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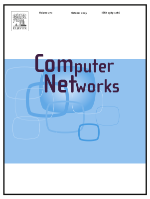

Survey paper

# The evolution of Dynamic Spectrum Sensing: A two-decade survey from foundations to frontiers

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ABSTRACT

The growing demand for wireless connectivity has heightened the need for efficient spectrum utilization. Dynamic Spectrum Sensing (DSS), a fundamental capability of Cognitive Radio Networks (CRNs), enables real-time identification of available spectrum without interfering with licensed users. While DSS has evolved significantly, a comprehensive overview capturing its full operational context remains lacking. This survey bridges that gap by systematically analyzing 62 peer-reviewed studies published between 2005 and 2024, selected based on explicit or implicit engagement with DSS and rigorous peer-review criteria. Employing a PRISMA-based methodology, we examine major sensing strategies, including energy detection, cooperative spectrum sensing, and machine learning, based methods, alongside application domains, technologies, and evaluation methods. Special attention is given to how DSS systems address dynamic environments, including time-varying channels and real-time decision-making. Key contributions include a comprehensive literature analysis covering research trends, experimental and implementation practices, as well as environmental variability. The survey also identifies critical open challenges, including security vulnerabilities in cooperative sensing, energy constraints in IoT deployments, and limited adaptability to dynamic and mobile environments. It offers a consolidated foundation for advancing DSS research and practice, guiding future efforts toward resilient, energy-aware, and adaptive sensing solutions for emerging contexts such as 6G networks, IoT, and satellite communications

## 1. Introduction

The exponential growth in wireless communication technologies and connected devices has placed unprecedented pressure on the radio frequency (RF) spectrum. Traditional static spectrum allocation policies often result in inefficient spectrum utilization, leaving many frequency bands underutilized across time and space. Cognitive Radio Networks (CRNs) have emerged as a promising solution to overcome this inefficiency by enabling opportunistic spectrum access through intelligent, adaptive decision-making. At the heart of CRNs lies Dynamic Spectrum Sensing (DSS), the ability to detect spectrum availability in real time, adapt to environmental conditions, and make informed decisions about spectrum usage without interfering with licensed users.

Over the past two decades, DSS has evolved significantly, driven by advances in signal processing, machine learning, cooperative techniques, and hardware platforms. As a result, the research landscape has become increasingly complex, encompassing a wide range of technologies, network environments, sensing strategies, and performance evaluation methods. While a number of surveys have addressed specific facets of spectrum sensing, such as cooperative strategies, machine learning integration, wideband sensing, and security issues, there remains a lack of a unified, comprehensive overview that captures the full operational context of DSS across domains and over time.

Previous works have made important contributions. Jaiswal et al. [1] and Garhwal and Bhattacharya [2] laid foundational insights into classical sensing methods and dynamic spectrum access models. Sun et al. [3] advanced the conversation by exploring wideband and sub-Nyquist sensing. In parallel, Khamayseh and Halawani [4], and Zhang et al. [5], delved into cooperative sensing in complex environments. More recent surveys, such as those by Upadhye et al. [6] and Song et al. [7], examined the integration of machine learning and its promise for 6G networks. Others, including Arafat et al. [8] and Shrivastava et al. [9], addressed game-theoretic models and security vulnerabilities in collaborative scenarios.

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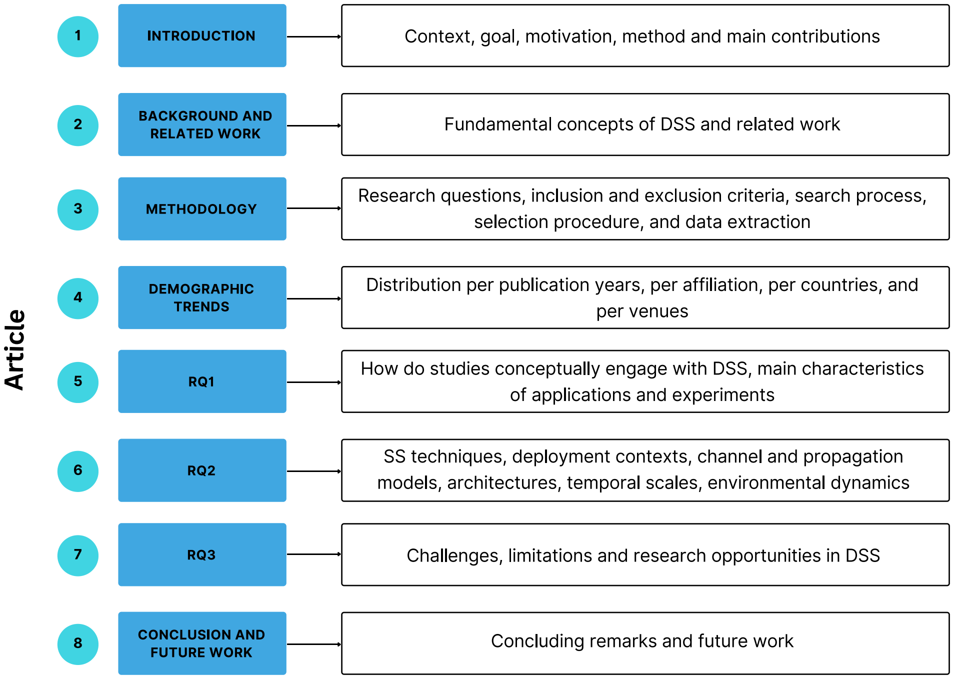

**Fig. 1.** Graphical outline of the article.

However, none of these works systematically dissect the holistic operation of DSS, especially when considering practical implementations, domain diversity, environmental challenges, and performance evaluation methods. To bridge these gaps, this survey presents a comprehensive review of DSS research spanning 2005 to 2024. To answer the research questions, we follow a rigorous methodology adapted from the PRISMA guidelines [10–12], including clearly defined inclusion and exclusion criteria, a reproducible search strategy, and structured data extraction. Our goal is not only to map the state of the art but also to identify trends among the main applications of DSS, the handling of environmental dynamics, and challenges and future research opportunities. The main contributions of this survey are as follows:

- A comprehensive analysis of DSS literature from 2005 to 2024, based on conceptual engagement, application domains, types of contributions, technologies, and sensing strategies
- A structured categorization of DSS contributions by domain, sensing strategy, technology, and evaluation methods.
- A mapping of experimental setups and implementation characteristics, covering sensing technologies, network types, architectural models, and temporal dynamics.
- An analysis of how DSS systems address environmental variability, such as time-varying channels, mobility, and real-time adaptation requirements.
- An identification of underexplored areas and future directions for research in DSS, relevant to both academic and industrial communities.

The remainder of this article is organized as follows: Section 2 provides background information on DSS and reviews related work. Section 3 outlines the methodology employed for the literature review, including the search strategy, research questions, selection criteria, and data extraction procedures. Section 4 presents a bibliometric analysis of the selected studies, highlighting trends related to publication years, leading countries, institutional affiliations, and types of publication venues. Sections 5, 6, and 7 present and discuss the findings for each research question. Finally, Section 8 concludes the paper by summarizing key insights and outlining future challenges and opportunities in DSS research. As a closing point, Fig. 1 provides the outline of the entire article as a way to summarize the structure and organization.

## 2. Background and related work

The proliferation of wireless communication technologies has dramatically increased the demand for radio spectrum, a finite and valuable resource. Traditional spectrum allocation policies, which rely on fixed and static assignment of frequency bands, have led to significant under-utilization of licensed spectrum resources [13–15]. Measurements conducted by the Federal Communications Commission (FCC) [16] and other regulatory entities have revealed that many allocated frequency bands remain idle for substantial periods and across geographical regions [15,17]. This inefficiency has motivated the development of Dynamic Spectrum Access (DSA) and Cognitive Radio (CR) technologies, which aim to improve spectrum utilization by enabling Secondary Users (SUs) to opportunistically access unused portions of the spectrum without causing harmful interference to Primary Users (PUs) [18].

A key part of cognitive radio operation is spectrum sensing, the process by which SUs detect the presence or absence of PUs in a given frequency band; and it is essential to identify available spectrum holes and to make informed decisions regarding spectrum access [19]. Various techniques have been developed to perform this task, including energy detection, matched filtering, cyclostationary feature detection, and eigenvalue-based methods [20–22]. As wireless environments become increasingly dynamic due to user mobility, time-varying channel conditions, and variable traffic loads, the need for DSS has emerged [23]. Unlike traditional sensing strategies that rely on periodic or static decision-making, DSS refers to adaptive and continuous sensing techniques that respond to the temporal and spatial fluctuations in spectrum availability. It incorporates real-time feedback, environmental awareness, and often machine learning or prediction mechanisms to optimize sensing performance and system throughput [24].

A key advancement in DSS is the adoption of Cooperative Spectrum Sensing (CSS), which has gained prominence for its ability to overcome limitations such as multipath fading, shadowing, and the hidden node problem [20]. CSS enables multiple cognitive radios to collaborate by sharing local sensing results, thereby improving detection reliability and reducing false alarms [25,26]. Depending on the fusion strategy, CSS can be implemented in centralized, distributed, or hybrid architectures, each with trade-offs in terms of latency, robustness, and communication overhead [20,27,28].

### 2.1. Related work

DSS is a key area of CRNs, enabling efficient utilization of the radio spectrum by detecting unused frequency bands. Over the years, numerous surveys have explored various facets of DSS, including cooperative strategies, machine learning applications, and wideband sensing techniques. Several surveys have defined the basis for understanding spectrum sensing in CRNs. Jaiswal et al. [1] presented an early comprehensive overview of spectrum sensing techniques, discussing methods such as energy detection, matched filtering, and cyclostationary feature detection. Their work highlighted the challenges associated with each technique, including noise uncertainty and computational complexity. Also, Garhwal and Bhattacharya [2] focused on DSA models, detailing various methods like command and control, exclusive-use, and shared-use models. Their survey emphasized the importance of spectrum sensing in enabling DSA and discussed game-theoretic approaches for spectrum allocation. Later on, Sun et al. [3] provided an in-depth analysis of wideband spectrum sensing, a critical aspect of DSS. They examined sub-Nyquist sampling techniques, including compressive sensing and multi-channel sub-Nyquist sampling, addressing challenges like hardware limitations and high sampling rates.

CSS has emerged as a vital strategy to enhance detection accuracy in CRNs. Khamayseh and Halawani [4] surveyed ML-based methods for CSS, categorizing approaches into supervised, unsupervised, and reinforcement learning. They discussed the advantages of ML in handling complex environments and improving sensing performance. Zhang et al. [5] explored CSS in cognitive wireless sensor networks, analyzing various spectrum sensing methods suitable for such networks. Their survey highlighted the benefits of CSS in mitigating issues like multipath fading and shadowing, which are prevalent in wireless sensor environments. Kaur and Aulakh [29] provided a detailed examination of CSS techniques, discussing system requirements, advantages, disadvantages, and key elements. Their work emphasized the significance of CSS in preventing interference with primary users and enhancing spectrum utilization.

The integration of ML into spectrum sensing has gained considerable attention. Upadhye et al. [6] surveyed ML algorithms applicable to CRNs, focusing on spectrum sensing and dynamic spectrum access. They discussed the potential of ML in addressing challenges like non-stationary environments and the need for real-time decision-making. Song et al. [7] examined spectrum sensing and learning technologies for 6G networks, emphasizing the role of ML in enabling dynamic spectrum sharing. Their survey covered classic narrowband and wideband sensing algorithms, as well as sub-sampling frameworks based on compressed sensing theory.

Game theory has been useful in modeling interactions among users in CRNs. Saad et al. [30] proposed coalitional games for distributed collaborative spectrum sensing, presenting a distributed algorithm for coalition formation. Their work demonstrated how secondary users could autonomously collaborate to enhance detection probability while considering cooperation costs. Arafat et al. [8] surveyed DSA techniques for LTE-Advanced networks, discussing the application of game-theoretic models in spectrum sharing scenarios. Their survey highlighted the importance of strategic interactions among users to optimize spectrum utilization.

Security is a critical concern in spectrum sensing, particularly in cooperative scenarios. Shrivastava et al. [9] surveyed security issues in cognitive radio-based cooperative sensing, identifying threats like spectrum sensing data falsification and primary user emulation attacks. They discussed various countermeasures, including reputation-based systems and trust management frameworks. With the advent of 5G and the anticipation of 6G networks, spectrum sensing techniques must evolve to meet new demands. Ramakrishnan et al. [31] conducted a comprehensive survey on effective spectrum sensing in 5G wireless networks, focusing on wideband sensing challenges and the need for advanced signal processing techniques.

While these works provide valuable insights into specific aspects of spectrum sensing, none offer a unified and detailed view of DSS in terms of its holistic operational context. In contrast, this survey provides a comprehensive and structured overview of DSS that goes beyond traditional taxonomies. Specifically, it identifies and analyzes the main application domains of DSS across diverse network types and deployment scenarios, and it investigates how DSS is practically implemented and addressed. Also, presents a thorough synthesis of channel and propagation models, including how fading, mobility, and noise conditions are treated in simulations and experimental studies. Explores how DSS approaches handle environmental dynamics, such as time-varying channels, traffic variability, and adaptive sensing strategies, an aspect often overlooked in prior surveys; and integrates and classifies performance metrics and evaluation methods, offering a comparative lens on how effectiveness is measured and benchmarked. In doing so, this survey fills a gap in the existing literature by not only capturing the technical view of DSS but also by providing an integrated perspective on when, where, how, and why dynamic sensing strategies are adopted. This work thus serves both as a technical reference and a roadmap for future DSS research and application.

## 3. Methodology

To identify relevant papers, we employed an adaptation of the PRISMA guidelines [10–12]. In the following subsections, we define the set of research questions (Section 3.1), the inclusion and exclusion criteria (Section 3.2), the search process (Section 3.3), and data extraction (Section 3.4).

### 3.1. Research questions

This survey aims to explore the state of the art in DSS, guided by the following Research Questions (RQs).

- **RQ1**: *What are the main applications of Dynamic Spectrum Sensing (DSS)?*
  - **RQ1.1**: How do studies conceptually engage with DSS?
  - **RQ1.2**: What are the main characteristics of the applications in DSS?
  - **RQ1.3**: What experimental approaches, performance metrics and software/hardware tools are used in DSS?
- **RQ2**: *How is Dynamic Spectrum Sensing addressed in the literature?*
  - **RQ2.1**: What are the dominant spectrum sensing techniques, network environments, architectures and temporal scales used for DSS?
  - **RQ2.2**: How do DSS approaches handle environmental dynamics, temporal variability, and real-time decision-making?
- **RQ3**: *What are the current challenges, limitations, and research opportunities in Dynamic Spectrum Sensing?*

**RQ1** focuses on mapping the broader research landscape by examining the applications, purposes, contributions, and key technologies associated with DSS. This includes identifying whether articles engage with DSS explicitly or implicitly (RQ1.1), characterizing the nature of the contributions and the recurring themes or problems addressed (RQ1.2), and summarizing how DSS has been operationalized through experiments or simulations, including the strategies, metrics, and tools used (RQ1.3). **RQ2** dives deeper into the technical aspects of DSS by examining how sensing is implemented across different contexts. This includes analyzing the technologies, architectures, network environments, and temporal dimensions that shape how DSS is designed and applied

(RQ2.1). RQ2.2 dives into how dynamics are actually handled, in terms of time-variability, decision-making under change, environment adaptation, and sensing-driven actuation. **RQ3** seeks to uncover the current limitations, unresolved challenges, and emerging research opportunities in DSS. It aims to consolidate open issues that hinder practical deployment and highlight directions for future exploration and innovation. Together, these research questions provide a comprehensive framework for understanding the state of the art and evolution of DSS across both theoretical and applied dimensions.

### 3.2. Inclusion and exclusion criteria

In order to evaluate the relevance of the studies, we excluded all publications that met any of the following criteria: (E1) studies unrelated to DSS, (E2) non-English publications, and (E3) publications such as non-primary studies, editorials, opinion pieces, doctoral papers, theses, course materials, magazines, or extended abstracts. We incorporated publications that satisfied at least one of the following criteria: (I1) studies with an explicit focus on DSS, (I2) studies with an implicit focus on DSS via supporting technologies or frameworks, (I3) research studies that underwent a peer-review process, and (I4) pertinent gray literature sources that met the previous criteria.

### 3.3. Search process

The database search was initially conducted on Google Scholar, and after that, we reviewed known repositories (IEEE Xplore, ACM Digital Library, SpringerLink, and Elsevier) to ensure comprehensive coverage. The searches were carried out during April 2025, using combinations of the search strings, as shown in Table 1. We did not set a predefined time frame, as our goal was to capture the full scope of relevant publications available at the time of the search. As a first approach, we evaluated the study analyzing the titles, abstracts and keywords. If we weren't able to make a decision, then the entire article was reviewed including introduction, methodology, results and conclusions. Initial screening was conducted by the first and second authors, with any discrepancies resolved through discussion among all authors to reach a consensus. To identify pertinent studies, we initially analyzed document titles and metadata. Following the database search, duplicate entries were eliminated.

In total, 6972 records were identified across all sources. After removing 472 duplicates, 187 in non-English language, 196 not available, 5691 not strictly related to DSS, 426 unique records proceeded to the screening phase. Next, during the screening phase, inclusion and exclusion criteria were applied. During title–abstract screening, 106 records were excluded for lacking methodological relevance or application description, leaving 320 studies for full-text assessment.

To strengthen transparency, we explicitly applied the PRISMA selection criteria at each stage of the process. During title–abstract screening, studies were retained only if they met the inclusion criteria (addressing DSS, presenting methodological or algorithmic contributions, and providing sufficient technical detail for extraction) and were excluded if any exclusion criteria applied (for example, focusing solely on static sensing, lacking methodological relevance, or not providing analyzable content). For studies in which relevance could not be determined from metadata, full-text eligibility assessment was performed on the 320 publications, after which 258 studies were excluded for reasons such as addressing only static sensing, lacking technical depth, or not targeting dynamic or adaptive mechanisms. This process ultimately left 62 publications included.

Although the research space around spectrum sensing is large, the final sample size reflects our strict inclusion criteria focused specifically on DSS. Many studies referencing spectrum sensing do not address dynamic behavior, adaptive mechanisms, or time-varying environments and were therefore excluded. The resulting 62 articles represent the most methodologically aligned and relevant works for answering our research questions.

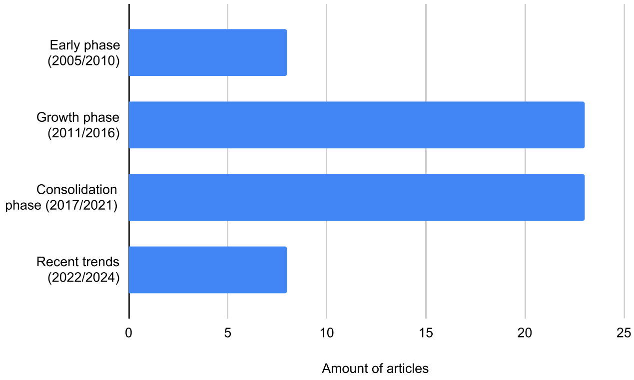

**Fig. 2.** Distribution of DSS studies across publication years.

### 3.4. Data extraction

The data items that were collected from each publication are title, publication year, affiliation, type of affiliation (academy, industry, shared affiliation), country, type of venue (conference, forum, journal, symposium, workshop), name of venue, and publisher, which provided contextual information. For RQ1, we extracted the engagement (explicit, implicit), primary objectives or purposes, types of contributions such as algorithms and frameworks, application domains, enabling technologies, types of experiments, performance evaluation metrics, and software tools or platforms employed. Later, for RQ2, we have identified spectrum sensing strategies and techniques, deployment contexts, channel and propagation models; architectural models, the temporal granularity of sensing, types of adaptation or reactivity, real-time or online capabilities, environmental awareness, and mechanisms for dynamic handling. Finally, for RQ3, we identified the challenges, limitations and research gaps.

## 4. Demographic trends

Following the eligibility assessment, we identified a final set of 62 publications from which relevant data were extracted to address the research questions. These studies are labeled P01 through P62. In particular, this section will focus on describing the demographic trends. Table 2 summarizes key demographic trends, including the temporal distribution (Section 4.1), types of affiliations (Section 4.2), primary contributing countries (Section 4.3), and publication venues (Section 4.4) of the analyzed publications.

### 4.1. Distribution across publication years

The publications range from 2005 to 2024, offering an almost two-decade perspective on DSS research trends. Fig. 2 contains the visual summary of the temporal distribution of the articles.

