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Analyzing the Impact of Network Variability on the Performance of Telesurgery

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Abstract—**The disparity in surgical care between urban and rural areas remains a significant challenge due to geographical and connectivity constraints. Telesurgery, enabled by digital twins, has emerged as a potential solution to bridge this gap. However, the reliability of telesurgical procedures is heavily influenced by network variability, including latency fluctuation, jitter, packet loss, and varying throughput. This paper investigates the impact of network instability on telesurgery key performance indicators (KPIs) and evaluates the correlation between network parameters and surgical precision, system responsiveness, and operational safety. To achieve this, we developed a Robotic Telesurgery Digital Twin (RTDT) framework that models network conditions and performs real-time risk analysis. Using Pearson, Spearman, and ANOVA correlation methods, we quantify the influence of network variability on telesurgical performance. Additionally, decision trees is used to predict high-risk scenarios before modeling stochastic network disruption with Monte Carlo. Simulation results indicate that a latency exceeding 150 ms results in a 98% failure rate in telesurgery. Additionally, packet loss greater than 30% can reduce surgical precision by 55%. Furthermore, a throughput below 150 Mbps drastically impacts the operation, leading to a 98% probability of failure. These findings highlight the importance of controlling latency, packet loss, and throughput variations to maintain reliable surgical performance.**

Index Terms—**Digital Twins, Network Variability, Telesurgery, Network Grading, Risk Analysis**

1 Introduction

The disparity in surgical care between urban and rural areas remains a significant global challenge in healthcare [1]. Despite advances in medical technology, many rural and underserved communities continue to face limited access to essential surgical services [2]. Residents in rural areas frequently face long travel distances to access surgical facilities, resulting in delayed treatment and potentially adverse health outcomes.

Although the geographic distance remains a major barrier to accessing surgical care in remote regions, advances in remote medical technologies, such as telesurgery, offer a promising way to overcome this challenge. However, the success of these solutions depends not only on bridging physical distance, but also on ensuring the stability and quality of the underlying network infrastructure. Unfortunately, rural areas often suffer from limited network resources, unstable connections [3], and inconsistent bandwidth, resulting in increased latency, jitter, and packet loss. These connectivity constraints introduce an additional layer of complexity, directly impacting the quality, safety, and feasibility of telesurgical procedures, which demand highly reliable and low-latency communication systems.

Given these interlinked challenges of distance and connectivity, it becomes imperative to understand how specific network parameters influence key performance indicators (KPIs) in telesurgery. This understanding is crucial for ensuring safe, efficient, and accessible surgical care across geographically dispersed regions.

To address these complex network-related challenges, digital twin technology has emerged as a promising solution in telesurgery [4]. By creating virtual replicas of the surgical environment and the network infrastructure [5], digital twins enable the simulation of various network conditions and their impact on surgical procedures. This capability enables the assessment of how fluctuations in network parameters [6] might impact surgical performance, providing valuable insights for preoperative planning and system optimization before actual deployment.

Building upon the digital twin remote surgery framework [5], the integration of real-time risk analysis further enhances the trustworthiness of telesurgical procedures. By analyzing potential risks associated with network variability in real time, digital twin remote surgery framework can provide immediate alerts and recommendations, allowing healthcare professionals to preemptively adjust surgical strategies (e.g., slowing robotic movement, switching to manual mode) or modify network parameters (e.g., reallocating bandwidth, switching to a more stable network path) to maintain surgical precision and safety.

This paper examines how network variability impacts telesurgery performance and patient safety. Through statistical analysis, we quantify the correlations between network parameters and surgical KPIs, including system responsiveness, task completion time, and haptic feedback quality. Network simulations validate these findings by replicating real-world scenarios, while risk analysis evaluates potential hazards based on severity and likelihood. This research provides a framework for assessing and mitigating network-related risks in remote surgical procedures, particularly in constrained environments.

The contributions of this paper are summarized as follows:

- We identify critical network parameters that can negatively affect telesurgical performance in dynamic network of rural zones.
- We investigate how fluctuations in network parameters affect key performance indicators that are essential for successful telesurgery operations.
- We develop risk assessment approach to categorize potential failures based on their severity and likelihood of occurrence under varying network conditions

The remainder of the paper is organized as follows. Section 2 reviews existing research efforts related to telesurgery and network variability. Section 3 introduces the architecture of the RTDT system, highlighting the role of the digital twin of the network in handling unstable network conditions. Section 4 highlights the significance of real-time network variability modeling and details the experimental setup. Performance evaluation and results are discussed in Section 5. Lastly, Section 6 concludes the paper and outlines potential future research directions.

