D3.3

Evaluation of operation optimization

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Authors	Pavlos Basaras (ICCS), Michael Brazitikos (VFI), Stavros Tsagalas (PCT), Athanasios Koumparos (VFI), Janez Sterle (ININ), Luka Koršič (ININ), Rudolf Susnik (ININ), Mirnik Jurij (Luka Koper), Budisan Alexandru (CONTI), Soster Dejan (Telekom Slovenia), Andoni Cortes Vidal (VICOMTECH), Laura Rabadan Ortega (VICOMTECH), Willenbrock Ralf (T-SYSTEMS), Grigutsch Ralf (T-SYSTEMS)
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Authorised by (Technical Coordinator)	Eusebiu Catana	ERTICO	28/11/2023
Authorised by (Quality Manager)	Mandimby RANAIVO R	AKKODIS	29/11/2023
Submitted by (Project Coordinator)	Eusebiu Catana	ERTICO	30/11/2023

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List of abbreviations and acronyms

Abbreviation	Meaning
3GPP	3rd Generation Partnership Project
4G/5G	4th/5th Generation (of cellular networks)
ADAS	Advanced Driver Assistance System
ADR	Accord européen relatif au transport international des marchandises Dangereuses par Route (European agreement concerning the international carriage of dangerous goods by road)
AI	Artificial Intelligence
API	Application Programming Interface
AR	Augmented Reality
ATP	Automated Tuck Platooning
BSS	Business Support System
CAD	Connected Automated Driving
CAM	Connected Automated Mobility
CAN	Controller Area Network (vehicular bus standard)
CCTV	Closed Circuit TeleVision
CMS	Container Management System
CNF	Cloud Native Functions
E2E	End-to-End
eFCD	Extended Floating Car Data
eMBB	Enhanced Mobile BroadBand
ETSI	European Telecommunications Standards Institute
FCD	Floating Car Data
FMS	Fleet Management System (vehicular communication standard)
FTED	Floating Truck and Emission Data
GHG	GreenHouse Gas
GLOSA	Green Light Optimal Speed Advisory
GNSS	Global Navigation Satellite System
GPRS	General Packet Radio Service
GPS	Global Positioning System
GPU	Graphics Processing Unit
HMI	Human-Machine Interface
IaaS	Infrastructure-as-a-Service
IoT	Internet of Things
IP	Internet Protocol
ISG	Industry Standardization Group
ITS	Intelligent Transportation Systems
KPI	Key Performance Indicator
LCM	Life Cycle Management

LCMM	Low Carbon Mobility Management
LL	Living Lab
LSP	Logistics Service Provider
LTE	Long-Term Evolution (4th generation of cellular networks)
M2M	Machine-to-Machine
MANO	MAnagement and Network Orchestration
MEC	Multi-access Edge Computing
MEP	MEC Platform
ML	Machine Learning
MNO	Mobile Network Operator
mMTC	Massive Machine-Type Communications
NFV	Network Functions Virtualization
NFVI	Network Functions Virtualization Infrastructure
NR	New Radio (5th generation of cellular networks)
NSA	Non-Standalone (5G network operation)
OBU	On-Board Unit
OEM	Original Equipment Manufacturer (often referred to car-makers)
OSS	Operations Support System
POI	Point of Interest
QoS	Quality of Service
RSU	Road-Side Unit
SA	Standalone (5G network operation)
SDK	Software Development Kit
SLA	Service Level Agreement
SME	Small-Medium Enterprise
TLF	Traffic Light Forecast
TMS	Traffic Management System
TOS	Terminal Operating System
UAV	Unmanned Aerial Vehicle
UC	Use Case
UHD	Ultra-High Definition (images)
URLLC	Ultra-Reliable Low Latency Communications
UWB	Ultra-Wide Band
V2X	Vehicle-to-anything (any ITS-enabled vehicle or infrastructure)
VIM	Virtual Infrastructure Manager
VM	Virtual Machine
VNF	Virtual Network Functions
VPN	Virtual Private Network
VR	Virtual Reality

VRU	Vulnerable Road Users
VSaaS	Video Surveillance-as-a-Service
WLAN	Wireless Local Area Network
WLTP	Worldwide-harmonized Light vehicles Test Procedure
WP	Work Package

EXECUTIVE SUMMARY

The deliverable D3.3 “Evaluation of operation optimization” reports on the results of the trials performed in the three Living Labs of the 5G-LOGINNOV project, the evaluation of the use cases as well as the evaluation of the 5G technology exploited across the three pilots in various 5G facilities (Public 5G-NSA, Private 5G-NSA and Private 5G-SA).

Particularly, the current report takes input from D1.4, D2.3, D3.1 and D3.2, and reports on the trials performed, the assessment of the performance of 5G technology, the assessment of application KPIs (Quantitative and Qualitative) and their impact in the logistics domain and the Port industry, within and outside a Port’s premises. Towards this direction, the methodology exploited per pilot/experiment/use case is briefly described and the relevant KPI metrics along with the collected data are presented accordingly.

Special attention has been dedicated to cross-pilot activities to ensure that the developed technology, technology enablers, and use cases are not isolated innovations exclusive to a single logistics Living Lab (LL). Instead, they are designed for seamless transferability to other LLs and European ports. This particular aspect was also among the focal points of interest at the final demonstration event of the 5G-LOGINNOV project that took place in LL Koper (Koper municipality, Slovenia) on the 7th of November, where the Project partners (among other activities) showcased how software and technologies exploited and developed at one site can be transferred to another, fostering potential interoperability of aforesaid services among many EU ports, logistics actors and the broader stakeholder community (c.f. Section 5).

In summary, the conclusion of the project's outcomes is presented alongside the well-defined objectives of the three pilots. The presentation also offers insights into the technology enablers and barriers, as well as the challenges encountered across different domains within the multi-stakeholder community of the 5G-LOGINNOV project.

1 INTRODUCTION

5G-LOGINNOV’s vision focused on enhancing/improving freight and traffic operations at Ports and Logistics hubs via innovative concepts, applications and devices supported by 5G technology, the IoT, AI-enabled data analytics, next generation traffic management systems, Cooperative, Connected and Automated Mobility (CCAM). The project’s scope with focus on large scale trials and pilots has been verified in real operating conditions in three Living Lab (LL) environments, namely, Athens (Greece), Hamburg (Germany) and Koper (Slovenia). While Athens and Koper LLs are focused on applications tailored to 5G and Smart Logistics within the Port premises, in Hamburg, the focus resides in hinterland, i.e., the interconnection of the Port with the road transport network and road infrastructure. In more detail, following the compute continuum paradigm various AI-service placement options have been considered (extreme-edge, edge and cloud) given the diverse set of requirements of the developed use cases (e.g., latency sensitive, or throughput intensive), creating a 5G ecosystem of cloud native interconnected Port assets (5G Trucks, 5G cranes, 5G Drones, 5G IoT). Details on the specific use cases and cross-pilot activities are thoroughly discussed in the remaining of the draft, promoting among others the *interoperability of the developed use cases* across the pilots of 5G-LOGINNOV ports.

The main objectives of 5G-LOGINNOV can be summarized as follows; **(i)** the support of the “Green” Port Industry vision by reducing the hub’s operation emissions. Particularly, a 5G based Green Light Optimum Speed Advisory (GLOSA) system has been developed coupled with precise positioning technology and Mutli-access edge computing (MEC), for combined coordination of vehicle platoon movements and traffic light infrastructure; **(ii)** enhance safety and security operations by developing a 5G&AI enabled collision warning system between trucks and personnel, as well as mission-critical AI-assisted drone surveillance; **(iii)** improve the efficiency of logistics operations via 5G&AI enabled video analytics services related to port control, logistics and remote automation.

The portfolio of 5G LOGINNOV use cases have been evaluated in various network deployment options, i.e., 5G-NSA private network (in Athens LL), public 5G-NSA network (Koper and Hamburg LLs), as well as private 5G SA network (Koper LL).

Finally, the project fostered various market opportunities building on the ecosystem of 5G technologies in the logistics domain, thus being a pillar of economic development and business innovation and promoting local innovative high-tech SME and Start-Ups via the published/tendered Open-calls. Particularly, 5 SMEs have been accepted to the 5G-LOGINNOV consortium, to develop their solution on the respective LLs and are summarized below:

- auTonomous dRones for marITime OperatioNs (**TRITON**) – Hellenic Drones, Koper LL.
- Real timE drowSiness detectiON, AlerTing and rEporting (**RESONATE**) – Libra AI, Athens LL
- 5G-Loginnov-4-Amazon (**5G4A**) – eShuttle, Hamburg LL
- TAXi-AD Data (**TAADD**) – uze! Mobility GmbH, Hamburg LL
- Intelligent Traffic Guidance System (**ITGS**) – Roads.AI, Hamburg LL

Detailed evaluation of the project’s results for all pilot sites are described in the next chapters.

1.1 Purpose of the deliverable

The present deliverable (D3.3) reports on the innovations that occurred in the project's three LLs, the outcomes of the use cases and trials that were conducted for all pilot sites to enhance the identified daily port operations/needs, the evaluation of the use cases in relation to the project's goals, and the identification of any deviations from the planned activities and objectives of 5G-LOGINNOV.

1.2 Intended audience

The dissemination level of D3.3 is a ‘public’ (PU) deliverable and available to members of the consortium, the Commission Services and those external to the project. It is specifically aimed at providing the 5G-LOGINNOV consortium members with an extensive set of guidelines and tools that contribute to the project’s promotion and diffusion, as well as to provide to any interested party (e.g., Telecommunications Industry, Road/Port/Terminal/Logistics/Maritime Operators/Authorities, SMEs, Research Institutes and more) with the lessons learned and a deep view on the technology enablers and limitations, as well as the challenges faced across the various domains and collaborating parties, throughout the completion of this high TRL project results, with focus on large scale trials and pilots verified in real operating conditions in the three LL environments of the 5G-LOGINNOV project.

2 EVALUATION IN ATHENS LIVING LAB

As part of the 5G-LOGINNOV project, the Athens LL developed a set of use cases and platforms which communicate over the private 5G NSA network with different types of end devices (5G-Trucks, 5G-Cranes, 5G-IoT, 5G UEs). 5G technology enables the use case innovations exploiting the eMBB service and low latency transmissions of 5G, including NFV-MANO based applications and service orchestration, private cloud computing and far-edge computing innovative solutions, computer vision and AI-enabled video analytics. In brief, the use cases which are thoroughly evaluated in the following sections, are focused to 5G&AI enabled services tailored to safety/security applications as well as for improving the efficiency of daily port operations (reduce costs, improve the utilization of human resources and automate logistics services). Figure 1 depicts a high-level overview of the deployed private 5G-NSA network, the 5G-IoT platform supported by PCT's private cloud infrastructure and 5G-IoT devices within the port premises for supporting the project's use cases. Briefly, the NSA core (Release 15) is shown below with various pools of MME, SGW-U and PGW-U core elements for redundancy and load balancing, as well as the private cloud infrastructure and 5G-IoT nodes deployed within the port premises, for the support of the various 5G&AI-enabled video analytics services.

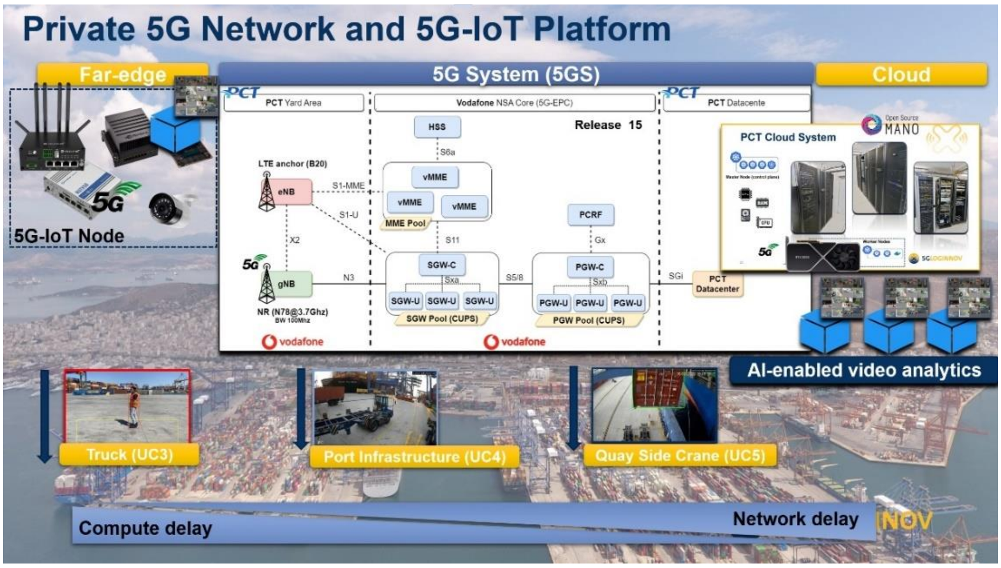


Figure 1: LL Athens - Private 5G network, Private Cloud and extreme-edge deployments for 5G-IoT nodes[a]

2.1 5G Network Evaluation

2.1.1 Network Deployment

The following Figures depict the deployed 5G radio access network (based on the Huawei RRU 5639w) at Piraeus Port and mapping in the port area. Vodafone's Core network operates outside the port premises, at Vodafone's datacentre, directly connected via fiber with the radio units installed in the Port. Particularly PCT's private 5G NSA network operates in band n78 at 3.7GHz with 100 MHz bandwidth, providing 5G connectivity to a subset of the port Piers (see following Figures), whereas the remaining port areas are fully covered via 4G. For more details regarding PCT's 5G network, please refer to [1]. Extensive evaluation of the network KPIs follow.

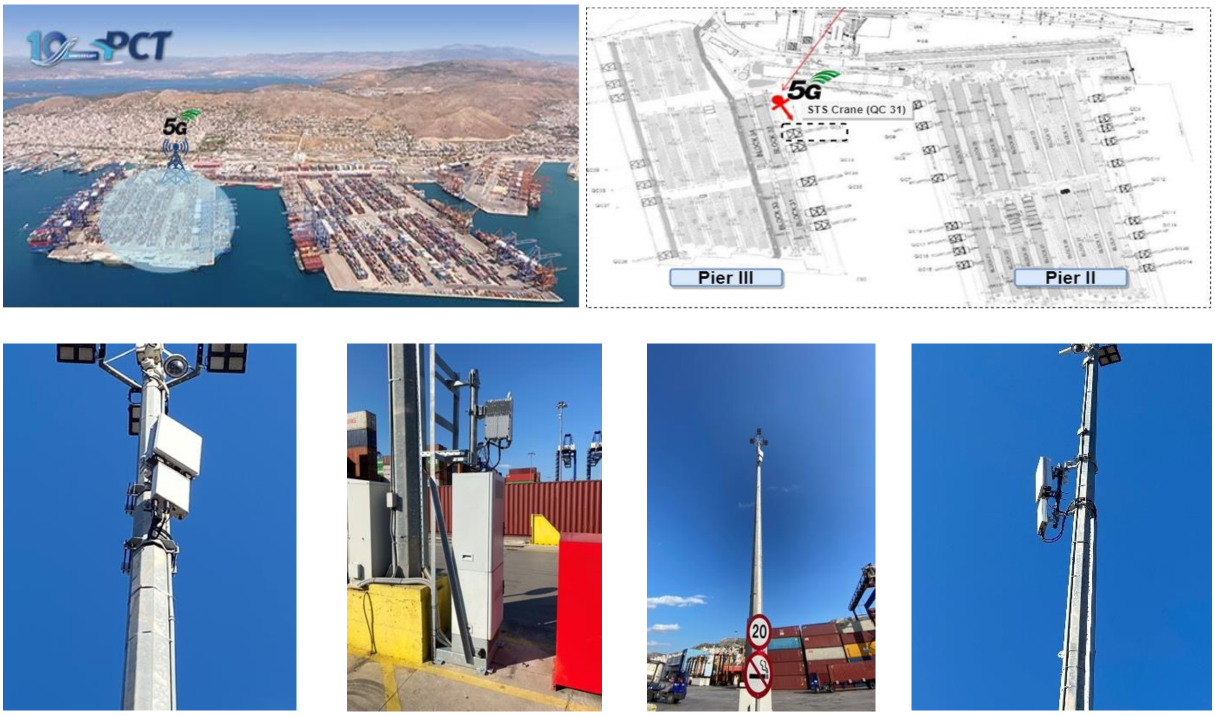


Figure 1b : LL Athens - deployed 5G radio access network at Piraeus Port and mapping in the port area

2.1.2 List of Key Performance Indicators

Table *1* describes the 5G network KPIs as defined in [2] (D1.4).

KPI	KPI ID	Target Value	Measured Value
Area Traffic Capacity	A-KPI19	Downlink 1500 Mbps Uplink 120 Mbps	**Achieved***
Bandwidth	A-KPI20	Specified by the max capacity of the RRU installed at PCT	**Achieved**
Connection Density	A-KPI21	Typically, up to 100 live sharing traffic - 1000 max attached	**Achieved***
Reliability	A-KPI22	99.9 (average)	**Achieved**
End-to-End Latency	A-KPI23	<20ms (average)	**Achieved**
One-way Latency	A-KPI24	<10ms (average)	**Achieved**

Table 1: LL Athens – KPIs list for the private 5G Network

The total capacity of the 5G cell (A-KPI19) installed in PCT is shown in Figure 2, provided by Vodafone, and is measured at about 1.5Gbps i.e., the total load the gNB can handle, while detailed evaluation of the remote radio unit installed is explained in the following sections. Note that the backhaul capacity interconnecting the BBU and the datacentre of PCT where our management platform and cloud infrastructure is deployed is limited by 1G fiber optic network, hence specifying the bottleneck of total network throughput for our experimentation.

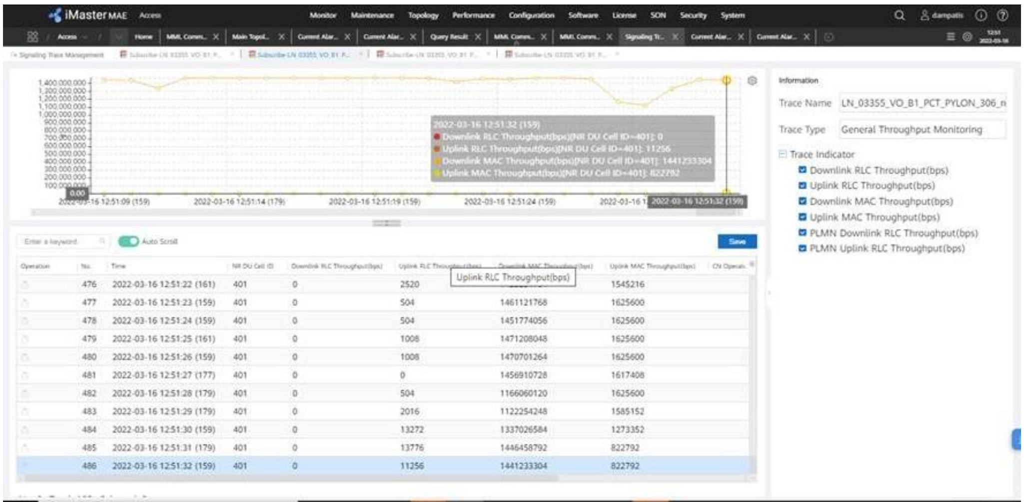


Figure 2: LL Athens - Total capacity of the 5G cell at PCT – (A-KPI19)

Regarding A-KPI19 (Area Traffic Capacity) we exploit a single remote radio unit (RRU) installed in the PCT, i.e., 1x RRU (Huawei AAU5639W 5G) with total traffic throughput served at the geographic area depicted in Figure 5, and evaluated in detail in the next sections based on A-KPI20 (Bandwidth) measurements.

With respect to A-KPI21 (Connection Density: total number of connected and/or accessible devices per unit area) we exploit a single RRU for the 5GLOGINNOV project to support all connected devices, hence based on the specifications of the device this is measured as 100 devices sharing traffic (fair scheduler) and 1000 (max) attached, as instructed by the provider.

2.1.3 Methodology and Measurement Tools

To facilitate the evaluation of the network KPIs we exploit a dual approach. We first exploit the 5G KPI monitoring software suite (i.e., qMON), provided by ININ. Detailed view on the test protocols exemplify how qMON is used, and is presented in [3]. Briefly, we exploit Samsung Galaxy S22 5G phone with qMON software (Figure *3*) and a backend system for data collection.

Figure 3: LL Athens - 5G KPIs monitoring system provided by ININ

Particularly, the qMON agent installed on the phone communicates with two virtual machines at the backend system of PCT. The VMs include the database system, control plane functionalities and visualization tools (Grafana). Through qMON control agent we create work orders (see Figure *4*), which basically define *continuous* experiments for latency (ping) and throughput (iperf3 downlink/uplink) measurements (A-KPI20 and A-KPI23).

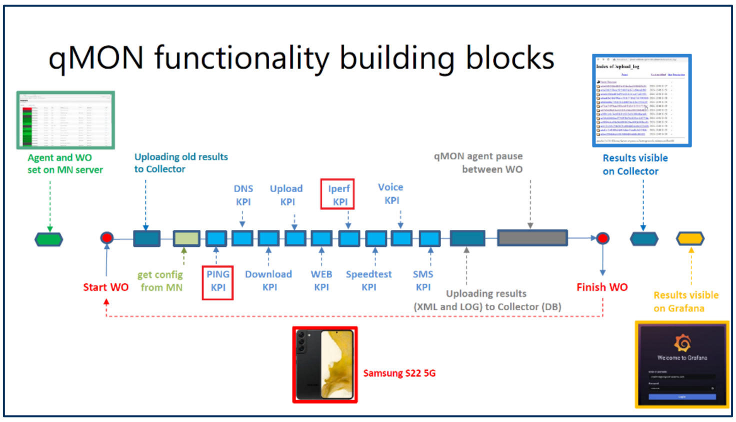


Figure 4: LL Athens - 5G KPIs monitoring system work orders provided by ININ

Via qMON we conducted several drive tests, where the 5G phone was inside a truck moving along the Port Piers, in order to establish a detailed map of network KPIs for supporting the 5G LOGINNOV use cases. Additionally, stationary tests where the phone was positioned at fixed locations within the Port premises were conducted. The following sections thoroughly present the accumulated results.

Finally, we perform also extensive numerical evaluation for the network KPIs via the 5G-IoT nodes deployed at several locations (crane, truck, pillar) within the Port area, which compose the 5G-IoT system that hosts the cloud native AI services tailored to logistics and safety applications. The tests are conducted with legacy iperf3 and ping tools (not via qMON) from the 5G-IoT nodes.

2.1.4 Results

2.1.4.1 5G Drive Test Evaluation

Figure 5 depicts the 5G drive test conducted within the Port of Piraeus in Piers II and III. The dots represent latency and throughput tests (downlink and uplink) as we drive within the Port premises. Relevant KPIs are A-KPI20 and A-KPI23. We conducted multiple trips following the routes depicted in Figure 5 where the green dots represent 5G connection and the blue ones correspond to LTE connectivity. The area of interest for the Athens LL experimentation and measurements is focused around the area with 5G connectivity (i.e., green dots) for all use cases.

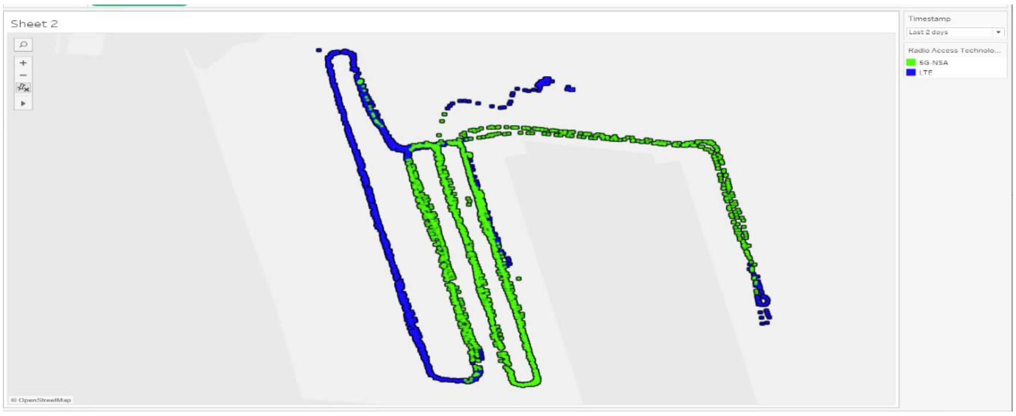


Figure 5: LL Athens - 5G drive test routes at Piers II and III, showcasing 5G and 4G coverage

Figure 6, Figure 7 and Figure 8 showcase the various measurements for downlink and uplink tests. We observe about 450Mbps in downlink and about 92Mbps in uplink for the mobile drive continuous monitoring tests. Figure 8 also depicts the changes between 4G and 5G. The drops in the observed data rate for uplink and downlink measurements are the interruptions of the experiments due to handovers to the 4G network, and then re-establishment of the 5G session.

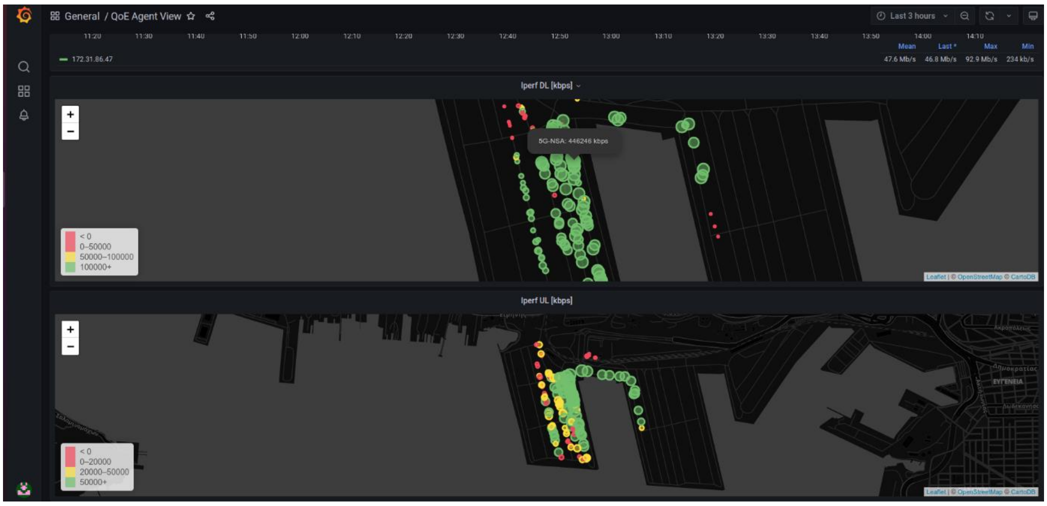


Figure 6: LL Athens - 5G drive test downlink measurements – (A-KPI20)

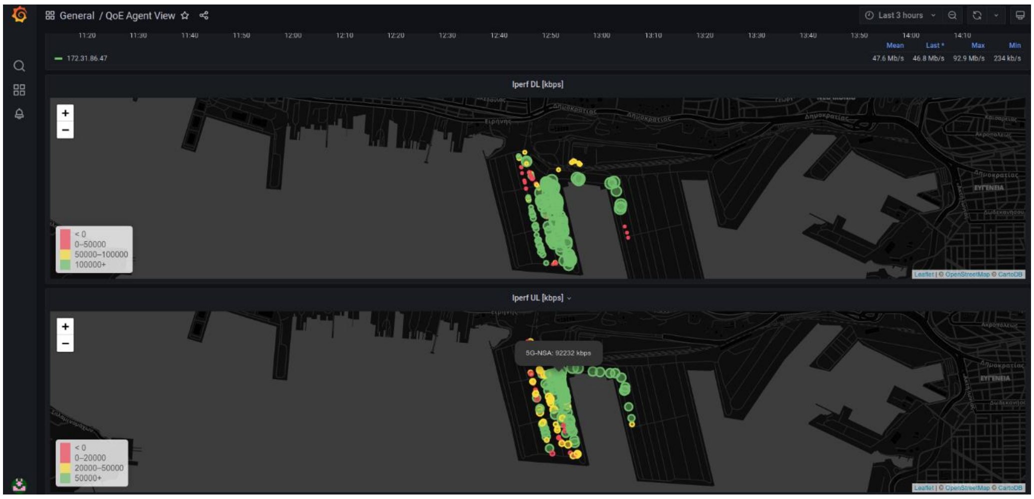


Figure 7: LL Athens - 5G drive test uplink measurements – (A-KPI20)

Figure 8: LL Athens - 5G drive test downlink and uplink measurements in 1.5 hours driving – (A-KPI20)

Next in Figure 9 we present the results from the latency (ping) measurements. The initially illustrated increased values are 4G measurements, before entering the Pier with 5G connectivity. As already noted since the software stack from ININ (qMON) is installed behind several firewalls at PCT's datacentre, we observe a slight increase in the latency values. For instance, we observe an average latency close to 20 ms, with minimum and maximum values around 18 and 40ms, respectively. In Section 2.1.4.2 we illustrate the relevant latency plots at the 5G-IoT nodes, not bound by the same firewall limitation.

Figure 9: LL Athens - 5G drive test latency (ping) measurements – (A-KPI23)

Figure 10 depicts the 5G (@100Mhz) and 4G (@40Mhz) channel bandwidth utilization illustrating the handover occurrence during the drive test. Evidently, we use 5G data plane carriers only, i.e., 4G channel carries only control plane information when the UE is connected to the gNB. Finally, Figure 11 encapsulates radio signal parameters (RSRP, RSRQ, SINR and RSSI) during the drive tests.

Figure 10: LL Athens - 5G drive test showcasing 5G and 4G channel bandwidth utilization

Figure 11: LL Athens - 5G drive test radio signal measurements (RSSI, SINR, RSRP, RSRQ)

2.1.4.2 5G IoT System Evaluation

In this section we illustrate PCT's private 5G network capabilities for supporting the 5G-LOGINNOV use cases on the 5G-IoT system which corresponds to stationary IoT nodes mounted on quay side crane (QC) 31 and Pillar within the Port terminal (c.f. Sections 2.3 and 2.4). We first evaluate the 5G capabilities from the 5G-IoT nodes with legacy iperf3 and ping tools (relevant for A-KPI20 and A-KPI23).

Via this approach we also thoroughly benchmark the performance of the 5G IoT nodes and 5G modems (i.e., Robustel R5020 5G IoT Router and Teltonika's Industrial IoT router RUTX50) exploited by the use cases. As this system is not bound by additional firewall rules (as in the case of qMON), we also showcase the difference e.g., in latency measurements compared to qMON. Additionally, qMON is also used as part of this set of experiments where we place the Samsung Galaxy S22 phone in a fixed location with minor mobility within Pier III, to increase the traffic load on the network.

Particularly, the x-axis samples in Figure 12, Figure 13 and Figure 14 are average values (also showing min, max and median) for 10 minutes of continuous tests. In total from s1 to s12 we illustrate continuous measurements for 120 minutes of continuous network traffic. As illustrated in Figure 12, the average latency is about 16ms (in contrast to the 20ms average latency observed though qMON due the intermediate firewalls). For A-KPI24 (one-way latency) we refer to this KPI as half-RTT and can be calculated from Figure 12, on average, about 8ms. Similarly for the throughput measurements (Figure 13 and Figure 14) we observe maximum values of about 540Mbps in downlink and around 135 in uplink, whereas the average respective values are close to 440 and 120Mbps. In the following sections (2.2, 2.3 and 2.4) we will also showcase the data rate incurred by the 4K streams transmitted from trucks, cranes, and pillar nodes.

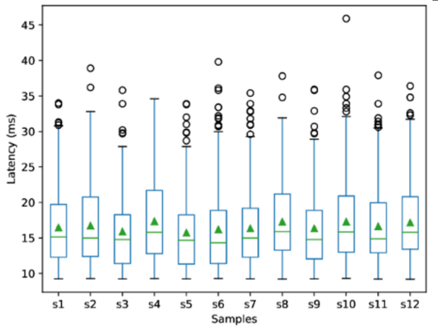


Figure 12: LL Athens - 5G IoT test, latency (ping) measurements – (A-KPI23)

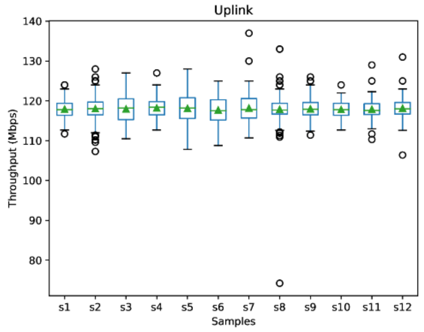


Figure 13: LL Athens - 5G IoT test, uplink measurements – (A-KPI20)

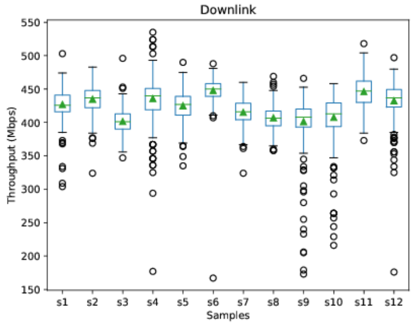


Figure 14: LL Athens - 5G IoT test, downlink measurements – (A-KPI20)

Table 2: LL Athens - Latency and Throughput tests – (A-KPI20 and A-KPI23)

Regarding A-KPI22 (Reliability), the following figures in Table 3 illustrate a subset of the obtained results exploiting: the ping tool for sending network layer packets from the 5G-IoT node towards the cloud infrastructure (Figure 15); and UDP iperf3 which reports the lost datagrams for two traffic scenarios, i.e., typical voice call of about 100kbps data traffic (Figure 16), and the video data rate as experienced by the high definition cameras deployed in PCT with average data rate of about 10Mbps (Figure 17). Particularly, for the ping command the packet losses are measured via echo ICMP reply message timeouts (No answer yet), whereas for the case of UDP we compare the Lost/Total Datagrams sent. On average we observe above 99.9% on successful packets transmissions. Using a more robust coding and modulation scheme could improve the 5G air interface' reliability.

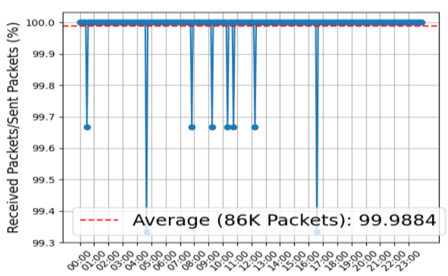


Figure 15: LL Athens - Ping tests for network reliability – (A-KPI22)

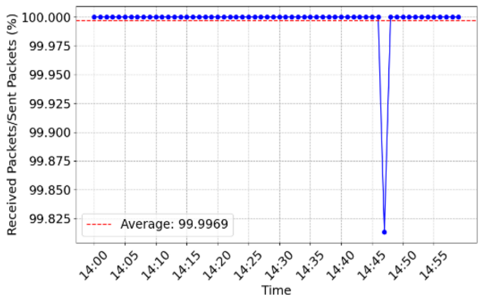


Figure 16: LL Athens - iperf3 UDP 100kbps test for network reliability – (A-KPI22)

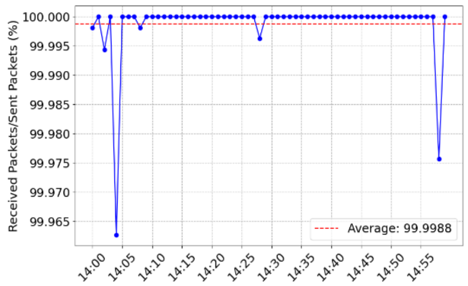


Figure 17: LL Athens - iperf3 UDP 10Mbps test for network reliability – (A-KPI22)

Table 3: LL Athens – Reliability test with various network tools in different configurations – (A-KPI22)

2.2 UC3: 5G&AI enabled collision warning system

2.2.1 Description and Motivation

Piraeus Container Terminal relies heavily on internal yard trucks for the horizontal movement of containers between stacking areas and loading/unloading areas for vessels and road/rail. Along the routes followed by the trucks within the Port area (about 2.5 square kilometres) for facilitating the daily port operations, personnel engaged in different Port activities might be in close proximity. Given the size of the truck (and carried cargo), potential blind spots from the perspective of the truck driver could cause an accident with severe consequences. Towards this direction UC3 is focused in providing a cloud native 5G&AI enabled collision warning service between trucks and people in proximity. The developed service utilizes video streams (from a high-resolution camera installed on the truck) transmitted over 5G (uplink) to PCT's private cloud infrastructure, where the AI containerized service resides, and infers the presence of people in truck's close proximity. In case of positive inference, rapid alerts are delivered to the truck driver to avoid the accident. The Figures [table 4a]below depict typical truck routes within the Port premises, within the range of the gNB.

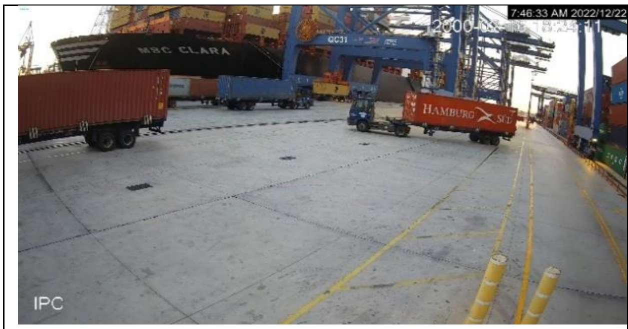


Table 4: LL Athens – typical truck routes within the Port premises and within the range of the gNB (a)

2.2.2 Use Case Setup

In Figure *18* we present the high-level architecture and software components of the use case, and Table depicts real installations on a yard truck and another vehicle exploited for the evaluation of the service in multiple routes within the Port premises. The system is customizable to deliver either a rapid alert by means of a small packet that triggers sound alerts for the driver, or by delivering via 5G downlink the inferenced/annotated video stream at the 5G tablet installed at the driver's cabin (Table , left). The annotated video can be additionally delivered to PCT's central monitoring platform for authorized supervision.


Table 4: LL Athens - PCT truck and commodity vehicle equipped with 5G interface and high definition cameras with a gimbal to absorb vibrations (b)

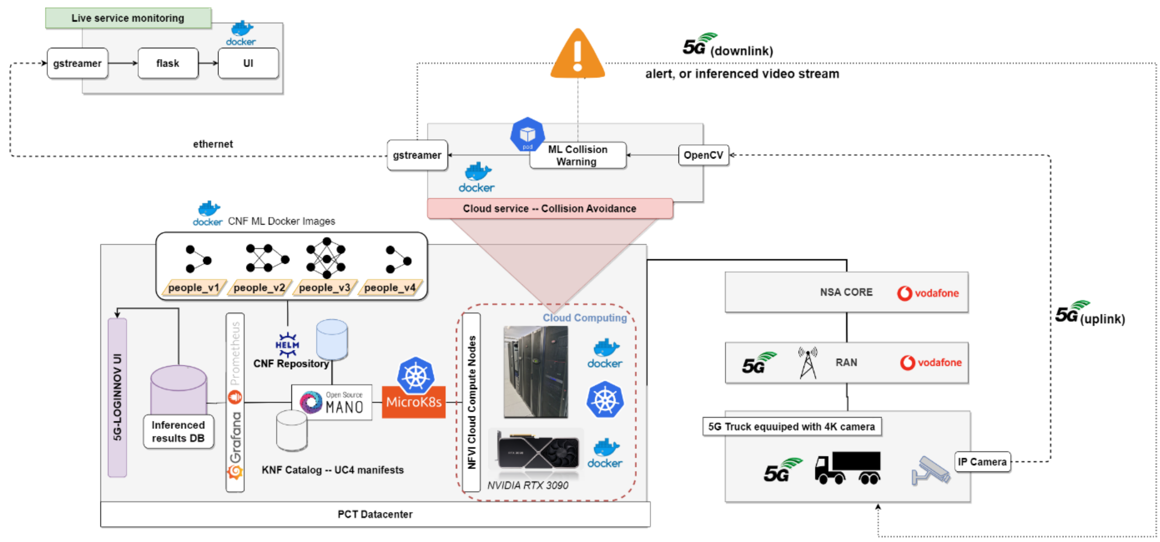


Figure 18: LL Athens - 5G&AI enabled collision warning service architecture

Particularly, continuous high-resolution video streams (uplink) are transmitted from the vehicle over 5G to the CNF residing at PCT's private cloud node which exploits the NVIDIA RTX 3090 GPU for expediting the AI service processing time. We define the person in proximity to truck criterion via the yellow bounded area as shown in Table *5*. In case of positive inference (i.e., a person is detected within the bounding box) rapid alerts are delivered to the truck driver by exploiting the low latency 5G network. Particularly, inferenced video streams are transmitted over 5G (downlink) to a tablet (Samsung Galaxy Tab S8 5G) installed on the truck's cabin, alerting the driver for the event, Table *5* (left). Additionally, the annotated video is sent to PCT's central monitoring platform for authorized operations supervision. In case of negative event (i.e., no person detected in proximity or people detected outside the designated area) the service is customizable, were either a black screen is shown at the tablet or the annotated streams are delivered to the truck driver as shown in Table *5* (right) with no alerts.

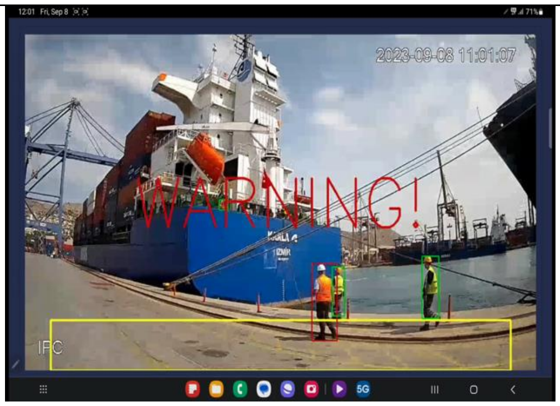
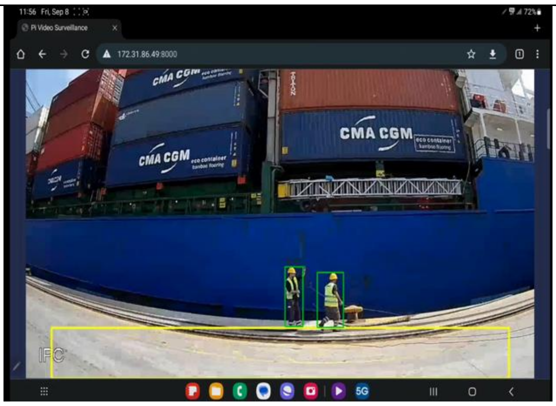
	

Table 5: LL Athens - Collision Warning System example alerting the driver for people in proximity to the truck

2.2.3 List of Key Performance Indicators

Table *6* describes the logistics and technical KPIs relevant for UC3 as defined in [2] (D1.4).

KPI	KPI ID	Measured Value
Model Inference Time	A-KPI11	Depends on the ML model configuration and the video frame size c.f. Section 2.2.5
Model Accuracy/Reliability	A-KPI12	Depends on the ML model configuration and the video frame size c.f. Section 2.2.5
End-to-End Latency	A-KPI23	<20ms (average)
One-way Latency	A-KPI24	<10ms (average)
Deployment Time	A-KPI3	30 seconds (average)
User Experienced Data Rate	A-KPI25	<12Mbps (uplink, average)

Table 6: LL Athens - KPIs list for UC3

User experienced data rate (A-KPI25) is presented thoroughly in Sections 2.3 and 2.4 and is the same for UC3 (we exploit similar cameras). For this use case, the focus resides in monitoring the per video frame transmission delay and processing delay and is thoroughly illustrated in the following sections.

2.2.4 Methodology and Measurement Tools

To evaluate the 5G&AI enabled collision warning service we performed various trips/routes within the Port with 5G coverage (Figure 5). This use case is a mission critical service (with stringent latency requirements) and has many sources of delay: (i) video legacy operations (encoding/decoding); (ii) frame transmission delay and (iii) the frame processing time required by the AI service. In the following we explain our configuration setup to measure the various delay sources, and the use case evaluation.

Cluster Clock Sync: When focusing on mission critical services with tight delay constraints (e.g., collision warning systems), it is of paramount importance to accurately measure the delay of critical decisions, and thus the transmission and processing delay of critical video frames. In a typical setup, a Network Time Protocol (NTP) is used to synchronize the clocks of computer systems over a network. However, the accuracy of an NTP server distribution model, can result in several tens of milliseconds clock difference across the distributed devices. This depends on how symmetric network routes between the servers and client are, how stable the network delay is and client's clock, and how accurate are the servers themselves[1]. To alleviate this drawback, we connect each k8s compute node (extreme-edge and cloud) with a GPS receiver (connected via a serial port) creating stratum-1 devices, which also provide a pulse per second (PPS) signal to sync the local device clocks more accurately with the satellite system. Table 7 depicts information about the GPS system of cloud and extreme-edge nodes (5G truck, 5G-Crane and 5G-IoT devices) and the achieved accuracy, i.e., the local clock offset from the satellite clocks as obtained from *Chrony*. We observe a clock difference of only a few microseconds. In the following, we exploit this negligible offset to accurately measure the one-way transmission delay of packets and frames (Figure *20* - Figure *23*).

Network configuration: Regarding the conducted experiments we tested LTE, LTE-A and 5G-NSA. For experiments based on 4G connectivity we exploit two LTE configurations: single carrier LTE, operating in frequency band B7 with a 20Mhz channel bandwidth, and LTE-A (advanced) where the device is configured in dual carrier aggregation mode combining B3 and B7 frequency bands, with a

[1] https://chrony.tuxfamily.org/index.html

20Mhz channel bandwidth, each. For the 5G experimentation, we used B20 and N78 frequency bands for control (LTE anchor) and data plane (NR user plane) functions, respectively, with a 100Mhz channel.

Per frame transmission delay: We measure the transmission delay of the 4K frames over the LTE, LTE-A and 5G interfaces. To measure the per frame network delay we employ GStreamer[2] tool with the Real-time Transport Protocol (RTP) where we create a 4K video streaming session from the vehicle. On the server side we use tcpdump to capture and timestamp RTP packets as they are observed by the network interface card at send time, and similarly for RTP packets at reception (client side). To eliminate clock drift (and deviation) of the devices we employ the stratum-1 clock (GPS/PPS) setup as explained before. Lastly, by using the Mark-field (Figure *19*) of the RTP header we can distinguish all packets that create a single video frame, and thus calculate the video frame transmission delay over the various network configurations (from the 5G-truck towards PCT's private cloud).

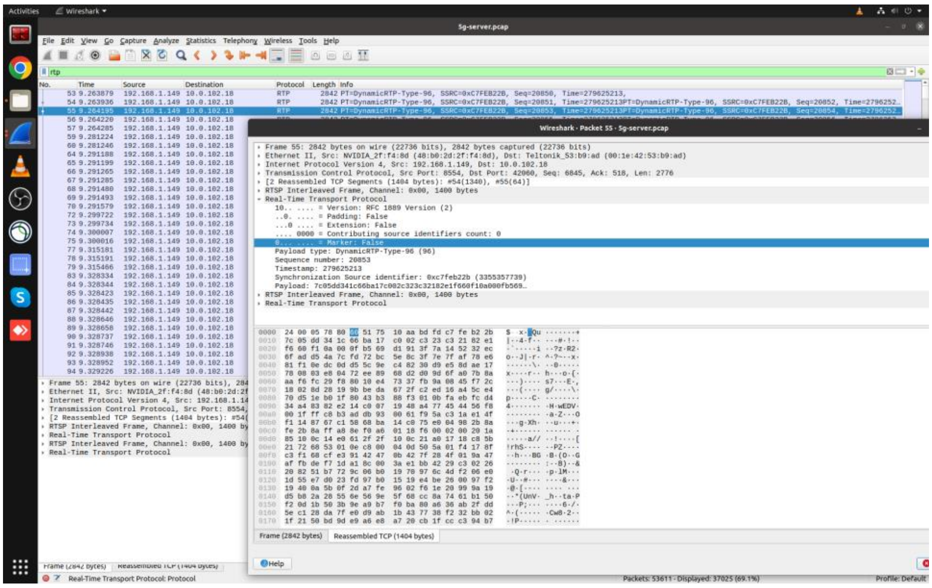


Figure 19: LL Athens - Wireshark example trace of RTP packets and mark-field indicating the end of a video frame

[2] GStreamer is an open-source multimedia framework that provides a pipeline-based architecture for creating multimedia services.

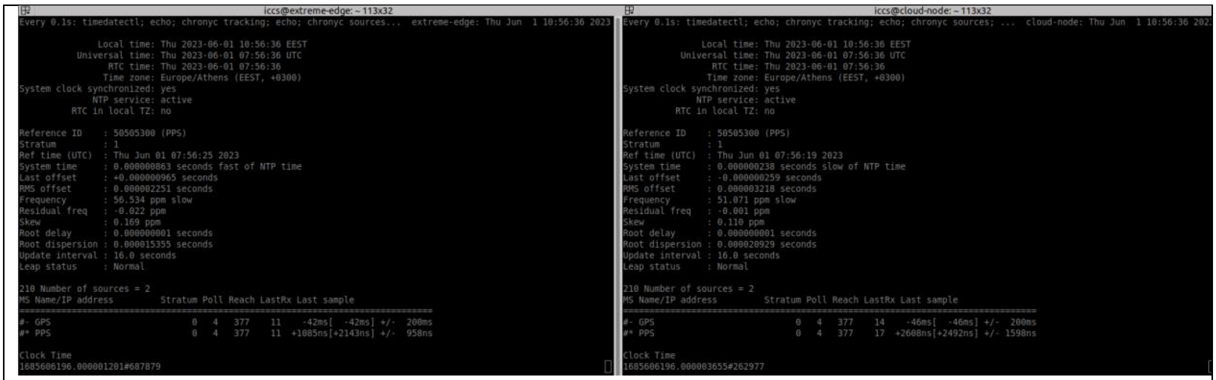


Figure 20: LL Athens - Clock sync between extreme-edge node and cloud node based on GPS and PPS signals

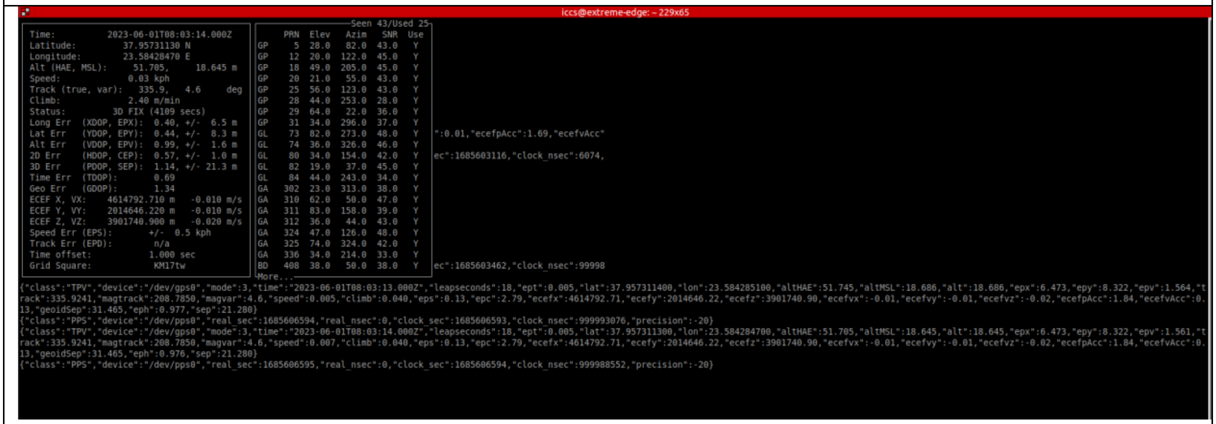


Figure 21: LL Athens - Extreme-edge node, cgps (Stratum 0)

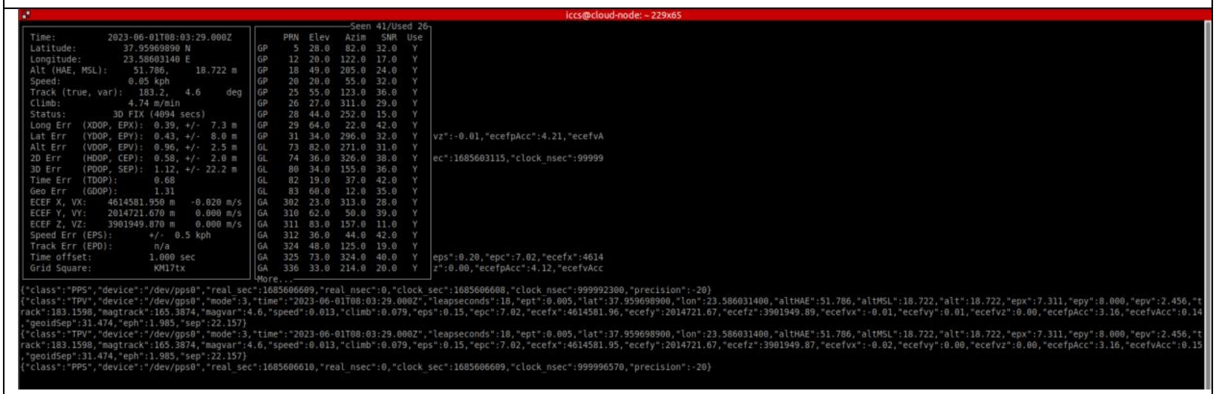


Figure 22: LL Athens - Cloud node, cgps (Stratum 0)

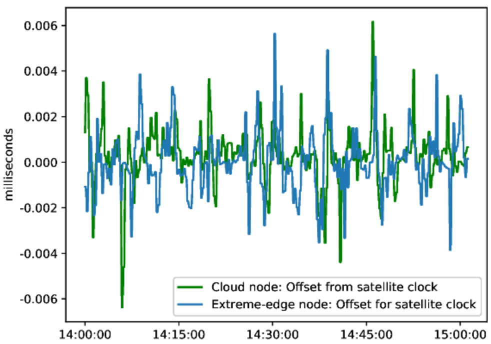
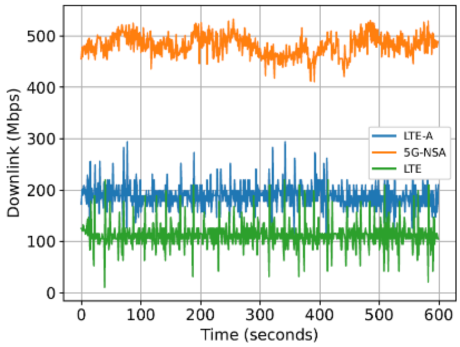


Figure 23: LL Athens - Time offset between local clock and satellite clock of cloud and extreme edge node on truck.

