

Solar-based and battery-assisted energy harvesting systems for IoT: A systematic survey

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ABSTRACT

Solar energy harvesting combined with battery storage is a key enabler for achieving long-term autonomy in Internet of Things (IoT) systems. However, existing research remains fragmented across heterogeneous hardware design strategies, energy-management techniques, and applications spanning a wide range of domains, often addressing isolated technical aspects without providing a comprehensive system-level perspective. Following the PRISMA guidelines, this systematic survey synthesizes 25 primary studies selected from an initial corpus of 357 publications on solar-based, battery-assisted Energy Harvesting Systems (EHS) for IoT. The review examines four complementary dimensions: hardware architectures, energy-aware hardware and software strategies, deployment domains, and reported performance outcomes together with their associated limitations and challenges. The analysis reveals persistent open issues related to solar intermittency, resource-constrained IoT devices, long-term autonomous operation, environmental reliability, and the lack of standardized design and benchmarking frameworks. Based on these findings, the survey identifies key methodological and technological research gaps and discusses future directions toward more self-sustainable solar-powered IoT nodes. To the best of our knowledge, this is the first PRISMA-compliant systematic survey that provides a holistic synthesis of hardware architectures, energy-management strategies, application-domain requirements, and benchmarking and reproducibility challenges in solar-based, battery-assisted IoT EHS.

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1. Introduction

Energy Harvesting Systems (EHS) emerged in the early 2000s within the context of Wireless Sensor Networks (WSNs), with the primary goal of extending the lifetime of battery-powered sensor nodes. These nodes were originally designed to be small and simple, yet subject to severe resource constraints, particularly in terms of energy availability. A typical sensor node integrates a low-power microcontroller with limited memory, capable of executing periodic single-threaded tasks; a set of sensors and/or actuators; a wireless communication interface; and an energy source, typically a battery. However, batteries gradually deplete depending on the application workload, eventually leading to device failure and requiring replacement or maintenance operations that are often impractical or costly in real deployments. Early studies report that, in the absence of advanced energy management strategies, node lifetimes were often limited to only a few days [1], traditionally depending on the configured duty cycle.

To address these limitations, sensor nodes began incorporating energy harvesting capabilities, enabling them to extract energy from the environment and convert it into electrical power to sustain operation and recharge batteries. This marked the emergence of EHS. Early approaches focused primarily on solar energy [2–6], which remains the most widely adopted source due to its abundance and relatively high conversion efficiency compared to alternatives such as piezoelectric, vibration-based, thermoelectric, acoustic, or wind energy. Nevertheless, solar energy harvesting is inherently dependent on environmental conditions, including light availability, diurnal cycles, and seasonal variations, which may limit its applicability in certain scenarios.

The amount of energy that a harvester can generate depends on both the characteristics of the primary energy source (e.g., solar radiation, vibration, or wind) and the efficiency of the conversion process. Kansal et al. [6] classify energy sources according to two key properties: *controllability*, defined as the ability to regulate energy generation on demand, and *predictability*, defined as the ability to model and forecast energy availability over time. Solar energy is typically uncontrollable but highly predictable, enabling accurate estimation of future energy availability. These properties have motivated extensive research on energy prediction models, which, combined with knowledge of device energy consumption (i.e., energy profiles) and battery dynamics (charging and discharging behavior), support both the proper dimensioning of EHS and the development of energy management strategies. A key concept in this context is *energy neutrality*, defined as the condition in which the energy consumed over a given period does not exceed the energy harvested, ensuring that the battery state of charge does not decrease over time. Achieving energy neutrality requires intelligent scheduling of sensing, computation, and communication tasks, enabling not only extended lifetime but also potentially perpetual operation.

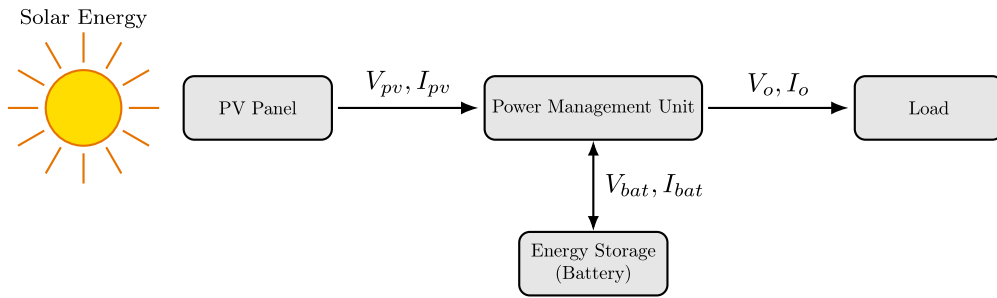


Fig. 1. Diagram of blocks of a solar-based EHS.

As WSNs have evolved into the broader Internet of Things (IoT) paradigm, sensor nodes have become pervasive devices deployed across diverse environments. Advances in hardware and communication technologies have significantly enhanced their capabilities; however, these improvements also lead to increased energy demands. As a result, energy availability remains a primary constraint for sustained operation, particularly in scenarios where devices are deployed in remote or outdoor environments without access to the power grid. In such contexts, EHS play a critical role by enabling continuous energy replenishment, thereby transforming energy from a limiting factor into a manageable resource. Beyond extending battery lifetime, EHS have become a key enabler of long-term autonomy, reduced maintenance costs, and improved sustainability in large-scale IoT deployments. This evolution has driven a shift from simple energy harvesting add-ons toward integrated system designs that jointly consider energy harvesting, storage, and management, enabling adaptive and energy-neutral operation.

1.1. Solar-based energy harvesting system design

A solar EHS typically comprises the following four components: a harvester, a power converter, an energy storage, and the load. Fig. 1 shows a block diagram of the solar-based EHS that is considered in this survey.

The *energy harvester* consists of a photovoltaic (PV) module that converts solar radiation into electrical energy through the photovoltaic effect. A PV module is formed by multiple photovoltaic cells, typically based on crystalline silicon or thin-film technologies, connected in series to increase voltage and in parallel to increase current. The maximum output power $P_{\max}$ of a PV module is specified under Standard Test Conditions (STC), defined by an irradiance of 1000 W/m^2 , a spectral distribution corresponding to air mass 1.5, and a cell temperature of 25°C . In practice, these conditions are rarely met, and the actual output power depends on environmental factors such as irradiance, temperature, and incidence angle. A simplified estimation of the generated power can be expressed as $P_{\text{out}} = D \cdot \eta \cdot S$, where D is the solar irradiance, η is the conversion efficiency of the PV module, and S is the effective surface area. Solar irradiance varies over time due to diurnal and seasonal cycles, as well as geographical location and weather conditions. Additionally, the angle of incidence between the solar radiation and the panel surface affects the effective irradiance received. These variations have motivated the development of solar energy prediction models that estimate the temporal distribution of harvested energy [7]. Key electrical parameters of PV modules include the open-circuit voltage V_{oc} , defined as the maximum voltage under no-load conditions, and the short-circuit current I_{sc} , defined as the current when the output terminals are shorted. These parameters characterize the operating limits of the module and are essential for the design of downstream power conditioning and energy management circuits.

The *Power Management Unit* (PMU) is responsible for regulating and conditioning the energy flow from the PV module to both the load and the energy storage element. Its primary function is to ensure stable voltage and current levels, preventing harmful fluctuations that could damage system components. In addition, the PMU enforces protection mechanisms such as overcharge prevention, by limiting the energy supplied to the battery when it reaches full capacity, and over-discharge protection, by disconnecting the load when the battery state of charge falls below a safe threshold. In typical solar-based EHS, the PMU includes DC–DC power converters that adapt the PV output voltage and current (V_{pv}, I_{pv}) to match the requirements of the storage element (V_{bat}, I_{bat}) and the load. Depending on the system design, the PMU may also manage multiple power paths, dynamically routing energy either directly from the PV module or from the battery to the load. Advanced PMUs often integrate microcontroller-based control logic to implement Maximum Power Point Tracking (MPPT) techniques, which aim to maximize the energy extracted from the PV module. Since the power output of a PV panel depends on environmental conditions and load characteristics, MPPT algorithms continuously adjust the operating point of the system to track the maximum power point, effectively optimizing the equivalent load seen by the panel.

Due to the inherent intermittency and uncontrollability of solar energy, periods of low or no energy generation are unavoidable, particularly during nighttime or adverse weather conditions. The role of the *energy storage* element is therefore to buffer excess energy when available and supply it during such periods, ensuring continuous operation. Traditionally, rechargeable batteries have been the primary storage solution in EHS. More recently, capacitors and supercapacitors have gained attention as complementary or alternative storage technologies, mainly due to their longer cycle life, higher power density, and wider operating temperature range. However, these technologies also present trade-offs, including higher cost, lower energy density compared to batteries, and increased self-discharge rates, which can limit their suitability for long-term energy storage.

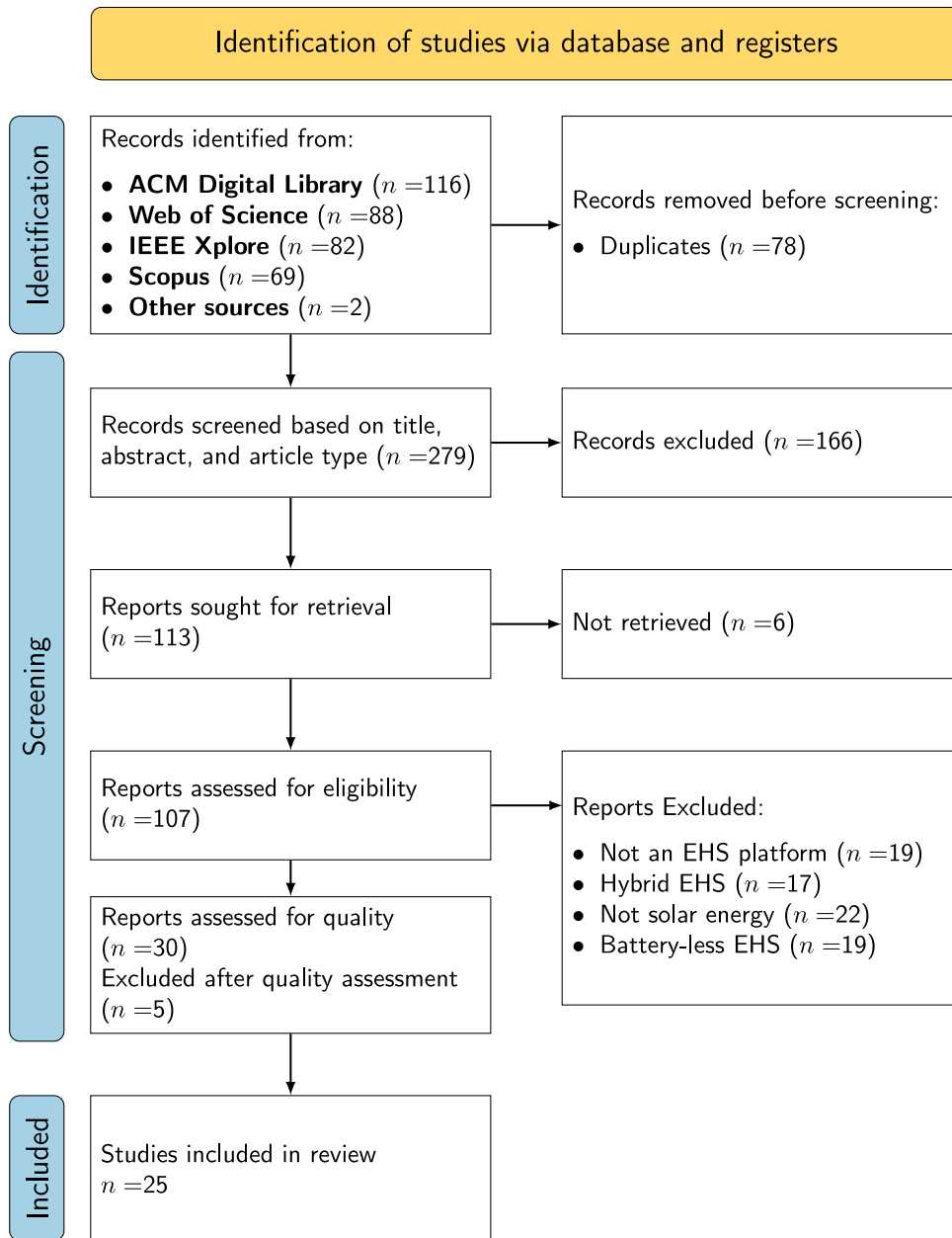


Fig. 2. PRISMA flow diagram of the study selection process.