2 Related Work

Robotic telesurgery relies heavily on robust, low-latency, high-bandwidth connectivity to enable seamless communication between the surgeon and the remote robotic system. The effectiveness of telesurgery depends on the real-time transmission of high-resolution video, haptic feedback, control signals, and sensor data. Existing communication technologies [7] used for this purpose span a range of wired, wireless, and hybrid connectivity. For wireless connectivity, 5G and 6G networks are becoming game-changers in robotic telesurgery [8]. Unlike 4G, they offer ultra-low latency (as low as 1 ms), high bandwidth, and support for device-to-device communication (D2D) with network slicing. This ensures that critical surgical data are transmitted in near real-time, even under high traffic conditions. In some cases, satellite communication is used for telesurgery, especially in remote or underserved areas with limited access to 5G or fiber-optic infrastructure. While satellite links can enable global connectivity, they have higher latency (typically 300–600 ms) due to the long distance between ground stations and satellites.

Morohashi et al. [9] discuss how seamless uninterrupted connectivity is a critical enabler for the success of robotic telesurgery. Unlike traditional surgery, telesurgery relies on real-time, bidirectional data exchange between the surgeon and the surgical robot. In [10], the authors show the impact of interrupted connectivity. Surgeons face delayed responses, misaligned robotic arm movements, and disjointed video feeds, increasing the risk of errors such as accidental cuts or misplacement of surgical instruments. According to [11], inadequate bandwidth in communication networks can significantly impact surgical performance and increase surgeon fatigue, highlighting the critical need for stable and high-capacity network connections in telesurgery.

Although reliance on 5G and 6G networks in telesurgery has significantly reduced latency [7], the availability of 5G infrastructure is still limited in many regions, especially in rural or underserved areas. Furthermore, satellite-based connectivity, often used as a backup in remote locations, has higher latency due to the time it takes for signals to travel to and from satellites, which could further disrupt critical surgical tasks. Another key connectivity challenge is network reliability and fail-safe mechanisms. By forecasting when and where disruptions might occur, proactive measures such as switching to alternative communication paths or increasing buffer times can help mitigate surgical interruptions. Despite these advancements, accurately predicting network disruptions and implementing real-time responses remains a significant challenge.

A key limitation lies in the reliance on traditional network models in telesurgery, which are often built on static configurations. These models, while providing baseline performance estimates, fail to capture the dynamic nature of high-stakes surgical environments.

Therefore, the concept of Digital Twins (DTs) has emerged in network management [11], offering a virtual replica of the telesurgery network that continuously synchronizes with real-world conditions. This allows for real-time monitoring, predictive analysis, and proactive adjustments to network parameters, helping mitigate latency spikes, packet loss, and throughput degradation before they impact the surgical procedure. By leveraging real-time network telemetry, AI-driven modeling, and system logs, a virtual replica of the telesurgery network is created and continuously synchronized with live data. Network digital twins (NDTs) are continuously updated to reflect the current state of the network. Although NDTs offer significant advantages, their implementation in telesurgery remains challenging due to the need for extensive real-time data collection, high-performance computing resources, and seamless integration into current network infrastructure. However, recent advances in networking technologies, edge computing, and machine learning are increasingly addressing these challenges, making practical deployment achievable.

Risk analysis in networked systems involves identifying potential threats, assessing their likelihood, and evaluating their potential impact. In the context of telesurgery, existing frameworks assess either network-related risks or surgical procedure risks in isolation, rather than considering their interdependencies. While some studies [12] have proposed risk assessment methods for telesurgery, they often lack real-time capability and fail to account for the dynamic nature of network conditions. Additionally, current risk analysis approaches rarely consider the specific challenges of rural healthcare settings, where network instability may introduce unique risk factors. There is a notable absence of integrated risk assessment frameworks that can provide immediate, actionable guidance based on both network conditions and surgical requirements.

A key limitation in prior work is the lack of an integrated approach that dynamically correlates network behavior with surgical performance. While some works discuss network failures as a potential risk, they often treat them as isolated events rather than continuously evolving conditions. Furthermore, most existing network models rely on deterministic network assumptions and do not incorporate real-time risk assessment mechanisms in rural zones. In this paper, we address these gaps by monitoring changes in network conditions, predicting the impact of variability on surgical performance, and categorizing potential failures based on their severity and likelihood.

