












RESEARCH DIRECTIONS AND MODELING GUIDELINES FOR INDUSTRIAL INTERNET OF THINGS APPLICATIONS

Giampaolo Cuzzo , Enrico Testi , Salvatore Riolo , Luciano Miuccio , Gianluca Cena , Gianni Pasolini , Luca De Nardis , Daniela Panno , Marco Chiani , Maria-Gabriella Di Benedetto , Enrico Buracchini, and Roberto Verdone 

ABSTRACT

The Industrial Internet of Things (IIoT) paradigm has emerged as a transformative force, revolutionizing industrial processes by integrating advanced wireless technologies into traditional procedures to enhance their efficiency. The importance of this paradigm shift has produced a massive, yet heterogeneous, proliferation of scientific contributions. However, these works lack a standardized and cohesive characterization of the IIoT framework coming from different entities, like the 3rd Generation Partnership Project (3GPP) or the 5G Alliance for Connected Industries and Automation (5G-ACIA), resulting in divergent perspectives and potentially hindering interoperability. To bridge this gap, this article offers a characterization of (i) the main IIoT application domains, (ii) their respective requirements, (iii) the principal technological gaps existing in the current literature, and, most importantly, (iv) we propose a systematic approach for assessing and addressing the identified research challenges. Therefore, this article serves as a roadmap for future research endeavors, promoting a unified vision of the IIoT paradigm and fostering collaborative efforts to advance the field.

INTRODUCTION

The advent of the fourth industrial revolution, commonly referred to as Industry 4.0, is revolutionizing the manufacturing landscape through the integration of Information and Communications Technologies (ICT) [1]. This paradigm shift is characterized by the digitalization of production processes, and the adoption of cyber-physical systems that seamlessly blend physical assets with digital technologies. In this regard, the Industrial Internet of Things (IIoT) emerges as a pivotal facilitator within the Industry 4.0 framework, driving

the Industry 4.0 paradigm from traditional, rigid industrial processes to interconnected, adaptive, and more efficient systems, by envisioning the adoption of wireless communications in traditional industrial processes to augment their efficiency and security [2]. Industrial assets, such as robotic arms or valves, are equipped with wireless devices to support applications like analytics, monitoring, and control (detailed descriptions are provided in [3]).

In light of this, factories pivot away from the traditional reliance on extensive wired communication technologies, embracing wireless solutions that unlock unprecedented levels of flexibility and adaptability [1]. Wi-Fi[®], for instance, delivers high performance and user-friendly operation at a low cost but lacks energy efficiency, making it impractical for large-scale deployments involving battery-powered devices. LoRa[®], on the other hand, offers long-range, low-power connectivity, making it well-suited for non-real-time monitoring applications, though its network throughput is severely limited. Similarly, ZigBee[®] and Bluetooth[®] are effective for short-range, low-power communication, ideal for specific applications like asset tracking or environmental monitoring, but they also struggle with limited data throughput [1]. 5th Generation (5G) New Radio (NR) also emerged as a viable candidate for industrial communications thanks to key features such as Ultra-Reliable Low-Latency Communications (URLLC), the Non-Public Network (NPN) paradigm, and integration with the widely adopted Time-Sensitive Networking (TSN) standard [2], [4]; as of today, however, it remains both complex and expensive to deploy and maintain. Overall, the real-world adoption of these technologies remains limited because they are unable to comprehensively address all the diverse, stringent, and co-located requirements inherent in industrial environments.

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Giampaolo Cuzzo (corresponding author) is with WiLab, Consorzio Nazionale Interuniversitario per le Telecomunicazioni (CNIT), 40133 Bologna, Italy; Enrico Testi, Gianni Pasolini, Marco Chiani, and Roberto Verdone are with the Department of Electrical, Electronic, and Information Engineering "Guglielmo Marconi" (DEI), University of Bologna, 40136 Bologna, Italy; Salvatore Riolo, Luciano Miuccio, and Daniela Panno are with the Department of Electrical, Electronic, and Computer Engineering (DIEE), University of Catania, 95124 Catania, Italy; Gianluca Cena is with the Institute of Electronics, Computer and Telecommunication Engineering (IEIT), National Research Council of Italy (CNR), 10129 Turin, Italy; Luca De Nardis and Maria-Gabriella Di Benedetto are with the Department of Information Engineering, Electronics and Telecommunications (DIET), University La Sapienza, 00185 Rome, Italy; Enrico Buracchini is with Telecom Italia, 00166 Rome, Italy.

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This limitation highlights the necessity for further innovation and sets the stage for the development of next-generation mobile radio networks. In this regard, the academic world is already intensively shaping such evolution, by proposing important paradigm shifts, like the use of the THz band, radar in next-generation Base Stations (BSs), or Artificial Intelligence (AI)-radio communication interplay.

Despite this ambitious evolutionary trend, the majority of contributions to the literature do not account for the specificities of industrial environments (e.g., heterogeneous traffic), potentially limiting their practical value in that context.

This may be attributed to the lack of a standardized and cohesive characterization of the next-generation IIoT framework, since different entities, such as 3rd Generation Partnership Project (3GPP) and 5G Alliance for Connected Industries and Automation (5G-ACIA), propose their own perspective and nomenclature for IIoT application domains and Key Performance Indicators (KPIs).

To address this ambiguity, this article aims to:

1. Provide a holistic description of the main characteristics of industrial contexts, in terms of nomenclature, Application Domains (ADs), KPIs, and traffic types;
2. Characterize the IIoT requirements for future wireless communications by performing a meticulous examination of the literature, encompassing white papers and standards, and by unifying their divergent aspects (e.g., consolidating different terminologies that refer to the same KPI);
3. Identify the principal technological gaps in the current literature and present our perspective on the emerging research themes across various layers of the ISO-OSI standard;
4. Propose guidelines for assessing and addressing the identified research challenges to promote reproducibility and compatibility among different scientific contributions.

