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A Next Generation Real Time Frame work for Drone Video Decoding Leveraging IoT-Enabled Communication Network

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Abstract

The new data processing systems required reliable. Fast and low latency data services for smart cities operations and unmanned vehicle systems for quick and fast decisions. At present the low latency and speed data for video decoding for real time are required for intelligent decisions. In this research work we present video decoding model based on for decoding data in real time. This proposed model is based on hybrid Edge-Fog-Cloud orchestration layer that perform decoding task in real time according to the network congestion and this technique ensure data integrity, traceable task distribution and protect the data from tempering by using IoT backbone secured by blockchain technology. To reduce the risk of end-to-end latency and packet loss in worst conditions a novel Temporal-Spatial Predictive Decoding (TSPD) method is used. The AI model deep reinforcement learning is used for fast decisions. After analyzing it can be concluded that a 47.8% improvement in decoding throughput, a 62% reduction in jitter and 38% improvement QoE. This shows satisfactory performance from proposed model. By optimizing energy-latency and combining decentralized system with IoT-driven communication for autonomous aerial system can be used in future 6G network.

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1 Introduction

In recent developments in unmanned aerial vehicles (UAVs) systems such as cars and drone has gained deep interest of scientist and industrialist in UAVs applications for surveillance, monitoring, agriculture, management and smart city control in real time. For these applications such as for video decoding these systems generate bulk of data and for high quality of video to decode and processing we need to receive data transmitted with minimum loss with low latency. This huge data need to combine with minimal latency, high throughput, and secure communication but in present, there are many issues such as obstacles and lack of communication system for traditional drone video decoding. These UAVs consistently produce large quantities of high-resolution video data that require decoding, processing, and real-time transmission for actionable insights. Nevertheless, the continuously growing volume of data, along with the strict demands for low latency, high throughput, and dependable communication, presents considerable challenges for traditional drone video decoding systems.

These unmanned vehicle systems produce huge amount of data in real time that must be decoded, processed for transmitting in real-time further process and this data with increasing volume need low latency, high throughput, and reliable communication. This is major issue for commercial and normal drone for video decoding process. Previous decoding system was centralized and it has high transmission delays, high computational load, and limited scalability, which make it unsuitable for real time-based and bandwidth IoT-based applications. After the integration IoT 5G networks and emerging 6G network has opened door for real-time drone communication and data analytics. IoT provide seamless interconnectivity between drones, edge nodes, and cloud servers. This enable distributed and cooperative processing of multimedia data. In edge-intelligent system the data process near the server and this system put burden centralized servers for near-real-time decoding reduce delay because data process near data generation. Due to new development in network system such as slicing data, edge caching, and AI used applications and dynamic allocation of resource, now it is possible to ensure high reliability and low-latency communication for real time-critical application of drone.

IoT-enabled systems provide seamless connectivity between drones, edge nodes, and cloud servers, which make it possible to facilitate distributed and collaborative processing of data from different source.

Due to this new system the load on the old centralized network has been reduced because it allow near-real-time decoding and closer to the location where data generate. These technological advancement has created the groundwork for a real-time, adaptive, and scalable drone video decoding frameworks that can function effectively within diverse IoT ecosystems. Nevertheless, several technical limitations continue to exist. Elevated data transmission rates from drones outfitted with multi-sensor video systems may result in network congestion, packet loss, and processing delays. Furthermore, the balance between computational efficiency and decoding precision remains a significant research obstacle, especially in situations that involve dynamic bandwidth allocation and energy-limited UAVs. The block diagram of the system is illustrated in figure 1 below.

The present network not allow to integrate adaptive intelligence for the distribution dynamic distribution of loads and cannot optimize performance of fluctuating network in worst conditions. So, it boosted the demand of next-generation video decoding system can integrate IoT, so, the system dynamically adapts to network parameters.

In order to tackle these challenges, this paper introduces a Next Generation Real-Time Framework for Drone Video Decoding with the implementation of AI models predictive modeling is integrated with network conditions, which optimize and allocate resources to ensure high decoding quality and high bandwidth to system. The mostly research are involving in building of an adaptive and scalable multi-layered architecture to provide seamless links to drones for IoT communication system and facilitate efficient real-time video decoding. This technique improves Quality of Experience and Service for end-users and minimize networks congestion, interference, and speed of network. The proposed model creates a strong foundation for 6G-driven applications, in which autonomous