3 Empowering Telesurgery with Digital Twins

A. System Architecture

As introduced in [13], Robotic Telesurgery Digital Twin (RTDT) framework includes two distant surgical zones connected to a 5G network for high data transfer. The first surgical zone contains medical assistance personnel, the patient, and the surgical robotic arm, while the second surgical zone contains digital twins of both the patient and surgical arm, which the surgeon will control via a console unit. The extended framework in Fig. 1 consists of three main components: the Physical Twin Surgical Zone, the digital twin surgical zone, and the network digital twin. The physical twin surgical zone represents the real-world surgical environment, including the patient, surgical robot, and medical assistance staff. It is equipped with visual, tactile, motion, physiological, and environmental sensors to capture and transmit critical data for real-time monitoring. An edge node processes sensor data, prioritizing essential information before transmission via a router and a 5G modem to ensure low-latency communication. The digital twin surgical zone creates a real-time virtual replica of both the patient and the robot, allowing for enhanced preoperative planning, intraoperative adjustments, and real-time feedback to the surgeon. The network digital twin (NDT) extends this concept by modeling the 5G network infrastructure, including the User Equipment (UE) Layer, Radio Access Network (RAN), Core Network (CN), and Multi-Access Edge Computing (MEC). By continuously tracking network conditions and dynamically adjusting communication parameters such as adaptive modulation schemes, handover strategies, network slicing allocations, and QoS prioritization. These adjustments are

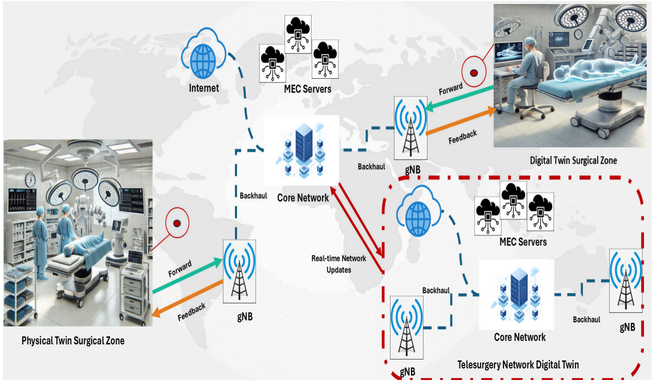


Figure 1: Robotic Telesurgery Digital Twin Architecture

implemented through software-defined networking (SDN) policies, machine learning-based traffic prediction, and time-sensitive networking (TSN) mechanisms. With these capabilities, the NDT enables proactive network optimization, mitigating disruptions and enhancing surgical precision.

B. Design Objectives

The RTDT framework aims to improve the reliability and efficiency of telesurgery by emulating the real-time dynamics of the surgical network, allowing proactive adjustments to the allocation of network resources, ensuring stable and low latency communication between surgical zones. RTDT continuously monitors and adapts to changing network conditions, preventing performance degradation due to fluctuations in connectivity. Our proposed system has four main goals towards modeling and handling the consequences of network variability in rural environment as follows:

1) Anticipate potential connectivity issues by simulating different traffic loads, and failure scenarios.
2) Identify network parameters and telesurgery KPIs directly affected by network variability.
3) Quantify the correlation between network parameters and telesurgery KPIs.
4) Assess potential risks under variable network conditions.

4 Experiemntal Setup

A. Real-Time Network Variability

Network variability in telesurgery is influenced by RTDT demand-based and environment-based factors. RTDT demand-based factors include bandwidth utilization and throughput, ensuring smooth data transmission, while task priority, concurrent tasks, and task switching frequency affect network load and resource allocation.

Environment-based factors impact real-time performance, with latency and jitter affecting responsiveness, packet loss reducing data integrity, and SNR and CQI determining signal reliability. Network congestion and power consumption further influence stability.

Since procedural efficiency is the core objective of RTDT, surgical KPIs must be clearly defined and systematically categorized to ensure reliable and seamless telesurgery operations. For instance, system performance KPIs focus on network stability, including latency, jitter, and synchronization. Medical outcome KPIs assess surgical accuracy, task completion time, and error rates. User experience KPIs measure system usability and surgeon stress. Safety KPIs ensure fail-safe mechanisms, data integrity, and error recovery. Resource utilization KPIs optimize energy efficiency and network resource allocation. In this study, we focus on the system performance KPIs as shown in Table 1.

