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• **RESEARCH PAPER** •

Industrial Wireless/Wired Integrated Transmission: Risk-Sensitive Co-design of 5G and TSN Protocols

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Abstract In order to realize flexible manufacturing with dynamic requirements, the factory network needs to provide full process deterministic transmission by flexible access and reliable forwarding. For this reason, combining the 5th generation (5G) communication technology with time-sensitive networking (TSN) standards is a promising and proper solution. However, industrail wireless communication has inherent defects such as the diverse quality of service (QoS) of industrial data, the complex signaling process which brings extra delay and the severe long tail of delay's distribution. These defects all lead to nondeterminacy of wireless network. To address this issue, we propose a heterogeneous time-sensitive network (HTSN) co-designed by 5G and TSN. To provide hierarchical deterministic delivery of the whole process in HTSN, we design a dynamic low delay access mechanism based on the semi-persisitent scheduling (SPS) and develop a multi-priority forwarding policy base on the per-stream filtering and policing (PSFP) mechanism of TSN standards. After formulating the high-order model of total delay, a risk-sensitive reinforcement learning strategy is proposed to reduce the tail of delay and so realize deterministic delivery. Simulations on a hot rolling production scenario demonstrate that HTSN guarantees the total delay meets timeline and has a more centralized distribution, which promotes the determinacythe of the full process.

Keywords industrial cyber physical system (ICPS), 5G-TSN codesign, wireless/wired integrated network, risk-sensitive reinforcement learning, industrial internet of things (IIoT)

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1 Introduction

With the promotion of the fourth industrial revolution(also known as industry 4.0), the manufacturing industry is converted from traditional industrial automation to intelligent manufacturing, where the latter one integrates monitoring, communication, control and can make decisions independently. To realize this target, intelligent manufacturing needs to provide deterministic communication from the industry field to the remote centre in order to guarantee the timely delivery of data and the online control of the system. As one of the main scenarios of intelligent manufacturing, flexible production requires dynamic access and full coverage monitoring without blind areas. Moreover, reliable and deterministic forwarding of data is essential to improve the robustness of the control system. As a result, the timely delivery of data through the whole process is crucial for industrial transformation and upgrade to realize low latency and high reliability transmission and meet the dynamic application requirements.

As a new generation of wireless communication, the 5G technology is expected to expand industrial informatics and automation into much broader contexts [3]. As one of the most important scenarios of 5G, URLLC has the characteristics of high reliability up to 99.9999% and low delay down to millisecond [26], which is appropriate for intelligent manufacturing, smart grid and other precise control scenarios. These scenarios require extremely high reliability, otherwise it may cause severe economic losses and safety problems [3]. Besides, massive machine type communication (mMTC) is another scenario 5G aims for, which is designed for monitoring and data collection. Unfortunately, it still faces three main problems to apply 5G technology to industry field: (1) Due to the complex signaling process of dynamic

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access mechanism, the conventional cellular network failed to guarantee the strict timelines of industrial automation. (2) The industrial field has many defects such as the complex environment, the limited radio resources, the severe interference and the long tail of delay distribution that lead to unreliability. (3) The data's QoS requirements are diverse and safety data dynamically burst, which make it difficult to deliver data on demand.

Contrary to the 5G technology, TSN standards ensure the determinacy and reliability for its innovative mechanisms such as gate control list (GCL) and time-aware shaper (TAS), which is suitable for deterministic communication scenarios represented by flexible manufacturing. Moreover, TSN gateway can deliver data in a guaranteed time window with bounded low latency, low-delay variation and extremely low data loss [26]. However, as a new generation of network standards, TSN is designed for standard ethernet, which inherits the defects of wired transmission such as the limited coverage, the higher cost of maintenance, the complexity of installation, etc. As a consequence, deploying TSN alone is still a challenge which is hard to realize.

Therefore, it is necessary to propose a more flexible and deterministic transmission architecture to meet the requirements of flexible factors (data, environment, applications, etc.) while taking into account the advantages of 5G and TSN. To address this problem, we propose an architecture co-designed by 5G and TSN named HTSN, the contributions of this paper are summarized as follows.

- **HTSN: a 5G-TSN integrated time-sensitive network framework:**
  Aiming to provide flexible deterministic transmission of the whole process, we propose a co-design framework HTSN, in which the data accesses flexibly through the 5G network and forwards determinately via the TSN network. The data's deterministic delivery is realized through the adaptive adjustment of the two transmission stages.
- **Predictive multi-priority wireless scheduling mechanism:**
  In order to meet the transmission demands of different QoS data, we design a preemption-based wireless multi-priority scheduling mechanism based on semi-persistent scheduling (SPS). Considering the limited resources, we pre-allocate sensors based on the correlation of the sensors' trigger to reserved areas to save time and improve resource utilization.
- **Adaptive queue injection mechanism of TSN gateway:**
  Taking into account the nondeterminacy of 5G transmission, we propose an adaptive queue injection mechanism based on the PSFP mechanism to adjust the priority of data within the TSN network. In order to better offset the jitter of wireless communication, we give the relationship between the priority of queues and the delay of the TSN network as a reference of TSN queue's selection.
- **Risk-sensitive stategy for the total delay:**
  In consideration of the tail of the transmission delay, we propose a risk-sensitive utility function which consists of the expectation, variance and third-order central moment of the total delay. So the delay curve is more centralized by reinforcement learning learns the number of reserved RB and the TSN queue. Thus, the data with different QoS can achieve timely end-to-end (E2E) delay and the concentrated delay leads to deterministic transmission.

2 Related Works

With the smart factory concept proposition, the communication demand is more strict in industrial automation, which requires lower latency and higher reliability. The accompanying problem is how to take full advantage of the limited resources in the factory to satisfy the different QoS data. The industrial revolution could bring four issues to focus on: the dynamic requirements of applications, the fine-grained delay characteristics(the tail of delay), the complex signaling process of traditional uplink cellular networks, and the different levels of the criticality of data, which corresponds to main two topics in HTSN: heterogeneous network framework and Real-time scheduling of wireless communications.

2.1 Heterogeneous Network Framework

2.1.1 *Wireless/Wired Hybrid Network*

In recent years, the combination of the wireless and wired networks has attracted significant attantions [30–33]. The authors in [30, 31] concentrate on using software-defined networking (SDN) to provide centralized control of the wireless/wired network. But the heterogeneous frameworks under SDN diverse.

[30] proposes a network where wireless and wired transmission are used in parallel to make up for the shortcomings of the other one. [31] proposes a multi-path transmission mechanism under the framework from wired to wireless to promote the transmission performance of the video. Except for SDN, [32] proposes a protocol to support multimedia traffic in hybrid wireless/wired networks, which efficiently utilizes the wireless link with coexisting TCP flows and can provide satisfactory QoS for delay-sensitive multimedia applications. As for the industry, [33] points out that since current wireless networks are not suitable to fulfill the applications' requirements, hybrid wired-wireless networks have to be developed in order to support the implementation of industrial CPS. However, they only focus on the hybrid transmission based on the traditional TCP/IP network.

2.1.2 *5G-TSN Integrated Network*

Recently, the TSN industry white paper points out that the URLLC scenario of 5G is the key to realize industrial internet. How to implement TSN function in 5G technology is the research hotspot. For this issue, Ericsson proposes a 5G-TSN integration conception in [34], where SDN controller manage the whole network and TSN protocols are applied in 5G user plane to guarantee strict E2E delay. Futhurmore, Ericsson thinks that the integration of URLLC in the manufacturing process has great potential to accelerate the transformation of the manufacturing industry [35]. Nevertheless, these combination of 5G and TSN are only preliminary ideas which still have a long way to be implemented.

