Evaluation of Combined Network Slicing and MEC Toward Mobile Robot Applications in 5G Networks

Andrés Meseguer Valenzuela, Jose Vera Pérez, Javier Silvestre Blanes, and Víctor Sempere Payá

Abstract

Wireless communications have been used widely for monitoring purposes in different applications such as smart metering, environmental sensing, industrial asset tracking or healthcare monitoring. However, the enhancement of wireless technologies such as Wi-Fi and 5G NR provides new opportunities for innovative applications. Especially in robotics, improvements in terms of throughput, latency, and reliability are enabling new use cases that vary from remote teleoperation of mobile robots to edge processing of multi-robot fleet systems. These scenarios target the increase of energy efficiency, productivity and security of automated processes for industry. Verticals such as manufacturing are demanding due to the coexistence of humans and machines. These shared locations are sensitive to productivity issues such as deadlocks and bottlenecks for mobile robots, and security matters such as labor accidents. In this sense, mobile robots require the processing of sensor data to detect humans on time to avoid accidents. This application is limited by the computational costs to process data in robots using intelligent algorithms. Therefore, it is necessary to offload data from mobile robots to high-performance servers located in the network at lowest latency. From a communications perspective, this application provides a challenge to ensure that safety information, intended to avoid accidents, is transmitted properly while many elements are connected to the wireless network. Hence, the integration of slicing and edge processing capabilities remain essential to prioritize the offloading of robot sensor data. Following this scope, this work provides an evaluation of a current Network Slicing solution to support multiple stream for mobile robot applications, prioritizing an application of obstacle avoidance for human safety to showcase the relevance of slicing and edge process offloading capabilities in these scenarios.

Introduction

Human-robot collaboration has become a pivotal element in the evolution of industrial environments, offering promising advancements in productivity, flexibility, and above all, safety. To achieve truly efficient interaction, robots must be capable of perceiving and understanding their surroundings in real time, enabling them to react appropriately and avoid hazardous situations or operational bottlenecks that reduce productivity. However, the inherent limitations in onboard computational power restrict a robot's ability to perform such complex situational analyses locally. This challenge demands the offloading of processing tasks to external computing resources, making low-latency communication a critical enabler of Multi-Access Edge Computing (MEC).

Nonetheless, connectivity constraints or temporary connection losses pose significant challenges in safety-critical scenarios, necessitating robust fallback mechanisms to ensure operational safety. In these contexts, the absence of stable connectivity can impede the timely offloading of high-bandwidth sensor data, thereby limiting the robot's ability to make real-time safety-critical decisions. To address this, robots must be capable of transmitting sensor data efficiently, even in environments where multiple devices contend for limited bandwidth. This type of scenario is mainly common in manufacturing verticals where ensuring fast and reliable connectivity becomes even more challenging due to the number of simultaneous connected devices. For example, a collaborative robot might need to instantly reroute its path to avoid collision with another platform or human, demanding ultra-reliable and low-latency communication.

To address these constraints, 5G private networks emerge as a robust solution, offering high reliability, reduced latency, and allocated spectrum availability. When coupled with Network Slicing techniques – designed to prioritize, guarantee, and monitor specific data flows – and

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Andrés Meseguer Valenzuela (corresponding author) is with the Instituto Universitario de Investigación Mixto de Tecnología de Informática (IUMTI), Universitat Politècnica de València (UPV), 46022 Valencia, Spain, and also with the Instituto Tecnológico de Informática (ITI), 46022 Valencia, Spain; Jose Vera Pérez is with the Instituto Tecnológico de Informática (ITI), 46022 Valencia, Spain; Javier Silvestre Blanes is with the Instituto Tecnológico de Informática (ITI), 46022 Valencia, Spain, and also with the Departamento de Informática de Sistemas y Computadores (DISCA), Universitat Politècnica de València (UPV), 03801 Alcoy, Spain; Víctor Sempere Payá is with the Instituto Tecnológico de Informática (ITI), 46022 Valencia, Spain, and also with the Departamento de Comunicaciones (DCOM), Universitat Politècnica de València (UPV), 46022 Valencia, Spain.

edge process offloading – to apply computationally demanding algorithms – these networks can effectively support scenarios with stringent requirements, such as human-robot interaction and obstacle avoidance. This combination lays the groundwork for intelligent coordination systems where responsiveness and adaptability are paramount.