TABLE 1: Telesurgery KPIs

KPI Category	KPI Description
System Performance	**Latency**: $<$200ms delay in surgeon-robot response. **Jitter**: Minimized variations in data arrival. **Packet Loss**: $<$1% data loss for reliable control. **Reliability**: $>$99.999% uptime for uninterrupted surgery.
Medical Outcomes	**Task Time**: Comparable to traditional surgery. **Surgical Accuracy**: Sub-millimeter precision. **Error Rate**: As close to zero as possible.
User Experience	**Usability**: Intuitive interface, minimal training. **Surgeon Stress**: Reduced cognitive load.
Safety	**Fail-Safe Mechanisms**: 100% redundancy in failures. **Data Integrity**: No data corruption or loss.
Resource Utilization	**Bandwidth**: Prioritized for critical surgical data. **Energy Efficiency**: Optimized power consumption.

TABLE 2: Telesurgery Network Parameters

Network Parameter	Impact
Latency	High latency affects precision and feedback.
Jitter	Variability in packet arrival times leads to unstable robotic movements and disrupted video streams. Must be minimized for smooth operation.
Packet Loss	Percentage of lost data packets. Critical for maintaining accurate robotic commands and video feeds.
Bandwidth	Maximum data transmission capacity. Impacts video resolution, haptic feedback, and control signal reliability.
Synchronization	Alignment between surgeon commands, robotic execution, and feedback. Desynchronization causes delays and surgical inefficiencies. Minimal time drift is essential.
Signal-to-Noise Ratio (SNR)	Low SNR leads to data loss and degraded communication, impacting latency and throughput.
Throughput	Ensures seamless operation of high-definition video, haptic feedback, and control signals.

Table 2 presents the critical network parameters that influence telesurgery performance and their corresponding impacts on surgical operations. Understanding these parameters and their effects is crucial to maintaining surgical precision and safety, particularly in environments with limited or unstable network infrastructure.

B. Network Variability Dataset

After identifying the key network parameters and telesurgery performance indicators, we built a network digital twin of RTDT in MATLAB to simulate how the network behaves during laparoscopic liver resection telesurgery. The simulation models a 5G-enabled telesurgical setup spanning 2000 miles between two surgical zones. We collected two datasets: one for a stable network condition (baseline) and another for disrupted network scenarios caused by path loss, congestion, interference, and hardware failures.

The Surgical Network Variability Dataset aims to quantify the impact of network fluctuations on telesurgery performance and reliability. It incorporates a detailed record of critical network parameters: latency, jitter, packet loss rate, throughput, bandwidth capacity, and signal-to-noise ratio (SNR). These metrics are correlated with key performance indicators (KPIs) of the telesurgery system, including task completion time, system responsiveness, haptic feedback fidelity, video stream quality, and overall system reliability. The dataset's hierarchical decomposition of surgical procedures into distinct tasks and sub-tasks allows for granular analysis of network influence on specific surgical actions.

To assess network stability, the dataset categorizes conditions as Stable, Unstable, or Critical, based on standard thresholds [14]. A Stable network keeps latency low (50–100 ms), jitter minimal (0–3 ms), and packet loss under 5%, ensuring smooth operation. An Unstable network sees higher latency (100–150 ms), increased jitter (3–6 ms), and packet loss between 5–15%, which can lead to noticeable delays and inconsistencies. A Critical network, with latency over 150 ms, jitter between 6–12 ms, and packet loss climbing to 15–30%, poses a serious risk, potentially causing disruptions in surgery. By linking network variability to surgical workflow disruptions, this dataset serves as a valuable tool for evaluating network resilience, optimizing telesurgical actions during network disruptions.

C. Network Parameters and Surgical KPIs Correlation

Given the complexity of telesurgical procedures, correlation analysis can quantify how variations in network conditions influence surgical outcomes. To evaluate the impact of network variability on telesurgery performance, we employ four statistical methods:

- **Pearson Correlation** Measures linear relationships between network parameters and surgical KPIs. It identifies direct proportionality but assumes normally distributed data.
- **Spearman Correlation** Captures nonlinear, monotonic relationships, making it suitable for threshold effects in network fluctuations.
- **ANOVA** Compares surgical KPIs across different network states, determining if performance degrades significantly under unstable or critical conditions.

