

When Multipath QUIC Meets Model Predictive Control and Band Sparse Network Coding: A Novel Multipathing Solution for Video Streaming over Heterogeneous Wireless Networks

Yuanlong Cao, Haopeng Zhang, Ming Jiang, Yirui Jiang, Jinquan Nie and Zhi Liu *Senior Member, IEEE*

Abstract—Multipath Quick UDP Internet Connections (MPQUIC) integrated with network coding technology presents a promising solution for enhancing the Quality of Experience (QoE) of video services in heterogeneous wireless networks. However, a key challenge arises when encoding nodes transmit potentially non-beneficial encoded packets while waiting for endpoint decoding acknowledgments (ACKs). This behavior limits effective transmission rates, resulting in reduced real-time streaming performance and a degraded QoE for wireless end-users. In this paper, we propose MP²-QUIC, which addresses these challenges through a novel adaptive Model Predictive Control (MPC) framework for MPQUIC that optimizes both congestion window and encoding redundancy parameters via a discrete state transition model. This approach ensures robust performance across heterogeneous wireless networks by incorporating operating point linearization and leveraging the Central Limit Theorem. It enhances effective throughput while maintaining strict real-time video streaming constraints. It further employs Band-Sparse Network Coding (Band-SNC) to minimize computational complexity at endpoints, while utilizing queuing theory principles to determine optimal encoded packet quantities. This integrated approach significantly enhances end-user QoE, and the experimental results demonstrate MP²-QUIC's superior performance compared to existing MPQUIC encoding solutions, yielding a 68.85% reduction in peak decoding overhead and marked improvements in Peak Signal-to-Noise Ratio (PSNR).

Index Terms—Heterogeneous wireless networks, video streaming, network coding, transmission efficiency, QoE.

I. INTRODUCTION

IN contemporary wireless transmission environments [1], [4], [5], [6], Multipath Quick UDP Internet Connections (MPQUIC) [7] has transformed real-time communication applications such as video conferencing, ultra-high-definition video streaming, and Teleoperation Driving (ToD) [2], [3], [8]. Leveraging its unique parallel transmission capabilities,

MPQUIC has significantly improved the Quality of Experience (QoE) for wireless streaming media [9], [10]. This innovation is particularly impactful, given that media traffic constitutes a substantial share of internet usage [11]. Furthermore, Ericsson forecasts [12] predict that wireless networks will handle 74% of media traffic by the end of 2024, underscoring the pivotal role of wireless communication in determining streaming service quality and end-user satisfaction [13].

MPQUIC offers several advantages over traditional transport layer protocols, excelling in connection management and transmission flexibility. Among its notable features are zero Round-Trip Time (0-RTT) handshakes [14], [15] and multi-stream multiplexing [16]. Moreover, MPQUIC supports seamless connection migration through the use of a 64-bit Connection ID (CID), ensuring stable connections even as path four-tuple indices change, thereby eliminating the need for reconnection. The protocol's efficiency is reflected in its widespread adoption: according to W3Techs [18], QUIC powers at least 33.2% of internet traffic, and 25% of the top 10 million websites—including major platforms like YouTube and Facebook—have implemented HTTP/3 to enhance network performance and user experience. Despite these strengths, effective congestion control remains a critical factor in maximizing user-perceived QoE in internet video transmission systems, as it directly impacts user retention and the revenue of video service providers [19].

Existing multipath congestion control mechanisms [20] are primarily designed to optimize performance under static network conditions. However, these approaches face significant challenges when applied to dynamic and heterogeneous wireless environments. In such settings, frequent path state fluctuations and asymmetric resource distribution limit the control plane's ability to fully utilize available paths, leading to suboptimal bandwidth efficiency. This inefficiency is particularly problematic in streaming media transmission, which demands high real-time performance and throughput. Poor utilization of multipath bandwidth exacerbates issues such as increased receiver-side reordering overhead, frequent buffering events, and degraded video quality, all of which significantly diminish the user's QoE.

The integration of network coding technology with MPQUIC offers a promising solution to these challenges. Leveraging the rateless properties of network coding [21], senders can generate an unlimited number of encoded packets

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Yuanlong Cao, Haopeng Zhang, Ming Jiang, Jinquan Nie are with the School of Software, Jiangxi Normal University, Nanchang, 330022, China. (e-mail: ylcao@jxnu.edu.cn; hpzhang@jxnu.edu.cn; mjiang@jxnu.edu.cn; jqnie@jxnu.edu.cn)

Yirui Jiang is with the Saïd Business School, University of Oxford, OX1 1HP, UK. (e-mail: yirui.jiang@cranfield.ac.uk)

Zhi Liu is with The University of Electro-Communications, Tokyo, 182-8585, Japan. (e-mail: liu@ieee.org)

within each batch. This approach is especially advantageous in multipath scenarios characterized by variable or unpredictable packet loss rates. By dynamically adapting to changing network conditions, network coding enables senders to maximize bandwidth utilization across all available paths, thereby enhancing data transfer efficiency in dynamic and heterogeneous wireless networks [21].

The combination of MPQUIC and network coding technology for video stream transmission serves as a powerful solution for enhancing QoE in heterogeneous wireless networks [22]. However, optimizing streaming media service quality remains a significant challenge [23]. One major limitation arises from the rateless nature of network coding: transmission nodes continue to send packets until they receive acknowledgment (ACK) signals. This process often results in the transmission of redundant encoded packets that have already been successfully decoded [24]. This phenomenon, termed information lag, leads to inefficient bandwidth utilization and can severely degrade real-time video streaming performance and user QoE, especially under unstable network conditions.

To address these challenges, we propose MP²-QUIC, an innovative solution that integrates Model Predictive Control (MPC) [25] with MPQUIC and Band-Sparse Network Coding (Band-SNC) [26]. This approach is specifically designed to enhance streaming media services in heterogeneous wireless networks, where achieving low latency and superior QoE is critical. MP²-QUIC represents a substantial advancement over our previous work, which utilized classical Proportional Integral Derivative (PID) control theory [27]. While PID controllers are constrained to linear error corrections, MP²-QUIC enables dynamic adjustments of multiple control parameters, including transmission redundancy and congestion window size. This capability allows the system to adapt more effectively to fluctuating network conditions. Moreover, MP²-QUIC integrates both hard and soft constraints into its model framework, significantly enhancing system stability and robustness. These constraints effectively mitigate transmission instabilities, ensuring consistent performance across a wide range of bandwidth scenarios.

MP²-QUIC implements a discrete state transition mathematical model to optimize video streaming in dynamic wireless environments. The model addresses challenges from path state fluctuations and uneven resource distribution by dynamically adjusting congestion windows and encoding redundancy across transmission links. Through sparse network coding integration, MP²-QUIC reduces packet loss impact while streamlining endpoint encoding and decoding processes. The system employs precise prediction mechanisms at the source to control encoded and parity packet quantities per batch, effectively mitigating bandwidth inefficiencies caused by encoding delays.

The primary contributions of this paper are summarized as follows:

- Firstly, MP²-QUIC's integration of adaptive MPC with operating point linearization and the Central Limit Theorem enables precise system state approximation at each time step. This framework optimizes link throughput

while meeting strict real-time video streaming requirements in heterogeneous wireless environments.

- Secondly, MP²-QUIC's incorporation of Band-SNC technology. This approach strategically concentrates the non-zero elements of encoding vectors within a banded region, reducing packet loss costs and simplifying end-side encoding and decoding processes. The outcome is a notable improvement in the efficiency of streaming media data transmission across heterogeneous wireless networks.
- Finally, MP²-QUIC introduces a novel performance metric based on queuing models, termed the link robustness rate. This metric integrates the link's effective utilization rate with predicted decoding success probability at the destination node. Based on queuing theory models, this metric enhances end-user QoE in heterogeneous wireless networks.

The structure of this paper is organized as follows: Section II explores the MPQUIC protocol, offering a review of state-of-the-art research in network coding and control theory while identifying current limitations. Section III provides an in-depth analysis of the design and implementation architecture of the MP²-QUIC model. Section IV presents a detailed performance evaluation of MP²-QUIC, benchmarking it against existing MPQUIC encoding solutions. Finally, Section V concludes the key findings and discusses promising avenues for future research.

II. RELATED WORKS

A. The Application of MPQUIC in Streaming Media Transmission

MPQUIC has gradually emerged as a leading protocol in media streaming applications, recognized for its superior throughput and low latency characteristics. Key advancements in this domain include the Earliest Completion First (ECF) algorithm proposed by Lim et al. [28], which builds upon the foundations of MPTCP. ECF leverages path-specific RTT information to optimize path utilization, yielding significant performance enhancements in video streaming applications. Expanding on this progress, Nguyen et al. [29] introduced FQ-SAT, an innovative MPQUIC scheduler that integrates Q-learning with fuzzy logic techniques, achieving notable improvements in the timing of frame arrivals for video streams.

To address the limitations of traditional multi-path scheduling algorithms in meeting MPQUIC specifications and video streaming QoE requirements, Han et al. [30] developed a sophisticated MPQUIC scheduler based on multi-agent deep reinforcement learning. This approach effectively considers MPQUIC's unordered queue memory utilization and diverse QoE metrics, enabling dynamic optimization of both the receive buffer size and QoE. Complementing these efforts, the research presented in [23] proposed a QUIC-based multi-path partially reliable transmission protocol. This solution incorporates priority-based and deadline-aware schedulers to mitigate prevalent video streaming issues such as re-buffering and frame freezing.

