Draft new Recommendation ITU-T Y.3441 (formerly Y.det-qos-req-ml-jrs)

QoS requirements and framework for deterministic communication services enabled by machine learning based joint resource scheduling

Summary

The communication services are usually transmitted across heterogeneous networks with different access technologies, which makes QoS assurance for end-to-end deterministic communication services more complexed. Machine learning (ML)-based joint resource scheduling could reduce the algorithm complexity due to its capability to make optimized online scheduling and resource allocation among multiple networks based on the services and networks states. Therefore, this Recommendation specifies the QoS requirements, framework and operational procedures to support deterministic communication services across heterogeneous networks including IMT-2020 and beyond enabled by ML-based joint resource scheduling.

Keywords

Deterministic communication services; heterogeneous networks; ML-based joint resource scheduling; QoS requirements and framework

Table of Contents

1. Scope 3

2. References 3

3 Definitions 3

3.1 Terms defined elsewhere 3

3.2 Terms defined in this Recommendation 4

4 Abbreviations and acronyms 4

5 Conventions 4

6 Overview 4

7 QoS requirements 5

7.1 High-level requirements 5

7.2 Requirements for Inter-TD agent 6

7.3 Requirements for Intra-TD agent 6

7.4 Requirements for the reward quantification 6

8 Framework 7

8.1 Capabilities of Inter-TD agent 8

8.2 Capabilities of Intra-TD agent 8

9 Example operational procedure 9

9.1 Model training 10

9.2 ML model test 11

9.3 Model deployment 11

10 Security consideration 11

Appendix I 12

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1. Scope

This Recommendation specifies the requirements, framework and example operational procedure for deterministic communication services enabled by ML-based joint resource scheduling across heterogeneous networks including IMT-2020 and beyond, the scope of this Recommendation is as follows.

- QoS requirements
- Framework
- Example operational procedure

2. References

The following ITU-T Recommendations and other references contain provisions, which, through reference in this text, constitute provisions of this Recommendation. At the time of publication, the editions indicated were valid. All Recommendations and other references are subject to revision; users of this Recommendation are therefore encouraged to investigate the possibility of applying the most recent edition of the Recommendations and other references listed below. A list of the currently valid ITU-T Recommendations is regularly published.

The reference to a document within this Recommendation does not give it, as a stand-alone document, the status of a Recommendation.

[ITU-R M.2083] Recommendation ITU-R M.2083-0 (2015), *IMT Vision – Framework and overall objectives of the future development of IMT for 2020 and beyond*.

[ITU-T E.800] Recommendation ITU-T E.800 (2008), *Definitions of terms related to quality of service*.

[ITU-T Y.3121] Recommendation ITU-T Y.3121(2023), *QoS requirements and framework for supporting deterministic communication services in local area network for IMT-2020.*

[ITU-T Y.3170] Recommendation ITU-T Y.3121(2018), *Requirements for machine learning-based quality of service assurance for the IMT-2020 network.*

[ITU-T Y.3172] Recommendation ITU-T Y.3172(2019), *Architecture framework for machine learning in future networks including IMT-2020.*

3 Definitions

3.1 Terms defined elsewhere

This Recommendation uses the following terms defined elsewhere:

3.1.1 technology domain [ITU-T Y.3121]: a sub-network of a local area network adopting single physical layer and data link layer scheme, with which the devices can send and receive information without interworking module.

3.1.2 local area network [b-ITU-T H.322]: A shared or switched medium, peer-to-peer communications network that broadcasts information for all stations to receive within a moderate-sized geographic area, such as a single office building or a campus. The network is generally

owned, used and operated by a single organization. In the context of this Recommendation, LANs also include internetworks composed of several LANs that are interconnected by bridges or routers.

3.1.3 machine learning (ML) [ITU-T Y.3172]: Processes that enable computational systems to understand data and gain knowledge from it without necessarily being explicitly programmed.

3.2 Terms defined in this Recommendation

None.

