QoS and Privacy-Aware Routing for 5G-Enabled Industrial Internet of Things: A Federated Reinforcement Learning Approach

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***Abstract*—The development and maturity of the fifth-generation (5G) wireless communication technology provides the industrial Internet of Things (IIoT) with ultra-reliable and low-latency communications and massive machine-type communications, and forms a novel IIoT architecture, 5G-IIoT. However, massive data transfer between interconnecting industrial devices also brings new challenges for the 5G-IIoT routing process in terms of latency, load balancing, and data privacy, which affect the development of 5G-IIoT applications. Moreover, the existing research works on IIoT routing mostly focus on the latency and the reliability of the routing, disregarding the privacy security in the routing process. To solve these problems, in this article, we propose a quality of service (QoS) and data privacy-aware routing protocol, named QoSPR, for 5G-IIoT. Specifically, we improve the community detection algorithm info-map to divide the routing area into optimal subdomains, based on which the deep reinforcement learning algorithm is applied to build the gateway deployment model for latency reduction and load-balancing improvement. To eliminate areal differences, while considering the privacy preservation of the routing data, the federated reinforcement learning is applied to obtain the universal gateway deployment model. Then, based on the gateway deployment, the QoS and data privacy-aware routing is accomplished by establishing communications along the load-balancing routes of the minimum latencies. The validation experiment is conducted on real datasets. The experiment results show that as a data privacy-aware routing protocol, the QoSPR can significantly reduce both average latency and maximum latency, while maintaining excellent load balancing in 5G-IIoT.**

***Index Terms*—Fifth generation (5G), federated reinforcement learning (FRL), industrial Internet of Things (IIoT), secure routing.**

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I. Introduction

THE technological developments and advances in Internet of Things (IoT) and the fifth-generation (5G) wireless communication, and the increasing need for leveraging the potential of smart machines and getting benefits from real-time analysis of data collected by industrial devices have recently driven the rise of the 5G-enabled industrial Internet of Things (5G-IIoT) [1], [2]. In 5G-IIoT, massive heterogeneous interconnected industrial devices embedded with sensors, software, actuators, etc., communicate and share information remotely with each other without human interaction through using the massive machine-type communication and ultra-reliable low-latency communication (URLLC) models in 5G [3], [4]. Employing 5G technology enables IIoT devices to enhance their connectivity, latency, and bandwidth, and has transformed traditional industry to smart industry. According to incomplete statistic, the number of IIoT devices grows at the speed of 31% year-over-year, and it is about to exceed 50 billion by 2020, which will lead to huge amount of data be generated and transmitted in the network [5]. Two situations, i.e., massive industrial devices connectivity and massive data transfer, jointly pose the challenges to the 5G-IIoT routing in terms of quality of service (QoS), such as latency and load balancing, and data privacy.

QoS and data privacy are the foundation for the further development and spread of 5G-IIoT. Therefore, it is necessary to design a highly efficient and data privacy-aware routing protocol suitable for 5G-IIoT. Despite the fact that IIoT routing [4], [6]–[10] has already attracted a lot of attention from both academia and industry, the routing protocol for low-power and lossy networks is introduced as the standard routing protocol for IIoT networks. However, current research works on IIoT routing mostly focus on both latency and reliability of the routing, and lack the consideration of privacy security in routing process.

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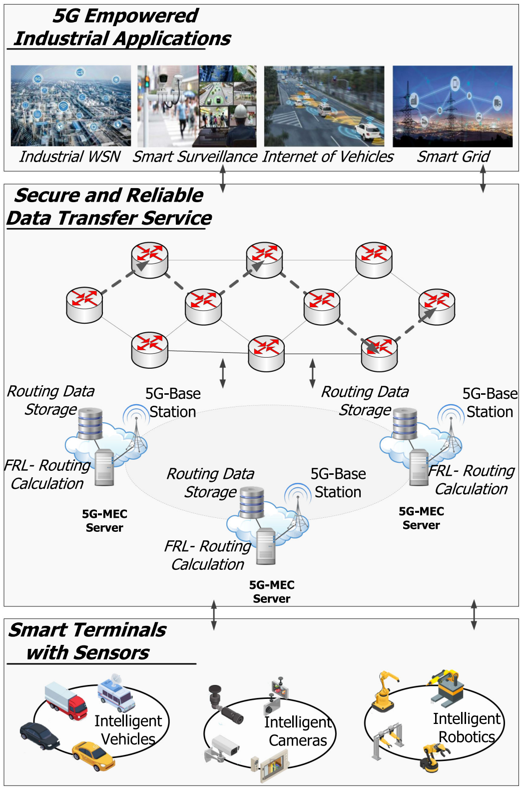

Fig. 1. Secure and reliable data transfer architecture for 5G-IIoT.

Meanwhile, the research works that comprehensively consider routing performance and data privacy security also have few achievements.

