IoT

Review

AI-Inspired Non-Terrestrial Networks for IIoT: Review on Enabling Technologies and Applications

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Abstract: During the last few years, various Industrial Internet of Things (IIoT) applications have emerged with numerous network elements interconnected using wired and wireless communication technologies and equipped with strategically placed sensors and actuators. This paper justifies why non-terrestrial networks (NTNs) will bring the IIoT vision closer to reality by providing improved data acquisition and massive connectivity to sensor fields in large and remote areas. NTNs are engineered to utilize satellites, airships, and aircrafts, which can be employed to extend the radio coverage and provide remote monitoring and sensing services. Additionally, this paper describes indicative delay-tolerant massive IIoT and delay-sensitive mission-critical IIoT applications spanning a large number of vertical markets with diverse and stringent requirements. As the heterogeneous nature of NTNs and the complex and dynamic communications scenarios lead to uncertainty and a high degree of variability, conventional wireless communication technologies cannot sufficiently support ultra-reliable and low-latency communications (URLLC) and offer ubiquitous and uninterrupted interconnectivity. In this regard, this paper sheds light on the potential role of artificial intelligence (AI) techniques, including machine learning (ML) and deep learning (DL), in the provision of challenging NTN-based IIoT services and provides a thorough review of the relevant research works. By adding intelligence and facilitating the decision-making and prediction procedures, the NTNs can effectively adapt to their surrounding environment, thus enhancing the performance of various metrics with significantly lower complexity compared to typical optimization methods.

Keywords: deep learning (DL); high-altitude platforms (HAPs); industrial internet of things (IIoT); machine learning (ML); satellite networks; unmanned aerial vehicles (UAVs)

1. Introduction

The fifth-generation (5G) and beyond 5G (B5G) vision does not only represent a significant upgrade of mobile broadband communications, but it will bring new unique network and service capabilities towards the evolution of Internet of Things (IoT) [1,2]. The IoT is an information network that encompasses a large family of applications and transparently enables the deployment of a massive number of often miniaturized, low-cost, low-complexity, and low-power interconnected physical objects, generally referred to as machine-type devices (MTDs), which interact and cooperate without human intervention. As the consumer-focused IoT is exponentially expanding around the world, its strong potential in critical applications in the industrial sector, for which the term Industrial IoT (IIoT) is typically used, becomes more explicit [3,4]. The IIoT, a sub-segment of the IoT, is the latest catalyst to process automation and was introduced by General Electric. By integrating ultra-low power sensors interacting with data processing, micro-controller units (MCUs), advanced network and communication technologies, as well as powerful cloud-based analytics, IIoT intends to enable cyber-physical systems (CPSs). Applying IIoT and CPSs to the industrial domain brings closer the physical machines and the digital world and facilitates the autonomous prediction of failures, the triggering of the maintenance processes, and the provision of self-organized logistics to respond to the changes in the production. IIoT also enables the realization of the Industry 4.0 concept, where 4.0 represents the fourth industrial revolution relying on advanced intelligent networking technologies [5].

The industrial applications cover a broad spectrum of use cases and each one has its own set of challenges. On the one hand, a wide variety of licensed or unlicensed industrial, scientific, and medical (ISM) standard microwave or millimeter-wave (mm-wave) frequencies should be used on a global, regional, or national basis, in order to establish wireless connections in the era of IIoT depending on the requirements and the limitations of each application scenario [6]. At these frequencies, advanced antennas should be designed to address the sensing and detection/tracking of objects, as well as the onward transmission over the wireless IIoT networks. In this respect, antenna attributes, such as compactness, simplicity, low-cost, stability, directivity, wider beam-scanning, radiation efficiency, and mutual-coupling between the radiating elements, are of great importance. Therefore, metamaterial-based leaky-wave antennas (LWA) [7], planar broadband antennas based on meandered line loops [8], wideband printed monopole antennas [9], and densely packed array antennas with embedded metamaterial electromagnetic bandgap (EMBG) structures [10] represent candidate antenna solutions. On the other hand, the endmost goal of shaping an IIoT ecosystem is the creation of a network of remoted factories that can effectively and autonomously adapt to production requirements and share their resources. Besides the above, some special IIoT applications would require coverage in rugged and remote locations, e.g., desert, valley, ocean, and forest, beyond the indoor and outdoor radio coverage of conventional cellular networks. In such situations, there exist commercial and engineering difficulties of exclusively constructing and/or exploiting terrestrial networks and obtaining connectivity with reasonable capital expenditure (CAPEX) and operation and maintenance expenditure (OPEX).

To achieve ubiquitous connectivity and materialize the vision of IIoT, supplementing and extending the terrestrial communication networks is indispensable [11]. In this context, non-terrestrial networks (NTNs) constitute the driving infrastructure to obtain global IIoT and extend radio coverage by exploiting the available degrees of freedom from both the space- and air-based nodes [12–14]. Nevertheless, integrating NTNs in ultra-dense heterogeneous networks (UDHNs) [15,16] with a density of possibly thousands of nodes per square kilometer and applying innovative physical layer (PHY) techniques cannot be directly feasible. The reasons are the special features of the spaceborne and airborne platforms, the particularity of the propagation environment, as well as the problems imposed by the underlying radio propagation channels. As far as complex, dynamic, and mission-critical communication scenarios with requirement for ultra-reliable and low-latency communications (URLLC) are concerned, artificial intelligence (AI) [17–19] can revolutionize the decision-making processes with respect to the maintenance of the radio connections as well as the processing and distribution of data. Specifically, AI includes a number of sophisticated algorithms, techniques, and methods and achieves the emulation of the human brain reasoning process, enabling the ability to extract specific knowledge and repeating motifs from a series of observations. In Figure 1, the key enablers of the NTN-based IIoT landscape are synopsized with the intelligence introduced by the AI-based methods, providing real-time insights and allowing IIoT core elements to reach their full potential. These key enablers should be harmonically combined and coordinated to satisfy the individual demands of each application scenario and stand for the cornerstone for future IIoT applications.

This ambiguous landscape regarding the NTNs, IIoT, and AI has motivated the present review paper, whose contribution is twofold. Firstly, this paper aims to shed light on the NTN-based IIoT and provide an overview of emerging IIoT applications. Secondly, this paper underlines the unique challenges that arise when implementing IIoT scenarios and investigates the adoption of AI techniques. To the best of the authors' knowledge, previous relevant surveys and tutorials considered only airborne platforms and AI methods, without emphasizing the IIoT applications and principle. More specifically, these works studied the communication aspects [20], the design of radio access networks (RANs) [21], the interference management [22], the object detection and image recognition [23,24], the trajectory and placement [25], and the planning, motion control, and situational awareness [26]. On the contrary, this paper focuses on the deployment of a wide range of AI techniques on both spaceborne and airborne platforms exclusively for the IIoT, describes the benefits of these techniques in specific IIoT scenarios, and identifies fertile research areas.

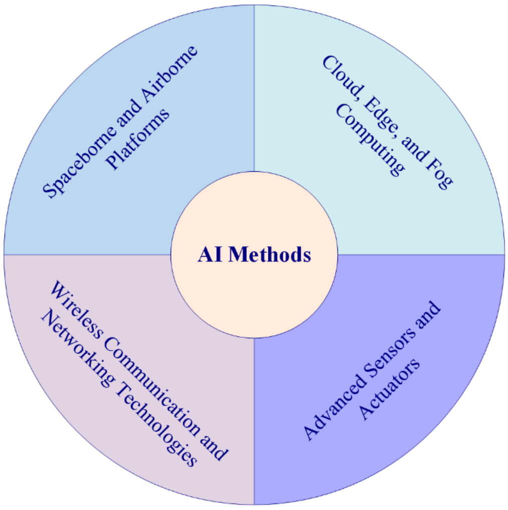

Figure 1. Key enablers for globally accelerating the adoption of non-terrestrial network (NTN)-based Industrial Internet of Things (IIoT).

The rest of the paper is organized as follows. Section 2 focuses on the indispensability of the wireless communication technologies within factory halls. Section 3 categorizes the types of aerospace communication technologies, emphasizes their advantages, and presents the state of art in advanced wireless techniques for NTNs. Section 4 outlines potential IIoT applications and services. Section 5 underlines the challenges of the NTN-based IIoT and highlights the advanced AI technologies that intend to enrich its capabilities. Section 6 surveys recent research work on AI methods for NTN-based IoT and underlines open research issues. Finally, conclusions are drawn in Section 7.