- *2005–2010* (*Early Phase*): These years mark the formative phase of DSS research. Only a handful of influential works emerged during this period, for example, P03 [23] in 2005, P27 [32] in 2009, often laying foundational theories or frameworks. This phase saw relatively low publication volume.
- *2011–2016* (*Growth Phase*): This period witnessed a noticeable increase in publication activity, reflecting growing academic interest and early technological adoption. Contributions became more diversified, with studies from the USA, China, and Canada dominating the landscape.
- *2017–2021* (*Consolidation Phase*): This period experienced steady output and the formation of regional clusters, especially from China, India, and the USA. *IEEE Access*, *IEEE IoT Journal*, and other high-impact journals became common publication venues. Multiple works

**Table 1**
Query and search strings used.

| Query | Search Query |
|---|---|
| 1 | *“Dynamic Spectrum Sensing” **OR** “dynamic spectrum access” **OR** “spectrum sensing” **OR** “spectrum awareness”* **AND** *“cognitive radio” **OR** “spectrum management” **OR** “spectrum sharing” **OR** “radio environment” **OR** “opportunistic spectrum” **OR** “CRN” **OR** “CR”* **AND** *“technique” **OR** “method” **OR** “architecture” **OR** “framework” **OR** “strategy” **OR** “algorithm” **OR** “model”* |
| 2 | *“Dynamic Spectrum Sensing” **OR** “spectrum sensing”* **AND** *“machine learning” **OR** “deep learning” **OR** “artificial intelligence” **OR** “reinforcement learning” **OR** “neural network”* **AND** *“cognitive radio” **OR** “CRN” **OR** “opportunistic spectrum”* |
| 3 | *“Dynamic Spectrum Sensing” **OR** “spectrum sensing”* **AND** *“wideband” **OR** “ultra-wideband” **OR** “multiband” **OR** “broadband”* **AND** *“cognitive radio” **OR** “spectrum management”* |
| 4 | *“Dynamic Spectrum Sensing” **OR** “spectrum sensing”* **AND** *“testbed” **OR** “real-world” **OR** “deployment” **OR** “prototype” **OR** “experimental”* **AND** *“cognitive radio” **OR** “wireless network”* |

**Table 2**
Summary of main demographic trends.

| Category | Top Entries |
|---|---|
| Affiliation Type | Academy (57), Industry (1), Shared (4) |
| Venue type | Conference (34), Journal (23), Symposium (5) |
| Top countries | China (21), USA (16), India (11), Canada (6), UK (4), Pakistan (3), South Korea (3), Japan (3) |
| Publication year | 2005 (1), 2009 (3), 2010 (4), 2011 (4), 2012 (4), 2013 (3), 2014 (2), 2015 (5), 2016 (5), 2017 (3), 2018 (6), 2019 (6), 2020 (6), 2021 (2), 2022 (3), 2023 (2), 2024 (3) |

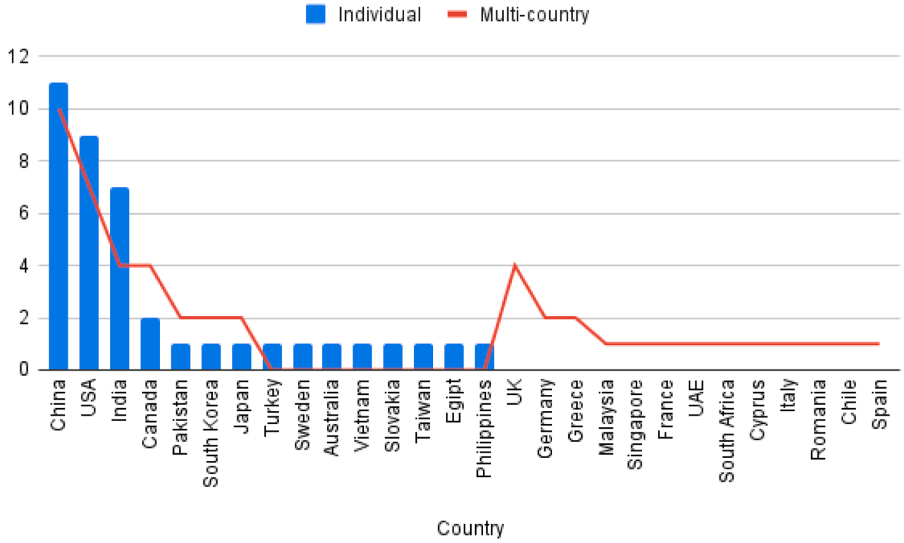

**Fig. 3.** Distribution of Countries: Individual and multi-country affiliation values.

during this phase featured cross-border collaboration and improved modeling techniques, including AI-based approaches.

- *2022–2024* (*Recent Trends*): The most recent years indicate a resurgence of interest, particularly in India and China. There is a notable trend toward real-world applicability and energy-aware or cooperative sensing techniques. These papers suggest that DSS research is evolving in response to 5G and Beyond-5G (B5G) developments.

### 4.2. Distribution of affiliation

Across the 62 analyzed articles, academic institutions overwhelmingly dominate the research on DSS. Over 90% of the studies are affiliated with academic institutions, either individually or in collaboration with others. A small number of papers reflect shared affiliation, typically involving academia–industry or academia–government collaborations, such as the *Air Force Research Laboratory*, and *Cisco Systems*.

Only one study explicitly originated solely from an industrial entity: *Nokia Research Center* (P03 [23]). This suggests that while industry has an interest in DSS research, the intellectual and experimental contributions are largely being developed in academic environments. Collaborations across multiple universities and international borders are also common, indicating a healthy degree of cross-institutional and interdisciplinary cooperation in this domain.

### 4.3. Distribution of countries

The distribution of countries contributing to DSS research reveals a globally engaged and collaborative research community. A few countries stand out as major contributors, most notably China, India, the USA, and Canada, indicating regional leadership in the field. Fig. 3 illustrates the number of publications associated with each country, distinguishing between articles with single-country affiliations (represented by bars) and those involving multi-country collaborations (represented by the line trend). China appears in both individual and multi-country affiliations. This leadership reflects not only a national interest in cognitive radio and 5G/6G development but also a strong academic presence from institutions such as *Tsinghua University*, *Southeast University*, and *Sun Yat-Sen University*. China’s contributions span foundational algorithmic research and system-level implementations.

India follows as a key player, particularly visible in recent years. Indian researchers are frequently represented in conference publications and focus on applied engineering solutions. The growth of India’s presence signals an expanding interest in spectrum innovation within its

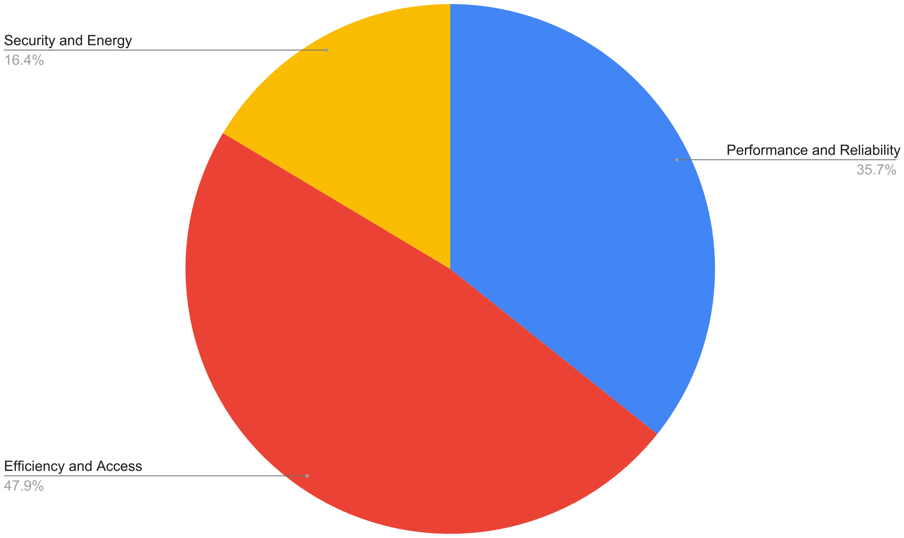

**Fig. 4.** Performance-oriented, access-oriented and security/energy-oriented purposes in DSS.

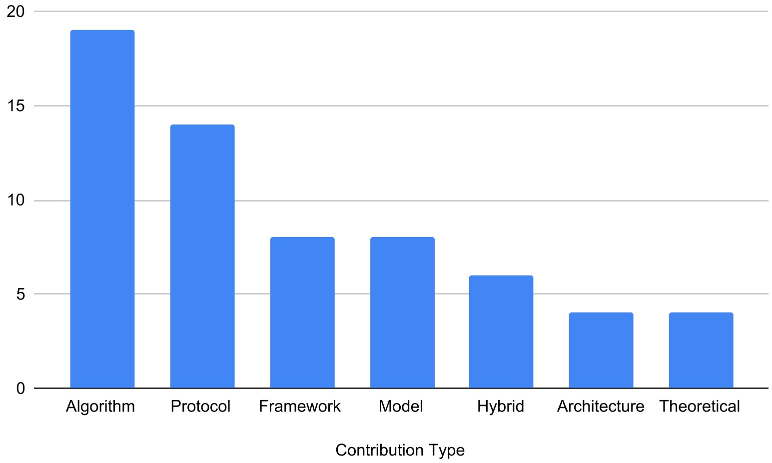

**Fig. 5.** Trends among contribution types in DSS.

academic and technological ecosystem. The USA has maintained consistent engagement across the timeline, contributing to both theoretical and experimental aspects of DSS. Renowned institutions such as the *University of Michigan*, *Rice University*, and *University of Southern California* are frequently cited. Canada also makes a notable impact, contributing independently and through frequent collaborations with the USA and China. Canadian work often emphasizes modeling, theoretical exploration, and architecture-level considerations, with institutions such as the University of Waterloo and Carleton University playing prominent roles.

The overall pattern underscores a strong culture of international collaboration. More than one-third of all contributions involve authors from multiple countries. China leads in both individual (11) and collaborative (10) works. Similarly, the USA and India exhibit a balanced profile of solo and partnered research, reflecting their research infrastructure and openness to global partnerships. The UK is notable for contributing exclusively through collaborations, reinforcing its role as a partner in joint initiatives.

The dominance of China, India, and the USA reflects regions with strong governmental and academic investment in spectrum innovation, but the limited industrial participation suggests that DSS is still transitioning from research to deployment. The concentration of outputs in academia indicates that technology transfer remains gradual, with industry adoption lagging behind due to integration complexity, regulatory uncertainty, and the need for real-world testbeds. These trends highlight that DSS, while conceptually mature, is still in an early commercialization stage.

### 4.4. Distribution of venues

The articles are spread across a mix of conferences (54%), journals (37%), and symposia (8%). The articles were mostly published in IEEE conferences, such as *IEEE Global Telecommunications Conference (GLOBECOM)*, *IEEE International Conference on Communications (ICC)*, *IEEE Vehicular Technology Conference (VTC)*, and *IEEE Military Communications Conference (MILCOM)*. These platforms are preferred for early dissemination of novel ideas, especially among North American and Asian researchers. Later on, journals like *IEEE Access*, *IEEE Transactions on Cognitive Communications and Networking*, *IEEE Internet of Things Journal*, and *IEEE Systems Journal* are frequent choices. These journals offer a platform for in-depth theoretical, experimental, and simulation-based work. The prominence of journals in recent years indicates a maturing field with robust peer review.

Venues like *IEEE International Symposium on Dynamic Spectrum Access Networks (DySPAN)* and *IEEE International Conference on Sensing, Communication, and Networking (SECON)* provide a focused audience for spectrum management topics. Though smaller in volume, they carry high relevance to DSS researchers. The balance between the venues sug-

**Table 3**
Categorization of articles related to Dynamic Spectrum Sensing (DSS).

| Category | Art. | Key Traits | Article IDs |
|---|---|---|---|
| Explicit | 33 | "Dynamic Spectrum Sensing" in title; core contribution in sensing adaptation | P01 [33], P02 [34], P03 [23], P04 [35], P05 [36], P06 [37], P07 [38], P08 [39], P09 [40], P10 [41], P11 [42], P16 [43], P18 [44], P19 [45], P21 [46], P22 [47], P32 [48], P33 [49], P34 [50], P35 [51], P36 [52], P37 [53], P38 [54], P39 [55], P40 [56], P41 [57], P42 [58], P43 [59], P44 [60], P49 [61], P53 [62], P60 [63], P62 [64] |
| Indirect | 29 | Enable or enhance DSS via thresholds, reinforcement learning, sensing architecture, others | P12 [65], P13 [66], P14 [67], P15 [68], P17 [69], P20 [70], P23 [71], P24 [72], P25 [73], P26 [74], P27 [32], P28 [75], P29 [76], P30 [77], P31 [78], P45 [79], P46 [80], P47 [81], P48 [82], P50 [83], P51 [84], P52 [85], P54 [86], P55 [87], P56 [88], P57 [89], P58 [90], P59 [91], P61 [92] |

gests a dual strategy: initial dissemination at conferences followed by more rigorous elaboration in journals. The articles illustrate a globally collaborative, academically driven, and increasingly maturing field of DSS research. China, India, and the USA are the most prominent contributors, with growing participation from Europe and Asia-Pacific regions. The timeline of publications reveals an upward trend in interest and sophistication, with a shift from theoretical foundations toward practical implementations aligned with next-generation wireless technologies. The diversity of publication venues further reflects the richness and inter-disciplinarity of the field.

Taken together, these demographic trends suggest that DSS research has matured through cycles of foundational exploration, methodological diversification, and recent application-driven interest. The steady rise of contributions from Asia and North America mirrors the global push toward spectrum-intensive technologies such as 5G, IoT, and tactical communications. The dominance of academic authorship indicates that DSS remains primarily an innovation-driven research topic rather than a fully industrialized technology, while the prevalence of conference publications shows that the field values rapid dissemination of emerging ideas.

## 5. RQ1: What are the main applications of Dynamic Spectrum Sensing?

To comprehensively understand the role of DSS in the context of spectrum management and wireless communication, this research question explores its principal applications and scholarly contributions. The aim is to map how DSS has been conceptualized (Section 5.1), implemented (Section 5.2), and evaluated (Section 5.3) in the literature, shedding light on both the theoretical and practical aspects that define the field.

### *5.1. RQ1.1: How do studies conceptually engage with DSS?*

This subsection examines the extent to which DSS is conceptually centered in the reviewed studies. Specifically, it investigates whether DSS is the primary focus of research (explicit engagement) or whether it is addressed as part of a broader system or methodology (implicit engagement). Understanding the level of conceptual emphasis helps clarify the positioning of DSS within the research landscape and distinguishes between studies driven by theoretical interest in DSS versus those applying it to support other innovations.

To analyze how the research community conceptually engages with DSS, we introduce a classification that highlights groups of contributions based on how DSS is framed (see Table 3). From this, we were able to distinguish two main categories based on the nature and centrality of their contributions: (1) *Explicit Dynamic Spectrum Sensing Contributions*, and (2) *Indirect or Enabling Contributions to DSS*.

The first category includes studies in which DSS is the primary focus and objective. These articles typically introduce novel sensing algorithms, optimization techniques, system architectures, or adaptive mechanisms specifically designed to improve the effectiveness and efficiency of spectrum sensing under dynamic conditions. In this category, articles are being included when: a) the presence of terms like *"Dynamic Spectrum Sensing"* in the title; b) a primary contribution centered on the design, enhancement, or evaluation of DSS techniques, that could include diverse technologies; and c) focus on adaptation mechanisms for sensing in mobile, time-varying, or multi-user environments. In total, 33 articles fall into this category, with their primary aim being the advancement of sensing strategies that can robustly operate under dynamic spectral environments.

The second category *Indirect or Enabling Contributions to DSS* comprises studies that, while not directly proposing new DSS techniques, contribute to the broader ecosystem that enables or improves DSS. These contributions may involve: a) the development of supporting technologies such as reinforcement learning frameworks, blockchain-enabled trust mechanisms, or spectrum access models; b) improvements in spectrum sensing architectures, threshold optimization, or sensing scheduling; and c) the use of DSS as a component within larger systems like Dynamic Spectrum Access (DSA), cognitive IoT, and UAV communications, where sensing is treated as an enabler rather than the primary research focus. For instance, P12 [65] focuses on access strategies, but inherently relies on accurate DSS. P27 [32] presents an adaptive sensing architecture, and P50 [83] proposes a dynamic threshold strategy for mitigating Spectrum Sensing Data Falsification (SSDF) attacks, indirectly enhancing the reliability of DSS. These contributions are essential to operationalizing DSS, making them integral to the broader research agenda. A total of 29 articles are categorized as Indirect, reflecting the supporting roles these works play in strengthening or contextualizing DSS.

The distinction between explicit and indirect DSS contributions is important for two main reasons. The first one is that not all valuable contributions to DSS use the term explicitly. Recognizing indirect contributions avoids overlooking relevant innovations. The second one is that this categorization provides a structured view of how DSS is studied, from core algorithmic developments to broader architectural or application-level enhancements. By recognizing both categories, we capture a more holistic view of the DSS landscape and reveal how foundational sensing capabilities are deeply interconnected with broader network intelligence, security, and efficiency goals.

### *5.2. RQ1.2: What are the main characteristics of the applications in DSS?*

In this section, we focus into the diverse landscape of DSS contributions by categorizing the research in terms of its primary objectives or purposes (Section 5.2.1), types of contributions such as algorithms (Section 5.2.2), application domains (Section 5.2.3), and enabling technologies (Section 5.2.4). This analysis provides a thematic overview of the motivations behind DSS research and helps highlight the areas where innovation and impact are most concentrated.

#### *5.2.1. Applications of DSS: Purposes*

A broad array of research purposes emerged, with many studies addressing multiple objectives simultaneously. This overlap is evident in Table 4, where the sum of values exceeds the total number of articles. These purposes reflect the multifaceted challenges and ambitions in developing DSS techniques that are not only efficient but also adaptive, secure, and tailored to diverse real-world scenarios.

**Table 4**
Main purposes of Dynamic Spectrum Sensing (DSS).

| Main Purpose | Description | Articles IDs |
|---|---|---|
| **Improve spectrum efficiency** | Enabling better spectrum utilization by detecting and exploiting spectrum holes or dynamically allocating channels | P02 [34], P04 [35], P05 [36], P06 [37], P07 [38], P08 [39], P09 [40], P10 [41], P11 [42], P12 [65], P13 [66], P14 [67], P15 [68], P17 [69], P18 [44], P20 [70], P21 [46], P23-P34 , P36 [52], P38 [54], P39 [55], P40 [56], P41 [57], P44-P49, P51 [84], P52 [85], P54 [86], P55 [87], P57 [89], P58 [90], P59 [91] |
| **Improve spectrum sensing accuracy, reliability** | Enhancing detection performance, accuracy, and robustness of DSS methods under dynamic, noisy, or adversarial conditions | P01 [33], P03 [23], P07 [38], P11 [42], P16 [43], P19 [45], P31 [78], P33 [49], P34 [50], P35 [51], P37 [53], P39 [55], P42 [58], P53 [62], P55 [87], P56 [88], P60 [63], P61 [92], P62 [64] |
| **Enhance security or protect against attacks** | Protecting DSS from malicious behaviors like SSDF, improving secure sensing and robustness | P01 [33], P15 [68], P29 [76], P33 [49], P50 [83], P62 [64] |
| **Reduce energy consumption, improve energy efficiency** | Minimizing power usage in sensing tasks, essential for battery-constrained or mobile devices | P01 [33], P04 [35], P13 [66], P30 [77], P38 [54], P43 [59], P57 [89] |
| **Protect PUs from interference** | Ensuring PU protection while allowing SUs to access spectrum without causing harmful interference | P03 [23], P05 [36], P07 [38], P23 [71], P25 [73], P36 [52], P41 [57], P45 [79], P54 [86], P57 [89] |
| **Improve network throughput, transmission quality** | Maximizing data rates and reliable communication through improved sensing and spectrum access | P04 [35], P13 [66], P14 [67], P20 [70], P24 [72], P30 [77], P44 [60], P46 [80], P48 [82], P51 [84], P52 [85] |
| **Enable cooperative, distributed, collaborative sensing** | Implementing distributed, multi-user sensing to enhance accuracy, coverage, and scalability | P01 [33], P08 [39], P09 [40], P15 [68], P27 [32], P29 [76], P48 [82] |
| **Adapt to dynamic or mobile environments** | Responding to channel variation, user movement, and dynamic PU activity during spectrum sensing | P10 [41], P13 [66], P19 [45], P31 [78], P34 [50], P36 [52], P53 [62] |
| **Enable intelligent, adaptive sensing or access** | Using ML, adaptive thresholds, or learning to make sensing more efficient and context-aware | P06 [37], P22 [47], P28 [75], P30 [77], P33 [49], P42 [58], P53 [62], P60 [63] |
| **Support fair access, sharing, scheduling** | Enabling fair, efficient, and incentive-based spectrum access and scheduling among multiple SUs | P25 [73], P28 [75], P29 [76], P47 [81], P48 [82] |
| **Improve QoS, meet application requirements** | Ensuring Quality of Service (QoS) in terms of latency, reliability, or bandwidth for specific applications | P14 [67], P23 [71], P30 [77], P40 [56] |
| **Reduce false alarms, missed detections** | Decreasing incorrect sensing decisions to increase reliability and reduce interference or inefficiencies | P07 [38], P11 [42], P33 [49], P39 [55], P49 [61], P53 [62], P56 [88], P60 [63] |
| **Improve detection in low-SNR, adverse conditions** | Ensuring accurate sensing when signal quality is degraded | P13 [66], P16 [43], P19 [45], P34 [50], P37 [53], P39 [55], P55 [87], P56 [88] |

The most dominant objective, appearing in over 85% of the reviewed studies, was to *improve spectrum efficiency*. This aligns with the foundational goal of DSS: dynamically identifying and utilizing underused frequency bands to maximize spectral utilization in increasingly congested and heterogeneous environments. This objective is particularly critical for emerging wireless systems facing growing spectrum scarcity. To achieve this, researchers have explored a diverse range of strategies. For example, P02 [34] proposed enabling asynchronous and cooperative access to spectrum holes, allowing secondary users to opportunistically exploit underutilized bands even when primary user protocols are unknown. In IoT-focused contexts, P04 [35] tackled the challenge of dynamic access to licensed channels, facilitating spectrum sharing among low-power and data-constrained devices.

Meanwhile, P05 [36] introduced interference-aware transmission optimization, where secondary users adjust their transmission parameters to avoid disrupting primary users. To reduce sensing overhead, P08 [39] employed collaborative compressive sensing to detect shifts in channel occupancy more efficiently. Decentralized scenarios were addressed in P09 [40], which supported distributed and cooperative sensing without relying on centralized infrastructure. Mobility-aware sensing was demonstrated in P10 [41], where collaborative compressive sensing was used to track and localize mobile primary users, enabling adaptive spectrum reuse in cognitive radio networks. To handle wideband environments, P11 [42] focused on fast, accurate, and low-complexity sensing techniques essential for real-time responsiveness across multiple channels. Expanding on this, P12 [65] enabled dynamic spectrum access in IoT deployments by supporting spatial spectrum reuse, while P13 [66] advanced energy-aware and low-SNR-tolerant approaches for ultradense IoT and machine-to-machine (M2M) communications. Collectively, these efforts underscore the centrality of spectrum efficiency as a unifying goal, addressed through a spectrum of customized technical innovations.

A significant number of contributions also aimed to *enhance the accuracy and reliability of spectrum sensing*, especially under challenging or uncertain conditions such as low Signal-to-Noise Ratio (SNR), fading channels, user mobility, or adversarial interference. For instance, P03 [23] developed interference-avoidance strategies for narrowband signals in Ultra-Wideband (UWB) environments, P07 introduced wavelet-based denoising to reduce false alarms in energy detection, P19 [45] focused on mitigating detection degradation due to fluctuating primary user activity, P31 [78] used dynamic clustering to improve sensing under fading channel conditions, P33 [49] proposed mechanisms to defend against smart jamming while preserving SU performance, and P56 [88] tackled missed detection under adversarial interference.

*Security and trust* also emerged as a key concern, particularly in cooperative sensing environments vulnerable to SSDF, Insistent SSDF (ISSDF) and other malicious attacks that threaten cooperative sensing environments. For instance, P01 [33] addressed SSDF and ISSDF threats while improving energy efficiency and detection reliability, P15 [68] tackled malicious behavior in cooperative IoT-based DSS, while P29 [76] and P50 proposed secure and distributed sensing architectures to eliminate single points of failure and resist tampering.

