

Software-defined Dynamic 5G Network Slice Management for Industrial Internet of Things

Ziran Min*, Shashank Shekhar†, Charif Mahmoudi†, Valerio Formicola‡, Swapna Gokhale§, Aniruddha Gokhale*

*Dept. of CS, Vanderbilt University, Nashville, TN, USA. Email: {ziran.min, a.gokhale}@vanderbilt.edu

†Siemens Technology, Princeton, NJ 08540, USA. Email: {shashankshekhar, charif.mahmoudi}@siemens.com

‡ Dept. of ECE, California Polytechnic in Pomona, Pomona, CA, USA. Email: vformicola@cpp.edu

§Dept. of CSE, University of Connecticut, Storrs, CT, USA. Email: swapna.gokhale@uconn.edu

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 software-defined, 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) the 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) the implementation of a software-defined solution that incorporates the heuristics to dynamically and autonomously provision and manage 5G network slices that deliver predictable communications to IIoT use cases. Empirical studies evaluating DANSM on our testbed comprising a Free5GC-based core and UERANSIM-based simulations reveal that the software-defined DANSM solution can efficiently balance the traffic load in the data plane thereby reducing the end-to-end response time and improve the service performance by completing 34% more subtasks than a Modified Greedy Algorithm (MGA), 64% more subtasks than First Fit Descending (FFD) and 22% more subtasks than Best Fit Descending (BFD) approaches all while minimizing operational costs.

Index Terms—5G, Software Defined Networking (SDN), Dynamic network slice management, Industrial Internet of Things (IIoT), Autonomous systems, Predictable performance.

I. 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 delivers the goals of Industry 4.0 like automation, safety, timeliness, reliability and resilience is termed as the Industrial Internet of Things (IIoT) [1], [2].

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 onsite and move towards the Lights-out Factory vision [3]. 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 (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 [4].

The above-mentioned remote robotic repair IIoT use case consists of different sub-tasks, such as workpiece scanning, defect detection, tool path generation, workpiece milling, and milling monitoring each with different priorities [5]. The network requirements of the different involved sub-tasks are varied, which poses 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 IIoT use case illustrates a multi device and multi sub-task architecture. Such a 5G-enabled adaptive robotic repair IIoT system will require multiple co-existing network slices to deliver a real-time network solution. Moreover, considering the topology relationships among all sub-tasks and the different network resource consumption of each sub-task, the network resources that are assigned to multiple network slices must be based on sub-task priority. Further, any heavy network traffic generated by the sub-tasks will inevitably lead to queue buildup on the network data plane.

Previous studies have shown that high queuing delays within a 5G network lead to rate variability [6] and adversely affects QoS [7]. To address the aforementioned needs and challenges in applying multiple network slices to the IIoT scenarios, we present a software-defined approach called Dynamic and Autonomous Network Slice Management (DANSM). Since the 5G core by design separates the control plane from the data plane offering different functionalities as cloud-native microservices, DANSM can easily be offered as an additional control plane microservice. To that end this paper makes the following contributions:

- To efficiently utilize the network resources and improve network scalability, we present a topology sorting algorithm to compute the sub-task priority, which determines the dynamic and autonomous assignment/release 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 queuing model of the data plane traffic, and propose a heuristic algorithm to schedule the sub-tasks and dynamically manage the network resources based on the sub-task priority.
- 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.
- We show extensive empirical results evaluating our ideas.

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

II. BACKGROUND AND RELATED WORK

This section provides background on 5G and then describes related research on dynamic management for network slicing, which is relevant to this research.

A. 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 and are part of what is called 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 separate algorithms are needed to effectively manage these slices.