While current MPQUIC research in media streaming predominantly focuses on stream and path scheduling optimiza-

tion, the increasing adoption of advanced wireless communication technologies introduces both opportunities and challenges. These technologies provide enhanced transmission capabilities but also bring greater network instability. As wireless network usage at terminal points continues to grow, developing robust and efficient video transmission solutions for heterogeneous wireless environments has become increasingly critical. This pressing challenge forms the central focus of our research investigation.

B. The Role of Network Coding in Streaming Media Delivery

Network coding has emerged as a transformative approach to optimizing network transmission, offering superior resilience to interference and enhanced bandwidth utilization. Building on these foundational advantages, Xu et al. [31] proposed an enhanced MPTCP implementation incorporating pipeline network coding. This innovation introduced an economic encoding coefficient rule designed to minimize encoding and decoding delays. Although network coding substantially improves link transmission reliability, its deployment incurs additional processing overhead, potentially reducing effective data payloads and impacting real-time streaming performance.

Recent advancements have refined the application of network coding in streaming media. Taghouti et al. [21] developed a padding reduction methodology leveraging coded Macro-Symbols (MS), thereby reducing packet padding overhead and improving transmission efficiency. In a complementary study, Yin et al. [32] introduced a parallel decoding algorithm based on LU decomposition. This algorithm dynamically adjusts network coding redundancy and stream resolution through predictive modeling of video stream quality, achieving significant performance gains.

In the context of vehicular networks, Ni et al. [33] addressed the challenges of burst packet loss and peak delays in video transmission. Their integrated solution combined MPQUIC with network coding, consolidating multiple cellular networks into a unified cloud connection to overcome limitations of individual operators. Similarly, Chhange et al. [34] introduced a specialized coding transmission system for Wi-Fi edge environments. Their modular plugin architecture demonstrated exceptional performance in HTTP-based video streaming over wireless networks.

Despite these advancements, a critical challenge remains: addressing the inherent latency associated with network coding implementations. Our research seeks to fill this gap by introducing an adaptive MPC framework. This approach predicts the optimal number of encoded and parity packets for each transmission batch by analyzing real-time network indicators such as packet loss rate and round-trip time (RTT). By combining with this innovation, we have developed a comprehensive video streaming transmission system tailored for heterogeneous wireless networks, delivering enhanced stability and a superior quality of experience for wireless users.

C. MPC in Streaming Media Transmission

MPC provides substantial advantages in streaming media transmission by dynamically optimizing resource allocation

based on real-time system states and predicted network conditions. This adaptability is particularly critical for maintaining stable performance in rapidly evolving network environments. As a result, the integration of MPC technology has attracted significant research attention, particularly in the contexts of ultra-high-definition video transmission and wireless Virtual Reality (VR) applications.

Recent studies have explored various innovative implementations of MPC in streaming media. Li et al. [35] proposed JUST360, which integrates a joint utility model with MPC to dynamically optimize tile-specific bit rate strategies. Similarly, Chen et al. [36] enhanced the reliability of VR streaming by embedding MPC into a constrained Markov decision process framework, effectively optimizing resource allocation for tile retransmissions. Xu et al. [37] introduced an edge-assisted framework based on MPC theory, leveraging strategic Super-Resolution (SR) deployment to optimize user QoE. Additionally, Kan et al. [38] augmented MPC capabilities with Bayesian Neural Networks (BNNs), enabling statistical throughput prediction using historical data.

Despite these advancements, current approaches to combining MPC with video stream QoE optimization face notable challenges. One key limitation is the insufficient consideration of optimization costs associated with nonlinear system models, which can lead to control latency. Such latency delays the implementation of decisions, hindering timely system responses to dynamic environmental changes. To address these issues, our proposed model employs Taylor expansion and the central limit theorem for operating point linearization. This method significantly reduces optimization costs while mitigating both latency and steady-state errors in the control system. Consequently, our approach ensures more efficient video stream transmission and improved QoE performance.

III. SYSTEM ARCHITECTURE AND DESIGN

Adaptive MPC [39], operating within the well-established MPC framework [40], incorporates an online model update mechanism designed to address system dynamics and uncertainties. The control process unfolds as a continuous cycle: at each control interval, adaptive MPC uses the current system model to predict future behavior while concurrently updating the model with real-time input-output data. This dual functionality enhances both prediction accuracy and control performance. The system generates an optimal control sequence based on the updated model, executes the initial control action to influence the system state, and repeats this iterative process in subsequent intervals, ensuring adaptive and responsive control in the face of dynamic system changes.

The architecture of MP²-QUIC (see Fig. 1), integrates adaptive MPC with Band-SNC to optimize MPQUIC transmission. This architecture exploits adaptive MPC's feedback mechanism to dynamically adjust parameters in real time within heterogeneous network environments. The system employs two primary performance metrics—link robustness rate and Peak Signal-to-Noise Ratio (PSNR)—to enable continuous, real-time optimization of network coding redundancy and congestion window size.

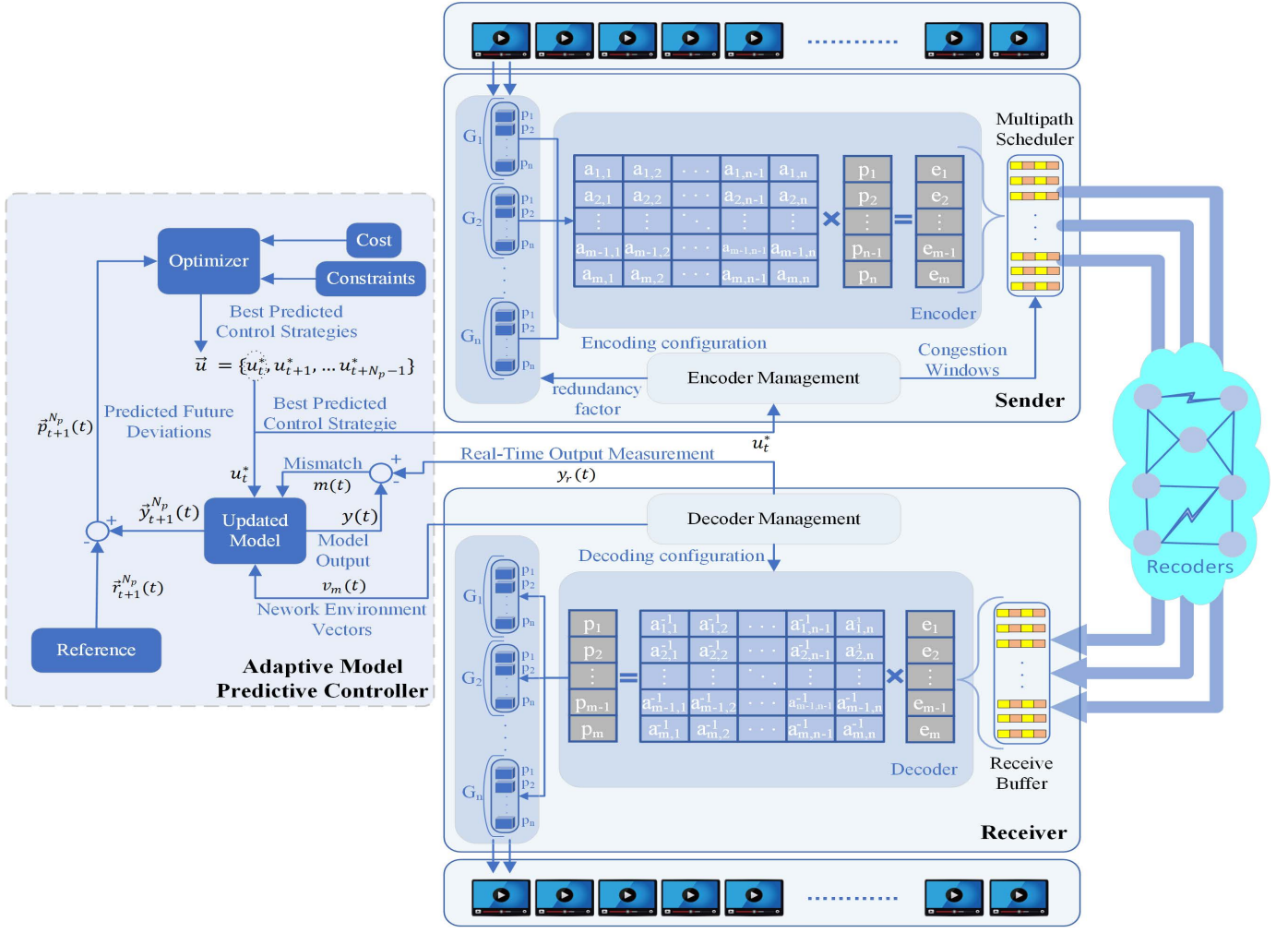


Fig. 1. The Architecture of MP²-QUIC.

During video streaming transmission, the MPQUIC sender segments raw data into n source data packet groups ($G_1, G_2, \dots, G_n$). Each group is pre-encoded to generate intermediate parity packets. When transmission opportunities arise, the encoding manager performs linear combinations of each source data packet group with their respective intermediate parity packets to create encoded packets. Each encoded packet is assigned a random encoding coefficient, derived from the Galois field, ensuring robust and efficient data transmission.

The coding management module enhances transmission efficiency by dynamically determining the optimal number of encoded packets, based on current network conditions and transmission requirements. Each packet's encoding vector matrix utilizes a band structure to arrange non-zero elements, implementing band coding to concentrate these elements within specific matrix regions. This strategy effectively reduces the number of non-zero coefficients during encoding, while maintaining matrix sparsity. As a result, both decoding time and overhead at the MPQUIC receiver are minimized.

