2024 IEEE 10th World Forum on Internet of Things (WF-IoT) | 979-8-3503-7301-1/24/$31.00 ©2024 IEEE | DOI: 10.1109/WF-IoT62078.2024.10811351

Dynamic Task Scheduling for Digital Twins to Meet Telesurgery Real-Time Requirements

Hebatalla Ouda*, Khalid Elgazzar†, Hossam S. Hassanein*
School of Computing, Queen's University, Kingston, Ontario, Canada
Ontario Tech University, Oshawa, Ontario, Canada
**20htfa@queensu.ca*, †*khalid.elgazzar@ontariotechu.ca*, **hossam@cs.queensu.ca*

***Abstract*—Recent developments in 6G technology are projected to revolutionize applications with stringent real-time requirements, such as telesurgery. This paper presents a novel approach for supporting real-time decision-making in remote surgery by leveraging digital twins to overcome distance barriers. We address the communication challenges inherent to telesurgical digital twins and introduce an end-to-end formulation of data synchronization using Integer Linear Programming (ILP). We propose various grouping strategies for critical surgical tasks to support dynamic task scheduling within the telesurgical digital twin environment. These strategies include Interrelated Dependency (IRD), Highest Priority-Nearest Deadline (HPND), Shortest Transmission Time (STT), and Shortest Validity Time (SVT). We apply the knapsack approach to optimize task scheduling, aiming to maximize the sum of task priorities while minimizing the number of tasks that miss their deadlines. Performance evaluation shows that the HPND grouping strategy yields better results than other grouping strategies across key performance metrics, including transmitted task size, task priorities, and the reduction of tasks that miss their deadlines.**

***Index Terms*—Digital Twins, Synchronization, Telesurgery, Data Freshness, Knapsack Modeling**

1 Introduction

The emergence of digital twin technology (DT) in the midst of the Industry 5.0 revolution has generated significant attention in various domains [1], including aerospace, agriculture, smart cities, manufacturing, supply chain, smart transportation, and healthcare. Leveraging a combination of advanced technologies—including the Internet of Things (IoT), edge computing, deep and reinforcement learning, extended reality (XR), 3D modeling, tactile internet, haptic communication, and 6G and beyond networks—Digital Twins (DTs) provide seamless integration and transformative capabilities [2]. Before the advent of DT technology, healthcare systems depended primarily on physical interactions between clinicians and patients for monitoring, diagnosis, treatment, and surgical procedures [3]. The COVID-19 pandemic underscored the limitations of traditional healthcare delivery methods, prompting the widespread adoption of telemedicine and telehealth practices [4] to mitigate infection risks. Although remote medical consultations proved effective in many cases, they struggled to address complex medical scenarios that required in-person examinations. The introduction of digital twins will revolutionize healthcare systems [5] by enabling contactless medical services through virtual replicas of patient anatomy [6], medical equipment, clinical setups and surgical environments in a cyber-physical space.

The advancement of 6G technology plays a crucial role in the evolution of digital twin technology, especially in the areas of holographic and haptic communication [7], as well as telesurgery [8]. With ultra-low latency and reliability requirements exceeding 99.9999%, 6G networks will enable real-time feedback and rapid decision-making [9] in telesurgery, significantly improving patient outcomes.

The shift from traditional telesurgery to remote surgery enhanced by digital twin technology marks a significant transformation in surgical practice. In remote or hard-to-reach areas, such as rural locations, confined environments, or war zones, the integration of remote surgery with digital twins will allow patients and expert surgeons to overcome the challenges posed by long-distance travel. Moreover, digital twin technology enables thorough preoperative simulation and planning [10], allowing surgical procedures to be precisely simulated and optimized in advance. This approach facilitates predictive modeling to identify the most effective surgical strategies, minimize postoperative complications, and improve outcomes. Furthermore, the use of digital twins mitigates the risks associated with communication disruptions, providing surgeons with a reliable reference to guide procedures, even when real-time connectivity is compromised.

Latency issues arise as medical data travels between the surgical zones, leading to synchronization challenges and delays in real-time digital twin surgeries [11]. Efficient task grouping and scheduling before transmission to surgical digital twins are crucial in optimizing telesurgical procedures by minimizing delays and resource utilization, while ensuring seamless coordination between the surgical team and digital twins. Dynamic task scheduling enables remote surgeons to adapt quickly to changing surgical requirements, thus improving surgical precision and minimizing the risk of wrong decisions based on outdated data states. Thus, optimized task grouping and scheduling are imperative for maximizing surgical efficiency and patient outcomes in telesurgery scenarios.