Finally, the *load* represents the energy-consuming subsystem, typically comprising a microcontroller unit (MCU), one or more communication interfaces (e.g., radio transceivers), and sensors and actuators. The energy consumption of the load is highly application-dependent and is determined by both the hardware configuration and the operational profile, including the time spent in different power states (e.g., active, idle, sleep). For instance, consider a device with two operating states: active, drawing a current of $I_{\text{active}} = 50$ mA, and idle, drawing $I_{\text{idle}} = 30$ mA. Assuming a duty cycle of 10% in the active state, the average current consumption can be estimated as: $I_{\text{avg}} = \text{DC} \cdot I_{\text{active}} + (1 - \text{DC}) \cdot I_{\text{idle}} = 32$ mA, which directly impacts the overall energy demand of the system.

1.2. Related surveys and positioning of the work

The literature contains a wide range of surveys that approach the topic from different perspectives and disciplines, from the materials, system design, applications, and energy management techniques. Table 1 summarizes a representative set of previous surveys, showing that existing reviews typically focus on specific aspects of EHS, such as RF energy harvesting, energy prediction,

Table 1

Previous survey studies on energy harvesting systems. Column 3 indicates whether the survey focuses exclusively on solar energy harvesting, and Column 4 indicates whether it focuses exclusively on battery-based energy storage.

Survey	Year	Solar-only	Battery-only	Main contribution
[8]	2022	✗	✗	EHS for pipeline monitoring systems
[9]	2022	✗	✗	RF Energy Harvesting
[10]	2023	✗	✗	Energy-prediction methods for EHS
[11]	2024	✗	✓	Approaches for optimizing power systems for wearable and flexible electronics
[12]	2025	✗	✗	Classification of EHS in terms of energy sources, types of energy, and transducers
[13]	2026	✓	✓	Energy storage batteries for solar-based EHS
[14]	2026	✓	✗	Advancements in photovoltaics (PV) and thermoelectric (TE) technologies
Ours	2026	✓	✓	PRISMA-based review, comparative analysis of solar/battery-based EHS design for IoT

battery integration, photovoltaic technologies, or general classifications of energy sources and transducers. However, no previous survey provides a comprehensive and comparative analysis of hardware architectures, energy-management and energy-neutrality strategies, application-domain requirements, and benchmarking and reproducibility practices. These dimensions constitute the main distinguishing contributions of the present survey.

1.3. Rationale and objectives

Solar-powered and battery-equipped EHS have emerged as a promising solution to enable energy autonomy in IoT devices, particularly in scenarios where battery replacement or recharging is impractical. Despite the increasing number of studies in this area, the research landscape remains fragmented, with heterogeneous approaches to hardware design, energy management, and system integration. This lack of a unified perspective limits the ability of researchers and practitioners to systematically evaluate existing solutions, identify best practices, and address current limitations. To address this gap, this systematic review aims to synthesize the state of the art on solar-based, battery-equipped EHS for IoT by following the PRISMA methodology [15,16]. Specifically, the review is guided by the following Research Questions (RQ):

- **RQ1: EHS Comparison for IoT.** What solar-powered, battery-equipped EHS have been proposed in the context of the Internet of Things, and how do they compare with each other?
- **RQ2: Hardware and Software Strategies.** What hardware and software design strategies are adopted in solar-based EHS for IoT, including storage technologies, energy management techniques, and system architectures?
- **RQ3: Application Domains.** How are solar-based EHS tailored to specific IoT application domains (e.g., smart homes, industrial IoT, environmental monitoring, and wearables), and what domain-specific requirements influence their design?
- **RQ4: Achievements, Challenges, and Limitations.** What performance outcomes, challenges, and limitations have been reported for solar-based EHS in IoT, and what research gaps remain for enabling their large-scale and long-term deployment?

These research questions define the scope of the review and guide the subsequent phases of the PRISMA methodology, enabling a systematic search and selection process to identify the relevant studies.

1.4. Contributions of this work

This work provides a systematic and comparative analysis of solar-based, battery-assisted EHS for IoT from a holistic system-level perspective. The main contributions are summarized as follows:

- (i) *PRISMA-based systematic review:* A reproducible literature review covering the period 2005–2025 was conducted following the PRISMA methodology, including quality assessment and risk-of-bias analysis, resulting in a final corpus of 25 primary studies.
- (ii) *Multidimensional comparative framework:* The selected studies are analyzed across four complementary dimensions: hardware architectures, energy-aware hardware and software strategies, application-domain requirements, and reported performance outcomes together with their associated limitations and challenges.
- (iii) *Cross-study benchmarking synthesis:* The survey provides a transversal comparison of evaluation methodologies, harvesting evidence, operational lifetime, energy-management strategies, and energy-neutrality considerations, highlighting the lack of standardized reporting practices and publicly available datasets.
- (iv) *Identification of open research challenges and future directions:* The survey synthesizes the main unresolved issues related to solar intermittency, environment-aware EHS sizing, long-term autonomous operation, benchmarking and reproducibility, reliability and resilience, and emerging intelligent energy-management approaches.

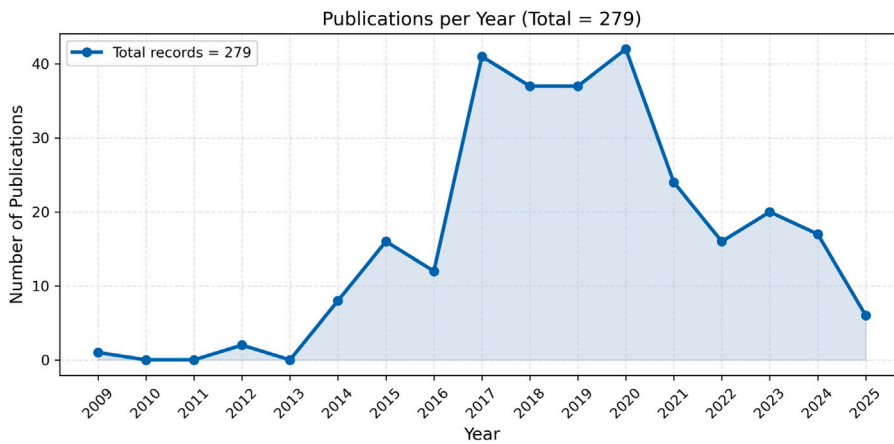


Fig. 3. Number of publications per year.

2. Method

This systematic survey is based on the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) methodology, which is grounded in the principles of transparency, reproducibility, and methodological rigor. PRISMA provides a structured framework for conducting systematic reviews through a clearly defined sequence of four phases: (1) *Identification* involves a comprehensive search across multiple databases and sources to collect all potentially relevant records; (2) *Screening* consists of examining the titles and abstracts of the retrieved records to remove duplicates and exclude studies that are clearly irrelevant to the research question; (3) *Eligibility* refers to the full-text assessment of the remaining articles to determine whether they meet the predefined inclusion and exclusion criteria, with reasons for exclusions documented; and (4) *Included* comprises the set of studies that successfully pass all previous stages and are incorporated into the qualitative and/or quantitative synthesis of the review. The summary of the process is depicted in Fig. 2, which illustrates the PRISMA flow diagram and reports the numbers of studies retained in each phase. The following subsections describe each phase of the methodology in depth.

2.1. Identification

The identification phase defines the search strategy used to retrieve relevant studies. In this work, the search process is based on three groups of keywords:

- **K1:** “energy harvesting” AND “solar”;
- **K2:** “platform” OR “system design” OR “hardware design”;
- **K3:** “IoT” OR “Internet of Things”.

K1 aims to capture studies addressing EHS that rely on solar energy as the primary energy source, including those incorporating energy storage components such as batteries or supercapacitors. K2 targets works focused on platform or system design, encompassing architectural aspects, energy management strategies, and hardware–software co-design. K3 explicitly restricts the scope to the IoT domain, including sensor nodes, embedded systems, and IoT platforms. Regarding their contribution to the research questions, K1 and K2 are primarily aligned with RQ1 and RQ2, as they focus on system design and energy harvesting strategies; K3 is mainly related to RQ3, as it ensures the inclusion of IoT-specific applications. The combination of K1, K2, and K3 enables a comprehensive analysis that also supports RQ4 by identifying trends, challenges, and limitations across the selected studies. The search was limited to articles published between January 1st, 2005, and April 30th, 2025, covering a time span of 20 years. However, it should be noted that the inclusion of IoT-related keywords (K3) implicitly introduces a temporal constraint, as research in this domain became prominent in the early 2010s. Only studies published in English were considered.

Four major electronic databases were used as information sources: Scopus, IEEE Xplore, ACM Digital Library, and Web of Science. In addition to database searches, two additional studies were identified through manual inspection of references and domain knowledge. The initial search yielded a total of 357 records (ACM Digital Library = 116, Web of Science = 88, IEEE Xplore = 82, and Scopus = 69, Other sources = 2). After removing 78 duplicate records, 279 unique studies remained (ACM Digital Library = 111, Scopus = 68, IEEE Xplore = 61, and Web of Science = 37, Other sources = 2). These 279 records were then used as input for the subsequent screening phase. Fig. 3 illustrates the annual distribution of publications, showing a higher concentration between 2017 and 2020, followed by a decline that stabilizes in the subsequent years. It should be noted that only the first four months of 2025 are included in the analysis.

2.2. Screening

In the screening phase, the initial set of 279 records retrieved during the identification stage is filtered to remove studies that do not meet the basic requirements for inclusion. This phase involves the examination of titles and abstracts to assess the relevance of each record according to a predefined set of exclusion criteria (EC). This step enables the removal of studies that, despite matching the search terms, are not aligned with the scope or objectives of the review. Records that pass this stage are considered potentially eligible and are retained for the subsequent eligibility phase. In addition, an intermediate step is performed to verify the availability of the full text for each selected study, ensuring that only accessible articles proceed to full-text assessment. The detailed exclusion criteria applied during this phase are described in the following paragraphs.

Title and abstract screening. To determine whether a study is relevant for further assessment, four exclusion criteria (EC) were defined:

- **EC1:** The publication is a survey, review, short paper (four pages or fewer), invited paper, magazine article, project description, award, dissertation, proceeding, demo abstract, research-in-practice paper, book, or book chapter.
- **EC2:** The proposed system is not fully implemented (e.g., design-only) or addresses only a partial component of the EHS (e.g., processor, antenna, PMU, or circuit).
- **EC3:** The publication is unrelated to the design or development of hardware platforms or system architectures (e.g., purely theoretical models or non-technical discussions).
- **EC4:** The publication focuses exclusively on algorithms, datasets, frameworks, methodologies, or simulations without a complete system implementation.

