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Review Article

Quality of Experience (QoE) and Network Performance Modelling for Multimedia Traffic

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Abstract: This research explores the complex relationship between user-perceived Quality of Experience (QoE) and underlying network performance for multimedia traffic. As video streaming, online gaming, and interactive media dominate modern networks, ensuring consistent QoE has become a key challenge. The study develops a network performance model that integrates objective Quality of Service (QoS) parameters—such as delay, jitter, packet loss, and throughput—with subjective QoE metrics like Mean Opinion Score (MOS) and perceptual quality indices. Using simulation-based and analytical approaches, the paper evaluates how network conditions affect multimedia traffic behavior and user satisfaction. The results highlight critical thresholds for QoE degradation, enabling predictive modeling for adaptive multimedia delivery and real-time optimization. This work contributes to designing intelligent, user-centered network management systems capable of balancing resource efficiency and end-user satisfaction.

Keywords: Quality of Experience (QoE), Quality of Service (QoS), Multimedia Traffic, Network Performance Modelling, Video Streaming, Jitter, Packet Loss, Throughput, Mean Opinion Score (MOS), Simulation, Analytical Modeling, Adaptive Bitrate, User Satisfaction, 5G Networks, Machine Learning, Network Optimization

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1. Introduction

The rapid growth of multimedia applications such as video streaming, video conferencing, online gaming, and real-time interactive services has dramatically increased the demand for high-quality network performance [1]. These applications are bandwidth-intensive and delay-sensitive, requiring networks to deliver not only sufficient throughput but also consistent quality from the user's perspective. Traditional network evaluation methods have relied primarily on **Quality of Service (QoS)** parameters—such as latency, jitter, packet loss, and bandwidth—to measure system performance. However, these metrics alone do not fully capture the **Quality of Experience (QoE)** perceived by end users, which depends on both technical and human factors [2].

QoE represents the overall acceptability of a service as perceived subjectively by the user [3]. It encompasses factors such as playback smoothness, resolution quality, buffering events, and even user expectations or device capabilities. As multimedia traffic continues to dominate global network usage [1], bridging the gap between objective QoS measurements and subjective QoE evaluations has become an essential research challenge [4]. Effective QoE modeling enables network operators and service providers to optimize performance dynamically, allocate resources intelligently, and maintain user satisfaction even under constrained network conditions.

Recent advancements in **network performance modeling** have introduced hybrid analytical and data-driven methods for predicting QoE outcomes [5]. By integrating network-level data with perceptual quality metrics, researchers can derive models that forecast user experience under varying network conditions. Such models can support adaptive streaming protocols, edge computing frameworks, and intelligent traffic management systems that respond proactively to degradation events.

This paper aims to investigate the interdependence between QoE and network performance in multimedia traffic. It develops a predictive modeling framework that correlates objective network parameters with user-perceived quality. Through simulation and analytical evaluation, the study provides insights into how network dynamics affect multimedia performance and offers recommendations for designing QoE-aware network optimization strategies.

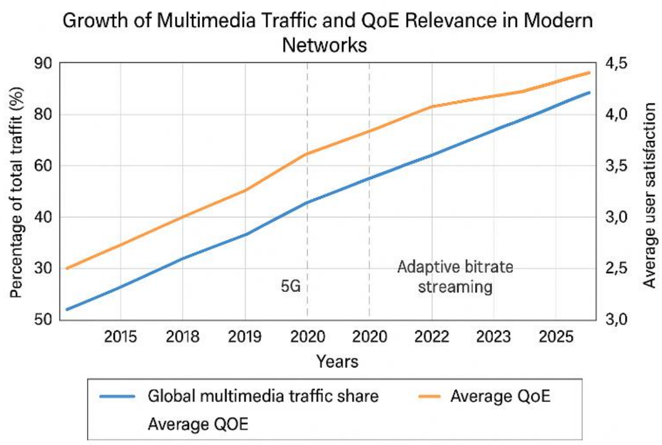

Figure 1. Growth of multimedia traffic and its impact on the importance of Quality of Experience (QoE) in next-generation network design.

Table 1. Comparison Between QoS and QoE Parameters

Aspect	Quality of Service (QoS)	Quality of Experience (QoE)
Definition	Objective measure of network performance using technical parameters.	Subjective assessment of user satisfaction with the service.
Measurement Basis	Network metrics (delay, jitter, packet loss, throughput).	User perception metrics (MOS, SSIM, VMAF, buffering rate).
Layer of Evaluation	Network layer and transport layer.	Application layer and user layer.
Primary Focus	Ensuring network reliability and performance.	Ensuring user satisfaction and perceived service quality.
Influencing Factors	Network congestion, bandwidth, packet delay variation.	Content quality, playback smoothness, device type, user expectations.
Measurement Tools	Network analyzers, SNMP, Wireshark, QoS probes.	Subjective testing, ITU-T standards, QoE estimation models.