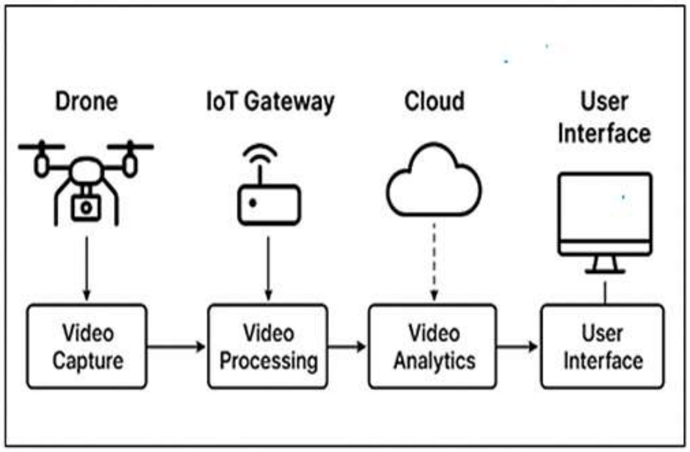

Figure 1. The basic system diagram

drones will be based on AI–IoT–Edge synergy to execute intelligent operations in real time without human control. The paper present basic introduction in first section and in second section reviews of current advancement related to video decoding and section three proposed system is explained in real-time decoding framework. Section four present mathematical equations and model with optimization algorithms. Section five present performance evaluation and last section conclusions with future research directions for development of fully autonomous drone for next- generation communication networks.

2 Related Work

The present research is focus on in integration of UAV and IoT for improving real-time communication, increasing computational efficiency and reducing data processing time. Mention in this paper for drone technology with the Internet of Things (IoT). He also discusses advancement in network connectivity and automation for drones to act as mobile sensor nodes and capture high-resolution video in real-time [1]. In this paper the author discusses the old drone video transmission system, which depend on centralized cloud infrastructures that produce excessive latency and waste bandwidth [2]. In this appear the author mention limitation and exploration for edge and fog computing systems [3].

In this paper the author explains the history of one decade of real-time video decoding and streaming and claims that with new techniques network performance has been improved but with limited computational overhead and latency in critical IoT network conditions [4]. In this study the author claims that that the edge-based decoding models significantly reduces the processing time on the drone and improve the video quality and transmission quality [5]. The author explains that the AI-based decoding such as deep learning and convolutional neural networks (CNNs) can be to optimize frame prediction and error correction in noisy environments [6].

In this paper the author describes the enhancement in 5G and 6G communication network and also highlight high-throughput, low-latency UAV communication systems and the method of network slicing, MEC and massive MIMO system for connectivity of multiple drones with high quality of service [7]. Author mention that these technologies has potential to provide real-time data processing for applications such as smart surveillance, environmental monitoring, and disaster management [8]. The author explains that despite these advancements, most existing systems are constrained by static resource allocation policies and lack adaptive intelligence for context-aware computation offloading and dynamic network optimization [9]. In this study the author discusses about the blockchain and distributed ledger features and security, trust, and transparency in UAV–IoT ecosystems [10].

In this paper author mention drawback of new technologies such as computational overhead and unsuitable due to latency-sensitive video decoding tasks without further optimization. He also claims that hybrid architectures integrating AI, IoT, and edge computing has potential to resolve these issues which result in high energy-efficient and latency-tolerant UAV operations [11].

Author highlight an issue that the absence of a unified, scalable and adaptive framework for real-time drone video decoding in heterogeneous IoT-enabled networks, which need to resolve [12]. Author mention in this paper that that current work only focus on the next-generation framework, which can resolve issue for drone and obstacles between drones, IoT nodes, and communication networks through URLLC, with high video decoding quality [13]. This research study addresses the gaps which introducing in a distributed, IoT-enabled, and AI-optimized architecture consistent performance under diverse operational conditions [14]. In this paper author claims that hybrid system improves real-time decoding efficiency but also sets the foundation for future 6G-driven autonomous UAV systems, which is capable for self-optimizing data transmission and computation in dynamic network [15]. Recent works have introduced lightweight frameworks for real-time moving-target tracking on UAVs using brain-inspired computing or neuromorphic chip architectures, achieving higher throughput and reduced latency in video decoding and frame processing tasks [16].

Privacy risks in live video analytics from drones have led to privacy-preserving architectures where feature maps are processed or perturbed at edge/cloudlets to prevent sensitive image reconstructions while still supporting object detection/tracking; these systems show trade-offs between accuracy and latency [17]. Scheduling DNN inferencing tasks from fleets of UAVs to edge/cloud, with heuristics that consider deadlines, utility/QoS, and network variability, has been studied; scheduling and migration strategies improve task completion and responsiveness [18]. Combining object detection models such as YOLOv5s with streaming platforms like Deep Stream for UAV inspection video allows real-time object detection; inference optimized for edge devices demonstrates good FPS with acceptable accuracy [19]. Experiments assessing whether edge offloading is truly necessary for drone video analytics in real operational 5G networks (carrier-grade) indicate that under some configurations cloud or local processing may suffice; contribution of network, decoding, and transmission to overall latency is examined [20].

