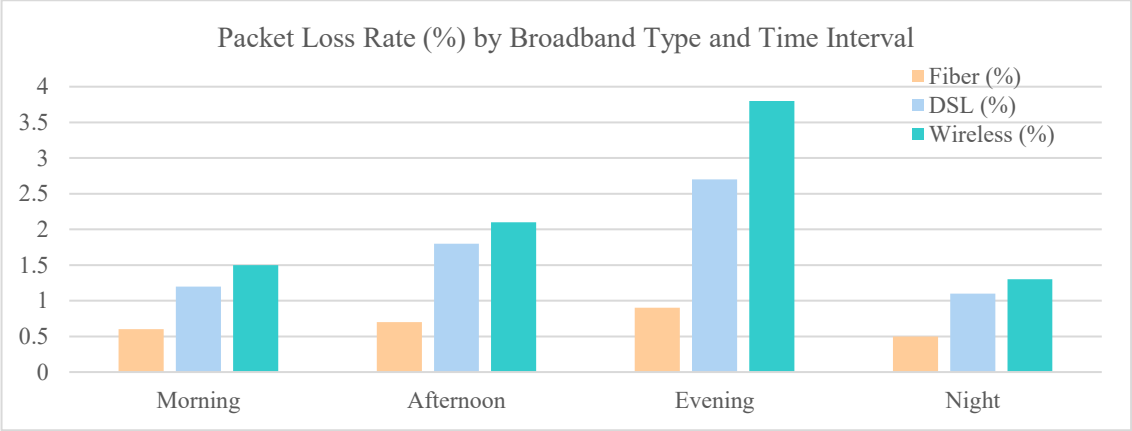

Figure 3: Average packet loss rate (%) by broadband type and time interval

Figure 3 highlights the fact that packet loss occurs the most with wireless and DSL networks during the peak evening hours. Wireless networks have the highest packet loss at 3.8%, DSL networks follow with a 2.7% loss while fiber networks maintain their packet loss under 1%. Fiber networks provide the most reliable performance throughout the day while shared networks like wireless are prone to

congestion-related losses (Parichehreh et al., 2018). All of this demonstrates the need of incorporating dynamic bandwidth and improving infrastructures during peak hours.

Table 1: Classification Accuracy of Packet Loss Patterns by Network Type

Broadband Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Fiber Optic	94.3	92.8	91.6	92.2
DSL	87.5	85.2	84.7	84.9
Wireless	82.1	80.4	79.2	79.8

According to table 1 this modem classifies packet loss patterns across broadband types with reasonable accuracy. Fiber networks performed best achieving the highest accuracy at 94.3% due to their stability. DSL showed moderate performance with 87.5% accuracy, while wireless had the lowest at 82.1%. Precision and recall trends follow this order as well, with fiber having fewer false positives and wireless missing more burst events. The results highlight the model's reliability while shedding light on more performant alternatives in constantly changing conditions.

Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \qquad (5)$$

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Equation (5) is used to measures the proportion of total correct predictions (both positive and negative) among all predictions. It gives an overall correctness rate for the classifier.

Precision:

$$Precision = \frac{TP}{TP + FP} \times 100 \qquad (6)$$

Equation (6) indicates the percentage of correctly predicted positive instances out of all instances predicted as positive. A high precision means fewer false positives.

Recall:

$$Recall = \frac{TP}{P + FN} \times 100 \qquad (7)$$

Equation (7) shows Recall (also known as sensitivity or true positive rate) reflects how many actual positive instances were correctly identified by the model. A high recall means fewer false negatives.

F1-Score:

$$F1 - Score = 2 \times \frac{Precision + Recall}{Precision \times Recall} \qquad (8)$$

The equation (8) shows F1-score which is the harmonic mean of precision and recall. It balances both metrics and is particularly useful when the class distribution is imbalanced.

5 Conclusion

This study performed a detailed examination of the packet loss phenomenon within the context of urban broadband network infrastructures, integrating real-time data collection, statistical modeling, and machine learning for classification routines. The study found that packet loss is a lossy process which is sensitive to the infrastructure used and varies with time; noticeably, wireless and DSL technologies

suffered much greater loss rates during peak usage hours than fiber optic connections. The classification model, along with the proposed Burstiness Factor, showcased mastery capture of the phenomenon's temporal nature, which enabled exact identification of sporadic, bursty, and persistent loss with a high degree of precision. These findings lay a solid groundwork for enhanced network provisioning and urban network management in a dense urban environment aiming to improve the user's Quality of Experience (QoE).

The establishment of a real-time adaptive response framework that dynamically reroutes traffic or applies other corrective actions during identified loss bursts could serve as a basis for further research. Other broadband performance metrics, such as jitter and latency, could also be integrated as QoS parameters to enable a multi-metric evaluation. The introduction of cloud monitoring systems along with edge computing could improve responsiveness and scale. Given the anticipated surge in urban internet demands, broadband infrastructure and policy anticipate need long-term planning models, driven by AI and trend analysis, to ensure resilient and equitable access.