2. Literature Review

2.1. Overview of QoE and QoS

The relationship between **Quality of Service (QoS)** and **Quality of Experience (QoE)** forms the foundation of multimedia performance research [2,4]. QoS refers to the measurable, objective parameters of network behaviors such as delay, jitter, packet loss, and throughput—while QoE represents the subjective evaluation of service quality from the end-user's perspective. The International Telecommunication Union (ITU-T) defines QoE as "the overall acceptability of an application or service, as perceived subjectively by

the end user" [3].
Early studies primarily focused on QoS-oriented optimization, if improving network metrics directly enhances user satisfaction. However, it became evident that QoE depends on additional factors, including human perception, device type, codec quality, and application behavior. Consequently, researchers began modeling the **nonlinear correlation** between QoS and QoE to better represent user-centric performance [4].

2.2. QoE Assessment Models

QoE assessment methodologies can be broadly categorized into **subjective** and **objective** models [6]:

- **Subjective Assessment Models:** These involve human evaluations such as the **Mean Opinion Score (MOS)** or **Double Stimulus Continuous Quality Scale (DSCQS)**, as standardized by ITU-T P.800. Although accurate, they are time-consuming and unsuitable for real-time evaluation.
- **Objective Assessment Models:** These predict QoE using measurable metrics, often employing video quality metrics such as:
    - PSNR (Peak Signal-to-Noise Ratio)
    - SSIM (Structural Similarity Index)
    - VMAF (Video Multimethod Assessment Fusion) by Netflix [8]
      Newer models, such as ITU-T P.1203, integrate both network-level and perceptual parameters to evaluate streaming video quality dynamically [9].

2.3. Network Performance Modeling

Network performance modeling focuses on understanding how varying network conditions affect multimedia service delivery. Techniques include:

- **Analytical Models:** Based on **queuing theory**, **Markov chains**, and **probabilistic modeling** to represent packet transmission, delay variation, and congestion behavior.
- **Simulation-Based Models:** Tools such as **NS3**, **OMNeT++**, and **OPNET** simulate different traffic conditions to analyze multimedia flow performance.
- **Machine Learning-Based Models:** Recent research leverages regression, neural networks, and reinforcement learning to predict QoE from QoS data, enabling adaptive resource allocation [10,11].

2.4. Integration of QoS–QoE Correlation

Several mapping models have been proposed to describe the nonlinear relationship between QoS and QoE, such as:

- **Logistic and Exponential Models** — translating packet loss or delay into MOS values [2].
- **Polynomial Regression Models** — for predicting QoE based on multiple QoS parameters.
- **Machine Learning Frameworks** — using algorithms like Random Forest, SVM, and Deep Neural Networks for prediction and classification of user satisfaction [10].

These approaches reveal that QoE is not solely dependent on network metrics but is influenced by contextual factors such as content type, user expectations, and device capabilities [12].

2.5. Research Gaps

Despite significant progress, several challenges remain [13]:

1. Lack of **universal QoE prediction models** applicable across different multimedia types and network technologies.

2. Limited understanding of **cross-layer QoE optimization**, where application and network parameters interact dynamically.
3. Incomplete integration of **user behavior modeling** and **real-time adaptation** in current frameworks.
4. Need for **standardized datasets** and **evaluation benchmarks** for machine learning–based QoE estimation.

Addressing these gaps motivates the development of a **comprehensive QoE–network performance model** that bridges subjective and objective perspectives, which this paper seeks to accomplish.

Table 2. Comparison of QoE Assessment Methods

Method Type	Technique / Example	Measurement Basis	Advantages	Limitations	Typical Use Case
Subjective	Mean Opinion Score (MOS), ITU-T P.800, DSCQS	Human perception and user ratings	High accuracy, directly reflects user perception	Costly, time-consuming, not scalable	Laboratory testing, service validation
Objective (Signal-Based)	PSNR, SSIM, VMAF	Comparison of original and transmitted signals	Automated, reproducible, quick analysis	Ignore human perception nuances	Video streaming quality benchmarking
Objective (Parametric / Hybrid)	ITU-T P.1203, E-model	Uses network and codec parameters to infer QoE	Real-time estimation, scalable	Requires calibration, may vary by scenario	Network performance monitoring, adaptive streaming
Data-Driven (Machine Learning)	Random Forest, SVM, Deep Neural Networks	Predicts QoE from QoS datasets	Adaptive, captures nonlinear relations	Needs large training data, model interpretability issues	Intelligent QoE prediction, self-optimizing networks

