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Bridging depths and data in mines: 5G-based point cloud mapping in unstructured environments

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Abstract
Underground mines pose significant challenges, including hazardous working conditions, limited access, and the need to ensure the safety of human workers. Digital transformation through the integration of modern technologies is essential to mitigate these challenges and enhance the overall safety and efficiency of mining operations. This paper addresses the pressing need for 5G connectivity for the digital transformation of underground mines and demonstrates its application through a live 3D point cloud mapping by a mobile robot. The results of the experiments conducted to validate the network's performance for such a use-case are presented. The first experiment involved testing the latency of the network over a test drift at various loads. The second experiment involved mapping the drift and streaming the 3D point cloud map of the drift over the 5G network. These initial experiments emphasize the potential of the 5G-enabled automation in underground mines and holds promise in digitalizing underground mining operations.

Keywords 5G · Underground mines · Point cloud mapping · Network latency · Digital transformation

1 Introduction

The fourth industrial revolution has played a crucial role in various sectors, laying the groundwork for future industrial development. The mining and construction industries too have witnessed a notable shift in focus, marked by the adoption of strategies that incorporate cutting-edge technologies. Ongoing efforts are underway to seize the vast opportunities arising from this transition.

Digital transformation (DT) in the mining sector revolves around the integration of advanced digital technologies and modern methodologies to automate and digitalize various facets of mining operations. At its core, this transformation is built upon three fundamental pillars: data, connectivity, and decision-making (Ebert and Duarte 2018). The interaction between these components is illustrated in Fig. 1.

Data, the first pillar, plays a pivotal role in the process of DT. Recent advancements, have opened up vast amounts of data in mining from various sources, including photogrammetric data sourced from UAV surveys and equipment performance data with unprecedented level of detail. Furthermore, contemporary mining operations are enhanced by sensors enabling real-time monitoring of the mining environment. These sensors measure various attributes such as temperature, remote monitoring of machine health and maintenance and the operational state of heavy equipment through tele-remote operations. Leveraging these data enables mining companies to gain valuable insights, optimize processes, and make informed decisions (Soofastaei 2020).

The second pillar, connectivity, forms the infrastructure that binds the disparate elements of a mining operation into a cohesive and interconnected network. Enabling seamless data exchange along with real-time communication between different components necessitates the need for robust connectivity. This leads to improvement in overall operational efficiency, allowing for timely responses to dynamic conditions within the mining environment.

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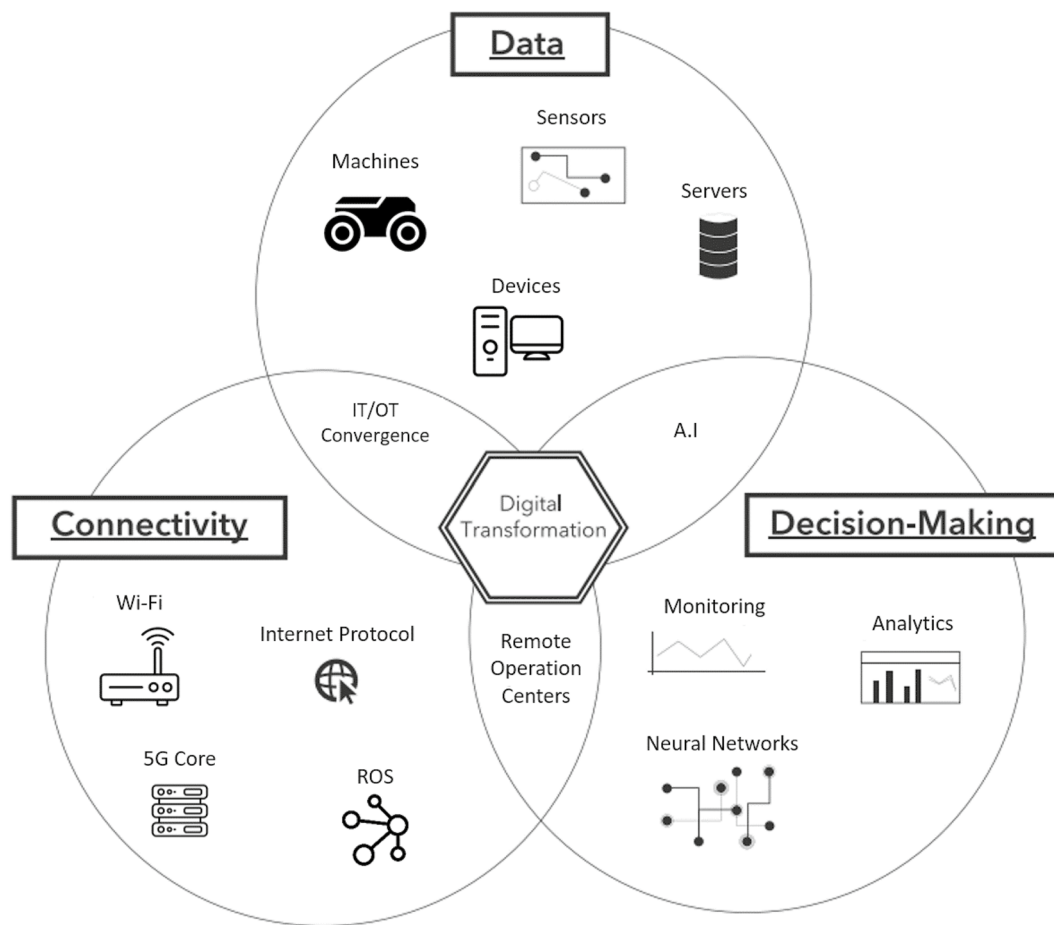
Fig. 1 The different pillars of digital transformation in mining (Young and Rogers 2019)