2. Integration of Wireless Connectivity into the Industrial Domain

To provide IIoT services and massive machine type communications (mMTC) [27] supporting millions of IoT devices with intermittent activity and transmission of small data packets, advanced information, network, and communication technologies should be adopted by traditional industries. The convergence between industrial networks and traditional networks is also known as IT/OT convergence, where the operational technology (OT) refers to highly reliable and secure industrial networks and products, and information technology (IT) refers to the Internet and the end-to-end (E2E) flow control [28]. Similar to the IoT, the notion of IIoT relies on the availability of radio connections among the devices within an industrial environment. In massive IIoT, the data transmission is infrequent and not persistent, whereas the latency requirements are not tight. However, in mission-critical IIoT applications, system designers should consider a number of factors regarding the ubiquitous connectivity of the vast number of devices to guarantee the end-user experience and prevent failures and severe consequences in a systematic, secure, and cost-effective manner. More specifically, critical IIoT goes beyond massive IIoT and enhanced mobile broadband (eMBB), which aims at maximizing the data throughput without ensuring extremely low latency radio access and high E2E reliability [29]. Additionally, safeguarding the operation of IIoT against cyber-physical attacks is requisite. Figure 2 depicts the main requirements of critical IIoT applications.

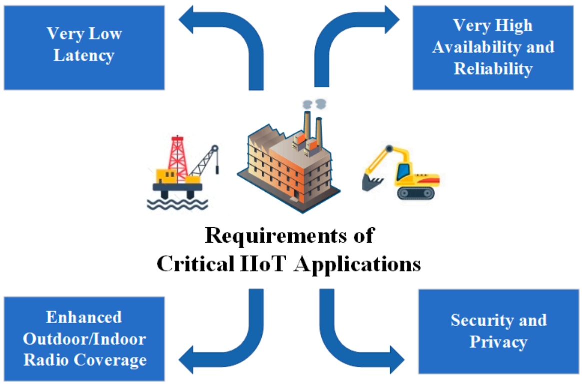

Figure 2. Key design requirements of critical IIoT, enabling efficient and innovative services across a wide range of industry verticals.

Although the majority of the devices in an industrial environment can be interconnected through homegrown wired technologies, e.g., Fieldbus technology [30], the most progressive manufacturers have started to integrate wireless Internet protocol (IP)-enabled solutions for industrial sensing and control systems. The introduction of short- and long-range wireless communications for locally and remotely connected IIoT entities, respectively, enhances flexibility, improves security, and significantly reduces the operational cost for deployment and maintenance, while driving new revenue through IIoT-based solutions. For localized IIoT scenarios, short-range networks based on wireless industrial standards, including ISA100.11a and WirelessHART, are the most convenient, since they take advantage of the unlicensed spectrum and maximize the battery life [31]. Other wireless standards and protocols providing limited range and low-power consumption, such as wireless fidelity (Wi-Fi) HaLow based on Institute of Electrical and Electronics Engineers (IEEE) 802.11ah, IPv6 over low-power wireless personal area networks (6LoWPAN), ZigBee, Bluetooth low energy (BLE), and near field communication (NFC), may suffice depending on the application requirements. Besides the above, exploiting current and future conventional cellular networks and low-power wide area network (LPWAN) 3rd Generation Partnership Project (3GPP) standards, e.g., Extended Coverage-Global System for Mobile Communications for the IoT (EC-GSM-IoT), Narrowband-IoT (NB-IoT), and Long-Term Evolution for Machines (LTE-M), as well as non-3GPP standards [6], e.g., Long Range (LoRa) and SigFox, could satisfy the needs for long-range communication of IIoT applications in the near term. Currently, terrestrial wireless networks offer a limited radio coverage of approximately 20% across the territories of China and U.S. [32].

3. NTNs for IIoT Applications

In IIoT applications, the effective wireless connectivity is not only requisite for the data transmission between the multiple nodes but also represents a key factor to ensure the safety of personnel or citizens in remote locations, especially in cases with environmental hazards or in emergency situations. As previously mentioned, the IIoT can exploit both 3GPP cellular-based and non-3GPP license-free terrestrial infrastructures. The former allows for large-scale device deployments aided by the mobile network operators and supports widely adopted wireless standards. However, a huge number of base stations is indispensable for global radio coverage. In addition, the terrestrial communication infrastructure is sensitive to natural disasters, e.g., earthquakes and floods. To further extend the IIoT connectivity into remote and industrialized areas and enhance the reliability and resiliency of services, the aerospace infrastructure should be leveraged. NTNs are capable of simultaneously interconnecting a massive number of devices that struggle for connectivity, while ensuring the successful management of data-intensive applications, redundant connections at critical sites, low latency, and enhanced capacity. In addition, NTNs represent an ideal fit for supervisory control and data acquisition (SCADA), since they ensure the delivery of wireless services in challenging environments with highly mobile and dispersed nodes.

The successful operation of space-air-ground integrated networks (SAGINs) that provide connectivity for the IIoT envisages the synergetic and seamless integration of heterogeneous wireless networks with distinct capabilities [33]. From a wireless communications engineering standpoint, the heterogeneity of the aforementioned networks corresponds to highly variable service requirements with respect to key metrics, such as the E2E communication delay and the data traffic. Since reliable communications are a prerequisite for critical IIoT applications, the choice of appropriate types of satellites and aerial platforms, such as those described below, heavily depends on the size, altitude, mobility issues, autonomy level, and specific application needs. Figure 3 demonstrates a SAGIN consisting of heterogeneous communication infrastructures and multiple network segments in space, air, and ground for cost-effective, flexible, and large-scale IIoT applications and services, e.g., Earth observation, navigation, and telecommunications. In this envisioned and promising SAGIN-based paradigm, satellite-to-ground (S2G), satellite-to-air (S2A), air-to-air (A2A), air-to-ground (A2G), and ground-based radio links exist, whereas typical limitations posed by single network segments are effectually resolved.

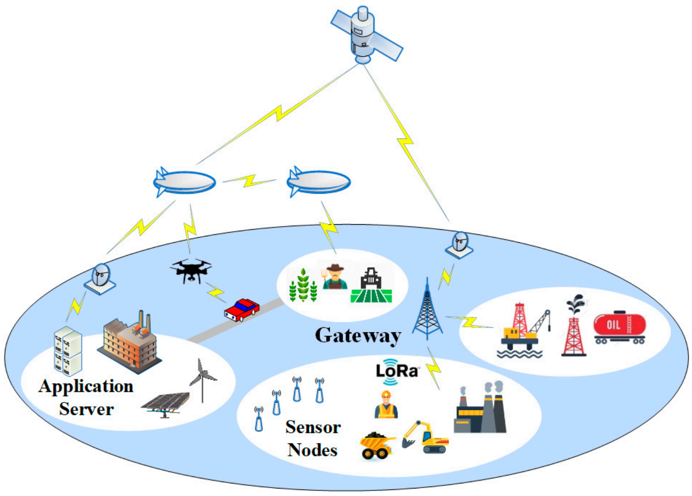

Figure 3. Simple representation of a space-air-ground integrated network (SAGIN) for IIoT applications that includes space, air, and ground network components and aims at cooperatively expanding radio coverage over large areas and facilitating the collection, as well as the coordination, of multi-dimensional data.

3.1. Overview on Spaceborne Platforms for IIoT

Satellites constitute the main representative of NTNs and refer to spaceborne vehicles in low earth orbit (LEO), medium earth orbit (MEO), geostationary earth orbit (GEO), or in highly elliptical orbit (HEO). Over the past 30 years, satellites have been typified as the unique means of achieving global coverage. More importantly, satellites can potentially promote mMTC [34] and the Internet of Remote Things (IoRT) [35] when terrestrial constraints in terms of connectivity exist over a wide geographical area. A typical example of IoRT is the global sensor network (GSN) for remote environment observation, where massively connected IoT sensor networks are connected via LEO satellites [36]. Aiming at evolving the satellite technology with regard to IoT and realizing the Internet of Space Things (IoST) [37], Iridium Communications Inc., McLean, VA, USA, a major commercial solution provider, has launched Iridium NEXT satellites for Earth and space sensing, supporting payloads of up to 50 kg, called SensorPODs. Besides this, Inmarsat, as the leader in global mobile satellite communications services, predominantly used the L-band (1–2 GHz), which supports an extremely low data rate for IoT applications. As IIoT takes hold over the next few years, the network traffic will be significantly increased. Moreover, large data volumes generated from multiple sensors should be aggregated to perform prescriptive and predictive analytics and provide real-time services, such as surveillance and monitoring using closed circuit television (CCTV). Hence, a higher bandwidth technology, notably Ka- and Ku-bands, will facilitate the establishment of a broad range of satellite-based IIoT applications. High throughput satellites (HTS), e.g., ViaSat-1 and EchoStar XVII, operating at the Ka-band, provide more than 100 Gbps of throughput. Although the majority of IIoT scenarios may not require such throughput performance, the significant benefit of Ka/HTS is the dramatic reduction in the transmission cost-per-bit. With the exploitation of the Ku-band, the large number of open Ku-band satellites can be leveraged and ensure lower spectrum cost than L-band. Although using Ka- and Ku-bands seems beneficial, rain substantially affects signal propagation in mm-wave frequencies and a dominant line-of-sight (LoS) signal is required for sufficient radio coverage due to the severe attenuation of the non-line-of-sight (NLoS) links. Since the utilization of the IPv6 is a precondition for the successful deployment of IIoT systems leading to the huge number of simultaneously interconnected nodes, the Digital Video Broadcasting—Return Channel via Satellite—Second Generation (DVB-RCS2) standard supports this protocol [38], whereas the DVB-RCS2+M standard adds mobile and mesh capabilities.