*Energy consumption* was identified as another critical area, particularly for battery-limited CR and IoT devices, where energy efficiency directly affects device longevity and system viability. For example, P04 [35] optimized sensing and switching processes to lower energy use in

CR-IoT operations; P13 [66] reduced sampling rates and power needs for spectrum sensing in ultradense environments; P30 [77] proposed joint optimization of energy, latency, and throughput; and P43 [59] aimed to minimize energy costs in CSS among mobile CR nodes.

Many studies also emphasized the importance of *protecting PUs* from harmful interference, highlighting the regulatory and ethical imperative of ensuring that secondary spectrum access does not disrupt licensed communications. As examples, P05 [36] improves sensing/aggregation via DRL to increase SU success while reducing interference to PUs, P23 [71] balanced link maintenance with PU protection in dynamic access scenarios, and P45 [79] focused on minimizing SUs-PUs collisions through opportunistic access strategies.

Improving *network throughput and transmission quality* was another key objective, where for example, P07 [38] enabled more efficient transmissions by exploiting spectrum holes, P36 [52] used real-time traffic awareness to improve DSS scheduling, and P41 [57] facilitated accurate sensing of radar waveforms despite noise, enhancing throughput potential. In pursuit of *greater scalability and robustness*, several studies explored cooperative, distributed, or intelligent sensing mechanisms: P13 [66] employed clustering and learning for distributed sensing in dense IoT setups, P14 [67] introduced ML-based adaptive sensing to meet QoS demands; while P44 [60] and P48 [82] proposed hybrid cooperative sensing with adaptive spectrum allocation to boost system reliability.

Other emerging themes included: *adapting to mobile and dynamic environments*, such as tracking mobile PUs (P10 [41]) and supporting dynamic allocation under fading conditions (P34 [50]); and *fair access and intelligent sharing*, like in P36 [52], which ensures balanced SU access under dynamic load. *Quality of Service (QoS)* guarantees, such as ensuring SU QoS while protecting PUs (P23 [71]) and enabling seamless operation in high-traffic scenarios (P40 [56]). Reducing *false alarms and missed detections* was also a focus: P11 [42] improved wideband detection with low complexity and high accuracy, P33 [49] balanced performance under jamming while reducing false alerts, and P49 [61] targeted spectrum hole detection while minimizing false alarms.

Lastly, a notable number of articles targeted *improving detection performance under adverse conditions*, including low-SNR and dynamic PU conditions (P13 [66], P19 [45]), fading and asynchronous channels (P34 [50]), and detection under noise and false alarm constraints (P39 [55]). These efforts are especially important in scenarios such as rural networks, vehicular systems, or disaster recovery, where clean signal conditions cannot be guaranteed. Collectively, these findings suggest that DSS research is evolving beyond basic detection tasks toward more application-aware, context-sensitive, and resilient spectrum sensing strategies.

Finally, Fig. 4 shows that efficiency- and access-driven goals dominate the field ( 48%), with most studies focusing on dynamic channel use, adaptive access, and cooperative sensing. This confirms that maximizing spectrum utilization remains the community's top priority. Performance and reliability objectives form the second major cluster ( 36%), emphasizing accuracy, robustness, lower false alarms, and resilience in low-SNR or rapidly changing conditions, issues that directly affect real-world deployments. Security and energy-focused work make up a smaller but meaningful share ( 16%), addressing emerging needs around adversarial resilience, PU protection, and energy-aware operation. Overall, the distribution shows a field progressing from traditional accuracy concerns toward more adaptive, secure, and resource-efficient DSS strategies. As summarized in Table 4, the literature increasingly emphasizes making DSS systems not only more efficient but also more intelligent, secure, and aligned with the diverse needs of next-generation wireless networks.

### 5.2.2. Applications of DSS: Type of contributions

A diverse range of contribution types were identified in the articles, each targeting different aspects of DSS and related domains such as CRNs, CR-IoT, and spectrum access frameworks. These types are: algorithms, frameworks, models, architectures, protocols, theoretical contributions, and hybrid contributions, as can be seen in Table 5 and Fig. 5.

*Algorithms* dominate as the most common form of contribution, offering innovative strategies for improving spectrum sensing accuracy, energy efficiency, or decision-making processes. For instance, P01 [33] presents a probabilistic decision fusion algorithm that enhances CSS through optimized weighting based on prior knowledge. Similarly, P05 [36] introduces a deep reinforcement learning algorithm for DSS and aggregation in multi-channel wireless networks, which optimizes performance by learning which channels to sense and use based on feedback. These contributions aim to refine the decision-making capabilities of spectrum sensors under diverse network conditions.

*Protocols* are crucial in defining communication procedures for spectrum negotiation and access. For example, P34 [50] describes a MAC protocol that incorporates lightweight DSS capabilities to optimize spectrum access delays in IoT scenarios. This type of contribution is essential for integrating DSS into broader network systems with strict timing and coordination constraints. As for *Policies*, for example, P05 [36] presents a sensing-selection policy in which the cognitive user adopts a learning-based strategy to estimate the most promising segment of channels based on prior ACK feedback, giving preference to segments with higher historical vacancy rates. This adaptive approach aims to maximize successful transmissions while minimizing interference with primary users.

*Frameworks* constitute another frequent category, often used to structure, test, or evaluate DSS methodologies. P20 [70], for example, proposes a modular simulation framework that enables benchmarking of various sensing algorithms under unified scenarios. P29 [76] introduces a cognitive engine framework that incorporates learning-based modules for dynamic environment adaptation. Frameworks such as these often integrate multiple functional components like sensing, learning, and access control to support cross-layer optimization and adaptability in CRNs.

*Models* are also a frequent contribution type, focusing on realistic abstraction and simulation of environments, channel conditions, or cognitive behaviors. For instance, P10 [41] develops a statistical propagation model tailored for rural TV White Space (TVWS) scenarios, which helps evaluate sensing performance under non-urban fading conditions. Meanwhile, P38 [54] introduces a model of PU behavior that facilitates prediction-enhanced sensing strategies. These models often serve as testbeds or theoretical foundations for further algorithmic or architectural developments.

*Hybrid contributions* are common, where an article may combine two or more types. For example, P19 [45] presents both a theoretical model for PU activity and a novel algorithm that leverages it for context-aware sensing, while P42 [58] integrates an architecture and algorithm to jointly optimize node selection and sensing schedules. P55 [87] introduces a dynamic-state framework and a flexible estimation algorithm.

*Architectures*, though less frequently seen, contribute by defining system-level blueprints that integrate sensing, communication, and decision-making layers. In P07 [38], a layered DSS architecture is presented for vehicular networks, enabling efficient spectrum reallocation in high-mobility scenarios. Another notable contribution is P37 [53], which proposes a distributed architecture for Cognitive Radio Sensor Networks (CRSNs) that allows for localized cooperative sensing and decentralized spectrum decision-making, reducing overhead and improving responsiveness.

*Theoretical contributions* often offer proofs, analyses, or complexity evaluations that inform the design and limitations of practical techniques. P28 [75], for instance, conducts an information-theoretic analysis of sensing thresholds and false alarm rates in multi-user environments, providing valuable benchmarks for system calibration. It is also important to mention that a subset of articles (P05 [36], P15 [68], P21 [46], P26 [74], P35 [51], P43 [59], P53 [62]) have proposed approaches to detect or mitigate SSDF, Byzantine attacks, trust frameworks for cooperative sensing, malicious user detection, or secure decision fusion. We have also identified AI-based approaches (P05 [36], P09 [40],

**Table 5**
Types of research contributions in Dynamic Spectrum Sensing (DSS).

| Contribution Type | Description | Count | Articles IDs |
|---|---|---|---|
| **Algorithm** | New or improved algorithms for sensing, thresholding, access control, cooperative sensing strategies, spectrum handoff, sensing time optimization, or energy-efficient decision-making. | 19 | P01 [33], P05 [36], P06 [37], P08 [39], P11 [42], P13 [66], P14 [67], P15 [68], P19 [45], P22 [47], P27 [32], P30 [77], P31 [78], P32 [48], P36 [52], P42 [58], P43 [59], P49 [61], P58 [90] |
| **Protocol / Policy** | Design Dynamic Spectrum Access (DSA) policies, cooperative spectrum etiquette, sensing scheduling, access control rules, and cognitive MAC protocols for fair and efficient use. | 14 | P03 [23], P07 [38], P08 [39], P10 [41], P14 [67], P18 [44], P20 [70], P25 [73], P27 [32], P30 [77], P32 [48], P38 [54], P46 [80], P59 [91] |
| **Framework** | Provides modular platforms or software systems to test or support DSS functions. | 8 | P20 [70], P23 [71], P26 [74], P35 [51], P39 [55], P44 [60], P50 [83], P59 [91] |
| **Model** | Introduces analytical or statistical models of spectrum, propagation, or behavior. | 8 | P10 [41], P17 [69], P21 [46], P28 [75], P33 [49], P38 [54], P40 [56], P60 [63] |
| **Architecture** | Proposes structural designs or techniques for DSS-enabled systems or networks. | 4 | P07 [38], P18 [44], P25 [73], P41 [57] |
| **Theoretical** | Offers complexity analysis, trade-off evaluations, or optimality conditions. | 4 | P16 [43], P28 [75], P46 [80], P47 [81] |
| **Hybrid** | Combines algorithm, architecture, model, or framework elements. | 6 | P19 [45], P24 [72], P29 [76], P37 [53], P42 [58], P55 [87] |

**Table 6**
Domain categories in Dynamic Spectrum Sensing (dss).

| Domain Category | Example Contexts | Count | Article IDs |
|---|---|---|---|
| **Cognitive Radio Networks (CRNs)** | General CRNs, multi-user CRNs, wideband CRNs, cooperative sensing, ad hoc CRNs | 28 | P01 [33], P05-P10, P19 [45], P21-P29, P31 [78], P33 [49], P34 [50], P35 [51], P36 [52], P37 [53], P39 [55], P40 [56], P44 [60], P47 [81], P53 [62] |
| **Dynamic Spectrum Access (DSA)** | DSA in CRNs, listen-before-talk policy, radar-dense or digital TV UHF environments | 13 | P02 [34], P23 [71], P24 [72], P27 [32], P28 [75], P34 [50], P36 [52], P41 [57], P45 [79], P54 [86], P55 [87], P57 [89], P58 [90] |
| **Cognitive Radio for IoT (CR-IoT)** | CR-IoT networks, CIoT, massive machine-type comms, industry 5.0, 5G/6G IoT | 6 | P04 [35], P11 [42], P12 [65], P13 [66], P14 [67], P15 [68] |
| **TV White Spaces (TVWS)** | IEEE 802.22, spectrum access in TV bands, geolocation-based access, M2M over TVWS | 5 | P11 [42], P13 [66], P48 [82], P50 [83], P56 [88] |
| **Wireless Sensor/Ad Hoc/Mobile Networks** | WSNs with energy harvesting, ad hoc CRNs, DSA in wireless sensor or mobile environments | 4 | P16 [43], P17 [69], P18 [44], P42 [58] |
| **Satellite and Vehicular Networks** | Satellite systems (GSO/NGSO), CIoV, UAV for disaster/public safety | 4 | P20 [70], P46 [80], P51 [84], P52 [85] |
| **Generic CR Systems** | Generic mention of CR or wireless comms such as ISM band, unspecified CR systems | 3 | P03 [23], P30 [77], P60 [63] |
| **Cognitive Radio Sensor Networks (CRSNs)** | CRSNs, mobile CRSNs | 2 | P38 [54], P43 [59] |
| **Rural Networks** | Community cellular networks, rural connectivity | 1 | P59 [91] |

P12 [65], P14 [67], P21 [46], P22 [47], P29 [76], P32 [48], P45 [79], P46 [80], P47 [81], P51 [84], P54 [86]) that mark a clear shift toward more autonomous and context-aware DSS systems.

Overall, the DSS literature reflects a healthy and multifaceted research landscape. The focus on algorithm development, and AI integration demonstrates the field's commitment to improving core sensing capabilities. Simultaneously, increasing contributions on application scenarios, architectures, and security reflect a shift toward practical deployment and system-level thinking. The balance between theoretical modeling, practical adaptation, and emerging AI techniques suggests a field that is both deepening its technical rigor and broadening its real-world relevance.

### 5.2.3. *Applications of DSS: Domains*

To understand the distribution and focus of recent research on DSS, we classified the studies according to their primary application domains. As shown in Table 6 and Fig. 6, the dominant category is *Cognitive Radio Networks (CRNs)*, which accounts for 28 out of 62 articles. These works commonly explore multi-user coordination, spectrum sensing strategies, and spectrum management in general-purpose CRNs, often under both static and dynamic environmental conditions. *Dynamic Spectrum Access (DSA)* emerged as another prominent focus, represented in 13 studies. Many of these works integrate DSA mechanisms within CRNs, often addressing policy enforcement such as listen-before-talk (P36 [52]), interference mitigation in radar-intensive environments (P41 [57]), or specific regulatory constraints such as those in the 700 MHz UHF band (P58 [90]).

The intersection of CR with the Internet of Things (CR-IoT) is an increasingly significant area, with articles (for example, P04 [35], P11 [42], P12 [65], and P13 [66]) targeting scalability, energy efficiency, and adaptability for dense machine-type communication, particularly within 5G and Industry 5.0 contexts. Some studies like P14 [67] and P15 [68] explicitly bridge CRN principles with emerging paradigms such as the Cognitive IoT (CIoT). *Cognitive Radio Sensor Networks (CRSNs)* and *Wireless Sensor/Ad Hoc/Mobile Networks* are moderately represented (2 and 4 articles, respectively). These domains focus on constrained environments where sensing must be adaptive to mobility (P43 [59]) or power limitations (P16 [43]).

Research in *Satellite and Vehicular Networks* reflects the expansion of CR technologies into space-based systems and vehicular communi-

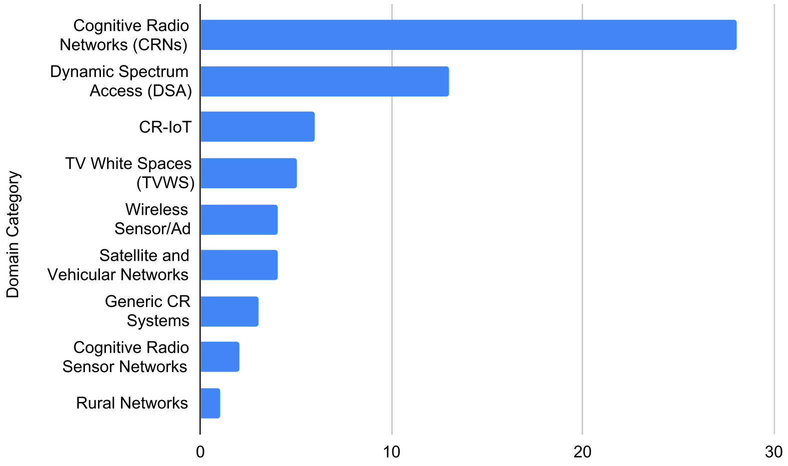

**Fig. 6.** Trends among domain categories in DSS.

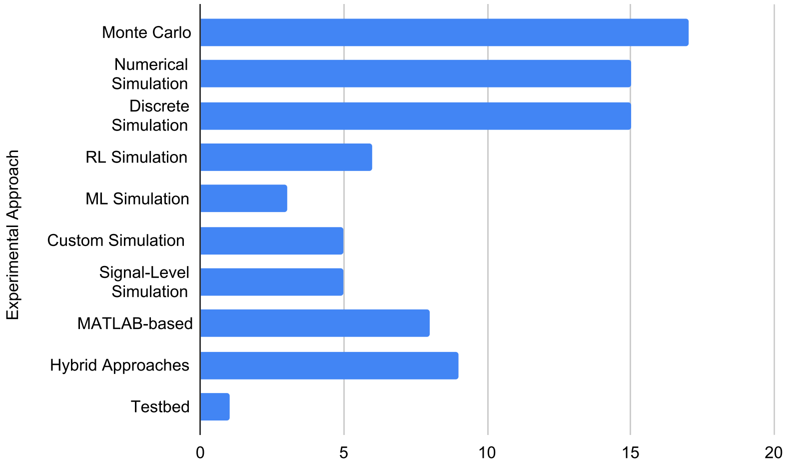

**Fig. 7.** Trends among experimental approaches in DSS.

cations. These studies emphasize spectrum coexistence between Non-Geostationary and Geostationary Satellite Orbit systems or disaster resilience via UAV-based CRN deployments (P20 [70], P46 [80], P51 [84], P52 [85]). Meanwhile, *TV White Spaces (TVWS)*, long considered a promising frontier for opportunistic spectrum access, are addressed in 5 articles (P11 [42], P13 [66], P48 [82], P50 [83], P56 [88]), showcasing geolocation-enabled access and IEEE 802.22 implementations.

Only a single study (P59 [91]) targets a particular domain or scenario, *rural areas*, highlighting a research gap and suggesting the need for further efforts in deploying CR technologies to enhance connectivity in remote communities. Finally, 3 studies (P03 [23], P30 [77], P60 [63]) were classified under *Generic CR Systems*, as they referred to cognitive radio paradigms in general terms or explored frequency bands, like ISM, without domain-specific alignment. This domain-based analysis not only reveals the maturity and breadth of CRN research but also highlights emerging directions, for example: CR-IoT, and satellite-vehicular fusion, and underexplored areas such as rural deployment, signaling valuable opportunities for future investigation.

### 5.2.4. *Applications of DSS: Technologies and techniques*

The literature surveyed leverages a diverse array of technologies and techniques to support DSS (see Table 7). For clarity, we distinguish between techniques, which refer to algorithmic or mathematical methods employed to perform tasks such as decision-making, optimization, or signal classification; and technologies, which refer to infrastructural or systemic tools, software or hardware, used to implement or support these techniques in real-world settings. Based on this distinction, we organize the contributions into three primary categories: (1) *Artificial Intelligence and Machine Learning techniques*, (2) *Optimization and Mathematical Modeling techniques*, and (3) *Advanced and Emerging Technologies*. It is important to note that this section does not cover traditional signal processing techniques, such as energy detection, compressive sensing, and cooperative or collaborative sensing; which will be addressed in detail in Section 6.

The first category, *Artificial Intelligence (AI) and Machine Learning (ML)*, encapsulates algorithmic strategies that enable cognitive radios to make intelligent, adaptive decisions. Reinforcement Learning (RL), including Deep RL variants like Deep Q-Networks (DQN) and Double Deep Q-Learning (DDQN), is widely used (P05 [36], P12 [65], P20 [70], P21 [46], P45 [79], P46 [80], P48 [82]) to optimize spectrum access strategies in dynamic environments, particularly in cooperative and multi-agent scenarios. Markov Decision Processes (MDPs) (P05 [36], P18 [44], P20 [70], P21 [46], P46 [80]) frequently underpin these RL approaches by modeling the sequential nature of access decisions. Supervised and unsupervised learning methods also contribute, with approaches such as logistic regression and density-based clustering used to enhance sensing accuracy (P17 [69], P22 [47], P32 [48], P41 [57], P45). Furthermore, AI-based optimization techniques, including Genetic Algorithms (GAs) and game-theoretic strategies, are employed to support cooperative decision-making and spectrum allocation (P24 [72], P28 [75], P30 [77], P38 [54], P39 [55], P43 [59], P44 [60], P47 [81]).

The second group, *Optimization and Mathematical Modeling*, includes formal methods that facilitate efficient resource allocation and signal inference. Convex optimization plays a critical role in solving problems

**Table 7**
Technologies in DSS: Use cases, Applications, and Combinations.

| Technology | Related Techniques | Common Use Cases | Key Areas of Application | Article IDs | Combination |
|---|---|---|---|---|---|
| **Reinforcement Learning (RL)** | Deep Q-Networks (DQN), Q-learning, Multi-Agent RL | Spectrum decision-making, cooperative sensing | Cognitive radio, dynamic spectrum access, IoT | P05 [36], P12 [65], P20 [70], P21 [46], P45 [79], P46 [80], P48 [82] | P05, P20, P21, and P46 (with MDP), P45 (with ML), P48 (with CSS, RL) |
| **Optimization Algorithms** | Convex optimization, Genetic algorithms (GA), scheduling algorithms | Spectrum sensing optimization, network resource allocation | CRNs, IoT, mobile ad hoc networks | P10 [41], P24 [72], P28 [75], P38 [54], P39 [55], P43 [59], P44 [60], P47 [81] | P10 (with CS), P24, P38, P44, and P47 (with CSS), P28 (with Game Theory), P47 (with SDR) |
| **Machine Learning (ML)** | Supervised learning, unsupervised | Spectrum analysis, decision-making optimization | Spectrum sensing, classification, data fusion | P17 [69], P22 [47], P32 [48], P41 [57], P45 [79] | P17 (with CSS), P32 (with SDR), P45 (with RL) |
| **Markov Decision Processes (MDPs)** | Sequential decision-making, optimal policies | Optimizing dynamic spectrum access, cooperative sensing | Cognitive radio, ad hoc networks, mobile communications | P05 [36], P18 [44], P20 [70], P21 [46], P46 [80] | All articles combine with RL |
| **Game Theory** | Stackelberg game, Nash equilibrium, incentive mechanisms | Spectrum leasing, access control, incentive modeling | Cognitive radio, spectrum sharing, wireless networks | P25 [73], P28 [75], P30 [77], P42 [58] | P28, P30, and P42 (with Optimization), P25 (with GeoDB) |
| **Software-Defined Radio (SDR)** | Signal processing, flexible radio experimentation | Real-world signal acquisition, spectrum sensing | Cognitive radio, experimental setups, SDR-based sensing | P16 [43], P32 [48], P47 [81] | P32 (with ML), P47 (with Optimization) |
| **Geolocation Databases** | Prior knowledge, spectrum coordination | Optimized spectrum access, dynamic allocation | TV white space, mobile networks, IoT | P13 [66], P25 [73] | P25 (with Game Theory) |
| **Blockchain** | Distributed ledger, consensus mechanisms | Secure data sharing, trust management | Cognitive radio, collaborative sensing, IoT | P29 [76] | Not combined with others |
| **Network Function Virtualization (NFV)** | Virtual Machines (VMs), Virtual Utility Functions (VUFs) | Spectrum agility, dynamic network management | Cognitive radio, 5G, IoT | P14 [67] | Not combined with others |

like sparse signal recovery in dynamic compressive spectrum sensing (DCSS), as seen in several studies (P10 [41], P24 [72], P28 [75], P38 [54], P44 [60], P47 [81]). Game theory is leveraged to conceptualize spectrum access as a strategic interaction among users (P25 [73], P28 [75], P30 [77], P42 [58]), exploring scenarios like cooperative leasing and competitive bidding. Stochastic and probabilistic models, including Markov Chains, Monte Carlo methods, and Cumulative Sum (CuSum), are used to represent spectrum dynamics under uncertainty and guide decision-making (P05 [36], P14 [67], P18 [44], P20 [70], P46 [80]). Meanwhile, graph-based algorithms such as Progressive Edge Growth (PEG) and bipartite matching support network-level optimization and cooperative sensing (P10 [41], P24 [72], P39 [55]).