Informed decision-making—the third pillar—empowers mining entities, by contributing to improved productivity, resource utilization, and overall operational performance.

Thus, in the context of DT, emphasizing the significance of a stable interconnected network capable of streaming data with minimal latency is crucial. Additionally, given that mining sites are frequently situated in remote and dynamically changing environments, the scalability of the network requires a wireless infrastructure.

Yet, traditional wireless technologies like WiFi are unlikely to meet the coverage, latency, bandwidth, and reliability requirements presented by innovative use-cases.

The emergence of 5G technology shows potential to meet these demands. Specifically, the promise of 5G communication networks to attain large bandwidths, low latencies, and high reliability facilitates the implementation of diverse new strategies for the digital transformation of the industry (Shafi et al. 2017).

Despite the potential, there are limited studies and use-cases on the digital transformation of construction and underground mines using 5G, particularly in comparison to production environments. The inherent challenges of unstructured and dynamic environments in construction and mining have acted as barriers to the widespread adoption of digital technologies. Unlike the relatively controlled setting of manufacturing, the constant movement of heavy machinery and personnel, coupled with the ever-expanding nature of underground mines, has posed unique challenges for the seamless integration of digital tools and solutions.

This paper contributes to the existing literature by showcasing the successful integration of 5G connectivity with mobile robots for live 3D point cloud mapping. In doing so, insights on the potential of 5G in underground mining are gained through a practical use-case.

2 Related work

The following section describes the existing literature categorized into digital transformation, mapping in underground mines and 5G in mining. In Sect. 2.1, existing literature on digital transformation in mining and

construction is discussed, outlining its potential benefits. A specific use-case of DT is detailed in Sect. 2.2 and finally, the previous studies covering the integration of 5G technology in mining is referenced in Sect. 2.3.

2.1 Digital transformation

The construction and mining sectors are presently experiencing a digital transformation, heading toward the evolution of more interconnected and intelligent systems. Recent studies have centered on the automation of construction machinery to improve efficiency and safety on construction sites (Lee and Brell-Cokcan 2023, 2023a, b).

In Lee and Brell-Cokcan (2023), the researchers introduced a novel methodology employing a deconstruction machine to enhance the overall autonomy level, which leads to increased controllability and safety along deconstruction processes. In another stream of the work, a reinforcement learning (RL) framework is utilized to enable construction machines to discover efficient control approaches for accomplishing tasks autonomously, without human intervention. The policies formulated by these agents can aid human operators by offering task-space control (Lee and Brell-Cokcan 2023a) or transferring the obtained knowledge through virtual fixtures back to the human operator (Lee and Brell-Cokcan 2023b).

The mining sector is also undergoing a digital transformation by adopting modern technologies to automate and digitalize various processes of the workflow. Digital transformation (DT) can take various forms in mining such as remote operation centers (ROC) that facilitate remote control and monitoring of mining operations; positioning devices that enable tracking of people, equipment, and other assets, leading to increased security and productivity and analytic models for predictive maintenance of machinery (Sganzerla et al. 2016). The need for digital transformation (DT) in the mining industry arises from the increasing prevalence of digital technology such as automation, cameras, sensors, touchscreens, artificial intelligence, etc. DT can help mining companies increase efficiency and productivity, and leverage digital technology for additional gains. Furthermore, the long-term success of the mining industry is dependent on a labor force with new skills (data management, analytics, digital literacy, etc.) (Young and Rogers 2019). Therefore, DT is necessary for mining companies to remain competitive and relevant in the digital age. Some aspects where DT has been introduced in mining are: underground mapping of mines, using network technologies (WiFi, 4 G, 5G) and IoT for communication in mines.