The realization of IIoT and machine-to-machine (M2M) communications can be further reinforced owing to the investments in terrestrial segment technologies, i.e., compact, electronically steerable, and/or phased-array transceivers, as well as the cost-effective CubeSat platforms [37,39] based on micro-, nano-, and pico-satellites, operating as access points. Based on the Northern Sky Research (NSR), the satellite IoT (S-IoT) market will include more than 5.3 million terminals by 2024, whereas the European, Middle Eastern, and African (EMEA) market is expected to reach US$495 million in revenue by 2024. In the context of S-IoT applications, Inmarsat was the first to join the LoRa Alliance as its first satellite member and combine a low-power, low-data-rate, long-range, wide area network (LoRaWAN) on the ground with a satellite mesh in the sky. Actility, an industry leader in LPWAN, has recently become part of Inmarsat's Certified Applications Provider Programme (CAPP). Aided by this partnership, a global L-band satellite connectivity platform can be effectively combined with Actility's ThingPark IoT management platform. Hence, an integrated solution for IIoT can be provided by third-party companies which are in compliance with the specifications of Inmarsat's satellite network.

Although the satellite networks have a huge initial cost, they still constitute the exclusive means of wireless connectivity in traditional maritime and aeronautical markets. The spaceborne networks can support navigation, Earth observation, emergency rescue, and communication/relaying as well as strongly enhancing the terrestrial backhaul networks. HTS can provide effective backhauling of aggregated IIoT traffic and transfer data from LPWANs nodes to cloud platforms. GEO satellites are widely available and can enable multicast/broadcast and trucking of video and other data across a large area or a central site while providing data distribution to local cell sites. LEO satellite constellations require less on-the-ground power and smaller antennas due to the significantly lower orbit altitude (normally lower than 2000 km) and smaller propagation losses. Since most IoT terminals are small-sized and energy-constrained, the aforementioned benefits of LEO satellites are substantial. The CubeSats are also expected to contribute to the cost-effective and extended radio coverage for the IIoT operating at relatively low altitudes, i.e., <1000 km, without suffering from the traditional satellite drawbacks, e.g., long development cycles, high costs, increasing congestion, lack of sequential redundancy, and high-risk exposure [37,39]. In addition, the form factor of CubeSats, typically $10 \times 10 \times 10$ cm^3, allows for the integration of accurate attitude determination and control systems (ADCS) and effective solar panels, which in turn increases the range of applications. However, constellations with multiple CubeSats in several orbital planes are indispensable for extended coverage due to the small footprint of a single CubeSat. Satellites have also a major role in assisting IIoT systems to meet low latency requirements. Although GEO satellites' latency of 250 ms (500 ms round-trip time—RTT) is acceptable for many IIoT applications and is comparable with the RTT of a long terrestrial link (100–200 ms), MEO and LEO satellite constellations allow for lower latency in the special case of voice and video transmission (less than 100 ms RTT). The competence of satellite networks in terms of the latency, even in the case of harsh propagation conditions, is partially due to the adoption of adaptive coding and modulation (ACM), as foreseen in the DVB—Satellite—Second Generation (DVB-S2) standard.

3.2. Overview of Airborne Platforms for IIoT

Beyond satellites, NTNs indicate networks or segments of networks with high- and low-altitude platforms (HAPs/LAPs) or airborne vehicles acting as aerial transceivers that operate at altitudes ranging between 8 and 50 km above ground level [40–42]. The term HAP defines both aircrafts flying in a roughly circular tight path in the stratosphere layer and quasi-stationary, solar-powered, non-pollutant, and environmentally friendly airships [43]. Besides the above, LAPs fly at lower altitudes, in the troposphere, and intend to accomplish diverse missions. Among them, unmanned aerial vehicles (UAVs) [44] constitute a type of small fueled aircraft employed for short time periods and allow for a rapid relay-based deployment of a multi-hop communication backbone [45]. Indicative types of UAVs are drones, remotely piloted vehicles (RPVs), pilotless aircrafts, and robot planes, whose size may significantly differ. Since the links of terrestrial systems are often blocked, aerial platforms have great potential to attain a higher chance of LoS communication with the ground users and thus enhance the coverage and connectivity. It is also noted that flying ad-hoc networks (FANETs) among aerial platforms are also envisioned [46], owing to possible connectivity and coverage restrictions of terrestrial and/or satellite networks. Prospective 5G, B5G, and IIoT systems are expected to include UAVs as autonomous communicating nodes or aerial relays for attaining highly reliable connections between sensors and data collection points at high elevation angles and across urban, suburban, and rural terrains [47]. Both HAPs and LAPs can be rapidly deployed and moved on-demand and can also carry a range of sensors, including geospatial sensor technologies gathering massive amounts of valuable data [41]. To retain the high level of stability required for critical IIoT applications and prevent displacements in any direction (e.g., roll, pitch, and yaw effects) due to wind and pressure variations, flight control tilt sensors along with accelerometers and gyroscopes can be exploited, combined with ultrasonic sensors for obstacle avoidance. These aerial platforms may be supplied with electro-optical sensors and radars, achieving adequate resolutions for data acquisition purposes. To enhance the surveillance and monitoring applications, low- or high- resolution red-green-blue (RGB) cameras are required, whereas normalized difference vegetation index (NDVI) cameras are recommended for unrivalled precision farming. Moreover, UAV-based light imaging, detection, and ranging (LIDAR) is suggested for efficient mapping and localization [48]. Besides this, the hyperspectral depth and thermal sensors facilitate the creation of aerial thermal imaging for analysis and reporting. Moreover, 3GPP suggested the deployment of aerial platforms for Long-Term Evolution (LTE) standard [49], whereas the notion of the nomadic relay was proposed by the IEEE 802.16s Relay Task Group [50]. In 2016, the Radio Technical Commission for Aeronautics (RTCA) aspired to introduce UAVs into the national airspace system [51]. The National Aeronautics and Space Administration (NASA) and Federal Aviation Administration (FAA) have also cooperatively considered the integration of UAVs into the airspace system of United States [52], while in Europe, Single European Sky ATM Research (SESAR) has intended to meliorate air traffic management (ATM) in order to overcome challenges arising from large UAV swarms and the different types of UAVs [53]. In this regard, a UAV swarm network architecture with multiple layers for IoT scenarios was presented in [54], and a low-latency routing algorithm (LLRA) was proposed that relies on the position and the connectivity of the UAVs. From an industry perspective, Google has recently initiated Project Loon, which aims at leveraging balloons in high altitudes as a means of provision of broadband services in remote locations [55]. Moreover, Facebook [56] has attempted to use solar-powered drones to serve Internet access to underdeveloped or sparsely populated countries. Additionally, Microsoft has deployed balloons equipped with cameras and sensors that wirelessly communicate with the Azure IoT platform in order to send the telemetry data to the field gateway through the constrained application protocol (CoAP) [57]. Qualcomm has also investigated the use of UAVs for fourth-generation (4G) communications and beyond [58]. Table 1 provides a perspective on available communication technologies that are capable of extending the coverage for the IIoT.

Table 1. Comparison of long-range terrestrial and non-terrestrial communication technologies.

	Terrestrial Networks		Non-Terrestrial Networks					
			Spaceborne				Airborne	
	Cellular	**Low-Power Wide Area Network (LPWAN)**	**Geostationary Earth Orbit (GEO)**	**Medium Earth Orbit (MEO)**	**Low Earth Orbit (LEO)**	**CubeSats**	**High-Altitude Platform (HAP)**	**Low-Altitude Platform (LAP)**
Altitude (km)	-	-	35,786	3000	<3000	<1000	17-22	<15
Mobility	Static	Static	Static to Earth	Medium	High	High	Quasi-Stationary	Varying Speeds
Round-Trip Time (ms)	Lowest	Lowest	500	<100	<100	~10	Low	Low
Throughput	Medium to High	Low	Low to High	Low to High	Low to High	Low to High	Low to High	Low to High
Radio Coverage	Urban and Suburban	Urban	Global	Global	Global	Global	Global	Global
Propagation Loss	Least	Least	Highest	High	Medium	Medium	Low	Low
Network Complexity	Complex	Complex	Simple	Medium	Complex	Complex	Medium	Medium
Resources	Rich	Rich	Limited	Limited	Limited	Limited	Limited	Limited
Cost	Medium	Medium to Low	High	High	High	Medium	Medium	Medium to Low