Based on this foundation, the development of human-robot collaboration frameworks involves the integration of a variety of advanced technologies. These range from the implementation of 5G connectivity and edge computing architectures. While several recent studies have explored individual components of this approach, there remains a need for deeper investigation, particularly into how robotic-specific requirements can be embedded into communication infrastructures. In this context, ongoing standardization efforts, such as those led by IEEE [1], are beginning to outline relevant frameworks, yet significant gaps still need to be addressed to achieve truly harmonized systems. These gaps include the lack of standardized mechanisms to dynamically allocate network resources based on robotic application needs and limited integration between robotic control systems and communication layers [2]. These aspects have started to gain attention in 5G architecture, but they are especially prominent in emerging 6G, for instance, using integrated AI agents that automate resource allocation attending to robotic needs.

This research takes a step forward by evaluating the effectiveness of current Network Slicing solutions within the specific context of industrial robotics. By focusing on the applicability and performance of these technologies in real-world collaborative scenarios, this work contributes to bridging the gap between theoretical capabilities and operational deployment. Additionally, this work presents an innovative experimental use case that combines MEC and Network Slicing, providing requirements for current standardization efforts. Unlike prior work, this paper provides a quantitative experimental validation of a MEC-based slicing solution under realistic network conditions, demonstrating its impact on safety and latency in mobile robot navigation.

The structure of this article is organized as follows. The "State of the Art" section reviews the state of the art concerning Network Slicing implementations and MEC. The "Network Slicing Evaluation" section delves into the evaluation of a current Network Slicing solution. This section also outlines the high-level approach of the experiments conducted in this work. In the "Mobile Robot Application" section slicing and MEC capabilities are applied into a robot application for obstacle avoidance. Finally, the "Conclusion" section offers a comprehensive discussion and draws the main conclusions of the study.

State of the Art

In recent decades, advancements in wireless technologies have focused on enhancing data transmission capabilities while ensuring compliance with key Quality of Service (QoS) parameters, including throughput, latency, jitter, and reliability. Regarding cellular communications, the 3rd Generation Partnership Project (3GPP) has provided specifications to increase the capabilities of the technology. Currently, the 5th Generation of Cellular Communications (5G) has been the latest mature step to provide further enhancement. 5G offers faster speed, lower latency, and greater network capacity than 4G.

Additionally, 5G introduced Network Slicing, which continues to improve the performance of the traditional enhanced mobile broadband (eMBB) services and enables new uses cases based on the specified ultra-reliable low-latency communication (URLLC) and massive machine-type communications (mMTC), supporting innovations like IoT, smart cities, autonomous vehicles, and real-time and deterministic applications.

Network Slicing offers customization, flexibility and efficiency to meet different requirements that vary depending on the vertical or use case application. The deployment of network slices requires from the use of orchestration aspects over the network. For this aim, the Network Slice Selection Function (NSSF) is used to provide proper selection of slices for a user or application depending on its requirements [3]. This network function uses different slice identifiers. Firstly, the Slicing Service Type (SST) defines the general category of the slice and is directly associated with specific types of services. Secondly, the Slicing Differentiator (SD) value is used to distinguish between multiple slices sharing the same SST, allowing for more granular service differentiation by specifying additional requirements for a given slice [4].

This 3GPP standard covers many aspects related to the methodology, configuration and performance evaluation processes of the different network slices of an infrastructure. However, commercial implementations of the standard may remain at earlier releases, while the specification is being enhanced year by year with new improvements.

Based on the 3GPP specifications, a network slice will be identified by the Network Slice Selection Assistance Information (NSSAI) value, comprised of an SST and SD values. Each NSSAI could be configured with standard values or non-standard values, since the support of all the standardized SST values is not mandatory for mobile operators. Table 1 summarizes the standardized SST values as described in the 3GPP Release 19 [5].

Once the required NSSAI session is established by requesting the service to the Access and Mobility Management Function (AMF), a Protocol Data Unit (PDU) session must be initiated, controlled by the Session Management Function (SMF). This PDU session follows one of the predefined QoS Flows, defined by the QoS model presented in the 3GPP specification [5]. This QoS model defines two types of data flows, the Guaranteed flows bit rate (GBR) and the non-guaranteed flow bit rate (Non-GBR).