The adaptive MPC framework follows a systematic control process, beginning with the calculation of the current output

error $m(t)$ based on the measured output $y_r(t)$. The system then employs the optimizer-generated optimal future predictive control strategy u_t^* to compute the output at the next time step, $\tilde{y}_{t+1}^{N_p}(t)$. By comparing this with the target output $\tilde{r}_{t+1}^{N_p}(t)$, the system calculates the output deviation $\tilde{p}_{t+1}^{N_p}(t)$. This deviation information enables the optimizer to refine the system's behavior based on observed responses.

The optimization process generates a series of future optimal control strategies $\vec{u}$, which adhere to predefined control constraints. The system then applies the initial control input u_t^* to the network transmission system before advancing to the next time step, $t + 1$. At each step, the adaptive MPC recalculates control inputs for subsequent time steps ($t + 2, t + 3, \dots, t + N_p$), where N_p represents the prediction horizon, ensuring ongoing dynamic system optimization.

The control input u_t^* consists of two critical components: encoding redundancy and the congestion window size. At each sampling interval, the adaptive MPC optimally computes these control variables and transmits them to the sender's encoding manager. The encoding manager then applies these inputs by adjusting both the Band-SNC substream encoding redundancy and the MPQUIC congestion window size, thereby optimizing

network transmission performance.

MP²-QUIC significantly improves network transmission efficiency and stability by reducing data loss and minimizing transmission delays. Through the dynamic adjustment of encoding redundancy and congestion window size, the system exhibits strong adaptability to varying network conditions, ensuring consistent, high-quality video streaming across heterogeneous wireless networks.

A. Definition of the System Cost Function

Computer network systems operate on discrete time intervals aligned with the geometric multiples of the computer's internal clock cycles. This fundamental characteristic establishes the inherently discrete nature of network control systems.

Our system model incorporates both state and control variables. The state variables comprise the link robustness rate L_k and PSNR P_k , while the control variables include the congestion window size c_k and redundancy r_k . Based on these parameters, we formulate the discrete cost function,

$$J = \sum_k^{N-1} q_1(L_{k+d-1} - L_{\text{ref}})^2 + q_2(P_{k+d-1} - P_{\text{ref}})^2 + t_1(c_k - c_{\text{ref}})^2 + t_2(r_k - r_{\text{ref}})^2 + f_1(L_{N+d-1} - L_{\text{ref}})^2 + f_2(P_{N+d-1} - P_{\text{ref}})^2, \quad (1)$$

The prediction horizon is denoted by N , while L_{ref} , P_{ref} , c_{ref} , and r_{ref} represent the target reference values for their respective system variables. The optimization process incorporates weighting coefficients q_1 , q_2 , t_1 , t_2 , f_1 , and f_2 , whose magnitudes reflect the relative importance assigned to minimizing specific state errors. Terminal cost components, expressed as $(L_{N+d-1} - L_{\text{ref}})^2$ and $(P_{N+d-1} - P_{\text{ref}})^2$, place particular emphasis on the system's state at the conclusion of the prediction horizon. These terminal components play a crucial role in ensuring the system converges effectively toward reference values, thereby enhancing both system stability and tracking performance.

The equation (1) can be expressed in matrix notation as follows,

$$\begin{aligned} E_{k+d-1} &= \begin{bmatrix} L_{k+d-1} - L_{\text{ref}} \\ P_{k+d-1} - P_{\text{ref}} \end{bmatrix}, \\ C_k &= \begin{bmatrix} c_k - c_{\text{ref}} \\ r_k - r_{\text{ref}} \end{bmatrix}, \\ E_{N+d-1} &= \begin{bmatrix} L_{N+d-1} - L_{\text{ref}} \\ P_{N+d-1} - P_{\text{ref}} \end{bmatrix}; \end{aligned} \quad (2)$$

$$Q = \begin{bmatrix} q_1 & 0 \\ 0 & q_2 \end{bmatrix}, \quad T = \begin{bmatrix} t_1 & 0 \\ 0 & t_2 \end{bmatrix}, \quad F = \begin{bmatrix} f_1 & 0 \\ 0 & f_2 \end{bmatrix}; \quad (3)$$

From equation (1), we derive the system's cost function in matrix form,

$$J = \sum_k^{N-1} E_{k+d-1}^T Q E_{k+d-1} + C_k^T T C_k + E_{N+d-1}^T F E_{N+d-1}, \quad (4)$$

B. System Model Design

In the Band-SNC framework, we define encoding redundancy as the additional data introduced during transmission to enhance reliability and mitigate the impact of packet loss. This redundancy allows receivers to reconstruct the original information from the partially received data when packet loss occurs. Formally, the encoding redundancy is expressed as,

$$r = \frac{N}{G}, \quad (5)$$

where N represents the number of encoded data packets in a band, and G denotes the combined count of original data packets and parity packets within the band.

Consider a band transmission of N encoded data packets, comprising G original data packets and $N - G$ redundant data packets. Successful decoding requires the receiver to obtain at least G linearly independent decoding vectors. Consequently, the probability of successful decoding, P_{success} , is expressed through the cumulative probability of a binomial distribution,

$$P_{\text{success}} = \sum_{i=G}^{rG} \binom{rG}{i} (1 - \epsilon)^i \epsilon^{rG-i}, \quad (6)$$

where ϵ denotes the link's packet loss rate.

To characterize network transmission systems, we employ the M/M/1 queue model [41], with packet arrival rates following a Poisson distribution with parameter λ . Through an analysis of link utilization and its effective payload, we introduce a novel performance metric: the link robustness rate. This metric combines both link utilization and the probability of successful decoding, offering a comprehensive evaluation of transmission link robustness in systems utilizing network coding techniques. As shown in equation(7),

$$L = \frac{P_{\text{success}} \cdot \lambda_{\text{cur}}^{\text{eff}}}{\lambda_{\text{cur}}}, \quad (7)$$

where $\lambda_{\text{cur}}^{\text{eff}}$ represents the effective arrival rate, indicating the rate at which valid payloads successfully reach the destination node. In contrast, λ_{cur} refers to the total arrival rate of data at the receiving node per second.

The introduction of the link robustness rate allows for a comprehensive evaluation of the stability and reliability of the transmission system. This metric goes beyond a simple assessment of link utilization by factoring in the probability of successful packet decoding during transmission. By doing so, it facilitates the precise identification and optimization of network transmission bottlenecks, ultimately improving overall network performance and QoE.

In the traditional congestion control mechanism of the MPQUIC protocol, the sliding window regulates the amount of transmittable data at any given time. The window size is determined by two primary components: the receiver's receive window and the congestion window. This sliding window mechanism imposes constraints on the current transmission rate. When all data within the sliding window is transmitted, the window size is reduced to zero until the first acknowledgment (ACK) is received, at which point the window advances.

After one RTT, the expected arrival of the ACK allows for the transmission of the next packet sequence. Under conditions

of unlimited bandwidth, the maximum transmission rate at any given time is expressed as,

$$snd = \frac{\min(c, rw)}{RTT}, \quad (8)$$

where c and rw represent the current congestion window and receiver window sizes, respectively.

The current total arrival rate λ_{cur} incorporates redundant data in its calculation. With snd_{cur} representing the current sending rate and d denoting the one-way link delay, we express the current arrival rate as,

$$\lambda_{cur} = (1 - \epsilon) \cdot snd_{cur-d} = r \cdot \lambda_{cur}^{eff} \quad (cur - d > 0), \quad (9)$$

where ϵ represents the packet loss rate of the current link, r denotes the redundancy factor, which quantifies the proportion of redundant data within the effective payload of the current transmission link.

PSNR serves as a fundamental metric for assessing user QoE during video streaming transmission. This metric provides quantitative insights into video transmission quality, where higher PSNR values correspond to superior video stream quality. As defined in [42], PSNR establishes a direct relationship between network transmission performance and user experience, enabling effective evaluation of how network resource allocation strategies impact user QoE,

$$PSNR = 20 \log_{10} \left(\frac{br_{max}}{\sqrt{(tp_{exp} - tp_{crt})^2}} \right), \quad (10)$$

Here, br_{max} represents the average bitrate of the transmitted video stream, tp_{exp} denotes the expected average throughput provided by the external simulator, and tp_{crt} indicates the actual average throughput.

Taking into account the packet loss rate ϵ and combining equations (8) and (9), we can express the effective payload rate of successful data arrival (tp_{crt}) as,

$$tp_{crt} = \lambda_{cur}^{eff} = \frac{(1 - \epsilon) \cdot \min(c_{cur-d}, rw_{cur-d})}{r \cdot RTT}. \quad (11)$$

1) Introduction of Auxiliary State Variables: Network transmission systems exhibit inherent delay characteristics, where control variables at the sender—specifically the congestion window size c_k and redundancy r_k —affect the receiver after a fixed time delay d . This temporal displacement means that control actions initiated at time k manifest their effects at the receiver only after d time units. To effectively model this delay characteristic, we implement an approach that introduces auxiliary state variables, decomposing the delay process into a sequence of intermediate states.

Our methodology incorporates the delay d into the system model by representing the control input transmission through d delay steps using auxiliary state variables, thereby establishing an augmented state-space model. The process begins with defining the control input vector and introducing d auxiliary state vectors to capture historical control inputs,

$$u_k = \begin{bmatrix} c_k \\ r_k \end{bmatrix}, \quad (12)$$

$$\begin{cases} x_k^0 = u_k \\ x_k^1 = x_{k-1}^0 = u_{k-1} \\ x_k^2 = x_{k-1}^1 = x_{k-2}^0 = u_{k-2} \\ \vdots \\ x_k^{d-1} = x_{k-1}^{d-2} = \dots = u_{k-(d-1)} \end{cases} \quad (13)$$

These auxiliary state variables function as a sequential buffer, maintaining a record of control inputs across the previous d time steps. The augmented state vector integrates these auxiliary state variables with the system's original state variables—link robustness rate L_k and PSNR P_k —as follows,

$$X_k = [L_k, P_k, x_k^0, x_k^1, \dots, x_k^{d-1}]^T, \quad (14)$$

where $[x_k^0, x_k^1, \dots, x_k^{d-1}]$ represents the complete set of auxiliary variables at time instance k .