3.3. State of the Art in Wireless Communication and Networking Technologies for NTNs

Although the mean volume of data transmitted to and from IIoT nodes may not be substantial, greater bandwidths may be imperative to meet the stringent latency prerequisite. Additionally, new requirements for enhanced spectral efficiency, higher throughput, and sufficient bandwidth continuously emerge. In this respect, the multiple-input multiple-output (MIMO) [59] and massive MIMO [60] technology can revolutionize NTNs by exploiting spatial diversity and multiplexing as well as serving multiple ground nodes through multi-user (MU) MIMO [61]. In this direction, the extension of the DVB—Satellite to Handheld (DVB-SH) [62] and DVB—Next Generation Handheld (DVB-NGH) [63] standards to introduce MIMO configurations has been suggested with minor modifications. Besides the above, the mm-wave frequencies have been proposed as key enablers of 5G and IoT systems to attain sufficient bandwidth [60]. As the performance of radar systems is limited by target scintillations, the application of MIMO techniques to synthetic aperture radars (SARs) can also greatly improve the resolution and sensitivity as well as detection and estimation performance of NTN-based applications for the IIoT by exploiting the diversity of target scattering [64]. Data rates in the multigigabit regime can be achieved using free-space-optical (FSO) inter-satellite, inter-platform, satellite-to-platform, satellite-to-ground, and platform-to-ground connections [65,66]. Additionally, non-orthogonal multiple access (NOMA) represents a promising solution to facilitate the evolution of mMTC and improve the spectral efficiency by enabling non-orthogonal data transmission and exploiting successive interference cancellation (SIC) [42]. To update the quality of service (QoS), mobile-edge computing (MEC) represents a promising candidate technology [67]. The extension of MEC by exploiting the advances of NTNs can be performed in two directions: the introduction of the mobility of the MEC nodes and the multi-hop interconnection among the MEC nodes. As cloud and fog computing and networking can promote the cooperation of diverse networks, the UAVs' energy-efficient deployment for caching data in fog-based IoT systems was described in [68], focusing on a probabilistic/randomized content placement algorithm and using stochastic geometry. Additionally, software-defined radio (SDR), software-defined networking (SDN) [69], and network function virtualization (NFV) [70] could redefine the network architecture and bring flexibility and cost-efficient deployment and runtime of customized networks. In [71], SDN/NFV and microsatellite technology were integrated into the S-IoT concept, whereas SDN/NFV-enabled flying and ground moving networks were considered in [72]. The feasibility of multi-UAV SDN-enabled drone base stations (DBS) for emergency and surveillance monitoring scenarios was also studied in [73] and emphasis was placed on the effectiveness issues and cybersecurity aspects.

4. Potential IIoT Applications

A wide variety of challenging applications is foreseen for IIoT [74,75]. These applications can be categorized into two groups: the delay-tolerant ones related to mMTC and forecasting/monitoring applications and the delay-sensitive ones regarding enhanced SCADA, time-critical IIoT, and URLLC. The former ensures E2E massive connectivity and energy efficiency, but at the expense of augmented delay. More specifically, delay-tolerant applications tend to be those encompassing large land and remote or sea areas, e.g., energy and smart grid, oil and gas pipeline integrity, and tracking of mining trucks. Applications regarding disaster and crisis management in industrial environments are also worth mentioning. Despite the link with factories, manufacturing, and heavy industries, the term IIoT is also used to describe several IoT applications outside of the consumer IoT in the context of facility management, such as agriculture, transport systems, and healthcare. Figure 4 summarizes indicative types of sensors and potential applications with respect to the NTN-based IIoT.

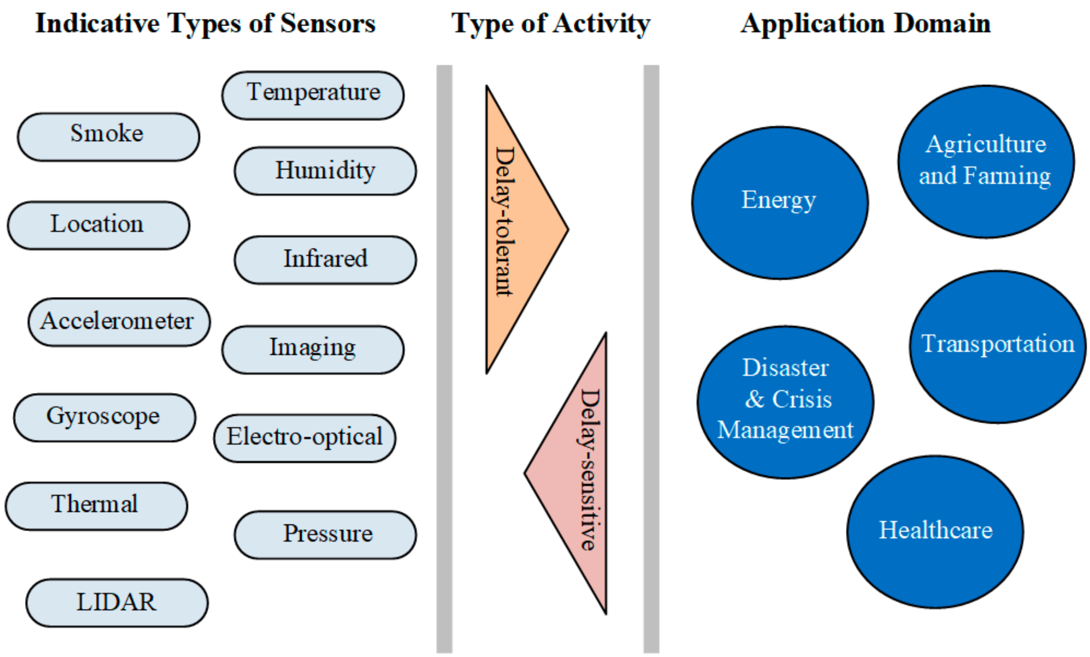

Figure 4. Various types of specialized sensors and industrial applications for the NTN-based IIoT ecosystem for both the massive machine type communications (mMTC) -based delay-tolerant and ultra-reliable and low-latency communications (URLLC) -based delay-sensitive scenarios.

4.1. Energy Applications

By employing NTNs, various electric grid automation and metering applications can be handled, whereas the incorporation and productive use of the major energy resources and the electric grid infrastructure can be supported by involving smart sensors, smart meters, and smart control [76]. In oil and gas production sites, where adverse environments and burdensome operating conditions are observed, NTNs can be also beneficial by monitoring and transmitting sensor data related to wellhead production, drilling control, distribution logistics, pipeline monitoring, and asset security. The measured operational parameters are initially transmitted to a control room. Then, using SCADA, set-points are arranged and control settings are expedited. By exploiting intelligent NTNs in energy systems together with sophisticated sensors, companies can remotely collect meaningful data and thus attain real-time vital insights into the E2E operational condition of their projects, e.g., solar panels and wind turbines, depending on the environmental conditions, and ensure that the systems work at the maximum possible efficiency. Moreover, by using remote installations of UAVs, the human inspection of the facilities would be avoided.

4.2. Disaster and Crisis Management Applications

As far as natural disasters or large-scale unexpected events occur, terrestrial networks may be overloaded or totally devastated. During these urgent situations, NTNs have the ability to provide more effective services compared to traditional infrastructures. More specifically, NTNs can successfully sustain applications, including video surveillance and structural monitoring, as well as facilitate structural monitoring and protection of critical infrastructures, e.g., dams, bridges, power stations, nuclear reactors, etc. [77]. Additionally, NTNs can strengthen security and access controls with respect to border control, flood warning, earthquake detection, early warning for possible fire disasters, weather and environmental monitoring, coastline and pipeline surveillance, and trafficability of maritime routes, e.g., detection of icebergs, and synthetic aperture radar applications. Besides the above, emergency networks via circular flight tracks of HAPs and LAPs can be realized to continuously observe regional hotspots and hazard areas or provide emergency vehicle guidance and inform rescue services [78].

4.3. Agriculture and Farming Applications

The deployment of NTNs in the agriculture and farming sector mainly targets the efficient management of water resources and irrigation systems and the monitoring of weather and climatological conditions. To succeed in these objectives, multiple sensor nodes should be deployed at different points across farming land and large remote plantations. In this direction, a LoRaWAN gateway can provide ubiquitous connectivity to these sensors and send data via satellites or aerial platforms to central cloud platforms that will then analyze this data and guide the agriculture and farming activity. This procedure intends to optimize water usage and irrigation schedules for precision agriculture, ensures consistent soil-water content for all plants, enables intelligent resource management in a particular area, and decreases the amount of land required for production purposes. Using NTNs, farming operations can also be monitored all the way from harvest to delivery [79,80]. Therefore, farmers can make better decisions about the planting and harvesting of crops. Moreover, a long-range and reliable network for the tracking of livestock and keeping sight of their location, health, and safety is also viable by using tracking devices on each one of the animals.

4.4. Transportation Applications

NTNs can ensure the safety and effective management of the transportation infrastructure and realize the Internet of Vehicles (IoV) by expanding the use of networking vehicles, sensors, and controls [81]. Specifically, the smarter use of road and rail transportation can be enabled and important applications can be supported, e.g., signaling and routing and alerts for road and weather conditions. The global positioning system (GPS) though satellites can determine the positioning of each vehicle, whereas HAPs represent a feasible solution for data acquisition in IoV, especially in rural areas. Besides the above, the monitoring of vehicular traffic via autonomous UAVs employing cameras or sensors is also viable. By taking advantage of NTNs, the operation of commercial autonomous shipping can be enabled along with future commercial marine vessels, smart ports, and cargo logistics [82].