D. Network Disruption Risk Assessment

We categorize surgical risks associated with each network parameter as low, moderate, high, or critical based on their severity and likelihood. This risk mapping is the basis for predicting potential network failures and implementing preventive measures such as dynamically adjusting network resource allocation, task scheduling, or failover mechanisms before surgical performance is compromised. before surgical performance is compromised. We implement a dual-layer risk assessment methodology combining real-time decision tree classification with probabilistic Monte Carlo simulation analysis. In the first layer, decision trees provide continuous classification of network conditions, categorizing system states as stable, unstable, or critical based on real-time metrics to identify early warning indicators, particularly degradation in key parameters such as jitter and packet loss rates. The second layer employs Monte Carlo simulation techniques to perform an in-depth probabilistic analysis of long-term risk patterns. It can predict the frequency and severity of scenarios in which the combined network parameters exceed safety thresholds, allowing the development of evidence-based mitigation strategies.

5 Results and Discussion

To assess the reliability of the RTDT network, we examine the correlation between network parameters and surgical KPIs to identify the key factors that directly influence surgical performance.

We also evaluate how fluctuations in network conditions impact the probability of failure, enabling real-time classification of network health to ensure seamless and reliable telesurgery operations.

A. Correlation Analysis

The correlation between network parameters and surgical KPIs is determined using the general correlation equation [15]:

$$\mathrm{Corr}(X,Y) = \frac{\mathrm{Cov}(X,Y)}{\sigma_X \sigma_Y} \tag{1}$$

where:

- $\mathrm{Corr}(X,Y)$ represents the correlation between two variables X (network parameter) and Y (surgical KPI).
- $\mathrm{Cov}(X,Y)$ is the covariance of X and Y, indicating how changes in one variable correspond to changes in the other.
- σ_X and σ_Y are the standard deviations of X and Y, respectively.

For Pearson's correlation coefficient, the equation simplifies to:

$$r = \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum (X_i - \bar{X})^2} \cdot \sqrt{\sum (Y_i - \bar{Y})^2}} \tag{2}$$

where:

- X_i and Y_i are individual sample points of network parameters and KPIs, respectively.
- $\bar{X}$ and $\bar{Y}$ represent the mean of the respective variables.
- $\sum$ denotes summation over all data points.

This coefficient measures the strength and direction of a linear relationship between network parameters and surgical KPIs, ranging from -1 (strong negative correlation) to $+1$ (strong positive correlation). A value close to 0 suggests little to no correlation between the two variables.

Table 3 presents the Pearson correlation coefficients between key network parameters and surgical KPIs, highlighting their direct impact on telesurgery performance. The results show a strong positive correlation ($r = 1.00$) between system response and latency, confirming that increased latency directly delays surgical actions as shown in Fig. 2a. Conversely, the quality of the haptic feedback exhibits a strong negative correlation ($r = -1.00$) with latency, indicating that as latency increases, the quality of the force feedback deteriorates, potentially impairing surgical precision.

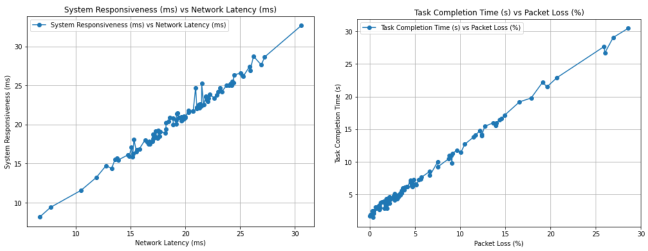
Additionally, both task completion time and error rate have a high positive correlation with packet loss ($r = 0.97$ and $r = 0.98$, respectively), suggesting that increased packet loss leads to prolonged task execution and a higher likelihood of surgical errors as observed in Fig 2b. Similarly, video quality is negatively correlated with packet loss ($r = -0.90$), which indicates that greater packet loss results in degraded video clarity as shown in Fig 2d .

Lastly, reliability is strongly correlated with throughput ($r = 1.00$) in Fig 2c , indicating that higher data transmission rates contribute to a more stable and dependable network, reducing the risk of communication disruptions during surgery.