2.2 Mapping in underground mines

Mapping in underground mines is an important use-case for DT for several reasons. First, it helps to ensure the safety of workers by identifying potential hazards and risks, such as unstable rock formations or areas prone to flooding. Second, accurate maps can also help to optimize mining operations by identifying areas with high concentrations of valuable minerals. Additionally, mapping can be used to monitor changes in the rock mass, such as subsidence caused by mining activities, which can help to prevent accidents and ensure the long-term stability of the mine (Borg et al. 2017). According to Rouček (2019), in security and search-and-rescue scenarios, robots are supposed to create a map of the affected area and identify locations of potential victims or other relevant objects. These robots can be designed to perform tasks that are too dangerous or difficult for humans to do, and to reduce the risk of human injury or death in underground mines.

There have been multiple attempts at generating maps of underground mines using autonomous guided vehicles (AGV). Lösch (2018) discussed the design and requirements of an autonomous robot for exploring and generating 2D maps in an underground mine. The robot is equipped with 2D laser scanner, IMU, and wheel encoders allowing it to operate in harsh environments where wireless communication is limited. In another attempt, Rouček et al. describe a multi-robot system developed by the CTU-CRAS team for the DARPA Subterranean Challenge (Rouček 2019). Ebadi et al. surveyed recent progress and discussed future opportunities for simultaneous localization and mapping (SLAM) in underground mine mapping (Ebadi 2023a). The paper discussed the attempts by multiple teams in developing multi-robot centralized systems focusing on pushing the boundaries of autonomous robotic exploration and mapping in complex underground environments. The main focus of these challenges is to increase the safety and efficiency of underground search-and-rescue missions.

2.3 5G in mining

Borg et al. (2017) discussed the need for a high-speed, low-latency network to support the real-time transfer of LiDAR data from underground vehicles to the surface. The network must be able to support a large number of connected devices and provide reliable coverage throughout the mine.

Establishing a network in an underground mine poses communication challenges due to the physical and dynamic environment, requiring a robust, reliable, economical, and flexible infrastructure. The physical environment is often hot, humid, and dusty, which can affect the transmission of radio frequency signals. Underground mines are dynamic environments with regular movement of people and

machinery, so the need to keep track of where equipment is and where people are, while keeping both safe, is paramount. Communications infrastructure needs to be such that it does not obstruct equipment nor is stopped from operating by the presence of equipment between transmitters and receivers. Finally, communication solutions for underground operations need to be sufficiently flexible to deal with the different bit rates, latency, and loss requirements of the applications that use them (Branch 2021).

To handle the large amount of data required during autonomous navigation and mapping in the DARPA Subterranean challenge, the CTU-CRAS team employed three different wireless networks with varying levels of reliability, bandwidth, and latency (Rouček 2019). The existing wireless networks are often limited in their range, throughput and latency capacities for large-scale operations. Existing solutions to bypass these limitations include resource management like compression and down-sampling of sensor data, hierarchical map representation, and sparse pose-graph for localization (Ebadi 2023b).

The emergence of 5G technology shows potential to meet these demands. Specifically, the promise of 5G communication networks to attain large bandwidth, low latencies, and high reliability facilitates the implementation of diverse new strategies for the digital transformation of the industry (Borg et al. 2017). Emontsbotz (2024) presented the successful outcomes of field trials for the application of 5G networks in construction sites and underground mines, highlighting the potential for future advancements in these industries. The study emphasizes the unique challenges and requirements of these industries, and the need for adaptable and flexible wireless communication networks to meet their specific demands.

Branch (2021) compared 5G and WiFi in the context of underground mining communications. While WiFi is commonly used to provide connectivity to devices in the extraction drive, it has limitations in terms of distance and variable delay. On the other hand, 5G promises increases in bit rates, low energy consumption, and low latencies, making it a potentially attractive technology for underground mining. The distributed nature and movement to the cloud of costly base station functionality make 5G a much more economic proposition for use in extraction drives than previous cellular generations. Rao et al. presented a 5G-based architecture for underground coal mine fleet management systems, leveraging the benefits of 5G to address the challenges of unreliable communication and precise positioning in the underground environment (Rao 2022).

Although, the potential for 5G in the context of DT has been identified, there is limited literature on practical implementations of DT using 5G in underground mines. The aim of this paper is to bridge this gap by evaluating the performance of 5G in mining through a practical use-case viz. live 3D mapping using a mobile robot. Moreover, the knowledge gained here can be transferred to 5G enabled use-cases in dynamic above-ground environments such as construction sites.

3 Experimental setup

This section is broken down into descriptions of the underground mine (Sect. 3.1), the hardware system (Sect. 3.2), the software used for processing and communicating the data (Sect. 3.3), the network configuration which was used for the experiments defined here (Sect. 3.4), and the general description of the use-case (Sect. 3.5).