2) Establishing the augmented state-space model: Our adaptive MPC system utilizes two state variables: link effective utilization L_k and PSNR P_k , alongside two control variables: congestion window size c_k and redundancy r_k . The system dynamics are characterized by updates to link robustness rate L_k and PSNR P_k , which depend on both the current state at time step k and the control inputs (congestion window size and redundancy) from time step $k - d$. We express this relationship through the following discrete state transition equation,

$$\begin{bmatrix} L_{k+1} \\ P_{k+1} \end{bmatrix} = f(\eta, x_k^{d-1}), \quad (15)$$

where $\eta = [L_k, P_k]^T$, and $x_k^{d-1} = u_{k-(d-1)}$ denotes the control input at time $k - d$. The auxiliary state variables evolve according to,

$$\begin{cases} x_{k+1}^0 = u_{k+1} \\ x_{k+1}^1 = x_k^0 \\ x_{k+1}^2 = x_k^1 \\ \vdots \\ x_{k+1}^{d-1} = x_k^{d-2} \end{cases} \quad (16)$$

To enhance analytical clarity, we rewrite the state update equation in matrix form,

$$X_{k+1} = AX_k + BU_k, \quad (17)$$

$$A = \begin{bmatrix} \Theta & 0 & 0 & 0 & \dots & 0 & \Gamma \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 \\ 0 & I & 0 & 0 & \dots & 0 & 0 \\ 0 & 0 & I & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & I & \dots & 0 \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ 0 \\ I \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \quad (18)$$

where matrix Θ captures the self-feedback relationships between state variables, quantifying how the previous time step's link robustness rate and PSNR influence the current state. This matrix can be determined through simulation or empirical analysis. Matrix Γ characterizes the impact of time-delayed control inputs ($k - d$) on state evolution.

Given that the state variables encompass the system's output variables—specifically, the link robustness rate L_k and PSNR P_k —we represent the output equation as follows,

$$Y_k = CX_k, \quad (19)$$

where the output matrix C is,

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 1 & 0 & 0 & 0 & \dots & 0 \end{bmatrix}. \quad (20)$$

Through the combination of equations (7) and (9), we derive the functional relationship between L_k and the control inputs $c_{k-(d-1)}$ and $r_{k-(d-1)}$,

$$L_k = \frac{P_{\text{success}} \cdot \lambda_{\text{cur}}^{\text{eff}}}{r_{k-(d-1)} \cdot \lambda_{\text{cur}}^{\text{eff}}} = \frac{P_{\text{success}}}{r_{k-(d-1)}}. \quad (21)$$

Analysis reveals that $r_{k-(d-1)}$ has a direct influence on effective link utilization. Computing the partial derivatives with respect to $c_{k-(d-1)}$ and $r_{k-(d-1)}$ yields,

$$\frac{\partial L_k}{\partial c_{k-(d-1)}} = 0, \quad \frac{\partial L_k}{\partial r_{k-(d-1)}} = -\frac{P_{\text{success}}}{r_{k-(d-1)}^2}. \quad (22)$$

The functional relationship between P_k and the control variables $c_{k-(d-1)}$ and $r_{k-(d-1)}$ can be derived using equations (10) and (11). Which can be expressed as,

$$P_k = 20 \log_{10} \frac{br_{max}}{\sqrt{\left(t_{\text{exp}} - \frac{(1-\epsilon) \cdot \min(c_{k-(d-1)}, r_{k-(d-1)})}{RTT \cdot r_{k-(d-1)}} \right)^2}}. \quad (23)$$

Under the assumption of an infinite reception window, we obtain the following partial derivatives for c_k and r_k ,

$$\frac{\partial P_k}{\partial c_{k-(d-1)}} = \frac{20 \cdot (1-\epsilon)}{\ln 10 \cdot r_{k-(d-1)} \cdot RTT} \cdot \frac{1}{t_{\text{exp}} - \frac{(1-\epsilon) \cdot c_{k-(d-1)}}{r_{k-(d-1)} \cdot RTT}}, \quad (24)$$

$$\frac{\partial P_k}{\partial r_{k-(d-1)}} = -\frac{20 \cdot (1-\epsilon) \cdot c_{k-(d-1)}}{\ln 10 \cdot r_{k-(d-1)}^2 \cdot RTT} \cdot \frac{1}{t_{\text{exp}} - \frac{(1-\epsilon) \cdot c_{k-(d-1)}}{r_{k-(d-1)} \cdot RTT}}. \quad (25)$$

Analysis reveals that the partial derivatives of state variables with respect to $c_{k-(d-1)}$ and $r_{k-(d-1)}$ generate both partial and total system effects, resulting in nonlinear state transition equations. Video streaming transmission systems require precise network data delivery with minimal latency. However, conventional nonlinear system optimization approaches, such as gradient descent and Newton's method [43], incur substantial computational overhead, making their direct application impractical for video streaming control optimization.

Examination of the system model reveals a distinctive characteristic: while the state transition equation exhibits nonlinearity, the cost function maintains linearity. Additionally, the temporal variation in variables like $c_{k-(d-1)}$ and $r_{k-(d-1)}$ induces changes in system parameters. This variability causes the matrices Θ and Γ , which depend on these variables, to

become time-varying, thereby transforming the model into a time-varying system.

To address these challenges, we implement an integrated approach combining operating point linearization with adaptive MPC as the primary control mechanism. This method effectively manages both nonlinear and time-varying system characteristics by transforming the system into a local linear model. The model updates at each time step based on current system states and parameters, ensuring continuous adaptation to dynamic system changes. This approach enables the application of linear control methods for optimal control strategy determination, significantly reducing computational costs while enhancing optimization performance.

3) Operating Point Linearization: Operating point linearization provides a method for approximating nonlinear systems through linear models at equilibrium points. This method involves expanding nonlinear functions into Taylor series at the equilibrium point, retaining only the linear components (0th and 1st-order terms) while eliminating higher-order terms to construct a simplified linear mathematical model.

For our analysis, we define $k-(d-1)$ as δ . To linearize the system at operating point (c_δ^*, r_δ^*) , we apply Taylor expansion to derive the linearized system equations,

$$f(\eta, x_k^{d-1}) \approx f(\eta^*, c_\delta^*, r_\delta^*) + \frac{\partial f(\eta, c_\delta, r_\delta)}{\partial c_\delta} \bigg|_{c_\delta=c_\delta^*, r_\delta=r_\delta^*} (c_\delta - c_\delta^*) + \frac{\partial f(\eta, c_\delta, r_\delta)}{\partial r_\delta} \bigg|_{c_\delta=c_\delta^*, r_\delta=r_\delta^*} (r_\delta - r_\delta^*) + \dots, \quad (26)$$

where $f(\eta, x_k^{d-1})$ denotes the nonlinear expression with respect to (η, x_k^{d-1}) . In accordance with linearization principles, we retain only the constant and first-order terms from the Taylor expansion, discarding higher-order derivatives to maintain linear approximation accuracy.

Through the application of equations (21), (22), and (26), we derive the Taylor expansion of the system at operating point (c_δ^*, r_δ^*) for L_k as follows,

$$L_{k+1} \approx \frac{P_{\text{success}}^*}{r_\delta^*} - \frac{\partial L(r_\delta)}{\partial r_\delta} \bigg|_{r_\delta=r_\delta^*} (r_\delta - r_\delta^*). \quad (27)$$

The linear approximation of L_k near the operating point is expressed in equation (27). This approximation transforms the original nonlinear relationship into a linear combination of c_k and r_k , facilitating the implementation of adaptive MPC in network transmission system design.

An examination of the link robustness rate function in equation (7) reveals a significant computational challenge. The binomial distribution's cumulative probability calculation involves multiple combinatorial terms, where the binomial coefficient $\binom{r}{i}^G$ grows substantially with increasing values of r and G . This growth leads to an escalating number of terms requiring summation during partial derivative calculations, resulting in heightened computational complexity.

To mitigate this computational burden, we apply the Central Limit Theorem to approximate the binomial distribution using

the Cumulative Distribution Function (CDF) of the normal distribution, as shown in Equation (28),

$$P(X \leq k) \approx \Phi \left(\frac{k + C - np}{\sqrt{np(1-p)}} \right), \quad (28)$$

where $\Phi(z)$ denotes the CDF of the standard normal distribution, defined as $P(Z \leq z)$, while $Z \sim N(0,1)$. The parameters n and p represent the number of trials and the probability of success per trial, respectively, while k indicates the maximum number of successes for the cumulative probability calculation. Additionally, a continuity correction factor, C , is introduced to improve the accuracy of the approximation.

According to the Central Limit Theorem, when the sample size n is sufficiently large [44], the CDF of the binomial distribution $B(n, p)$ can be approximated by the CDF of the normal distribution $N(np, np(1-p))$.

Fig. 2 presents the CDFs of both distributions across various parameter configurations, with accuracy assessed using the Root Mean Square Error (RMSE). For smaller sample sizes (e.g., $n = 10, p = 0.1$), the normal distribution provides a relatively imprecise approximation, resulting in an RMSE of 0.0221.