Table 7: LL Athens - Syncing clocks of distributed devices via GPS/PPS signals

2.2.5 Results

Detailed evaluation of network KPIs have been presented in Section 2.1 capturing A-KPI-19 to A-KPI25 (see Table 1). Here we present a subset of those KPIs relevant for the use case testing, along with the comparison of various network configurations (LTE, LTE-A and 5G-NSA) to get more insights in the performance of the various networks and the 5G&AI-enabled collision warning system requirements.



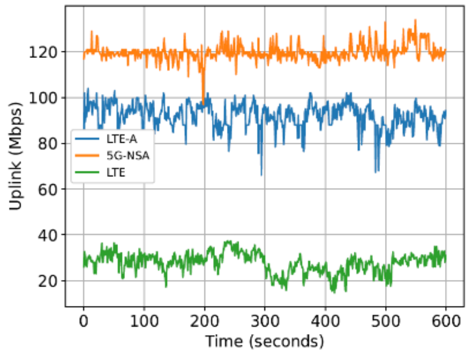


Table 8: LL Athens - Cellular networks (LTE, LTE-A and 5G) benchmarking based on iperf3 tools for throughput measurements

The results obtained for the 5G-NSA network are similar to the ones presented in Section 2.1.4.2. With respect to the various network configurations (Table *8*) we observe (on average) about 480Mbps downlink for 5G, 190Mbps in LTE-A and about 100Mbps for LTE, whereas in uplink we observe about 120, 90 and 30Mbps, respectively (A-KPI20). Evidently, the additional spectrum resources of 5G allow for higher bandwidth availability, enabling higher data rates. Considering network latency (Figure *24*), we provide our measurements for packet round-trip times (RTT) in all network configurations measured via ping. For the LTE configurations (no significant difference is observed between LTE and LTE-A) we recorded about 28ms RTT time (on average), whereas in 5G we measured latency of about 18ms (A-KPI23).

Figure *25* shows our measurements corresponding to the transmission delay of 4K frames for the different networks, from the camera installed on the truck. We observe video frame latency of about 30ms for 5G, 45ms for LTE-A and about 60ms for LTE, on average. Evidently, the 5G network provides the faster medium for delivering high resolution video frames which is pertinent for applications with real time constraints.

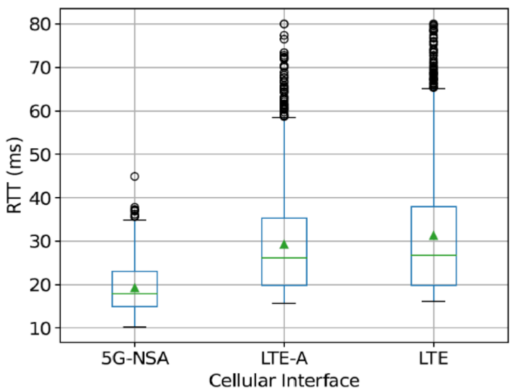


Figure 24: LL Athens - RTT for the various network configurations

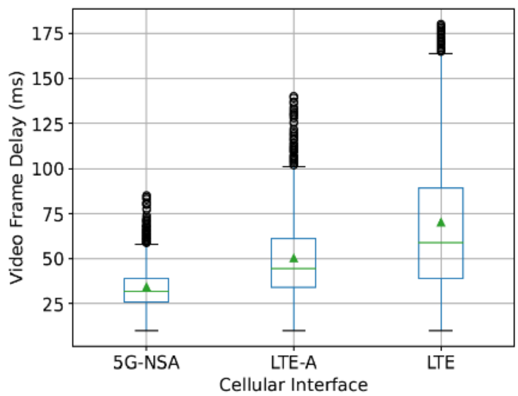


Figure 25: LL Athens - Per frame network transmission delay at 4K resolution

With respect to inference accuracy (A-KPI12) of the AI service, as objects (people) within the highlighted yellow area (Table *5*) are relatively close to the moving vehicle, we observed very few positive/negatives for YOLOv5n and YOLOv5s CNN models [4] and almost none for those presented in Table *9*. Detailed evaluation for A-KPI12 and human presence detection is shown in Section 2.3.5 where the service is challenged to detect people at distant locations as captured by the 5G-IoT nodes deployed on fixed port infrastructure. For the inference time (A-KPI11) we illustrate on Table *9* the effect of the video frame size[3] and YOLOv5 CNN model size [4] on the inference time for the cloud deployment (average results for 30K frames). Evidently, the general rule of thumb as also illustrated by the values below, is that the inference time increases, when we use higher resolution video frames or a more complex CNN model.

Cloud Computing (ms)				
Frame size	SD	HD	FHD	4K
YOLOv5x	12.9	35.1	66.2	245
YOLOv5l	10.1	18.7	37.3	133
YOLOv5m	8	11.8	23.2	77

Table 9: LL Athens - Inference time of UC3 for extreme-edge and cloud deployments - (A-KPI11)

To understand the **end-to-end service delay (e2e-SD)** when exploiting the cloud infrastructure for the collision warning service we aggregate the following delay sources: frame transmission delay (Figure 25), the AI service inference time (Table 9), and finally the alert delivery delay. For the alert delivery we test two scenarios; (i) a small packet notification which triggers an ***audible notification***, or delivering the ***full inferenced video stream*** at the tablet (5G downlink) installed in the vehicle.

For the alert delivery delay, when transmitting a small packet, e.g., a sound trigger, this can be considered as a small packet/notification to the system of the truck and is measured as half-RTT, or one-way latency (Figure 24), i.e., less than 10ms for 5G. Hence, the e2e-SD is approximately 30ms for the frame transmission delay, 23ms of frame processing time (e.g., FHD, v5m) and about 9ms for triggering the alert, accumulating a total latency of about 62ms for the 5G-NSA network. The following table summarizes the e2s-SD for all network and CNN model configurations at the cloud deployment scenarios.

Cloud processing – end-to-end service delay (**e2e-SD**) – (LTE, LTE-A, 5G-NSA) in milliseconds												
Frame size	SD			HD			FHD			4K		
Network	LTE	LTE-A	5G	LTE	LTE-A	5G	LTE	LTE-A	5G	LTE	LTE-A	5G
v5x	86.9	71.9	50.9	109.1	94.1	73.1	140.2	125.2	104.2	319	304	283
v5l	84.1	69.1	48.1	92.7	77.7	56.7	111.3	96.3	75.3	207	192	171
v5m	82	67	46	85.8	70.8	49.8	97.2	82.2	61.2	151	136	115

Table 10: LL Athens - End-to-end service delay in various network CNN and video resolution setups

Evidently 5G provides the smallest e2e-SD for all cases. In the case of delivering the *inferenced video stream* at the tablet we showcase in the following the glass-to-glass experimentation. In more detail at the tablet we use *envyen*, an app that shows current time at ms accuracy and we face the camera to

[3] Note that the frames are transmistted over 5G uplink at 4K resolution, and are then resized by the ML service to expedite the processing time.

the tablet to show the end-to-end application layer delay. This includes the frame transmission delay and frame processing time as demonstrated in Figure *25*, Table *9* and Table *10*, but also the video application layer latency that includes encoding and decoding operations (H264, @20fps) of video frames. In Figure *26*, the yellow boxes indicate the added delay induced for creating an additional video session from the cloud node towards the tablet via *gstreamer*. Evidently, higher resolutions (e.g., 1080p, 4K) and higher frame rates (e.g., 10fps, 30fps) require more data to be processed, increasing encoding and decoding times. Additionally, the hardware capabilities of the camera, software configuration of the *gstreamer* pipelines, codec complexity (H.264 or HEVC) and the hardware capabilities of the UE for efficient decoding, also contribute as potential sources of delay, but also cases for improvement.

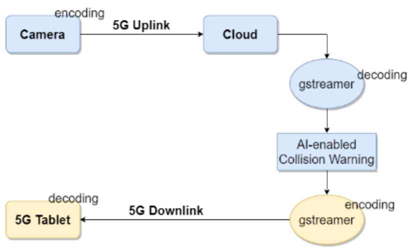


Figure 26: LL Athens - Delay sources for the end-to-end collision warning system

The results in Table 11 represents streaming on the downlink HD video at 20fps with H264 codec and gstreamer. On the righthand side of each figure, we observe current time and on the left-hand side we see the delay, i.e., past time. On average, we observed about 200-250ms of delay. When using higher framerate or higher resolution we observed larger values which would render the collision warning system impractical. However, this is not attributed to the 5G network delay or, the AI processing delay (as show in Figure 25, Table 9 and Table 10), but rather on the inherent latency delay sources of video streaming sessions as discussed above.

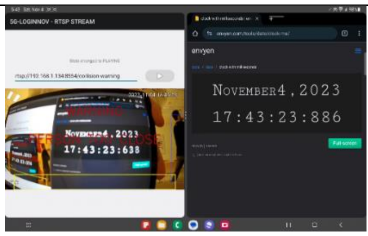
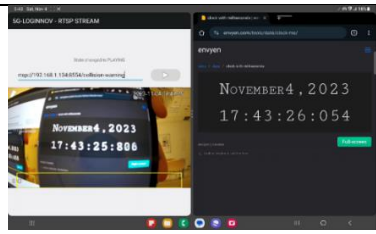
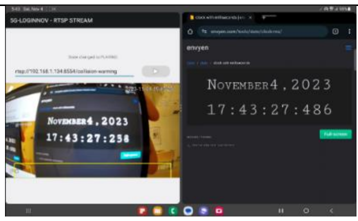
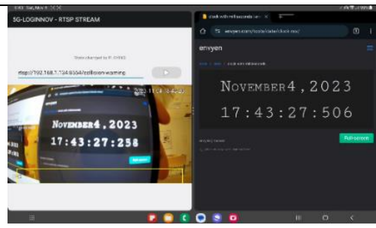
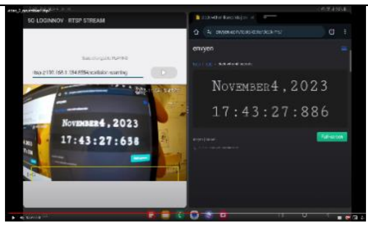
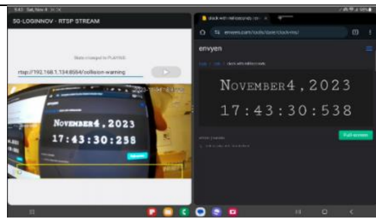
	
	
	

Table 11: LL Athens - Glass to glass experimentation for 5G&AI-enabled collision warning system

In summary, for the collision warning system based on *audible alerts* the total latency can be as low as 50ms (depending on the configuration points shown in Table *10*), whereas for the case where the *inferenced video streaming* is delivered to the truck this delay can be up to 250ms. Considering the speed limitations within a port environment at 20Km/h or 5.5m/s the truck will be roughly ahead about 0.3 meters for the audible alert and 1.5 meters for the inferenced video stream, alerting the drive in more detail about the visual environment in the truck's vicinity. Hence, the two setups should be used in conjunction for mission critical services such as collision avoidance.

Finally, we evaluate A-KPI3 (Deployment Time) of the CNF which is the same for UC3, UC4 and UC5 and is presented only in this Section. Figure *27* depicts the OSM deploy time extracted from the open source MANO (OSM) manifest deployment logging (osm-deploy on the x-axis), as well as the CNF image pull time for downloading the ML image at the respective host (extreme-edge or cloud). The results are average values over 50 measurements. We observe first that the image pull time for UC4 is about 2.5 minutes (which is basically determined by the host's throughput and the image size), whereas the deployment time from OSM (Release 13) for both cloud and extreme-edge orchestration decisions takes about 30 seconds, i.e., for the CNF to be active and running in the kubernetes cluster.

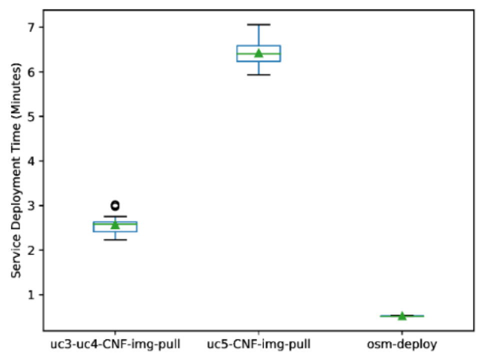


Figure 27: LL Athens - Service Deployment Time for UC3, UC4 and UC5 – (A-KPI3)

2.3 UC4: Optimal surveillance cameras and video analytics

2.3.1 Description and Motivation

Frequent incidents involving boom collisions, gantry collisions or stack collisions along with the presence of stevedoring personnel within the Port area make the risk for serious bodily injuries considerable. Hence, detecting the presence of people in high-risk areas, e.g., areas with intensive crane and/or truck operations, is of paramount importance for the Port operator for ensuring a safer environment in daily operations for employees and visitors. Additionally, AI-enabled surveillance can further aid Port security by detecting the presence of people in restricted areas, e.g., close to a warehouse area. Towards this direction, UC4 focused on the development of a cloud native 5G&AI-enabled human presence detection service. The developed solution exploits the eMBB service of 5G to transmit high resolution (uplink) video streams of the relevant areas, which are exploited by the developed ML service for the inference task of human presence detection and based on the inference result generate in real-time respective alerts (i.e., live inference/annotated streams to PCT's central monitoring system or to handheld devices, e.g., 5G smartphones, exploited by mobile security patrol shifts close by). Figure *28* and Figure *29* illustrate the view angles of the two 4K cameras exploited by the service, with the former (mounted on quay side crane 31) depicting people in proximity to the rails of the crane, and the latter (mounted on a pillar at Pier III) illustrating an area with increased truck traffic. Figure *30* and Figure *31* depict how the inferenced video streams (bounded boxes or segmented) are delivered to the central monitoring platform or handled/mobile 5G devices.

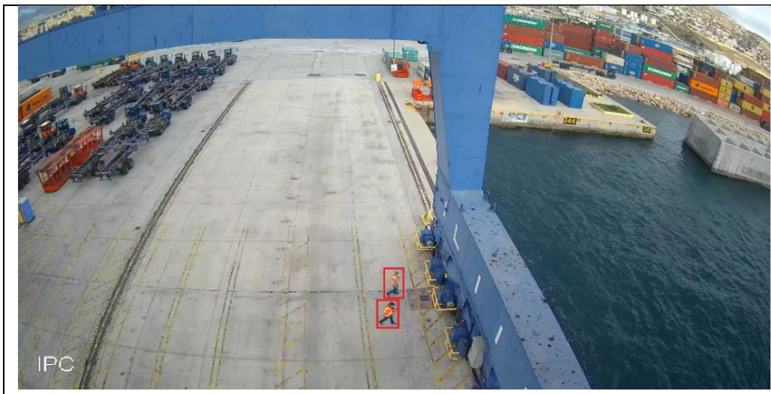


Figure 28: LL Athens - People detected close to QC31 rails (Area 1 view)

Figure 29: LL Athens - Truck traffic area, no personnel allowed (Area 2 view)

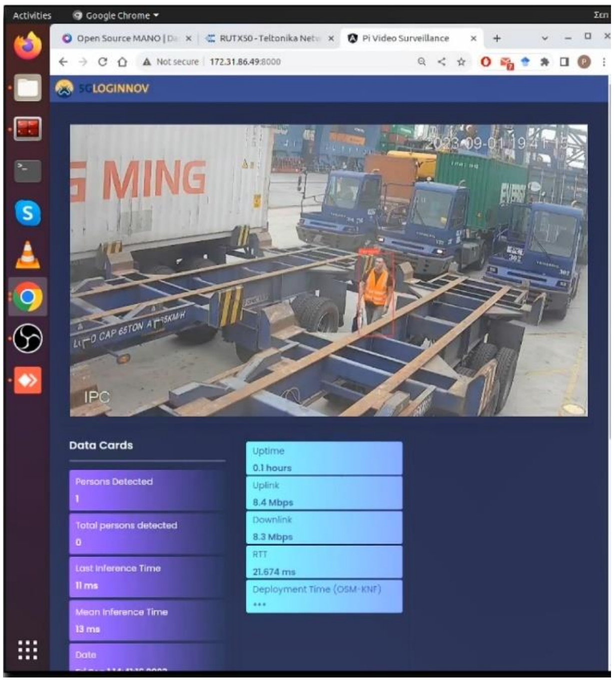


Figure 30: LL Athens - User interface for events monitoring with inferenced video stream (bounded boxes) to 5G handheld devices or central monitoring platform.

Figure 31: LL Athens - Inferenced (segmented) video streams delivered to 5G handheld devices or central monitoring platform.

In addition to the fact that this use case increases safety measures of the employees' workplace, it also opens up opportunities to optimize (i.e., redistribute) the use of human resources in different port operations, e.g. by reducing the patrol frequency at the risk areas (currently frequent patrols are distributed to inspect risk/prohibited areas), as this service is automated by the use case.

2.3.2 Use Case Setup

Figure *32* showcases the architecture components of the use case, and Figure *33* (including Table 12 and Table *13*) depict real installations within the Port area. We exploit two high resolution cameras for inspecting two areas: a 4K camera deployed at quay side crane (QC) 31 (Area 1, Table *12*) which monitors the area close to the crane's base/rails (Figure *28*), as well as a camera with a view angle towards an area (Area 2, Table *13*) with increased truck traffic (Figure *29*). Both areas are considered high risk areas due to crane operations and moving trucks. The 5G-enabled AI service can be deployed (as a CNF) on two locations of the 5G-LOGINNOV infrastructure. The first deployment option, i.e., the extreme-edge, utilizes two NVIDIA Jetson AGX Xavier devices for the two monitored areas; one device mounted on QC 31 and the other device installed on a Pillar at Pier III. For this case, the AI processing is utilized on the extreme-edge node (i.e., incurring zero network delay as the 4K cameras are connected to the Jetson node via ethernet), and inferenced uplink 4K video streams are transmitted over the 5G network to PCT's monitoring platform. The second deployment option, i.e., PCT's private cloud, employees the NVIDIA RTX 3090 GPU equipped on the cloud infrastructure. For this scenario, unprocessed 4K video streams (uplink) are delivered over 5G to the CNF deployed on the cloud node (from Area 1 and Area 2), where we exploit the massive computation capability of the node to decrease the ML processing time, but, at the expense of network delay. Similarly, inferenced video streams may be delivered to 5G handheld devices (downlink, eMBB) of patrol shifts, or the PCT's monitoring platform. Extensive numerical evaluation for both scenarios is presented in Section 2.3.5.

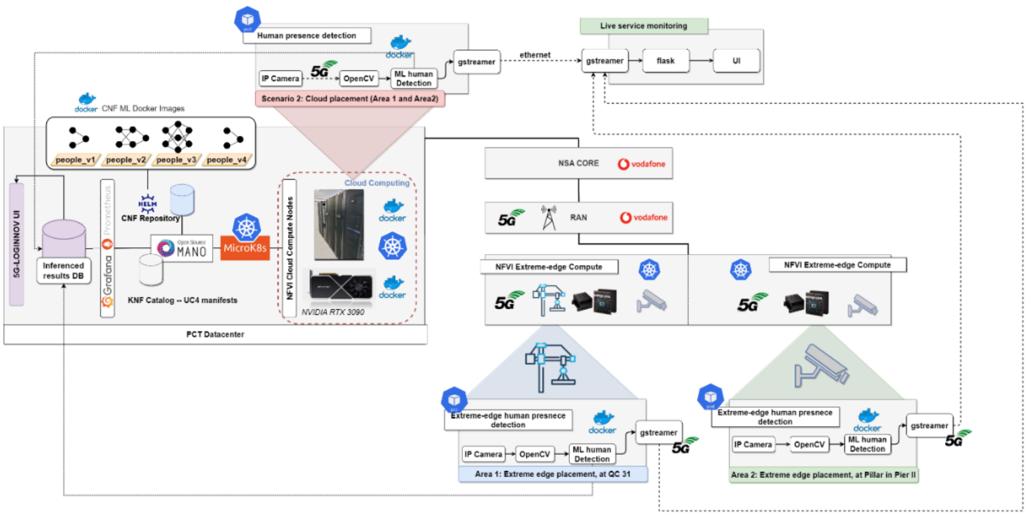


Figure 32: LL Athens - Human presence detection service architecture at extreme-edge and cloud

Figure 33: LL Athens - Components/installations of the 5G&AI enabled human presence detection use case

Table 12: LL Athens - QC Crane installation of 4K camera, compute node and 5G Interface (Area 1)

Table 13: LL Athens - Pillar Node Installation of 4K camera, compute node and 5G interface (Area 2)

2.3.3 List of Key Performance Indicators

Table *14* describes the logistics and technical KPIs relevant for UC4 as defined in [2] (D1.4).

KPI	KPI ID	Measured Value
Human resource optimization (person-hours)	A-KPI9	Qualitative
Model Inference Time	A-KPI11	Depends on the ML model configuration and the video frame size c.f. Section 2.3.5
Model Accuracy/Reliability	A-KPI12	Depends on the ML model configuration and the video frame size c.f. Section 2.3.5
End-to-End Latency	A-KPI23	<20ms (average)
Deployment Time	A-KPI3	30 seconds (average)
User Experienced Data Rate	A-KPI25	<12Mbps (uplink, average)

Table 14: LL Athens - KPIs list for UC4

A-KPI23 corresponds to the round-trip time (RTT) values as obtained from the ping tool between the 5G-IoT nodes and the cloud management platform, where we observed on average values below 20ms. For the 5G&AI-enabled video surveillance the end-to-end service delay includes the delay for the video encoding and decoding procedures, frame transmission delay, frame processing delay (or inference time as given by A-KPI11), and finally the delivery of the alert in terms of positive inference. This end-to-end service value is presented thoroughly in Section 2.2.5. Similarly, A-KPI3 (Deployment Time) was evaluated in Section 2.2.5.

A-KPI9 refers to the exploitation of human resources (person hours) spent for monitoring, surveillance and physical patrol shifts (for safety/security applications). Based on legacy procedures (before 5G-LOGINNOV), PCT utilizes 4 physical patrol shifts per day (2 persons per shift) assisted by personnel at the video surveillance center. The core benefit of the 5G&AI-assisted video surveillance is on the scale for concurrent monitoring of the full Port area space (currently about 300 cameras are deployed), in addition to the current physical assisted patrol/monitoring schedules. Hence this KPIs is shown as a qualitative KPI, indicating that concurrent (5G&AI-assisted) monitoring of the full Port space could be achieved through UC4.

2.3.4 Methodology and Measurement Tools

The ML service for human presence detection was trained by obtaining data from the daily port operations from the relevant cameras (view angles) depicted in Figure *28* and Figure *29*, under varying light conditions (including morning and mid-day streams). Particularly, three versions of the YOLOv5 [4] neural networks were exploited (small, medium and large, for more details please refer to [4]), fine-tuned via exploiting the 4K frames obtained from the 5G-LOGINNOV cameras. Hereafter, we refer to the three versions of the developed service as people_v1, people_v2 and people_v3, based on the three YOLOv5 base models used, i.e., small, medium and large, respectively. The different models vary in size (with respect to their ML parameters), which has a direct impact in the accuracy of the ML service as well as its execution time. Additionally, all algorithms can perform resizing of the input image to a specific size before serving the image to the ML pipeline. For example, a 4K frame can be resized to a Full HD or lower resolution. This configuration reduces the required ML service processing time per frame, but, it may also result in loss of information, e.g., people far away from the camera will appear smaller in resizing, which could result in detection failure. All such parameters are thoroughly evaluated in Section 2.3.5 for the two deployment options (extreme-edge and cloud).

Finally, a fourth version (namely, people_v4) for the human presence detection service was developed, where we consider V1 model as the base. In this approach no frame resizing is performed. 4K frames are used as input, where each frame is split in four equal sized frames (Figure *34*). By exploiting the GPU parallel processing capabilities, the four images are processed concurrently by the CNF residing either on the cloud or far-edge. This step incurs an additional processing delay (when compared e.g., to V1), however, as no resizing is performed, we incur no information loss.

Figure 34: LL Athens - 4K frame split into 4 equal sized parts (no resizing) exploited by the people_v4 algorithm

To evaluate the developed ML services, we obtained video footage from the aforesaid 4K camera installations, spanning across several days and varying working hours, in order to evaluate the service's performance under different light conditions (e.g., during morning and mid-day shifts). We present here the results from 600 selected frames for evaluating the service targeted detection events, i.e., presence/absence of people. The extracted stream parts contain events with crowds of different sizes (e.g., from 2-10 people) where we evaluate the accuracy of the model in detecting all such occurrences. Additionally, as people are constantly moving, the detection efficiency of the developed ML algorithms is also put to the test based on different camera angles, and at various distances within each camera's field of view. In the following section we provide an extended evaluation of all developed solutions and CNF placement options (extreme-edge and cloud). For all inferenced results (and positive inferences) the CNF opens a connection also to the 5G-LOGINNOV database (as shown in Figure *35*) to store the outcome of the processed frames for later inspection (also servicing as the ground truth in our evaluation).

Table 15: LL Athens - Sample outputs from Areas 1 and 2 of the 5G&AI enabled human presence detection service

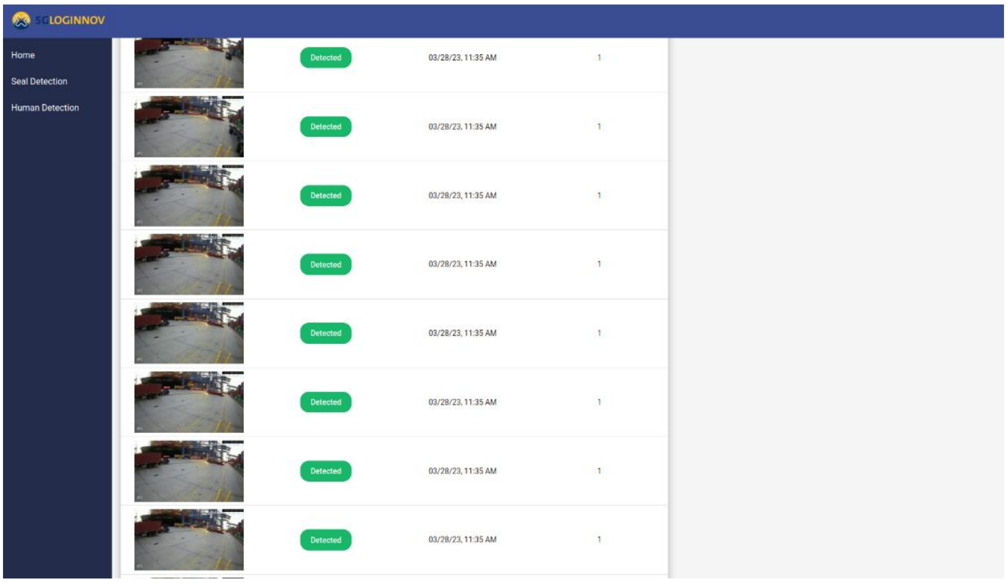


Figure 35: LL Athens - Database UI hosting the inferenced results of processed frames for UC4

2.3.5 Results

Table *16* provides the summary of the results for A-KPI11, i.e., Model inference time, for the 5G&AI-enabled human presence detection service at the extreme-edge (Figure *36*) and private cloud (Figure *37*). Evidently as the image resize parameter increases (x-axis) the inference time per frame also increases for both far-edge and cloud deployments. For instance, resizing a 4K frame to 640p (standard definition, SD) and considering people_v1 model, we measured about 25ms per frame inference time, or, about 30fps of inferenced video streaming (Figure *36*). For the same case, if the frame is resized to 1920p (Full High Definition, FHD), we obtain about 100ms per frame, or, about 10fps of inferenced video streaming. Similar qualitative results are observed for all developed solutions. It is also straight forward to observe that when the CNF is deployed to the cloud (Figure *37*), equipped with increased computing capabilities (compared to the extreme-edge case), the inference time is significantly decreased, e.g., for people_v1 and 1920p the inference time is about 10ms, or, 100fps of inferenced video streaming. Similar results can be seen for the evaluation of people_v2, people_v3 and people_v4.

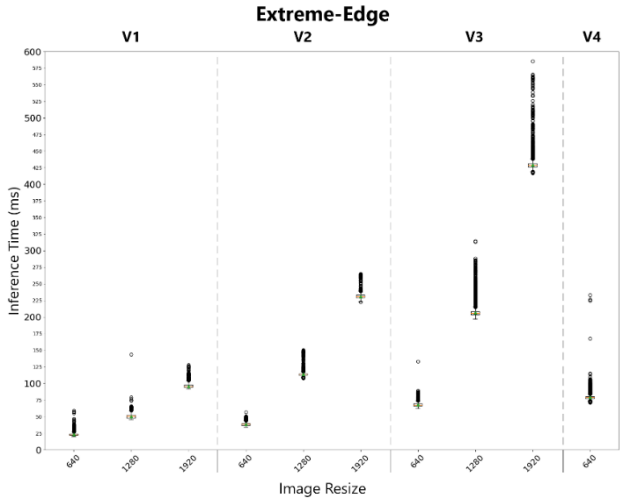


Figure 36: LL Athens- Inference time for human presence detection -- extreme edge

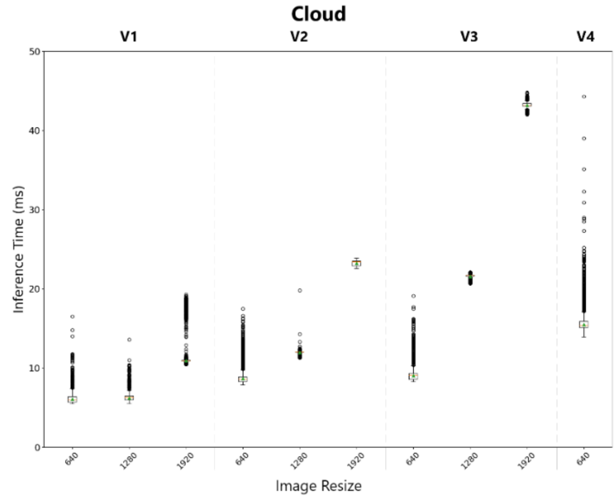


Figure 37: LL Athens - Inference time for human presence detection -- Cloud

Table 16: LL Athens - Evaluation of Model Inference time of UC4 – (A-KPI11)

In Table 17 we summarize the results according to our evaluation where we showcase for each configuration the True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN), of all developed methodologies (Model Accuracy/Reliability A-KPI12). Each row of the table depicts different resizing options of a particular model. Table 18 depicts performance metrics for all tested models in more detail. Evidently, the best performance is achieved by the yolov5 large model (46.5M parameters, vs nano 1.9M, small 7.2M, medium 21.2M, xlarge 86.7M) at an input size of 1280p. As expected, when the 4K image is resized to SD, we incur information lose, and thus we observe inferior performance, e.g., less TP, compared to FHD resolution. This observation also applies for all evaluated cases.

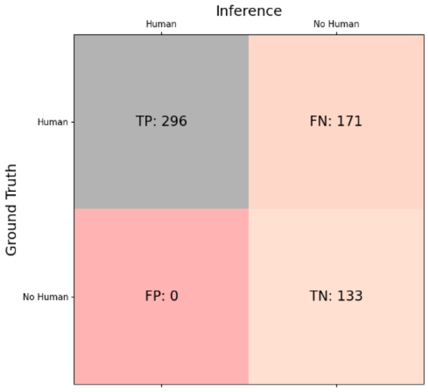


Figure 38: LL Athens - people_v1 resized at 640

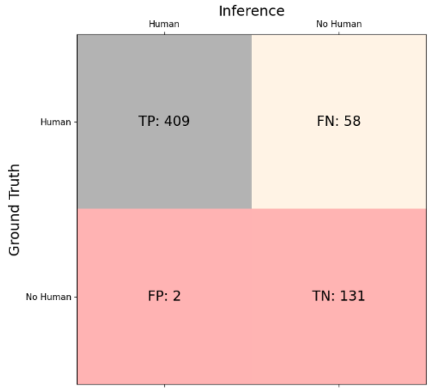


Figure 39: LL Athens - people_v1 resized at 1280

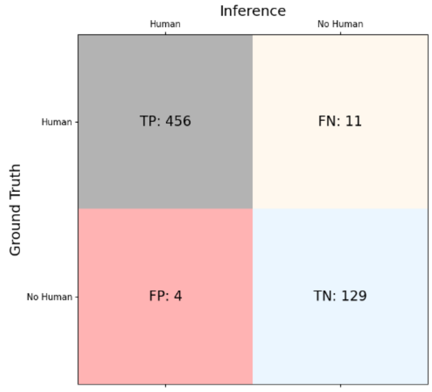


Figure 40: LL Athens - people_v1 resized at 1920

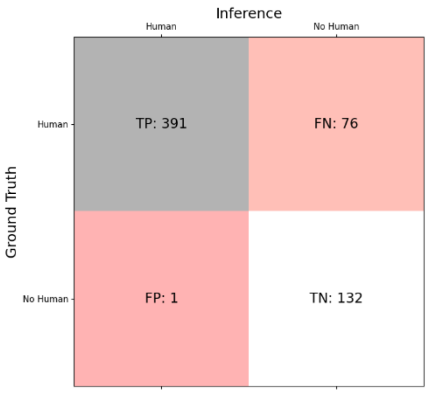


Figure 41: LL Athens - people_v2 resized at 640

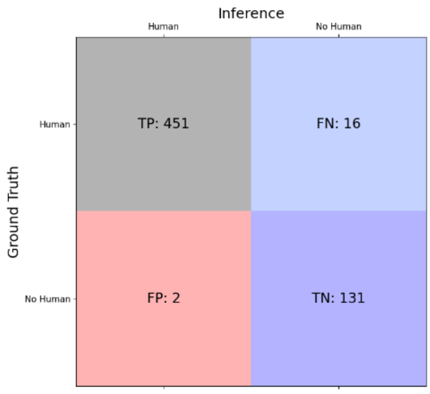


Figure 42: LL Athens - people_v2 resized at 1280

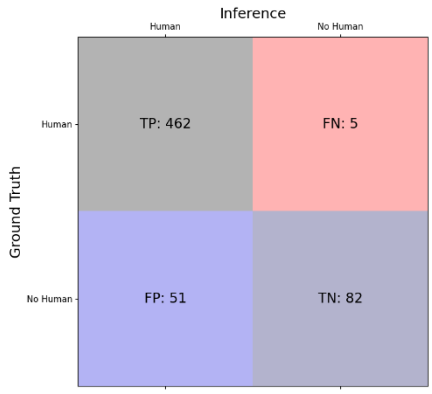


Figure 43: LL Athens - people_v1 resized at 1920

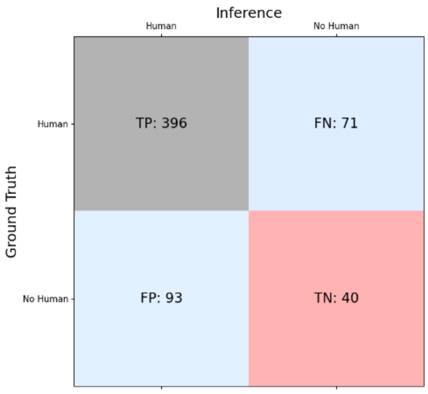


Figure 44: LL Athens - people_v3 resized at 640

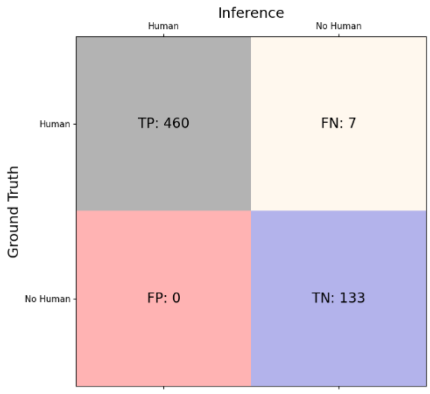


Figure 45: LL Athens - people_v3 resized at 1280

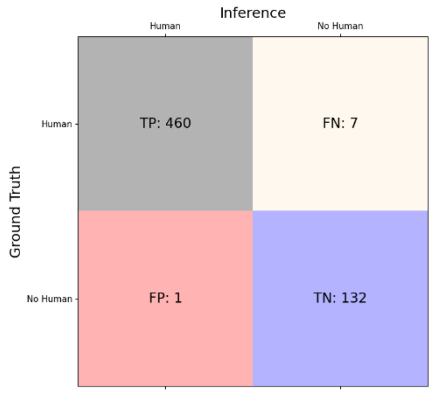


Figure 46: LL Athens - people_v3 resized at 1920

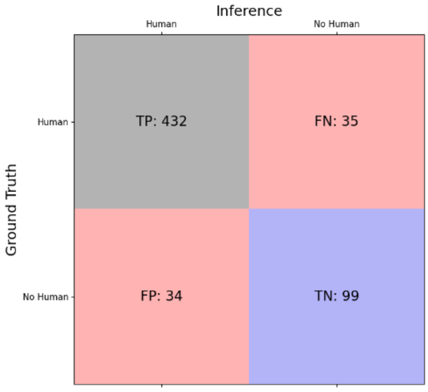


Figure 47: LL Athens - people_v4 resized at 640

Table 17: LL Athens - Evaluation of Model Accuracy/Reliability of UC4 – (A-KPI12)

Model	Accuracy	Precision	Recall	F1 score
people_v1 (640p)	0.658	1.000	0.633	0.775
people_v1 (1280p)	0.880	0.995	0.876	0.932
people_v1 (1920p)	0.970	0.991	0.977	0.984
people_v2 (640p)	0.846	0.997	0.837	0.910
people_v2 (1280p)	0.964	0.996	0.966	0.981
people_v2 (1920)	0.970	0.979	0.989	0.984
people_v3 (640p)	0.836	0.973	0.850	0.907
people_v3 (1280p)	0.986	1.000	0.985	0.993
people_v3 (1920p)	0.984	0.998	0.985	0.991
people_v4	0.920	0.989	0.926	0.956

Table 18: LL Athens - Mean Average Precision (mAP) and Precision/Recall derived metrics for all evaluated models of UC4

Table *19* depicts the effect of the video frame size (x-axis) and YoloV5 CNN model size (y-axis) on the inference time, power consumption for cloud and extreme-edge deployments (average results for 30K frames from PCT camera installations). To measure the average power consumption of cloud and extreme-edge CNFs, we exploit NVIDIA's native tools, namely, *tegrastats* for the Jetson device and *nvidia-smi* for the GPU RTX 3090, that isolate the power consumption used by the GPU for processing video frames. Hence, we measure the energy footprint of the AI services focusing on the video analytics tasks, i.e., object detection. The general rule of thumb as also illustrated by heatmaps below, is that inference time and power consumption increase, when we use higher resolution video frames or a more complex CNN model.

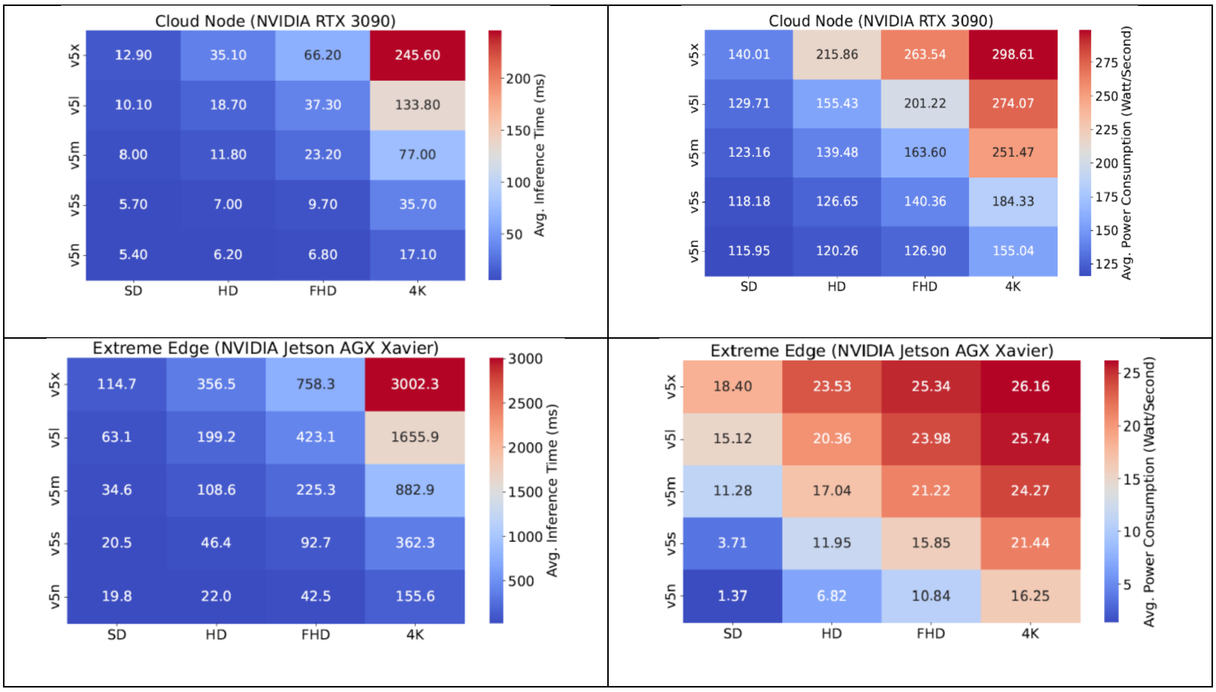


Table 19: LL Athens - Inference time and power consumption of video analytics services in cloud and extreme-edge deployments for the various YoloV5 configurations and video frame resolutions.

Figure *48* depicts the 5G uplink experienced data rate (User Experienced Data Rate, A-KPI25), i.e., the consumed (and necessary) bandwidth utilized by the 4K cameras (relevant to UC4, UC3 and UC5) deployed within PCT. Each sample point on the x-axis (s1, s2,..,s7) represents the average data rate over 3600 seconds/samples (i.e., 1 hour of continuous 4K video streaming), totalling an entire working shift duration of about 7 hours. For clarity we present the results from Area 2 (Table 13 and Figure *29*) as it is similar for the other 4K monitored areas. We observe that the average streaming requirements are about 9.5Mbps where we also depict the observed upper and lower boundaries, with encoding mode: H.264, 4K resolution of 3840*2160 at 20fps.

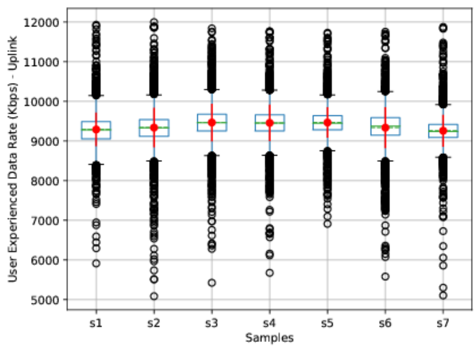


Figure 48: LL Athens - Uplink User Experienced Data Rate – (A-KPI25)

2.4 UC5: Automation for ports: port control, logistics and remote automation

2.4.1 Description and Motivation

Detecting the presence (or absence) of container seals for containers inbound at a port is of paramount importance for the port operator, as the presence of a seal validates the integrity of the container contents. It is not rare however for containers to arrive with broken/absent seals and missing content, especially when their transportation plan involves transhipments; in such cases, the involved ports should be able to prove that the container left the port with its seals intact or pay the claimed financial reimbursements. Typical containers locked and sealed are shown in the following two figures.

A mother vessel at PCT requires (on average) about 3000 stevedore moves (depending on the vessel size) to complete loading (and/or unloading) operations. Manual seal-presence check requires one person at the foothold/base of the crane where the quay side crane operations take place (Figure *49*), and about 10-30 seconds to manually inspect each container, until the crane operator proceeds to the next container movement. Reducing this time by e.g. 3 seconds per container, results to 9000 seconds (or 2.5 hours) reduction of vessel stay at the port and removes the need for human presence at an area with high safety risks. Towards this direction, this use case takes advantage of the private 5G NSA network at the port of Piraeus and advanced computer vision techniques (AI-enabled video analytics) to automatically detect the presence (or absence) of container seals during the loading (and unloading) process of vessels, thus automating and expediting the port operations, improving the utilization of human resources as well as increasing the employee's safety.

Figure 49: LL Athens - Manual check for container seal

2.4.2 Use Case Setup

Figure *50* depicts the architecture of the use case, whereas Figure *51* showcases real components/installations. At PCT, the quay side crane (QC) 31 is equipped with a wide-angle camera, continuously capturing 4K video of the crane's activity (vessel loading/unloading operations). Following the compute continuum paradigm, we evaluate two deployment options of the 5G enabled AI service, i.e., at the extreme-edge (on NVIDIA Jetson AGX Xavier device mounted on the QC cockpit, scenario

1, Table *12*), or at the 5G LOGINNOV cloud node residing beyond the 5G core network of Vodafone, at PCT's datacentre, hosting NVIDIA RTX 3090 GPU (scenario 2, Table *13*) to accelerate the processing time of the ML service. In scenario 1 the processing takes place on the extreme-edge node and we exploit the eMBB service of 5G to deliver uplink inferenced/annotated 4K video streams at PCT's central platform for live monitoring of loading/unloading operations. For scenario 2, unprocessed 4K video frames are transmitted over 5G to the AI container residing at PCT's cloud node, where the processing takes place. Numerical evaluation for both scenarios is presented in Section 2.4.5

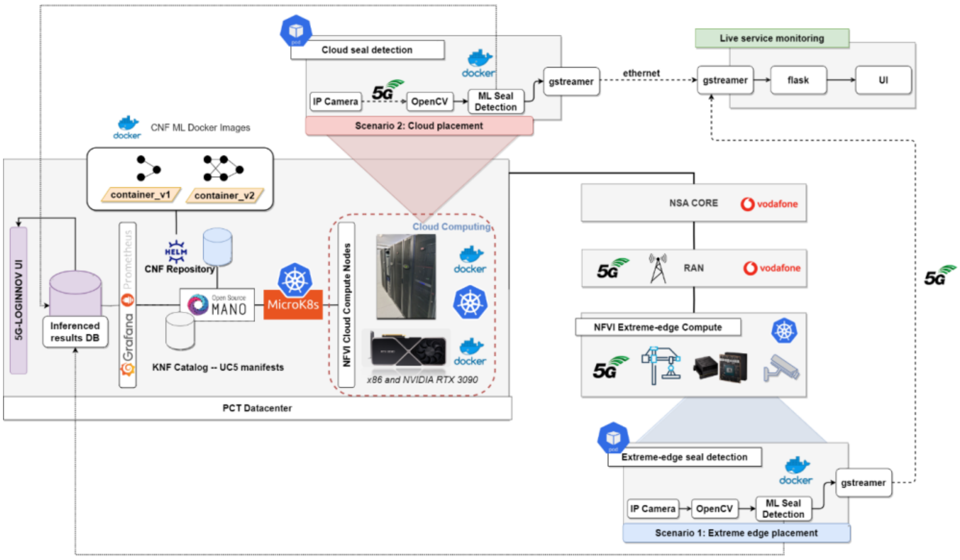


Figure 50: LL Athens - Seal detection service architecture at extreme-edge and cloud

Figure 51: LL Athens - Components/installations of the 5G&AI enabled container seal detection use case

The service orchestration of the ML service and service components has been documented in detail in [1], including the presentation of the MANO platform (software and hardware wise), service instantiation flows, lifecycle management operations, etc. As illustrated in Figure *51*, Port assets exploited for the use case validation include QC 31, a 4K camera mounted on QC 31 for continuously monitoring crane operations, a 5G modem to establish broadband communication between the crane and PCT's datacentre, an NVIDIA Jetson AGX Xavier device for facilitating the extreme-edge placement (scenario 1) as well as a dedicated cloud server, located at PCT's datacentre hosting an NVIDIA RTX 3090 GPU to facilitate the cloud deployment case (scenario 2).

The ML seal detection service is packaged as a CNF (orchestrated via OSM and kubernetes) based on the described placement options, i.e., the kubernetes worker nodes. The model is composed of two consecutive ML services: a) *container detection* and b) *seal detection*. Particularly, from the original 4K frames, we first extract the part of the frame which corresponds to the container with focus on the container door, and in the sequence on the extracted image, we search for the container seal.

2.4.2.1 Container Detection

For the container detection algorithm, we exploit two different versions, hereafter coined container_v1, and container_v2, where both versions exploit the same seal detection ML model.

For **container_v1** a pre-trained U2Net [5] is used to extract a mask of the most salient object in a frame, in that case the container which passes in front of the camera. The mask is used for background removal. Then, the image's contours are calculated and are matched (or not) with the contour of a typical container.

For **container_v2** a pre-trained medium sized YOLOv5 [4] neural network was re-trained on 2000 images with containers and 2000 images without containers. During training the network's first 23 high-level layers were frozen, meaning that only the last layer of the network was fine-tuned to the task.

2.4.2.2 Seal Detection

Seal detection: Another medium sized YOLOv5 [4] network was trained from scratch for 100 epochs on a manually annotated dataset of images with containers and their seals. The dataset consists of 50.000 images, which was augmented via random perspective transformations into 500.000 images. To avoid any overfitting, the best scoring model on the validation set was stored.

2.4.3 List of Key Performance Indicators

Table *20* lists the logistics and technical KPIs relevant for UC5 as defined in [2] (D1.4).

KPI	KPI ID	Measured Value
Vessel Operation Completion Time	A-KPI10	16% (estimated average)
Model Inference Time	A-KPI11	125ms @extreme-edge 35ms @cloud (average)
Model Accuracy/Reliability	A-KPI12	Depends on the ML model configuration c.f. Section 2.4.5
Human resource optimization (person hours)	A-KPI9	Qualitative
Deployment Time	A-KPI3	30 seconds (on average)
User Experienced Data Rate	A-KPI25	<12Mbps (uplink, average)

Table 20: LL Athens - KPIs list for UC5

A-KPI10 explains the reduction of vessel stay at the port premises, i.e., the time required for the vessel operations to be completed. Figure 52 depicts for the period of 01-01-2022 to 10-10-2023 the number of containers movements (load/unload operations) realized at the Port of Piraeus. The time required for a single container move is approximated at about 2 minutes (including the manual seal check process). This value is a practical observation as it depends on various factors, e.g., cargo type and weight, the cargo weight distribution, position of the container on the vessel, crane move type, e.g., twin/tandeem, weather conditions, crane operator experience, etc. Given these considerations, if we allocate 10 seconds for the container seal (manual) process, UC5 (automates) expedites (on average) the container movements for *Coastal* vessels from 108.46 to 90.38 minutes, for *Feeder* vessels from 3085.02 to 2570.85 minutes and for *Main trade* vessels from 3821.78 to 3184.81 minutes. On average this results in about 16% reduction in the vessel stay at the Port premises.