B. Comparison with Prior Work

Dynamic network slicing technology, which virtualizes shared physical networks by providing multiple network services, is widely researched by both academia and industry. For example, Xiao *et al.* [8] 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 proposed architecture can significantly maximize utilization while balancing the workloads on fog nodes. In [9], 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.* [10] leverage 5G orchestration functionalities to support dynamic network slicing, which 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 [10] proposes a dynamic slicing approach to assign and redistribute resources among multiple tenants over 5G networks, where the 5G core network is treated as a black box and its details ignored. In their simulation, the authors focused on the control plane complexity and considered only the tenant's requests. In contrast, our approach focuses on both the control plane and data plane requests. Moreover, we also consider the role of 5G core functions and utilize 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.

In summary, our work utilizes a software-defined, 5G-based dynamic slicing approach to allocate network resources for the IIoT usecases with different sub-tasks having different priorities, while satisfying the real-time and high throughput requirements. Compared to previous dynamic slicing-based

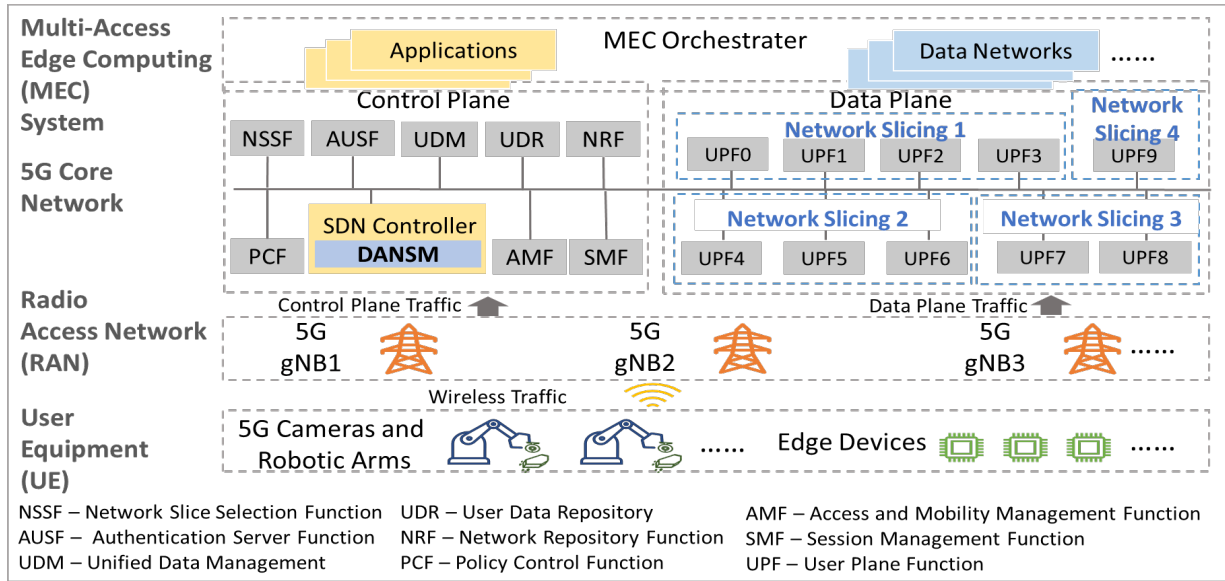


Fig. 1. System Architecture Showing DANSM Deployment

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 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.

III. METHODOLOGY

This section describes DANSM, which is designed to operate in a 5G ecosystem shown in Figure 1. We first provide details on a concrete industrial use case to describe the research. Finally, we describe the DANSM approach in detail.

A. IIoT 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 UEs¹ in our use case comprise cameras, robot arms and edge devices, which are assigned to different repair tasks each of which generates various types and volumes of data. An adaptive robotic repair task consists of 5 sub-tasks: workpiece scanning, defect detection, tool-path generation, robot milling and milling monitoring. Note that our industrial IIoT use case serves only as a driving example to describe and evaluate our research; the DANSM research described here is broadly applicable beyond this case study.

As part of the adaptive robotic repair workflow, a 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* that is sent to the robotic arm. On receiving the repairing tool path, the robotic arm will start milling the target workpiece. The 5G camera will also monitor the milling process 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 sub-task's 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 different sub-tasks. 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 edge services, such as the tool path generation sub-task within an adaptive robotic repair.