4 Abbreviations and acronyms

This Recommendation uses the following abbreviations and acronyms:

5G The 5th Generation mobile network

A2A Application to Application

DS-TT Device-Side TSN Translator

DRL Deep Reinforcement Learning

DDPG Deep Deterministic Policy Gradient

E2E End to End

GCL Gate Control List

ML Machine Learning

QoS Quality of Service

RL Reinforcement Learning

TD Technology Domain

TSN Time-Sensitive Networking

U2U User device to User device

5 Conventions

None.

6 Overview

Deterministic communication services require bounded latency, high reliability and bounded jitter. In practical scenarios, the vertical services are usually transmitted across heterogeneous networks with different access technologies, which makes QoS assurance for end-to-end deterministic communications of vertical services too complexed to achieve optimal resource allocation results. Machine learning provides an efficient approach to deal with complexed problems that cannot be solved by traditional mathematical models, the machine learning model can interact with environment, and be trained to make online optimization decision according to well-designed QoS assurance objectives. Therefore, ML-based joint resource scheduling for heterogeneous networks can provide solid QoS assurances for end-to-end deterministic communication services.

Deterministic communication services transmitted across multiple TDs could be classified into three traffic classes as sporadic burst traffic, periodic time-sensitive traffic, real-time traffic and non-deterministic traffic [b-3GPP TR 22.804]. The characteristics of each traffic are described as follows.

- Sporadic burst traffic relates to applications such as emergency stops and failure alarms in machine running scenario, these applications are triggered by specific events or errors. The packet size of sporadic burst traffic is always small, but it is sensitive to transmission latency and reliability.
- Periodic time-sensitive traffic is generated periodically with a given transmission deadline. Moreover, this type of traffic is also sensitive to data transmission latency and reliability. Motion control and cooperative control in industrial scenario are common applications of periodic time-sensitive traffics.
- Real-time traffic relates to the applications such as video monitoring, and these applications will be periodical or sporadic, and require not very strict latency, but have requirements on transmission rate.
- Non-deterministic traffic has no strict requirements on latency and reliability, but some applications need minimal transmission rate guarantee. Data collection and software update belong to non-deterministic traffic.

[ITU-T Y.3170] specifies high-level requirements and functional architecture of machine learning-based QoS assurance for the IMT-2020 network. [ITU-T Y.3121] describes the framework to support deterministic communication services across multiple technology domains (TDs) in local area network and defines three QoS groups for end-to-end data transmission, including A2A QoS, U2U QoS and intra-domain QoS. For the scenario of the deterministic communication services transmitted across multiple technology domains (TDs), data transmission procedure involves not only IMT-2020, but also other local area networks, such as WiFi. Therefore, this Recommendation specifies requirements, framework and operational procedures for deterministic communication enabled by ML-based joint resource scheduling across heterogeneous networks including IMT-2020 and beyond.

7 QoS requirements

ML-based joint resource scheduling has capability to learn the network environment, QoS-related data, and then take the optimal resource allocation actions to satisfy QoS requirements of all the traffics. In order to achieve this objective, besides of ordinary requirements for machine learning-based QoS assurance for IMT-2020 network defined in [ITU-T Y.3170], additional requirements are specified to support deterministic communications across heterogeneous networks enabled by ML-based joint resource scheduling . In order to enable the ML-based joint resource scheduling, two types of ML-enhanced scheduler are involved as Inter-TD agent and Intra-TD agent. The Inter-TD agent is responsible for resource scheduling to guarantee deterministic communication over heterogeneous networks, and the Intra-TD agent is responsible for resource scheduling to guarantee deterministic communication in each TD according to the QoS related information from inter-TD agent. The following sub-sections define the high-level and detailed QoS requirements, respectively.

7.1 High-level requirements

The following are the high-level requirements for deterministic communication across heterogeneous networks enabled by the ML-based joint resource scheduling.

- It is required that at least one inter-TD agent is defined for QoS assurance decision-making across heterogeneous networks.
- It is required that the inter-TD agent and intra-TD agents could share their QoS assurance decision-making results with each other.