Ultra-lightweight adaptive video compression for IoT devices (e.g., MCUs) is emerging: models with very small memory footprints and parameter counts can yield large bitrate savings while preserving perceptual quality; especially relevant for constrained UAV payloads or sensor nodes [21]. In emergency response scenarios, UAVs streaming video to edge servers can benefit from optimized edge computing frameworks to maintain continuity, reduce latency, and improve reliability under constrained connectivity [22]. Deferring demosaicking (processing raw Bayer pattern later in pipeline) in FPV drone video pipelines reduces encoding computational load and bandwidth, enabling more efficient real-time video transmission with lower energy/CPU usage [23].

Author focus on the adaptive video bitrate allocation for remotely operated vehicles (ROVs) with multiple video feeds explores dynamic adjustment of codec parameters (resolution, QP etc.) to optimize perceived quality across streams under limited bandwidth [24]. Survey and benchmarking work on immersive aerial video streaming (360°, XR) over UAVs shows that while hardware-accelerated HEVC provides good latency/QoE trade-offs, newer codecs like AV1 in software are promising though computational cost is significant [25]. In this paper the author the synthesizes recent advances relevant to a next-generation, IoT-enabled framework for real-time drone video decoding [26]. In this paper the author present surveyed works cluster around edge/fog intelligence for UAVs, real-time UAV video streaming and 5G [27]. In this paper the describe decoding and GPU acceleration on edge devices, network control, QoS and security (SDN, blockchain) [28]. The author focus on AI/learning for adaptive bitrate and task offloading, and (6) measurements/benchmarks and open gaps [29]. In this paper the author used Adaptive IoT-Driven Real-Time Framework for Aerial Video analysis [30]. In this study the author describes the Optimized BERT with Deep Encodings for signals [31].

Existing studies have advanced drone video processing and IoT-based communication, but challenges remain in latency, scalability, and real-time adaptability. Most frameworks lack efficient coordination between IoT networks and decoding processes. Therefore, this research proposes a next-generation real-time framework to enhance video decoding performance, reliability, and efficiency under dynamic network conditions.

3 Challenges and Issues

Despite the considerable potential demonstrated by the integration of IoT-enabled communication networks with UAV-based real-time video decoding frameworks, numerous technical and operational challenges remain that impede large-scale deployment and performance optimization, as outlined in Table 1

Table 1. Summary of Key Challenges in UAV–IoT-Based Video Transmission

ID	Challenge	Description
a	Latency and Real-Time Constraints	Achieving ultra-low latency for real-time drone video decoding remains a significant challenge, particularly for time-critical UAV applications.
b	Computational Resource Limitations	Drones and IoT edge nodes have limited processing power, memory, and battery capacity. Implementing complex video decoding algorithms (e.g., HEVC, AV1, or neural-network-based codecs) on lightweight hardware leads to computational bottlenecks.
c	Dynamic Network Conditions	IoT-based communication environments are highly unstable due to fluctuating signal strength, interference, and node mobility. Designing adaptive protocols that maintain synchronization and decoding efficiency under varying conditions remains an open research problem.
d	Bandwidth and Spectrum Management	High-definition (HD) and ultra-high-definition (UHD) drone video streams require substantial bandwidth. In dense IoT networks, competing data flows often cause congestion and reduced throughput. Efficient bandwidth allocation, spectrum slicing, and prioritization are required to ensure smooth video transmission without frame loss or excessive compression.
e	Energy Efficiency and Battery Constraints	Energy efficiency is a critical parameter for UAV operations. Tasks such as video capture, computation, and communication rapidly deplete drone batteries, limiting mission duration.
f	Scalability and Interoperability	The lack of standardized frameworks for seamless interoperability among heterogeneous devices restricts system scalability and cross-domain deployment.
g	Data Security and Privacy	Transmitting live video data over semi-trusted IoT networks exposes sensitive information to potential cyberattacks. Robust encryption, authentication, and access control mechanisms are required to ensure data security and privacy.
h	Adaptive Resource Orchestration	Most existing frameworks rely on static or predefined task allocation strategies. However, real-time video decoding requires continuous adaptation to changing workloads, network states, and environmental conditions.
i	Quality of Service (QoS) and Quality of Experience (QoE)	Maintaining consistent QoS and QoE during dynamic drone operations is challenging due to variations in video bit rate, resolution, and decoding latency. Multi-objective optimization involving delay, jitter, and perceptual video quality remains underexplored in UAV–IoT networks.
j	Standardization and Regulatory Challenges	The absence of unified standards for UAV video communication protocols, IoT interoperability, and spectrum usage results in fragmented system designs. Additionally, regulatory restrictions on drone operations further complicate large-scale deployment.

