

A Survey on Ambient IoT: Use Cases, Standardization, Enabling Technologies, and Research Directions

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Abstract—Ambient IoT (A-IoT) is an emerging paradigm that enables connectivity for IoT devices powered by ambient energy or wireless power transfer (WPT). This survey provides a holistic and detailed overview of the technology landscape, starting with device classification and environmental impact, and moving on to use cases and ongoing standardization efforts in 3GPP, IEEE, and ETSI. It reviews the technological building blocks of A-IoT devices, including energy harvesting and power management circuits, low-power wake-up and backscatter radios, and approaches for on-device and edge intelligence. At the network level, the paper explores architectures and protocols for WPT, low-power protocols for both backscatter and active communication, solutions for resource management, and A-IoT security protocols. Practical insights are drawn from experimental testbeds and real-world deployments. Finally, the survey outlines major research directions, from scalable WPT and interoperable protocols to context-aware scheduling, lightweight security, and reproducible field trials. This work provides a roadmap for researchers and industry to advance A-IoT as an integral part of future 6G networks.

Index Terms—Ambient IoT, 6G, zero energy devices, energy neutral devices, wireless power transfer, energy harvesting, backscatter, low-power communications.

I. INTRODUCTION

THE Internet of Things (IoT) enables the connection of a wide variety of physical objects (i.e., “things”) to the Internet or other communication networks, allowing them to exchange data with computers and people across the world [1]. IoT devices act as a bridge between the physical and digital world, as they collect data about physical phenomena via on-board sensors. That data is subsequently fed into the digital world, where it is processed and converted into meaningful information, from which actionable insights can be derived. These insights can then be fed back into the IoT devices, in order to control the physical world via on-board actuators. Since its inception, the IoT concept has become widely popular, with an estimated 15 billion connected IoT devices deployed worldwide in 2023,

and a predicted growth to over 38 billion devices by 2029 [2].

Currently, IoT devices are almost exclusively powered by primary (i.e., non-rechargeable) batteries. Batteries are cheap and provide a convenient and reliable energy supply. However, with the growing number of connected devices, it is becoming apparent that purely relying on batteries is incompatible with a sustainable IoT [3]. Batteries limit device lifetime, which will only become worse as devices and applications become more demanding and computationally intensive. This results in the need for frequent maintenance to replace batteries, or even worse, the device entirely. This is not only prohibitively expensive, but also catastrophic for the environment, resulting from immense amounts of e-waste and dangerous chemicals dumped in our environment [4].

During the last decade, researchers have striven to solve the IoT's battery problem, coining terms such as A-IoT [5], Internet of Battery-Free (or Battery-Less) Things [3], Zero-Energy IoT [6], [7] and Energy-Neutral Devices [8]. These different terms carry subtly different meanings, but give rise to similar research challenges. We use energy-neutral operation to denote the condition that cumulative energy consumption does not exceed the sum of initially stored and harvested energy, subject to storage-capacity constraints [9]. The term battery-free or battery-less IoT device specifically refers to the lack of a battery, generally replaced by a small energy buffer (e.g., (super)capacitor) in combination with energy harvesting (EH) [3]. Zero-energy devices are a recently coined term, that similarly refers to battery-free devices that rely on harvested energy [6], [7]. In this paper, we will mainly use the term A-IoT, which has also been adopted by standardization bodies such as the 3rd generation partnership project (3GPP). It is considered an umbrella term for IoT systems that rely on EH, rather than primary batteries. However, no constraints are put on the type of energy buffer they use, which can be a (super)capacitor, or a rechargeable battery.

A-IoT devices can achieve decades-long energy autonomy, and therefore reduced maintenance costs and increased device lifetime. Depending on the application and environment, a variety of ambient or dedicated energy sources can be exploited to power A-IoT devices, including light, vibrations, temperature gradients, or electromagnetic waves [10]. A-IoT devices can be either active or passive [6]. Passive devices are triggered by an external device to wake up, and rely on backscatter communication (BC) [11]. Their power budget is generally limited to 1–100 μ W. In contrast, active devices are more powerful, and can initiate uplink communications using an active radio transceiver. Their power budget generally ranges from 100 μ W to 10 mW.

In contrast to primary batteries, which provide a stable energy source, ambient EH is in general highly variable and unpredictable, with significant temporal and spatial effects [3]. Active wireless power transfer (WPT) can provide more stability by design, but is limited in the amount of power it can supply, due to the significant efficiency losses that increase with distance. These issues often result in intermittent on-off behaviour, due to unexpected power failures resulting from low power efficiency and variability. This poses significant challenges, both in terms of hardware and software design

for A-IoT devices and networks. Hardware challenges include the need for small and low-power EH and power management circuits, as well as low-power active and passive radio transceivers. Meanwhile, software challenges include solutions for intermittent computing, low-overhead and low-power communications and networking protocols, and embedded artificial intelligence (AI).

A. State-of-the-Art and Contributions

This article offers a comprehensive survey of the literature from 2018 to 2025 in the broad area of A-IoT, focusing on use cases, standardization, device and network technologies, testbeds, and field trials. It covers both hardware and software aspects, as well as active and passive A-IoT. The year 2018 is chosen purposefully, as this is right after the seminal paper by Hester and Sorber, titled “*The Future of Sensing is Batteryless, Intermittent, and Awesome*”, was published [12]. This work kick-started nearly a decade of research on A-IoT.

In recent years, various other surveys and tutorials have appeared that discuss A-IoT. However, each of them focuses on one or a few aspects of A-IoT devices or networks. In contrast, we follow a holistic approach. The relevant related works are summarized in Table I. Several related works have focused specifically on passive A-IoT, providing a survey or tutorial-style overview on backscatter hardware, signal processing, and protocols [13], [14]. This contrasts our work, which also considers active A-IoT devices. Other studies have focused specifically on the recent standardization efforts of 3GPP on A-IoT [5], [6], [15], [16], [17]. However, these works are all magazine-style tutorial papers that do not provide an in-depth overview of the state of the art (SotA). Moreover, their focus is specifically on the upcoming 3GPP standard, and thus omits other standardization efforts, aspects related to power management and EH, and intermittent computing. As 3GPP is focusing mainly on passive devices in the near future, active A-IoT is also not specifically considered in these works.

A few recent works follow a more holistic approach, considering a broader range of A-IoT aspects [7], [18], [20], [21]. The works by López et al. [7] and Naser et al. [18] are high-level magazine-style tutorials and do not survey the SotA in detail. The survey by Cai et al. [20] focuses specifically on battery-free Wireless Sensor Networks (WSNs), discussing WPT, backscatter protocols, and multi-hop routing and omitting aspects related to ambient EH, intermittent computing, and security. Moreover, it does not consider hardware-focused works. The closest related work is the recent survey by Abbas et al. [21], which adopts a similar holistic view to ours. However, its scope is limited to cellular technologies and 3GPP standardization efforts, and it does not consider high-layer networking aspects, security, intermittent computing, or detailed low-power radio hardware design. Our work thus provides a broader view on A-IoT research, including standardization efforts beyond 3GPP, and a wider range of hardware and software aspects related to A-IoT devices and networks. Our main contributions here are

TABLE I
EXISTING SURVEYS AND TUTORIALS ON A-IoT

	Device Types	Standardization	Hardware	PHY	Network	Security	Computing	Year	Ref.
Tutorials	Passive	–	✓	✓	–	–	–	2018	[13]
	Passive	–	✓	✓	–	–	✓	2023	[18]
	Active & Passive	–	–	–	Layer 2	–	✓	2023	[19]
	Active & Passive	3GPP	–	–	Layer 2	–	–	2024	[15]
	Active & Passive	3GPP	–	✓	Layer 2	–	–	2024	[6]
	Passive	3GPP	✓	✓	Layer 2	–	–	2024	[16]
	Active & Passive	3GPP	–	–	Layer 2	–	–	2024	[17]
	Active & Passive	3GPP	–	✓	Layer 2	–	–	2025	[5]
Surveys	Active & Passive	–	✓	✓	Full Stack	–	✓	2025	[7]
	Passive	–	✓	✓	Layer 2	–	–	2020	[14]
	Active & Passive	–	–	✓	Full Stack	–	–	2023	[20]
	Active & Passive	3GPP	✓	✓	Layer 2	–	–	2024	[21]
	Active & Passive	3GPP, IEEE, ETSI	✓	✓	Full Stack	✓	✓	2026	Ours

- A novel inclusive definition of A-IoT devices, encompassing both active and passive device types, and providing an abstract device architecture, classification methodology, and environmental impact analysis.
- A detailed overview of A-IoT use cases, based on a thorough survey from the scientific literature, standardization efforts, and relevant research projects.
- A high-level overview of A-IoT-related standardization efforts in 3GPP, Institute of Electrical and Electronics Engineers (IEEE), and European Telecommunications Standards Institute (ETSI).
- A survey of research on A-IoT device technologies, including hardware (i.e., power management, EH, WPT, low-power active and passive radios), physical layer (PHY) design (i.e., backscatter, modulation), and device intelligence (i.e., intermittent computing, low-power AI, and computational offloading).
- A survey of research on A-IoT network technologies, including WPT network design, communication and network protocols, resource allocation strategies, and network security.
- A survey of existing large-scale experimental studies, measurements, and field trials related to A-IoT.
- An overview of future research directions, based on a holistic analysis of the broad SotA related to A-IoT.

B. Structure of the Survey

The structure of this survey follows the taxonomy as shown in Fig. 1. We start by characterizing A-IoT devices in Section II, including their performance, capabilities, and life cycle. Subsequently, we discuss relevant standardization activities and A-IoT use cases in Section III. Next, we move to surveying relevant device and network technologies, in Section IV and V respectively. Experimental setups and validation are discussed in Section VI. Finally, the paper is wrapped up with a discussion on future research directions in Section VII and conclusions in Section VIII.

Table II summarizes the current status of research progress and standardization of the different topics discussed in Sections IV and V. Standardization progress is classified

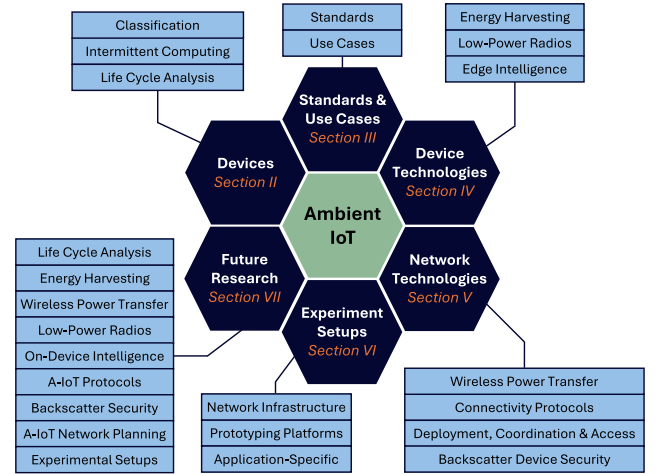


Fig. 1. Taxonomy showing the outline of this survey paper.

across three stages (not started, study item, ratified), or marked as not relevant for Standards Development Organizations (SDOs) (e.g., hardware circuits or algorithms are usually not considered relevant for standardization). Research maturity is also classified across three stages (early stage, well-understood, or commercial), where the first one is associated with exploratory research, while the third one specifies that commercial solutions are already available. Note that this classification considers specifically A-IoT-specific research. For example, on-device learning algorithms and active communications protocols are in general well understood or even commercially available, but this is not the case for algorithms and protocols that take the specific limitations and requirements of A-IoT devices into account.

II. AMBIENT IOT DEVICES

Fig. 2 illustrates the general architecture of an A-IoT node, either passive, relying on BC, or active, actively initiating uplink communications [6]. Multi-source EH systems enable either simultaneous utilization or switching among energy sources. The application-related hardware can include memory, sensors, interfaces, etc. The amount of energy storage and the technology used depend on the application. Most notable types of energy storage include electrostatic storage

TABLE II

STANDARDIZATION PROGRESS AND RESEARCH MATURITY OF THE TOPICS DISCUSSED IN SECTIONS IV AND V

	Technology	Standardization Progress	Research Maturity
Section IV: Device Technologies	Section IV-A: Energy Harvesting		
	RF harvesting circuits	not relevant	commercial
	Power management units	not relevant	commercial
	Section IV-B: Low-Power and Backscatter Radios		
	Wake-Up Radios	ratified standard	well-understood
	Backscatter radios	ratified standard	commercial
	Ambient backscatter	ratified standard	well-understood
	Section IV-C: On-Device and Edge Intelligence		
	On-Device Intelligence	not relevant	well-understood
	Device-Edge Offloading	not relevant	well-understood
Section V: Network Technologies	On-Device learning	not relevant	early stage
	Energy-Aware Task Scheduling	not relevant	well-understood
	Section V-A: Wireless Power Transfer Networks and Protocols		
	Energy Transfer Architectures	study item	well-understood
	Energy Transfer Synchronization	study item	early stage
	WPT protocols	study item	well-understood
	Section V-B: Connectivity Protocols		
	Backscatter protocols	ratified standard	well-understood
	Active protocols	study item	early stage
	Section V-C: Deployment, Coordination, and Access Management		
	Deployment optimization	not relevant	early stage
	Distributed Network management	not relevant	early stage
	Duty Cycling and Wake-Up	study item	well-understood
	Admission and Synchronization	ratified standard	well-understood
	Section V-D: Network Security for Backscatter Devices		
	Lightweight Authentication	study item	early stage
	Lightweight Key Agreement	study item	early stage
	Secrecy-Aware Communication	study item	early stage

TABLE III

HARVESTER TECHNOLOGIES AND MAX./AVERAGE POWER DENSITIES [24], [29], [30]

Technology	Power density	Target values by 2030
PV	max. 32.5 mW/cm ²	35 mW/cm ²
TEG	ave. 20 mW/cm ²	70 mW/cm ²
Microbial fuel cells	ave. 5 mW/cm ³	500 mW/cm ³
Piezoelectric	ave. 1 mW/cm ³	5 mW/cm ³
Triboelectric	ave. 50 mW/cm ²	300 mW/cm ²
Electrostatic	ave. 20 mW/cm ³	200 mW/cm ³
Vibration EM	ave. < 1 mW/cm ³	3 mW/cm ³
RF-EH	max. 40 μ W/cm ²	20 mW/cm ²

broad body of literature [24], with certain estimates informed by data extrapolation and trend analysis. These values are also influenced by a range of underlying factors, such as the excitation frequency [25], load resistance [26], [27], and separation between the layers [28] in the case of a triboelectric transducer, among others.

A. Device Classification

Device classification refers to the division of devices into multiple classes based on certain criteria e.g., communication capabilities, resource constraints. Device classification can serve three purposes. From a network perspective, it helps identify the required radio access network (RAN) functionality [31] and infrastructure. From the user's perspective, it helps in selecting suitable devices for specific environmental conditions. From a research perspective, it helps the research community to devise class-specific solutions. However, with the diverging capabilities of A-IoT devices, in terms of sensing, actuation, computation, and communication performance, their classification has become a challenging issue.

A classification of devices based on data-flow-related quality-of-service (QoS) requirements is presented in [8]. Although six device classes were defined, only one belongs to the A-IoT category, and it was characterized solely by communication-related performance metrics without taking into account other important operational metrics of A-IoT devices, related to sensing, computing, and actuation. Reference [32] classifies A-IoT devices according to their energy storage capacity and their ability to generate RF signals for transmission. Specifically, [32] introduces three device types: Device A, B, and C. Device A and B use BC, while Device C supports active communication. Device A has no energy storage capability, while Device B has it in the form of a small capacitor.

However, modern A-IoT devices comprise a wide diversity of hardware components in addition to transmitting circuitry and energy storage (Fig. 2). This calls for a more fine-grained description of a device's architectural features, such as type of energy storage, type of communication circuitry, types of memory and computing processors. One way to encompass the essence of performance and hardware-specified categorizations is to classify A-IoT devices based on the combination of these categorizations, as was done in [22] for devices that exclusively rely on harvested energy for their operation. Reference [22] classifies A-IoT devices into four broad classes:

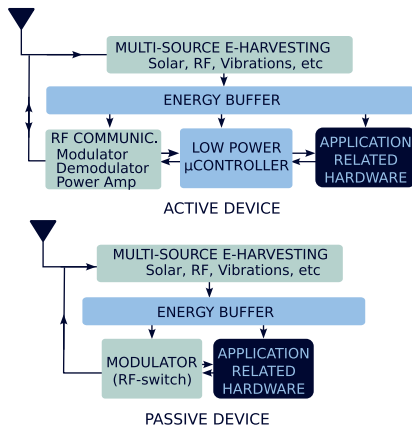


Fig. 2. General architecture of active and passive A-IoT-nodes.

(e.g., polymer and supercapacitors), electrochemical storage (e.g., rechargeable batteries and pseudocapacitors), and their hybrids (Li-Ion and more recent Na-Ion) [22]. Selecting the most appropriate energy storage technology for an application must take into account several technological characteristics, e.g., energy density, power density, self-discharge, and maximum number of cycles [23]. The main EH technologies include photovoltaic (PV), Thermoelectric Generator (TEG), microbial fuel cells, piezoelectric, triboelectric, electrostatic, vibration electromagnetic (EM) and radio frequency (RF)-EH [24]. Their currently achieved and expected power densities are provided in Table III. Note that the numerical values in Table III are indicative in nature, and have been derived from a

TABLE IV
A-IoT DEVICE CLASSES IN [22]

Class	Energy Storage	Communication Support
UP	no or minimal storage	reflection based
DB	tiny supercapacitor	intermittent
DP	small battery or robust supercapacitor	intermittent but reliable
CO	battery	active

- 1) ultra passive (UP) devices do not retain energy. They only function when they are illuminated by an external energy source. Their capabilities are inherently limited to basic identification, signal reflection, and minimal sensing, relying on passive interactions.
- 2) duty-cycled barebone (DB) devices have a small, short-term energy buffer in the form of capacitors, they can accumulate minimal amounts of energy and operate intermittently in short bursts, e.g., performing basic on-device sensing, rudimentary data processing, or brief communication tasks on a duty-cycled schedule.
- 3) duty-cycled persistent (DP) devices benefit from small, rechargeable energy storage to run persistently on scheduled duty cycles. These devices can perform moderate sensing, basic data logging, and low-complexity actuation, while buffered energy allows periodic wake-ups for measurements, intermittent computing, and communication via BC or low-power active protocols.
- 4) continuous operation (CO) devices feature robust or continuous EH with sufficiently large rechargeable storage and somewhat advanced computation and processing features. They support active communication protocols. They are expected to function autonomously, self-adapt to changing conditions, and integrate more advanced analytics such as machine learning (ML) inference.

The differentiating characteristics of these classes are summarized in Table IV. This broad four-category classification gives most weight to the energy storage capability as this further dictates the type of operation that the other components can perform. Reference [22] defines a further refinement into subclasses of higher granularity by taking into account six device capability categories: energy storage, incoming energy, processing, peripherals, communication, and memory.

Depending on their class, A-IoT devices may accomplish computational tasks through: i) On-Device Intelligence (O-DI), which employs Tiny Machine Learning (TinyML) techniques (e.g., compact AI models, reinforcement learning, and transfer learning) [33], [34], [35], [36], [37], [38], [39] to enable inference under strict resource constraints; ii) Device-edge offloading, which leverages trade-offs among energy consumption, latency, and accuracy through mechanisms such as split computing [40] and federated learning [41]; iii) On-device learning, which supports continual and personalized adaptation directly on the device using approaches such as TinyOL [42] and TinyTL [43], specifically designed to operate within tight memory, computation, and energy budgets. iv) Energy-aware task scheduling [44] and offloading [45], which dynamically manages computational

workloads to optimize performance under fluctuating energy availability.

B. Intermittent Computing

The realization of these functionalities in A-IoT devices is inherently constrained by intermittent energy availability, making intermittent computing a fundamental operating paradigm for A-IoT devices. Intermittent computing approaches can be broadly classified into checkpointing-based, task decomposition-based, and hybrid approaches. Checkpointing-based approaches preserve forward progress by periodically or selectively storing the execution state in non-volatile memory, enabling computation to resume from the most recent checkpoint after a power failure [46]. In contrast, task decomposition-based approaches preserve progress by partitioning applications into smaller subtasks that can be safely re-executed upon failure, thereby avoiding the need for frequent state preservation [47]. Hybrid approaches combine the advantages of both paradigms by integrating checkpointing with adaptive task decomposition.