3.1 Sondershausen underground mine

The Sondershausen salt mine, operated by Glückauf Sondershausen Entwicklung- und Sicherungsgesellschaft mbH (GSES), has been in operation since 1883. The deposit is extracted using room-and-pillar mining at 650–750 ms depth. Approximately 230,000 tons of raw materials are extracted annually and transported to the surface via skip haulage. GSES also operates an underground storage site for non-recyclable waste and backfill mining, in which waste from mining, construction and industry is used to backfill cavities created by mining operations. The mine covers an area of 32 km^2 and has approximately 80 km of open tunnels called drifts. The mine layout is characterized by parallel drifts intersected perpendicularly by crosscut drifts at regular intervals, creating a checkerboard pattern. The drifts are rectangular, measuring 5 ms in height and 8 ms in width. The 5G trial field comprises two drifts, A and B, at a depth of -700 m. Drift A is a straight tunnel that spans approximately 950 m in length. The tunnel's terrain features height variations of about 50 m. The radio equipment is mounted at the start of the drift and aligned with the drift's central axis. At an angle of around 45°, Drift B diverges from Drift A and extends for 350 m until it terminates at a crushing station that delineates the trial field's boundary. The network and live mapping tests were conducted in Drift A (Fig. 2).

3.2 Mobile robot platform

The mobile robot utilized in this project is based on a commercial platform, INNOK, provided by Innok Robotics (see Fig. 3). The INNOK platform has a four-wheel differential drive, making it the ideal mobile platform for the narrow tunnels of underground mines. Each of its wheels is equipped with odometry encoders whose measurements are read out using a USB-CAN Bus module.

To ensure full visibility of the environment and to monitor robot's operational state, a variety of sensors have

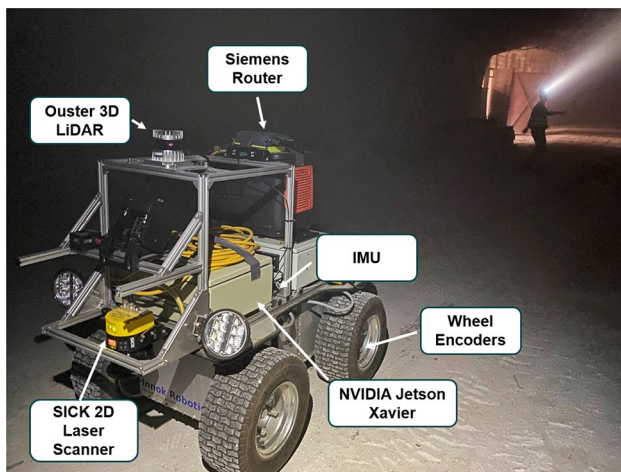**Fig. 2** Trial field in the Sondershausen mine, junction of drift A and B

Fig. 3 The INNOK mobile robot used in this work. It carries several sensors such as a IMU, 3D LIDAR and a 2D Laser Scanner. An Nvidia Jetson Xavier module is used for onboard computing and a Siemens 5G-router was used to transfer the data over the network

been integrated into the robot. Placed at the center of the base, an inertial measurement unit (IMU), specifically the Xsens MTi-30-2A8G4, offers critical information about rotational speed and acceleration. Additionally, the robot is outfitted with a 2D laser scanner, the Sick micro Scan 3, which aids in obstacle detection and the creation of 2D environment maps for localization tasks. For 3D visualization of the workspace, the Ouster OS1 128 3D LiDAR was mounted at the front of the mobile robot.

The INNOK comes equipped with a compute module with all the sensor drivers pre-installed. However, it lacked the capacity to simultaneously process data from multiple sensors and run various localization and mapping

algorithms. Hence, the NVIDIA Jetson AGX Xavier (32GB) module was chosen to replace it.

The experiments in this study required us to remotely communicate with the INNOK over 5G with a control PC. To establish bi-directional wireless communication between the INNOK and the control PC, the Jetson was connected to a 5G capable router (Siemens SCALANCE MUM856-1).

3.3 Software setup

The software setup of our robot, including communication with the various onboard sensors and processing of the same information, was built using the ROS framework. ROS is an open-source middleware framework built to facilitate the development of robotic systems. It provides libraries, tools and packages which allow for hardware abstraction, inter process communication, diagnostics and other processes which are crucial for building robotic applications (Quigley et al. 2009).

The raw data from the sensors were read out using existing ROS packages which were then published as ROS messages. To localize the the INNOK accurately in the drift, a stable source of odometry was required. For this purpose, the robot_localization package was used to combine the odometry/pose information from the different sensor modules. Furthermore, to navigate remotely between waypoints in the test drift, the slam_toolbox and the move_base packages were used.

To ensure consistent environmental measurements and to prevent issues resulting from time discrepancies between these two PCs, the Chrony (2022) package was utilized to synchronize their system clocks. Here, the system clock of the Control PC was used as the reference for the Jetson's clock.