A total of 166 records were excluded at this stage, resulting in 113 studies remaining for further assessment (ACM Digital Library = 50, IEEE Xplore = 35, Scopus = 17, Web of Science = 9, Other sources=2).

Not retrieval. Prior to the eligibility phase, six studies could not be retrieved in full text and were therefore excluded. As a result, 107 studies were considered for full-text assessment.

2.3. Eligibility

In the eligibility phase, a full-text assessment of the remaining 107 studies was conducted to determine their final inclusion in the review. This assessment was based on two inclusion criteria (IC):

- **IC1:** The energy harvesting system (EHS) is based exclusively on solar energy.
- **IC2:** The EHS incorporates a battery as the energy storage component.

Consequently, based on criteria IC1 and IC2, this study excludes the works that use energy sources other than solar energy and hybrid approaches, as well as battery-free systems (e.g., those based on capacitors or supercapacitors) and approaches without explicit energy storage strategies (e.g., intermittent computing). After applying these criteria, 77 studies were excluded, resulting in a final set of 30 studies included in the review (ACM Digital Library = 7, IEEE Xplore = 14, Scopus = 6, Web of Science = 2, Other sources = 2).

2.4. Quality assessment

The quality assessment constituted the final step in determining the set of studies to be included in this systematic survey. The assessment was applied to the 30 studies retained after the eligibility phase in order to evaluate their methodological rigor, reporting completeness, and suitability for inclusion in the final synthesis.

The quality assessment methodology was based on a set of *Quality Assessment Rules* (QARs). Each rule contributed a maximum of 1 point to the overall quality score. The score assigned to each QAR followed a five-level scale: *fully addressed* = 1, *above average* = 0.75, *average* = 0.5, *below average* = 0.25, and *not addressed* = 0. The overall quality score of a study was computed as the sum of the scores obtained for the seven QARs, resulting in a maximum possible score of 7 points. A threshold of 3.5 points was established for study inclusion. Studies scoring 3.5 or higher were considered to provide sufficient technical and methodological quality to support the research questions addressed in this survey, whereas studies scoring below this threshold were excluded from the final synthesis. The threshold corresponds to the midpoint of the maximum achievable score and was selected to ensure that only studies providing at least a moderate level of completeness and methodological soundness were retained.

The assessment was initially performed using the predefined QAR rubric, and borderline cases were subsequently discussed among the authors until consensus was reached regarding the final score and inclusion decision. The following seven QARs were defined. All of them were derived from the objectives of the survey and were aligned with the four research questions addressed in this work:

- **QAR1:** Is the solar-based EHS sufficiently described, including the photovoltaic panel, power management unit, energy storage, and load?

Table 2

Discarded papers after quality assessment because they received a score lower than 3.5 out of 7.

Id.	Reference	QAR1	QAR2	QAR3	QAR4	QAR5	QAR6	QAR7	Score
26	[17]	0.75	0	0	0.5	0.75	1.00	0.25	3.25
27	[18]	0.75	0	0	0.5	0.75	1.00	0.25	3.25
28	[19]	0.75	0.50	0	0.75	0.25	0.75	0.25	3.25
29	[20]	0.75	0.50	0	0.25	0.25	0	0.25	2.00
30	[21]	0.50	0	0	0	0.25	0.75	0.25	1.75

- **QAR2:** Is the IoT node hardware platform sufficiently specified, including the microcontroller, communication interfaces, sensors, and storage components?
- **QAR3:** Is the energy-management or software strategy clearly described, including scheduling, adaptive sampling, prediction, duty-cycling, or other energy-aware mechanisms?
- **QAR4:** Is the target IoT application domain and deployment context clearly identified?
- **QAR5:** Does the study report relevant outcomes, achievements, limitations, or challenges related to the proposed EHS?
- **QAR6:** Does the study provide experimental validation, simulation results, or a real-world deployment supporting its claims?
- **QAR7:** Are the evaluation methodology, performance metrics, and analysis procedures sufficiently detailed and technically justified to allow interpretation and potential reproducibility of the results?

For the sake of brevity, Table 2 reports only the studies that were excluded after the quality assessment process (score < 3.5). Based on this evaluation, five studies were discarded because they lacked a sufficiently complete definition of the EHS, provided only partial descriptions of the IoT platform or the energy-management strategy, or did not include adequate methodological or experimental evidence to support their conclusions. Consequently, the final set of studies included in this review consists of 25 papers.

2.5. Risk of bias assessment

The risk of bias of this systematic survey was assessed using the *Risk Of Bias In Systematic Reviews* (ROBIS) tool [22]. Although ROBIS was originally developed for healthcare-related systematic reviews, it was adapted in this work to the context of engineering and IoT research, where the objective is to evaluate the methodological robustness of the review process and the reliability of the synthesized evidence. ROBIS is organized into three phases: (i) assessment of relevance; (ii) identification of concerns with the review process; and (iii) judgment of the overall risk of bias. The following subsections describe how each phase was applied in the present survey.

2.5.1. Phase 1: Assessment of relevance

Since the research domain addressed in this survey differs from the healthcare-oriented context for which ROBIS was originally designed, minor methodological adaptations were introduced, as permitted by the ROBIS guidance, to better reflect the characteristics of solar-based IoT energy harvesting systems. The *PICO* (Participants, Intervention, Comparator, and Outcomes) framework was adapted to the present research domain as follows:

- **Participants:** IoT nodes integrating solar-based energy harvesting systems and rechargeable battery storage.
- **Intervention:** The integration of photovoltaic energy harvesting together with rechargeable batteries to support energy-neutral or self-sustainable IoT operation.
- **Comparator:** Not directly applicable to the engineering domain addressed in this study. Following the flexibility allowed by ROBIS, this element was replaced by a thematic classification of the selected studies according to the technical dimensions derived from the four research questions, including hardware architectures, storage technologies, power management strategies, and energy-aware software techniques.
- **Outcomes:** Findings related to energy-neutral operation, system autonomy, hardware and software design strategies, application-domain requirements, and the reported achievements, limitations, and challenges of solar-based EHS for IoT.

This initial phase confirmed a high degree of alignment between the objectives of the survey, the formulated research questions, and the body of evidence targeted by the PRISMA-based review process. The adapted PICO framework also ensured that the subsequent ROBIS assessment remained focused on the specific characteristics of solar-powered, battery-assisted IoT energy harvesting systems rather than on generic IoT or renewable-energy studies.

2.5.2. Phase 2: Identification of concerns with the review process

The second phase of ROBIS evaluates potential concerns in the review process through four domains: (i) study eligibility criteria; (ii) identification and selection of studies; (iii) data collection and study appraisal; and (iv) synthesis and findings. The signaling questions were answered using the standard ROBIS categories: **Y** (Yes), **PY** (Probably Yes), **PN** (Probably No), **N** (No), and **NA** (Not Applicable). Intermediate categories (**PY** and **PN**) were used when the available evidence suggested a likely positive or negative answer, but the review protocol did not provide sufficient formal documentation to support a definitive judgment. Table 3 provides the answer for each signaling question in each domain in phase 2.

Table 3
Summary of answers to signaling questions in phase 2 of ROBIS. **D: ROBIS Domain.**

D	Signaling question	Response
1	Were predefined objectives and eligibility criteria established?	Y
1	Were the eligibility criteria appropriate for the review questions?	Y
1	Were the eligibility criteria clearly specified?	Y
1	Were restrictions based on study characteristics appropriate?	Y
1	Were restrictions based on information sources appropriate?	Y
2	Did the search include an appropriate range of electronic databases?	Y
2	Were additional identification methods used?	PY
2	Were the search terms and structure likely to retrieve eligible studies?	Y
2	Were restrictions on date, format, or language appropriate?	PY
2	Were efforts made to minimize errors in study selection?	PY
3	Were efforts made to minimize errors in data collection?	PY
3	Were sufficient study characteristics reported for interpretation?	Y
3	Were all relevant study results collected for the synthesis?	Y
3	Was methodological quality formally assessed using predefined criteria?	Y
3	Were efforts made to minimize errors in the quality assessment process?	PY
4	Did the synthesis include all studies that should have been included?	Y
4	Were predefined analyses reported or justified when modified?	Y
4	Was the synthesis appropriate for the included studies and outcomes?	PY
4	Was between-study variation addressed in the synthesis?	Y
4	Were robustness analyses performed?	N
4	Were potential biases in primary studies considered in the synthesis?	PY

Domain 1: Study eligibility criteria. All signaling questions in this domain were answered positively (5Y), which indicates a **low level of concern**, as the inclusion and exclusion criteria were explicitly defined before the screening process and remained aligned with the objectives of the survey.

Domain 2: Identification and selection of studies. The responses to the signaling questions in this domain were 2Y and 3PY, which represents a **moderate level of concern**. Although four major scientific databases were systematically searched and the search strings were carefully designed, the review was restricted to English-language and indexed publications. In addition, the absence of a fully independent duplicate screening process may have introduced a limited risk of selection bias.

Domain 3: Data collection and study appraisal. The responses were 3Y and 2PY, which shows a **low-to-moderate level of concern**. A structured extraction template and predefined quality assessment criteria were applied consistently across all included studies. However, the lack of a fully independent duplicate extraction and appraisal procedure prevents a lower risk judgment.

Domain 4: Synthesis and findings. The responses were 3Y, 2PY and 1N, which presents a **moderate level of concern**. The synthesis was primarily narrative and taxonomic, which is appropriate for the substantial heterogeneity observed across the reviewed studies. Nevertheless, no formal robustness analyses, such as sensitivity analyses or publication-bias assessments, were conducted, and the variability in reported metrics limited the possibility of a standardized quantitative synthesis.

Summary of domain-level judgments. Taken together, the domain-level assessments indicate that the main sources of potential bias arise from publication and language restrictions, the lack of fully independent duplicate screening and extraction procedures, and the heterogeneity of the included studies. These considerations were incorporated into the overall ROBIS judgment presented in Phase 3.

2.5.3. Phase 3: Risk of bias in the review

The final phase of ROBIS synthesizes the findings from the previous domains to determine the overall risk of bias of the systematic review. This judgment considers whether the interpretation of the findings adequately addresses the concerns identified during the review process, whether the included studies are relevant to the formulated research questions, and whether the conclusions are derived from the overall body of evidence rather than from selectively emphasized results.

Considering the domain-level assessments (**Low, Moderate, Low-to-Moderate, and Moderate**), the overall risk of bias of this systematic survey was judged to be **Moderate**. Table 4 summarizes the risk level for each domain and the final score. Although the review followed a structured PRISMA-based methodology and applied predefined eligibility and quality assessment criteria, moderate concerns remain regarding study identification, selection procedures, and the absence of fully independent duplicate data extraction and appraisal processes. The restriction to English-language and indexed publications may have excluded relevant studies available in other sources or publication formats. Overall, the ROBIS assessment suggests that the conclusions of this survey are supported by the available evidence and are unlikely to be substantially affected by systematic bias.

3. Systematic survey: Results

Table 5 presents the final set of 25 selected papers, of which 16 were published in journals and the remaining in conference proceedings. The journals cover a broad range of research areas, primarily including Computer Science; Engineering, Electrical and

Table 4Graphical ROBIS Risk of Bias Summary for our survey. **Legend:** ⊕ Low Risk; ⊖ Low to Moderate; ⊕ Moderate;.