For the period Jan 1,2022 to Oct 10, 2023:

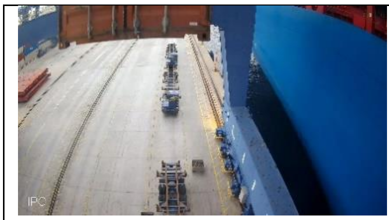
Vessel type	Count of Vessel Calls	Max Vessel size (m)	Min Vessel size (m)	Average Vessel size (m)	Average of Container Quantity	Average stay in terminal (days)	Average containers handled per day
Coastal	204	222	100	125	344,00	0,34	108,46
Feeder	2359	335	121	192	846,12	4,27	3085,02
Main Trade	1155	401	189	345	2140,86	2,27	3821,78
Grand Total	**3718**	**401**	**100**	**236**	**1221**	**2,29**	**7015,26**

Figure 52: LL Athens - PCT's average container handling per day and per vessel type

A-KPI9 refers to the exploitation of human resources (person hours) spent for the seal check process. Legacy procedures, i.e., manual seal check (before 5G-LOGINNOV) occupied about 78 hours per week handled by 2-person shifts. Human involvement can be completely removed from this service based on the accuracy of the AI service, and is qualitatively assessed for UC5.

2.4.4 Methodology and Measurement Tools

The dual ML solution was trained by obtaining data from the daily port operations at PCT. The quality of such a system is determined by the order of magnitude of data used to train and re-train the models (as described in 2.4.2), in order to increase the accuracy (i.e., correct inference) of the model, and thus the efficiency of the service. To *evaluate* the developed solution, we obtained more than 30 hours of footage from the 4K camera installed on QC 31, spanning across several days and varying working hours in order to obtain video feed with different light conditions (during morning and mid-day shifts). The evaluation presented in Section 2.4.5 includes 1000 container moves, where each container move is composed of several frames capturing the motion of the crane at the loading/unloading phase. As an example, Table *21* depicts part of the frames **for a single** container operation at 4K resolution and 25 frames per second. The detailed test protocol for this service is described in [3].

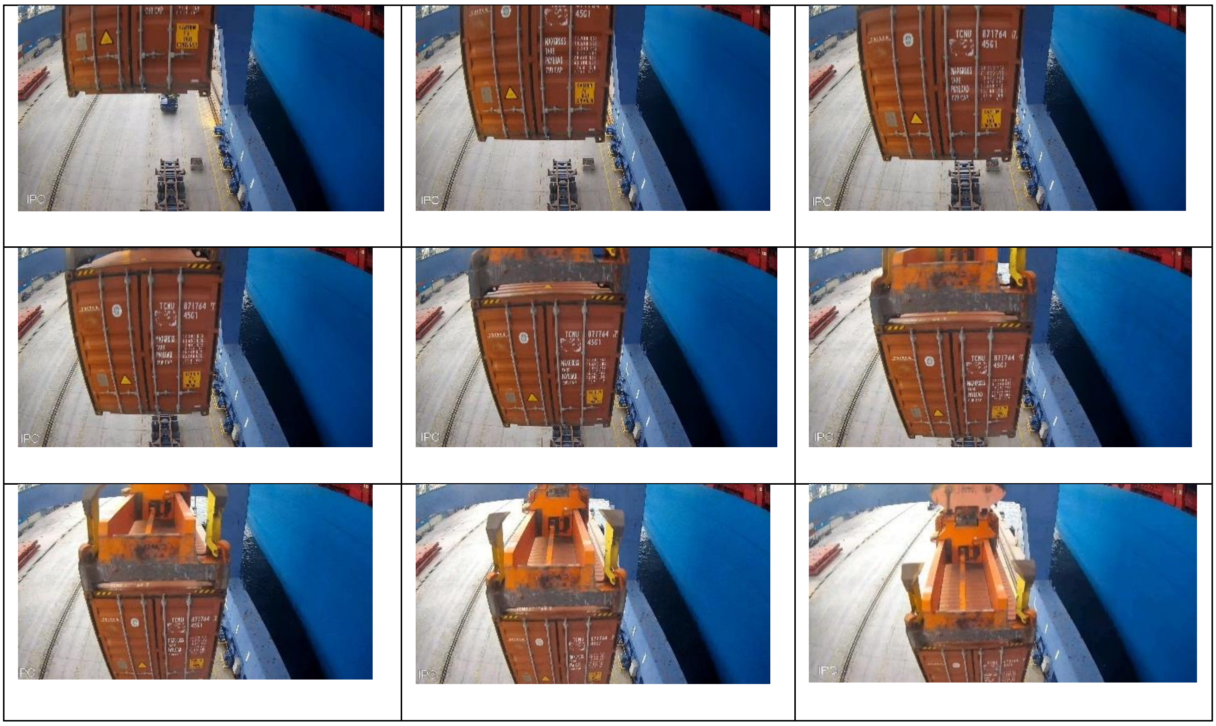


Table 21: LL Athens - A set of frames depicting a single container movement

For all inferenced results (and positive inferences) the CNF opens a connection also to the 5G-LOGINNOV database (as shown in Figure 53) to store the outcome of the processed frames for later inspection (also servicing as the ground truth in our evaluation).

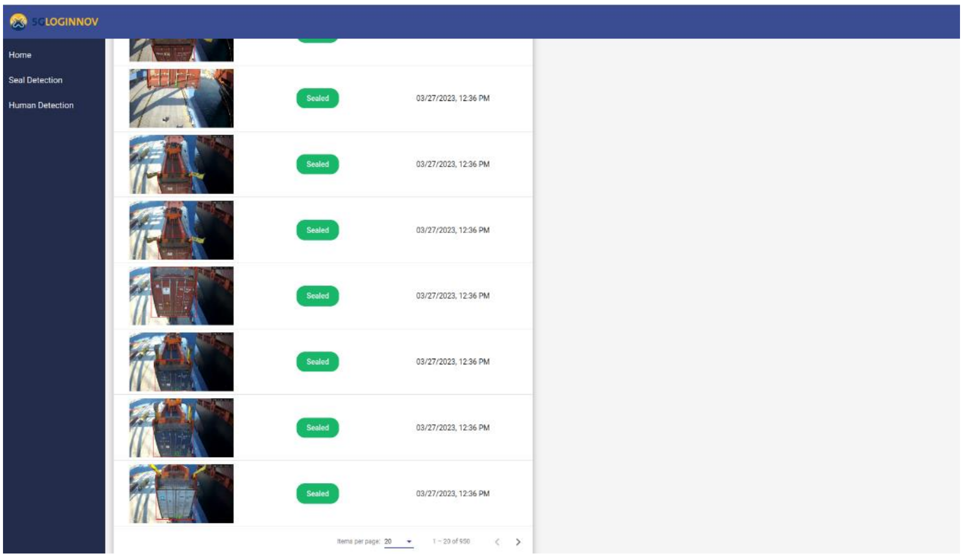


Figure 53: LL Athens - Database UI hosting the inferenced results of processed frames for UC5

Finally Table 22 illustrates snaphost of the user interface created for UC5, where the inferenced video stream is delivered to the central monitoring palfrom along with several data cards depicting the productivity level of the crane (e.g., how many container movements have been performed), network KPIs such as data rate and latency, as well as ML KPIs such as the inference time.

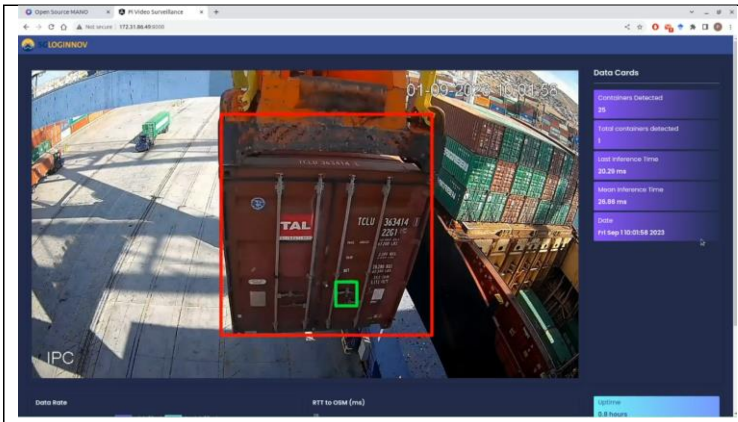
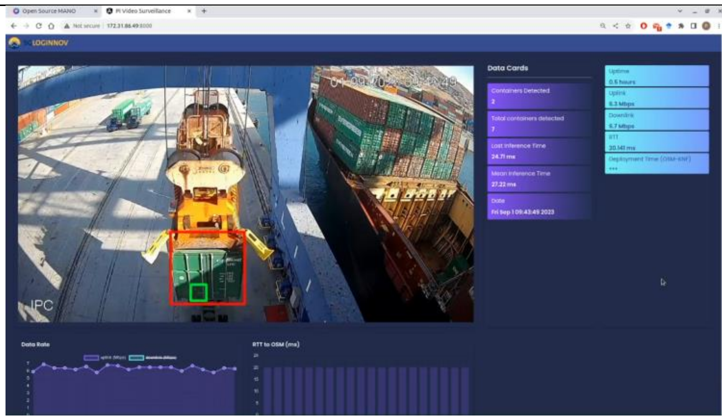
	

Table 22: LL Athens - User Interface for UC5

2.4.5 Results

Figure 54 provides the summary of the results for A-KPI11, i.e., Model inference time, for the 5G&AI enabled container seal detection service at the extreme edge and cloud deployment options of the 5G-LOGINNOV compute continnum. We provide the results for both developed solutions (container_v1 and container_v2) as described in Section 2.4.2. Note that each solution utilizes two models (container detection and seal detection) for the end-to-end service, which are sequential, thus, the service time is the aggregation of container time and seal time as depicted in the x-axis, i.e., about 170ms per frame for container_v1 model and about 120ms for container_v2, at the extreme edge. Hence, the live inferenced fps acquired via the (relatively) limited compute capabilities of the NVIDIA AGX Xavier extreme edge node is about 6fps and 9fps for container_v1 and container_v2, respecrtively. Similarly, moving to the cloud placement of the CNF exploting the NVIDIA GPU RTX 3090 compute, the acquired inferenced streams are about 14fps for container_v1 methodology and about 25fps for container_v2.

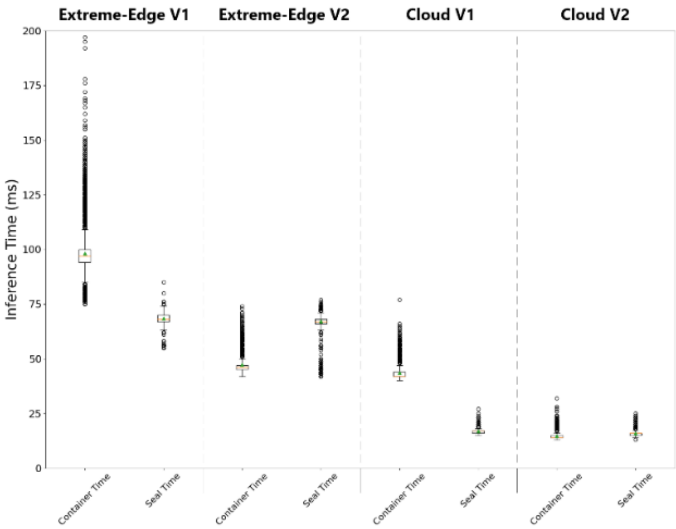


Figure 54: LL Athens - Inference time for container seal detection -- extreme edge and cloud placement – (A-KPI11)

In Table 23 we summarize the results according to our evaluation where we showcase for each configuration the True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN), of the two developed algorithms (Model Accuracy/Reliability A-KPI12). The first row shows the efficiency of both solution where we focus only on the container detection sub-task, whereas the second row is dedicated to the accuracy of the seal detection task. We observe that for both tasks' container_v2 has a better performance with higher TP/TN values and lower FP/FN values.

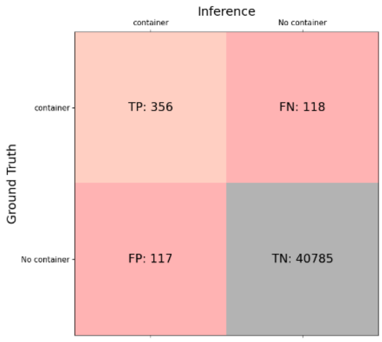


Figure 55: LL Athens - Container Detection Version-1 Evaluation

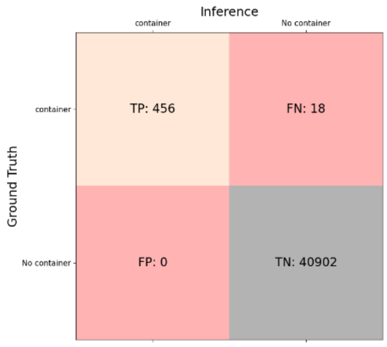


Figure 56: LL Athens - Container Detection Version-2 Evaluation

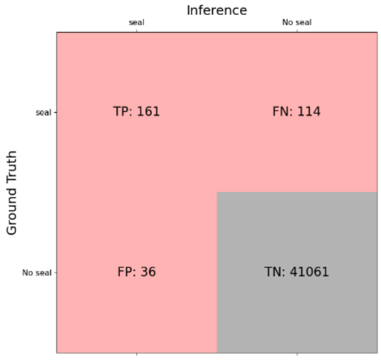


Figure 57: LL Athens - Seal Detection Version-1 Evaluation

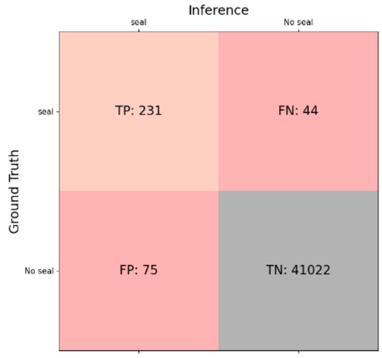


Figure 58: LL Athens - Seal Detection Version-2 Evaluation

Table 23: LL Athens - Evaluation of Model Accuracy/Reliability of UC5 – (A-KPI12)

A further and more detailed analysis for the accuracy of the developed solutions is presented in Table 24.

Model	Accuracy(T/(T+F))	Precision	Recall	F1 score
container_v1	0,994320379	0,752642706	0,751054852	0,751847941
container_v2	0,999564965	1	0,962025316	0,980645161
seal_v1	0,996374359	0,817258883	0,585454545	0,68220339
seal_v2	0,997123659	0,754901961	0,84	0,795180723

Table 24: LL Athens – Accuracy (true/(true+false)), Precision and Recall derived metrics for the True Positive class in Figure 55-Figure 58

Figure 59 depicts the 5G uplink experienced data rate (User Experienced Data Rate, A-KPI25), i.e., the consumed (and necessary) bandwidth utilized by the 4K camera installed on QC31 crane. We exploit the same camera hardware and (configuration options for the 4K streams) as in UC4. Similarly, the sample point on the x-axis (s1, s2,..,s7) represent the average data rate over 3600 seconds/samples (i.e., 1 hour of continuous 4K video streaming), totalling an entire working shift duration of about 7 hours.

We observe that the average streaming requirements are about 9.5Mbps where we also depict the observed upper and lower boundaries, with encoding mode: H.264, 4K resolution of 3840*2160 at 20fps.

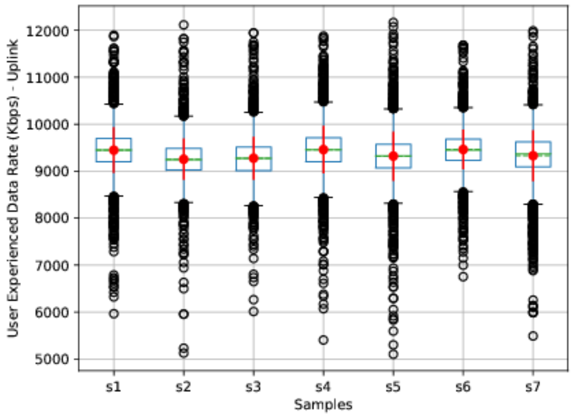


Figure 59: LL Athens - Uplink User Experienced Data Rate – (A-KPI25)

Next, we evaluate A-KPI3 (Deployment Time) of the CNF for UC5. Figure *60* depicts the OSM deploy time extracted from the open source MANO (OSM) manifest deployment logging (osm-deploy on the x-axis), as well as the CNF image pull time for downloading the ML image at the respective host (extreme edge or cloud). The results are average values over 50 measurements. We observe first that the image pull time for UC5 is about 6.5 minutes (which is basically determined by the host's throughput and the image size), whereas the deployment time from OSM (Release 13) for both cloud and extreme-edge orchestration decisions takes about 30 seconds, i.e., for the CNF to be active and running in the kubernetes cluster.

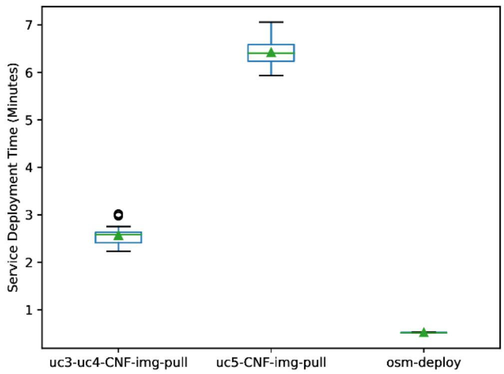


Figure 60: LL Athens - UC5 Service Deployment Time – (A-KPI3)

2.5 UC7: Predictive Maintenance

2.5.1 Description and Motivation

AI-assisted predictive maintenance powered by 5G technology becomes a pivotal tool in ensuring efficiency, safety, and sustainability in the maritime industry and the logistics supply chain. Particularly, the focus of this service within 5G-LOGINNOV and PCT reside in yard truck Port assets (about 200 trucks) that facilitate the daily port activities, and the prediction of possible breakdowns, reduction of the downtime for repairs, optimise stock of spare parts, increase the service life of yard vehicles and enhance operational efficiency through minimisation of breakdowns. The proposed tool captures historical and recent status data for the assets in question, utilized by the ML algorithm and driving a per yard-truck data driven approach (schedule of purchases, storage of parts, proactive maintenance), by taking advantage of 5G technology that provides a flexible, reliable and predictable environment to remotely keep track of the connected assets on a rea-time basis.

2.5.2 Use Case Setup

In addition to the video camera installed on the trucks for the collision warning service presented in Section 2.2, other on-truck sensors are utilized for extracting telemetry information from the trucks engaged in various daily port operations. Specifically, a 5G gateway (based on either Teltonika's RUTX50 industrial 5G gateway or Robustel R5020 5G IoT Router) is set up on the trucks to enable live data collection from the vehicles, and interconnection with the central traffic and operations monitoring system (TMS) located at PCT's datacentre, similar to UC3. The 5G gateway is interconnected (via ethernet) with various on truck data sources including CAN-Bus, container weight sensors, container presence sensors and GNSS for live monitoring of the performed work/activities. Figure *61* depicts the visualization tool for the accumulated telemetry.

Figure 61: LL Athens - Cellular connected yard trucks live operations monitoring

In addition to the live monitoring of the truck operations, the main focus of the proposed use case is to exploit an AI-assisted predictive maintenance service exploiting CAN-bus data, historical maintenance and break down data to predict future breakdowns of yard trucks as well as the parts that will be affected and relative spare parts required for the maintenance.

2.5.3 List of Key Performance Indicators

Table *25* describes the logistics KPIs relevant for UC7 as defined in [2] (D1.4).

KPI	KPI ID	Expected Impact
Parts in Stock	A-KPI13	Improved
Vehicle Breakdowns	A-KPI14	Improved
Vehicles Under Maintenance	A-KPI15	Improved
Vehicles Unexpected Breakdown	A-KPI16	Improved
Maintenance Costs of Vehicles	A-KPI17	Improved
Assets Idling	A-KPI18	Improved

Table 25: LL Athens - KPIs list for UC7

2.5.4 Methodology and Measurement Tools.

The use case of AI-assisted predictive maintenance involves the yard trucks of PCT engaged in the daily port operations. Predictive maintenance utilizes 5G-enabled condition monitoring, advanced inspections, and data analytics to predict yard truck component or equipment failure. It comprises different analytical algorithms in the context of predictive maintenance, providing a data-driven preventive maintenance schedule as well as a data-driven schedule of purchases. In order to provide this output, the AI-enabled service is connected to the TMS (Figure *61*) to draw CAN-Bus data from trucks as well as to PCT's Enterprise Asset Management System (EAMS) to draw historical maintenance data – both scheduled maintenance (as instructed by the OEM) and breakdowns, including truck parts utilized for repairs. The tool gives the flexibility to the user to select the historical data period that the prediction will be based on as well as the period and the specific spare parts for which the predictions need to be made (Table *26*).

	Description
System Input	Historical telemetry, maintenance and breakdown data of the yard trucks fleet for a period of two years
System Output	List of predicted dates of breakdown of yard truck (parts) along with spare part requirements for the fix/replacement
Success criterion	Accuracy of prediction

Table 26: LL Athens - AI-assisted predictive maintenance system input and output

PCT decided to focus on the prediction of fast-moving parts such as engine filters and tires (c.f. Section 2.5.5), that are purchased on a quarterly basis separately from parts that are rarely subject to breakdowns and most of the time, their life-span exceeds one year. Focusing on fast-moving parts allows to reduce inventory storage space and achieve cost savings. Two case scenarios were tested for PCT yard trucks. The purpose of the first scenario was to determine the maintenance schedule (i.e., proactive maintenance) for yard trucks while the second scenario focused on determining the number of the spare parts required for maintenance.

Particularly, for each separate vehicle the following information is stored on a weekly level.

- Total number of kms the vehicle has traveled during the past week.
- Total time in hours the vehicle was in move during the past week.
- Total cargo weight transferred by the truck during the past week.
- A list of maintenance actions performed on the specific vehicle during the past week. Each maintenance action essentially corresponds to the replacement of a specific part. In this work, we focused on 5 of the most « fast moving » parts, namely P1, P2, P3, P4, P5 (c.f. Section 2.5.5).

The ML algorithm uses as input the total number of kms the vehicle has travelled, total time in hours the vehicle was in move and the total cargo weight transferred by the vehicle since the last replacement of each one of the considered parts P1,…,P5, a total of 15 measurements. The output consists of estimations of the aforementioned quantities until the next replacement of each part, a total of 15 estimations.

Of note, the labels needed to carry on the supervised learning task at hand can be derived from the stored data in a straightforward manner.

A variety of basic regressors within a multi-output estimation scheme were used to attack the problem. Among them, and for randomized 5- to 10- fold cross validation schemes, Scikit's [1] k-Nearest-Neighbors and Decision Tree regressors outperformed all the rest with no significant performance differences between them. The aforementioned regressors demonstrated mean absolute errors which, when projected in time by the future schedule of each vehicle, resulted in timely estimation errors in the order of 1 to 2 weeks. In the scope of quarterly based spare part purchases policy followed by PCT this is well within the accepted margins.

2.5.5 Results

In order to determine the effects of applying the maintenance schedule suggested by AI-service we compare the decisions of authorized Port personnel based on experience, against the suggestions (when to take maintenance actions and which parts to purchase) derived by the ML service, for 2 quarters, i.e., Q4 of 2022 and Q1 of 2023.

To evaluate A-KPI14 (Vehicle Breakdowns), A-KPI15 (Vehicles Under Maintenance) and A-KPI16 (Vehicles Unexpected Breakdown) we exploit the evaluation of the algorithm based on the accuracy of the prediction in terms of true/false positives/negative rates. In more detail we observed the following; true negatives (i.e., no breakdown predicted and no breakdown actually occurred), were measured at a rate of about 85%, and true positives (i.e., breakdown predicted and occurred within 2 weeks), were at a rate of about 81%. Hence, if the suggested maintenance scheduled was applied and relevant parts predicted to fail were replaced according to the predictions, a direct impact can be expected on the aforementioned KPIs.

To evaluate A-KPI13 (Parts in stock) a comparison between the original purchase plans made by the port's personnel and the plans made by taking into consideration the estimations of the ML-system is depicted in Table 27, which were found satisfactory by the personnel responsible for the vehicles' maintenance planning, showing Q4 of 2022 and Q1 of 2023. Potential savings are attributed to A-KPI18 (Maintenance Costs of Vehicles).

Q4 of 2022/Q1 of 2023					
ID	Part Description	Qty Purchased (Q4/Q1)	Qty Occurred (Q4/Q1)	Qty Predicted (Q4/Q1)	Potential Savings (Q4/Q1) (%)
P1	Tyre 1200R22, 5 18PR	230/220	210/218	218/213	5.21/3.18
P2	Fuel Prefilter with water trap (Donaldson P550848 Kalmar)	50/45	37/41	35/39	10.81/13.33
P3	Hydraulic filter (Donaldson P171543)	70/65	53/58	59/61	15.7/6.1
P4	High capacity Allison transmission filters (P/N 29558329)	75/65	60/54	71/59	5.33/9.23
P5	Main Fuel Filter (Donaldson P550880)	40/35	30/28	27/32	3.33/8.57

Table 27: LL Athens - Evaluation of AI-assisted planning for spare parts purchase (Q4 of 2022 and Q1 of 2023).

A positive impact on A-KPI18 (Assets idling) can be also deduced from the abovementioned activities. AI assisted predictive/proactive maintenance scheduled (instead of reactive maintenance) based on the suggestions of the designed ML-system and carried out during idle periods, e.g., during shift changes, and not at the event of an unexpected breakdown, can result into time savings (i.e., less idle time) between 40-80 minutes (based on PCT's track record of such events). Additionally, in the case of proactive maintenance no disruption to related port operations would be incurred compared to the case were the truck needs repairs during an operation, e.g., while carrying a container to/from a vessel. Hence proactive maintenance, not only improves the assets idling time via data driven proactive maintenance schedules, but also maintains the work flow of other operations chains, e.g., the sequence of vessel loading uninterrupted.

We note that in Table *27*, there are cases where the Predicted Quantity fell short of the actual number of corresponding events (Occurred Quantity) during the Quarter under consideration. For the two quarters under consideration port personnel did not find this problematic, since there was always a small stock of pertinent parts. Adding a small *epsilon* in the predicted values may practically solve the majority of such cases which will impact A-KPI13 and A-KPI17. Regardless, results show that finer tuning of the algorithm, accomplished via training with more data and testing for more quarterly periods can be expected to result in more accurate and safer predictions, and more direct saving for the port assets and equipment.

Finally, by estimating the spare parts demand for a certain period, procurement departments can optimize their ordering and receiving processes, which can lower the administrative and parts costs - Maintenance Costs of Vehicles (A-KPI17)- and improve the overall delivery efficiency of spare/repair parts. Additionally, Inventory space for spare parts can be minimized and better managed A-KPI13 (Parts in stock).

In terms of operational efficiency, proactive maintenance and reduction of breakdowns entails many benefits for the port operator. The straightforward case is the reduced number of breakdowns that mainly affect the operations performed for vessels. Containers (as also illustrated in Section 2.4) are loaded/unloaded to ships following a specific sequence (flow) considering different parameters including the final destination of the cargo, cargo type, the weight and weight distribution, ensuring the minimization of stevedore moves (for quay side crane operations), the stability of the vessel and safe lashing/unlashing of containers on the vessel.

A single truck failure (e.g., engine breakdown resulting in immobilization of a truck) during a container movement/operation, requires restructuring of the vessel loading/unloading plan, either reserving the area around the broken truck for on-site repairs or transferring the container to another truck using a straddle carrier or a reach stacker and towing the broken truck to the designated repair area. Evidently, even if the actual repair time is usually short, the overall time required to resume truck operation after a breakdown is much longer.

2.6 UC2: Device Management Platform Ecosystem

2.6.1 Description and Motivation

The device management platform ecosystem serves as a robust backend system that is specifically designed to track and monitor vehicles, including trucks, and provide valuable feedback to operators such as managers and logistics teams. In the context of this project, we utilized trucks that were already being monitored on the platform, both within and outside of the port area. While the majority of their travel occurred outside the container terminal, it was essential to consider their time, space, and occupancy in the vicinity of the port as it affects the in-port operations, closely intertwined with yard trucks.

To make informed decisions about traffic conditions outside, towards, and within the port, we relied on the data available through the platform. This information was derived from a GPS location-based system, encompassing parameters such as timestamp, speed, location, and vehicle-specific data like engine status (idling, off, or moving). By leveraging this data, we were able to assess traffic and mobility conditions both outside the port and within its premises. Further analysis allowed to get insights of port operation, focusing the truck loading procedures.

During the project review, it was emphasized that showcasing and capitalizing on the capabilities of 5G technology within port operations was of an interesting concept in relation to the device management platform ecosystem and the project's context. Following the recommendations and engaging in discussions with fleet experts, we identified a specific need expressed by truck drivers – the desire for improved awareness of their surroundings while manoeuvring. This need presented the perfect opportunity to harness the capabilities of the platform, address feedback from reviewers, utilize the features of 5G (including high bandwidth, low latency, and support for multiple subscribers with high-quality video streaming), and ultimately develop a new product while respecting the security and personal data of the drivers.

The result of this was the creation of a mobile application specifically tailored for the context of this project, designed to complement the existing IoT Device Management Platform. The mobile application encompasses two distinct functionalities. Firstly, it offers GPS location tracking and provides drivers with relevant information regarding port operations. Secondly, it provides a multi-camera video feed from other trucks equipped with the same application. Thirdly it offers a manager / driver communication means altogether. Essentially, the product serves as a unique video conferencing application that facilitates parking trucks by offering real-time video feeds from different perspectives, as a communication tool between fleet managers and drivers and a tracking device. This innovation significantly enhances drivers' situational awareness during manoeuvring and contributes to overall operational efficiency within the port.

2.6.2 Use Case Setup

IoT platform is utilized in the project in 2 distinct methods. First its data from trucks adjacent to the port and inside the port are used to enhance route and fuel efficiency and reduce empty truck runs. Second the platform is extended with video collection and broadcasting capabilities targeting a newly developed mobile application; this was a request that originated during the review and was well received comment that added.

The following assets were used during the testing of the living lab.

- Port Assets
    - Port area
    - Trucks (from VI customer base) – 21 trucks used.
- Software components
    - Linux Based VM
    - Mobile Application Development Software (Android Mobile Application)
    - Custom coded web server (data capture server)
    - Custom desktop and mobile application for testing (Ping, open close connections, video rate logging)
    - Video conference open-source server – GRPC Live Kit server
    - Existing IoT Platform – Staging Environment for RnD
- Software Libraries
    - Track and Know tools – Hotspot Analytics
- Hardware components
    - IoT Devices – Teltonika FMB130, FMB640
    - 5G Enabled mobile phones: Samsung A22 5G
    - 5G Modem RM500Q-AE
- Information on trucks, technologies, emissions, and standards.
- Identification of truck operations within the port related to external trucks
    - Operational of external truck tasks
        - Entrance to the main gate
        - Loading/unloading at the main stash
        - Trip to the exit gate
        - Weigh measurement
        - Customs paperwork
        - Exit from gate.
    - Operational duration
        - Average duration since entry up to the main square loading 15,4 minutes
        - Average duration since the completion of the task at main square up to the exit gate is 25,3 minutes.

2.6.3 List of Key Performance Indicators

Table *28* describes the logistics and technical KPIs relevant for UC2 as defined in [2] (D1.4).

KPI	KPI ID	Expected Impact
Percent of Empty Containers Runs	A-KPI4	Qualitative*
Mean time of container job	A-KPI5	Qualitative*
Time needed for the device to open a network connection	A-KPI6	<55ms for 5G
CO_2 Emissions	A-KPI7	Improved
Fuel Consumption	A-KPI8	Improved
End-to-End Latency	A-KPI23	<20ms (average)
One-way Latency	A-KPI24	<10ms (average)
User Experienced Data Rate	A-KPI25	Depending on the number of concurrent application video streams c.f. 2.6.5

Table 28: LL Athens - KPIs list for UC2

KPIs A-KPI4, A-KPI5, A-KPI7, A-KPI8 are relevant to the Device Management Platform and the location of truck inside and outside targeting to reduce the time an external truck operates in the port and increasing fuel efficiency. These scenarios don't require the capabilities of the 5G network in terms of latency or data rate, but rather the capabilities of 5G to support a massive number of connected devices, i.e., the fleet of external trucks (i.e., device density) along the route towards/from the port area.

For A-KPI4 and A-KPI5 limited data were collected from the operations of external trucks. Due to the sensitivity and strict confidentiality of such port operation processes, it was not allowed by the authorities to collect data of the size of magnitude that will allow an adequate analysis and evaluation of the KPIs. Hence a qualitative assessment took place and is reported in the Section 2.6.5.

For KPIs A-KPI6, A-KPI23, A-KPI24, A-KPI25 this UC also includes a mobile application as "Around corner camera" to assist truck drivers while parking or manoeuvring. In this added scenario, real-time crystal-clear video feed from other trucks is essential as the reasoning is to replace the truck mirrors while manoeuvring when the mirror (or onboard camera) is not sufficient.

2.6.4 Methodology and Measurements Tools

As mentioned, this use case holds two different cases in effect. The **first case** is to leverage the external truck location outside and inside the port. 14 Vehicles were estimated for the experiment, but 21 where actually used, since more trucks operated at the port since the beginning of the project. The following data were gathered from the trucks, speed, GPS coordinates, timestamp and engine status (moving, idling and off). This information is used, along with PCT input of the port operations to redistribute traffic towards the port and to estimate possible fuel savings and in effect, NOx and CO_2 reduction. The whole area of the port was used, not only the area with 5G coverage, since for this part of the use case the 5G network doesn't not offer any additional benefits.

Figure *62* depicts the truck depots participating in the analysis. The trucks originate from adjacent areas of the port (red circles 1 to 5).

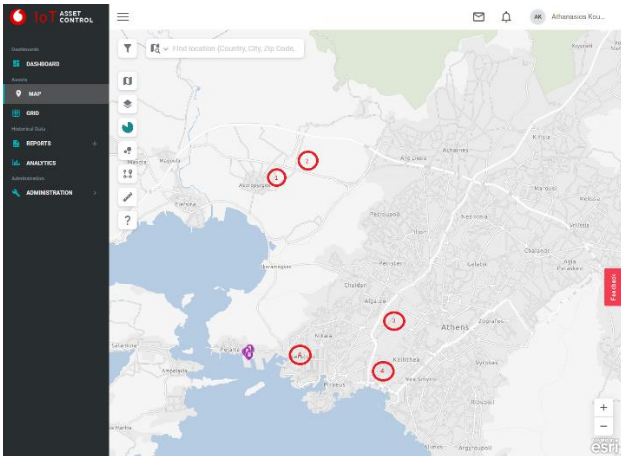


Figure 62: LL Athens - Truck depots for UC2 evaluation

Routes from these vehicles were recorded during the test period of April / May 2022 along with older data of the area to get the background traffic of the area.

- Vodafone Device Management Platform (outside and inside the port area)

The Device Management Platform was used to visualize the actual routes of the trucks and also the simulated routes. This gave an overview to an expert in port logistics to suggest the possible alternatives that could potentially offer better fuel economy. Details of the VFI trucks are shown in the following table.

TRUCK_NAME	TRUCK_ID	LOGISTICS_OPERATOR	DEVICE
Truck01	23459	Customer A	FMB120
Truck02	23460	Customer A	FMB120
Truck03	23463	Customer A	FMB120
Truck04	24041	Customer B	FMB120
Truck05	26753	Customer C	FMB120
Truck06	26757	Customer C	FMB120
Truck07	26761	Customer C	FMB120
Truck08	26762	Customer C	FMB120
Truck09	39264	Customer D	FMB120
Truck10	39265	Customer D	FMB120
Truck11	39270	Customer D	FMB120
Truck12	9418	Customer E	FMB640 +5 Fuel_Can bus
Truck13	9415	Customer E	FMB640
Truck14	23462	Customer A	FMA120
Truck15	9952	Customer F	FMB630 +5 Fuel_Can bus
Truck16	9958	Customer F	FMB630 +5 Fuel_Can bus
Truck17	18109	Customer G	FMB640 + 5 Fuel Can Bus
Truck18	18110	Customer G	FMB640 + 5 Fuel Can Bus
Truck19	18112	Customer G	FMB640 + 5 Fuel Can Bus
Truck20	18114	Customer G	FMB640 + 5 Fuel Can Bus
Truck21	18115	Customer G	FMB640 + 5 Fuel Can Bus

In this dataset only truck data where used, not small passenger cars with different acceleration and deceleration capabilities where used. Once data were captured and analysed (traffic and runs) we performed scenarios where trucks followed recommendations on the traffic, empty spots and container loading. The analysis process was based on hot spot analysis using the expertise of the Track and Know project (H2020 No 780754). Hot spots idling and non-moving trucks were identified. While loading / unloading a truck a hot spot was expected since at that time the truck is not moving but idling. However other locations within the port premises that identified as hot spots were areas of truck waiting. This information was used to deduce wait times and unnecessary idling engine times. The visualization tools provided by the device management platform provided an easy identification of the hot spots. The benefit and possible reduction of wait times, CO/NO emissions (A-KPI7) and fuel reduction was possible by holding trucks outside of the port at the heaviest peak times and at best not to depart from origin.

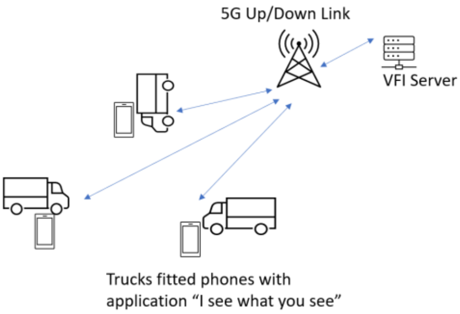
As can be seen on the following map (Figure *63*), the external trucks are seen at the following operating points, for 2 opposite operations.

- An empty truck arrives and picks up a container from the stack.
- A loaded truck arrives and leaves a container to the stack.

The stash is the place where the containers remain before being loaded at the ship or when unloaded from the ship. The empty truck passes through the customs with no delay as no paperwork is required, on the other hand loaded trucks are expected to pass paperwork through customs. This port operation is the first hot spot (regarding delay and wait time with idling engine). Once the truck is in the yard, the distance travelled is within 1Km range. The truck is headed at the loading crane. This operation takes a couple of minutes. However, delays can occur; this is the second hot spot.

Figure 63: LL Athens - Identified Hotspots, areas of idling

The second case was the parking assistant. To achieve this a mobile application was developed (screenshots follow). This is a mobile application software that relies on the IoT Platform to manage driver login and location data, whereas is extended with multicast video capabilities for live video feed from various sources. Within the test context 4 vehicles were selected for testing. During the testing a truck would manoeuvre while the driver would view the truck and its surrounding from nearby trucks. Especially on 90º corner parking this feature was well received. While modern trucks have cameras, this scenario showcased an extra security feature; at areas that external cameras don't have visibility.



Following the scenarios defined in D3.2 storyboards parking / moving scenarios was carried out with the use of the mobile application as a parking assistant. Of course, for safety reasons the truck drivers used outside assistance and used their mirrors as is required by traffic law.

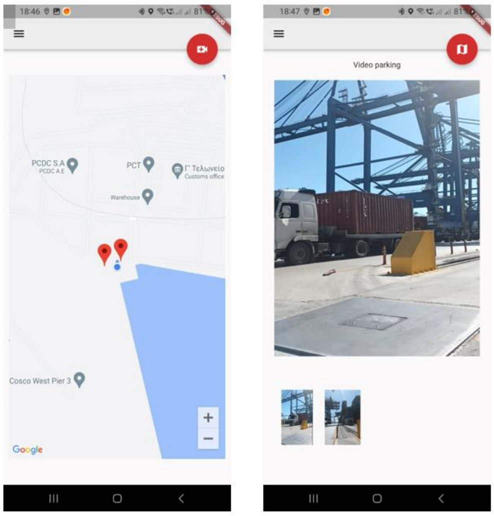
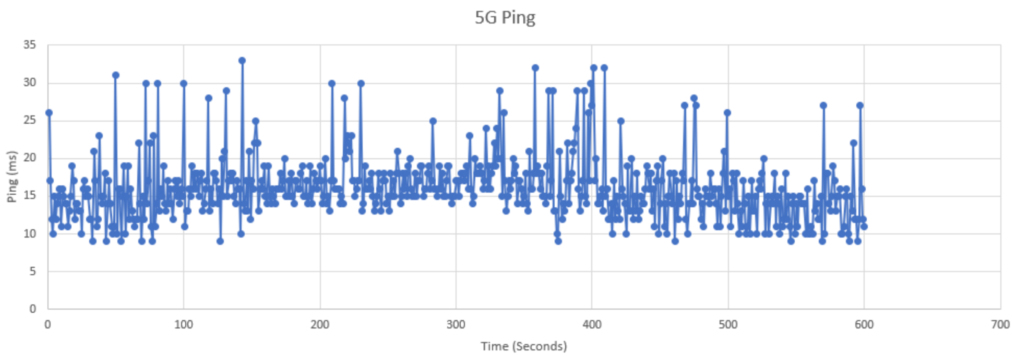


Figure 64: LL Athens - UC2 parking application user interface

2.6.5 Results

In order to test the latency (ping) 2 methods where used. One with the application Network Analyzer Pro (mobile phone Samsung A22 5G) and a second option via a coded C# application using the System.NET.HTTP library to perform the ping action and log the results. A laptop with the 5G Modem RM500Q-AE connected at the UTP port. A subset of the results is shown in the following figure, where we observe on average 16.3ms (A-KPI23) for the 5G network, and in coherence with the results of Section 2.1.4. Similar, to Section 2.1.4, A-KPI24 (one-way-latency) is assumed half RTT, i.e., on average <10ms.



In order to test the A-KPI6, a web server was set up on the other side of the server. A series of HTTP requests were performed and the dates where logged on both the client machine and the server. Both machines where UTC coordinated via the internet. This duration includes not only the traffic, but the SSL certificate handling, server package decoding and DB storage. The same packet of 238Bytes was used as payload, this packet requires 48ms to be logged in the database a local server; including the CPU and DB resources required. For the test scenario 600 attempts took place and recorded the time left and registered at the database. During that, the time was 65 ms for the 4G network and 55 for the 5G network. This leads to the expected average ~17ms one way for the 4G and ~8ms for the 5G. The half travel time includes firewall and internal data routing. While this isn't a pure network only test it indicates the reduction of time for 5G in contrast a 4G connection.

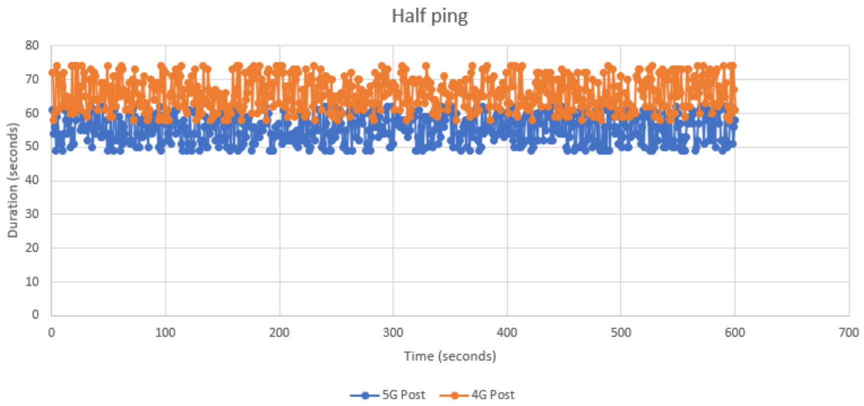


Figure 65: LL Athens - Time required for a device to open a network connection with the server – (A-KPI6)

The Close/Open scenario was selected to see whether the time to attach to network (data) is different (lower) in a 4G network than a 5G network. For this purpose, a test app was developed in Flutter SDK that pings a server, detects the network connection time between on and off. Modern versions of Android do not allow the program to alter the connectivity, but this app detects the time it takes to reconnect. The result for 10-minute test didn't reveal any noticeable difference as the average duration was in the order 950-1150 milliseconds on both networks. This duration includes the duration of the phone's (Samsung A22 5G 2022) resources, CPU time and data log used while making the connection. No noticeable difference for the user while using the mobile application if a connection is resumed, 5G versus 4G connection.

Figure 66: LL Athens - 4G / 5G average open close connection testing

The application build for the truck driver uses video feed from other devices. To test this scenario, we used 2 different tools and methodologies. Since the framework the application was built upon (Google Flutter, LiveKit GRPC library) doesn't offer data transfer logging we tested following two tools. VLC video player was used and large video files of 10-minute videos where loaded on the same machine (laptop with 5G Modem RM500Q-AE on the UTP port). During test the 4G network managed to stream 4 videos at high bit rate but the forth video didn't load at high enough speed, reaching only 200kbps.The same test was performed at a 5G network, 4 videos with no drop-in bit rate. The bit rate includes the actual rendered video and the buffered video. This test is an indication of the 5G capabilities of download video. More detailed results are presented at the other UCs of LL Athens.

Screen shots of the application below. To test and gather data, a browser JavaScript was used to load videos and record the bytes loaded per seconds. This gave a bit rate with the same results as the above test. This usage of the application is the one requiring 5G, to cater multiple drivers with multiple feeds and improve the quality of the user experience with multiple streams at a higher resolution.

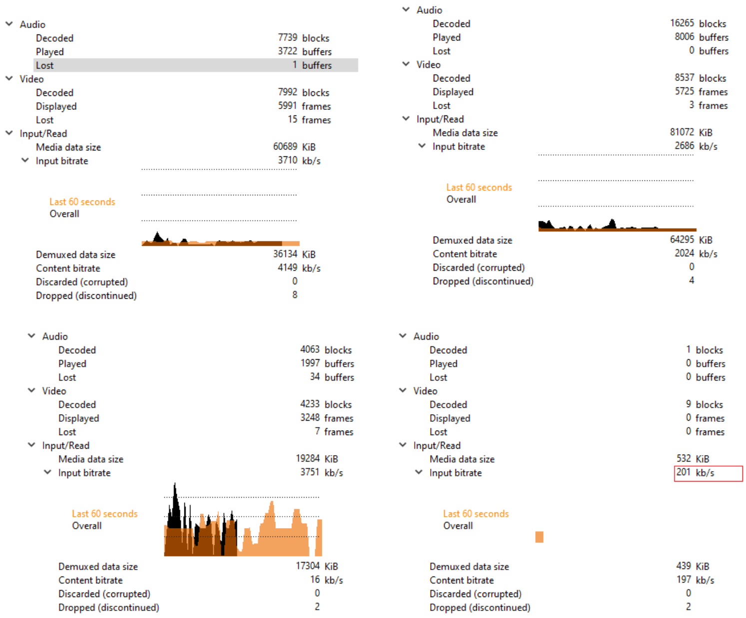


Figure 67: LL Athens - 4G Video feed, indicative VLC video streaming client

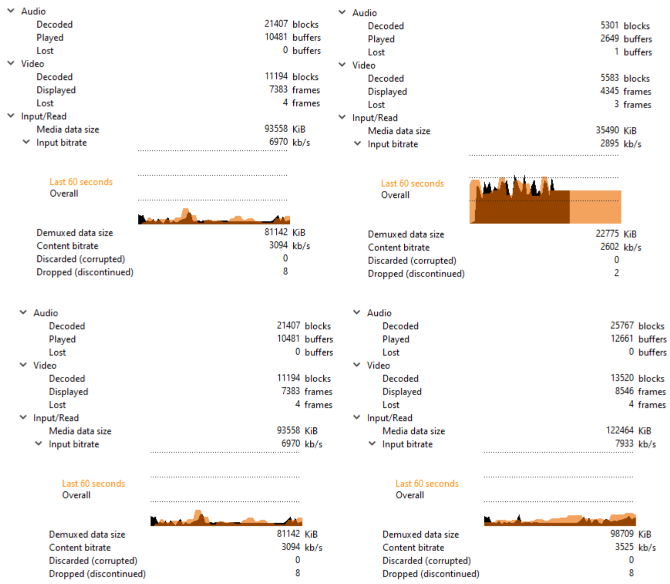


Figure 68: LL Athens - 5G Video Feed, indicative VLC video streaming client

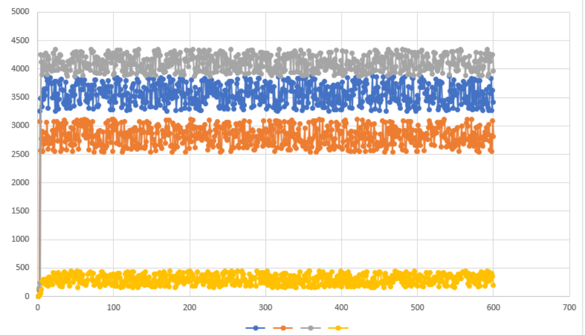


Figure 69: LL Athens - 4G Video feed bitrate of concurrent streams

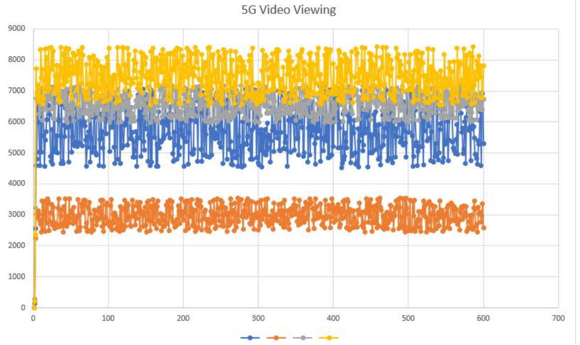


Figure 70: LL Athens - 5G Video feed bitrate of concurrent streams

The use of the IoT Fleet Platform is targeted also as mentioned to use the information from connected external trucks that operate outside and inside the port to improve the operations within the port (A-KPI4 and A-KPI5). The key points that reduce the port operations performance are the wait times at customs (just outside the port) and inside the port at the loading / unloading next to the containers stack. Here we focus on the latter.

In more detail, external trucks arrive to the port stack area to be loaded with a container. In each stack area the same port asset (i.e., a straddle carrier) is performing loading/unloading operations to trucks sequentially. Hence, when trucks arrive with no coordination to the stack area, there is a growing queue of vehicles waiting to be loaded, which increases the wait time of trucks and traffic congestion within the port, hence, the mean time of container job (A-KPI5) completion for external trucks. Via the VFI platform the loading / unloading (of containers) can be improved by coordinating the external truck depot locations (Figure 62) to schedule their trucks to arrive at pre-defined time slots. Based on PCT's logs, the average time of the external truck job completion time is about 40 minutes. To expedite this time, the VFI platform exploits the external truck location and estimated time of arrival on the port customs, and communicates pertinent information with the aforementioned truck depots so as to delay/reschedule their departure from the depots according to the delays experienced within the Port (aggregated at the VFI platform). In detail, this is achieved by the following actions.

- Trucks from nearby depots (Figure *62*) are connected to the VFI platform, continuously consuming information from the VFI assoicated trucks inside the port
- VFI associated external trucks calculate their average wait time at the port stack areas
- Based on the above, trucks at depots, reschedule their departure time accordingly ; However, in stack areas, other external trucks (not part of the VFI fleet) can contribute to the delays. In

this case information from multiple VFI trucks is taken into account (if available) to provide an estimate of the expected wait time.

For the duration of the trials 21 vehicles were enrolled in the VFI platform and 24 routes where identified. The routes are depicted on the following map.

Figure 71: LL Athens - Common truck routes within the port

The following map snapshots indicate cases for trucks operating inside the port with higher wait times (left), and lower wait times (right).

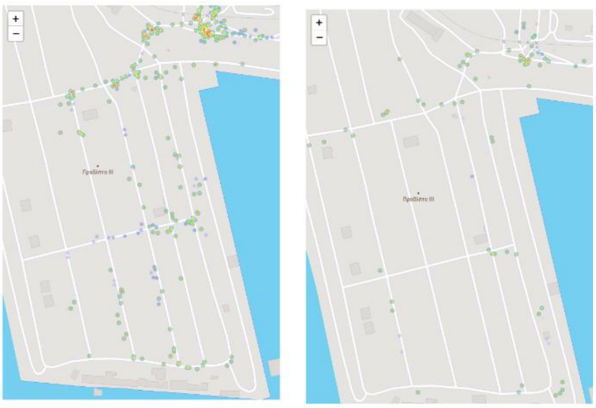


Figure 72: LL Athens - High and low idling duration time

While a reduction of congestion and waiting times at the port can be expected (A-KPI5), the results could be further improved by accounting the following. Data from trucks on the Fleet Management Platform do not represent the majority of trucks operating within the port; only a small fraction of the trucks operating send data to the platform. To streamline and make more efficient the port operations all trucks operating must be centrally orchestrated. This is challenging, as external fleet operators utilize fleet management platforms from various vendors (with different operational requirements, security protocols, etc.), or in some cases trucks are not even connected.

The following table illustrates the average wait times of truck per day that operated inside the port. A large number of trucks operating inside the port belong to logistics companies that are not Vodafone Innovus customers and the following table indicates a small fraction of the actual wait times per truck. Due to the small sample size the idling times may vary significantly. The consumption (A-KPI8) in lt/h is measured by trucks with CAN BUS sensors; not all trucks have these sensors so the estimation for all trucks is estimated (for Euro 5 Diesel trucks) at 3lt/hour.