To request a determined QoS Flow, a QoS Profile must be provided to the SMF, including the following QoS parameters:

- 5G QoS Identifier (5QI): a standardized scalar value mapped to a specific combination of 5G QoS performance.
- Allocation and Retention Priority (ARP): usually used for admission control in case of resource limitations.

SST	SST value	Definition
eMBB	1	Enhanced Mobile Broadband
URLLC	2	Ultra Realiable low latency Comms.
MIoT	3	Massive IoT
V2X	4	Vehicular to everything
HMTC	5	High-Performance Machine-Type Comms
HDLLC	6	High Data Rate and Low Latency Comms.

TABLE 1. Standardized SST Values.

5QI Value	Type	Example services
2	GBR	Conversational video
3		Real Time Gaming
6	Non-GBR	Video Buffered Streaming
80		Augmented reality (Low latency eMBB)
83	Delay critical GBR	Discrete Automation
88		Interactive services, motion tracking, AI/ML inference.

TABLE 2. Standardized 5QI Values.

- QoS Parameters of the PDU session such as: PDU Set Delay Budget (PSDB); PDU Set Error Rate (PSER); and PDU Set Integrated Handling Information (PSIHI).
- Guaranteed Flow Bit Rate (GFBR), Maximum Flow Bit Rate (MFBR) and Maximum Packet Loss Rate (UL and DL) for the GBR flows configured.

This QoS profiles need to be mapping to the Access Network (AN) resources, according to the Policy and Charging Control (PCC) rules, as shown in [5]. Based on the standardized 5QI, a set of 5G QoS characteristics are defined in terms of the following performance indicators:

- Resource type (Non-GBR, GBR, Delay-critical GBR).
- Priority level: used to differentiate between QoS Flows of the same UE.
- Packet Delay Budget (PDB): upper bound for the time that a packet may be delayed between the UE and UPF.
- Packet Error Rate
- Maximum Data Burst Volume: mandatory for Delay-critical resources, indicating the largest amount of data that the AN requires to serve.

Slicing configurations have been tested in different works such as [6] where a Proof-of-Concept (PoC) prototype demonstrates the flexibility of network slice management. The PoC showcases how it can provision custom slices to meet the diverse requirements based on a priority policy.

While Network Slicing is enabled to ensure that communication requirements are met, MEC provides capabilities to facilitate that processes can be executed in edge premises. MEC was adopted by ETSI and 3GPP to facilitate the orchestration of processes that must be executed in larger computational infrastructure deployed over large cellular networks. This adoption provides modifications in terms of network architecture. Based on [7], MEC platforms targeted for orchestration of computation services must be interconnected to 5G Core Network at two different levels. Firstly, an application layer that communicates with the data network using n6 interface. Secondly, a management layer that binds the Network Exposure Function (NEF) with a MEC orchestrator is defined to ensure the exposure of application and capabilities.

The combination of two different concepts, MEC and Network Slicing, provides a complete solution to offload processes on time. However, this integration, which is currently under definition, supposes a challenge in terms of network architecture. Reference [8] showcases a prototype of 6G architecture to combine MEC and Network Slicing. Following this concept, Network Slice management and MEC App slice management work together to ensure the QoS.

Integrating MEC with Network Slicing is expected to enhance both system productivity and energy efficiency, particularly relevant in robotics applications where end devices are constrained by limited computational capacity and battery autonomy. Mobile robots, for instance, require substantial processing power to execute algorithms such as Simultaneous Localization and Mapping (SLAM). Offloading these tasks to the edge not only improves the performance of SLAM but also reduces energy consumption by minimizing onboard computation. Furthermore, it enhances responsiveness to external events (e.g., obstacle avoidance), thanks to lower latency enabled by efficient communication and edge processing.

Current standardization efforts such as P1955 [1] are focused on the improvement of cellular communications architecture to facilitate the usage of 6G into further robot centered applications such as SLAM. 6G technology goes one step further, not only enhancing 5G through new and advanced mechanisms, improved modulation schemes and higher frequency bands, but also by integrating innovative solutions directly into the network infrastructure. These include, for instance, the incorporation of native AI agents to the network [9] and the application of Integrated Sensing and Communication (ISAC) [10], which enables new uses case for robotic applications.