References

[1] Afanasyev, M., Chen, T., Voelker, G. M., & Snoeren, A. C. (2008, October). Analysis of a mixed-use urban wifi network: when metropolitan becomes neapolitan. In *Proceedings of the 8th ACM SIGCOMM conference on Internet measurement* (pp. 85-98). https://doi.org/10.1145/1452520.1452531

[2] Al Jahdhami, M. A., El-Saleh, A., Alhammadi, A., & Shayea, I. (2024, July). Comparative Study of Indoor Performance Metrics in Ibra City's Mobile Broadband Networks, Oman. In 2024 6th International Conference on Communications, *Signal Processing, and their Applications (ICCSPA)* (pp. 1-6). IEEE. https://doi.org/10.1109/ICCSPA61559.2024.10794218

[3] Alay, Ö., Lutu, A., García, R., Peón-Quirós, M., Mancuso, V., Hirsch, T., ... & Lonsethagen, H. (2022). MONROE: Measuring mobile broadband networks in Europe. In *Building the Future Internet through FIRE* (pp. 155-187). River Publishers.

[4] Al-Shehri, S. M., Loskot, P., Numanoğlu, T., & Mert, M. (2017). Metrics for broadband networks in the context of the digital economies. In *Broadband Communications Networks-Recent Advances and Lessons from Practice*. IntechOpen.

[5] Baltrūnas, D., Elmokashfi, A., & Kvalbein, A. (2015, April). Dissecting packet loss in mobile broadband networks from the edge. In *2015 IEEE conference on computer communications (INFOCOM)* (pp. 388-396). IEEE. https://doi.org/10.1109/INFOCOM.2015.7218404

[6] Baltrunas, D., Elmokashfi, A., Kvalbein, A., & Alay, Ö. (2016, May). Investigating packet loss in mobile broadband networks under mobility. In *2016 IFIP networking conference (IFIP networking) and workshops* (pp. 225-233). IEEE. https://doi.org/10.1109/IFIPNetworking.2016.7497225

[7] Beyene, F., Negash, K., Semeon, G., & Getachew, B. (2023). CMOS Technology: Conventional Module Design for Faster Data Computations. *Journal of VLSI Circuits and Systems, 5*(1), 42–48. https://doi.org/10.31838/jvcs/05.01.06

[8] Borella, M. S. (2000). Measurement and interpretation of internet packet loss. *Journal of Communications and Networks, 2*(2), 93-102. https://doi.org/10.1109/JCN.2000.6596738

[9] Brik, V., Rayanchu, S., Saha, S., Sen, S., Shrivastava, V., & Banerjee, S. (2008, October). A measurement study of a commercial-grade urban wifi mesh. In *Proceedings of the 8th ACM SIGCOMM Conference on Internet Measurement* (pp. 111-124). https://doi.org/10.1145/1452520.1452534

[10] Dischinger, M., Haeberlen, A., Gummadi, K. P., & Saroiu, S. (2007, October). Characterizing residential broadband networks. In *Proceedings of the 7th ACM SIGCOMM conference on Internet measurement* (pp. 43-56). https://doi.org/10.1145/1298306.1298313

[11] Doniyorov, A., Polvonov, J., Jalolova, S., Sattorova, Z., Yakubova, M., Gaybullaev, O., Abdullaev, A., & Abdukarimov, A. (2024). Designing inclusive cities – the role of urban architecture in enhancing accessibility for the visually impaired. *Archives for Technical Sciences, 2*(31), 393–402. https://doi.org/10.70102/afts.2024.1631.393

[12] El-Saleh, A. A., Alhammadi, A., Shayea, I., Hassan, W. H., Honnurvali, M. S., & Daradkeh, Y. I. (2023). Measurement analysis and performance evaluation of mobile broadband cellular networks in a populated city. *Alexandria Engineering Journal, 66*, 927-946. https://doi.org/10.1016/j.aej.2022.10.052

[13] Eltahir, I. K. (2007, August). The impact of different radio propagation models for mobile ad hoc networks (MANET) in urban area environment. In *The 2nd International Conference on Wireless Broadband and Ultra Wideband Communications (AusWireless 2007)* (pp. 30-30). IEEE. https://doi.org/10.1109/AUSWIRELESS.2007.80

[14] Fang, H., Zhao, H., Wang, F., Chou, Y. C., Chen, L., Shi, J., & Liu, J. (2025). Streaming media over LEO satellite networking: A measurement-based analysis and optimization. *ACM Transactions on Multimedia Computing, Communications and Applications, 21*(9), 1-24. https://doi.org/10.1145/3694976

[15] Fida, M. R., Acar, E., & Elmokashfi, A. (2019, October). Multiway reliability analysis of mobile broadband networks. In *Proceedings of the Internet Measurement Conference* (pp. 358-364). https://doi.org/10.1145/3355369.3355591

[16] Klavin, C. (2024). Analysing antennas with artificial electromagnetic structures for advanced performance in communication system architectures. *National Journal of Antennas and Propagation, 6*(1), 23–30. https://doi.org/10.31838/NJAP/06.01.04