Truck	Day AVG Idling Time minutes)	Estimated Consumption lt/h
Truck01	25	1,25
Truck02	65	3,25
Truck03	55	2,75
Truck04	35	1,75
Truck05	45	2,25
Truck06	37	1,85
Truck07	61	3,05
Truck08	66	3,3
Truck09	45	2,25
Truck10	35	1,75
Truck11	33	1,65
Truck12	33	1,65
Truck13	52	2,6
Truck14	31	1,55
Truck15	27	1,35
Truck16	15	0,75
Truck17	28	1,4
Truck18	34	1,7
Truck19	39	1,95
Truck20	22	1,1
Truck21	19	0,95

For testing some trucks were asked to delay (via a message to the mobile application) the arrival inside the port area (from customer close to the port in areas around 15-20 Km close to port). The following table represents trucks with 15-minute delay of arrival.

Truck	Day AVG Idling Time minutes)	Estimated Consumption lt/h	Previous Average Consumption	% Change In Consumption
Truck01	23	1,15	1,25	-10
Truck03	49	2,45	2,75	-30
Truck04	36	1,8	1,75	5
Truck06	42	2,1	1,85	25
Truck07	57	2,85	3,05	-20
Truck10	27	1,35	1,75	-40
Truck11	27	1,35	1,65	-30
Truck13	47	2,35	2,6	-25
Truck16	24	1,2	0,75	45
Truck19	33	1,65	1,95	-30

3 EVALUATION IN HAMBURG LIVING LAB

3.1 LL Hamburg Use Cases

Hamburg Living Lab is located on the test field for “connected and automated driving” (TAVF) in the City of Hamburg. The living lab uses the public 5G network operated by the Deutsche Telekom.

With the living lab, the potential of leveraging positive environmental impact by using 5G in data exchange for traffic management outside the port and the hinterland is demonstrated. The living lab deployed a methodology to capture the effect of the traffic infrastructure on regional emissions, making them comparable (standardised) by quantifying such influences under defined status of congestion and other relevant factors (driver profile, vehicle profile, loading, etc.).

For Hamburg LL, the following Use Cases are deployed:

Use Case 8/9: Floating Truck & Emission data (FTED) by 5G IoT devices.

Use cases 8 and 9 are aimed at collecting Floating Truck & Emission data (FTED) by 5G IoT devices, on-board units and nomadic devices. Analysing FTED data according to the ISO-23795 standard [2] leads to microscopic emission models per vehicle for the air pollutants CO2, NOx, PM and noise, all directly linked to acceleration and energy performance index (API, EPI). But applying the ISO-23795 standard for carbon footprint monitoring, requires stable data transmission and precise positioning, even more when using ISO-23795 for NOx, PM and noise where Newtonian Physics turned out to be non-linear relative to fuel consumption detection per floating car.

Use Case 10: Green Light Optimal Speed Advisory (GLOSA)

Green Light Optimal Speed Advisory (GLOSA) helps drivers to avoid harsh braking, which is one of the main causes for increased fuel consumption and CO2 emissions. In 5G-LOGINNOV, it is planned to use GLOSA for truck platoons and to showcase a mid-term migration path for using GLOSA in Automated Truck Platoons based on 5G technology. From 5G projects and publication [3], it is well-known that Vehicle-to-Infrastructure (cellular V2X) for vehicle platooning has End-to-End (E2E) latency requirements of 20ms time frames and up to 350m minimum ranges, prerequisites, which can only be achieved with the URLLC functionalities of the 5G network. Performance requirements for advanced driving including collision avoidance (10ms E2E latency) and cooperative lane change (25ms E2E latency) have the same low latency communication characteristics and cannot implemented without 5G mobile networks. In 5G-LOGINNOV, GLOSA based Truck Platoons will demonstrate a migration path towards higher SAE levels of Automation starting with basic functionalities including 5G test cases and test runs foreseen in use case 10, GLOSA based Automated Truck Platoons.

Use Case 11: Sustainable traffic management.

Sustainable traffic management uses different type of on- and above ground sensors to detect traffic density and traffic volume. With well-defined thresholds describing the Level-of-Services “free/dense/congested”, traffic management actions are set by public authorities to reduce congestion and negative environmental impact. Floating vehicle data is one of these sensors complementing as flow sensor the traditional on-street equipment. In 5G-Loginnov, the floating vehicle sensor network use 5G Services to design a special scenario solution implemented by Swarco and their myCity product in the Go-to-Market phase for improving cities’ environmental footprint.

All use cases include Real-Time Tracking & Enhanced Visibility features for traffic managers by monitoring FTED speed profiles and congested road segments, services which once again require stable data transmission and precise positioning (5G prerequisite).

All Hamburg KPIs defined for evaluation, are horizontal elements of use case 8/9, 10 and 11. As an example, we will use the measurement of standstill, which is an important KPI of all three use cases. The KPI is measured by ISO-23795-1 compatible smartphone LCMM APP, by tec4u telematic device as well as by Continental IoT Box in use case 8/9. But standstill is at the same time heavily influenced by Time-to-green traffic light assistance APP GLOSA making it also to an important element of use case 11 (environment based smart city traffic management). As all KPIs are 5G enabled, the 5G NSA KPIs also are horizontally cov are 5G enabled, the 5G NSA KPIs also are horizontally cov are 5G enabled, the 5G NSA KPIs also are horizontally covering all use cases. Given this horizontal set-up, the Hamburg team executed trials and evaluation according to KPIs, which are 5G enabled, the 5G NSA KPIs also are horizontally covering all use cases. Given this horizontal set-up, the Hamburg team executed trials and evaluation according to KPIs, which are 5G enabled, the 5G NSA KPIs also are horizontally covering all use cases. Given this horizontal set-up, the Hamburg team executed trials and evaluation according to KPIs, which are 5G enabled, the 5G NSA KPIs also are horizontally covering all use cases. Given this horizontal set-up, the Hamburg team executed trials and evaluation according to KPIs, which are 5G enabled, the 5G NSA KPIs also are horizontally covering all use cases. Given this horizontal set-up, the Hamburg team executed trials and evaluation according to KPIs, which are 5G enabled, the 5G NSA KPIs also are horizontally covering all use cases. Given this horizontal set-up, the Hamburg team executed trials and evaluation according to KPIs, which are all 5G enabled. This includes the 5G NSA KPIs which are also covering horizontally all use cases. It must be mentioned that the KPI based trial set-up is different to Koper and Athens given the use case design behind.

3.1.1 Technical setup

The LL Hamburg illustrated new functionalities of 5G as MEC, precise positioning as uRLLC can improve the efficiency of logistic operations, but on the other hand, also prove that improved 5G network functionalities as mMTC and eMBB are essential for any future mobile network application.

In this context, the LL Hamburg used MEC, 5G enabled precise positioning, uRLLC, mMTC and eMBB in its use cases according to their functional abilities.

MEC and uRLLC

UC 10 will establish a V2X information system by combining 5G functionalities with GLOSA to enable automated truck platooning. The optimised trajectory planning for automated vehicle manoeuvring across intersections enabled by real-time information on current and predicted traffic light signalling will require reliable connectivity and analytic capability with a low latency below 10ms. By using a MEC between the 5G core network and the connected vehicles with reducing network transfer delays to meet the specific ultra-reliable and low-latency requirements necessary to serve automated truck platoons.

The MEC will bring the analytics of the LL-Hamburg uses cases much closer to the connected vehicles by processing and combining mission-critical traffic information with manoeuvres of the vehicles and infrastructure data from the cloud. Efficient and safe driving inside a platoon requires information being shared among the platoon as synchronous as possible. The following vehicles should be on-time aware of relevant actions of the leading vehicle (imminent reduction/increasement of speed), otherwise unnecessary braking or the dissolvement of the platoon cannot be prevented.

The uRLLC functionality is furthermore a prerequisite for the required precise positioning used in all four use cases of the LL Hamburg. While precise positioning of stationary objects does not require the use of 5G technologies, the application on fast-moving vehicles as passenger cars, light, and heavy commercial vehicles requires the improved connectivity capabilities of 5G as uRLLC. Under consideration of the movement of the platoon, the impact of uRLLC will further be improved by 3GPP Release 16, which introduces enhancements of session continuity and therefore reduces the influence a handover has on the reliability of low latency services.

Precise Positioning

The LL Hamburg used 5G enabled precise positioning on lane-level for all use cases.

This requires an accuracy of the position within an error bound of lateral of 0,57m (0,10m for 95%) and longitudinal of 1,40m (0.48m for 95%) on freeways [23]. Therefore, conventual GNSS position information will not be sufficient. Secondly, the given position must be provided in a high frequency and a low latency to be reliable in a fast-moving vehicle.

The four use cases will combine uRLLC with the precise positioning service Skylark that provides accuracy for the position of up to 0.10m. Figure 73 shows the Skylark service co-branded by Deutsche Telekom, a partnership that was already announced in March 2020 [8] with further product details published in [7]. It should be noted that network centric Precise Positioning Services do not necessarily require 5G and are already available in 4G/LTE. Nevertheless, when it comes to rolling out any type of scalable service uptake, e.g., reliable Floating Truck Emission Data use cases (UC8/9) or Collision Warning for Automated Truck Platoons in a European Metropolitan Region such as Hamburg, the core functions of the 5G network uRLLC, MEC and network slicing become crucial elements of the services planned to be implemented in Hamburg.

Figure 73: Precise Positioning Service as planned to be used in LL Hamburg

5G Security Requirements

Rising security concerns regarding the transfer of sensitive video surveillance data to the cloud, MEC is enabling the processing of video data within the edge of AI-enabled 5G CCTV networks. Instead of sending all video surveillance data to the cloud, MEC reduces security risks by processing the data locally and transferring filtered data to the cloud.

Logistic use cases in the Hamburg LL result in deep security, safety, and data protection challenges, and require a holistic approach to security. Due to its growing ecosystem complexity, logistic applications raise deep security, safety, and data protection concerns. Strong protection is therefore mandatory. To provide direction in approaching cybersecurity, several standards, regulations, and directives in various stages of maturity are proposed for providing security assurance and guidance.

Protection mechanisms are needed in: truck/car, network, and back-end tiers; all software and hardware levels; and for the full data life-cycle. Some of the main security and privacy points of vigilance are the following:

1. User (people, cars, infrastructure) in the ecosystem have become targets of choice for hackers: the number of attacks recently discovered and published is continuously growing.

2. Safety and security can no longer be handled separately: failures and threats blend into interaction vulnerabilities as trucks are cyber-physical systems.

3. The connected logistic ecosystem is data-shaped: different data are collected, analysed, and shared with all ecosystem stakeholders through multiple paths, and must be protected. A key trade-off for protecting data at rest, and in transit, is finding the right balance between data integrity, critical for the safety of vehicles and their surroundings, and data privacy, to minimize the amount of collected data.

Key questions for protection include for each stakeholder the choice of the most relevant tier to deploy security mechanisms. Should an end-to-end approach to security be adopted, using cross-cutting security management planes, or should tier-by-tier solutions be favoured. The main security requirements can be summarized in the following items:

- Cultivating a cybersecurity culture.
- Adopting a cybersecurity life cycle for complete development over the life cycle.
- Assessing security functions through testing phases: self-auditing & testing.
- Managing a security update policy.
- Providing incident response and recovery.

Taken together these general guidelines should ensure a secure delivery of services in the ecosystem.

5G Architecture and technologies

The LL Hamburg set-up is mainly based on the idea to use telco products (DTAG) as the basis for the use case demonstration. Standard 5G in combination with MEC (MobilEdgeX as product) is the network backbone for the lab. DTAG connections are also used to link mobile devices (e.g. trucks), RSU's (e.g. traffic lights), and the related backbone infrastructure (e.g. TMS Traffic Management System from SWARCO). Dedicated functions, especially with requirements for low network delay, will be deployed in a so-called MEC environment. MEC deployment is based on standard procedures like Docker.

Figure 74 demonstrates this relation between the components in the LL Hamburg.

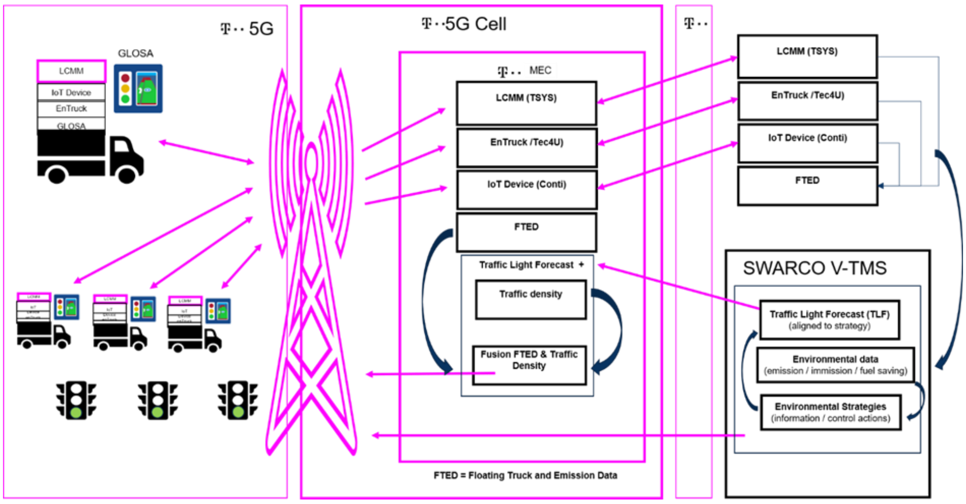


Figure 74: Hamburg Living Lab overview

3.1.2 5G Network Architecture

The 5G mobile network is a big step to provide many new features for Telco customers. The following pictures illustrated the main components for a 5G network.

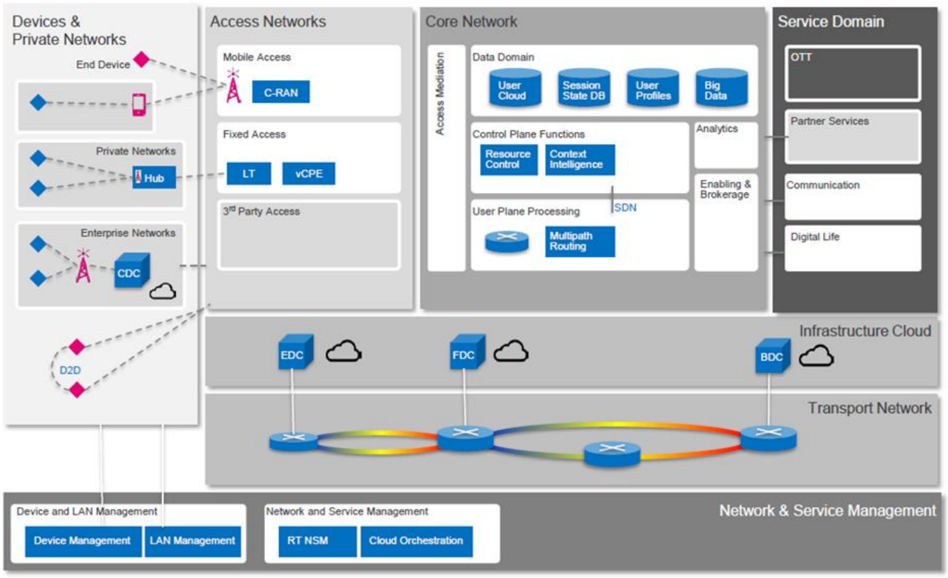


Figure 75: 5G Main Components

From a core network evolution perspective, there are two main steps to supporting 5G New Radio (NR). The first step – a 5G Evolved Packet Core (EPC) with 5G NR Non-Standalone (NSA) operation – is to move forward from the existing EPC. This is the current situation for LL Hamburg (5G production network Deutsche Telekom AG - 3GPP R15).

There are three major advantages for 5G:

- **Massive machine to machine communications** – also called the Internet of Things (IoT) that involves connecting billions of devices without human intervention at a scale not seen before.
- **Ultra-reliable low latency communications** – mission-critical including real-time control of devices, industrial robotics, vehicle to vehicle communications and safety systems, autonomous driving, and safer transport networks.
- **Enhanced mobile broadband** – providing significantly faster data speeds and greater bandwidth. New applications will include fixed wireless internet access for homes, outdoor broadcast applications without the need for broadcast vans, and greater connectivity on the move.

In the 5G NSA approach, the existing 4G core (EPC) is working as an anchor network mainly for signalling purposes. This EPC is combined with new extended radio functions – focused on the provisioning of additional mobile bandwidth capabilities (5G New Radio – 5GNR). T-Mobile / Deutsche Telekom is using additional frequencies from old UMTS solutions (2,1 GHz band) to offer more capacity for the clients. This function (dynamic frequency usage) is adapted from 3GPP R16.

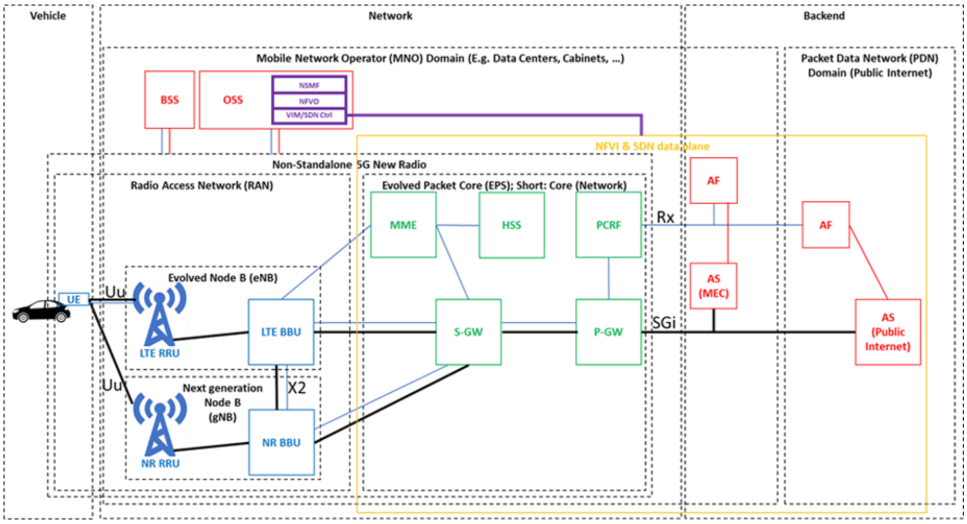


Figure 76: 5G Main Components 5G NSA Solution

Table 29 provides a summary of the 5G technologies to be deployed in the Hamburg Living lab.

Table 29: 5G Technologies LL Hamburg

5G Service/Application	Deployed
Radio Access Network	Production network 3,6 Ghz / 2.1 Ghz
Number of cell sites	3,6 GHz more than 20 sites / 2.1 GHz over 98% full coverage in Hamburg
Frequencies used	3.6 GHz / 2.1 GHz
Frequency Bandwidth	2,1 GHz – 20 MHz / 3,6 GHz 90 MHz
Mobile Core	3GPP R15 with DSS
Virtualised infrastructure	only partly
Orchestrator	DTAG internal
Network Slicing	not deployed yet
MEC	available (MobileEdgeX)

3.1.3 Technologies and innovations deployed

Figure 77 gives an overview of the logistics terminal operation inside the Port of Hamburg. As one can see, the river Elbe divides the city of Hamburg into two parts, i.e a northern and southern section relative to the river. It can be seen that most of the terminals for container handling are in the southern part of the city. For these terminals, the multimodal accessibility for container delivery to the road (motorway) and rail (cargo hubs) are crucial for the overall ports' operation efficiency. This is of special importance as 10,000 TEU container ships nowadays are complemented by "XXL-size" cargo ships transporting up to 24,000 containers. These "Mega"-Container ships must be navigated safe and fast along the Elbe river to Hamburg's main terminals, located in the southern part of the city. The challenge for such a sensitive ecosystem is to ensure an efficient organization along the entire multi-modal transport chain including the specifics of water, road, and rail cargo altogether. Therefore, the City of Hamburg published the first I.T.S. policy directive for the promotion of logistics and I.T.S. innovation projects in April 2016 and extended it in June 2018 [19], with a focus on political support measures linked to the I.T.S. world congress organised in October 2021 in Hamburg.

The strategic balance of conflicting requirements linked to port logistics and low emission zones in the city centre, the professional handling of goods' transport along the multi-modal supply chain as well the efficient hand over from Mega-Containerships to last mile hub- and micro-hub warehouses became one of important KPIs of the I.T.S. policy directive.

Figure 77: Geographical distribution of Container-Terminals and 5G-Loginnov test Fields

In 5G-Loginnov, the contribution to the overall political challenge is planned to be implemented in the 2 rectangular boxes one can see in Figure 78. The red coloured rectangular box in the upper part of Figure 28 shows the location of the Test field for Autonomous and Connected Driving (TAVF) and is located directly in the "heart" of the city. The Road network and infrastructure of TAVF belong to the traffic authority of the city and all traffic light intersections of the test field are equipped:

- with "classical" V2X technology using 802.11p WLAN communication standard and
- with "cellular" V2X technology using 5G Release 16 mobile communication of the Deutsche Telekom AG providing 5G services to the public.

With regards to 5G infrastructure aspects in TAVF, Use Case 10 is the most relevant making use of the 5G features low latency communication (uRLLC) and 4K Video broadband communication (eMBB). To navigate a platoon stable and safe within the busy urban road network of Hamburg, avoiding collision with Vulnerable Road Users (VRUs) such as pedestrians and bicycles a special APP will be used known as GLOSA (Green Light Optimal Speed Advisory). As shown in Figure 78, the innovation lies in the uplink of traffic light Signal Phase and Time information combined with the specific Topology Information of the Intersection leading to a SPAT/MAP message which is transmitted to the 5G-Mobile Edge Server of Deutsche Telekom and from there to the GLOSA APP. Additionally, 5G enabled Precise Positioning will be used to enhance the accuracy of the GLOSA-APP and to improve the collision warning alert message. It should be mentioned that for 5G enabled GLOSA truck platoons, Vehicle-to-Vehicle messages with latency requirements of less than 25 Milli-Seconds are needed as stated by Chandramouli and Liebhart [2].

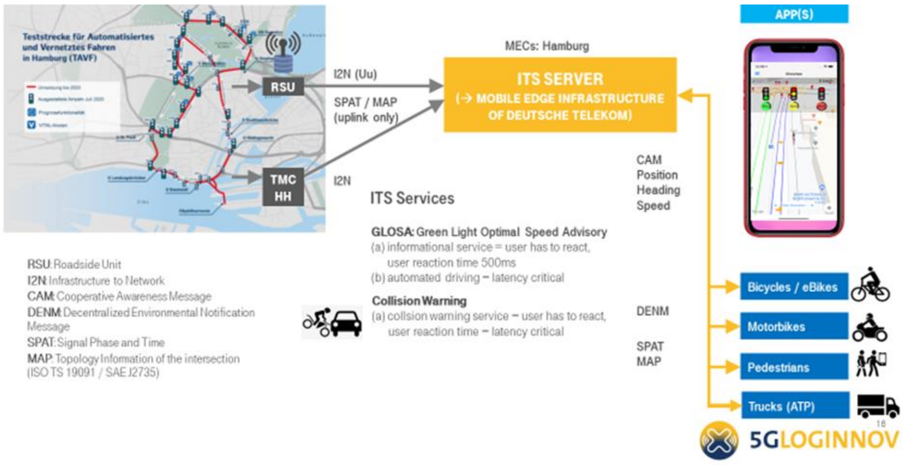


Figure 78: GLOSA APP technology as planned in the TAVF test Field

The innovative approach planned in Hamburg is to measure the environmental impact of traffic management actions linked to traffic light signalling used in 5G enhanced GLOSA (red coloured box in Figure 78) as well GHG savings possible when extending Green Light for truck platoons based on I.T.S. G5 and 5G enhanced Floating Truck Emission Data analysis offered by T-Systems smartphones, Continental IoT devices and tec4u Entruck on-board-units. Additionally, Continental and tec4U will implement 5G technologies in their devices and existing applications to be able to enable a native use of 5G technologies. The significant savings expected will also be used for business deployment as fuel savings give stimulus for logistics service providers to join the project and the overall I.T.S. strategy of the city of Hamburg as well as the port of the future implementation plans announced by the Hamburg Port Authority (HPA).

3.2 LL Hamburg KPIs

KPIs selected by Hamburg LL are not referred to each UC but they all measure aspects of the three demonstrated UCs. All KPIs are defined in relation to the 5G technical setup and the use cases described in the chapters before.

KPI ID	**H-KPI1**
Measurable objectives and indicators	Increase average truck speed in single vehicle mode with equipped vehicles (vehicles for LL Hamburg will be equipped with devices for Entruck, Conti IoT and LCMM)
KPI	Increase average truck speed in single mode up to 5%

KPI ID	**H-KPI2**
Measurable objectives and indicators	Reduction of acceleration in single mode (vehicles for LL Hamburg will be equipped with devices for Entruck, Conti IoT and LCMM)
KPI	Reduction of average acceleration activities in single mode up to 5%

KPI ID	**H-KPI3**
Measurable objectives and indicators	Reduction of stillstand time in single mode (vehicles for LL Hamburg will be equipped with devices for Entruck, Conti IoT and LCMM)
KPI	Reduction of stillstand time in single mode up to 5%

KPI ID	H-KPI4
Measurable objectives and indicators	Increase average truck speed in platoon vehicle mode with equipped vehicles (vehicles for LL Hamburg will be equipped with devices for Entruck, Conti IoT and LCMM)
KPI	Increase average truck speed in platoon mode > 5%

KPI ID	H-KPI5
Measurable objectives and indicators	Reduction of acceleration in platoon mode (vehicles for LL Hamburg will be equipped with devices for Entruck, Conti IoT and LCMM)
KPI	Reduction of average acceleration activities in platoon mode > 5%

KPI ID	H-KPI6
Measurable objectives and indicators	Reduction of stillstand time in platoon mode (vehicles for LL Hamburg will be equipped with devices for Entruck, Conti IoT and LCMM)
KPI	Reduction of stillstand time in platoon mode > 5%

KPI ID	H-KPI7
Measurable objectives and indicators	Reduction of fuel consumption in single mode (vehicles for LL Hamburg will be equipped with devices for Entruck, Conti IoT and LCMM)
KPI	Reduction of fuel consumption in single mode up to 10%

KPI ID	H-KPI8
Measurable objectives and indicators	Reduction of CO_2 emissions in single mode (vehicles for LL Hamburg will be equipped with devices for Entruck, Conti IoT and LCMM)
KPI	Reduction of CO_2 emission in single mode up to 10%

KPI ID	H-KPI9
Measurable objectives and indicators	Reduction of fuel consumption in platoon mode (vehicles for LL Hamburg will be equipped with devices for Entruck, Conti IoT and LCMM)
KPI	Reduction of fuel consumption in single mode up to 20%

KPI ID	H-KPI10
Measurable objectives and indicators	Reduction of CO_2 emissions in platoon mode (vehicles for LL Hamburg will be equipped with devices for Entruck, Conti IoT and LCMM)
KPI	Reduction of CO_2 emission in platoon mode up to 20%

KPI ID	H-KPI11
Measurable objectives and indicators	Optimize Energy Performance Index 'EPI - cl per ton and km' (vehicles for LL Hamburg will be equipped with devices for LCMM)
KPI	Increase value of 'EPI - cl per ton and km' up to 10% for vehicle trips

KPI ID	H-KPI12
Measurable objectives and indicators	Optimize Acceleration Performance Index 'API - KWh per ton and km' (vehicles for LL Hamburg will be equipped with devices for LCMM)
KPI	Increase value of API 'KWh per ton and km' up to 10% for vehicle trips

KPI ID	H-KPI13
Measurable objectives and indicators	5G bandwidth on urban roads
KPI	Extended cellular bandwidth on urban roads by 5G network

KPI ID	H-KPI14
Measurable objectives and indicators	Positioning quality on urban road networks with 5G
KPI	Positioning quality on urban road networks with 5G by 10 cm

KPI ID	H-KPI15
Measurable objectives and indicators	Signal latency in the 5G environment using Mobile Edge Computing
KPI	Average signal latency in the 5G environment will be reduced thru Mobile Edge Computing (MEC) to 10 ms during vehicle trips

ID	H-KPI16
Measurable objectives and indicators	Packed Error Rate (PER) in 5G NSA production network
KPI	Average rate of packed errors during 5G data transmission from vehicle to backend. The KPI will be measured while performing the different use cases. Reduction of PER by 10%.

3.3 Technical baseline test setup in 2021

All Hamburg KPIs listed in chapter 3.2, cover several of the use cases deployed in Hamburg. Therefore, the technical set-up in the initial phase 2021 had a focus on collecting data in both single and platoon mode with trips from different road segments relevant for Hamburg's Port operation. This horizontal approach overarching all use cases by collecting trips in road networks of relevance is shown in Figure 78. By equipping rental cars and selected fleets of SME winners Taxi-AD and eShuttle baseline trips were registered IT-Backends of T-Systems (LCMM Smartphones), tec4u (entruck) and Continental (IoT-Backend). Figure 79 depicts a typical in-vehicle set-up and the starting point of the trips in the city centre of Hamburg close to the test track TAVF.

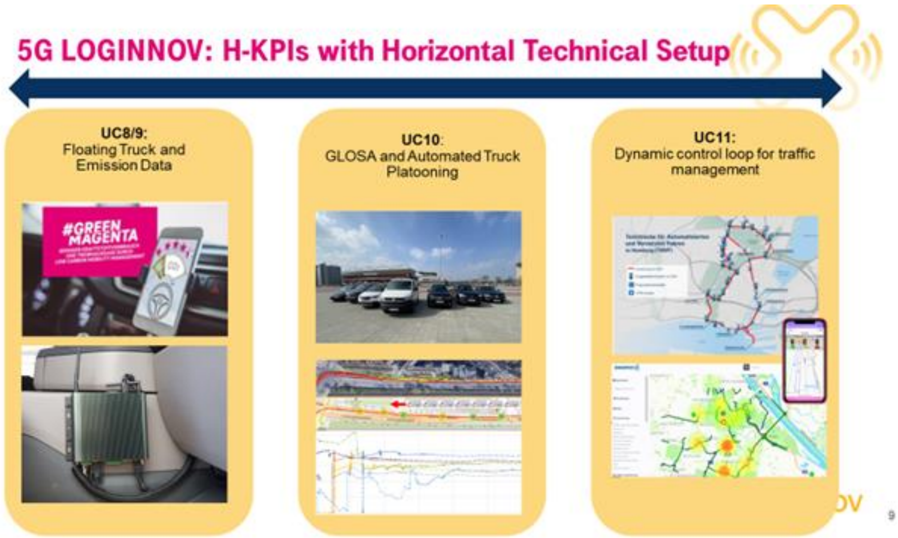


Figure 79: HKPIs covered by use cases targeting operational efficiency in Hinterland

The baseline detection covered three periods of dedicated trip records using LCMM, entruck and Continental IoT-Box. In March 2021, a total number of 52 trips was recorded followed by 43 trips recorded June same year. For the baseline determination, the energy equation of ISO-23795-1 was used and Skylark DTAG Precise Positioning Service applied for improved position input in the baseline evaluation. For the purpose of comparison, eShuttle and Taxi-Ad trips were recorded with LCMM and entruck on-board enabling additional data collection on road segments of the operational importance in Hamburg. It has to be mentioned that 2021 was impacted heavily by Covid, including reduced road traffic. Nevertheless, port operation and logistics showed the same rush-hour phenomena known without Covid, therefore we decided to use 2021 trips recorded as baseline for KPI detection.

3.4 Use Case trials in 2022

Compared to 2021, year 2022 was still characterized by Covid and periods of release. The following information for each storyboard summarizes the organizational and technical setup, on operated number of trips in the TAVF area and provides additional data and screenshots. All storyboards have been specified in D3.1 and the storyboards have been successfully performed during the Trials#1 -#3 in Hamburg in 2022.

In general, we have differentiated during the trials between single mode and platoon mode setups. The following overview is focusing on this. Chapter 3.4.1 to chapter 3.4.6 give details about the 2022 trials comparing applied use case technologies relative to 2021 baseline. For trial #1 phase, a total number of 50 trips was recorded followed by trial #2 week counting 40 trips whereas in trial #3 week 85 trips were counted. For KPI evaluation, the storyboards defining the trial scenarios distinguished single and platoon mode to find impact of GLOSA and Time-to-Green information available inside the vehicle for driver assistance.

3.4.1 Trial #1 Single Mode

Date: **13.09.-15.09.2022 Trial #1**
Processed and by: **T-Systems**
Trial #1 Setup:
vehicles in the trial: 3
Vehicle #1 with Entruck, Conti IoT Box, LCMM+Glosa
Vehicle #2 with LCMM+Glosa
Vehicle #3 with LCMM+Glosa, Qualipoc and LCMM@Skylark
overall trips single mode: 8
trips tec4u: 8

trips Conti IoT Box: 8
trips with EnTruck, Conti Iot Box, LCMM+Glosa: 8
trips with LCMM@Skylark: 8
#trips Qualipoc (5G and 4G cellular network measurement): 8

3.4.2 Trial #1 Platoon Mode

Date: 13.09.-15.09.2022 Trial #1
Processed and by:T-Systems
Trial #1 Setup:
 # vehicles in the trial: 3
Vehicle #1 with Entruck, Conti IoT Box, LCMM+GLOSA
Vehicle #2 with LCMM+GLOSA
Vehicle #3 with LCMM+GLOSA, Qualipoc and LCMM@Skylark (Others)
 # trips with EnTruck, Conti Iot Box, LCMM, GLOSA
 # overall trips platoon mode: 11
 # trips tec4u: 11
 # trips Conti IoT Box: 11
 # trips with EnTruck, Conti Iot Box, LCMM: 11
 # trips with LCMM@Skylark: 11
#trips Qualipoc (5G and 4G cellular network measurement): 11

3.4.3 Trial #2 Single Mode

Date:04.10.-06.10.2022 Trial #2
Processed and by:T-Systems
Trial #2 Setup:
 # vehicles in the trial: 3
Vehicle #1 with Entruck, Conti IoT Box, LCMM+Glosa
Vehicle #2 with LCMM+Glosa
Vehicle #3 with LCMM+Glosa, Qualipoc and LCMM@Skylark (others)
 # overall trips single mode: 19
 # trips tec4u: 6
 # trips Conti IoT Box: 6
 # trips with EnTruck, Conti Iot Box, LCMM+Glosa: 6
 # trips with LCMM@Skylark: 4
#trips Qualipoc (5G and 4G cellular network measurement): 8

3.4.4 Trial #2 Platoon Mode

Date: 04.10.-06.10.2022 Trial #2
Processed and by: T-Systems
Trial #2 Setup:
vehicles in the trial: 3
Vehicle #1 with Entruck, Conti IoT Box, LCMM, GLOSA (HH…)
Vehicle #2 with LCMM, GLOSA (PS Logi …)
Vehicle #3 with LCMM, GLOSA, Qualipoc and LCMM@Skylark (Others)
trips with EnTruck, Conti Iot Box, LCMM, GLOSA
overall trips platoon mode: 26
trips tec4u: 8
trips Conti IoT Box: 8
trips with EnTruck, Conti Iot Box, LCMM: 8
trips with LCMM@Skylark: 10
#trips Qualipoc (5G and 4G cellular network measurement): 11

3.4.5 Trial #3 Single Mode

Date: 22.11.-25.11.2022 Trial #3
Processed and by: T-Systems
Trial #3 Setup:
vehicles in the trial: 3
Vehicle #1 with Entruck, Conti IoT Box, LCMM +Glosa
Vehicle #2 with LCMM+Glosa
Vehicle #3 with LCMM+Glosa, Qualipoc and LCMM@Skylark (others)
overall trips single mode: 42
trips tec4u: 11
trips Conti IoT Box: 11
trips with EnTruck, Conti Iot Box, LCMM+Glosa: 11
trips with LCMM@Skylark: 10
#trips Qualipoc (5G and 4G cellular network measurement): 8

3.4.6 Trial #3 Platoon Mode

Date: 22.11.-25.11.2022 Trial #3
Processed and by: T-Systems
Trial #3 Setup:
vehicles in the trial: 3
Vehicle #1 with Entruck, Conti IoT Box, LCMM, GLOSA (HH…)

Vehicle #2 with LCMM, GLOSA
Vehicle #3 with LCMM, GLOSA, Qualipoc and LCMM@Skylark (Others)
 # trips with EnTruck, Conti Iot Box, LCMM, GLOSA
 # overall trips platoon mode: 46
 # trips tec4u: 12
 # trips Conti IoT Box: 12
 # trips with EnTruck, Conti Iot Box, LCMM: 12
 # trips with LCMM@Skylark: 9
#trips Qualipoc (5G and 4G cellular network measurement): 11

3.5 Results & KPI evaluation

For the sake of KPI evaluation, baseline determination in 2021 had a pool of 95 recorded trips compared to 175 trips recorded and available for evaluation from year 2022. All Hamburg KPIs were defined as environmental and social benefits, highlighting quantities with regards to vehicles in motion and traffic flow characteristics such as average speed, acceleration (braking) and standstill in single and platoon mode. After data analysis and elimination of erroneous trip data due to GNSS failure or other obvious data mismatch, the traffic related Hamburg KPIs gave the following final result.

Compared to 2021 recorded baseline, Table 30 shows that KPI expectations were not only achieved but impressively exceeded. Average speed was 24% better in single and even 32% better in platoon mode, standstill reduced 58% in single and 54% in platoon mode. The KPI threshold of reducing standstill by 5% and increasing speed by 5% was much lower than the successful usage of Time-to-Green and Traffic Light Assistance APP recommendations implemented by the Hamburg project team T-Systems, Swarco, tec4u and Continental. It has to be mentioned that traffic flow is difficult to reproduce in the sense of reliable statistics. Nevertheless, given the fact that data and trip collection took place in different time periods but similar times of the day, baseline in 2021 and trials in 2022 reflect Hamburg's road and traffic condition quite well.

With regards to acceleration, two different measurement values were recorded and used. One reflects braking or negative acceleration behaviour per trip normalized by seconds with speed above zero multiplied by 10 for better readability. This improved in single mode, but not >5% in platoon mode. One of the reasons might be that human, non-automated vehicle platooning forces drivers to follow, thus, to accelerate more than in single mode. Again, our data evaluation proved that normalization of energy and acceleration is useful as different vehicles with different weights lead to different savings. Overall, results for EPI and API confirm the outstanding >30% improvement relative to baseline determination.

H-KPI	Mode	Unit	Trial #1	Trial #2	Trial #3	2021 Baseline Trial #0	Notes	KPI/[%]
Speed (H-KPI1,4)								
5,13	single mode mit Glosa	m/s	5,31	5,32	4,93		No Glosa	24%
5,47	platoon mode mit Glosa	m/s	5,63	5,33	5,49	4,14		32%
Acceleration (H-KPI2,5)								
-1,41	single mode mit Glosa	(10xm/s2) /sec(v>0)	-1,29	-1,51	-1,43		Ohne Glosa	13%
-1,55	platoon mode mit Glosa	m/s2	-1,37	-1,59	-1,69	-1,62		4%
Standstill (H-KPI3,6)								
370	single mode mit Glosa	sec	319	358	410		No Glosa	58%
341	platoon mode mit Glosa	sec	362	361	321	633		54%
Fuel Consumption (H-KPI7,9)								
5,13	single mode mit Glosa	ltr./100km	5,31	5,32	4,93		No Glosa	34%
6,06	platoon mode mit Glosa	ltr./100km	6,21	5,70	6,20	7,80		22%
CO2 Consumption (H-KPI8,10)								
0,92	single mode mit Glosa	kg/100km	0,92	0,86	0,95		No Glosa	36%
0,95	platoon mode mit Glosa	kg/100km	1,07	0,88	0,95	1,43		33%
Energy performance index value EPI (H-KPI11)								
4,39	Alle Trips	ltr./ton/100km	4,20	4,31	4,54	5,35	No Glosa	18%
Acceleration performance index value API (H-KPI12)								
6,72	Alle Trips	mj/ton/100km	5,83	7,01	7,33	7,12	No Glosa	6%

Table 30: Overview of the twelve traffic related Hamburg KPIs

The project team defined three 5G related KPIs which cannot be grouped and compared into 2021 and 2022 measurements but took place by Rohde and Schwarz and Skylark equipment in 2022. Download and upload could be confirmed in the three trial periods, the same holds for the Packed Error Rate (H-KPI15). For Precise Positioning, improvements down to 10cm levels were found which means lane detection for autonomous driving needs such technology for ensuring safety in urban road conditions.

Available 5G bandwidth on urban roads (H-KPI13)					
204	DL	mbit/s	182	231	199
58,5	UL	mbit/s	52,3	63,1	60,1
Positioning quality on urban road networks with 5G (H-KPI14)					
12,2	no correction	m	14,6	11,3	10,7
0,6	correction	m	0,8	0,5	0,5
Latency by 5G cellular communication in urban areas (H-KPI15)					
	Upload Latency Edge	ms			
21,6	**Download Latency Edge**	ms	23,4	19,9	21,5
	Upload Latency Cloud	ms			
25,3	**Download Latency Cloud**	ms	27,5	24,9	23,5
Packed Error Rate (PER) in 5G NSA production network (H-KPI16)					
12	%		12,3	13,6	10,1

Table 31: 5G NSA network, related Hamburg KPIs

4 EVALUATION IN KOPER LIVING LAB

As part of the 5G-LOGINNOV project novel 5G technologies and cutting-edge prototypes were implemented, tested and verified in the Living Lab Koper (LL Koper), which were tailored for the particular port environment. These include a 5G NSA system deployed over public infrastructure extended with a private core network operating on band n7 (20 Mhz of spectrum) and n78 (100 Mhz of spectrum), 5G SA systems as fully private mobile system infrastructure operating on band n78 (20 Mhz of spectrum) with support for 5G slicing and assured QoS, MANO-based services and network orchestration, Industrial IoT devices, AI/ML based video analytics, drone-based and wearable camera-based security monitoring, etc.

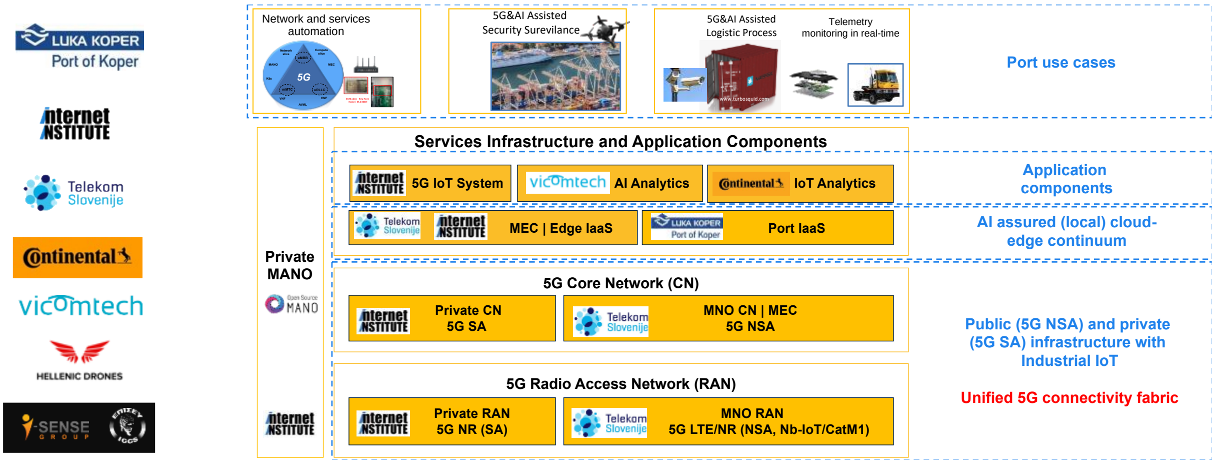


Figure 80: LL Koper - Deployed system capabilities following a modular design approach.

The deployment of the 5G mobile network in the Port of Koper was not only a development challenge, but also an operational one. Use of high end 5G SA devices were depended on the availability of commercial chipsets and 5G products, especially those related to the support of eMBB and mMTC features. To add true added value to the deployed 5G systems cloud infrastructure in the port was extended with the AI capabilities (GPU cards) and three groups of uses cases with several demonstrators were investigated and verified in the port operational environment with the target to optimise logistic processes, ensure port security and workers safety.

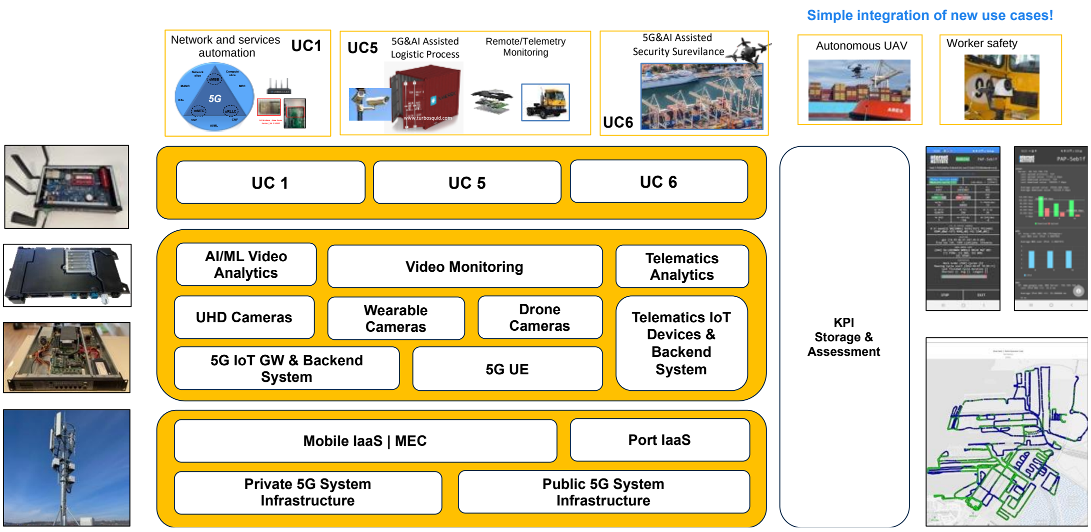


Figure 81: Deployed Koper LL capabilities using the principles of the open ecosystems.

4.1 5G Network deployment and evaluation

4.1.1 5G NSA Network Deployment

A 5G NSA (Non-Standalone) private network refers to a type of 5G network architecture that relies on existing 4G infrastructure for certain functionalities. In a Non-Standalone 5G network, the 5G radio access network (RAN) is deployed alongside the existing 4G core network. The User Plane of the Evolved Packet Core (EPC) was strategically deployed on-premise of LL Koper. This local deployment facilitates efficient data forwarding and processing within the organization's premises, ensuring low-latency data transmission. The Control Plane, responsible for signaling and control functions, continues to operate within the established 4G public core network infrastructure, ensuring a seamless transition to 5G.

The 5G NSA network in LL Koper is designed exclusively for port (private) operations, providing enhanced security and control over network resources and traffic flows. The PGW and SGW (data plane) parts of the core network are deployed on-premise in the LL Koper facility, while the HSS and MME (control plane) remain part of Telekom Slovenije's public network. Operating on dedicated spectrum bands (n78 and n7) allocated to the organization ensures reliable and interference-free connectivity within the defined coverage area.

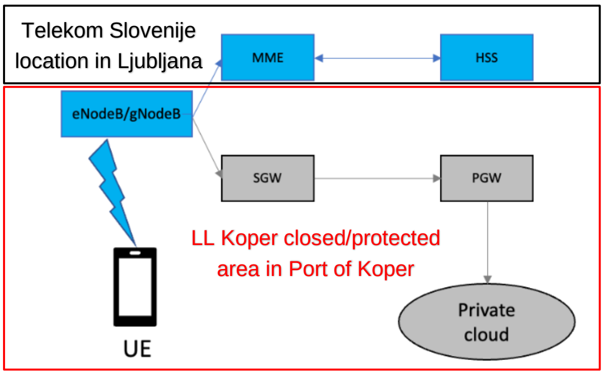


Figure 82: LL Koper – 5G NSA network architecture used in Port of Koper.

The presented architecture ensures that all mobile data and data flows generated in LL Koper never leaves the physical area of the Port of Koper.

Figure 83: LL Koper – 5G NSA core network (SGW and PGW element) in Port of Koper cloud facility.

Figure 84: LL Koper – 5G NSA RAN deployed in Port of Koper.

4.1.2 List of Key Performance indicators

KPI	KPI ID	Target Value	Measured Values
Area Traffic Capacity	K-KPI12	6.25 Mbps	**Achieved***
Bandwidth	K-KPI14	LTE 65 MHz + NR 100MHz	**Achieved**
Connection Density	K-KPI15	37.500 devices/km2	**Achieved***
Availability	K-KPI13	99,98 %	**Achieved**
End-to-End Latency	K-KPI17	25 ms	**Achieved**
One-way Latency		15 ms	**Achieved**

Table 32: LL Koper – Performance KPIs for the 5G NSA network.

All of the presented KPIs were measured with the dedicated tools, as presented in the following chapters. The only exceptions are K-KPI12 and K-KPI15, which were calculated using the radio network planning tools from Telekom Slovenije.

4.1.3 Methodology and Measurement Tools

On private 5G-based mobile services provided by the national MNO (Mobile Network Operator) we obtained KPIs from the monitoring and control systems of the radio access network that we use for the public network. We calculated certain KPIs from raw data. For instance, KPIs such as End-to-End Latency and One-way Latency were derived from RTT (Round-Trip Time) measurements or measurements between the device and the server.

To gather performance metrics for the 5G network, we employed the ININ Quality Monitoring System, qMON[4], within the LL Koper environment. qMON is a suite of network performance testing and monitoring tools seamlessly integrated into a centrally managed product designed for mobile, fixed, and

[4] The qMON System is a commercial test automation tool from ININ that was extended to support 5G testing capabilities in the 5G-PPP project 5G-INDUCE, Grant Agreement ID: 101016941.

cloud environments. It facilitates end-to-end measurements, realistic load generation, automation of testing and measurement, and consists of four main system components (Figure 85):

- Distributed autonomous qMON agents integrated into mobile 5G User Equipment (UE) or fixed devices, including the Samsung Galaxy Series mobile phone and M2M clients, such as industrial x86 platforms (iBase and Avalue). Software clients are also packaged as Virtual Network Functions (VNF), Virtual Machines (VM), or Docker containers.
- Centralized cloud-based system management (qMON Manager).
- qMON Reference Server supporting network (e.g., Iperf servers) and application reference points (e.g., ETSI Kepler Web server) to perform end-to-end performance testing.
- Centralized measurements results (KPIs) collector and database (qMON Collector) supporting real-time monitoring and advanced cloud-based analytics (qMON Insight component). The analytics are powered by either enterprise-ready MySQL/ms-SQL tools or a cloud-native Prometheus-based stack, both supporting Grafana, while advanced post-analytics is provided by Tableau.

The system is capable of measuring and collecting over 100 KPIs related to network, services, applications testing (DNS, ping, FTP UL, FTP/HTTP DL, iPerf UDP/TCP, web, etc.), as well as 5G and radio testing (e.g., RSSI, RSRP, SNIR, TxPower, etc.). Tests and measurements are executed between agents or between the agent and a qMON Reference Server.

In LL Koper, we deployed Reference Servers on Portable NFVI Edge with private 5G SA system, LL Koper Cloud, and for additional reference to verify LL Koper outside connectivity, in Telekom Slovenije Cloud in Ljubljana.

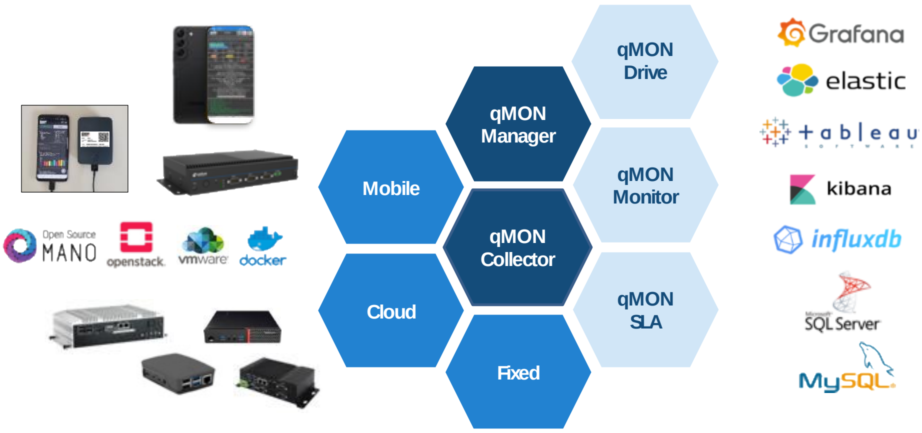


Figure 85: LL Koper - Deployed qMON 5G Test Automation System

The qMON system was employed in LL Koper for various tests, including 5G drive testing, end-to-end Quality of Service (QoS) and Quality of Experience (QoE) monitoring of network and services, 5G NR coverage and performance assessment, and live 5G network and service troubleshooting. The qMON agents used included commercial 5G UEs based on Samsung S20, Samsung S21, Samsung S23, and OnePlus 9 smartphones, as well as a 5G IoT Gateway from ININ extended with qMON agent capabilities that were deployed on stationary locations in LL Koper (STS Crain, Light tower) and on Terberg trucks to perform continuous drive testing of the 5G NSA mobile network and to verify performance of a private 5G SA network.