2.2 Real-time Scheduling of Wireless Communications

2.2.1 *Risk-sensitive Transmission*

As stated in the introduction, the risk is a notion in financial mathenatics [5], which we want to resort to measure the risk of transmission delay. For wireless communication, the risk is equivalent to the loss of valuable information due to the instability and randomness of wireless transmission. For example, the quality of the stochastic channel may cause a variation of latency, which will incur emergency information lost when the variation is higher [6]. What's more, some fine-grained characteristics of delay in queueing networks, such as the delay distribution and probability boundary(the tail of delay) are all critical while most works only care about the average delay rather the worst delay [7]. In existing works, [8, 9] study URLLC and low-latency communication to evaluate the performance under the influence of traffic dispersion and network density, which all focus on maximizing the average delay of network throughput or minimizing the average latency without providing any guarantee of the higher moment such as variance, skewness, kurtosis, etc. [10] [11]take mean and variance both into account to capture the tail of delay and optimize the bandwidth and transmission power without considering frequency diversity. Object to maximize the throughput of eMBB traffic, [12]takes burst URLLC traffic into account and assumes it is a Rayleigh distribution, while the burst traffic is actually dynamic sporadic.

2.2.2 *Semi-persisitent Scheduling*

Due to the complex "scheduling request-scheduling grant(SR-SG)" signaling mechanism, the conventional dynamic access scheme of the cellular network cannot satisfy the strict delay requirements [13]. To this end, a fast uplink access scheme based on SPS is proposed in LTE Release 13 [14], whereby the uplink resources are assigned in advance to reduce the "SR-SG" overhead, which is suitable for C-MTC in industrial automation [15]. However, SPS was designed for VoIP originally, the transmission of which is fixed and known, while the QoS of C-MTC devices varies and the scheduling request is time-varying and even dynamic sporadic [16]. For this, [17] proposes an adaptive SPS scheme to adjust the resources in the next transmission via buffer report. Moreover, to make further use of unused resources, other devices can be granted partial scheduling resources that were assigned in a semi-persistent way based on device-to-device(D2D), which may lead to extra latency [18].

2.2.3 *QoS-aware Wireless Transmission*

Since the mixed-critical data coexists and has different demand regarding latency and reliability [19], supporting transmission of data with different levels of criticality is the essential requirement of the industrial wireless network(IWN) [20], in which the priority of data can be established according to the urgency or criticality of applications [21]. For example, as mentioned in [22], there are four different types of information in the industry: the safety/emergency information, which requires the highest reliability and the lowest latency, the regulate/monitor control information, which possesses the lenient requirements, the open-loop control information which allows minutes level delay and the monitoring information which has no requirements. To deal with this problem, [23] proposes a TDMA-based multichannel superframe strategy to keep the superiority of each priority with full radio channel reuse while the strategy is implemented for cluster-based IWN without considering burst data. Similarly, a multi-priority scheme named p-persistent is proposed in [24] based on CSMA, which guarantees the transmission of high priority at the expense of longer delay of low priority data and still doesn't take burst traffic into account.

3 Overview of HTSN

As is illustrated in Figure 1, the whole framework of the HTSN consists of two parts: the 5G network and the TSN network which are coupling. The 5G network is composed of a set of $\mathcal{S} = (s_1, s_2, \dots, s_S)$ sensors, communication nodes and controllers, etc. Different sensors obtain different QoS data with different types. The TSN network consists of a set of $\mathcal{G} = (g_1, g_1, \dots, g_G)$ TSN gateways which also work as 5G micro base stations (BS). The 5G BSs are in charge of the assignment of the radio resource blocks (RBs) $\mathcal{R} = (r_1, r_2, \dots, r_R)$, where one RB denotes a series of time-frequency domains radio resource and is sufficient to transmit most of the traffic generated by sensors [1]. RB's corresponding time period, denoted by *Subslot*, is the minimum non-divisible time unit. And the corresponding frequency band of RB is a channel, which is flat fading and homogeneous. Thus, there is no difference between each RB for all sensors except for their time sequence. The industrial field data from different sensors (temperature sensors, vibration sensors, etc.) is transmitted via shared time-frequency radio resources to TSN gateways, then is sent to the remote data centre via the wired TSN network.

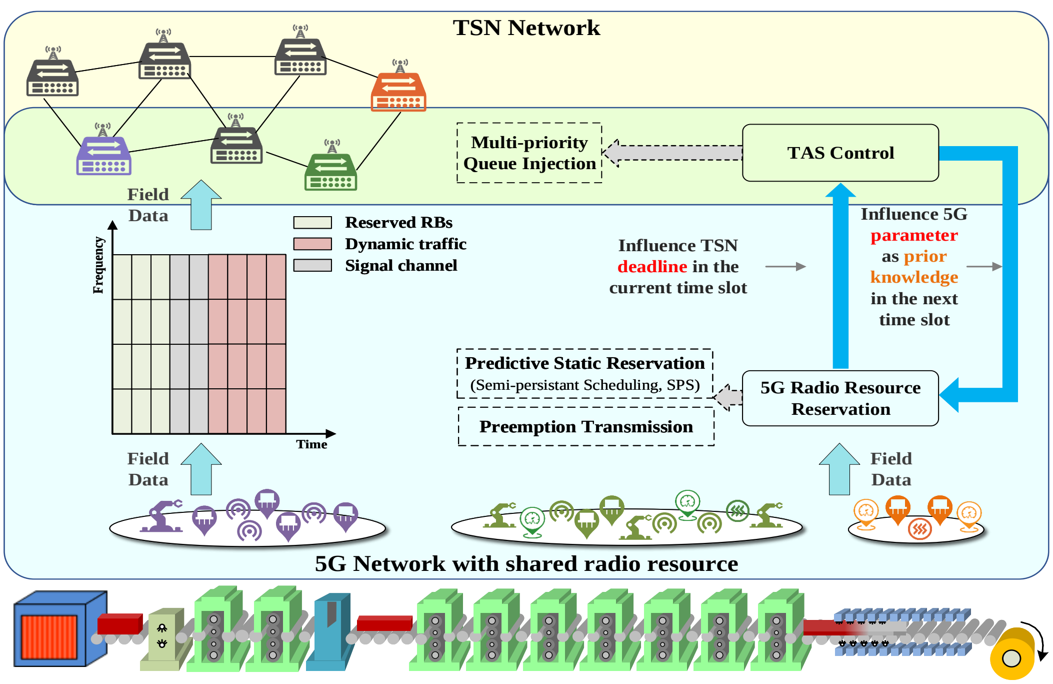

Figure 1 The framework of HTSN

Due to the different QoS requirements of sensors, field data is divided into three groups: (1)Non-scheduled (NS) Traffic, which is sporadically triggered by safety monitoring data and has the highest priority. (2)Time Critical (TC) Traffic, which is the primary type of data and the amount of it is much larger than NS Traffic. (3)Best Effort (BE) Traffic, which has the lowest priority and follows the best-effort forwarding rules. In industry, such as steel rolling production process, data is transmitted periodically, and so we only consider the scale of transmission in one cycle, denoted by transmission time interval (TTI). In each TTI, reserved nodes, signaling, and dynamic access nodes are predictive transmitted in turn, and will be scheduled by priority. Considering the highest priority and the sporadically triggered feature of the NS Traffic, we set a preemption mechanism, where NS Traffic can preempt any data as soon as it is triggered. Note that the priority of NS traffic is the same as TC traffic ever since it is embedded in the HTSN. Based on the PSFP mechanism in the IEEE 802.1Qci protocol, TSN gateways assign different Gate IDs to traffic with a different internal priority value (IPV), which is related to its QoS demands. Traffic arrived at the gateway is injected into the TSN's sending queue with corresponding Gate ID. Thus, traffic is scheduled hierarchically in the TSN network to achieve its time sensitivity.

