Flow-Level Required Throughput and 5QI Driven Adaptive TDD Slot Allocation Method

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***Abstract*—With the proliferation of smart devices, the diversification of applications is accelerating. In response to this trend, research and development of the 5th generation mobile communication system (5G) has progressed as a communication infrastructure capable of meeting high-quality communication demands. In 5G, the uplink (UL) for transmission from User Equipment (UE) and the downlink (DL) for transmission to UE are separated using Time Division Duplex (TDD). In current specifications, the standard TDD slot configuration is static and prioritizes DL transmission. However, since the communication quality required by applications varies widely, it remains challenging to fully satisfy all requirements using only current 5G technologies. In this paper, to address the issue where current static base station control cannot adapt to fluctuations in diverse application requirements, we propose an adaptive TDD slot allocation method based on application requirements and flow priorities using required throughput and the 5G QoS Identifier (5QI), and evaluate its effectiveness. Simulation results demonstrate that the proposed method outperforms baselines relying solely on 5QI or required throughput. Compared to the 5QI-only scheme, it improves low-priority flow throughput by approximately 18% while maintaining high-priority performance. Furthermore, it drastically enhances high-priority QoS compared to the throughput-only scheme, improving delay by 595% and error rate by 647%. These results confirm that considering both metrics enables optimal allocation without excess or deficiency.**

***Index Terms*—5G, RAN, TDD, 5QI.**

I. Introduction

The rapid proliferation of smart devices has accelerated the diversification of applications. In response to this trend, the Fifth Generation Mobile Communication System (5G) has been developed and deployed as a communication infrastructure capable of meeting high-level and diverse communication requirements [1]. However, given the broad spectrum of Quality of Service (QoS) requirements demanded by these applications, satisfying all such demands completely using only current 5G technologies remains a challenge.

In 5G Time Division Duplex (TDD) systems, radio resource slots are allocated to either Uplink (UL) or Downlink (DL) [2]. In current deployments, however, TDD slot configurations are typically static and DL-centric, making them unable to adapt to fluctuations in traffic demand. Meanwhile, with the advancement of IoT, application requirements have become increasingly diverse. This leads to a coexistence of flows with different priorities, making it difficult to satisfy all requirements simultaneously using static configurations. Specifically, traffic volume and flow priority are distinct factors that must be balanced in slot allocation; focusing on only one is insufficient. For instance, allocating slots based solely on traffic volume may allow low-priority, high-volume flows to monopolize resources, thereby increasing latency for time-critical, high-priority packets. Conversely, prioritizing only priority levels may lead to mismatches with actual demand, resulting in reduced resource utilization efficiency.

In a previous study, we proposed a method to dynamically adjust TDD DL/UL slot allocation according to time-varying channel conditions, focusing on video streaming applications [3]. We conducted simulation-based evaluations to analyze the relationship between channel variations and slot allocation patterns. The results demonstrated that the proposed method improved the communication quality of video applications by over 16% compared to static slot allocation. However, that study focused specifically on a single application scenario and did not consider situations where multiple flows with different requirements coexist.

In the Beyond 5G era, functionalities enabling dynamic TDD slot allocation are being introduced, and their specific implementation methods are currently under investigation [4]. As a specific approach, autonomous control methods utilizing Deep Reinforcement Learning (DRL) have attracted significant attention in recent years. For instance, Reference [5] proposes a dynamic DL/UL resource allocation scheme based on DRL. This study demonstrated that by learning optimal TDD configurations in response to complex environmental variations, the overall system throughput could be significantly improved compared to static TDD schemes. However, such learning-based methods face challenges. First, the stochastic nature of DRL, particularly during the exploration phase, introduces instability. The time required for convergence is often incompatible with the millisecond-level traffic fluctuations in 5G, leading to performance degradation during sudden bursts. Second, DRL agents typically optimize for long-term cumulative rewards (e.g., total system capacity). This objective makes it difficult to provide deterministic guarantees for strict per-flow QoS requirements, such as those defined by 5QI, as the model may sacrifice individual priorities to maximize the aggregate metric.