Figure 86: LL Koper - qMON Agent deployment for stationary and drive testing of the 5G NSA mobile network – (Left) 5G IoT GW on STS Crane, (Middle) 5G IoT GW on Terberg truck, (Right) Samsung S21 on port van.

As part of the final test for the TRITON use case from Hellenic Drones, we also conducted drone-based testing of a 5G NSA mobile network to assess the 5G NR coverage and performance of a mobile system in areas that are difficult to access. An example of the results of the drone test, showcasing 5G NR coverage with RSRP signal levels, is presented in Figure 87.

Figure 87: qMON assured 5G testing with the Samsung S23 test phone on a drone (figure on the left), and the results of the 5G NR coverage in LL Koper (figure on the right).

4.1.4 Results

To evaluate and confirm the targeted Key Performance Indicators (KPIs) for the deployed 5G NSA network, a series of drive and continuous monitoring tests on stationary locations were conducted in LL Koper. Following the initial deployment of the 5G NSA network, the first drive test using qMON 5G test automation systems (Figure 88) was performed in February 2022 to assess network performance and coverage. The analytics of the 5G NR coverage test are presented in Figure *89*, revealing that in some targeted 5G demonstration areas, the NSA radio layer was lacking. The initial drive test served as input for optimizing the deployed 5G RAN, leading to the activation of additional cells operating on band n78.

Figure 88: LL Koper - Drive test setup using qMON system on commercial smart phones.

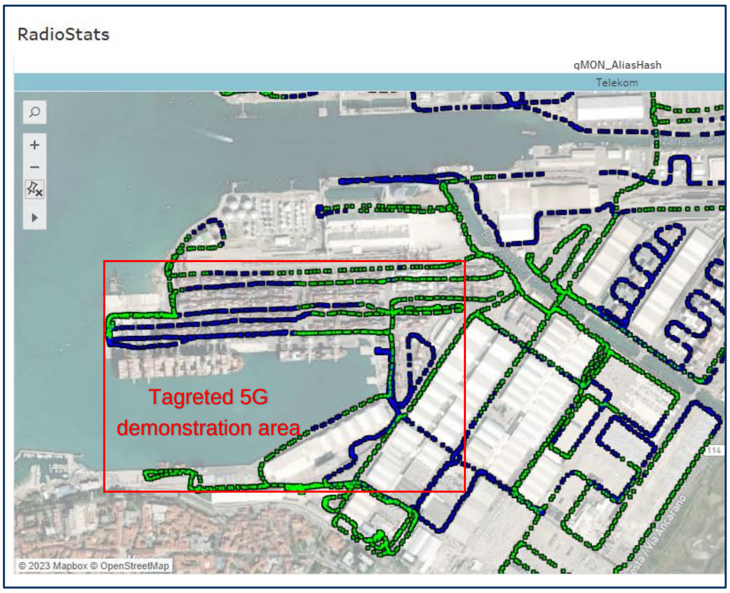


Figure 89: LL Koper - Drive test results showcasing LTE and NSA coverage on qMON Analytics – February 2022.

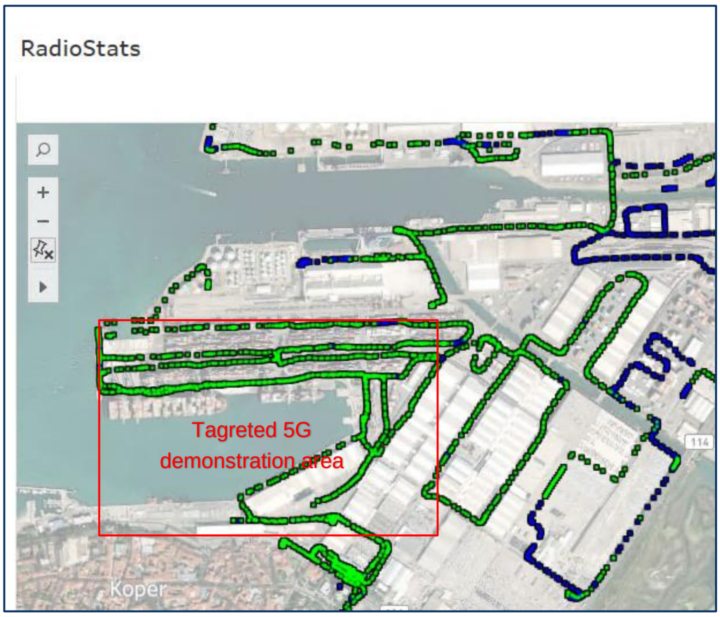


Figure 90: LL Koper - Drive test results showcasing LTE and NSA coverage on qMON Analytics – April 2023.

To validate the results of the newly deployed 5G NR cells, an additional drive test was conducted in April 2023. As evident in the qMON analytics (Figure *90*) the coverage with 5G NR in the targeted demonstration area reached 100%. Subsequent to this, a detailed assessment of performance metrics was carried out. Figure 91 illustrates that the 5G NSA channel bandwidth capacity assigned to the 5G User Equipments (UEs) is up to 160 MHz of spectrum (K-KPI14 - combined LTE and 5G NR layer). The assessment of the 5G NR signal level indicates that the minimum Reference Signal Received Power (RSRP) never dropped below -105 dBm, aligning with the planned conditions and ensuring stable radio performance even at the cell's edge (end of the container yard).

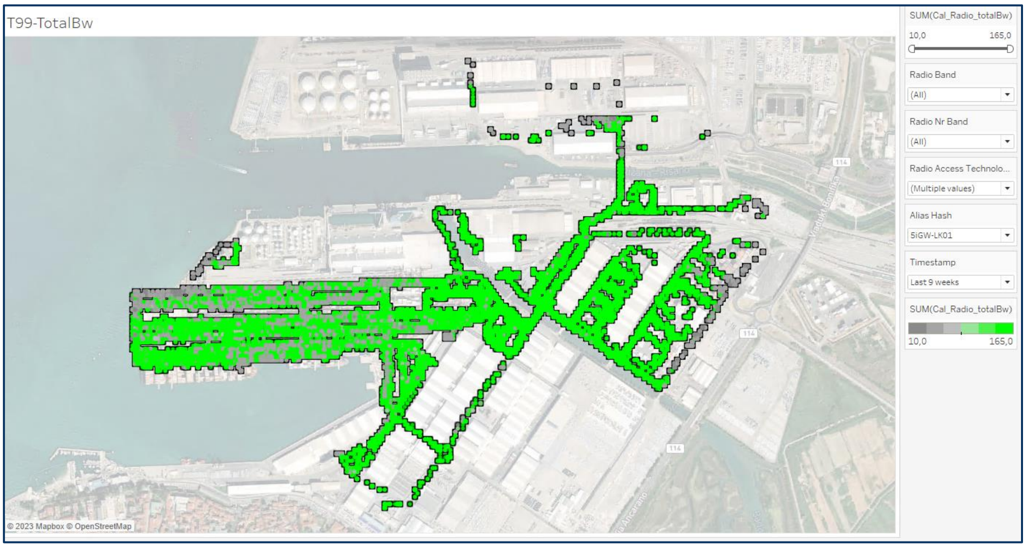


Figure 91: LL Koper - Drive test results showcasing total available channel BW (K-KPI14).

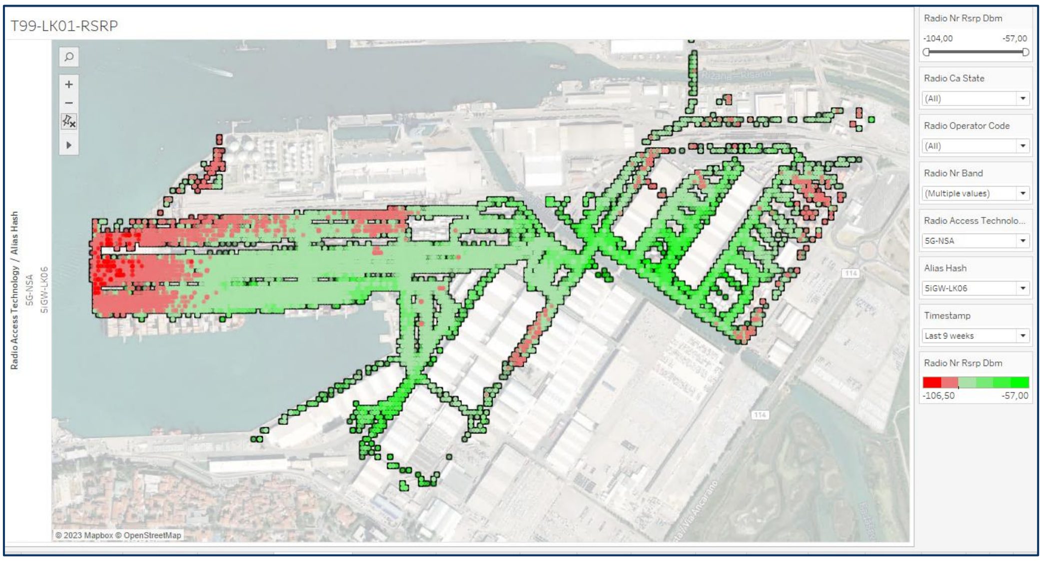


Figure 92: LL Koper - Drive test results showcasing 5G NR signal level coverage.

4.1.4.1 Continuous 5G drive testing with yard trucks

To evaluate the deployed 5G NSA network under realistic operational conditions, ININ's 5G IoT GW with the qMON agent was deployed on five yard trucks (Terberg), which are used daily in the port operation for the transhipment of containers on the container terminal in LL Koper. When the yard trucks are operational the qMON system enables continuous network performance monitoring of the 5G NR radio metrics (e.g., RSRP, RSRQ, SINR, TxPower, channel BW and other radio performance metrics are sampled with the 1,5 s interval) and data plane performance, including download and upload throughput and latency. Performance metrics are collected, showcased, and visualized in real-time directly on the 5G GW management or in the backend analytics. For more in-depth analytics, collected metrics are exposed to BI tools such as Tableau.

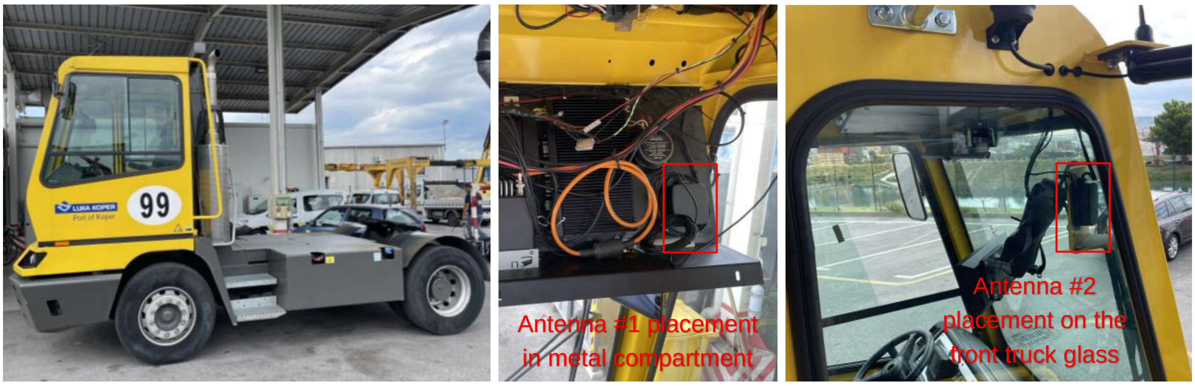


Figure 93: LL Koper - Yard truck equipped with ININ's 5G GW and qMON agent (left), placement of the 5G GW antennas (middle and right).

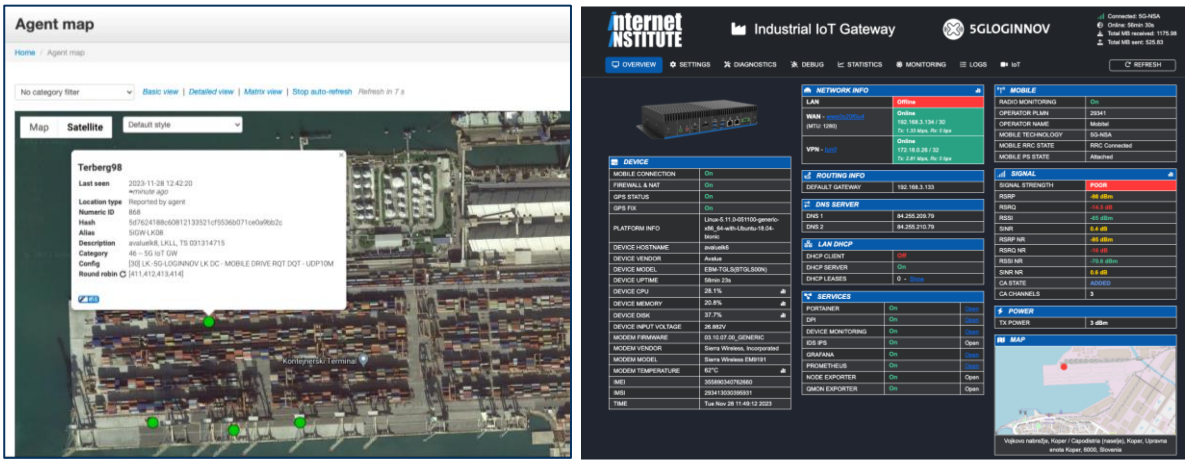


Figure 94: LL Koper – Centralized cloud management system showing operational yard trucks with deployed qMON agents (left) and 5G GW management system displaying real-time 5G NR performance status (right).

As an example, the results for the 24-hour 5G drive period for one of the yard trucks are presented in the figures below. The Figure 95 depict the 5G drive testing with yard trucks, showcasing 24-hour end-to-end latency (K-KPI17) and downlink and uplink throughput performance (K-KPI14) on a time graph.

The measured end-to-end latency (K-KPI17) was 26.4 ms (mean), with a minimum of 8.5 ms and a maximum of 83.4 ms. In the case of downlink direction, the achieved speed to the LL Koper cloud was 177 Mbps (mean), with a minimum of 21 Mbps and a maximum of 360 Mbps. For uplink direction, achieved throughput speeds were 39 Mbps (mean), with a minimum of 7 Mbps and a maximum of 143 Mbps.

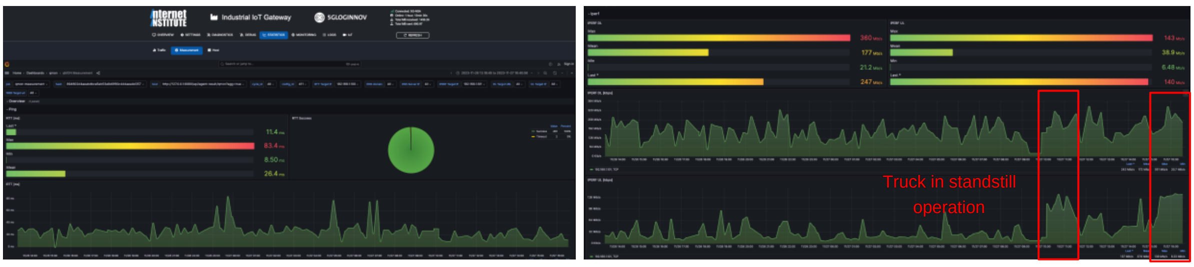


Figure 95: LL Koper – 5G drive testing with yard trucks showcasing 24 h RTT (left) and throughput 5G (right) performance on a time graph.

Since the deployed LL Koper 5G NSA base stations from Telekom Slovenije are shared with commercial mobile traffic, observed variations in performance metrics (Figure 95) can be attributed to the current load of the RAN and, in the case of downlink and uplink throughput, also to the current radio conditions (e.g., RSRP and SINR signal levels) that vary depending on the truck location in the port yard. For the RSRP signal level (Figure 96), it is -90.2 dBm (mean), -66 dBm (max), and -115 dBm (min), clearly showing changing 5G NR channel conditions that can be observed in demanding industrial environments.

Also, due to the fact that the placement of the 4 antennas supporting 4x4 MIMO on the 5G GW deployed in the yard trucks is in a suboptimal location (Figure 93). *One* 2x2 antenna is inside the metal structure in the truck cabin, another 2x2 antenna is on the front truck glass. This also contributes to the degradation of the overall 5G NR performance, which could be improved by placing the 4x4 antenna on the roof of the yard truck.

Figure 96: LL Koper – 5G drive testing with yard trucks showcasing 5G NR (NSA) performance variation on a time graph.

With the post-analytics of the collected metrics, several aspects of the operational 5G NSA network can be visualized on the GIS to be assessed and used for the ongoing optimization of the deployed mobile network in LL Koper.

Some of the used optimisation metrics such as achieved radio signal coverage, operational bands and available throughput are presented on the Figure 97, Figure 98, Figure 99 and Figure 104, respectively. They showcase combined measured values for all 5 yard trucks for the duration of 2 months.

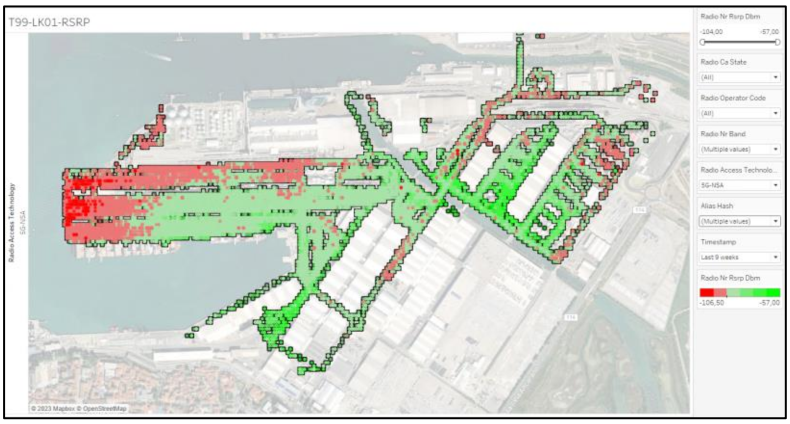


Figure 97: LL Koper - Evaluating 5G NSA system using drive testing using 5 yard trucks – RSRP level network coverage

Figure 98: LL Koper - Evaluating 5G NSA system with drive testing using 5 yard trucks – 5G NR operational bands.

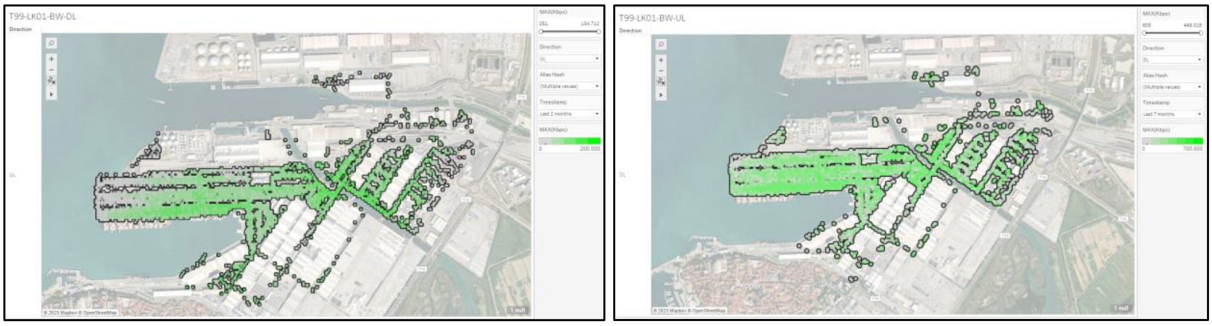


Figure 99: LL Koper - Evaluating 5G NSA system with drive testing using 5 yard trucks – DL and UL throughput on a map.

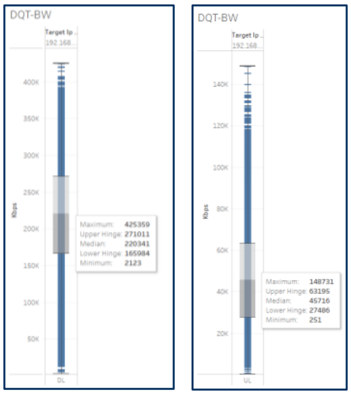


Figure 100: LL Koper - Evaluating 5G NSA system using drive testing using 5 yard trucks – Cumulative DL (left) and UL (right) throughput presented as box plot.

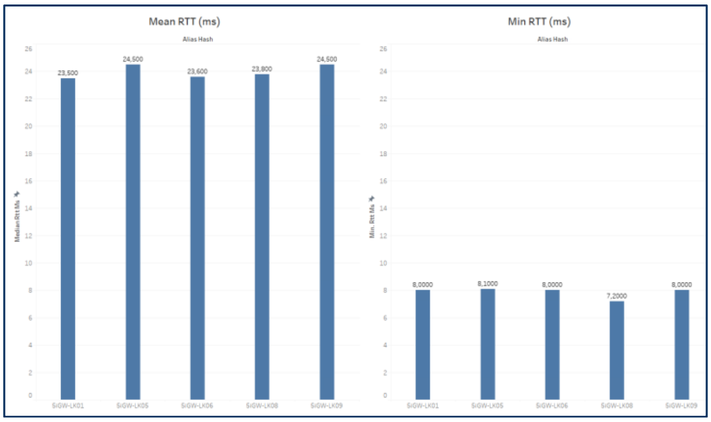


Figure 101: LL Koper - Evaluating 5G NSA system with drive testing using 5 yard trucks – end-to-end latency (K-KPI17)

The achieved end-to-end latency (K-KPI17), as depicted in (Figure 101), falls within the expected range, being less than 25 ms (mean) for all yard trucks during the two-month testing period. Additionally, the one-way delay, calculated by dividing the end-to-end latency by half 12.5 ms (mean), is within the targeted KPI range.The detailed steps and optimization methods used present confidential information and are restricted to the operational teams of Telekom Slovenije; they are not captured in the report.

4.1.4.2 Continuous 5G network performance monitoring using strategic locations in the port

To complement continuous drive testing conducted with yard trucks, ININ's 5G GW with integrated qMON agents were strategically positioned on the port STS crane (Figure 86), and another one in the power shelter (Figure 86), and they were utilized for continuous 5G NSA network performance monitoring. In this case, ININ's 5G IoT GW operated with uninterrupted power, as such, the qMON system facilitates continuous 24/7 network performance monitoring of 5G NR radio metrics (e.g., RSRP, RSRQ, SINR, Tx Power, channel BW, and other radio performance metrics sampled at 1.5s intervals) and data plane performance, including download and upload throughput and latency.

Similar to drive testing with yard trucks, performance metrics are collected and can be showcased and visualized in real-time directly on the 5G GW or in the backend analytics. For more in-depth analytics, the collected metrics are also exposed to BI tools such as Tableau.

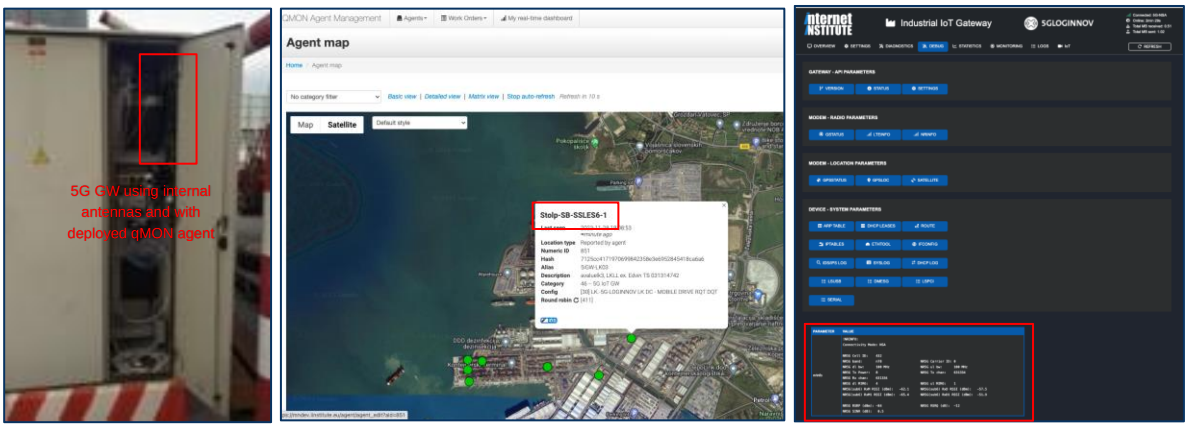


Figure 102: LL Koper – Power shelter equipped with ININ's 5G GW and qMON agent (left), Centralized management system showing operational qMON agent (middle) and 5G GW management displaying real-time 5G NR performance status (right).

Results for the 7-day period of the deployed 5G GW operating in continuous mode (24/7) at the power shelter are presented in the figures below. Figure 103 depicts the 5G NR results for a stationary deployed 5G GW, showcasing the 7-day radio network performance (RSRP, RSRQ, SINR, TX Power) on a time graph:

- NR RSRP values: -98.5 dBm (mean), -91 dBm (max), -104 dBm (min);
- NR SINR values: 0.33 dB (mean), 1.20 dB (max), 0 db (min);
- NR RSRQ values: -12.5 dB (mean), -8 dB (max), -18 db (min);
- NR Tx Power values: 18.5 dBm (mean), 21 dBm (max) -32 dBm (min).

From a radio perspective (with a mean RSRP value of -98 dBm), the 5G GW is located on the 5G NR cell edge. Consequently, the overall end-to-end performance is degraded, as observed in the achieved values for the downlink and uplink throughput testing (Figure 104). However, due to the fact that the 5G GW is positioned at a stationary location, 5G NR signal is uniform, more stable, and predictable compared to the 5G drive test results with yard trucks (Figure 96).

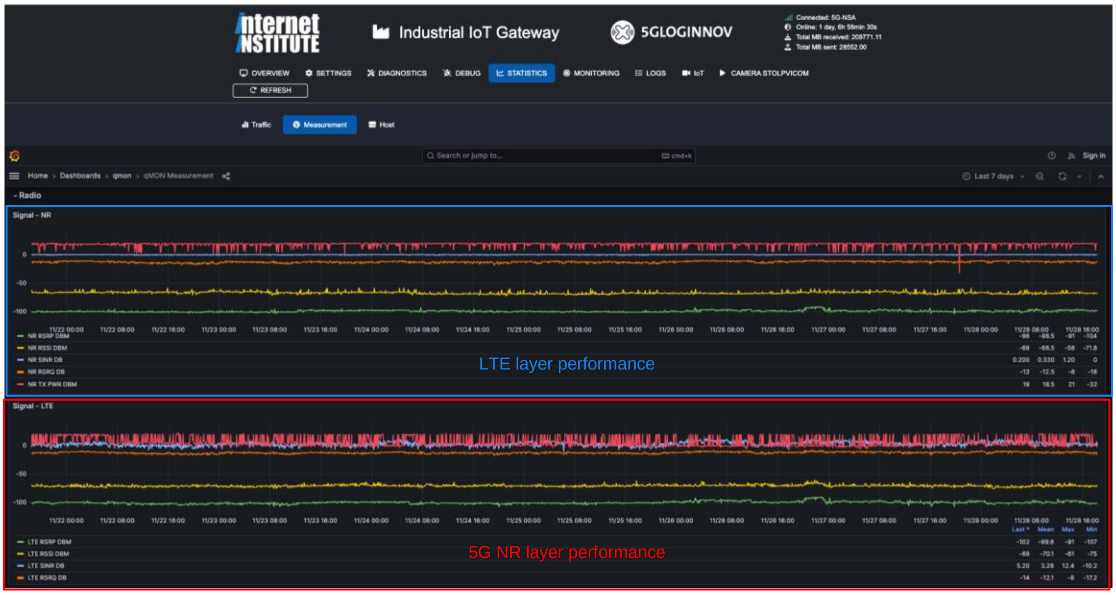


Figure 103: LL Koper – Continuous 5G NSA testing with a stationary deployed 5G GW, showcasing 5G NR performance over 7-day period.

Figure 104 depicts the end-to-end throughput results for a stationary deployed 5G GW, showcasing the 7-day performance of the 5G NSA network (uplink and downlink throughput between the 5G GW and LL Koper cloud) presented on a time graph:

- Downlink speed values: 225 Mbps (mean), 345 Mbps (max), and 6.97 Mbps (min);
- Uplink speed values: 21.0 Mbps (mean), 43.4 Mbps (max), 4.81 Mbps (min).

The achieved maximum download and upload speed is limited due to the severely degraded 5G NR signal at the cell edge and as a consequence, more robust modulation and coding scheme need to be applied to the 5G NR radio. Variations in the throughput that are less than maximum can be attributed to the utilisation of the base station with the commercial traffic, as the base station is shared. Daily network utilisation cycles can be also clearly seen, where during the night, the network is less utilised and as such, the download and upload performance is higher than during the day cycles.

Figure 104: LL Koper – Continuous 5G NSA testing with a stationary deployed 5G GW, showcasing downlink and uplink throughput over 7-day period.

Figure 105 depicts the end-to-end latency results for a stationary deployed 5G GW, showcasing the 7-day performance of the 5G NSA network (Round-Trip Time between the 5G GW and LL Koper cloud) presented on a time graph: End-to-end latency (K-KPI17): 15.5 ms (mean), 80.6 ms (max), 8.10 ms (min). In addition, the percentage of the successful ICMP tests during the observed 7 day period shows an reliability of the 5G NSA of 100% (K-KPI18).

End-to-end latency of 15.5 ms presents a promising result for 5G NSA network operating in TDD mode and a 5G GW placed on the cell edge. As in the case of drive testing, the variation in the end-to-end latency can be attributed to the utilization of the 5G NR with commercial traffic, where 5G UEs compete for the same radio resources.

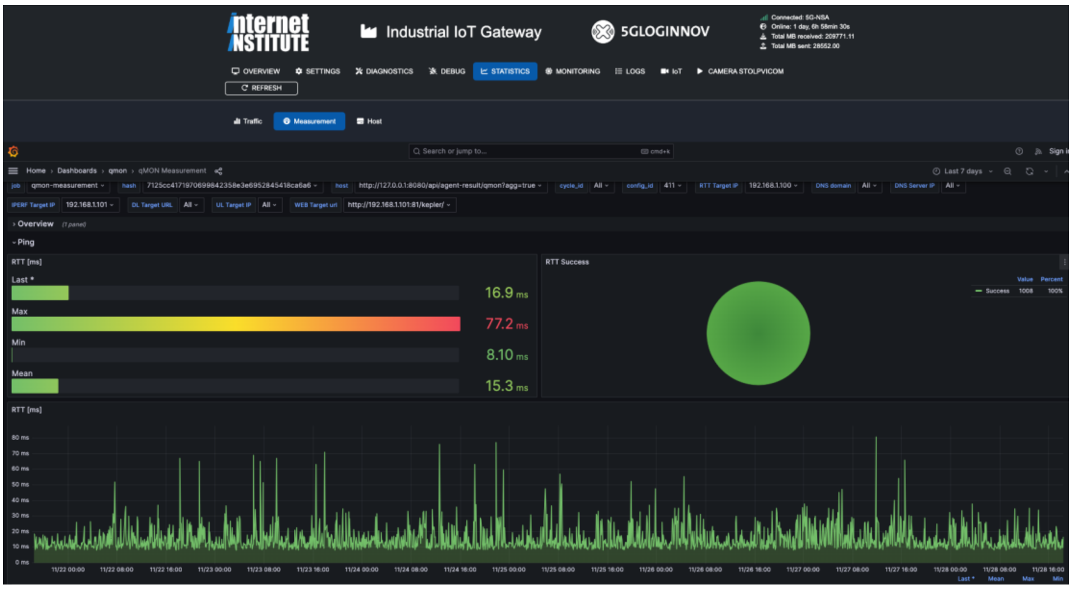


Figure 105: LL Koper – Continuous 5G NSA testing with a stationary deployed 5G GW, showcasing end-to-end latency over 7-day period.

Figure 106 depicts the results for a stationary deployed 5G GW, showcasing the 7-day performance of the 5G NSA network for the browser application accessing web services deployed on a LL Koper cloud. Web MOS is a metric that assesses quality of experience for the users using web applications5.

5 A novel user satisfaction prediction model for future network provisioning https://link.springer.com/article/10.1007/s11235-013-9853-4

Performance is assessed by Web MOS measurement and is presented on a time graph. Web MOS factor values: 4.17 (mean), 4.37 (max), 3.32 (min). In addition, the percentage of the successful Web tests during the observed 7-day period shows an reliability of the 5G NSA of 100% (K-KPI18).

Variation in Web MOS can be mainly attributed to the needed download time of a complex web application and is tightly dependent on the observed variation in the download throughput.

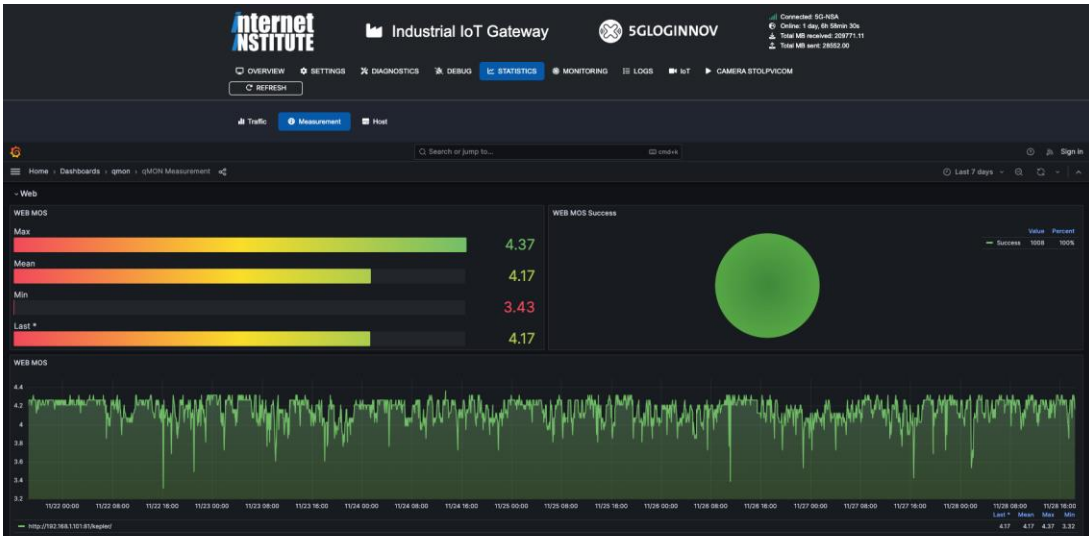


Figure 106: LL Koper – Continuous 5G NSA performance testing with a stationary deployed 5G GW, showcasing web-based application performance over 7-day period.

4.2 UC1: Management and Network Orchestration platform (MANO)

As already mentioned in the initial project review, the name of the use case UC1 is not descriptive enough of the all-actual targets, but it remained in its original form due to alignment with the signed GA.

4.2.1 Description and Motivation

The motivation behind UC 1 was to improve the 5G capabilities and network performance in LL Koper by deploying a Private 5G system operating in SA mode and an Industrial IoT Gateway. This gateway is designed to support both NSA and SA networks, facilitating the connection of non-5G devices (e.g., UHD cameras) and other sensors. With the 5G SA we target to achieve better network performance (e.g., low latency) and to support more advanced network services, such as eMBB and mMTC, for the most demanding port use cases. The Private 5G system and the Industrial IoT Gateway, developed by ININ, enabled LL Koper to create a compact and flexible private network that can be deployed, configured, and managed in a cloud-native way, using container-based technologies and orchestration mechanisms. Deployed system supports slicing features that allows us to allocate dedicated network resources and parameters for different types of traffic and IoT devices.

ININ deployed and tested a Private 5G System designed and developed for the critical-communications verticals in the sister ICT 42 project, Int5Gent[6]. The motivation for developing the private 5G system was to provide a compact and flexible solution for high-performance and reliable connectivity needed in critical infrastructures, such as ports. ININ's Private 5G, called MobileONE, is a compact 5G network that operates in 5G SA mode and integrates 5G RAN and 5G Core Network capabilities (up to 3GPP Release 17 specifications). It provides a compact NFVI environment (x86 based Network Appliance, 1U

[6] Integrating 5G enabling technologies in a holistic service to physical layer 5G system platform, Grant agreement ID: 957403, https://int5gent.eu/.

size) that can run 5G RAN and 5G core network functions on a single Kubernetes instance. Kubernetes platform supports container-based deployment of 5G network functions, MANO-compliant orchestration and other cloud-native mechanisms (e.g., self-healing, scaling etc.). ININ deployed the 5G CN and 5G RAN as network functions (NF) and corresponding network services (NS) using Kubernetes deployment principles that can be orchestrated by MANO/OSM network orchestrator.

One of the main challenges that we faced when the 5G-LOGINNOV project started (September 2020) was the limited availability on a market of industrial-grade IoT gateways that supported 5G operation in SA mode. This mode offers better system performance (e.g., latency, uplink bandwidth), reliability, and security for IoT applications than NSA mode. Therefore, ININ decided to extend its rMON IoT platform[7] with a new gateway that supports 5G SA capabilities and other advanced functions such as eMBB and mMTC slicing. These functions enable LL Koper to deliver assured bandwidth with slicing support and low latency for eMBB applications, as well as M2M connectivity for mMTC applications. ININ's rMON IoT platform also incorporates a centralised cloud-based management and device monitoring platform that was extended with cloud-native capabilities and options for MANO/OSM-based orchestration. This allows us to deploy, configure, and manage 5G-based IoT network functions and services in a flexible and scalable way, using container-based technologies and optional orchestration mechanisms. The new gateway platform incorporates also advanced functions, such as compute and storage capabilities that can be used for running containerised application (e.g., running ININ's 5G test automation systems qMON[8]) at the far-edge. As such prepared gateway system was used to support several use cases in the LL Koper (UC5, UC6, UC3) and to support automation of 5G performance monitoring of the deployed NSA and SA mobile networks in the LL Koper.

Today, in addition to the 5G-LOGINNOV project, the developed Industrial gateway platform from ININ is used in several 5G-PPP projects. To support 5G connectivity for the railway systems (Int5gent project[9]) to assure 5G network performance testing of the smart factory (5G-INDUCE project[10]) and the smart port (5G-VITAL project[11]) and as a platform that was extended with the NEF and CAPIF capabilities in the 5G-EVOLVED project[12].

4.2.2 Use Case Setup

Private 5G system was prepared with the options to expose the key 5G RAN and Core network parameters (e.g., MCC/MNC, Band, BW, Cell ID, PCI) using virtual network function descriptors (VNFD) and network service descriptors (NSD). Private 5G System was used to demonstrates the potential of 5G for various use cases and scenarios in the operational port environment that require advanced 5G security services, low latency communications or high throughput requirements in the uplink direction, i.e., Drone and wearable cameras real time video streaming.

[7] https://www.iinstitute.eu/pdf/Brosura_rMON-Maj2022.pdf
[8] https://www.iinstitute.eu/pdf/Brosura_qMON-2022.pdf
[9] https://www.int5gent.eu/
[10] https://www.5g-induce.eu/
[11] https://www.vital5g.eu/
[12] https://evolved-5g.eu/

Figure 107: LL Koper - ININs Private 5G SA System components.

Due to the fact that, in Slovenia, the foreseen tender for the private network deployments targets dedicated frequencies in the range of 2300 – 2320 MHz and 3400 – 3420 MHz that could be also used for the 5G network deployment in the Port of Koper, the RRU with n78 band and a channel bandwidth of 20 MHz operating in TDD mode was the primary operational profile for the deployment of the private 5G RAN in the LL Koper.

Figure 108: LL Koper - Private 5G System testing in Luka Koper/Port of Koper (April 2022).

Prepared (figure left) and deployed (right) Private 5G System in LL Koper showcasing portability and flexibility of the solutions – System testing in April 2022. Key capabilities of the Private 5G mobile system are presented in the tables that follows.

gNb components	Features supported up to the 3GPP release 17
5G NR BBU Prepared and deployed as a single container	All 5G FDD and TDD bands (sub-6G Bands)
	Slicing eMBB, mMTC, with QoS Flows (3GPP 5QI)
	NG interface (NGAP and GTP-U) to 5GC
	XnAP gNb-gNb
	Up to QAM 256 DL UP to QAM 256 UL
	DATA SCS: 15 and 30 KHz SBS SCS: 15 and 30 KHz
5G NR RRU N78, directional and omnidirectional antenna options were verified	up to 20W per port
	Up to 50 MHz BW
	2x2 MIMO DL 2x2x MIMO UL

Table 33: LL Koper - 5G NR capabilities of the Private 5G SA System.

5G CN Component	Features supported up to the 3GPP release 17
Compact 5G core network Prepared and deployed as a single container	AMF, AUSF, SMF, UPF, UDM and 5G-EIR
	Encryption | AES, SNOW3G, ZUC
	Encrypted SUPI/IMSI registration (ECIES)
	USIM Auth | XOR, Milenage, TUAK 5G-AKA
	Slicing with QoS Flows (3GPP 5QI)
	Interfaces | NG (NGAP and GTP-U)
	Local CMAS and ETWS messages

Table 34: LL Koper - Core network capabilities of the Private 5G SA System.

The following figures present the private 5G system management capabilities that show some of the deployed configuration and system provisioning capabilities.

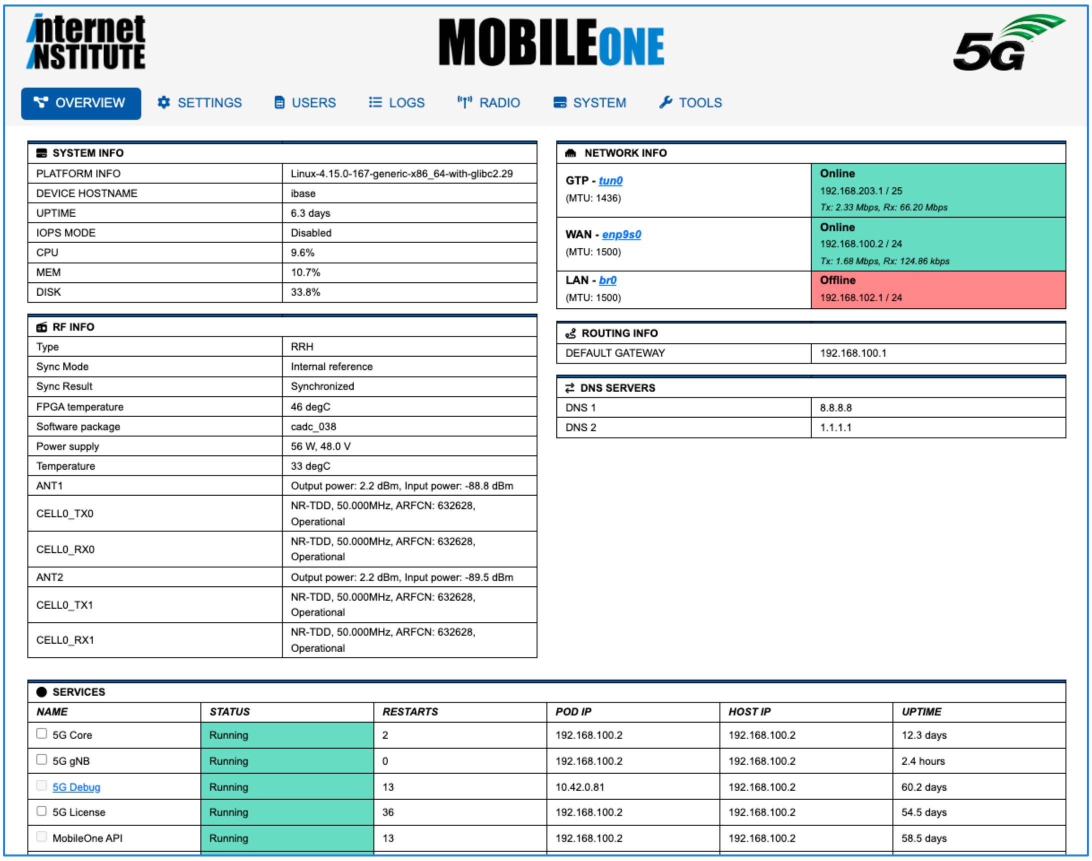


Figure 109: LL Koper - Private 5G SA System management overview of the operational system components.

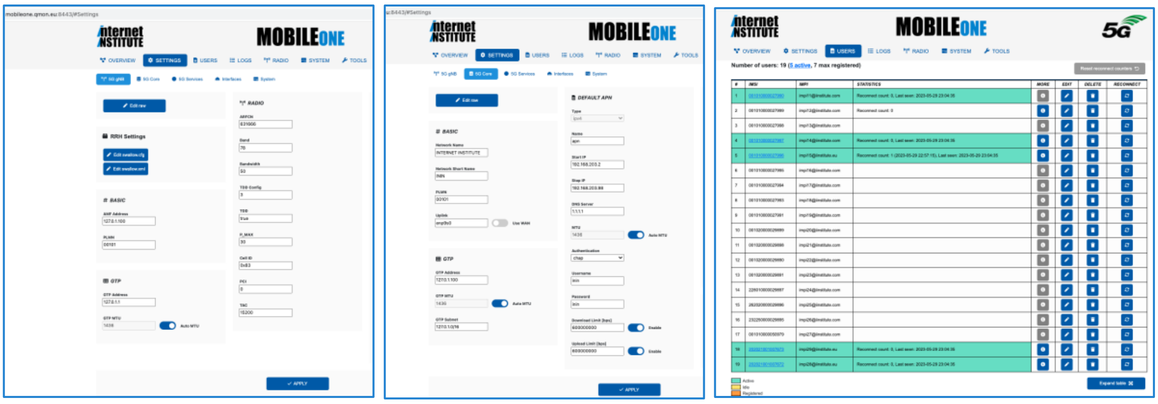


Figure 110: LL Koper - Private 5G SA System management with exposed key configuration parameters of the 5G NR (left), 5G core network (middle) and user provisioning (right).

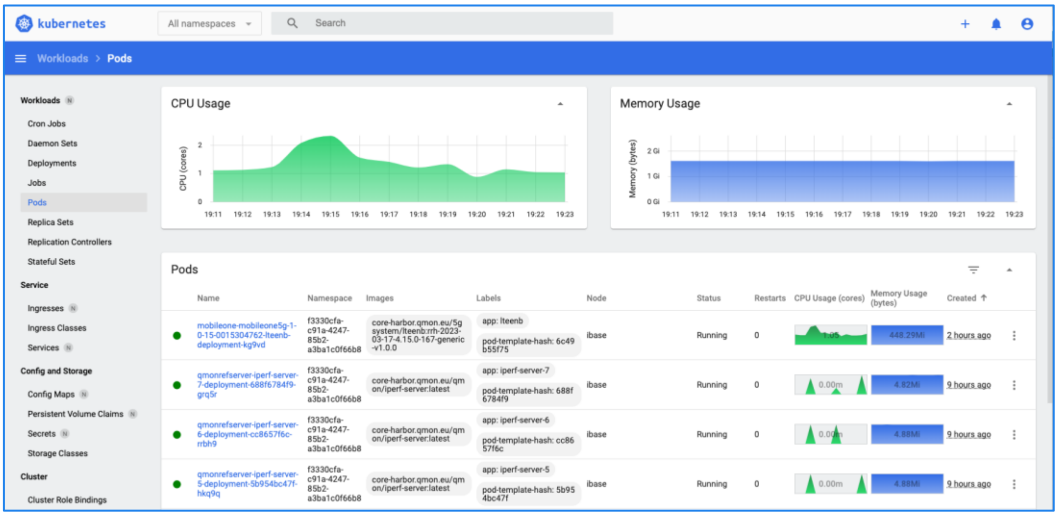


Figure 111: LL Koper - Kubernetes management showing deployed 5G BBU, 5G CN and qMON system pods.

In the LL Koper, a comprehensive ecosystem has been established, featuring not only the Private 5G system but also the rMON IoT platform equipped with developed Industrial 5G Gateways to support the activities of UC1, UC3, and UC6. The components of the rMON IoT platform, including the rMON Manager and rMON collector functions (Figure 111), were prepared using the cloud-native capabilities of Kubernetes, complemented by the support of MANO/OSM orchestration.

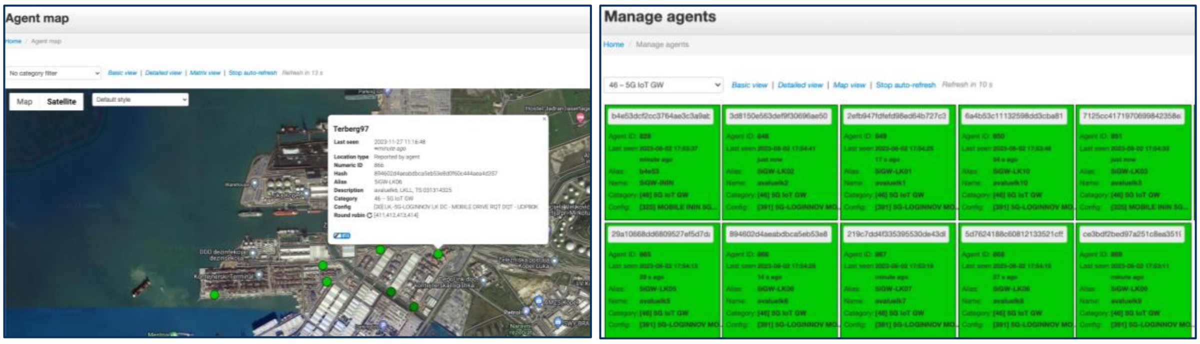


Figure 112: LL Koper - Cloud-based management of the deployed 5G IoT Gateway showcasing a map view (figure on the left) and 5G GW status (figure on the right).

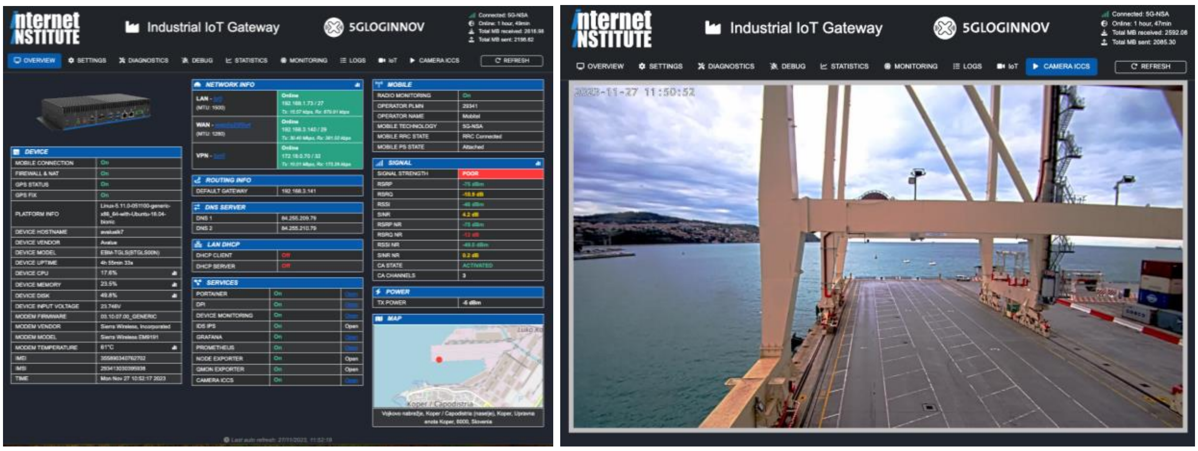


Figure 113: LL Koper - Local 5G Gateway management showcasing device status (figure on the left) and connected STS camera video stream (figure on the right).

To ensure seamless connectivity, ININ's 5G Gateways were strategically deployed on the STS cranes (Figure 114) and light towers (Figure 115). This placement guarantees the continuous transmission of video streams from the deployed UHD cameras, contributing to automating container transhipment and enhancing surveillance monitoring.

Figure 114: LL Koper - Deployment of the shelter on the STS crane (figure on the left) with Industrial 5G GW inside (figure on the middle) and connected UHD camera (figure on the right).

Figure 115: LL Koper - Light tower with deployed UHD camera (figure on the left), power shelter (figure on the middle) with deployed 5G GW (figure on the right).

Furthermore, additional ININ's 5G Gateways were strategically integrated into the Terberg trucks. These deployments serve a dual purpose: first, they provide a robust platform for the deployment of qMON 5G test automation capabilities, showcasing continuous 5G network monitoring capabilities within the LL Koper. Second, they play a pivotal role in facilitating the deployment of cameras for the worker safety use case (UC3), a collaborative effort with LL Athens as part of cross-Living Lab activities.