This paper focuses on the role of surgical tasks scheduling towards achieving communication synchronization between physical and virtual replicas and delivering risk-free robotic telesurgical digital twins. We prioritize sending the most critical interrelated tasks to enable precise decision-making at the surgeon's interface while ensuring data freshness within the designated timeframe, without exceeding data expiration deadlines.

The contributions of this paper are summarized as follows:

- We introduce a novel vision of remote surgery, integrating the existing Da Vinci Surgical onsite platform with advanced digital twin technology.

- We formulate the synchronization problem between two distant surgical zones in the robotic telesurgery DTs environment.
- We propose diverse grouping approaches for surgical tasks and investigate the impact of task grouping on dynamic scheduling and real-time synchronization in telesurgery.
- We compare different surgical tasks grouping optimization models to ensure the efficient tasks scheduling and transmission of critical, highest priority surgical tasks while minimizing the number of tasks that miss their deadlines.

The remainder of the paper is organized as follows. Section 2 sheds light on existing research efforts. Section 3 presents the definition of RTDT, as well as the opportunities and challenges. Section 4 describes the problem formulation, RTDT system modeling, and experimental setup. Performance metrics and results are discussed in Section 5. Section 6 concludes the paper and presents potential future directions.

2 Related Work

The deployment of digital twins in the healthcare domain has emerged as a transformative innovation [12], revolutionizing the traditional paradigms of medical care. Medical DTs, virtual replicas of physical entities such as patients and clinical environments, have gained traction due to their potential to improve diagnostic accuracy, treatment efficacy, and patient outcomes. In healthcare, digital twins leverage data from wearable sensors, medical imaging, electronic health records, and real-time monitoring systems [13] to create dynamic and personalized models of patient physiological conditions. These virtual representations enable surgeons to simulate various surgical scenarios, predict potential outcomes, and optimize therapeutic interventions tailored to individual patient needs.

For surgical planning using digital twins, the authors in [14] explain how surgeons can engage in virtual experimentation with diverse surgical approaches, thereby assessing the feasibility and outcomes of various techniques while proactively anticipating potential surgical challenges or complications. Throughout surgical procedures, digital twins can serve as invaluable reference tools for surgeons. By superimposing virtual models on real-time imaging data acquired within the operating zone, surgeons gain enhanced spatial awareness and precision in navigating patient anatomy. Although considerable attention has been paid to the role of digital twins in the surgical use case, the literature lacks a comprehensive exploration of the potential impact of digital twin deployment on existing remote surgery practices.

Cakir et al. [15] implement a simulation framework for DT communication and perform an analysis of network topologies (core, distribution, access) and flow configurations and end-user network occupancy. They evaluated the performance metrics (delay, jitter, packet loss) of the DT synchronization using the twin alignment ratio metric. Nevertheless, their simulation period of 20 sec is impractical within the time constraints of real-time remote surgery ($<$ 150ms).

The authors in [16] investigate digital twin synchronization issues through continual learning in a Mobile Edge Computing (MEC) environment, aiming to maximize the total utility gain for improved model accuracy. They explore two novel optimization problems: the static digital twin synchronization problem per time slot and the dynamic digital twin synchronization problem for a finite time horizon. They evaluated the performance of the proposed algorithms through simulations, which demonstrate their promise by outperforming counterpart benchmarks by no less than 13.2% in terms of total utility gain.

The job shop scheduling problem has garnered significant academic attention, leading to studies on various aspects such as static, dynamic, initiative, and distributed scheduling. Fang et al. [17] study how smart manufacturing dynamically impacts the execution of the scheduling plan. Their findings show that digital twins offer a promising solution for quickly responding to smart manufacturing workshop disturbances through rescheduling. They propose a new DT-based job shop scheduling approach, with the aim of providing more accurate data for rescheduling and timely response to dynamic events in physical workshops. While the DT-based approach addresses real-time and accurate scheduling challenges in smart manufacturing, developing a scheduling evolution mechanism to enhance scheduling adaptability based on real-world data is still needed.