To solve abovementioned problems, we first present a secure and reliable data transfer architecture for 5G-IIoT. As shown in Fig. 1, the proposed architecture can be divided into three layers. Specifically, the first layer presents the 5G industrial applications (i.e., industrial wireless sensor networks, smart surveillance, Internet of Vehicles, and smart grid) that the proposed architecture can support, in which the secure and reliable data transfer is required. Such demand is addressed by the services provided in the second layer. As a mature artificial intelligence technology, the machine learning technology [11] is applied to achieve QoS and data privacy-aware routings. Therefore, mobile edge computing (MEC) servers [12] of the second layer utilize the federated reinforcement learning (FRL) to discover the reliable and secure routing in a privacy-preserving manner for those data collected from smart devices in the third layer.

Since the traditional routing protocol cannot support URLLCs, gateway deployment-based routing protocol designs [13]–[17] can reduce communication latency and improve communication reliability as well. In addition, as a deep integration of the reinforcement learning algorithm and the federated learning framework [18], the FRL-based method facilitates the efficient routing protocol design with data privacy preservation. According to abovementioned analysis and the proposed architecture, in this article, we develop a QoS and data privacy-aware routing protocol, named QoSPR, based on gateway deployment for 5G-enabled IIoT. The contribution of this article is outlined as follows.

1) To accomplish the QoS and data privacy-aware routing, considering the impact of gateway deployment on both latency reduction and load-balancing improvement, a deep reinforcement learning (DRL) method is designed to deploy gateways within each routing area. Based on the gateway deployment, a QoS routing protocol is developed to establish the communication between each pair of sensors, gateways, or sensor and gateway along the load-balancing route of the minimum latency. Moreover, to eliminate the areal differences, considering the privacy preservation of routing data, an FRL algorithm is developed to design the universal QoS routing protocol for URLLCs in 5G-IIoT.
2) To reduce the complexity of the routing protocol design, a novel info-map based subdomain division algorithm is developed under the load-balancing constraint and the maximum latency constraint. According to the subdomain division, the QoS routing protocol is designed with less complexity.
3) The validation experiment is conducted on real datasets. The experiment results show that as a data privacy-aware routing protocol, the QoSPR can significantly reduce both average latency and maximum latency, meanwhile maintain excellent load balancing in 5G-IIoT.

The rest of this article is organized as follows. The related work is introduced in Section II. The system model is given in Section III. The implementation details of the proposed strategy QoSPR are presented in Section IV. The performance evaluation is given in Section V. Finally Section VI concludes this article.

II. Related Work

The routing protocol design for IIoT has drawn a great attention with plenty of excellent works proposed.

Traditional routing protocols have been proved efficient. In [4], Fu *et al.* developed a greedy perimeter stateless routing algorithm in three dimensions. Specifically, the next hop of a packet is decided by nodes and their neighbors in both greedy forwarding pattern and surface forwarding pattern. In [6], Liu *et al.* presented an antijamming routing protocol with the assured SNR. Specifically, the radio communication range is limited to guarantee a satisfying SNR of the received signal. Node or link failure is tolerated by jammed areas mapping, for which routing paths can bypass the jammed regions. In [7], Shi *et al.* gave the solution to the distributed graph routing and autonomous scheduling problem, in which transmission schedules and graph routes are obtained by field devices. In [8], Guo *et al.* considered the problem of the dynamic change of the flow and propose a QoS-aware secure routing protocol with low latency and high security using the DRL to achieve. In [9], Yang *et al.* proposed a QoS-enhanced routing protocol for cognitive and social IIoT. This protocol is delay-sensitive and loadbalance-aware during the data transmission. In addition, social activities protection is considered in the routing protocol design. In [10], Bellavista *et al.* designed a multilayer routing protocol using fog computing. In this protocol, payload types and values are used to find the optimal configures and paths to achieve the multilayer routing. These research works adopt a variety of methods (i.e., the greedy search, the granular analysis, the fog computing, and the machine learning) and theories (i.e., the communication theory,

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the graph theory, and the social theory) to design efficient routing protocols. Although these protocols can provide QoS routings, they cannot support URLLCs in 5G-IIoT communication scenarios.

There are plenty of routing protocols designed based on gateway/controller deployment. In [13], Omar *et al.* solved the minimum cost Internet gateway deployment problem using the binary integer programming, based on which a data packet routing scheme is developed to reduce the end-to-end latency. In [14], Savas *et al.* formulated the switch-controller based routing as an integer linear problem and a heuristic algorithm is proposed to solve such problem of large instances against single point failures caused by disasters. In [15], Ge *et al.* developed an optimal gateways deployment mechanism in the long time scale of 5G wireless backhaul networks. Then, they design a wireless backhaul route schemes in the short time scale of 5G wireless backhaul networks for the cost efficiency maximization. In [16], Liu *et al.* considered the problem of the joint placement of controllers and gateways and propose a simulated annealing and clustering hybrid solution to maximize the network reliability and minimize the average latency for routing decision-making. In [17], Qureshi *et al.* proposed a novel routing protocol based on the intersection gateway and connectivity to solve the problem of disconnection, interference, high latency, while considering the traffic density and the node moving directions. In [19], Torkzaban *et al.* adopted the linear program to solve the joint satellite gateway placement problem and then for the terrestrial network a routing protocol is proposed for overall cost and average delay.