In checkpointing-based approach, checkpoints may be introduced at different abstraction levels, such as manually within the application program, automatically at compile time through compiler analysis and instrumentation, or dynamically at runtime using energy-aware monitoring mechanisms. Depending on the implementation strategy, checkpointing may be performed using static or periodic checkpoint insertion, control flow graph-based [46], control-data flow graph-based [48] checkpoint placement, or adaptive energy-aware checkpointing [49] that dynamically determines checkpoint locations based on the available energy. Most common challenges in checkpointing-based approaches include energy/time overhead, Sisyphean execution, and timing/state inconsistency.

In task decomposition-based approaches [47], [50], [51], tasks are decomposed into smaller subtasks such that they can complete within the available harvested energy budget. Subsequently, these approaches incorporate energy-aware task scheduling to improve execution reliability and reduce rollback overhead during power interruptions. Most common challenges in task decomposition-based approaches include optimal subtask sizing, reducing task scheduling overhead, dependency management, and ensuring task idempotency.

Hybrid approaches [52], [53] combine the benefits of both task decomposition- and checkpointing-based approaches to improve efficiency and reliability. For example, watchdog timer-based checkpointing and task decomposition mechanism was proposed in [54]. In this approach, applications are initially executed as coarse-grained tasks. However, upon repeated execution failures, the failed tasks are progressively decomposed into finer-grained subtasks while intermediate execution states are preserved through checkpointing. This adaptive strategy mitigates repeated rollback and recomputation, thereby preventing Sisyphean execution.

Intermittent computing requires careful selection of controllable system parameters, such as capacitor size and the upper (V_{high}) and lower (V_{low}) voltage thresholds, where V_{high} defines the voltage level to start task execution and V_{low} the cutoff to prevent failure. These parameters define the amount

of usable stored energy and thus establish the fundamental feasibility condition of executing a given task within a single energy cycle. For instance, a task requiring 75 mJ can be supported solely by the stored energy in a capacitor of approximately 18 mF when operating between $V_{high} = 3.1$ V and $V_{low} = 0.9$ V [55], since this configuration provides sufficient usable energy for task completion. However, even when such feasibility is ensured, the energy harvesting rate plays a decisive role in determining how frequently the task can be executed. For example, with a harvesting rate of $100\mu\text{W}$, the capacitor would take on the order of 750 s to recharge from V_{low} to V_{high} . In contrast, if the harvesting rate increases to 1 mW, the same capacitor can be recharged in roughly 75 s, enabling significantly more frequent execution of the same task. This illustrates that storage-related parameters and the harvesting rate are complementary factors in determining overall task feasibility, where the former ensures task-level completeness and the latter governs the achievable frequency of execution.

C. Device Life Cycle Assessment

As the number of IoT devices rapidly scales in massive networks, their environmental impact grows. A life cycle assessment (LCA) reflects this impact by evaluating the full lifespan of the devices, from raw material extraction to end of life (EoL) management, highlighting system components with the most impact and enabling technology comparisons. A comparison is typically made based on the Global Warming Potential expressed in kgCO_2eq . This is a measure of how much infrared thermal radiation a greenhouse gas added to the atmosphere would absorb over a given time frame, as a multiple of the radiation that would be absorbed by the same mass of added CO_2 . Key sources of environmental impact include integrated circuits (ICs), energy storage and EH systems, printed circuit boards (PCBs), and casings, contributing to an estimated total carbon footprint of 1–10 kgCO_2eq for a typical IoT device [56]. While seemingly modest on a per-unit basis, this impact scales considerably given billions of IoT devices deployed worldwide. A significant portion of this impact originates from the ICs, primarily due to their resource-intensive and energy-demanding manufacturing processes [56]. These processes require substantial electricity, large volumes of ultra-pure water, rely on the extraction of rare materials, and often generate hazardous waste. Similarly, environmental impact of energy storage devices, such as batteries or (super)capacitors, is mainly due to the extraction of scarce raw materials and their limited recyclability [23], and possible leakage of toxins [57]. PCBs require energy-intensive fabrication processes and hazardous chemicals. Their impact scales with the number of layers and area of the PCB. Finally, the impact of casings largely depends on material choice and EoL treatment, particularly their recyclability [58].

Many LCA studies assume static operation after deployment, while real-world IoT systems with lifetimes exceeding 10 years often require maintenance due to component aging and failure. Electronic components can degrade over time, potentially leading to system failures. Energy storage components, such as batteries and capacitors, are particularly

prone to degradation and may require replacement during the device's lifetime, as they can fail due to thermal stress [58], or general wear-out mechanisms. Their production and disposal can significantly contribute to the total device footprint over the device's lifetime [59]. Beyond physical hardware maintenance, software obsolescence poses a significant threat to the long-term viability of IoT deployments. over-the-air (OTA) firmware updates are essential for extending device lifetimes by enabling the remote delivery of security patches, bug fixes, and performance optimizations without physical intervention [60]. This continuous software support prevents premature decommissioning due to evolving security threats or protocol incompatibilities. While OTA mechanisms introduce a marginal operational energy overhead [60], the resulting extension of the service life reduces the overall environmental footprint by delaying the need for replacement hardware.

To reduce the environmental impact of IoT systems, several strategies can be employed. One approach is the reduction of energy usage [61], often achieved through the use of ultra-low-power hardware components. Because A-IoT devices typically operate with low energy requirements, further reductions in energy consumption primarily translate into smaller energy storage buffers. Technologies such as wake-up receivers [62], BC [11], data pre-processing, edge computing, and AI-driven network optimization [61] help to reduce the energy consumption. Moreover, energy harvesters reduce or eliminate battery use [61], [63], while using eco-friendly or biodegradable materials and sustainable manufacturing practices further reduces the overall environmental footprint [64]. Meanwhile, designing for EoL early in development ensures that components and modules can be reused or recycled effectively. Even uncrewed aerial vehicles (UAVs) can be used to service IoT nodes [23], [65] by supplying additional energy to constrained nodes or replacing components at EoL [66].

Careful node design is required to obtain an ecologically responsible solution. Simple design choices, such as optimizing the layout to minimize board area, reducing the number of layers, selecting fewer or more integrated ICs, can decrease the overall environmental footprint. From a sustainability perspective, high integration and sealed devices limit reusability and recyclability, affecting environmental sustainability. Energy harvesting via solar panels can reduce operational footprint, but network operation itself also contributes significantly to energy use. End-of-life strategies, including the careful consideration of biodegradable components [67], are critical to minimize ecological impact and extend device lifetimes. While sustainability also encompasses economic and social dimensions, a detailed discussion of these aspects falls outside the scope of this work, which focuses primarily on the environmental lifecycle impacts of IoT systems. A case-by-case LCA is essential to identify the key impacts.

III. STANDARDIZATION AND USE CASES

A. Relevant Standardization Activities

Modern cellular communication standards target a big range of IoT use cases [68], [69], [70], [71], [72], [73], [74], [75]. However, these SotA connectivity solutions cannot directly support ultra-low complexity, EH A-IoT, which

TABLE V
COMPARISON OF THE MAIN STANDARDIZATION TRACKS FOR A-IoT

SDO	A-IoT application/device focus	Specification scope	Positioning for A-IoT
3GPP [77]–[84]	Native cellular support for battery-free and ultra-low-power devices in licensed 5G/NR evolution.	Defines use cases, service requirements, core-network support, security studies, RAN topologies, device classes, and normative work on passive and higher-end active A-IoT devices. Includes backscatter-based D2R, paging, RA, data transmission, coexistence with NR, and positioning support.	Most end-to-end and system-complete track. It aims to integrate A-IoT into mainstream cellular networks, but currently remains tied to licensed spectrum, NR compatibility constraints, and phased release evolution.
IEEE [85]–[89]	Ultra-low-power ambient-power communication over WLANs and enabling synchronization for distributed wireless power transfer.	Focuses on MAC/PHY amendments for harvested-energy stations, simplified modulation, asynchronous low-duty-cycle access, use of sub-1 GHz and 2.4 GHz bands, and support for both backscatter and limited active transmission. P3343 complements this with spatiotemporal synchronization for coordinated ETs.	Provides a flexible unlicensed-spectrum path and concrete low-power MAC/PHY mechanisms, but is narrower than 3GPP at the system level and is centered on WLAN-style operation rather than full cellular service architecture.
ETSI [90]–[100]	Regulatory and technology framework for low-power short-range operation, RFID-like access, cybersecurity baselines, and DECT-based low-power networking relevant to A-IoT.	Specifies harmonized SRD and RFID access conditions, coexistence constraints, duty-cycle/LBT behavior, cybersecurity guidance, and low-power networking through DECT-2020 NR and DECT ULE.	Acts less as a single end-to-end ambient-IoT air interface and more as an enabling standards and regulatory layer. Its main value is in spectrum access rules, interoperability constraints, security baselines, and complementary low-power technologies that can host or constrain practical A-IoT deployments.

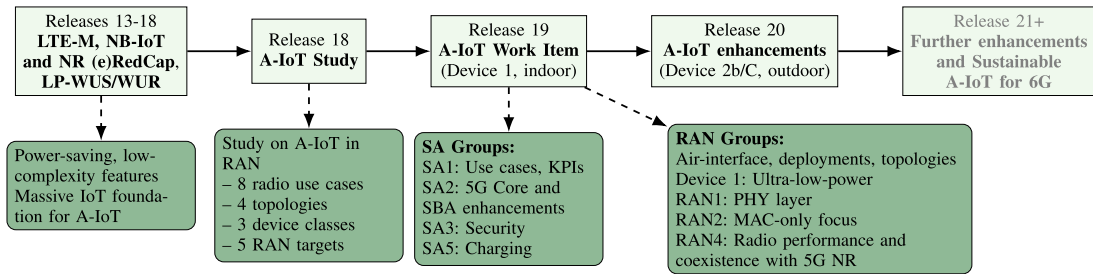


Fig. 3. A timeline for the progression of A-IoT standardization efforts within the 3GPP.

introduces a fundamentally different set of device capabilities and operational constraints. Indeed, legacy solutions were not designed to address the massive scale, ultra-low complexity (including μ W-level to mW-level power budgets and ultra-low cost/capabilities), lightweight communication, intermittent availability due to EH dependence, and micro-payload traffic of A-IoT devices and corresponding applications. To this end, various standardization bodies are currently looking for communication solutions for such devices.

In the following, we give an overview of the efforts of 3GPP in cellular technology supporting A-IoT devices, IEEE studies and 802.11 amendments aiming to enable Ambient Power (AMP) communication and establish relevant mechanisms, and ETSI short-range devices (SRDs) and Digital Cordless Telecommunications (DECT) specifications relevant to A-IoT and wireless powering of devices. Table V summarizes the different standardization perspectives relevant to A-IoT. In particular, it highlights that 3GPP, IEEE, and ETSI address A-IoT at different technical scopes and levels of abstraction, which provides important context for interpreting the use-case requirements and KPI targets discussed later in Section III-B.

1) *3Rd Generation Partnership Project (3Gpp)*: 3GPP is an international standards body responsible for mobile cellular technologies and has been committed to developing IoT (among other) communication solutions. Fig. 3 provides a chronological narrative of 3GPP's structured approach to A-IoT standardization, highlighting the key releases, Technical Specification Groups (TSGs), and technical aspects being addressed.

In 2022, 3GPP initiated work on A-IoT as part of its ongoing IoT standardization efforts [81]. Although A-IoT devices

were not explicitly addressed in early specifications, there was significant work on low-complexity and power-saving features for massive IoT use cases. This focus, particularly evident in Long-Term Evolution Machine Type Communication (LTE-M) and narrowband IoT (NB-IoT) technologies introduced in Release 13 in 2016 [100], [101], materializing 3GPP efforts to standardize Low Power Wide Area (LPWA) solutions for IoT applications [102], laid a solid technical foundation. Moreover, subsequent releases (Release 14–18) included enhancements to both NB-IoT and LTE-M, such as improved power efficiency and extended coverage. Formal studies around A-IoT began in Release 18, exploring aspects such as device capability, air interface characteristics, and associated network topologies [103], within the context of massive machine-type communications (mMTC) and in parallel with work on specifications to accommodate cost- and energy-efficient NR reduced capability (RedCap) user equipments (UEs) addressing higher-end IoT applications [80], [104]. Another important foundation for A-IoT design was laid with NR low-power wake-up signal (WuS)/wake-up radio (WuR) design in Release 18, where UE can remain powered off with only its low-power receiver part listening for wake-up triggers. In Release 19, A-IoT was elevated to a formal work item for NR, focusing on lower-tier, passive A-IoT device relying on BC [82]. Specification efforts continue in Release 20 for NR, focusing on higher-tier A-IoT devices capable of active transmission.

Two TSGs in 3GPP have been working on A-IoT definition and design. The system aspects (SA) groups lead on system aspects such as use cases, service requirements and architecture, etc. The RAN groups explore the corresponding radio access aspects, including air interface design and coexistence

with NR technologies. Under the SA and RAN organization, several working groups (SA#, RAN#) further specialize in different aspects of the standardization efforts.

Regarding SA and as part of the Release 19 standardization effort, SA1 launched a study item [76] to analyze A-IoT applications, focused on documenting use cases, traffic scenarios, service requirements and key performance indicators (KPIs). In parallel, SA2 worked to explore how the 5G Core and Service-Based Architecture can be extended (e.g., via new network functions) and to define procedures for identification, subscription, registration, connection management, and transport data for these devices [78]. Other SA working groups are currently looking into security aspects (SA3) [79], and the charging aspects (SA5) of A-IoT devices. Moving into normative status, [77] will be capturing key functional requirements for ultra-low-power communication procedures, positioning support, power-management schemes, data exposure, and security for battery-free, EH devices, as well as service requirements for the typical A-IoT use cases.

Regarding RAN and as part of Release 18 in 5G-Advanced, the study TS 38.848 [80] defined eight RAN representative use cases and evaluated them across four connectivity topologies considering three generic device classes, which are elaborated in Section III-B. It then mapped these combinations to deployment scenarios based on whether the device and reader (base station (BS) or UE) are indoors or outdoors, and established a set of RAN design targets derived from SA's service requirements. From these targets, the study formulated a non-exclusive list of needed RAN functionalities (excluding core-network functions) and concluded with a preliminary feasibility assessment covering device aspects (i.e., power consumption, complexity, mobility, and density), coverage, user experienced data rate, maximum message size, latency, and positioning accuracy. This study laid the foundation for the subsequent Release 19 normative work, wherein RAN work groups have been specifying [105] the so-called A-IoT "Device type 1" that targets extremely low-power operation (1 μ W peak), includes on-board energy storage, has an RF envelope detector and low-cost clocks that cannot maintain tight synchronization with the network. This device performs no active amplification in either reader-to-device (R2D) or D2R paths. Instead, its uplink (D2R) transmission relies on backscattering an externally supplied carrier wave.

The command and inventory representative use cases with direct and bidirectional communication between the A-IoT device and BS reader ("Topology 1") and "Deployment Scenario 1" (device indoor / BS indoor) have been prioritized, with frequency range 1 (FR1) licensed frequency-division duplexing (FDD) as targeted spectrum (R2D in downlink (DL) spectrum and D2R/carrier-wave in uplink (UL) spectrum) [105]. The supported traffic types include Device-terminated (DT) and Device-originated device-terminated triggered (DO-DTT).

More specifically, RAN Working Group 1 (RAN1) has been focusing on PHY specification aspects for R2D and D2R directions, including modulation and coding design, timing acquisition and synchronization, multiplexing and multiple access, scheduling information. RAN Working Group 2

(RAN2) is focusing on upper-layer RAN protocols to support A-IoT communication. Unlike typical 5G NR cellular protocols, which support multiple layers (such as MAC, Radio Link Control (RLC), packet data convergence protocol (PDCP), service data adaptation protocol (SDAP)), A-IoT supports only MAC layer due to device and use case limitations. Normative work has been concentrating on standardizing aspects around three major areas, namely paging, RA, and data transmission. RAN Working Group 4 (RAN4) main tasks are to define RF performance metrics to ensure the ultra-low-power and low-cost requirements are met while maintaining reliable communication and compatibility with 5G NR networks. To this end, the studies there have focused on RF requirements impact, carrier-wave interference cancellation feasibility, testability issues for IoT device, and co-existence between A-IoT and NR, whereas extensive evaluations of various interference cases indicate the feasibility of such co-existence [106].

Recently, for Release 20 NR, a new study item (with planned subsequent work item) has been approved to address specifications for higher-end A-IoT "Device type 2b" and "Device type C", with a few hundred μ W and ≤ 1 mW to ≤ 10 mW peak power consumption, respectively, active radio capabilities for generation D2R transmission, and overall higher capabilities (R2D and/or D2R amplification, better clocks for synchronization, intermediate-frequency (IF) and/or zero-IF envelope detector receiver) [83]. Outdoor scenarios and device-originated autonomous (DO-A) traffic type are now also included in the focus of this release. It is noted for clarification that 3GPP has used two name classifications for A-IoT devices: Device A/B/C (at RAN level, i.e., 3GPP TR 38.848) and Device 1/2a/2b (at RAN WGs level, i.e., 3GPP TR 38.769) and there is no one-to-one mapping of these classes, e.g., Device-2b is not synonymous to Device-C.

Going forward, further enhancements are expected in future 3GPP releases for A-IoT to cover more device types, topologies, and deployments, and to become part of "Day-1" 6G networks (i.e., 3GPP Release 21 and beyond).

2) *Institute of Electrical and Electronics Engineers (IEEE)*: IEEE is a global organization that develops industry standards, publishes peer-reviewed research, and hosts conferences in electrical engineering, computing, and related technologies to advance innovation and interoperability. This subsection introduces IEEE contributions to PHY and MAC layer design in the context of AMP communication.

a) *IEEE 802.11bp*: The IEEE 802.11bp amendment [84] is currently under development within the IEEE 802.11 Working Group, aiming to enable AMP communication, targeting WLAN stations (STAs) that operate on harvested RF energy. The amendment defines modifications to both the MAC and PHY layers to support ultra-low-power communication, facilitating the deployment of battery-free IoT devices, as shown in Fig. 4. These enhancements are designed to accommodate the stringent energy constraints of EH, with a focus on BC, but also implements active transmission, synchronization protocols, and energy-aware processing.

At the PHY, IEEE 802.11bp proposes the adoption of simplified modulation schemes optimized for minimal energy consumption. Candidate schemes include on-off keying (OOK)

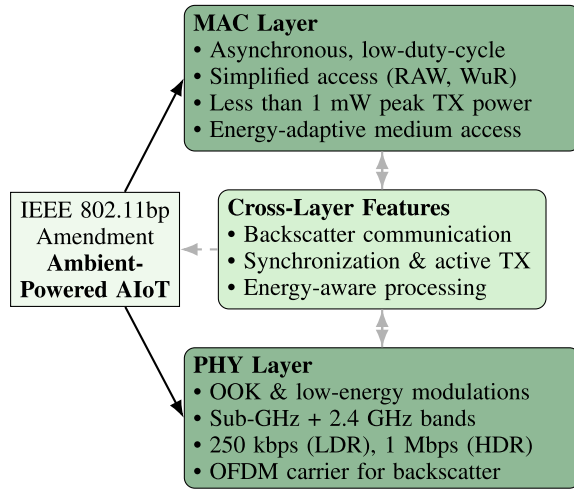


Fig. 4. Technical breakdown of the proposed IEEE 802.11bp amendment for A-IoT devices. MAC and PHY are co-designed to support ultra-low-power BC.

and variants derived from IEEE 802.11ah [86] and IEEE 802.11ba [87], selected for their compatibility with EH circuitry and low-power operation. The amendment supports operation in both sub-1 GHz (e.g., 868 MHz in Europe - ETSI, 915 MHz in the US - Federal Communications Commission (FCC)) and 2.4 GHz industrial, scientific and medical (ISM) bands. Two data rates are under consideration: a low data rate (LDR) mode at approximately [per-mode = symbol]250kbit/s and a high data rate (HDR) mode at [inline-per-mode = symbol]1Mbit/s [85]. Broadband carrier waveforms, such as orthogonal frequency-division multiplexing (OFDM) with 20 MHz bandwidth, are proposed for use as carrier signals in monostatic BC configurations [85].