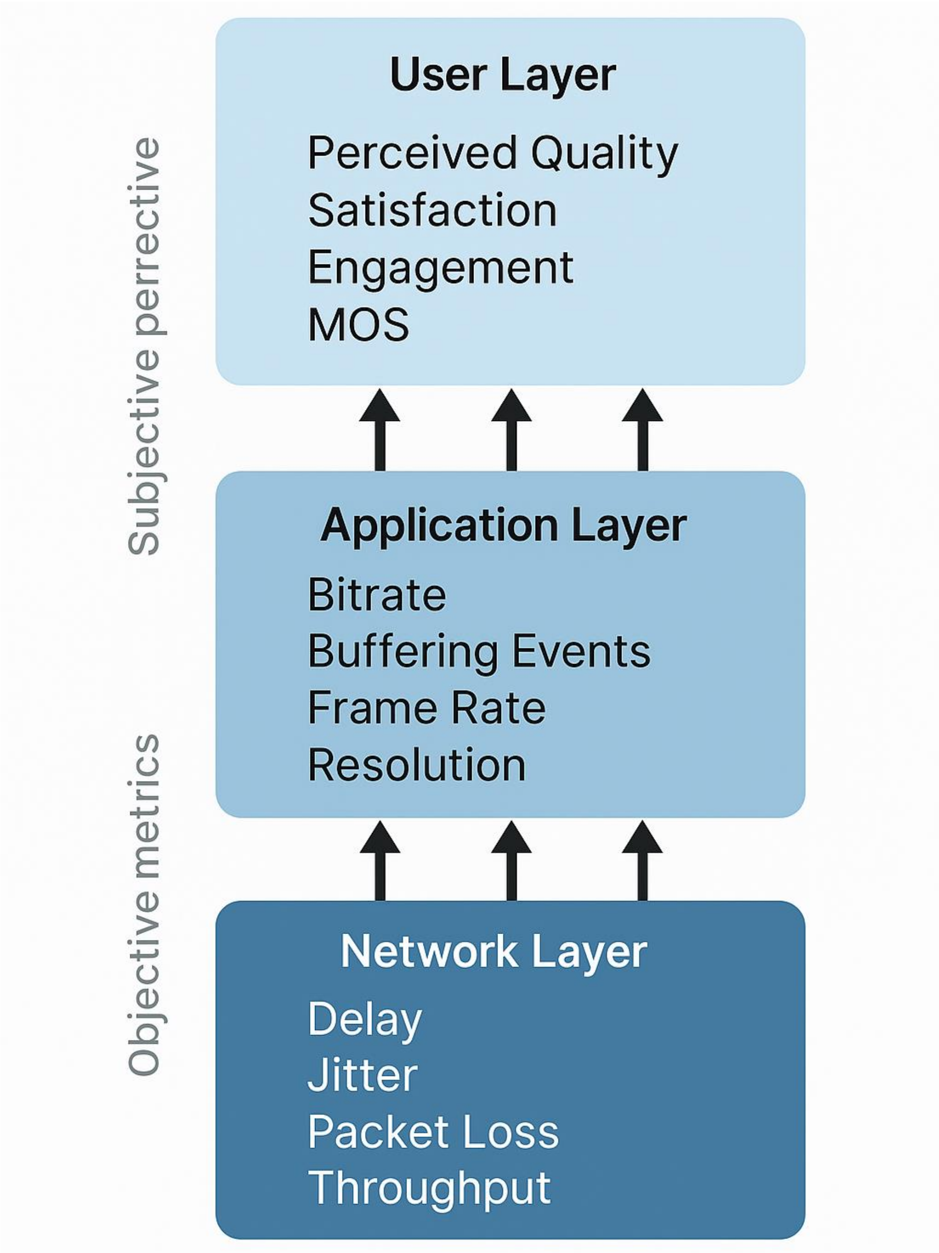

Figure 2. Conceptual framework illustrating the mapping between QoS parameters, application behavior, and user-perceived Quality of Experience (QoE).

3. Theoretical Framework

The theoretical framework establishes the conceptual and mathematical foundation linking **network-level performance metrics (QoS)** with **user-perceived service quality (QoE)**. It forms the basis for developing predictive models that translate objective network parameters into subjective user satisfaction indicators.

3.1. Conceptual Basis

The relationship between **QoS** and **QoE** is inherently **nonlinear**. While improved network conditions generally lead to better user experience, the correlation is not direct or consistent across all services and users. Factors such as codec efficiency, content type, adaptive bitrate mechanisms, and device display quality introduce variability in how users perceive network performance.