The varied data volumes from the adaptive repair devices, however, can lead to network congestion, causing a number of queues to build up, particularly in the data plane, thereby increasing the queuing and service times of the adaptive repair system, and hence adversely impacting the performance of the adaptive repair. Further, if an *ad hoc* 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 adversely impacting manufacturing productivity.

B. Priority-based and Queuing-theoretic Modeling

To address the unpredictable waiting time issue, we introduce the notion of *Task Priority* and *UE Priority*. Task

¹See Section II-A for background on 5G and terminology.

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 that 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 [11] on the task flowchart, which represents the topology relationship among repair sub-tasks as shown in Figure 2. 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.

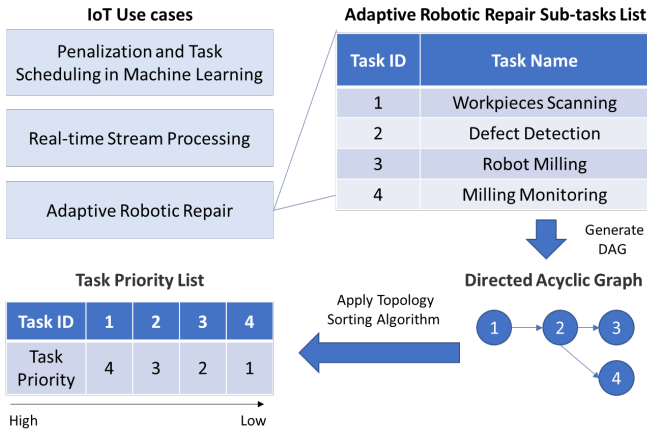


Fig. 2. DAG Flowchart

Prior studies have adopted the M/M/1 and M/M/N queuing models to schedule IoT network packets in both wired [12], [13] and wireless networks [14]. Additionally, studies have shown that both wired [15] and wireless [16] traffic follow Poisson distribution in IoT scenarios. Since the robotic repair task is an IIoT usecase and backed by success of prior efforts, we use the M/M/1 model 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 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 UEs 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

assigned to a specified network slice, and the resource² within the network slice is dynamically changed based on sub-task priority and real-time UE request rates. These decisions are made by DANSM software-defined design operating from the 5G control plane.

C. Optimization Problem Formulation

Our system queuing model is shown in Figure 3 while Table I shows the variables used in the problem formulation described in this section.

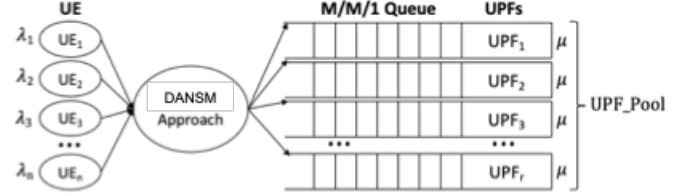


Fig. 3. System Queuing Model

We assume there are n UEs and the request rate of the i^{th} UE is denoted by λ_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 α and the *Task Priority*. The α is provided by the users and can decide the initial size of each network slice.

In the UPF Pool, there are αtp_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 $[1, \alpha tp_1]$. We assume $\alpha = 1$, $r = 10$ and use the example in Figure 2. Then, the 1^{st} network slice will have $\alpha tp_1 = 1 * 4 = 4$ UPFs, and the index range of 1^{st} network slice in the UPF_Pool is $[1, 4]$. Likewise, the 2^{nd} network slice will have $\alpha tp_2 = 1 * 3 = 3$, the index 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 αtp_k UPFs prepared for the k^{th} network slicing and the range of k^{th} network slicing in the UPF_Pool is $[\alpha \sum_{m=1}^{k-1} tp_m, \alpha \sum_{m=1}^k tp_m]$. We assume that there are total K sub-tasks, thus $\alpha \sum_{m=1}^K tp_m = r$. 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 μ . The UE to UPF assignment is stored in the binary matrix X . The matrix element x_{ij} is 1, if the i^{th} UE is assigned to j^{th} UPF, otherwise x_{ij} is 0.