IIoT APPLICATION DOMAINS

In this section, we clarify the different and sometimes contrasting nomenclatures used in the literature to describe application domains for the IIoT. Our goal, rather than proposing modifications or additions to existing naming conventions, is to provide a clearer understanding of these terms and to facilitate their consistent usage across various contexts.

NOMENCLATURE

One of the main characteristics of the IIoT literature is the presence of multiple synonyms, which may easily lead to misunderstanding. To solve this ambiguity, we hereby provide a list, in the form of a dictionary including the most common synonyms, that aims to merge the various IIoT terms and also constitutes the common nomenclature for this article:

- *Industrial Application/Use Case (UC)*: It indicates a single, specific, and self-contained industrial application, e.g., assembly lines, thermal monitoring, etc.;
- *Industrial AD*: It indicates a family of industrial UCs, such as motion control, process monitoring, etc.;

- *Factory/Manufacturing Plant/Production Plant/Industry Plant*: It indicates an industrial facility made of one or more buildings;
- *Industrial Asset*: It refers to any element present within a factory or building (e.g., robotic arms, pumps, valves, pistons, etc.);
- *Device/User Equipment (UE)/Node/Tag*: It denotes a wireless-enabled component (e.g., a microcontroller board embedding sensors and/or actuators) associated with a given industrial asset of a UC, such as an Automated Guided Vehicle (AGV) transporting goods all over the factory, to monitor and/or control its operation;
- *BS*: It denotes a fixed radio transceiver that connects wireless devices, whether fixed or mobile, in its coverage area to the network infrastructure, serving as a pivotal node for signal transmission and reception.

AD1: MOTION CONTROL

Motion control is among the most challenging and demanding closed-loop control application domains in industrial environments [3]. A motion control system (see Fig. 1) is responsible for controlling the movement of industrial assets in a well-defined manner and is composed of three main elements: sensor(s), actuator(s), and a controller. The sensors gather data from the environment and send the actual values to the motion controller. In the opposite direction, the motion controller sends a command to the actuators which thereupon perform the corresponding action(s) on one or several processes (this may also include simple software updates).

Different motion controllers may also need to communicate to cooperate in a coordinated and tightly coupled manner when performing a shared task [3].

Example of UCs: Machine tools, packaging machines, printing machines, assembly lines.

AD2: PROCESS MONITORING

Process monitoring is an essential aspect of any industrial plant, allowing the tracking of operations and assets to enhance productivity and product quality, while concurrently minimizing waste, downtime, and energy consumption.

As depicted in Fig. 1, data concerning production processes is gathered through a myriad of devices strategically placed in the plant and functions such as the well-known Supervisory Control and Data Acquisition (SCADA). This data is then transmitted through the network, often at regular intervals, to designated data repositories (located either on local premises or in the cloud). Subsequently, the information becomes available for processing tasks, such as data visualization and predictive maintenance, empowering industry owners with valuable insights.

Example of UCs: Temperature, vibration, or thermal monitoring.

AD3: MOBILE CONTROL PANELS

Industrial assets currently rely on control panels known as Mobile Control Panels (MCPs). These devices are intended for configuring, monitoring, debugging, controlling, and maintaining machines, robots, cranes, or production lines (see Fig. 1). MCPs might also incorporate safety

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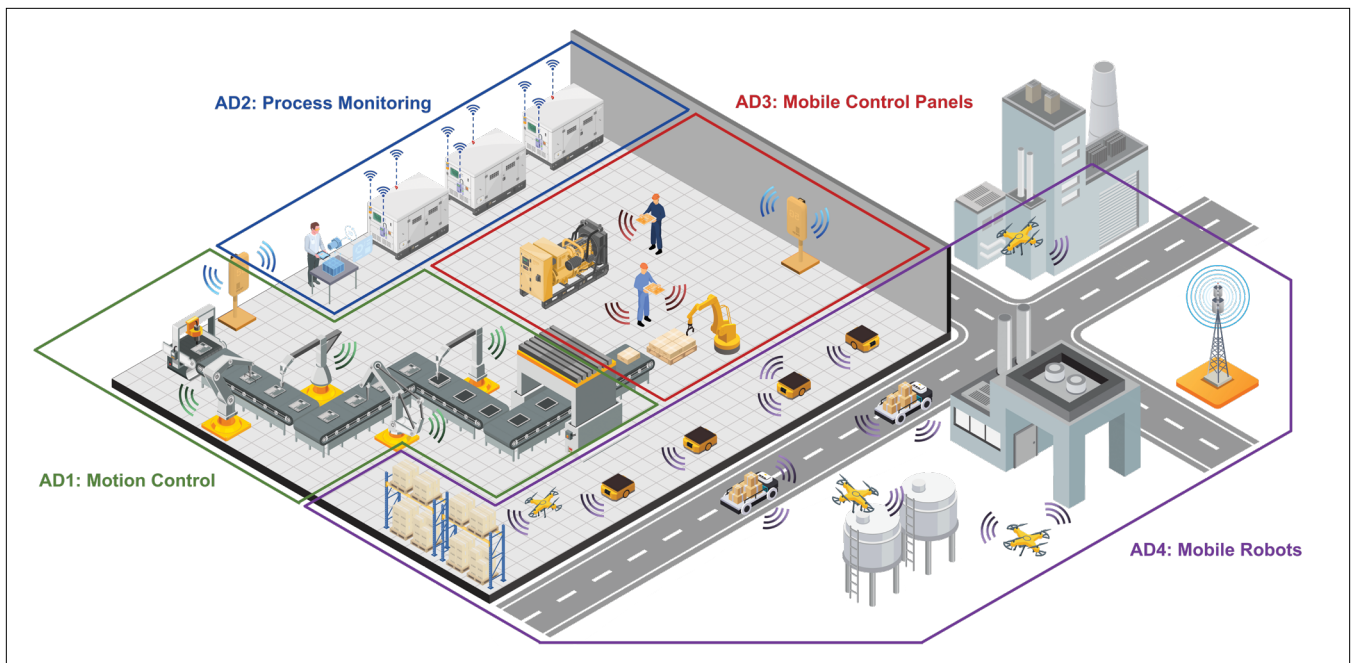


FIGURE 1. Illustration of the main IIoT ADs: in green, an example of motion control system implemented in an assembly line (AD1); in blue, a plethora of sensors gathering data from the production plant (AD2); in red, mobile control panels handled by workers and controlling industrial machinery (AD3); in purple, fleets of mobile robots interacting with the factory plant and extending network coverage to outdoor remote areas (AD4).

features, such as an emergency button to halt machine operation in hazardous situations, preventing harm to individuals or damage to assets. For the same reason, MCPs may need to support the special “enabling device mode” as well. In this scenario, the operator must manually keep the enabling device switch in a specific stationary position. Failure to do so will result in the controlled equipment promptly moving to a safe stationary position, guaranteeing that the operator’s hand(s) stay on the panel (rather than under a molding press, for example), and that the operator does not suffer from any electric shock or the like.