To address these limitations, this paper proposes a deterministic dynamic TDD slot allocation method that directly leverages both 5QI priority and required throughput. Unlike learning-based approaches that rely on black-box optimization, our method determines slot allocation by explicitly incorporating 5QI-based priorities and actual data demands as control parameters. We demonstrate through simulations that the proposed scheme can effectively satisfy diverse application requirements without the latency and instability associated with online learning.

II. Related Work

To overcome the inefficiencies of Static TDD, various dynamic TDD schemes have been investigated. Recently, data-driven approaches, particularly those based on Deep Reinforcement Learning (DRL), have attracted significant attention. For instance, Reference [5] demonstrated that DRL can optimize resource allocation in high-mobility Heterogeneous Networks (HetNets) by learning from complex environmental interactions. However, while DRL-based methods excel at maximizing system-wide capacity, challenges remain regarding their real-world deployment. The objective functions in conventional DRL tend to prioritize aggregate throughput over specific service requirements, such as the 3GPP-defined 5QI (5G QoS Identifier). Consequently, it is difficult to provide strict QoS guarantees for critical applications.

Therefore, to realize practical base station control, we propose a dynamic TDD slot allocation method utilizing 5QI priority and required throughput. Unlike methods that prioritize aggregate throughput, our proposal adopts an algorithm based on individual flow throughput demands and standardized 5QI. We evaluate the communication quality through simulations to demonstrate the effectiveness of the proposed method.

III. Proposed Method

In this paper, we propose an adaptive TDD DL/UL slot allocation method to satisfy diverse application requirements that vary dynamically over time. Figure 1 illustrates the control procedure of the proposed method. This section describes the detailed process, ranging from the initialization phase to the control execution by the base station.

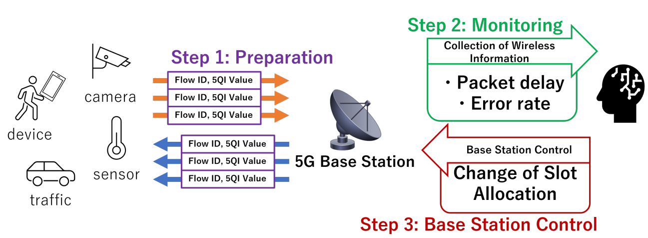

Fig. 1. Proposed Method.

A. Preparation (Step 1)

In the initialization phase, we select and manage the information necessary for control. First, we adopt required throughput and priority based on 5QI as metrics to quantify application requirements. Required throughput indicates the bandwidth needed by an application. We use this metric because understanding the bandwidth demand of each flow is indispensable for determining the appropriate TDD slot allocation. Meanwhile, 5QI priority enables prioritization based on both packet latency and error rate requirements. Given the mixture of high- and low-priority traffic, incorporating 5QI allows the system to suppress excessive resource allocation to low-priority applications and preferentially allocate resources to high-priority ones. The objective is to maintain the highest possible quality of service for critical applications. In this phase, we assume that the required throughput and 5QI for each application are known a priori, and these values are associated with each flow and stored in the system.

B. Monitoring (Step 2)

In the monitoring phase, we adopt packet delay and packet error rate—key parameters defined in 5QI—as the metrics for evaluating application quality. While throughput is a common performance metric, it is often insufficient in environments where multiple flows compete for resources. In such scenarios, latency and error rate requirements may be violated even if the throughput demands are met. Therefore, our method selects packet delay and error rate as the primary metrics to accurately monitor the QoS.

The proposed method monitors packet delay and error rates in real-time. It triggers the base station control phase whenever the measured values fail to satisfy either the pre-registered delay or error rate requirements. Implementing this monitoring mechanism requires careful consideration of the processing latency from monitoring to control execution, as well as the appropriate duration for monitoring. Therefore, parameters such as the information collection cycle and slot switching timing should ideally be determined through real-world experiments. However, since real-world evaluation has not yet been conducted, this paper simplifies the scenario and evaluates the effectiveness of the method assuming ideal base station control. Here, ideal base station control assumes that all incoming flows and their compliance with delay and error rate requirements are known a priori. Furthermore, it assumes that if requirements are not met, the optimal slot allocation for that specific scenario has already been calculated.

