Digi-Infrastructure: Digital Twin-enabled Traffic Shaping with Low-Latency for 6G Smart Cities

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***Abstract*—Digital twin (DT)-based smart cities are anticipated to achieve seamless integration between physical and digital objects to satisfy an enormous number of users across all domains. Therefore, the infrastructure of 6G smart cities has become an important topic. Many types and data priorities exist in 6G smart cities; therefore, data traffic management is challenging. Current solutions may face challenges adjusting to swiftly evolving network circumstances and the unexpected rise of time-sensitive data. They require flexibility to handle non-periodic, unforeseen, and time-sensitive traffic, such as mission-critical applications. While current research explores the combination of Time-Sensitive Networking (TSN) and 5G, the evolution to 6G also necessitates the integration of TSN and DT technology to achieve deterministic networking. Therefore, taking advantage of DT in data traffic management, we propose a DT-enabled traffic shaping architecture called Digi-infrastructure, consisting of an intelligent traffic shaper inspired by TSN. Our proposed shaper comprises two components: the first component is a frame classification method established on Deep Reinforcement Learning (DRL) to address the dynamic scheduling problem by minimising the end-to-end delay. The second component is an intelligent gate control mechanism that considers the time, queue status and specified transmission time of traffic classes according to priority based on latency requirements without using a gate control list or timing data gate control. Finally, our solution improves infrastructure connectivity, efficiency, and latency.**

***Index Terms*—6G Smart Cities, DQN, Digital Twin, ns-3, Traffic Shaper, Low-Latency.**

I. Introduction

Fifth-generation (5G) networks have paved the way for revolutionary advancements in wireless communication, offering increased bandwidth, lower latency, and improved connectivity. However, as the digital landscape continues to evolve rapidly, the demands on communication networks are growing exponentially. The emergence of the sixth generation (6G) networks is poised to address these escalating demands by focusing on ultra-reliable and low-latency communications, which form the bedrock for fostering a plethora of mission-critical applications with stringent requirements on end-to-end (E2E) delay and reliability [1]. For instance, augmented reality (AR) demands ultra-low E2E delays ranging from 1 to 10 milliseconds. Meeting these demands poses unique challenges, particularly in smart cities, where the convergence of physical and digital worlds creates a complex web of interconnected systems and data streams.

The vision of smart cities is taking centre stage in 6G technology. 6G smart cities are envisioned to seamlessly integrate the physical and digital realms, offering innovative solutions to the challenges faced by modern metropolises, such as traffic management, surveillance, energy distribution, and health care. However, realising these aspirations hinges on robust and adaptable infrastructure supporting the diverse and dynamic data traffic that permeates urban environments. This emphasises the demand for Digital Twin (DT) technology and a robust traffic shaper to address the unique challenges of 6G cities' infrastructure.

A. Why Do We Need DT and Intelligent Traffic Shaper for Infrastructure of 6G Smart Cities?

The motivation behind incorporating DT into 6G smart cities' infrastructure lies in its seamless ability to bridge the physical and digital worlds. By creating real-time or near-real-time virtual replicas of physical objects and systems, DTs provide a robust simulation model that facilitates advanced analysis, testing, configuration, and system optimisation [2]. This reduces ongoing expenses, particularly for network infrastructures, and enhances the adaptability and scalability of city systems. Its role becomes increasingly critical in 6G cities, where seamless connectivity, ultra-high reliability, high data rates, and low latency are essential for properly functioning mission-critical applications.

Moreover, the smart cities data becomes more diverse, with varying types and priorities in 6G. The proper functioning of 6G applications depends on the real-time capabilities of the communication networks. The challenge lies in efficiently managing heterogeneous data traffic, including non-periodic, unforeseen, and time-sensitive, such as those generated by mission-critical applications. Traditional network solutions may require assistance adjusting to swiftly evolving network conditions and the sudden appearance of time-sensitive traffic. The IEEE 802.1 Task Group has introduced Time-Sensitive Networking (TSN) standards to achieve the networks' stringent latency and reliability requirements. These standards

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extend Ethernet technology to provide deterministic communication for time-critical applications. TSN defines several methods for ensuring or improving real-time transmission over Ethernet, but the challenge remains in adapting TSN to the unpredictable and diverse data traffic in smart cities. To address this limitation, a method is needed to swiftly detect changes in network conditions, accurately classify network traffic, and ensure uninterrupted system operation without interruptions or pauses. While existing research has primarily considered the combination of TSN and 5G, 6G smart cities also require TSN integration, complemented by DT. This fusion is essential to achieve deterministic networking, which is crucial for supporting mission-critical applications with strict demands on ultra-low delay and high reliability.