For this aim, it is necessary to obtain requirements of robotics uses cases, in addition to measure the current gaps of commercial network solutions. Both aspects ease the path for empowering robotics with cellular communications. Therefore, following this approach, the next section compares available infrastructure for Network Slicing to identify the performance of current solutions.

Network Slicing Evaluation

Slicing profiles allow the separation of data streams with different QoS parameters. Considering a manufacturing environment with heterogenous data flows, communication from mobile robots must be prioritized due to their time-critical nature. Following standardization efforts by 3GPP and current commercial solutions on Release 17, an evaluation of Network slicing performance is provided, considering two common slicing profiles in demanding environments such as high throughput for data sensor sharing (eMMB) and low latency for control information (URLLC).

The Network Slicing solution that is analyzed is based on Amarisoft Core Network. Its development is centered on the usage of NSSAI which is transferred between the UE and the Core Network to ensure that a given UE can demand a PDU session within a specific slice. However, there is no current implementation of slicing at PHY/MAC level to assign physical radio resources to each slice. Therefore, Network Slicing is evaluated considering a priority policy during package transmission, instead of allocating radio resources per slice. However, this approach may face performance degradation under heavy traffic loads or high device density, as there is no resource isolation at the PHY/MAC level, which may compromise latency guarantees.

An experimental deployment based on this solution has been executed to obtain insights about the performance considering two slices (eMBB and URLLC). For this aim, an Amarisoft Callbox Mini is used to set up a 5G network in n40 band. This device facilitates deployments by providing an all-in-one solution that integrates Core Network and Radio Access Network. The radio setup makes usage of 20MHz bandwidth (allocated for 5G private network in Spain). In addition, the network is configured to increase the uplink (UL) throughput by using more radio resources than for downlink (DL). This aspect is essential in industry applications where end devices must share data with MEC servers.

Additionally, a couple of radio amplifiers are attached to the Amarisoft device to ensure the quality of the radio interface with an extended coverage, which will be more relevant in the robotic PoC. Table 3 summarizes the testbed configuration:

Parameter	Detail
Device	Amarisoft Callbox Mini
Frequency	2370 – 2390 MHz
Layers	2x2 MIMO
Slot configuration	5ms period, 1 slot DL, 8 slots UL
End devices	2x RM500Q
Slices	eMMB (SST: 1) URLLC (SST: 2)

TABLE 3. Network Deployment Setup.

The first evaluation with the solution tests the overall performance of the network considering that each slice is used individually at different moments. Fig. 1. shows that both slices provide similar values in terms of throughput, achieving up to 70Mbps UL and 15Mbps DL. These values are satisfactory considering that UL streaming is essential for real applications based on process offloading [7]. The second test targets the performance analysis when both slices transmit with equal priority at the same time. The results showcase that both networks compete for radio resources. The last slicing test is performed providing a higher priority level to the eMBB slice. As it is depicted, once the eMBB slice requires more performance, URLLC throughput drops, ensuring QoS for eMMB slice.

These tests can be compared to other implementations such as [12], where an Open-RAN (ORAN) Network Slicing solution based on Open Air Interface Core Network is depicted. In this work, radio resources are allocated at physical layer in function of the slicing configuration. Therefore, each slice has a limited radio capacity, providing boundaries in terms of performance. Despite this approach offers a control limitation over the transmission of different slices, it can be less efficient in scenarios where the number of devices and throughput required varies constantly.

The evaluated Network Slicing solution has provided suitable behavior for applications where the transmission through a specific slice must be ensured. The following section provides an example of robot centered application considering this scope.

Mobile Robot Application

Autonomous Mobile Robots (AMR) are becoming increasingly prevalent in various manufacturing applications, such as warehouse logistics, where these devices need to deliver items to different locations. Other scenarios consider the usage of mobile manipulators where arm robots are mounted over AMRs. These applications provide challenges in terms of Human Robot Interaction (HRI) as robots normally work in human shared environments. Most of the issues are related to safety when AMRs need to move between different locations through these environments. Therefore, AMRs need to apply SLAM techniques to detect obstacles using multiple sensors.