Example of UCs: Remote control, or emergency stop.

AD4: MOBILE ROBOTS

Mobile robots will play a crucial role in next-generation industrial environments thanks to their capacity to assist in work processes, transport goods and assets, extend radio coverage, and provide support and rescue in safety-critical conditions and hard-to-reach areas. Mobile robots are typically divided into AGVs, ground units primarily used in indoor environments, and Unmanned Aerial Vehicles (UAVs) that can be deployed both indoors and outdoors, as depicted in Fig. 1. Usually, one or more centralized units (e.g., the guidance control system) facilitate bidirectional traffic exchange with the robots, overseeing navigation and data collection. Direct inter-robot communications might be necessary for cooperative task completion. Additionally, robots may need to interact with (or control) machinery inside or outside the buildings to enhance production and ensure security standards.

Example of UCs: Video-operated remote control, video streaming, cooperative driving.

IIoT CHARACTERIZATION

We then hereby describe the main KPIs, the typical traffic types, and requirements to be adopted in the IIoT paradigm.

KPIs

The UCs of the ADs described in the previous section cover diverse requirements, which has prompted both 3GPP and 5G-ACIA to provide various KPIs instrumental for IIoT applications. These KPIs encompass several metrics essential for assessing the performance of industrial communication systems. To describe them, we employ metrics specified in 3GPP documents [4], [5], [6], and by 5G-ACIA in its documents (e.g., [2]). A weakness identified in the collective analysis of the aforementioned documents is the use of different terminologies to refer to the same concept. To consistently address the definition of KPIs, we assemble the nomenclature used by both entities. The resulting comprehensive list of KPIs is detailed in Table 1, and incorporates names adopted in [2], [4], [5], [6], acronyms used in this article, along with their respective definitions and units. These KPIs have been grouped into two macro-categories related to the communication service and the positioning service.

The former category is related to the Communication Service Interface (CSI), i.e., the interface between the industrial application and the underlying wireless communication system. This interface is the primary reference point where different traffic flows, their principal requirements, and associated KPIs are defined. Notably, there is an important difference in the metric definition between the industrial application (a.k.a., communication service) and the wireless communication system. Specifically, referring to the wireless communication system,

	KPI name	KPI acronym	KPI description	Unit
Communication service	End-to-End latency / Latency	E2EL	Time allotted to transfer a message from the moment it is transmitted by the source CSI to the moment it is successfully received at the destination CSI. It is a one-way latency, thus the loop-back latency would be twice the E2EL	ms
	Message Size / Typical Payload Size	MS	The maximum size of the user data packet delivered from the application to the ingress of the communication system and from the egress of the communication system to the application	Bytes
	Transfer Interval / Cycle Time	TI	Time difference between two consecutive transfers of data from an application to the wireless communication system via the service interface	ms
	Survival Time	ST	Maximum time interval over which the communication service can fail to meet the application message delay requirement before an application layer failure occurs, leading to the communication service being considered as unavailable	ms
	Communication Service Availability / Availability	CSA	Amount of time during which the E2E communication service is delivered according to the agreed-upon QoS, divided by the total time in which the system is expected to deliver the E2E service	
	Communication Service Reliability / Reliability	CSR	Mean value of time intervals between consecutive unavailability events for the communication service	year
	Service Bit Rate / User Experienced Data Rate	SBR	Minimum rate measured at the CSI required to achieve a satisfactory user experience	Mbps
Positioning service	Horizontal Accuracy	HA	Distance between the estimated position and the actual position (ground truth) in the horizontal x-y plane	m
	Vertical Accuracy	VA	Distance between the estimated position and the actual position (ground truth) in the vertical axis z	m
	Heading Accuracy / Heading	HEA	Absolute value of difference between the measured direction of movement and actual direction	degrees
	Speed Accuracy	SA	Absolute value of the difference between measured speed and actual speed	m/s
	Positioning Service Availability / Availability	PSA	Percentage of time in which the positioning service can satisfy a positioning request	%
	Positioning Service Latency / Latency	PSL	Time between a positioning request and the corresponding reply by the positioning service	ms

TABLE 1. List of communication service and positioning KPIS [2], [4], [5], [6].

“reliability” is measured as the percentage of successfully delivered packets within the required time frame, focusing on individual packet losses

without considering their temporal distribution. However, industrial applications often prioritize consecutive packet losses differently. Losing a

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single packet may minimally impact the network performance, while losing several consecutive packets could lead to application failure. To address this, specific KPIs are introduced in the communication service perspective (see Table 1). The Survival Time (ST) is introduced to quantify the time an application service can tolerate without receiving an expected message, allowing to define Communication Service Availability (CSA) and Communication Service Reliability (CSR). It is worth noting that we intentionally excluded the jitter as it is typically expressed as a function of other KPIs (e.g., End-to-End Latency (E2EL)) [3], [4], [5].

Regarding positioning, it is typically provided as a dedicated service. It may run either on top of the communication infrastructure or on a dedicated positioning infrastructure, such as a Global Navigation Satellite System (GNSS) or an Ultra-Wide Band (UWB) positioning system. The dedicated set of KPIs describes the requirements imposed on the positioning service in terms of availability and accuracy of the position information and motion (i.e., speed and heading).

