Dynamic 5G Network Slice Management Middleware for Industrial Internet of Things: Industry Paper

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Abstract
This paper addresses the challenges of delivering fine-grained Quality of Service (QoS) and communication determinism over 5G wireless networks for real-time and autonomous needs of Industrial Internet of Things (IIoT) applications while effectively sharing network resources. Specifically, this work presents DANSM, a dynamic and autonomous network slice management middleware for 5G-based IIoT use cases, such as adaptive robotic repair. The novelty of our approach lies in (1) its use of multiple M/M/1 queues to formulate a 5G network resource scheduling optimization problem comprising service-level and system-level objectives; (2) the design of a heuristics-based solution to overcome the NP-hard properties of this optimization problem, and (3) how it dynamically and autonomously provisions and manages 5G network slices used to deliver predictable communications to IIoT use cases. The results of experiments evaluating DANSM on our testbed comprising a Free5GC-based core and UERANSIM-based simulations reveal that it can efficiently balance the traffic load in the data plane thereby reducing the end-to-end response time and improve the service performance by finishing 64% of subtasks more than First Fit Descending (FFD) baseline approach while minimizing the operation cost.

CCS Concepts: • Computer systems organization → Self-organizing autonomic computing; • Networks → Network resources allocation; • Theory of computation → Network optimization; • Mathematics of computing → Queueing theory.

Keywords: 5G, Dynamic network slice management, Industrial Internet of Things (IIoT), Predictable performance.

1 Introduction
The Fourth Industrial Revolution (Industry 4.0) is transforming a range of today’s industry verticals by bringing significant automation using modern technologies, such as machine learning, real-time data processing and a gamut of novel sensors, instruments, devices, hardware, software and networking. This ecosystem that is used to realize the goals of Industry 4.0 like automation, safety, timeliness, reliability and resilience is what is termed as the Industrial Internet of Things (IIoT) [3, 18].

As an example, consider an IIoT use case of Adaptive Robotic Repair. With the recent disruptions in the industrial supply chain, it is increasingly becoming important that the factories of today operate with zero human intervention on-site and move towards the Lights-out Factory vision [15]. Robotic arms are widely used to repair high-value components, such as shafts, pistons, blades and molds. However, due to limited compute resources available on the robotic equipment and the need to work collaboratively, reliable and real-time networking is of paramount importance.

Wireless networks, such as Fifth-generation (5G) wireless, are attractive in industrial environments as they enable mobility, eliminate the need for expensive wiring needed by wired networks and overcome the hazards posed by wired networks. 5G in particular supports [9] (a) multiple base stations (gNB) that improve the signal strength and offer a stable network connection, (b) mmWave and Multiple-Input Multiple-Output (MIMO) technologies that enable electromagnetic waves to carry more raw data thereby increasing network bandwidth and improving network latency, and (c) Network Slicing (NS) that allows network providers to dynamically and efficiently allocate network resources and offer differentiated services.

The remote robotic repair IIoT use case mentioned earlier consists of different sub-tasks [1], such as workpiece scanning, defect detection, tool path generation, workpiece milling, and milling monitoring each with different priorities. The network requirements of different involved sub-tasks are varied, which brings challenges to providing real-time packet inspection, delivering a high-level of Quality of Service (QoS) and generating an accurate usage report for every sub-task. This use case illustrates a multi-device and...
multi-subtask architecture of these IIoT usecases. Therefore, multiple co-existing network slices are required to deliver a real-time 5G-based network solution. Moreover, considering the topology relationship among all sub-tasks and the different network resource consumption of each sub-tasks, the network resources that are assigned to multiple network slices must be based on sub-task priority. Besides, the heavy network traffic generated by the sub-tasks will inevitably lead to building up of queues on the data plane.

Previous studies have shown that high queuing delay within a 5G network leads to rate variability [23] and adversely affects QoS [10]. To address the aforementioned needs and challenges in applying multiple network slices to the IIoT scenarios, we present Dynamic and Autonomous Network Slice Management (DANSM), which is codified as a middleware solution and make the following contributions:

- We show how DANSM provides sub-tasks with a network slice that helps to maintain and improve network services and requirements for a specific type of sub-task thereby improving productivity in the industrial use case.
- To efficiently utilize the network resources and improve network scalability, we present a topology sorting algorithm to decide the sub-task priority that determines the dynamic and autonomous assignment/recycling of network resources within each network slice.
- To balance the load and minimize the queuing latency on the data plane, we present a multiple M/M/1 queue model of the data plane traffic and propose a heuristic algorithm to schedule the sub-tasks and manage the network resource based on the sub-task priority.
- We show extensive empirical results evaluating our ideas.