The MAC layer is being adapted to support asynchronous, low-duty-cycle operation. Key features include simplified MAC protocols inspired by IEEE 802.11ah's restricted access window (RAW) [86, ch. 10.22.5] and IEEE 802.11ba's WuR mechanisms [87]. These adaptations aim to reduce channel spamming and wasting energy during medium access, enabling efficient operation under intermittent power availability. Communication protocols are tailored to operate within a peak power of less than 1 mW, ensuring compatibility with ambient EH capabilities.

b) *IEEE SA P3343*: Joint downlink beamforming with multiple distributed ETs can improve the received power budget and reduce outage probability, while enabling more flexible spatial control of interference. However, it also gives rise to challenging synchronization requirements, as we discuss in Sec. V-A. IEEE SA P3343 [88] aims to establish algorithms and performance bounds for spatiotemporal synchronization, i.e., the joint inference of spatial and temporal states in networks of distributed ETs. The spatial states typically comprise ET position and orientation. The temporal states typically comprise clock timing offsets (TOs), carrier frequency offsets (CFOs), and carrier phase offsets (CPOs). The ETs are assumed to be equipped with antenna arrays, enabling them to resolve incident signals in the angular domain. For directional beam steering, the ET's orientation

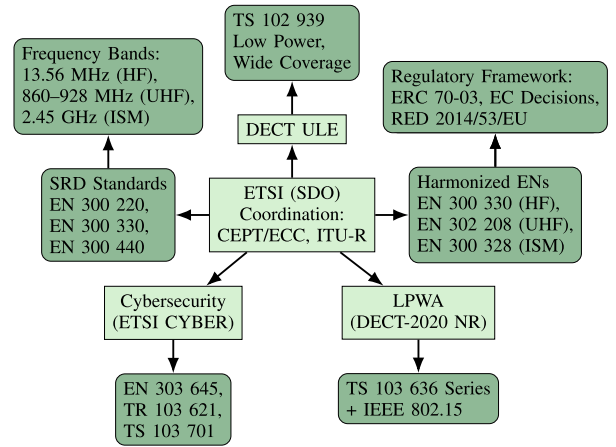


Fig. 5. Relevant ETSI standards for A-IoT.

must be known or estimated, which adds to the complexity of the spatial synchronization problem. The most demanding yet most rewarding aspect of this joint estimation problem is establishing phase-coherent operation among distributed ETs. This implies challenging real-time estimation of unknown clock phases (online phase calibration), but offers significant performance gains. If solved successfully, full spatiotemporal synchronization will transform a network of distributed ETs into a very large jointly coherent synthetic ET, enabling efficient WPT [107].

c) *IEEE SA P3735*: A new IEEE working group was formed in September 2025 to work on a standard for radiative wireless power transfer. The group is in its early stages, and no documents have been published at the date of writing.

3) *European Telecommunications Standards Institute (ETSI)*: ETSI, as a recognized SDO, is responsible for defining harmonized technical specifications and standards. One such specification is for SRDs, notably [89], [90], [91]. These standards apply to device operations across multiple frequency bands, including 13.56 MHz (high frequency (HF) band), 860 MHz to 928 MHz (ultra-high frequency (UHF) band), and 2.45 GHz (ISM band). These standards are developed in close coordination with the Electronic Communications Committee (ECC) of the European Conference of Postal and Telecommunications Administrations (CEPT) and the ITU - Radiocommunication Sector (ITU-R), ensuring regulatory coherence and spectrum harmonization across International Telecommunication Union (ITU) Region 1, which includes Europe, Africa, and parts of the Middle East.

Key ETSI deliverables relevant to A-IoT include:

- 1) [90] for HF RFID and near-field communication (NFC);
- 2) [92] for UHF RFID, including their operational constraints in the 865 MHz to 868 MHz band and advanced interference mitigation techniques such as LBT, adaptive frequency agility, and duty cycle limitations, which support efficient coexistence in dense device environments. Reference [92] is very relevant topic for other standards in the A-IoT domain;
- 3) [93] for 2.4 GHz ISM band devices.

These harmonised European standards establish essential guidelines for radio equipment, including emissions, duty

cycle constraints, and channel access protocols. The regulatory framework underpinning these standards is structured around CEPT/European Radiocommunications Committee (ERC) recommendations [108], [109], [110], European directives such as the former recommendation [111] and its successor [112] and national declarations submitted to the European Commission (EC).

In parallel, ETSI has recognized the growing importance of cybersecurity in pervasive IoT. The formation of the Technical Committee CYBER reflects a strategic initiative to develop standards that enhance resilience, data protection, and device authentication across these ecosystems [94]. A forward-looking cybersecurity roadmap outlines areas where additional regulation and technical standards are required to safeguard A-IoT applications, particularly in critical sectors such as logistics, healthcare, and infrastructure. Though initially aimed at home devices, these standards help protect A-IoT deployments where physical access to devices is impractical:

- 1) [94] establishes baseline requirements and provisions of cyber security for consumer IoT, which sets goals for cybersecurity without mandating particular methods or technologies;
- 2) [95] provides guidance on how to assess and assure IoT products against provisions in [94];
- 3) [96] is complementary to [94] and [95], illustrating some example implementations meeting provisions in [94].

The ETSI DECT-2020 NR working group has initiated an approach to LPWA networking [97] within the broader context of mMTC, addressing requirements that are also relevant to A-IoT use cases. The ETSI TS 103 636 document series [97] specifies device features optimized for low power consumption, enabling long operational lifespans using coin-sized cell batteries [113]. These mesh-based sensor networks are often based on the IEEE 802.15 standards family [114]. Furthermore, DECT-2020 NR has been recognized as part of the IMT-2020 technology family by the ITU.

Within ETSI, the Technical Committee DECT also developed DECT ULE, an evolution of the traditional DECT standard, formalized through the TS 102 939 series [98], [99]. DECT ULE devices are designed for ultra-low power consumption and extended coverage, aligning closely with the core objectives of A-IoT. Compared with existing technologies such as IEEE 802.11, IEEE 802.15, and Bluetooth low energy (BLE), DECT ULE offers significantly lower power operation (100–1000 times) and broader coverage (10–100 times). To meet ultra-low power requirements, DECT ULE is tailored for specific application scenarios and operates over shorter ranges than traditional DECT systems.

4) Global Regulatory Context and Regional Adoption:

Ambient IoT is increasingly being shaped by global technical standardization, but its practical deployment is not globally uniform, constrained by the ITU-R Regulations. Although 3GPP, IEEE, and other standardization bodies define portable specifications and amendments, radio access conditions and market adoption remain region-dependent [75], [80], [81], [84]. In practice, this means that the feasibility of deploying a given ambient IoT technology depends not only on the standard itself, but also on local spectrum rules, certification

conditions, and ecosystem maturity. These are determined by national regulators such as the FCC in the United States, or by the multitude of national regulatory authorities in Europe implementing spectrum regulations harmonized through CEPT and the European Commission. These frameworks dictate transmit power, duty cycles, and interference mitigation requirements. Thus, global standardization does not automatically translate into globally uniform deployment.

A particularly relevant example is UHF RFID and related SRD regulation, which provides one of the clearest regulatory precedents for passive, backscatter-based, and battery-free ambient IoT devices. In Europe, UHF RFID is regulated in the 865 MHz to 868 MHz band under ETSI EN 302 208, whereas the United States commonly uses the 902 MHz to 928 MHz band and Japan uses the 920 MHz to 925 MHz band [92]. Similar fragmentation appears more broadly across SRD regulation, where band availability, duty-cycle constraints, and coexistence rules vary by region [89], [108]. Consequently, passive tags and ultra-low-power backscatter devices cannot assume a single globally uniform RF design. This necessitates ‘multi-band’ hardware designs, which increases complexity and cost for silicon manufacturers aiming for a global stock keeping unit (SKU). A complementary lesson comes from cellular IoT is that although both NB-IoT and LTE-M were standardized within 3GPP, NB-IoT gained stronger momentum in China and parts of Europe (driven by government-backed initiatives for massive IoT in stationary utility metering), whereas LTE-M saw stronger uptake in the United States (due to the availability of existing LTE infrastructure and a market focus on mobile asset tracking), reflecting differences in operator strategy, legacy infrastructure, and ecosystem support [68], [69]. For 3GPP-based ambient IoT, the current work in Release 19 also remains rooted in licensed cellular operation, with FR1 licensed FDD spectrum as the target baseline [77]. It is noted though that the coexistence with unlicensed bands (e.g., 2.4 GHz or 5-6 GHz) is a critical discussion point for achieving higher required device connection densities.

These regional differences have direct implications for A-IoT deployment. They increase the need for multiple hardware and certification variants, complicate interoperability and cross-border operation, and are particularly relevant for global logistics, asset tracking, and supply-chain monitoring use cases. More broadly, they reduce economies of scale and raise deployment cost. For this reason, future A-IoT standardization should consider regulatory portability and multi-region operability as deployment requirements, rather than treating them as secondary implementation details.

B. Use Cases

One of the first steps in A-IoT development, as in any other technology, is to identify and analyze its use cases. This allows to determine the main requirements that A-IoT must meet while aligning them with the needs of the users that the technology will serve. 3GPP and IEEE, as international standardization bodies that usually lead the definition of communication technologies, as well as the AMBIENT-6G project as a research and innovation initiative, are already addressing this task. In this section, the work performed by

these initiatives regarding the A-IoT use case identification and definition is discussed. Additionally, Table VI shows a summary of these use cases, classifying them according to the initiative that proposes them and indicating the device classes described in [22] that best fit each use case.

1) *Use Cases in 3GPP*: The work from 3GPP relative to the definition of A-IoT use cases started in Rel. 19 projects of SA groups. In TR 22.840 [76], thirty use cases were defined and analyzed. The use cases explored in this cover different applications in both indoor and outdoor scenarios. Use cases like automated warehousing, intralogistics in automobile manufacturing or automated supply chain distribution are oriented to industrial applications. Healthcare applications are covered in use cases like medical instruments inventory management and positioning, online modification of medical instruments status or elderly health care, and rural applications in agriculture or livestock farming are covered by smart agriculture, smart grazing dairy farming, smart pig farm or controller in smart agriculture. Use cases related to civilian applications are also included with sensors in smart homes, airport terminals/shipping ports, finding remote lost items, smart laundry, forest fire monitoring or museum guide. In this study, the use cases were described at high-level and several KPIs were provided, covering end-to-end latency, user-experienced data rate, message size, coverage range, device speed or transfer interval and other relevant service parameters.

Almost in parallel, within Rel. 18 projects of RAN, the study of A-IoT was initiated and defined representative use cases in TR 38.848 [115], to drive definition of RAN-level deployment scenarios and connectivity topologies. To do this, two categories were used. The first category (Grouping A) is based on the deployment environment for each use case in SA study, including indoor, outdoor and indoor/outdoor environments. The second category (Grouping B) is based on the functionality/application reported in SA study, and included inventory, sensors, positioning and command. Combining the different subcategories of each grouping results in eight different representative Use Cases (rUCs), (as they were named by 3GPP): rUC1 Indoor inventory, rUC2 Indoor sensors, rUC3 Indoor positioning, rUC4 Indoor command, rUC5 Outdoor inventory, rUC6 Outdoor sensors, rUC7 Outdoor positioning, rUC8 Outdoor command. In later releases, these rUCs are used to classify more specific use cases.

2) *Use Cases in IEEE*: The work carried out by IEEE 802.11bp AMP Amendment on the use case analysis for AMP IoT technology (which is the name given by IEEE to A-IoT) was presented in [116]. In this document, eight use cases for AMP IoT devices in WLAN are identified: smart manufacturing, data center, logistics/warehouse, smart home, smart agriculture, indoor positioning, smart power grid, and fresh food supply chain.

While some of the use cases defined by IEEE are similar to those analyzed by 3GPP, new ones like data center or smart manufacturing are also included. Similarly to the work performed by 3GPP, IEEE also analyzed functional requirements and KPIs. However, this analysis is less detailed, as only a limited number of KPIs are included and their definition is inconsistent across the various use cases identified. These KPIs

include coverage range, data rate, moving speed, positioning accuracy, service lifetime or readout interval.

This document also presents an analysis of the technical gap that exists in each use case between different SotA solutions, and how AMP IoT can be used to overcome these gaps. The analysis identifies that current IoT solutions have limitations like manual label scanning, short communication range, high deployment and maintenance costs, and reliance on batteries or wired power transmission. AMP IoT addresses these gaps by enabling battery-free and maintenance-free devices with improved communication distance and lower deployment costs. The information provided by this analysis shows the benefits of AMP IoT and how they help improving current IoT networks or even implement new functionalities and services.

3) *Use Cases in AMBIENT-6G*: AMBIENT-6G is a research and innovation project funded by the Horizon Europe SNS-JU program. The project focuses on A-IoT technology, and its core objective is to look for solutions to enable standardized sixth-generation (6G) connectivity for A-IoT devices. In its early stages, AMBIENT-6G project carried out a use case analysis for the A-IoT technology, including 11 use cases divided in three main use case families: hard-to-reach devices, massive-scale sensor networks and extreme-lifetime applications [117]. This analysis represents a step forward from previous work by standardization bodies. Although some use cases already appear in the standardization activities of 3GPP and IEEE, the analysis was expanded to include a greater number of KPIs and functional requirements, as well as an analysis of the impact of A-IoT on each use case through key value indicators (KVI) in the environmental, social, economic and innovation fields. Moreover, several new use cases were proposed, including electronic shelf labels, in-body or wearable medical sensors, asset tracking and monitoring, industrial predictive maintenance and cooperative mobile robots.

Although 3GPP, IEEE, and AMBIENT-6G describe partially overlapping ambient IoT use cases, their KPI sets are not directly comparable on a one-to-one basis. 3GPP provides the most structured service-requirement view, IEEE 802.11bp reports a smaller and less uniform set of WLAN-oriented indicators, and AMBIENT-6G broadens the analysis with additional functional KPIs and KVIs. Across the three sources, the most consistently recurring dimensions are latency, communication range or coverage, data rate, positioning accuracy, mobility, and reporting interval. Therefore, the values reported by these initiatives should be interpreted as use-case- and framework-specific targets rather than universally harmonized benchmarks.

IV. DEVICE TECHNOLOGIES

This section outlines key device technologies enabling energy-efficient operation of A-IoT devices. The design of A-IoT devices is best understood as a tightly coupled EH, power management, communication, and computation stack rather than as a set of independent components. It covers EH and power management, low-power radio technologies for communication, and advances in on-device and edge

TABLE VI
SUMMARY OF A-IoT USE CASES INTRODUCED IN SECTION III-B

Use Case	Source	Description
Automated warehousing	3GPP, IEEE	Autonomous inventory handling and tracking using A-IoT devices.
Medical instruments inventory management and positioning	3GPP	Monitoring and location tracking of medical tools.
Substations in smart grids	3GPP, IEEE	Sensing and control for real-time monitoring of electrical substations.
Non-public networks for logistics	3GPP	Private wireless networks enabling secure, low-latency communication for logistics operations and asset tracking.
Intralogistics in automobile manufacturing	3GPP	A-IoT-enabled coordination within automotive production environments.
Sensors in smart homes	3GPP, IEEE, AMBIENT-6G	Environmental monitoring, security, and automation in residential settings.
Airport terminals/shipping ports	3GPP	Large-scale A-IoT deployments in airports/shipping ports.
Finding remote lost items	3GPP	Location-aware A-IoT tags for finding lost objects across wide areas.
Location services	3GPP	A-IoT-enabled real-time geolocation and mapping.
Relative positioning	3GPP	Positioning of A-IoT devices with respect to reference points.
Online modification of medical instruments status	3GPP	Remote configuration and operational updates of connected medical devices.
Personal belongings finding	3GPP, AMBIENT-6G	A-IoT-based item tagging for quick identification and finding of personal objects.
BS environmental supervision	3GPP	Continuous monitoring of environmental and safety parameters in telecom infrastructure rooms.
Indoor positioning	3GPP, IEEE	Localization of IoT devices within enclosed spaces for navigation and asset tracking.
Smart laundry	3GPP	A-IoT-enabled automation and monitoring of clothes washing system.
Automated supply chain distribution	3GPP	A-IoT-enabled end-to-end monitoring in supply chains.
Device activation and deactivation	3GPP	Remote control of operational states to optimize energy consumption and security.
Fresh food supply chain	3GPP, IEEE	Temperature and humidity monitoring to ensure quality of fresh food.
Forest fire monitoring	3GPP	Distributed sensing for detection of fire risks in remote forest areas.
Smart agriculture	3GPP, IEEE, AMBIENT-6G	Soil, crop, and environmental monitoring for optimized agriculture.
Museum guide	3GPP, AMBIENT-6G	A-IoT systems providing interactive, context-sensitive information to visitors.
Smart grazing dairy farming	3GPP	Livestock monitoring for efficient dairy production.
Smart pig farm	3GPP	Monitoring systems for pig farming operations.
Smart manhole cover safety monitoring	3GPP	Detection of structural anomalies or danger in urban manholes.
Smart bridge health monitoring	3GPP, AMBIENT-6G	Bridge structural monitoring for predictive maintenance of bridges.
Elderly health care	3GPP	Wearables for continuous health monitoring and emergency alerting for seniors.
End-to-end logistics	3GPP, AMBIENT-6G	End-to-end control and monitoring in logistics chains.
Pressure powered switch	3GPP	A-IoT switch activated by mechanical pressure for maintenance-free operation.
Device permanent deactivation	3GPP	Irreversible shutdown of A-IoT devices.
Controller in smart agriculture	3GPP	Control systems for automated irrigation, fertilization, and crop management.
Smart manufacturing	IEEE	Automation of manufacturing processes for optimized industrial production.
Data centre	IEEE	Environmental and asset monitoring for efficient and reliable data center operations.
Electronic shelf label	AMBIENT-6G	A-IoT price tags for dynamic pricing and inventory synchronization.
In-body or wearable medical sensors	AMBIENT-6G	A-IoT devices for continuous medical monitoring and diagnostics.
Asset, Product, Tool, and Item Tracking	AMBIENT-6G	Real-time assets location and monitoring.
Industrial predictive maintenance	AMBIENT-6G	Early fault detection and maintenance scheduling in industrial equipment.
Cooperative mobile robots	AMBIENT-6G	Robotic systems autonomously collaborating.

intelligence, including task scheduling and wireless network applications.

A. Energy Harvesting (EH)

EH has emerged as a key enabling technology for realizing sustainable A-IoT deployments. By scavenging energy from the surrounding environment, A-IoT devices can operate autonomously for extended periods without requiring frequent battery replacements or external power sources [118]. The harvested energy is typically stored in a small rechargeable battery or supercapacitor, providing a stable supply to support continuous operation even during periods of insufficient energy availability. In many cases, hybrid approaches that combine multiple harvesting modalities are adopted to maximize energy availability across varying environmental conditions. Furthermore, advances in ultra-low-power electronics, adaptive energy management circuits, and intelligent duty-cycling mechanisms have significantly enhanced the feasibility of EH for A-IoT applications.

A-IoT devices can leverage a diverse set of ambient energy sources, including solar energy (outdoor and indoor lighting), mechanical sources such as vibration and piezoelectric effects, and thermal gradients. These sources differ significantly in terms of power density, intermittency, and environmental dependency as shown in Table III. For instance, solar energy can provide relatively high and stable power under favorable conditions, whereas mechanical and thermal sources are typically sporadic and application-specific. EH field trials provide a complementary lesson. Real energy sources are non-stationary, spatially heterogeneous, and strongly affected by installation details. Light harvesting is affected by orientation, shadowing, dirt, spectrum, and occupancy patterns. Mechanical and kinetic harvesting depend on motion statistics rather than average activity alone. Thermoelectric harvesting depends on maintaining a thermal path and a usable gradient, not only on the existence of a hot or cold surface. RF harvesting depends on distance, fading, traffic load, regulatory limits, and the availability of dedicated or ambient emitters. Field-tested devices and platforms, including ambient-light powered NB-IoT and BLE devices, multi-source and electric-field powered sensor nodes, vibration-powered platforms, motion-powered wearables, thermal infrastructure monitors, and underwater acoustic-powered systems, demonstrate that source modeling and mechanical integration are as important as transducer selection [119], [120], [121], [122], [123], [124], [125], [126], [127].

Prior studies on A-IoT also recognize this diversity of energy sources, while noting that system-level investigations, particularly within 3GPP, primarily emphasize radio frequency EH (RF-EH) due to its tight integration with communication and backscattering mechanisms [15]. In the following subsections, we narrow our focus to RF-EH and power management units (PMUs), which play a pivotal role in enabling practical battery-free systems.