Finally, *Advanced and Emerging Technologies* provide the infrastructure to deploy these techniques in practical systems. Blockchain is explored as a secure, decentralized solution for managing spectrum-related data and establishing trust in collaborative environments (P29 [76]). Network Function Virtualization (NFV) is integrated into cognitive radio networks to enhance flexibility and scalability in spectrum management (P14 [67]). Software-Defined Radio (SDR), often combined with platforms like GNU Radio and USRP, enables real-time signal processing and experimental validation (P16 [43], P32 [48], P47 [81]). Additionally, Geolocation Databases are employed in conjunction with collaborative sensing strategies to support dynamic and spatially-aware spectrum access, particularly in contexts like TV white spaces and IoT environments (P13 [66], P25 [73]).

### *5.3. RQ1.3: What are the main experimental approaches, performance metrics and software tools used in DSS?*

To understand how DSS methods are evaluated and validated, this section focuses on the experimental and simulation practices reported in the literature. It identifies the main types of experiments (Section 5.3.1), performance evaluation metrics (Section 5.3.2), and software tools or platforms employed including software libraries, hardware testbeds, among others (Section 5.3.3). This allows us to assess the methodological rigor and technical orientation of DSS research.

#### *5.3.1. Experimental approaches*

In the analysis of DSS literature, a variety of experimental approaches were employed to evaluate and validate the proposed methods (see Table 8 and Fig. 7), where simulations were by far the most selected approach. In this context, the most prevalent type was *Monte Carlo simulation*, found in 17 articles. These simulations utilize randomized trials to assess the statistical performance of sensing algorithms, particularly under variable conditions such as noise, SNR, and fading. Their popularity stems from the ability to provide statistically meaningful performance metrics such as probability of detection ($P_d$) and false alarm ($P_f a$), through repeated, randomized experiments. This approach is especially common when evaluating energy detection techniques or cooperative sensing strategies. For instance, in P11 [42], Monte Carlo simulation was used to estimate detection probabilities under varying SNRs and filter counts with fixed false alarm rates.

*Discrete-event and discrete-time simulations* closely followed as commonly used methodologies, appearing in a significant portion of the reviewed literature. These models simulate the behavior of communication systems by representing network operations as events or processes occurring in discrete time slots. They are particularly suited for scenarios involving CRNs, where the timing and order of events, such as sensing, transmission, and channel switching, must be carefully modeled to assess the overall protocol performance or detect vulnerabilities such as malicious attacks or channel contention.

*Numerical simulations*, reported in 15 articles, represent another significant approach. These simulations rely on mathematical models or synthetic datasets to evaluate algorithmic performance. Unlike Monte

**Table 8**
Experimental approaches in DSS.

| Type | Description | Count | Article IDs |
|---|---|---|---|
| **Monte Carlo Simulation** | Randomized numerical simulations to assess statistical performance metrics over many iterations | 17 | P02 [34], P08 [39], P11 [42], P19 [45], P24 [72], P28 [75], P34 [50], P35 [51], P37 [53], P40 [56], P55 [87], P57 [89], P58 [90] (part), P60 [63], P61 [92], P62 [64], P31 [78] |
| **Numerical Simulation** | Mathematical evaluation using predefined models or synthetic data (not necessarily random sampling) | 15 | P01 [33], P03 [23], P12 [65], P13 (part), P17 [69], P18 [44], P23 [71], P25 [73], P27 [32], P31 [78], P36 [52], P38 [54], P39 [55], P49 [61], P60 [63] |
| **Discrete-Event, Discrete-Time Simulation** | Event/time-slot based modeling of network behaviors and strategies | 15 | P05 [36], P06 [37], P08 [39], P09 [40], P10 [41], P14 [67], P20 [70], P21 [46], P26 [74], P29 [76], P30 [77], P33 [49], P40 [56], P43 [59], P54 [86] |
| **MATLAB-based Simulation** | Simulation explicitly implemented in MATLAB (may include DE, MC, or analytical) | 8 | P14 [67], P34 [50], P42 [58], P47 [81], P48 [82], P49 [61], P57 [89], P58 [90] |
| **Reinforcement Learning Simulation** | Simulation of learning agents such as DQN, DDQSA, and MARL in synthetic environments | 6 | P20 [70], P21 [46], P45 [79], P46 [80], P52 [85], P54 [86] |
| **Signal-Level Simulation** | Focuses on signal behavior, waveform generation, noise modeling, SNR, and sensing | 5 | P07 [38], P41 [57], P31 [78], P56 [88], P60 [63] |
| **Hybrid (Analytical, Numerical)** | Combines derived equations/models with numerical evaluation (no randomness or Monte Carlo explicitly) | 5 | P16 [43], P23 [71], P25 [73], P35 [51], P57 [89] |
| **Custom Simulation** | Author-developed simulation not tied to known tools or frameworks; scenario-based | 4 | P04 [35], P15 [68], P51 [84], P53 [62] |
| **Hybrid (Experimental, Simulation)** | Combines real-world hardware-testbed with software-based simulations | 4 | P13 [66], P16 [43], P47 [81], P58 [90] |
| **ML, Classification Simulation** | Supervised learning with synthetic-labeled data; classification of spectrum states | 3 | P22 [47], P32 [48], P56 [88] |
| **Pure Experimental, Testbed** | Physical experiments using hardware (for example: USRP, mobile devices); no software-only simulation | 1 | P59 [91] |

Carlo methods, they do not necessarily involve randomness but instead use predefined input conditions to validate analytical results or test system performance under controlled scenarios. Numerical simulations are often favored when the models are deterministic or when an analytical derivation is complemented with synthetic performance validation. For instance, in P08 [39], the authors conducted numerical simulations to evaluate the effectiveness of their proposed DSS algorithm. Their study focused on the algorithm's capability to promptly detect changes in channel occupancy status. As long as channel status changes do not occur simultaneously, the algorithm is designed to identify each transition individually. The authors report the success rate of change detection based on 500 randomly generated instances, each involving a single change in channel status.

A subset of studies adopted *hybrid simulations* that combine analytical derivations with numerical evaluations. These five articles used closed-form equations to model system behavior and then applied numerical techniques to evaluate performance under specific assumptions or parameter settings. This hybrid approach enhances the credibility of theoretical contributions by demonstrating their validity through simulations. For example, P16 [43] conducted two experiments using GNU Radio and USRP: one measured Fast Fourier Transform (FFT) computation time across different sampling rates and FFT sizes, and the other measured the combined time for frequency switching and signal detection by shifting from a noise-only to a signal-present band.

An emerging category involves *Reinforcement Learning (RL)-based simulations*, observed in six articles. These studies simulate intelligent agents, such as those using Deep Q-Networks (DQN), Double Deep Q-SARSA (DDQSA), or multi-agent RL, in synthetic environments to learn optimal spectrum access or sensing policies. RL simulations are particularly valuable in dynamic environments, where agents must adapt to changing spectrum conditions over time.

A smaller set of articles, specifically three, applied *supervised machine learning* techniques for classification tasks. These simulations typically involved labeled datasets, either synthetic or derived from signal models, to train classifiers for identifying spectrum states, modulated signals, or potential interferers. Although less common than RL approaches, these simulations contribute to the growing body of work on signal classification in DSS. For example, the authors in P22 [47], performed AI-based simulation using MATLAB to generate a labeled dataset of 600 samples, which they used to train and test a machine learning model for classifying channel states as idle, middle, or busy.

Another four studies employed *custom simulations*, characterized by simulation methodologies that are either uniquely developed for the specific study or not explicitly linked to standard simulation tools. These simulations often serve as early-stage prototypes or tailored implementations, prioritizing scenario-specific validation over methodological standardization or reproducibility. For example, P04 [35] presents comparative algorithmic simulations tailored for CR-IoT environments. P15 [68] employs a custom simulation incorporating synthetic attack models and sensing behaviors. P51 [84] develops an event-driven simulation framework with repeated trials to evaluate learning behavior over time. P53 [62] uses a custom simulation to model dynamic spectrum environments with varying sparsity, comparing adaptive and fixed sampling strategies.

In four studies, *signal-level simulations* were used to focus on physical-layer phenomena such as waveform generation, noise behavior, and signal detection under varying SNR conditions. These simulations are crucial for understanding the sensing performance at a more granular, signal-processing level. For example, P31 [78] uses signal-level simulations to evaluate Bit Error Rate (BER) performance under Rayleigh fading, varying SNR values, and inter-user channel error rates. The setup includes 10 secondary users, fading channels, and obstacles, analyzing how different inter-user error probabilities impact sensing reliability Fig. 8. Eight studies explicitly reported the use of *MATLAB-based simulations*, either as the primary simulation environment or in conjunction with other tools. MATLAB remains a dominant platform in DSS research due to its extensive signal processing libraries and ease of modeling communication systems. These simulations often overlap with Monte Carlo,

**Table 9**
Performance metrics in Dynamic Spectrum Sensing (DSS).

| Metric Category | Description | Count | Article IDs |
|---|---|---|---|
| **Detection Metrics** | Probability of Detection (Pd), Missed Detection Rate, Probability of False Alarm (Pf), others | 23 | P01 [33], P03 [23], P04 [35], P07 [38], P10 [41], P11 [42], P13 [66], P15 [68], P17 [69], P19 [45], P28 [75], P31 [78], P34 [50], P35 [51], P36 [52], P37 [53], P38 [54], P39 [55], P40 [56], P42 [58], P44 [60], P47 [81], P49 [61] |
| **Throughput and Efficiency** | Throughput, Spectrum Utilization, Spectral Efficiency, Data Rate, Access Rate | 17 | P02 [34], P04 [35], P07 [38], P12 [65], P14 [67], P18 [44], P20 [70], P24 [72], P27 [32], P28 [75], P30 [77], P36 [52], P38 [54], P40 [56], P45 [79], P46 [80], P47 [81] |
| **Statistical and Probabilistic Metrics** | ROC Curves, PDF Analysis, Confidence Intervals, Error Distribution, SNR Impact | 8 | P03 [23], P13 [66], P17 [69], P19 [45], P37 [53], P43 [59], P44 [60], P47 [81] |
| **Optimization Metrics** | Utility, Sensing Cost, Number of Samples, Task Allocation Fairness, Scheduling Quality | 7 | P08 [39], P18 [44], P25 [73], P26 [74], P31 [78], P42 [58], P48 [82] |
| **Energy and Resource Metrics** | Energy Consumption, Energy Efficiency, Cost, Environmental Impact | 7 | P04 [35], P08 [39], P24 [72], P25 [73], P29 [76], P30 [77], P38 [54] |
| **Learning and RL Metrics** | Reward, Q-value, Convergence of RL Agents, Action Accuracy | 6 | P05 [36], P12 [65], P21 [46], P25 [73], P45 [79], P46 [80] |
| Computation and Algorithmic Performance | CPU Time, Convergence Time, Processing Complexity | 5 | P09 [40], P11 [42], P13 [66], P20 [70], P25 [73] |
| **Robustness, Resilience, or Attack Resistance** | Impact of Jamming, False SU Attacks, Trust Score, Error Under Adversarial Conditions | 5 | P01 [33], P15 [68], P33 [49], P41 [57], P43 [59] |
| **Delay, Latency, or Time** | Processing Time, Delay, Task Completion Time, Sweep Time | 5 | P04 [35], P14 [67], P16 [43], P20 [70], P34 [50] |
| **Classification and Accuracy Metrics** | Precision, Recall, F1-Score, Classification Accuracy, Sensitivity, Specificity | 3 | P17 [69], P22 [47], P32 [48] |

discrete-time, or numerical techniques but are distinguished by their tool-specific implementation.

Additionally, four studies used *hybrid experimental and simulation methods*, combining real-world testbeds with software-based simulations. This approach allows researchers to cross-validate algorithmic performance both in controlled simulation environments and under real-world conditions. It often indicates a higher level of research maturity, where simulations are supplemented by physical testing using platforms such as software-defined radios. For example, P58 [90] simulates wavelet-based energy detection over the 700 MHz UHF TV band using MATLAB/Simulink, modeling signal transmission under Additive white Gaussian noise (AWGN) and decomposing the band into 32 subbands. The simulation identifies free channels by comparing subband power levels to noise-based thresholds. Results are validated through real-world signal measurements and crosschecked using FFT analysis.

Finally, only one study (P60 [63]) reported a *pure experimental testbed approach*, relying entirely on physical hardware for performance evaluation. Although rare, such studies are critical in demonstrating the practical applicability and deployment feasibility of DSS techniques. Overall, the observed trends reveal a strong reliance on simulation-based validation in DSS research, with Monte Carlo and discrete-time methods dominating due to their general applicability and flexibility. Meanwhile, the increasing use of reinforcement learning simulations reflects a shift towards adaptive and intelligent spectrum sensing approaches, suggesting a growing interest in AI-driven solutions in the field.

### *5.3.2. Performance metrics*

Researchers frequently validate their proposals through simulations or benchmarks, often comparing their methods against classical techniques or recent baselines. This pattern underlines the community's strong focus on empirical validation and highlights the incremental nature of many contributions. The surveyed articles reveal a consistent reliance on *classical detection metrics* to evaluate the efficacy of DSS strategies. Numerous studies, including P04 [35], P10 [41], P13 [66], P19 [45], P35 [51], and P44 [60], utilize metrics like Probability of Detection ($Pd$) and Probability of False Alarm ($Pf$) to quantify a system's ability to correctly identify the presence or absence of PUs.

Beyond these, several works such as P37 [53] and P47 [81] incorporate Receiver Operating Characteristic (ROC) curves to illustrate the trade-off between $Pd$ and $Pf$ over varying thresholds, providing a graphical view of system sensitivity. The importance of Missed Detection Rate is also highlighted in papers like P01 [33], P03 [23], and P42 [58], especially under noisy or uncertain channel conditions. Some studies like P03 [23] and P34 [50] further explore the impact of SNR on sensing accuracy, helping assess how robust a method is in low-SNR environments Table 9. In parallel, *throughput and efficiency metrics* play a critical role in determining the practicality of DSS schemes for real-world deployments. Articles such as P02 [34], P04 [35], P12 [65], P18 [44], and P30 [77] examine Throughput, Spectral Efficiency, Spectrum Utilization, and Access Rate to evaluate how well DSS enables SUs to make use of underutilized spectrum without interfering with PUs. The impact of intelligent access strategies is visible in studies like P45 [79] and P46 [80], where the combination of data throughput and intelligent learning techniques is shown to enhance spectrum access opportunities. They used AI-based decision-making to pick the best times and channels for transmitting data, which made it possible to use the spectrum more effectively. Moreover, P36 [52] and P38 [54] demonstrate how throughput is often linked to energy efficiency or sensing policies in optimized systems; since on well-designed DSS systems, you can't just think about throughput on its own; it's often tied to how energy-efficient the system is or how the sensing process is scheduled.

*Energy and resource usage metrics* are increasingly prioritized, particularly in low-power or distributed settings such as CR-IoT or wireless sensor networks. Key studies like P04 [35], P29 [76], and P30 [77] analyze Energy Consumption and Energy Efficiency as primary evaluation criteria, seeking to reduce battery drain and resource costs. Others, such as P38 [54], propose hybrid indicators combining spectral and energy efficiency to offer a more integrated view of system performance, especially under mobility or scalability constraints. Environmental factors,

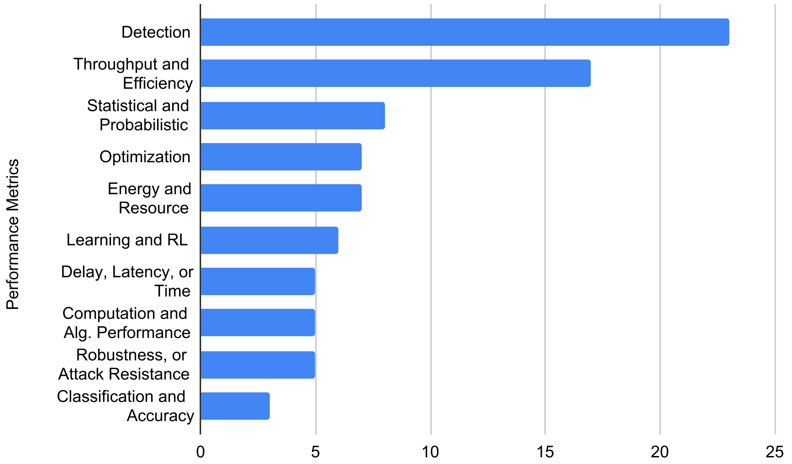

**Fig. 8.** Trends among performance metrics in DSS.

including sustainability and device longevity, are implicitly addressed through these energy-centered metrics.

A number of recent studies such as P05 [36], P21 [46], P25 [73], and P46 [80], employ *learning-based or Reinforcement Learning (RL) metrics*, including Cumulative Reward, Q-value evolution, Action Selection Accuracy, and Convergence Time. These are used to measure how effectively an agent learns to optimize its sensing decisions over time. P12 [65] and P45 [79] explore how reward-based optimization can be constrained or guided by real-world variables such as energy limitations or access priority, enabling more adaptive and intelligent DSS systems.

*Delay, latency, and time-based measures* are particularly vital for applications requiring real-time responsiveness or low-latency communication. P04 [35], P14 [67], and P20 [70] track Processing Time, Delay per Task, Sweep Time, and other timing variables to understand how quickly a system can react to spectrum changes. These metrics become central in mission-critical domains, like emergency communications, where sensing must be both fast and reliable. P16 [43] and P34 [50] contribute by highlighting how increased latency can deteriorate overall network performance.

For systems involving a model classification, studies such as P17 [69], P22 [47], and P32 [48] make extensive use of standard Accuracy, Precision, Recall, F1-score, Sensitivity, and Specificity metrics. These are crucial when evaluating how well a classification model can distinguish between occupied and unoccupied spectrum states. For instance, P22 [47] demonstrates exceptional classification performance using supervised ML, reporting up to 99.1% accuracy in feature-based detection scenarios. These metrics help ensure that ML models are not only accurate but also balanced in false positive and false negative rates.

Articles like P09 [40], P11 [42], and P13 [66] examine *computational and algorithmic performance metrics*, such as CPU Usage, Convergence Time, and Algorithmic Complexity, which are key to evaluating scalability and feasibility in constrained environments. P25 [73], for example, considers how quickly and efficiently a sensing algorithm converges to optimal behavior, providing insights into its suitability for deployment in DSA systems with limited processing resources.

A smaller but important subset of articles evaluates *robustness, resilience, and security metrics*, especially under adversarial or error-prone conditions. Studies such as P01 [33], P15 [68], P33 [49], and P43 [59] assess how DSS schemes withstand Jamming, Byzantine Attacks, or False SU Behavior. Metrics like Trust Score Fluctuation and Error Rate under Attack provide valuable indicators of system reliability in the face of malicious or deceptive actors.

Several optimization-focused papers such as P08 [39], P18 [44], P25 [73], and P42 [58] use *optimization-specific metrics* like Utility, Sensing Cost, Sample Size, and Task Allocation Fairness. These are used to balance sensing quality with system constraints such as energy, delay, or channel availability. P26 [74], for example, optimizes scheduling quality across distributed nodes to enhance sensing coordination and resource fairness. Finally, a set of studies uses *statistical and probabilistic performance measures* to provide deeper theoretical validation. These include Probability Distribution Functions (PDFs), ROC Curve Analysis, Confidence Intervals, Estimation Error, and SNR-driven Analysis, as used in P03 [23], P19 [45], P37 [53], and P44 [60]. Such statistical metrics are essential in simulations or real-world tests to ensure robustness under stochastic conditions or channel variability.

### 5.3.3. *Software tools in experiments*

Among the 62 surveyed articles on DSS, MATLAB emerges as the most explicitly cited software environment for simulation and algorithm development, demonstrating its widespread acceptance in this domain (see Fig. 9). For example, P11 [42], P14 [67], P34 [50], and P35 [51] directly state MATLAB usage for simulating spectrum sensing methods, while P42 [58], P44 [60], and P48 [82] use it for CSS optimization and auction schemes. Even hardware interfacing applications, such as P47 [81], utilize MATLAB combined with LabVIEW and NI USRP drivers for real-time spectrum sensing implementations. The presence of MATLAB in signal processing and numerical analysis is evident across multiple studies like P56 [88] and P57 [89], highlighting its versatility for stochastic and detection algorithm simulations.

Python is also explicitly mentioned but in fewer articles relative to MATLAB. It is commonly used for machine learning and data analysis tasks within DSS research. These tools are often used in combination. For instance, in P22 [47], MATLAB was first used to generate the labeled dataset. Subsequently, the actual machine learning model was developed and tested in Python, using the Scikit-learn library to implement the Gradient Boosting algorithm, Pandas and Seaborn libraries for ML model development and visualization. Deep reinforcement learning approaches such as P45 [79], P46 [80] and P52 [85] rely heavily on Python with TensorFlow for implementing complex neural networks. The synergy between Python and TensorFlow is particularly strong in these studies, with P05 [36] also employing TensorFlow for DRL applications. Moreover, Python supports real-time signal processing workflows combined with GNU Radio and USRP hardware platforms, as seen in P32 [48], indicating its utility in both software simulations and hardware integrations.