Although these routing protocols are designed based on the optimal gateway deployment, the load-balancing performance is disregarded. In addition, previous studies neglect the gateway-to-gateway latency. However, in 5G-IIoT, both sensor-to-gateway latency and gateway-to-gateway latency should be considered to support URLLCs. By employing the DRL, the QoS ensured routing can be designed efficiently. However, the complexity of the DRL is high. To reduce the complexity of the routing protocol design, the routing area should be divided into subdomains that poses a great challenge. In this article, a QoS and data privacy-aware routing protocol, named QoSPR, is designed to address these problems for 5G-IIoT.

III. System Model

To realize the QoS and data privacy-aware routing for 5G-IIoT, two entities, namely the Regional Routing Computation Center (RRCC) and the Areal Routing Computation Center (ARCC), are considered. The ARCC is responsible for the routing of a specific area. Considering the QoS assurance, both latency reduction and load-balancing improvement are the optimization goals in routing protocol design. Note that the existing protocols focus on the sensor-to-gateway latency, neglecting the gateway-to-gateway latency and the load-balancing performance. In this article, both average latency and maximum latency between gateways and sensors are considered in the areal routing protocol design under the load-balancing constraint. We assume that each ARCC is trustworthy. On the other hand, the RRCC is in charge of the routing of the entire region that consists of several areas. Due to areal differences, the FRL algorithm is employed by the RRCC to design the universal data privacy-aware routing protocol.

TABLE I
Main Notations and Symbols

Symbols	Descriptions
v_i	ith sensor
l_{v_i,v_j}	round trip latency between nodes v_i and v_j
c_i	maximum request flow sent by v_i
g_i	ith gateway
$\mathcal{C}$	maximum load capacity of each gateway
$\mathcal{G}$	set of gateways
$\mathcal{N}_i$	set of sensors in the ith sub-domain
ε	load balancing factor
$L_{s-g-avg}$	average latency between sensors and gateways
$L_{s-g-max}$	maximum latency between sensors and gateways
$L_{g-g-avg}$	average latency between gateways
$L_{g-g-max}$	maximum latency between gateways
B^{ave}	average bit for community entrance
Q_{ξ^Q}	critic network Q with parameter ξ^Q
π_{ξ^π}	actor network π with parameter ξ^π
γ	discount factor
τ	learning rate
$f_{\xi^\pi}(\cdot)$	function maps the state space to the action space
$g_k(\cdot)$	k-nearest-neighbor mapping function

In the routing protocol design, each areal network is modeled as a graph $G = (V, E)$, where V and E denote the node set and the edge set, respectively. To be specific, each node $v_i \in V$ represents a device (i.e., sensor or gateway), while each edge $e_i \in E$ represents the communication link between devices. Each sensor communicate with the gateway by the 3GPP/TS38.211(5G-NR) protocol through wireless channels, while gateway-to-gateway communications are established through wired channels. The distance between a pair of devices v_i and v_j is denoted by d_{v_i,v_j}. The round trip latency between this pair of devices, denoted by l_{v_i,v_j}, is calculated by $l_{v_i,v_j} = 2d_{v_i,v_j}/2 \times 10^8$. In addition, we assume that all gateways are homogeneous with the maximum load capacity $\mathcal{C}$. Table I presents the notions used throughout this article.

IV. Implementation of the Proposed QoSPR

The proposed QoSPR consists of two modules, namely the dynamic subdomain division and QoS and data privacy-aware routing protocol design based on gateway deployment. Specifically, the gateway deployment should provide 5G-IIoT applications with load-balancing and low-latency communications. Since the optimal gateway deployment is less difficult to be implemented on domains of small scale, we develop an improved info-map algorithm that considers each domain as a community to dynamically divide each routing area into subdomains under the load-balancing constraint. According to the division, a gateway deployment model is built using the DRL algorithm to properly determine the location of each gateway. Then, the QoS routing can be realized by letting each pair of nodes communicate with each other along the route of the least latency. However, applying the gateway deployment model and the corresponding routing protocol of a specific area to another area might cause the significant growth of the latency and the severe degradation of the throughput due to the topological differences between two areas. Besides, the private routing data of one area should be kept from another for data privacy preservation. Thereby, the FRL is employed to construct the universal gateway deployment model, based on which the universal routing protocol is designed accordingly.

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A. Dynamic Subdomain Division

Most of previous studies on subdomain division suffer from higher latency and lower throughput because the number of subdomain is set based on subjective experiences disregarding the actual network topologies. Thereby, the subdomains should be divided dynamically considering both load-balancing constraint and latency constraint. Let c_i denote the maximum request flow sent by the node v_i to the gateway g_i within the subdomain d_i. Then, each subdomain in the network must satisfy the following constraints:

$$\mathcal{C} \geq \sum_{v_i \in \mathcal{N}_i} c_i \tag{1}$$

where $\mathcal{N}_i$ denotes the set of nodes in the ith subdomain and $\mathcal{N} = \{\mathcal{N}_1, \mathcal{N}_2, \ldots, \mathcal{N}_k\}$. In addition, the load balancing between subdomains should be evaluated by

$$|\sum_{v_i \in \mathcal{N}_i} c_i - \sum_{v_j \in \mathcal{N}_j} c_j| \leq \varepsilon \tag{2}$$