- It is recommended that at least one intra-TD agent is defined in a single TD for QoS assurance decision-making in a single TD,
- It is recommended that the appropriate reward quantification should be designed for inter-TD agent and intra-TD agent, respectively.

NOTE – The reward quantification is used for ML model training, aiming to train the Inter-TD and Intra-TD agent to make optimal resource scheduling decision to provide stable deterministic communication assurance for sporadic burst traffic, periodic time-sensitive traffic and real-time traffic.

7.2 Requirements for Inter-TD agent

The following are the requirements for the Inter-TD agent.

- It is required to collect network state information of each TD, including available resources, channel quality, buffer state and so on.
- It is required to make QoS metrics decomposition decision for each TD, aiming to calculate the maximum residential time, acceptable packet loss rate, minimal guaranteed rate in each TD according to service information and network state information of each TD.
- It is required to deliver the QoS decomposition results to the Intra-TD agent in each TD.
- It is required to store following data for model training, including network state information, QoS metrics decomposition result, actual performance information of each TD.
- It is recommended to collect end-to-end QoS-related service information of all the traffics before the decision-making of Inter-TD agent.

7.3 Requirements for Intra-TD agent

The following are the requirements for the Intra-TD agent.

- It is required to collect network state information in related TD, including active user device, traffic volumes, buffer state in both network and user device side, available network resources.
- It is required to make the scheduling and resource allocation decisions in the TD based on the collected network state information and QoS-related metrics delivered from Inter-TD agent.
- It is required to collect actual network performance information after the resource scheduling decision in each TD.
- It is required to store the following data for model training of intra-TD agent, including network information of TD, resource scheduling decision result in a single TD, actual network performance information after the execution of resource scheduling decision.
- It is recommended that intra-TD agent can learn characteristics of each traffic in a single TD.

7.4 Requirements for the reward quantification

The reward quantification is not only related to the QoS assurance objective, but also affect the training outcome of agent. Therefore, reward quantification is essential for QoS assurance of deterministic communication enabled by ML-based joint resource scheduling. The requirements for the reward quantification are list as following.

- It is required that the reward quantification should indicate the QoS assurance objective of key traffics.

NOTE1 – Some reward quantification examples are given for different key traffics: reward quantification should provide latency guarantee for sporadic burst traffics, latency and reliability guarantee for periodic time-sensitive traffic, data transmission rate for real-time traffic.

- It is required that the reward quantification should evaluate whether the actual network performance can satisfy the QoS requirements of each traffic or not after the execution of resource scheduling decision made by Inter-TD and Intra-TD agents.

NOTE2 – if the actual network performance can satisfy the QoS requirements of each traffic, a positive reward value is given, otherwise, a negative reward value is given.

- It is required that the cumulative reward value is increasing with training procedure and is converged after predefined training epochs.

8 Framework

The QoS assurance framework of deterministic communication enabled by machine learning based joint resource scheduling is given in Figure 1.

For inter-TD agent, it is used to learn how to decompose E2E QoS metrics of key traffics into resource requirements in each TD, such as delay budget, guaranteed transmission rate, transmission power and so on.

For intra-TD agent, it is used to learn how to allocate resources and schedule various traffics to provide required QoS demands decomposed from inter-TD agent in each TD.

These two types of agent should interact with each other, and the decision-making of inter-TD agent would be affected by the actions taken by intra-TD agent.