B. Related Works

Some works in the literature focus on solving dynamic scheduling problems using learning methods. Zhao *et al.* proposed a dynamic scheduling algorithm to solve the dynamic scheduling problem based on the DQN algorithm in a manufacturing environment [3]. The results showed that their algorithm performs better than the traditional Q-learning algorithm. Recently, the impact of scheduling using the DRL algorithm to reduce the weighted E2E latency in wireless networks has been considered in [4]. The finding shows that the technique performs low-latency transmission even when the critical mission changes dynamically. For Vehicular Ad Hoc networks, Qi *et al.* offered a multi-task Deep Reinforcement Learning (DRL)-based scheduling approach [5]. The findings revealed that the method outperformed the particle swarm optimisation algorithms and the least-connection scheduling regarding overall reward. Nevertheless, these works cannot efficiently address time-sensitive or mission-critical dynamic scheduling problems.

Several publications focus more on deterministic networking. Huang *et al.* proposed a cyclic queuing and forwarding mechanism to address bandwidth, cycle, and queue issues in E2E scheduling, along with a cycle-specified version [6]. Another work shows that bounded latency can be achieved through priority-based communication using admission control and a distributed reservation system, even with a non-TSN Ethernet switch [7]. Kim *et al.* proposed an enhanced version of Time-Aware Shaper (TAS) [8]. To ensure real-time performance, they designed a rule for the timely transmission of urgent traffic. Using Network Simulator 3 (NS-3), Striffler *et al.* scrutinised the performance of time synchronisation in combined 5G and TSN networks [9]. They discovered that due to the contrast between a typical TSN clock and the 5G system clock, even minor frequency offsets among the 5G system's ingress and egress could result in substantial synchronisation issues.

DT-assisted smart city concept has recently gained researchers' attention. Masaracchia *et al.* comprehensively reviews the current 6G network services which used DT, analysing the research advancements and emphasising the objections and upcoming developments [10]. For autonomous core networks in smart cities, another work suggests an intelligent detection technique with DT assistance [11]. None of the works mentioned above focused on traffic shaping using machine learning methods to support seamless cyber-physical interaction for 6G city infrastructure.

C. Contributions

This paper proposes a comprehensive framework called Digi-infrastructure, which integrates DT with an intelligent traffic shaper inspired by TSN standards to address the multifaceted challenges of 6G smart cities' infrastructure. It provides seamless cyber-physical interaction, improving the infrastructure's connectivity and latency to satisfy the enormous number of users across smart cities. The proposed intelligent traffic shaper consists of a DRL-based frame classification method and an intelligent gate control mechanism. Our contributions include:

- To enable seamless cyber-physical interaction in 6G smart cities' infrastructure, we suggest a Digi-infrastructure inspired by TSN standards.
- We provide a DRL-based frame classification method to solve the dynamic scheduling problem related to non-periodic or unexpected but time-critical traffic.
- We proposed an intelligent gate control mechanism that considers time, queue status, and delays based on the latency requirements without using a gate control list or timing data gate control.

The rest of the paper is organised as follows. Section II gives a general look at the most common traffic shapers. The proposed method and the performance evaluation are in Section III and Section IV, respectively. Section V concludes the paper.

II. Popular Traffic Shaper Methods

A *traffic shaper* controls the volume and rate of traffic transmitted to the network. Many traffic shapers are proposed, and this section provides information about the most common individual traffic shapers.