where ε is the load-balancing factor and a less ε indicates a more balanced load between subdomains, and vice versa. Since each subdomain will be deployed a gateway g_i, we then give four types of latencies considered in this article, namely the average latency between sensors and gateways $L_{\text{s-g-avg}}$, the average latency between gateways $L_{\text{g-g-avg}}$, the maximum latency between gateways $L_{\text{g-g-max}}$, and the maximum latency between sensors and gateways $L_{\text{s-g-max}}$, as follows:

$$L_{\text{s-g-avg}} = \frac{1}{|\mathcal{N}|} \sum_{\mathcal{N}_i \in \mathcal{N}} \sum_{v_j \in \mathcal{N}_i} \frac{l_{v_j, g_i}}{|\mathcal{N}_i|} \tag{3}$$

$$L_{\text{g-g-avg}} = \frac{2}{|\mathcal{G}|^2 - |\mathcal{G}|} \sum_{g_i, g_j \in \mathcal{G}} l_{g_i, g_j} \tag{4}$$

$$L_{\text{s-g-max}} = \max_{\mathcal{N}_j \in \mathcal{N}, v_i \in \mathcal{N}_j} l_{v_i, g_j} \tag{5}$$

$$L_{\text{g-g-max}} = \max_{g_i, g_j \in \mathcal{G}} l_{g_i, g_j} \tag{6}$$

where $\mathcal{G}$ denotes the set of gateways. Given the demand on URLLC in 5G-IIoT, the maximum latency between each sensor and the gateway of a specific subdomain, denoted by $L_{\text{s-g-max}}$, should be less than 1 ms, i.e.,

$$L_{\text{s-g-max}} < 1 \text{ ms}. \tag{7}$$

We then present the four-step subdomain division algorithm by adding the load-balancing constraint and the latency constraint to the original info-map method as follows.

1) Initialize sensor nodes and treat each node as an independent community.
2) Randomly sample a sequence with a random/fixed length of nodes in the topology graph.
3) Try to assign each node to its neighbor's community, and calculate the average bit B^{ave}, i.e., $B^{\text{ave}} = q_{\nwarrow} H(Q) + \sum_{m=1}^{k} p_{\mathcal{S}(d_m)\rightleftharpoons} H(p_{\mathcal{S}(d_m)})$, where $q_{\nwarrow}$ represents the event probability of entering the community and $H(q)$ is the corresponding event entropy; $p_{\mathcal{S}(d_m)\rightleftharpoons}$ represents the probability of the event of moving between nodes within the community and the event of leaving the community, and $H(p_{\mathcal{S}(d_m)})$ is the corresponding event entropy. If the average bit value is less than the current value, then assign this node to the community with the largest bit value deviation under the constraints (1), (2), and (7).
4) Repeat previous steps until the division results of each subdomain no longer change.

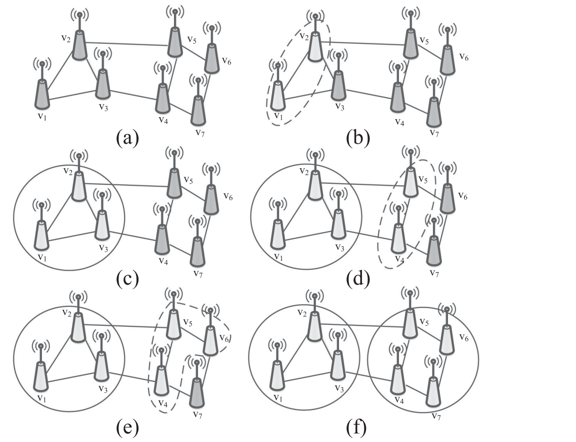

Fig. 2. Example of the subdomain division.

For clarity, Fig. 2 gives the example about how to divide the area of seven nodes into two subdomains. Each node is initialized as a single community and the average bit value B^{ave} is then calculated. Then, we randomly sample a node sequence of length 5, i.e., v_1, v_3, v_5, v_6, v_7. Since node v_1 is closed to two neighbor communities v_2 and v_3, we calculate the average bit value $B^{\text{ave}}_{v_1,v_2}$ and $B^{\text{ave}}_{v_1,v_3}$. Suppose we have $B^{\text{ave}}_{v_1,v_2} < B^{\text{ave}}_{v_1,v_3} < B^{\text{ave}}$, the community v_2 is considered as the community candidate for node v_1 only if the constraints (1), (2), and (7) are satisfied. Similarly, the subdomain division process for the remaining nodes v_3, v_5, v_6, and v_7 is shown in Fig. 2(c)-(e). Fig. 2(f) gives the final two communities, in which nodes v_1, v_2, and v_3 form a community while v_4, v_5, v_6, and v_7 form another community.

B. QoS and Privacy-Aware Routing Protocol Design Based on Gateway Deployment

Given the variety of 5G-IIoT applications that might have unique demands on $L_{\text{s-g-avg}}$, $L_{\text{g-g-avg}}$, $L_{\text{g-g-max}}$, or $L_{\text{s-g-max}}$, the gateway deployment should take all latencies into consideration under the load-balancing constraint and the maximum latency constraint.