However, the accuracy of the approximation improves significantly as the sample size increases. With a fixed probability p , the distribution curves exhibit notable convergence at $n = 30$ or $n = 50$, with RMSE values decreasing to 0.0085 and 0.0058, respectively. When maintaining $n = 30$ and varying p to 0.3 and 0.5, the binomial distribution aligns nearly perfectly with the normal distribution, yielding exceptionally low RMSE values of 0.0023 and 0.0004, respectively. These results strongly support the theoretical implications of the Central Limit Theorem.

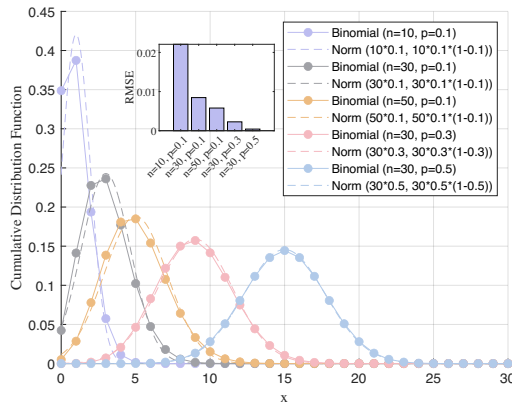


Fig. 2. CDF Comparison: Binomial vs. Normal Distributions.

This approximation simultaneously offers significant computational benefits while preserving high accuracy. Fig. 3 and Fig. 4 present a comparative analysis of the optimization costs and memory requirements for solving the Taylor expansion expression for the link robustness rate, L_k , using both distributions. These comparisons span coding redundancy values r ranging from 1 to 30.

Our performance analysis differentiates between the transient and steady-state computational costs. The transient phase

arises when the control module encounters substantial network environment fluctuations or undertakes initial optimization processes, necessitating re-linearization to determine optimal control strategies. In contrast, the steady-state phase occurs under network stability, enabling the system to leverage previously computed Taylor expansions for linearized solutions, thereby avoiding costly re-computation process.

Performance measurements during the transient phase reveal marked differences. Optimization using the binomial and normal distribution requires 72.434 seconds and 0.022 seconds, respectively. This pronounced disparity in transient optimization costs stems from the binomial distribution's complex Taylor expansion, which involves intricate summation bounds, combinatorial terms, and exponential function chain rules, resulting in significantly higher computational demands.

Memory utilization patterns further highlight these performance discrepancies. During the transient phase, the binomial distribution exhibits considerable memory overhead, with usage ranging from 4.51 MB at minimum redundancy to 32.55 MB at a redundancy factor of 30. Such resource demands pose compatibility challenges for legacy routing devices, potentially compromising system stability and limiting deployment flexibility.

In contrast, the normal distribution demonstrates superior efficiency, leveraging partial derivatives of exponential and polynomial functions for Taylor expansion. This approach benefits from well-established mathematical tools and optimized libraries specifically designed for normal distribution inference. Memory consumption remains consistently low across operational phases, even as redundancy increases, with peak utilization reaching only 3.04 MB during the transient phase and 0.60 MB in the steady state. In steady-state operation, optimization costs diminish significantly for both distributions: the binomial distribution requires 0.057 seconds, while the normal distribution completes optimization in 0.012 seconds.

Those analyses above reveals that employing the binomial distribution imposes significant computational and memory constraints during the system's transient phase. To mitigate these challenges, we approximate the binomial distribution as a normal distribution using the Central Limit Theorem. This approximation significantly improves the efficiency of control system optimization and parameter tuning, thereby ensuring the practical applicability and computational feasibility of adaptive MPC in multi-path transmission scenarios.

Therefore we derive the Taylor expansion of the system at operating point (c_δ^*, r_δ^*) for P_{k+1} by substituting equations (23), (24), and (25) into equation (26), as follows,

$$P_{k+1} \approx 20 \log_{10} \frac{br_{max}}{\sqrt{\left(tp_{exp} - \frac{(1-\epsilon) \cdot c_\delta^*}{r_\delta^* \cdot RTT} \right)^2}} + \frac{\partial P(c_\delta, r_\delta)}{\partial c_\delta} \bigg|_{\substack{c_\delta = c_\delta^* \\ r_\delta = r_\delta^*}} (c_\delta - c_\delta^*) + \frac{\partial P(c_\delta, r_\delta)}{\partial r_\delta} \bigg|_{\substack{c_\delta = c_\delta^* \\ r_\delta = r_\delta^*}} (r_\delta - r_\delta^*). \quad (29)$$

Through Taylor expansion of equations (27) and (29)

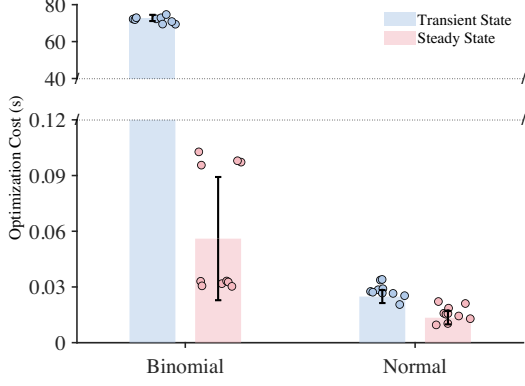


Fig. 3. Transient and Steady-State Optimization Cost: Binomial vs. Normal.

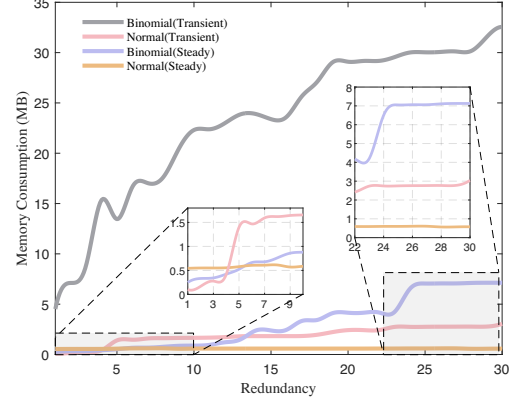


Fig. 4. Transient and Steady-State Memory Consumption: Binomial vs. Normal

followed by numerical calculations in MATLAB with the corresponding substituted values, we obtain the linearized state transition matrix for the nonlinear functional relationships L_{k+1} and P_{k+1} at operating point (c_δ^*, r_δ^*) ,

$$\Theta = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad (30)$$

$$\Gamma = \begin{bmatrix} 0 & \frac{\sqrt{2}G[1+r_\delta^*(1-\epsilon)]e^{\frac{G[r_\delta^*(\epsilon-1)+1]^2}{2\epsilon r_\delta^*(\epsilon-1)}} + \sqrt{\pi r_\delta^* \epsilon} \Delta \text{erfc}}{2\sqrt{-\pi G(r_\delta^*)^5 \epsilon (\epsilon-1)}} - \frac{20 \cdot (1-\epsilon) \cdot c_\delta^*}{\ln 10} \cdot \frac{1}{r_\delta^* \cdot \Upsilon} \\ \frac{20 \cdot (1-\epsilon)}{\ln 10} \cdot \frac{1}{\Upsilon} \end{bmatrix} \quad (31)$$

where,

$$\Upsilon = r_\delta^* \cdot RTT \cdot \left(t_{p_{\text{exp}}} - \frac{(1-\epsilon) \cdot c_\delta^*}{r_\delta^* \cdot RTT} \right), \quad (32)$$

$$\Delta \text{erfc} = \text{erfc} \left(\frac{G\sqrt{2r_\delta^* \epsilon}}{2\sqrt{-G(\epsilon-1)}} \right) - \text{erfc} \left(\frac{\sqrt{2}G(1+r_\delta^*(1-\epsilon))}{2\sqrt{-G r_\delta^* \epsilon (\epsilon-1)}} \right), \quad (33)$$

The complementary error function $\text{erfc}(x)$ [45] is expressed as,

$$\text{erfc}(x) = \frac{2}{\sqrt{\pi}} \int_x^\infty e^{-t^2} dt. \quad (34)$$

At last, the complete linearized system state transition equation is derived by substituting matrices Θ and Γ into equation (18).

C. Optimization Modeling

The MPC problem can be solved through various approaches. When dealing with a discrete system characterized by linear cost functions and state transition equations, the system's cost function can be transformed into a standard Quadratic Programming (QP) formulation [46] through recursive computation and matrix operations. This transformation enables the use of established QP solvers [47] to determine the optimal control sequence within specified constraints.