The synergy between the Private 5G system and the rMON IoT platform, augmented by the strategic deployment of ININ's 5G Gateways, exemplifies a holistic approach to connectivity and automation in the Living Lab environment. This integrated solution not only supports specific use cases but also lays the foundation for a dynamic and adaptive infrastructure, fostering innovation and efficiency in diverse operational scenarios.

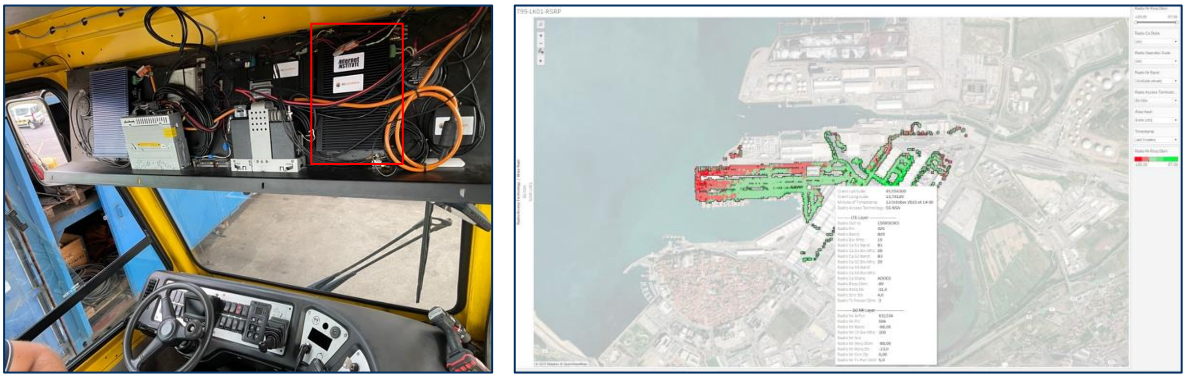


Figure 116: LL Koper - 5G IoT Gateway deployment on Terberg truck (figure on the left) used for drive testing and 5G performance analytics in the port (figure on the right).

Demonstrations of ININ's Private 5G system and the developed 5G Industrial Gateway were conducted on several occasions for industrial partners and Slovenian governmental officials. Notable events included the AKOS Industrial event (Agency for Communication Networks and Services of the RS) in September 2023 in Ljubljana (Figure) and the 5G-LOGINNOV final event in Luka Koper/Port of Koper, Slovenia, in November 2023 (Figure 117). On both occasions, national TV (www.rtvslo.si) was present, reporting the events for the news[13].

Figure 117: AKOS Industrial event[14] in Ljubljana, Slovenia - Displaying the capabilities of private 5G SA systems (figure on the left and in the middle) and reporting on national TV (RTV Slovenija)[15] (figure on the right).

[13] RTV Slovenia show about the 5G and 6G: https://365.rtvslo.si/arhiv/znanost-in-tehnologija/174989963
14 https://www.linkedin.com/posts/internet-institute-ltd_5g-5g-6g-activity-7114690731109187584-A2Bi?utm_source=share&utm_medium=member_desktop
[15] https://365.rtvslo.si/arhiv/znanost-in-tehnologija/174989963

Figure 118: Final 5G-LOGINNOV event in Koper, Slovenia - Showcasing capabilities of private 5G SA systems.

4.2.3 List of Key Performance Indicators

The presented table summarizes 5G network and deployment KPIs defined for the UC1 in (5G-LOGINNOV, D1.4: Initial specification of evaluation and KPIs, 2022), the targeted values, and the final measured values achieved during testing and verification in LL Koper. Detailed explanations of the tools used, test methodologies, and final measured values, along with results comments, are presented in the chapters that follow.

System	KPI	KPI ID	Target Value	Measured Value
Dedicated private 5G SA mobile system	Bandwidth	K-KPI14	Downlink	Depends on the used 5G NR channel bandwidth and assigned TDD profile
	Bandwidth	K-KPI14	Uplink	Depends on the used 5G NR channel bandwidth and assigned TDD profile
	End-to-End Latency	K-KPI17	20 ms	**Achieved**
5G IoT backend system	Components Onboarding and Configuration (Backend)	K-KPI1	5 min (per single component)	**Achieved**
	Deployment Time (Backend)	K-KPI2	15 min	**Achieved**
	Time to Scale (Backend)	K-KPI3	5 min	**Achieved**
	Service Availability (Backend)	K-KPI4	99,99 %	**Achieved**
	Components Onboarding and Configuration (Agent)	K-KPI5	3 min (per single component)	**Achieved**
	Deployment Time (Agent)	K-KPI6	5 min	**Achieved**

System	KPI	KPI ID	Target Value	Measured Value
Dedicated private 5G SA mobile system	Components Onboarding and Configuration (Backend)	K-KPI7	10 min (per single component)	Achieved
	Deployment Time (Backend)	K-KPI8	20 min	Achieved
	Time to Scale (Backend)	K-KPI9	10 min	Achieved
	Service Availability (Backend)	K-KPI10	99,99 %	Achieved
	Slice Reconfiguration (Backend)	K-KPI11	5 min	Achieved

Table 35: LL Koper - UC1 Key Performance Indicators

4.2.4 Methodology and Measurement Tools

To verify the developed and deployed 5G systems, several functional, interoperability, and performance tests were initiated, and dedicated tools were prepared and integrated into the LL Koper.

For 5G NR, 5G core network, and end-to-end performance testing, ININ's qMON systems were utilized to assess several radio performance metrics (e.g., RSRP, RSRQ, SINR, CQI, channel BW, MIMO mode, etc.) and data plane performance, including download and upload throughput, latency. For more details about the qMON system please check the chapter 4.1.3. Based on the test type different qMON agent form factors were used, such as integrated qMON agent software on the ININ's Industrial IoT GW (Figure 119), a dedicated smartphone with the qMON agent application, and RPi-based qMON agent for performance and application-based testing on the Nokia FastMile 5G gateway. To support different test methodologies qMON reference server instances were deployed on the cloud in LL Koper and on the same Edge Kubernetes NFVI as the private 5G system.

Figure 119: LL Koper - qMON agent analytics integrated with industrial IoT Gateway

Management and debugging capabilities of the private 5G system included integrated 5G NR real-time performance tracing (CQI, MCS, retransmits, bitrate, MIMO mode, PHR levels) and 5G system signalling tracing intercept capabilities for capturing MIB, SIB, RRC, AS and NAS-related signalling messages.

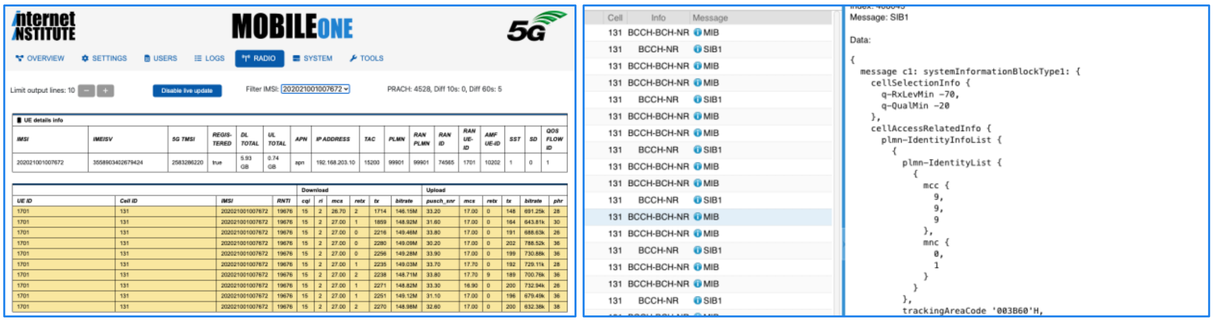


Figure 120: LL Koper - Real-time 5G NR performance monitoring (figure on the left) and signaling debugging capabilities of the private 5G system.

Similar capabilities were developed and applied to the ININ's Industrial IoT GW, with integrated 5G NR real-time performance monitoring (RSRP, RSRQ, SINR, TX Power) and network debugging capabilities (Figure 120).

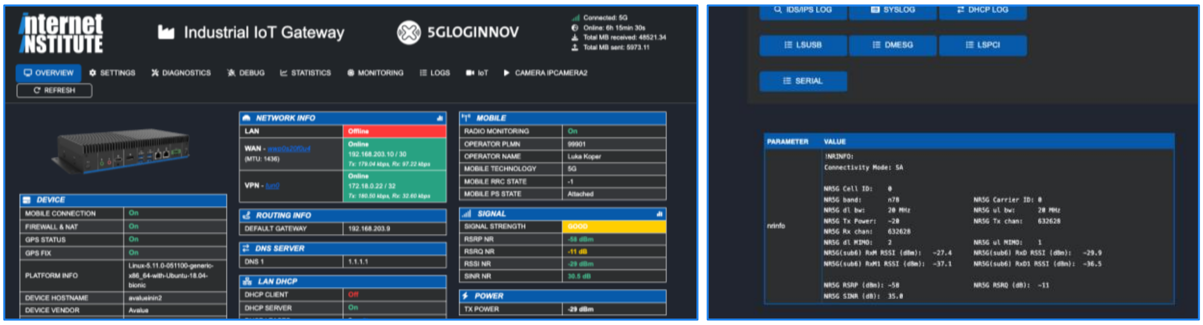


Figure 121: LL Koper - Real-time 5G NR status monitoring (figure on the left) and 5G NR modem debugging capabilities of the Industrial IoT GW.

Additionally, the management and debugging capabilities of Kubernetes (Figure) and MANO/OSM (Figure) were employed to assess the private 5G system and IoT backend system components' deployment times and other operational metrics.

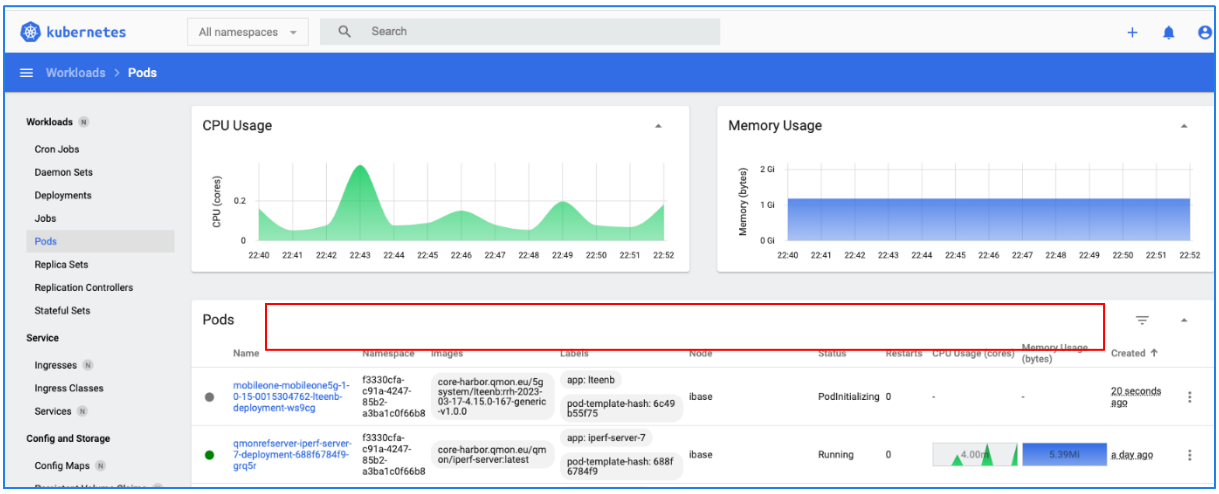


Figure 122: LL Koper - Kubernetes management showcasing the status of deployed private 5G system components.

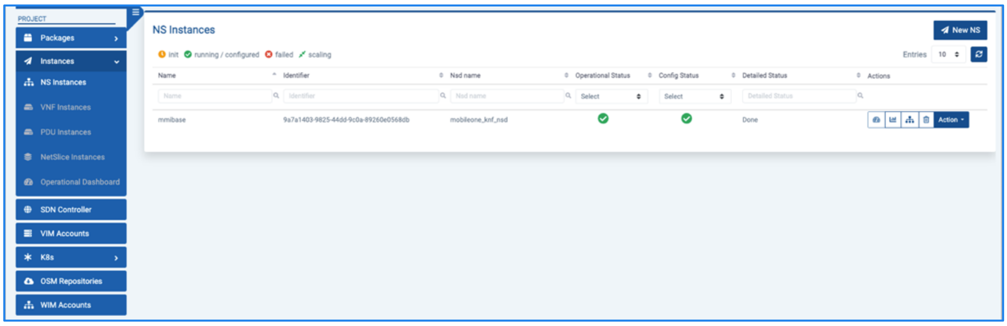


Figure 123: LL Koper - MANO/OSM management showcasing the status of deployed NSDs for the private 5G system components.

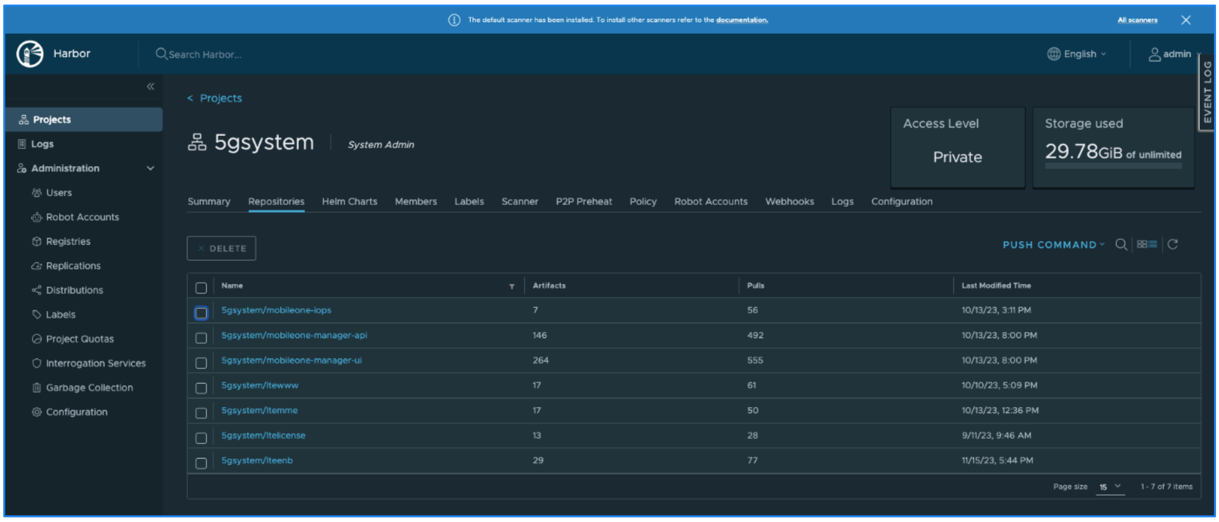


Figure 124: LL Koper - ININ's local Harbor repository with private 5G system components.

While some tests, such as the assessment of system deployment times, were performed manually, others supported by dedicated 5G test automation tools like ININ's qMON system, enabled full automation of test procedures. As such, several million KPI samples were taken during the duration of the 5G-LOGINNOV project, enabling the adoption of an iterative test and development approach. Test results were conveyed to the DevOps team, modifications were made to the systems, and the same tests were repeated.

4.2.5 Results

In the following sections, the results of the functional, interoperability, and performance testing for the utilized Private 5G system and the developed and deployed Industrial 5G IoT system from ININ are provided.

4.2.5.1 Deployment and operational KPI for a private 5G SA mobile system

We conducted a series of tests to measure the deployment and operational KPIs of private 5G SA mobile system, which was deployed on the Edge NFVI with the support of the MANO/OSM orchestrator. The mobile system consists of two main components: a BBU and a 5G CN. The test procedures included the following KPIs:

- **Components Onboarding and Configuration** (Backend): This KPI presents the time it takes to onboard and configure a single component of the system (i.e., BBU or 5G CN). The achieved values for the BBU and the 5G CN were 5 minutes and 4 minutes, respectively, which are faster than the target value and indicate a high optimisation of the process.

- **Deployment Time** (Backend): This KPI presents the elapsed time from the moment the deployment is started via the orchestrator until the system is ready to use. The achieved values for the BBU and the 5G CN were 2 minutes and 30 seconds, respectively, which are much shorter than the target value and indicate efficient deployment.

- **Time to Scale** (Backend): This KPI presents the elapsed time from the moment the scaling request is triggered until the component is scaled and ready to use. The achieved values for the BBU and the 5G CN were 3 minutes and 2 minutes, respectively, which are shorter than the target value and indicate flexibility and adaptability of the private mobile network.

- **Service Availability** (Backend): This KPI presents the percentage of successful service tests (WEB) to the reference service endpoint over a period of time. The measured value for the system was 99.99865%, which is higher than the target value and indicates a reliable and stable system.

- **Slice Reconfiguration** (Backend): This KPI presents the time it takes to reconfigure the slices of the system, which are logical networks with different performance and QoS parameters for different types of traffic and 5G UEs. The achieved values for the BBU and the 5G CN were 3 minutes and 2 minutes, respectively, which are faster than the target value and indicate a responsive and customizable system.

Management and debugging capabilities of the used Kubernetes and MANO/OSM systems were employed to assess the deployment times and other operational metrics of the private 5G system components. Several manual runs were triggered to collect observed metrics.

The results show that private 5G SA mobile system achieved or surpassed the target values for all the deployment and operational KPIs, demonstrating its high performance and suitability.

System	KPI	KPI ID	Target Value	Achieved Value
Dedicated private 5G SA mobile system	Components Onboarding and Configuration (Backend)	K-KPI7	10 min (per single component)	BBU: 5 min 5G CN: 4 min
	Deployment Time (Backend)	K-KPI8	20 min	BBU: 120 s 5G CN: 30 s
	Time to Scale (Backend)	K-KPI9	10 min	BBU: 180 s 5G CN: 120 s
	Service Availability (Backend)	K-KPI10	99,99 %	99,99865 %
	Slice Reconfiguration (Backend)	K-KPI11	5 min	BBU: 180 s 5G CN: 120 s

Table 36: LL Koper - Deployment and operational KPIs for a private 5G SA mobile system

4.2.5.2 Deployment and operational KPI for 5G IoT backend system

A series of tests were conducted to assess the deployment and operational KPIs of 5G IoT backend system, developed to support industrial IoT applications and services in the LL Koper. The 5G IoT backend system comprises three main components: a Manager, a Reference, and a Reporter. The Manager oversees the management and monitoring of IoT devices and the network, while the Reference provides a service endpoint for IoT devices to connect and communicate. The Reporter collects and reports data and performance metrics from IoT devices and the network. Additionally, the system includes an Agent, a software component running on IoT devices enabling interaction with the backend system.

The tests covered the following KPIs:

- **Components Onboarding and Configuration** (Backend): Measures the time to onboard and configure a single backend system component. Manager, Reference, and Reporter component achieved 3 minutes, 5 minutes, and 5 minutes, respectively, indicating a high optimisation of the onboarding process.

- **Deployment Time** (Backend): Measures the time from orchestrator initiation to backend system readiness. Manager, Reference, and Reporter components achieved 120 seconds, 60 seconds, and 180 seconds, respectively, demonstrating efficiency of the deployment procedure.

- **Time to Scale** (Backend): Measures the time from scaling request initiation to backend component readiness. Manager, Reference, and Reporter component achieved 140 seconds, 80 seconds, and 200 seconds, respectively, showing a flexible and adaptable system.

- **Service Availability** (Backend): Measures the percentage of successful service tests (WEB) to the reference service endpoint over time. Backend system achieved 100%, indicating a highly reliable and stable system.

- **Components Onboarding and Configuration** (Agent): Measures the time to onboard and configure a single agent on the IoT device. Agent achieved 150 seconds, showcasing high process efficiency.

- **Deployment Time** (Agent): Measures the time from orchestrator initiation to agent readiness. Agent achieved 120 seconds, demonstrating quick and easy deployment.

Management and debugging capabilities of the used Kubernetes and MANO/OSM systems were employed to assess the deployment times and other operational metrics of the 5G IoT backend system components. Several manual runs were triggered to collect observed metrics.

The results demonstrate that our 5G IoT backend system meets or exceeds the target values for all deployment and operational KPIs, highlighting its high performance and suitability for various IoT applications and services over the 5G network.

System	KPI	KPI ID	Target Value	Achieved Value
5G IoT backend system	Components Onboarding and Configuration (Backend)	K-KPI1	5 min (per single component)	Manager: 3 min Reference: 5 min Reporter: 5 min
	Deployment Time (Backend)	K-KPI2	15 min	Manager: 120 s Reference: 60 s Reporter: 180 s
	Time to Scale (Backend)	K-KPI3	5 min	Manager: 140 s Reference: 80 s Reporter: 200 s
	Service Availability (Backend)	K-KPI4	99,99 %	100 %
	Components Onboarding and Configuration (Agent)	K-KPI5	3 min (per single component)	150 s
	Deployment Time (Agent)	K-KPI6	5 min	120 s

Table 37: LL Koper - Deployment and operational KPIs for 5G IoT backend system.

4.2.5.3 ININ's 5G IoT GW functional testing

We performed various functional tests on deployed Industrial IoT Gateway to verify its 5G capabilities and performance in different scenarios and configurations in the port environment. The tests included the following aspects:

- ***5G NR transmission mode****:* ability to transmit and receive data using different 5G NR modes, such as FDD and TDD.
- ***5G NR MIMO mode****:* support for MIMO options, which enhances the data rate and reliability of 5G NR signals by using multiple antennas.
- ***Supported 3GPP Access****:* GW compatibility with different 3GPP access technologies, such as 5G SA, 5G NSA, LTE, HSPA.
- ***GNSS:*** Support for global navigation satellite system (GNSS) services, such as GPS, GLONASS, and Galileo, which provide accurate positioning and timing information.
- ***APN:*** ability to connect to different access point names (APNs), which identify the network services and settings for the gateway's data connection.
- ***BW limiting****:* ability to limit the bandwidth of 5G NR connection, by setting a maximum value.
- ***5G NR Slicing - Network Delegated****:* support for 5G NR slicing, which allows the creation of multiple logical networks with different performance and quality of service (QoS) parameters on the same 5G NR and 5G CN network. We used the network delegated approach, which means the 5G CN assigns the slice parameters to the gateway based on its service profile in UDM.
- ***Mobile Network Type*** *(Test, Private, Public):* ability to connect to different types of mobile networks, such as test, private, or public, depending on the targeted use case.
- ***Combining 4G and 5G carriers*** *(LTE CA + 5G NR):* ability to combine 4G and 5G carriers, using LTE carrier aggregation (CA) and 5G NR dual connectivity (DC), to achieve higher data rates.
- ***Cell Broadcast Alert****:* ability to receive and display broadcast alert messages, such as emergency or safety notifications, initiated on the management of the private 5G system.

We evaluated the gateway's performance and functionality in different use cases and scenarios (UC3, UC5, UC6), such as eMBB and mMTC, in the real port environment. The table that follows presents a summary of the test results.

ININ 5G IOT GW functionality	Options	Result
5G NR transmission mode	TDD FDD	Pass Pass
5G NR MIMO Mode	DL SISO UL SISO DL 2x2 MIMO UL 2x2 MIMO DL 4x4 MIMO UL 4x4 MIMO	Pass Pass Pass Not available Pass Not available
Supported 3GPP Access	5G SA 5G NSA	Pass Pass

ININ 5G IOT GW functionality	Options	Result
	4G 3G	Pass Pass
GNSS	GPS, GLONAS, Galileo	Pass
APN	Auth none PAP Authentication CHAP Authentication	Pass Pass Pass
IP Assignment	Dynamic IP Static IP	Pass Pass
BW limiting	APN Aggregated Max BW	Pass
5G NR Slicing - Network Delegated	eMBB, SST 1, SD 0 mMTC SST 3, SD 10 GBR slice with strict BW non-GBR slice non-GBR slice with BW limit	Pass Pass Pass Pass Pass
Mobile Network Type (Test, Private, Public)	Private: 99901 Test: 00101 Commercial: 29341 Commercial: 29340 Commercial: 20201 Commercial: 22288 Commercial: 24004	Pass Pass Pass Pass Pass Pass Pass
Roaming	Verified at several EU Operators	Pass
Combining 4G and 5G carriers (LTE CA + 5G NR)	Verified at commercial Operators	Pass
NR band n78 (SA)	20 MHz 30 MHz 40 MHz 50 MHz 100 MHz	Pass Pass Pass Pass Pass
NR band n77 (SA)	20 MHz 30 MHz 40 MHz 50 MHz 60 MHz 90 MHz 100 MHz	Pass Pass Pass Pass Pass Pass Pass
NR band n28 (SA)	20 MHz	Pass
5G NSA FDD bands	Supporting 11 FDD bands	Pass
5G NSA TDD bands	Supporting 9 TDD bands	Pass
Broadcast Alert	Receiving EU Alert messages	Not available

ININ 5G IOT GW functionality	Options	Result
Temp	5G Modem operating up to +80ºC	Pass
802.3 Interfaces	1 Gbps, 2.5 Gbps	Pass

Table 38: LL Koper - ININ's 5G IoT GW - Functional test results.

4.2.5.4 Private 5G SA System – Functional, Interoperability and Performance Testing

In the following chapter, test results from functional, interoperability, and performance testing are provided. To ensure test diversity and heterogeneity, in addition to the Private 5G SA mobile system and 5G IoT GW from ININ, several commercial smartphones (Samsung Galaxy S23, OnePlus 8, OnePlus 9) and the Nokia FastMile gateway were used.

Private 5G System Test type		ININ 5G IOT GW	OnePlus 9	Nokia FastMile 5G GW	Samsung Galaxy S23
5G NR TDD Config	TDD 2 TDD 3 TDD 5	Pass Pass Pass	Pass Pass Pass	Pass Pass Pass	Pass Pass Pass
5G NR MIMO Mode	DL SISO UL SISO DL 2x2 MIMO UL 2x2 MIMO	Pass Pass Pass -	Pass Pass Pass -	Pass Pass Pass Pass	Pass Pass Pass -
APN	PAP user/pass CHAP user/pass	Pass Pass	Pass Pass	Pass Pass	Pass Pass
IP Assignment	Dynamic IP Static IP	Pass Pass	Pass Pass	Pass Pass	Pass Pass
BW limiting	APN Aggregated Max	Pass	Pass	Pass	Pass
5G NR Slicing	eMBB, SST 1, SD 0 mMTC SST 3, SD 10 GBR slice with strict BW non-GBR slice non-GBR slice with BW limit	Pass Pass Pass Pass Pass	Pass Pass Pass Pass Pass	Pass Pass Pass Pass Pass	Pass Pass Pass Pass Pass
PLMN (MCC MNC) / Private, Test, Public	99901 00101 20201[16]	Pass Pass Pass	Pass Pass Fail	Pass Pass Pass	Pass Pass Fail
Roaming	Different 5GS and USIM PLMNs	Pass	Pass	Pass	Pass
NR band n78 RRU with n78/n77	20 MHz 40 MHz 50 MHz	Pass Pass Pass	Pass Pass Pass	Pass Pass Pass	Pass Pass Pass

[16] 5G SA mode on a commercial Smartphones (e.g., OnePlus 9, Samsung S23) is supported only on whitelisted commercial networks.

Private 5G System Test type		ININ 5G IOT GW	OnePlus 9	Nokia FastMile 5G GW	Samsung Galaxy S23
NR band n77 RRU with n78/n77	20 MHz 40 MHz 50 MHz	Pass Pass Pass	Fail Fail Fail	Fail Fail Fail	Pass Pass Pass
Broadcast Alert	Receiving EU Alert messages	Fail	Pass	Fail	Pass

Table 39: LL Koper - Private 5G SA System - Functional and interoperability test results

4.2.5.5 Private 5G SA System – Advanced Security Testing

State-of-the-art 5G SA security capabilities, such as secure 5G UE registration with encrypted SUPI/IMSI identity using asymmetrical encryption[17] (public and private system keys) and data plane integrity, were enforced on the private 5G systems. Verification was conducted by intercepting the signalling and data plane messages (traces) on the mobile system. A dedicated 5G SA-capable USIM module was used and prepared with the public asymmetric key derived from the private key used by the private mobile system in the port.

The results presented in the following Figure 125 showcase the successful deployment and operation of advanced 5G security services negotiated during the registration procedure between the private 5G SA mobile system and the utilized 5G UE. The presented traces are valid for the Samsung Galaxy S23 5G UE.

Security function	5G SA	4G/NSA
Encrypted (SUPI/IMSI) (private network registration)	✓	✗
Temporary identity GUTI	✓	✓
Control plane privacy	✓	✓
Control plane integrity	✓	✓
Data plane privacy	✓	✓
Data plane integrity	✓	✗

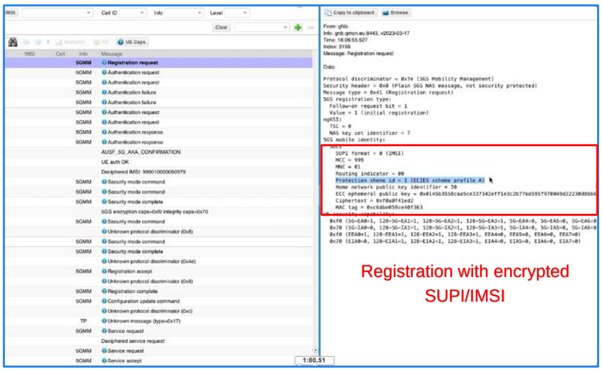


Figure 125: LL Koper - Private 5G SA mobile network supporting advanced 5G security services.

4.2.5.6 End-to-end 5G slicing with strict BW guaranties

The slicing capabilities of ININ's private 5G system was verified for the support of network-delegated 5G NR slicing. This feature allows to create multiple logical networks (eMBB and mMTC) with different performance and QoS parameters on the same 5G NR cell and the connected 5G CN network. The 5G CN assigns the slice parameters to the attached 5G UE based on its service profile in the UDM.

[17] Elliptic Curve Integrated Encryption Scheme (ECIES).

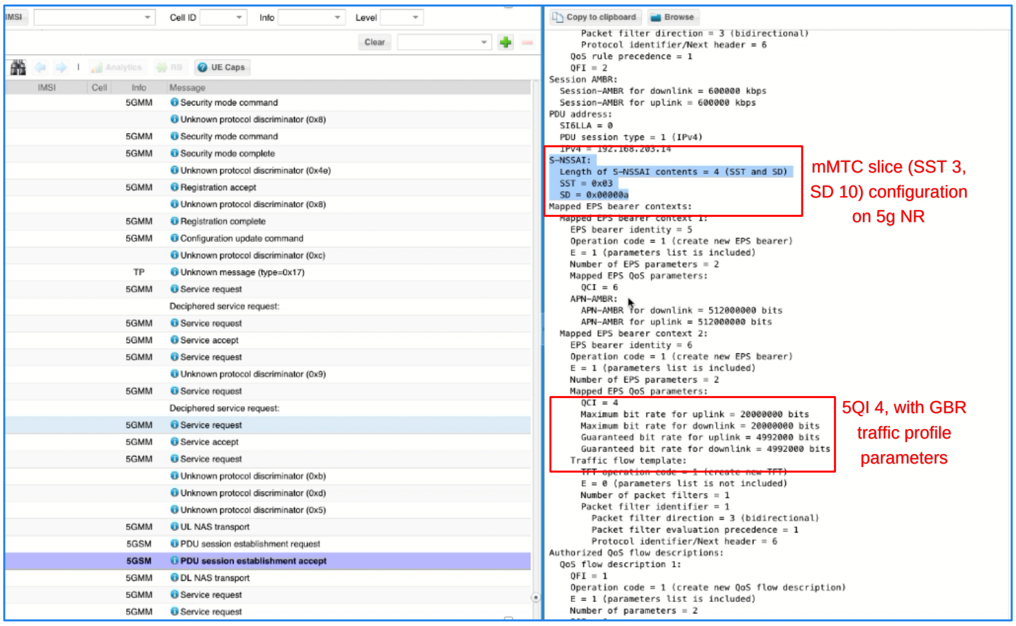


Figure 126: LL Koper - 5G SA signalling with strict BW reservation using mMTC slice

We utilized the signalling tracing capabilities of the private mobile system to verify the delegation of slicing parameters from the control plane perspective. In addition, qMON-generated traffic was employed at the end to test the correct downlink and uplink enforcement from the data plane perspective. The slicing behaviour was verified using different 5G NR operational modes, including optimizing TDD profiles and MIMO parameters. The test results are summarised in the following table and figures.

Private 5G System Test type		ININ 5G IOT GW	OnePlus 9	Nokia FastMile 5G GW	Samsung Galaxy S23
TDD Config PLMN: 99901 MIMO 2x2 Band: n78 P_max: 30 dBm Cell Power per port: 30 dBm Directional antenna: eMBB: SST 1, SD 0 Slice BW: no limit	TDD 2 TDD 3 TDD 5	Pass Pass Pass	Pass Pass Pass	Pass Pass Pass	Pass Pass Pass
MIMO Mode PLMN: 99901 Band: n78 5G NR BW: 20 MHz P_max: 30 dBm Cell Power per Port: 30 dBm Directional antenna: eMBB: SST 1, SD 0 Slice BW: no limit	DL SISO UL SISO DL 2x2 UL 2x2	Pass Pass Pass -	Pass Pass Pass -	Pass Pass Pass Pass	Pass Pass Pass -
BW limiting per 5G UE PLMN: 99901 MIMO: 2x2 Band: n78 5G NR BW: 50 MHz P_max: 30 dBm Cell Power per Port: 30 dBm Directional antenna: eMBB: SST 1, SD 0 Slice BW: no limit	DL 20 Mbps UL 20 Mbps[18]	Pass Pass	Pass Pass	Pass Pass	Pass Pass
5G NR SLICING PLMN: 99901 MIMO: 2x2 Band: n78 5G NR BW: 50 MHz P_max: 30 dBm Cell Power per Port: 30 dBm Directional antenna: eMBB: SST 1, SD 0	GBR slice with strict BW non-GBR slice non-GBR slice with BW limit	Pass Pass Pass	Pass Pass Pass	Pass Pass Pass	Pass Pass Pass
NR BW test PLMN: 99901 MIMO: 2x2 Band: n78 P_max: 30 dBm Cell Power per port: 30 dBm Directional antenna eMBB: SST 1, SD 0 Slice BW: no limit	20 MHz 40 MHz 50 MHz	Pass Pass Pass	Pass Pass Pass	Pass Pass Pass	Pass Pass Pass

Table 40: LL Koper - Private 5G SA System – Interoperability and performance test results

ON the following figure an example of test results is presented for the employed mMTC slice featuring a Guaranteed Bit Rate (GBR) traffic profile. The specified slice parameters for this test configuration were as follows: GBR DL/UL Throughput: 9 Mbps (Minimum), Max DL/UL Throughput: 20 Mbps.

This configuration allowed us to evaluate and assess the performance of the mMTC slice under the defined GBR traffic profile, focusing on its ability to maintain a minimum throughput of 9 Mbps while also reaching a maximum throughput of 20 Mbps, if available on the 5G NR cell.

[18] Radio conditions on the 5G UE side needs to be satisfactory.

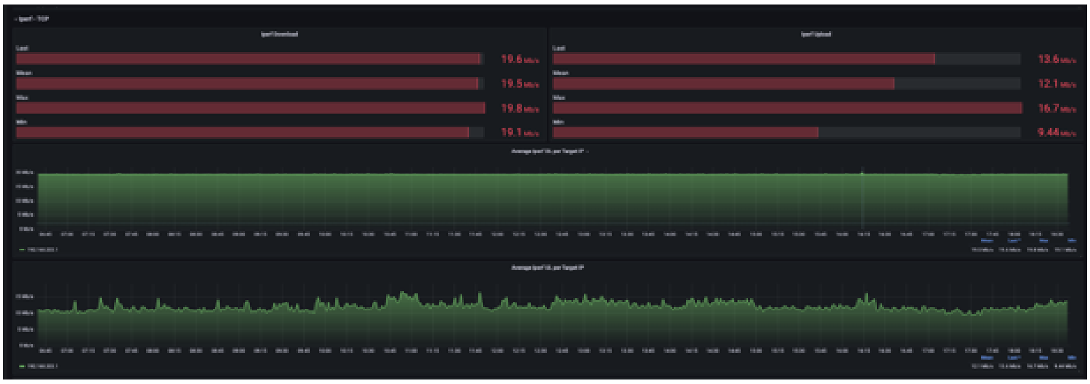


Figure 127: LL Koper - Private 5G SA - Throughput test results visualisation for mMTC slice with strict BW requirements

More results and findings from bandwidth performance testing scenario are detailed in the subsequent sections of this report.

4.2.5.7 Bandwidth

As indicated at the beginning n78 RRU with 2x2 was selected for the deployment of the private 5G system in the LL Koper with the channel bandwidth of 20 MHz in TDD mode. Based on the foreseen usage of the private 5G system in the port environment 4 different TDD profiles were prepared and verified:

- TDD 6 profile that was optimised for the uplink intensive port applications such as real-time video streaming.
- TDD 5 profile was prepared to equally balance available TDD NR slots between uplink and downlink traffic.
- TDD 3 and TDD 2 profile were used to assure high downlink throughput for the port applications that need to utilize traffic delivered to the 5G UE.

The test results are depicted in the table below. For the reference we included also the results in the case of using 50 MHz of channel bandwidth.

Some of the presented KPI performance limitations (achieved download and upload throughput) in the results below are attributed to the narrow 5G NR channel bandwidth of 20 MHz that was used, and not to the limitations of the deployed Private 5G SA system or used 5G UE devices.

Used RRU with BBU settings	5G NR Channel BW	Private 5G System Test type	DL Throughput	UL Throughput
5G NR RRU n78 2x2 DL MIMO 2x2 UL MIMO QAM 256 (up to)	Channel BW **20 MHz**	TDD 6 **(uplink intensive)**	Max: 29,2 Mbps Min: 27,5 Mbps Mean: 28,3 Mbps	**Max: 57 Mbps** Min: 50,7 Mbps Mean: 54,9 Mbps
		TDD 5 (Balanced)	Max: 93,0 Mbps Min: 89,3 Mbps Mean: 91,8 Mbps	Max: 36,5 Mbps Min: 33,0 Mbps Mean: 34,8 Mbps
		TDD 3 (downlink intensive)	Max: 113 Mbps Min: 110 Mbps Mean: 112 Mbps	Max: 28,5 Mbps Min: 26,6 Mbps Mean: 27,6,7 Mbps
		TDD 2 **(downlink intensive)**	**Max: 136 Mbps** Min: 134 Mbps Mean: 135 Mbps	Max: 16,9 Mbps Min: 15,5 Mbps Mean: 16,4 Mbps
	Channel BW **50 MHz**	TDD 6 **(uplink intensive)**	Max: 52,1 Mbps Min: 134 Mbps Mean: 80,6 Mbps	**Max: 258 Mbps** Min: 244 Mbps Mean: 231 Mbps

Table 41: LL Koper - Private 5G SA - Throughput test results using 20 MHz NR BW (K-KPI14).

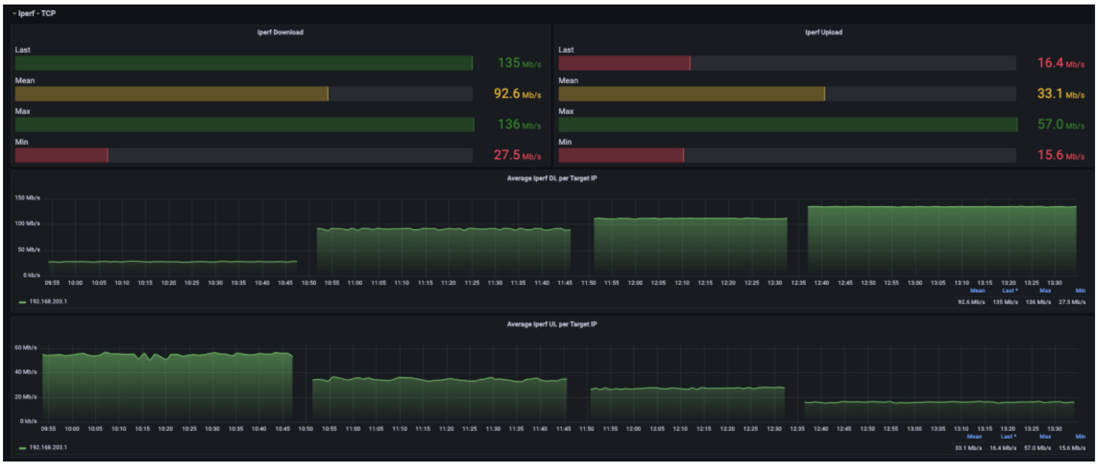


Figure 128: LL Koper - Private 5G SA - Throughput test results using 20 MHz NR BW (K-KPI14)

In Figure measurement results are presented on a time scale from left to right, corresponding to TDD 6, TDD 5, TDD 3, and TDD 2 profiles deployed on the RRU using a 20 MHz 5G NR spectrum.

The testing results show that the 5G NR system performance and suitability depend on the channel bandwidth and the application requirements. For applications that are not bandwidth-intensive, such as sensor readings and real-time telemetry collection, the system can provide adequate service quality using 20 MHz of spectrum. However, for applications that are bandwidth-intensive, such as video streaming and cloud computing, the 5G system needs more spectrum to achieve higher throughput and lower latency. The results indicate that using 50 MHz of spectrum can increase the uplink throughput up to 258 Mbps (Figure), which is a significant improvement compared to 20 MHz of spectrum (uplink throughput up to 57 Mbps).

However, this may not be enough to fully utilize the potential of 5G technology used for future smart ports. Therefore, we recommend using 100 MHz of spectrum or more for the private 5G deployments to enable more advanced and diverse applications and services for the future smart port use cases.

Figure 129: LL Koper - Private 5G SA - Throughput test results using 50 MHz NR BW (K-KPI14)

Measurement results presented on a time scale – 50 MHz of spectrum using uplink intensive TDD profile

4.2.5.8 Availability

We conducted a long-term test to measure the availability of our deployed private 5G system and rMON 5G IoT backend. We selected a timeframe of more than three weeks (from July 5, 2023 to July 28, 2023) to verify the stability and reliability of the deployed systems under different conditions and scenarios. We used two metrics to evaluate the availability of the systems:

- The percentage of successful connection tests (RTT) for the deployed private 5G system to assure not only that system components were operational but also to verify actual connectivity between industrial 5G gateway and reference endpoint in 5G network.

- Percentage of successful service tests (Web) for the rMON 5G IoT backend system to assure accessibility of the backend services components.

$$\text{Availability } (\%) = \left(\frac{\text{Successful Tests}}{\text{Total Tests}}\right) \times 100$$

The connection tests measured the round-trip time (RTT) of the ICMP packets between the 5G gateway and the reference point in 5G network, which also reflects the latency and responsiveness of the system. The service tests (Web) measured the availability and performance of the rMON IoT backend service endpoint, which also reflects the functionality and quality of service (QoS) of the system. We used qMON system to automate the test process and to assure periodically. We compared the results with the expected outcomes and the specifications to assess the availability of the system.

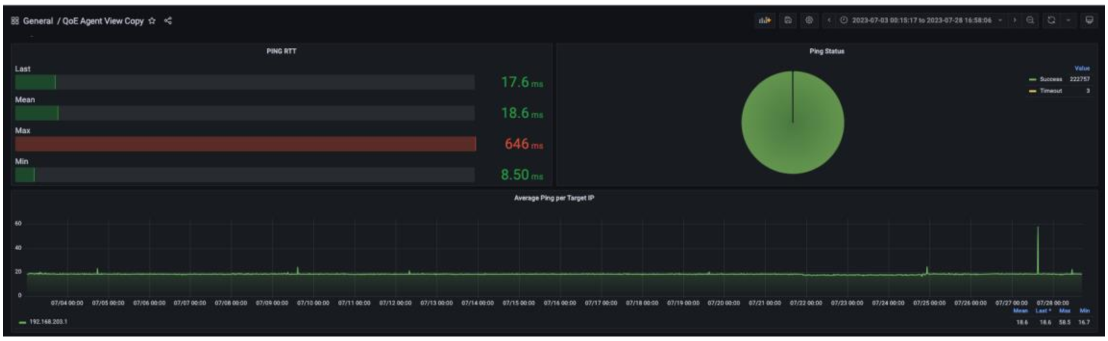


Figure 130: LL Koper - Availability of the private 5G systems (K-KPI10)

For the private 5G systems (K-KPI10), during the test duration, 222.760 ICMP messages were sent, and 3 of them were lost (Figure), accounting for an availability of 99,99865 %.

Figure 131: LL Koper - Availability of the Enhancing 5G IoT backend (K-KPI4)

For the Enhancing 5G IoT backend system (K-KPI4), during the test duration, 21.949 Web services tests were run (Figure 131), and all of them were successful, accounting for an availability of 100 %.

4.2.5.9 End-to-End Latency

We measured the end-to-end latency (K-KPI17) of deployed private 5G system as part of a long-term test to verify its availability. A timeframe of more than three weeks (from July 5, 2023 to July 28, 2023) was selected. We used the round-trip time (RTT) measurement to calculate the end-to-end latency, which is the time it takes for an IP ICMP Echo Request packet to travel from the source host (5G UE) to the dedicated destination host in the 5G network and back. We performed the measurement using two different TDD profiles, which define the allocation of uplink and downlink resources for the 5G NR system. The following TDD profiles were operational:

- TDD 5: This is a balanced profile, where the uplink and downlink TDD slots are equally distributed. This profile provides a fair trade-off between latency and throughput. The results of the latency measurement using this profile are shown in Figure 132.

- Dedicated TDD profile: This was a customized profile, where the RAN resources were carefully planned to minimize the latency on the 5G NR air interface. This profile sacrifices some throughput to achieve lower end-to-end latency. The results of the latency measurement using this profile are shown in Table 42.

The results show that the end-to-end latency of private 5G system varies depending on the TDD profile and the network load. The (mean) latency using the TDD 5 profile was 18,6 ms, while the (mean) latency using the dedicated profile was 11,8 ms. The minimum latency using the TDD 5 profile was 8,5 ms, while the minimum latency using the dedicated profile was 7,6 ms.

Used RRU with BBU settings	5G NR Channel BW	Private 5G System Test type	End-to-End Latency (K-KPI17)
5G NR RRU n78 2x2 DL MIMO 2x2 UL MIMO QAM 256 (up to)	Channel BW **20 MHz**	TDD 5 (Balanced)	Max RTT: 646 ms Mean RTT: 18,6 ms Min RTT: 8,5 ms
		TDD profile optimised for low latency	Max RTT: 20,7 ms Mean RTT: 11,8 ms Min RTT: 7,6 ms

Table 42: LL Koper - End-to-End latency results (K-KPI17).

The results indicate that the dedicated TDD profile can reduce the mean latency compared to the TDD 5 profile, but at the cost of lower throughput. The results also indicate that the latency increases with the network load, as more packets compete for the same radio resources. The results demonstrate the flexibility and adaptability of deployed private 5G system to meet different latency requirements and use cases.

Figure 132: LL Koper - TDD profile optimised for low latency (K-KPI17).

4.3 UC5: Optical Character Recognition of container markings and Container Damage Detection

4.3.1 Description and Motivation

In the context of port management, ensuring the traceability of containers emerges as a pivotal factor in orchestrating the seamless transportation of cargo. This multifaceted endeavour encompasses various facets, including the meticulous identification of containers and the rigorous examination of their structural integrity. Given the challenging conditions to which containers are subjected, there is an inherent risk of damages that could compromise their overall robustness. Consequently, a compulsory visual inspection becomes imperative not only for the identification of containers but also to ascertain the containers' soundness and resilience in the face of harsh environmental elements and other potential stressors.

This visual inspection of cargo containers is essential to maintain the safe and correct transportation of goods. This process is comprised by the detection of different elements that feature the container: the BIC code identifier, IMGD markers that could be adhered to the container surface or the different damages the surface could present (Figure 133). In addition, other parameters related to operational processes are interesting such as the orientation of the container during the loading or unloading procedures to and from vessels.

Damages	BIC & ISO codes	IMGD markers
		

Figure 133: LL Koper - UC5 - Elements to be detected

As previously mentioned in this document, a mother vessel typically requires approximately 3000 stevedore moves (depending on the vessel size) to complete loading operations. Each of these manoeuvres requires a visual inspection of the containers to ensure that their conditions are suitable for shipment or loading onto trucks. Like many automation processes, the primary objective of an automatic visual inspection system is to decrease the time required for these inspections. This reduction in time not only minimizes the duration the vessel must remain stationary at the port but also eliminates the necessity for human presence in the loading/unloading area, thereby enhancing the safety of the process and mitigating associated risks.

4.3.2 Use Case Setup

As analysis must be made for all the faces of the container, the architecture of the use case is comprised by five cameras as depicted in Fig 883each of one covering one of the faces. However, to cover all the area from the side of the beam closest to the container two cameras are necessary, so that the whole container can be acquired.
The quayside crane (QC) is equipped with five wide-angle cameras, continuously capturing 1080p (with the possibility of reaching 4k) video of vessel loading/unloading operations. The container analysis is performed in an on-premises AI-assured cloud infrastructure connected via LL Koper 5G to the STS cameras (Figure 134).

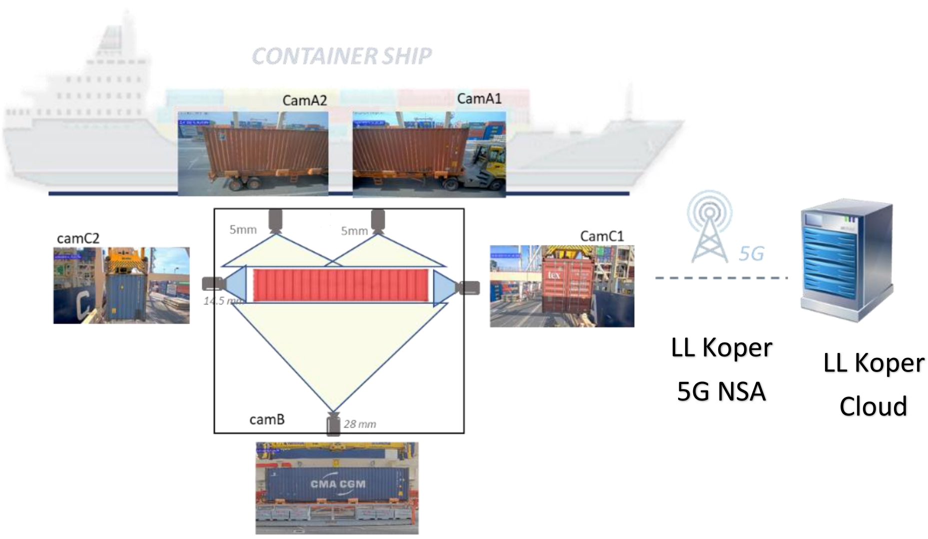


Figure 134: LL Koper - UC5 - Real component installation scheme

That architecture is primarily influenced by two different factors. The first factor is the computation capabilities essential for model inference, demanding a high-performance computer that, with severe restrictions, must be installed in the facilities due to access and security regulation issues. The second factor is the available bandwidth. In 5G networks, this enables the transmission of substantial data volumes necessary for streaming content from five cameras at 1080p resolution.

The server installed in LL Koper features an Intel Xeon Gold 6132 2.6G processor, 128G RAM memory and NVIDIA Tesla T4 GPU graphic card to accelerate the processing time of the deep learning models inference. The 5G NSA from Telekom Slovenije was exploited to deliver uplink non-processed 1080p video streams at the central server for its analysis. Information is later sent to update the information at the LL Koper cloud.

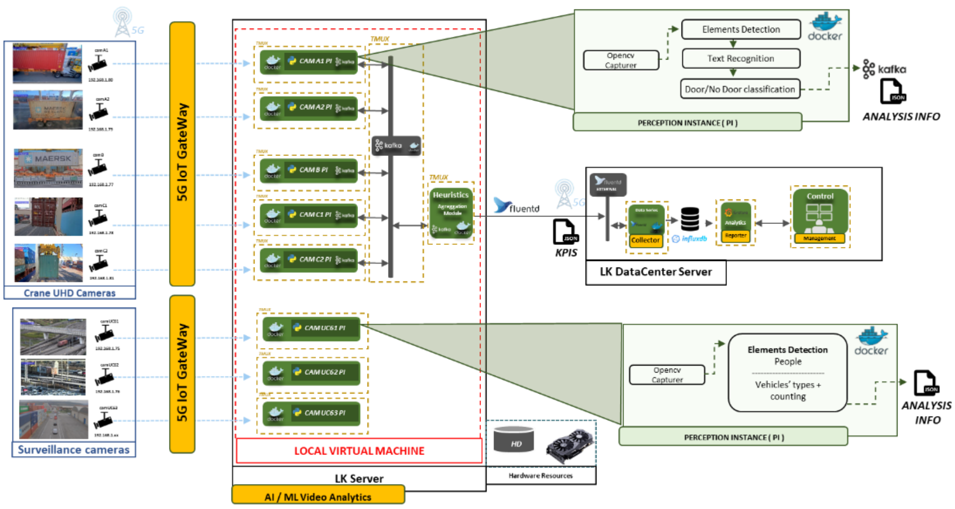


Figure 135: LL Koper - UC5 - System architecture

The ML visual inspection procedure algorithms (a.k.a. perception instance) are implemented in python and installed in five different docker containers, see Figure 134, one for each camera. The inner pipeline of each perception instance is described in Figure 135. And it is comprised of several stages. The execution flow of each instance varies depending on the elements present in the image.