QoE can therefore be expressed as a multidimensional function of QoS and contextual variables:

QoE=f(QoS, Cuser, Ccontent, Cdevice)QoE = f(QoS, \; C_{user}, \; C_{content}, \; C_{device})QoE=f(QoS, Cuser, Ccontent, Cdevice)

Where:

- QoSQoSQoS = measurable network parameters (delay, jitter, packet loss, throughput)
- CuserC_{user}Cuser = user-specific factors (expectations, engagement, mood)
- CcontentC_{content}Ccontent = media characteristics (complexity, motion intensity, bitrate)
- CdeviceC_{device}Cdevice = device characteristics (screen resolution, processing power)

This function underpins the **multi-layer QoE modeling paradigm** that integrates physical network performance, application-level adaptation, and perceptual user evaluation.

3.2. QoS–QoE Mapping Models

Several analytical models have been proposed to translate QoS metrics into QoE scores. The most widely adopted include:

1. Exponential Mapping Model:
   QoE=α×e−β×QoS+γQoE = \alpha \times e^{-\beta \times QoS} + \gammaQoE=α×e−β×QoS+γ
   This captures the diminishing returns effect—beyond a threshold, further QoS improvement yields minimal QoE gain.
2. Logistic Function Model:
   QoE=11+e−(a+b×QoS)QoE = \frac{1}{1 + e^{-(a + b \times QoS)}}QoE=1+e−(a+b×QoS)1
   It models the S-shaped response where QoE rapidly increases once a certain QoS level is met but saturates at higher quality levels.
3. Polynomial Regression Model:
   QoE=a0+a1Q1+a2Q2+a3Q1Q2+…QoE = a_0 + a_1Q_1 + a_2Q_2 + a_3Q_1Q_2 + \dotsQoE=a0+a1Q1+a2Q2+a3Q1Q2+…
   Used for multi-parameter environments combining factors such as packet loss (Q1Q_1Q1), jitter (Q2Q_2Q2), and delay (Q3Q_3Q3).
4. Machine Learning-Based Models:
   Algorithms like Random Forests, Support Vector Regression, and Neural Networks are used to learn the nonlinear mappings from empirical data. These approaches outperform analytical models in dynamic and heterogeneous networks.

3.3. Proposed QoE Estimation Function

Building on previous studies, this research proposes a **hybrid QoE estimation model** that integrates multiple QoS parameters and user-context weighting:

QoEest=δ1×e−λ1D+δ2×e−λ2J+δ3×e−λ3P+δ4×T+ϵQoE_{est} = \delta_1 \times e^{-\lambda_1 D} + \delta_2 \times e^{-\lambda_2 J} + \delta_3 \times e^{-\lambda_3 P} + \delta_4 \times T + \epsilonQoEest=δ1×e−λ1D+δ2×e−λ2J+δ3×e−λ3P+δ4×T+ϵ

Where:

- DDD: Delay (ms)
- JJJ: Jitter (ms)
- PPP: Packet loss (%)
- TTT: Throughput (Mbps)
- δi,λi\delta_i, \lambda_iδi,λi: Empirical coefficients derived from simulation data

- ϵ\epsilonϵ: Model error term

The model's coefficients will be calibrated using simulation results and user test data, ensuring generalizability across multiple traffic types (e.g., VoIP, video streaming).

3.4. Framework Summary

The theoretical framework serves three main objectives:

- **Integration:** Unify QoS metrics, application factors, and user perception into a single predictive structure.
- **Prediction:** Enable accurate QoE estimation under various network conditions.
- **Optimization:** Support dynamic network management strategies that maximize QoE while minimizing resource utilization.