Assuming that all the UE request arrivals are mutually independent and follow a Poisson process, then the load on the system is represented by $\sum_{i=1}^n \lambda_i$. The total load should be less than $r\mu$ for a stable system. The load of the j^{th} UPF is represented by:

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

²A resource corresponds to the number of UPFs.

TABLE I
LIST OF VARIABLES

Symbol	Meaning
n	the number of User Equipments (UEs).
S	Task priority list $S = \{(task_1, tp_1), (task_2, tp_2), (task_3, tp_3), \dots, (task_K, tp_K)\}$; total K sub-tasks, which are mapped to K network slices; $task_k$ is the id of k^{th} task and k^{th} network slice; tp_k is the task priority of k^{th} task.
UPF_Pool	A provisioned UPF pool $UPF_Pool = \{upf_1, upf_2, upf_3, \dots, upf_r\}$; total r UPFs; upf_r is the id of r^{th} UPF.
α	The coefficient of the number of UPFs in UPF_Pool , $\alpha \in \mathbb{Z}$; $\alpha \sum_{m=1}^K tp_m = r$. In the UPF_Pool , there are αtp_1 UPFs prepared for the 1 st network slice; the index range of UPFs within the 1 st network slice in the UPF_Pool is $[1, \alpha tp_1]$. There are αtp_k UPFs prepared for the k^{th} network slice and the index range of k^{th} network slice in the UPF_Pool is $[\alpha \sum_{m=1}^{k-1} tp_m, \alpha \sum_{m=1}^k tp_m]$.
λ_i	the request rate of i^{th} UE.
μ	the service rate of all UPF.
X	the UE requests to UPF assignment matrix; $x_{ij} = 1$ means that i^{th} UE send requests to j^{th} UPF, $x_{ij} \in \{0, 1\}, \forall i, j$.
θ_j	the load of j^{th} UPF.
$\bar{\theta}_k$	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.

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

$$\bar{\theta}_k = \frac{1}{\alpha tp_k} \sum_{j=\alpha \sum_{m=1}^{k-1} tp_m}^{\alpha \sum_{m=1}^k tp_m} \theta_j \quad (2)$$

Applying Little's law, the expected queuing time on the j^{th} UPF before a request from an UE is served can be represented by:

$$W_q = \frac{\theta_j}{\mu(\mu - \theta_j)} \quad (3)$$

and the expected end-to-end response time between an UE and j^{th} UPF, which is the sum of the request queuing time and the UPF service time, is represented by:

$$W_s = W_q + \frac{1}{\mu} = \frac{1}{\mu - \theta_j} \quad (4)$$

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:

$$W_t = \frac{l_{i,j}}{d_{i,j}} \quad (5)$$

The overall latency between i^{th} UE and j^{th} UPF, which is the sum of queuing latency, the UPF service time and transmission time, is represented by:

$$W_s + W_t = \frac{1}{\mu - \theta_j} + \frac{l_{i,j}}{d_{i,j}} \quad (6)$$

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

$$G_k(X) = \frac{1}{\alpha tp_k} \sum_{j=\alpha \sum_{m=1}^{k-1} tp_m}^{\alpha \sum_{m=1}^k tp_m} \left(\sum_{i=1}^n (W_s + W_t) \right) \quad (7)$$

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:

$$V_k(X) = \frac{1}{\alpha tp_k} \sum_{j=\alpha \sum_{m=1}^{k-1} tp_m}^{\alpha \sum_{m=1}^k tp_m} \left(\sum_{i=1}^n (W_s + W_t)^2 \right) - (G_k(X))^2 \quad (8)$$