TRAFFIC TYPES

The KPIs listed in Table 1 refer to diverse traffic flows at the CSI. Specifically, traffic flows can be categorized into three types, described as follows.

- **Periodic Deterministic Communication (PDC)** refers to sending messages of size Message Size (MS) at a constant Transfer Interval (TI) with stringent requirements on both E2EL and CSA.
- **Aperiodic Deterministic Communication (ADC)** consists of messages sent aperiodically, i.e., there is no fixed TI between consecutive messages. Despite the lack of a pre-set sending time, the requirements for E2EL and CSA remain stringent [4]. Note that, for this specific traffic type, MS, TI, and ST are not defined. Therefore, its characterization relies solely on the Service Bit Rate (SBR).
- **Non-Deterministic Communication (NDC)** encompasses all traffic types other than periodic/aperiodic deterministic communication. In this case, there are no requirements either in terms of E2EL or CSA. As in the case of ADC, the traffic is defined through SBR.

REQUIREMENTS

The requirements at the CSI for the various IIoT ADs and corresponding UCs are summarized in Table 2. The term “N/A” therein represents “not applicable” and is used for KPIs that are not defined.

Additionally, Table 3 shows the positioning requirements for AD3 and AD4, in accordance with the 3GPP technical specifications that do not include AD1 and AD2. Specifically, for AD3, a range of values is specified across various scenarios, while AD4 requirements are categorized based on the type of industrial assets under consideration (AGVs vs UAVs), reflecting their distinct mobility characteristics. As can be observed from Table 3, AD4 imposes notably more stringent requirements than AD3.

RESEARCH DIRECTIONS AND MODELLING GUIDELINES

In this section, we identify the key technological gaps in the current literature and offer our perspective on how emerging research fields could address these gaps to fulfill the next-generation IIoT requirements.

RESEARCH DIRECTIONS

After a detailed analysis of the IIoT ADs and their characterization, we provide an overview of the major technology gaps in this field, focusing on the most promising research directions and emphasizing the pivotal challenges that will be addressed in the upcoming years.

Terahertz and Optical Communications. In the last decades, TeraHertz (THz) and optical communications have emerged thanks to their capability of achieving exceptionally high data rates in short-range scenarios, offering huge bandwidths and enabling high-throughput applications. These technologies can largely benefit industrial indoor communication scenarios as AD1 and AD3, which demand low E2EL and stringent CSA, while also catering to the high throughput needs of AD2.

Open Challenges: Both THz and optical communication systems face various challenges due to environmental factors and technical limitations [7]. First of all, such systems often rely on highly focused, narrow beams that must be accurately aligned to avoid signal losses. Overcoming this challenge requires innovative solutions in beam focusing, alignment mechanisms, and possibly adaptive systems that can adjust for misalignments in real-time. Moreover, molecular absorption in the THz spectrum by water vapor or other molecules commonly found in industrial indoor environments can generate additional noise, affecting the quality and reliability of communication systems.

Network as a Sensor. THz communications allow for the development of compact, miniaturized components that enable the integration of multiple antennas and transceivers in small devices (e.g., wearables), facilitating precise and distributed sensor deployment and data collection mechanisms. In this context, next-generation industrial network paradigms envision leveraging the communication network as a sensor, to gather real-time data on industrial processes, environmental conditions, and machinery statuses. Moreover, it is expected that next-generation devices will possess Integrated Sensing and Communication (ISAC) capabilities, leveraging on the high spatial resolution of mmWave and THz technologies. The integration of communication and sensing paradigms, along with the capability to gather data from numerous distributed sensors form the basis for AD2 and AD3. Furthermore, the high-precision positioning and tracking systems for vehicles and devices in both indoor and outdoor environments (e.g., AD4) are essential to enable next-generation networks to meet the requirements and ensure safety standards.

Open Challenges: The high density of obstacles (e.g., machinery) in indoor industrial environments can hinder signal propagation causing reflections,

Application Domain (AD)	Use Case (UC)	Traffic type	E2EL [ms]	MS [Bytes]	TI [ms]	ST [ms]	CSA	CSR [years]	SBR [Mbps]
AD1: Motion Control	Machine tool	PDC	< TI	50	0.5	0.5	$1 - [10^{-5}, 10^{-7}]$	≈ 10	N/A
	Packaging machine		< TI	40	1	1	$1 - [10^{-6}, 10^{-8}]$	≈ 10	N/A
	Printing machine		< TI	20	2	2	$1 - [10^{-6}, 10^{-8}]$	≈ 10	N/A
	Machine in assembly line		< TI	1000	≤ 50	50	$1 - [10^{-6}, 10^{-8}]$	≈ 10	N/A
	Software updates	NDC	N/A	N/A	N/A	N/A	N/A	$\approx \frac{1}{12}$	≥ 1
AD2: Process Monitoring	Temperature sensor	PDC	< 100	20	100 to 60000	$3 \times TI$	$1 - 10^{-4}$	$\geq \frac{1}{54}$	N/A
	Vibration sensor		< 100	25000	≤ 1000	$3 \times TI$	$1 - 10^{-4}$	$\geq \frac{1}{54}$	N/A
	Thermal camera		< 100	250000	≤ 1000	$3 \times TI$	$1 - 10^{-4}$	$\geq \frac{1}{54}$	N/A
AD3: Mobile control panels	Remote control of assembly robots or milling machines	PDC	< TI	40 to 250	4 to 8	= TI	$1 - [10^{-6}, 10^{-8}]$	$\approx \frac{1}{12}$	N/A
	Remote control of mobile cranes or mobile pump		< TI	40 to 250	< 12	12	$1 - 10^{-8}$	≈ 1	N/A
	Emergency stop		< 8	40 to 250	8	16	$1 - [10^{-6}, 10^{-8}]$	$\approx \frac{1}{365}$	N/A
	Data transmission in parallel to remote control	ADC	< 30	N/A	N/A	N/A	$1 - [10^{-6}, 10^{-8}]$	$\approx \frac{1}{12}$	>5
AD4: Mobile robots	Video-operated remote control	PDC	< TI	15000 to 25000	10 to 100	= TI	$< 1 - 10^{-6}$	≈ 1	N/A
	Cooperative driving		< TI	40 to 250	10 to 50	= TI	$< 1 - 10^{-6}$	≈ 10	N/A
	Machine control		< TI	40 to 250	1 to 10	= TI	$< 1 - 10^{-6}$	≈ 10	N/A
	Video streaming	ADC	< 10	N/A	N/A	N/A	$< 1 - 10^{-6}$	$\approx \frac{1}{54}$	> 10
	Real-time video streaming to the guidance control system	NDC	N/A	N/A	N/A	N/A	N/A	$\approx \frac{1}{12}$	> 10

TABLE 2. CSI requirements for different ADS [4], [5].