	Domain 1	Domain 2	Domain 3	Domain 4	Overall
Our IoT Survey	⊕	⊕	⊖	⊕	⊕

Table 5

Summary of the 25 studies of the survey. **Legend: Type:** Journal (J)/Conference (C). **Area (only for journal publications):** TEL (Telecommunications), CC (Computer Science), IS (Information Systems), EEE (Electrical and Electronic Engineering), INS (Instrumentation), GEO (Geosciences), GEE (Geological Engineering), ENV (Environmental Sciences), ENVS (Environmental Studies), CHE (Chemical Engineering).

Id.	Ref.	Name	Year	Type	Area
1	[23]	EnHANT	2015	J	TEL, CC, IS
2	[24]	–	2016	J	EEE
3	[7,25]	–	2018	C	–
4	[26]	–	2019	J	TEL, CC, IS, EEE
5	[27,28]	–	2019	C	–
6	[29]	–	2020	C	–
7	[30]	–	2020	C	–
8	[31]	WaterGrid-Sense	2020	J	EEE
9	[32]	–	2021	C	–
10	[33]	APMD	2022	J	EEE, INS
11	[34]	–	2022	J	CC, TEL, EEE
12	[35]	–	2023	J	GEO, GEE, ENV
13	[36]	–	2023	J	ENV, ENVS
14	[37,38]	Eternal-Thing	2023	J	CC
15	[39]	EcoTrack	2023	C	–
16	[40]	–	2023	C	–
17	[41]	–	2023	J	EEE, INS
18	[42]	–	2024	C	–
19	[43]	–	2024	J	CC, IS
20	[44]	–	2024	J	TEL, CC, IS, EEE
21	[45]	–	2024	J	CHE
22	[46]	IWAST	2024	C	–
23	[47]	tinyMAN	2024	J	TEL, CC, IS
24	[48]	–	2024	J	TEL, CC, IS
25	[49]	PERMIT	2025	J	TEL, CC, IS

Electronic; Telecommunications; Environmental Science; and Chemical Engineering. These results highlight the interdisciplinary nature of solar-based EHS for IoT, which combine advances in hardware design, communication technologies, electrical engineering and energy management strategies. Fig. 4 presents the keyword co-occurrence network, illustrating the main research topics and their interconnections across the analyzed studies. In this map, keywords are represented as nodes whose size is proportional to their number of occurrences, while the links between nodes indicate co-occurrence relationships between topics. As observed, the largest nodes correspond to the most frequently used keywords, namely Internet of Things (17 papers), Energy Harvesting Systems (13 papers), monitoring (10 papers), Wireless Sensor Networks (9 papers), and solar energy (7 papers). In the following subsections, the selected studies are analyzed in relation to the research questions defined in Section 1, providing a structured synthesis of their contributions.

3.1. RQ1: Overview and comparison of selected EHS platforms

Table 6 and 7 present a comparison of the 25 selected platforms through four dimensions: MCU/Platform, sensors/actuators, communication technologies and EHS design. The analysis reveals a clear stratification of IoT platforms into three main categories: the first category corresponds to single-board computers (SBCs), such as Raspberry Pi, are employed in a subset of works requiring higher computational capabilities, typically at the expense of increased energy consumption [27,29,41,42,49]; One particular case combines a microcontroller with an SBC in a hybrid architecture [30]; the second category, which is the largest, includes microcontroller-based platforms, characterized by their low power consumption and flexibility. Based on the primary communication technology of the IoT node, a distinction can be made between microcontrollers that use a dedicated transceiver, either integrated onto the same board or as an additional module [23–25,31–34,36,39,40,43–46,48], and those that integrate processing and wireless communication into a single chip, such as the ESP8266, ESP32, or CC2652R [26,35,47], an integration that reduces the number of components and simplifies the design of the IoT node. Finally, a distinct category comprises custom-designed or ASIC-based solutions, which integrate energy harvesting and processing functionalities at the circuit level, enabling highly optimized designs in terms of energy efficiency, albeit at the cost of reduced flexibility and generality [37,38].

Regarding communication technologies, the reviewed platforms span almost the entire spectrum of IoT wireless solutions, covering nearly the entire spectrum of wireless options available for IoT systems. In fact, some platforms incorporate more than

Table 6

Comparison of IoT EHS platforms by platform, communication technology, and sensors. The identifiers for the studies correspond to those in Table 5. ND: not described. IMU: Inertial Measurement Unit; AQ: Air Quality.

Id.	Platform	Category	Communication	Sensors
1	Mica2	MCU	UWB	ND
2	C8051F921	MCU	RFID	Accelerometer, light, gas, temperature
3	Feather M0	MCU	LoRa/WiFi	Current, voltage, temperature, humidity, wind
4	ESP8266 ^a	SoC	WiFi	ND
5	Raspberry Pi	SBC	WiFi/GSM	Temperature, humidity, PM, CO ₂ , V/I
6	Exynos 5422	HPC	3G/4G	Power, UV, light, temperature, pressure, humidity
7	Arduino+RPi	Hybrid	WiFi	Accel., microphone, temp., humidity, smoke, fire, AQ
8	ND	MCU	LoRa	Pressure, pulse, V/I
9	PIC24	MCU	Sub-GHz	Fuel gauge, temperature, humidity, UV, accelerometer
10	STM32	MCU	NB-IoT	Multi-gas, PM, temperature, humidity
11	Arduino	MCU	LoRa	Current + GSM/GPS
12	ESP32	SoC	LoRa/WiFi	Soil moisture, rainfall, tilt
13	Arduino	MCU	WiFi	Temperature, humidity, UV, light, V/I
14	Custom ASIC	ASIC	Custom	Temperature (integrated)
15	nRF52833	SoC	LTE	IMU, temperature, humidity, GPS
16	STM32L0	MCU	BLE	Ambient light
17	Raspberry Pi	SBC	3G	G-sensor, GPS
18	Raspberry Pi	SBC	ND	Fingerprint, actuators
19	Atmel 32u4	MCU	LoRa	Soil sensors
20	PIC24	MCU	Sigfox	UV, temp., humidity, pressure, wind, particles, sound
21	ND	MCU	BLE	Heart rate, SpO ₂ , IMU
22	ATSAMD21	MCU	LoRa	Environmental sensors, microphone, buttons
23	CC2652R	SoC	WiFi	IMU, temperature, humidity, light
24	STM32	MCU	UWB/LoRa	Accelerometer, location
25	Raspberry Pi	SBC	WiFi	Temperature, humidity, soil, camera

^a Indicates that the main communication interface is integrated on the chip.

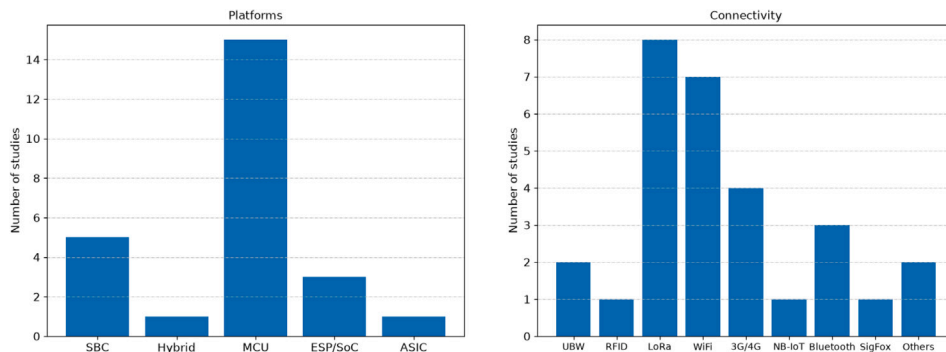


Fig. 5. Platform distribution (on the left) and communication technology (on the right) used by the 25 platforms selected for this study.

batteries are only found in a small number of legacy or older, low-cost designs [23,34]. This distribution reflects a strong alignment between battery selection and system-level requirements, particularly in terms of energy demand, form factor, and deployment constraints. In contrast to photovoltaic components, the design of energy management circuits exhibits more consistent patterns. A significant proportion of the reviewed platforms incorporate dedicated energy harvesting integrated circuits, particularly the BQ25570 [24,32,44,46,48] and BQ25504 [33,47] which provide features such as MPPT and efficient energy conversion under low-input conditions. These components are especially well-suited for solar-powered IoT systems operating under variable environmental conditions. Alternatively, some studies rely on simpler DC–DC converters or linear regulators, which offer lower complexity but reduced energy efficiency. A limited number of works propose custom power management solutions, typically in highly optimized or application-specific designs. Nevertheless, as observed in other EHS components, a non-negligible subset of studies does not fully specify the energy management architecture, limiting the reproducibility of the proposed systems.

An analysis of the architectures reveals, overall, an imbalance in the level of formalization among the three subsystems. Energy storage and load management tend to rely on standardized solutions, such as lithium batteries and commercial integrated circuits, and are typically described in relation to the node's consumption. The photovoltaic subsystem, on the other hand, remains poorly characterized: in much of the reviewed literature, neither the module technology nor its power output is specified, which limits the ability to reproduce or compare the designs. This imbalance, coupled with the absence of a systematic characterization of the components in several of the systems, suggests that the joint co-design of harvesting, storage, and consumption, as well as their systematic and reproducible formulation, remain open challenges in solar-powered IoT systems.

Table 7

Detailed characterization of the EHS in the selected platforms. **Legend:** **ND:** Not described. **AGM:** Absorbent Glass Mat. **OPV:** Organic photovoltaic panel; **FPCB:** Flexible Printed Circuit Lithium Ceramic Battery. **Li-Po:** lithium polymer battery; **Li-ion:** lithium-ion battery; **NiMH:** nickel-metal hydride; **PbA:** lead-acid; **c-Si:** crystalline silicon; **a-Si:H:** hydrogenated amorphous silicon, flexible; **Mono-Si:** monocrystalline silicon; **Poli-Si:** polycrystalline silicon; **SPVT:** dual-function photovoltaic transducer, EH and light detection.