A. Time-Aware Shaper

It offers a time-division multiplexing approach, specified by IEEE 802.1Qbv. The primary concepts of this method are gated queues, time synchronisation, and gate control lists (GCL). The backbone of the TAS method is time synchronisation specified in 802.1AS, and all items share the exact reference time in the clock area. TAS uses GCL to open and close each egress queue gate dynamically. TAS is a unique method for transmitting data with extremely minimal latency. However, deployment, time synchronisation, and GCL schedule creation make implementation challenging and have a high overhead. It is also not appropriate for aperiodic traffic.

B. Leaky Bucket Shaper

Based on the leaky bucket algorithm, it serves as an effective traffic shaping by adjusting network traffic to prevent data loss and manage burst traffic efficiently. Its primary function is converting irregular burst traffic into a steady, constant-rate

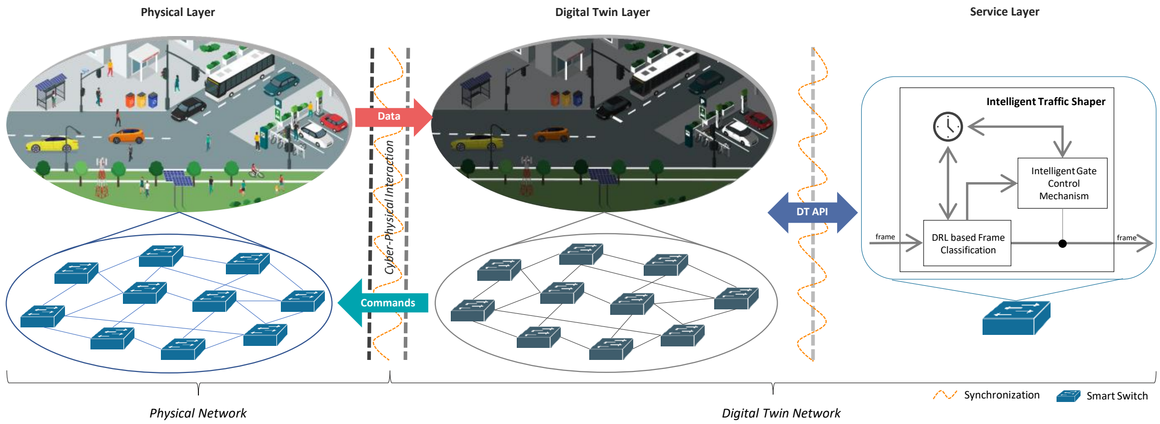

Fig. 1. The proposed Digi-infrastructure architecture.

flow, thereby averting network congestion and packet loss. It smokes incoming bursts, ensuring the network receives a consistent data flow. It maintains constant transmission rates even when the input traffic experiences abrupt fluctuations by imposing constraints and not granting idle hosts credit.

C. Token Bucket Shaper

It excels at traffic control and minimising packet loss and jitter. It operates based on the token bucket algorithm and effectively shapes traffic regarding network parameters, preventing data loss. This shaper allows burst traffic up to a specified rate and can be controlled precisely. It ensures quality of service by delivering packets only when sufficient tokens are available; otherwise, packets are queued. Tokens are used as packets are transmitted, and the bucket size can limit the burst size, ensuring better control over traffic shaping and quality of service.

D. Credit-Based Shaper

Credit-Based Shaper (CBS), defined by IEEE 802.1Qav, uses a credit method to allocate rates for various priority classes. It handles high-priority traffic that utilizes bandwidth for an extended period and inhibits other transmissions. In comparison to the TAS, CBS deployment is comparatively easy. CBS assigns a rational bandwidth per class by keeping a credit to minimize bursts and control lower-priority types from being starved. It can be considered as a token bucket-based per-class shaper.

E. Asynchronous Traffic Shaper

Asynchronous Traffic Shaper (ATS), defined by IEEE 802.1Qcr, achieves restricted low-latency transmission without global time synchronisation. It sets similar traffic determinism without requiring strict timing synchronisation. Contrary to TAS, it is versatile in managing mixed traffic, such as random traffic, and does not need time synchronisation. ATS enables per-hop latency boundaries, especially when combined with per-priority queuing in dynamic or safety-critical applications where clock synchronisation would introduce a single extra point of failure.