Specifically, the delay of the 5G network $T^{5G}(t)$ and TSN network $T^{TSN}(t)$ in TTI t are coupled and interacted, as shown in Algorithm 1, where $T^{sum}(t) = T^{5G}(t) + T^{TSN}(t)$. In each TTI, the total amount of RBs is fixed, so that the larger the number of reserved RBs $|\mathcal{R}_{\mathrm{r},t}|$ for pre-allocation in TTI t, the smaller the number of RBs for dynamic access. Note that $|\mathcal{R}_{\mathrm{r},t}|$ is much smaller than the number of field sensors (i.e.,$|\mathcal{R}_{\mathrm{r},t}| \ll |\mathcal{S}|$). If the traffic with strict delay demand has a large $T^{5G}(t)$, then it should be injected into a high priority queue Q_t of TSN gateways to offset the time deviation caused by the previous 5G stage. On the other hand, what we care about is the total delay of HTSN, so the $T^{5G}(t)$ and the $T^{TSN}(t)$ both play an important role.

Example 1. We take the rolling production process as an illustration. As shown in Figure 1, the 5G BS is installed in the TSN gateway as a local control center with learning ability. At the beginning of each TTI, the BS decides the number of reserved RBs according to the history data collected from the previous steel rolling line. Reserved sensors transmit before dynamically scheduled sensors without a handshaking mechanism that greatly cuts down the delay. Based on the transmission situation in 5G and the data's demand obtained in prior, the BS learns the priority of TSN gateway's queue. Thus, the full process time-sensitivity of data is satisfied via HTSN.

Algorithm 1 Transmission Interaction of 5G and TSN

Input: Delay demand of TC traffic $T^{ddl}(t)$;
Output: The delay of TSN network $T^{TSN}(t)$
The number of reserved RBs in the next TTI $|\mathcal{R}_{\mathrm{r},t+1}|$
The priority of TSN Gateway's queue in the next TTI Q_{t+1}

```
|R_{r,0}| = 0, Q_0 = 0, T^{sum}(0) = 0;
while i ⩽ t do
    T^{5G}(i) = F(|R_{r,i}|, T^{sum}(i))
    Calculate the time deviation between T^{5G}(i) and T^{ddl}(i)
    T^{TSN}(i) = F_{Q_i}(T^{ddl}(i) − T^{5G}(i))
    T^{sum}(i) += T^{5G}(i) + T^{TSN}(i)
    Update |R_{r,i}|, Q_i
end while
```

4 System Model

4.1 Preemption Based Predictive Multi-priority 5G Transmission

As discussed in the previous section, there are two stages of 5G transmission: (1) Predictive assignment of sensors which are the most correlated (2) Multi-priority field data's embedding. To this end, we propose a preemption based multi-priority scheduling mechanism. To transmit data on its demand, the mechanism pre-allocate sensors according to its correlation learned by the Naive Bayesian model.

4.1.1 *Preemption Based Multi-priority Scheduling Mechanism*

As mentioned before, in industrial process automation, there is a massive amount of different QoS data generating all the time, which should be served on their time demand as well as importance. However,

Table 1 The Condition of Preemption and Trigger on Fixed Reserved RBs

$\gamma_i = \zeta_i \varphi_i$	**1**	**0**
ζ_i	$r^t_{\mathrm{brt},i}$ is preempted	$r^t_{\mathrm{brt},i}$ is not preempted
φ_i	s^t_i is triggered	s^t_i is not triggered

the time-frequency radio resources in the factory are shared by all the sensors on equal, which may lead to an additional queueing delay for data that is urgent and critical. As a solution, separateing resources into two parts to serve dedicated data could reduce queueing delay at the cost of low resource utilization. For this, we propose the preemption mechanism, which permits data with higher priority to preempt low priority data in order to nearly realize no-wait transmission while guaranteeing resource utilization. Moreover, due to the repeatability and complexity of conventional dynamic access procedures, reserving uplink resources to sensors in advance without signaling procedure is a suitable way to reduce access delay of traffic. Thus, reserving sensors that with more relevance to those in the last TTI can acquire a lower 5G delay in the next TTI.

According to the traffic's QoS, we split radio resources into four parts in time order: reserved RBs $\mathcal{R}_{\mathrm{res}}$,($\mathcal{R}_{\mathrm{res}} \subset \mathcal{R}$), RBs for signaling transmission, RBs to transmit TC traffic and RBs to transmit BE traffic, as shown in Figure 2. Taking into accounts burst traffic that carries valuable information, we set one fixed reserved RB each subslot to transmit burst NS traffic in the next subslot as soon as it arrives. The fixed reserved RBs overlap four parts, and so the longest delay of TC traffic is less than or equal to $2 * Subslot$. There comes a proplem: what if the NS traffic arrives while the fixed reserved RB has been allocated to a sensor already? That should be discussed according to whether the assigned sensor is triggered in table 1 as follows, where $r^t_{\mathrm{brt},i}$ denotes fixed reserved RB at i-th subslot of TTI t, s^t_i denotes the sensor assigned to $r^t_{\mathrm{brt},i}$, $\varphi_t = \sum_{i=1}^{|\mathcal{R}_{\mathrm{r},t}|/c} \varphi_i$ denotes the number of fixed reserved RBs which the corresponding sensor is triggered in reservation area, $\zeta_t = \sum_{i=1}^{|\mathcal{R}_{\mathrm{r},t}|/c} \zeta_i$ denotes the number of NS traffic in reservation area and $\gamma_t = \sum_{i=1}^{|\mathcal{R}_{\mathrm{r},t}|/C} \gamma_i$ denotes the number of reserved RBs that is preempted while its allocated sensor is triggered.

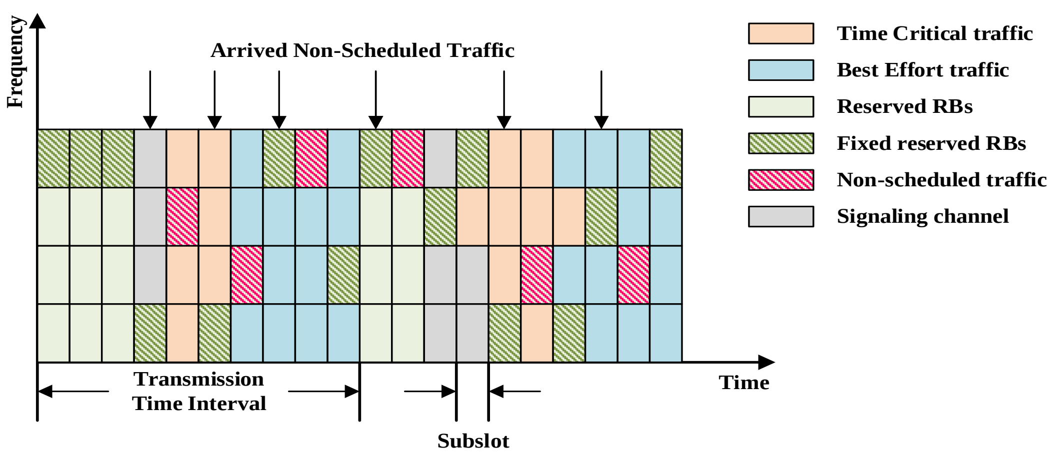

Figure 2 Embedment of multi-priority data in 5G NR

Then the number of RBs which are neither triggered nor preempted in reservation area can be:

$$|\mathcal{R}_{\mathrm{r},t}| - (|\mathcal{S}_{\mathrm{t},t}| + \zeta_t - \gamma_t) \tag{1}$$

where $C = \{c_1, c_2, c_3...\}$ is the set of channels and the number of channels is $|C|$. Thus the total number of high priority sensors at TTI t, including TC traffic and embedded NS traffic, is given by:

$$\begin{aligned} |\mathcal{S}_{\mathrm{h},t}| &= |\mathcal{R}_{\mathrm{r},t}| - [|\mathcal{R}_{\mathrm{r},t}| - (|\mathcal{S}_{\mathrm{t},t}| + \zeta_t - \gamma_t)] + |\mathcal{S}_{\mathrm{c},t}| + |\mathcal{S}_{\mathrm{b},t}| - \zeta_t \\ &= |\mathcal{S}_{\mathrm{t},t}| + |\mathcal{S}_{\mathrm{c},t}| + |\mathcal{S}_{\mathrm{b},t}| + \varphi_t - \gamma_t \end{aligned} \tag{2}$$

where $|\mathcal{S}_{\mathrm{h},t}|$ is the total number of high priority sensors scheduled at TTI t, $|\mathcal{S}_{\mathrm{c},t}|$ and $|\mathcal{S}_{\mathrm{b},t}|$ is the number of sensors generating TC traffic for dynamic access and the number of sensors generating NS traffic respectively.

Ignore the preemption of NS traffic, sensors allocated to reserved RBs are scheduled firstly, followed by dynamic access sensors with extra signaling delay, the BE traffic is scheduled in the end if there are any resources left. The whole transmission process is as Figure 3 shows. It worth mentioning that we here only focus on the delay of TC traffic, which is the length from the beginning of the current TTI to the last TC sensor transmitted. The 5G delay can be calculated as follows:

$$T^{5G}(t) = \left\lceil \frac{|\mathcal{R}_{\mathrm{r},t}| + (|S_{\mathrm{c},t}| + |S_{\mathrm{b},t}| - (\zeta_t - \gamma_t))(1+\delta)}{|C|} \right\rceil * T_{RB} \tag{3}$$

where T_{RB} is the time duration corresponding to one RB, δ is the proportion of signaling in the overall transmission and $\lceil * \rceil$ represents the smallest integer which $*$ is less than or equal to.

It can be seen from Figure 2 that the influence of one TC sensor can be large or small. If it is exactly the only one sensor embedded at the last column of TC traffic, the influence of it is large. Otherwise, if there are $(|C|-1)$ sensors embedded at the last column of TC traffic, the influence is small.

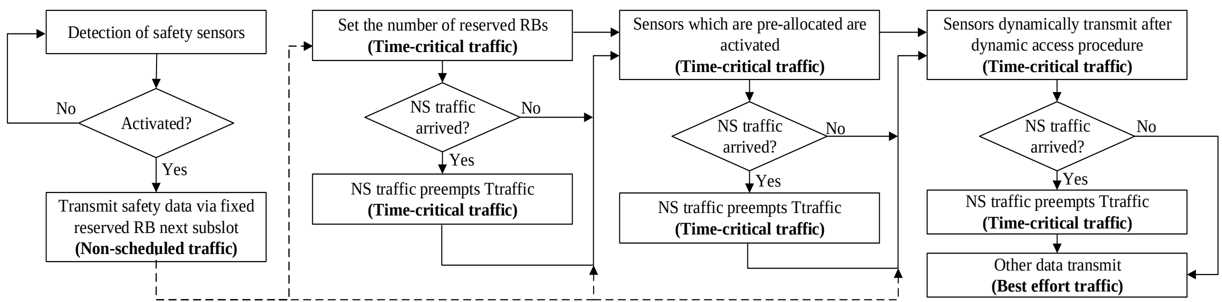

Figure 3 Preemption Based Multi-priority Data Transmission Process

4.1.2 *Sensor Predictive Selection Based on Naive Bayesian Model*

Obviously, the utilization of reserved resources is determined by whether sensors assigned to the reserved trigger. So a high prediction precision is necessary to let the transmission delay as low as possible. Considering the coupling characteristic of the process in industrial automation, the trigger of some sensors may increase the probability of other sensors nearby depending on the current process [2]. Based on this, calculate the correlation between sensors at two adjacent TTI is the key to predictively select sensors to be reserved. Here we don't care about the relationship between sensors but only concern the correlation between their trigger. In the literature [3], since the Naive Bayesian model simplifies the assumption of conditional independence, we spply it to learn the correlation of sensors.

Let $\boldsymbol{x^t} = \{x_1^t, x_2^t, ...\}$ denotes the set of sensors triggered at last TTI, we select sensors to make up the set $\boldsymbol{y^t} = \{y_1^t, y_2^t, ...\}(\boldsymbol{x^t} \cap \boldsymbol{y^t} = \varnothing)$, which may be triggered at the next TTI with a high probability. Note that the scale of $\boldsymbol{y^t}$ lies on the threshold we set and is not related to the scale of $\boldsymbol{x^t}$.

In order to explore the correlation between sensors, the access history is used to get the trigger probability of sensor s_i as $\mathbb{P}(s_i)(s_i \in \mathcal{S})$, then three metrics are used to measure the correlation between the set $\boldsymbol{x^t}$ and a sensor y_i^t as follows [4]:

1) **Conditional probability**: Conditional probability at TTI t is the probability that sensors out of $\boldsymbol{x^t}$ will trigger after any sensors in $\boldsymbol{x^t}$ that has been triggered, which can be obtained by:

$$\mathbb{P}_{\mathrm{C}}(y_i^t \mid \boldsymbol{x^t}) = \sum_{x_j^t \in \boldsymbol{x^t}} \frac{\mathbb{P}(y_i^t, x_j^t)}{\mathbb{P}(x_j^t)} \tag{4}$$

where $\mathbb{P}_{\mathrm{C}}(y_i^t, x_j^t)$ is the joint probability of y_i^t and x_j^t.

2) **Mutual information (MI)**: As described in information theory, MI can measure the development of trigger probability of y_i^t after $\boldsymbol{x^t}$ is triggered, which is given by:

$$\mathbb{P}_{\mathrm{MI}}(y_i^t, \boldsymbol{x^t}) = \sum_{x_j^t \in \boldsymbol{x^t}} \mathbb{P}(y_i^t, x_j^t) \log_2 \frac{\mathbb{P}(y_i^t, x_j^t)}{\mathbb{P}(y_i^t)\mathbb{P}(x_j^t)} \tag{5}$$

where $\mathbb{P}(y_i^t, x_j^t) = \mathbb{P}_{\mathrm{C}}(y_i^t \mid x_j^t) * \mathbb{P}(x_j^t)$.