4.5. Medical Applications

As the Healthcare IIoT (HealthIIoT) will have a remarkable influence across the IIoT-driven healthcare industry [83], NTNs can strongly support welfare and mission-critical HealthIIoT applications [84]. Apart from extending coverage through S-IoT configurations, the deployment of UAVs as wireless relays can enhance data communication in body area networks (BANs), thus facilitating the provision of low-cost and timely HealthIIoT, e.g., real-time diagnosis and prescription, in remote and inaccessible areas [85]. In this direction, UAVs can initially collect data from wearable biomedical sensors that detect abnormal health conditions and then send the information to central devices. Additionally, UAVs can be used for monitoring endemics/epidemics at any area and remotely recording people's vital signals, e.g., body temperature and heart rate, as has been proven by the recent COVID-19 outbreak [86]. Patients and the aging population can be served by NTN-based telemonitoring and medical diagnosis from their homes through IoT-powered in-home healthcare (IHH) services, whereas interaction though videoconferencing between medical personnel and patients at home is also viable. Moreover, high bandwidth links can accommodate real-time medical imaging and remote robotic surgery [87]. To further improve the interaction of users with the NTN-aided HealthIIoT, recognizing the emotions of users via AI-based methods is also foreseen [88]. However, medical information should be protected from unauthorized access and publicly posting personal information should be avoided. Hence, data protection in the form of digital watermarking and authentication is crucial in a HealthIIoT system.

5. Challenges of NTN-Based IIoT and the Emergence of AI

Although the spaceborne and airborne platforms have the potential to revolutionize the IIoT, they still try to attain maturity. The major challenges and influencing factors in enabling the successful and long-term operation of NTN-based IIoT are listed below.

- **Particularities of spaceborne and airborne platforms:** NTNs have distinctive attributes, including highly dynamic network topologies, orbits, and/or flight trajectories, as well as weak communication links among the network elements. Besides these, possible displacements of the aerial platforms in any direction and at a varying speed may take place due to the winds or pressure variations of the troposphere and stratosphere layers. There also exist on-board computation inefficiency and energy constraints stemming from the limited battery capacity.
- **Application of communication and networking technologies:** As far as ultra-dense NTN-based IIoT networks are concerned, it is not straightforward to adopt well established wireless standards and protocols, as well as conventional design methods of typical terrestrial networks. More importantly, conventional communication and networking technologies encompass several inherent limitations, as far as non-linear and unexpected phenomena prevail, and a massive number of devices exists. Under these circumstances, channel estimation is a complex and non-trivial process. Therefore, a lack of channel state information (CSI) is inevitable. It is well known that the knowledge of CSI controls important parameters of PHY, such as power allocation, the type of modulation, the management of resources, and the interference mitigation [89]. This issue becomes much more complex when accurate and timely CSI is required (e.g., in massive MIMO systems) or when advanced signal processing algorithms are exploited.
- **Computing offloading:** Since the spaceborne and airborne platforms represent resource-constrained devices, the provision of computation-intensive services necessitates the offloading of applications to cloud servers with centralized and sufficient computation resources. However, in remote areas, edge/cloud infrastructures are usually unavailable.
- **Inter-operability among the heterogeneous types of wireless networks:** NTNs have to deal with mutual interference due to the diverse nature of communication technologies within the same system or the coexistence of heterogeneous systems, which limits the performance and capabilities of the entire system.
- **Target detection and data acquisition:** The inspection, collection, and analysis of structured and unstructured sensor data to extract information and construct IIoT applications typically presupposes human intervention. Nevertheless, accomplishing autonomous, self-configured, and self-optimized network operations in real time within the heterogeneous and multi-dimensional NTN-based IIoT is uncommonly complex.

To handle the aforementioned challenges and effectively respond to uncertainties, the IIoT network elements should be context-aware and learn and make decisions from the collected and exchanged data. In this respect, AI technologies, which have been adopted in several forms in terrestrial networks [90–92], are seen as promising for implementation in NTN-based IIoT, enabling the transformation of "connected things" to "connected intelligence". Although cognitive radio technologies have been investigated for around 20 years [93], the intelligence introduced in them is limited to solving problems regarding spectrum access. As the intelligence expands to service orchestration and network management, cognitive wireless communications are expected to evolve into intelligent radio communications [94,95], where interdisciplinary approaches can be implemented from the field of communication engineering and the IT sector.

5.1. Classification of AI Techniques

AI constitutes a generic term that invokes various techniques, which are summarized in Figure 5. Among these techniques, machine learning (ML) [96], a subset of AI, consists of supervised and unsupervised learning, as well as reinforcement learning (RL), and can improve the performance of a system in processing a particular task without the need for reprogramming. The ML techniques that rely on artificial neural networks (ANNs) are capable of extracting, predicting, and characterizing nonlinearities from massive datasets. Evolutionary ML techniques are deep learning (DL) [97] and deep RL (DRL) [98], which use multi-layered ANNs to deliver high accuracy and aim to teach a system how to autonomously learn through direct interaction with the environment, just like humans, without guidance from an external supervisor and without the need to provide standardized and defined models of knowledge. DL techniques constitute universal function approximators with superior algorithmic learning abilities, regardless of the complexity of the system. In this way, non-linear problems can be solved and systems can successfully respond to unprecedented and undefined conditions. Since the implementation of DL involves the use of ANNs, DL models are sometimes referred to as deep neural networks (DNNs) [99]. In DL-based recurrent neural networks (RNNs), which are appropriate for modeling sequential data, e.g., natural language and time series, the output from a previous step of a process is fed as an input into the current step [100]. Besides the above, the more powerful DL-based convolutional neural networks (CNNs) are suitable for spatial data, e.g., images, and are constructed on multiple layers of convolving trainable filters, implying a hierarchical increase in the complexity [101]. It is noted that the learning algorithms are represented by weights, optimizing E2E performance through appropriate training methods.

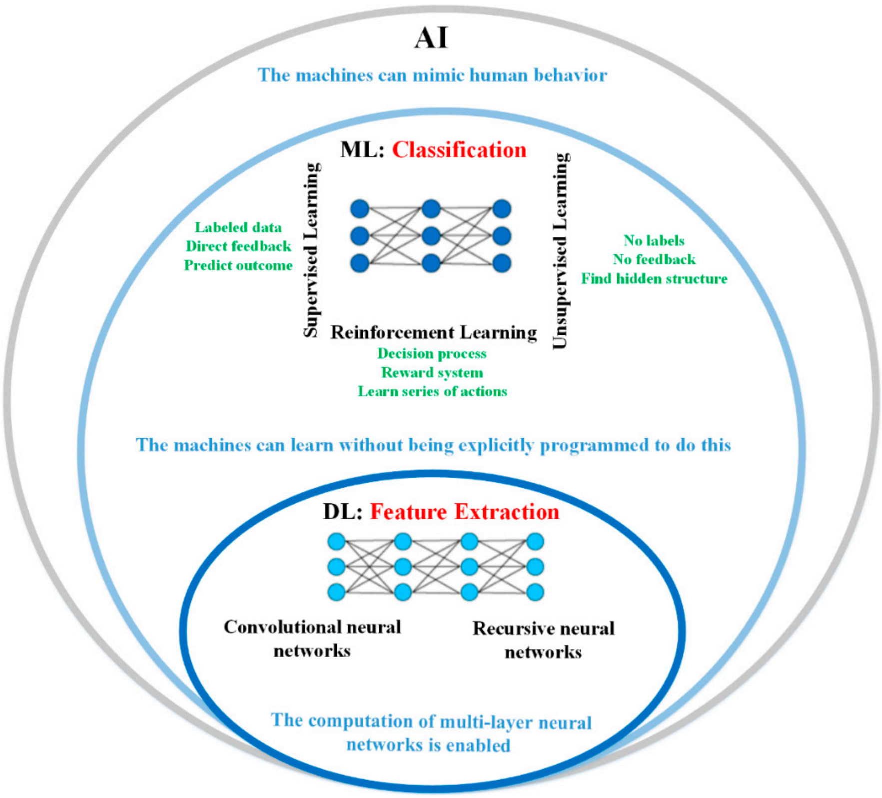

Figure 5. Summary of potential and powerful AI technologies for the NTN-based IIoT that intend to enable end-to-end (E2E) optimization of network operations in complex environments without human intervention via training, learning, and prediction processes.