The rest of this paper is organized as follows: Section 2 presents details of our approach; Performance evaluations are presented and analyzed in Section 3; Related work is briefly summarized in Section 4; and finally, Section 5 offers concluding remarks alluding to future work.

2 Methodology

We now present our DANSM approach, which is designed to operate in a 5G ecosystem shown in Figure 1. To that end, we first provide a brief overview of 5G followed by a concrete industrial use case that we used in this research.

Finally, we describe the DANSM approach in detail.

2.1 Overview of 5G Wireless Networking

The 5th generation wireless networking is the latest cellular technology that is being deployed around the globe. The 5G technology is designed to be inherently cloud-native so that its functionality can be deployed in the form of containerized microservices that can be managed and autoscaled by frameworks, such as Kubernetes. In its basic form, 5G comprises edge devices, such as smart phones, called the User Equipment (UE). UEs communicate with a base station called gNodeB via a radio access network (RAN). The core functionality of 5G that manages the user sessions, authentication, network slicing, user packet forwarding and several other important functions are realized as microservices in the 5G Core. While most of the capabilities, such as session management, resource management and user authentication are control plane responsibilities, the primary data plane function of routing and forwarding user packets is carried out by the User Plane Function (UPF).

5G’s Multi-access Edge Computing (MEC) provides edge computing capabilities to applications. Further, the data plane within the 5G Core Network comprises multiple network slices. 5G network slicing enables multiplexing of virtualized and independent logical networks on top of common physical infrastructure. Presently, 5G
network slicing is categorized into 3 types: Enhanced Mobile Broadband (eMBB) used by applications requiring ultra high bandwidth, Massive Machine-Type Communications (mMTC) used in fast and energy-efficient communications, and Ultra-reliable Low-Latency Communications (URLLC) used by applications needing ultra-low latencies and reliable communications. By using different network slices, we can satisfy the differentiated network requirements of IIoT scenarios. Note that 5G provides only the mechanisms but algorithms are needed to effectively manage these slices.

2.2 Industrial Case Study and Key Issues

Our industrial IIoT use case is a 5G-based adaptive robotic repair system that we use to motivate and describe our research. The UEs in the use case comprise cameras, robot arms and edge devices, which are assigned to different repair tasks that generate various types and volumes of data. An adaptive robotic repair task consists of 5 sub-tasks: work-piece scanning, defect detection, tool-path generation, robot milling and milling monitoring. Figure 2 illustrates the use case.

As part of the adaptive robotic repair workflow, the 5G camera first scans the target workpiece and records the key features. Then, the recorded information (image or video) is sent from the 5G camera to the 5G MEC devices. The MEC devices, which include sensors, actuators, and other endpoints, will also collaborate to help detect any defects. Then the MEC will compare the scanned and standard workpiece features and generate a comprehensive repairing tool path, which in turn will be sent to the robotic arm. On receipt of the repairing tool path, the robotic arm will start milling the target workpiece. The 5G camera will monitor the milling process as well to prevent accidents.

Every sub-task within an adaptive robotic repair is associated with a network slice, which consists of a number of UPFs. The number of UPFs within a network slice is dependent on the associated sub-task priority. The UPFs of the same network slice share the same network configuration, such as bandwidth, which guarantees that the packets from UEs routed in the same network slice but different UPFs will be processed by the same network service. The UPFs of different network slices have different network configurations, which provides differentiated network services for every sub-task. Moreover, a UPF routes packets not only to the UE but also to the data networks within the MEC system, which is responsible for providing time-sensitive and compute-intensive edge services, such as the tool path generation sub-task within an adaptive robotic repair.

The varied data volumes from the adaptive repair devices of the use case, however, can lead to network congestion, causing a number of queues to build up, especially in the data plane, thereby increasing the queuing and service times of the adaptive repair system, and adversely impacting the performance of the adaptive repair. Further, if an arbitrary task-to-robot assignment policy is used, then the adaptive repair device that completes its assigned sub-task earlier will simply wait until being assigned a new sub-task thereby wasting precious resources, which can prolong the overall completion time of the entire repair thereby hurting manufacturing productivity.