Currently, sensing capabilities are based on different devices such as RGB cameras, LiDAR sensors or depth cameras. In some cases, the analysis of sensor data requires large computational efforts to extract key information such as obstacle detection. For example, the deconstruction of point clouds using combined RGB and depth streams are demanding processes due to vectorial calculations of extensive data that must be executed.

Following this approach, an experimental use case is developed to demonstrate the capabilities of combined MEC and Network Slicing. For this aim, an AMR is equipped with a combined RGB and depth sensor. With this device, the robot must detect an obstacle, in addition to generating a point cloud which is normally utilized for mapping. The robot starts the application by moving forward until the obstacle is detected. For this reason, a cone, acting as an obstacle, is placed two meters ahead of the robot to trigger the stop mechanism.

The processing of sensor information is executed using Robot Operating System (ROS) nodes written with Python in the Jetson Nano mounted in the robot. This software acquires data from the camera (Intel Realsense D455) achieving both depth and RGB images. Lately, a ROS node

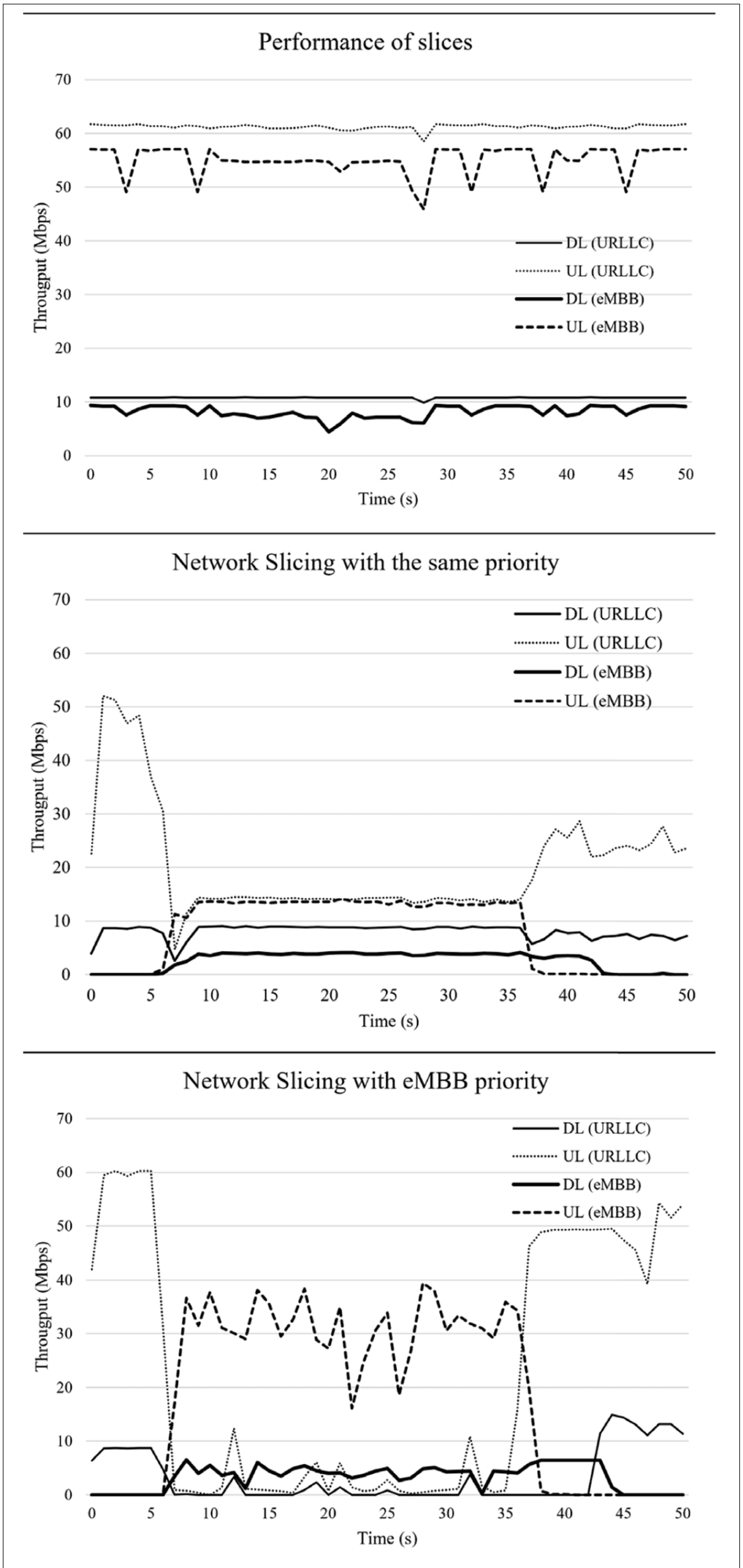

FIGURE 1. Evaluation results of Network Slicing.