In our proposed linear time-invariant adaptive MPC system, we express the predicted state as a linear combination of the initial state and future control inputs, yielding the matrix form,

$$\mathbf{x}(j+1) = A_{n \times n} \mathbf{x}(j) + B_{n \times p} \mathbf{u}(j), \quad (35)$$

$$\mathbf{x}_{n \times 1} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}, \quad \mathbf{u}_{p \times 1} = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_p \end{bmatrix}. \quad (36)$$

Within this formulation, at time step j , we denote the predicted input and system state as $\mathbf{u}(j | j)$ and $\mathbf{x}(j | j)$ respectively. For the subsequent time step $j+1$, the predicted input becomes $\mathbf{u}(j+1 | j)$ with corresponding system state $\mathbf{x}(j+1 | j)$. This pattern extends to the prediction horizon's final time step, where $\mathbf{u}(j+N-1 | j)$ represents the input and $\mathbf{x}(j+N-1 | j)$ denotes the system state, followed by the immediate post-horizon state $\mathbf{x}(j+N | j)$. These predicted inputs are consolidated into a vector,

$$\mathbf{X}_j = \begin{bmatrix} \mathbf{x}(j+d-1 | j) \\ \mathbf{x}(j+d | j) \\ \vdots \\ \mathbf{x}(j+i | j) \\ \mathbf{x}(j+N+d-1 | j) \end{bmatrix}, \quad \mathbf{U}_k = \begin{bmatrix} \mathbf{u}(j | j) \\ \mathbf{u}(j+1 | j) \\ \vdots \\ \mathbf{u}(j+i | j) \\ \mathbf{u}(j+N-1 | j) \end{bmatrix}. \quad (37)$$

Assuming that the system's output at the current time step corresponds to its state and the reference value is $\mathbf{r} = 0$, the system error can be represented by $\mathbf{x}$. By incorporating this relationship with equation (4), we present a refined cost function as shown in equation (38),

$$J = \sum_k^{N-1} [\mathbf{x}(j+k+d-1 | j)^T Q \mathbf{x}(j+k+d-1 | j) + \mathbf{u}(j+k | j)^T T \mathbf{u}(j+k | j) + \mathbf{x}(j+N+d-1)^T F \mathbf{x}(j+N+d-1)], \quad (38)$$

This expression can be reduced to the standard QP form,

$$J = \mathbf{x}_j^T G \mathbf{x}_j + 2\mathbf{U}_j^T E \mathbf{x}_j + \mathbf{U}_j^T H \mathbf{U}_j, \quad (39)$$

$$G = M^T \bar{Q} M, \quad E = C^T \bar{Q} M, \quad H = C^T \bar{R} C + \bar{T}, \quad (40)$$

$$\bar{Q} = \begin{bmatrix} Q & 0 & \cdots & 0 \\ 0 & Q & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & F \end{bmatrix}, \quad \bar{T} = \begin{bmatrix} T & 0 & \cdots & 0 \\ 0 & T & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & T \end{bmatrix}, \quad (41)$$

where the term $x_j^T G x_j$ remains as a constant that can be omitted during minimization.

The objective function of the QP problem for our proposed adaptive MPC system thus takes the form,

$$\min_U J = 0.5 \times U_j^T H U_j + U_j^T E x_j, \quad (42)$$

where factor 0.5 is incorporated to maintain consistency between the quadratic form of the objective function and its gradient, facilitating more efficient gradient computations. This formulation enables the effective solution of the QP problem through standard QP solvers, yielding optimal control inputs across the prediction horizon.

IV. EXPERIMENTAL ANALYSIS

This section evaluates the performance of MP²-QUIC in traditional, reliable, real-time video transmission scenarios, comparing it against three MPQUIC encoding solutions: Rand-SNC [48], Bats-SNC [49], and WindWrap-SNC [50].

A. Experimental Establishment

1) *Network Topology*: The experiments were conducted on the proposed model and comparison algorithms using the Network Simulator (NS-3.33) platform to assess their performance relative to other MPQUIC encoding solutions. The simulations employed a specific network topology (Fig. 5) and modeled a heterogeneous wireless network environment using various parameter configurations outlined in Table I. Default socket and connection flow buffer sizes were set to 4 MB and 1 MB, respectively. Each encoding batch comprised 178,000 bytes, with individual encoded packets sized at 1,050 bytes. The congestion control algorithm utilized was QUIC-NewReno [51], and the MinRTT path scheduling strategy was applied, while all other parameters adhered to the default MPQUIC configuration. Each simulation ran for 50 seconds, with unrestricted constant bit rate (CBR) traffic to emulate a streaming transmission scenario.

Details of the SNC settings are provided in Table II. Encoding was performed using a Galois field (GF) of size 2⁸. Each batch included ten pre-encoded parity packets based on GF(256). The base offspring size for Bats-SNC was set to 100, while the offspring size for other encodings was 120. At the receiver side, the Overlap-Aware decoding algorithm [48] was uniformly applied. It is important to note that these parameters are adjustable based on specific network environments and performance requirements.

In our experimental topology (see Fig. 5), the MPQUIC Sender (Encoder) and Receiver (Decoder) serve as the end-points for data transmission, while a Media Storage Server converts video streams into byte streams to enable constant-rate transmission to the sender's buffer. The system architecture features multiple network segments, each characterized

TABLE I
EXPERIMENTAL SETTINGS

Parameter	Value
Data Size	178000Bytes
Package Size	1050Bytes
Backbone Path Bandwidth	10Mbps
Backbone Path Delay	20ms
Wired Path Bandwidth	2Mbps
Wired Path Delay	5ms
Wireless Path bandwidth	1Mbps
Wireless Path Delay	100ms
SocketSndBufSize	4MB
StreamSndBufSize	1MB
SocketRcvBufSize	4MB
StreamRcvBufSize	1MB
Congestion Control Strategy	QuicNewReno
LossRate	5%

TABLE II
SPARSE NETWORK CODING SETTINGS

Parameter	Value
Galois Field	2 ⁸
Number of Precoding Packets	10
Base Subgeneration Size(BATS)	100
Subgeneration Size	120
Precode Type	GF(256)
Decoding Algorithm	Overlap-Aware
Seed	-1

by distinct properties. The topology comprises a wired link connecting the MPQUIC Sender to four routing nodes with recoding capabilities ($R_{1,1}$, $R_{1,2}$, $R_{1,3}$, and $R_{1,4}$), while the links operate at 2 Mbps with a 5 ms transmission delay. These nodes are interconnected via a backbone network (10 Mbps/20 ms), linking them to the next set of recoding-enabled routing nodes ($R_{2,1}$, $R_{2,2}$, $R_{2,3}$, and $R_{2,4}$). The MPQUIC Receiver simulates an IEEE 802.11 Wi-Fi network, which connects to the four recoding routing nodes with a bandwidth of 1 Mbps and a transmission delay of 100 ms.

To evaluate the system's performance, we simulate data stream transmission under a Bernoulli packet loss model, which effectively represents typical conditions in heterogeneous wireless networks. To ensure statistical reliability and mitigate the influence of random variations, all performance metrics are derived from the average of 50 stable simulation runs, with outliers excluded. This methodology enables a rigorous evaluation of different encoding schemes under varying packet loss rates.

2) *Comparison Algorithms*: Compared to RLNC, the encoding vector matrix of SNC is sparse, resulting in lower computational overhead and faster encoding and decoding speeds. Consequently, SNC is particularly well-suited for streaming transmission scenarios. For this reason, this paper evaluates three MPQUIC encoding solutions and compares their performance with that of MP²-QUIC. These three coding schemes have been further optimized for real-time communi-

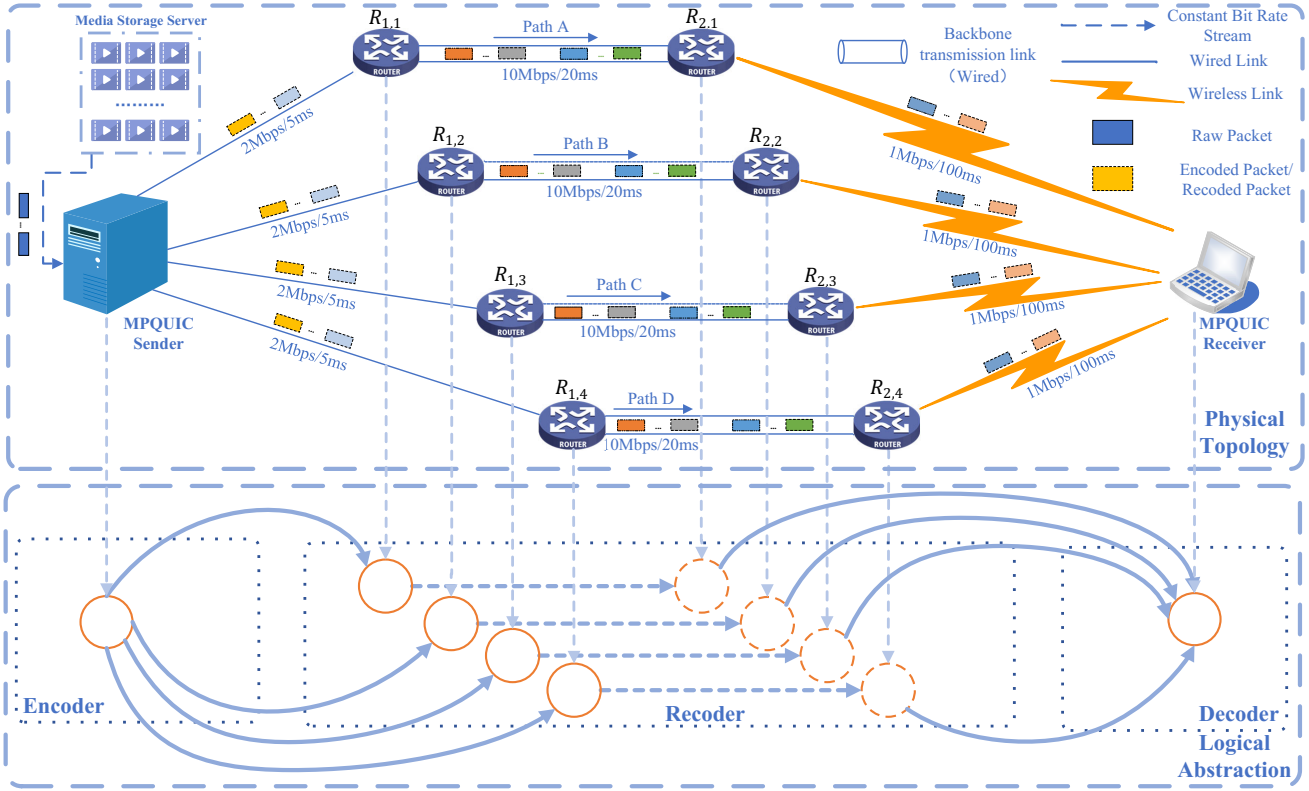


Fig. 5. Topology diagram.

cation, streaming transmission, and low-latency applications.