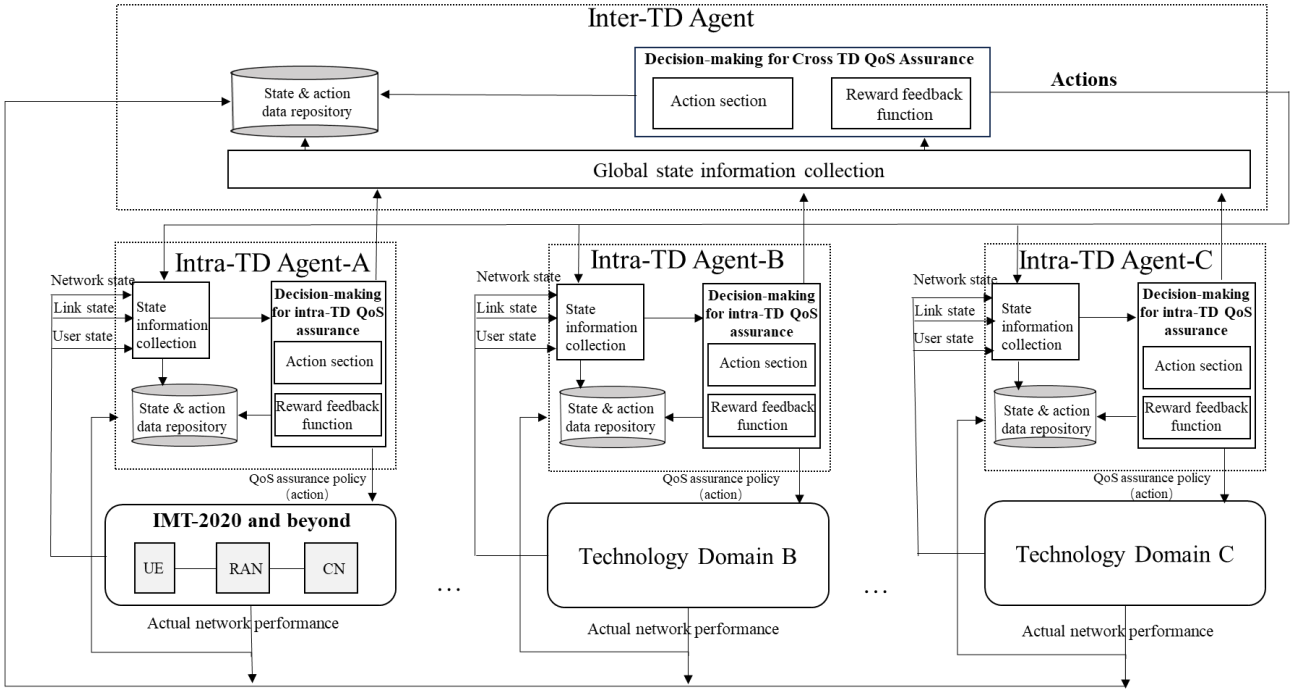

Figure 1. The QoS assurance framework of deterministic communication across heterogeneous networks enabled by ML-based joint resource scheduling

As indicated in Figure 1, the IMT-2020 and beyond acts as one TD from the point of E2E traffic transmission, the related Intra-TD collects raw data of user, link and network state from IMT-2020 and beyond, and the Intra-TD agent makes resource scheduling decision and communicate to the related function entity in IMT-2020, such as PCF and UPF. Then the raw data of actual network performance after the scheduling is transmitted to both Inter-TD agent and Intra-TD agent of each TD.

8.1 Capabilities of Inter-TD agent

In order to achieve the optimal joint resource scheduling decision, there are several capabilities are defined for Inter-TD agent.

(1). Global state information collection

Inter TD agent interacts with all distributed intra-TD agents to collect environment state information of all TDs, including user device numbers, traffic volumes, the QoS-related data of all traffic types, channel quality states and the available network resources for each TD.

NOTE – all the state information should follow the Markov Decision Process.

(2). Global decision-making for cross TD QoS assurance

In order to achieve optimal resource scheduling policy for Inter-TD QoS assurance, two capabilities, action selection function and reward feedback function, are defined as follows:

1) Action selection

Inter-TD agent defines the action space including but not limited to the deadline, minimum data transmission rate and transmission reliability for each traffic type. The action spaces can be discrete or continuous. The inter-TD agent selects decision actions from the action space by the neural network.

2) Reward quantification and feedback

The reward quantification indicate optimization object of joint resource scheduling for deterministic communication services across multiple TDs. After the Inter-TD agent operates a resource scheduling policy, a reward value will be calculated according to the actual network performance, then this reward value is fed back to the Inter-TD agent for further training process.