3) **Chi-square text (χ^2)**: Chi-square (χ^2) text is a suitable way to estimate the relevance of two sensors by comparing $\mathbb{P}(y_i^t, x_j^t)$ and $\mathbb{P}(y_i^t) * \mathbb{P}(x_j^t)$, so to judge whether these two sensors are dependent. The χ^2 text metric is defined by:

$$\mathbb{P}_{\chi^2}(y_i^t, \boldsymbol{x^t}) = \sum_{x_j^t \in \boldsymbol{x^t}} \frac{(\mathbb{P}(y_i^t, x_j^t) - \mathbb{P}(y_i^t) * \mathbb{P}(x_j^t))^2}{\mathbb{P}(y_i^t) * \mathbb{P}(x_j^t)} \tag{6}$$

The aim of these three metrics are all to evaluate the correlation between y_i^t and $\boldsymbol{x^t}$, thus we can select the most relevant sensors to $\boldsymbol{x^t}$ to be reserved predictively at next TTI for higher resources utilization and lower transmission delay. Thus we use a policy to choose which sensor to reserve as:

$$\Pi^{select} = \begin{cases} 1, & \text{if } \mathbb{P}(y_i^t, \boldsymbol{x^t}) \geqslant \alpha \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

As we can know form [4], sensors with lower triggering frequency will obtain a higher ranking in the χ^2 test than in the MI. Based on this, we propose a sensor selection mechanism which is outlined in Algorithm 2 for a good practicability. Note that the elements of history access samples set of i-th circulation h_i is boolean.

In this policy, we use a different metric to measure the correlation of sensors according to different scenarios, which can improve the precision of sensor selection and then guarantee the preemption based multi-priority scheduling mechanism.

Algorithm 2 Sensor Selection Algorithm(SSA)

Input: Access samples at last TTI $\boldsymbol{x^t} = \{x_1^t, x_2^t, ...\}$;
History access samples $H_n = \{h_1, h_2, ..., h_n\}$;
Trigger time set $T = \varnothing$, $\boldsymbol{y^t} = \varnothing$;
Output: Predictive select sensors sets $\boldsymbol{y^t} = \{y_1^t, y_2^t, ...\}$;

while $j \leqslant n$ **do**
  $T = h_j$
end while
while $i \leqslant |\boldsymbol{x^t}|$ **do**
  if $T(i) \leqslant \beta$ and $y_i^t \notin \boldsymbol{x^t}$ **then**
    $\mathbb{P}(y_i^t, \boldsymbol{x^t}) = \mathbb{P}_{\chi^2}(y_i^t, \boldsymbol{x^t})$;
  else $\{T(i) > \beta$ and $y_i^t \notin \boldsymbol{x^t}\}$
    $\mathbb{P}(y_i^t, \boldsymbol{x^t}) = \mathbb{P}_{\mathrm{MI}}(y_i^t, \boldsymbol{x^t})$;
  end if
  if Π^{select} **then**
    $\boldsymbol{y^t} = \boldsymbol{y^t} \cup \{y_i^t\}$;
  end if
end while

4.2 Queue Injection Mechanism of TSN Gateways

As mentioned in Section 2, there are several queues of each port of TSN gateways, which may have different priorities when transmitting via the TSN network. Traffic arrived with different QoS will be injected into different TSN queue. The coordinate of TAS and GCL can make sure the data forwarding TSN network can be deterministically delivered within its time demand and keep its priority.

PSFP mechanism proposed by IEEE 802.1Qci points out that each traffic arrived own a priority number, named IPV, to be obeyed to transmit traffic heterogeneously in the TSN network. In more details, every traffic will be assigned a Gate ID to match its IPV number, each Gate ID represents a TSN queue, and so the traffic with different IPV will be injected into different queues. It can be seen that the key to decide which queue to inject is the number of IPV, so we propose a queue injection mechanism of TSN gateways to offset the delay and jitter caused by 5G network based on IPV; thus, we can reduce the transmission delay of the whole industrial process.

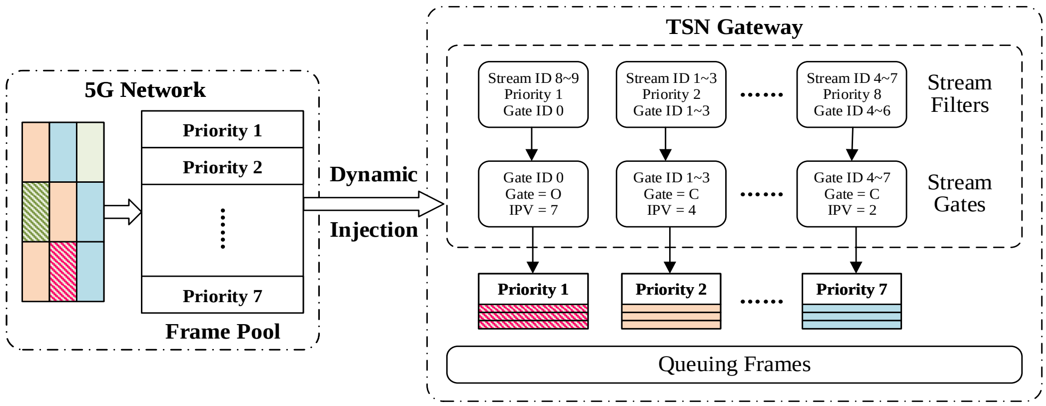

Figure 4 Injection Mechanism of TSN Queue Based on PSFP

Outlined in Figure 4, the traffic from the 5G network will be firstly gathered into a frame pool, whereafter data generated within a TTI is classified into different priorities, based on which traffic is assigned different IPV numbers and then injected into different TSN queue dynamically.

Firstly, we divide the forwarding delay of each TSN gateway into x parts:

$$\Delta = \frac{T_s^{max} - T_s^{min}}{x}, x = 1, 2, \ldots\ldots \tag{8}$$

where T_s^{max} and T_s^{min} denotes the longest and the shortest forwarding delay of TSN gateway respectively, x is the number of queues of a TSN port, which is usually eight.

Thus we can simply get the forwarding deadline of each queues as follows:

$$\Lambda\left(Q_t\right) = T_s^{min} + Q_t * \Delta, Q_t = 1, 2, \ldots, x \tag{9}$$

where Q_t is the priority number of TSN queues at TTI t. Therefore we get the forwarding delay function of Q_t, which can be used to calculate the delay of TSN network and get the number of Q_t in reverse.

The transmission delay of TSN network is calculated by:

$$T^{TSN}(t) = H\left\lceil \frac{|\mathcal{S}_{\mathrm{h},t}| * D * \Lambda\left(Q_t\right)}{\theta^l T_{\mathrm{cyc}}} \right\rceil T_{\mathrm{cyc}} \tag{10}$$

where $|\mathcal{S}_{\mathrm{h},t}|$ has been given in Section 4.1, H is the number of hops in TSN network with fixed start and end, D is the fixed amount of data one RB transmit, T_{cyc} is the forwarding cycle of TSN gateways and θ^l is the lowest data rate of TSN network.

Based on the TSN network delay we get before, the value of Q_t obtained from $\Lambda\left(Q_t\right)$ is given by:

$$Q_t = \arg \min_{1 \leqslant Q_t \leqslant x} \left(T^{TSN}(t) - \left(T_t^{ddl} - T^{5G}(t)\right)\right) \tag{11}$$

where T_t^{ddl} is the delay demand of TC traffic arrived at TTI t, and $T_t^{5G}(t)$ is the transmission delay of previous 5G network.

Thus the whole transmission delay of HTSN at TTI t is given by:

$$T^{sum}\left(T^{5G}(t), T^{TSN}(t)\right) = T^{5G}(t) + T^{TSN}\left(Q_t, \mathcal{F}\left(T^{5G}(t)\right)\right) \tag{12}$$

Obviously, the delay of 5G network $T^{5G}(t)$ and the delay of TSN network $T^{TSN}(t)$ is coupling and interact each other.