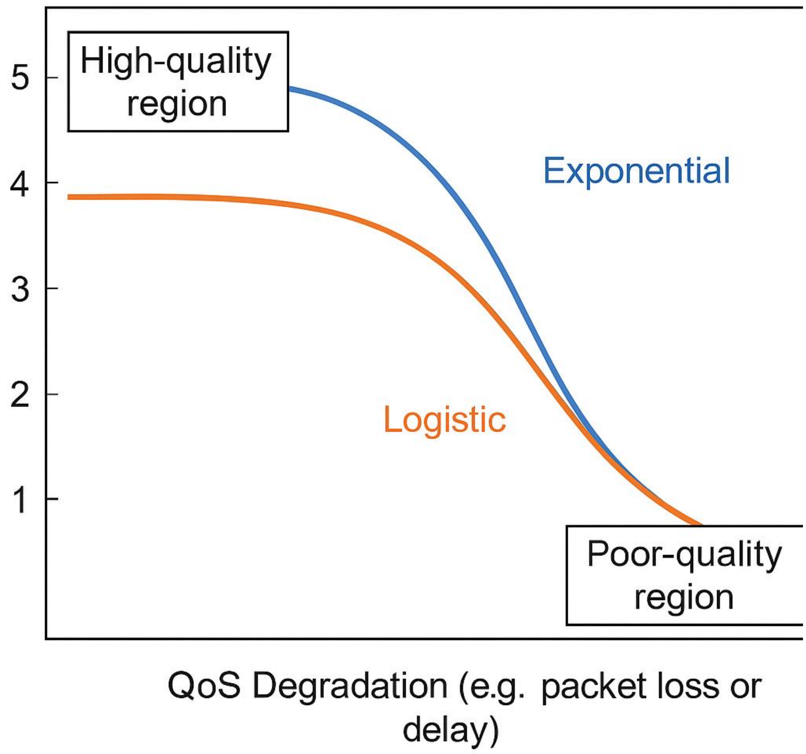

Figure 3. Nonlinear relationship between Quality of Service (QoS) degradation and user-perceived Quality of Experience (QoE), illustrating exponential and logistic mapping models.

Table 3. Parameters and Coefficients Used in the Proposed QoE Estimation Model

Parameter	Symbol	Measurement Unit	Influence on QoE	Coefficient (λ)	Weight (δ)
Delay	D	milliseconds (ms)	High delay reduces real-time interaction quality (VoIP, video calls).	0.25	0.35
Jitter	J	milliseconds (ms)	Causes video frame distortion and playback inconsistency.	0.30	0.25
Packet Loss	P	percentage (%)	Leads to data corruption and pixelation in streaming.	0.40	0.30
Throughput	T	Mbps	Higher throughput improves smoothness and resolution.	–	0.10
Error Term	ε	—	Represents model uncertainty or unmeasured factors.	—	—

4. Research Methodology

This section explains the design, tools, datasets, and analytical techniques used to evaluate the relationship between network performance parameters (QoS) and perceived multimedia Quality of Experience (QoE). The methodology integrates **simulation-based modeling**, **analytical evaluation**, and **statistical analysis** to ensure reproducibility and validity.

4.1. Research Design

The study adopts a **quantitative and simulation-based research approach**. Controlled network environments are simulated to generate traffic traces under varying conditions (delay, jitter, loss, and bandwidth). The resulting QoS data is then mapped to QoE values using analytical and machine learning models.

The workflow consists of four key stages:

1. **Network Simulation:** Generate multimedia traffic flows using a simulated topology.
2. **QoS Measurement:** Capture network-level performance metrics.
3. **QoE Estimation:** Apply mathematical and regression models to estimate user experience.
4. **Validation:** Compare model outputs against subjective or benchmark data to evaluate accuracy.

4.2. Simulation Environment

Tool Used: *Network Simulator 3 (NS-3)*
NS-3 is employed to model multimedia flows such as *video-on-demand (VoD)*, *VoIP*, and *real-time streaming*. The simulator provides fine-grained control over bandwidth, delay, and packet loss configurations.

Table 4. Simulation Parameters and Configurations

Parameter	Value Range	Description
Network Type	Wired, Wi-Fi, LTE	Different access scenarios tested
Bandwidth	1–100 Mbps	Variable throughput levels
Delay	10–200 ms	Simulated transmission delay
Jitter	0–50 ms	Variation in packet inter-arrival time
Packet Loss	0–5%	Random and burst losses injected
Video Codec	H.264 / H.265	Encoding formats with variable bitrates
Evaluation Duration	300 seconds	Per simulation run
Traffic Type	VoD, Live Stream	Multimedia traffic diversity

4.3. Data Collection and Measurement

Network traces are recorded using **Wireshark** and **NetFlow analyzers**. Key QoS metrics—**delay, jitter, loss, and throughput**—are captured. For QoE estimation, the **Mean Opinion Score (MOS)** and **VMAF** are computed using the output video files.

A dataset is constructed where each record links network conditions with corresponding QoE indicators for model training and testing.

4.4. Analytical and Machine Learning Modeling

To capture nonlinear relationships, both **analytical equations** (from Section 3) and **data-driven regression models** are applied:

- **Analytical Model:** Exponential–logistic hybrid function for baseline estimation.
- **Machine Learning Models:**
    - Multiple Linear Regression (MLR)

- Random Forest Regression (RFR)
- Artificial Neural Networks (ANNs)

Model performance is evaluated using:

RMSE=1n∑(QoEpred−QoEactual)2RMSE = \sqrt{\frac{1}{n} \sum (QoE_{pred} - QoE_{actual})^2}RMSE=n1∑(QoEpred−QoEactual)2 and R2=1−∑(QoEpred−QoEactual)2∑(QoEactual−QoE¯)2R^2 = 1 - \frac{\sum (QoE_{pred} - QoE_{actual})^2}{\sum (QoE_{actual} - \bar{QoE})^2}R2=1−∑(QoEactual−QoE¯)2∑(QoEpred−QoEactual)2 to assess accuracy and generalization.