C. Base Station Control (Step 3)

In the base station control phase, the system selects the most appropriate TDD slot allocation pattern. The following describes the detailed method for calculating and determining this pattern.

1) Weight Calculation for Each Flow: In this step, we calculate weights based on required throughput and 5QI priority to quantify the importance of each flow. However, required throughput varies across a very wide range, from a few kbps to several Gbps, whereas 5QI priority takes limited values between 1 and 100. Given this significant discrepancy in scale, simply combining them would be biased. Therefore, our goal is to normalize these metrics to a common scale. This ensures fair consideration of both factors, allowing the system to satisfy the requirements of each flow without over- or under-provisioning.

First, the normalization of required throughput is performed using (1) and (2). Equation (1) calculates the total sum of the required throughputs for all flows traversing the base station. In Equation (2), the required throughput of each individual flow is divided by this total sum. This yields a normalized value representing the proportion of each flow's demand relative to the total traffic.

$$TotalTP = \sum_{i \in AllFlows} RequiredThroughput_i \tag{1}$$

$$NormalizedTP_f = RequiredTP_f / TotalTP \tag{2}$$

Next, regarding 5QI priority, a smaller value is defined to indicate a higher priority level. Therefore, we compute the reciprocal of the 5QI value using Equation (3) to ensure that higher-priority flows are assigned larger weights. Similarly, the normalization process involves calculating the sum of these reciprocals for all flows, as shown in Equation (4). Then, in Equation (5), the individual reciprocal is divided by this aggregate sum. This yields a normalized value representing the relative priority of each flow within the system.

$$InversePri_f = 1/Priority_f \tag{3}$$

$$TotalInversePri = \sum_{i \in AllFlows} InversePri_i \tag{4}$$

$$NormalizedPri_f = InversePri_f / TotalInversePri \tag{5}$$

We calculate the weight for each flow by multiplying the normalized values, as shown in Equation (6). This approach ensures that fluctuations in both metrics are fairly reflected in the final weight. By using this weight in subsequent calculations, we aim to balance both indicators and satisfy the requirements of each flow without excess or deficiency.

$$Weight_f = NormalizedTP_f \times NormalizedPri_f \tag{6}$$

2) Optimal DL/UL Ratio Selection: In this step, we calculate the appropriate DL/UL allocation ratio using the flow weights derived in Equation (6). First, we calculate the total sum of weights for DL and UL flows separately, using Equations (7) and (8). Next, we use these aggregate weights in Equation (9) to calculate r, which represents the appropriate DL allocation ratio.

$$DL_{weight} = \sum_{f \in DL} Weight_f \tag{7}$$

$$UL_{weight} = \sum_{f \in UL} Weight_f \tag{8}$$

$$r = DL_{weight} / (DL_{weight} + UL_{weight}) \tag{9}$$

TABLE I
TDD SLOT PATTERN

	TDD0	TDD1	TDD2	TDD3	TDD4	TDD5
DL:UL:S	8:1:1	7:2:1	5:3:2	4:4:2	3:5:2	2:6:2
DL ratio	0.889	0.778	0.625	0.500	0.375	0.250

3) Selection of TDD Slot Pattern: In this step, we select the optimal slot allocation pattern using the target DL allocation ratio r derived in Equation (9). First, the DL ratios of the candidate TDD slot allocation patterns (listed in Table I) are calculated in advance. Next, we compare the calculated ratio r with the DL ratio of each candidate pattern. Specifically, we select the pattern that minimizes the absolute difference $|r - \text{DL ratio}|$; that is, the pattern closest to the ideal allocation derived by our method. The slot allocation patterns in Table I are those specified for Local 5G in Japan to support diverse wireless environments and application requirements.