calculates spatial points based on both images which are captured at 1280x720p. Once the point cloud is obtained, a threshold is applied to detect if there is any object close to the robot. If any obstacle is detected, the ROS node stops the AMR. In addition, to prevent operation during possible connection losses, a failsafe operation assumes to stop the robot if the communication with the remote ROS node is interrupted.

This process is computationally demanding due to the application of vector calculations and the amount of data to process. More specifically, the robot needs around 900 milliseconds to process each frame if the execution is performed locally in the robot. This is insufficient in dynamic environments where obstacles can appear eventually.

Therefore, the combination of MEC and Network Slicing can play a key role in this scenario to improve the performance of the use case by reducing computing time to detect obstacles and ensuring communications to control the robot. With the objective of adopting a combined MEC slicing approach, some modifications are provided and depicted in Fig. 2.

Firstly, a 5G UE is mounted in the AMR to transmit data from the camera using the 5G SA network from the previous section. More specifically, RGB and depth information are published independently using two ROS topics based on Data Distribution Service (DDS) protocol. This streaming supposes uplink network traffic (depicted using blue arrows in Fig. 2). Secondly, a ROS node in the MEC platform receives both topics to calculate the point cloud and detect if there is any obstacle by applying a threshold filter. In case an obstacle is detected, the ROS node in the MEC stops the robot by using ROS topic /*cmd_vel* (downlink network traffic represented by green arrows in Fig. 2). For the application, a rack computer with 16 cores at 2.1GHz and 32GB RAM is used to emulate the MEC platform.

Despite the computational capacity in the edge, the feasibility of this application is dependent on the performance of the network. If sensor data arrives with large delay due to network's bad capacity, the robot will not avoid the obstacle. Therefore, Network Slicing is necessary to ensure that data is transmitted on time, mainly if other devices targeted for non-critical applications are communicating simultaneously.

With the objective of analyzing the importance of Network Slicing into this case, prioritization tests from the "Network Slicing Evaluation" section are replicated. Following this approach, the AMR is assigned to the eMBB slice (UE 1 in Fig. 2) and a separate UE connected to a Raspberry Pi 4B is attached to a URLLC slice (UE 2 in Fig. 2). Based on previous slicing tests from the "Network Slicing Evaluation" section, UE 2 is constantly transmitting the maximum quantity of data to ensure that the 5G radio interface is saturated, when UE 1 transmits data from the robot sensor. For this aim, iperf tools are used to generate both downlink and uplink UDP traffic through URLLC slice. Table 4 permits to showcase the main differences in terms of use case performance, when the point cloud and obstacle avoidance is executed locally, or offloading data using 5G with and without slicing priority.

Based on the results, executing the application using MEC combined with Network Slicing and priority levels leads to a 37.5% reduction in processing time compared to the local