(3). Storing state & action data

Inter TD-agent stores the detailed information as an array, formulated as <network state, selected action, reward value, network performance after action, new network state>. All stored arrays are used for model training of Inter-TD agent.

8.2 Capabilities of Intra-TD agent

Intra-TD agent mainly focuses on how to adaptively make optimal actions to provide the QoS assurance for deterministic communication in a single TD. Several capabilities are defined for Intra-TD agent.

(1). State information collection

Intra-TD agent collects environment state information in each TD, including channel quality state, user numbers, the available network resources, queueing packets amounts and head of line delay for

each dispatched user. Furthermore, the Intra-TD agent should collect the end-to-end QoS metrics decomposition result from Inter-TD agent.

NOTE – all the state information should follow the Markov Decision Process.

(2). Decision-making for Intra-TD QoS assurance

In order to achieve optimal resource scheduling policy for Intra-TD QoS assurance, two capabilities, action selection function and reward feedback function, are defined as follows:

1). Action selection

Based on the collected network state information, Intra-TD agent select the appropriate action from action space, the actions include but not limited to the scheduled user, the allocated network resources for each dispatched user. The action spaces can be discrete or continuous, and selected actions act as the resource allocation decision.

2). Reward quantification and feedback

Intra-TD agent use this capability to evaluate the performance of selected action, if the action can provide the QoS assurance for each traffic, a positive reward value is given, otherwise, a large negative reward value is given. The quantified reward value is fed back to Intra-TD agent for further training process.

(3). Storing state & action data

Intra-TD agent stores the detailed information as an array, formulated as <network state, selected action, reward value, network performance after action, new network state>. All stored arrays are used for model training of Intra-TD agent.

9 Example operational procedure

For both Inter-TD and Intra-TD agents, they are the scheduler based on ML model, they need to go through the following operational procedure before taking effect, including model training, model test and model deployment, the example operational procedure of ML-based agent for joint resource scheduling to guarantee deterministic communication across heterogeneous networks is given as Figure 2.

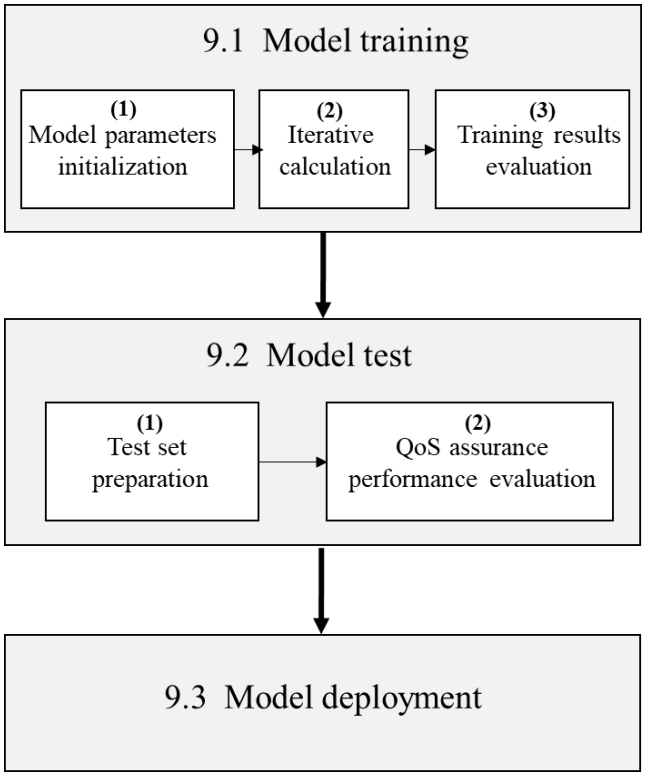

Figure 2. The operational procedures of ML-based joint resource scheduling

9.1 Model training

The purpose of model training is to enable the ML model of Inter-TD and Intra-TD agents to adaptively make resource scheduling action according to network states and traffic type. The model training procedure directly affects the performance of Iner-TD and Intra-TD agents for scheduling.