The authors in [18] explore a multi-task scheduling problem to enhance monitoring accuracy in flight control system testing (FCST). They analyze battery levels, transmission power, and accuracy relationship, formulating an expectation probability maximization problem. Three critical factors affecting accuracy are identified, leading to the proposal of an accuracy-oriented testing task scheduling (AOTS) algorithm. Despite contributions to monitoring response and accuracy, disparities between scheduling schemes and real-time running conditions persist. All proposed studies focus only on the wireless channel bandwidth and its utilization, without considering the other performance metrics that affect the real-time synchronization between the physical space and its digital representation. Moreover, the effect of applying different grouping strategies on the surgical task scheduling is under-investigated.

3 Robotic Telesurgery Digital Twins (RTDTs)

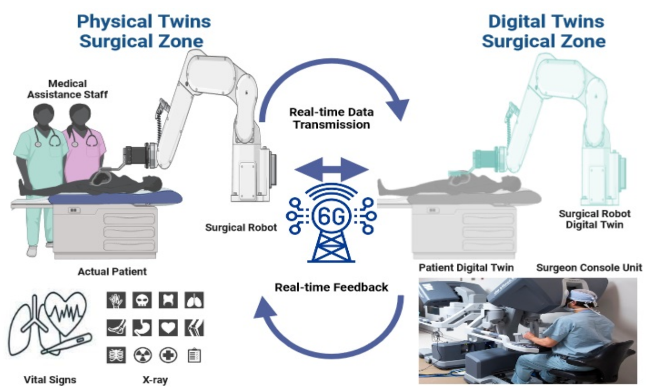


Figure 1: Robotic Telesurgery Digital Twin Architecture

RTDTs open up a new level of surgical experience behind the existing immersive practice in the Da Vinci Research Kit [19]. The surgeon will be able to perform the entire operation using an identical digital twin of the surgical robot on a digital replica of the patient's body with fully tactile senses instead of relying on visual information from 3D cameras. Fig. 1 represents the system architecture of robotic telesurgical digital twins where there are two distant surgical zones connected to a 6G 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.

For RTDTs to function effectively, it is crucial to address specific network requirements, including delay, jitter, and loss rate. Delay refers to the time it takes for data to travel from the source to the destination. In a telesurgical context, low latency is essential to ensure real-time feedback and precise control of the surgical robot.

Jitter is the variation in packet arrival times, which can disrupt the smooth operation of robotic systems if not minimized. High jitter can cause inconsistent control signals, leading to potential surgical errors. Loss rate represents the percentage of data packets lost during transmission. A low loss rate is critical in RTDTs to maintain the integrity of the transmitted information, ensuring that the surgeon's commands and sensory feedback are accurately conveyed. Ensuring minimal delay, jitter, and loss rate is paramount to achieving the high level of performance required for robotic telesurgery.

4 Telesurgery Digital Twins System Modeling

A. Problem Statement

In remote DT surgical zones, surgeons depend on current task status from the patient zone, which requires a maximum data transmission time of 150 milliseconds and a data validity deadline of 300 milliseconds [20] to ensure precise decision-making during procedures.These procedures consist of multiple tasks, classified by their risk level and assigned corresponding priorities. In Fig. 2, we illustrate various data transmission scenarios from the physical twin to its digital counterpart. For example, vital sign information is transmitted within the designated time frame (*Transm1*) and delivered to the corresponding DT for processing (*Process1*) before the validity deadline (*Valid1*), ensuring synchronization between the DT and the real-world entity. Conversely, in the second scenario involving the Da Vinci robot's connectivity status, transmission occurs within the allocated time (*Transm2*), but processing (*Process2*) exceeds the validity deadline (*Valid2*), resulting in misalignment between the DT and the real-world entity due to the expired data. Therefore, physical-digital twins synchronization is crucial to ensure that digital twins accurately reflect real-world entities in real-time, enabling reliable surgical decisions. However, the existing literature discusses real-time synchronization without adequately addressing the practical challenges encountered in real-life implementations. In reality, achieving real-time synchronization poses significant difficulties due to communication delays and inaccuracies, which are barriers against the seamless exchange of data between DTs and their physical counterparts. Consequently, there is a need to formulate the synchronization of RTDTs to optimize the transmission of the highest priority surgical data for the surgeon while ensuring that the validity time deadline of these data is not missed.