1) Areal Gateway Deployment Model Training With the DRL: According to the abovementioned analysis, we have to solve the following optimization problem:

Problem 1:

$$\min\ (\alpha L_{\text{s-g-avg}}/L_{\text{s-g-max}} + \beta L_{\text{g-g-avg}}/L_{\text{g-g-max}})$$

$$\text{s.t.}\quad 1)\ \mathcal{C} \geq \sum_{v_i \in \mathcal{N}_i} c_i$$

$$2)\ |\sum_{v_i \in \mathcal{N}_i} c_i - \sum_{v_j \in \mathcal{N}_j} c_j| \leq \varepsilon$$

$$3)\ L_{\text{s-g-avg}} < 1 \text{ ms}$$

$$4)\ \alpha + \beta = 1.$$

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To solve this problem, the coefficients α and β should be dynamically adjusted. To this end, we apply the deep deterministic policy gradient algorithm in the Wolpertinger architecture [21], namely WDDPG, to obtain the optimal coefficients α and β. In WDDPG, there are four neural networks, i.e., the actor network π, the critic network Q, the target actor network π', and the target critic network Q', the parameters of which are represented by ξ^{π}, ξ^{Q}, $\xi^{\pi'}$, and $\xi^{Q'}$, respectively. And all three factors of the WDDPG, namely the state, the action, and the reward, are defined as follows.

1) *State:* The state $s \in \mathcal{S}$ should consider all four latencies, i.e., $s = (L_{\text{s-g-avg}}, L_{\text{s-g-max}}, L_{\text{g-g-avg}}, L_{\text{g-g-max}})$, thus reflecting the condition of the areal network under the current gateway deployment.
2) *Action:* Since each pair of coefficients will result in a specific solution to the Problem 1, the coefficients and the gateway deployment consist of the action $a \in \mathcal{A}$, i.e., $a = (\alpha, d^g_{v_1}, d^g_{v_2}, \ldots, d^g_{v_n})$, where $d^g_{v_i} = 1$ only if a gateway will be deployed on the location of v_i. Due to the real-time demands of 5G-IIoT communications, we only consider the coefficient α ranging from [0,1] with the increment of 0.2. Moreover, we add the similar constraint to the latency $L_{\text{g-g-max}}$, i.e., $L_{\text{g-g-max}} < 2$ ms to guide the gateway deployment. That suggests that only a limited number of locations can meet such constraint.
3) *Reward:* The gateways should be deployed to reduce all latencies under the load-balancing constraint and the maximum latency constraint. According to Problem 1, the reward r is given by

$$r = -(\alpha L_{\text{s-g-avg}}/L_{\text{s-g-max}} + \beta L_{\text{g-g-avg}}/L_{\text{g-g-max}}). \quad (8)$$

To train the WDDPG, the following loss function is used to update the critic network Q with N experiences randomly sampled:

$$\mathcal{L}(\xi^Q) = \frac{1}{N}\sum_i [\mathcal{Y}_i - Q_{\xi^Q}(s_i, a_i)]^2 \quad (9)$$

where

$$\mathcal{Y}_i = r_i + \gamma \cdot Q_{\xi^{Q'}}(s_{i+1}, \pi_{\xi^{\pi'}}(s_{i+1})). \quad (10)$$

Then, the gradient ascent method is used to update the actor network π with the following gradient:

$$\nabla_{\xi^\pi} f_{\xi^\pi}|_{s_i} \approx \frac{1}{N}\sum_i \nabla_a Q_{\xi^Q}(s,\hat{a})|_{\hat{a}=f_{\xi^\pi}(s_i)} \cdot \nabla_{\xi^{pi}} f_{\xi^\pi}(s)|s_i \quad (11)$$

where the choice of action is refined by selecting the highest scoring action according to Q_{ξ^Q}, i.e.,

$$\pi_{\xi^\pi}(s) = \underset{a \in g_k \circ f_{\xi^\pi}(s)}{\arg\max}\ Q_{\xi^Q}(s,a). \quad (12)$$

Note that in (12), the function f_{ξ^π} is defined to map the state representation space to the action representation space, i.e.,

$$f_{\xi^\pi}(s) = \hat{a}. \quad (13)$$

Considering that the proto-action $\hat{a}$ provided by the function f_{ξ^π} might not be a valid action a, a k-nearest-neighbor mapping function that maps a continuous space to a discrete action set is defined as

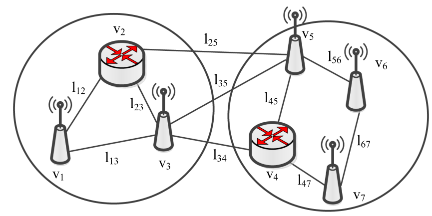

Fig. 3. Example of the gateway deployment.

$$g_k(\hat{a}) = \underset{a\in\mathcal{A}}{\overset{k}{\arg\min}}\, |a - \hat{a}|_2. \quad (14)$$

Next, the parameters of the target critic network $\xi^{Q'}$ and the target actor network $\xi^{\pi'}$ are duplicated from that of the critic network ξ^Q and the actor network ξ^π with a learning rate τ.