Hardware platforms and specific software tools are distinctly mentioned in fewer works but serve important roles. For example, P13 [66] integrates Texas Instruments DSPs, Xilinx FPGA, and RFeye nodes for real-time sensing, while P16 [43] and P32 [48] utilize GNU Radio and USRP for experimental setups involving physical radio front-ends. Java-based tools such as BonnMotion (P43 [59]) are used for modeling mobility in wireless sensor networks. OpenBTS (P59 [91]) supports cellular

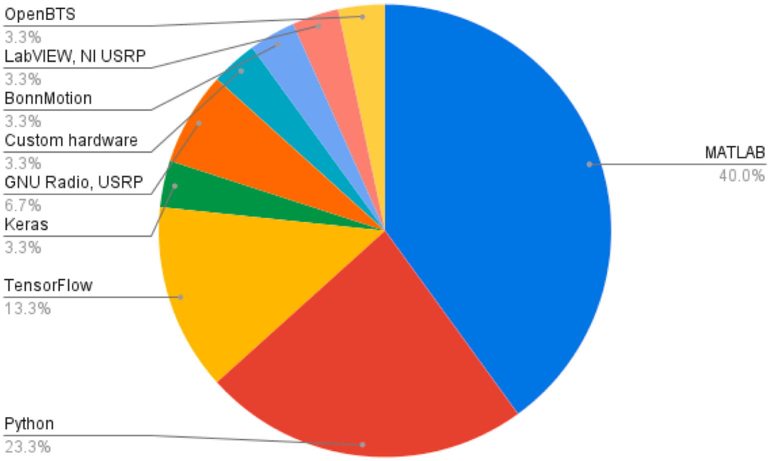

**Fig. 9.** Most employed software and hardware tools in DSS.

network emulation in community networks. These hardware-software hybrid approaches underline the practical deployment focus in some DSS studies. In contrast, many articles do not explicitly disclose their simulation environments. These studies often imply the use of MATLAB or similar numerical computing tools based on the description of their methods, Monte Carlo simulations, or the nature of signal processing and wireless communication analyses involved, for example, in P01 [33], P02, P04 [35], P06 [37], P08 [39], P12 [65], P23 [71], P28 [75], and P36 [52]. However, since explicit tool mentions are missing, these cannot be counted as confirmed usage.

Overall, while many articles omit detailed accounts of their simulation environments, those that do reveal a preference for MATLAB in general signal processing simulations and Python-based stacks in AI-driven research. GNU Radio and USRP hardware are essential in SDR and real-time implementations, and a few studies combine multiple layers of hardware and software for end-to-end system validation. These patterns highlight a bifurcation between traditional simulation approaches and AI-enhanced, hardware-integrated experimental designs in DSS research.

## 6. RQ2: How is Dynamic Spectrum Sensing addressed in the literature?

While the first research question explored the contributions and purposes behind DSS research, this second research question shifts the focus toward how DSS is implemented in practice. It investigates the technical and structural characteristics of DSS approaches, with the goal of understanding their diversity, evolution, and real-world applicability. By examining the configurations, spectrum settings, and operational contexts in which DSS is applied, this offers insights into the architectural and engineering decisions that shape the field. The question is divided into two specific sub-questions to capture different dimensions of DSS implementation (see RQ2.1 in Section 6.1 and RQ2.2 in Section 6.2).

### 6.1. *RQ2.1: What are the dominant spectrum sensing techniques, networks environments, architectures and temporal scales used for DSS?*

This subsection analyzes the foundational design choices in DSS implementations, focusing on the variety of spectrum sensing strategies and techniques (Section 6.1.1), deployment contexts (Section 6.1.2), channel and propagation models (Section 6.1.3), architectural models (Section 6.1.4) and the temporal granularity of sensing (Section 6.1.5). By examining these elements, we identify how DSS systems are structured to meet different operational demands and environments.

#### 6.1.1. *Spectrum sensing techniques and strategies*

The trends in sensing strategies addressed across the articles reflect a broad evolution toward adaptivity, intelligence, and cooperation in DSS, as can be seen in Table 10. A clear trend is the dominance of *Energy Detection (ED)* methods, which remain the most widely employed approach due to their simplicity and relatively low computational cost. Variants of ED such as standard thresholding, double-threshold detection, and threshold tuning appear frequently, with articles like P02 [34], P04 [35], P32 [48], and P58 [90] exemplifying this trend by applying ED to various frequency bands and network conditions. It is often enhanced with techniques like FFT-based analysis, double-thresholding, or Neyman-Pearson detection. These form the benchmark methods against which more advanced techniques are evaluated.

Closely related is the widespread use of *Cooperative Spectrum Sensing (CSS)* or simply *cooperative sensing* [20], with strategies involving fusion centers or distributed decision-making among secondary users. These cooperative models range from simple OR/AND rules to more complex schemes integrating reputation systems, trust management, or mobility-awareness to address challenges like malicious users or variable SNR conditions. Articles such as P01 [33], P31 [78], and P50 [83] utilize CSS techniques to aggregate sensing data and improve robustness against fading and shadowing effects, especially in challenging environments like mobile ad hoc or IoT networks.

Researchers also increasingly explore Dynamic or *Adaptive Sensing strategies* that optimize sensing parameters such as thresholds, sensing intervals, and channel selection dynamically based on environmental conditions or historical data. Studies including P05 [36], P06 [37], and P36 [52] demonstrate how adaptive methods enable more efficient spectrum utilization by tuning sensing behavior in real time, which is crucial for fast-varying spectrum scenarios.

Another emerging direction is *Compressive Spectrum Sensing (CSS)*, which reduces the burden on sensing hardware and bandwidth, enabling sparse signal reconstruction with fewer samples. Several works have applied it such as P08 [39], P10 [41], and P53 [62], addressing signal sparsity to reduce sampling requirements while still reliably detecting spectrum occupancy. This is often used in combination with Kalman filtering, Monte Carlo methods, or adaptive sampling strategies. This approach is especially suited for wideband sensing challenges common in cognitive IoT and 5G applications and low-power IoT devices.

*Reinforcement Learning* (RL)-based Sensing has also started to play a role as seen in articles such as P05 [36], P21 [46], and P54 [86], where intelligent agents learn sensing policies to maximize throughput and minimize interference dynamically. Also including Deep Q-Networks, bayesian frameworks and fuzzy logic, these models are particularly valued for their ability to handle partial observability, non-stationary environments, and channel uncertainty. Rather than relying purely on sig-

**Table 10**
Main spectrum sensing techniques in Dynamic Spectrum Sensing (DSS).

| Techniques | Article IDs |
|---|---|
| **Energy Detection (ED)** (standard, threshold-tuned, double-threshold, others) | P02 [34], P03 [23], P04 [35], P06 [37], P07 [38], P09 [40], P16 [43], P19 [45], P29 [76], P32 [48], P34 [50], P35 [51], P36 [52], P37 [53], P40 [56], P44 [60], P47 [81], P49 [61], P50 [83], P56 [88], P58 [90], P59 [91], P62 [64] |
| **Cyclostationary Detection** | P17 [69], P19 [45], P49 [61] |
| **Wavelet-based or Spectral Feature Sensing** (wavelet transform, spectral correlation) | P07 [38], P58 [90] |
| **FFT-based Sensing** (for energy or classification) | P03 [23], P16 [43], P32 [48], P58 [90] |
| **Compressive Spectrum Sensing (CSS)** | P08 [39], P10 [41], P13 [66], P53 [62] |
| **Machine Learning-based Sensing** (logistic regression, fuzzy logic, learning-based) | P06 [37], P17 [69], P32 [48], P54 [86], P55 [87] |
| **Reinforcement Learning (RL)-based Sensing** (Q-learning, DQN, MARL, others) | P05 [36], P20 [70], P21 [46], P45 [79], P51 [84], P54 [86] |
| **Geolocation or External Data-Assisted Sensing** | P12 [65], P13 [66] |
| **Wideband Sensing** (Filter Banks, Multiband, others) | P11 [42], P30 [77], P45 [79], P60 [63] |
| **Sensing using Bayesian or Statistical Inference** (MAP, Neyman-Pearson, CuSum) | P19 [45], P40 [56], P55 [87], P56 [88], P57 [89] |

nal energy, they model and predict spectrum usage patterns, enhancing decision-making in dynamic or dense network conditions. This reflects a shift toward more autonomous spectrum management frameworks. Instead of RL, the authors in [93] have introduced a 3D spatial spectrum sharing framework for CRNs that integrates massive MIMO structures, Direction-of-Arrival estimation, and DL–based spectrum sensing. DL is used to perform spectrum prediction and sensing without relying on reinforcement learning, and a two-stage scheduling mechanism is implemented to maximize coverage and optimize transmission rates.

*Additional techniques* like Wavelet-based sensing (P07 [38], P58 [90]), Cyclostationary detection (P17 [69], P19 [45]), and Threshold adaptation/optimization (P35 [51], P44 [60], P60 [63]) are used to improve detection accuracy in noisy or complex signal environments by exploiting signal features beyond simple energy levels. Literature has also shown the proposal of a CVDS–KSCN method [94], as a dynamic spectrum estimation and secondary-user selection framework for CRNs; using a Chebyshev distance–based Harmonious Vector Estimation scheme and a Kolmogorov–Smirnov Convolutional Neural Network is employed to identify optimal SUs.

*Hierarchical and multi-stage sensing strategies* (P13 [66], P30 [77]) aim to combine the strengths of multiple sensing methods, allowing flexible trade-offs between detection accuracy and computational cost. Trust and reputation-based approaches (P01 [33], P15 [68]) address security concerns by mitigating malicious sensing data injection, which is vital in cooperative scenarios. For instance, P58 [90] exemplifies the integration of wavelet-based spectral sensing with simulation and experimental validation on real-world signals, while P31 [78] highlights cooperative sensing combined with robust space-time block coding techniques to improve performance over fading channels.

There is also increasing attention to *application-specific enhancements* such as mobility-aware strategies in vehicular and UAV networks (P20 [70]), security-focused designs that defend against SSDF (P50 [83]) or Byzantine attacks (P09 [40]), and geolocation and database hybrid models which offload part of the sensing task to external data sources (P13 [66], P25 [73]).

Finally, several articles simulate sensing strategies within *game-theoretic frameworks*, emphasizing incentive-driven or pricing-based models for spectrum sharing. These strategic simulations mark a shift toward more economically and policy-aware DSS architectures. For instance, studies such as P25 [73] and P28 [75] model collaborative sensing and channel access through Stackelberg and congestion games, incorporating stochastic optimization and graph-based algorithms to balance performance and participation incentives. P30 [77] explores a cross-layer reconfiguration scheme based on potential games, while P42 [58] leverages coalitional game theory and adaptive thresholding to enhance cooperative sensing efficiency.

Overall, the sensing strategies demonstrate a transition from basic energy detection to more context-aware, collaborative, intelligent, and resource-optimized sensing solutions. This evolution reflects the growing complexity of spectrum environments and the corresponding need for DSS mechanisms that are not only accurate and fast but also robust, scalable, and secure.

### 6.1.2. Deployment contexts

The articles analyzed cover a variety of deployment contexts or network environments in which DSS is applied, specifically within CRNs, IoT, Mobile Networks, TV White Space (TVWS), satellite communication, and other wireless systems. These environments highlight the adaptability and wide applicability of DSS across diverse contexts. Table 11 summarizes the most addressed network environments.

*Cognitive Radio Networks (CRNs)* are the most prevalent environments for DSS. This includes both ad-hoc and structured CRNs, with varying levels of complexity. Many articles highlight CRNs operating under dynamic conditions with multiple SUs and PUs, where spectrum sensing is critical for efficient spectrum sharing. Simulated environments with Rayleigh fading and Rician channel models are common, as these models replicate real-world wireless conditions. CRNs are often deployed in environments where the availability of spectrum is unpredictable, and DSS ensures that SUs can opportunistically use spectrum without causing interference to PUs. For example, P01 [33] studies DSS in both CRNs and hybrid CR-MANETs, highlighting the adaptability of DSS to mobile and ad hoc configurations. P10 [41] presents a simulation scenario with 20 CR nodes and mobile primary users, modeling highly dynamic environments. P31 [78] and P54 [86] employ Rayleigh and Rician fading models, emphasizing realistic propagation conditions. P18 [44] and P21 [46] focus on multi-user CRNs, with centralized and coordinated spectrum access.

*TV White Space (TVWS)* environments are another frequent setting for DSS, often in the context of CRNs. These environments are characterized by unused TV broadcast frequencies, which can be dynamically allocated to secondary users through spectrum sensing. TVWS is a promising solution for providing broadband access in rural and underserved areas. The use of TVWS is typically combined with database-driven spectrum sharing, where DSS can detect idle channels in TV bands for use by secondary users. P13 [66] demonstrates DSS applied to TVWS through field tests with a CR-enabled TD-LTE system. P25 [73] focuses on database-driven architectures in white space channels, while P48 explores DSS in TVWS bands within CRNs.

**Table 11**
Network environments where Dynamic Spectrum Sensing (DSS) is deployed and their key characteristics.

| Network Environment | Key Characteristics |
|---|---|
| **Cognitive Radio Networks (CRNs)** | Ad-hoc and structured CRNs, dynamic spectrum sharing, multiple SUs/PUs, Rayleigh fading, Rician channels |
| **TV White Space (TVWS)** | Spectrum sharing in unused TV bands, database-driven access, rural broadband |
| **Internet of Things (IoT) and Machine-to-Machine (M2M)** | Low-SNR, bandwidth constraints, dense device deployments, integration with 6G, CRNs |
| **Mobile Networks (5G/6G)** | Mobile, ad-hoc, hybrid CR-MANETs, real-time spectrum sensing, DSA |
| **Satellite Systems (GSO/NGSO)** | Spectrum sharing in satellite communication, interference management between space and terrestrial systems |
| **Vehicular Networks (CIoV)** | High mobility, real-time communication, spectrum management for vehicle-to-vehicle and vehicle-to-infrastructure |
| **Ad-hoc and General Wireless Networks** | Temporary, flexible deployments, spectrum sharing in emergency, military, or disaster zones |
| **Simulation and Testing Environments** | Use of SDRs, MATLAB, LabVIEW for controlled simulations of spectrum sensing in various network environments |

*IoT and M2M communications* contexts feature prominently, with CRNs enabling spectrum sharing between various IoT devices. Many of these systems are characterized by low-SNR environments, bandwidth constraints, and the need for efficient spectrum use. IoT environments often combine CRNs with advanced technologies like 6G, providing a future-oriented perspective on DSS. These systems often incorporate highly dense IoT device deployments, where spectrum sensing is vital to manage interference and optimize the use of available spectrum. For instance, P04 [35] studies DSS in clustered wireless sensor networks within IoT scenarios with low-SNR conditions. P12 [65] addresses spectrum access in shared environments where IoT devices are secondary users. P14 [67] and P15 [68] explore DSS in 6G-enabled and CIoT contexts, emphasizing future communication paradigms.

*Mobile Networks*, especially in 5G/6G scenarios, frequently incorporate DSS as part of their spectrum management. The adaptability of DSS in mobile environments is critical, particularly in scenarios involving mobile ad hoc networks (MANETs) and hybrid systems (CR-MANETs). These environments often require real-time spectrum sensing to adapt to changing network conditions as users and devices move across various geographical areas. Many studies simulate CRNs within mobile environments, highlighting the role of DSS in improving network capacity and reducing interference. P01 [33] includes CRNs, MANETs, and CR-MANETs in its discussion. P02 [34] and P06 [37] simulate mobile scenarios with half-duplex nodes and dynamic spectrum conditions. P55 [87] addresses mobile CRNs with real-time responsiveness and dynamic PU activity.

*Satellite Systems*, both geostationary (GSO) and non-geostationary (NGSO), have emerged as important settings for DSS. These systems share similarities with terrestrial CRNs but are focused on space-based communication. DSS plays a role in spectrum management by ensuring interference-free communication between satellites and terrestrial systems. Their importance lies in supporting global connectivity, bridging coverage gaps, and handling unique challenges such as long propagation delays, high mobility, and dynamic link conditions. These networks are particularly relevant in the context of global communication and for providing connectivity in remote or rural areas. P46 [80] introduces a satellite spectrum sharing framework involving NGSO and GSO systems, while P52 [85] further develops this by simulating underlay access for satellite-terrestrial coexistence with DSS-enabled interference management.

*Vehicular Networks*, such as Cognitive Internet of Vehicles (CIoV), are another application for DSS. In these environments, vehicles communicate with each other and with infrastructure to share information related to traffic, safety, and route optimization. DSS is used to manage spectrum in these dynamic and highly mobile environments, ensuring that vehicle communication is efficient and interference-free. For example, P51 [84] applies DSS to CIoV scenarios, considering high-mobility fading channels and spectrum-sharing challenges.

In addition to the more specific network types, several studies refer to *General Wireless Networks and Ad-Hoc Systems* including ad-hoc sensor networks and systems with fixed or mobile nodes. These networks are often deployed in scenarios where flexibility and dynamic spectrum access are necessary, such as emergency communications, military networks, or temporary setups in disaster zones. The role of DSS in these systems is to facilitate real-time spectrum sharing and improve overall network performance. P17 [69] focuses on ad hoc sensor networks where DSS supports dynamic access in decentralized topologies. P20 [70] discusses CRNs for UAV-based disaster recovery, demonstrating the utility of DSS in urgent and ad hoc deployments. P42 [58] also addresses ad hoc networks with flexible spectrum needs.

**Table 12**
Channel and propagation models in DSS.

| Model Type | Count |
|---|---|
| AWGN (Additive White Gaussian Noise) | 17 |
| Rayleigh Fading Channel | 14 |
| Markov Models (PU/Channel States) | 10 |
| Path Loss Models | 9 |
| Statistical SNR-based Models (Fixed/Randomized) | 8 |
| Log-Normal Shadowing / Rician / WINNER II / TVFF | 4 |
| Real-World RF Environments (Experimental) | 4 |
| Geometric or Deterministic (Distance-based) Models | 4 |
| Gaussian Mixture Noise Models | 1 |

Several articles mention the use of *Simulation Environments* to test DSS techniques, as described in Section 5.3. These simulations are used to model different network conditions, including fading channels, shadowing, and mobility. Testing on platforms like software-defined radios (SDRs) and using tools such as MATLAB and LabVIEW is common. These environments enable researchers to simulate real-world conditions and evaluate the performance of DSS techniques in controlled settings before deployment.

The trends in the network environments where DSS is deployed reveal a strong emphasis on CRNs, which dominate the landscape due to their flexibility and ability to operate in dynamic, unpredictable spectrum environments. Other notable environments include TVWS, IoT networks, and mobile networks, with a focus on optimizing spectrum usage in contexts like rural broadband, 5G/6G, and vehicular communication systems. Satellite systems are emerging as an important area for DSS, particularly for managing spectrum between space-based and terrestrial networks. Finally, simulation environments play a critical role in testing DSS techniques under various channel conditions, which is key for refining spectrum sensing methods before real-world deployment Fig. 10.

### *6.1.3. Channel and propagation models*

In the DSS literature, the treatment of channel and propagation models varies significantly, reflecting the diversity of application contexts and research objectives (see Table 12). The most frequently adopted models are the *Additive White Gaussian Noise (AWGN)* and *Rayleigh fading channels*, appearing in 17 and 14 articles respectively. These models are often used due to their analytical simplicity and ability to represent basic wireless noise and multipath fading environments. AWGN models typically serve as a baseline for assessing detector performance, as seen in studies like P07 [38], P13 [66], P35 [51], and P49 [61], where noise is modeled using standard Gaussian assumptions to evaluate sensing accuracy. Rayleigh fading is employed to reflect more realistic multipath effects in urban or mobile settings, as demonstrated in P02 [34], P04

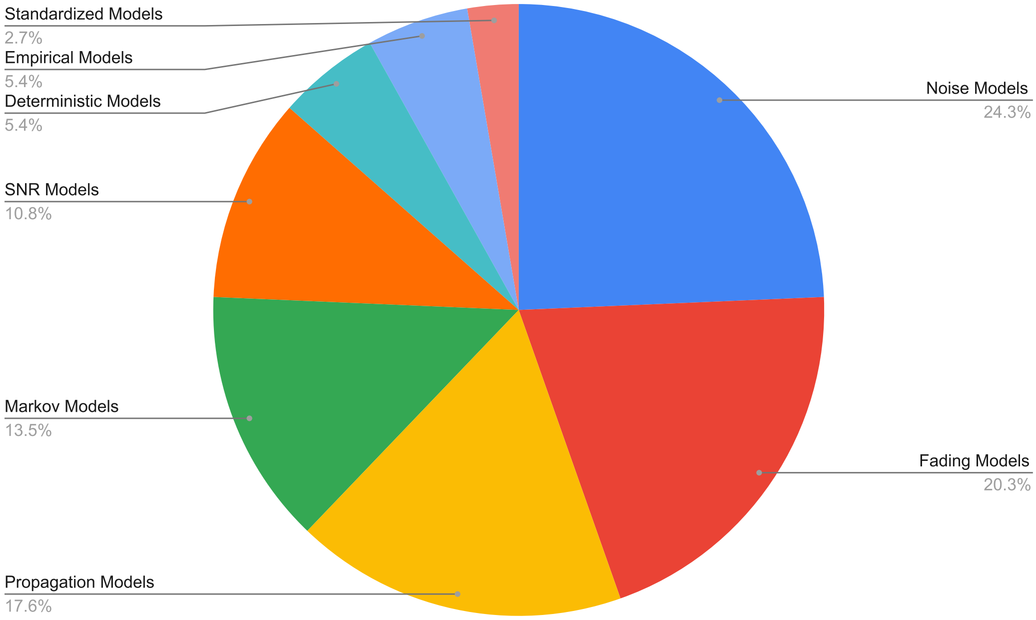

**Fig. 10.** Trends in channel and propagation models.

[35], and P40 [56], where fading is modeled across primary channels or transmission links to analyze robustness under varying signal conditions.

*Markov models* are also commonly used, especially to model PU activity or binary channel occupancy transitions, rather than physical propagation per se. These approaches emphasize stochastic behavior and temporal dynamics of spectrum availability rather than spatial propagation. For instance, P05 [36] and P29 [76] implement two-state or PU-state Markov models to simulate channel activity patterns, while P55 combines a Markov chain with a Time-Varying Frequency-Flat (TVFF) fading model for time-varying fading simulation.

*Path loss models* are adopted to simulate signal attenuation over distance, sometimes with environmental parameters such as path loss exponents. Several of these are part of hybrid simulations combining fading or interference with distance-based attenuation. Examples include P25 [73], which integrates path loss with geographic interference ranges, and P28 [75], which uses a path loss exponent ($\mu = 3.5$) with uniformly distributed SNRs to drive weighted spectrum access decisions.

Meanwhile, a small but important set of articles explore more advanced or specific channel models, including log-normal shadowing, Rician fading, WINNER II (standardized channel model), and TVFF models. For example, P08 [39] applies both Rayleigh fading and log-normal shadowing in separate channel types to assess environmental variability, P54 [86] uses the WINNER II and Rician models for standardized evaluation scenarios, and P55 [87] develops a DSMC-based TVFF model to capture time-varying fading behavior.

A substantial portion of the literature does not explicitly describe physical-layer propagation or fading models. In these cases, the studies abstract channel behavior into probabilistic states, logical rules, or focus purely on high-level sensing logic and decision-making algorithms. P14 [67] and P15 [68] exemplify this trend by omitting propagation details and instead modeling PU presence and activity abstractly. P21 [46], and P22 [47] also avoid detailed signal modeling, focusing instead on access control policies and data-driven approximations of channel quality.