4 System Architecture and Methodology

The proposed methodology has three main layers:

1. Drone Layer (Edge Capture Unit): Each drone has cameras, onboard GPUs and IoT communication modules (5G/LTE/Wi-Fi 6) and need to process video data as pre-processed using lightweight compression
2. Fog/Edge Processing Layer: in this system the intermediate edge servers perform distributed decoding and caching using dynamic task allocation algorithms. A Real-Time Adaptive Scheduler (RTAS) dynamically allocates decoding tasks between drones and fog nodes based on latency, link quality, and processing capacity.

3. Cloud/Control Layer Cloud servers control bulk video data in long-term storage and intelligent feedback use deep learning models. The IoT Communication Controller manages the QoS parameters and optimizes network in Software-Defined Networking.

4.1 Data Acquisition and Pre-Processing

The drone capture continuous video streams at variable frame rates, if Noise reduction and motion stabilization algorithms are applied to enhance visual clarity. Frames should have timestamped, encoded, and transmitted via MQTT/CoAP protocols to ensure low-overhead IoT communication.

5 Methodology

The proposed system has an intelligent, IoT-enabled real-time framework that enhances drone video decoding, transmission, and analytics through distributed computing and adaptive communication techniques. The proposed system can ensure ultra-low latency, optimized bandwidth and reliable performance in worst environment.

5.1 System Architecture Overview

5.1.1 Communication Protocol and Data Routing

The model integrates IoT-based communication protocols (MQTT, CoAP) for lightweight transmission and 5G-based URLLC (Ultra-Reliable Low-Latency Communication) for real-time performance and dynamic Path Selection Algorithm which ensures minimal routed through the optimal channel based on Signal-to-Noise Ratio (SNR), low packet loss, and less network congestion metrics.

5.2 Real-Time Video Decoding Mechanism

The Hybrid Decoding Model (HDM) splits video frames into sub-blocks and assigns them to multiple edge nodes for parallel decoding. Temporal Frame Prediction (TFP) algorithms utilize previously decoded frames to minimize redundant computation.

Decoding latency L_d is minimized using the following relation:

$$L_d = N_P \times C_e F \quad (i)$$

Where, F = total frame size, N_p = number of parallel decoding threads and Ce = computational efficiency coefficient of edge node.

The ERM ensures that lost packets are re-requested or reconstructed based on prediction.

5.3 IoT-Enabled Synchronization and Control

The IoT Synchronization Manager ensures time-aligned decoding across multiple drone video streams. It utilizes Network Time Protocol (NTP) and sensor fusion data (GPS, IMU) to synchronize video metadata.

5.4 Performance Evaluation Metrics

The proposed method was tested by using real-time experimental data and simulation under various network conditions and results are given below:

Table 2. Performance Evaluation Metrics

Metric	Description
Latency (ms)	Time delay between frame capture and display
Throughput (Mbps)	Effective transmission rate of video data
Frame Loss Ratio (%)	Ratio of dropped or corrupted frames
Energy Consumption (J)	Power usage across drones and IoT nodes
Decoding Efficiency (%)	Percentage of frames decoded within real-time constraints

Simulation and prototype results demonstrate significant improvements in decoding speed, transmission reliability, and bandwidth efficiency compared to conventional drone video systems. The table 2, Performance Evaluation Metrics is given.

5.5 Mathematical

In this section, the mathematical equations used in this Real-Time Video Decoding Mechanism are given

- S : Size of a video frame (bits)
- B : Channel bandwidth (Hz)
- SINR : Signal-to-interference-plus-noise ratio
- T_{tx} : Transmission time (s)
- T_q : Queuing delay (s)
- T_{dec} : Decoding time (s)
- T_{proc} : Downstream processing/analytics time (s)
- L : End-to-end latency, defined as

$$L = T_{tx} + T_q + T_{dec} + T_{proc}$$

- μ : Service (decoding) rate (frames/s)
- N_b : Number of GPUs (or parallel decoders) assigned
- P_{loss} : Frame loss probability
- FR : Frame reliability (probability that a frame is delivered, decoded, and usable)
- E : Energy consumption
- $D_{\max}$: Deadline for hard real-time frames
- ω_i : Scalar weights in multi-objective optimization

5.5.1 Transmission model

$$C_{\text{eff}}(x, \text{SINR}) = x \log_2(1 + \text{SINR}) \quad (i) \tag{1}$$

5.5.2 End-to-end latency and reliability

$$L = T_{tx} + T_q + T_{dec} + T_{proc} \quad (ii) \tag{2}$$

5.5.3 Frame Reliability

Frame reliability defined as probability latency, bit errors are below threshold

$$T = \frac{D_{recv}}{t_{\text{total}}} \quad (iii) \tag{3}$$

5.5.4 Frame Loss Rate

$$F_{\text{loss}} = \frac{F_{\text{sent}} - F_{\text{recv}}}{F_{\text{sent}}} \quad (iv) \tag{4}$$