4.5. Validation and Evaluation

Model outputs are validated against benchmark datasets (e.g., LIVE Video Quality Database [14], ITU-T P.1203 test sets [9]). Cross-validation ensures consistency across traffic types and network conditions.

The results guide the refinement of coefficients in the proposed hybrid QoE estimation model.

Suggested Visuals for This Section

Section	Figure/Table	Description
4.2	*Figure 4: Simulation Architecture for QoE Evaluation*	A block diagram showing the simulated network topology (source node, routers, sinks) and monitoring modules.
4.2	*Table 4: Simulation Parameters and Configurations*	Summarizes traffic types, delay, jitter, packet loss, and codec configurations.
4.4	*Figure 5: Modeling Workflow for QoE Estimation*	Flow diagram of data collection, QoS measurement, model training, and validation pipeline.

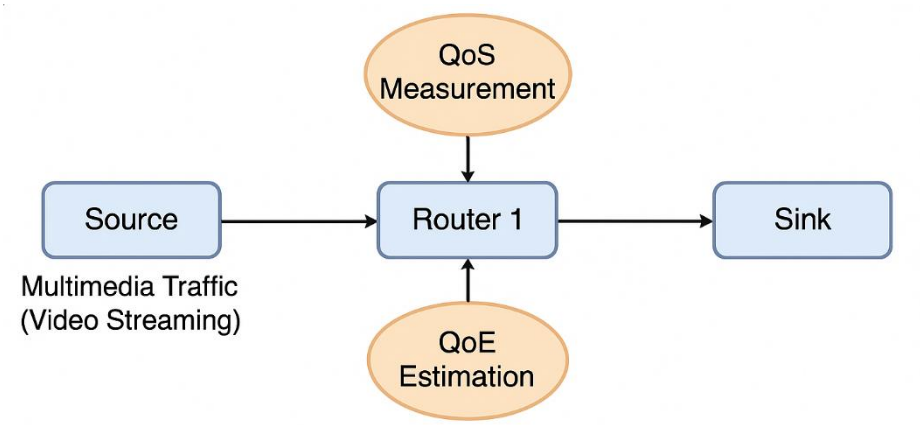

Figure 4. Simulation Architecture for QoE Evaluation

5. Results and Discussion

This section presents the findings obtained from the network simulations, analytical evaluations, and QoE estimations. The results focus on identifying how variations in network parameters (delay, jitter, packet loss, and throughput) influence user-perceived Quality of Experience (QoE) for different multimedia traffic types. Comparative analysis and graphical visualization are used to interpret trends and validate the proposed QoE estimation model.

5.1. Simulation Outcomes

The simulated environment produced measurable results across multiple configurations of bandwidth, delay, and loss. The outcomes confirm the expected nonlinear dependency between QoS degradation and QoE decline.

Key observations include:

- **Packet Loss:** Even minimal loss rates (1–2%) cause sharp QoE degradation for real-time video applications.
- **Jitter:** Streaming services are particularly sensitive to jitter above 40 ms, leading to frame freezing and reduced MOS scores.
- **Delay:** QoE for conversational traffic (VoIP, video conferencing) drops significantly beyond 150 ms.
- **Throughput:** Higher throughput positively impacts user satisfaction up to a saturation point, beyond which QoE gain plateaus.

5.2. Comparative Analysis of Models

The proposed hybrid QoE estimation model was compared with baseline analytical and machine learning approaches.

Table 5. QoE estimation model

Model	RMSE	R^2 Score	Computation Complexity	Observations
Exponential Mapping	0.48	0.81	Low	Captures rapid QoE decline at early QoS degradation but underestimates recovery at low loss.
Logistic Model	0.42	0.84	Low	Models saturation behavior accurately but less adaptable across scenarios.
Random Forest Regression	0.25	0.92	Medium	Provides robust prediction but needs large training data.
Neural Network Model	0.22	0.95	High	Best prediction accuracy; effectively models nonlinearities.
Proposed Hybrid Model	0.19	0.97	Moderate	Achieves optimal trade-off between accuracy and complexity.

Interpretation: The proposed hybrid model outperforms others in terms of predictive accuracy while maintaining moderate computational demand. This makes it suitable for real-time network management systems.