1) *RF Energy Harvesting*: RF-EH technologies are broadly classified into ambient RF-EH, exploiting existing communication signals, and dedicated WPT, using intentionally emitted

signals. The latter requires infrastructure support and a corresponding control plane, and is treated in Section V-A, while the former is subject to challenging channel state information (CSI) estimation, unpredictable directionality and timing of energy arrival, the need for flexibility in frequency band selection, and the requirement for a wide dynamic power range in concurrent ambient-dedicated systems.

Several notable research contributions address these issues. In [128], an ML-aided RF-EH receiver was proposed to intelligently switch between ambient RF-EH and WPT, optimizing overall performance. Hybrid combining circuits, capable of harnessing power from multiple frequency bands, were demonstrated in [129]. Advanced hybrid RF-EH combiner designs were investigated in [130], considering energy consumption optimization through methods such as brute force, sequential testing, and codebook-based strategies. An automatic distribution network routing RF signals to optimal rectification branches without external controls was introduced in [131]. Antenna designs specifically optimized for ambient or dedicated RF-EH were contrasted in terms of directivity, gain, and polarization in [132]. A review on antenna technologies for RF-EH circuits was provided in [29]. Fundamental aspects critical to designing circuits with wide dynamic power ranges, necessary for efficient concurrent harvesting, were thoroughly discussed in [133], and [134]. In real-world RF environments, performance degrades due to signal interference, mobility, and multi-source variability. Current rectifiers, impedance-matching networks, and multi-band harvesting architectures still lack the efficiency and adaptability needed to deliver stable and scalable energy for practical A-IoT deployments.

2) *Power Management Units*: A PMU forms the central building block of EH systems. Its fundamental function is to manage the intermittent, dynamic power output from the energy harvester, ensuring reliable power delivery. There are three major phases of operation in a PMU: cold start, maximum power point tracking (MPPT), and voltage boosting. The PMU scavenges energy from the harvester during the cold start phase and then boosts the output to provide a stable voltage. MPPT ensures that the maximum power from the harvester is extracted by providing a matched load. The cold start circuit is often achieved using charge pumps, which initially charge from a low harvester output to boot the main boost converter [135].

SotA designs include a Dickson charge pump driven by a ring oscillator [136]. The boost circuit can be either a switched capacitor or an inductor-based switching regulator but efficiency is limited due to transfer losses and discrete conversion ratio (e.g., an n -stage charge pump can only boost voltage up to 2^n). Recent works try to achieve high conversion efficiency through reconfigurable charge pumps [137], [138]. On the other hand, inductor-based boost converters achieve higher efficiency but at the cost of a larger form factor and are mainly suitable for harvesters with higher output voltages like solar cells. The majority of commercial PMUs are inductor-based [139], [140]. Certain inductor-based boost converters employ transformer-based topologies to achieve extremely low cold start. The transformer, often with a zero-threshold metal-oxide semiconductor field effect transistor (MOSFET), can

generate oscillations at very low input voltages [141], [142], enabling autonomous bootstrap.

As the energy demand for A-IoT nodes increases, multi-source EH becomes more useful. However, harvesting energy from multiple sources requires the PMU to manage a wide range of electrical characteristics. SotA solutions [143] include inductor-sharing direct current (DC)-DC converters or multiple DC-DC converters followed by an energy combiner. Chamanian et al. proposed a multisource PMU using a shared inductor topology [144], where each source is buffered before boosting through a single inductor boost converter. The design can harvest energy from 6 μ W to 60 mW with 80% efficiency and uses an analogue computer for MPPT for each source (solar, piezoelectric, biofuel cell). A collaborative energy harvester using a shared inductor was proposed in [145], where voltage from a piezoelectric harvester or solar cell biases a TEG to extract maximum power.

Although inductor-sharing reduces form factor, it limits MPPT since the inductor interfaces with a temporary capacitor rather than the source. An alternative is using separate DC-DC converters for each source and combining outputs using an energy combiner as a multisource harvester, achieving 88% efficiency [121]. Another solution in [146], a multisource energy combiner with MPPT that merged four sources with an analogue ranking circuit and switched capacitor combiner, achieving 87.2% efficiency. The PMU is a crucial building block of A-IoT, but research often focuses only on improving DC-DC efficiency. In capacitor-buffered A-IoTs, the size and threshold of the energy buffer are highly sensitive to the source, load, and computation methods [147], [148]. It is advantageous to use multiple capacitors or dynamically adjustable buffer sizes by modifying threshold voltages, but PMUs with such dynamic buffer sizes are seldom researched [149], [150]. An ideal multisource-PMU would support various sources without hardware modifications, enabling faster deployment and re-usability of A-IoT architectures. Despite some industrial efforts [151], seamless multi-source EH remains largely unexplored.

3) *Lessons Learned*: The surveyed EH literature shows that the performance of A-IoT systems is determined not only by the harvester itself but also by the interaction among energy acquisition, power management, and storage. While RF-EH, solar, thermal, and vibration harvesting can individually sustain low-power operation, their effectiveness strongly depends on environmental conditions and on the PMU's ability to efficiently handle intermittent and highly variable inputs. Furthermore, multi-source harvesting consistently improves energy availability, but introduces additional complexity in source coordination, MPPT, and energy-buffer management, making system-level integration as important as harvester efficiency. Field deployments further reveal that nominal harvesting performance is often a poor predictor of long-term operation, as installation conditions, source dynamics, and environmental variability frequently dominate achievable energy yield. Across many surveyed systems, PMU design, cold-start capability, and energy-buffer management emerge as equally important determinants of system performance as the energy transducer itself.

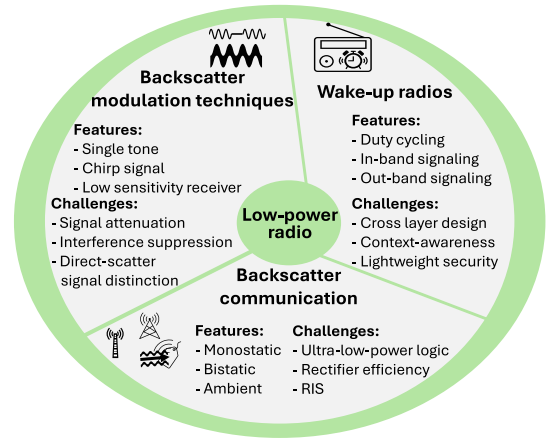


Fig. 6. Features and challenges related to low-power radios.

B. Low-Power and Backscatter Radios

Low-power radios are increasingly reducing active RF operation through selective activation, reflection-based signaling, and simplified receiver architectures. This subsection reviews recent advances in wake-up radios, BC, and backscatter modulation techniques. A pictorial summary of the relevant features and future research challenges is given in Fig. 6.

1) *Wake-Up Radios*: Conventional mechanisms, such as duty cycling, conserve energy by deactivating the radio interface and microcontroller unit (MCU) during idle periods; however, they increase latency and packet loss, as devices in deep sleep cannot receive data in real-time [152]. WuR technologies address these issues by enabling always-on, ultra-low-power listening that activates the main radio only when necessary, to render 1000 times less power than conventional radios [24], [153].

Architecturally, WuRs includes passive designs (e.g., envelope detectors, super-regenerative receivers (RXs)) with sub- μ W power but limited selectivity, and active designs (e.g., injection-locked oscillators, on-chip local oscillators) that offer better sensitivity and interference rejection under 100 μ W [62]. Hybrid approaches combining EH and small batteries are also being explored [24]. In-band WuRs reuse resources, while out-of-band designs reduce interference but increase complexity [154].

From standardization perspective, 3GPP introduced WuRs in Release 15 through PHY WuSs, with Releases 16 and 17 adding group-based wake-ups, energy-efficient physical downlink control channel (PDCCH) monitoring, and cross-slot scheduling for 15–30% energy savings [155], [156]. Non-cellular solutions (e.g., BLE) have also achieved over 10-year lifespans and sub-2s latency targets [157]. Li2BC, a visible light communication (VLC)-based front end, further enables ultra-low-power activation using pulse width modulation (PWM)-driven Light Emitting Diode (LED) light and a PV cell for energy and data reception [158].

Deploying WuRs introduces system-level trade-offs. Because they must detect wake-up signals, misdetections and false alarms can increase latency or waste energy [24], [159], [160], while resource management is complicated by

uncertain sleep patterns and hardware trade-offs between in-band and out-of-band designs [7]. Beamformed WuS at mm-waves adds complexity for locating and activating sleeping devices [7]. Emerging ML-based scheduling can mitigate these challenges by leveraging device context [159].

Future research must co-design WuR hardware and cross-layer protocols to deliver secure, context-aware, and cost-efficient solutions. This co-design should integrate energy and wake-up sensitivity metrics at the hardware level with higher-layer scheduling and decision-making policies [161]. Specifically, the WuR circuitry must interact seamlessly with control planes that utilize context information such as energy availability, information freshness, task relevance, and medium conditions. Additionally, lightweight security measures should be embedded in the wake-up process to prevent false activations and unauthorized access.

2) *Backscatter Radios*: Backscatter radios enable the exploitation of existing electromagnetic waves for data transmission. Typical systems modulate and reflect incoming RF signals with embedded data. Main configurations include monostatic, bistatic, and ambient backscatter [162]. Monostatic uses a single antenna for transmission and reception, but suffers from round-trip propagation loss scaling with the fourth power of distance. Bistatic separates transmitter and receiver, reducing losses and self-interference. Ambient backscatter [163] leverages environmental RF sources without dedicated carriers.

Backscatter devices employ passive RF components such as positive-intrinsic-negative (PIN) diodes, Schottky diodes, transistors, and MOSFET-based RF switches [11], [164]. PIN diodes modulate impedance through small DC biases enabling amplitude-shift keying (ASK). Schottky diodes with low forward voltage and fast switching serve in rectifiers handling μW – mW -level power [11]. bipolar junction transistor (BJT)s and MOSFETs provide load modulation, with BJTs favoring linearity at higher power, while nW -level MOSFET switches enable precise impedance control [11]. RF harvesters with matching networks and rectifiers yield 10–100 μW near Wireless Fidelity (Wi-Fi) access points (APs) [165]. Piezoelectric and thermoelectric harvesters generate tens of μW from vibrations and temperature gradients [164], [166]. These harvested energy buffers in supercapacitors power low-power MCU or logic, toggling RF switches at low duty cycles ($<10\%$) to recharge between transmissions [11], [167]. Upon detecting ambient RF sources, switches decode and modulate reflected signals received by readers [165], minimizing average power and enabling battery-free operation.

Antenna design impacts impedance modulation and EH efficiency. Printed dipole, monopole, and patch antennas on flexible substrates reduce cost and size [168], [169], [170]. Microstrip patches provide 5–8 dBi gain and conformal mounting. Matching networks, with discrete inductors and capacitors, achieve $>70\%$ power transfer efficiency while presenting proper impedance for backscatter [11].

Advances in inkjet and 3D printing have enabled cost-effective, flexible backscatter devices [168]. Conductive inks on flexible substrates operate at tens of μW with rectifier

efficiencies above 60% at 2.45 GHz [171]. Stretchable electronics enable wearable and implantable tags, powered by kinetic EH, such as smart fabrics integrating backscatter and BLE for vital-sign monitoring [172]. Printed biodegradable tags deployed for agricultural sensing demonstrate environmental sustainability [173]. Transient electronics using conductive polymers and water-soluble substrates allow harmless degradation post-lifespan [174], [175]. Future work includes new materials (flexible) for enhanced rectifier efficiency, ultra-low-power logic for sub- μW operation, and improved modulation for multi-megabit rates.

3) *Ambient Backscatter*: LoRaBackscatter is a long-range BC prototype that significantly outperforms traditional short-range backscatter systems [184]. The design utilizes a sticker-form factor antenna from an Alien Squiggle RFID tag, connected to low-cost hardware. To address signal attenuation over long distances, the RF source transmits a continuous single-tone signal at 915 MHz with a transmitting power of 30 dBm and a 6 dBi antenna gain. This high power spectral density (PSD) single-tone signal compensates for the extremely weak backscattered signal at the receiver, which can be as low as -135 dBm.

Unlike conventional backscatter systems, the proposed LoRaBackscatter device generates a continuously changing frequency known as a chirp signal. The chirp frequency continuously increases for bit ‘0’ or is cyclically shifted for bit ‘1’, referred to as chirp spread spectrum (CSS) modulation. Different from other backscatter device (BD) implementations, the load impedance in LoRaBackscatter uses multiple impedance states controlled by a switch network. The BD MSP430 operates with ultra-low power consumption of just 9.25 μW , comparable to RFID devices in the same order of magnitude [184]. Benefiting from the exceptional sensitivity of the LoRa receiver (-149 dBm), the proposed ambient backscatter communication (AmBC) achieves a communication range of up to 475 m in experimental trials. The study in [177] introduces a novel AmBC system concept utilizing BD polarization conversion. This conversion is leveraged by a dual-polarized receiver antenna to suppress interference from the direct path. The BD changes the polarization from linear to circular to differentiate between the direct and scattered signals. A backscatter radio summary corresponding to source and modulation is given in Table VII. It gives an overview of different ambient signal sources and modulation techniques. In [176], the low-cost multi-antenna AmBC receivers are implemented and the authors propose a narrowband reference signal extraction method to overcome wideband antenna effects, hardware impairments, and complex propagation, achieving acceptable BER in real environments. Focus on low-power modulation and receiver designs, offering digital and analog tag schemes in [179] includes pseudo-FSK, S-BPSK, coded backscatter, and FM-based analog modulation, achieving long ranges and robust operation.

4) *Lessons Learned*: Across these low-power radio families, the survey reveals a recurring implementation trade-off between device simplicity and infrastructure complexity. Passive and semi-passive backscatter devices can reach very

TABLE VII
SUMMARY OF AMBIENT BACKSCATTER COMMUNICATION

Ambient signal source	AmBC Modulation	Year	Ref.
random OFDM; 483 MHz	OOK; multi-antenna	2023	[177]
2.44 GHz single tone	OOK; 50 kHz; Polarization from linear to circular	2020	[178]
Carrier frequency 2.4 GHz	two polarization patterns; energy detector & least square error receiver	2020	[179]
FM radio; center frequency 88MHz - 108 MHz	FM, pseudo FSK and Shifted BPSK; 20 Hz - 20 kHz or 53 kHz	2019	[180]
UHF TV signal; 10 MHz @ 539 MHz	M-PSK; 20 kbps	2019	[181]
LTE PSS & SSS; 752 MHz	BPSK	2020	[182]
Wi-Fi; DBPSK-802.11b	pulse width modulation; 9.2 pkts/s	2023	[183]
Wi-Fi CSI; 20 MHz @ 2.4 GHz	shifts the frequency of the Wi-Fi signal by ± 20 MHz	2023	[184]

TABLE VIII
SUMMARY OF ON-DEVICE AND EDGE INTELLIGENCE METHODS MENTIONED IN SECTION IV-C

Characterization	Technique	Training	Ref.
TinyML (Model Design, Inference, and Applications)			
Energy-aware model selection balancing accuracy, energy, latency.	TinyML	R	[44]
Thresholded One-Versus-All (OVA) inference adapting to battery/buffer states.	TinyML	R	[186]
Multimodal human activity recognition (HAR) for stress recognition.	TinyML	R	[187]
Energy-aware TinyML for face identification.	TinyML	R	[188]–[190]
Ultra-low power (ULP) camera-based people counting with CNN.	TinyML	R	[191]
Wearable-based HAR with lightweight deep neural network (DNN).	TinyML	R	[192]
Dynamic wireless network traffic prediction.	TinyML	R	[193]
Air quality monitoring and data imputation.	TinyML	R	[194]
Indoor asset tracking via deep learning.	TinyML	R	[37]
Kernel-based nonlinear BLE location estimation.	TinyML	R	[195]
PhiNets for efficient object detection.	TinyML	R	[196]
Energy-based task selection and vehicular CO ₂ monitoring.	TinyML	R	[36], [197]
Biodiversity monitoring via bat sound recognition.	TinyML	R	[198]
FPGA-based TinyML architecture design.	TinyML	R	[199]
Semi-supervised deep learning for HAR.	TinyML	R	[200]
Various Tiny deep learning applications (sensor linearization, RF fingerprinting, positioning, pre-distortion, symbol detection, intrusion detection, data extraction).	TinyML	R	[33], [45], [201]–[205]
Federated Learning and Hybrid Approaches			
Federated learning (FL) optimization for TinyML devices, energy-aware frameworks, anomaly detection.	FL	R,(L)	[41], [206], [207]
SplitGP: Split + FL with personalized inference and multi-exit networks.	Split+FL	R,(L)	[208]
SplitGuard: protecting split learning via model integrity verification.	Split	R,(L)	[209]
On-device/Incremental Learning and Fine-Tuning			
Tiny Online Learning (TinyOL): incremental output-layer-only learning.	TinyOL	L	[42]
Tiny Transfer Learning (TinyTL): bias-only fine-tuning reducing memory overhead.	TinyTL	R,L	[43]
Fully Quantized Training (FQT) sparse gradient updates for on-device adaptation.	Quant.+TinyML	L	[210]
Tunable-width CNN, Once-for-All Neural Architecture Search (NAS) for scalable on-device learning.	TinyML	R,(L)	[211], [212]
Other Methods and Schedulers			
AsTAR: adaptive scheduler for EH IoT devices.	Scheduler	-	[213]
OTA deployment and on-demand TinyML model switching.	OTA-TinyML	R	[214]
Survey on on-device ML benefits in IoT (privacy, latency).	On-device ML	R	[215]

R: Remote training; L: Local training; (L): Partial/optional local training; "-": Not applicable.

low device-side power, but require favorable carrier placement, robust separation between the direct and scattered paths, and readers with sufficient dynamic range. WuRs provide asynchronous availability, but require wake-up signals that remain detectable under interference and hardware variability while avoiding unnecessary activations. Low-power active radios reduce dependence on external carriers and simplify bidirectional operation, but the energy buffer must absorb peak-current events caused by synchronization, channel access, transmission, and reception. This implies that the most practical A-IoT radio is not always the radio with the lowest instantaneous device power. Instead, deployability depends on the complete energy cost of discovery, synchronization, addressing, acknowledgement, security, and retransmission under the expected source and channel dynamics.

C. On-Device and Edge Intelligence

Fig. 7 illustrates four key research directions in on-device and edge intelligence. Together, they capture the core design space for scalable, adaptive edge AI systems, with key works summarized in Table VIII. The simpler A-IoT classes cannot participate in true online adaptation, since UP nodes operate solely on instantaneous harvested power and cannot retain state, and DB devices offer only transient storage, losing state on every brownout, restricting the latter to simple reactive heuristics.

1) *On-Device Intelligence*: On-device ML shifts intelligence from cloud servers to edge hardware [214], reducing latency, bandwidth use, and privacy risks. TinyML enables real-time inference directly on embedded devices [215] with strict memory, compute, and energy constraints, without cloud

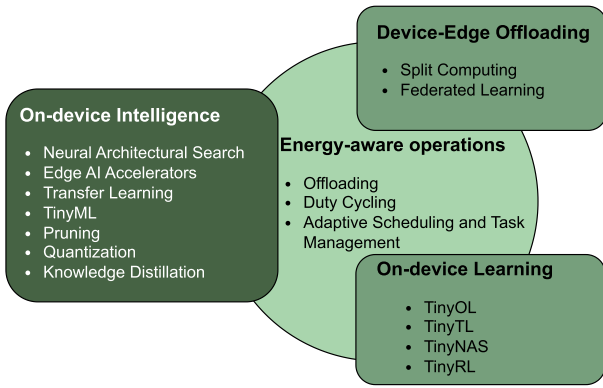


Fig. 7. Conceptual overview of the four major research directions in on-device and edge intelligence: (i) O-DI for efficient inference on constrained devices; (ii) device-edge offloading to balance latency, accuracy, and energy; (iii) on-device learning for continual, personalized adaptation; and (iv) energy-aware task scheduling to optimize resource use.

dependence [216]. The benefits include faster response times, enhanced privacy through local data retention, personalization via continual learning, and reduced energy consumption by minimizing transmissions.

A-IoT systems, particularly DP devices, operate under intermittent and stochastic energy availability, where computation must adapt dynamically to fluctuating power conditions rather than fixed budgets. Thus, instead of optimizing for energy efficiency alone, system designs must ensure energy-neutral operation and avoid energy depletion while maintaining acceptable inference quality [217]. Consequently, minimizing communication [7] and maximizing O-DI [196] are not only efficiency goals but prerequisites for system survivability and long-term autonomy.