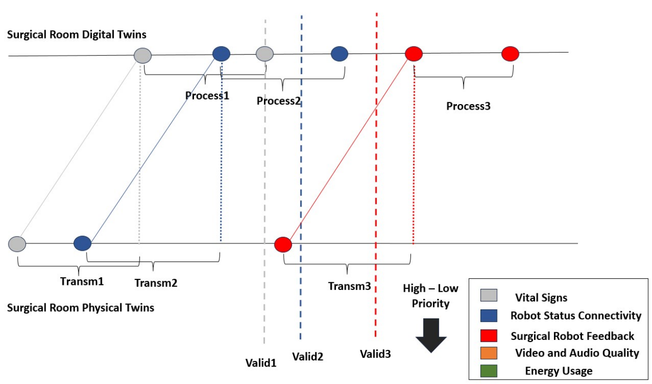


Figure 2: The Timeline of Surgical Tasks in RTDT

B. System Modeling

Consider $T = \{T_1, T_2, \ldots, T_n\}$ as a set of surgical tasks within the actual surgical zone. Each task T_i has a starting time s_i and travels within fiber optics channel with capacity C during transmission time $tran_i$ in milliseconds based on the task's data size $tasksize_i$ in MB. The priority of each task is denoted by p_i with v_i as the validity deadline time in milliseconds. x_i as a binary decision variable where $x_i = 1$ if T_i is transmitted, and 0 otherwise. d_i as a binary variable where $d_i = 1$ if T_i misses its deadline, and 0 otherwise. M is a deadline penalty with a sufficiently large constant value if $d_i = 1$. The problem formulation is given by the equations from (1 - 9). Equation (3) represents our task scheduling objective function to maximize the priority sum of transmitted surgical tasks in Equation (1) and minimize the number of tasks that fail to meet their validity deadlines in Equation (2). Our objective function has multiple constraints. The capacity constraint in Equation (4) ensures that the size of transmitted tasks per group does not exceed the channel capacity. In each group, the assigned task either meets the validity deadline or is penalized when missing its deadline according to the deadline constraint in Equation (5) where the sum of the starting time and propagation time of each task must not exceed its validity deadline.

We ensure that medical interrelated surgical tasks are assigned to the same group according to the grouping constraint in Equation (6). For instance, making small incisions in the abdomen for laparoscopic instruments is medically interrelated with inserting a trocar and placing the laparoscope for visual guidance. So, if task a is selected and it has a medical dependency relation with task b, then task b will be assigned to the same group. Equation (7) represents the unique selection constraint where each task is either selected once or not at all.

$$Z_1 : \text{Max} \sum_{i=1}^{n} p_i \cdot x_i \tag{1}$$

$$Z_2 : \text{Min} \sum_{i=1}^{n} d_i \tag{2}$$

$$Z = \lambda \cdot Z_1 + (1 - \lambda) \cdot Z_2 \tag{3}$$

s.t.

$$\sum_{i=1}^{n} \text{tasksize}_i \cdot x_i \leq C, \quad \forall i \in \{1, \ldots, n\} \tag{4}$$

$$s_i + \text{tran}_i \leq v_i \cdot x_i + M \cdot d_i, \quad \forall i \in \{1, \ldots, n\} \tag{5}$$

$$x_a = x_b \tag{6}$$

$$x_i \in \{0, 1\} \tag{7}$$

$$d_i \in \{0, 1\} \tag{8}$$

C. RTDT Dataset Characteristics

We illustrate the feasibility of RTDT by simulating a gallbladder surgery scenario in which a remote surgeon must remain continuously informed and updated with multiple sets of medical data to effectively perform various surgical tasks. These tasks include making incisions, dissecting tissues, applying clips, retracting organs, ligating blood vessels, mobilizing tissues, extracting the gallbladder, and ensuring hemostasis. To achieve this, we create a time-series dataset specifically for the robotic telesurgical environment, modeling the gallbladder procedure with 100 surgical tasks that differ in transmission time and data validity deadlines. This comprehensive, synthesized dataset allows for the replication of diverse scenarios without compromising modeling accuracy, facilitating the evaluation of parameter impacts on surgical outcomes. The attributes for each task in the gallbladder dataset are detailed in Table **??**.