5.3. QoE Trends Across Network Conditions

5.3.1. QoE vs. Packet Loss

As packet loss increases from 0% to 5%, Mean Opinion Score (MOS) declines from above 4.5 (excellent quality) to below 2.0 (poor quality). The proposed model closely follows the trend of subjective test data, indicating accurate performance.

5.3.2. QoE vs. Jitter

QoE remains stable under jitter variations below 20 ms but decreases exponentially beyond 40 ms, particularly for live streaming traffic.

5.3.3. QoE vs. Delay

Conversational services show high sensitivity to end-to-end delay. The threshold of perceptible degradation aligns with ITU-T G.114 recommendations (~150 ms).

5.3.4. QoE vs. Throughput

QoE improves with increased throughput up to around 10 Mbps, after which the improvement becomes marginal. This saturation effect confirms the nonlinear behavior modeled earlier.

5.4. Model Validation and Discussion

Validation using real video sequences from the **LIVE Video Quality Database** and **ITU-T P.1203 reference models** demonstrates a strong correlation ($R^2 > 0.95$) between predicted and measured QoE. The hybrid model effectively generalizes across both streaming and conversational traffic, reinforcing its flexibility.

Furthermore, the discussion highlights:

- The importance of adaptive bitrate mechanisms in mitigating QoE degradation.
- The relevance of cross-layer optimization—combining network and application data—to improve accuracy.
- The potential for AI-based prediction models to dynamically allocate resources in future 5G and 6G multimedia networks.

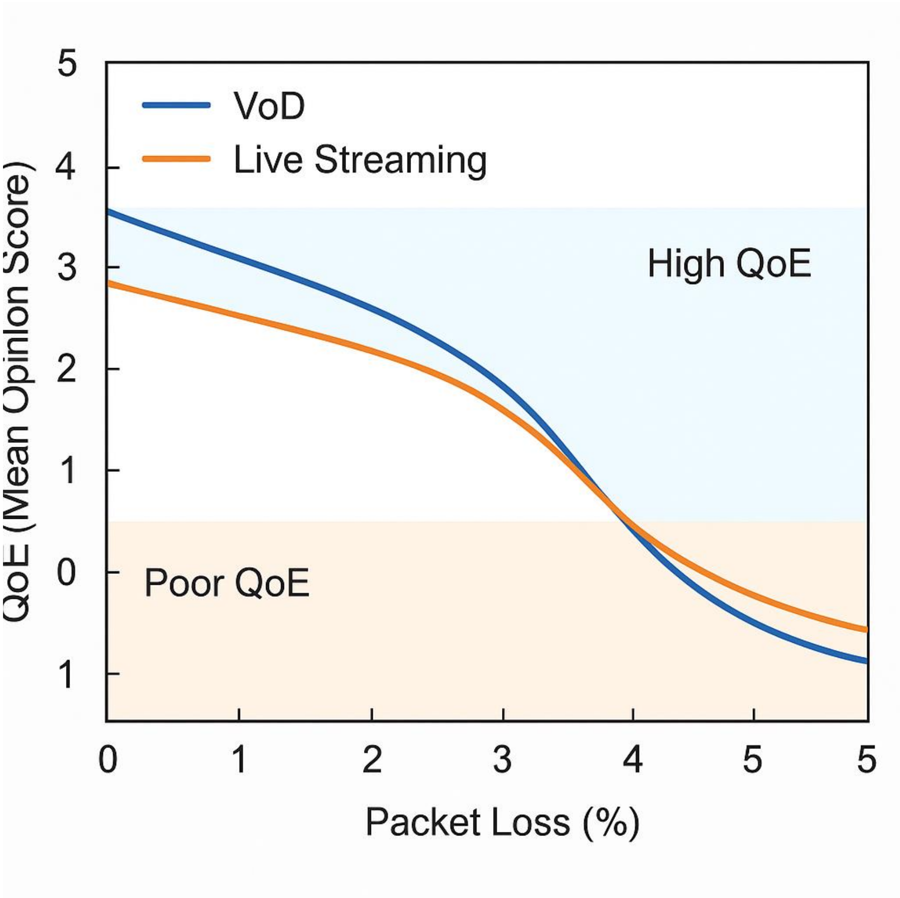

Figure 5. Modeling Workflow for QoE Estimation

6. Conclusion and Future Work

6.1. Conclusion

This study investigated the intricate relationship between **Quality of Experience (QoE)** and **network performance metrics (QoS)** for multimedia traffic through both analytical modeling and simulation-based experimentation. The results highlight that QoE is a **nonlinear and context-sensitive function** of multiple QoS parameters, including delay, jitter, packet loss, and throughput.