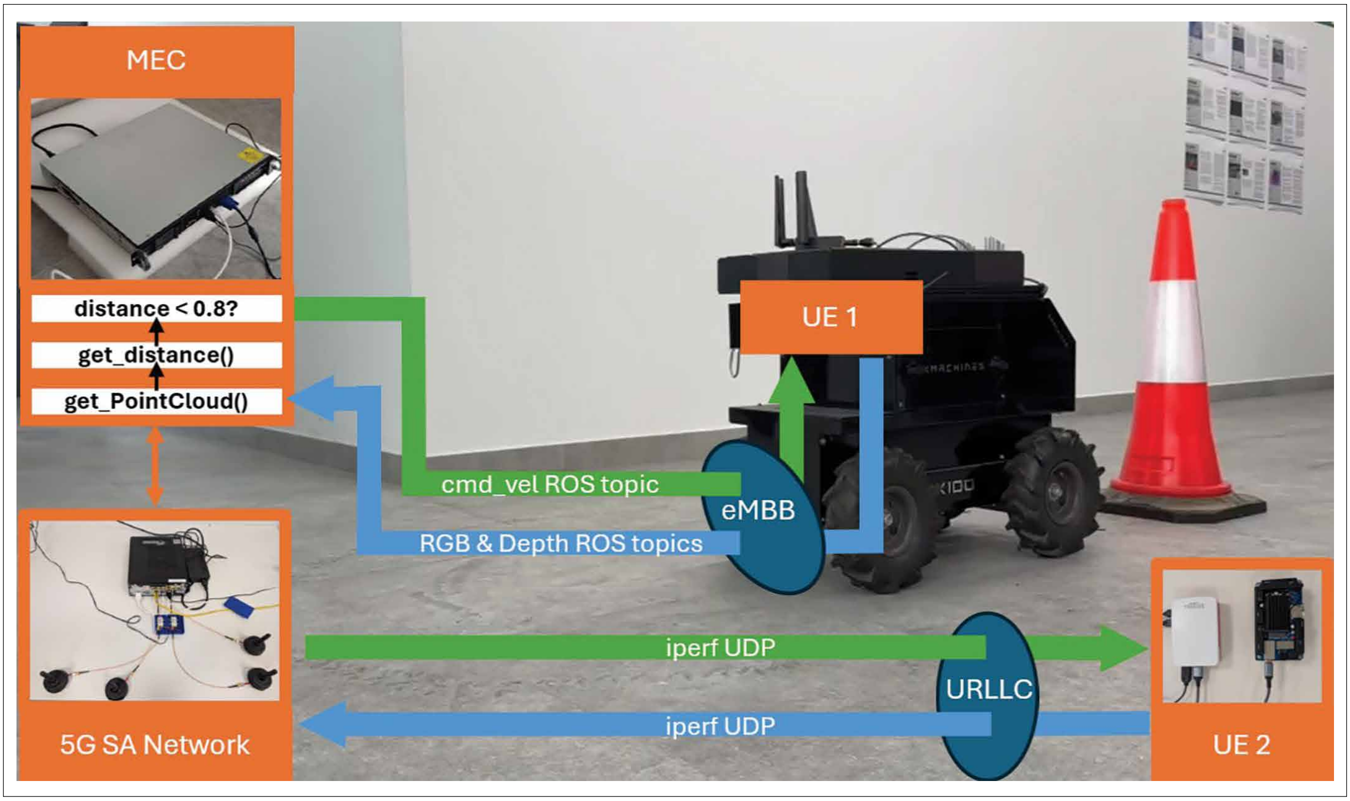

FIGURE 2. Network diagram of the application.

Scenario	Avg. Point Cloud Processing time (s)	Max. velocity (m/s)
Local	0.8	0.2
Slicing without priority	-	-
Slicing with eMMB priority	0.5	0.3

TABLE 4. Use Case Results.

processing approach. Moreover, the use of slicing priority enables a higher maximum velocity, demonstrating that offloading sensor data processing over 5G connectivity allows the robot to move faster while still maintaining effective obstacle avoidance capabilities. In contrast, when slicing priority is not applied, the robot fails to avoid collisions -even though processing time is reduced- due to delayed transmission of sensor and control data caused by network congestion. This highlights the importance of prioritization mechanisms in maintaining both low latency and reliable performance.

Conclusion

This work has presented an evaluation of current slicing capabilities, focusing on two distinct approaches to implementing Network Slicing. The solution tested in a laboratory environment provides priority-based management, offering suitable performance to ensure network capacity for end devices with stringent requirements. This approach is particularly valuable in scenarios where differentiating data streams is more critical than planning and allocating radio resources. Applications within this scope can be found in manufacturing vertical where multiple devices such as shopfloor sensors and PLCs need to transmit data. However, mobile robots pose an even greater challenge due to their mobility across different areas, such as in logistics applications. As these robots move through the manufacturing environment, the number of devices connected to a given radio unit may vary over time. Therefore, to maintain a consistent network performance, it is essential for slicing policies to incorporate priority levels.