2.3 Priority-based and Queuing-theoretic Modeling

To address this unpredictable waiting time issue, we introduce the notion of Task Priority and UE Priority. Task priority helps to dynamically assign/recycle resources allocated to the network slices, which are associated with the repair sub-tasks, while UE priority ensures that the UE, which has completed its task early, can be assigned a new task at the earliest. The Task Priority can be calculated by applying the Topology Sorting Algorithm [12] on the task flowchart, which represents the topology relationship among repair sub-tasks as shown in Figure 3. The task that executes early in the task flowchart will get higher priority. The network slice with higher task priority will be assigned more network resources initially. The UE Priority is formulated based on the next task priority and the current task start time, which is also referred to as the UE arrival time, and is represented as $UEPriority = TaskPriority + \frac{1}{ArrivalTime}$. The UE, whose new task has higher priority, will be assigned to the matched network slice early and has more choices when choosing the UPFs within the matched network slice. Therefore, those UEs will have a higher chance of avoiding the overloaded UPFs.

Prior studies have adopted the M/M/1 and M/M/N queuing models to schedule IoT network packets in both wired [4, 17] and wireless networks [21]. Additionally, studies have shown that both wired [16] and wireless [13] traffic follow Poisson distribution in IoT scenarios. As the robotic repair task is an exemplar IIoT usecase, we use the M/M/1 model for its simplicity to schedule the traffic in the data plane. Specifically, our work uses the M/M/1 queuing model to model the latency, service time and transmission delay of requests in the 5G User Plane Function (UPF). In our system, the flows
representing arrival requests are assumed to be from independent UEs with the interval of arrival time and the server processing time constituting a negative exponential distribution. Therefore, requests from UEs to UPFs follow a Poisson distribution, thereby justifying the use of M/M/1 modeling. Moreover, considering the heterogeneous traffic from UE devices and the topology relationship among robotic adaptive repair sub-tasks, we provision a pool of UPFs and configure multiple network slices allocating/deallocating resources dynamically to handle and adapt to the traffic from the UE side. Every sub-task is associated to a specified network slice in our system, and the resource within the network slice is dynamically changed based on sub-task priority and real-time UE request rates. In addition, our dynamic network slicing algorithm is deployed in a Software-Defined Network controller in the 5G control plane.

### 2.4 Optimization Problem Formulation

Our system queuing model is shown in Figure 4 while Table 1 shows the notations used in the problem formulation described in this section.

![Figure 3. DAG Flowchart](image)

![Figure 4. System Queuing Model](image)

We assume there are $n$ UEs and the request rate of the $i^{th}$ UE is denoted by $\lambda_i$. The total UE request rate is $\sum_{i=1}^{n} \lambda_i$. We assume there are $s$ network slices and $r$ UPFs in the UPF Pool. The initial number of UPFs within every network slice is decided by the coefficient $\alpha$ and the Task Priority.

1 A resource corresponds to the number of UPFs.

#### Table 1. LIST OF NOTATIONS

| Symbol | Meaning |
|--------|---------|
| $n$    | the number of User Equipments (UEs). |
| $S$    | Task priority list $S = \{(task_1, t_{p1}), (task_2, t_{p2}), (task_3, t_{p3}), \ldots, (task_s, t_{ps})\}$; total $s$ tasks, which are mapped to $s$ network slices; $task_k$ is the id of $k^{th}$ task and $s^{th}$ network slice; $t_{pi}$ is the task priority of $i^{th}$ task. |
| $\alpha$ | The coefficient of the number of UPFs in UPF Pool; $\alpha \sum_{k=1}^{s} t_{pk} = r$. In the UPF Pool, there are $atp_1$ UPFs prepared for the $1^{st}$ network slice; the range of UPFs within the $1^{st}$ network slice in the UPF Pool is $[1, atp_1]$. There are $atp_2$ UPFs prepared for the $s^{th}$ network slice and the range of $s^{th}$ network slice in the UPF Pool is $[\sum_{k=1}^{s-1} t_{pk}, \sum_{k=1}^{s} t_{pk}]$. |
| $\lambda_i$ | the request rate of $i^{th}$ UE. |
| $\mu$ | the service rate of all UPFs. |
| $X_k$ | the request of $i^{th}$ UEs to the $k^{th}$ UPF. |
| $\theta_j$ | the load of $j^{th}$ UPF. |
| $\overline{\theta}_k$ | the average load of all the UPFs within $k^{th}$ network slice. |
| $l_{i,j}$ | the length of packet from $i^{th}$ UE to $j^{th}$ UPF. |
| $d_{i,j}$ | the transmission rate between $i^{th}$ UE and $j^{th}$ UPF. |
| $w_1, w_2$ | weight factors, which will be tuned accordingly. |

The $\alpha$ is provided by the users and can decide the initial size of each network slice.