The current traffic shapers have benefits and drawbacks regarding different traffic types. For instance, leaky buckets are simpler and more suitable for basic policing. In contrast, token buckets provide better control and are often used for traffic-shaping scenarios where precise control and timing are critical. Traffic shapers can also be employed either individually or in groups. Combining ATS and CBS can provide certain advantages regarding latency, bandwidth utilisation, and cyclic dependency resolution; however, it also introduces complexity, potential performance issues, and management challenges [12]. Furthermore, recalculating the schedule for each non-isochronous occurrence of traffic is highly complex, time-consuming, and challenging.

III. Proposed Method

“Digi-infrastructure” contains a physical network with a physical layer that includes real objects and a DT network with DT and service layers. Fig. 1 depicts our three-layered architecture, which aligns with the Internet Engineering Task Force’s (IETF) DT network concept. After implementing the proposed approach, we called the network switch a smart switch.

The smart switch includes an intelligent shaper consisting of a DRL-based frame classification method and an intelligent gate control mechanism. Fig. 2 illustrates our intelligent shaper architecture, which enables seamless cyber-physical interaction. After frames enter the smart switch, the frames are classified frame by frame using the DRL-based frame classification method, which is our proposed scheduler. The classified frames are transmitted regarding their priority and network conditions. In our system, the DRL-based scheduler classifies the frames according to their priority, and then the intelligent gate control mechanism makes the last decision to transmit frames.

A. DRL-based Frame Classification Method

Frames are taken to the DRL-based classification separately. We define periods, like 802.1Qbv, to send frames to the system. Therefore, we also defined a buffer/queue state, which is a dynamic variable that represents the status of a queue at

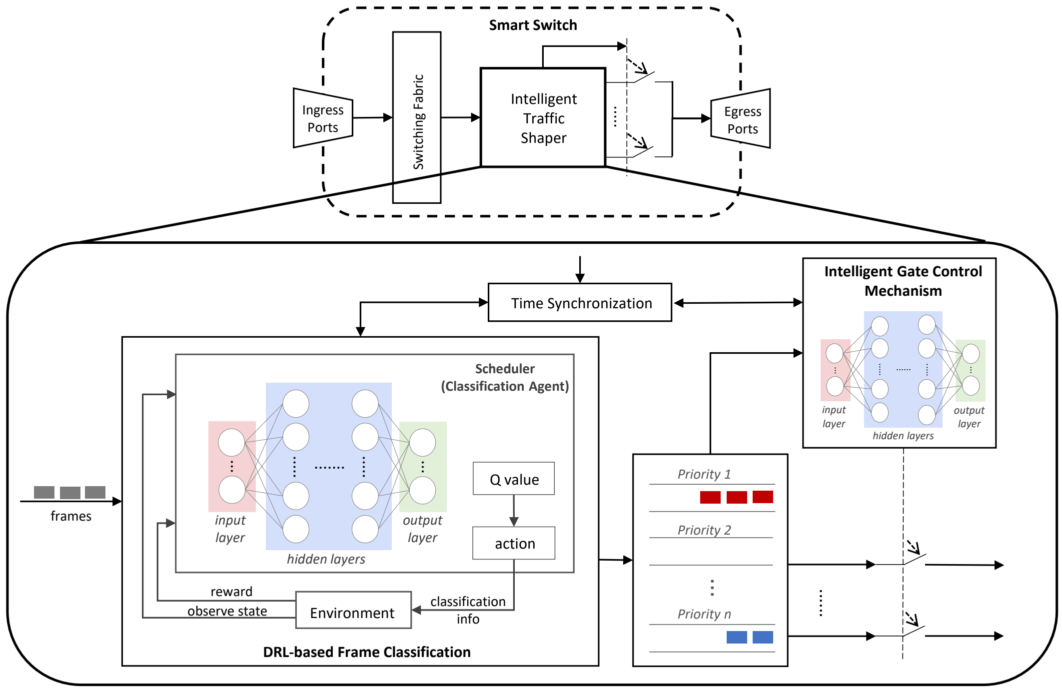

Fig. 2. The proposed intelligent traffic shaper.

each time slot in a specific time. This buffer state is updated based on the number of transmitted frames and the maximum buffer size. It aims to model how the buffer state changes over time as frames are sent and the buffer reaches its maximum capacity. It is not cached externally but is maintained and utilised within the system to manage frame transmission and scheduling decisions.