Numerous works demonstrate TinyML in various domains (cf., Table VIII). However, most of these works implicitly assume continuous power availability, only valid for CO devices. Thus, challenges remain significant. A-IoT devices are constrained in compute, memory, and energy, but in DP devices these constraints become time-varying and non-deterministic due to reliance on EH [217], [218]. This introduces new trade-offs beyond model compression, including when to compute, how much to compute, and whether to compute at all, depending on the harvested energy profile. Balancing model performance and compression [210], [218] is therefore insufficient on its own. Models must also be energy-adaptive and interruption-resilient.

Cold-start remains a core challenge for ML-based wake-up management in A-IoT, as newly deployed nodes lack both historical energy data and often an initialized model [161]. The ability to address this depends strongly on the device's energy-storage class, which determines what it can sense, retain, and sustain during early operation. In the first deployment phase, nodes must rely on mechanisms that assume no prior knowledge. Zero-history heuristics [219] are therefore the only universal starting point, though they still require minimal observation and short-term retention of key parameters. DP devices can preserve state of charge (SoC) history across cycles, enabling gradual improvement through

cautious exploration, while CO devices support finer temporal resolution and greater stability. To accelerate convergence, transfer-based initialization can provide population priors or shared templates, and cloud-assisted bootstrapping can supply pre-trained models, provided the device has sufficient energy to communicate.

Using multiple specialized models can improve efficiency by reducing unnecessary computation. In A-IoT, such multi-model strategies also enable graceful degradation, in which simpler models are selected under low-energy conditions and more complex models under surplus energy availability. Prior work demonstrates this via multimodal HAR and stress detection [186], adaptive thresholding [185], and energy-aware model selection [44].

NAS-based approaches further support the A-IoT paradigm by tailoring architectures to hardware constraints. TinyNAS co-designs networks and inference libraries for MCUs [215], while Once-for-All (OFA) [211] enables dynamic sub-network selection. These methods are particularly relevant as they enable runtime adaptability, allowing models to scale their complexity in response to instantaneous energy availability.

Pruning, quantization, and knowledge distillation remain essential, but in A-IoT they must be complemented with energy-aware scheduling, adaptive inference, and cross-layer co-design to ensure sustained, autonomous operation under energy harvesting constraints.

2) *Device Edge Offloading*: ML inference in A-IoT systems is strongly constrained, enabling execution either locally or via edge/cloud offloading. The most common methods used with A-IoTs are split computing and FL. Split computing distributes DNN layers across devices and the edge to jointly optimize latency, energy neutrality, and privacy under highly variable ambient conditions. FL complements split computing by enabling decentralized training.

For example, I-Split [220] identifies split points using Grad-CAM without retraining. However, I-Split is too complex to run locally and can only be executed in the cloud, but it creates static split points (per class) that can be used by the A-IoTs. SplitGuard [208] improves security against training-hijacking attacks, but is less effective on energy-constrained A-IoTs. Communication costs must be minimized, e.g., using accumulated gradients and compression. In multi-access edge computing (MEC)-based [221] A-IoT deployments, task partitioning must explicitly account for stochastic energy arrivals and sensing-driven computation patterns. reinforcement learning (RL)-based offloading, originally designed for relatively stationary channel and energy models, is adapted for A-IoT to handle non-stationary, energy-harvesting states and environment-driven dynamics, improving delay and task reliability under uncertainty [222].

FedIoT [206] applies FL to A-IoT cybersecurity but incurs high communication overhead. Energy-aware FL optimizes scheduling based on harvested energy [205]. Ficco et al. [41] further integrate FL and Transfer Learning (TL) for online TinyOL, reducing bandwidth via Message Queuing Telemetry Transport (MQTT) but facing energy and data heterogeneity challenges. Hybrid approaches combine both paradigms: SplitGP [207] dynamically balances local and remote

inference using multi-exit networks, though its communication and storage demands limit applicability to ultra-constrained devices. Over-the-air TinyML (OTA-TinyML) [213] enables scalable remote deployment of TinyML models but relies on stable connectivity and hardware-specific optimization.

Energy-aware operation in A-IoTs using TinyML requires accurate estimation of per-layer energy consumption and latency to support device-edge offloading decisions. Partitioning depends on available energy, bandwidth, and optimization objectives such as latency or accuracy. While regression-based layer models can estimate energy and latency across layer types [223], [224], they require extensive data and scale poorly in large A-IoT deployments [225]. A more practical approach is direct on-device profiling, where per-layer runtime and energy are empirically measured and used by the scheduler [226], [227]. This measurement-based method offers higher accuracy and enables fine-grained optimization for offloading and model compression [228], but in A-IoTs even the energy needed for profiling can impact on the device performance.

3) *On-Device Learning*: This paradigm largely assumes stable energy and computing availability, which does not hold in A-IoT systems, where devices operate under strict energy neutrality and intermittent execution. Recent work explores enabling partial on-device training of ML models [229], moving toward adaptive behavior without full cloud dependence. However, in A-IoT, the challenge extends beyond reducing computation: training must be schedulable under stochastic energy arrivals, bounded storage, and intermittent availability, requiring tight coupling between learning algorithms and system-level resource management. Also, large data transfers (e.g., gradient updates) should be minimized.

Progress is driven by lightweight model optimization techniques such as quantization, pruning, and knowledge distillation [7], [230], [231]. While originally designed for efficient inference, their adaptations, e.g., quantization-aware training, iterative pruning, and online distillation, enable on-device updates. Emerging paradigms such as TinyOL [42] enable incremental learning by restricting updates to a small subset of parameters (e.g., output layers), significantly reducing memory and compute demands. Similarly, TinyTL [43] supports low-memory fine-tuning by freezing most parameters and minimizing activation storage. Recent approaches, such as Deutel et al. [209], combine fully quantized training with sparse gradient updates to reduce computational and communication overhead. These improvements align well with A-IoT constraints, as they limit both state persistence requirements and energy expenditure per update. Nevertheless, such approaches introduce a fundamental trade-off: reduced model plasticity versus energy feasibility, which is more pronounced under highly variable energy budgets. Also, their applicability depends on the ability to enable execution by careful scheduling across intermittent power cycles without violating consistency, which may even require custom hardware-aware optimization.

Overall, enabling on-device learning in A-IoT is not solely a matter of model efficiency but of co-design across learning, scheduling, and energy management. Unlike conventional IoT, where optimization targets latency or throughput,

A-IoT systems must ensure energy-neutral, interruption-resilient learning, often prioritizing long-term adaptability over immediate accuracy gains.

4) *Energy-Aware Task Scheduling*: Task scheduling is critical for A-IoTs to ensure reliability under fluctuating harvested energy. A-IoT approaches should enforce energy causality, i.e., tasks execute only when sufficient energy is available.

Energy-neutral operation requires maintaining residual energy $E_{k+1} \geq E_{min}$, where E_{k+1} depends on initial state, charging efficiency η , harvested energy e_i , and task cost c_j for decision x_{ij} [232]. A common model is $E_{k+1} = \min(E_{max}, E_k + \eta e_k - \sum_j c_j x_{ij})$, capturing energy inflow, consumption, and storage bounds.

At the system level, protocols such as T2 [233] coordinate intermittently powered nodes via token passing and tiering to avoid overlap and meet deadlines. Multi-exit TinyML complements this with confidence-gated execution: a low-cost inference (EX1) escalates to a higher-accuracy stage (EX2) only if $E_{avail} \geq E_{req, EX1 \rightarrow EX2} + \Delta$. This realizes intra-task scheduling conditioned on confidence and energy, ensuring no power failures while maximizing utility per energy.

Without non-causal energy knowledge, reactive strategies dominate. InK [234] and threshold policies trigger execution based on capacitor voltage V_c , e.g., $V_c \geq V_{req}$ [235]. AIMD-based schemes adapt task rates to energy trends. Here, task admission is implicitly driven by instantaneous energy rather than explicit optimization. On-device RL (e.g., MAQS [236]) models control as a Markov decision process (MDP) and accelerates learning via “Phantom Q-updates”, leveraging the monotonic relation between task rate and voltage. States encode energy and backlog, and actions map to task or offloading choices.

Task selection and model adaptation further improve efficiency. Sabovic et al. [44] scale TinyML model complexity with energy availability. Checkpointing preserves progress under intermittency [237] but incurs overhead [24], mitigated by bounded execution [238], efficient designs [239], and energy-aware triggers [240], [241], [242], [243]. These mechanisms decouple progress from strict energy availability.

Optimization remains central when deadlines and constraints must be enforced [244]. Mixed Integer Linear Programming (MILP)-based schedulers optimize task allocation over short horizons, predicting that a few tasks often suffice to avoid outages and meet deadlines [244]. Model predictive control extends this via lightweight online convex optimization, dynamically offloading tasks to maximize the minimum battery level [245]. Complementary approaches handle uncertainty via prediction and stochastic modeling, improving energy availability [246], prediction accuracy [247], transmission robustness [248], and task completion guarantees [249]. They differ in handling uncertainty via prediction, worst-case optimization, or online adaptation, and how future energy is integrated.

5) *Lessons Learned*: The device-level literature shows that the main barrier between laboratory prototypes and deployable A-IoT systems is not the absence of any single component. Rather, the barrier is the mismatch between component-level

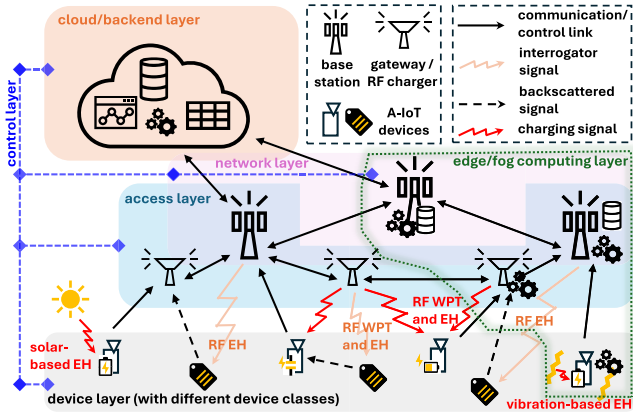


Fig. 8. Layered network architecture for A-IoT servicing and support. There are six key layers: i) A-IoT device layer, composed of heterogeneous devices ranging from ultra-passive tags to more versatile, active devices; ii) access layer, which comprises readers, gateways, and RF ETs that serve as the primary interface and/or support to the A-IoT devices; iii) network layer, responsible for connectivity and routing across local and wide-area networks; iv) edge/fog computing layer, which enables local processing and adaptive control; v) cloud/backend layer, offering large-scale data aggregation, storage, analytics, and control logic; and vi) a control and management layer that orchestrates coordination, policies, resource scheduling, fault-detection, and system-wide security enforcement, all for QoS assurances.

feasibility and full-stack operation under variable energy, variable channels, installation constraints, and application-specific deadlines. A laboratory prototype can demonstrate a low-power rectifier, a sensitive backscatter link, or a TinyML inference task under controlled inputs. However, a deployable device must also cold-start, store energy without excessive leakage, wake up at the correct time, discover or be discovered by the network, communicate reliably, protect basic control operations, and recover after energy failures. Therefore, the relevant performance metric is not only peak harvested power, receiver sensitivity, or inference accuracy, but the probability that the complete sensing, computing, and communication transaction finishes before the energy buffer is depleted.

The overarching lesson is that future A-IoT devices should be designed for graceful degradation under energy scarcity. A deployable device should reduce sensing rate, model complexity, payload size, or link ambition before it fails. This requires co-design across harvesters, PMUs, storage, radios, embedded software, and network protocols. It also requires evaluation with shared traces, reproducible testbeds, and application-level success metrics such as event detection probability, freshness of information, maintenance interval, and lifetime environmental impact. Such evaluation will make the transition from compelling prototypes to robust A-IoT products more predictable.

V. NETWORK TECHNOLOGIES

This section focuses on key SotA network technologies enabling A-IoT, highlighting their evolution and role in providing power delivery, reliable connectivity, coordination, and secure operation. Large-scale A-IoT systems rely on the seamless integration of these technologies across devices, networks, and backend intelligence, as illustrated in Fig. 8.

A. WPT Networks and Protocols

Innovative ET architectures are gaining increasing attention as a means to reduce power consumption and hardware complexity, alongside flexible deployment strategies across heterogeneous platforms to meet on-demand energy requirements. Moreover, CSI-limited/free charging protocols are appealing to reduce costly overhead, while phase and frequency synchronization aspects at the ETs require careful attention.

1) *ET Architectures*: Physically large arrays, whose aperture is comparable to the propagation distance, are promising to enhance end-to-end WPT efficiency and enable near-field beam spotting/focusing [250], [251]. Emerging architectures such as lens antenna arrays, reflective intelligent surface (RIS)-equipped ET, and dynamic metasurface antennas are crucial here to reduce the number of RF chains and thus power consumption, complexity, and cost [24]. Lens arrays apply spatial phase shifts to yield a sparse beamspace representation, which is exploited in [252]. Furthermore, a performance analysis was carried out in [253] for a 2-bit programmable lens antenna. The implemented prototype demonstrated accurate beam control while avoiding bulky and expensive phase shifters. In the case of RIS-equipped ETs, a collocated digital transmitter illuminates the RIS, which then reflects it with phase shifts [254], [255]. Therefore, an air interface replaces the analog network, with good performance trade-offs even with a single RF chain, as shown in [254]. Further studies of power consumption in [255] demonstrate that such ETs are more efficient in the massive antenna regime than conventional beamforming. Finally, dynamic metasurface antennas consist of densely packed, sub-wavelength-spaced reconfigurable metamaterial elements that, through individual tuning, perform analog signal-processing functions directly in the aperture, avoiding dedicated circuitry [256]. WPT beamforming design for such ETs is investigated in [257], while waveform optimization is studied in [258], showing that dynamic metasurface antennas can outperform traditional counterparts in terms of power consumption.

In distributed antenna systems (DAS), multiple BSs throughout the service area coordinate to extend coverage, mitigate path loss and blockage, and homogenize energy delivery. Radio stripes, a low-complexity DAS with the antennas embedded along flexible cables, have been considered for WPT. Their beamforming design and deployment problem are investigated in [259] and [260], respectively. Meanwhile, the RadioWeaves DAS testbed in [261] showcases a room-sized infrastructure of 280 antennas for near-field WPT. Several experimental studies here have evaluated synchronization requirements [251] and waveform and protocol design [262].

In Movable Antennas (MA)-equipped ETs, radiation patterns are modified by changing the positions of the elements in the array. A study of an MA-equipped ET in [263] reveals that it requires less transmit power than arrays with fixed antennas and highlights how aperture variations shift devices between near- and far-field operation. The spatial flexibility of MAs has been further exploited in [264] for boosting the received power in non-line-of-sight (NLoS) scenarios under strict electromagnetic radiation constraints.

2) *ET Deployment and Synchronization*: Deploying multiple ETs allows eliminating blind spots and matching energy demands to supply more efficiently. Static ET placement is investigated to balance harvested energy versus deployment cost [265] and maximize worst-case energy reception without CSI or devices' location information [266]. Further enhancements include directional ET orientation for peak power delivery [267], and self-sustained ETs harvesting ambient energy [134].

Robotic WPT, via moving or flying ETs, dynamically shortens charging distances, potentially reducing the number of required ETs. Moreover, in [268], a survey of general scenarios and use cases for flying ETs is presented, underscoring how service requirements, hardware limitations at the ETs, and regulations shape the complexity of trajectory optimization algorithms. Furthermore, experimental validation of an adaptive joint trajectory and beamforming optimization for mobile ETs is carried out in [269]. The critical bottlenecks of robotic WPT are addressed in [270] considering hot battery swaps, onboard ambient EH circuits, and laser charging approaches.

Finally, synchronization among cooperative ETs is essential to maximize WPT efficiency through coherent beamforming (based on instantaneous or statistical CSI or service area geometry). Experiments in [251] on the Techtile testbed [271] compared coherent and non-coherent transmit-diversity schemes, and revealed that stringent phase-coherency requirements can be relaxed in some scenarios, as moderated synchronization errors have limited effects on the received power.

3) *WPT Protocols*: CSI acquisition drains considerable energy resources from A-IoT devices and the performance of CSI-based systems decays quickly as the number of served devices increases [272]. Accordingly, CSI-free beamforming strategies have been developed in [250], [251], [262], [264], [266], [272], and [273], which rely on devices' location information or charging area geometry. Meanwhile, experimental evaluations in [262], and [274] demonstrated that adaptive single- and multi-tone excitations can effectively charge A-IoT devices with unknown locations and depleted batteries. The single-tone scheme achieved a faster device response at reduced transmit power. In the context of ML-driven techniques, a deep RL approach is proposed in [275] to minimize ET energy consumption while guaranteeing target EH requirements. Moreover, an RL-based strategy is employed in [276] to minimize information outage probability under average received power constraints.

4) *Lessons Learned*: While both EH circuit and ET architectures continue evolving, most optimization frameworks still rely on nonlinear models derived from simplified architectures, such as single-diode rectifiers, and idealized array assumptions. Consequently, the resulting performance insights are not always fully representative of the harvested power in practical deployments. Moreover, ET architectures with physically large aperture arrays introduce antenna-integration challenges due to feeding network complexity and mutual coupling, which are still insufficiently captured by current WPT models. Furthermore, although experimental studies suggest that synchronization requirements in distributed ETs may be relaxed,

practical deployments may require tighter coordination and adaptive synchronization mechanisms than those observed in controlled laboratory settings. Finally, the surveyed protocols consistently indicate that A-IoT devices cannot sustain frequent CSI acquisition and feedback procedures. Fortunately, practical WPT systems are expected to operate predominantly under line-of-sight (LoS) conditions to remain competitive. Hence, incorporating such assumptions into simulation and experimental studies is key to accelerating the development of scalable low-complexity WPT protocols.

B. Connectivity Protocols

Connectivity protocols for A-IoT can leverage either passive or low-power active communication. The former relies on backscattering techniques and is preferred for extremely low power transmissions, while the latter uses active transmission/reception and is often suited for devices with higher power budgets. Both have received significant attention in research, as summarized in Table IX, and suit different classes of devices (cf. Section II) and use cases.

1) *Backscatter Communications*: In [277], the authors modify the 3GPP Release 19 A-IoT MAC protocol [278] to serve various queues based on priorities. The A-IoT device first sends a beacon, followed by transmitters sending beacons to assist data transmission. Depending on its energy state, the A-IoT device selects a suitable transmitter, which then sends high-priority packets within a defined time window. Once completed, the transmitter schedules low-priority packets.