4.3 Risk-sensitive Utility Formulation

As mentioned in Section 1, considering the unreliability of 5G network, the higher-order quantity of wireless delay should be involved in the optimal problem. In this regard, we apply entropic risk measure $\frac{1}{\rho}\ln\left(\mathbb{E}\left[\exp\left(\rho T_i^{\mathrm{E2E}}\right)\right]\right)$ and formulate a risk-sensitive minimization utility problem of the whole transmission delay of HTSN with as follows:

$$\begin{aligned} &\min_{\{|\mathcal{R}_{\mathrm{r},t}|, Q_t\}} \frac{1}{\rho} \ln(\mathbb{E}[\exp(\rho \sum_{m=1}^{t-1} T_m)]) \\ &\text{s.t.} \ \ |\mathcal{R}_{\mathrm{r},t}| \leqslant \left|\Pi^{select}\right| \\ &1 \leqslant Q_t \leqslant 8 \end{aligned} \tag{13}$$

where $\mathbb{E}[*]$ is the expectation operator, $\left|\Pi^{select}\right|$ represents the number of selected candidate sensors.

As we can see from the problem, the number of the reserved RBs depends on the threshold α we set, since $\Pi^{select} = 1$ while $\mathbb{P}(y_i^t, \boldsymbol{x^t}) \geqslant \alpha$. In fact, there exist a trade-off of the number of reserved RBs $|\mathcal{R}_{\mathrm{r},t}|$ for the following reasons. If $|\mathcal{R}_{\mathrm{r},t}|$ is too small, then most of the sensors still need to access the 5G network dynamically with a high handshaking delay, which may violate the low latency demand of NS traffic and TC traffic. On the other hand, if $|\mathcal{R}_{\mathrm{r},t}|$ is too big but the prediction precision cannot be guaranteed, then the time-frequency resources left for sensors that access dynamically will be insufficient for scheduling. Thus, the reserved resources will also be wasted a lot. Therefore, the number of α is a critical factor to balance this trade-off in order to prevent the amount of $|\mathcal{R}_{\mathrm{r},t}|$ is too high or too low.

What's more, the entropic risk measure $\frac{1}{\rho}\ln\left(\mathbb{E}\left[\exp\left(\rho T_i^{\mathrm{E2E}}\right)\right]\right)$ can be expanded out as $\frac{1}{\rho}\ln(\mathbb{E}[\exp(\rho\mathcal{T})]) = \mathbb{E}[\mathcal{T}] + \frac{\rho}{2!}\operatorname{Var}(\mathcal{T}) + \frac{\rho^2}{3!}\mathbb{E}\left[(\mathcal{T}-\mathbb{E}[\mathcal{T}])^3\right] + ...$, where $\mathcal{T}$ denotes the cumulate time $\sum_{m=1}^{t-1} T_m$. It is obviously that the optimal object takes into account the variance $\operatorname{Var}(\mathcal{T})$ of $\mathcal{T}$ and the third central moment $\mathbb{E}\left[(\mathcal{T}-\mathbb{E}[\mathcal{T}])^3\right]$ of $\mathcal{T}$. Note that the skewness of $\mathcal{T}$ equals to $\mathbb{E}\left[(\mathcal{T}-\mathbb{E}[\mathcal{T}])^3\right]/\operatorname{Var}((\mathcal{T}))^{\frac{3}{2}}$. In other words, we formulate the optimization problem in the view of the mean, varience, skewness and other high-order quantity of the cumulate time $\sum_{m=1}^{t-1} T_m$. Additionally, the parameter $\rho > 0$ reflects the weight of high-order statistics.

Due to the function $\frac{1}{\rho}\ln(*)$ is monotonically increasing, we can remove it and focus on an equivalent utility problem as follows:

$$\begin{aligned} \min_{\{|\mathcal{R}_{\mathrm{r},t}|, Q_t\}} &\ \mathbb{E}[\exp(\rho \sum_{m=1}^{t-1} T_m)] \\ \text{s.t.} &\ |\mathcal{R}_{\mathrm{r},t}| \leqslant \left|\Pi^{select}\right| \\ &\ 1 \leqslant Q_t \leqslant 8 \end{aligned} \tag{14}$$

which can be expanded by Maclaurin series expansion analogously, i.e., $\mathbb{E}[\exp(\rho\mathcal{T})] = 1 + \rho\mathbb{E}[\mathcal{T}] + \frac{\rho^2}{2!}\mathbb{E}[\mathcal{T}^2] + \frac{\rho^3}{3!}\mathbb{E}[\mathcal{T}^3]$.

It is challenging to solve the minimization problem because of the dynamic network state and the unknown environment factors of each TSN gateway. Thus, we leverage the principles of multi-armed bandits(MAB) in reinforcement learning to optimize the long-term transmission delay in a decentralized manner.

5 Gradient Multi-armed Bandits Algorithm(GMAB)

As mentioned in Section 6, the number of reserved RBs $|\mathcal{R}_{\mathrm{r},t}|$ brings a trade-off. There are three paremeters are influences by this trade-off such as the injection of TSN gateways' queue, the total delay, and the resources utilization of HTSN via exploration and exploitation. Each TSN gateway needs to make decisions based on a limited action set every TTI to find out the optimal policy to reserve RBs and inject queue while guarantee the current delay meets the delay demand as well. This predictive pre-allocation problem with no prior knowledge is skin to the famous multi-armed bandits' problem [3, 27, 28], which also concerns the balance of multiple arms' exploration and exploitation to gain the long-term rewards via trying to choose different arms.

We here leverage the gradient multi-armed bandits(GMAB) tool to solve the predefined problem since it only focuses on the relative preferences between actions rather than the value of the action itself. In particular, each TSN gateway acts as an agent which selects an action to maximize the long-term rewards. The action set is defined as $k = \left(k_1, k_2, \ldots, k_{|k|}\right)$, where $k_i = (|\mathcal{R}_{\mathrm{r},i}|, Q_i)$ denotes the corresponding action of the i-th arm. The policy agent made at TTI t is given by $\pi_t = \{\pi_t(1), \pi_t(2), \ldots, \pi_t(|k|)\}$, which means the agent chooses the i-th arm with probability $\pi_i(t)$ at TTI t. Here we denote the long-term delay in (14) as a utility function $U_t = -\exp(\rho\sum_{m=1}^{t-1} T_m)$. The main step of GMAB algorithm are outlined as follows:

- Each TSN gateway is given an initial policy: $\pi_0 = \{\pi_0(1), \pi_0(2), \ldots, \pi_0(|k|)\}$, and the same preference of each action $H_t(k_i)$ (i.e.$H_0(k_i) = 0$ for all i in $|k|$).
- At every TTI t, each TSN gateway selects actions according to the policy updated at last TTI $t-1$, then obtain an utility $U_t = -\exp(\rho\sum_{m=1}^{t-1} T_m)$ as the reward of the actions selected.
- Wherever, TSN gateways calculate the probability of each action by a soft-max distribution based on the preference got before:

$$\Pr\left\{k_i = \left(\left|\mathcal{R}_{\mathrm{r},i}\right|, Q_i\right)\right\} \doteq \frac{e^{H_t(k_i)}}{\sum_{j=1}^{|k|} e^{H_t(k_j)}} \doteq \pi_t(k_i) \tag{15}$$

then get the new policy π_t.