IV. EVALUATION IN DIVERSE SCENARIOS

In this section, we evaluate the effectiveness of the proposed method for adaptively controlling TDD DL/UL slot allocation in response to dynamically changing and diverse application requirements. To conduct this evaluation, we constructed the simulation topology shown in Figure 2 using the ns-3 network simulator [8] and the 5G-LENA module [9]. This simulator allows for flexible parameter configuration of 5G base stations and detailed collection of radio information. We apply the six different TDD slot allocation patterns listed in Table I to this topology, measure the communication quality of each flow, and evaluate the effectiveness of the proposed method.

A. Base Station and UE Settings

In the topology shown in Figure 2, 20 User Equipment (UE) nodes are connected to a single base station (gNB). All UEs are stationary and placed at a fixed distance of 5 m from the gNB. The remote server and the gNB are connected via a wired link with a bandwidth capacity of 1 Gbps. The configuration parameters for the gNB are listed in Table II.

B. Generating Random Scenarios

To evaluate the effectiveness of our proposed adaptive slot allocation method under time-varying and diverse application requirements, we generated 100 random simulation scenarios. In the topology shown in Figure 2, traffic flows for both DL and UL are randomly selected from the list in Table III. The detailed selection procedure is described below. Consequently, the base station handles a traffic load ranging from a minimum of 20 flows (10 DL, 10 UL) to a maximum of 40 flows (20 DL, 20 UL). This setup establishes an environment where diverse application requirements contend for resources in both DL and UL directions across all scenarios.

- **DL Flow Selection:** The server is configured to always initiate a flow to UEs 1 through 10 by randomly selecting one application type from Table III. In contrast, the server randomly determines whether to generate traffic for UEs

11 through 20. If a flow is generated, it similarly selects one application at random from Table III. Consequently, the number of Downlink (DL) flows is guaranteed to be between 10 and 20.

- **UL Flow Selection:** UEs 1 through 10 are configured to always initiate a flow to the server by randomly selecting one application type from Table III. In contrast, UEs 11 through 20 randomly determine whether to generate traffic. If a UE becomes active, it similarly selects one application at random from Table III. Consequently, the number of Uplink (UL) flows is guaranteed to be between 10 and 20.

C. Application Requirement Settings

The priority level, Packet Delay Budget (PDB), and Packet Error Rate (PER) corresponding to each 5QI value shown in Table III are specified by 3GPP, along with example services [6]. In this study, the required throughput was determined based on the typical applications associated with each 5QI, as listed in Table IV [10].

D. Simulation Environment and Conditions

As mentioned in Section III-B, we evaluate the effectiveness of the proposed method using 100 simulation scenarios, each lasting 10 seconds. We apply the proposed method to these scenarios and measure the resulting performance. For comparison, we also evaluate two baseline methods: one using only 5QI priority and the other using only required throughput as the metric for slot allocation. By comparing these methods, we evaluate the necessity of considering both throughput and priority. To specifically evaluate the ability to allocate resources optimally to high-priority flows, we defined two distinct flow groups for this evaluation.

- **5QI Value 69, 2, 9: A flow group characterized by equivalent required throughput but distinct 5QI priorities.** specifically, it includes **priorities 5 (high), 40 (medium), and 90 (low).** This group was prepared to evaluate the effectiveness of priority-aware control when throughput demands are identical. By measuring the performance of these flows under each method, we evaluate whether the proposed method allocates slots to high-priority flows without excess or deficiency.
- **Other Flows:** A flow group with diverse 5QI priorities and required throughputs. We reproduced various network congestion levels by introducing a mixture of flows, including high-throughput (25 Mbps), medium-throughput (10 Mbps), and low-throughput (50 Kbps) traffic.

E. TDD Slot Pattern Selection Statistics

Figure 3 illustrates the optimal DL allocation ratio r for each scenario, calculated using Equation (9) described in Section III. The results indicate that the calculated ratio r varies depending on the method. Specifically, in Scenario 4, where both 5QI priority and required throughput metrics favor DL transmission, the proposed method allocates a large ratio to the DL. In contrast, in Scenario 46, where the two metrics prioritize opposite directions, the proposed method calculates an intermediate allocation ratio. Thus, the proposed method determines the appropriate slot allocation by weighing both 5QI priority and required throughput.