In this work, we aim to minimize both the mean and the variance of queuing latency and the transmission time for all the network slices. 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:

$$\min F(X) = \sum_{m=1}^K (w_1 G_m(X) + w_2 V_m(X)) \quad (9)$$

$$\text{s.t.} \quad \sum_{i=1}^n \lambda_i x_{ij} < \mu, \forall j \quad (10)$$

$$\sum_{j=1}^r x_{ij} = 1, \forall i \quad (11)$$

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

$$\alpha \sum_{m=1}^K tp_m = r \quad (13)$$

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 μ ; 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 that has higher priority will have more prepared UPFs in the UPF pool.

D. 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 [17]. 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.

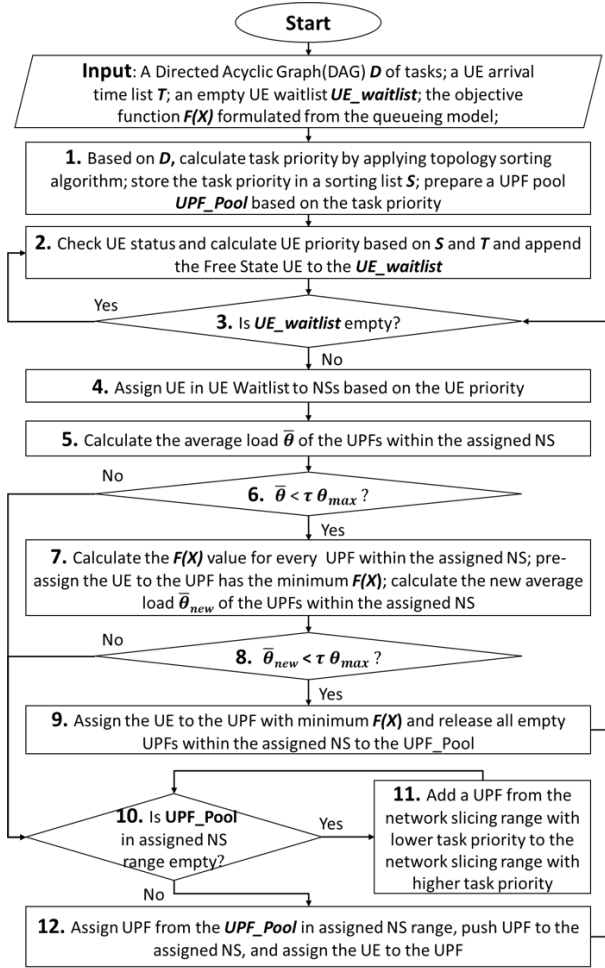


Fig. 4. Heuristic Scheduling Algorithm Involving an Autonomous Feedback Loop

We use our adaptive robotic repair case study to present our heuristic algorithm shown as a flowchart in Figure 4. 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 $UE_waitlist$, 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 works as follows: In step 1, our algorithm will calculate the task priorities by utilizing D and apply the Topology Sorting Algorithm [11] on D . Figure 2 shows how to generate a DAG and calculate the task priorities for a multi sub-tasks IIoT usecase. Then, the algorithm will store the task priority in a list S and create a UPF pool, which stores a number of available UPFs for all the network slices. 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 are 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.

The algorithm will then 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.

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 τ . If this is the case, we assume all the UPFs within the matched NS are at a 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 goes to step 11 and pulls a UPF from the NS range with lower priority and elevates 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