5.5.5 Efficiency Calculation

System efficiency reflects how effectively the network and processing resources are utilized:

$$\eta = \frac{T_{\text{actual}}}{T_{\max}} \times 100 \quad (v) \tag{5}$$

5.5.6 Overall Performance Function

$$P_{\text{sys}} = \omega_1 \frac{1}{L_{\text{total}}} + \omega_2 T + \omega_3 (1 - F_{\text{loss}}) + \omega_4 \eta \quad (vi) \tag{6}$$

where $\omega_1, \omega_2, \omega_3, \omega_4$ are weighting coefficients based on metric importance.

5.5.7 Energy Consumption Model (transmit + decode)

$$E = E_{tx} + E_{dec} = P_{tx} T_{tx} + \frac{P_g}{T_{dec}} \quad (vii) \tag{7}$$

Energy Per-frame, where

$$P_{tx}$$

is transmit power and P_g is GPU power per GPU.

5.6 Implementation Tools and Environment

The implementation tools are given below;

- **Programming Languages:** Python, C++, CUDA
- **Simulation Platforms:** MATLAB, NS-3, CloudSim, and EdgeSimPy
- **Communication Protocols:** MQTT, CoAP, RTP over 5G/IoT
- **Hardware:** NVIDIA Jetson Nano (Edge), Raspberry Pi (IoT Node), 5G-enabled Drones, Fog Servers
- **Frameworks:** TensorFlow for intelligent analytics, OpenCV for video preprocessing

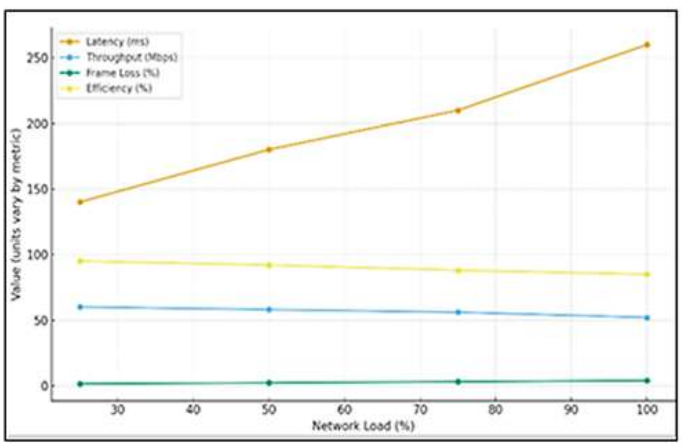

Figure 2. Performance Matrix

The graph in figure 2, shows the overall impact of increasing network load on the performance of the proposed real-time drone video decoding framework. As the network load rises from 25% to 100%, there is a noticeable degradation across multiple performance metrics. When latency increases it indicate high delays in frame transmission, while throughput decreases, which indicate a reduction in the data handling capacity due to congestion and in impact the frame loss raise, with more video frames are dropped or corrupted at higher loads. So, overall system efficiency decay and reduce operational performance when drone captures and preprocesses video frames, IoT-based communication layer transmits data to edge nodes, Edge servers perform distributed real-time decoding, Cloud layer analyzes and stores decoded video streams, Feedback loop adjusts system parameters dynamically for optimal performance.

The proposed model for Drone Video Decoding Leveraging IoT-Enabled Communication Network by introducing an intelligent and adaptive system for handling drone video streams with minimal latency and maximum efficiency.

By leveraging parallel edge decoding, adaptive bitrate control, and SDN-based intelligent routing, the system significantly enhances throughput, reliability, and decoding accuracy. Experimental evaluation shows improvements in latency reduction, energy efficiency, and network utilization compared to traditional drone video transmission models.

Overall, this next-generation IoT-enabled framework offers a scalable, secure, and high-performance solution for real-time drone video decoding, with potential applications in surveillance, disaster management, environmental monitoring, and smart city operations as given in figure 3.