5.2. Potential Advantages of Learning Techniques in NTN-Based IIoT

The application of AI techniques to NTNs would enable the further exploration of fundamental and heretofore unexplored features of NTNs and the development of innovative communications and networking technologies including new architectures, sophisticated algorithms, and protocol designs. More specifically, the design of PHY can be optimized to increase flexibility in spectrum access, whereas the radio channel can be accurately estimated and modeled using a limited number of measured data and avoiding extensive measurements. In addition, the implementation of AI in NTNs would allow these networks to have seamless autonomous communication on each type of radio channel in the presence of interference, fading, and attenuation and enable the coexistence of NTNs with terrestrial networks without requiring prior mathematical analysis and modeling. Additionally, while optimization of performance in conventional communications systems is independently handled in each distinct stage (e.g., encoding, modulation, and detection), further improvement is expected to be achieved if E2E performance optimization is realized though AI. In the context of network operation, AI can be used for efficiently handling the optimization of resource allocation and congestion avoidance. Additionally, the management of large satellite constellations and UAV swarms can be facilitated without the need for centralized coordination. In the different cells of UDHNs, where handovers are frequent, AI methods could be applied to learn and adapt terminals to spatio-temporal changes so as to maintain low power consumption while attaining an exceptional QoS level. Moreover, intelligent spaceborne and airborne platforms would be capable of sensing their surroundings and learning the network variations, mapping out areas, tracking IIoT objects, and responding directly and successfully to real-time changes in the radio channel. Recent studies have argued that learning a communication system from E2E can be realized by considering this system as an autoencoder [102]. The autoencoder describes a DNN which is trained to recreate the input as the output, while the radio channel is structured as a set of levels with stochastic and deterministic behavior. As the information has to pass through multiple levels, the network must adopt a robust representation of the incoming messages at each level. Figure 6 illustrates the structuring elements of a prospective NTN in which learning techniques are applied. In this intelligent NTN, a data transmission and reception unit facilitates the exchange of IIoT data streams among devices, a data conversion unit with analog-to-digital converters (ADCs) and digital-to-analog converters (DACs) enables signal conversion, a control unit controls information and inspects data exchange among network entities, and an AI-based advanced learning mechanism allows for effective action prediction.

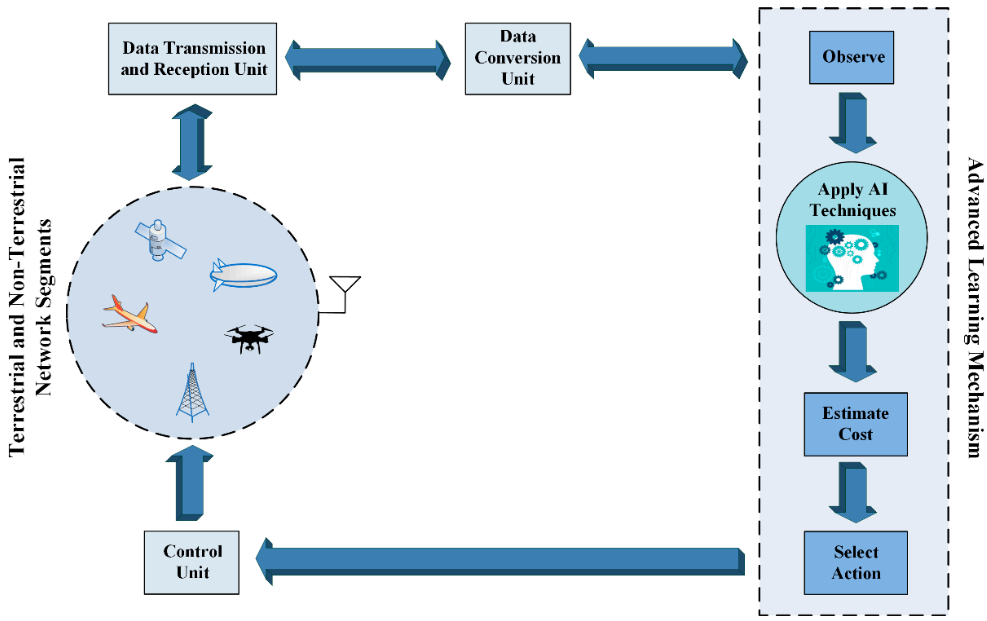

Figure 6. Block diagram of an intelligent and autonomous NTN consisting of space, air, and ground network segments that meets the demands of challenging IIoT applications and complex propagation environments.

6. Overview of Existing AI Techniques for NTN-Based IIoT

In an effort to stay competitive with terrestrial networks, NTNs strive to pursue the evolution in AI technology and take advantage of the meaningful research achievements in this area [17]. Nevertheless, the application of AI techniques to NTN-based IIoT has been significantly less studied compared to conventional terrestrial networks. In this section, recent research efforts on this sector are thoroughly discussed. Additionally, these research efforts are summarized in Table 2.

6.1. Spaceborne-Based Intelligent IIoT

Recently, AI solutions have been proposed to handle in an optimal or near optimal manner a wide range of communication and networking issues of spaceborne platforms in varying and unexpected operating conditions to maintain reliability and efficient utilization of the resources and accomplish specific application missions. Among these issues, (i) the power allocation, (ii) the energy consumption, and (iii) the computing offloading represent the most challenging ones. However, contradictory requirements should be also fulfilled, including the low latency and enhanced throughput and coverage as well as the vast number of interconnected devices.

To enable massive access in S-IoT, a NOMA downlink system was considered in [103] involving a satellite source node and multiple ground nodes, where the nodes in the same spot beam coverage synchronously shared the same frequency. For this system, a DL-based adaptive moment estimation (Adam) algorithm was developed to jointly optimize the decoding order of SIC and the long-term power allocation. In this regard, a neural network was used, acting as an approximation function that was capable of calculating the SIC decoding order given the queue and channel states. The results underlined the accuracy and efficiency of this method requiring only a few iterations with respect to the long-term network utility, average arriving rate, and queue delay. Nevertheless, large amounts of datasets are essential for training. A DL-based multi-objective optimization of the resource allocation in CubeSats-based IoST networks was proposed in [104], using an ensemble DNN and a random hill-climbing algorithm to control the weights of the neurons. The resource-constrained CubeSats were equipped with reconfigurable plasmonic reflect arrays, whereas real satellite trajectory data of the Iridium NEXT were utilized for training. According to the results, the inter-satellite links are capable of supporting multi-Gbps throughput in low Earth orbits. In [67], an MEC-enhanced S-IoT network with limited computation and energy resources was optimized in terms of energy consumption and processing latency. This network consisted of multiple satellites acting as edge computing nodes connected to multiple satellite gateways for IoT nodes that were distributed in a remote area. In this respect, a Lagrange multiplier method was employed in dynamic environments to realize the computing and communication optimization of the resource allocation, while a DRL-based deep Q-network (DQN) was also collaboratively exploited to handle the off-loading decision.

In [105], the role of edge computing and DL in S-IoT image data target detection was discussed and a reference three-layer architecture was presented. According to this architecture, the data for target detection can be collected from both the S-IoT edge and cloud nodes through appropriate sensors, while the optimization training of the DL algorithm that handles the efficient computing offloading can be accomplished in advance and then transferred to the satellites. The results placed emphasis on the reduction of the delay of acquiring images from satellites and the improvement of the performance with respect to the target detection as well as the backhaul bandwidth preservation. Based on these results, it was obvious that edge intelligent computing can intercept purposeless data transmission and processing and also enhance the utilization of bandwidth. An S-IoT edge intelligent computing architecture was also described in [106] that effectively accelerates the data processing by adopting edge computing and DL methods. More importantly, S-IoT edge computing and distributed S-IoT intelligent computing architectures were presented. The former constitutes a three-layer architecture that comprises three parts, i.e., S-IoT cloud nodes, S-IoT edge nodes, and the ground data center. In this architecture, the computing power of each layer gradually increases as the processes move from the edge to the cloud. The latter, instead of performing this analysis at the cloud on the ground, enables direct data analysis at the satellites' sensors in a distributed lightweight DNN training manner, thus saving the network bandwidth that would be expended by data acquisition. On the other hand, the inference stage is locally realized. The simulation results in terms of the connectivity and coverage performance suggested that the lightweight DNN model is the most appropriate one for S-IoT-based scenarios. As far as SAGINs are concerned, an IoT edge/cloud remote computing offloading approach was presented in [107]. In this approach, UAVs were employed to support near-user edge computing, with their edge servers' computation resources virtualized as virtual machines (VMs), whereas the satellites aimed at attaining radio access to the cloud computing. The offloading decision was formulated as a Markov decision process (MDP). Additionally, a DRL-based computing offloading method was proposed in order to learn the network's dynamic conditions and handle complexity issues.

6.2. Airborne-Based Intelligent IIoT

One of the main potential barriers of implementing airborne-based IIoT systems is the limited on-board capabilities of the aerial platforms that restrict their endurance, communication, sensing, and computation capabilities. In this sense, the majority of previous works on the adoption of AI techniques have studied the separate or joint optimization of (i) energy consumption that involves energy harvesting and wireless power transmission (WPT), allowing for remotely recharging platforms; (ii) task offloading based on edge computing; (iii) path planning, trajectory, and horizontal and/or vertical placement with respect to ground or flying objects, and (iv) detection, identification, and tracking of objects.