Following the evaluation of different Network Slicing configurations in terms of throughput, these setups were applied into a robot-based obstacle avoidance application. The results demonstrate that applying slicing with prioritization significantly improves the robot's reaction time by enabling the offloading of sensor data processing. This confirms that the integration of MEC and Network Slicing can enhance navigation capabilities of AMRs by reducing application latency and ensuring reliable communications.

Nevertheless, further research is needed to explore the architectural-level compatibility between robotics and communication technologies such as MEC and Network Slicing. The integration of these concepts presents several challenges, particularly when dealing with data transmission based on ROS topics. These topics may need to be accessible from different edge locations within MEC infrastructure, which can complicate system design and affect performance. A key limitation of this approach is its dependency on stable 5G connectivity. In the event of connection loss or severe congestion, safety-critical functions such as obstacle avoidance could be compromised. Future work should explore hybrid mechanisms that combine local fallback processing with MEC-based offloading to ensure operational safety.

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Biographies

Andrés Meseguer Valenzuela (Member, IEEE) (ameseguer@iti.es) was born in Sueca, Valencia, Spain, in 1996. He received the B.S. degree in industrial electronics engineering and automation and the M.S. degree in computer engineering and robotics from the Universitat Politècnica de Valencia in 2018 and 2019, respectively, where he is currently pursuing the Ph.D. degree in robotics, automation, and computer engineering. He is currently a Research and Development Engineer with the Advanced Communication and Industrial Informatics Group, Instituto Tecnológico de Informática (ITI), Valencia. He is the author of different research publications related to mobile robots and 5G communications applied to robotic scenarios.

Jose Vera Pérez was born in Lorca, Murcia, Spain, in 1993. He received the B.S. and M.S. degrees in telecommunications engineering from the Universitat Politècnica de València (UPV), Spain, in 2015 and 2017, and the Ph.D. degree in telecommunication engineering in 2021, with a focus on optimization mechanisms for industrial wireless sensor networks. He is currently a Research and Development Engineer with the Advanced Communication and Industrial Informatics Group, Instituto Tecnológico de Informática (ITI), Valencia. He is the author of several recent research papers related to wireless sensor networks for industrial communications. His research interests include private 5G networks, low-power wireless communications, Industry 4.0, industrial automation, and cybersecurity.

Javier Silvestre Blanes (Member, IEEE) was born in Alcoy, Valencia, Spain, in 1965. He received the M.S. and Ph.D. degrees in computer architecture in 1999 and 2003, respectively. In 1999, he joined the Department of Computer Architecture, Universitat Politècnica of València, as a part-time Associate Lecturer, where he was promoted to an Assistant Lecturer in 2004, and has been an Associate Professor since 2010. In 2009, he joined the Instituto Tecnológico de Informática (ITI), where his research and development area (industrial computing, communications, and image processing), participating in research and development projects both individually and in cooperation with other entities. He has more than 34 papers in international peer-reviewed conferences, 28 articles published in journals of impact JCR, and eight book chapters, related to the sector of industrial communications, heterogeneous networks, multimedia networks, image processing, and computer vision. He has carried out research stays abroad, with the University of Aveiro, Portugal, and Anglia Ruskin University, Cambridge, U.K. He is a member of the Industrial Electronics Society (IES), belonging to the IEEE, where he also belongs to the Sub-Committee FA10 Computer Vision and Human–Machine Interaction in Industrial and Factory Automation, belonging to the IES-IEEE Factory Automation Committee. Since 2005, he has been participated as a member of the organizing committee or a member of the program committee of numerous international conferences of the IEEE Industrial Electronics Society.

Víctor Sempere Payá (Member, IEEE) received the first degree in industrial electronics, the second degree in computer engineering, and the Ph.D. degree in telecommunications engineering from the Universitat Politècnica de València (UPV), Valencia, Spain, in 1987, 1993, and 1998, respectively. He is currently an Associate Professor with the Department of Communications, UPV, where he teaches industrial communications and public access networks. He is also the Director of the Advanced Communications and Industrial Informatics Group, Instituto Tecnológico de Informática (ITI). Since 1996, he has authored or co-authored more than 60 technical papers in journals and international conferences. He has managed more than 50 research and technological projects. His current research interests include factory communications, real-time communications, and quality of service (QoS) in networks. He has served as a program committee member for several conferences in the area of factory communications.