Regarding multiple access, different BD modulation schemes may be considered according to specific situations, including frequency division multiple access (FDMA) [279], [280], orthogonal frequency-division multiple access (OFDMA) [281], [282] and CSS [184], [283], [284], [285] based approaches. FDMA is robust under harsh NLoS environments with extreme sensitivity [280]. OFDMA [281], [282] is a multi-carrier technique that assigns orthogonal subcarriers to different devices, allowing higher concurrency than FDMA but requiring strict synchronization among communication components. OmniScatter [280] provides a coordination-free OFDM system with a limited data rate. The OFDMA implementation in [281] achieves a lower range than CSS systems, e.g., about 100m for OFDMA implementation in LoS settings. Another OFDMA implementation is DigiScatter [282], which supports large concurrent transmission. Meanwhile, CSS is used with LoRa backscatter in [184] and by NetScatter [283]. The work by Talla et al. [184] was the first study to introduce CSS in AmBC, achieving communication ranges up to 100 m with data rates of 0.3 kbps–1.8 kbps in the 915 MHz ISM band. This pioneering work paved the way for MobiScatter and OsTAG, enabling long-range, low-power AmBC networks. MobiScatter [285] supports concurrent transmissions from a moving drone. OsTAG [284], improved from LoRa backscatter [184], has less chip area while achieving a comparable 100m-level communication range. In brief, FDMA is recommended for simple, high-throughput tag identification; OFDMA for high-density, high-capacity networks with flexible data rates; and CSS for long-range, massive-concurrency scenarios with low data rates. The specific technology should be selected

TABLE IX
SUMMARY OF ASSESSMENT AND OPTIMIZATION STUDIES DESCRIBED IN SECTION V-B

	Characterization	Protocol	Research type	Ref.
Backscatter	Modification of MAC to serve multiple queues based on their priorities.	3GPP Release 19 A-IoT	Simulation	[281]
	Assessment of FDMA based network.	RFID	Prototyping	[283]
	Assessment of network based on cyclic shift phase CSS modulation.	LoRa backscatter	Prototyping	[287]
	Design and assessment of OFDMA backscatter tag.	Custom Wi-Fi backscatter	Prototyping	[285], [286]
	Design and assessment of CSS based backscatter tag.	Custom	Prototyping	[288], [289]
Active	Design and assessment of coordination-free FDMA network.	Custom	Prototyping	[284]
	Overview of application-oriented techniques for A-IoT.	LPWAN	Survey	[290]
	Analysis of different energy-aware packet transmission algorithms.	LoRaWAN	Simulation	[291]
	System model for a battery-free LoRaWAN class A device.	LoRaWAN	Simulation	[119]
	Mathematical model to estimate the probability of successful packet delivery.	LoRaWAN	Math. modeling	[292]
	Energy-aware communication with EH prediction.	LoRaWAN	Simulation	[291]
	Design of a battery-free NB-IoT device, evaluation on sample application.	NB-IoT	Prototyping	[120]
	Comparative analysis of different channel access schemes.	NB-IoT	Simulation	[296]
	Proactive WPT framework for fast uplink grant.	NB-IoT	Simulation	[297]
	Prototype of sound sensor platform powered by multi-source EH.	IEEE 802.15.4 (Zig-bee)	Prototyping	[122]
	Prototype of battery-free sensors in the vicinity of high-voltage power lines.	IEEE 802.15.4 (Zig-bee)	Prototyping	[123]
	Analysis of duty-cycle based polling and WuR based data communication.	BLE	Simulation	[299]
	Mathematical model to estimate the queue occupancy and downlink latency.	BLE	Math. modeling	[300]
	Design and assessment of a battery-free BLE device.	BLE	Prototyping	[121]

based on environmental factors and cost considerations, with OmniScatter for harsh environments, DigiScatter for high-rate flexibility, NetScatter or MobiScatter for wide-area coverage, and OsTAG for ultimate low-cost scalability.

2) *Active Communications*: The support of active A-IoT devices poses a great challenge due to the higher energy consumption. low-power wide-area network (LPWAN) technologies offer a wide coverage range with relatively low power and have therefore been considered a natural candidate to provide active A-IoT connectivity. Due to the A-IoT devices' intrinsic constraints, including inaccurate timing circuits, application-oriented techniques are crucial. These are discussed in [286], while highlighting the benefits of “think before you talk” and “race to sleep” strategies. Among LPWAN technologies, long-range wide-area network (LoRaWAN) has gained much attention due to its flexibility and ease of deployment [287]. Performance evaluation of battery-free class A LoRaWAN A-IoT devices is conducted in [118], [287], and [288] for different energy storage capacitance values, data rates, and turn-on voltage thresholds. In [118], the feasibility of A-IoT LoRaWAN is studied using simulation. The results showed that a 4700 μ F capacitor can operate at an EH rate in the order of 1 mW, even when transmitting more than once per minute. In [288], a mathematical model based on Markov chains is developed to estimate the probability of a successful packet delivery. This model can serve as a guide for A-IoT device designs depending on the application specification (transmission interval, payload size, uplink and downlink patterns) and environmental conditions (EH rate). An energy-aware communication protocol is proposed in [287]. The simulation results show that even a simple conservative energy-aware policy significantly improves the system performance.

Unlike LoRaWAN, NB-IoT uses licensed spectrum, avoiding channel restrictions and severe interference from neighboring networks. To save energy, the NB-IoT device can switch to Extended Discontinuous Reception Mode (eDRX) or power saving mode (PSM) states [286]. In eDRX, it periodically wakes for paging to check buffered downlink data, whereas in PSM it powers off most circuitry. In [119], a prototype of a battery-free NB-IoT device is designed. The study investigates the EH rate needed to support a sample application periodically exchanging UDP packets with 8 bytes of payload without intermittently turning on and off.

Energy spent on channel access plays a crucial role in the total energy consumption of the device. Multiple channel access mechanisms are considered for future low-power cellular networks, among which the most popular are i) random access using a preamble selected from a predefined set [289]; ii) grant-free with or without non-orthogonal multiple access (NOMA) [290], transmitting data using randomly selected resources, i.e., without negotiation with the BS; and iii) fast uplink grant [291], also known as configured grant, in which a BS predicts the activity of the devices and provides them grants in advance, ideally even before data packets appear in the devices' queues.

The selection of the channel access mechanism depends on the use case. For example, for strictly periodic traffic, the BS can schedule resources in advance using fast uplink grant. However, when traffic or energy availability is highly dynamic and unpredictable, fast uplink grant may lead to the waste of channel resources. For these cases, random access and grant-free mechanisms may be more beneficial. Studies [292], [293] compare the performance of these schemes in terms of outage probability and energy consumption. Both reveal a high potential for the fast uplink grant scheme, especially for predictable traffic patterns. In [160], using the experiments

TABLE X
COMPARISON OF ACTIVE WIRELESS COMMUNICATION PROTOCOLS CONSIDERED IN SECTION V-B

	LoRaWAN	BLE	NB-IoT	IEEE 802.15.4
Spectrum	Unlicensed (sub-1GHz)	Unlicensed (2.4 GHz)	Licensed (sub-1GHz)	Unlicensed (sub-1GHz/2.4 GHz)
Coverage	Long-range: >10 km in rural areas	Short-range: 3 – 5 m with A-IoT devices, extendable with friend nodes	Long-range: kilometers	Short-range: meters, extendable with mesh topology
Data rate	Up to 50 kbps (SF7)	1 Mbps	Up to 250 kbps	Up to 250 kbps
Power consumption (TX)	~ 100 mW	~ 20 mW	~ 100 mW (and way more depending on power class)	~ 20 mW
Power consumption (RX)	~ 30 mW	~ 30 mW	~ 100 mW	~ 15 mW
Power consumption (sleep)	~ 20 μ W	~ 10 μ W	~ 20 μ W	~ 10 μ W
A-IoT capabilities	With 1 mW harvesting, it can transmit 1 byte every 9 s in uplink only and every 60 s in presence of DL traffic with 4.7 mF and 47 mF capacitor, respectively [292].	Ultra-low power, requires 300 μ W harvesting and 0.47 mF capacitor to transmit 8 bytes every 5 s [121].	Requires 1.5 F capacitor to acquire connection. With 2.5 F capacitor, it can transmit 8 bytes every 60 s [120]. Recommended to use grant-free access and/or fast uplink grant to reduce energy consumption (12x) [296].	With 2.2 mF capacitor and 83 μ W harvesting, it can transmit small packet with sensor data every 40 s [123]

from [294], outdated CSI is employed to improve the energy efficiency of grant-free access. It is shown that the overhead of uplink CSI measurements for initial access can be drastically reduced due to the low time variability of CSI. The same principle can be used for random access.

While LPWAN technologies are a good fit for low-power communications, they offer rather limited throughput. For higher throughput in the short range, BLE and IEEE 802.15.4 are the two prevalent technologies. In [121], and [122], battery-free IEEE 802.15.4 (Zigbee) communication platforms are designed and prototyped. In [121], multi-source EH is used to power the ADMP401 sound sensor. In [122], electric field EH is used to power the sensing module featuring temperature, light, humidity, and external power reading.

In [120], [295], and [296], performance of BLE for battery-free devices is studied. The BLE Mesh specification introduces a friendship feature that allows the A-IoT node to offload the incoming channel listening task to a friend node that can temporarily buffer the corresponding data. This feature reduces the overall energy consumption at the cost of increased downlink latency. To maintain friendship and get buffered data, A-IoT node must poll its friend node before the defined timeout. A mathematical model designed in [296] allows estimating the queue occupancy at the friend node and the corresponding downlink latency, as well as the necessary capacitance and polling interval according to the application needs. A prototype of such a BLE A-IoT device is designed and evaluated in [120]. In [295], direct polling was compared with a WuR-based approach [297], wherein the A-IoT node contacts its friend when receiving a special wake-up signal in order to receive buffered downlink information and consequently reduce downlink latency. Direct polling is shown to perform better only in the case of low-power harvesting (up to 400 μ W). This is due to the additional power consumed by the wake-up radio, which becomes significant at low EH rates.

The reader may further refer to Table X for a comparative analysis of the communications protocols considered in this section.

3) *Lessons Learned:* The design of A-IoT connectivity protocols is mainly driven by the extremely strict energy constraints of the devices, regardless of whether backscatter or active communications are used. In backscatter systems, various modulation and multiple access schemes have been adopted, with clear trade-offs between throughput, range, and device density. In active communications systems, energy limitations are addressed through energy-aware transmission policies, duty cycling, and the use of power-saving modes. In both cases, communication performance is strongly dependent on energy availability, motivating designs that adapt transmission patterns, channel access, and communication protocol parameters to energy harvesting conditions and application requirements. It should be noted that A-IoT connectivity remains highly dependent on the target use-case, with different technologies occupying their distinct niches.

C. Deployment, Coordination, and Access Management

A-IoT networks require careful deployment given intrinsically low and/or spatially heterogeneous energy availability, as well as efficient mechanisms for coordination and medium access. This is surveyed and discussed in the following, while emphasizing the need for deployment optimizations accounting for node placement, EH conditions, sensing quality, connectivity performance, long-term operation, and network-triggered A-IoT device management functions, such as duty cycling, admission, and synchronization, to be both context- and device-capability-aware.

1) *Deployment Optimization:* Deployment in A-IoT involves deploying A-IoT devices, ETs (cf. Section V-A.2), and/or data-collection entities such as readers or gateways to ensure sensing, connectivity, and sustained operation across the target area. Compared with conventional IoT,

this problem is more challenging because operation depends not only on coverage and communication range but also on the local availability of harvestable energy, which may vary significantly across space, giving rise to energy-rich and energy-scarce regions. Deployment decisions, therefore, need to jointly account for connectivity performance, task relevance and energy-neutral operation. As evinced below, the literature on A-IoT deployment optimization is rather scarce.

The optimal deployment of directional A-IoT networks for target coverage is studied in [298], including a joint optimization of device locations, sensing directions, communication routes to the BS, and the EH capability provisioned at each node. The work in [299] addresses deployment optimization for perpetual target coverage while explicitly accounting for the spatial heterogeneity of both sensing utility and harvestable energy. The results reveal that deployment should not only guarantee target coverage but also exploit the joint spatial structure of energy availability, target distribution, and cooperative sensing quality, which is especially meaningful in the presence of localized energy hotspots and dead zones. Meanwhile, [300] further incorporates long-term reliability into deployment by accounting for the thermal dependence of solar panels, electronics, and batteries. The developed framework shows that deployment affects not only whether a node can operate but also how long it can remain dependable in the field. Finally, [301] studies RFID reader placement with adjustable reader range for complete tag coverage in industrial scenarios, explicitly accounting for reader-to-reader and reader-to-tag conflicts. The results here reinforce that dense deployments must be conflict-aware and should jointly consider reader placement and service-region shaping rather than relying on purely coverage-maximizing layouts.

2) *Distributed Management*: With its broad radio coverage and ample energy resources, network infrastructure can serve as a central hub for collecting A-IoT devices' information and coordinating networking, computing, and energy allocation/transfer tasks. To relieve network management functions from a large control burden, given that A-IoT deployments may be extremely dense in particular regions, the A-IoT device coordination functionality may be distributed between different operation regions. For instance, [302] proposes a distributed management scheme for hybrid industrial networks with EH devices, leveraging IEEE 802.15.4e and the routing protocol for low power and lossy networks to enable localized resource reservation and intermittent node coordination. This approach reduces control overhead compared to centralized solutions while maintaining reliability in energy-constrained environments.

One possible approach is to use MEC technology, in which edge clouds that overlay the RAN can help coordinate A-IoT device operations locally. However, MEC is not the only solution, as a simple legacy solution would still be effective. In the case of cellular mobile communication protocols, such as 5G NR, one way to flexibly manage A-IoT devices is to keep their Radio Resource Connection (RRC) states (i.e., A-IoT device states indicating whether an RRC connection has been established with the serving BS) [303] simple or even consider no RRC states. With minimal or no RRC state, the A-IoT

device can dynamically select an access node based on instantaneous conditions such as energy level, link quality, and task urgency (e.g., in an asset tracking or an intrusion detection scenario). Further, there is no need for full RRC reconfiguration or context transfer during mobility or intermittent operation, which significantly reduces signaling overhead. Essentially, such a configured A-IoT device will effectively operate as a stateless, opportunistic sensor in a multi-access environment, making connectivity decisions on-the-fly. This behavior aligns with the A-IoT vision of ultra-lightweight, context-aware connectivity, where devices prioritize goal effectiveness and energy efficiency over inflexible session continuity.

3) *Context-Aware Duty-Cycling and Wake-up Protocols*:

As A-IoT deployments must increasingly support stricter performance requirements, recent efforts have shifted from static duty-cycling schedules to adaptive strategies incorporating contextual information [161], [304]. Solutions using fixed thresholds or traffic prediction are proposed in [159], but suffer in dynamic or large-scale deployments. To overcome these limitations, spatial correlations and ML have been considered to guide device scheduling. For instance, clustering-based scheduling and Voronoi-based partitioning can improve scalability by enabling localized coordination and prioritizing device wake-ups in dense environments. As a result, redundant sensing is minimized, and coverage efficiency is enhanced, as demonstrated in [304], [305], and [306].

These techniques are often complemented by ultra-low-power WuRs, allowing asynchronous waking up of idle nodes and on-demand data acquisition with minimal energy overhead [307]. Meanwhile, ML techniques have been proposed to manage sleep-wake transitions under uncertain EH and traffic conditions. Indeed, RL agents have been shown to outperform static policies by adapting to real-time changes in device state and environmental inputs [161], [308]. More recently, transformer-based architectures, with their powerful sequential modeling and policy optimization capabilities, have become appealing for edge environments [309]. These methods integrate long-term temporal dependencies and context-awareness into activation policies. Still, considerable effort is required to achieve scalable, energy-efficient, and dependable coordination in dense, distributed A-IoT networks, particularly by leveraging hybrid ML approaches and cross-layer context awareness [310].

4) *Admission & Synchronization for A-IoT Devices*: Widely used WSN standards, such as WirelessHART ISA 100.11a, and IPv6 over the TSCH mode of IEEE 802.15.4e (6TiSCH), assume a stable power supply at the devices; thus, they do not adapt well to A-IoT device networks. More specifically, [311] indicates energy-intensive network joining and periodic synchronization to nearby routers as two phases that are inherent to all relevant industry standards and do not account for the intermittency of A-IoT devices. Multiple studies proposed solutions and optimizations for these protocols to support A-IoT devices as end devices and routers in WSNs. In [311], procedures for joining the network and maintaining synchronization were proposed, suggesting *ad hoc* joining and non-synchronized communication strategies for low energy consumption. In [312], an energy-aware scheduler was

proposed to adjust the size of the unicast slot based on predictions of energy consumption and storage level based on telemetry data provided by A-IoT devices. The authors demonstrate that the scheduler significantly improves the success rate and the A-IoT devices' uptime, albeit at the expense of increased latency, making it suitable for non-critical applications.

Meanwhile, [313] proposes estimating the residual energy and number of hops for each path for data routing in large-scale industrial IoT systems based on IEEE 802.15.4a MAC. To provide real-time data routing with minimum power consumption, the authors propose a data aggregation and re-routing algorithm through different clusters. A similar problem is addressed by [314], which proposes the incorporation of a reliable node synchronization protocol based on number theory to ensure successful synchronization regardless of the energy conditions of A-IoT devices.

Finally, there is the issue of A-IoT device reachability; that is, A-IoT devices do not often support full/steady connection due to energy limitations. This motivated recent studies on RAN and Core network (CN) collaboration to achieve BD reachability, as discussed in [315]. Specifically, when a BD has no association with RAN reader(s), e.g., during the discovery phase, the reader(s) could attempt to identify or locate BDs in proximity and report the discovered association to CN. This allows CN to send service requests to the most recent RAN reader(s) to initiate communication with the BD instead of blindly sending the request to all readers in a service area.

5) *Lessons Learned:* Spatial and temporal heterogeneity in harvestable energy fundamentally reshapes classical network design principles, making mere coverage-centric or connectivity-driven deployment strategies insufficient. Field evidence consistently shows that energy availability, sensing utility, and communication quality are correlated, and their joint spatial structure must be explicitly exploited. In practice, this means that optimal deployments are rarely uniform. Instead, they must adapt node density, sensing orientation, and infrastructure placement to localized energy-rich and energy-scarce regions, while also accounting for long-term reliability-affecting factors, such as environmental conditions and hardware degradation. Moreover, many models assume stable or slowly varying energy inputs, whereas real deployments exhibit sharp fluctuations that impact node uptime and coordination feasibility. This mismatch has direct implications for system design and access management: rather than relying on persistent connectivity or globally optimized configurations, A-IoT deployments benefit from loosely coupled, regionally optimized layouts and control mechanisms that can operate effectively under partial and intermittent node participation.

A complementary insight is that lightweight, context-aware, and decentralized operation is not only a design preference but also a necessity for scalability and robustness. Mechanisms that depend on strict synchronization, energy-intensive network admission, or continuous connectivity (common in conventional WSN and cellular systems) break down under intermittent powering and dense device populations. In contrast, approaches based on adaptive duty cycling, wake-up

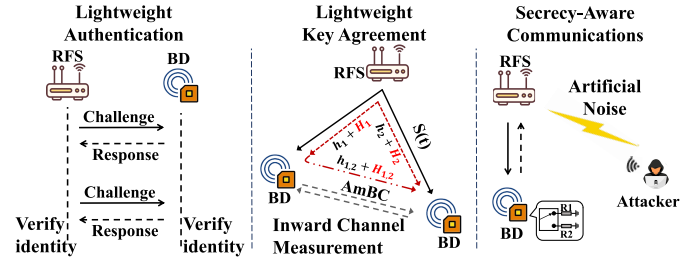


Fig. 9. Overview of the security methods for BC network.

radios, opportunistic access, and stateless or minimally stateful coordination have proven significantly more resilient, as they allow devices to react to instantaneous context (e.g., energy levels, link conditions, task urgency) rather than maintain costly global state. Importantly, practice reveals that locally suboptimal but adaptive decisions often outperform globally optimized but rigid schemes, especially when energy uncertainty and intermittence in device availability are high. This suggests that future A-IoT systems should prioritize graceful degradation, cross-layer context awareness, and distributed intelligence, leveraging learning-based adaptation, where beneficial, but avoiding over-reliance on heavy signaling or precise synchronization that cannot be sustained in realistic EH environments.

D. Network Security for Backscatter Devices

Most existing security solutions focus on battery-powered IoT by applying upper-layer cryptographic algorithms for data confidentiality, encryption, and authentication. These are not generally affordable for passive A-IoT devices relying on BC, which suffer from severe constraints on processing, memory, and power budgets. As a result, PHY security has become a practical alternative, allowing lightweight security solutions for BC systems. This has led to three key research directions: PHY authentication, PHY key agreement, and secrecy-aware communication, as illustrated in Fig. 9. In the following, we review each of these directions in detail, complemented by Table XI, which provides a structured comparison of existing works by categorizing them across different BC models (e.g., monostatic, bistatic, AmBC, and tag-to-tag), and explicitly mapping each study to its addressed security problem, interaction type, performance metrics, and considered threat models.

1) *Lightweight Authentication:* Authentication in BC systems is essential to protect low-power interactions between BDs and APs, or among multiple BDs. Due to severe energy and hardware limitations, conventional cryptography is often impractical, motivating lightweight, non-cryptographic solutions based on PHY or hardware-level fingerprints [346]. For instance, unique tag reflection coefficients can be extracted using OFDM-based designs [316], enabling robust environment-independent identification. Finger-based authentication further enhances security by modulating signal phase via fingertip interaction, producing user-specific RF signatures [317]. In addition, [318] exploits the intrinsic instability of EH oscillators to generate power-dependent transmission patterns for secure tag identification without extra circuitry.