Application Domain (AD)	Use Case (UC)	HA [m]	VA [m]	HEA	SA	PSA [%]	PSL [ms]
AD3: Mobile control panels	Multiple	1-5	3	10	N/A	90-99.9	1000-5000
AD4: Mobile robots	Involving AGVs	0.3	3	10	0.5	99.9	10
	Involving UAVs	0.1	0.1	2	0.5	99.9	10

TABLE 3. Positioning requirements for AD3 and AD4 [6].

scattering, and attenuation. The development of ad-hoc network layout design paradigms and innovative signal processing techniques is crucial for guaranteeing high communication and sensing performance. Recently, Reconfigurable Intelligent Surfaces (RIS) have emerged as a means to optimize communication links and improve sensing coverage, nevertheless introducing an additional layer of complexity to network management [8]. Moreover, localizing and tracking objects transitioning from outdoor to indoor scenarios (and vice versa), as well as combining multi-technologies indoor localization techniques to meet the desired requirements, are still open problems.

Massive Multiple Access. The simultaneous connections of thousands of Internet of Things (IoT) devices can take advantage of small-cell or cell-free communication systems, in which cutting-edge low-power radio access techniques allow for higher coverage and capacity. While traditional macro cells might face limitations mainly due to propagation issues, small-cell/cell-free systems enable localized connectivity, providing reliable wireless communication in specific zones within the factory [9]. Such systems can help industrial networks meet the scalability and flexibility requirements even in dynamic environments with varying device densities (e.g., AD2).

This approach holds significant importance in establishing a cohesive framework for scientific endeavors aimed at addressing the research gaps previously highlighted. Indeed, the applicability of existing literature contributions to IIoT environments strongly depends on the level of realism of their underlying assumptions and characterizations.

Open Challenges: Since the multitude of potentially interfering IoT devices usually send sporadic data to the BS developing innovative protocols for massive random access is a promising solution to reduce network access time. However, among their primary unresolved issues there is the problem of channel estimation, which worsens when dealing with short packets subject to significant interference, and the substantial latency introduced by interference cancellation mechanisms.

Artificial Intelligence. The pervasiveness of AI in contemporary industrial production plants (encompassing AD1 to AD4) is revolutionizing the way industries operate and optimize their processes [10]. Modern edge-AI allows for data processing closer to the source, supporting quicker decision-making and reducing latency in time-sensitive applications. Additionally, online learning algorithms enable systems to adapt and learn from dynamic environments, improving performance and resilience in changing conditions. Furthermore, the revolution of Large Language Models (LLMs) can assist intent-based orchestration by interpreting and processing natural language commands or intents from human operators. This simplifies network management and configuration, enhancing operational efficiency.

Open Challenges: At the moment, the development of faster AI models that can easily adapt to new dynamic scenarios without the need for extensive and energy-consuming retrainings is one of the most important open challenges.

Vehicular Communications. Mobile robots, particularly relevant to AD4, will play a significant role in modern industries by supporting production processes. In particular, UAVs can act as mobile base stations or relays, establishing network connectivity even in areas with challenging terrain or temporary infrastructure needs, or during emergencies. To enable mobile robot operations, a robust backbone network ensuring efficient and dependable communication within the robots and the control systems is required. In this context, Vehicle-to-Everything (V2X) emerging standards facilitate communication among mobile robots, infrastructure, and other devices, improving safety and traffic management. In particular, the possibility to have sidelinks that allow devices in spatial proximity to communicate efficiently, forming ad-hoc networks in environments with limited infrastructure or in scenarios requiring rapid data exchange, is of paramount importance.

Open Challenges: Jointly optimizing the trajectories of mobile robots and managing radio resources while fulfilling application requirements and ensuring security standards is still an open problem. Multi-Agent Deep Reinforcement Learning (MADRL)-based solutions have been recently proposed; however, these techniques require long training phases and are not easily adaptable to new scenarios. Moreover, integrating V2X standards into industrial wireless networks is one of the biggest challenges at the moment.

Security and Safety. The last point we want to highlight is the need for robust encryption algorithms and authentication mechanisms in all ADs to ensure data integrity and confidentiality within industrial wireless networks, safeguarding sensitive information [11]. Equally critical, especially in industrial environments involving human-machine

interaction, is functional safety, which focuses on preventing hazardous failures by ensuring reliable operation of safety-critical systems, even under fault conditions (see Fig. 2). From a communication standpoint, achieving functional safety requires dedicated safety communication protocols capable of verifying the integrity, authenticity, and timeliness of transmitted data. Addressing these challenges necessitates integrating safety communication protocols with encryption and authentication techniques to meet stringent E2EL requirements.

Open Challenges: In addition to the previously mentioned need for new encryption and authentication techniques, the problem of designing fast and accurate intrusion detection systems, capable of monitoring large portions of the spectrum, and identifying and mitigating potential threats (i.e., jammers) or unauthorized access attempts is still open. Finally, as quantum computing advances, the threat to traditional cryptographic methods grows. Preparing for post-quantum security involves deploying encryption algorithms resistant to quantum attacks, ensuring long-term data protection.

As an experimental demonstration of some of these research directions, Figure 2 shows the results of one of our PoC that leverages the interplay between AI and 5G NR for enhancing safety in a real-world UC belonging to the AD4 family.