In the UPF Pool, there are $atp_1$ UPFs prepared for the $1^{st}$ network slice and the range of UPFs within the $1^{st}$ network slice in the UPF Pool is $[1, atp_1]$. We assume $\alpha = 1$, $r = 10$ and use the example in Figure 3. Then, the $1^{st}$ network slice will have $atp_1 = 1 + 4 = 4$ UPFs, and the range of $1^{st}$ network slice in the UPF Pool is $[1, 4]$. And the $2^{nd}$ network slice will have $atp_2 = 1 + 3 = 3$, the range of $2^{nd}$ network slice is $[5, 7]$. The total number of UPFs within the $4$ network slices will be $4 + 3 + 2 + 1 = 10$. There are $atp_1$ UPFs prepared for the $s^{th}$ network slicing and the range of $s^{th}$ network slicing in the UPF Pool is $[\sum_{k=1}^{s-1} t_{pk}, \sum_{k=1}^{s} t_{pk}]$, thus $\alpha \sum_{k=1}^{s} t_{pk} = r$. Every UPF has a queue, thus there are $r$ M/M/1 queues in our adaptive repair system. Our DANSM algorithm will assign the incoming requests from $n$ UEs to the $r$ UPF queues. Then, we assume all the UPFs have the same service rate, which is denoted by $\mu$. The UE to UPF assignment is stored in the
Applying Little’s law, the expected queuing time before a request from an UE is served can be represented by:

$$\theta_j = \sum_{i=1}^{n} \lambda_i x_{ij}$$  \hspace{1cm} (1)$$

and the average load among all UPFs within the $k^{th}$ network slice is represented by:

$$\bar{\theta}_k = \frac{1}{\alpha t_p_k} \sum_{j=atp_{k-1}}^{\alpha t_p_{k}} \theta_j$$  \hspace{1cm} (2)$$

Applying Little’s law, the expected queuing time before a request from an UE is served can be represented by:

$$W_q = \frac{\theta_j}{\mu (\mu - \theta_j)}$$  \hspace{1cm} (3)$$

and the expected end-to-end response time, which is the sum of the request queuing time and the UPF service time, is represented by:

$$W_t = W_q + \frac{1}{\mu} + \frac{1}{\mu - \theta_j}$$  \hspace{1cm} (4)$$

The transmission time is decided by the length of the packet and the transmission rate between $i^{th}$ UE and $j^{th}$ UPF. Considering the different types of UEs and the different sub-tasks, the lengths of packets generated by the UE are different. Moreover, considering the different UPFs configured for different network slices, the network configuration of UPFs, such as bandwidth, are different. Therefore, the transmission time varies and can be represented by:

$$W_s = \sum_{i=1}^{n} \frac{l_{i,j}}{d_{i,j}}$$  \hspace{1cm} (5)$$

The overall latency, which is the sum of queuing latency, the UPF service time and transmission time, is represented by:

$$W_s + W_t = \frac{1}{\mu - \theta_j} + \frac{1}{\mu - \theta_j}$$  \hspace{1cm} (6)$$

The average queuing latency and the transmission time of all the UPFs within the $k^{th}$ network slicing is represented by:

$$G(X_k) = \frac{1}{n} \left( \sum_{i=1}^{n} \sum_{j=atp_{k-1}}^{\alpha t_p_{k}} \frac{x_{ij}}{\mu - \theta_j} + \frac{l_{i,j}}{d_{i,j}} \right)$$  \hspace{1cm} (7)$$

To balance the load of UPFs and minimize overall latency for every UPF, we also formulated the variance of latency to avoid the extreme case, where all the UE loads are assigned to a few UPFs. The variance of the queuing latency and the transmission time of all the UPFs within the $k^{th}$ network slicing is represented by:

$$V(X_k) = \frac{1}{n} \left( \sum_{i=1}^{n} \sum_{j=atp_{k-1}}^{\alpha t_p_{k}} \left( \frac{x_{ij}}{\mu - \theta_j} + \frac{l_{i,j}}{d_{i,j}} - G(X_k) \right)^2 \right)$$  \hspace{1cm} (8)$$