Id.	PV (technology, power)	Energy storage	Power management unit
1	a-Si + OPV, ND	NiMH (150 mAh)	ND
2	a-Si:H, 56.9 mW	FPCB (170 mAh)	BQ25570
3	Mono-Si, 2 W	Li-Po (2 Ah)	MCP73871
4	Mono-Si, 10 W	NiMH (3.9 Ah)	Passive voltage reducer
5	ND, ND	PbA (200 Ah)	ND
6	ND, 50 W.	AGM (2 × 9 Ah)	Epsolar Tracer-A 10
7	Poli-Si, 5 W	PbA (12 Ah)	DC-DC regulator
8	ND	Li-ion (1 Ah)	ND
9	ND, ND	Li-Po (ND)	BQ25570
10	Poli-Si, ND	Li-Po (4 Ah)	BQ25504
11	Mono-Si, 3.5 W	NiMH (2.5 Ah)	TP4056
12	c-Si, ND	ND (500–1000 Wh)	ND
13	Mono-Si, 3 W	Li-Po (500 mAh)	Seedstudio Li-Po Rider Pro
14	ND, ND	ND	Custom PMU
15	Mono-Si, 492 mW	Li-ion (3000 mAh)	BQ25570
16	SPVT, non-commercial	ND	SPVT, non-commercial
17	ND, ND	ND	ND
18	Poli-Si, ND	ND	ND
19	ND, 0.5 W	Li-ion (2.5 Ah)	ND
20	c-Si, 93 mW	Li-Po (500 mAh)	BQ25570
21	Multi-cell PV array, ND	Li-ion (800 mAh)	SPV1050
22	a-Si:H, 93 mW	Li-Po (500 mAh)	BQ25570
23	Flexible PV cell, ND	Li-Po (12 mAh)	BQ25504
24	a-Si:H, 92 mW	Li-Po (50 mAh)	BQ25570
25	Mono-Si, 6 W	Li-ion (4.4 Ah)	ND

3.2. RQ2: Hardware and software strategies

The sustained operation of an IoT node powered by solar energy and a battery is subject to a fundamental constraint: the available energy is limited and varies over time. The literature reviewed addresses this problem by combining two complementary approaches. The first approach consists of reducing the IoT node's power consumption through the selection of efficient, low-power components. The second approach consists of managing the available energy by adapting the IoT node's behavior to environmental conditions and, in the most advanced cases, anticipating them through prediction. These two approaches are rarely applied in isolation: *hardware* decisions limit the scope of action for the software, and *software* strategies exploit the capabilities provided by the hardware, such that the system's efficiency arises from the co-design of both levels rather than from the separate optimization of each [29,40,49]. Fig. 6 presents a taxonomy of techniques in the three categories. The following subsections elaborate on these approaches and discuss the trade-offs that shape their application in devices with limited resources.

3.2.1. Hardware design strategies

The first approach to sustaining operation under a tight energy budget is to reduce the IoT node's power consumption. At the hardware level, this strategy begins with the selection of energy-efficient components, such as low-power microcontrollers and sensors with configurable sleep modes, which enable intermittent operation, and is complemented by the design of an efficient energy harvesting system. Complementarily, communication modules are one of the main energy consumers, directly impacting the EHS dimensioning. The following paragraphs describe the main characteristics of the identified hardware strategies.

Energy harvesting and storage. Most systems rely on photovoltaic panels as the primary energy source, with significant variability in size and capacity depending on the application domain [24,29,33,43,49]. Low-power nodes (e.g., wearables or indoor systems) typically employ small or flexible PV modules [24,45], while outdoor and industrial deployments use larger panels (up to tens of watts) to sustain higher energy demands [29,49]. Energy storage is predominantly based on rechargeable batteries, including Li-Ion, Li-Po, and NiMH technologies [24,25,33,40], with capacities ranging from a few mAh in wearable devices to several Ah in industrial systems [49].

Power management units (PMU). Efficient power management is a key hardware design aspect. Several works integrate dedicated PMUs with MPPT capabilities [24,40,47], enabling optimal energy extraction under variable irradiance conditions. Other approaches prioritize simplicity and cost by using linear regulators [33], although at the expense of lower efficiency. Advanced designs incorporate custom PMUs or fully integrated on-chip EHS solutions [37], addressing ultra-low-power operation and, in some cases, security and reliability concerns.

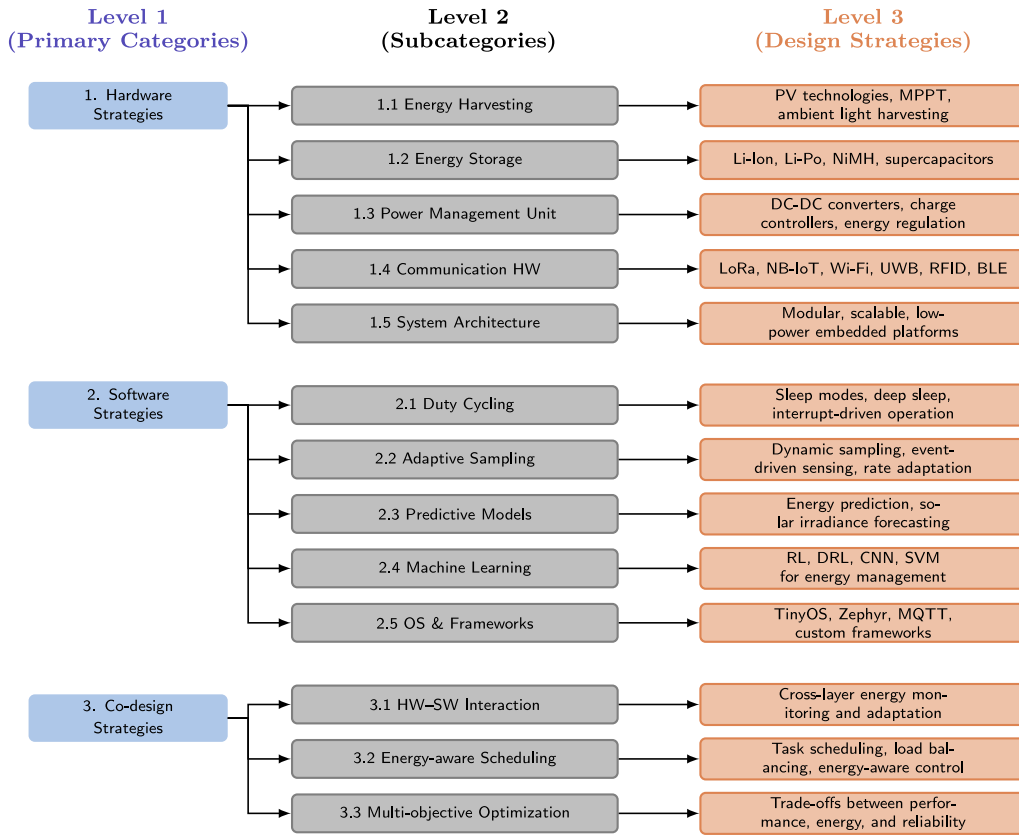


Fig. 6. Three-level taxonomy of hardware, software, and co-design strategies adopted in solar-based EHS for IoT systems.

System architecture and modularity. Many platforms adopt modular architectures, allowing flexible integration of sensing, communication, and energy harvesting components [25,40,46]. This is particularly evident in experimental platforms and cross-domain systems [23,25], where adaptability is prioritized over strict optimization. In contrast, application-specific designs (e.g., wearables or industrial nodes) tend to be more tightly integrated to minimize size, cost, and energy consumption [24,36,45].

Communication technologies. are strongly influenced by applications requirements. Low-power wide-area technologies such as LoRa and NB-IoT are widely used for long-range outdoor deployments [31,35,41,47], while short-range protocols (e.g., IEEE 802.15.4, UWB) are preferred for indoor or high-precision applications such as localization [24,39,48].

3.2.2. Software and energy management strategies

The second approach seeks to make better use of available solar energy by adjusting the IoT node's behavior to accommodate availability that cannot be controlled. The distinction from the previous approach is not always clear and frequently these techniques require the hardware support for an effective implementation. The following paragraphs describe the main software strategies used to achieve energy-efficient operation.

Duty cycling and low-power operation. The duty cycle adaptation, presented as an energy-saving technique, becomes a management technique when it ceases to be fixed and begins to adjust dynamically. While a fixed duty cycle is calibrated once and does not respond to available energy, an adaptive duty cycle modifies the frequency of the IoT node's activity based on conditions, and constitutes the most basic form of management. A fundamental strategy across nearly all systems is aggressive duty cycling [40,47], where nodes remain in sleep mode for the majority of the time and only activate periodically for sensing and communication. Techniques such as deep sleep modes, interrupt-driven execution, and sequential sensor activation are widely adopted to minimize idle power consumption.

Adaptive sensing and transmission. Several works implement adaptive strategies that adjust sensing rates, transmission frequency, or task execution based on environmental conditions or energy availability [35,39,44]. For example, sampling rates may increase during critical events and decrease during stable periods, while event-driven communication is used to reduce unnecessary transmissions.

Predictive and learning-based energy management. More advanced approaches incorporate predictive models and Machine Learning techniques to optimize energy usage. These include solar energy prediction using regression or support vector machines

(SVM) [29], model predictive control (MPC) for task scheduling [49], and reinforcement learning (RL)-based frameworks for real-time adaptation [47]. These strategies enable proactive energy management under dynamic environmental conditions.

Operating systems and software frameworks. Several platforms rely on lightweight operating systems such as TinyOS [23], supporting modular and energy-aware application development. In addition, custom firmware and middleware frameworks are often developed to implement energy management policies and facilitate data acquisition and communication.

3.2.3. Co-design and cross-layer optimization

A key observation across the reviewed literature is the increasing importance of hardware–software co-design. Efficient solar-based EHS systems are not achieved through isolated optimizations, but through coordinated design decisions across multiple layers [29]. Hardware capabilities such as MPPT, battery monitoring, and energy-aware sensing are tightly coupled with software strategies that dynamically adapt workload and duty cycles [40,49]. Similarly, communication protocols and sensing tasks are often co-optimized with energy availability, leading to systems that continuously adapt to environmental conditions. Moreover, some works explore multi-objective optimization, balancing competing goals such as sensing quality, latency, and energy sustainability [47]. This is particularly relevant in resource-constrained IoT devices, where trade-offs must be carefully managed. This tradeoff reinforces a cross-cutting observation in the reviewed literature: efficient solar-powered EHS are not achieved by optimizing each component in isolation, but rather through the co-design of hardware and software [29,40,49]. The tradeoff between complexity and resources is deeply analyzed in following subsection.

3.2.4. The trade-off between sophistication and resources

The more sophisticated the management strategy, the higher its computational and memory costs. In its simplest form, adaptation is reactive: the IoT node modifies its behavior based on its instantaneous energy state or observed conditions, but without anticipating how these will evolve [35,39,44]. A higher level incorporates solar output prediction: since solar energy, although uncontrollable, is highly predictable, estimating future generation allows for energy usage planning before a deficit or surplus occurs. Predictive and machine learning techniques offer the best performance, but their requirements often exceed the capabilities of low-power platforms, which, as shown in Section 3.1, constitute the majority of deployed IoT nodes. This circumstance explains why several of the most advanced solutions run on platforms with greater computing capacity, such as SBCs [29,49], or are evaluated through *offline* analysis of the collected data, and why their transfer to a microcontroller requires lightweight versions of the algorithms. A recurring feature in studies that incorporate prediction is that it is typically computed separately from the operation of the IoT node. In many cases, solar production estimates are obtained outside the device, either on higher-capacity platforms or through subsequent analysis of the collected data. This decoupling is reasonable, given the computational cost of the most accurate models, but it leaves a gap: prediction gains value to the extent that it informs management policies that determine, during operation, how and when to use the available energy. In several of the reviewed studies, this link does not materialize on the IoT node itself, since the predicted information is used for characterization purposes or evaluated in terms of accuracy, without being integrated into an embedded decision-making mechanism that translates it into concrete management actions. Finally, the most advanced works integrate forecasting into decision frameworks that explicitly aim for efficient and, in some cases, energy-neutral operation: MPC applied to task scheduling [49] and reinforcement learning-based frameworks for real-time adaptation [47] represent the most sophisticated end of this spectrum.

Fig. 7 summarizes this analysis. In it, the reviewed studies are organized according to the management strategy they adopt and the context in which it is implemented, further distinguishing between field validation and validation conducted in a laboratory or through simulation. The resulting distribution clearly highlights the tension described: static and reactive strategies are primarily executed on the IoT node itself and validated in the field, while predictive and learning-based strategies are shifted to platforms with greater capacity or are not integrated into the node at all. No studies were identified that incorporate prediction embedded in the IoT node and validated under real operating conditions, a combination that, while not unfeasible, remains unexplored in the analyzed corpus.