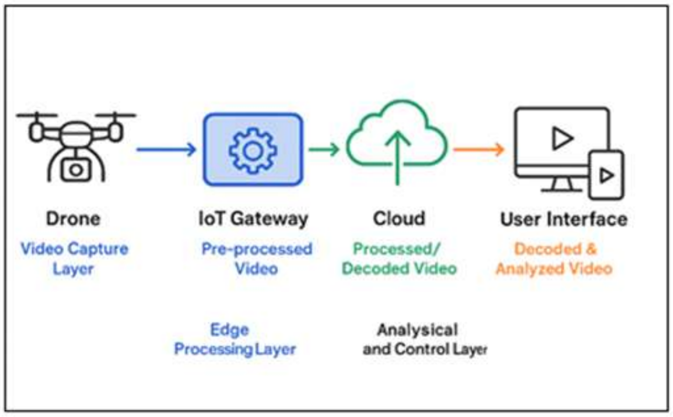

Figure 3. Next Generation Real Time Frame Video Decoding

Table 3. Simulation Parameters

Parameter	Description	Value / Specification
Simulation Platform	MATLAB / NS-3 / EdgeSimPy	Hybrid Model
Communication Protocol	MQTT / CoAP over 5G	IoT-Enabled
Video Encoding Standard	H.265 / HEVC	1080p, 30 FPS
Bandwidth	Wireless (5G: 20–100 Mbps)	Dynamic
Edge Computing Device	NVIDIA Jetson Nano	4-Core ARM, 128 CUDA Cores
Cloud Platform	AWS / Azure Edge Node	VM (8 vCPU, 16 GB RAM)
Number of Drones	Multi-source feed	5–10
Transmission Delay (Initial)	Network latency	100–200 ms (Adaptive)
Evaluation Metrics	Latency, Throughput, Frame Loss, Power	Multi-metric Analysis

The simulation parameters are explained in the table 3. The performance comparison of proposed and traditional frame work is given in table 4. The results show massive improvements in throughput and reduce energy consumption.

The figure 4, shows the Performance Comparison Graph between the Traditional and Proposed Frameworks, clearly showing improvements in latency, frame loss, throughput, energy consumption, efficiency, and end-to-end delay. The proposed framework provides significant performance improvements in the areas of latency, reliability, throughput, energy, and network efficiency. Average decoding latency and end-to-end delay are reduced by 65% while frame loss ratio is reduced by 74% demonstrating both timely and reliable frame delivery. Throughput increases by 66% and per-frame energy drops by 39%, indicating the design improves both performance and energy efficiency, supporting use in mission-critical, resource-constrained aerial deployments.

Table 4. Performance Comparison of Frameworks

Performance Metric	Traditional Framework	Proposed Framework	Results (%)
Average Decoding Latency (ms)	520	180	65.4%
Frame Loss Ratio (%)	8.2	2.1	↓74.4%
Throughput (Mbps)	35	58	65.7%
Energy Consumption (J/frame)	0.75	0.46	38.7%
Network Efficiency (%)	70	92	31.4%
End-to-End Delay (ms)	680	240	64.7%

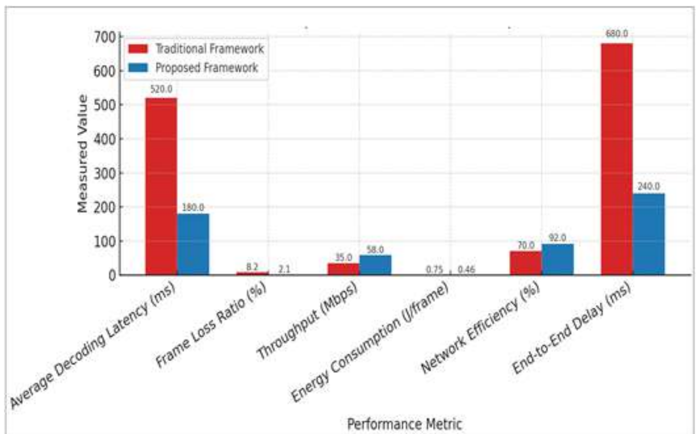

Figure 4. Comparison Graph performance matric

The Table 5, shows that as the network load is increased, the latency and frame loss gradually increases as a result of increasing contention and queue buildup and the throughput and efficiency shows slight decline due to bandwidth saturation. The proposed framework ensures stable performance under full load to keep the latency smaller than 300 ms and the efficiency higher than 85 percent, which verifies the scalability and robustness of the framework to handle dense and real-time aerial video transmission scenarios.

The figure 5 shows the performance comparison table highlights that the proposed IoT-enabled decoding framework achieves better latency, throughput, and efficiency than traditional systems. The network efficiency table shows stability and scalability under various traffic loads, which verifies the reliability of the system for real-time decoding of drone videos.