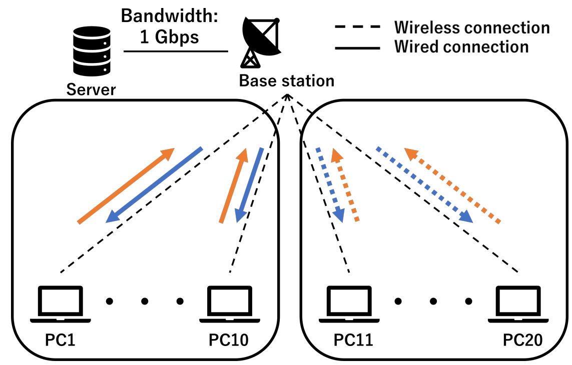

Fig. 2. Evaluation Topology.

TABLE II
BASE STATION SETTINGS

Parameter		Set value
Central frequency		4.8GHz
Bandwidth		100MHz
Subcarrier spacing		30kHz
Modulation order	DL	6
	UL	8
Number of antennas	BS	2×4
	UE	2×2

Figure 4 shows the TDD configurations selected by comparing the calculated ratio r with the DL ratios of the available patterns in Table I and choosing the one that minimizes the difference. This figure demonstrates that the optimal allocation selected differs depending on the scenario and the method employed. Comparing Figure 3 and Figure 4, we observe that the selected ratios closely match the calculated values across scenarios, confirming that appropriate allocations are being made.

F. Evaluation Results

The simulation results for 5QI values 69, 2, and 9 are presented in the following figures: Figure 5 for required throughput satisfaction, Figure 6 for delay requirement satisfaction, and Figure 7 for error rate requirement satisfaction. In

TABLE III
PREPARED APPLICATION REQUIREMENTS

5QI Value	Priority	Latency	Error Rate	Required Throughput
69	**5**	60 ms	10^{-6}	5 Mbps
1	20	100 ms	10^{-2}	100 Kbps
85	21	5 ms	10^{-5}	10 Mbps
83	22	10 ms	10^{-4}	5 Mbps
2	**40**	150 ms	10^{-3}	5 Mbps
4	50	300 ms	10^{-6}	25 Mbps
7	70	100 ms	10^{-3}	1 Mbps
8	80	300 ms	10^{-6}	50 Kbps
9	**90**	300 ms	10^{-6}	5 Mbps

TABLE IV
APPLICATIONS FOR EACH 5QI VALUE

5QI Value	Application
69	Service Control Signaling: Critical control messages that require URLLC (Ultra-Reliable Low Latency Communications) performance.
1	Conversational Voice: Modeled assuming the high-quality mode of EVS (Enhanced Voice Services).
85, 83	AR/VR and Industrial Automation: Applications where URLLC capabilities are mandatory to ensure safety and precision.
2	Conversational Video: For HD quality (720p/1080p) calls, a throughput range of 1.5 Mbps to 5 Mbps is recommended [10].
4	Non-Conversational Video: For 4K (UHD) buffered streaming, a stable bandwidth of 20 – 25 Mbps is required.
7	Interactive Gaming: Assumes a mix of real-time game control data and voice chat traffic.
8, 9	IoT Data and Buffered Video: Traffic types that are generally delay-tolerant.