Rand-SNC: This SNC design is tailored for next-generation wireless technology scenarios. It employs sparse random linear network coding to minimize the transmission overhead associated with encoding coefficients and to reduce decoding complexity, enhancing network reliability and throughput. As a result, Rand-SNC is especially advantageous in streaming transmission scenarios with stringent low-latency requirements.

Bats-SNC: This algorithm generates a fixed number of encoded packets by forming random subsets of source packets and applying RLNC to each subset. Its unique batch sparsity implementation improves data transmission efficiency while reducing the overhead of encoding coefficient transmission. Furthermore, its decoding complexity is less sensitive compared to systematic encoding schemes, making it highly suitable for dynamic communication channel conditions.

WindWrap-SNC: As a variant of band coding, WindWrap-SNC addresses the "wrap-around problem" inherent in band coding matrices [26] through pre-coding. This method reduces encoding complexity and streamlines the decoding process. Moreover, WindWrap-SNC enhances the robustness of network transmission by employing randomized encoding combinations, making it particularly effective in environments characterized by high packet loss and in low-latency transmission scenarios demanding real-time performance.

B. Simulation Result

Our comprehensive performance evaluation of MP²-QUIC investigates its capabilities in comparison to existing MPQUIC encoding solutions, with a particular emphasis on end-user QoE in heterogeneous wireless networks. The analysis is structured around three key sections.

The first section evaluates fundamental transmission metrics to establish baseline performance. We assess goodput, which measures the effective rate of payload data transmission, alongside the encoding packet delivery rate and network latency. A critical metric in this evaluation is the count of successfully received valid encoded packets—those contributing directly to the decoding process. By systematically comparing these baseline metrics across diverse network conditions, we develop a robust benchmark for assessing the fundamental transmission capabilities of each solution. This benchmark serves as the foundation for subsequent analyses of decoding efficiency and QoE performance.

The second section examines decoding performance, focusing on decoding time and its associated costs. Decoding costs are defined as the relationship between successfully decoded packets and the original data packets within each transmission batch. Decoding time is particularly significant as it directly impacts packet reordering efficiency and video frame restoration rates. Our analysis of decoding overhead sheds light on how redundancy mechanisms influence successful decoding

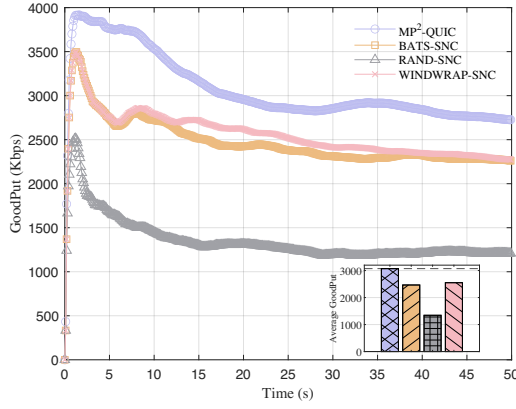


Fig. 6. Comparison of Goodput with Different Solutions.

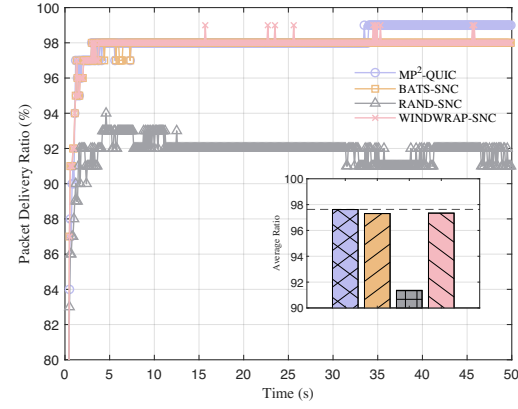


Fig. 7. Comparison of Packet Delivery Ratio with Different Solutions.

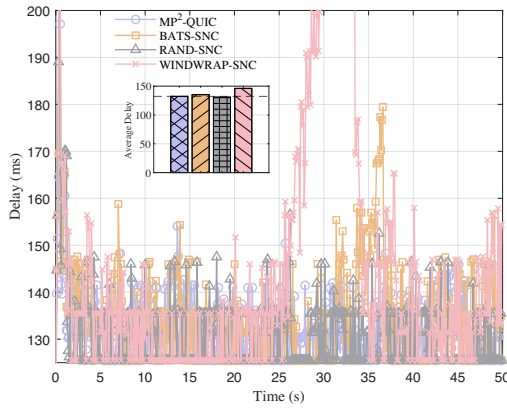


Fig. 8. Comparison of Delay with Different Solutions.

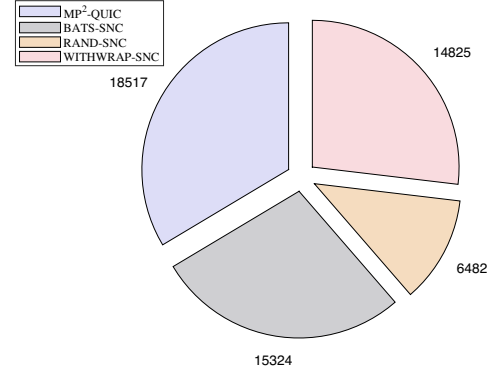


Fig. 9. Comparison of Valid Encoded Rtpackets with Different Solutions.

rates and overall transmission efficiency. This enables precise evaluation of network coding strategies across a variety of operational scenarios.

The third section addresses QoE performance through a detailed analysis of PSNR and jitter metrics. Network jitter, which quantifies variations in packet arrival intervals, serves as a critical indicator of system stability; excessive variations can significantly degrade decoder performance and compromise user experience. PSNR measurements provide a quantitative assessment of playback quality, offering a reliable evaluation of streaming media transmission stability by analyzing real-time transmission quality at the receiving end. Together, these metrics deliver comprehensive insights into the quality of the end-user experience.

1) *Benchmark Performance Evaluation:* The performance analysis of goodput measurements, (see Fig. 6), underscores the superior transmission capabilities of MP²-QUIC. Initially, the solution maximizes transmission rates to approach the optimal PSNR before rapidly stabilizing at a rate of 2766.56 Kbps. By comparison, Rand-SNC, Bats-SNC, and WindWrap-SNC stabilize at goodput rates of 1209.61 Kbps, 2260.84 Kbps, and 2317.65 Kbps, respectively. Throughout the simulation, MP²-QUIC maintains an average goodput of 3071.62 Kbps, reflecting improvements of 2.29-fold over Rand-SNC,

1.25-fold over Bats-SNC, and 1.20-fold over WindWrap-SNC. These results consistently highlight the enhanced goodput performance and efficient link utilization achieved by MP²-QUIC.

The analysis of encoded packet delivery ratios (see Fig. 7), reveals MP²-QUIC's rapid convergence to a 98% efficiency rate during the initial simulation phase, followed by a further improvement to 99% stability after 32 seconds of operation. On average, MP²-QUIC achieves an encoding packet delivery ratio of 97.618%, surpassing its counterparts: Rand-SNC at 91.333%, Bats-SNC at 97.306%, and WindWrap-SNC at 97.340%. The performance gap between MP²-QUIC and the other schemes widens progressively as the simulation advances.

Industry benchmarks for audio communication specify that latency becomes perceptible to users at approximately 150 ms [52]. For video communications, latency thresholds impacting the QoE are observed at 300 ms.

As shown in Fig. 8, MP²-QUIC consistently maintains latency below 150 ms, averaging 132.327 ms. This compares favorably to Rand-SNC (130.95 ms), Bats-SNC (135.213 ms), and WindWrap-SNC (146.209 ms). Although Rand-SNC achieves slightly lower latency, this is attributable to suboptimal throughput utilization rather than superior performance.

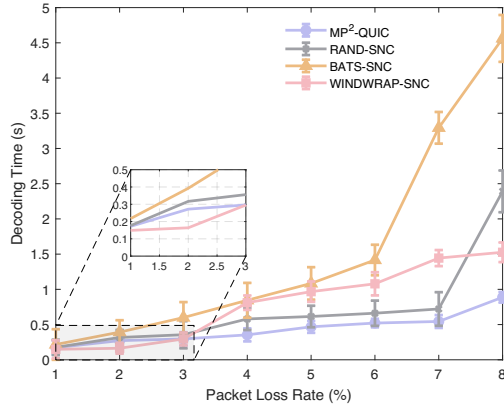


Fig. 10. Decoding Time of Comparison for Different Solutions under Different Network Conditions.

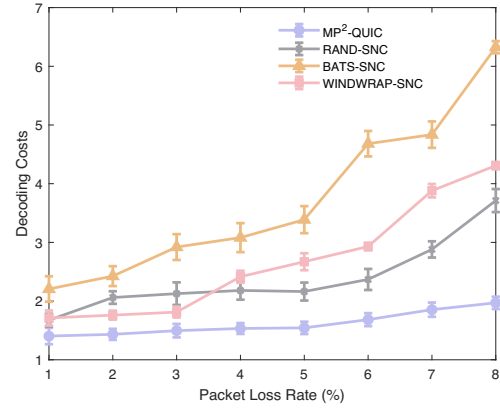


Fig. 11. Decoding Costs of Comparison for Different Solutions under Different Network Conditions.

In contrast, both WindWrap-SNC and Bats-SNC experience concerning latency spikes of 265.262 ms and 179.446 ms, respectively, whereas MP²-QUIC maintains stable and reliable latency performance.