D. Experimental Setup

1) Grouping Surgical Tasks

Each surgical action is crucial to the overall success of the procedure. Organizing these tasks into groups based on their medical

TABLE 1: Description of Gallbladder RTDT Dataset

Attribute	Description
Group ID	Categorization of tasks based on different levels of priority, transmission time, or validity time distributions.
Task ID	Unique task identifier for easy referencing and tracking throughout the RTDT procedure
Task size (MB)	Amount of data associated with each surgical task.
Starting time (ms)	The generation time of each task within the operation timeline.
Transmission time (ms)	Duration required to transmit task data in real-time between surgical sites.
Validity time (ms)	Data freshness deadline of each surgical task.
Priority	Relative importance assigned to tasks, guiding decision-making during the procedure.
Fiber optics channel capacity (Gbps)	Maximum data volume that can be transmitted simultaneously.

interrelationships or synchronization requirements is essential for several key reasons. By grouping tasks with similar characteristics or objectives, surgeons can more effectively prioritize their actions, optimize resource allocation, and anticipate potential challenges or complications. This strategy helps minimize intraoperative surprises, improves resource utilization, and reduces the risk of errors or delays during surgery. We categorize the grouping strategies into two main types and develop optimization models for task scheduling based on these strategies. The first category focuses on the medical relationships between task sets and examines their impact on surgical zone synchronization. The second category draws inspiration from operating system scheduling techniques, defining three grouping strategies: Highest priority-nearest deadline(HPND), shortest transmission time(STT), and shortest validity time(SVT).

Grouping Optimization Models: To investigate the factors that affect real-time synchronization between physical and virtual surgical zones, we defined four distinct models:

a) Interrelated Tasks Grouping Model:

In this model, we assign interrelated surgical tasks to the same group, considering all constraints except for maximum priority and minimum missing deadlines objectives. This simulates scenarios in which surgeons require a batch of dependent information to make specific surgical decisions effectively.

b) Highest Priority-Nearest Deadline (HPND) Model:

The HPND model is crucial for real-time surgical decisions, emphasizing the grouping of dependent medical tasks. It considers both maximum priority and minimum missing deadlines objectives, facilitating effective synchronization between surgical zones.

c) Shortest Transmission Time (STT) Model:

In the STT model, surgical data tasks are grouped based on task size, which affects transmission time. This model ensures that surgeons receive multiple surgical information quickly by prioritizing tasks with the shortest transmission time.

d) Shortest Validity Time (SVT) Model:

TABLE 2: Optimization Parameters

Symbol	Parameter	Value
T	Number of surgical tasks	100
G	Number of transmitted groups	10
Transs_max	Maximum transmission time for tasks in each group	150 ms
Validity_max	Maximum freshness deadline for each task	300 ms
Channel_Capacity	Maximum Capacity of the Fiber Optics Channel	10 Gbps

To improve surgical precision and minimize intraoperative complications, the SVT model organizes surgical data tasks based on the patient's and surgical robot's validity status. Priority is given to tasks with the shortest validity time.

2) Simulation Setup

All optimization models are implemented in Python using the gallbladder surgery dataset and Gurobi solver with the parameters listed in Table 2 to find the near-optimal solution for the RTDT task scheduling problems toward full synchronization between the surgical locations.

5 Results and Discussion

We define four performance metrics to assess our implemented grouping optimization models. First, the total priority of the transmitted tasks, the ratio of missed deadlines, the channel capacity utilization ratio, and the power consumption at the end of the task scheduling. Based on these four metrics, we evaluated the performance of medical-related grouping models and OS-inspired grouping models.

A. Task Priority

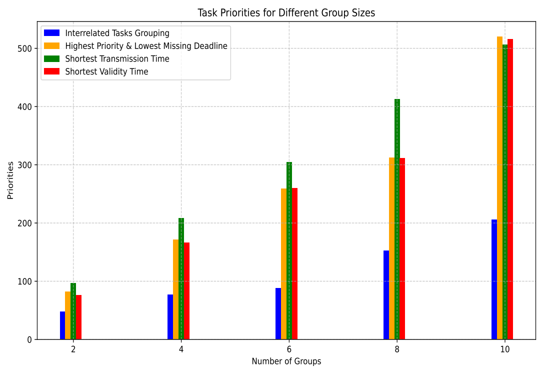
The total priorities of the tasks reflect the level of importance assigned to the transmitted tasks, which is crucial for critical decision making. This importance is highlighted in Fig. 3a, where the HPND model consistently outperforms other grouping models as the number of transmitted groups increases; this occurs because the HPND grouping prioritizes the selection of top-priority tasks before transmitting them to the DT surgical zone. The STT model exhibits high-priority levels for small group numbers, as these groups typically contain fewer tasks with high-priority levels assigned. However, as the scalability of surgical tasks and groups increases, the effectiveness of the STT model diminishes. The HPND model consistently meets the RTDT synchronization objective by efficiently sending critical surgical tasks, regardless of the varying number of tasks and groups.