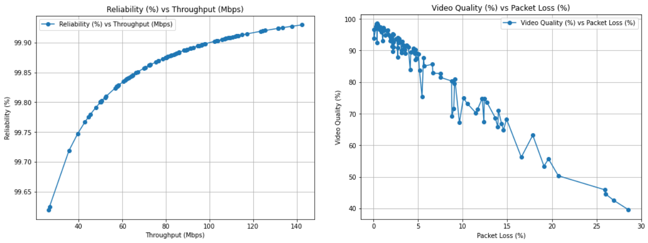
TABLE 3: Pearson Correlation

KPI	Network Parameter	Pearson Coefficient
System Responsiveness	Latency	1.00
Haptic Feedback Quality	Latency	-1.00
Task Completion Time	Packet Loss	0.97
Video Quality	Packet Loss	-0.90
Error Rate	Packet Loss	0.98
Reliability	Throughput	1.00

Table 4 highlights the nonlinear relationships between network parameters and telesurgery KPIs using Spearman correlation. Unlike Pearson, which captures linear dependencies, Spearman assesses monotonic trends. System responsiveness and latency ($\rho = 0.95$) maintain a strong monotonic relationship, assuring that increased latency consistently delays robotic responses. Similarly, haptic feedback quality ($\rho = -0.92$) declines as latency increases, reflecting a consistent but nonlinear degradation in tactile perception. Additionally, task completion time and error rate ($\rho = 0.96$) exhibit strong positive correlations with packet loss, meaning that



(a) System Responsiveness vs Latency (b) Task Completion vs Packet Loss



(c) Reliability vs Throughput (d) Video Quality vs Packet Loss

Figure 2: Correlation trends between network parameters and telesurgery KPIs

TABLE 4: Spearman Correlation

KPI	Network Parameter	Spearman Coefficient
System Responsiveness	Latency	0.95
Haptic Feedback Quality	Latency	-0.92
Task Completion Time	Packet Loss	0.96
Video Quality	Packet Loss	-0.88
Error Rate	Packet Loss	0.96
Reliability	Throughput	0.99

as packet loss increases, delays and errors accumulate even if the rate of change varies. Conversely, video quality ($\rho = -0.88$) declines with packet loss, indicating nonlinear deterioration in visualization. Finally, reliability and throughput ($\rho = 0.99$) demonstrate a near-perfect monotonic trend, underscoring the importance of high data rates for maintaining network stability.

The results of ANOVA analysis, highlighting the statistical significance of network parameters on telesurgery KPIs as shown in Table 5 . The F-statistic quantifies the variance between different network conditions, while the p-value indicates statistical significance.

Furthermore, reliability is highly dependent on throughput ($F = 35.14, p = 0.000$), indicating that higher data transmission rates ensure stable network performance. System responsiveness and haptic feedback quality are significantly impacted by latency ($F = 30.22, p = 0.000$; $F = 25.76, p = 0.001$), emphasizing the importance of low-latency connections for real-time control and precise force feedback.

Overall, the low p-values confirm that network variability significantly affects telesurgery KPIs.

B. Risk Analysis

As an initial step in risk analysis, we establish the correlation between network parameter fluctuations and their impact on surgical outcomes, as outlined in Table 6.

TABLE 5: ANOVA Analysis

KPI	Network Parameter	F-Statistic	P-Value
Task Completion Time	Packet Loss	18.42	0.002
Video Quality	Packet Loss	18.42	0.002
Error Rate	Packet Loss	21.67	0.001
Reliability	Throughput	35.14	0.000
System Responsiveness	Latency	30.22	0.000
Haptic Feedback Quality	Latency	25.76	0.001

TABLE 6: Network Parameters and Associated Surgical Risks

Network Param	Associated Risk
Latency	Delayed response from robotic systems causing surgical imprecision or errors.
Jitter	Unstable arrival of robotic movements status or video feedback disrupting surgical flow.
Packet Loss	Loss of critical commands or haptic data leading to incomplete or incorrect actions.
Bandwidth	Insufficient bandwidth degrading video quality or interrupting haptic feedback.
SNR	Poor signal quality causing retransmissions, delays, or complete system failure.
Synchronization	Misaligned actions and feedback resulting in operational inefficiencies or patient harm.

1. Risks Qunatification

We assign quantitative scores to potential risks as follows:

$$R = P \times I$$

Where R is the risk score, P is the probability of occurrence, and I is the impact on KPIs. Based on the risk score, we classify risks into low, moderate and high classes.

2. Risk Severity Assessment

In Table 7, we formulate a risk matrix based on the severity of the consequences (risk score for impact on surgical outcomes) and the likelihood (probability of occurrence).