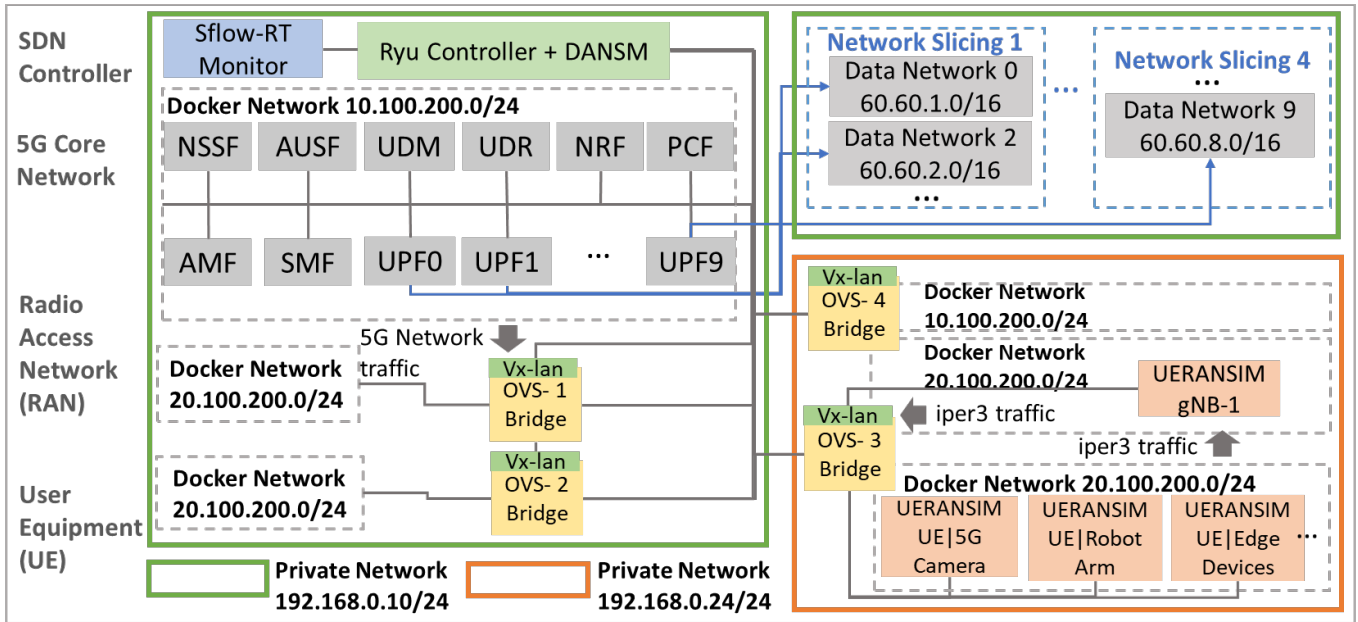


Fig. 5. Experiment Testbed (Two physical machines were used and indicated in green and orange boxes.)

the maximum load times τ , 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 $\bar{\theta}_{new}$. Then, in step 8, the algorithm will check if $\bar{\theta}_{new}$ is less than the maximum load times τ . If yes, the algorithm will go to step 9 and the UE will be physically assigned 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 $UE_{waitlist}$ 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 UPFs.

E. DANSM Implementation

DANSM provides software-defined resource management 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. DANSM is implemented in Python.³

IV. EMPIRICAL EVALUATION

This section reports on the results of extensive evaluations we conducted validating our proposed DANSM approach.

³DANSM is available in open-source from <https://github.com/minziran/DANSM>.

A. Experimental Setup

Our evaluation setup is depicted in Figure 5. 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 [18]. We used Free5GC [19] as our 5G core network and implemented our DANSM middleware within the Ryu controller [20] 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.

Validation using 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 [21] and monitored by sFlow-RT [22]. The traffic from UERANSIM is generated using iPerf3 [23]. 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).

B. Baseline Algorithms

We compared DANSM with the Modified Greedy Algorithm (MGA), which is a heuristic algorithm we developed in prior work and applied to the dynamic switch migration problem [12]. 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 changes.

We also compared DANSM with conventional bin packing algorithms: First Fit Descending (FFD) and Best Fit Descending (BFD) algorithms [24]. 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 slices and assign the UE to a UPF where it fits the tightest.