B. Missing Deadline Ratio

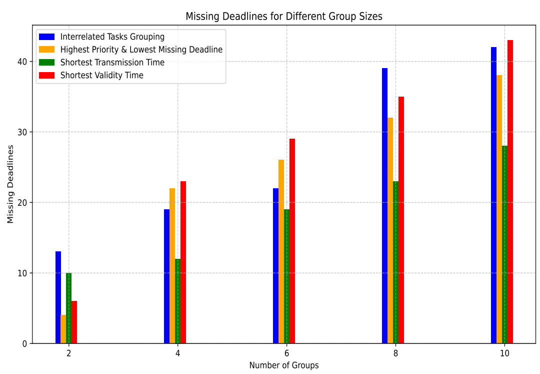
The missing deadline rate represents the proportion of tasks that fail to reach the digital twins' side and be processed within the data expiry or validity deadline. A lower ratio indicates fewer incorrect surgical decisions based on expired data. We investigated the impact of different numbers of transmitted groups and different numbers of tasks per group on the missing deadline rate. For instance, we vary the number of tasks per group, 20 to 100, and consider groups of 2, 4, 6, 8, and 10. In Table 3, we compare all grouping optimization models in terms of the missing deadline ratio based on the number of missing tasks in Fig. 3b and consider the total number of tasks per group. The interrelated tasks grouping and the SVT models exhibit the highest missing deadline rates because they prioritize the selection of medical-related tasks or those with minimum expiration deadlines, without considering the impact of transmission time. In contrast, the HPND and STT models balance between transmission time and the nearest deadline when grouping the surgical tasks thus, achieving fewer missing deadline rates accordingly.

TABLE 3: Missing Deadline Ratio (%) for Grouping Models

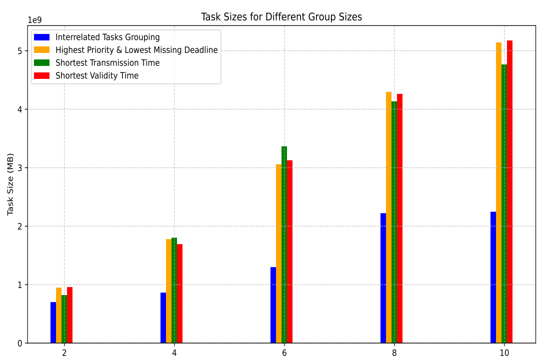
Model / # of Groups	2	4	6	8	10
Interrelated Tasks Grouping	65	47	36	48	42
HPND	20	55	43	40	38
STT	50	30	31	28	28
SVT	30	57	48	43	43



(a) Tasks Priorities



(b) Missing Deadline Tasks



(c) Tasks Data Sizes

Figure 3: Performance Metrics Based on # of Groups

C. Channel Capacity Utilization

Since the higher number of transmitted tasks implies a better utilization of the allocated channel bandwidth, we target the grouping strategy with a high utilization ratio. We measure the channel utilization ratio of each grouping model using the total data transmitted by each model as shown in Fig. 3c and the total fiber optics channel capacity using the following equation.

TABLE 4: Channel Utilization (%) for Grouping Models

# Groups	Interrelated Grouping	HPND	STT	SVT
10	21.43	49.01	45.40	49.28
8	21.13	40.95	39.38	40.61
6	12.38	29.14	32.07	29.72
4	8.22	16.92	17.11	16.10
2	6.64	8.99	7.83	9.06

$$\textbf{Channel Utilization (\%)} = \frac{\text{Total Data Transmitted in (t) ms}}{\text{Total Channel Capacity}} \times 100 \tag{9}$$

Since the HPND and SVT models employ a greedy strategy to assemble a large number of tasks, the resulting groups have larger sizes than other grouping models. This trend is evident in Table 4, where the HPND and SVT models consistently produce maximum task sizes. Furthermore, these sizes increase with the number of groups. Consequently, this leads to the highest channel utilization among all the grouping models across different group counts. High channel utilization ensures that a large volume of real-time information is transmitted to the surgeon on the digital twin side, thereby speeding up decision making during the procedure.