Fig. 3 shows the example of the gateway deployment. There are two communities, each of which is built under the load-balancing constraints (1) and (2) and the maximum latency constraint (7). We assume that $l_{23} < l_{12}$, $l_{12} < l_{56} + l_{45}$, $l_{12} < l_{47} + l_{67}$, $l_{56} < l_{47}$, $l_{45} < l_{67}$, $l_{56} + l_{67} < l_{45} + l_{47}$, and $l_{23} + l_{34} < l_{25} + l_{45}$. Then, the reward r is calculated as $r = -\alpha\frac{3(l_{12}+l_{23})+2(l_{45}+l_{47}+l_{56}+l_{45})}{12(l_{56}+l_{45})} - \beta$. If the location of one gateway is shifted from node v_4 to node v_5, then the reward r is calculated as $r = -\alpha\frac{3(l_{12}+l_{23})+2(l_{45}+l_{56}+l_{56}+l_{67})}{12(l_{45}+l_{47})} - \beta$. Thereby, in WDDPG, the locations v_2 and v_5 that can maximize the reward are chosen for the optimal gateway deployment.

2) Universal Gateway Deployment Model Training With Federated Reinforcement Learning: Recall that applying the gateway deployment model of a specific area to another area might result in higher latency and lower throughput due to the areal differences in topology. In addition, the routing data of each area should be kept from other areas for data privacy preservation. In addition, as a joint training technology, the FRL can build the universal model without accessing the private dataset of each participant.

Thereby, the FRL is employed in QoSPR to obtain the universal routing protocol. Specifically, first, each ARCC trains the areal gateway deployment model and uploads the model to the RRCC. Then, the RRCC assigns each areal model a weight and sends the weighted average model back to each ARCC. Next, each ARCC provides the RRCC with the feedback according to the difference between the application of the weighted average model and that of the areal gateway deployment model on the corresponding areal topology. Based on the feedback, the RRCC reassign each areal model a new weight and calculate the weighted averaged model again. This process is repeated until the difference in model application is minimum. Since the discovery of optimal weights requires the continuous space searching, the WDDPG is employed in the FRL. We define the state, the action, and the reward of the FRL as follows.

1) *State:* Let the ratios between the latency based on the universal model and that based on local models be the state s, i.e., $s = (\frac{L^1}{L^u}, \frac{L^2}{L^u}, \ldots, \frac{L^k}{L^u})$, where L^i and L^u denote the weighted latency (8) using the areal gateway deployment model of the ith ARCC and the universal model provided by the RRCC, respectively.

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2) *Action:* The set of weights consist of the action a, i.e., $a = (\omega_1, \omega_2, \ldots, \omega_k)$.
3) *Reward:* The reward r should be designed based on the latency deviation, i.e., $r = \sum_i^k \frac{L^i}{L^u}$.

Once the FRL converges, the optimal weighs are discovered, based on which the universal gateway deployment model is constructed.

3) Routing Protocol Design: Once the universal gateway deployment model is constructed, we can design a two-layer routing protocol to ensure both QoS and data privacy-awareness.

1) *First layer routing:* For each subdomain, the communications between devices including sensors and the gateway are established along the routes of the minimum latencies.
2) *Second layer routing:* For cross subdomain communications, the gateways relay the communication data along the route of the minimum latency.

It is worth to mention that by introducing the Wolpertinger architecture to the DDPG algorithm, the complexities of training of the areal gateway deployment model and the universal gateway deployment model will be greatly reduced. Because the discrete space searching is implemented using the WDDPG to discover both optimal weights and gateway deployments rather than searching the continuous space using the DDPG. It can be deduced that the complexity of the proposed QoSPR is bound by $O(n_1 \cdot n_2, \ldots, n_m)$, where n denotes the number of with $1 \leq m \leq n \cdot c_{\max}/\mathcal{C}$, $n_i = \mathcal{C}/c_i$, and $c_{\max} = \max\{c_i\}$.

V. Performance Evaluation

A. Experiment Setup and Performance Metrics

The performance of the proposed QoSPR is validated in Python on a computer equipped with Intel Core i7 processor, 64 GB running memory, and Win7 system. The experiment is conducted on realistic network topologies obtained from two individual datasets: 1) the Internet Topology Zoo [22] and 2) the Russian Cities found at the URL "https://github.com/pensnarik/russian-cities/blob/master/russian-cities.json." In general, both datasets provide the metadata in the records, i.e., longitudes and latitudes of nodes, a URL showing where the data was obtained, the date that the map was representative of the network, etc. In addition, the number of nodes and links between them are required. For instances, in the Internet Topology Zoo dataset, the Internet2 OS3E contains 34 nodes and 42 links, and the Germany50 contains 50 nodes and 88 links, while in the Russian Cities, we extract the topology that contains 200 densely populated nodes and 450 links in the western area of Russia. For each topology, we take half of nodes as training data, while the rest are used as testing data. In addition, we randomly generate the maximum request flow c_i for each node and the maximum load capacity $\mathcal{C}$. The proposed QoSPR is compared with the baseline approaches RASCAR [14], SAA [16], and FRP [20] in terms of the average latency, the maximum latency, and the load balancing with the variation of the coefficient α.