3.3. RQ3: Application domains

Fig. 8 presents the distribution of application domains across the selected studies. As observed, a wide range of application scenarios is addressed in the literature. For the sake of clarity, applications have been grouped into eight categories: smart cities and infrastructures, industrial IoT, energy-aware systems, security and smart home, wearables and healthcare, environmental and agricultural monitoring, localization and tracking, and miscellaneous. Smart cities and infrastructure-related applications represent the most prominent domain, followed by industrial IoT deployments. Environmental monitoring and agriculture applications also account for a significant portion of the literature, highlighting the relevance of solar-based EHS in long-term outdoor sensing scenarios. Wearable and healthcare systems constitute another important category, where energy efficiency and compactness are critical constraints. In contrast, domains such as localization, security, and indoor energy-aware systems are less represented, indicating potential research opportunities.

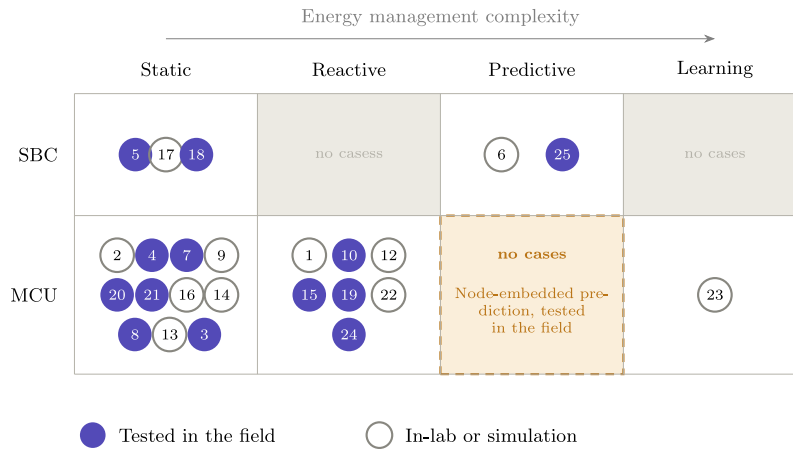


Fig. 7. Energy management strategies from the reviewed studies, categorized by their implementation context. The horizontal axis ranks the strategies by increasing complexity, and the vertical axis indicates where the management is implemented. The shading in each study distinguishes field validation from validation conducted in a laboratory or through simulation. Cells marked as *no cases* contain no studies in the analyzed corpus; among them, the one highlighted in amber (corresponding to predictive strategies embedded in the IoT node and validated in the field) represents a technically desirable scenario that has not yet been explored in the reviewed studies.

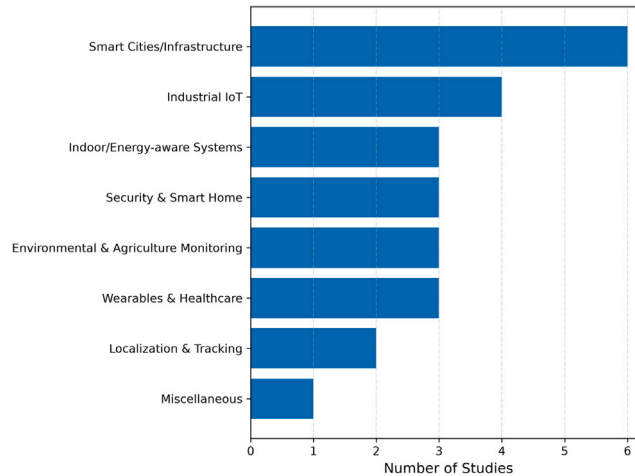


Fig. 8. Application domains addressed in the selected studies.

3.3.1. Smart cities and infrastructures

Six studies [7,26,27,30,33,44] address smart-city and infrastructure scenarios, where solar-based EHS must support long-term outdoor operation, heterogeneous sensing workloads, and reliable communication. The work in [7] presents a modular testbed for collecting real-world energy-harvesting datasets, including electrical and environmental variables, and provides a publicly available dataset obtained through a multi-month deployment in Ciudad Real (Spain). In [26], a sustainable environmental monitoring node deployed in Soacha (Colombia) combines photovoltaic harvesting, battery storage, and low-rate wireless communication, demonstrating stable operation under different weather conditions over a six-month period. A different perspective is provided by [27], which integrates IoT sensing nodes into a solar-tree structure for smart street-lighting and air-quality monitoring applications. The emergency-management platform proposed in [30] extends the domain toward infrastructure safety by combining environmental and structural sensing with a CNN-based pavement damage classification system and a highly energy-efficient duty-cycled operation. The Advanced Pollution Monitoring Device presented in [33] focuses on large-scale urban pollution monitoring using NB-IoT connectivity and a custom low-power particulate matter sensor, emphasizing long-term autonomy, robustness, and cost-effectiveness. Finally, the smart-beach system described in [44] combines environmental monitoring, safety services, and public information delivery using solar-powered distributed nodes and heterogeneous communication technologies such as LoRa and Wi-Fi. This work illustrates how certain smart-city applications must balance energy efficiency with higher data-rate and multimedia service requirements.

3.3.2. Industrial IoT (IIoT)

Industrial IoT applications impose stringent requirements in terms of reliability, long-term autonomy, robustness under harsh environmental conditions, and minimal maintenance [29,31,36,40]. The predictive energy-management approach proposed in [29] combines solar irradiance modeling, power-generation estimation, and support vector machine (SVM) techniques to dynamically manage the energy budget of a high-performance embedded platform powered by photovoltaic harvesting and battery storage. WaterGrid-Sense [31] targets smart water-management infrastructures by integrating multiple sensing and communication components and experimentally validating power-consumption and communication-reliability aspects in a real deployment environment. The low-cost platform presented in [36] emphasizes scalable and cost-effective industrial deployments in remote outdoor environments, incorporating adaptive energy-saving behavior to cope with changing solar conditions and adverse weather. In contrast, the integrated EH-ALS system proposed in [40] combines ambient-light sensing and photovoltaic harvesting in a single transducer, reducing component count, system complexity, and maintenance requirements. Together, these studies show that IIoT-oriented EHS designs prioritize robustness, scalability, and adaptive energy management over extreme miniaturization.

3.3.3. Energy-aware cross-domain systems

Some studies do not target a specific application domain but instead propose general-purpose platforms or methodologies that can be adapted to multiple IoT scenarios [23,34,49]. The EnHANTs architecture [23] combines a programmable platform, ultra-wideband impulse-radio communication, and photovoltaic harvesting to support multi-hop networking and energy-harvesting experimentation. The solar-powered LoRa-based platform in [34] targets infrastructure and power-distribution monitoring through a real-world deployment in an operational electrical network, highlighting the importance of reliable energy supply in critical monitoring scenarios. PERMIT [49] introduces a predictive energy-management framework that dynamically adapts sensing tasks according to current energy availability while continuously updating solar-generation predictions based on battery-state information. This work illustrates the increasing relevance of predictive and adaptive energy-management strategies for improving the autonomy of solar-powered EHS across heterogeneous IoT domains.

3.3.4. Security and smart home

Security-related applications introduce additional constraints beyond energy efficiency, including reliability, resilience to attacks, and continuous availability [37,41,42]. The work in [37] follows a Security-by-Design paradigm and proposes Eternal-Thing, a custom CMOS-based EHS that integrates aging-aware and Trojan-detection mechanisms directly into the harvesting circuitry. This work highlights the importance of trustworthy energy-harvesting architectures for critical IoT deployments. The self-powered AIS system presented in [41] targets tracking and safety-oriented applications such as marine navigation and remote asset monitoring, where continuous positioning and communication significantly increase energy demand. The smart door-lock system described in [42] represents a typical smart-home scenario in which uninterrupted operation and responsiveness are essential, although the harvesting subsystem is only partially described. Collectively, these studies illustrate how security- and safety-critical applications require EHS designs that prioritize reliability and sustained energy availability.

3.3.5. Wearables and healthcare

Wearable applications require solar-based EHS to satisfy strict constraints on flexibility, compactness, portability, and ultra-low power consumption [24,45,47]. The flexible RFID-based wearable proposed in [24] combines photovoltaic harvesting with battery assistance to support indoor localization and low-power wireless communication. The self-powered health-monitoring device presented in [45] integrates physiological sensing with a flexible photovoltaic module and lightweight machine-learning techniques for activity-level classification, illustrating the trend toward intelligent wearable systems. The tinyMAN framework [47] applies reinforcement-learning-based energy management to dynamically adapt system behavior according to fluctuating energy availability while maintaining operation within the limited memory and energy budgets typical of wearable IoT devices. These studies demonstrate that wearable EHS designs must simultaneously optimize flexibility, user comfort, sensing functionality, and intelligent energy management.

3.3.6. Environmental and agricultural monitoring

Environmental and agricultural monitoring is characterized by long-term outdoor deployments, harsh environmental conditions, limited accessibility, and highly variable solar availability [32,35,43]. The precision-agriculture platform described in [43] integrates heterogeneous soil sensors with a solar-based EHS designed for unattended operation under harsh outdoor conditions, emphasizing energy-efficient power-management decisions. The landslide early-warning system proposed in [35] combines environmental sensing, LoRa communication, and solar harvesting to maintain operation during prolonged rainfall periods, when energy availability decreases while monitoring requirements become more critical. The greenhouse-monitoring system in [32] adapts both communication technology and EHS design to the particular conditions of agricultural environments, including vegetation-induced signal attenuation and reduced indoor solar irradiance. These works show that environmental-monitoring applications require EHS solutions capable of coping with seasonal variability, adverse weather, and difficult maintenance conditions.

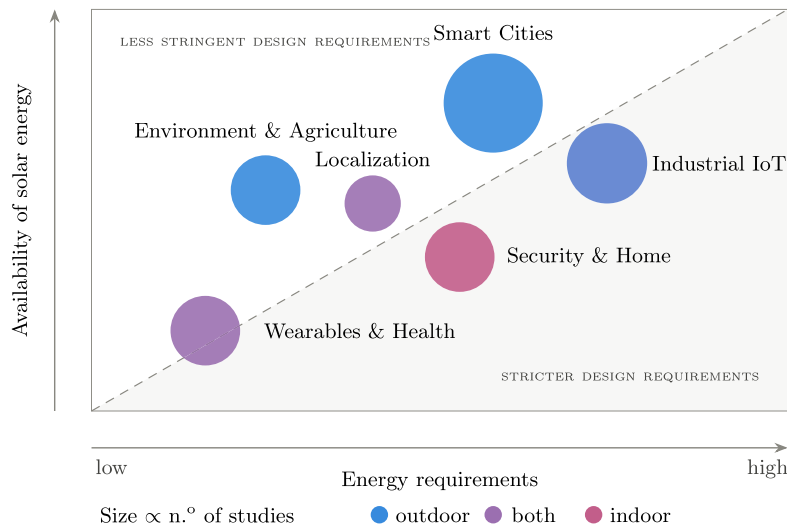


Fig. 9. Design space for solar EHS systems by application domain. Each domain is qualitatively positioned based on the application's energy demand and the availability of solar resources at the site. The size of each bubble is proportional to the number of papers in the corpus within that domain, and its color indicates the deployment environment, on a scale ranging from the exterior (blue) to the interior (red), with intermediate shades representing domains present in both environments. The shaded region corresponds to the combinations with the highest EHS design demands, where high demand coincides with low resource availability.