Three steps for Model training are defined as model parameters initialization, iterative calculation and training results evaluation.

(1). Model parameters initialization

First, the network state parameters are initiated according to state information collection capability of Inter-TD and Intra-TD agent, besides of these, the following parameters should be initiated for model training:

- Reward quantification parameters.
- Training episode: the time duration for model training.
- Resource scheduling cycle.

NOTE – one episode may include several resource scheduling cycles.

(2). Iterative calculation

This is the main part of model training. For each resource scheduling cycle, the inter-TD and intra-TD agents select actions from action space according to current network state. Then, the actual QoS performance (such as delay, jitter or throughput) after action are obtained to calculate reward value for each active traffic. For Inter-TD agent and each Intra-TD agent, the total reward value are calculated in one episode, and there are hundreds of episodes for model parameter calculations before obtaining a well-trained ML-model.

(3). Training results evaluation

In one episode, a total reward value is obtained for Inter-TD agent and each Intra-TD agent, respectively. With increasing of training episode, the reward value changes from low to high, and finally keeps minor fluctuations regardless the change of episode, which means the model training of Inter-TD agent and multiple Intra-TD agents are completed; otherwise, it should go back to iterative calculation step to repeat training process.

9.2 ML model test

The purpose of ML model testing is to evaluate whether the trained ML-model can make appropriate resource scheduling decision to satisfy the various traffics QoS requirements or not.

(1). Test set preparation

In this step, different users and traffics with various QoS requirements are prepared to test the performance of ML model of Inter-TD agent and Intra-TD agents. For each set, there are different number of users with various traffic types, and the traffic period, packet size, packet numbers are also different for each traffic.

Furthermore, the network initial parameters are also different, such as available resources, channel states, scheduling periods and so on.

(2). QoS assurance performance evaluation

The trained ML-models of Inter-TD agent and Intra-TD agents are operated based on the traffics and initial parameters defined in the test set. Then, the trained ML-model will take actions for resource scheduling according to network state and traffic type.

After execution of output actions, the QoS-related performances are obtained, such as delay, throughput, packet loss rate, and so on. If the performances meet the QoS requirements of related traffic, it means the ML-model of Inter-TD or Intra-TD agent is acceptable and can be deployed for practical operation. Otherwise, it will return back to model training procedure for another round training.

9.3 Model deployment

After previous procedures, the ML-model of Inter-TD agent or Intra-TD agent are trained to make appropriate resource scheduling decision, and it can be deployed into actual network environment.

NOTE: Once the network involved for deterministic communication service transmission is changed, the ML model of Inter-TD and Intra-TD agent should be re-trained according to the procedure defined in clause 9.1 and 9.2. And the re-trained ML-model should be deployed again too.

10 Security consideration

The QoS assurance for deterministic communication across heterogeneous networks enabled by ML-based joint resource scheduling includes data from user equipment, network devices, and management entities, which are subject to security and privacy measures. Sensitive information should be protected as a high priority in order to avoid leaking and unauthorized access. Security and privacy concerns should be aligned with the requirements specified in [b-ITU-T Y.2701] and [b-ITU-T Y.3101].

Appendix I

An example of QoS assurance for deterministic communication services across 5G and TSN enabled by machine learning based joint resource scheduling

(This appendix does not form an integral part of this Recommendation.)

Deterministic communication seriously relies on efficient end-to-end scheduling, however, while scheduling considers both 5G and TSN domains presents significant challenges. The fundamental differences between 5G and TSN, including their physical layer technologies and MAC protocols, add to the difficulty. Therefore, 5G-TSN joint scheduling is a cross-domain problem and it should coordinate resources in different network domain.