We have formulated a dynamic scheduling problem to minimise the average frame delay and optimise frame transmission. Our scheduling problem can be defined as a Markov Decision Process (MDP) problem, which aims to effectively manage the transmission of frames in a network to minimise average frame delay. MDP is a stochastic control process that operates in discrete time. It gives a mathematical structure characterising decision-making. To this end, we defined the following states: classified frames, average delay, and queue state at a particular time. In our problem, the scheduler observes the current conditions and makes a frame classification decision. The queue state and frame delay are returned to the scheduler after classification. In the next time slot, the scheduler makes another decision, and so on. The main objective is to develop a robust policy that minimises average frame delay for this definition.

MDP problems can be solved using the RL techniques. In RL, the agents learn via their interactions with their environment. The Q-learning algorithm is a popular RL method. It desires the best policy, maximising reward over time. Once the state and action spaces are continuous and broad, RL cannot solve it as they do in our problem. RL utilises a DNN to reach the mapping table to overcome this limitation. It combines the benefits of RL and deep learning while being more efficient than RL [13]. Therefore, we employ a DRL technique, specifically the Deep Q-Network (DQN) algorithm, to address our MDP problem for frame classification.

We specified the state space based on time. Since the reward function represents the algorithm's goal, it is essential for DRL. So, we defined the reward function based on time. To train the agent logically, we can represent it as an optimisable formula. The loss function is essential for DRL as it reveals how much our estimates vary from our targets. For instance, a forecast might indicate that delivering a frame to one of its candidate priority queues is more valuable. It can gain additional rewards by transferring this frame to a higher priority queue. Therefore, we desire to minimise the gap between the estimated and objective values. Our DRL-based approach uses estimated values to assess the potential outcomes of various scheduling decisions. These estimated values guide our scheduler in making frame classification and scheduling choices. The ultimate objective values represent our goal of minimising average frame delay within the 6G city environment. We also defined our loss function based on time.

Moreover, our defined queue/buffer state is one of the components of the state space that the DRL agent observes. The DRL agent uses this observed state and average frame delay to make decisions about frame classification and scheduling to minimise average frame delay. We used the M/M/m queueing model to calculate the metrics, like average frame delay, by taking advantage of the queueing theory. We employ prediction and target networks in our DRL architecture to facilitate this learning process. The prediction values generated by the prediction network inform our scheduling decisions. These values help us estimate the expected rewards associated with different actions. Meanwhile, the target values, representing our desired outcomes, guide the learning process. These values are essential for training our DRL agent to make optimal decisions that minimise frame delay. The target networks are a crucial component of our approach. These networks mirror the structure of the prediction network but have some of their parameters frozen. The frozen parameters help stabilise the training process and ensure the agent converges to an optimal policy. During training, we periodically update the target network parameters by copying them from the prediction network, allowing our agent to learn and adapt over time.

Our DRL-based scheduler begins by selecting a priority queue for the current frame. The frame is added to the appropriate priority queue line. The reward and the new system status can then be observed. Based on the data, we compute the maximum goal Q value and then discount it. Finally, we add the existing reward to the discounted target Q value to get the target value. Since the prediction and target values may differ, using the same network to calculate them takes work. As a result, during the training phase, we employ an architecture that includes the target and prediction networks for learning. With a few parameters frozen, the target network is structured similarly to the prediction network. Parameters are replicated from the prediction to the target network for each iteration, resulting in more robust training because the target network is specified.

B. Intelligent Gate Control Mechanism

It plays a critical role in ensuring determinism in transmission while minimising packet loss problems. It accomplishes this by prioritising traffic, dynamic queue management, framing preemption, and adhering to specified transmission times. Collectively, these mechanisms ensure that time-critical frames are prioritised, preempted when necessary, and transmitted within specified time limits. Thus, it minimises the likelihood of packet loss and guarantees reliable and low-latency communication for mission-critical applications.