*Statistical SNR-driven models* appear in 8 articles, where SNR values are fixed or drawn from distributions (uniform, exponential) to drive performance analysis, especially in cooperative sensing. P24 [72] uses fixed and exponential SNR distributions to simulate heterogeneous sensing conditions, while P30 [77] and P28 [75] vary SNRs based on system constraints or environmental factors to influence detection thresholds. Four studies conduct real-world experiments in RF environments (for example, indoor Wi-Fi or rooftop antenna setups), implicitly capturing real channel behaviors without analytically modeling them. P13 [66] and P32 [48] perform empirical measurements in real environments (indoor/outdoor, 2.4 GHz Wi-Fi) to validate theoretical assumptions, bypassing the need for synthetic propagation models.

Additionally, *geometric and deterministic models* (4 articles) simulate attenuation through distance-based signal decay or probabilistic channel gain variations. In P20 Shamsoshoara et al. [70], a deterministic distance-based model defines signal decay without incorporating multipath, while P42 [58] simulates attenuation with fixed parameters, for example, $\mu = 3$ and Gaussian noise without fading.

Finally, specialized approaches include Gaussian mixture noise models and abstract channel modeling intended for future extensions. These are rare but demonstrate efforts to explore more nuanced or atypical noise characteristics. For instance, P37 [53] introduces a Gaussian mixture noise model to analyze more complex noise environments, and P56 [88] mentions potential extensions toward probabilistic fading and shadowing models while currently using a basic additive noise setup.

### 6.1.4. Architectures

Multiple architectural paradigms are employed to support DSS, each with distinct trade-offs in coordination, complexity, and scalability (see Table 13). *Centralized architectures* typically rely on a fusion center or a central controller to aggregate data and make final decisions. For instance, in P08 [39], a centralized model is used where multiple CR nodes send data to a fusion center responsible for spectrum recovery. Similarly, P10 [41] implements a central fusion center that aggregates compressed measurements from CR nodes to jointly recover spectrum occupancy. This approach is echoed in works such as P15 [68] and P35 [51], where distributed sensing is followed by centralized decision-making, as cognitive users transmit one-bit local sensing outcomes to a fusion center. P20 [70] adds another example of full centralization via a High Altitude Platform (HAP) that manages decision-making and task assignments during emergencies. P50 [83], P33 [49], and P57 [89] further reinforce the dominance of centralized logic in scenarios where control and coordination efficiency are paramount.

Conversely, *distributed and decentralized architectures* eliminate reliance on a central entity, enabling nodes to act independently or in cooperation with local peers. In P01 [33], the architecture is fully dis-

**Table 13**

Architectural models in Dynamic Spectrum Sensing (DSS).

| Architecture Type | Description | Articles IDs |
|---|---|---|
| **Centralized** | A central unit or fusion center performs spectrum decision-making based on data collected from sensing nodes. | P08 [39], P10 [41], P12 [65], P15 [68], P20 [70], P25 [73], P32 [48], P33 [49], P35 [51], P38 [54], P39 [55], P43 [59], P44 [60], P45 [79], P47 [81], P48 [82], P50 [83], P57 [89] |
| **Decentralized - Distributed** | Sensing and decision-making are performed independently by individual nodes, often with local or no coordination. | P01 [33], P02 [34], P03 [23], P04 [35], P06 [37], P07 [38], P09 [40], P11 [42], P14 [67], P17 [69], P21 [46], P23 [71], P24 [72], P26 [74], P27 [32], P28 [75], P29 [76], P36 [52], P37 [53], P46 [80], P52 [85], P54 [86], P55 [87], P59 [91], P61 [92], P62 [64] |
| **Hybrid (distributed sensing, centralized coordination or fusion)** | Combines local sensing at distributed nodes with centralized control or decision fusion. | P13 [66], P18 [44], P30 [77], P31 [78], P51 [84], P53 [62] |
| **Clustered - Local Coordination (semi-distributed)** | Distributed sensing is enhanced through localized coordination using cluster heads or coalition leaders. | P04 [35], P30 [77], P42 [58], P59 [91] |

tributed, relying on cooperative sensing without central coordination. This pattern recurs in P06 [37], where multiple selfish SUs independently optimize their sensing strategies with no knowledge of others. Similarly, P11 [42] and P24 [72] adopt decentralized approaches in which each SU conducts local measurements without shared control. In P03 [23], local sensing by MB-OFDM receivers ensures fully autonomous operation, while P29 [76] employs blockchain nodes where every SU acts independently as both a sensor and verifier. Decentralized agent behavior is also central to P52 [85], where NGSO satellites autonomously adapt based on local sensing and feedback, bypassing any central controller.

Some systems adopt *hybrid architectures*, combining distributed sensing with centralized coordination or decision fusion. For instance, P18 [44] exemplifies this by allowing SUs to perform distributed sensing while a Central Controller (CC) handles scheduling. P30 [77] shows another hybrid model, integrating multiband cooperative sensing across IoT nodes with centralized coordination via cluster heads and control channels. P51 [84] also balances both paradigms, using distributed vehicle-based sensing while delegating final decisions to a centralized base station. P53 [62] follows suit by letting CR nodes sense independently and then sending outputs to a fusion center for adaptive control, creating a tightly integrated hybrid loop.

Additionally, some architectures reflect *localized cooperation or clustered coordination*, offering a middle ground between full distribution and centralization. In P04 [35], for example, nodes operate in distributed clusters coordinated via cluster heads and control channels, enabling collaborative yet localized decision-making. Similarly, P42 [58] proposes a coalition-based distributed model where each coalition elects a head node to serve as a local fusion center, preserving decentralization while facilitating structured coordination. P59 [91] supports distributed cooperative sensing among mobile devices, with localized sensing also conducted by the BTS, illustrating a dual-layered approach to distribution.

In conclusion, the chosen architecture deeply influences how sensing, decision-making, and coordination are handled across the system. Centralized models offer control and synchronization benefits but may face scalability limits, while distributed and decentralized approaches improve autonomy and robustness at the cost of increased coordination complexity. Hybrid and clustered solutions attempt to merge the best of both worlds, tailoring architectural decisions to specific performance, deployment, and application needs Table 14.

### 6.1.5. Temporal scales

Based on the analysis, *Short-term sensing* dominates as the prevailing temporal strategy in DSS, with most studies emphasizing real-time responsiveness and slot-based decision-making. For instance, many works such as P03 [23], P04 [35], P06 [37], and P16 [43] focus explicitly on minimizing sensing time through rapid slot-level or per-channel observations, enabling fast detection and reaction to changes in PU activity. Models in P09 [40] and P10 [41] also operate on short time slots, integrating frequent sensing and idle or consensus phases to dynamically update PU occupancy. In the case of P08 [39], the real-time detection of spectrum occupancy is specifically tailored for fast-changing environments, a trait similarly present in P13 [66], P21 [46], P23 [71], and P29 [76], where sensing occurs per slot to facilitate agile spectrum access.

Several approaches embed adaptive learning or estimation techniques within short-term sensing frameworks. For example, P01 [33] and P15 [68] incorporate trust accumulation or behavior modeling across rounds while still operating under round-based sensing. P11 [42] and P31 [78] pursue slot-wise detection using recent or instantaneous information, while P18 [44] and P20 [70] follow slotted sensing cycles combined with iterative decision-making. This short-term logic extends to learning-driven methods such as in P05 [36] and P52 [85], where RL is used with a short-term sensing horizon but directed toward optimizing longer-term goals.

Other studies particularly address fast detection mechanisms or windowed observation techniques. P33 [49] uses fine sensing tied to super frame durations for spectrum identification, and P34 [50] applies sliding windows to handle short observation periods for rapid classification. Similarly, P41 [57] and P49 [61] utilize data persistence or short observation windows to maintain reactivity. The overwhelming reliance on short-term windows is evident in papers like P35 [51] through P40 [56], as well as P42 [58] through P48 [82], which treat each slot as an isolated sensing event, often embedded in constrained decision models that assume limited PU state changes per sensing period.

In contrast, a subset of studies focuses on long-term sensing by modeling PU behavior or optimizing access over extended periods. For example, P12 [65], P19 [45], and P43 [59] approach spectrum access as a cumulative learning process, with policies refined over multiple iterations or long sensing durations. Long-term trust and participation metrics also appear in P55 [87] and P62 [64], where user history shapes future involvement and sensing reliability. Additionally, P26 [74] and P30 [77] emphasize environment modeling and adaptive strategies that unfold over broader time scales.

Some studies do a *hybrid approach*, bridging both temporal dimensions by combining immediate sensing with long-term optimization or learning. In P01 [33], short-term decisions are made per round, but trust is accumulated across time, while P17 [69] integrates immediate occupancy detection with periodic database updates. Similarly, P14 [67] uses short-term sensing to adapt spectrum roles, but updates channel reservations at fixed intervals. P27 [32] captures both real-time sensing and an initial long-term learning phase, and P24 [72] explicitly separates reactive (short-term) and proactive (long-term) sensing mechanisms. P54 [86] integrates short-slot sensing with deep reinforcement

**Table 14**
Temporal scales in Dynamic Spectrum Sensing (DSS).

| Temporal Scale | Brief Description | Articles IDs |
|---|---|---|
| **Short-term Sensing** | Sensing and decision-making occur in real-time or over very short durations (like per time slot, per frame, or per sensing window). Emphasizes responsiveness, adaptability, and immediate detection of PU activity. | P02 [34], P03 [23], P04 [35], P05 [36], P06 [37], P08 [39], P09 [40], P10 [41], P11 [42], P13 [66], P14 [67], P16 [43], P18 [44], P20 [70], P21 [46], P22 [47], P23 [71], P25 [73], P28 [75], P29 [76], P31 [78], P32 [48], P33 [49], P34 [50], P35 [51], P36 [52], P37 [53], P38 [54], P39 [55], P40 [56], P41 [57], P42 [58], P44 [60], P45 [79], P46 [80], P47 [81], P48 [82], P49 [61], P50 [83], P51 [84], P53 [62], P56 [88], P57 [89], P58 [90], P59 [91], P60 [63], P61 [92] |
| **Long-term Sensing** | Involves aggregation or learning over multiple sensing rounds or extended time periods. Used for estimating environment trends, building trust or reputation models, or optimizing long-term strategies. | P12 [65], P19 [45], P24 [72], P26 [74], P30 [77], P43 [59], P55 [87], P62 [64] |
| **Hybrid (Short-term and Long-term)** | Combines immediate spectrum decisions with long-term knowledge accumulation, trust modeling, or learning-based optimization. Balances responsiveness with adaptability to longer-term patterns. | P01 [33], P15 [68], P17 [69], P27 [32], P36 [52], P41 [57], P52 [85], P54 [86] |

learning to capture dynamic behavior over time. P52 [85] and P36 [52] represent further hybrids, using immediate slot-based sensing while optimizing decisions over thousands of simulated cycles.

In summary, short-term sensing remains the operational backbone in DSS, supporting real-time decision-making in dynamic environments. However, long-term models are gaining relevance for cumulative optimization and trust modeling. Hybrid strategies that blend both temporal scopes are particularly promising in balancing immediate reactivity with sustainable performance improvements over time.

## *6.2. RQ2.2: How do DSS approaches handle environmental dynamics, temporal variability, and real-time decision-making?*

This section explores the adaptability and responsiveness of DSS systems. It focuses on how various approaches account for the dynamic nature of network environments through types of adaptation or reactivity (Section 6.2.1), temporal dynamics (Section 6.2.2), real-time or online capabilities (Section 6.2.3), environmental awareness (Section 6.2.4), and mechanisms for dynamic handling (Section 6.2.5). Understanding these mechanisms is crucial for evaluating the robustness and practical feasibility of DSS in dynamic or mission-critical contexts.

### *6.2.1. Types of adaptation or reactivity in DSS*

Based on the analysis of the articles (see Table 15), DSS in CR and IoT systems demonstrates a rich diversity of adaptive and reactive mechanisms that enable efficient spectrum utilization under changing environmental, user, and network conditions. Among the prominent types of adaptation is context-aware and mobility-based reactivity, exemplified in P01 [33] and P10 [41]. These systems respond dynamically to PU presence or absence and SU mobility, adjusting trust levels and excluding malicious nodes to counter attacks (P01), or using Kalman filtering to predict spectrum states and track PU movement for adaptive access (P10). Trust-based reactivity also appears in P15 [68], which adjusts sensing windows based on node reputations to mitigate SSDF attacks.

Learning-based adaptations are common, as seen in P02 [34], P05 [36], and P06 [37], where RL or online algorithms iteratively optimize sensing policies. P05 adapts segment selection for channel aggregation via RL feedback, while P06 uses online learning algorithms to prioritize channels dynamically based on recent sensing success. Temporal adaptations emerge in P12 [65] and P24 [72], with RL tuning transmission probabilities and sensing strategies iteratively, reflecting responsiveness to interference and observed outcomes. Particularly, in P24 [72], temporal adaptation is reflected in the design of flexible sensing schedules (sequential, parallel, and hybrid) that allow users to iteratively adjust their sensing strategies depending on network size, channel availability, and uncertainty, thereby improving throughput while balancing complexity. Similarly, P12 [65] employs reinforcement learning to iteratively tune transmission probabilities in IoT networks without direct sensing capabilities, enabling devices to self-organize and adapt access behavior over time based on interference patterns and observed outcomes. Together, these works illustrate how responsiveness to evolving spectrum conditions, whether through optimized scheduling or learned access probabilities, is central to enabling robust and efficient DSA.

Systems often implement event-triggered or signal-driven reactivity, with FFT-based binary hypothesis testing in P03 [23] and sensing matrix updates triggered by PU activity changes in P08 [39]. Early detection leads to reduced sensing duration in P16 [43], while P19 [45] uses weighted cumulative sum (CuSum) statistics to quickly detect PU status changes, emphasizing sensitivity to abrupt spectrum shifts.

Collaborative and distributed adaptation mechanisms are central to many works. Dynamic clustering, energy-aware routing, and consensus-based updates (P04 [35], P09 [40]) enable SUs to cooperate in spectrum sensing, adjusting behaviors based on shared spectrum occupancy knowledge. P17 [69] and P23 [71] further refine cooperation by balancing sensing overheads with false positive management through adaptive link maintenance and sensing strategies.

Priority- and service-driven adaptations, such as fuzzy logic-based channel allocation (P14 [67]) and short- versus long-term adaptation coordination in TVWS (P13 [66]), reflect QoS considerations integrated into sensing and access decisions. Signal preprocessing adaptations (P07 [38]) and feedback-driven scheduling adjustments (P18 [44]) further highlight the multi-layered responsiveness of systems. Spatial reactivity is represented by adaptive exclusion zones (P25 [73]) and UAV motion/task adaptations (P20 [70]), while deep learning-based dynamic decisions (P21 [46], P27 [32]) showcase advanced model-driven spectrum sensing strategies.

Dynamic Spectrum Sensing and allocation are increasingly opportunistic and feedback-driven. In P30 [77], IoT nodes reoptimize sensing parameters and channel assignments in real-time, while in P31 [78] adaptive clustering selects SU pairs based on instantaneous channel state information (CSI), improving sensing accuracy and adapting space-time coding based on decoding success. ML techniques for spectrum occupancy classification appear in P32 [48], which adjusts detection thresholds reactively to noise via logistic regression, and P33 [49], where sensing is triggered selectively to optimize costs against threats like smart jammers.

Dynamic signal processing adaptations, such as sliding window observation in P34 [50], threshold and sample size variation in P35 [51], and sensing time adjustment in P36 [52], demonstrate responsiveness to SNR and interference fluctuations, balancing detection performance

**Table 15**
Types of adaptation and reactivity in Dynamic Spectrum Sensing (DSS).

| Type of Adaptation / Reactivity | Brief Description | Articles IDs |
|---|---|---|
| **Context-aware and mobility-based reactivity** | Systems respond dynamically to PU presence/absence and SU mobility; trust adjustment and attack mitigation mechanisms included | P01 [33], P10 [41], P15 [68] |
| **Learning-based adaptation** | Use of RL, online algorithms, and other ML methods to iteratively optimize sensing policies and channel prioritization | P02 [34], P05 [36], P06 [37], P12 [65], P24 [72], P21 [46], P27 [32], P46 [80] |
| **Temporal adaptation** | Adjustment of sensing/transmission times, thresholds, and decision windows in response to temporal variations in PU activity and interference | P12 [65], P24 [72], P16 [43], P19 [45], P36 [52], P44 [60] |
| **Event-triggered and signal-driven reactivity** | Sensing strategies triggered or adapted based on specific events, signal detections, or abrupt PU behavior changes | P03 [23], P08 [39], P16 [43], P19 [45], P34 [50], P35 [51], P37 [53] |
| **Collaborative and distributed adaptation** | Dynamic clustering, consensus algorithms, cooperative sensing, and adaptive coordination among SUs to improve sensing accuracy and reduce overhead | P04 [35], P09 [40], P17 [69], P23 [71], P38 [54], P41 [57], P57 [89], P61 [92] |
| **Priority- and service-driven adaptation** | QoS-aware channel allocation and mode switching based on service requirements, fuzzy logic, and priority levels | P13 [66], P14 [67], P18 [44], P51 [84] |
| **Spatial reactivity** | Adaptive geographic zoning, exclusion zones, UAV motion and task adaptations for spatial spectrum access management | P20 [70], P25 [73] |
| **Signal preprocessing and feedback-driven adaptation** | Adaptive noise reduction, sliding window processing, and feedback-based sensing schedule adjustments | P07 [38], P18 [44], P34 [50], P58 [90] |
| **DSS and allocation** | Opportunistic, feedback-driven sensing and real-time channel reassignment to optimize spectrum use in IoT and CR systems | P30 [77], P40 [56], P49 [61] |
| **ML-based classification** | Spectrum occupancy classification using logistic regression and selective sensing triggered by threat assessment | P32 [48], P33 [49] |
| **Node-level adaptation and optimization** | Adaptive censoring, node selection, energy-efficient sleep/awake scheduling, and optimization of sensing weights via algorithms like particle swarm optimization | P38 [54], P39 [55], P43 [59] |
| **Threshold adaptation** | Dynamic adjustment of detection thresholds and sample sizes according to noise, SNR, or signal features to maintain detection performance | P35 [51], P37 [53], P42 [58], P50 [83], P60 [63] |
| **Policy-driven and MDP-based adaptation** | Markov Decision Process frameworks and policy adaptation for dynamic channel access and long-term reward optimization | P45 [79], P44 [60] |
| **Genetic algorithm and fair scheduling adaptation** | Adaptive channel allocation and scheduling responding to PU activity using genetic algorithms | P47 [81] |
| **Spectrum trading and fusion center adaptation** | RL for bidding strategies and dynamic fusion rule adjustments to enhance sensing robustness | P48 [82], P50 [83] |
| **Vehicular and satellite system adaptations** | Dynamic mode switching, power control, and transmission policy adaptation for vehicular and satellite cognitive radios | P51 [84], P52 [85], P53 [62] |
| **Advanced sensing techniques and hardware adaptations** | Novel sensing approaches such as bi-stable oscillators, wavelet-domain energy detection, and frequency scanning optimizations | P56 [88], P58 [90], P59 [91] |
| **Cooperative relay and transmission adaptations** | Cooperative relaying and power control to optimize sensing cooperation and transmission strategies among secondary users | P61 [92] |

and sensing efficiency. Node-level adaptations, including censoring and selective sensing (P38 [54]), optimize resource use by continuing sensing only until confident decisions are reached. Adaptive optimization techniques like particle swarm optimization in P39 [55] adjust weights continuously to enhance detection in varying channel and noise conditions.

Slot allocation dynamically reacts to PU activity (P40 [56]), and real-time clustering incorporates streaming radar data for spatiotemporal modeling (P41 [57]). Threshold updates through gradient descent (P42 [58]) and dynamic node sleep/awake scheduling (P43 [59]) further enhance energy efficiency and detection quality. Traffic-aware adaptations redefine sensing and transmission strategies (P44 [60]), and Markov Decision Process-based policies (P45 [79]) dynamically optimize long-term channel access. DRL with double deep Q-learning guides joint channel and power decisions for NGSO satellites in cognitive satellite networks in P46 [80], while genetic algorithms maintain fair channel allocation responsive to PU activity in P47 [81].

Spectrum trading and fusion center adaptations (P48 [82], P50 [83]) adjust bidding and decision thresholds to mitigate attacks and improve robustness. Opportunistic spectrum hole detection (P49 [61]) and adap-

**Table 16**
Temporal aspects in DSS.

| Aspect | Characteristics | Articles IDs | Notes |
|---|---|---|---|
| **Explicit Time Modeling** | Discrete representation via time slots, TDMA cycles, or sensing indices; often uses Markov processes for prediction. | P02 [34], P05 [36], P06 [37], P09 [40], P11 [42], P25 [73], P27 [32], P29 [76], P33 [49], P34 [50] | Supports predictive scheduling and dynamic thresholding; aligns with practical frames (ms to s). |
| **Implicit Time Handling** | Time not modeled explicitly; emerges from sensing sequences, signal sampling, or processing windows. | P03 [23], P07 [38], P08 [39], P28 [75], P30 [77], P31 [78], P32 [48], P35 [51] | Temporal structure embedded in processing rounds or sample sequences without modeling historical correlations. |
| **Real-Time Responsiveness** | Sensing and decision-making operate in real-time or near-real-time with frequent updates. | P04 [35], P10 [41], P12 [65], P13 [66], P25 [73], P30 [77], P31 [78] | Enables fast adaptation; uses instantaneous SNR, TDMA scheduling, or low-latency feedback. |
| **Use of Historical Data / Prediction** | Historical sensing data used in probabilistic models (like Markov, Bayesian, Kalman) to inform future sensing. | P01 [33], P02 [34], P06 [37], P10 [41], P12 [65], P25 [73], P26 [74], P27 [32], P33 [49], P35 [51] | Improves sensing efficiency through learning and forecast mechanisms. |
| **Temporal Granularity** | Granularity ranges from microseconds to seconds; governed by protocol, sample frequency, or slot design. | P02 [34], P03 [23], P05 [36], P06 [37], P13 [66], P25 [73], P30 [77], P31 [78], P32 [48], P33 [49], P34 [50] | Designs reflect LTE subframes, IEEE 802.22 CDT slots, or processing window durations. |

tive mode switching with power control (P51 [84]) illustrate dynamic access management in vehicular and satellite contexts (P52 [85]).