In 5G-TSN industrial networks, multiple applications coexist and transmit simultaneously. High-priority data streams typically involve critical tasks and real-time control applications, called as periodic time-sensitive traffic. Medium-priority data streams may involve diagnostics, condition monitoring, and applications such as remote surveillance and visual inspection. Video flows are considered as real-time traffic due to their real-time transmission requirements and higher bandwidth demands. It's supposed that 5G-TSN network consisting of M TSN users and N video users, which are denoted as two different flow sets $\boldsymbol{F}_t$ and $\boldsymbol{F}_v$:

$$\boldsymbol{F}_t = \{f_{t,1}, f_{t,2}, \dots, f_{t,M}\} \quad \text{(I-1)}$$

$$\boldsymbol{F}_v = \{f_{v,1}, f_{v,2}, \dots, f_{v,N}\} \quad \text{(I-2)}$$

As illustrated in Figure I.1, the process for 5G and TSN joint scheduling for downlink data transmission are based on an AI agent. This agent, functioning as a logical entity within the gNB, is responsible for making flexible resource scheduling decisions. By learning from the environment, the agent can determine the appropriate "action".

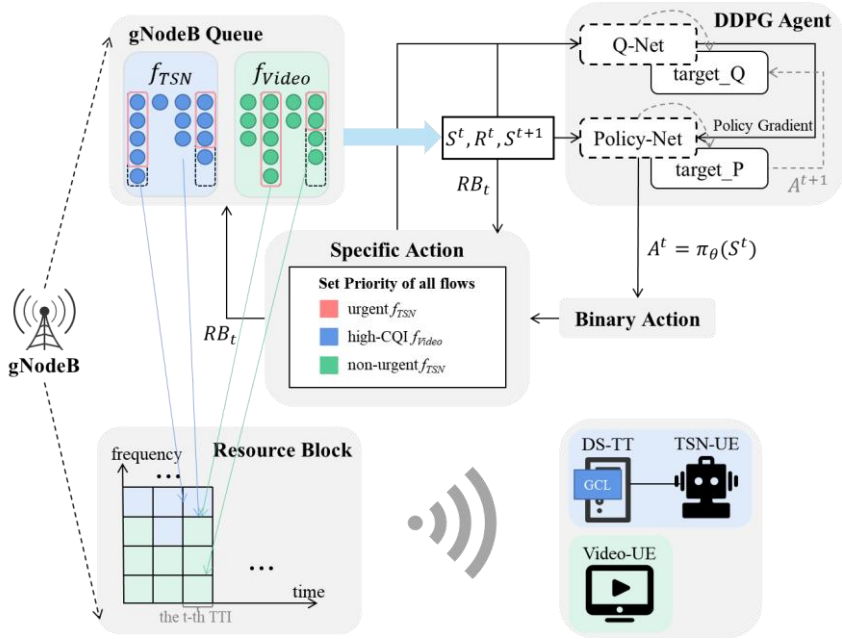

Figure I.1 Joint resource scheduling across 5G and TSN

In this scenario, the deep Q-learing model is applied for resource scheduling, as DDPG agent in Figure I.1, which acts as Inter-TD agent. In deep Q-learning, the output typically includes multiple dimensions of Q-values corresponding to each action. In contrast, DDPG, derived from the Actor-Critic framework, aims to enhance policy optimization efficiency and computational speed beyond that of standard DRL. The actor network in DDPG learns a deterministic policy, enabling it to map

extensive state spaces to actions, which facilitates fine-grained control outputs. Thus, this section proposes a DDPG-based resource scheduling algorithm designed to determine the optimal result, making it well-suited for tasks involving multiple users.

(1) State space

The state serves as an observation of the current environment, where the agent makes decisions based on it. The future state relies only on the current one, maintaining the memoryless property. In this study, the agent's decisions on scheduling and resource allocation are based on the state of each application queue in the gNB and the GCL settings of TSN for the time-triggered queue in the DS-TT. Consequently, the state space is defined as follows:

$$\boldsymbol{S} = \{\boldsymbol{RB_{exp}}, \boldsymbol{L}, \boldsymbol{D_{nor}}, \boldsymbol{G}\} \tag{I-3}$$