MODELING GUIDELINES

In the following, we present modeling guidelines for industrial environments that adhere to the IIoT characterization given by this paper. This approach holds significant importance in establishing a cohesive framework for scientific endeavors aimed at addressing the research gaps previously highlighted. Indeed, the applicability of existing literature contributions to IIoT environments strongly depends on the level of realism of their underlying assumptions and characterizations. Moreover, the comparison between different solutions is possible only when they rely on common models.

Specifically, in our vision, the performance evaluation of networking protocols, algorithms, mathematical models, and other solutions is highly influenced by several key factors that characterize the industrial environment under consideration. Consequently, we will thereby describe each factor in detail, by providing indications on how to model them and examples of how to apply these rules for the considered IIoT ADs.

a) Number of Devices: The number of devices strictly depends on the type of AD. In general terms, it can be either fixed or variable. In the former case, the number is typically decided based on the number of industrial assets that should be monitored or controlled via wireless devices. However, this complete knowledge of the environment is difficult to achieve in reality as it requires indications from industrial partners. Hence, the most common approach is to consider an average number of devices per square meter, such that the total number of devices can be obtained according to a Poisson distribution.

b) Service Area: The service area is the overall physical space where the AD is applied. In the case of ADs referring to a single building (e.g.,

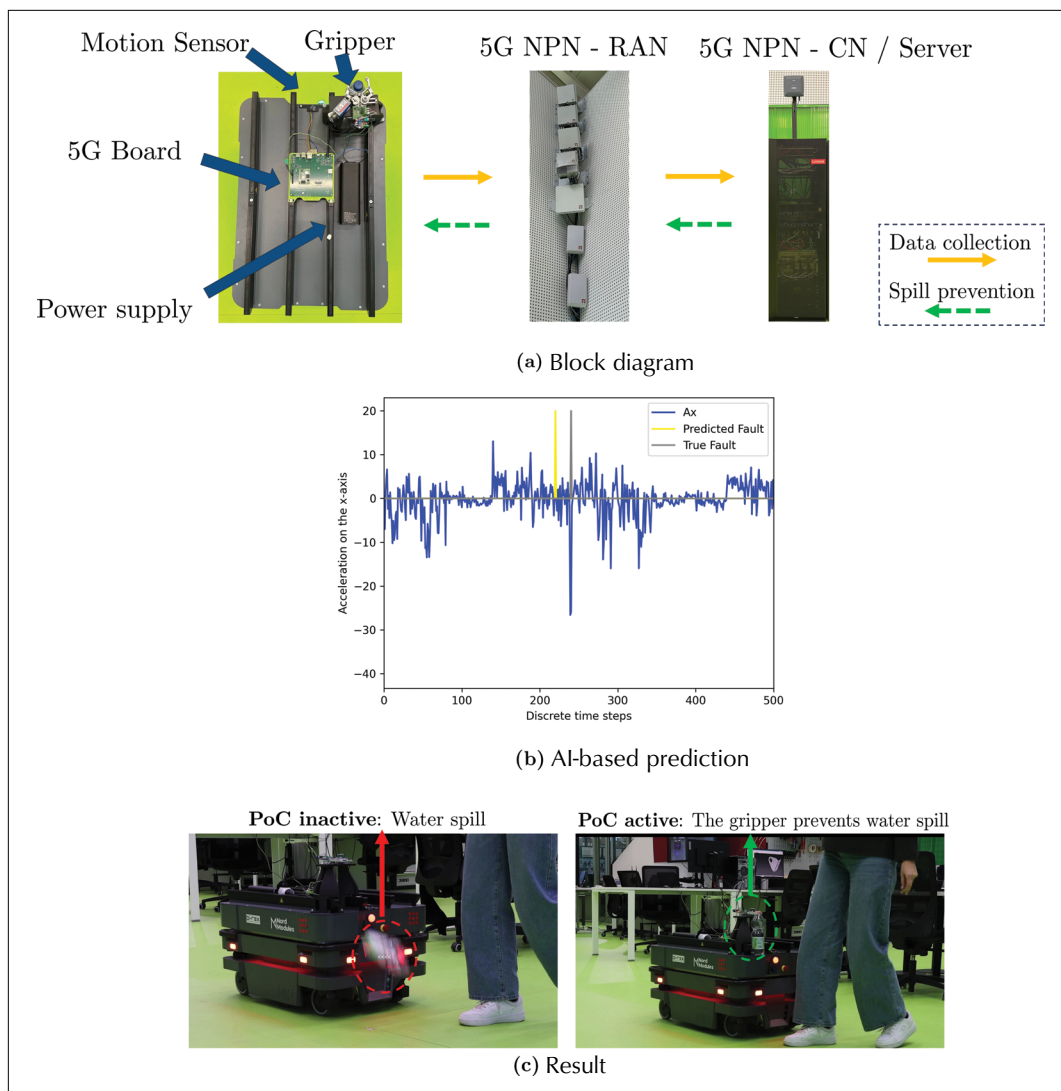


FIGURE 2. Experimental PoC for AD4. The focus of this PoC is on mitigating risks associated with an Autonomous Mobile Robot (AMR), which autonomously navigates industrial spaces and transports hazardous liquids. Although the AMR is equipped with emergency systems (e.g., proximity sensors and lasers) that trigger abrupt stops to avoid collisions, sudden braking can lead to liquid spills, posing a threat to human operators. The block diagram of the considered solution is illustrated in a). The AMR is equipped with a motion sensor, and the collected data are sent to a local 5G board powered by a power bank. The board transmits the data to a local server via a private 5G NPN, consisting of a dedicated Radio Access Network (RAN) and Core Network (CN). The local server, housed within the same rack as the 5G CN, hosts AI algorithms that process real-time motion data to predict potential spills. An example of a prediction is shown in b), where the x-axis acceleration (A_x in the legend) is plotted over time, with time discretized based on the 10 ms acquisition periodicity of the motion sensor. The yellow vertical bar indicates the instant of the anticipated AI-based prediction, while the gray label marks the actual moment of the spill. When a risk is detected, the AI system utilizes the 5G connection to activate a custom-built gripper to secure the liquid (represented in our tests by a water bottle), thereby ensuring operator safety and maintaining operational efficiency. In c), the left image shows the result when the PoC is inactive (i.e., the water bottle falls due to a sudden obstruction), while the right photo demonstrates how the proposed IIoT solution successfully prevents this outcome by accurately predicting the spill and activating the gripper in advance.