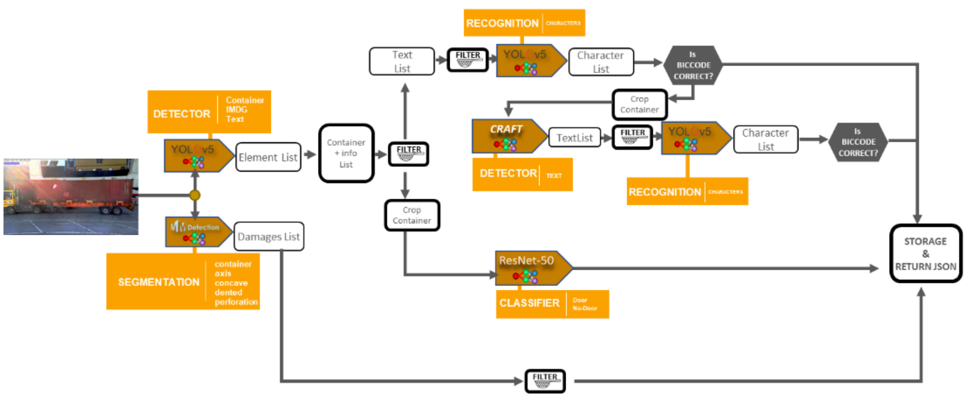


Figure 136: LL Koper - UC5 - Perception instance pipeline scheme

The heuristic module is comprised of several Python scripts that continuously check the messages sent to a messaging broker (Kafka) by the perception instances, as shown in Figure . Once a timeout is detected (meaning no more messages are being sent for a while), the heuristic module decides whether a container is being operated or not. It could be a container that just passed by in front of the camera without stopping, for example.

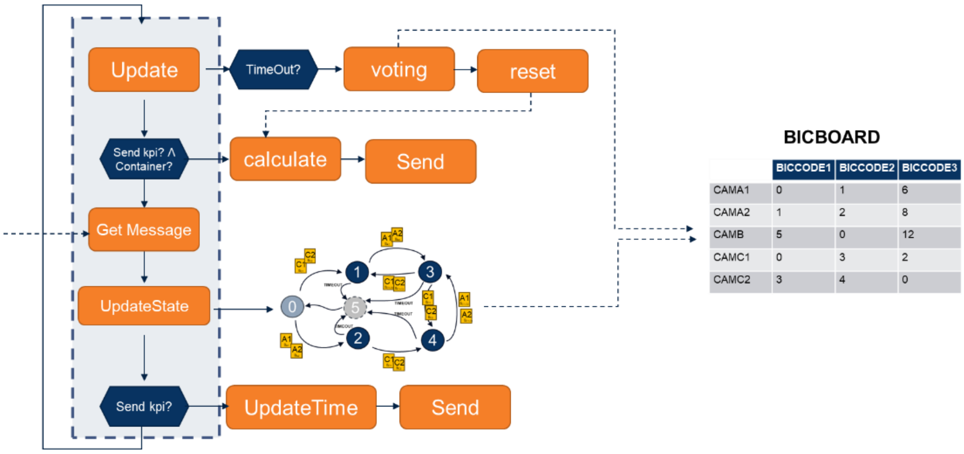


Figure 137: LL Koper - UC5 - Decision module functional architecture

The perception instances undertake various tasks (see Figure 137) to gather the required information for the system:

Visual objects detection: A pre-trained large sized YOLOv5 [19] neural network was finetuned on coco dataset[20] with synthetic labelled images[21,22] and later finetuned from here with real images. In the synthetic images all kind of elements can be found, whereas in the real images only containers, texts and certain IMDG markers can be identified. During training, the network started with pre-defined weights and was allowed to change weights on all the layers, this process is usually known as finetuning.
Damages detection: Due to the absence of real images depicting damages, and the resulting subpar performance when applied to real data, caused by the domain gap between real and synthetic images, this module has been removed from the pipeline. Only a laboratory analysis has been conducted. A segmentation model has been used to address this task, and the training was carried out using synthetic images from the SeaFront dataset.
Text detection: A CRAFT model was used to detect text within the container (once it has been detected). This module is only used when the prompt detection with YOLOv5 model does not detect text but detects container. CRAFT model has proven to be a robust alternative to be considered for text detection. In this case this model is combined with the previous more generalist detector.
OCR: Another large sized YOLOv5 network was finetuned for 150 epochs on a synthetically generated and annotated dataset of images with different true type fonts (ttf) and then it was fine-tuned again with dataset composed of labeled real text crops.
The synthetic dataset was composed by 1297 images, 1034 for training and 264 for validation and the real dataset consists of 786 images, 686 images for training and 100 images for validation.
Door/No Door classifier: To classify the presence of a door on a container face, a ResNet50 model has been selected. It was fine-tuned using already pre-trained weights with a dataset composed of synthetic and real images. The synthetic dataset comprised of 612 door images and 612 no-door images, as this approach allowed us to easily generate a balanced dataset. The real dataset consisted of 2275 door images and 3262 no-door images.

[19] https://zenodo.org/record/7347926
[20] https://cocodataset.org
[21] Guillem Delgado, Andoni Cortés, Estíbaliz Loyo. Pipeline for Visual Container Inspection Application using Deep Learning. In Proceedings of the 14th International Joint Conference on Computational Intelligence IJCCI 2022, ISBN 978-989-758-611-8, ISSN 2184-2825, pages 404-411. DOI: 10.5220/0011590900003332
[22] Guillem Delgado, Andoni Cortés, Sara García, Estíbaliz Loyo, Maialen Berasategi, Nerea Aranjuelo, Methodology for generating synthetic labeled datasets for visual container inspection, Transportation Research Part E: Logistics and Transportation Review, Volume 175, 2023, 103174, ISSN 1366-5545, https://doi.org/10.1016/j.tre.2023.103174. (https://www.sciencedirect.com/science/article/pii/S136655452300162X)

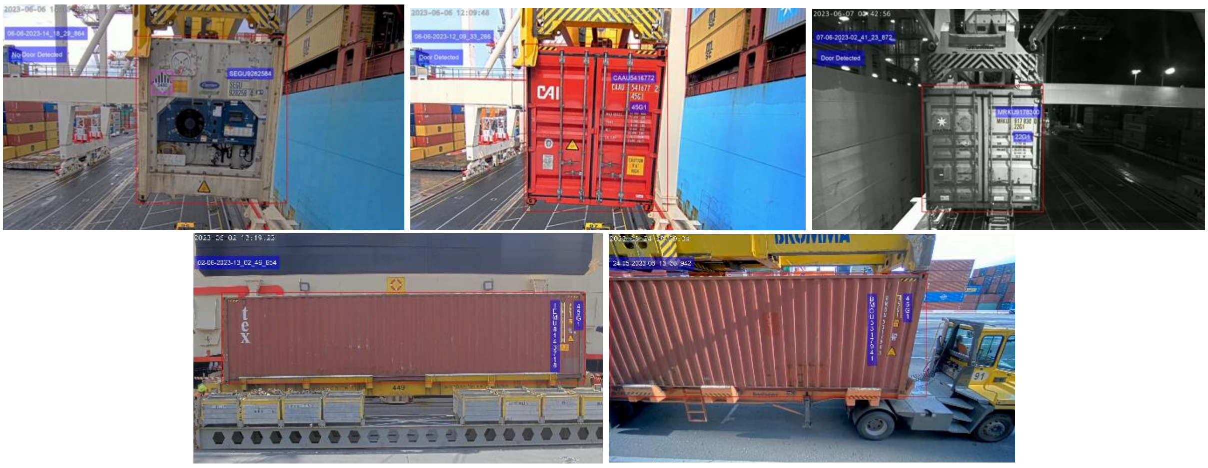


Figure 138: LL Koper - UC5 - Perception instance pipeline scheme

Therefore, UC5 is specifically designed to minimize the inspection time for containers, ultimately leading to a reduction in economic costs within the logistics chain. This is achieved by leveraging the high-speed, low-latency communication capabilities of 5G technology to efficiently track and inspect containers during their presence within the port premises.

4.3.3 List of Key Performance Indicators

KPI	KPI ID	Target Value
Model accuracy/reliability	K-KPI19	Depends on the ML model configuration and the video frame size
Model Inference Time	K-KPI20	Depends on the ML model configuration, the video frame size and the hardware architecture

Table 43: LL Koper - KPI List for UC5 Optical Character Recognition of container markings and Container Damage Detection.

4.3.4 Methodology and Measurement Tools

The deep learning models employed in this solution have been trained using a combination of real and synthetic data. The performance of the system is ultimately defined by the quality of the data relevant to the target scenario. The evaluation has been conducted at two distinct levels: the **perception instance** and the **overall system**.

In response to a shortage of annotated data, the initial strategy involved training and testing algorithms with synthetic data. Thus, **SeaFront Dataset** (see Figure 139) was created by combining Blender and python to generate a diverse and representative dataset.

Figure 139: LL Koper - UC5 - Some examples of synthetically generated containers

The dataset was consisted of 7910 images for training and 1978 images for validation. The elements randomly added to the surface of the container 3D model included BICCODES, ISOCODES, IMDG stickers or markers, as well as visible damages such as axis deformation, dented damage, perforations, holes, etc. (see Figure 140). Additionally, other stickers and effects like corrosion, texture, shadows, external elements, hdr backgrounds, etc. were incorporated. It is worth noting that a dataset of any size could be created using the developed scripts, provided the required time.

Figure 140: LL Koper - UC5 - Some synthetically generated container that exhibit damages

However, not all the items for the different tasks presented equal modelling difficulty; synthetic containers for container detection proved to be straightforward, followed by text lines and IMDG also for detection. In contrast, damages for damages detection and identification showcased a wide variety of different visual perceptions and the generational capacities of the scripts, along with Blender, were not able to shape all the intricacies.

To address the domain gap between synthetic and real data, and once the cameras were available to capture data, a **real dataset** was created. This real dataset was exploited to fine-tune and to evaluate perception instances, not the overall system due to desynchronization issues between frames provided by videos recorded from different cameras.
To evaluate perception instances, 70 different 30-minutes videos were gathered. Out of these, 20 videos were used to fine-tune the models that were initially trained with synthetic data. The remaining videos were employed for the evaluation process. Accuracy was calculated by comparing the predictions made by the pipeline for each sequence with a ground truth text file containing the correct BIC and ISO codes for the sequence.

The acquired videos include approximately 700 container moves, where each container move consists of several frames capturing the motion of the crane during the loading/unloading phase. These videos were recorded in various weather and operational conditions and at different times of the day.

In conclusion, elements with a more straightforward and robust structure (strong intra-class visual features), such as the container itself and the text blocks, yield higher detection accuracy compared to elements that generate more diverse features or exhibit greater inter-class variability (damages, IMDGs, optical character recognition) when applying synthetic trained models to real data.

Due to the absence of IMDG markers they have only been evaluated in the laboratory with synthetic images, as well as damages. However, in the case of IMDG markers the model used in the detection stage of the deployed system is prepared to identify them.

As for the binary classification module (door / no-door), a ResNet classification model has been fine-tuned from the synthetic trained model with a dataset with 2275 door real images and 3262 no door real images. Evaluations has been made with 520 door images and 680 no-door images (see Figure).

Figure 141: LL Koper - UC5 - Door images (upper row) and no-door images (lower row)

On the other hand, the system's evaluation is carried out manually through an analysis of the predictions generated by the decision module (see Figure 142). This analysis takes place after the decision module has received and reviewed the information from the perception instances and has decided whether there is a container in operation or not.

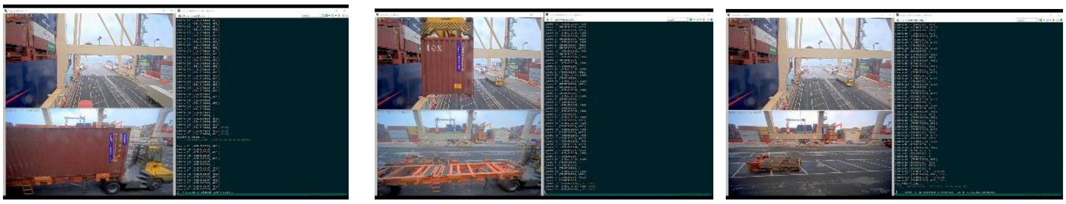


Figure 142: LL Koper - UC5 - Regular evaluation process for the decision module

4.3.5 Results

4.3.5.1 K-KPI19 Model accuracy/reliability

As there are several models involved in the result, a more detailed study was conducted.

The **perception instance** approach measures the different perception instances' accuracy separately by processing each video and comparing its output with a list (a text file) that includes containers arriving on that specific video.

Initially, we conducted tests using synthetic data, achieving satisfactory results in almost all tasks. However, when applied to real data, the performance significantly dropped, particularly in the damage segmentation task. Therefore, this document presents only laboratory results for the damages segmentation part, while the remaining tests were conducted on real images acquired from the cameras installed in the port.

The damages detection tasks were addressed training a Mask R-CNN model with synthetic data and testing it with the test part of the synthetic dataset:

Mask R-CNN	AP	APS	APM	APL
Precision	67.5	12.4	45.9	77.8
Recall	71.7	13.2	50.9	77.7

Table 44: LL Koper - UC5 - Precision and Recall of the damage segmentation model with synthetic label data

As can be seen in the table 44, the results are modest, and with small objects, the model has difficulties to segment them correctly. This indicates that more labelled data, particularly with small and medium damages is likely necessary to improve performance. Additionally, some modifications in the architecture could also be helpful.

In the case of the IMDG stickers detection task, both analyses, with synthetic and with real images, were carried out. The detection of IMDG markers is available in the final pipeline, but the number of IMDG markers in the real dataset is very small (11 markers in the entire 72-video dataset). All IMDG markers are recognized. However, this is not representative because as mentioned above the number of markers is small and, moreover, they are of the same type. Therefore, the following table 45 provide the result of the detection model for the test part of the synthetic per class and globally.

Model	P	R	map50	map
YOLOv5-L	0.754	0.898	0.792	0.734

Table 45: LL Koper - UC5 - Evaluation metrics for Yolov5l for synthetic IMDG detection

Class	P	R	AP50	AP
text	89	87.9	91.5	73.2
C1.1	54.5	59.3	65.2	59.0
C1.2	29.3	42.8	28.9	26.0
C1.3	28.9	49.9	30.3	27.4
C1.4	30.6	54.7	34.5	31.3
C2.1	50.4	65.4	53.3	47.8
C2.2	46.4	71.6	47.7	42.4
C2.3	87.3	98.7	98.9	87.6
C2.4	80.5	96.5	97.0	87.8
C2.5	43.1	72.7	46.3	40.7
C3.1	45.7	86.3	47.8	42.8
C3.2	49.2	83.1	51.5	45.7
C4.1	85.0	97.7	98.8	89.9
C4.2	90.8	95.6	97.4	88.0
C4.3	89.0	96.6	98.3	89.2
C4.4	85.5	97.5	97.9	88.7
C5.1	90.4	97.1	98.4	89.6
C5.2	91.4	96.0	97.6	89.3
C5.3	83.8	97.1	97.9	89.3
C6.1	47.2	69.0	49.0	44.1
C6.2	65.3	78.3	80.7	72.6
C7.1	78.0	94.6	95.0	85.1
C7.2	47.1	88.4	52.1	46.4
C7.3	85.1	88.0	92.6	83.7
C7.4	51.9	91.5	52.6	46.0
C8.1	88.7	98.4	98.5	89.3
C9.1	87.5	97.3	97.3	86.9
container	100	100	99.5	99.5

Table 46: LL Koper - UC5 - Evaluation metrics per class for Yolov5l for synthetic IMDG detection

Regarding the binary classification task, which is only applied with cameras C1 and C2 providing information about the actual orientation of the container during loading or unloading operations, it has proven to be robust and stable after the fine-tuning process from synthetic data. The ResNet-based classification model has been tested with an additional test dataset composed of 520 real door images and 680 real no-door images. The results in the test dataset include 1195 TP (true positives) and 5 FP (false positives), i.e., the model achieves an accuracy of 0.995.

The remaining tests have been conducted with real data, providing an approximate understanding of how the overall system will function for the five installed cameras.

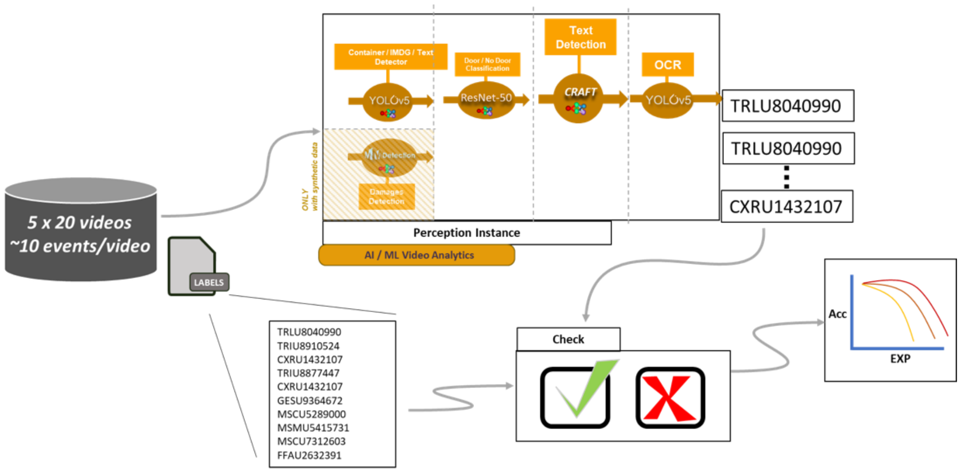


Figure 143: LL Koper - UC5 - PI's evaluation process scheme

The validation process was conducted as depicted in the graphic above. The perception instance pipeline was executed for each of the 5 cameras, up to a total of 20 test videos for each camera. These videos contained a varied number of events, typically ranging from 5 to 15.

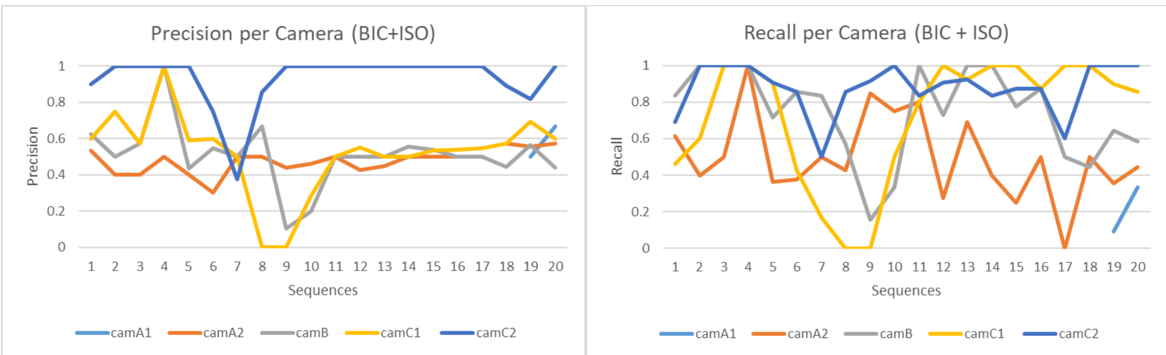


Figure 144: LL Koper - UC5 - Precision and Recall of the different cameras, considering both the BIC and ISO codes

Cameras C1 and C2 appear to be more robust and stable, as expected, with an average precision of 0.72 and average recall of 0.52 for camera C1 and 0.87 and 0.92 for camera C2. However, the lower values are mainly due to the absence or lack of ISO code detection as in these graphics, we are considering the detection of both identification numbers, which are not always present.

ISO code characters are occasionally misclassified. This occurs because most of the containers appearing in the training footage belong to a single type, which is more common and recognized more accurately during the character recognition stage.
To overcome this issue and achieve better results, we need a more diverse set of real training data.

Another analysis has been conducted using the obtained results, focusing solely on the BIC Code itself. This provides a more precise perspective on the accuracy of the algorithm, as the absence of the ISO code is not factored into the calculations.

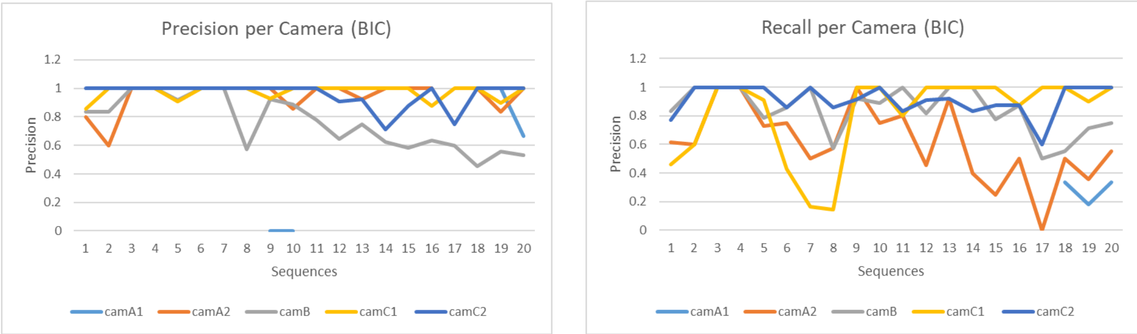


Figure 145: LL Koper - UC5 - Perception instance pipeline scheme

In this second approach (Figure 145), it is notable that Camera C2 achieves the best results with an average precision of 0.95 and an average recall of 0.91. This is directly linked to the resolution of the container in the image. For example, Camera B experiences a drop in precision when capturing sequences at night, as the camera's mechanism for handling low-light situations causes it to lose focus in the originally targeted area. A similar situation occurs with Camera A1 and Camera A2.

The **overall system** approach involves measuring the actual output of the system in real-time, directly from the cameras, with all perception instances operational. The evaluation is conducted directly on the system's predictions—specifically, on the containers it ultimately detects and their associated BIC and ISO codes. This assessment, performed manually on various days, encompassed a total of 100 different operations involving diverse containers and operations.

Element	TP	FP	Accuracy
BIC + ISO Code	100	4	0.961

Table 47: LL Koper - UC5 - Overall system performance

While the accuracy of individual perception instances may fall below 0.9 depending on the camera, the combination of analyses from various perception instances has demonstrated greater stability and comparable accuracy to the best-performing individual instance.

4.3.5.2 K-KPI20 Model Inference Time

Computation time has been measured in three different scenarios: NVIDIA Tesla V100 32 GB, Tesla T4 16GB and CPU. This analysis is conducted in several levels. For each module an inference time is calculated to determine the time consumed by that concrete task. Afterwards the overall execution time is also calculated.

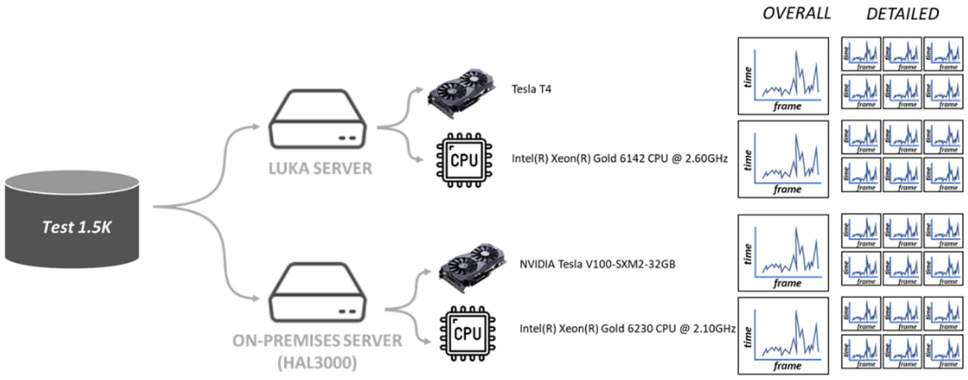


Figure 146: LL Koper - UC5 - Perception instance pipeline scheme

As depicted in the graphs, GPU execution consistently lags CPU execution by an entire order of magnitude. While GPU execution typically ranges from approximately 50 ms to 800 ms, CPU execution can extend up to 7 seconds, especially in cases with a high number of detected texts.

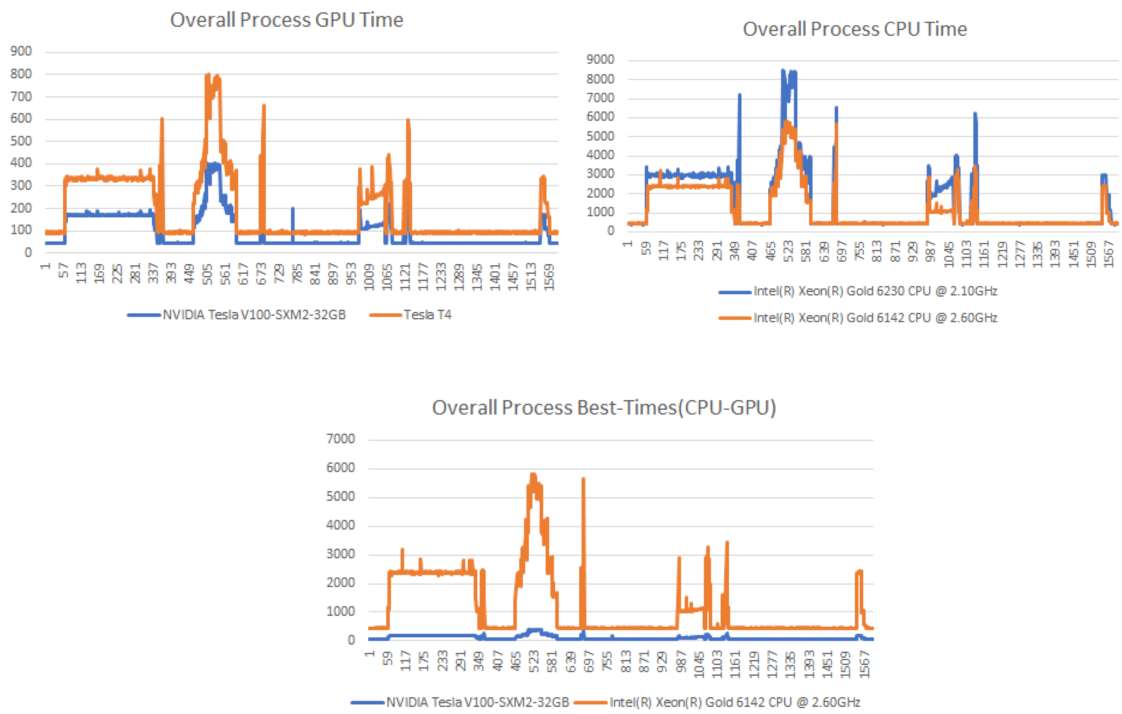


Figure 147: LL Koper - UC5 - Different execution cost results across different hardware platforms

When examining the optimal scenario, it becomes evident that not all modules exhibit equal time consumption. OCR and Craft execution time is deeply related to the number of text detections obtained from the detection module, so detection stage is more stable. Certain modules significantly contribute to the overall execution time, warranting further scrutiny and exploration for potential enhancements.

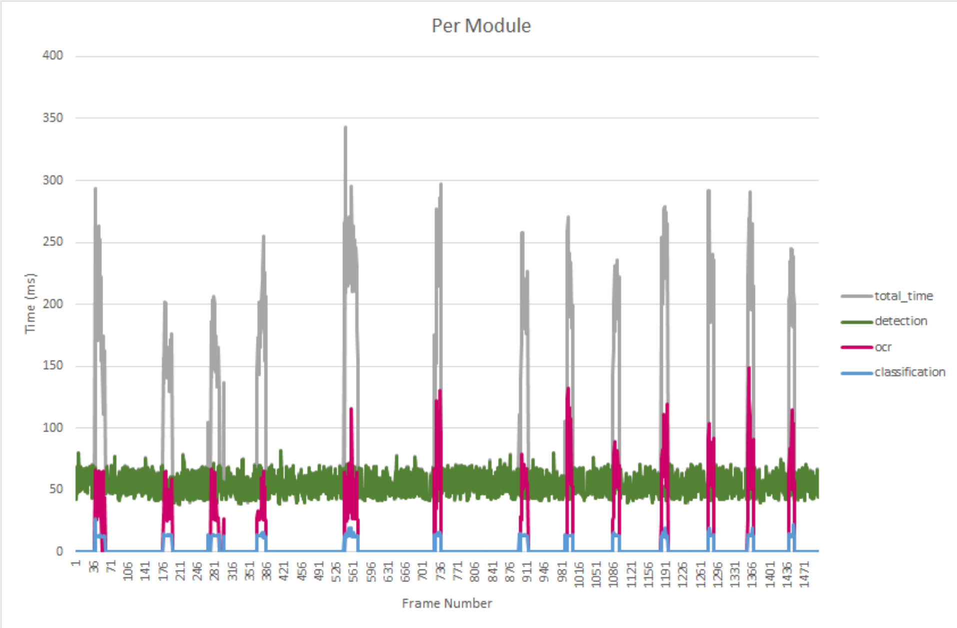


Figure 148: LL Koper - UC5 - Cost execution for the distinct modules

4.4 UC5: Monitoring Port Terminal Trucks with Telematics IoT device

4.4.1 Description and Motivation

To have real-time information and visibility about the operational status of port assets, such as yard trucks, is a key input to optimize operational flow and predict maintenance. The Continental 5G IoT device allows the collection of telemetry data both via the vehicle CAN interface (e.g., fuel consumption) and from the on-board GNSS module (speed, acceleration, standstill time, etc.). The device can operate in several 5G NR bands; below are presented the used bands in LL Koper:

Telemetry IoT device used 5G cellular bands	
Cellular network	**RF bands**
5G NSA (SA)	n7, n78

Table 48: LL Koper - UC5 - 5G NR operational bands for telematics IoT device.

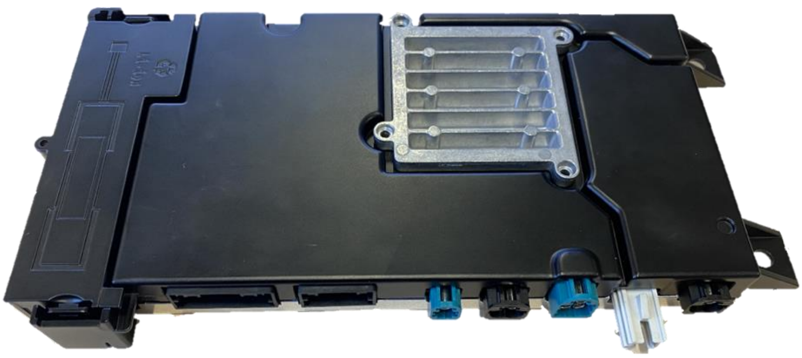


Figure 149: LL Koper - UC5 - Top view of used Telematics IoT device.

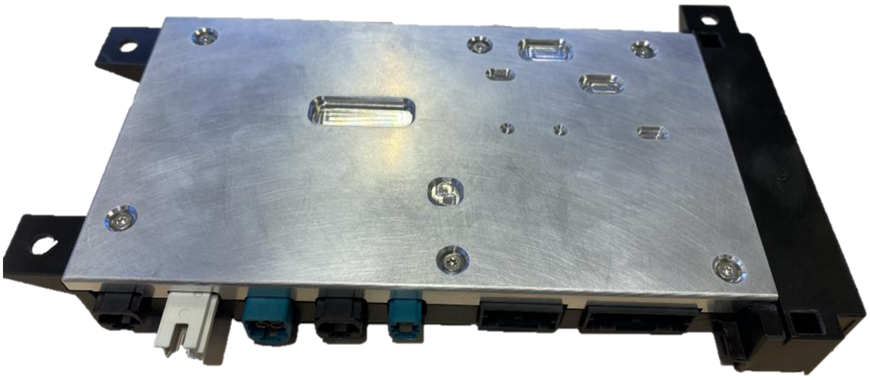


Figure 150: LL Koper - UC5 - Bottom view of used Telematics IoT device.

As mentioned before in this document, a mother vessel requires about 3000 stevedore moves (depending on the vessel size) to complete loading operations. Each of these manoeuvres requires a visual inspection of the container itself to check if its conditions are correct to be shipped or loaded on the truck. As in many automation processes, the main goal of an automatic visual inspection system is to reduce this time and thus, the time the vessel must stay stopped at the port, also removing the need for human presence at the loading/unloading area increasing the safety of this process minimizing risks.

4.4.2 Use Case Setup

Vehicles operating in the Luka Koper/Port of Koper were equipped with Continental Telemetry IoT devices supporting 5G, that allow the collection of telemetry data (e.g., fuel consumption, speed, acceleration, standstill time etc.).

Figure 151: LL Koper - UC5 - Installing Telemetry IoT devices in Port Terminal Trucks.

These IoT devices transmit collected data in real-time, using the 5G NSA network in LL Koper, to a backend present in the Koper IT infrastructure. The overall architecture of the system is defined below:

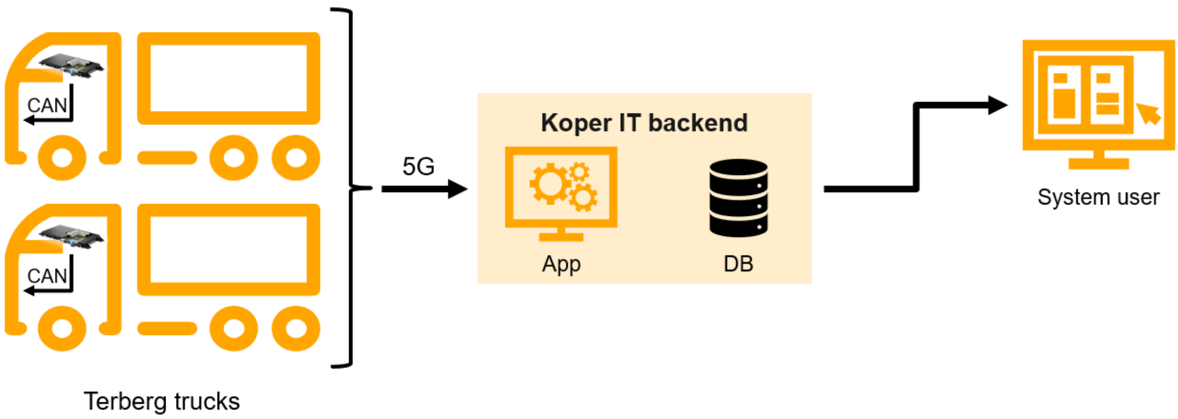


Figure 152 System Architecture of Terminal Truck Monitoring System

IoT devices are connected to the vehicle CAN network via an inductive connection. The IoT devices read and interpret all the messages on the CAN network, filtering out only the relevant messages, which it then stores internally. Depending on the frequency of the messages, some data is averaged out before being sent (e.g. vehicle speed). The collected data is packaged and sent every second via MQTT to the backend.

The backend consists of 2 servers:

- Application server: collects data via MQTT, interprets data and calculates KPIs, web server for application used by end user
- Database server: stores collected and calculated data

Collected data is organized into trips, on which KPIs are calculated. Trips are defined as a series of unbroken operations (e.g. container pickup, contained delivery) performed by a single vehicle within the port area. Once the trips are identified, the application server automatically calculates relevant KPIs and stores them in the database.

A web application developed in Python and running on top of NGINX allows the end users to visualize the collected and calculated data.

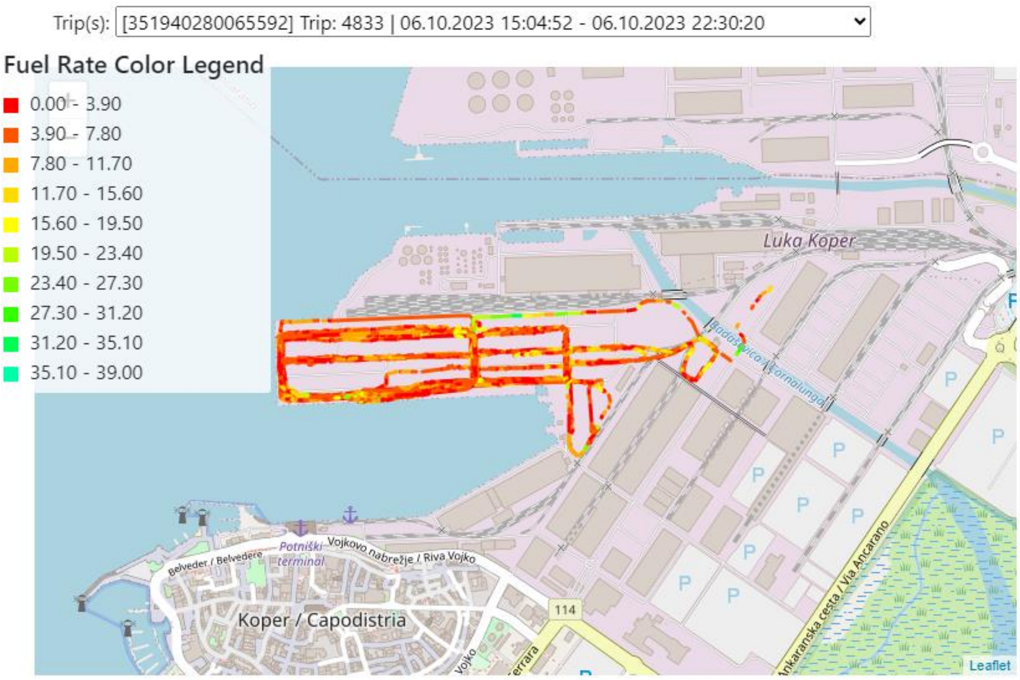


Figure 153: LL Koper - UC5 - Example of trip overview.

4.4.3 List of Key Performance Indicators

The presented KPIs were collected from the operational port trucks. Due to the sensitivity and strict confidentiality of the port operational data, the KPIs with IDs K-KPI25 and K-KPI28 were removed from all public 5G-LOGINNOV deliverables and reports and are only available to the European Commission and reviewers upon request.

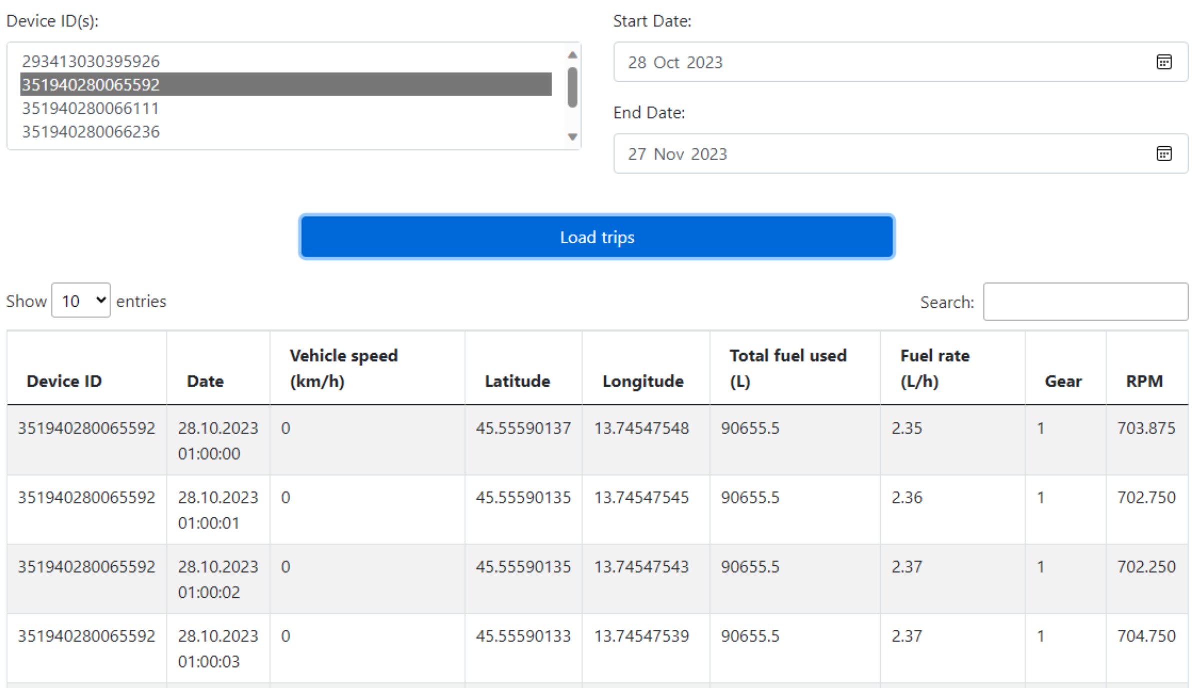
KPI	KPI ID	Target Value
Time Trucks Parked in the Area	K-KPI25	Time spent with engine stopped, over the given period
Average Speed	K-KPI26	Average speed for a trip

Truck Acceleration and deceleration	K-KPI27	Average acceleration, in m/s^2, for a trip
Truck Stand Still Time	K-KPI28	Time spent in idle, for a trip
Fuel Consumption (in operation and standstill)	K-KPI29	Average fuel consumption, for a trip

Table 49: LL Koper - UC5 - KPIs related to monitoring Port Terminal Trucks with Telematics IoT device.

4.4.4 Methodology and Measurement Tools

The deployed web application was used for both collection of raw data, as well as trip identification and calculation of related KPIs.



Device ID	Date	Vehicle speed (km/h)	Latitude	Longitude	Total fuel used (L)	Fuel rate (L/h)	Gear	RPM
351940280065592	28.10.2023 01:00:00	0	45.55590137	13.74547548	90655.5	2.35	1	703.875
351940280065592	28.10.2023 01:00:01	0	45.55590135	13.74547545	90655.5	2.36	1	702.750
351940280065592	28.10.2023 01:00:02	0	45.55590135	13.74547543	90655.5	2.37	1	702.250
351940280065592	28.10.2023 01:00:03	0	45.55590133	13.74547539	90655.5	2.37	1	704.750

Figure 154: LL Koper - UC5 - example of raw telemetry data collected from a vehicle.

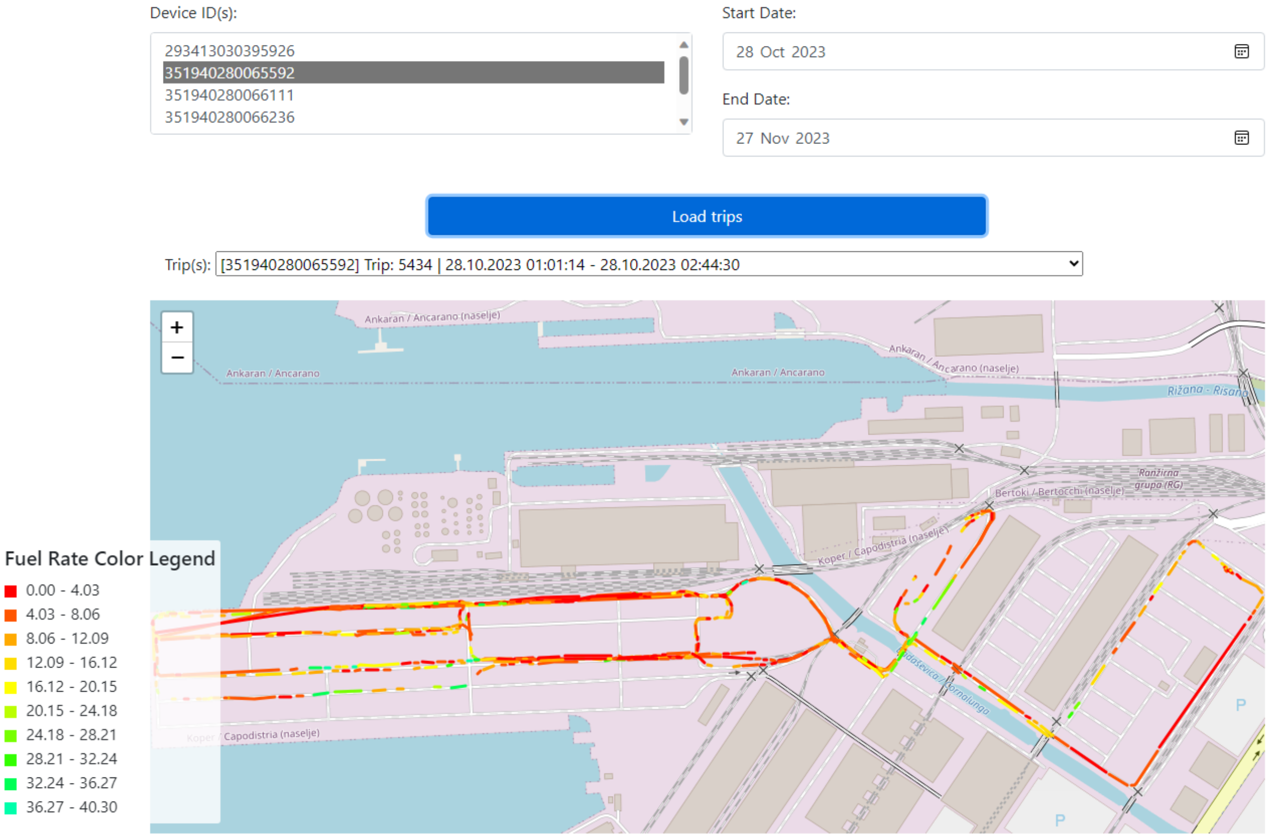


Figure 155: LL Koper - UC5 - Example of trip visualization, with heat map of fuel consumption.

On average, each vehicle performed approx. 150 trips per month. The calculated trip KPIs were then used to determine the overall KPIs for Living Lab Koper; the same data can be used to better understand differences between the vehicles, as well as allowing correlation with other information (e.g., temperature), that could further allow the Koper port to improve logistics operations within the port area.

Device ID(s):

293413030395926
351940280065592
351940280066111
351940280066236

Load trips

Show 10 entries

Search:

Device ID	Trip ID	Start date	End date	Distance (km)	Standstill time (h)	Standstill consumption (L/h)	Operating time (h)	Operating consumption (L/h)	Operating consumption (L/100km)	Average speed (km/h)
351940280065592	5285	24.10.2023 20:15:23	24.10.2023 21:29:13	5.136	[redacted]	[redacted]	[redacted]	2.425	47.221	4.240
351940280065592	5286	24.10.2023 22:06:14	25.10.2023 01:01:10	15.165				6.406	42.241	4.179
351940280065592	5321	25.10.2023 01:01:11	25.10.2023 01:49:51	2.018				1.490	73.836	2.484

Figure 156: LL Koper - UC5 - Trip KPI visualization for a vehicle.

4.4.5 Results

4.4.5.1 K-KPI25 Time trucks parked

While this information is not directly connected by the IoT devices, the lack of transmitted information will represent periods where the IoT device is powered off and, thus, the vehicle is parked (i.e. vehicle ignition is off).

Given this, we can simply calculate the time each vehicle is parked within a given amount of time. While some variation is visible between the different vehicles, the values are relatively consistent, hovering at an average of [redacted] spent parked.

IoT device ID	Average (% of day)	Min (% of day)	Max (% of day)
351940280065592	[redacted]	[redacted]	100.00
351940280066111	[redacted]	[redacted]	100.00
351940280066236	[redacted]	[redacted]	100.00
351940280066434	[redacted]	[redacted]	100.00

Table 50: LL Koper - UC5 - Time trucks parked values.

4.4.5.2 K-KPI26 Average speed

Average speed is determined based on the raw data collected form the vehicles. The raw speed is obtained in 2 different manners:

- Directly from the vehicle, based on data collected from the CAN communication bus
- Through GNSS data collected internally by the IoT device itself

The speeds collected in these 2 manners are correlated, in order to obtain the most reliable resulting data.

IoT device ID	Average speed (km/h)	Max speed (km/h)
351940280065592	5.6	43
351940280066111	5.55	39
351940280066236	7.39	41
351940280066434	5.98	39
351940280067374	4.6	29

Table 51: LL Koper - UC5 - Average speed values.

As can be clearly seen an outlier can be identified rather easily: the vehicle on which IoT device 351940280066236 is installed in has both a higher average speed, as well as a higher max speed than any other device.

Looking at the max and average speed for a single vehicle, for over a hundred trips, you can see that, while there are variations between trips (mainly due to significant differences in operation time), the trendline for max speed and average speed are stable:

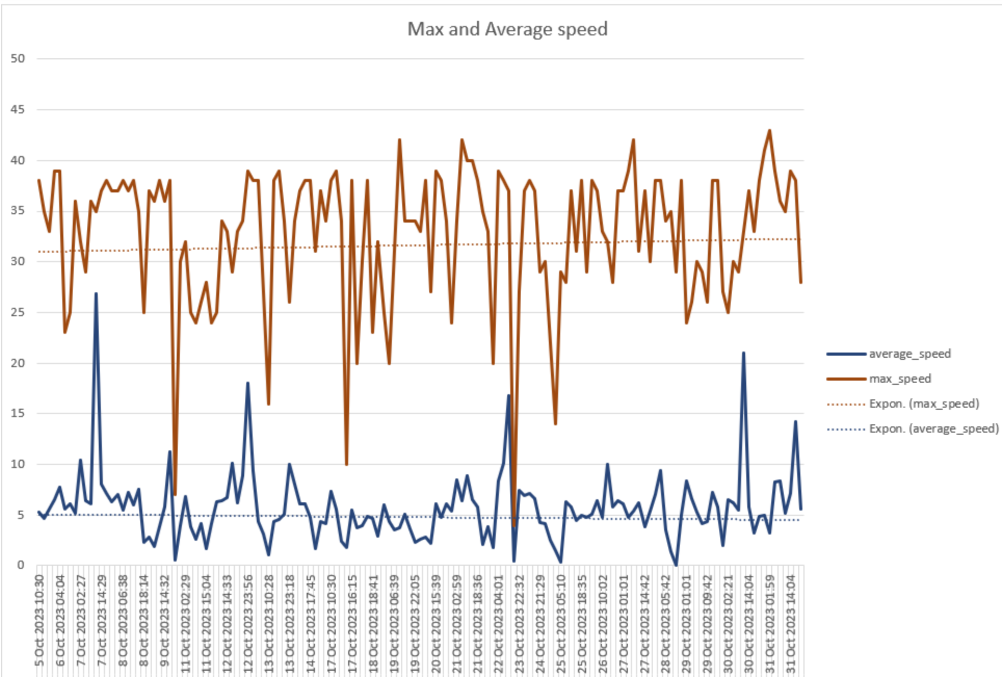


Figure 157: LL Koper - UC5 - Trendlines for max and average speed for a vehicle over a month.

4.4.5.3 K-KPI27 Truck acceleration and deceleration

Maximum acceleration and deceleration are important in determining overall driving behaviour; higher values correlate should typically correlate with higher fuel consumption, thus leading to higher operating costs. In addition, they can also increase the wear on the vehicles. Vehicle acceleration and deceleration are calculated based on the vehicle speed obtained by the IoT devices.

IoT device ID	Average max. acceleration (m/s^2)	Average max. deceleration (m/s^2)
351940280065592	13.42	-13.23
351940280066111	9.4	-9.61
351940280066236	9.79	-13.32
351940280066434	10.01	-11.48
351940280067374	2.12	-4.25

Table 52: LL Koper - UC5 - Truck acceleration and deceleration.

4.4.5.4 K-KPI28 Standstill time

Standstill time represents the part of a trip in which the vehicle is stationary (typically while containers are loaded and unloaded). Standstill time is important, as the vehicle has its engine on during this time, thus still consuming fuel. The aim is to reduce the standstill time as much as possible, to both improve port operations, as well as to reduce costs related to fuel.

While there is significant variation between vehicle on individual days, the average standstill time for trips over a one-month period is uniform:

IoT device ID	Average standstill time (% of day)
351940280065592	[redacted]
351940280066111	[redacted]
351940280066236	[redacted]
351940280066434	[redacted]
351940280067374	[redacted]

Table 53: LL Koper - UC5 - Standstill time.

4.4.5.5 K-KPI29 Fuel consumption

The most meaningful KPI from a financial perspective is fuel consumption, since that directly correlates to expenditure. Since overall standstill time can influence the result of fuel consumption, the KPI was broken down into 2 distinct parts:

- Fuel consumption in standstill. This value should be fairly stable for a given vehicle given similar conditions (e.g. temperature)
- Fuel consumption in operation. This value is strongly related to driving patterns, such as acceleration and braking, maximum speed, as well as trip length

Thus, we have the following results for the fuel consumption in standstill:

IoT device ID	Standstill fuel consumption (L/h)
351940280065592	3,46
351940280066111	3,51
351940280066236	1,4
351940280066434	2,66

Table 54: LL Koper - UC5 - Fuel consumption.