We classify frames into priority queues, divided into critical and non-critical or more. After organising frames into their respective queues, we must decide on their transmission order based on their priorities. However, in our system, we go beyond mere priority-based decisions. We consider the queue states and frame delays, aligning our transmission decisions with the latency requirements of each class priority. Utilising the queueing theory, we computed metrics like frame delay using the M/M/1 queueing model. To achieve this, we introduced an intelligent gate control mechanism determining which traffic queue is permitted to transmit. Instead of relying solely on a fixed gate control list or timing data gate control, our approach employs a neural network to dynamically evaluate each traffic queue's readiness for transmission. A neural network consists of layers, with each layer comprising linear operations and non-linear activation functions. The previous layer's output serves as input to the next layer, and through a process called backpropagation, the network learns the appropriate weights for these operations.

Our gate control mechanism is implemented using a fully connected feed-forward structure. This structure aims to estimate the function based on input parameters and learning weights, with these parameters tailored to yield the best function approximation. We used a linear activation function for the time allocation. We also used the dropout method to prevent overfitting. It considers input factors such as time, queue states containing frame information, and the specified transmission times of traffic classes based on latency requirements. Additionally, we account for frame preemption similar to TSN. An overview of how our proposed mechanism operates:

- Suppose that we have two priority queues as critical (Q1) and non-critical (Q2); the frames in Q1 are non-preemptive, and the frames in Q2 are preemptive.
- If we have a frame in Q1 and do not have a frame in Q2, Q1 is permitted to transmit, and Q2 is not permitted.
- If we have a frame in Q2 and do not have a frame in Q1, Q2 is allowed to transmit, and Q1 is not allowed.
- When the frames are available in Q1 and Q2 simultaneously, Q2 is not permitted, so the frame of Q2 is preempted. After the Q1 frame is transmitted, Q1 is not allowed, and Q2 starts to transmit.
- We defined the traffic class's specified transmission time based on the class priority's latency requirements, like in TAS, to avoid starvation of Q2.
- We also defined a threshold value to check the fill rate of queues.
- When the specified transmission time of Q1 is finished, there is no frame transmission in Q2, and the fill rate of Q2 is higher than the threshold after the frame transmits in Q1. Q2 transmits the frames until the queue is empty or the specified transmission time is finished.

This mechanism enhances TSN determinism by dynamically considering queue states, frame delays, and latency requirements when making transmission decisions, ensuring optimal real-time performance.

The selection of distinct learning-based methods in the components is motivated by the unique demands and objectives they address. Our classification method leverages DRL, which excels in navigating intricate decision spaces and learning optimal policies due to the complexity of decision-making required to minimise average frame delay. Our gate control mechanism, focused on real-time traffic prioritisation and dynamic queue management, harnesses deep neural networks for their efficiency in pattern recognition and rapid decision-making. This diverse approach arises from the specific challenges each component aims to tackle.

IV. Performance Evaluation

To test the performance of our approach, we defined a simple topology with two priority queues: critical and non-critical. The simulation uses the NS-3 (version 3.31) and NS-3 AI, which are discrete-event network simulators [14]. Results are collected simultaneously and combined with NS-3 and AI network monitoring output.

According to the IEEE TSN task group, there are two types of traffic: isochronous (periodic) and random (sporadic) traffic. To conduct an exhaustive evaluation, we consider random and periodic traffic. We produced random traffic with critical and non-critical frames using independent Poisson processes at

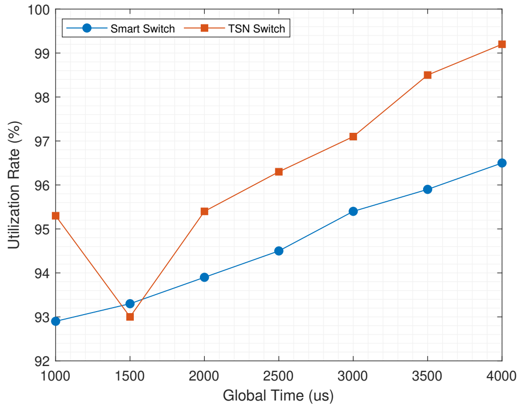

Fig. 3. The utilization rate comparison.