3.3.7. Localization and tracking

Localization applications exhibit very different requirements depending on whether they operate in indoor or outdoor environments [39,48]. The indoor asset-tracking system evaluated in [48] employs IEEE 802.15.4z ultra-wideband technology and demonstrates long-term self-sustainable operation under variable indoor lighting conditions, highlighting the importance of low-duty-cycle operation and efficient power management when harvested energy is scarce. EcoTrack [39] addresses outdoor localization by combining GNSS positioning, LTE-M connectivity, and a solar-based EHS to support wide-area tracking and remote hazard monitoring while maintaining energy-neutral operation. Together, these studies illustrate the strong influence of communication range, positioning technology, and energy availability on the design of localization-oriented EHS platforms.

3.3.8. Miscellaneous

The IWAIST platform [46] represents a flexible and modular IoT architecture intended for heterogeneous sensing scenarios. Its interchangeable sensor and power modules allow the system to be adapted to different application contexts, including classroom air-quality monitoring and indoor/outdoor acoustic measurements. From an EHS perspective, this flexibility requires adaptable power-management strategies capable of handling variable sensing and communication workloads, prioritizing reconfigurability over optimization for a single application domain.

To provide a high-level perspective on how application requirements influence the design of solar-based EHS, Fig. 9 illustrates a conceptual design space relating energy availability and energy demand across different IoT domains. Each domain occupies a different region in this space, reflecting the trade-offs between energy input conditions and system requirements. This visualization highlights how domain-specific constraints drive distinct EHS design strategies. The observed heterogeneity confirms that there is no universally valid EHS configuration: each domain requires a different balance between generation, storage, and consumption. The fact that the design is determined by the application scenario highlights the need to approach EHS sizing systematically, explicitly considering resource availability and the consumption profile.

3.4. RQ4: Achievements, challenges, and limitations

This section synthesizes the main achievements, limitations, and open challenges reported in the reviewed literature. Instead of presenting a paper-by-paper analysis, this section presents the common trends and recurring issues that characterize the current state of the field and reveal the main research gaps.

3.4.1. Achievements

The reviewed studies demonstrate that the field has reached a remarkable level of maturity on several fronts.

Demonstrated feasibility of energy-neutral IoT operation. The reviewed studies demonstrate that the field has reached a remarkable level of maturity on several fronts. The technical feasibility of powering IoT nodes using solar energy and batteries has been solidly demonstrated: the reviewed studies cover a wide range of domains, scales, and communication technologies, and several studies report real-world deployments sustained during months [18,39,47,48]. These results confirm the feasibility of energy-neutral operation when the EHS design is carefully adapted to environmental conditions.

Advances in low-power EHS hardware architectures. Hardware innovations represent a capital contribution. At the component level, there is a clear convergence toward standardized storage and management solutions, such as lithium batteries and commercial UGCs, which simplify the design and improve the energy harvesting efficiency. Several works propose optimized low-power designs, including custom sensing platforms [35], ultra-low power nodes with aggressive duty cycling and integrated solutions combining energy harvesting with sensing functionalities [40]. Additionally, domain-specific optimizations [41], such as low-power particulate matter sensors or greenhouse-aware communication strategies, demonstrate how tailoring system design to application requirements can significantly improve efficiency.

Evolution toward adaptive and predictive energy management. The literature has progressed from simple consumption reduction to strategies capable of reacting and adapting the IoT node's behavior to available energy, and even anticipating it through prediction (see Fig. 7). Predictive and adaptive approaches, including MPC [49], reinforcement learning-based frameworks [47], and adaptive sampling techniques [39], have demonstrated the ability to significantly improve system performance. For instance, tinyMAN achieves up to 17% higher device utilization while reducing battery constraint violations by 80%, whereas adaptive sampling approaches outperform static configurations by up to one order of magnitude in efficiency.

Evidence of long-term autonomous operation. Overall, these advances confirm that the energy self-sufficiency of IoT nodes is an achievable goal rather than merely a theoretical possibility.

3.4.2. Limitations

Despite these important advances, significant challenges remain, as highlighted in the following paragraphs.

Intermittency and variability of the solar resource. A major constraint is the intermittency inherent to solar harvesting, particularly under adverse or highly variable environmental conditions. For example, some systems are unable to sustain continuous operation during low irradiance periods, such as prolonged rainfall [49] or nighttime indoor conditions [40]. In other cases, solar harvesting is insufficient to fully recharge batteries within a single day, delaying energy recovery and limiting performance [33].

Limited hardware resources. A second important limitation arises from the constrained hardware resources of IoT devices, including restricted memory, computational power, and battery capacity, which limit the deployment of advanced algorithms [39,40,44]. In some cases, design trade-offs lead to suboptimal configurations, such as always-on systems without proper sleep modes or prototypes where the EHS is not sufficient to fully power the device [35]. This aspect, as previously described in Section 3.2, introduces a trade-off between the sophistication of the management strategies and the resources of the IoT node: the most promising techniques, based on prediction and machine learning, are rarely executed on the low-power platforms that make up the majority of deployments, which limits their real-world applicability.

Lack of EHS design and evaluation methodologies. Several works are highly application-specific [34,42], making it difficult to generalize their design to other domains. This dependence on the application domain hinders the transfer of solutions between scenarios and requires a case-by-case redesign. The heterogeneity of solar resources, which varies by orders of magnitude between outdoor and indoor environments, exacerbates the problem, compounded by the lack of justification for sizing decisions: components are specified, but the criteria used to select their technology or size are rarely documented, preventing objective comparisons and the reuse of best practices. On the other hand, a significant proportion of studies incompletely document essential aspects of the EHS, such as the photovoltaic subsystem or the energy management architecture, which makes it difficult to replicate and compare results. The lack of guidelines for EHS design, the dependence on application requirements, and the incomplete documentation of deployments negatively affect design reproducibility and make it difficult to evaluate systems using standardized benchmarks and well-defined metrics.

Insufficient long-term validation. Another important limitation concerns the duration and realism of the experimental validation. A large fraction of the studies rely primarily on simulations or provide only short-term experimental evaluations. Although several works report field deployments, relatively few assess operation continuously over extended periods and under full seasonal conditions, which is precisely the scenario that autonomous IoT nodes must face in real-world environments. The combination of limited methodological transparency and insufficient long-term validation explains why the transition from validated prototypes to reliable, large-scale, and maintenance-free deployments remains one of the main unresolved gaps in the field.

Security and resilience of EHS. These aspects remain largely underexplored in the field of solar-based EHS. Although isolated works such as Eternal-Thing [37] integrate aging-aware and Trojan-detection mechanisms directly into the harvesting circuitry, the development of secure, fault-tolerant, and reliable EHS architectures continues to be an important open research challenge.

3.4.3. Challenges and open research directions

The analysis reveals several key challenges that must be addressed to enable large-scale and long-term deployment of solar-based EHS in IoT.

Robust energy neutrality under dynamic conditions. A primary challenge is achieving robust energy neutrality under highly dynamic and unpredictable conditions. Solar energy availability varies significantly due to weather, seasonal changes, and environmental factors, requiring systems to dynamically adapt their operation. While predictive and adaptive algorithms show promising results [47, 49], their effectiveness is still limited by model accuracy, computational overhead, and the need for real-time decision-making.

Table 8

Visual synthesis of the main open challenges identified in solar-based EHS for IoT.

Legend: ★★★: broadly addressed in current literature; ★★☆: partially addressed.

★☆☆: challenge remains largely unexplored.

Challenge	Maturity
Robust energy neutrality under dynamic conditions	★★☆
Intelligence integration in resource-constrained IoT nodes	★★☆
Long-term reliability and environmental robustness	★★☆
Communication-energy cost and connectivity trade-offs	★★★
Standardized evaluation and scalability assessment	★★☆
Lack of EHS design methodologies	★☆☆

Intelligence integration in resource-constrained IoT nodes. Another critical challenge is the integration of advanced intelligence into resource-constrained devices. Techniques such as machine learning and optimization can significantly improve energy management, but their computational requirements often exceed the capabilities of low-power embedded platforms. This creates a gap between algorithmic advances and practical deployment [47,49].

Long-term reliability and environmental robustness. Reliability and robustness also remain open issues, particularly in harsh environments. Systems deployed in outdoor or industrial settings must withstand extreme temperatures, humidity, dust, and corrosion [31]. Moreover, long-term operation introduces challenges related to battery aging, hardware degradation, and maintenance-free operation. Security further complicates this landscape, as highlighted by works addressing hardware-level attacks and aging effects in EHS design [37].

Communication energy cost and connectivity trade-offs. Long-range communication technologies such as LoRa, NB-IoT, or UHF-based systems increase energy consumption, creating a tension between connectivity requirements and energy availability [41,47]. Similarly, indoor localization systems face challenges due to the high power consumption of UWB transceivers [48].

Standardized evaluation and scalability assessment. There is a lack of standardized evaluation methodologies and large-scale validation. Many works rely on short-term experiments or limited deployments, making it difficult to compare solutions and assess their scalability. The availability of public datasets [18] represents a step forward, but more comprehensive benchmarking frameworks are needed.

EHS design methodologies. There is a lack of environment-aware EHS design methodologies capable of systematically sizing photovoltaic panels, storage elements, and power-management subsystems according to the available solar resource and application workload [49]. Most reviewed studies rely on ad-hoc design decisions, with limited consideration of optimization criteria related to energy availability, cost, reliability, and operational lifetime. Consequently, oversizing is often used as a safety margin to ensure energy availability, increasing system cost and battery stress, while undersizing may compromise long-term autonomous operation. This lack of standardized design pipelines remains an important methodological gap in current solar-based EHS research.

Table 8 summarizes the main open challenges in solar-based, battery-equipped EHS and their maturity level.

4. Discussion

The challenges identified throughout the review also highlight important opportunities for future research. Future progress in solar-based EHS for IoT will likely depend on more adaptive and intelligent energy-management strategies, the broader adoption of predictive and learning-based techniques, the consolidation of hardware–software co-design, and the availability of standardized and reusable design and evaluation methodologies. Addressing these issues will require interdisciplinary approaches that integrate hardware innovation, energy-aware algorithms, environmental modeling, and system-level optimization to enable truly sustainable and large-scale IoT deployments.

4.1. Cross-study evaluation and benchmarking

One of the most evident findings of the systematic review is the strong heterogeneity of the evaluation methodologies used across solar-based EHS proposals. Table 9 summarizes the evaluation methodologies adopted in the 25 selected studies, together with the harvesting evidences collected during the evaluation, the reported lifetime, the energy management strategy used and if the energy neutrality condition was explicitly addressed during the process. The comparison highlights the substantial heterogeneity of the evaluation methodologies used in the literature, ranging between laboratory validation, simulations, partial field experiments, and real-world deployments, which constitute, as shown, the smaller fraction within the studies considered. During the experiments, the reported harvesting evidence varies considerably, ranging from solar generation production, output voltage measurements, or more specific metrics. A very few samples of studies collect detailed datasets including solar production, harvested energy, and battery state-of-charge evolution, that are used for different purposes and they are not always published. This heterogeneity limits the possibility of establishing normalized quantitative benchmarks across platforms. Most of the studies implement some technique of energy management, either hardware or software, ranging from hardware strategies based on sleep modes to reduce

Table 9

Cross-study synthesis of quantitative evidence reported in the 25 selected studies, including photovoltaic harvesting evidences, reported operational lifetime, energy-management strategies (EM), benchmarking and evaluation metrics and energy-neutral degree of achievement (EN). **ND:** Not described. **h:** hours. **d:** days. **m:** months. **y:** years.