C. 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 6 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 0 mins to 5 mins, 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 15 mins, 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. At 25 mins, the UPF average load of DANSM is 70% of BFD, 91% of MGA, and 93% of FFD. In addition, the standard deviation of UPF load of

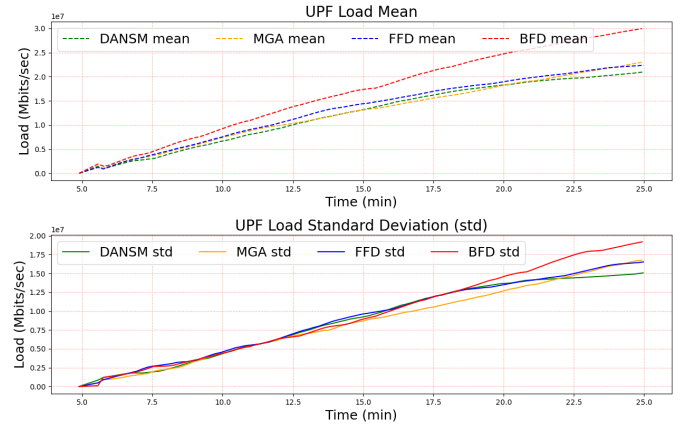


Fig. 6. Data Plane Load Mean and Standard Deviation (std)

BFD is 1.28 times more than DANSM. 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.

D. 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 7 and Figure 8. In Figure 7, the x-axis indicates the subtask names and the y-axis indicates the average response time for TCP transmission. In Figure 8, the x-axis shows the time and the y-axis shows the number of subtasks executed in the 25 mins. The results indicate that our DANSM approach outperforms MGA, FFD and BFD in both the time spent on the sub-tasks 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 8 shows that DANSM finished 34% more subtasks than MGA, 64% more subtasks than FFD and 22% more subtasks than BFD 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.

E. 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 sub-task 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

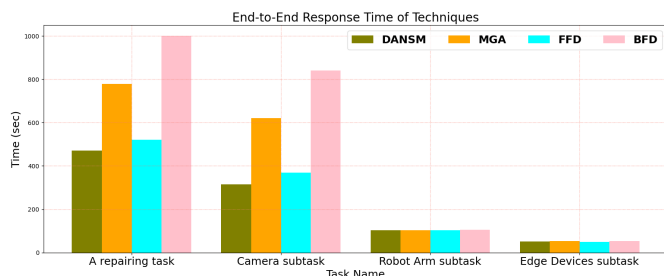


Fig. 7. End-to-End Response Time

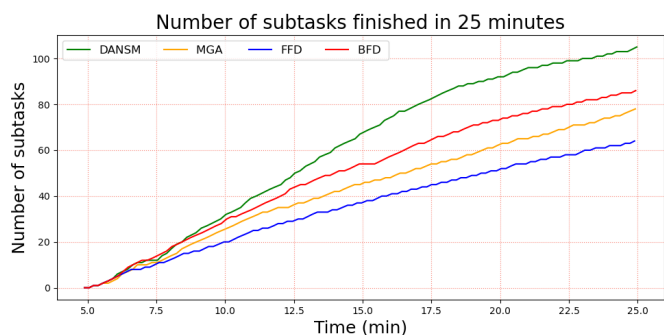


Fig. 8. Number of subtasks completing in 25 minutes

reducing the end-to-end latency that is critical in real-time industrial settings.

V. CONCLUSION AND FUTURE WORK

This paper presented DANSM, which is a software-defined solution that executes as a containerized microservice in the control plane of the 5G core. DANSM offers dynamic and autonomous network slice management to meet the QoS needs of IIoT applications. The paper demonstrated DANSM’s capabilities for a 5G-based adaptive robotic repair use case from the manufacturing domain. The key contributions in DANSM include a sub-task priority allocation algorithm, a queuing theory-based optimization problem formulation to minimize queuing delays and improve latencies, and a heuristics approach to solve this optimization problem at runtime.

We 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.

DANSM is available in open-source from <https://github.com/minziran/DANSM>.

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