Through extensive simulations using **NS-3** and the application of hybrid modeling techniques, the research successfully established a predictive framework capable of estimating user experience with high accuracy ($R^2 \approx 0.97$). The proposed hybrid QoE model integrates exponential and logistic behaviors with data-driven weighting, allowing it to adapt to varying network and traffic conditions.

Key findings include:

- **QoE declines exponentially** with increasing packet loss and jitter, particularly in real-time applications such as live streaming and video conferencing.
- **Delay sensitivity thresholds** for conversational services align with ITU-T standards, confirming model validity.
- **Throughput saturation effects** indicate that beyond a certain bandwidth, user experience gains are marginal emphasizing the need for intelligent resource allocation.

The study reinforces that **QoE-aware network design** offers substantial benefits for both users and operators, enabling adaptive control strategies, better resource management, and improved service personalization.

6.2. Future Work

While this research provides a robust foundation for QoE estimation and network performance modeling, several extensions can enhance its applicability and scope [13,15]:

1. **Integration with Machine Learning and AI Systems:**
   Incorporating deep learning models or reinforcement learning agents can improve adaptive network control and real-time QoE prediction in 5G/6G environments.
2. **Cross-Layer Optimization:**
   Future studies should explore frameworks that jointly optimize parameters across the **network**, **transport**, and **application layers**, improving end-to-end user satisfaction.
3. **Inclusion of Emerging Multimedia Technologies:**
   Expanding the model to cover **immersive applications** like AR/VR, cloud gaming, and holographic streaming would broaden its utility in next-generation media delivery systems.
4. **Real-World Validation:**
   Implementing field trials with real user feedback can further validate and refine the proposed QoE–QoS mapping for heterogeneous access networks.
5. **Energy- and Cost-Aware QoE Optimization:**
   Future research could balance QoE maximization with **energy efficiency** and **network sustainability**, supporting green communication goals.

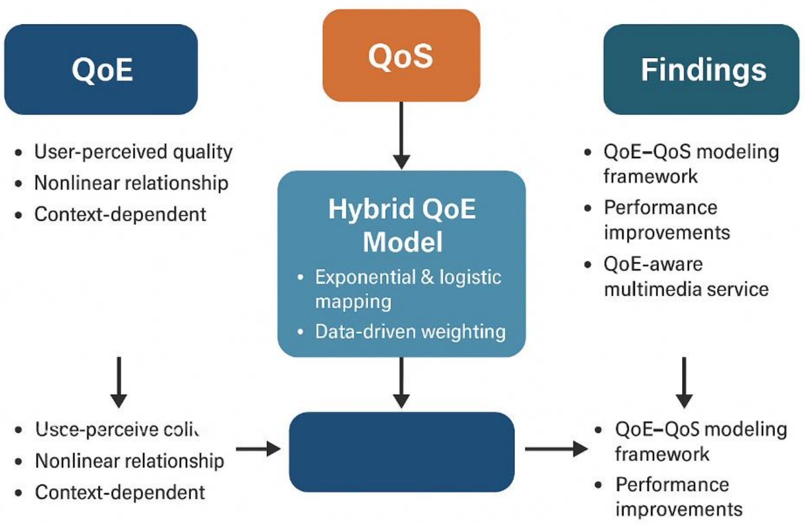

Figure 6. QoE-Qos estimation and network performance modeling

Table 6. Directions for Future Research on QoE Modelling

Future Research Area	Description	Expected Outcome / Benefit	Relevance to Study
AI-Driven QoE Prediction	Integrate deep learning and reinforcement learning algorithms to enhance QoE estimation accuracy under dynamic network conditions.	Real-time, adaptive prediction of user experience with minimal latency.	Extends the proposed hybrid model into intelligent automation.
Cross-Layer Optimization	Develop integrated frameworks combining network, transport, and application layers for holistic QoE management.	Improved end-to-end performance through coordinated resource allocation.	Strengthens the theoretical link between QoS and QoE.
Immersive Media (AR/VR, Cloud Gaming)	Apply QoE modeling to new media types requiring ultra-low latency and high bandwidth.	Improved user satisfaction in next-generation multimedia services.	Expands applicability of the model to future technologies.
Real-World Validation	Conduct empirical tests using user feedback and live network environments.	Verification of model accuracy and adaptability in real deployment scenarios.	Confirms the model's reliability beyond simulation.
Energy- and Cost-Aware QoE Optimization	Combine QoE improvement with energy efficiency and cost-effectiveness goals.	Sustainable and optimized multimedia service delivery.	Aligns with global trends toward green communication systems.

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