1) *Average latency:* The average latency is calculated utilizing (3) or (4). A lower average latency indicates a better system performance.
2) *Maximum latency:* The maximum latency is computed using (5) or (6) to support the URLLC for 5G-IIoT applications.
3) *Load balancing:* Since the proposed QoSPR achieves the subdomain partition according to the load-balancing constraint (2), we use another index λ to measure the load balancing from the perspective of the scatter of sensors, i.e., $\lambda = \sqrt{\frac{1}{|\mathcal{N}|}\sum_{i=1}^{|\mathcal{N}|}(|\mathcal{N}_i| - \frac{n}{|\mathcal{N}|})^2}$, where n denotes the number of nodes of the entire network. This suggests a less λ suggests a better load balancing.
4) *Algorithm convergence:* The convergence of the algorithm determines its application. For example, the 5G-IIoT applications demand highly efficient and fast convergent algorithms.
5) *Privacy preservation:* In the routing protocol design, the privacy of routing data is crucial. Compared with traditional schemes, the routing server might expose private routing data at a certain rate R. Thereby, the percentage of routing data exposed is utilized to measure the privacy preservation of routing protocol.

The training network of the QoSPR is the deep neural network that consists of three fully connected layers. The relu is the activation function of the first layer and the second layer, while the tanh is the activation function of the third layer. The loss is calculated with the mean square error and the optimizer used in the training is the Adam optimizer. In addition, the episode in the simulation is set to 400. In addition, we set the discount factor γ and learning rate τ to 0.9 and 0.1, respectively.

B. Experiment Results

1) Average Latency: Fig. 4 shows the effect of the coefficient α of the QoSPR on average latency under different topologies Internet2 OS3E, Germany50, and Russian Cities, which are shown in Fig. 4(a)–(c), respectively. Observed from Fig. 4, we find that both average latency and average maximum latency are lower than 1 ms because the maximum latency constraint is set to 1 ms in the QoSPR design to support the URLLC for 5G-IIoT. In addition, the average latency $L_{\text{s-g-avg}}$ and $L_{\text{g-g-avg}}$, and the average maximum latency $L_{\text{s-g-max}}$ and $L_{\text{g-g-max}}$ under the Russian Cities topology are only 0.1 ms more than that under the topology of either Internet2 OS3E or Germany50, considering the fact that the scale of the Russian Cities topology is at least five times larger. This suggests that the proposed QoSPR can provide QoS routing for various 5G-IIoT applications. The overall average latencies, i.e., the gateway-to-gateway latency $L_{\text{g-g}}$ and the sensor-to-gateway latency $L_{\text{s-g}}$ under all topologies, while the coefficient α is varying from [0,1] with the increment of 0.2 for each approach, are shown in Fig. 5. Although the SAA performs better than RASCAR and FRP, the proposed QoSPR achieves the lowest overall average latency under all topologies. This is because the QoSPR aims to minimize both sensor-to-gateway latency and gateway-to-gateway latency; however, the optimization goal of the SAA is to maximize the network reliability under the latency constraint. It is evident that QoSPR can realize QoS routing that supports the URLLC for 5G-IIoT applications.

2) Load Balancing: Fig. 6 shows the load balancing comparison for all approaches. Compared with baselines, the proposed QoSPR achieves higher load balancing for each network topologies. Note that SAA performs a little worse than QoSPR. However, SAA achieves a more balanced load compared with both RASCAR and FRP. This is because the SAA considers the

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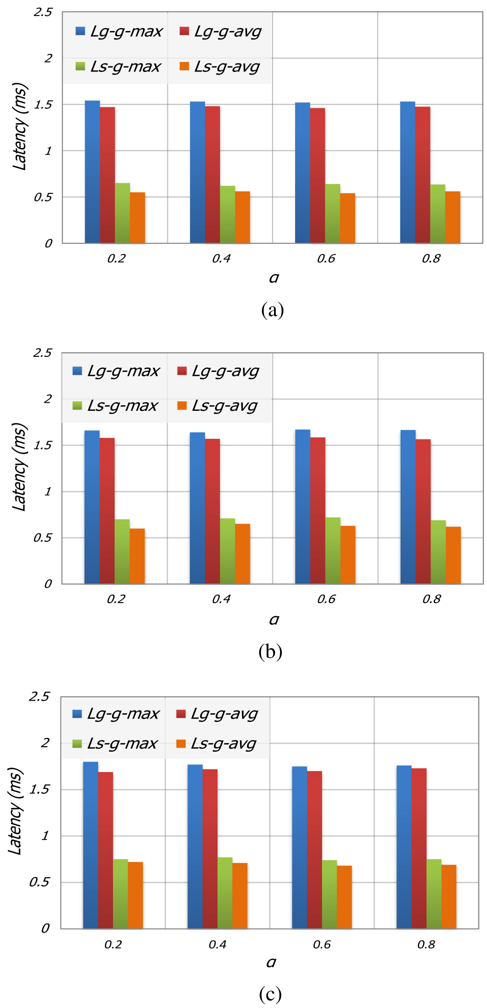

Fig. 4. Effect of the coefficient α on average latency under topologies. (a) Internet2 OS3E. (b) Germany50. (c) Russian Cities.

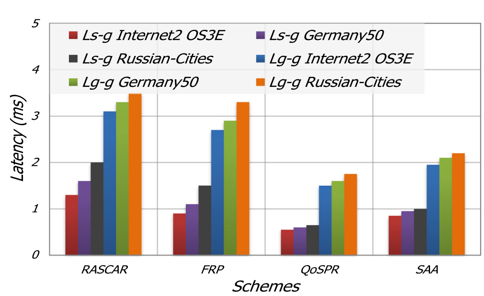

Fig. 5. Average latency comparison under all topologies.