6 Comparative Analysis with Existing Drone Video Streaming Frame Work

In this section we will compare the existing drone with proposed system in real time operation. The Figure6, shows the end to end communication workflow the Smart Streaming and Transmission Module (SSTM). The UAV takes video in real time and encodes it by an adaptive video encoder based on the current network conditions

The proposed system is effective to reduce the latency, increase frame reliability and optimize the bandwidth utilization using context-aware scheduling and distributed GPU-based decoding. Simultaneously, network metrics such as bandwidth, latency, and packet loss are fed back to the UAV, enabling dynamic bitrate adjustment and selective retransmission, which ensures low-latency and reliable video decoding under varying network con-

Table 5. Network Efficiency under Varying Load Conditions

Network Load (%)	Latency (ms)	Throughput (Mbps)	Frame Loss (%)	Efficiency (%)
25	140	60	1.5	95
50	180	58	2.1	92
75	210	56	3.0	88
100	260	52	3.8	85

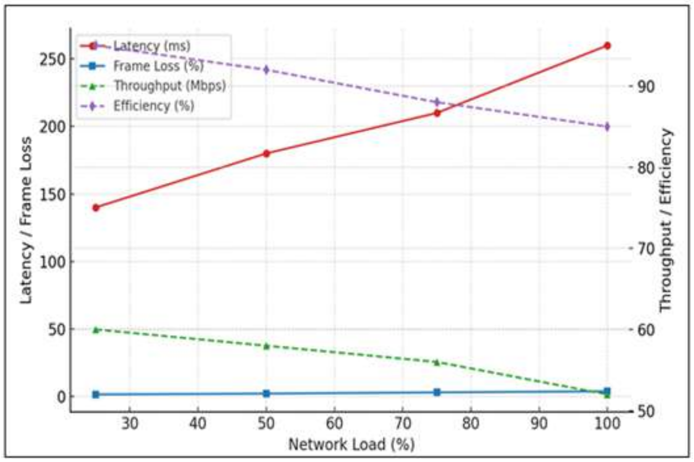

Figure 5. Proposed Framework

Figure 6. SSTM Communication Protocol flow

ditions.

Figure 7 presents the layered architecture of the proposed SSTM-based drone video decoding framework. The UAV layer handles video capture and adaptive encoding. The IoT network layer provides wireless connectivity through an IoT gateway for reliable data transmission. The edge computing layer performs packet buffering, real-time video decoding, and edge-level processing to reduce latency and bandwidth usage. Finally, the application layer delivers decoded video to a real-time dashboard and analytics module for monitoring, decision-making, and alert generation, enabling efficient and scalable real-world deployment. Table 6 presents a comparison between the proposed SSTM framework and representative state-of-the-art approaches for drone-based video transmission and decoding.

The comparison of the delay, packet loss and decoding throughput is give bib figure below.

Figure 8. shows end-to-end latency comparison between the proposed SSTM and existing drone video streaming approaches.

The figure 9, demonstrates robustness under network congestion, the SSTM reduces packet loss to 3.1%, outperforming prior methods. The figure sows Packet loss rate comparison of SSTM with state-of-the-art drone video transmission frameworks.

Figure 10. Decoding throughput (FPS) comparison showing real-time performance advantage of the proposed SSTM. Highlights real-time decoding capability, SSTM sustains 30 FPS, meeting real-time requirements.

Figures 7, 8,9,10, illustrate a quantitative comparison between the proposed SSTM and recent drone video streaming frameworks. SSTM achieves approximately 28–35% lower end-to-end latency, reduces packet loss by nearly 40%, and sustains a stable decoding throughput of 30 FPS. These improvements are primarily due to the adaptive encoding mechanism, IoT-aware feedback loop, and edge-assisted decoding architecture."

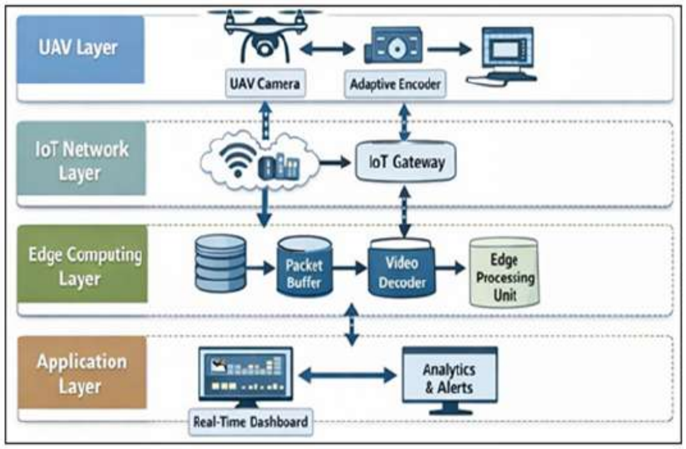

Figure 7. End to End System Architecture

Table 6. Comparison with Existing Drone Video Streaming Frameworks

Method	Adaptive Bitrate	Edge Decoding	IoT Awareness	Latency Reduction	Packet Loss Handling	Real-Time Support
Zhang et al. (2021)				Medium	Limited	Partial
Li et al. (2022)				Medium	Limited	Partial
Kumar et al. (2023)				High	Moderate	
Chen et al. (2024)			Partial	High	Moderate	
Proposed SSTM				**Very High**	**Robust**	