3.4 Network setup

An overview of the network setup for the experiments is shown in Fig. 4. A stand-alone 5G core was set up in the designated control room. To ensure a direct link, the control PC was tethered to the Enterprise LAN switch via ethernet cable. The Enterprise LAN switch has a direct SFP+ (10 Gbit/s) connection to the 5G core. The control PC served as the centralized hub for communication from which the operator could visualize, monitor and control the INNOK. As mentioned in Ebadi (2023a), centralized architectures, where the sensor data from the robots are transferred to a remote server, are a popular approach in robotic exploration. Such a system allows for a human operator to analyze local and global maps which enables mission-planning. Hence, we opted to design our test experiment to reflect such a system.

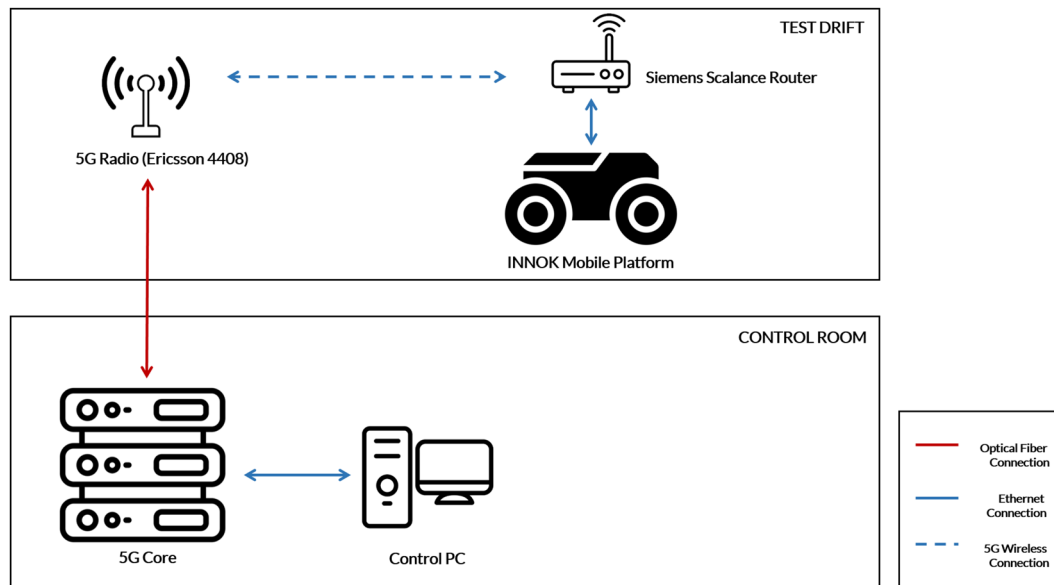The 5G test field is operated with two 5G radios (Ericsson 4408). The radios were connected to the 5G core using

Fig. 4 The network setup in the underground mine

single-mode fiber optic cables and were mounted on the ridge in the middle of the route to ensure even network coverage.

The Siemens router mounted on the INNOK provided the Jetson access to the 5G network. The router was then configured to communicate with the control PC over the 5G network.

Setting up ROS communication between multiple remote machines connected to different LANs, was a non-trivial task. Typically, ROS implementations reside within local networks where robots and PCs coexist within the same LAN. Our experimental configuration, however, demanded a cross-LAN communication paradigm, requiring PCs to interact using their public IP addresses.

Since ROS communicates all data as plain text, it is recommended to use encrypted communication protocols while exposing the ROS-enabled systems to the internet. The common methods to establish such a connection are the following:

1. Virtual private network (VPN) (such as OpenVPN OpenVPN 2023)
2. ROS-based cloud solutions (like Husarnet Husarnet 2023)
3. Port forwarding

VPNs and cloud solutions are considered the more secure solution. However, they come with some drawbacks. The tunneling and encryption protocols in VPNs can add additional network overhead. As for cloud-based solutions, they require routing the network packets to a remote server which is not part of the stand-alone 5G core. As both these

alternatives were not optimal for assessing the network's performance in the underground mine, and considering the temporary nature of the experimental setup, the port forwarding solution was selected.

The process of establishing bi-directional communication between two ROS machines involved the following steps:

1. **Port forwarding**:
   The initial step involved enabling port forwarding on both the Core and the Siemens router. By ensuring that the designated ports were open, the messages can be between various nodes on both the computers.
2. **Host configuration for node discovery**:
   To enable ROS nodes on each PC to identify those operating on the other, the */etc/hosts* file on each PC was modified to include the public IP address of the other.
3. **ROS master configuration**: The final step involved configuring the *ROS_MASTER_URI* environment variable on both the control PC and the Jetson. The control PC was designated as the ROS master. The *ROS_MASTER_URI* variable on the Jetson was set to the public IP address of the control PC and to *localhost* on the control PC.