Markov process-driven sampling and fusion (P53 [62]), feedback-informed SU learning (P54 [86]), and stochastic PU activity modeling (P55 [87]) enrich sensing strategies by recovering hidden channel states and minimizing collisions. Innovations in sensing hardware and algorithms, such as noise-enhanced bi-stable oscillators (P56 [88]) and wavelet-domain energy detection (P58 [90]), provide nonlinear and frequency-domain adaptive responses to spectrum occupancy. It is worth mentioning that a nonlinear response to spectrum occupancy means the sensing hardware or algorithm doesn't just react in a simple, proportional way to whether the spectrum is busy or idle. Mobile station frequency scanning adapts dynamically (P59 [91]), while cooperative relay strategies (P61 [92]) optimize transmission power and sensing cooperation, supporting robust multi-node sensing networks.

Together, these studies reveal that DSS is characterized by a multifaceted, highly dynamic interplay of temporal, spatial, trust-based, service-driven, collaborative, and learning-based adaptations. Systems continuously evolve sensing parameters, cooperation patterns, decision rules, and resource allocations in real-time, driven by environmental feedback, PU/SU behavior, and network requirements. This rich adaptability underpins the growing sophistication and effectiveness of DSS mechanisms in enabling efficient, resilient spectrum utilization in diverse wireless scenarios.

### 6.2.2. *Temporal aspects*

Temporal dynamics are a critical factor in the design and evaluation of DSS systems, as they directly impact sensing accuracy, responsiveness to environmental changes, and overall spectrum utilization efficiency. Across the articles, temporal aspects manifest in diverse ways (see Table 16), including explicit time modeling, implicit treatment of temporal processes, real-time or near real-time decision-making capabilities, historical data usage for prediction or adaptation, and various levels of time granularity.

Most of the articles such as P02 [34], P05 [36], P06 [37], P09 [40], P11 [42], P25 [73], P27 [32], P29 [76], P33 [49], and P34 [50] employs *explicit temporal modeling frameworks* where time is represented discretely through sensing indices, time slots, or TDMA cycles. This explicit treatment allows algorithms to capture temporal correlations in channel states or PU activity, often modeled via Markov chains or first-order Markov processes. Such modeling supports predictive mechanisms that utilize historical transition probabilities and channel fading statistics to inform sensing schedules or threshold adjustments. The granularity of time in these models typically aligns with sensing slots or frames, ranging from milliseconds to seconds, reflecting practical considerations in wireless systems. For example, P02 [34] models ON/OFF channel states with exponential distributions and time-slotted sensing, P25 [73] enforces discrete time slots with deadlines for sensing tasks and dynamic pricing to manage participation over time, and P33 [49] aligns decision-making with IEEE 802.22 superframes using 160 ms CDT slots. P27 [32] samples channel occupancy periodically with adaptive intervals, estimating mean occupancy using Markov models, while P29 [76] structures all system activities into fixed time slots governed by a discrete-time Markov process.

Several articles (for example, P03 [23], P07 [38], P08 [39], P28 [75], P30 [77], P31 [78], P32 [48], and P35 [51]) adopt an *implicit temporal perspective*, where time is not modeled as a separate variable but is inherent in the signal sampling process or sequential sensing rounds. For instance, P03 [23] integrates multiple OFDM symbols per frame for fine-grained temporal resolution, while P28 [75] models ON-OFF dynamics via transition rates without long-term forecasting. Similarly, P30 [77] and P31 [78] use short sensing intervals or TDMA-based structures for sequential decision-making but do not explicitly model temporal correlations or leverage historical data. P35 [51] implicitly models time through sensing duration tied to sample count and historical SNR-Pd trends, suggesting adaptation based on empirical patterns. In P32 [48], time is implicitly encoded in FFT-based spectral snapshots processed in fixed-length digital windows, and in P07 [38] and P08 [39], signal segmentation and recursive recovery occur over successive frames without an explicit time variable.

Most DSS approaches emphasize *real-time or near real-time responsiveness* to spectrum environment dynamics. Decision-making at each sensing interval or slot is a common feature, enabling prompt adaptation to PU activity or channel state changes. Articles like P04 [35], P10 [41], P12 [65], P13 [66], P25 [73], P30 [77], and P31 [78] illustrate systems that update sensing parameters, detection thresholds, or sampling strategies iteratively based on current observations and occasionally on historical data. For example, P04 [35] supports low-latency reporting with TDMA scheduling, P10 [41] uses Kalman filtering for real-time estimation, and P13 [66] aligns sensing decisions with 10 ms LTE frames. P25 [73] dynamically adjusts sensing task pricing and completion deadlines per time slot to ensure fast sensing cycles. P30 [77] processes results within sensing frames using instantaneous SNR, while P31 [78] uses energy detection under stable CSI assumptions, implying sequential updates in real-time without deep forecasting.

Around half of the articles explicitly incorporate *historical sensing data or probabilistic models* to predict future spectrum availability or optimize sensing schedules (for example, P01 [33], P02 [34], P06 [37], P10 [41], P12 [65], P25 [73], P26 [74], P27 [32], P33 [49], and P35 [51]). Bayesian filtering, Markov models, and stochastic process pre-

**Table 17**
Overview of real-time and online capabilities in Dynamic Spectrum Sensing (DSS).

| Capability Type | Brief Description | Article IDs |
|---|---|---|
| **Slot-wise, Time-step Decision-Making** | Sensing or access decisions made per time slot, using current and/or past observations for PU activity or channel status. | P04 [35], P05 [36], P07 [38], P09 [40], P18 [44], P29 [76], P30 [77] |
| **Dynamic Thresholding, Online Adaptation** | Real-time adjustment of thresholds, spectrum opportunity detection, parameter tuning, and pricing control using current or recent sensing data. | P08 [39], P13 [66], P24 [72], P25 [73], P35 [51], P36 [52], P42 [58], P60 [63] |
| **Real-time Cooperative Sensing and Decision Fusion** | Online updates to sensing strategies, cluster formation, and centralized or distributed fusion of decisions in response to streaming data. | P06 [37], P22 [47], P31 [78], P33 [49], P36 [52], P43 [59], P44 [60], P50 [83], P57 [89] |
| **Feedback-Driven Reconfiguration, Online Learning** | Adaptive reconfiguration of channels sensing order, policy updates, and agent behavior using runtime feedback, ACK/NACK signals, and DRL. | P15 [68], P24 [72], P33 [49], P46 [80], P52 [85], P56 [88], P62 [64] |
| **Near Real-time Processing** | Signal processing and decision-making occur in quasi-real-time per cycle or frame, but may lack continuous learning or adaptive feedback. | P01 [33], P03 [23], P14 [67], P27 [32], P32 [48], P37 [53] |
| **Partial, Limited Online Operation** | Basic real-time functions (like access decisions) without learning, or use of offline-trained models with delayed updates. | P02 [34], P19 [45], P20 [70], P22 [47], P41 [57], P43 [59] |
| **Integrated Real-time Responsiveness** | Systems combining multiple real-time features (for example, sensing, adaptation, decision-making) to support robust spectrum access under dynamic conditions. | P38 [54], P39 [55], P40 [56], P45 [79], P47 [81], P48 [82], P49 [61] |

dictions are commonly employed to capture temporal correlations and improve sensing efficiency. For instance, P01 [33] aggregates trust values over time, P06 applies Markov learning with discounting, and P10 [41] forecasts usage via Kalman filters. P25 [73] fuses past propagation models and cumulative contributions for more accurate mapping. P26 [74] applies renewal theory using past occupancy data to optimize sensing periods and idle channel search delays. P27 [32] uses weighted past samples to predict occupancy dynamics with decreasing sample intervals, while P33 [49] uses prior OFF-state durations and transition probabilities to estimate PU return times. In P35 [51], decision thresholds are influenced by prior SNR-performance plots, implying long-term behavioral learning.

The reviewed literature exhibits considerable variation in *temporal granularity*, influenced by system design and application context. While some models focus on discrete time slots or sensing indices with granularity of milliseconds to seconds (for example, P02 [34], P05 [36], P06 [37], P13 [66], P25 [73], and P33 [49]), others rely on signal sample-level timing (working on the smallest units captured by the analog-to-digital converter) or broader sensing intervals dictated by communication protocols (for example, P03 [23], P07 [38], P30 [77], and P31 [78]). P02 [34] uses short dwell times and rapid sampling, P05 [36] and P06 [37] operate in abstract time slots or model defined units of time, and P03 [23] achieves microsecond-level resolution. P13 [66] aligns to LTE's 10 ms subframes, P25 [73] operates in deadline-driven slots where time slots that are scheduled based on a fixed time limit by which sensing or transmission must be completed, and P33 [49] uses 160 ms CDT slots. In contrast, P31 [78] and P32 [48] imply sensing granularity through processing windows and sampling frequency without numerical specification, and P34 [50] handles temporal resolution at the level of overlapping sample windows to capture correlation between adjacent signal segments.

Overall, DSS research demonstrates a balanced mix of explicit and implicit temporal modeling, with a strong emphasis on real-time decision-making to handle dynamic spectrum environments. Predictive approaches leveraging historical data appear pivotal for optimizing sensing performance, though not universally adopted. Temporal granularity choices align with practical constraints and differ according to application domains, highlighting the importance of contextual system design.

### 6.2.3. *Real-time or online capabilities*

Across the 62 articles analyzed, a clear trend emerges showing how DSS research increasingly embraces real-time or online operational paradigms to manage environmental dynamics, temporal variability, and decision-making under uncertainty (see Table 17). The implementation of these capabilities varies in complexity and purpose, reflecting the diversity of application contexts, from IoT and CRNs to satellite and mobile systems.

A dominant pattern across studies is *slot-wise or time-step decision-making*, where systems make sensing or access decisions per time slot using current and sometimes previous observations. This model supports responsiveness to PU activity or changes in channel conditions. For instance, P04 [35] performs collaborative sensing with dynamic routing and real-time spectrum use decisions, P05 [36] employs reinforcement learning for continuous action selection without prior knowledge of system dynamics, and P07 [38] processes FFTs and PSDs at each slot for timely decisions. P09 [40] implements real-time energy detection and consensus-based decision-making, while P18 [44] updates scheduling vectors and transmission probabilities using ACK/NACK feedback. Similar models are seen in P29 [76], which allows SUs to sense, bid, and update blockchains all within a single time slot, and in P30 [77], where IoT nodes feed local sensing results into an m-out-of-K fusion rule applied dynamically at a central entity.

*Dynamic thresholding and online adaptation* are also prevalent. P08 [39] integrates previously sensed and current partial measurements in real-time, P24 [72] dynamically determines spectrum opportunities in each slot, and P25 applies online pricing control to regulate user participation. In P13 [66], spectrum sensing is embedded into each LTE frame for instant decisions in CR-enabled TD-LTE, while P60 [63] adapts parameters dynamically for interference robustness. P36 [52] exemplifies this by using dynamic thresholding within a listen-before-talk framework in each sensing cycle. P35 [51] continuously monitors Pd and adjusts thresholds based on real-time SNR readings, while P42 [58] leverages iterative gradient descent updates for thresholds during operation.

*Real-time cooperative sensing and decision fusion* further reinforce temporal responsiveness. In P06 [37], strategies for channel access are updated online without offline training. P31 [78] features dynamic cluster formation and real-time SU decision exchange, which are fused at a base station, and P33 [49] applies feedback in each CDT slot to optimize sensing decisions within a 2-second constraint. P22 [47] and P36 [52] emphasize cooperative strategies with fusion centers, while P43 [59] and P44 [60] perform PU classification using statistical or cyclic sensing models. In P50 [83], local data from SUs is fused by a central entity, with reputation scores and thresholds updated online. P57 [89] uses real-time data aggregation and decision-making in cooperative setups.

Several studies highlight *reconfiguration and feedback* as central to online responsiveness. P15 [68] introduces cyclic fusion center decisions with frame-wise reputation updates. In P24 [72], the controller dynamically changes sensing order in each slot. P33 [49] modifies sensing order and user allocation using performance-based feedback. P56 [88] and P62 [64] exemplify systems where sensing configurations evolve based on runtime feedback and current conditions. P46 [80] and P52 [85] employ DRL agents that update policies online based on observations and acknowledgments (ACKs), thereby ensuring continual learning and adaptation.

There is also evidence of systems operating in *near real-time*, processing signals per observation cycle with current data but without continuous learning. For instance, P01 [33] updates trust and decisions iteratively, P03 [23] processes FFTs at microsecond intervals, and P14 [67] reconfigures channels based on fuzzy logic during SU transmissions. P27 [32] fine-tunes sensing parameters dynamically, though not under strict real-time constraints. P32 [48] performs classification via logistic regression on FFT data, with suitability for near real-time despite reliance on an offline-trained model. Similarly, P37 [53] supports online detection using bootstrap-based thresholding with slight delays.

Conversely, a smaller subset of articles shows *limited or partial online operation*. P02 [34] enables real-time access decisions but lacks adaptive learning. P20 [70] uses Q-learning for UAV policy updates but does not respond continuously to signal changes. P19 [45] and P22 [47] rely on batch processing and offline-trained models, only periodically updating decision logic. P41 [57] supports incremental data handling and stream-based responsiveness but retains offline clustering. P43 [59] opts for statistical approximations over time-slot updates to save energy, illustrating trade-offs between immediacy and resource consumption.

Overall, these patterns indicate a maturing DSS landscape that increasingly integrates context-aware, incremental, and adaptive real-time processing. This responsiveness, central to many systems such as P38 [54], P40 [56], P45 [79], P47 [81], and P48 [82], supports more reliable spectrum access and efficient usage amid volatile spectrum conditions. As shown in P39 [55] and P49 [61], the use of real-time optimization and opportunistic sensing strengthens DSS's ability to adapt to the dynamic nature in PU behavior, interference, and network state. This evolution underscores the critical role of temporal sensitivity and operational agility in next-generation spectrum management.

### 6.2.4. Environmental awareness

Environmental awareness in DSS systems is a multifaceted construct that reflects how sensing agents perceive, model, and respond to the spectral, spatial, temporal, and adversarial dimensions of their wireless environments. Across the analyzed studies, systems exhibit varying levels of sophistication in modeling environmental cues, ranging from basic energy detection to advanced characterizations of signal properties, channel behavior, and trust dynamics (see Table 18). A dominant theme is *awareness of PU activity*, typically inferred through energy detection. Systems like P02 [34], P28 [75], P45 [79], P47 [81], and P48 [82] use received signal energy or binary channel states to determine PU presence. This binary classification serves as the foundation for higher-level decisions in trust modeling (P01 [33]), auction strategies (P48 [82]), and resource allocation (P26 [74]). Later on, an adaptive nonlinear predistortion technique has been designed to improve signal linearity and spectrum efficiency in mMIMO-enabled CRNs [95]. Similarly, energy detection outcomes help guide trust-aware routing in P01 [33] and affect feedback-driven sensing in P05 [36].

Beyond energy levels, many systems incorporate *noise and interference awareness* to enhance detection accuracy. P03 [23] models the environment using a mix of thermal noise, quantization noise, and narrowband interference, while P07 [38] applies wavelet-based denoising to isolate signals under low SNR. P04 [35], P14 [67], and P24 [72] explicitly model SNR, SINR, and fading to better interpret sensing reliability. Similarly, P30 [77], P38 [54], and P39 [55] use local and reported SNR/SINR and noise variance to inform channel assignment and node selection.

*Channel fading and propagation effects* represent another layer of environmental modeling. P04 [35] and P22 [47] use link gain, CSI, and SIR for routing and interference assessment. P31 [78] and P36 [52] simulate Rayleigh fading and path loss to compute detection accuracy under realistic propagation conditions. P34 [50] integrates channel impulse response and noise modeling, while P35 [51] combines fading with AWGN for robust sensing.

Many systems also incorporate *temporal awareness*, recognizing the dynamic behavior of PU signals. P06 [37] and P14 [67] model temporal channel utilization, often with Markov processes. P18 [44] adds retransmissions and packet loss as temporal metrics, while P27 [32] analyzes burstiness and occupancy durations. P33 [49] estimates PU return probabilities based on time since last seen, and P44 [60], P51 [84], P54 [86], and P55 [87] use Markov or hidden Markov models to capture temporal state transitions, with some incorporating RL (P51 [84], P54 [86]) for adaptive decision-making.

*Spatial and mobility awareness* further enriches environmental sensing. P10 [41] and P25 [73] consider user location and spatial correlation in signal reports. P09 [40], P21 [46], and P43 [59] account for dynamic topologies and node mobility, while P51 [84] employs vehicle-based collaboration to improve spatial diversity in sensing. In P53 [62], spatial consistency across cognitive radios influences adaptive decision confidence. Systems also integrate channel quality and performance metrics into their awareness frameworks. P08 [39] constructs a matrix using channel gain, fading, and propagation loss for spectrum recovery. P20 [70] captures CSI, throughput, and interference for UAV-based emergency networks. P24 [72] adjusts assumptions based on sensor heterogeneity to reflect detection reliability more accurately.

*Adversarial and trust-aware environmental modeling* is evident in systems such as P01 [33], P15 [68], P25 [73], P33 [49], and P50 [83]. These works detect and respond to SSDF attacks or smart jamming by weighing sensing reliability against trust metrics. P25 [73], for example, incorporates node proximity and trustworthiness into report quality, while P15 [68] uses post-decision interference events to validate node behavior.

*Signal-level awareness* also plays a crucial role. P37 [53] uses cyclostationary features to detect signals at low SNR, while P49 [61] applies eigenvalue detection and modulation recognition for robust occupancy decisions. P56 [88] models signal amplitude, modulation, and interference in a multi-dimensional sensing environment. P41 [57] offers rich radar signal awareness, including pulse width and angle of arrival.

*Interference and power constraint modeling* are critical in maintaining spectrum coexistence. P12 [65], P42 [58], and P46 [80] measure aggregate interference and SINR, often integrating power limits and channel gain. P54 [86] uses ACK feedback to estimate throughput and adjust sensing decisions. P52 [85] tracks power/noise variations across subchannels to support adaptive strategies. Finally, *feedback and history-aware sensing* appear in P05 [36], P21 [46], and P54 [86], where sensing performance is continuously adapted based on previous outcomes, whether through ACKs or learning-based optimization. These systems reflect a shift toward environment-responsive cognitive networks that evolve their behavior over time.

Environmental awareness in DSS systems spans an impressive spectrum of modeling techniques and priorities, from simple binary energy detection (such as P02 [34] and P45 [79]) to comprehensive context-aware frameworks that integrate trust, interference, modulation, spatial distribution, and historical signal behavior (for example, in P25 [73], P41 [57], and P56 [88]). Each study contributes a unique perspective, underscoring that robust DSS requires an integrated understanding of

**Table 18**
Environmental awareness in Dynamic Spectrum Sensing (DSS) systems.

| Awareness Dimension | Description and Examples | Article IDs |
|---|---|---|
| **PU Activity** | Binary energy detection or channel state classification, used for trust modeling, auction/resource allocation, and trust-aware routing | P01 [33], P02 [34], P05 [36], P26 [74], P28 [75], P45 [79], P47 [81], P48 [82] |
| **Noise** | Noise modeling: thermal, quantization, and narrowband interference; denoising under low SNR, explicit SNR/SINR/fading modeling; used for node/channel selection | P03 [23], P04 [35], P07 [38], P14 [67], P24 [72], P30 [77], P38 [54], P39 [55] |
| **Channel and Propagation Effects** | Models using CSI, SIR, link gain; Rayleigh fading and path loss simulations, impulse response and AWGN | P04 [35], P22 [47], P31 [78], P34 [50], P35 [51], P36 [52] |
| **Temporal Dynamics** | Temporal PU behavior and utilization models; burstiness, packet loss, retransmissions; return probability estimates; Markov or hidden Markov models and reinforcement learning | P06 [37], P14 [67], P18 [44], P27 [32], P33 [49], P44 [60], P51 [84], P54 [86], P55 [87] |
| **Spatial and Mobility Awareness** | Location/spatial correlation in reports, dynamic topologies and mobility, vehicle-based collaboration, spatial consistency for adaptive confidence | P09 [40], P10 [41], P21 [46], P25 [73], P43 [59], P51 [84], P53 [62] |
| **Channel Quality and Performance** | Channel gain, fading, propagation loss for recovery; CSI, throughput, interference in UAV networks; heterogeneous sensor reliability modeling | P08 [39], P20 [70], P24 [72] |
| **Adversarial and Trust Modeling** | SSDF detection and smart jamming mitigation, trust-informed reporting based on proximity and behavior validation | P01, P15 [68], P25 [73], P33 [49], P50 [83] |
| **Signal-Level Features** | Cyclostationary features, eigenvalue detection and modulation recognition; amplitude, modulation, and interference modeling; radar features like pulse width and AoA | P37 [53], P41 [57], P49 [61], P56 [88] |
| **Interference and Power Constraints** | Aggregate interference, SINR, and power limits; throughput feedback using ACKs, subchannel power/noise tracking | P12 [65], P42 [58], P46 [80], P52 [85], P54 [86] |
| **Feedback and History Awareness** | Learning from sensing outcomes and ACKs, adaptation via performance-aware optimization | P05 [36], P21 [46], P54 [86] |

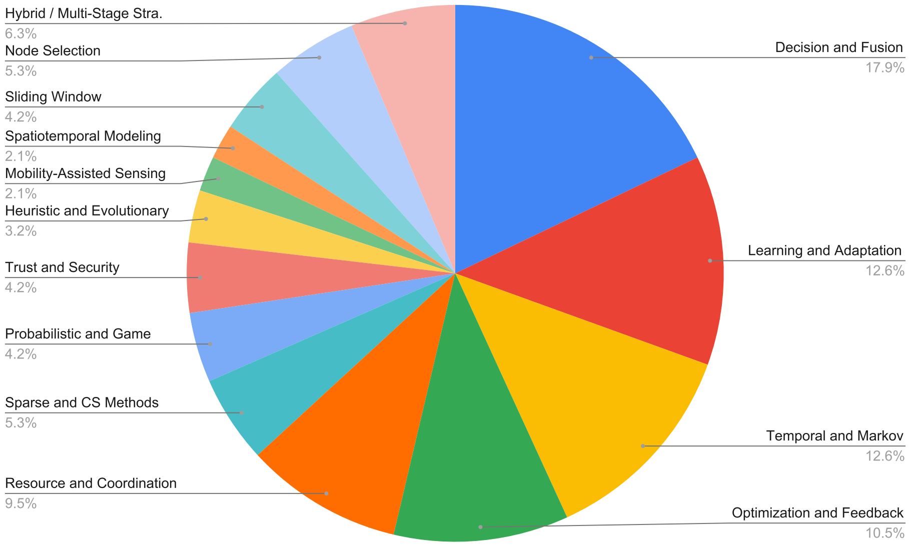

**Fig. 11.** Trends in dynamic handling in DSS.

both the radio environment and the dynamic context in which decisions unfold.