[17] Ma, S., Chou, Y. C., Zhao, H., Chen, L., Ma, X., & Liu, J. (2023, May). Network characteristics of leo satellite constellations: A starlink-based measurement from end users. In *IEEE INFOCOM 2023-IEEE Conference on Computer Communications* (pp. 1-10). IEEE. https://doi.org/10.1109/INFOCOM53939.2023.10228912

[18] Maier, G., Feldmann, A., Paxson, V., & Allman, M. (2009, November). On dominant characteristics of residential broadband internet traffic. In *Proceedings of the 9th ACM SIGCOMM Conference on Internet Measurement* (pp. 90-102). https://doi.org/10.1145/1644893.1644904

[19] Mishra, P., Kar, S., & Wang, K. C. (2025). Enhanced reliability in mobility scenarios using multi-connectivity with packet duplication for next-generation networks. *EURASIP Journal on Wireless Communications and Networking, 2025*(1), 43. https://doi.org/10.1186/s13638-025-02463-y

[20] Parichehreh, A., Alfredsson, S., & Brunstrom, A. (2018, June). Measurement analysis of tcp congestion control algorithms in lte uplink. In *2018 Network Traffic Measurement and Analysis Conference (TMA)* (pp. 1-8). IEEE. https://doi.org/10.23919/TMA.2018.8506522

[21] Rahim, R. (2023). Effective 60 GHz signal propagation in complex indoor settings. *National Journal of RF Engineering and Wireless Communication, 1*(1), 23-29.

[22] Rahman, F. (2024). Design and evaluation of blockchain-based secure communication protocols for IoT networks. *Electronics, Communications, and Computing Summit, 2*(2), 28–36.

[23] Rischke, J., Sossalla, P., Itting, S., Fitzek, F. H., & Reisslein, M. (2021). 5G campus networks: A first measurement study. *IEEE Access, 9*, 121786-121803. https://doi.org/10.1109/ACCESS.2021.3108423

[24] Romaniak, P., & Janowski, L. (2010, June). How to build an objective model for packet loss effect on high-definition content based on SSIM and subjective experiments. In *International Workshop on Future Multimedia Networking* (pp. 46-56). Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-13789-1_5

[25] Samizadeh, R. (2019). An integrated model for optimizing distribution network with considering assembly line balancing. *International Academic Journal of Science and Engineering, 6*(1), 178–187. https://doi.org/10.9756/IAJSE/V6I1/1910017

[26] Sindhu, S. (2024). A blockchain-enabled framework for secure data exchange in smart urban infrastructure. *Journal of Smart Infrastructure and Environmental Sustainability, 1*(1), 31–43. https://doi.org/10.17051/JSIES/01.01.04

[27] Sudhakar, R., Rajakumari, J., Poornima, S., & Ramya, V. (2019). A security threats and authentication approaches in wireless sensor networks. *International Journal of Communication and Computer Technologies, 7*(2), 1-3.

[28] Taleb, A. A., & Odeh, A. (2024). Effective Routing of Mobile Sink in Wireless Sensor Networks Using Steiner Trees. *J. Wirel. Mob. Networks Ubiquitous Comput. Dependable Appl., 15*(2), 135-151. https://doi.org/10.58346/JOWUA.2024.I2.010

[29] Tobagi, F. A. (2002). Fast packet switch architectures for broadband integrated services digital networks. *Proceedings of the IEEE, 78*(1), 133-167. https://doi.org/10.1109/5.52203

[30] Tuohy, S., Winterlich, A., McGinley, B., Glavin, M., Jones, E., Denny, P., & Kilmartin, L. (2016). Evaluating the influence of packet loss on visual quality of perception for high bandwidth automotive networks. *Signal Processing: Image Communication, 43*, 15-27. https://doi.org/10.1016/j.image.2016.01.004

[31] Velliangiri, A. (2024). Security challenges and solutions in IoT-based wireless sensor networks. *Journal of Wireless Sensor Networks and IoT, 1*(1), 8-14. https://doi.org/10.31838/WSNIOT/01.01.02

[32] Won-Bum, S., Doug-Young, S., & Ji-Tae, S. (2004). Packet loss pattern modeling of cdma2000 mobile Internet channel for network-adaptive multimedia service. *The Journal of Korean Institute of Communications and Information Sciences, 29*(1B), 52-63.

[33] Yang, F. (2022). *Towards Efficient Transport Mechanisms in Mobile Internet: Measurement and Optimization* (Doctoral dissertation, Sorbonne Université; University of Chinese academy of sciences).

[34] Zadobrischi, E., Beguni, C. M., & Căilean, A. M. (2025). Strengthening Road Safety and Mobility at the Urban Level with the Aim of Digitizing and Shaping Smart Cities Through Emerging Vehicular Communications C-V2X, DSRC, and VLC. *Electronics (2079-9292), 14*(2). https://doi.org/10.3390/electronics14020360

[35] Zhang, J., Yu, W., & Lu, C. (2019, June). Performance assessment of LTE/LTE-A based wireless networks for internet-of-things. In *2019 IEEE/ACIS 18th International Conference on Computer and Information Science (ICIS)* (pp. 18-23). IEEE. https://doi.org/10.1109/ICIS46139.2019.8940292

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