The analysis of valid encoded packets received (see Fig. 9), further validates MP²-QUIC's effectiveness. By the end of the simulation, MP²-QUIC successfully delivers 18,517 valid encoded packets. This represents a significant improvement over alternative approaches, with performance ratios of 2.86, 1.25, and 1.21 times of the number received by Rand-SNC, Bats-SNC, and WindWrap-SNC, respectively.

2) *Decoding Performance Evaluation*: Fig. 10 demonstrates the performance variations in average decoding time across MPQUIC encoding solutions under varying packet loss conditions. In environments with low packet loss rates (below 3%), coding delays have minimal impact on transmission link performance. However, as packet loss rates increase beyond 5%, encoding information delay becomes a significant performance factor. MP²-QUIC maintains exceptional performance even under severe network stress, with decoding times remaining under 1 second at 8% packet loss rates. In contrast, other solutions exhibit substantially higher decoding times: Rand-SNC at 2.39 seconds, Bats-SNC at 4.56 seconds, and WindWrap-SNC at 1.53 seconds.

The stability analysis reveals notable differences in decoding time variance across solutions. While Rand-SNC, Bats-SNC, and WindWrap-SNC show maximum variances of 0.1914, 0.3325, and 0.1393 respectively, MP²-QUIC achieves superior stability with a maximum variance of only 0.0992. These results demonstrate MP²-QUIC's ability to maintain consistent performance in dynamic network environments, particularly in delivering video frames to upper layers.

Fig. 11 illustrates the comparative analysis of decoding costs across MPQUIC encoding solutions under dynamic packet loss conditions. MP²-QUIC demonstrates superior performance in mitigating encoded information latency, maintaining a consistent decoding cost of approximately 1.55211 across highly dynamic heterogeneous wireless environments. Under severe network conditions with 8% packet loss, Rand-SNC and WindWrap-SNC exhibit significantly higher decoding costs of

3.7125 and 4.30833 respectively.

It should be noted that Bats-SNC shows particularly challenging performance characteristics, with decoding costs escalating to 6.325. While its batch random encoding approach reduces encoding coefficient transmission overhead, it introduces substantially higher decoding complexity. MP²-QUIC achieves significant improvements in peak decoding cost reduction compared to existing solutions: 46.92% versus Rand-SNC, 54.26% versus WindWrap-SNC, and 68.85% versus Bats-SNC.

3) *QoE Performance Evaluation*: In order to assess the ability of MP²-QUIC in improving user QoE under challenging network conditions, we conducted a comprehensive evaluation of four MPQUIC encoding solutions in a high packet loss environment (8

Industry standards indicate that network jitter exceeding 30-50 ms severely degrades the streaming media user experience, while jitter below 20 ms ensures smooth video playback [53]. The metric defined in Equation (10) [42] quantifies user-perceived quality by accounting for both throughput and packet loss effects. Additionally, the ITU T. P.800 standard [54] outlines the relationship between PSNR values and user-perceived quality levels, as presented in Table III.

TABLE III
RELATIONSHIP BETWEEN PSNR AND USER PERCEIVED QUALITY LEVELS

PSNR (dB)	User Perceived Quality Level	Quality Level Description
> 37	Excellent	Imperceptible
31 – 37	Good	Perceptible but not annoying
25 – 31	Fair	Slightly annoying
20 – 25	Poor	Annoying
< 20	Bad	Very annoying

Our comparative analysis of network jitter, shown in Fig. 12, highlights MP²-QUIC's superior performance, maintaining jitter levels below 20 ms for the majority of the testing period. In contrast, alternative coding mechanisms exhibited significant network jitter, stemming from their inability to

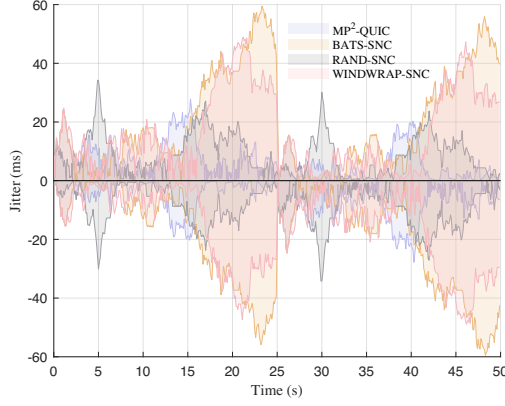


Fig. 12. Comparison of Network Jitter with Different Solutions.

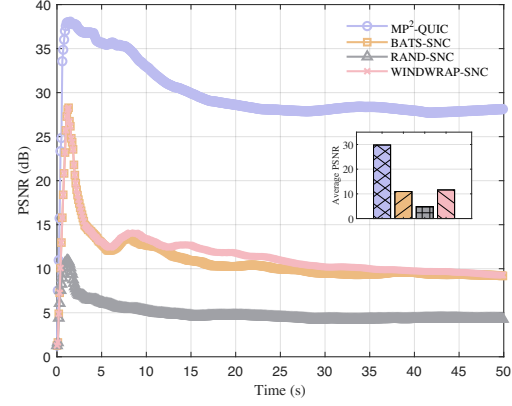


Fig. 13. Comparison of PSNR with Different Solutions.

efficiently manage link congestion and delays in encoding information.

The PSNR performance comparison (see Fig. 13), further underscores MP²-QUIC's advantages. By accurately predicting the required encoding packets for each batch, MP²-QUIC minimizes redundant packet transmissions, facilitating rapid decoding, data reordering, and timely delivery to upper-layer applications. Under stable link conditions, MP²-QUIC achieves a PSNR of 28.38 dB, a substantial improvement over Rand-SNC (4.33 dB), Bats-SNC (9.34 dB), and WindWrap-SNC (9.47 dB).

Overall, MP²-QUIC attains an average PSNR of 29.78 dB, representing improvements of 6.14, 2.72, and 2.57 times over the competing MPQUIC encoding solutions. These results highlight MP²-QUIC's effectiveness in enhancing video stream transmission performance across heterogeneous wireless networks, particularly under high packet loss conditions, leading to a significantly improved QoE for end users.

V. CONCLUSION

This paper presents an adaptive MPC strategy designed to enhance the Band-SNC congestion control mechanism in MPQUIC for heterogeneous wireless transmission scenarios, while addressing the latency of encoding information. Our approach integrates model prediction with feedback control, leveraging the Central Limit Theorem and operating point linearization to optimize system performance. We introduce a novel performance metric, grounded in queuing theory principles, to enable the adaptive MPC to accurately predict the required number of encoded packets for each transmission in the current batch.

Our experimental results demonstrate the superior performance of MP²-QUIC across multiple dimensions. The proposed solution achieves improved stability in both link latency and throughput, along with higher packet delivery rates. Compared to existing MPQUIC encoding solutions, MP²-QUIC results in a 1.77-fold increase in successfully received encoded packets, while reducing peak decoding overhead by 56.676%. Notably, in environments characterized by high packet loss, MP²-QUIC shows exceptional performance, with a 3.81-fold

improvement in PSNR metrics. These findings collectively underscore MP²-QUIC's ability to deliver superior effective throughput, reduced stable latency, and enhanced QoE.

Future research will focus on exploring the implementation of trajectory linearization techniques for real-time system modeling based on temporal trajectory evolution, with particular emphasis on addressing challenges in the network's "last mile" segment [55].

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Yuanlong Cao received the B.S. degree in computer science and technology from Nanchang University, China, in 2006, the M.S. degree in software engineering from the Beijing University of Posts and Telecommunications (BUPT), Beijing, China, in 2008, and the Ph.D. degree in communication and information system from the Institute of Network Technology, BUPT, in 2014. He is currently a Professor at the School of Software, Jiangxi Normal University, Nanchang, China. His research interests include multimedia communications, network security, and next-generation Internet technology.



Haopeng Zhang received the B.S. degree in the School of Information Engineering from the Shaoguan University, China, in 2022.

He is currently pursuing an M.S. degree in Management Science and Engineering at Jiangxi Normal University. His research interests include multipath transmission, next-generation network protocols, and Internet-related technologies.



Ming Jiang received the B.S. degree in the School of Electronics and Information Engineering from the Jinggangshan University, China, in 2022.

He is currently pursuing an M.S. degree in Network and Information Security at Jiangxi Normal University. His research interests include multipath transmission control protocol, next-generation network protocols, and cybersecurity.



Yirui Jiang is a Data Scientist, Artificial Intelligence, and Machine Learning expert. With a passion for extracting actionable insights from complex data sets, she brings a wealth of knowledge and expertise to the field of data science. She holds a B.S. degree in software engineering from Jiangxi Normal University, China, and a Ph.D. degree from Cranfield University, UK. She successfully applied her expertise to a wide range of projects, she is well-versed in tackling real-world challenges and driving data-driven decision-making. She thrive in interdisciplinary international teams, leveraging her expertise to foster collaboration and innovation.



Jinquan Nie received the B.S. degree in the School of Artificial Intelligence and Big Data at Hefei University, China, in 2022.

He is currently pursuing an M.S. degree in Management Science and Engineering at Jiangxi Normal University. His research interests include multipath transmission control protocol, cybersecurity and information management and systems.



Zhi Liu is an associate professor at the University of Electro-Communications, Japan. His research interests include video network transmission and mobile edge computing. He is an editorial board member of IEEE Transactions on Multimedia, IEEE Network and IEEE Transactions on Circuits and Systems for Video Technology. He is a Senior Member of IEEE.



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Cao, Yuanlong; Zhang, Haopeng; Jiang, Ming; Jiang, Yirui; Nie, Jinquan

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