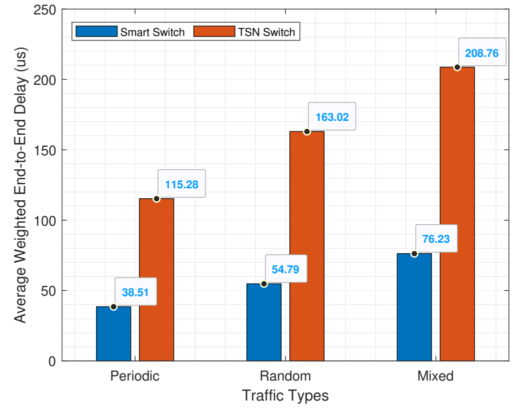

Fig. 4. The average weighted E2E delay comparison.

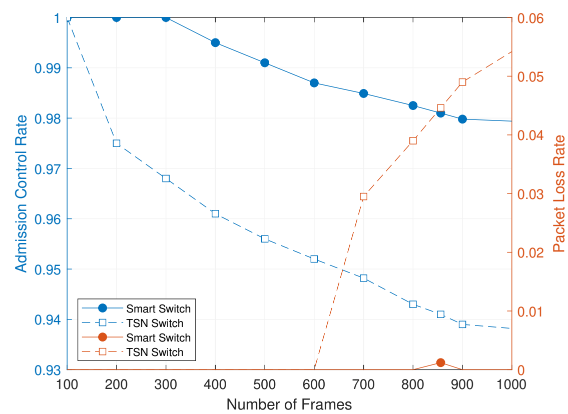

Fig. 5. The comparison of admission control and packet loss rates.

each traffic source with the same frame production rate. Each traffic source creates 580-byte data frames individually and at random. Then, we generated the periodic traffic with critical and non-critical traffic using Poisson distribution, the average stream per second as 1 to 20, the average stream duration as 2 to 5 seconds, and the number of frames per cycle as 1. In each source, packet traffic is transmitted, where each packet is 580 bytes in size. This traffic follows a consistent, uniform rate of periodic injection across the network. After traffic generation, we took the ".pcap" file of the frames. Then, we labelled them using Wireshark [15]. After that, we trained our frame classification method and gate control mechanism using supervised learning with five hundred thousand mixed (periodic and random) frame samples.

After training, we implemented it in the traffic control layer of the smart switch. We compared our proposed method with a TSN switch, including TAS, frame preemption (IEEE 802.1Qbu), and stream reservation protocol (IEEE 802.1Qcc). We generated mixed traffic and measured the total transmission time of all frames. We compared the queue utilisation rate to the total transmission and global times. Since our solution considers the queue status and the specified transmission time in the intelligent gate control mechanism, the TSN switch's queue utilisation rate is higher than ours; the lower queue utilisation means lower queue delay, as seen in Fig. 3.

We also measured the average weighted E2E delay for periodic, random, and mixed traffic. As seen in Fig. 4, our solution performs more than twice as well as the TSN switch and is more robust. We defined the admission control rate, which is calculated by combining the packet delivery ratio, bandwidth utilization, maximum cycle time, and traffic injection rate, each weighted by specific coefficients, to assess the network's capability to handle new data streams. Fig. 5 demonstrates that our solution offers superior admission control and packet loss rate performance compared to the TSN switch. This indicates a significant enhancement in network efficiency and reliability, crucial for the high-demand environment of 6G smart cities. These results validate the effectiveness of our proposed Digi-Infrastructure in handling diverse traffic types while maintaining optimal network performance.

V. Conclusion

In conclusion, we propose Digi-infrastructure, which consists of an intelligent traffic shaper inspired by TSN to provide seamless connectivity for 6G smart cities' infrastructure. We design a DRL-based frame classification method and an intelligent gate control mechanism to solve the dynamic scheduling problem by minimizing end-to-end delay. This work addresses traffic's dynamic and diverse nature in smart city environments and ensures low latency and high reliability, which is crucial for mission-critical applications. The successful implementation and testing of the proposed solution underscore its potential to revolutionize urban digital infrastructures, paving the way for more efficient, reliable, and advanced 6G smart city networks.

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