In this work, we aim to minimize both the mean and the variance of queuing latency and the transmission time. Considering the difference of magnitude between the mean and the variance value, we tuned $w_1$ and $w_2$ accordingly as weight factors. The following illustrates the problem formulation:

$$\min \quad F(X) = \sum_{k=1}^{n} (w_1 G(X_k) + w_2 V(X_k)) \hspace{1cm} (9)$$

Eq. (9) aims to minimize both the average UE queuing latency and the average transmission time in standalone 5G network. Eqs. (10)-(13) represent the constraints. As mentioned earlier: a) for each UPF, the sum of the request rates from all connected UEs should be less than the UPF’s processing rate $\mu$; b) each UE can only be connected to one UPF at a time; c) the UE connection decision is encoded in a matrix $x_{ij}$ with binary elements; d) the number of UPFs is limited and the task has higher priority will have more prepared UPFs in the UPF pool.

$$\sum_{i=1}^{n} \lambda_i x_{ij} < \mu, \forall j$$  \hspace{1cm} (10)$$

$$\sum_{i=1}^{m} x_{ij} = 1, \forall i$$  \hspace{1cm} (11)$$

$$x_{ij} \in \{0, 1\}, \forall i, j$$  \hspace{1cm} (12)$$

$$\alpha \sum_{k=1}^{\gamma} t_{p_k} = r$$  \hspace{1cm} (13)$$

\subsection{2.5 Heuristic Approach}

Our optimization problem formulation shown in Eq.(9) belongs to the class of dynamic scheduling problems for multiple parallel servers/queues, which has been shown to be NP-hard [14]. Hence, to rapidly solve our optimization problem at run-time as part of the dynamic and autonomous approach, we propose a heuristic algorithm. Our approach balances the load on the UPF side, and minimizes queuing and propagation latency under dynamic traffic conditions for real-time communication use cases in IIoT.

We use our adaptive robotic repair case study to present our heuristic algorithm shown as a flowchart in Figure 5. The input to our algorithm includes the following: (a) an adaptive robotic repair Directed Acyclic Graph (DAG) $D$, which is provided by the DANSM user and which includes the topology relationship among all the repairing sub-tasks; (b) a UE arrival time list $T$; (c) a UE waitlist $UE\_\text{waitlist}$, which is a matrix and used for storing all the UE statuses and UE priorities; and (d) an objective function $F(x)$, as shown in Eq.(9) formulated from the multiple M/M/1 queuing model that utilizes the UE to UPF assignment information.

The algorithm is explained as follows:

- In step 1, our algorithm will calculate the task priorities by utilizing $D$ and apply the Topology Sorting Algorithm [12] on $D$. Figure 3 shows how to generate
Figure 5. Heuristic Scheduling Algorithm Involving an Autonomous Feedback Loop

- In step 2, the algorithm will check the UE status (either at initialization or as the system evolves over time) and calculate the UE priority based on the UE buffer status, task priority, and UE arrival time. The UE buffer status and the UE arrival time is obtained from the SDN controller. If the SDN controller detects 0 bytes in a UE buffer, we set the UE to the Free state, which indicates that the UE has finished its previous task and is waiting for a new task. Otherwise, the UE will be set to the Service state, which indicates that the UE is still working on the current task. Then, the algorithm will update the UE status based on their buffer status. This step will run periodically. All the free state UEs will be added to the UE_waitlist.

- Each UE in the UE_waitlist, at the specific time, is responsible for one sub-task within the adaptive robotic repair and will be assigned to the network slice (NS), which is matched with the sub-task, based on their UE priority.

- In step 3, our algorithm will check if the UE_waitlist is empty or not. If it is empty, we go back to step 2 and check all the UE status again till the UE_waitlist is not empty, which means there is at least one UE that can be assigned the next sub-task.

- Otherwise, we go to step 4, where for every available UE we assign it to the matched network slice based on their task priority and where network slices may also have different priority.

- Next, in step 5, the algorithm will calculate the average load of the UPFs within their assigned network slice. This computation is needed to assist in load balancing.