- Subsequently, each TSN gateway update the preference of actions by:

$$\begin{aligned} &H_{t+1}(k_i) \doteq H_t(k_i) + \alpha\left(U_t - \bar{U}_t\right)\left(1 - \pi_t(k_i)\right), && \text{and} \\ &H_{t+1}(k_j) \doteq H_t(k_j) - \alpha\left(U_t - \bar{U}_t\right)\pi_t(k_j), && \text{for all } k_j \neq k_i \end{aligned} \tag{16}$$

  where $\alpha > 0$ is a step-size parameter, and $\bar{R}_t$ is the average of the rewards up to but not including TTI t, which can be computed incrementally [29].
- TSN gateways iteratively update its policy $\pi(t)$ respectively and make new decision abide by the latest policy, such that the likelihood of choosing the optimal action is proportional to its rewards.

Since we take high order quantity into account while formulating the minimization problem, the tail of transmission delay is optimized the same time the optimal policy is learned via reinforcement learning.

6 Numerical Results

6.1 Sensor Prediction Simulation

In this section, we evaluate the performance of the proposed HTSN framework based on some time-sensitive data with a deterministic deadline generated by monitoring sensors deployed along the hot rolling line. Sensors for monitoring temperature, humidity, pressure are randomly distributed to sense the manufacturing process to provide robust control via closed-loop feedback. They active periodically and generate TC traffic which is the main data we are concerned. Event-triggered sensors such as camera and vibration sensors only active as long as there occurs safety emergencies suddenly. They generate burst NS traffic, which has the highest priority and can preempt TC traffic.

Here, traffic from the different technological processes with own transmission deadline is transmitted at TTI in turns, what we need to do is to learn the correlation between sensors despite the interference brought by sensors that have no relationship with the arrivals of steels. We consider the trigger probability of field sensors as Table 2:

The performance of the predictive sensor selection algorithm is evaluated in terms of prediction accuracy(successful prediction ratio). We compare the performance of three correlation metrics(X2: Chi-square test, MI: Mutual Information, Cond: Conditional Probability) and the sensor selection algorithm we proposed on three sizes(3000, 4500, 6000) of data. Figure 5 shows how different correlation metrics diverse in the performance of prediction accuracy. It is obvious that the χ^2 metric as well as the conditional metric has the best performance while the iteration times is small, the prediction accuracy of Mutual Information is much lower and flat than the other two. But after several times of iteration, the difference of these three metrics' performance is inconspicuous and the prediction accuracy of them all converges to 0.8. Since the SSA algorithm we proposed always chooses the highest correlation, the performance of it is as good as the first two metrics. The high prediction accuracy guarantees the resource utilization of 5G and lay the foundation of the HTSN framework.

6.2 HTSN Simulation

Since the 5G network and TSN network are coupling and interactive, the main influence factor of HTSN is the number of reserved RBs $|\mathcal{R}_{\mathrm{r},t}|$. Thus, we simulate the relationship between $|\mathcal{R}_{\mathrm{r},t}|$ and delay of 5G/TSN. Figure 6 shows that as $|\mathcal{R}_{\mathrm{r},t}|$ growing, the delay of the 5G network decrease firstly and then increases. The lowest point of the delay curve is the trade-off point we mentioned before, which is because the prediction accuracy cannot reach 100% and assign sensors in prior would cause the waste of radio resource while we apply SPS in order to reduce the transmission delay originally. Here we set the

Table 2 Trigger of Sensors

Property	**Number**	**Number**
Proportion	40(2/3)	20(1/3)
Trigger Probability	0.8	0.2

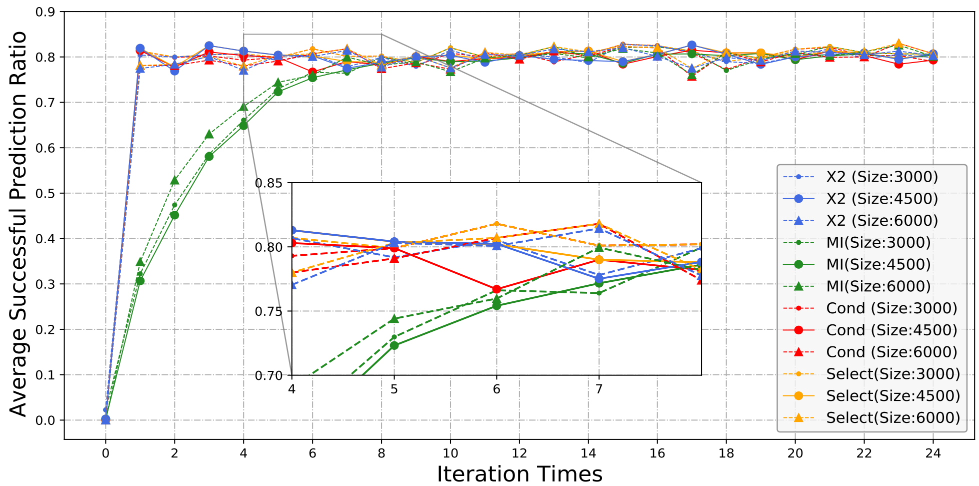

Figure 5 The prediction performance of different correlation metrics

total number of subslot is 15, and when $|\mathcal{R}_{\mathrm{r},t}| = 7$, the performance of the pre-allocation mechanism is optimal. What's more, the reason why delay of 5G network increases rapidly after the trade-off point is the limitation of radio resource, since the more $|\mathcal{R}_{\mathrm{r},t}|$ is reserved, the more resource is wasted, the fewer resources used for dynamic access and the lower reliability of transmission.

Based on the dynamic injection of the TSN queue, the indeterminacy of transmission caused by the 5G network can be made up by the TSN network to meet the strict transmission requirements of industry 4.0. Figure 7 shows the interaction of 5G and TSN as $|\mathcal{R}_{\mathrm{r},t}|$ growing. It can be seen that the delay of 5G and TSN has a near-ideal negative correlation via adjusting the TSN queue index self-adaptively. Given the deadline = 250s, the TSN network tries to save as many resources as it can under the premise of not violating the demand of the integral delay of HTSN. Obviously, the queue injection mechanism we proposed makes up for the shortcoming of the 5G network perfectly.

To further analyze the relationship between TSN queue and 5G delay, we give Figure 8, from which we can see that the queue index and 5G network delay also have a similar negative correlation. Since the queue index of TSN gateway is directly proportional to the delay of the TSN network, the general trend of the queue index curve and TSN delay curve is analogous. However, there are some step changes of the queue index as it is an integer. It can also be concluded that although we arrange a queue index between 0 and 8, we can't assign 5G traffic to the 8-th queue since the scheduling capability of the 5G network is not enough to realize low latency high-reliability transmission by itself.