TABLE XI
OVERVIEW OF DIFFERENT SECURITY TECHNIQUES, INTERACTION TYPES, AND THREAT MODELS IN BC SYSTEMS

Security Category	BC Model	Technique	Interaction Type	Metrics	Attacks	Reference
PHY Authentication	monostatic	Device Fingerprint	Tag-Reader	AA	IMP, RPL	[320], [321]
	monostatic	Device Fingerprint	Tag-Reader	AA	IMP	[322]
	bistatic	Channel Characteristics	Tag-Reader	TPR	IMP, CNF	[323]
	monostatic	Channel Characteristics	Tag-Reader	TPR, FPR, ROC	IMP, RPL, CNF	[324]–[326]
	bistatic	Tag Fingerprint	Tag-Reader	PFA, OP	IMP	[327]
	bistatic	Signal Feature, AI	Tag-Reader	TPR, FPR, AA	IMP, RPL	[328]
	monostatic	Reflection Power	Reader-Tag	TPR, FPR, ROC	IMP, RPL	[329]
	AmBC	Signal Correlation	Tag-Reader	TPR, FPR, ROC	IMP, RPL, CNF	[330]
	monostatic	Channel Coherence	Tag-Reader	TPR, FPR, ROC	IMP, RPL, CNF	[331]
	tag-to-tag	Channel Coherence	Tag-Tag	TPR, FPR, ROC	EAV, IMP, RPL, CNF	[332]
PHY Key Agreement	tag-to-tag	Reflection Power, RIS	Tag-Tag	TPR, FPR, ROC	IMP, RPL, CNF	[333]
	monostatic	Diffie-Hellman	Tag-Reader-Tag	TPR, FPR, AA	IMP, RPL, CNF	[334]
	tag-to-tag	Channel Characteristics	Tag-Tag	KGR, BDR	EAV, CC, SM	[335], [336]
	tag-to-tag	Polarization Conversion	Tag-Tag	KGR, EKP	EAV	[337]
	tag-to-tag	Channel Characteristics	Tags-Tags	KGR, BDR	EAV, CC, SM	[338]
	AmBC	EH	Tag-Reader	KGR, MI	EAV, JAM, SM	[339]
Secrecy-aware Communication	monostatic	Channel Correlation	Tag-Reader	SOP	EAV	[340]
	bistatic	Tag Selection	Tag-Reader	SOP	EAV	[341]
	bistatic	Optimal Reflection	Tag-Reader	ASC, SOP	EAV	[342]
	monostatic	Tag's Reflection	Tag-Reader	DP	EAV	[343]
	AmBC	Ambient Noise	Tag-Reader	SOP	EAV	[344], [345]
	AmBC	Cooperative Jamming	Tag-Reader	SOP	JAM	[346]
	AmBC	RIS	Tag-Reader	ASC, SOP	EAV	[347], [348]
	bistatic	Channel Differences	Tag-Reader	ASC, SOP	EAV	[349]

TPR: True Positive Rate; FPR: False Positive Rate; ROC: Receiver Operating Characteristic; BDR: Bit Disagreement Rate; KGR: Key Generation Rate; DP: Detection Probability; AA: Authentication Accuracy; MI: Mutual Information; SOP: Secrecy Outage Probability; ASC: Average Secrecy Capacity; OP: Outage Probability; SM: Signal Manipulation; IMP: Impersonation; RPL: Replay; CNF: Counterfeiting; JAM: Jamming; CC: Channel Control; EAV: Eavesdropping.

Beyond circuit-level features, spatial and propagation characteristics of backscattered signals can support authentication and spoofing detection, though they are sensitive to environmental dynamics. Controlled multipath signatures generated by passive tags enable localization and adversary detection, as demonstrated in [319], and have been extended to mobile scenarios through multi-stage re-authentication and attacker localization schemes [320]. Related approaches appear in [323], including symbiotic AmBC systems with NOMA, where space- and time-domain multiplexing aids authentication under channel uncertainty.

To address scalability, batch authentication schemes such as BatAu [321] and BatchAuth [322] authenticate multiple BDs simultaneously using joint channel features. Cross-domain authentication has also been explored via FL [324], enabling privacy-preserving verification, though scalability degrades with highly heterogeneous devices. Complementary designs reverse the authentication direction, allowing BDs to verify APs through secure WPT [325], while AuthScatter [327] enables mutual authentication using channel coherence and fading.

Recent studies further adapt PHY authentication to AmBC environments [326]. In tag-to-tag BC networks, energy charging patterns and channel coherence have been leveraged for key exchange under ultra-low-power constraints [328]. Moreover, voltage signatures extracted from EH and envelope detection circuits enable accurate passive tag-to-tag identification, with improved authentication range when integrated with RIS [329].

2) *Lightweight Key Agreement*: Lightweight key agreement serves as a fundamental enabler of secure communication in BC systems, allowing devices to establish shared secrets despite the absence of pre-configured trust or

centralized infrastructure. While the Diffie-Hellman protocol offers forward secrecy, its computational cost is prohibitive for resource-constrained BDs. To address these limitations, recent research in [331], and [332] has implemented PHY key generation designed explicitly for AmBC systems. These schemes exploit the reciprocal randomness inherent in wireless fading channels to generate robust and secure shared keys between BDs with minimal computational complexity. Such secrecy is conditional on the legitimate users having an information advantage over the eavesdropper, which is often justified through spatial decorrelation. This assumption relies on the fact that wireless fading channels decorrelate over space, such that an eavesdropper sufficiently separated from the legitimate devices observes statistically different channel realizations and therefore cannot reconstruct the same key material. In addition, an approach based on a non-coherent detector and polarization conversion is proposed in [333] to eliminate direct-link interference in the key generation between tags. However, the scheme adds hardware and signal-processing complexity in the form of dual-polarization components, polarization alignment, and extra processing paths for non-coherent detection, increasing cost, latency, and power consumption.

Most recently, research in [335] deployed smart AmBC devices to improve robustness against signal manipulation and jamming attacks. However, a general issue is that eavesdroppers located within the coherence distance may still observe partially correlated channels and infer portions of the generated key. This issue is particularly important in A-IoT systems, where devices are often static, low-complexity, and illuminated by the same ambient source, which may increase common-mode channel components and correlation among observations. Therefore, PHY key generation in AmBC

should be viewed as a conditional lightweight key establishment mechanism whose effectiveness depends on propagation geometry, channel richness, mobility, and the eavesdropper location.

3) *Secrecy-Aware Communications*: BC systems are inherently vulnerable to eavesdropping, particularly due to the lack of cryptographic protection imposed by hardware constraints. Early works, such as [347], proposed artificial noise injection at the reader to impair eavesdroppers while maintaining reliable legitimate communication. In multi-tag settings, secrecy can be improved through tag selection based on channel variations and EH constraints, as demonstrated in [336], [337], and [338]. Moreover, the work in [339] examined the covert-ness of BC systems by analyzing the eavesdropper's detection capability.

AmBC scenarios further intensify secrecy challenges due to mobility and imperfect channel state information. Accordingly, PHY security techniques in [340], [341], and [342] incorporate channel uncertainty and dynamic topologies, where cooperative jamming and NOMA enhance robustness against mobile eavesdroppers. In addition, RIS-assisted designs enable manipulation of the propagation environment to strengthen legitimate links, improving secrecy throughput and energy efficiency, albeit with potential trade-offs between interference suppression and energy focusing [343]. Finally, statistical modeling approaches in [345], and [344] provide analytical secrecy evaluation under realistic fading conditions. For generalized models such as the Fisher–Snedecor $\mathcal{F}$ distribution, accurate closed-form expressions were derived, offering deeper insight into secrecy performance across diverse propagation environments.

4) *Lessons Learned*: Lightweight authentication, PHY key generation, and secrecy-aware BC solutions that demonstrate strong performance in simulation or controlled laboratory environments often degrade significantly under practical deployment conditions. Indeed, real-world BC systems are highly sensitive to environmental dynamics, including mobility, multipath fluctuations, hardware heterogeneity, antenna misalignment, and variations in ambient illumination or interference. In particular, assumptions commonly adopted in theoretical studies, such as stable channel reciprocity, perfect synchronization, independent fading observations, or static propagation conditions, often become difficult to maintain in realistic A-IoT scenarios. Experimental studies further reveal that ultra-low-power BDs frequently exhibit hardware-induced variability, energy intermittency, and non-ideal backscatter responses that are not sufficiently captured by simplified analytical models. Field deployments also suggest that static or low-mobility environments may weaken spatial decorrelation assumptions used in PHY key generation, especially when devices share similar ambient illumination sources, increasing the risk of correlated observations at nearby eavesdroppers. These observations highlight the importance of moving beyond idealized assumptions and validating PHY security schemes under realistic propagation, mobility, and EH conditions.

VI. EXPERIMENTAL SETUPS, MEASUREMENTS, AND APPLICATIONS

This section surveys experimental validations of A-IoT systems in real-world environments. In contrast to Section IV and Section V, which detailed component-level and protocol-level technologies, the focus here is on fully integrated systems, platforms, and testbeds that have been tested at scale or in domain-specific applications. We concentrate specifically on large-scale field trials, deployment-driven prototypes, and application-targeted hardware platforms.

The material is categorized into three parts. First, we review *general-purpose network infrastructures* that provide repeatable environments for beamforming, connectivity, and WPT evaluations (Section VI-A). Second, we cover *general-purpose A-IoT devices* and prototyping toolchains that enable rapid adoption and experimental evaluation of device technologies (Section VI-B). Third, we highlight *application-specific demonstrators* validated with application-tailored A-IoT devices in realistic environments (Section VI-C).

A. General-Purpose Network Infrastructure

1) *Techtile—a Multi-Antenna RF-WPT Testbed*: Techtile [271] is a modular and scalable experimental testbed designed for research in wireless multi-antenna technologies, including RF-WPT. It consists of a grid of ceiling, wall, and floor tiles, each equipped with a USRP B210 software-defined radio (SDR), dual antennas, and a Raspberry Pi for local processing. Techtile consists of 280 antennas in total. All nodes are interconnected through a central server and time, and phase synchronized. Techtile enables precise control of distributed multi-antenna systems, allowing to experimentally investigate and evaluate beamfocusing strategies and waveform designs [251].

2) *Ambient-Powered Reflective Intelligent Surfaces*: Alamar et al. present a modular and scalable RIS for 2.4 GHz Wi-Fi using RFID-based distributed control to overcome the energy and scalability limits of centralized designs [348]. Each 915 MHz RFID-enabled tile controls a 4×4 array of unit cells with four-state RF switches for beamforming. Passive RFID links provide wireless configuration without a centralized controller, enabling independent tile addressing with only 21 μW per tile [348], [349]. Integrated solar cells power the system, which operates continuously under typical indoor lighting (200 lux to 500 lux). Field trials in LoS/NLoS conditions confirmed significant throughput gains, demonstrating that RFID-controlled, ambient-powered RISs can deliver scalable coverage and high energy efficiency for future A-IoT systems.

3) *Automated EH and Modeling Testbeds*: Complementary to device-level prototype platforms, a new generation of EH testbeds now provides rigorous, repeatable, and comparable evaluation of battery-free and intermittently powered systems. These infrastructures bridge the gap between controlled laboratory studies and real deployments, enabling developers to expose devices to realistic, time-varying power conditions while obtaining detailed visibility into how energy is harvested, stored, and consumed.

EStacker [350] introduces fine-grained, trace-driven experimentation that precisely controls the energy environment and generates detailed “energy stacks” breaking down how harvested energy is spent across hardware subsystems and application activities. This level of introspection is essential for diagnosing inefficiencies and validating energy-neutral operation. Similarly, Geissdoerfer et al. [351], [352] introduce the *Shepherd* platform, a low-cost open-source system capable of recording and replaying high-fidelity voltage and current traces. This testbed is publicly accessible through the Shepherd Nova [353] platform. Building on the need for standardized comparison, Schuff et al. [354] proposed *E-Cube*, an automated benchmarking facility combining controlled source-measure units with unified workflows to evaluate IoT designs under identical EH conditions. Finally, Jocqué et al. [355] presented *PLEASE*, a digital-twin environment that models the complete EH chain, including harvesters, storage, and PMUs. By capturing conversion losses, leakage, and diffusion effects and coupling these models with programmable hardware interfaces, *PLEASE* enables rapid hardware-software co-design and realistic emulation, supporting fast iteration from concept to deployment.

B. General-Purpose AIoT Prototype Platforms

A rich ecosystem of general-purpose platforms for battery-free and EH A-IoT has emerged over the past decade, each addressing different aspects of intermittent operation, sustainable embedded intelligence, and rapid prototyping.

1) *Multi-Ambient Power AIoT*: Riotee [356] is a compact, modular platform for fully battery-free prototyping on harvested indoor light, integrating EH, storage/power management, and a 2.4 GHz BLE-compatible radio. In contrast, Wireless Identification and Sensing Platform (WISP) [357] targets RF-powered systems and supports RF-EH and BC, with newer versions combining RF and photovoltaic harvesting. AsSTAR [358] complements these efforts with an energy-aware task scheduler that adapts execution to the available charge.

2) *ML-Capable AIoT*: Protean [359] offers a reconfigurable plug-and-play architecture built around a 32-bit ARM MCU with a hardware convolutional neural network (CNN) accelerator. Its Chameleon runtime ensures intermittence-safe execution across heterogeneous compute elements, while the Metamorph toolchain automatically transforms ML models into energy-aware, task-based implementations. This enables battery-free systems to execute data-intensive TinyML applications at orders-of-magnitude higher efficiency than earlier 16-bit MCU-based platforms, addressing a key bottleneck in future AIoT deployments.

3) *Vibration-Powered AIoT*: Finally, some platforms specialize in domain-specific harvesting modalities. ViPSN [123] introduced one of the first open-source vibration-powered IoT platforms, integrating piezoelectric transducers with enhanced energy management, sensing, and BLE communication. It is designed for the highly intermittent and transient nature of vibration energy. Its successor, ViPSN 2.0 [124], significantly expands the concept by supporting multiple transducer types (piezoelectric, electromagnetic, and triboelectric), hot-swappable interfaces, and an energy-indication power

management framework. It accommodates light-duty tasks such as fingertip-powered BLE beacons, high-power LoRa transmissions in marine environments, and even intermittent image capture.

4) *Light-Controlled and Light-Powered Backscatter Devices*: VLC has emerged as a promising method to both control and energize A-IoT, addressing the stringent energy constraints of A-IoT devices while exploiting the dual functionality of LED luminaires. Hybrid VLC/RF architectures use VLC as a directional downlink for configuration and photovoltaic EH, while relying on RF backscatter for an ultra-low-power uplink [360]. Background on EH, wake-up/front-end designs, and backscatter radios is covered in Section IV-A, IV-B and V-B. Representative demonstrations include BackVLC [361], PassiveLiFi [362], and light-powered/controlled backscatter tags, such as LiBD [363], [364] and Li2BC [158].

C. Application-Specific Demonstrators

Use-case motivations and requirements are discussed in Section III-B; here we focus on representative field-tested demonstrators and reported measurements, organized by application domain. Table XII summarizes the scenario-level metrics reported by representative demonstrators.

1) *Retail and Packaging*: Callebaut et al. present a preliminary study on the feasibility of RF-powered, battery-free ESLs designed with commercial off-the-shelf components, validated through the Techtile testbed [271] and systematically evaluated in terms of energy consumption, EH efficiency, and storage design. Experimental results show that the ESL can refresh its display within 4 m to 120 m depending on input power level and RF frequency, achieving EH efficiencies up to 30 %. A photovoltaic-powered, battery-free monitoring system was proposed in [365] to track product conditions such as temperature inside commercial dairy shipments using photovoltaic EH and optical wireless communication, with field evaluations confirming successful integration in cold-chain logistics and reliable alerting and data transmission without onboard batteries. In [366], a disposable NFC-powered tag embedded in fresh produce packaging was demonstrated, capable of detecting spoilage-indicator gases in spinach and readable via smartphone without a battery. Similarly, Douaki et al. [367] developed an NFC-enabled smart package integrating gas sensors and antioxidant release; deployed in fish preservation trials, it extended shelf life by up to 14 d without batteries, actively maintaining food quality through controlled preservative release.

2) *Logistics and Asset Tracking*: An experimental investigation into the feasibility of asset tracking using AmBC was conducted in [368], where tags were localized through opportunistic interactions with UEs in dense urban environments such as high-speed trains and underground metros. Despite inherent UE location inaccuracies, the approach achieved robust and privacy-preserving tracking performance. In parallel, Perera et al. [365] demonstrated battery-free smart packaging sensors capable of logging environmental parameters during storage and transit, relying on photovoltaic EH with supplemental RF energy top-ups to ensure uninterrupted

TABLE XII
BENCHMARK-ORIENTED SUMMARY OF APPLICATION-SPECIFIC A-IoT DEMONSTRATORS

Domain	Representative scenario	Energy / communication mode	Reported metrics	Benchmarking value
Retail and packaging	Battery-free ESLs and smart food packages [55], [369]–[371]	RF-WPT, photovoltaic NFC	EH, ESL refresh within 4 min to 120 min; EH efficiency up to 30 %; fish shelf-life extension up to 14 d	Update latency, energy-conversion efficiency, battery-free readout feasibility, and application-level quality preservation.
Logistics and asset tracking	Crowd-detectable tags, cold-chain sensing, and indoor asset localization [369], [372]–[374]	AmBC, photovoltaic EH, passive LoRa, hybrid VLC/RF	Passive LoRa backscatter range of 2.8 km; median positioning accuracy of 0.32 m; tag detection under mobility up to 90 km/h	Coverage, localization accuracy, mobility tolerance, and infrastructure dependence for tracking deployments.
Healthcare and safety	Wearable patches, posture/fall detection, motion-powered wearables, and orthopedic implants [126], [185], [375], [376]	LoRa BC, flexible RIS, kinetic EH, NFC	Fall-detection accuracy of 92.5 %; battery-free implant validated over 11 months; reliable motion-triggered transmissions under irregular motion	Diagnostic accuracy, operating duration, body-worn link robustness, and maintenance-free clinical feasibility.
Environmental and infrastructure monitoring	Water-leak detection, underground pipe monitoring, and underwater imaging [127], [128], [377]	Hydraulic, thermal, and acoustic EH; LoRa/LoRaWAN; BC	LoRa transmissions every 50 s; 16-node LoRaWAN deployment for over 1 year; daily telemetry success rate above 94 %	Reporting interval, node-scale reliability, deployment duration, and operation in hard-to-reach environments.
Smart agriculture and greenhouses	Plant stress sensing, greenhouse microclimate monitoring, tree sensing, and soil-moisture tags [378]–[381]	RF, solar, and wind EH; BLE, LoRa, and RFID	Battery-free plant sensor mass of 2.97 g; continuous greenhouse monitoring; month-long tree-sensor field trial; 90th-percentile soil-moisture error of 5 %	Sensor form factor, monitoring continuity, crop/soil estimation accuracy, and maintenance-free outdoor operation.
Industrial factory and predictive maintenance	Vibration-powered sensing platforms, thermal/vibration harvesters, and dense industrial tag coverage [124], [125], [165], [167], [305]	Piezoelectric, electromagnetic, triboelectric, thermal, and RFID-based operation	Vibration and thermal harvesters report power budgets on the order of tens of μ W; backscatter operation typically targets duty cycles below 10 %; ViPSN 2.0 supports BLE, LoRa, and intermittent image-capture workloads	Machine-duty-cycle energy availability, event-reporting latency, conflict-aware reader coverage, and maintenance-free predictive-maintenance readiness.
Wildlife and livestock monitoring	Wildlife tags, smart ranch nodes, and dairy-cattle body-temperature monitoring [382]–[384]	Solar/kinetic EH, bistable KEH, WPT, RFID, LoRa	More than 100 % voltage growth under weak excitation; average output power of 7 mW; field trial on 7 cows; LoRa reliability above 99 %	Animal-mounted energy autonomy, link reliability, welfare-compatible form factor, and long-term sensing continuity.
Home and consumer IoT	Smart home security and battery-free activity sensing [385], [386]	RF-powered backscatter, light harvesting, VLC	Activity-recognition accuracy of 96 %; operation at distances up to 60 m; event-camera decoding with microsecond temporal resolution	Indoor coverage, recognition accuracy, sensing latency, and battery-free user-interaction monitoring.

operation within refrigerated logistics chains. Extending this concept, [369] proposed PLoRa, a passive LoRa backscatter system achieving communication over 2.8 km; field trials across farms, offices, and multi-floor homes confirmed its suitability for long-range, battery-free logistics tracking with minimal infrastructure. Moreover, [370] introduced a hybrid VLC/RF method to track a tag that harvests energy from LEDs and communicates via VLC and RF backscatter, achieving a median positioning accuracy of 0.32 m in indoor trials.