The energy efficiency is a serious issue for disaster management through aerial platforms, as indicated in [108]. Thus, the optimization of the flight route of a UAV via a genetic algorithm was suggested during data collection from ground IoT nodes that intends to minimize the energy consumption. A decision tree ML-based classifier was also proposed to be capable of predicting the health risk status with high precision using vital signs data gathered from devastated areas, whereas the collected data were analyzed at the monitoring center in order to reduce energy consumption. To further enhance the energy efficiency, multiple UAVs can be employed, with individual tasks assigned to each of them. The use of aerial platforms flying in varying altitudes and elevation angles for the rapid deployment of a communication network in emergency situations was proposed in [109]. More specifically, an A2G physical propagation model along with a ML-based method based on a radial basis function (RBF) ANN were presented, aiming at providing optimized link budget performance and energy efficiency as well as enhanced LoS connections with rescue teams randomly distributed in an urban area. However, the inclusion of geolocations and relevant environmental information would offer more insights into the optimization process. A UAV-enabled communication scenario for a public safety network (PSN) was proposed in [110]. In this scenario, NOMA techniques were employed and the batteries of IoT nodes were recharged using wireless powered communication (WPC). To optimize the network lifetime radio frequency (RF) energy harvesting as well as overcome shortcomings related with centralized cellular connectivity, ML methods were adopted. Moreover, the IoT nodes were associated with particular roles, i.e., coalition heads operating as gateways or coalition members in a distributed manner by using the minority games (MG) theory [111]. To form coalitions among the IoT nodes while attaining energy efficiency and autonomous operation, an RL technique was applied that considers the member nodes as stochastic learning automata. Although extensive simulation results were provided, verifying these results using real-world testbeds is necessary in order to realize energy-efficient and self-adaptive PSNs. In [112], the wireless powered IoT (WP-IoT) was envisioned and a WPT system was presented that involved energy-constrained IoT sensors and a UAV serving as an RF energy transmitter. To determine the charging policy for these sensors and decrease the data packet loss rate, an ML framework of echo state networks (ESNs) combined with an improved k-means clustering algorithm was suggested, whereas the problem of mitigating interference among the IoT sensor nodes and optimally controlling the power was modeled as a mean field game (MFG).

Motivated by the benefits offered by edge computing, a three-layer MEC-based online big data processing IoT network was envisioned in [113], where hovering UAVs were deployed as edge servers. In addition, distributed sensors generating raw datasets and center clouds were included. The online optimization of the edge processing scheduling was realized through an algorithm based on Lyapunov optimization. In addition, a DRL algorithm was proposed in order to effectively optimize the path planning of the UAVs, and a CNN Q-network that enables action rewards prediction was trained using UAVs' observations of the surrounding environment. The simulation results with regard to data delay and power consumption demonstrated that the proposed algorithms can notably enhance service coverage. However, further investigation may be devoted to scenarios with intense mobility and coexistence with terrestrial cellular networks. To surpass the limitations of the computing power of ground IoT devices, an IoT system with multiple flexible and cost-effective UAV-based MEC mobile nodes and strong LoS propagation conditions was proposed in [114] that facilitates task offloading services. Aiming at optimizing the load balance among the UAVs while attaining adequate coverage and QoS, a differential evolution (DE)-based algorithm was developed to find a near-optimal UAV placement, whereas the access problem was formulated as a generalized assignment problem (GAP). Besides the above, a DRL-based task scheduling scheme was presented that improves the task processing efficiency of an individual UAV. The simulation results depicted that the proposed optimization framework can achieve superior performance compared to other benchmark solutions. The joint optimization of the multi-UAV three-dimensional (3-D) trajectory and the time resource allocation that leads to throughput maximization in a WPC network was handled in [115]. In this respect, a multi-agent deep Q-learning (DQL) approach was presented. Specifically, the WPC network consisted of UAVs acting as base stations providing energy signals in the downlink to wirelessly charge IoT devices. These devices sent data information in the uplink by exploiting the gathered energy. The numerical results verified the efficacy of the proposed learning scheme in terms of the maximization of the minimum throughput. Additionally, an intelligent IoT data harvesting scheme based on resource-constrained aerial base stations and multiple ground IoT sensors was proposed in [116] and a map-compression based ML solution was used. In this work, the propagation parameters in an urban area were assumed to be unknown and the UAV trajectory was optimized to increase data throughput based on 3-D map data, provided that the optimal channel parameters were adequately learned.

As effective tracking systems can fetch the trajectory of UAVs and detect abnormal behavior, the trajectory tracking of UAVs in 5G-IoT networks was optimized in [117], using a probability hypothesis density (PHD) filter along with an ML technique based on k-nearest-neighbor (kNN) and k-means clustering algorithms. The results in terms of the optimal subpattern assignment (OSPA) distance underlined that the proposed ML-based approach outperforms the conventional Gaussian mixture (GM) PHD filter [118], which cannot accurately track the dynamics of UAV targets and unfortunately generates false alarms. Nevertheless, tracking scenarios, where measured data from multiple sensors are used, should be also investigated. An intelligent UAV-based real-time monitoring and control system for an IIoT environment that leverages fog and cloud computing was proposed in [119], where the visual recognition of the photos captured by the UAV's camera was instantly performed in the cloud. To verify the reliability and efficiency of this system, a case study involving the visual supervision in a bulk concrete production plant via drones was described, where the International Business Machines (IBM) Watson DNN-based visual recognition service was exploited, and fog computing together with the Node-RED programming tool were used as the bridge among the layers of the IIoT. In [120], an intelligent UAV-based autonomous vision-based system for the inspection of power grids was proposed. In this system, optical images were used as the primary data source and deep residual networks (ResNets) [121] were adopted for classification, data analysis, and rapid and accurate identification of faults and damages of power line elements. The self-driving and autonomous inspections through UAVs can be facilitated by combining the ResNets with conventional navigation methods, e.g., GPS. To obtain visual identification of farmlands, a decentralized and heterogeneous intra-UAV swarm scheme, where the UAVs were equipped with multimedia or scalar sensors, was presented in [122]. In this scheme, a faster region-based convolutional neural network (RCNN) approach [123] was implemented in the low-power on-board computing system of the UAVs to track ground nodes. Since the data generation in each UAV varies and leads to significant processing delays, the optimization of computation resources in intensive processing tasks was handled using a Nash bargaining-based intra-edge processing data offload method, where the weights were pre-allocated based on the swarm architecture. More importantly, a central UAV node was responsible for video capture, while the other UAVs were only responsible for sensing purposes. Contrary to conventional star and mesh network topologies, the scalability of the proposed distributed aerial processing (DAP) offloading method in highly mobile environments offers substantially increased processing speeds while requiring fewer employed UAVs. To facilitate rescue operations and enable the virtual teleportation of rescuers to restricted areas after catastrophic events, UAV-IoT data capture and networking for remote scene virtual reality (VR) immersion can be exploited [124]. In this respect, the delivered expected immersion fidelity can be maximized through optimization of the network placement policy by adopting RL methods.

Table 2. Synopsis of the research work on AI-enhanced NTNs for IoT scenarios.

Reference	Platform	Optimization Target	AI Solution	Performance Metrics
Sun et al. [103]	Satellite IoT (S-IoT)	Decoding order of successive interference cancellation (SIC) and long-term power allocation	Deep learning (DL)-based Adam algorithm	Utility, data rate, and queue delay
Nie et al. [104]	Cubesat	Resource allocation	Deep neural network (DNN)	Bit-error-rate (BER) and data throughput
Cui et al. [67]	S-IoT	Latency and energy consumption	Deep Q-network (DQN)	Total cost and proportion of tasks
Wei et al. [105]	S-IoT	Image data target detection	DL-based	Connectivity, coverage, and processing delay
Wei et al. [106]	S-IoT	Data processing	DNN	Connectivity, coverage, and processing delay
Cheng et al. [107]	SAGIN	Computing offloading	Deep reinforcement learning (DRL)	Delay, run-time, total cost, and energy consumption
Ejaz et al. [108]	Unmanned aerial vehicle (UAV)	Energy efficiency	Decision tree classifier	Energy consumption
Almalki et al. [109]	Low-altitude platforms (LAPs) and high-altitude platforms (HAPs)	Link budget, energy efficiency, and connectivity	Radial basis function (RBF) artificial neural network (ANN)	BER, probability of blocking, probability of a call being delayed
Sikeridis et al. [110]	UAV	Lifetime radio frequency (RF) energy harvesting and connectivity	Machine learning (ML)-based	Consumed energy, harvested energy, energy availability
Li et al. [112]	UAV	Energy efficiency, charging policy, and interference mitigation	Echo state networks (ESNs) and k-means algorithm	Packet loss rate, signal-to-interference-noise ratio (SINR)
Wan et al. [113]	UAV	Path planning and action rewards prediction	DRL	Data delay and power consumption
Yang et al. [114]	UAV	Computing offloading	DRL	Reward for task scheduling and average slowdown of offloaded tasks
Tang et al. [115]	UAV	Data throughput	Deep Q-learning (DQL)	Minimum data throughput
Esrafilian et al. [116]	UAV	Trajectory	Map compression based	Data throughput
Tang et al. [117]	UAV	Trajectory tracking	k-nearest-neighbor (kNN) and k-means algorithms	Optimal subpattern assignment (OSPA) distance
Salhaoui et al. [119]	UAV	Visual recognition	DNN	Latency
Nguyen et al. [120]	UAV	Image recognition and object detection	Deep residual networks (ResNets)	Detection of common faultson power line components
Mukherjee et al. [122]	UAV	Tracking ground targets	Faster region-based convolutional neural network (RCNN)	Processing time and speed
Chakareski et al. [124]	UAV	Delivered expected immersion fidelity	RL	Network capacity, network rate mismatch, and packet loss rate