AD1), the typical building size ranges from 100 m² to 1 km², whereas the building height is from 5 m to 25 m [3]. Conversely, when considering entire factories (e.g., AD4), the service area can be much larger, i.e., up to 100 km². These reference numbers are drawn from both existing literature, and real industry plants¹.

c) Device Distribution: An important key factor when characterizing the industrial ADs refers to the spatial models, that is, indicating how the devices can be located in the service area. Similar to the considerations made for the number of devices, the most common spatial distribution models are deterministic or random. In the former case, additional knowledge of the

industrial environment is needed (e.g., the position of the industrial assets), whereas, in the latter case, devices are typically distributed uniformly in either the entire service area or spatially limited in specific regions of the factory and/or building (e.g., when considering sensors mounted on a given machine). Notice that joint considering of both a random number and spatial distribution of devices entails contemplating a Poisson Point Process (PPP). It is worth highlighting that BSs should rather be situated deterministically to provide a sufficient level of coverage to all devices.

d) Mobility: Information regarding the potential speed and movement types of the different industrial entities enhances the ability to

¹ See, e.g., those affiliated with the BIREX Competence Center for the Industry 4.0, which can be accessed at: <https://bi-rex.it/en/partners/>.

characterize specific aspects, such as the radio channel, which in turn impacts network performance. In industrial environments, there are mainly three types of mobility. Devices can be (i) stationary (e.g., motion controllers or MCPs for AD1 and AD3), (ii) moving along pre-defined routes (e.g., AGVs for AD4) or (iii) moving in a correlated way (e.g., UAVs for AD4). Besides the straightforward characterization of case (i), the most common mobility model for case (ii) is the random walk stochastic process, where devices move from their current location by randomly choosing direction and speed. Typically, the speed is chosen randomly from 10 to 70 km/h [4]. Regarding case (iii), the most common correlated mobility models fall into two main categories: i) reference-based models, such as the Reference Point Group Mobility (RPGM) model, that determine the positions of devices with respect to the trajectory of a common reference point; ii) behavioral models, where the correlation between mobility patterns emerges by the application of a common set of rules to all devices. Recently, models that merge the simplicity of reference-based models with the accuracy and flexibility of rule-based models were also proposed [12].

e) Traffic Models: The modelling of traffic types is another fundamental aspect to be considered. It describes how data are generated by devices. Typically, data generation by a traffic source is modeled as a stochastic process with two main random variables, (i) size of the generated data (i.e., MS), and (ii) time interval between two subsequent data generation instants (i.e., TI). The values of MS and TI can be either fixed according to specific KPIs (see Table 2), or variable. In the latter case, the distribution of MS and TI is typically obtained by collecting traffic traces and analyzing the behavior of real industrial applications. Alternatively, common stochastic models such as Poisson, Negative Exponential, and Generalized Beta distributions are commonly employed. Intriguingly, spatio-temporal Markov Decision Processes also serve as a viable representation of the correlations among data generated by proximate devices (e.g., sensors associated with the same industrial machine) [13].

f) Channel Models: Industrial environments possess distinctive characteristics that render wireless propagation inherently unique and distinguishable from other radio channels. Typically, industrial premises exhibit larger dimensions and/or greater height compared to office or residential buildings. Furthermore, the size, density, and spatial distribution of industrial equipment can vary significantly from one case to another but, on average, constitute a highly dense scatterer environment. In light of these peculiarities, it becomes imperative to tailor channel models to suit industrial scenarios adequately. For instance, the 3GPP has proposed a path loss model specifically designed for indoor factories² [14]. However, more detailed wideband approaches can be obtained by leveraging (i) ray-tracing tools, as propagation in factories is likely to be more site-specific than propagation in usual residential or office environments, (ii) channel measurements, as a proper calibration method for ray-tracing tools, or (iii) the utilization of AI.

Indeed, the latter is recently gaining attention to discern the intricate relationship between common propagation markers and the key properties of industrial environments [15].

We would also like to remark that experimental validation of models is inherently challenging in complex industrial systems due to limitations in current measurement techniques and data acquisition methods, which often struggle to capture the multidimensional interactions and dynamic behaviors necessary for comprehensive validation.

CONCLUSION

In this article, we presented a comprehensive characterization of the IIoT framework, a key enabler of the emerging fourth industrial revolution. Our focus included clarifying the diverse and sometimes conflicting contributions from entities like 3GPP and 5G-ACIA in terms of nomenclature, ADs, KPIs, and traffic types. After a careful literature analysis, we also outline the main IIoT requirements by harmonizing heterogeneous terminologies. Most importantly, we offered an overview of the main research topics and challenges within the IIoT paradigm according to the evolution of mobile radio networks, highlighting the potential for innovative industrial applications. Finally, we proposed modeling guidelines as a foundational framework for future research endeavors, addressing the identified research directions towards next-generation IIoT.

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² It is noteworthy that the term "factory" in 3GPP corresponds to the term "building" used in this article.

BIOGRAPHIES

GIAMPAOLO CUOZZO (Member, IEEE) (giampaolo.cuozzo@wilab.cnit.it) received the B.S. degree (Hons.) in electronics and telecommunications engineering from the University of Bologna in 2017, the M.S. degree (Hons.) in telecommunications engineering in 2019, and the Ph.D. degree in electronics, telecommunications, and information technologies engineering (ET-IT) in 2022. He is currently the Head of Research with the National Laboratory of Wireless Communications (WiLab), CNIT (the National, Inter-University Consortium for Telecommunications). His research interests include the study, development, and validation of 6G networks for the Industrial Internet of Things.