Id.	Evaluation/Benchmark	Harvesting evidence	Lifetime	EM strategy	EN ^a
1	Laboratory validation	None	1 d	Energy-harvesting adaptive policies	Yes
2	Simulation + real deployment	Average consumption and system autonomy	138 d	Sleep modes	Partial
3	Real deployment	Solar power generation ^b	64 d	None	Yes
4	Real deployment	Solar power generation, sunshine, and voltage	18,2 h-2 d	None	Yes
5	Real deployment	Solar power generation	4 m	MPPT	Partial
6	Laboratory validation	Adaptive behavior system to energy availability	ND	Sleep modes; Solar power generation prediction; task scheduling	Partial
7	Simulation + Real deployment	ND	ND	Sleep modes	No
8	Laboratory validation + real deployment	RSSI and SNR	26 d	Sleep modes	Partial
9	Laboratory validation	Output voltage (3 V)	ND	Duty cycle adaptation	Partial
10	Laboratory validation	None	ND	Nyquist-based optimum sampling strategy; Power control mechanism for the PM sensor's	No
11	Real deployment	ND	ND	None	No
12	Laboratory validation + real deployment	ND	ND	Adaptive sampling; deep sleep modes	No
13	Laboratory validation	Solar power generation and output voltage estimation	ND	Adaptive energy-saving modes	No
14	Simulated in CMOS 90-nm technology	Output voltage (3–3.55 V)	ND	None	No
15	Simulation by using three real-world datasets	Harvested energy/day, Localizations/day; Evolution of the battery's SoC	2 y	FSM-based adaptive sampling algorithm	Yes
16	Laboratory validation	ND	ND	Sleep modes	No
17	Real deployment	ND	1 week	None	No
18	Laboratory validation	Charging batteries using solar panel	ND	ND	No
19	Laboratory validation + real deployment	ND	ND	Deep sleep modes; Long measurement intervals	No
20	Real deployment	Solar power generation and energy consumption of the nodes	Several y	Adaptive sampling and transmission intervals and deep sleep modes	Yes
21	Real deployment	Operational stability; power performance and accuracy classification activity	ND	Variable sampling frequencies & Efficient charge management	No
22	Real deployment	ND	ND	Sleep-modes, interrupt-based communication	No
23	Simulation + real deployment	Average daily utility; n° of battery constraints violations	ND	Reinforcement learning	Partial
24	Simulation + real deployment by using a real-world dataset	Datasets for localization (unpublished)	700 d	None	Yes
25	Simulation + real deployment	Maximize utility of sensing	ND	Model Predictive Control & Solar power generation prediction	Partial

^a **Yes** indicates explicit evidence of energy-neutral or self-sustainable operation demonstrated through real deployment or long-term experimental validation; **Partial** indicates the use of adaptive, predictive, or optimization-based energy-management mechanisms intended to approach energy-neutral operation, but without explicit long-term validation of sustained autonomous operation; **No** indicates that no evidence of energy-neutral operation was reported; and **ND** indicates that the study did not provide sufficient information to assess this aspect.

^b <https://github.com/UCLM-ARCO/energy-harvesting-dataset>.

energy consumption, duty cycle adaptation, and adaptive or predictive energy-management mechanisms intended to approach energy-neutral operation, but without providing sufficient long-term validation. In fact, the reported operational lifetime is strongly associated with the sophistication of the energy-management strategy rather than with the harvesting subsystem alone. The longest reported lifetimes are typically achieved by combining solar harvesting with adaptive sampling, transmission scheduling, deep sleep modes, or predictive control mechanisms, whereas systems without explicit energy-management support generally report shorter operational periods or do not provide lifetime evidence. Explicit evidence of energy-neutral or self-sustainable operation remains relatively uncommon, with only a limited subset of studies demonstrating battery state-of-charge stabilization, long-term autonomous operation, or sustained energy-balanced behavior under realistic deployment conditions. In the table, the last column shows **Yes/Partial/No/ND** to indicate if this aspect was explicitly considered in the evaluation and if they provide lifetime operational in the experiments performed.

The analysis confirms that reproducibility remains a significant challenge in the field. Only a small number of studies provide publicly accessible datasets or sufficiently detailed benchmarking information to support independent replication and fair cross-platform comparison. Furthermore, the reviewed works report heterogeneous sets of evaluation metrics, making it difficult to compare photovoltaic harvesting performance, storage utilization, communication activity, and operational lifetime across platforms. To improve comparability, future evaluations should consistently report a minimum set of metrics including photovoltaic panel characteristics and environmental conditions, harvested energy measurements or solar production traces, battery capacity and state-of-charge evolution, load consumption profiles across active, idle, sleep, and transmission states, communication technology together with transmission interval and duty cycle, and the duration and conditions of the experimental deployment.

In addition, evaluation studies should clearly distinguish between laboratory validation, simulation-based assessment, short-term field experiments, and long-term real-world deployments, while documenting the workload, sampling configuration, and communication patterns used during the experiments. Finally, the publication of open datasets containing solar irradiance, harvested energy, battery state-of-charge, and application workload traces would substantially improve reproducibility, enable fairer cross-platform comparisons, and facilitate the development of standardized benchmarking frameworks for future solar-based EHS proposals in IoT environments.

4.2. Security, reliability, and resilience considerations

The systematic review reveals that reliability, resilience, and security considerations receive considerably less attention than energy harvesting efficiency and power-management optimization. Most reviewed studies evaluate the ability of solar-based EHS to sustain autonomous operation, whereas the robustness of such systems against faults, environmental degradation, or malicious interference is only marginally addressed.

From a reliability perspective, long-term autonomous deployments must cope with battery aging, photovoltaic degradation, sensor drift, and communication failures, all of which can progressively compromise energy-neutral operation. The limited availability of multi-season field studies makes it difficult to quantify how these factors affect system availability over extended operational lifetimes.

Resilience introduces additional requirements related to fault detection, graceful degradation, and adaptive recovery mechanisms. Future EHS architectures could incorporate lightweight battery management system (BMS) capabilities, including state-of-charge (SoC) and state-of-health (SoH) estimation, aging-aware control, and predictive maintenance indicators, into energy-management policies. Complementary energy-aware anomaly detection mechanisms capable of identifying abnormal consumption patterns, battery degradation, or communication faults before they compromise energy-neutral operation also represent a promising research direction for reliable and maintenance-free IoT deployments.

Security remains an even more underexplored dimension. Apart from isolated contributions such as Eternal-Thing [37], which incorporates aging-aware and Trojan-detection mechanisms into the harvesting circuitry, the reviewed literature provides very limited evidence of security-oriented EHS architectures. As solar-powered IoT systems become increasingly connected and autonomous, future research should investigate the interaction between secure low-power communication protocols, hardware trust mechanisms, energy-aware authentication, and protection against energy-depletion attacks. Addressing these aspects will be essential for deploying solar-based EHS in industrial, critical-infrastructure, and safety-sensitive IoT environments.

4.3. Future research directions for autonomous solar-based EHS

The challenges identified across the reviewed studies suggest that future research should move beyond isolated hardware or software optimizations toward integrated and environment-aware EHS design methodologies. Current deployments still rely predominantly on reactive or threshold-based energy-management mechanisms, whereas long-term autonomous operation under highly variable solar conditions requires predictive and adaptive decision-making capabilities.

A major research direction is the development of lightweight intelligent energy-management mechanisms capable of combining solar forecasting, battery state estimation, workload adaptation, and long-term autonomy objectives. The reviewed literature already reports promising results for model predictive control, reinforcement learning, and adaptive sampling strategies; however, their practical adoption remains constrained by computational overhead, memory limitations, and the scarcity of long-term validation under realistic deployment conditions. Emerging approaches such as TinyML and Federated Learning (FL) could enable local inference, collaborative adaptation, and reduced communication overhead in distributed EHS deployments, although they have not yet reached a mature level of adoption within the reviewed corpus. Future research should therefore focus on ultra-low-power embedded intelligence capable of operating continuously on resource-constrained IoT nodes while preserving energy-neutral behavior.

Another promising direction is the use of Digital Twin paradigms and environment-aware system modeling to support predictive optimization, battery-degradation analysis, fault diagnosis, and proactive maintenance of autonomous EHS platforms. By integrating photovoltaic generation models, storage behavior, workload evolution, and environmental conditions, these approaches could provide a systematic basis for adaptive co-design methodologies that jointly optimize harvesting, storage, communication, and application requirements.

Finally, the review highlights the need for environment-aware co-design methodologies that jointly consider solar resource availability, load profiles, storage behavior, and application requirements during the EHS design process. Such methodologies could reduce the widespread use of conservative oversizing practices, improve system reliability, lower deployment costs, and increase operational lifetime. In this sense, future progress in solar-based EHS is likely to depend not only on better harvesting components or smarter algorithms, but also on the availability of systematic design pipelines that integrate environmental modeling, energy management, and long-term autonomy objectives.

5. Conclusions

This survey has presented a PRISMA-based systematic review of solar-based, battery-assisted energy harvesting systems for IoT. Starting from an initial corpus of 357 publications retrieved from major scientific databases, the systematic selection process resulted in a final set of 25 studies that explicitly address the design, implementation, and evaluation of autonomous solar-powered IoT platforms. The review has provided a comparative analysis of application domains, hardware architectures, energy-management strategies, operational lifetime evidence, and energy-neutrality achievements, together with a cross-study assessment of benchmarking and reproducibility practices.

The analysis reveals a rapidly evolving field in which significant progress has been achieved toward self-sustainable IoT deployments. Real-world implementations demonstrate that energy-neutral operation is feasible when harvesting, storage, and consumption are carefully adapted to environmental conditions. A key insight emerging from the cross-study comparison is that long-term autonomy is determined less by the absolute size of the photovoltaic or storage subsystem than by the ability of the platform to dynamically adapt sensing, communication, and processing workloads to the available energy budget. The most successful deployments consistently combine solar harvesting with adaptive sampling, transmission scheduling, deep sleep mechanisms, or predictive energy-management policies, whereas static configurations rarely provide convincing evidence of sustained autonomous operation under realistic conditions.

At the same time, the review highlights persistent limitations related to solar resource variability, the trade-off between the sophistication of energy-management solutions and the limited hardware resources of IoT nodes, the absence of environment-aware EHS design methodologies, insufficient long-term validation, and the limited availability of standardized evaluation frameworks and open datasets. These findings suggest that future progress will depend on tighter hardware–software co-design, lightweight intelligent energy-management mechanisms, adaptive communication strategies, and reliability-aware architectures capable of addressing battery aging, environmental degradation, and maintenance-free operation. In parallel, the establishment of common benchmarks, standardized evaluation metrics, and publicly available datasets will be essential to improve reproducibility and enable fair comparison across platforms. Ultimately, advancing toward truly sustainable solar-powered IoT systems will require shifting from application-specific, ad-hoc EHS implementations toward reusable, environment-aware design and evaluation methodologies that systematically balance harvesting capability, storage capacity, workload adaptation, and deployment conditions.

CRedit authorship contribution statement

Soledad Escolar: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Stefano Chessa:** Writing – review & editing, Visualization, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Antonio Caruso:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Melisa Kuzman:** Writing – review & editing, Investigation, Formal analysis, Data curation, Conceptualization. **Jose Luis Mira:** Writing – review & editing, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

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Data availability

No data was used for the research described in the article.

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