3) *Healthcare and Safety Monitoring*: In the domain of ultra-low-power body-worn sensing, Talla et al. [184] developed backscatter-based flexible epidermal patches and smart contact lenses that employ LoRa BC to extend communication range beyond BLE and WiFi, enabling fully battery-free health telemetry. Similarly, Xie et al. [371] introduced a low-cost, inkjet-printed thin-film RIS fabricated on flexible Polyethylene terephthalate (PET) substrates for human posture sensing, achieving a fall-detection accuracy of 92.5 % in indoor trials through harmonic beam steering and support vector machine (SVM)-based classification. Further advancing energy-autonomous wearables, Jin et al. [125] proposed motion-powered BLE devices featuring hybrid mechanical and electrical energy buffer-release mechanisms; field evaluations showed that these energy buffer-release mechanism-equipped systems reliably trigger data transmissions even under low or irregular motion conditions, outperforming conventional designs. Complementing these efforts, Kasper et al. [372]

demonstrated a fully battery-free orthopedic implant communicating via NFC, validated in live animal trials over 11 months of continuous bone-healing monitoring without battery replacement.

4) *Environmental and Infrastructure Monitoring*: Nepal et al. [373] presented a hydro-powered water leak detector integrating layered electrochemical harvesters [383], achieving autonomous long range (LoRa) transmissions every 50 s solely from harvested hydraulic energy during in-situ evaluations. Complementarily, Boebel et al. [126] deployed battery-free sensor nodes powered by soil-pipe thermal gradients on municipal infrastructure in Switzerland, forming a 16-node LoRaWAN network that operated continuously for over a year with a daily telemetry success rate exceeding 94 % for pressure and temperature monitoring. Extending energy-neutral sensing to aquatic environments, Afzal et al. [127] demonstrated a fully submerged, battery-free imaging system powered by acoustic energy, capable of performing color imaging and BC for the observation of marine flora, fauna, and pollutants in real-world ocean trials.

5) *Industrial Factory and Predictive Maintenance*: Industrial A-IoT demonstrators are closely linked to factory asset monitoring, predictive maintenance, and intralogistics, but end-to-end factory pilots with shared benchmark metrics remain less common than retail, logistics, or infrastructure trials. The most relevant experimental evidence currently comes from vibration-powered platforms such as ViPSN and ViPSN 2.0 [123], [124], component-to-system studies of piezoelectric

and thermoelectric harvesting for vibration-rich or thermally graded industrial environments [164], [166], and conflict-aware RFID reader placement for industrial tag coverage [301]. These works indicate that factory benchmarking should report not only harvested power, but also source variability over machine duty cycles, cold-start time, event-detection probability, reporting interval after a fault signature, link reliability near metallic equipment, reader-to-reader/tag conflict rate, and maintenance-free operating duration.

6) *Smart Agriculture and Greenhouses*: Cappelle et al. [374] demonstrated a lightweight (2.97 g), battery-free RF-powered inertial measurement unit (IMU) for real-time plant stress monitoring via micro-movements in lettuce leaves. Complementary work explored energy-autonomous agriculture, including solar-powered Bluetooth beacons for continuous greenhouse microclimate sensing [375], zero-energy smart greenhouses using integrated control and AI [384], and solar-powered, ML-enabled edge systems for pest detection [385]. Extending autonomy further, Kudyba et al. [386] introduced a UAV-assisted A-IoT platform that wirelessly powers and collects encrypted BLE data from battery-free sensor tags across large agricultural areas.

7) *Wildlife and Farm Animal Monitoring*: Nasser et al. [378] proposed and simulated a dual-source ambient-powered animal tag combining solar and kinetic EH for wildlife tracking. Their NB-IoT-capable prototype supports Global Positioning System (GPS)-based localization and motion inference using harvested current, with all hardware modules experimentally validated. Similarly, Kong et al. [379] presented a near-zero-energy system for smart ranch and greenhouse applications based on a bistable KEH that converts the mechanical motion of animals into electrical energy. By amplifying low-frequency leg movements, the system achieves more than 100 % voltage growth under weak excitation, providing an average output power of 7 mW—sufficient to continuously operate wireless IoT sensor nodes without batteries, thereby enabling long-term, maintenance-free monitoring of animal health and environmental conditions. Complementing these efforts, Vu et al. [380] introduced *eTag*, an energy-neutral, ear-mounted sensing system for real-time body temperature monitoring in dairy cattle. The device integrates a shared-coil architecture for both wireless charging and low-frequency RFID communication with a subcutaneously injected microchip temperature sensor, achieving perpetual operation through WPT replenishment during daily milking sessions. Field trials on seven Holstein cows confirmed accurate temperature tracking, over 99 % LoRa communication reliability, and full energy self-sufficiency.

8) *Home and Consumer IoT*: Lazaro et al. [381] demonstrated a smart home security system using RF-powered backscatter tags for intrusion detection, where battery-free sensors monitor door status and motion events through ambient RF reflections. Extending energy-autonomous sensing to visual intelligence, Scott et al. [382] introduced *Neuro-CamTags*, a long-range, battery-free platform that combines neuromorphic cameras with VLC for intelligent indoor environments. Each tag harvests ambient light to power its sensors

and transmits data by modulating LEDs, decoded by event-based cameras with μs temporal resolution. The system achieves 96 % activity recognition accuracy and operates at distances up to 60 m, supporting the low-power detection of temperature, pressure, sound, and user interaction.

9) *Lessons Learned*: The experimental literature shows that A-IoT maturity is uneven across the system stack. Network infrastructures and EH replay platforms increasingly provide controlled and repeatable evaluation of WPT, harvesting, and backscatter behavior, while application demonstrators show feasibility in retail, logistics, healthcare, infrastructure, agriculture, livestock, and consumer scenarios. However, the reported metrics remain highly scenario-specific. As summarized in Table XII, practical comparison requires application-level indicators such as refresh interval, localization or detection accuracy, reporting periodicity, deployment duration, telemetry success rate, and maintenance-free operating time, not only component-level metrics such as harvested power or link budget.

A second lesson is that field deployment details often dominate performance. Lighting conditions, machine duty cycles, animal motion, pipe-soil temperature gradients, user mobility, antenna orientation, and reader placement can change the usable energy and link reliability more than the nominal harvester or radio technology. Therefore, future experimental work should combine reproducible testbeds and digital twins with longer real-world trials, and report full-stack transaction success: whether the device can harvest, cold-start, sense, compute, communicate, and recover within the deadlines imposed by the target application.

VII. FUTURE RESEARCH DIRECTIONS AND OUTLOOK

In this section, we highlight open research directions related to A-IoT, based on the detailed analysis of the SotA conducted in previous sections.

A. Device Life Cycle Assessment

A main goal of A-IoT is reducing the environmental impact of IoT. Therefore more reliable LCA is required. Reliable data is essential for meaningful LCA, yet many datasets remain outdated or incomplete, especially for emerging technologies [387]. EoL data is particularly scarce [388], with recent recycling innovations often missing. This forces reliance on proxy data, increasing uncertainty and misrepresentation risks. Stronger industry collaboration is needed, as companies hold the most accurate production data. Sharing such information would make LCA databases more complete and reliable, enabling better evaluation of circular strategies. Future research should advance harmonized assessment frameworks. Beyond ISO 14040/14044 [389], initiatives like Product Environmental Footprint (PEF) and Organisation Environmental Footprint (OEF) [390] aim to standardize modeling rules, data quality, and 16 midpoint impact categories, with category and sector-specific guidance. When sustainability is a major concern, as it is in A-IoT, LCA is not sufficient to evaluate whether the environmental performance is good enough in the context of global environmental limits, where

backcasting, the idea to define a vision of a desirable future and then work backward from the vision to the present, is a great tool to define long-term sustainability goals [391].

B. Energy Harvesting

Deployable EH A-IoT systems require architectures that remain efficient under dynamic input ranges, multi-source operation, and workload variability. On the RF side, rectifiers, antennas, and matching networks must sustain performance across wide input ranges and multi-band spectra, demanding co-design of the RF front-end with fast, low-energy reconfigurable elements to track ambient RF conditions. Power management should evolve to modular, source-agnostic architectures, supporting distributed MPPT, ultra-low voltage cold start, and efficient harvesting. Another open challenge is achieving seamless multi-source energy harvesting without hardware modifications, enabling reusable and rapidly deployable A-IoT architectures across diverse energy environments. Adaptive buffering, such as reconfigurable capacitor banks or hierarchical storage structures, will allow matching intermittent energy with complex A-IoT workloads. Future work should also investigate dynamically adjustable energy buffers, as current PMUs rarely support adaptive buffer sizing despite the strong dependence of buffering requirements on energy source, workload, and storage dynamics. A clear path forward is integrated PMU stacks combining wide-range RF front ends, fine-grained storage control, and microwatt-level supervisory logic, complemented by hardware reference platforms for reproducible evaluation and scalable deployment.

C. Wireless Power Transfer

As ETs grow in aperture and bandwidth, signal processing complexity becomes a major bottleneck. In this context, DAS with decentralized baseband is promising: rather than routing all signals to a central processor, future ETs may use multiple APs with local processors exchanging low-dimensional information [392]. This improves scalability and enables flexible expansion. Since some APs have favorable channels while others are ineffective, activating all antennas for all users is inefficient, requiring intelligent user and AP association.

With sub-wavelength inter-antenna spacing and near-field operation becoming more common, WPT may exhibit strong electromagnetic coupling, making physically consistent modeling in beamforming and waveform design critical [393]. Future ETs may also operate in hybrid regimes where devices lie in reactive or radiative regions, potentially introducing trade-offs in precoder design due to differing channel models [394].

Research should explore integrating localization and sensing into WPT for joint safety and efficiency goals. Accurate sensing could detect living species entering beams and recompute precoders to meet exposure limits [256]. These techniques also enable efficient initial access, discovering A-IoT devices before they can be charged [271], [273]. Optimized beam sweeping is key to reducing time and energy use in discovering devices and living species.

Finally, most of the surveyed works about WPT in V, e.g., [256], [258], [262], [272], [275], adopt received RF power as a tractable design proxy, motivated by its non-decreasing relationship with the DC power. However, this does not fully capture the inherently nonlinear RF-to-DC conversion of practical rectifiers. A more rigorous treatment therefore calls for end-to-end system design that explicitly accounts for the strong interdependencies among the ET, channel, and RF-EH circuitry, whose coupled behavior ultimately determines the system performance. Such a framework remains an open research problem [256], as strong nonlinearities in WPT and high channel dimensionality make classical optimization challenging [395]. ML-aided methods can approximate nonlinear elements and learn system behavior from measurements, providing insights into the impact of different components on performance, enabling efficient circuitry design and simplifying optimization.

D. Low-Power Radios

Wake-up and backscatter radios are two key A-IoT communication innovations, each facing challenges at system, signal processing, and circuit levels. For *wake-up radios*, future work should incorporate context-awareness with minimal energy use on the device side. At the signal processing level, efficient wake-up signals and beamformers for reliable triggering in dense environments are needed. Circuit-level advances in ultra-low-power design must minimize leakage during sleep. For *BC*, research can leverage RIS to improve reliability, coverage, and energy efficiency, extending device lifetime. Signal processing should focus on adaptive modulation to separate desired signals from multipath, and jointly optimize modulation, reflection coefficients, and multiple access for large tag populations. Circuit-level progress in ultra-low-loss, tunable, and flexible materials for antennas and switches is essential to achieve nanowatt backscatter front-ends, enabling longer range under strict power and cost constraints.

E. On-Device Intelligence

The future of on-device intelligence in A-IoT focuses on adaptive, scalable, and energy-neutral AI systems that process data locally to ensure privacy, responsiveness, and sustainability. Several potential research directions define this path. First, efficient inference using TinyML [33], [34], [35], [36], [37], [38], [200], TinyRL [39], and compression [191] balances accuracy with hardware limits. Future work should explore self-evolving models that adapt to context and energy availability, and standardized evaluation benchmarks. A fundamental challenge remains cold-start operation, where newly deployed devices lack historical energy traces and initialized models, requiring learning and adaptation mechanisms that can operate under limited prior knowledge. Second, device-edge collaboration via split computing [40], federated learning [41], and remote updates improves latency and personalization [396]. Enhancements include adaptive offloading, and peer-to-peer model exchange. Third, privacy-preserving continual on-device learning with TinyOL [42] and TinyTL [43] enables incremental adaptation [397]. Future efforts

should develop secure learners, self-healing mechanisms, and hardware-software co-design for real-time adaptation. More broadly, enabling on-device intelligence in A-IoT requires tighter co-design of learning, scheduling, and energy management, rather than optimizing these components independently. Furthermore, many existing scheduling approaches rely on accurate energy prediction, motivating the development of robust scheduling mechanisms that remain effective under prediction uncertainty and highly dynamic harvesting conditions.

F. Interoperable and Context-Aware A-IoT Protocols

A key open issue in A-IoT systems is the lack of unified abstractions to support adaptive multi-modal communication, i.e., mechanisms that enable devices to dynamically select between backscatter, wake-up signaling, and active transmission based on energy availability and task requirements. Such interoperability should not rely on persistent connectivity or heavy signaling. Moreover, spatial energy availability must be more tightly coupled with wake-up radio-assisted and duty-cycled operation. A central challenge here is ensuring that devices activate opportunistically without missing task-critical events, under highly uncertain energy conditions.

Finally, energy-adaptive access management and lightweight synchronization remain unresolved. Conventional schemes assume stable connectivity and are ill-suited for intermittent devices, motivating predictive and context-aware access and admission policies. In collaborative settings, this extends to energy- and trust-aware participation control (e.g., in FL), requiring new frameworks that balance device availability, contribution value, and system longevity under partial observability.

G. Backscatter PHY Security

PHY security for BC systems should increasingly rely on adaptive and context-aware mechanisms capable of operating under highly dynamic propagation and hardware conditions. Rather than designing static authentication or key generation primitives, emerging solutions are expected to continuously learn and update secure device signatures from multimodal observations, including channel responses, harvested-energy patterns, and sensing traces. Another promising direction is the integration of lightweight intelligence directly into distributed BC infrastructures, enabling online calibration, self-adaptation, and cooperative threat awareness with minimal overhead. In particular, scalable coordination between BDs, MAC protocols, and WPT scheduling will become essential for secure and synchronized operation in ultra-massive A-IoT deployments.

Another open challenge is maintaining secure PHY key generation in static or low-mobility AmBC deployments, where shared ambient illumination and limited spatial diversity may produce partially correlated observations between legitimate devices and nearby eavesdroppers. Future schemes should therefore explicitly account for propagation geometry, channel richness, mobility, and adversary proximity when evaluating practical secrecy guarantees.

Meanwhile, secrecy-aware BC should move beyond static channels and rigid metasurfaces toward fluid and sensing-aware architectures. Fluid antenna systems [398] and fluid

RIS [399] can reshape backscatter channels, steering deep fades or destructive interference toward eavesdroppers while preserving reliability for legitimate devices. Combined with integrated sensing and communication (ISAC), metasurfaces could localize eavesdroppers and optimize reflection coefficients, fluid-element states, artificial noise, and tag strategies. Characterizing secrecy–reliability–sensing trade-offs and developing low-complexity online policies compatible with ultra-low-power devices remains largely unexplored.

Scalability and long-term maintainability remain largely underexplored in current BC security research, as most works focus on pairwise authentication or isolated key establishment. Therefore, research is required on distributed, adaptive, and low-overhead security coordination among potentially millions of battery-free devices. This calls for tighter co-design between PHY security, MAC protocols, WPT, synchronization, and energy management mechanisms. Finally, future BC security research should prioritize robustness, adaptability, interoperability, and deployment-aware evaluation rather than relying solely on analytical secrecy or authentication gains under idealized conditions.

H. Network Planning

Network planning for A-IoT remains rather underexplored, with studies mostly focusing on ET deployment optimization in RF-powered scenarios [265], [266], [267], [268], [269], [270]. Only a few works like [298], [299], [300], [301] have initially addressed A-IoT device deployment optimization. Future research should emphasize the latter, while treating A-IoT deployment planning as a joint energy-connectivity-sensing problem, leveraging energy maps and traffic models, and accounting for sensing/reporting requirements and device-class capabilities. This may require incorporating multi-objective formulations for device and reader/gateway/ET deployment optimization under constraints on energy neutrality, dependability, latency, interference, cost, maintainability, and environmental impact.

Notably, ambient energy, network dynamics, and application demand may vary significantly over time, making one-shot offline planning insufficient. One may leverage digital twins and measurement-driven models [350], [351], [352], [353], [354], [355] to emulate network dynamics and expected performance for deployment optimization, enabling co-design with WPT strategies, access and wake-up mechanisms, security procedures, and/or edge intelligence. These models should be periodically updated after deployment using network telemetry, enabling re-planning/deployment, reader selection/activation, duty-cycle adaptation, and workload migration as environmental and traffic conditions evolve. This is itself subject to optimization due to trade-offs between costly measurement/reporting overhead and reconfiguration-driven performance gains.

I. Experimental Setups & Measurements

This survey shows that A-IoT technologies have moved beyond conceptual speculation, yet most demonstrations remain limited to controlled pilots or short trials. Research

must now shift from feasibility studies to scalable, reproducible, long-term evaluations validating A-IoT as a dependable 6G component. On the network side, future efforts should build federated, multi-site infrastructures for reproducibility in beamforming, WPT, AmBC, and hybrid harvesting. Existing platforms [271], [348], [350], [353], [355] provide strong foundations, but lack unified benchmarking. Digital twins that model different harvesting modalities can bridge lab insights with field realities. Another important challenge is the lack of realistic long-duration energy traces and benchmarking methodologies for evaluating energy-aware scheduling and learning algorithms. Many existing studies rely on simplified or short-term energy assumptions, making it difficult to assess their robustness under real deployment conditions. For general-purpose A-IoT devices, research must evolve from isolated prototypes (e.g., Riotee [356], WISP [357], AsTAR [358], Protean [359], ViPSN [123], [124]) toward full-stack solutions with intermittence-safe runtimes, energy-introspective debugging, TinyML support, and unified abstractions for multi-source harvesters and hybrid radios. Predictability under energy scarcity must become a core design goal. On the *application side*, future work should prioritize long-duration deployments in various application domains, and address open questions related to durability, ecological footprint, secure onboarding, and privacy-preserving operation in dense deployments.

VIII. SUMMARY

Ambient IoT represents a paradigm shift toward sustainable, large-scale connectivity by enabling battery-free or energy-neutral devices that leverage EH and RF WPT. This survey provided a holistic overview of the state of the art, encompassing device classification and life cycle analysis; diverse use cases identified by standardization bodies and research projects; and ongoing efforts in 3GPP, IEEE, and ETSI to define protocols and interoperability frameworks for A-IoT. We reviewed enabling technologies at both device and network levels, including EH circuits, low-power radios, BC, wake-up receivers, and on-device intelligence, as well as network protocols for connectivity, coordination, and security. Furthermore, we highlighted experimental platforms and application-specific demonstrators that validate the feasibility of A-IoT in real-world scenarios.

Based on the in-depth SotA survey, several key open research challenges have been identified. A-IoT requires improved EoL data quality and harmonization of assessment frameworks to ensure accurate LCA. EH and management capabilities should be extended with source-agnostic PMUs and reconfigurable and adaptive energy buffering at microwatt operational levels. RF WPT would benefit from decentralized processing in DASs to overcome challenges in computational complexity, and should support hybrid near- and far-field regimes. Future wake-up radios should support reliable and selective device triggering in dense environments. BC coverage and energy efficiency could be improved with RIS assistance, as well as adaptive modulation schemes for multipath-rich environments. Future on-device ML techniques

should explore self-evolving methods with continual learning capabilities, going beyond SotA static model compression. Unified standardized interfaces are required to enable energy-efficient interoperability across passive and active A-IoT devices with widely varying capabilities. A-IoT communication protocols should adapt to real-time energy dynamics, consider contextual device and application information, and leverage AI-driven prediction models. In terms of security, environment-resilient PHY security for BC communication primitives should maintain discriminability and reciprocity, and support massive deployments through co-design with MAC protocols and WPT scheduling. A-IoT network planning remains largely underexplored and should evolve towards dynamic, measurement-driven multi-objective frameworks that jointly optimize energy, connectivity, and sensing. Finally, experimental setups should shift from controlled pilots and short-duration field trials, towards scalable, reproducible and long-term evaluations.

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