ENRICO TESTI (Member, IEEE) (enrico.testi@unibo.it) received the M.S. degree (magna cum laude) in electronics and telecommunications engineering for energy and the Ph.D. degree in electronics, telecommunications, and information technologies engineering from the University of Bologna, Italy, in 2018 and 2022, respectively. He is currently a Junior Assistant Professor with the Department of Electrical, Electronic, and Information Engineering "Guglielmo Marconi," University of Bologna. His research interests include artificial intelligence techniques for next-generation wireless networks, massive MIMO, and the satellite IoT.

SALVATORE RIOLO (Member, IEEE) (salvatore.riolo@unict.it) received the M.S. degree (Hons.) in telecommunications engineering and the Ph.D. degree in systems, energy, computer and telecommunications engineering from the University of Catania, Italy, in 2017 and 2021, respectively. He has been a Junior Assistant Professor of telecommunications with the Department of Electrical, Electronics and Computer Engineering (DIEEI), University of Catania, since January 2022. His scientific research interests include radio resource management for B5G/6G networks, massive machine-type communications, and the convergence of artificial intelligence with radio access networks.

LUCIANO MIUCCIO (Member, IEEE) (luciano.miuccio@unict.it) received the M.S. degree (Hons.) in telecommunications engineering and the Ph.D. degree in systems, energy, computer and telecommunications engineering (with the additional label of "Doctor Europaeus") from the University of Catania in 2018, and 2022, respectively. He is currently a Junior Assistant Professor with the Department of Electrical, Electronics and Computer Engineering, University of Catania. His scientific research interests include green networking, NOMA techniques, and AI for B5G/6G radio resource management.

GIANLUCA CENA (Senior Member, IEEE) (gianluca.cena@ieiit.cnr.it) received the M.S. degree in electronic engineering and the Ph.D. degree in information and system engineering from the Politecnico di Torino, Italy, in 1991 and 1996, respectively. Since 2005, he has been the Director of Research with the National Research Council of Italy (CNR-IEIIT). His research interests include wired and wireless industrial communication systems, real-time protocols, and automotive networks. Since 2009, he has been an Associate Editor of IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS.

GIANNI PASOLINI (Member, IEEE) (gianni.pasolini@unibo.it) received the M.Sc. degree in telecommunications engineering and the Ph.D. degree in electronic engineering and computer science from the University of Bologna, Italy. He is currently an Associate Professor with the University of Bologna, where he has been teaching telecommunications courses since 2003. His research interests include wireless communication systems, the Internet of Things, digital signal processing, and THz communications. He is a Founding Member of the National Laboratory of Wireless Communications (WiLab), National Inter-University

Consortium for Telecommunications (CNIT). He serves as an Associate Editor for IEEE OPEN JOURNAL OF THE COMMUNICATIONS SOCIETY.

LUCA DE NARDIS (Member, IEEE) (luca.denardis@uniroma1.it) was a Post-Doctoral Fellow with the University of California at Berkeley, Berkeley, in 2007. He is currently an Associate Professor with the Department of Information Engineering, Electronics and Telecommunications, Sapienza University of Rome. He authored or co-authored over 120 international peer-reviewed publications. His research interests include cognitive communications, medium access control, routing protocols, and wireless positioning systems.

DANIELA PANNO (Member, IEEE) (daniela.panno@unict.it) received the M.S. degree (Hons.) in electrical engineering from the University of Catania, Italy, in 1989, and the Ph.D. degree in electronic engineering and computer science engineering from the University of Palermo, Italy, in 1993. Since 1998, she has been an Associate Professor of telecommunications at the University of Catania. Her current research interests include the massive IoT scenarios, green networking, and AI-based radio resource management for B5G/6G networks.

MARCO CHIARI (Fellow, IEEE) (marco.chiani@unibo.it) has been a Frequent Visitor with the Massachusetts Institute of Technology (MIT), Cambridge, MA, USA, since 2003, where he holds a Research Affiliate appointment. He is currently a Full Professor of telecommunications with the University of Bologna. His research interests include information theory, wireless systems, statistical signal processing, and quantum information. He received the 2011 IEEE Communications Society Leonard G. Abraham Prize in the Field of Communications Systems, the 2012 IEEE Communications Society Fred W. Ellersick Prize, and the 2012 IEEE Communications Society Stephen O. Rice Prize in the Field of Communications Theory.

MARIA-GABRIELLA DI BENEDETTO (Fellow, IEEE) (mariagabriella.dibenedetto@uniroma1.it) is currently a Full Professor in telecommunications with the Sapienza University of Rome. She is also a Research Affiliate with the Research Laboratory of Electronics (RLE), Massachusetts Institute of Technology (MIT). Her research interests include wireless communication systems, impulse radio communications, and speech. She is a fellow of the Radcliffe Institute for Advanced Study, Harvard University, Cambridge, MA, USA. In 1994, she received the Mac Kay Professorship Award from the University of California at Berkeley.

ENRICO BURACCHINI (enrico.buracchini@telecomitalia.it) was an Electronic Engineer with Telecom Italia in 1994, with the focus on radio innovation across various locations of the company, including Italy, Austria, Greece, and Spain. Currently, as a Senior Project Manager, he coordinates the activities related to the evolution of 5G, having managed the project and several trials, including one in San Marino. Furthermore, as an Expert Speaker, he collaborates with TIM's Business Directorate in meetings with clients interested in 5G solutions. He also represents TIM in international standardization groups, including 3GPP RAN1 and ITU R 5D.

ROBERTO VERDONE (Senior Member, IEEE) (roberto.verdone@unibo.it) has been a Full Professor with the University of Bologna, since 2001. He is currently the Director of WiLab, the Italian Laboratory of Wireless Communications of CNIT. He is also the Co-Director of the Joint Innovation Center on "Intelligent IoT for 6G," Huawei. He published 200 scientific articles and a few books on various aspects of wireless communications. His main research interests include evolution from 5G to 6G and the Internet of Things.