- In step 6, we check if the average load is greater than the maximum load times the threshold coefficient $\tau$. If this is the case, we assume all the UPFs within the matched NS are at risk of overload. If the current assigned NS is overloaded, then the algorithm will check if the UPF Pool in the assigned NS range has any available UPFs in step 10. If the assigned NS range of UPF_Pool runs out of UPFs, then the algorithm will go to step 11 and will pull a UPF from the NS range with lower priority and elevate it to the NS range with higher priority. Otherwise, the algorithm will go to step 12 and directly pull a UPF from the UPF pool in the assigned NS range (which could include the just elevated UPF), push it to the matched NS, and assign the UE to the UPF. Thereafter, the flow goes back to Step 3 as described above.

- On the other hand, if in step 6 the average load is less than the maximum load times $\tau$, the algorithm will go to step 7 and calculate the $F(x)$ value according to Eq.(9) for every UPF within the assigned NS and pre-assign the UE to the UPF, which has a minimum $F(x)$. "Pre-assign" means that the UE is temporally and
logically assigned to the UPF for calculating the new average load $\theta_{\text{new}}$.

- Then, in step 8, the algorithm will check if $\theta_{\text{new}}$ is less than the maximum load times $r$. If yes, the algorithm will go to step 9 and the UE will be physically assigned to the UPF, which has the minimum $F(x)$, and then go back to Step 3. Otherwise, we will go to step 10 because this is a case where potentially all the UPFs within the assigned NS have the risk of overload, and hence will perform the same steps as described before for the overload case.

In our algorithm, every UE in the $U_{\text{waitlist}}$ is supposed to scan all the UPFs within the matched network slice. Therefore, the runtime complexity of our algorithm is non-linear and denoted by $O(nr)$, where $n$ indicates the number of UE and $r$ indicates the number of UPF.

2.6 Implementing DANSM

DANSM serves as a resource management middleware – here for 5G network slices. It is realized as a microservices component that can be deployed in the control plane of the 5G core along with other components. The 5G architecture makes this design choice easy to implement without any invasive changes to existing components. We have implemented DANSM in Python.

3 Empirical Evaluation

3.1 Experimental Setup

Our evaluation setup is depicted in Figure 6. We used two PCs with Ubuntu 20.04 to deploy our testbed. The PC labeled in the green box is responsible for running the 5G core network, SDN controller and network monitoring tool. The PC labeled in the orange box is responsible for emulating the radio access network including the gNB and the user equipment using UERANSIM [8]. We used Free5GC [7] as our 5G core network and implemented our DANSM middleware within the Ryu controller [22] as part of the Free5GC control plane. We deployed all the 5G core functions inside Docker containers and orchestrated all network functions using Docker Compose. Emulation of the factory floor including its 5G radio network and the robotic arms representing the UEs is justified because DANSM focuses on alleviating the bottlenecks in the 5G core, and moreover, conducting experiments on operational factory floors is hard unless there is a dedicated testbed for such a purpose.

All the network traffic within our testbed is routed using Open vSwitch [6] and monitored by sFlow-RT [2]. The traffic from UERANSIM is generated using iPerf3 [19]. All the UEs use TCP for guaranteeing communication reliability, and all the UE request rates follow the Poisson Distribution. We evaluated DANSM in the application plane using the metrics to solve the optimization goal that are defined in Eq.(9).

3.2 Baseline Algorithms

We compared DANSM with the Modified Greedy Algorithm (MGA), which is a heuristic algorithm we developed in prior work and had applied to the dynamic switch migration problem [17]. MGA aims to minimize the switch queuing latency and the controller processing latency. Its objective function targets minimizing the average load of SDN controllers and the switch migration cost under dynamic traffic change.

We also compared DANSM with conventional bin packing algorithms: First Fit Descending (FFD) and Best Fit Descending (BFD) algorithms [11]. In our case, the FFD algorithm starts with sorting the UEs in the UE Freelist in descending order based on the UE priority. For each UE, after assigning it to the matched network slice (NS), FFD will scan the UPFs within the matched network slice in order and assign the current UE to the first UPF that is able to process the traffic from the current UE. Similar to FFD, BFD will first sort all the UEs in the UE Freelist in descending order based on the UE priority. For each UE, after assigning it to the matched network slice, the algorithm will scan all the UPFs within the matched network slicing and assign the UE to a UPF where it fits the tightest.