3.5 Use-case description

Throughout the experimental phase, the INNOK traversed the drift, from designated starting point and progressing toward the specified endpoint, as depicted in Fig. 5. This trajectory specifically covered a section of the drift A where the 5G network coverage was established. Due to ongoing mining operations, involving large machine and
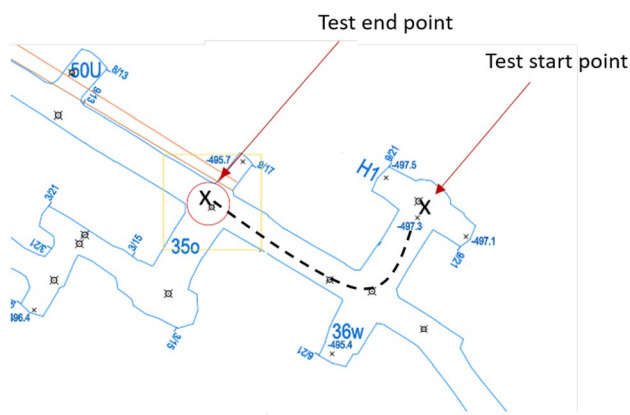
Fig. 5 The layout of the Sondershausen mine. The dashed line shows the test drive stretch where the network and 3D mapping tests were conducted

Fig. 6 The INNOK during the test drive in Drift A

trucks often driving through this section, the length of the test drive was limited to 60 m.

The network tests in the drift involved scrutinizing aspects such as latency and bandwidth to gauge the efficiency and robustness of the network under operational conditions.

In the course of the live 3D mapping assessments, the Ouster LiDAR, was employed to produce a 3D map of the drift. This map was continuously transmitted over the network to the control PC, offering real-time visual feedback to a remote operator. The network performance was analyzed throughout the duration of the mapping tests. Figure 6 shows the INNOK during the test drive.

In the sections below, a detailed description of both tests and the outcomes obtained from these experiments is provided.

4 Test drive

This section consists of two parts. Section 4.1 describes the first experiment conducted to measure the latency of the network and in Sect. 4.2 the live point cloud mapping experiment is detailed.

4.1 5G network performance

The experimental assessment aimed to scrutinize the round-trip time (RTT) performance within a 5G network under varying load conditions, considering its substantial relevance in network infrastructures and controlling mobile robots. To evaluate the latency within the 5G environment, the tests were conducted utilizing the *ping* utility to measure the RTT between the mobile robot platform and the control PC. First, the throughput of the 5G network was measured. The downlink and uplink throughput of the network were found to be approximately 600 Mb/s and 140 Mb/s, respectively. Then, the investigation explored how differing network loads, reflecting *Empty* conditions and loads approximately at *40%*, *70%*, and near *100%*, impact RTT behavior. These varied load conditions were instrumental in emulating real-world usage patterns and evaluating the network's responsiveness under differing traffic scenarios. The analysis sought to decipher the implications of RTT variations on 5G network performance, considering 5G's promises of ultra-low latency and high throughput. The tests were meticulously executed in the test drift of a real mining site to ensure the accuracy and reliability of the RTT data collected, see Fig. 6. By visualizing the RTT measurements using a box plot, this experiment aims to offer insights into how 5G networks perform under different load conditions, emphasizing the criticality of latency management in realizing the full potential of 5G technology.

Under minimal load *Empty*, the RTT maintained a comparatively low mean of approximately 10ms. As the load approached approximately *40%, 70%*, and near *100%*, a progressive escalation in RTT was observed, yielding mean RTT values of around 21 ms, 29 ms, and 104 ms, respectively. Also under escalating network loads, the standard deviations exhibited notable increments, indicating a greater instability in communication. The *Empty* network load condition yielded a standard deviation of approximately 4 ms. As the network load intensified to approximately *40%, 70%*, and near *100%*, the standard deviations increased to 11 ms, 12 ms, and 18 ms, respectively.

These increasing RTT and standard deviations underscore the amplified communication delay and instability,
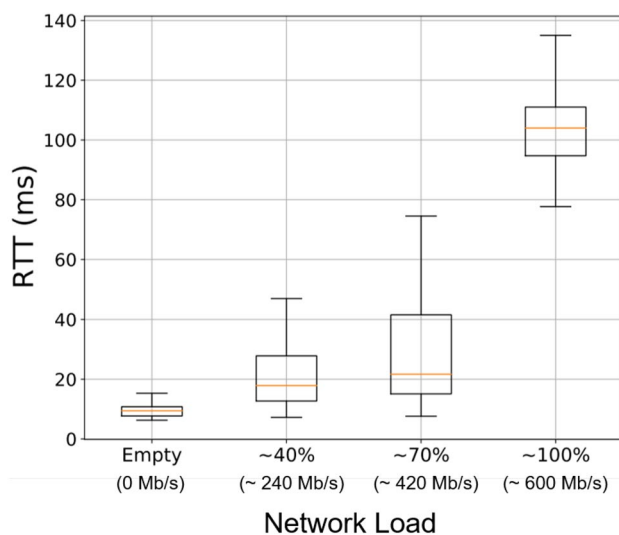
Fig. 7 Analysis of RTT variations conducted on the 5G network under different load scenarios