Except for $|\mathcal{R}_{\mathrm{r},t}|$, the ratio of signaling transmission is also a critical factor that influences the SPS within the 5G network and the delay of HTSN. The proposition of SPS is because of the long and complex signaling process of cellular networks, which may lead to unnecessary delay. Here, we formulate the extra delay caused by signaling as a signal ratio and plot the relationship between it and 5G delay. As Figure

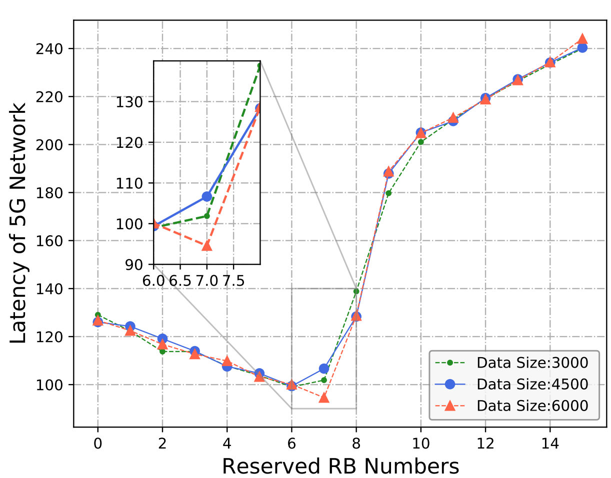

Figure 6 The varies of 5G delay with $|\mathcal{R}_{\mathrm{r},t}|$

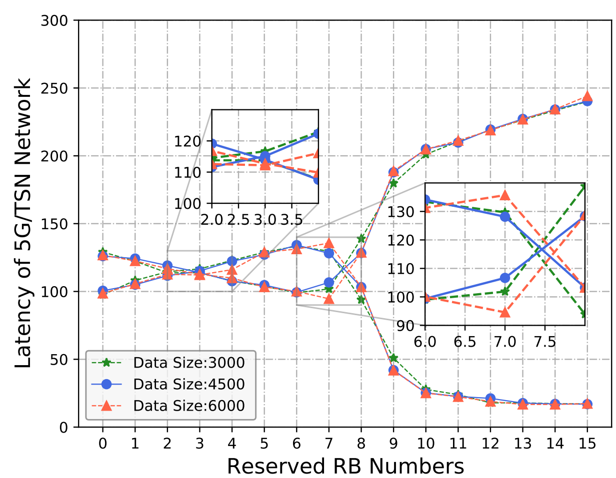

Figure 7 The varies of 5G and TSN delay with $|\mathcal{R}_{\mathrm{r},t}|$

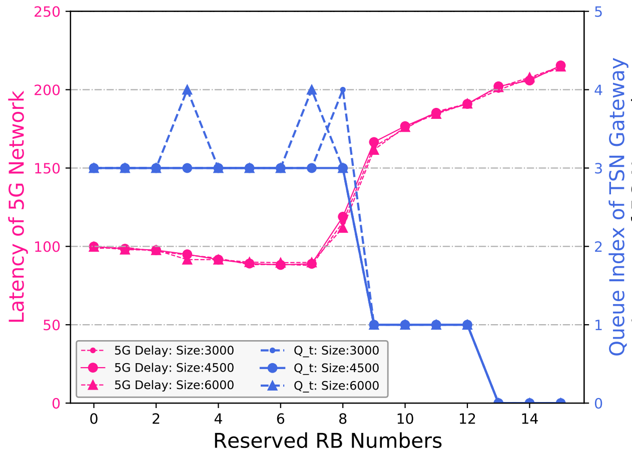

Figure 8 The varies of Queue and 5G delay with $|\mathcal{R}_{\mathrm{r},t}|$

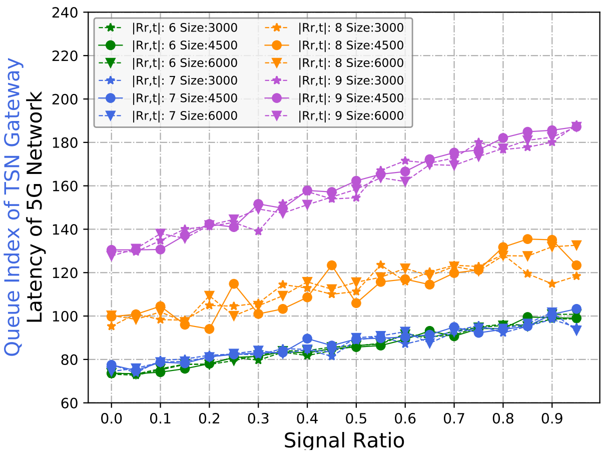

Figure 9 The varies of 5G delay with signal ratio

9 shows, we select $|\mathcal{R}_{\mathrm{r},t}|$ from 6 to 9 according to Figure 6 to find the influence among signal ratio, $|\mathcal{R}_{\mathrm{r},t}|$ and delay of 5G. It can be seen that no matter $|\mathcal{R}_{\mathrm{r},t}|$ is greater, equal or less than the trade-off point, the delay of 5G network increases with the increase of signal ratio. This is because $|\mathcal{R}_{\mathrm{r},t}|$ has nothing to do with the number of TC traffic; there always exists TC traffic to be dynamically scheduled due to the inaccuracy of prediction, so the increase of signal ratio will lead to the increase of the 5G network's delay.

6.3 Risk-sensitive Learning Simulation

To deal with the tail of 5G delay, we use a risk-sensitive utility function to optimize expectations as well as high order quantities of accumulative integral delay of HTSN. We evaluate our proposed HTSN framework as a whole in Figure 10, which delineates the improvement brought by the risk-sensitive utility. We repeat GMAB learning for three sizes(20,100,500) of independent runs, and each run we measure its performance with experience over 1000 time steps. With the increase of times of repetitions, the curve is more stable and the random error of relative difference from true reward is smaller. It can also be seen that the curve of risk-sensitive learning is steeper than the classical one, which means that the high order quantities are optimized while learning, and the delay distribution of HTSN is more aggregated with a shorter tail and higher reliability. What's more, with the increase of iteration times, the rate of convergence is faster.

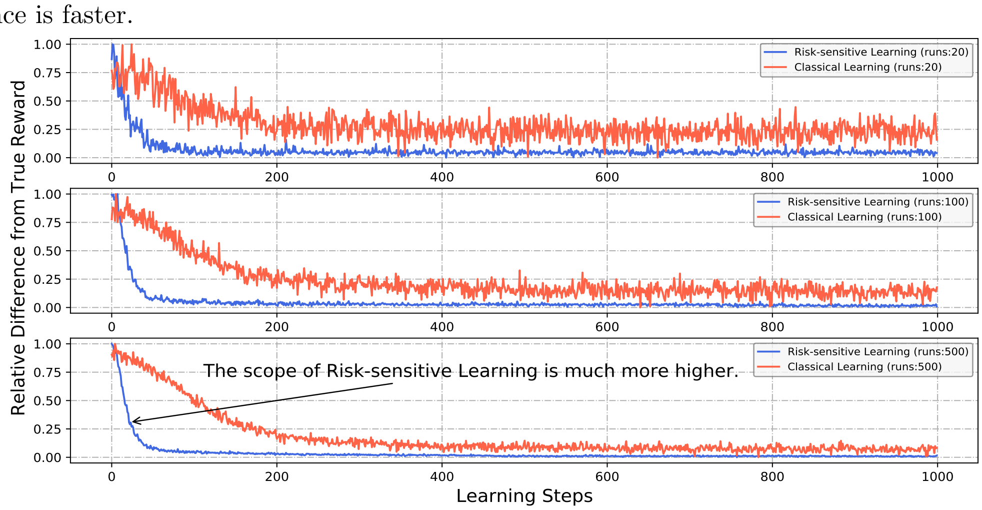

Figure 10 The performance of risk-sensitive reinforcement learning with different run times

7 Conclusion

In this paper, we propose HTSN, a 5G-TSN integrated framework that takes both advantages of 5G and TSN to provide deterministic transmission from the industrial field to the remote end. Within the 5G network, we propose preemption based multi-priority semi-persistent scheduling to satisfy diverse QoS requirements of field data by exploring the correlation between uplink traffics in industrial process automation. To make up for the nondeterminacy caused by 5G, a dynamic injection mechanism of TSN gateway's queue is applied here to guarantee the delay demand of the whole transmission. Through risk-sensitive reinforcement learning, HTSN has both advantages of 5G for its flexibility and TSN for its determinacy at the same time it reduces the long tail of delay to improve reliability, which also improves the utilization of radio resources via high prediction accuracy.

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