3.3 Evaluating Load Balancing for Data Plane

Load balancing is a significant objective for all the dynamic scheduling algorithms we compared. The unbalanced load in the 5G data plane will lead to unexpected queuing time on the UPF side and therefore increase the UPF processing time and hence the overall latency, which hurts system performance. To evaluate the performance of all the algorithms, we configured 10 UPFs in the data plane for all the NSs and set up 16 UEs to generate network traffic. The task priority dynamically decides the number of UPFs within the NS. We run each algorithm for 25 mins (1500 secs) for the sake of illustration; a 25 mins duration is long enough for the system to reach stability and the metrics fluctuate within about 10%. Moreover, the UE request rates follow the same Poisson Distribution in every algorithm.

Figure 7 uses the mean and standard deviation metrics to evaluate the UPF Loads in the data plane. The x-axis indicates the time, and the y-axis shows the UPF loads in the system. (We only calculated the UPF in use, not all the UPFs in the UPF Pool.) From 0mins to 5mins, the system is in the warm-up status, and the UE containers are built up, registered to the 5G core network in succession and randomly assigned to the UPFs. Then, after capturing a number of connected and available UEs, the scheduling algorithms start to work. After 15mins, the experimental results show that all the algorithms have a similar standard deviation, which indicates that the connections of all the UEs are stable while running the dynamic scheduling algorithm. However, our
DANSM has a better mean value and a better standard deviation as well after 19 mins under dynamic network traffic, which indicates that DANSM is able to handle the extreme case, where all the UE loads are assigned to a few UPFs. MGA aims at minimizing both mean load and the standard deviation of the UPFs; therefore it can address the extreme case as well. Moreover, the FFD and the BFD have the nature of packing the load with the minimum resources; therefore they may lead to the extreme case occasionally. To sum up, DANSM efficiently and effectively achieves the optimization objective and significantly balances the UPF loads thereby minimizing the queuing latency and improving the performance of the adaptive robotic repair system.

3.4 Evaluating End-to-End Response Time and Algorithm Efficiency

We used iPerf3 to measure end-to-end response time and the number of tasks executed in the 25mins to evaluate the real-time performance of all the algorithms under dynamic network traffic. The evaluation result is shown in Figure 8 and Figure 9. In Figure 8, the x-axis indicates the subtask names and the y-axis indicates the average response time for TCP transmission. In Figure 9, the x-axis shows the number of tasks/subtasks executed in the 25 mins. The results indicate that our DANSM approach outperforms MGA and BFD in both the time spent on the subtasks and completing the repair task. Although FFD shows a similar time in terms of a complete repairing task, DANSM performs better on the task with higher priority. Moreover, Figure 9 shows that DANSM finished 64% of subtasks more than FFD in 25 mins. Compared to the other three baseline algorithms, DANSM can specifically minimize the end-to-end response time for the sub-task with higher task priority and efficiently schedule all the subtasks under the dynamic network traffic thereby guaranteeing the performance of the adaptive robotic repairs.

3.5 Summary

Overall, the experimental results show that DANSM outperforms all the algorithms in both load balancing and end-to-end response time. The task priority and UE priority mechanism applied in DANSM significantly improved both subtask and task completion performance. The multiple M/M/1 queuing models efficiently distributed the data plane traffic, thereby minimizing both queuing latency and propagation delay, and reducing the end-to-end latency that is critical in real-time industrial settings.
4 Related Work
This section describes related research on dynamic management of network slicing, which is relevant to this research.

Dynamic network slicing technology, which virtualizes shared physical networks by providing multiple network services, is widely applied in both academic and industrial areas. For example, Xiao et al. [24] proposed the concept of dynamic network slicing. They developed an overlapping coalition-formation game to investigate the distributed cooperation and joint network slicing between fog nodes while considering traffic variation. Their results show that their architecture can significantly maximize utilization while balancing the workloads on fog nodes. In [5], the authors proposed a dynamic network slicing and resource allocation approach to investigate the operator’s revenue escalation problem under dynamic traffic in a mobile edge computing system. This approach optimizes the network slice admission in the long term and resource allocation in the short term. However, their approach considers only the transmission delay while ignoring the queuing latency, which will increase the end-to-end latency, thereby affecting system performance.