Plotted on a graph, the standstill fuel consumption for one of the vehicles looks like this:

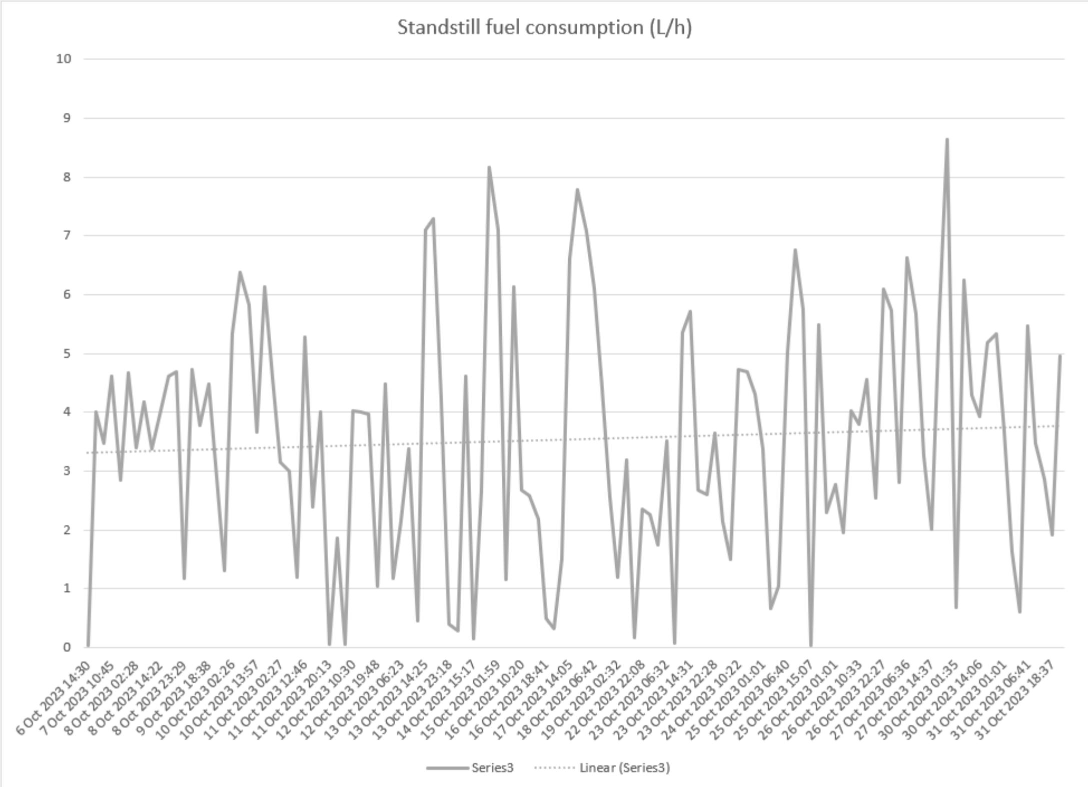


Figure 158: LL Koper - UC5 - Example of standstill fuel consumption.

As mentioned previously, fuel consumption in operation is dependent on several factors, including trip length. For a given vehicle the fuel consumption plotted on a graph is presented below:

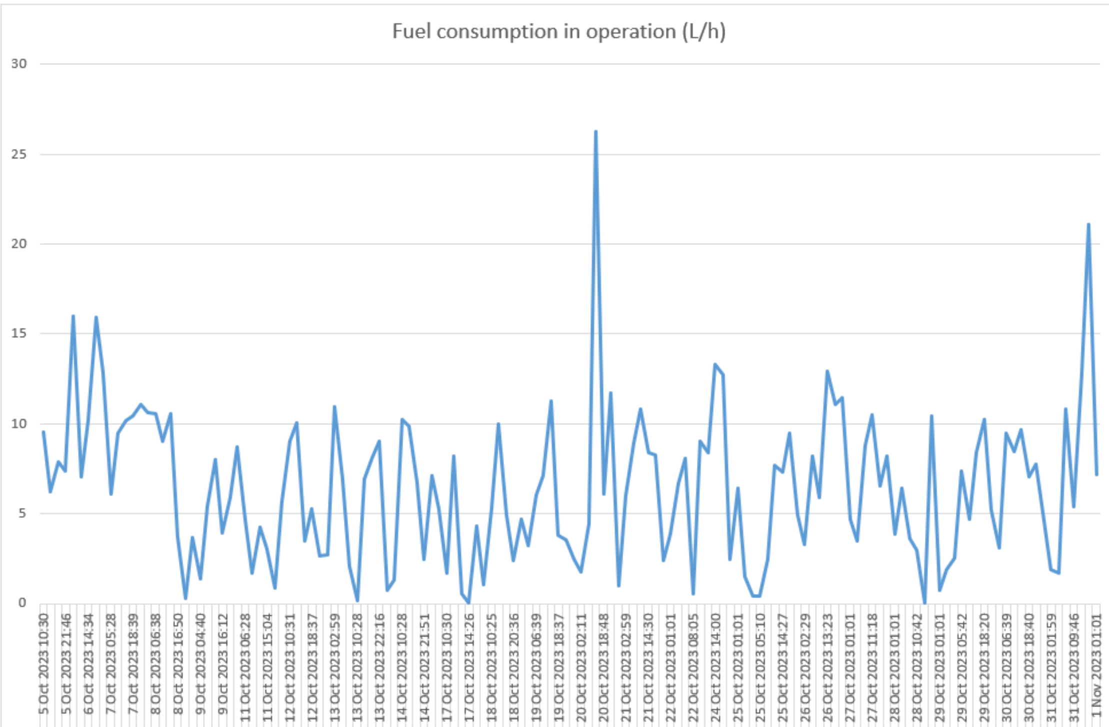


Figure 159: LL Koper - UC5 - Fuel consumption in operation (L/h).

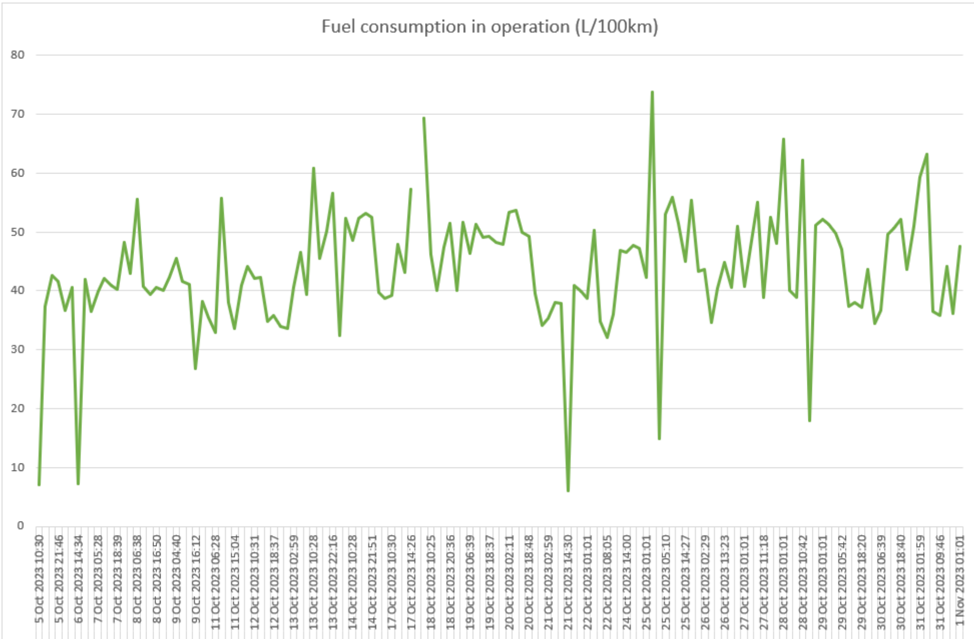


Figure 160: LL Koper - UC5 - Fuel consumption in operation (L/100km).

There is a strong variation in fuel consumption, if measured in L/h (default value returned by the vehicle). This variation can be explained by higher speeds or when the engine is under heavier load (such as when the vehicle is transporting a container vs. driving without one). However, the fuel consumption in L/100km is fairly stable within a given period of time.

The average fuel consumption, however, is fairly stable and consistent between the different vehicle, with a single vehicle being an outlier (same one with a significantly lower standstill fuel consumption):

IoT device ID	Standstill fuel consumption (L/h)
351940280065592	6,38
351940280066111	6,79
351940280066236	3,00
351940280066434	6,22

Table 55: LL Koper - UC5 - Standstill fuel consumption.

4.5 UC6: Mission Critical Communications in Ports

4.5.1 Description and Motivation

The logistics within a port extend beyond tracking containers, encompassing crucial elements for safer and more reliable operations. Security and vehicular capacity control are integral aspects contributing to enhanced operational efficiency. Security measures focus on securing restricted areas inaccessible to pedestrians, while managing vehicular capacity aims to prevent congestion and ensure smooth transit.

Within Use Case 6, various activities related to port security operations were introduced to LL Koper. Real-time video surveillance was implemented using 5G-enabled body-worn cameras carried by security personnel, supporting their routine and mission-critical tasks while enhancing personnel security. Additionally, UHD video surveillance cameras with night vision capabilities, strategically positioned and connected to the 5G network, monitored specific port areas, such as railway entrances, to bolster security services. A drone-based system was deployed for ad-hoc video surveillance, utilizing the 5G network to transmit real-time video streams to the port Security Operation Centre.

Complementing video-based security operations, an automated detection system employing Machine Learning (ML) and Artificial Intelligence (AI) for analysing video feeds was implemented. This system identifies and tracks objects, vehicles, and personnel movement in designated port areas. As part of AI-assisted use case, we aim to achieve two objectives. Firstly, we seek to detect individuals in restricted areas. Secondly, our goal is to identify and count vehicles in the port's access zones. This information will enable the port to have real-time visibility into the presence of vehicles within its premises.

Furthermore, a private security operations management and support system, equipped with dedicated applications, facilitated comprehensive security operations, including monitoring personnel/team status and positioning.

4.5.2 Use Case Setup

In UC6, the foundational communication infrastructure leverages 5G technologies deployed in UC1, such as UHD cameras on light towers and assured connectivity through an industrial 5G Gateway (see Figure 83). This serves as the baseline communication enabler, ensuring the reliability and resilience of the comprehensive real-time video surveillance system for mission-critical requirements. The system utilizes both commercial (NSA) and private 5G network services (SA).

4.5.2.1 Drone and body worn camera -based video streaming

We established real-time video surveillance by deploying 5G-enabled body-worn cameras by security personnel. This initiative aimed to enhance both their regular and mission-critical operations while providing an additional layer of personnel security (e.g., emergency button on worn camera). Simultaneously, drone-based surveillance was implemented to offer extended ad-hoc video surveillance support, leveraging the 5G network to seamlessly transmit video streams in real time to the port Security Operation Centre.

The initial phase involved installing and integrating various types and form factors of video sources, including body- and helmet-worn security camera extensions for smartphones and drone-based camera system (Figure 161). These sources were connected to the available 5G capabilities within LL Koper. Following a predefined security scenario, captured video streams from these deployed sources were transmitted in real-time across the established 5G system. Due to the unavailability of streaming devices with technology supporting 5G NSA or SA modes, a OnePlus 9 smartphone was utilized to connect wearable and drone-based systems and to ensure connectivity to the deployed NSA and private 5G SA networks. While the solutions were not operational grade, we were still able to assess the proposed concept of introducing real-time streaming over the 5G systems in the port environment. Subsequently, these streams were made available to the security and operational support teams within LL Koper.

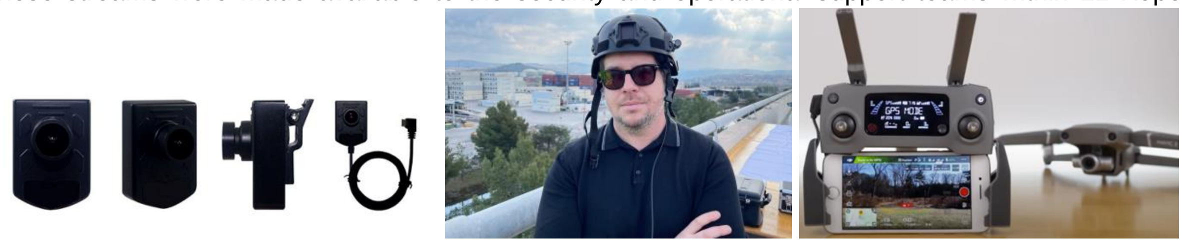


Figure 161: LL Koper - UC6 - Body and helmet-worn security camera extension for smartphone (figures on the left and middle), drone-based video streaming (figure on the right).

In the subsequent phase, professional body-worn cameras were integrated into the LL Koper environment, and a dedicated cloud-based application was developed by ININ to consolidate several video streams from various sources onto a single surveillance system. This application combined streams from wearables, drones, and other cameras (e.g., deployed UHD cameras in the port). Additionally, GIS-supported positioning of the video sources was ensured, and triggered alarms by security personnel were displayed on a map showcasing emergency situations encountered in the port (Figure 162).

Although we were waiting to purchase the professional cameras until the last stage of the 5G-LOGINNOV project, 5G technology was still not available in these market niches; thus, we were only able to directly utilize 4G capabilities of the deployed NSA system (LTE Radio only). For connectivity to the 5G NSA and private 5G SA systems, we again used smartphones with 5G support to connect professional cameras via Wi-Fi to deployed 5G networks in LL Koper. These limitations are solely due to the current limitations in the 5G chipset value chain, and we believe that as Private 5G SA systems expand globally, manufacturers will also integrate appropriate 5G NR support to the professional wearable devices.

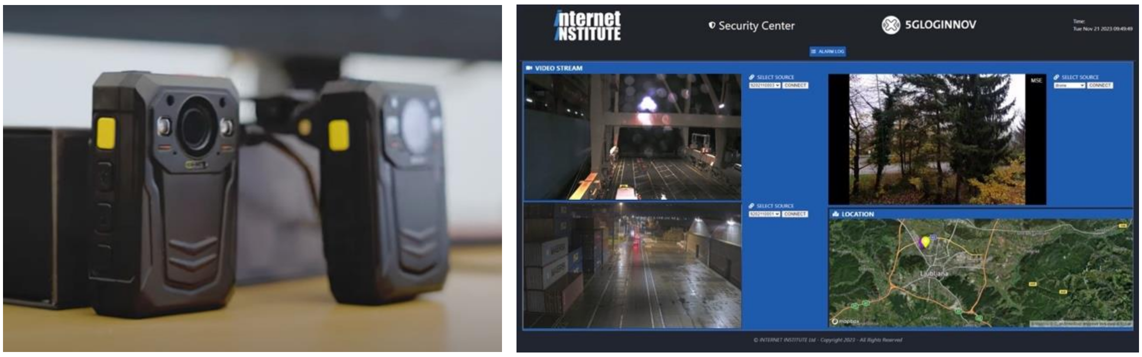


Figure 162: LL Koper - UC6 - Body worn security cameras (figures on the left), ININ's security center application (figure on the right).

The figures that follow showcase real-time video streaming testing with professional body-worn cameras (Figure) and drone-based surveillance (Figure 163) conducted in LL Koper.

Figure 163: LL Koper - UC6 – Demonstrating real-time video streaming as part of a final 5G-LOGINNOV event .

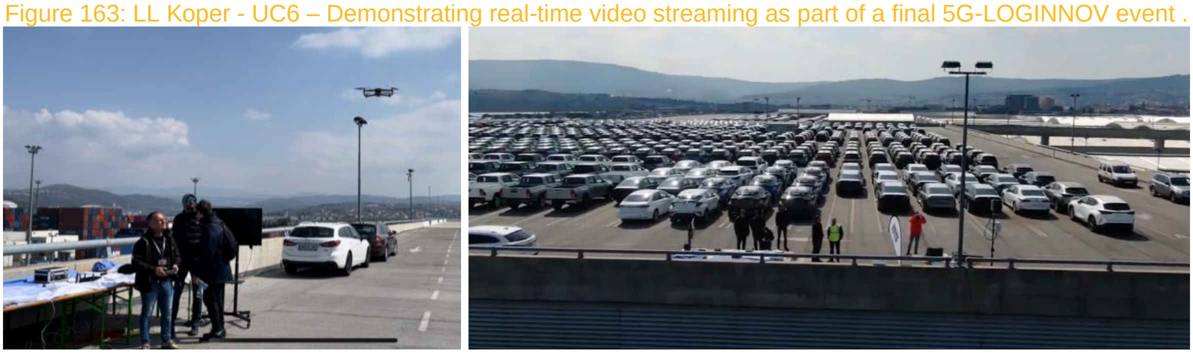


Figure 164: LL Koper - UC6 – Demonstrating drone-based video streaming as part of testing event

4.5.2.2 People and vehicle detections in a controlled area

Another objective of UC6 was to automate the detection of intruders within a pre-defined restricted area using AI/ML methods. To achieve this, Vicomtech developed an AI-assured visual detection system. The system comprises two different UHD and 5G-connected cameras installed on poles at varying heights, both focused on the same region but from different perspectives.

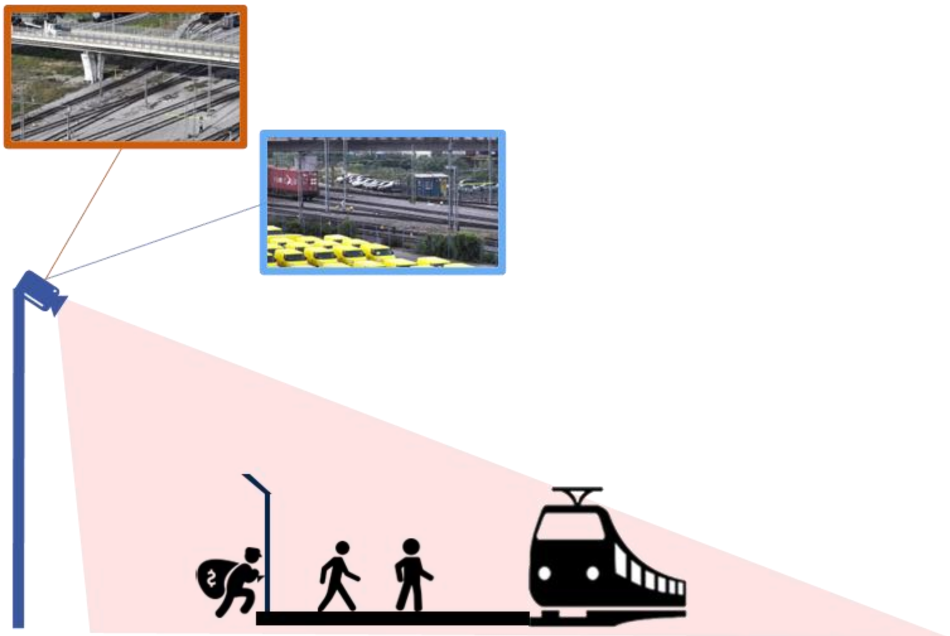


Figure 165: LL Koper - UC6 people detection simplified scheme

Each camera was configured with a designated region of interest (ROI) where detection was conducted. Whenever an intrusion was detected within the ROI, an alarm was activated to alert Luka's personnel and prevent unauthorized access.

Figure 166: LL Koper - UC6 - Person detection system

The second system is designed to manage the number of vehicles circulating within the port installations. It is installed on a gantry, typically positioned at the entrance to the port.

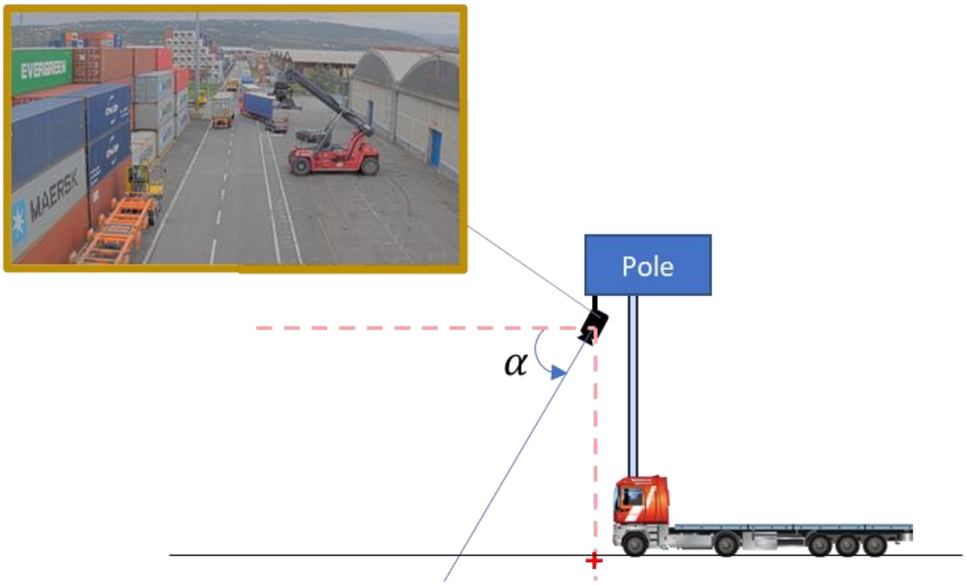


Figure 167: LL Koper - UC6 vehicle detection and counting simplified setup scheme

This system classifies vehicles in 5 different classes { vehicle, motorbike, bus, truck and towtruck }. However, it's worth noting that no motorbikes have been observed in the videos used for evaluation. This system tracks both vehicle entrances and exits at the defined the area, marked by a pre-configured line.

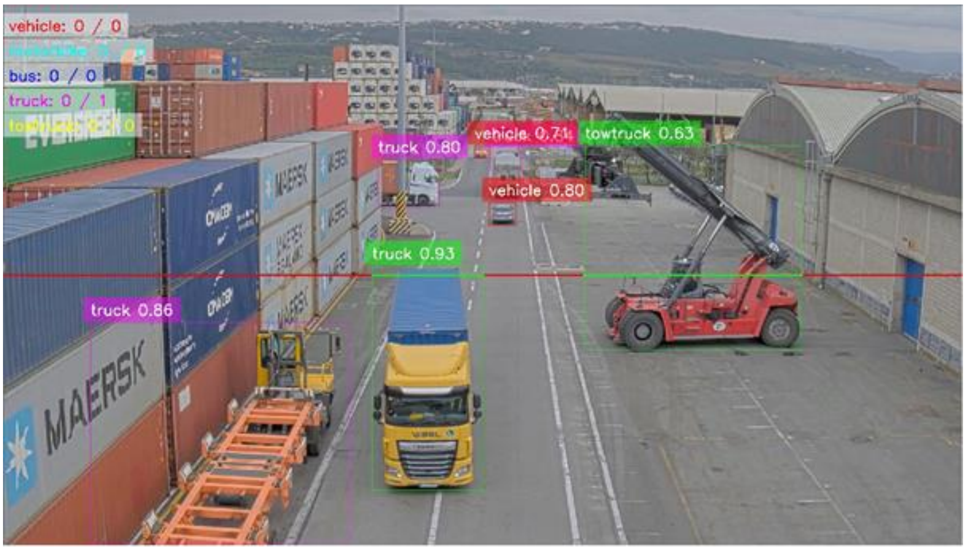


Figure 168: LL Koper - UC6 - Vehicle detection and counting system

4.5.3 List of Key Performance Indicators

As presented in the motivation section of UC6, we conducted two concurrent demonstrators: "Drone and body-worn camera-based video streaming" and "People and vehicle detections in a controlled area". The "Drone and body-worn camera-based video streaming" demonstrator was limited to functional and system usefulness verification in LL Koper, and the security operational procedures used during the demonstrator testing are for the port security strictly confidential.

Therefore, results from the following chapter onward are relevant only to the activities related to the "People and vehicle detections in a controlled area" demonstrator.

KPI	KPI ID	Target Value
Model accuracy/reliability (People detection)	K-KPI21	Depends on the ML model configuration and the video frame size
Model Inference Time	K-KPI22	Depends on the ML model configuration, the video frame size and the hardware architecture
Model accuracy/reliability (vehicle detection)	K-KPI23	Depends on the ML model configuration and the video frame size
Model Inference Time	K-KPI24	Depends on the ML model configuration, the video frame size and the hardware architecture

Table 56: LL Koper – KPIs list for UC6

4.5.4 Methodology and Measurement Tools

To tackle this assessment stage, several models were studied for these systems, including YOLO-NAS, YOLOR, YOLOv5 and YOLOv8. After empirical tests with the COCO dataset, YOLO-NAS and YOLOR performed worse than the Ultralytics[23] models. Furthermore, analysing the results achieved with these initial weights, YOLOv8 was better at detecting people than YOLOv5. Therefore, the human detector system uses the medium version of YOLOv8, and the vehicle detection and counting system uses the large version of YOLOv5, which is lighter than YOLOv8 and good enough.

To adapt the models to these problems, two different datasets were designed, one for each scenario. The images were obtained from two different cameras, in the case of the people detection system, with variability in the weather conditions and the moment of the day in which they were taken. The final datasets are summarised in the table below.

System	Model	Dataset size	Train size	Val size	Labels
People detection	Yolov8 medium	87 imgs	70 imgs	17 imgs	Person
Vehicle detection and counting	Yolov5 large	4K imgs	3K imgs	800 imgs	Vehicle Motorbike Bus Truck Tow truck

Table 57: LL Koper - UC6 datasets

Despite the lack of a large human dataset, the pretrained models allow the application to achieve acceptable results with this amount of data. A medium YOLOv8 model pretrained with the COCO dataset has been used to deal with the shortage of available data and its subsequent annotation during the project. The model was trained using fine-tuning to boost person detection task in this domain. This technique uses as initial step weights pre-trained in another domain and lets the model to modify all the

[23] https://github.com/ultralytics/yolov5

weights to find a better model, modelling its knowledge over the previous one to improve the detection of the pretrained model.

4.5.5 Results

4.5.5.1 K-KPI21 Model accuracy/reliability

The evaluation media of the human detection system consists of different videos of people walking within a restricted area. This is a set of 11.6K images taken from 32 different videos from both cameras at different times and weather conditions. Considering that all the frames show people inside the restricted area, if the system triggers the alarm, it is counted as a True Positive or success; if not, it is counted as a False Negative or failure. The graph below shows the behaviour of the system over time.

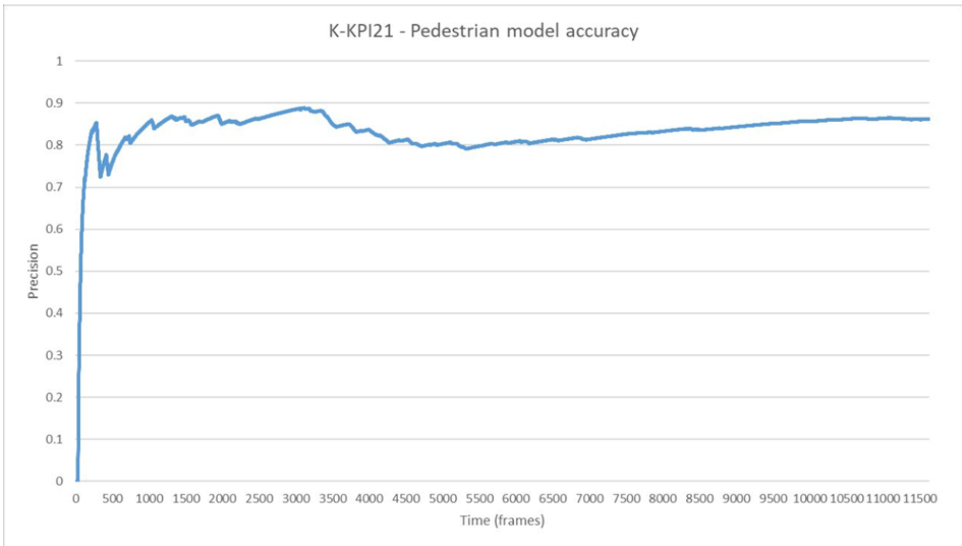


Figure 169: LL Koper - UC6 - Person detection system precision over time

The graph illustrates the evolution of the system's precision over time. Although it initially fails to detect people in the restricted area -the first frames-, it soon enhances and converges to a value of approximately 85% precision. The system demonstrates sufficient robustness over time to be considered a successful result.

To improve this value, the size of the dataset and the complexity of the model used could be increased. Firstly, adding more images to the dataset could bring more variability to the dataset, making the model more generic and more adaptable to new situations.

Secondly, increasing the complexity of the model may have a direct impact on the precision of the system, as its representation capability gets higher. However, the inference time may increase, for the same reason. In this case, we are working with YOLOv8 in its medium version.

4.5.5.2 K-KPI23 Model accuracy/reliability

The vehicle detection and counting system has been evaluated with 40K images taken from 73 30-minutes videos. The figure below shows the representation of each label in the ground truth. Neither in the training nor in the evaluation of the system was found any frame with a motorbike. For this reason, there are no objects labelled as motorbikes in the dataset and this class is not considered for the calculation of the K-KPI23.

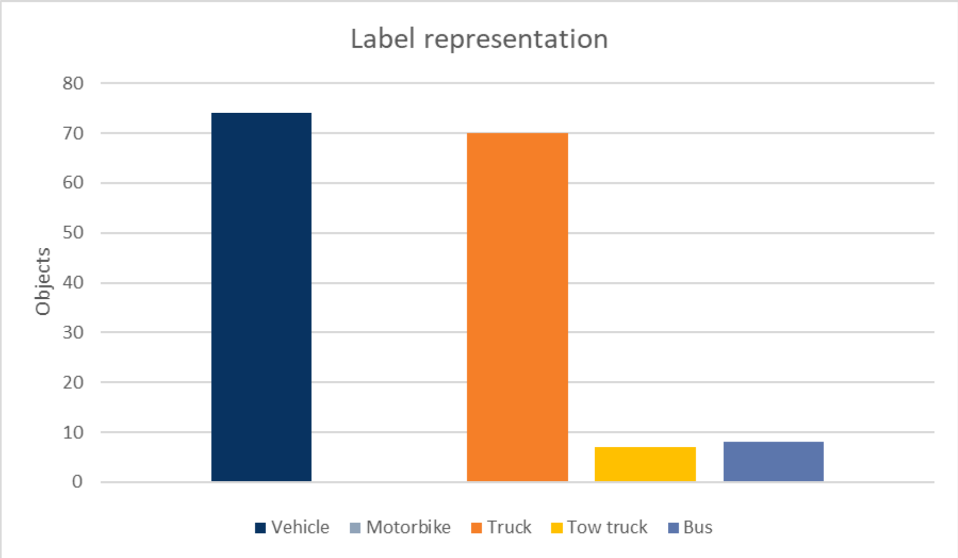


Figure 170: LL Koper - UC6 - Vehicle detection and counting ground truth label representation

Table 58 summarizes the results obtained after system analysis. It indicates the True Positives (TP), False Positives (FP) and False Negatives (FN) for each of the classes present in the dataset. With that information, the precision, recall and F1 score have been calculated for every class.

	TP	FP	FN	Precision	Recall	F1
Vehicle	67	2	7	0.971	0.905	0.937
Motorbike	0	0	0	---	---	---
Trucks	68	8	2	0.894	0.971	0.931
Tow Truck	6	1	1	0.857	0.857	0.857
Bus	1	0	7	1.0	0.125	0.222
Total	142	11	17			

Table 58: LL Koper - UC6 - K-KPI21vehicle detection and counting task

The dataset used is highly imbalanced, and the model performs better on common classes such as vehicles, trucks, and tow trucks, compared to buses and motorbikes, the latter being non-existent.

Starting from the fact that it is a highly unbalanced dataset, the model adapts better to the more common vehicles than to the rarer ones. In the case of buses, although the precision is 100%, the majority are labelled as trucks. This produces a very small recall. However, it is observed that the selected model has sufficient representational capacity to address the issue, although it is true that adding more images of less frequent classes would be necessary to balance the system.

To know the general metrics of the system, the macro and micro measurements are being used. The macro-averaged score is computing using the arithmetic mean, without weights, of all the per-class scores. Whereas micro averaging computes a global average score by counting the sums of the True Positives (TP), False Negatives (FN) and False Positives (FP). Those are the values represented on the Table 59.

	Precision	Recall	F1
Macro	0.931	0.715	0.737
Micro	0.928	0.893	0.910

Table 59: LL Koper - UC6 - Micro and Macro calculation of the evaluation metrics.

As seen in the table, when calculating metrics using micro-averaging, the imbalance error is somewhat diluted. In macro-averaging, however, equal importance is given to all classes, even though in the port, the presence of motorcycles and buses is much lower than that of trucks or vehicles. Therefore, using micro-averaging achieves a superior result to macro-averaging.

4.5.5.3 K-KPI22 – K-KPI24 Model Inference Time

For the inference time calculation, an initial study has been conducted using the YOLOv8m model on various hardware platforms: with different GPUs and CPUs to verify the relative time differences between the systems.

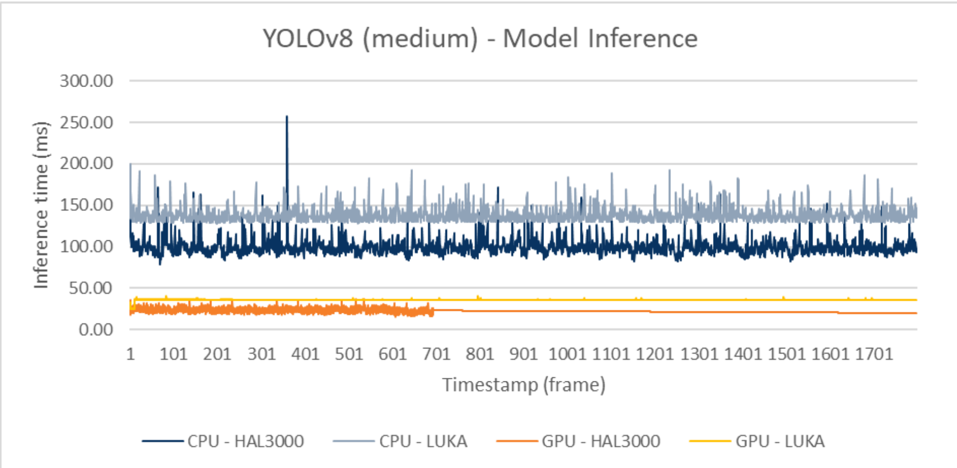


Figure 171: LL Koper - UC6 - YOLOv8 medium-sized inference time

As expected, the execution on the GPU NVIDIA Tesla V100-SXM2-32GB of a local server (referred to as HAL) yielded the best results, with the average time being orders of magnitude lower than the same inference on the CPU. Specifically, we are talking about approximately 3~4 times faster (from 100 ms in CPU to 30 in GPU).

A second experiment was conducted on the target server to obtain the KPIs. The inference time was obtained for two different models: YOLOv8m for person detection, corresponding to K-KPI22, and YOLOv5l for vehicle detection and counting, corresponding to K-KPI24.

To evaluate the model inference time, it has been used a dataset of 1.5K images.

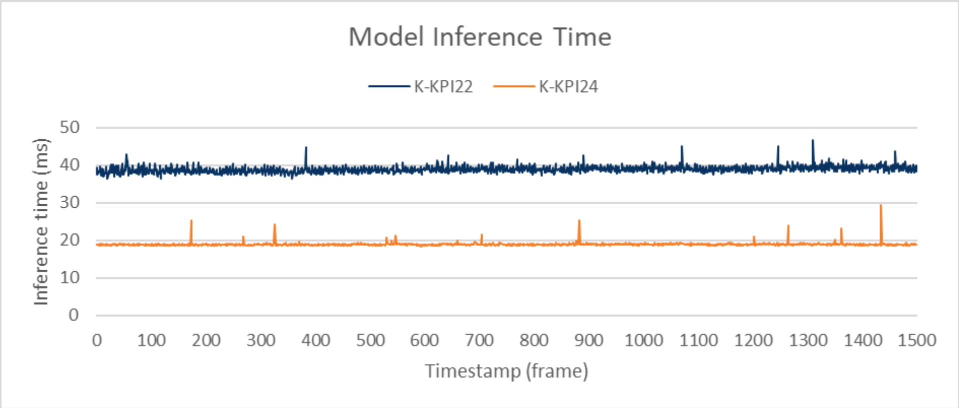


Figure 172: LL Koper - UC6 - inference time for UC6 models

	Mean	Standard deviation
K-KPI22	38.929	0.883
K-KPI24	18.922	0.477

Table 60: LL Koper - UC6 - metrics for UC6 modules KPI

The average execution time is 38 ms for K-KPI22 and 19 ms for K-KPI24. This difference is due to the different complexity of the two models and to an additional post-processing applied in the case of the human detector that checks whether a person is within an area or not using an image mask.

Peaks in the image are due to system overloads and are not significant as they do not depend on the model. To address them, system resources could be increased, or model resources could be reduced by pruning techniques or by reducing its complexity.

To decrease the execution time different methods could be applied, such as applying optimisation techniques to the model architecture (pruning, quantization...) and the usage of libraries focused on optimising performance on GPUs (tensorRT, ONNX).

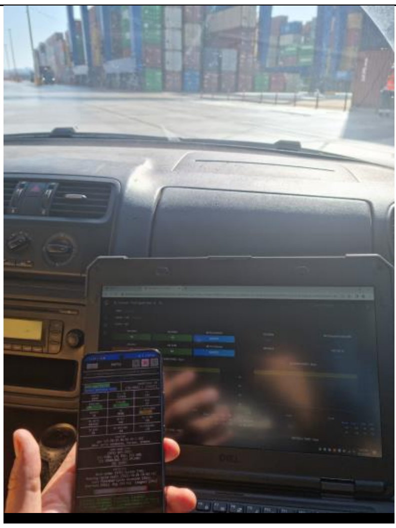
5 CROSS PILOT ACTIVITIES

For the cross-pilot activities the three Living labs collaborated in pairs.

5.1 Athens and Koper

Between Athens and Koper three activities took place. **First**, as described in Section 2.1.4 (with related images and measurements), the Athens site exploited the Quality Monitoring Suite (qMON) provided by ININ, for detailed monitoring of 5G network KPIs at PCT's private 5G-NSA network. Particularly, various drive tests exploiting qMON have been performed within the port premises (along the normal routes followed by yard trucks) as well as stationary (non-mobile) tests, providing a detailed view on the network capabilities and limitations within the port of Piraeus, for the support of Athens use cases. In this view we provide a holistic example of common frameworks as a unified KPI system across different ports enabling potential standardization in performance measurement. This makes it easier to compare performance metrics across different locations and facilities, facilitating better analysis and benchmarking. When multiple ports adopt similar KPI systems, it can drive industry-wide improvements.

It encourages a more collaborative approach where industry stakeholders can work together (particularly, PCT and Luka Koper/Port of Koper, Vodafone, Telekom Slovenia and ININ) to address common challenges and enhance overall efficiency and performance of their network deployments and infrastructure. Table 61 illustrates qMON 5G test automation system used in Athens case. For more details please see Section 2.1.4.



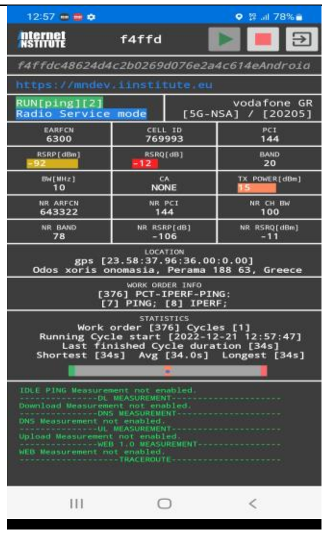


Table 61: Athens and Koper LLs cross pilot (case 1)

Second, Athens UC3 "5G&AI-enabled collision warning system" (evaluated in Section 2.2) has been tested also with a LL Koper Terberg yard-truck, including a 5G industrial gateway provided by ININ to facilitate cellular connectivity (see Section 4.2) with the LL Koper edge-computing infrastructure hosting the AI-assisted collision warning service provided by ICCS, over the 5G network of Telekom Slovenia. The use case was demonstrated live on the 5G-LOGINNOV's final event at Koper, in the 7th of November 2023. The demonstrations involved pre-recorded videos of the use case in Athens LL (left) and live demonstration at Koper (right), Figure 173 and Figure 174, as well as the preparation of the Koper edge-computing infrastructure (k8s compute nodes) hosting the AI service for collision avoidance and Terberg truck 99 (including 4K camera and 5G tablet UI) for UC3 live demonstration (Table 62) and evaluation.

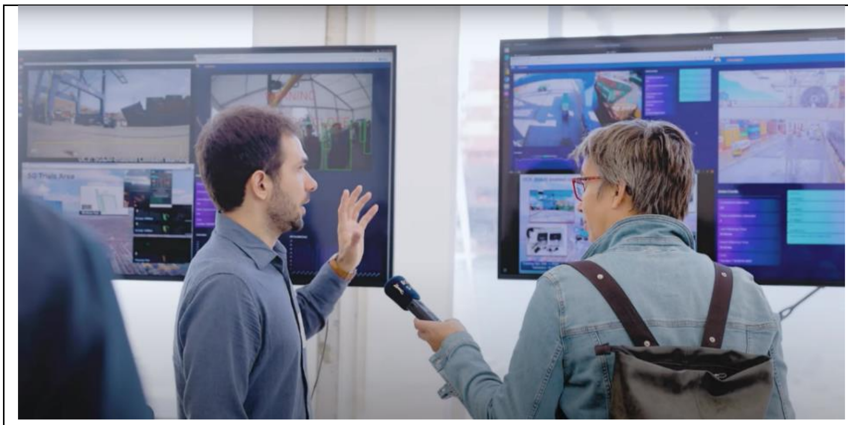
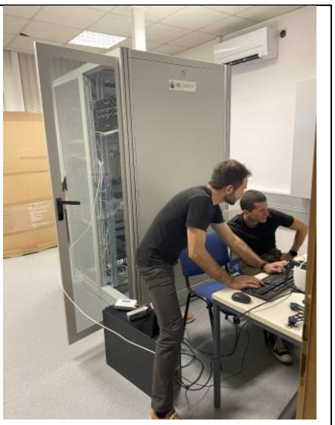
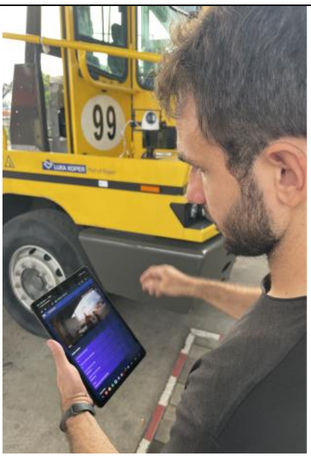
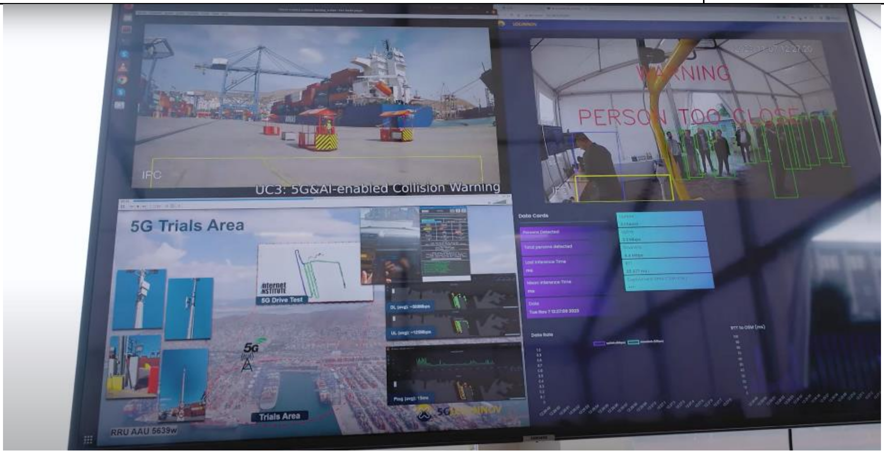
 Figure 173: UC3 live demonstration at the final event (a)	
	
 Figure 174: UC3 live demonstration at the final event (b)	

Table 62: Athens and Koper LLs cross pilot (case 2)

Qualitatively, the same conclusions were witnessed in LL Koper as in LL Athens, i.e., the two setups (sound alerts and inferenced video stream on the 5G downlink) should be used in conjunction for mission critical services (with stringent latency constraints) such as collision avoidance.

Third, Athens UC5 “5G&AI-enabled container seal detection” (evaluated in Section 2.4) was also ported in LL Koper exploiting the Quay side crane at Koper facilitating container load/unload operations, the 4K camera installed on the crane for crane operations monitoring, and the public 5G-NSA network of Telekom Slovenia for transmitting the video to the edge-computing datacentre, were the AI service resides for container seal detection. Table 63 illustrate footage from the Live demonstration event were the use cases were showcased live at the participants.

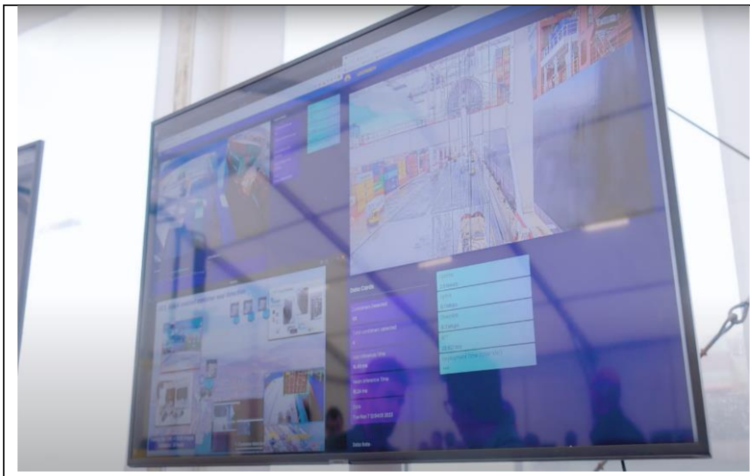


Figure 175: 5G&AI-enabled container seal detection at Koper LL showcased live at the final demonstration event (a)

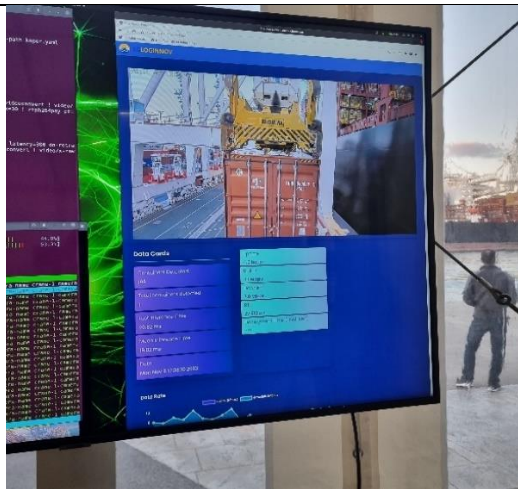


Figure 176: 5G&AI-enabled container seal detection at Koper LL showcased live at the final demonstration event (b)

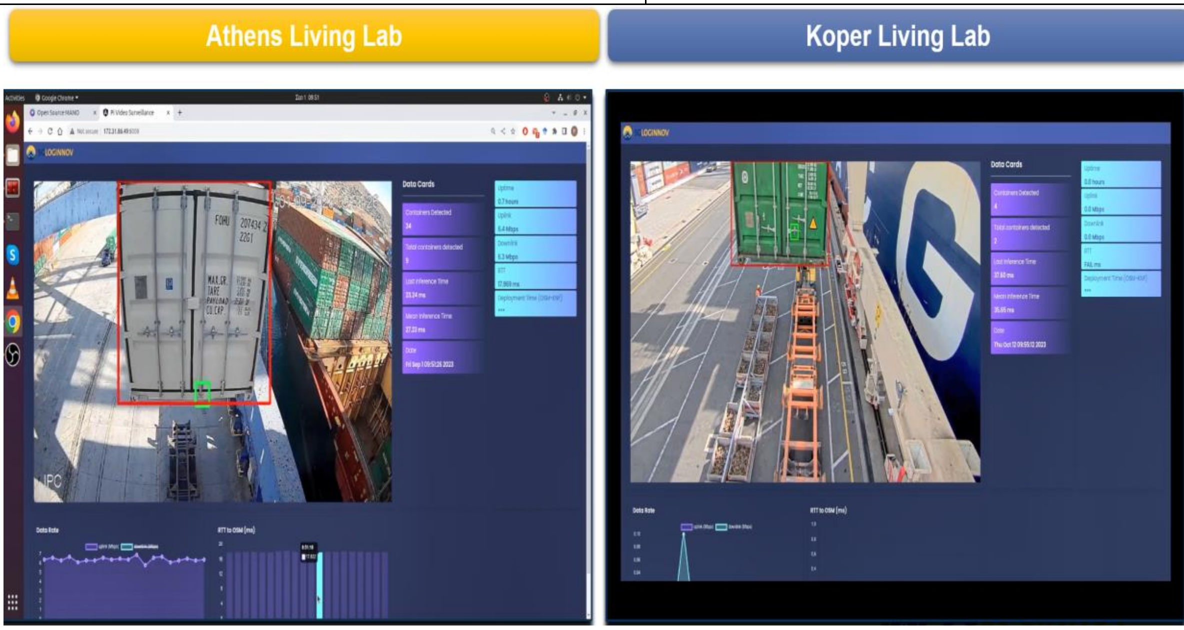


Figure 177: 5G&AI-enabled container seal detection Athens (left) and Koper (right)

Table 63: Athens and Koper LLs cross pilot (case 3)

The major take-away for this use case is the following. The AI service, was trained solely with data from Piraeus Port. The resulting ML algorithm was deployed also in Koper without further training and/or fine tuning of the model on data from Koper, demonstrating similar performance. This indicates that the designed ML algorithm is able to generalize regardless of the background of the images it receives as input, and thus has the potential to be easily deployed in different ports and varying respective background settings.

5.2 Koper and Hamburg

To verify the interoperability of the developed solution between Hamburg and Koper living labs, LCMM and GLOSA-related use cases were implemented and verified in the Port of Koper (Table 64).

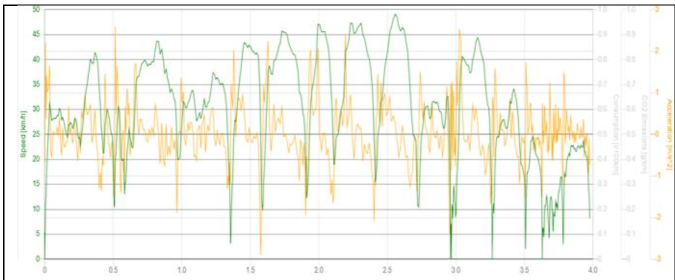



Table 64: Cross-Pilot feasibility – show case Luka Koper

As demonstrated at the final event in LL Koper, Hamburg KPI achievements, can easily be scaled up and transferred to Port of Athens and Luka Koper. Feasibility studies took place in 2023, Table 65 was recorded by Hamburg's project team in Luka Koper and uses LCMM and GLOSA in an exemplary manner.

Table 65 depict footage from the vehicles used in the Koper at the cross-pilot demonstration.


Table 65: Hamburg and Koper LLs cross pilot demonstration at final event in LL Koper (case 1)

5.3 Athens and Hamburg

More details about the Hamburg monitoring system (LCMM) at PCT yard trucks (consent involving the participating drivers was necessary) data will be presented at the final review meeting of 5G-LOGINNOV, on the 15th of February, 2024.

6 CONCLUSION

This report evaluated the performance of 5G technology and the performance of the identified 5G-LOGINNOV use cases via the trial activities of the project, in real operating Port conditions within and outside the Port environment. Various network deployment options were tested and benchmarked, particularly private 5G-NSA network at the port of Piraeus provided by Vodafone, public 5G-NSA network at Hamburg living lab, and two network deployments at Koper, i.e., public 5G-NSA by Telekom Slovenia and private 5G SA from ININ.

A portfolio of 5G technologies and use case enablers were tested, including NFV-MANO and MEC, slicing, precise positioning, far-edge and cloud computing, AI-assisted video/data analytics, 5G-IoT, next generation traffic management systems, Cooperative, Connected and Automated Mobility (CCAM) systems. The main focus and achieved goals for the project via exploiting 5G technological blocks was on applications tailored to safety and security, as well as on services that improve the efficiency of daily port operations (reduce costs, improve the utilization of human resources and automate logistics services via AI analytics), and on the improvement of the environmental footprint of port operations inside and outside the Port premises. Particular emphasis has been given in the cross-pilot activities to make sure that the lessons leaned and developed use cases and platforms can be easily transferred to other EU ports and logistics actors.

As highlighted by the activities of the 5G-LOGINNOV project, 5G technology has the potential to significantly enhance the functionality and efficiency of critical infrastructures, such as Ports, and has to become an integral of their evolution, towards a more sustainable logistics supply chain for the EU.

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