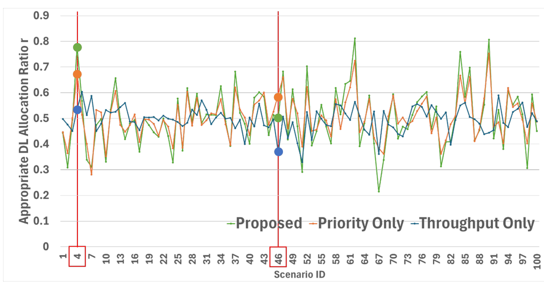

Fig. 3. Appropriate DL Allocation Ratio r in Each Scenario.

each figure, flows are arranged from left to right in descending order of 5QI priority, with the vertical axis representing the satisfaction rate. The circular markers in the graphs indicate the average satisfaction rate for each flow. Furthermore, each flow listed in Table III was selected uniformly more than 400 times across all 100 scenarios. This indicates that the satisfaction results are not affected by sample imbalance or the scarcity of specific flows. Therefore, we can conclude that the performance trends for each method are accurately represented.

The satisfaction rates for each metric are defined in Equations (10), (11), and (12).

$$\text{Throughput Sat.} = \begin{cases} 1.0 & (\text{Measured} \geq \text{Requirement}) \\ \frac{\text{Measured}}{\text{Requirement}} & (\text{Measured} < \text{Requirement}) \end{cases} \tag{10}$$

$$\text{Delay Sat.} = \begin{cases} 1.0 & (\text{Measured} \leq \text{Requirement}) \\ \frac{\text{Requirement}}{\text{Measured}} & (\text{Measured} > \text{Requirement}) \end{cases} \tag{11}$$

$$\text{Error Rate Sat.} = \begin{cases} 1.0 & (\text{Measured} \leq \text{Requirement}) \\ \frac{\text{Requirement}}{\text{Measured}} & (\text{Measured} > \text{Requirement}) \end{cases} \tag{12}$$

1) Comparison with 5QI-Priority-Only Approach: First, we compare the required throughput satisfaction (Fig. 5) between

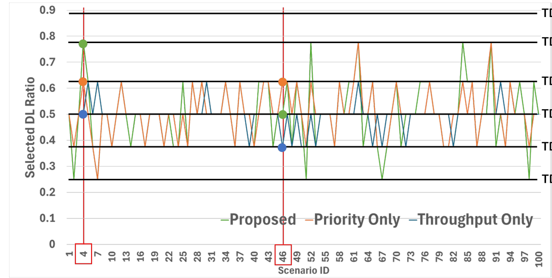

Fig. 4. Selected DL Ratio in Each Scenario.

the proposed method and the comparative method that considers only 5QI priority. For the high-priority flows (5QI: 5), both methods allocate slots preferentially. Consequently, the satisfaction distribution is clustered around 1.0, maintaining high performance. On the other hand, for low-priority flows (5QI: 90), while the comparative method suffers from performance degradation, the proposed method achieves an approximate 18% improvement in average satisfaction. Furthermore, the proposed method exhibits higher values for both the median and the third quartile, indicating an improvement in the overall distribution.

Similar trends were observed for delay and error rate satisfaction, as shown in Figures 6 and 7. For low-priority flows (5QI: 90), the proposed method improved delay satisfaction by approximately 23% and error rate satisfaction by approximately 32% compared to the comparative method. Regarding the distribution, while an improvement is evident for delay with the proposed method, the error rate satisfaction dropped significantly for both methods, showing no notable difference between them.

2) Comparison with Required-Throughput-Only Approach: Next, we compare the proposed method with the baseline method that considers only required throughput. Since the baseline method allocates slots based solely on throughput demand for the three flows with different priorities (5QI: 5, 40, 90), the average satisfaction and distribution (quartiles) became similar for all flows, as shown in Figure 5. This indicates that the baseline method fails to distinguish the differences in priority. In contrast, the proposed method showed clear differentiation based on priority. While the satisfaction of high-priority flows (5QI: 5) is maintained at a high level, that of low-priority flows (5QI: 90) decreases. This confirms that the system is functioning effectively: it reduces slot allocation for low-priority flows to ensure optimal allocation for high-priority flows.