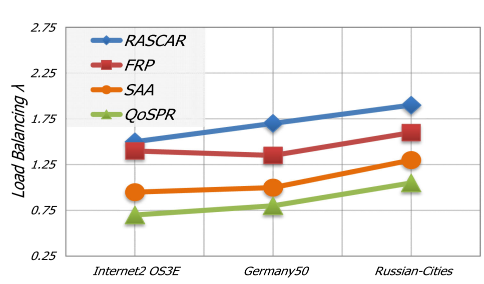

Fig. 6. Load balancing comparison under all topologies.

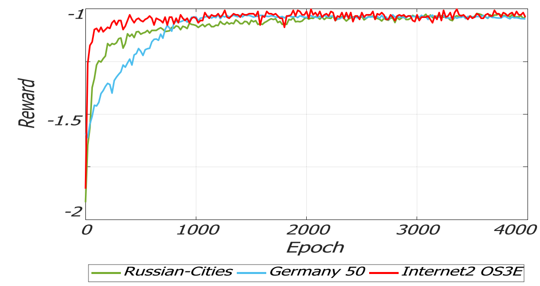

Fig. 7. QoSPR convergence under all topologies.

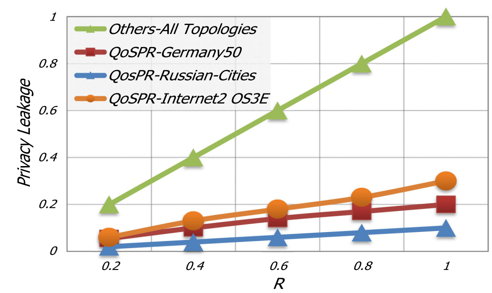

Fig. 8. Privacy preservation comparison under all topologies.

network reliability and the latency constraint, both of which help to establish the load-balancing routing. Observed from Fig. 6, we find that the proposed QoSPR can dynamically adjust the scale of each subdomain, thereby ensuring the load-balancing performance of the entire network for various 5G-IIoT applications.

3) Algorithm Convergence: Fig. 7 shows the convergence of QoSPR under all topologies in areal routing protocol design. The proposed QoSPR runs in maximum 4000 episodes. Since both Internet2 OS3E and Germany50 have less than 50 nodes and 100 links, the QoSPR starts to converge at about 1000 epochs. However, under the Russian Cities topology that has 200 nodes and 450 links, the QoSPR obtains the highest reward within 2000 epochs. Observed from Fig. 7, we find that the QoSPR converges slower while it is running under the topology of a larger scale. This is because the topology of a larger scale might result in a large difference between the average latency and the maximum one. This suggests that minimizing all latencies while maintaining the load balancing requires a large-scale search, thus resulting in a longer searching time.

4) Privacy Preservation: Fig. 8 shows the privacy leakage of QoSPR and all baseline approaches. Since all topologies differ in scale, we let each region consist of ten nodes. Observed from Fig. 8, we find that QoSPR exposes the least privacy as we expected. This is because as the topology grows large in scale, more areas will join the federated learning. If the universal routing model is exposed, then the areal model with the largest weight in the federated learning reflects the privacy leakage. Compared with QoSPR, baseline approaches will expose the majority of routing data as the rate R increases. It is evident that even if 100% private routing data are exposed, there are at most 30% of routing data leaked by QoSPR. This indicates the advantage of QoSPR in privacy preservation for 5G-IIoT applications.

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VI. Conclusion

The 5G-IIoT routing suffers from high latency, low load balancing, and data privacy leakage, which greatly affect the development of 5G-IIoT applications. To solve these problems, in this article, we propose QoSPR, for 5G-IIoT. Specifically, we improve the community detection algorithm info-map to divide the routing area into optimal subdomains under the load-balancing constraint and the maximum latency constraint, based on which the DRL algorithm is applied to build the gateway deployment model for latency reduction and load balancing. Then, to eliminate areal differences and meanwhile preserve areal private routing data, the federated reinforcement learning is employed to obtain the universal gateway deployment model. Eventually, the QoS and data privacy-aware routing is constructed by establishing communications along the routes of minimum latencies. The experimental results show that as a data privacy-aware routing protocol, the QoSPR can significantly reduce both average latency and maximum latency, while maintaining excellent load balancing. In fact, there exist plenty of routing attacks, i.e., sinkhole attack, selective forwarding attack, blackhole attack, wormhole attack, replay attack, etc., which can cause the QoS degradation for various 5G-IIoT applications. Thereby, preventing these routing attacks and meanwhile ensuring both QoS and data privacy-awareness are of great significance for our future work in the routing protocol design.

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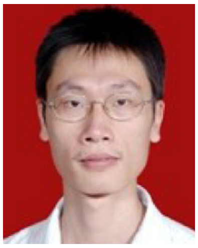

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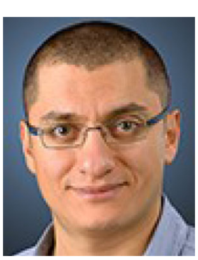

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