For example, critical risks arise when high latency causes delayed robotic responses, particularly during crucial surgical steps, potentially compromising precision and patient safety. High-risk scenarios include packet loss, which disrupts haptic feedback transmission, leading to incomplete or inaccurate tactile sensations for the surgeon. Meanwhile, moderate risks involve throughput limitations that degrade non-critical video streams, affecting visualization quality but not immediately threaten the procedure.

TABLE 7: Surgical Risks Matrix

Severity ↓ / Likelihood →	Low	Medium	High
High	Moderate Risk	High Risk	Critical Risk
Medium	Low Risk	Moderate Risk	High Risk
Low	Negligible Risk	Low Risk	Moderate Risk

Telesurgery Network Risk Dashboard

Network Condition & Risk Level

Critical Risk! Network is Unreliable (Class C)

Figure 3: RTDT Network Real-time Dashboard

3. Potential Risk Prediction

For real-time risk assessment within the RTDT network digital twin, we employ a Decision Tree model to predict network stability, and categorize network conditions into three distinct states: Stable, Unstable, and Critical as shown in Fig. 3 . The Decision Tree approach was selected for its rapid execution speed, transparent decision-making process, and rule-based classification structure that aligns with clinical decision-making. Our model is trained on the stochastic network disruption dataset that captures the complex dynamics of network behavior. The training features are the critical network parameters (latency, jitter, packet loss, throughput, and Signal-to-Noise Ratio (SNR)). The analysis reveals that specific parameter combinations, latency coupled with increased packet loss rates, serve as reliable predictors of network state degradation that could compromise surgical performance. When the model identifies critical parameter trends, the system can immediately initiate preventive measures such as bandwidth reallocation, data stream prioritization, or surgical task rescheduling. This proactive approach ensures continuous adaptation of network resources to maintain optimal conditions for telesurgical operations.

4. Stochastic Disruption Modeling

Beyond prediction, we employ Monte Carlo simulation with 50,000 iterations to model surgical risks under variable network conditions, providing quantitative risk assessment for proactive mitigation strategies. Fig. 4 reveals that latency and throughput present the highest failure probabilities (exceeding 90%), while packet loss significantly impacts video and haptic feedback quality. In contrast, jitter shows lower failure probability, suggesting less impact than sustained latency or packet loss on surgical operations.

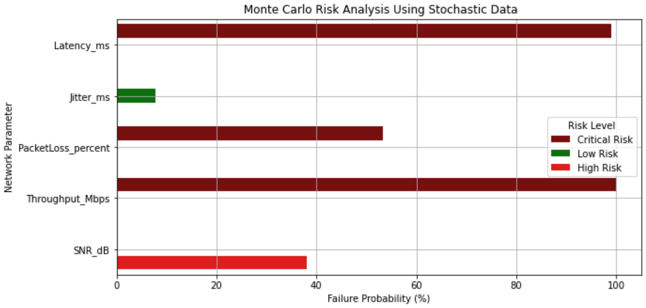


Figure 4: Impact of Network Variability on Telesurgery Failure

These findings highlight the critical need for real-time network monitoring and adaptive control mechanisms in telesurgery. To address the need for active network management in telesurgery, we developed an interactive dashboard shown in Fig. 3.It continuously tracks network status, classifying conditions into three categories: Class A (Stable), Class B (Unstable), and Class C (Critical). By analyzing dynamic network parameters and associated risks, the dashboard enables proactive decision-making for both surgical teams and network operators. For example, when network health indicators reach critical levels, operators can immediately initiate mitigation strategies, such as rescheduling procedures or reallocating network resources until stable conditions are restored.

6 Conclusion

This paper explores the impact of network variability on telesurgery performance by assessing the relationship between key network parameters and surgical KPIs. Through the RTDT framework, we simulate network fluctuations and evaluate their effects on system responsiveness, task completion time, and surgical precision. The findings reveal that latency, packet loss, and throughput fluctuations are the most critical factors influencing telesurgery reliability. To address these challenges, we propose a dual-layer risk assessment model, combining decision trees for real-time network classification and Monte Carlo simulations for probabilistic risk estimation. The results indicate that integrating network monitoring with predictive modeling can enhance the reliability of telesurgical procedures, particularly in resource-constrained environments. Future work will focus on adaptive network resource allocation and dynamic mitigation strategies to further improve telesurgery resilience against network instability.

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