D. Power Consumption

To investigate how altering the number of task groups influences the total power consumption of the edge device within the physical twin surgical zone, where task scheduling occurs, we assess the transmission time for varying numbers of groups for each optimization model. The Shannon-Hartley theorem provides a way to calculate the maximum achievable data rate over a noisy channel [21] by considering the optical signal noise ratio (OSNR) with a value of 20 dB. To calculate the power consumption of task scheduling in the edge device of the physical twin surgical zone, which operates at a power of 100 mW, we employ the following equations.

$$\textbf{SNR} = 10^{\frac{\text{OSNR}}{10}} \tag{10}$$

$$\textbf{Transmitted time of } T_i = \frac{\text{size of surgical task } (a)}{\text{Channel Bandwidth} \times \log_2(1 + \text{SNR})} \tag{11}$$

$$\textbf{Power consumption at the edge device (e)} = \text{Transmitted time of } T_i \times \text{power of edge device}(e) \tag{12}$$

The power consumed by the edge device is directly proportional to the volume of data being processed; smaller task sizes lead to lower power consumption. Consequently, interrelated tasks grouping exhibits the lowest power consumption across all groups due to its smaller task sizes, as shown in Table 5. However, despite its efficiency in power usage, interrelated tasks grouping falls short in meeting key performance metrics such as priority handling, deadline adherence, and channel utilization. In contrast, the HPND, STT, and SVT models demonstrate that power consumption by the edge device in the physical twin surgical zone increases proportionally with the number of transmitted groups. This is because a greater number of groups results in more tasks being processed, which in

TABLE 5: Power Consumption (mW) for Grouping Models

Model / # of Groups	2	4	6	8	10
Interrelated Tasks Grouping	8.3	10.3	15.6	26.6	27
HPND	11.3	21.3	36.7	51.6	61.7
STT	9.8	21.5	40.4	49.6	57.2
SVT	11.4	20.2	37.4	51.2	62.1

turn increases task sizes and requires the edge device to expend more power to manage the additional workload.

Based on the performance analysis of all grouping optimization strategies, we found that the HPND model is the most effective for scalable numbers of transmitted groups. This model achieves the dynamic task scheduling goals of RTDTs by balancing the selection of highest priority tasks, minimizing missed deadlines, and maximizing channel bandwidth utilization, ensuring full synchronization with optimal efficiency.

6 Conclusion

This paper explores the transformative role of digital twins in telesurgery, particularly in the context of emerging 6G technology. To optimize the task scheduling of Real-Time Digital Twins (RTDTs), we examine how variations in task group numbers and task grouping strategies impact the efficiency of dynamic real-time scheduling across RTDT surgical zones. Our comparative analysis of grouping strategies, such as interrelated tasks, HPND, STT, and SVT, demonstrates the superiority of the HPND model in prioritizing high-importance tasks, reducing missed deadlines, and maximizing channel resource utilization. In future work, we plan to integrate machine learning techniques into dynamic task scheduling, leveraging real-time network condition predictions to further enhance RTDT outcomes.

References

[1] Yuntao Wang, Zhou Su, Shaolong Guo, Minghui Dai, Tom H Luan, and Yiliang Liu. A survey on digital twins: architecture, enabling technologies, security and privacy, and future prospects. *IEEE Internet of Things Journal*, 2023.

[2] Sagheer Khan, Tughrul Arslan, and Tharmalingam Ratnarajah. Digital twin perspective of fourth industrial and healthcare revolution. *Ieee Access*, 10:25732–25754, 2022.

[3] Muhammad Turab and Sonain Jamil. A comprehensive survey of digital twins in healthcare in the era of metaverse. *BioMedInformatics*, 3(3):563–584, 2023.

[4] Geetanjali Sageena, Munish Sharma, and Ajita Kapur. Evolution of smart healthcare: Telemedicine during covid-19 pandemic. *Journal of The Institution of Engineers (India): Series B*, pages 1–6, 2021.

[5] Abid Haleem, Mohd Javaid, Ravi Pratap Singh, and Rajiv Suman. Exploring the revolution in healthcare systems through the applications of digital twin technology. *Biomedical Technology*, 4:28–38, 2023.