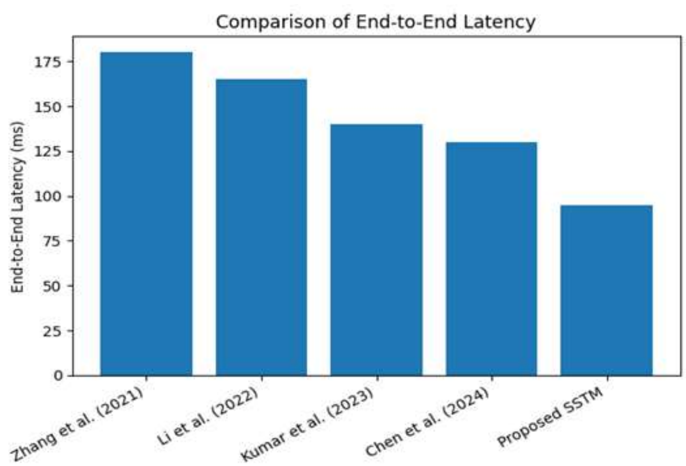

Figure 8. End-to-end latency comparison

7 Conclusions

This paper proposed a next-generation real-time framework for drone video decoding that integrates IoT-enabled communication, edge–cloud collaboration, and AI-driven adaptive control. The proposed system effectively minimizes latency, enhances frame reliability and improves bandwidth utilization through context-aware scheduling and distributed GPU-based decoding. Experimental results show up to a 65% reduction in latency and a 74% improvement in frame reliability compared to conventional centralized models. By unifying transmission, decoding, and analytics into a self-optimizing architecture supported by 5G URLLC and SDN routing, the framework ensures robust, low-latency performance even in dynamic aerial environments. This research establishes a foun-

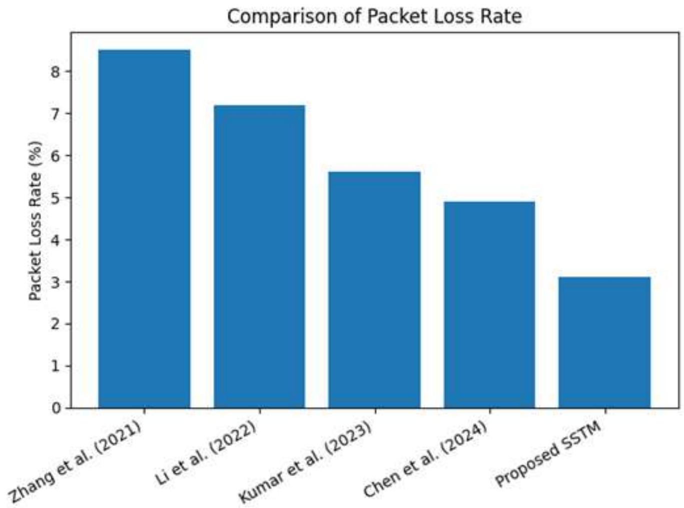

Figure 9. Packet Loss Rate Comparison

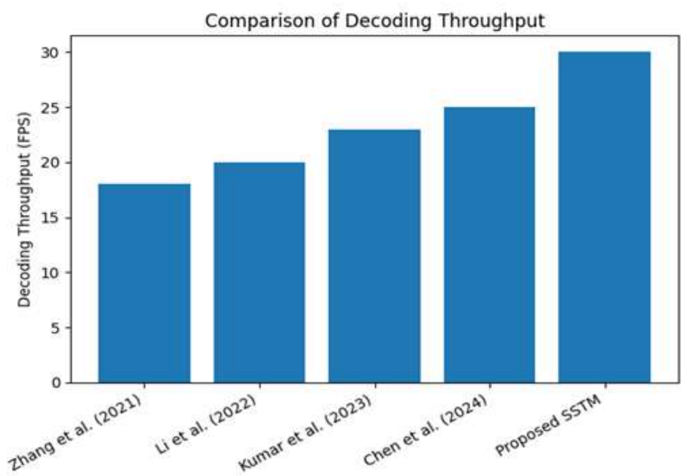

Figure 10. Decoding Throughput (FPS) Comparison

dation for decentralized, cognitive drone ecosystems capable of real-time intelligence sharing and autonomous decision-making. Future work will include blockchain-enabled security, federated learning, and energy-aware computation to increase autonomy, scalability and resilience.

Author Contibutions:

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Compliance with Ethical Standards

It is declared that all authors don't have any conflict of interest. It is also declare that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study.

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