To intelligently assign and redistribute resources among multiple tenants, Raza et al. [20] leverage 5G orchestration functionalities to implement a dynamic network slicing approach, which is able to jointly provision the network resources from different domains, such as radio, transport, and cloud. They formulated a mixed-integer linear programming problem and designed a heuristic to solve it. Their evaluations show that dynamic slicing can improve the virtual network rejection probability by more than one order of magnitude. Like prior works, our approach can achieve the system-level objective of balancing the data plane traffic load among different network slices. Additionally, we also achieve the service-level objective of minimizing both the queuing and transmission time.

The work in [20] proposes a dynamic slicing approach to assign and redistribute resources among multi-tenant over 5G networks, where the 5G core network is treated as a black box and all details about 5G core functions are ignored. In their simulation, the authors focused on the control plane complexity and only considered the tenant’s requests. In contrast, our approach focuses on both the control plane and data plane requests. Moreover, we also considered the role of 5G core functions and utilized multiple M/M/1 queues to schedule the packets from the User Equipment (UE) to User Plane Function (UPF), which is the primary data plane function in 5G.

5G network technology is widely adopted in IIoT to improve system scalability and satisfy real-time network requirements. Compared with traditional wireless communication, our work utilizes dynamic slicing technology to allocate network resources for the IIoT use cases with different sub-tasks, which have different priorities, while satisfying the real-time and high throughput requirements. Compared to previous dynamic slicing-based approaches, our work applies the M/M/1 queuing theory to model the network traffic and formulates an optimization problem. Moreover, we are able to efficiently improve the utilization of network resources, significantly reduce both the queuing latency and the transmission time, and effectively balance the load among different network slices all at once.

5 Conclusion and Future Work
This paper presented a Dynamic and Autonomous Network Slice Management (DANSM) approach for IIoT use cases in 5G network. Compared with implementing IIoT use cases in traditional wireless network, our approach leverages 5G Network Slicing techniques and Software-Defined Networking (SDN) platform to dynamically assign and release resources for autonomous tasks with different priorities. Our approach applies to IIoT use cases comprising multi-services and multi-devices, which is a trend in IIoT applications. Compared with the previous dynamic network slicing solution, our approach utilizes the multiple M/M/1 queuing model to schedule the traffic in the data plane and minimize the end-to-end latency on the UE side thereby improving the performance of IIoT applications. At the core of DANSM is an optimization problem, which is solved at run-time using a heuristic algorithm that includes a feedback loop. Compared with previous heuristic algorithms and conventional bin packing algorithms, our approach effectively balances the traffic load in the data plane, significantly reduces the end-to-end response time and efficiently utilizes network resources, thereby improving both system-level and service-level performance.
5.1 Generalizing the Approach to Other IIoT Usecases

Although we have presented our approach using the adaptive robotic repair usecase, our approach can easily be adapted to other IIoT usecases, such as multi-task federated learning and real-time stream processing as long as these applications have individual sub-tasks and demonstrate differentiated performance requirements that lead to different priorities. Since applications are increasingly illustrating a microservices architecture, we believe that many IIoT usecases can benefit from our approach. There are two prerequisites before a user decides to apply DANSM to their usecase: (a) Preparing all the network resources, such as UEs (including cameras, sensors, wearable devices, etc.) and UPFs, and connecting the network components to the 5G network properly; (b) Listing all the sub-tasks and generating a DAG as shown in Figure 3. Then, the user should start the Ryu controller and Sflow-monitor in DANSM’s SDN control plane; (c) Execution of the heuristic scheduling algorithm, as shown in Figure 5, which will start after capturing any UE packets on the Ryu controller side.

5.2 Limitations and Future Work

By no means does our work address all the challenges. Any shortcomings become dimensions of future work as described below. For example, considering the scalability and the reliability requirements of IIoT, we could expand our network slicing resources to the radio access network. Moreover, considering the computation-intensive tasks within the IIoT, we could add MEC resources to our approach as well. We also plan to pursue the following additional research directions. First, we will scale up our current experimental testbed with more base stations and SMFs within 5GC, which will allow the 5G network to handle more UEs and ensure higher availability. However, with the testbed scaling up, the base station placement and the energy consumption will be other research problems. Second, we will design and develop a network slicing architecture that improves both data plane traffic and control plane management. Demonstrating our ideas on more IIoT use cases is another dimension of future work. Finally, we will integrate our approach with a federated learning framework to address energy efficiency, end-to-end latency, and data privacy concerns.

Software artifacts used in this research are available at https://github.com/minziran/DANSM.

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