Table 1 The measured round-trip time for different network loads

Network load	0% (0 Mb/s)	40% (240 Mb/s)	70% (420 Mb/s)	100% (600 Mb/s)
RTT mean	10 ms	21 ms	29 ms	104 ms
RTT std. dev.	4 ms	11 ms	12 ms	18 ms

indicative of the network's reduced performance under higher load conditions. The observed changes emphasize the potential challenges for 5G highlighting the necessity for load-aware resource management strategies to maintain low-latency and robust communication within 5G networks (Fig. 7, Table 1).

4.2 Live 3D mapping performance

The incorporation of digital processes in mining unfolds many possibilities, particularly when implemented in tandem with the capabilities of 5G technology. Among the various potential applications, a standout use-case revolves around the mapping of the underground mine's constantly expanding layout. Recognizing the prevailing usage of manual 2D mapping techniques by GSES, the main focus was to create a static 3D point cloud maps for the drift.

The mapping experiments were conducted over the same section defined in Fig. 5. This test section had no ground-level obstructions and a gentle upwards slope. In addition to the structural considerations, the mining environment presented challenges, in the form of substantial particulate matter in the atmosphere. Coupled with the absence of lighting

within the drift, the effectiveness of camera-based mapping solutions was expected to be significantly compromised.

Consequently, a deliberate choice was made to use the Ouster LiDAR as the primary source for generating the 3D point cloud map using the KISS-ICP algorithm from University of Bonn (Vizzo 2023). KISS-ICP uses a point-to-point variant of the Iterative Closest Point (ICP) algorithm, which is computationally more efficient than other variants, thanks to a novel outlier rejection scheme. It generates a map based on a voxel grid that is used to store a subset of 3D points. Although, it was designed to be an lidar odometry solution, there was minimal drift in the odometry over the linear test drift throughout the tests. Thus, the map generated for the point cloud registration was visually accurate enough to be used for our purposes. Rather than aiming for an precise representation of the tunnels, our objective was to scrutinize the network performance when transferring large 3D point cloud maps from the INNOK to the control PC.

As such, the map from the KISS-ICP algorithm was chosen to be static point cloud map. The map was published on a ROS topic as *sensor_msgs/PointCloud2* message type. The Ouster LiDAR was operated at 1024×128 resolution with a rate of 10 Hz. As the experiment progressed, the generated map grew in size, and by the end of the test run, the generated point cloud averaged around 560 Mb/s approaching the 100% load of the network. The corresponding latency of the network also increased linearly, aligning with the results align with the network performance at 100 % load discussed in Sect. 4.1.

In Fig. 8, different views of the generated 3D point cloud map of the test drift are presented. To offer a comprehensive perspective, Fig. 9 overlays the generated map on the 2D layout of the underground mine. Our analysis of these maps is primarily qualitative, as a quantitative assessment falls beyond the scope of this paper. From Fig. 9, it becomes evident that the 3D map closely aligns with the cad drawings, despite the challenging environmental conditions and the absence of loop closure, indicating minimal *odometry drift* in the results. Thus, the generated map has the potential to be used in future applications like navigation, hazard monitoring and search and rescue.

5 Discussions and conclusion

As the mining industry continues to embrace the possibilities presented by digital transformation, the role of a network capable of high bandwidth and low latency will become increasingly pivotal. In this study, a mobile robot was used to generate a 3D point cloud map of the tunnels of an underground mine and the map was then live streamed to a remote PC over a stand-alone 5G network.