### 6.2.5. *Mechanisms for dynamic handling*

DSS systems must continuously adapt to the inherent environmental dynamics, temporal variability, and real-time constraints present in wireless communication environments. Across the surveyed literature, several dynamic handling mechanisms have appeared addressing changing spectral environments and PU activity. These span trust or reputation systems, adaptive thresholding, statistical inference, learning-based methods, probabilistic modeling, optimization, feedback control, and resource management (see Table 19 and Fig. 11).

Several studies emphasize *Trust and Reputation-Driven Mechanisms* as core dynamic elements. P01 [33] uses a distributed trust model with iterative observation and conflict resolution, P15 [68] adapts reputation windows and thresholds via interference feedback to counter malicious

**Table 19**
Dynamic handling mechanisms in Dynamic Spectrum Sensing (DSS).

| Mechanism | Article IDs |
|---|---|
| **Trust and Reputation-Driven Mechanisms** | P01 [33], P15 [68], P50 [83], P62 [64] |
| **Thresholding and Decision Fusion** | P01 [33], P02 [34], P03 [23], P04 [35], P07 [38], P09 [40], P10 [41], P11 [42], P13 [66], P16 [43], P35 [51], P36 [52], P37 [53], P38 [54], P42 [58], P50 [83], P60 [63] |
| **Statistical Modeling and Hypothesis Testing** | P02 [34], P03 [23], P04 [35], P09 [40], P19 [45], P34 [50] |
| **RL and Adaptive Decision-Making** | P05 [36], P12 [65], P20 [70], P21 [46], P46 [80], P48 [82], P54 [86] |
| **Markovian and Temporal Modeling** | P05 [36], P06 [37], P14 [67], P18 [44], P23 [71], P27 [32], P28 [75], P33 [49], P44 [60], P45 [79], P52 [85], P55 [87] |
| **Sparse Recovery and Compressive Sensing** | P08 [39], P10 [41], P11 [42], P30 [77], P53 [62] |
| **Feedback Control, Temporal Smoothing, and Optimization** | P07 [38], P13 [66], P16 [43], P26 [74], P36 [52], P39 [55], P42 [58], P43 [59], P50 [83], P60 [63] |
| **Control, Coordination, and Resource Management** | P02 [34], P04 [35], P09 [40], P13 [66], P14 [67], P15 [68], P16 [43], P17 [69], P51 [84] |
| **Probabilistic, Economic, and Game-Theoretic Models** | P23 [71], P24 [72], P25 [73], P29 [76] |
| **Heuristic and Evolutionary Approaches** | P47 [81], P49 [61], P56 [88] |
| **Spatiotemporal and Clustering Models** | P31 [78], P41 [57] |
| **Sliding Window Techniques** | P15 [68], P33 [49], P34 [50], P59 [91] |
| **Sensor/Node Selection and Clustering** | P30 [77], P31 [78], P38 [54], P41 [57], P61 [92] |
| **Multi-Stage / Hierarchical / Hybrid Strategies** | P13 [66], P14 [67], P24 [72], P30 [77], P33 [49], P49 [61] |
| **Mobility-Aided or UAV-based Sensing** | P20 [70], P43 [59] |

users, P50 [83] applies Bayesian reputation models for threshold and fusion weight adaptation; and P62 [64] integrates blockchain consensus for trust management within sensing cycles.

*Adaptive thresholding* emerges as a critical and widely applied mechanism. It is prevalent in P01 [33], P02 [34], P03 [23], P04 [35], P07 [38], P09 [40], P10 [41], P11 [42], P13 [66], P16 [43], P35 [51], P36 [52], P37 [53], P38 [54], P42 [58], P50 [83], and P60 [63], balancing detection accuracy and false alarms. Examples include energy detection with dynamic thresholds (P04 [35], P07 [38]), FFT sweep early termination (P16 [43]), CFAR-based threshold/sample size optimization (P35 [51]), and dual-threshold energy detection with censoring (P38 [54]).

Many studies address *Statistical Modeling and Hypothesis Testing* frameworks for dynamic sensing decisions. P02 [34] uses Maximum Likelihood Estimation for ON/OFF channel modeling; P03 [23], P04 [35], and P09 [40] rely on Gaussian and stochastic models, P19 [45] employs CuSum weighting for recent PU data emphasis, and P34 [50] integrates windowed DFTs and MMSE estimation for channel and decision fusion.

*Reinforcement Learning and Adaptive Decision-Making* frameworks feature prominently in dynamic handling. P05 [36] and P12 [65] use Q-learning and policy-gradient methods, P20 [70] applies multi-agent Q-learning with dynamic tuning, P21 [46] uses deep Q-networks (DQN/DDQN) with replay and $\epsilon$-greedy exploration, P46 [80] employs DDQSA with sliding windows and feedback, P54 [86] combines DQN with dropout and ACK feedback, and P48 [82] integrates auction-based bidding with RL.

*Markov Chains* and partially observable MDPs (POMDPs) underpin many temporal dynamic models, and they appear in P05 [36], P06 [37], P14 [67], P18 [44], P23 [71], P27 [32], P28 [75], P33 [49], P44 [60], P45 [79], P52 [85], and P55 [87]. P06 [37] couples Exp3 algorithm with Markov prediction, P14 [67] employs CTMCs for power/channel control, P33 [49] uses geometric forecasts from Markov ON/OFF models, P44 [60], and P45 [79] use MDPs with policy/value iteration, and P52 [85] models spectrum access as a POMDP with hypothesis testing.

Dynamic spectrum updates via *Sparse Recovery and Compressive Sensing* are explored in P08 [39], P10 [41], P11 [42], P30 [77], and P53 [62]. P08 [39] leverages joint sparsity and LS, P10 [41] uses Kalman filtering and $\ell_1$-minimization triggered by threshold exceedance, P30 [77] optimizes multiband sensing assignments via integer programming, and P53 [62] combines Bayesian inference, Markov processes, and adaptive thresholding for compressive sensing.

Several systems integrate *Feedback Control, Temporal Smoothing, and Optimization* for robust decisions. Temporal smoothing and feedback appear in P07 [38] (wavelet denoising), P13 [66] (reweighted sensing with broadcast feedback), P16 [43] (FFT sweep feedback). Optimization includes renewal theory-based sensing tuning (P26 [74]), interference control via log-concavity (P36 [52]), PSO acceleration (P39 [55]), gradient descent threshold tuning (P42 [58]), stochastic sensor activation (P43 [59]), and iterative threshold refinement (P50 [83], P60 [63]).

*Control and Coordination* frameworks manage sensing in networked environments. TDMA and control messaging in P02 [34] and P04 [35]; LTE stack modifications in P13 [66], AI decision-making with cooperative exchange in P17 [69]; dynamic power and mode control in P04 [35], P14 [67], and P51 [84], topology adaptation in P09 [40], as well as sliding window threshold and resource adaptation in P15 [68] and P16 [43].

*Probabilistic, economic and Game-Theoretic feedback* models add strategic layers. P29 [76] integrates cooperative sensing with auction-based access and blockchain consensus, P25 [73] employs Stackelberg and stochastic games to adapt incentives and boundaries, P24 [72] applies fusion-rule-based cooperative sensing adapting sensing times, and P23 [71] uses OFDM partial sensing with probabilistic parameters for overhead management.

*Heuristic Optimization and Evolutionary* algorithms contribute dynamic adaptation without explicit learning. P47 [81] applies genetic algorithms for channel assignment in response to PU events, P49 [61] surveys threshold adaptation techniques based on signal statistics, and P56 [88] uses stochastic resonance and nonlinear oscillators for dynamic signal enhancement.

For *Spatiotemporal and Clustering Models*, P41 [57] applies spatiotemporal modeling with adaptive Gaussian kernels and mean-shift clustering to form dynamic equivalence classes based on local density and time. P31 [78] uses dynamic clustering based on minimizing bit error rates and channel conditions with decision validation via RTS/CTS. In sum, DSS research employs a rich blend of trust systems, adaptive thresholding, statistical and temporal models, reinforcement learning, com-

**Table 20**
Main challenges addressed in Dynamic Spectrum Sensing (DSS).

| Application Domain / Context | Main Problems Addressed | Count | Article IDs |
|---|---|---|---|
| **Wideband Sensing / Partial Observability** | Compressive sensing under variable sparsity, DRL in partially observable environments, incomplete state information. | 10 | P05 [36], P06 [37], P10 [41], P11 [42], P19 [45], P24 [72], P27 [32], P52 [85], P53 [62], P54 [86] |
| **Learning-Based DSS and Decision Making** | Reinforcement learning, DRL, adaptive learning, Q-learning in unknown or changing environments. | 10 | P05 [36], P12 [65], P18 [44], P21 [46], P29 [76], P45 [79], P46 [80], P52 [85], P53 [62], P54 [86] |
| **Interference Mitigation and Coexistence** | Avoiding harmful interference, co-channel interference in NGSO/GSO satellites, interference with TVWS/GSM. | 8 | P03 [23], P17 [69], P21 [46], P32 [48], P40 [56], P52 [85], P56 [88], P59 [91] |
| **Threshold and Detection Strategy Design** | Dynamic/adaptive thresholds, CFAR, energy detection accuracy, sub-band detection tuning. | 8 | P16 [43], P32 [48], P35 [51], P37 [53], P49 [61], P55 [87], P58 [90], P60 [63] |
| **Sensing Overhead and Scheduling** | Reducing overhead, optimizing channel selection/sampling, joint relay selection, dynamic sampling rates. | 8 | P24 [72], P27 [32], P35 [51], P36 [52], P38 [54], P53 [62], P54 [86], P61 [92] |
| **Statistical Inference / Noise Handling** | Noise uncertainty, non-Gaussian noise, low-SNR environments, sensing error modeling. | 9 | P01, P32 [48], P35 [51], P37 [53], P49 [61], P54 [86], P55 [87], P56 [88], P58 [90] |
| **Spectrum Scarcity and Utilization** | Efficient reuse and allocation under scarcity, low-cost sensing for rural deployment. | 7 | P13 [66], P14 [67], P17 [69], P20 [70], P22 [47], P47 [81], P59 [91] |
| **IoT Limitations and Integration** | Low-cost hardware, limited SU sensing ability, constrained devices like in rural areas or TVWS). | 7 | P04 [35], P12 [65], P14 [67], P30 [77], P54 [86], P56 [88], P59 [91] |
| **Cooperative Sensing Optimization** | Fusion strategy optimization (MAP, threshold gain), probabilistic modeling, participation efficiency. | 7 | P09 [40], P28 [75], P38 [54], P39 [55], P42 [58], P57 [89], P61 [92] |
| **Mobility and Dynamic Networks** | Sensing with SU/PU mobility, dynamic channels (fading), aerial/satellite sensing. | 7 | P10 [41], P16 [43], P20 [70], P41 [57], P43 [59], P52 [85], P55 [87] |
| **Security and Malicious Behavior** | Spectrum sensing data falsification (SSDF, ISSDF), smart jamming, malicious SUs, false reports. | 6 | P01 [33], P15 [68], P33 [49], P48 [82], P50 [83], P62 [64] |
| **Energy Efficiency in Sensing** | Energy-constrained cooperative sensing, minimizing sensing energy, selective participation. | 5 | P04 [35], P13 [66], P30 [77], P38 [54], P43 [59] |
| **Dynamic PU Activity / Temporal Variability** | Time-varying PU activity, fading environments, sensing errors due to temporal shifts. | 5 | P19 [45], P31 [78], P44 [60], P54 [86], P55 [87] |
| **MAC Layer and Sensing Strategy** | Slot assignment, scheduling, MAC-sensing integration, frame-aware strategies. | 4 | P23 [71], P26 [74], P27 [32], P44 [60] |
| **Fairness, Sharing and SU Coordination** | Fair access, coordination under constraints, game-theoretic or auction-based sharing. | 4 | P06 [37], P21 [46], P28 [75], P47 [81] |
| **Remote / Space / Satellite DSS** | NGSO satellite sensing, satellite coexistence (NGSO vs. GSO), aerial/satellite DSS, long-distance dynamic sensing. | 4 | P20 [70], P41 [57], P46 [80], P52 [85] |
| **Virtualization, Incentives and Decentralization** | Incentive-compatible cooperative sensing, blockchain for decentralized DSS, virtual resource allocation. | 3 | P25 [73], P26 [74], P29 [76] |
| **PU/SU Synchronization and Protocol Uncertainty** | Asynchronous PU-SU interaction, unknown protocols, protocol timing misalignment. | 2 | P02 [34], P34 [50] |

pressive sensing, optimization, control protocols, game theory, heuristics, and clustering. These mechanisms balance accuracy, responsiveness, complexity, and robustness against noise, interference, and malicious attacks, enabling resilient spectrum sensing in dynamic wireless environments.

## 7. RQ3: What are the current challenges, limitations, and research opportunities in Dynamic Spectrum Sensing?

Despite significant progress in DSS research, various technical and contextual challenges continue to limit the efficiency, robustness, and scalability of current solutions. These limitations often arise from complex trade-offs between security, energy efficiency, environmental dynamics, and real-time constraints. Understanding these challenges not only highlights persistent research gaps but also reveals opportunities for developing more resilient, adaptive, and context-aware spectrum sensing frameworks. The following summarizes the most critical issues identified across the surveyed studies.

### *7.1. Technical and architectural challenges in DSS*

DSS encounters numerous technical, architectural, and environmental obstacles that complicate its practical deployment and limit its scalability in heterogeneous wireless environments (see Table 20). Security is a recurring concern, with persistent threats such as SSDF, intelligent SSDF (ISSDF), jamming attacks, and malicious SUs (P01 [33], P15 [68], P33 [49], P48 [82], P50 [83], P62 [64]). Cooperative spectrum sensing (CSS) is particularly susceptible to falsified reports, demanding more resilient and tamper-resistant fusion strategies [96,97].

A related architectural challenge is the assumption of perfect synchronization between PUs and SUs. As highlighted in P02 [34] and P34 [50], asynchronous DSA scenarios remain underexplored, despite their prevalence in large-scale decentralized CRNs. Interference management is another major hurdle in multi-band and multi-user contexts, with coexistence and mitigation strategies being critical for domains like TVWS, GSM, radar, and satellite communications (P03 [23], P17 [69], P21 [46], P32 [48], P40 [56], P52 [85], P56 [88], P59 [91]). Notably, MB-OFDM UWB systems struggle with narrowband incumbent interference (P03 [23]), and radar waveform similarity hinders accurate classification [98]. Energy constraints emerge prominently in CR sensor networks (CRSNs), where frequent full-node sensing depletes battery reserves (P04 [35], P13 [66], P30 [77], P38 [54], P43 [59]). Dynamic topologies exacerbate this, as continuous slot-wise re-optimization is unsustainable [99–101]. Wideband sensing and partial observability also pose substantial barriers (P05 [36], P06 [37], P10 [41], P53 [62]). Real-time sensing frameworks often integrate diverse toolchains like GNU Radio and MATLAB, introducing processing latency [102]. Detection reliability suffers from threshold sensitivity and the lack of prior signal knowledge in blind sensing methods [14].

Temporal and geographical dynamics further challenge DSS. Articles P19 [45], P31 [78], P44 [60], and P55 [87] address the necessity for robust detection under time-varying fading, which traditional static PDFs cannot handle effectively [103]. In some regions, outdated regulations and legacy business models prevent spectrum sharing despite demonstrated underutilization ([90,104]). The integration of DSS with IoT intensifies these challenges, requiring low-cost, low-power yet high-reliability sensing (P04 [35], P12 [65], P14 [67], P30 [77], P54 [86], P56 [88], P59 [91]). In M2M scenarios, overloaded unlicensed bands lead to QoS degradation [105], while local sensing remains vulnerable to fading, shadowing, and hidden terminals [106,107]. Optimization of cooperative sensing, fusion strategies, and participant incentives are actively explored (P09 [40], P28 [75], P38 [54]). Learning-driven DSS techniques, including RL, DRL, and Q-learning, enable adaptive sensing under uncertainty (P05 [36], P12 [65], P18 [44], P45 [79], P46 [80]); however, nature-inspired methods such as swarm optimizers can destabilize under dynamic conditions [108]. Advanced detection methods like CFAR and adaptive thresholding (P16 [43], P32 [48], P35 [51]) aim to improve performance but remain vulnerable to sophisticated attacks like smart jamming (P33 [49]). Mobility and environmental dynamism (P10 [41], P16 [43], P20 [70]) add further complexity by introducing channel non-stationarity and complicating MAC-level coordination (P23 [71], P24 [72], P26 [74], P35 [51], P54 [86]). Finally, resilience to noise and low-SNR contexts (P01 [33], P35 [51], P49 [61]), fairness in spectrum sharing (P06 [37], P21 [46], P28 [75]), and novel contexts like aerial or satellite-based DSS (P20 [70], P41 [57], P46 [80], P52 [85]) underline the multifaceted challenges that must be systematically addressed.

### 7.2. Systemic and practical limitations in DSS

Despite progress, DSS research faces enduring systemic limitations that restrict real-world applicability. Asynchronous coexistence remains largely unsupported, rendering MB-OFDM and similar systems vulnerable (P03 [23]). Power-intensive sensing operations continue to challenge CR-IoT nodes [105,109], with narrowband sensing further constrained by low-SNR performance and high computational cost [110]. Wideband sensing struggles with RF front-end limitations, intermodulation, and scanning inefficiencies [25,111]. Cyclostationary methods, while accurate, are resource-hungry and slow [112]. LTE and 5G architectures are not yet optimized for massive low-power IoT scenarios [113–115].

Cooperative approaches unrealistically presume perfect inter-node channels [116,117]. PSO remains misapplied in several studies [108, 118–121]. Clustering techniques like DBSCAN and DPC suffer from parameter sensitivity and rigid structural assumptions [122,123]. Static sensing is inadequate for dynamic CRSNs [124–128]. Satellite DSS models oversimplify detection probability and neglect errors [129,130]. Trust and reputation mechanisms lack robustness against adaptive attackers [131–133].

Cognitive link variability is often ignored or poorly captured [28]. Stochastic Resonance–based Spectrum Sensing (SRSS) approaches, while promising for enhancing detection under low SNR conditions, remain impractical for large-scale deployment due to their sensitivity to environmental variability and parameter tuning requirements [134]. Energy detection cannot reliably distinguish between noise and weak PU signals when noise uncertainty exceeds a small threshold, a limitation known as the *SNR wall* [19,135]. More advanced methods require known PU signal models [136] which may be unavailable (P58 [90]). Single-node ED is vulnerable to fading and shadowing [137,138]. SUs must halt transmissions during sensing, impacting real-time applications. Licensing frameworks further constrain entry into licensed bands, while unlicensed bands lack reliability for high-QoS uses [14]. Finally, most algorithms remain designed for static conditions, with limited adaptability for mobile or dynamic topologies [18]. Security-enhanced fusions and trust-weighted schemes exist [139,140] but still fall short in adversarial contexts [141].

**Key Challenges, Limitations, and Opportunities**

- **Security and Robustness:** Persistent threats (SSDF, jamming, malicious SUs); need resilient cooperative fusion (P01 [33], P15 [68], P33 [49], P48 [82], P50 [83], P62 [64]).
- **Synchronization and Coexistence:** Lack of asynchronous coexistence mechanisms; interference in multi-band settings (P02 [34], P03 [23], P34 [50]).
- **Energy Constraints:** High sensing overhead in CRSNs and IoT; trade-offs between coverage and node lifetime (P04 [35], P13 [66], P30 [77], P38 [54], P43 [59]).
- **Wideband and Partial Observability:** Latency and inefficiency due to multi-toolchain processing; poor performance under unknown signals (P05 [36], P06 [37], P10 [41], P53 [62]).
- **Dynamic Environments:** Ineffective static models for time-varying fading; geographical and policy barriers (P19 [45], P31 [78], P44 [60], P55 [87], P58 [90]).
- **Learning-Based Limitations:** RL/DRL instability in highly dynamic contexts; nature-inspired methods prone to swarm discontinuity (P05 [36], P12 [65], P18 [44], P45 [79], P46 [80]).
- **Detection Strategies:** Challenges with adaptive thresholding, CFAR, and virtualization; jamming vulnerabilities (P16 [43], P32 [48], P33 [49], P35 [51]).
- **Mobility and Coordination:** Non-stationary channels and user movement degrade reliability; MAC layer and scheduling inefficiencies (P10 [41], P16 [43], P20 [70], P23 [71], P24 [72], P26 [74], P35 [51], P54 [86]).
- **Trust and Reputation:** Outlier and reputation systems fail under dynamic malicious strategies; reliance on trusted nodes (P09 [40], P28 [75], P38 [54]).
- **Special Contexts:** Challenges unique to satellite, aerial, and remote DSS scenarios (P20 [70], P41 [57], P46 [80], P52 [85]).

## 8. Conclusions

DSS remains a critical enabler of efficient and intelligent spectrum usage in CRNs. This survey has provided a comprehensive and structured review of DSS research published between 2005 and 2024, highlighting how the field has evolved in response to technological advances and the growing complexity of wireless environments. By systematically analyzing 62 primary studies, we identified the core application domains, sensing strategies, technologies, and evaluation methods that define current DSS practices. We further examined how DSS systems address challenges related to temporal variability, mobility, and real-time decision-making. Our findings reveal both a maturity in certain areas, such as machine learning-based detection and cooperative sensing, as well as significant gaps in areas like cross-layer integration, large-scale deployments, and temporal modeling.

We conclude that future research should prioritize resilient, energy-aware, and learning-stable DSS solutions that adapt to mobility, coexistence, and adversarial environments while extending applicability to satellite, aerial, and IoT contexts. Equally important is a stronger emphasis on environmental adaptability, deployment realism, and performance reproducibility, supported by standardized benchmarks and interdisciplinary approaches. This survey thus serves as both a reference and a call to action for advancing robust and scalable DSS solutions in increasingly demanding wireless ecosystems.

## CRediT authorship contribution statement

**Mariana Falco:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization; **Antonio Scarvaglieri:** Writing – review & editing, Data curation, Conceptualization; **Fabio Busacca:** Writing – review & editing, Validation, Investigation, Conceptualization; **Farzam Nosrati:** Visualization, Validation, Data curation; **Daniele Croce:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition, Formal analysis, Data curation, Conceptualization.

## Data availability

Included in the article

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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