[6] Rajeswari Chengoden, Nancy Victor, Thien Huynh-The, Gokul Yenduri, Rutvij H Jhaveri, Mamoun Alazab, Sweta Bhattacharya, Pawan Hegde, Praveen Kumar Reddy Maddikunta, and Thippa Reddy Gadekallu. Metaverse for healthcare: a survey on potential applications, challenges and future directions. *IEEE Access*, 11:12765–12795, 2023.

[7] Kimia Kazemzadeh, Meisam Akhlaghdoust, and Alireza Zali. Advances in artificial intelligence, robotics, augmented and virtual reality in neurosurgery. *Frontiers in Surgery*, 10, 2023.

[8] Nandish P Kuruvatti, Mohammad Asif Habibi, Sanket Partani, Bin Han, Amina Fellan, and Hans D Schotten. Empowering 6G communication systems with digital twin technology: A comprehensive survey. *IEEE access*, 10:112158–112186, 2022.

[9] Chamitha De Alwis, Anshuman Kalla, Quoc-Viet Pham, Pardeep Kumar, Kapal Dev, Won-Joo Hwang, and Madhusanka Liyanage. Survey on 6G frontiers: Trends, applications, requirements, technologies and future research. *IEEE Open Journal of the Communications Society*, 2:836–886, 2021.

[10] Sophea Bonne, Will Panitch, Karthik Dharmarajan, Kishore Srinivas, et al. A digital twin framework for telesurgery in the presence of varying network quality of service. In *2022 IEEE 18th international conference on automation science and engineering (CASE)*, pages 1325–1332. IEEE, 2022.

[11] Barış Tan and Andrea Matta. The digital twin synchronization problem: Framework, formulations, and analysis. *IISE Transactions*, 56(6):652–665, 2024.

[12] Md Doulotuzzaman Xames and Taylan G Topcu. A systematic literature review of digital twin research for healthcare systems: Research trends, gaps, and realization challenges. *IEEE Access*, 2024.

[13] Bhanu Sharma, Deepak Kaushal, Sudhanshu Joshi, Manu Sharma, and Suhani Bafila. Transforming healthcare: Exploring the impact and potential of digital twin technology. In *2023 1st DMIHER International Conference on Artificial Intelligence in Education and Industry 4.0 (IDICAIEI)*, volume 1, pages 1–6. IEEE, 2023.

[14] Michaela Cellina, Maurizio Cè, Marco Alì, Giovanni Irmici, Simona Ibba, Elena Caloro, Deborah Fazzini, Giancarlo Oliva, and Sergio Papa. Digital twins: The new frontier for personalized medicine? *Applied Sciences*, 13(13):7940, 2023.

[15] Lal Verda Cakir, Sarah Al-Shareeda, Sema F Oktug, Mehmet Özdem, Matthew Broadbent, and Berk Canberk. How to synchronize digital twins? a communication performance analysis. In *2023 IEEE 28th International Workshop on Computer Aided Modeling and Design of Communication Links and Networks (CAMAD)*, pages 123–127. IEEE, 2023.

[16] Jing Li, Song Guo, Weifa Liang, Jianping Wang, Quan Chen, Yue Zeng, Baoliu Ye, and Xiaohua Jia. Digital twin-enabled service provisioning in edge computing via continual learning. *IEEE Transactions on Mobile Computing*, 2023.

[17] Yilin Fang, Chao Peng, Ping Lou, Zude Zhou, Jianmin Hu, and Junwei Yan. Digital-twin-based job shop scheduling toward smart manufacturing. *IEEE transactions on industrial informatics*, 15(12):6425–6435, 2019.

[18] Cheng Ren, Cailian Chen, Peizhe Li, Xiaojing Wen, Yehan Ma, and Xinping Guan. Digital twin enabled task scheduling for state monitoring in aircraft testing process. *IEEE Internet of Things Journal*, 2024.

[19] Claudia D'Ettorre, Andrea Mariani, Agostino Stilli, et al. Accelerating surgical robotics research: A review of 10 years with the da vinci research kit. *IEEE Robotics & Automation Magazine*, 28(4):56–78, 2021.

[20] Paola Picozzi, Umberto Nocco, Greta Puleo, Chiara Labate, and Veronica Cimolin. Telemedicine and robotic surgery: a narrative review to analyze advantages, limitations and future developments. *Electronics*, 13(1):124, 2023.

[21] Govind P Agrawal. *Fiber-optic communication systems*. John Wiley & Sons, 2012.