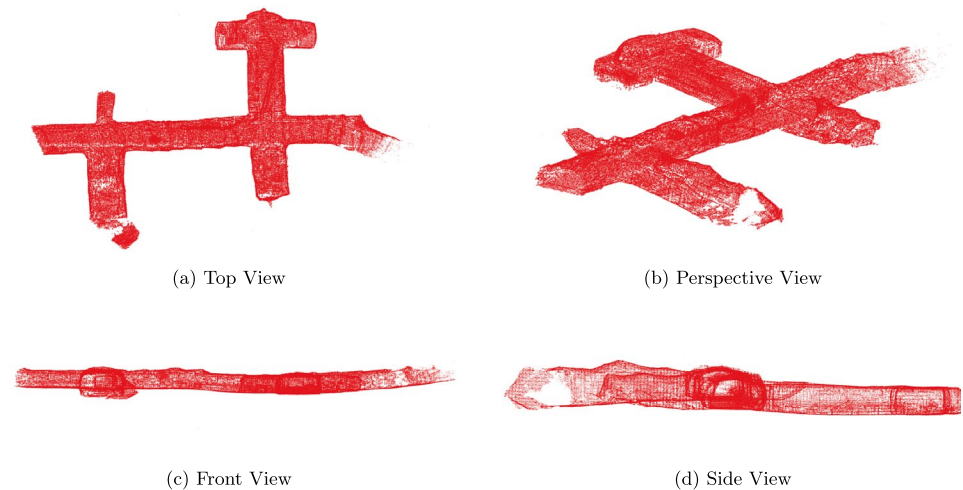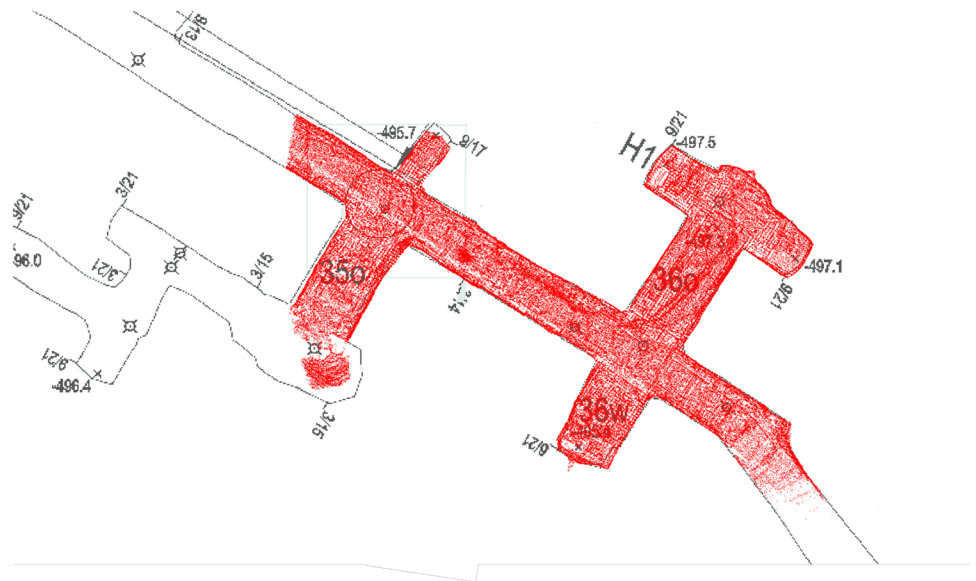**Fig. 8** The generated 3D point cloud map of the test drift of the Sondershausen mine (from different perspectives)

(a) Top View

(b) Perspective View

(c) Front View

(d) Side View

Fig. 9 A top-down overlay of the 3D point cloud map of the underground mine on the 2D drawing

- **Network latency**: The experimental assessments conducted in our study provide critical insights into the performance of 5G technology in the challenging context of dynamic environments such as underground mines. At lower network loads, the network was stable and the latency was as low as 10 ms. This characteristic aligns with the promises of 5G, emphasizing its potential to facilitate real-time communication crucial for applications like remote-controlled mining equipment. However, as our mapping experiments unfolded and the size of the generated map increased, the latency experienced a gradual escalation, particularly as the network load approached its maximum capacity. This observed spike in latency highlights a potential challenge when operating under high-throughput conditions such as multi-robot explorations in large-scale mines, signaling the need for further optimization and resource management.

- **Pointcloud map**: Despite unfavorable environmental conditions such as lack of lighting, loose terrain and presence of particulates in the atmosphere, the generated 3D map is visually close to the mine layout. This means that, going forward, the generated map can serve as a reliable reference for understanding the spatial layout of the mine, aiding in tasks such as navigation, obstacle avoidance, and overall situational awareness for mobile robots or autonomous vehicles operating in similar challenging environments.

The findings emphasize the importance of conducting more comprehensive studies to understand factors affecting 5G performance in the underground mining setting. Factors such as the size and complexity of data being transferred, the density of connected devices, and the dynamic nature of the mining environment all contribute to the network's behavior.

Additionally, a noteworthy avenue for future research lies in the direct comparison of 5G against existing technologies such as WiFi.

Our study, hence, serves as a foundational exploration into understanding the performance of 5G in underground mining, paving the way for more in-depth investigations and optimizations to harness the full potential of 5G technology in underground mines. Additionally, this provides an opportunity to extend this knowledge to the digitalization of tunneling processes in the construction sector.

6 Future scope

Based on the conclusions of this study, the future scope of integrating 5G technology with robotic underground mapping in mines envisions advancements in several key areas. We plan to develop better data compression algorithms and resource management methods to dynamically manage varying network load. Additionally, our future work includes developing multi-robot exploration algorithms specifically designed for complex underground mines. These developments will open up the possibility of using multi-robot systems for mapping large-scale underground mines.

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