This trend is also evident in the satisfaction rates for delay (Fig. 6) and error rate (Fig. 7). While the performance of low-priority flows degrades with the proposed method, it achieves drastic improvements for high-priority flows (5QI: 5) compared to the baseline: approximately 595% in delay satisfaction and 647% in error rate satisfaction. Focusing on the distribution of delay satisfaction, the third quartile for the comparative method remains extremely low at 0.19. In contrast, the proposed method achieves a first quartile of 0.95

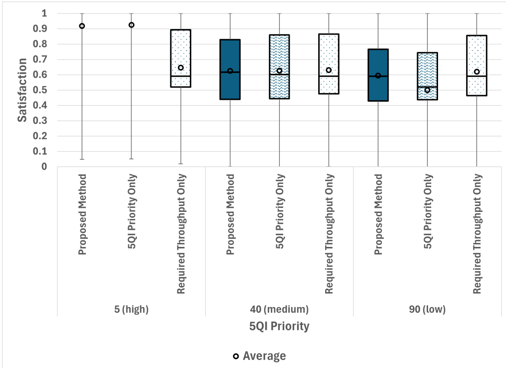

Fig. 5. Required Throughput satisfaction for each flow.

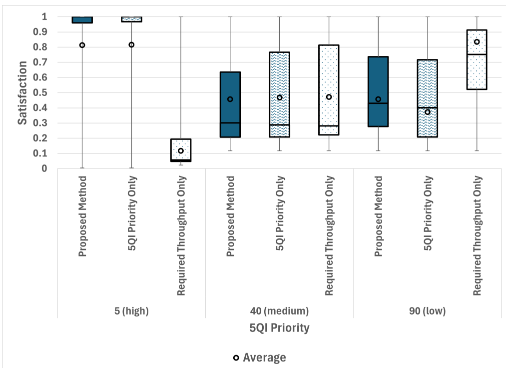

Fig. 6. Delay Requirement satisfaction for each flow.

and a third quartile of 1.0, indicating that requirements are satisfied in the vast majority of cases.

V. Conclusion

The widespread adoption of smart devices has accelerated the diversification of applications. In response to this trend, 5G has been deployed as a communication infrastructure capable of meeting high-level communication requirements. However, current base station configurations are typically static and fail to sufficiently adapt to traffic demand fluctuations caused by the dynamic nature of applications across time and space. To address this issue, this paper focuses on dynamic TDD slot allocation and proposes a control method that monitors and satisfies application requirements using both Required Throughput and 5QI Priority. Simulation results across 100 diverse scenarios demonstrate the effectiveness of the proposed method, which considers both metrics.

In this paper, we focused on dynamic TDD slot allocation for base station control and evaluated its effectiveness using a network simulator. However, this study evaluated the effectiveness of the method using simplified scenarios under the assumption of ideal base station control. For practical deployment, it is necessary to account for the processing latency from monitoring to control execution, as well as the appropriate monitoring interval. Therefore, we position this method not as a final solution, but as a deterministic baseline

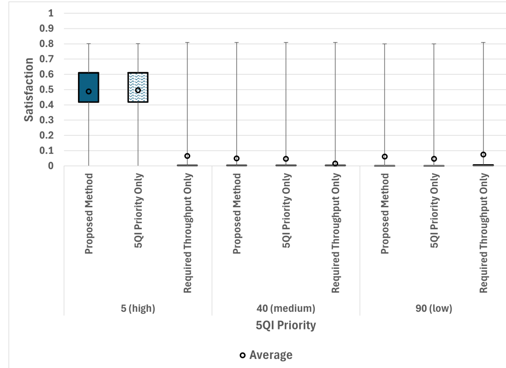

Fig. 7. Error Rate Requirement satisfaction for each flow.

essential for developing advanced adaptive RAN intelligence. To realize such evaluation, the utilization of the RAN Intelligent Controller (RIC) [11], which is currently being researched as a key technology for Beyond 5G, is indispensable.

In future work, we will investigate processing latency in the RIC and determine appropriate monitoring intervals. Specifically, we aim to implement the proposed method after verifying its effectiveness in a real-world environment through experiments that account for the time required from monitoring to control execution. This implementation will serve as a foundational framework, enabling the future development and comparative evaluation of data-driven learning approaches against this deterministic baseline in real-world environments.

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