where Each element of $\boldsymbol{S}$ is a vector, $\boldsymbol{RB_{exp}}$ represents the number of RBs required for each queue. $\boldsymbol{L}$ denotes the queueing packet number. $\boldsymbol{G}$ denotes the GCL state in DS-TT for time-triggered application. $G = 1$ means the GCL state of time-triggered queue in DS-TT is "OPEN", and $G = 0$ means "CLOSED" correspondingly. And $\boldsymbol{D_{nor}}$ indicates the normalized queueing delay, each of it is calculated as:

$$d_{normalized,i} = \frac{d_i}{d_{qos}} \tag{I-4}$$

(2) Action space

As mentioned earlier, if the agent's output action is the number of RBs scheduled for each flow, it could result in a high-dimensional action space. To address this, the action space in DDPG is limited to binary values: "1" indicates that the corresponding flow is scheduled in the current TTI, while "0" means it is not. Consequently, the RL model only needs to determine whether or not to schedule each flow. Therefore, the action space is defined as follows:

$$\boldsymbol{A} = \{p_i\}_{(M+N)*1} \quad p_i \in \{0,1\}, i \in \boldsymbol{F} \tag{I-5}$$

(3) Design of reward quantification

The design of reward quantification is significant to quantitative descript the optimization goal for RL training, which can guide the model to learn a better policy.

To provide guarantees for all flows in 5G-TSN architecture while improving overall system throughput. The reward quantification is designed as:

$$R(\varphi_i) = \begin{cases} \left(1 + \frac{d_i}{d_{qos}}\right) * \varphi_i & d_i \le d_{threshold}, i \in \boldsymbol{F}_t \cap G = 1 \\ -\left(1 + \frac{d_i}{d_{qos}}\right) * \varphi_i & d_i > d_{threshold}, i \in \boldsymbol{F}_t \cap G = 1 \\ \left(1 - \frac{d_i}{d_{qos}}\right) * \varphi_i & d_i \le d_{threshold}, i \in \boldsymbol{F}_t \cap G = 0 \\ -\left(1 - \frac{d_i}{d_{qos}}\right) * \varphi_i & d_i > d_{threshold}, i \in \boldsymbol{F}_t \cap G = 0 \\ 2 * \varphi_i & \forall i \in \boldsymbol{F}_v \end{cases} \tag{I-6}$$

where φ_i is defined as:

$$\varphi_i = \begin{cases} \delta * \overline{th}_i & \overline{th}_i \ge th_{min}, i \in \boldsymbol{F}_v \ or \ \forall i \in \boldsymbol{F}_t \\ 0 & \overline{th}_i < th_{min}, i \in \boldsymbol{F}_v \end{cases} \tag{I-7}$$

Eq. (I-7) expresses the requirement for $\boldsymbol{F}_t$. Considering the reliability of the d_i, the upper bound of it is restricted to $d_{threshold}$, which is lower than d_{qos} in $\boldsymbol{F}_t$, exceeding this threshold will result in penalties. Moreover, considering the characteristic of TSN domain, rewards increase when GCL is open and decrease when it is closed, and the magnitude of reward increase or decrease is positively correlated with d_i. In Eq. (I-7), δ is implemented to control the deviation between different φ_i, our goal is to make the range of different reward values within 1000. $\overline{th}_i$ is required to be higher than th_{min} in $\boldsymbol{F}_v$, otherwise, the reward is set to zero.
For each reward value of $\boldsymbol{F}_t$, the coefficient is always lower than 2, however, for flows in $\boldsymbol{F}_v$ that $\overline{th}_i \geq th_{min}$, the coefficient δ is directly set to 2. Hence, the reward value for $\boldsymbol{F}_v$ is slightly higher than that for $\boldsymbol{F}_t$. This design considers that $\boldsymbol{F}_v$ have larger packet size, thereby encouraging the scheduling of $\boldsymbol{F}_v$ while solidly ensure the delay guarantee of $\boldsymbol{F}_t$.

For the detailed ML-based joint resource scheduling across 5G and TSN, see [b-Zhang-2025].

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