6.3. Practical Limitations and Open Issues

The requirements for rapid, efficient, and real-time handling and processing of large amounts of data in the application of advanced AI methods are particularly high. Consequently, signal processing algorithms require parallel processing architectures and significant computational power. Hopefully, data availability is currently possible due to the development of sensory systems, the widening of storage in digital systems and the increase in data transmission speed. In addition, today's powerful graphics processing units (GPUs) together with libraries for DL [125–127] enable real-time parallel data processing, while clusters and cloud computing reduce the training time required by DL. Based on the review of the research results in this section, one can conclude that the forceful DL represents the most popular and widely used AI-based technique, enabling not only data classification but also feature extraction as soon as a large amount of training measured data is available and the computation capabilities are sufficient. Nevertheless, the limited processing capabilities and power resources of spaceborne and airborne platforms may discourage the application of DL. One may ideally move more computing power to space and air in the future, but current practical constraints enjoin the design and implementation of low-power and efficient DL solutions.

To overcome the limitations of resources, cloud-centric DL schemes can be used that require data transmission from the satellites and the aerial platforms to a centralized server. To avoid network overhead during transmissions to centralized entities and collaboratively and locally train DL-based learning models on IoT devices, employing federated DL (FDL) is proposed [128]. Besides the above, computationally simpler AI methods, e.g., RL, which can be implemented in a distributed manner and in resource-constrained devices, seem promising. As many critical applications require rapid learning procedures to obtain URLLC, introducing specific constraints into the optimization procedure and/or confidence scores to predictions can dramatically decrease the computation time. To further improve the performance of SAGINs and satisfy the requirements of quality of experience (QoE), jointly optimizing the communication, caching, energy, and computing resources is also suggested.

Finally, experimental testing of the proposed learning frameworks through measurements in realistic testbed environments is required in order to validate the hitherto theoretical results. In this regard, non-identical spaceborne and airborne types with variant orbits, velocities, altitudes, and antenna designs can be employed while conducting similar experiments.

7. Conclusions

Owing to the rapid advances in IT and the industrial infrastructure, IIoT is expected to be widely adopted to industries and expedite automated control, monitoring, management, and maintenance. In this paper, an overview of the role of NTNs in the future IIoT ecosystem has been provided. Since ubiquitous connectivity and long-range radio coverage are required in many critical IIoT applications, spaceborne and airborne platforms along with advanced sensing and wireless technologies can significantly enhance the QoS and QoE and strongly promote the evolution of IIoT. Although the IIoT market constitutes a significant opportunity for aerospace service providers, there exist many challenges and performance barriers to a successful IIoT deployment. To predict and mitigate these challenges and meet URLLC and mMTC presuppositions, recent research efforts have focused on advanced AI-based learning solutions with low complexity. This paper has highlighted how different AI algorithms have been adopted and evaluated for NTN-based IIoT applications depending on the type of the platform and the optimization target as well as the power and computational resources. Among these algorithms, DL is the most powerful one in terms of performing E2E optimization. Since the practical feasibility of DL depends on availability of a vast number of sensor data and adequate processing capabilities, other less demanding AI solutions with lower complexity, such as RL, have been considered. Overall, the combination of AI techniques and NTNs is expected to give great impetus to the establishment of IIoT and to act as a "human eye in the sky". However, future supplementary work and further advancements in this area, from the AI perspective, are needed. To this end, this paper has also underlined current limitations and discussed relevant open issues.

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Abbreviations

The following abbreviations are used in this manuscript:

3-D	Three-dimensional
3GPP	3rd Generation Partnership Project
4G	Fourth-generation
5G	Fifth-generation
6LoWPAN	IPv6 over low-power wireless personal area networks
A2A	Air-to-air
A2G	Air-to-ground
ACM	Adaptive coding and modulation
Adam	Adaptive moment estimation
ADC	Analog-to-digital converter
ADCS	Attitude determination and control systems
AI	Artificial intelligence
ANN	Artificial neural network
ATM	Air traffic management
B5G	Beyond 5G
BAN	Body area network
BER	Bit-error-rate
BLE	Bluetooth low energy
CAPEX	Capital expenditure
CAPP	Certified Applications Provider Programme
CCTV	Closed circuit television
CNN	Convolutional neural network
CoAP	Constrained application protocol
CPS	Cyber-physical system
CSI	Channel state information
DAC	Digital-to-analog converter
DAP	Distributed aerial processing
DBS	Drone base stations
DE	Differential evolution
DL	Deep learning
DNN	Deep neural network
DQL	Deep Q-learning
DQN	Deep Q-network
DRL	Deep RL
DVB-NGH	DVB—Next Generation Handheld
DVB-RCS2	Digital Video Broadcasting—Return Channel via Satellite – Second Generation
DVB-S2	DVB—Satellite—Second Generation
DVB-SH	DVB—Satellite to Handheld
EC-GSM-IoT	Extended Coverage-Global System for Mobile Communications for the IoT
eMBB	Enhanced mobile broadband
EMBG	Electromagnetic bandgap
EMEA	European, Middle Eastern, and African
ESN	Echo state network
FAA	Federal Aviation Administration
FANET	Flying ad-hoc network
FDL	Federated DL
FSO	Free-space-optical
GAP	Generalized assignment problem
GEO	Geostationary Earth orbit
GM	Gaussian mixture
GPS	Global positioning system
GPU	Graphics processing unit

GSN	Global sensor network
HAP	High-altitude platform
HealthIIoT	Healthcare IIoT
HEO	Highly elliptical orbit
HTS	High throughput satellites
IBM	International Business Machines
IEEE	Institute of Electrical and Electronics Engineers
IHH	IoT-powered in-home healthcare
IIoT	Industrial IoT
IoRT	Internet of Remote Things
IoST	Internet of Space Things
IoT	Internet of Things
IoV	Internet of Vehicles
IP	Internet protocol
IR	Infrared
ISM	Industrial, scientific, and medical
IT	Information Technology
kNN	k-nearest-neighbor
KPI	Key performance indicator
LAP	Low-altitude platform
LEO	Low Earth orbit
LIDAR	Light imaging, detection, and ranging
LLRA	Low-latency routing algorithm
LoRa	Long-range
LoRaWAN	Long-range wide area network
LoS	Line-of-sight
LPWAN	Low-power wide area network
LTE	Long-Term Evolution
LTE-M	LTE for machines
LWA	Leaky-wave antennas
M2M	Machine-to-machine
MCU	Micro-controller unit
MDP	Markov decision process
MEC	Mobile-edge computing
MEO	Medium Earth orbit
MFG	Mean field game
MG	Minority games
MIMO	Multiple-input multiple-output
ML	Machine learning
mMTC	Massive machine type communications
mm-wave	millimeter-wave
MTD	Machine-type device
MU	Multi-user
NASA	National Aeronautics and Space Administration
NB-IoT	Narrowband-IoT
NDVI	Normalized difference vegetation index
NFC	Near field communication
NFV	Network function virtualization
NLoS	Non-line-of-sight
NOMA	Non-orthogonal multiple access
NSR	Northern Sky Research
NTN	Non-terrestrial network
OPEX	Operation and maintenance expenditure
OSPA	Optimal subpattern assignment
OT	Operational technology
PHD	Probability hypothesis density

PHY	Physical layer
PSN	Public safety network
QoE	Quality of experience
QoS	Quality of service
RAN	Radio access network
RBF	Radial basis function
RCNN	Region-based convolutional neural networks
ResNet	Residual network
RF	Radio frequency
RGB	Red-green-blue
RL	Reinforcement learning
RNN	Recurrent neural network
RPV	Remotely piloted vehicle
RTCA	Radio Technical Commission for Aeronautics
RTT	Round-trip time
S2A	Satellite-to-air
S2G	Satellite-to-ground
SAGIN	Space-air-ground integrated network
SAR	Synthetic aperture radar
SCADA	Supervisory control and data acquisition
SDN	Software-defined networking
SDR	Software-defined radio
SESAR	Single European Sky ATM Research
SIC	Successive interference cancellation
SINR	Signal-to-interference-noise ratio
S-IoT	Satellite IoT
UAV	Unmanned aerial vehicle
UDHN	Ultra-dense heterogeneous network
URLLC	Ultra-reliable and low-latency communications
VM	Virtual machine
VR	Virtual reality
Wi-Fi	Wireless Fidelity
WPC	Wireless powered communication
WP-IoT	Wireless powered IoT
WPT	Wireless power transmission

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