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A Comparative Review of Intelligent Spectrum Management Systems as Information Services for Wireless Campus Networks and Library Connectivity

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ABSTRACT

Wireless devices, Internet of Things (IoT) applications, and digital information services are rapidly growing – with increased spectrum demand in university campuses and smart libraries. Intelligent spectrum management offers adaptive functions to enhance spectrum efficiency, mitigate interference, and ensure reliable connectivity in complex and crowded wireless networks. The conventional spectrum allocation, dynamic spectrum access, cognitive radio, machine learning, deep learning, reinforcement learning, and edge-assisted spectrum management techniques are comparatively analyzed in this review. The following characteristics of the reviewed systems are evaluated: spectrum utilization, spectral efficiency, throughput, latency, interference mitigation, energy efficiency, scalability, adaptability, and computational complexity. Their applications in campus Wi-Fi, IoT infrastructures, RFID based Libraries, Multimedia access and cloud based information services are given special consideration. Real-time adaptation, heterogeneous network coexistence, scalability, explainability, security, and practical deployment are identified as the limitations and future directions towards an autonomous, context-aware and AI-driven spectrum management in next-generation smart campus environments are highlighted.

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1. INTRODUCTION

The age of wireless connectivity has become a part and parcel of universities and educational institutions, which include communication system used in academic communication, digital learning, research work, administration works and access to online information resources. Spectrum demand is significantly growing in campus environments as the number of smartphones, laptops, Internet of Things (IoT) devices, laboratory equipment and smart-campus applications continue to proliferate. Electronic databases, cloud-based resources, multimedia offerings, RFID-based services, and other information services are further dependent on reliable wireless connectivity in modern "digital" and "smart" libraries. These diverse applications generate very dynamic traffic and put significant strain on the spectrum resources that are available for wireless applications.

Slowly changing environments can make conventional static spectrum allocation insufficient due to changes in user density and requirements, as well as network traffic levels, which may lead to spectrum congestion, interference, underutilized spectrum elements and inefficient resource allocation. These are overcome by intelligent spectrum management which is a dynamic approach that observes spectrum conditions and allocates the appropriate spectrum resources as required by network demand. Dynamic spectrum access, cognitive radio allows opportunistic and adaptive spectrum utilization, and Artificial Intelligence (AI) and Machine learning (ML) offer capabilities in spectrum sensing, occupation prediction, detecting interference, selecting spectrum channels and allocating resources. They can enhance the use of limited spectrum while maintaining

information throughput, latency, reliability and quality of service.

Previous reviews typically do not focus on the application of cognitive radio, spectrum sensing, dynamic spectrum access, or AI in wireless resource management, but rather only on one of them, and the convergence of these technologies into a single framework is generally not explored. In order to identify their strengths and weaknesses, scalability, adaptability and suitability to practice, a consolidated comparison is required. This review compares key intelligent spectrum management systems, focusing on intelligent wireless campus networks and smart library connections. It defines trends in technology, performance, research gaps and new directions to autonomous spectrum management. The methodology of the review, the technology classification, technology requirements for applications and the comparative results, together with future research directions, are then presented followed by the conclusions.

2. Review Methodology

This review uses a systematic approach to find the literature, to categorize it and to comparatively evaluate it with regard to intelligent spectrum management in wireless campus networks and smart library connectivity. Spectrum-sensing developments that have already taken place offer a useful starting point for spectrum-sensing assessment if intelligent wireless resource utilization is to be evaluated. Development on spectrum sensing is already available that can serve as a foundation for evaluating the spectrum sensing if intelligent wireless resource utilization is to be evaluated [1]. Smart-campus frameworks set the higher-level techno-service demands of connected learning setting [2]. More recently, AI-based spectrum sensing studies show that intelligent approaches are becoming more and more important for spectrum sensing and decision support [3]. Emerging challenges and research opportunities in the ongoing development of dynamic spectrum sensing are also evident [4]. The review goals are to explore the existing spectrum-management methods, understand how AI and ML are impacting spectrum sensing and allocation, and understand their applicability to dense campus wireless deployments. Cooperative sensing and sharing with the assistance of ML becomes a very relevant aspect in this evaluation [5]. The second direction for studying the intelligent and adaptive communication mechanisms is done through the ML paradigms for next generation of wireless networks [6]. The requirements of smart-library connectivity are addressed in particular, and the differences between existing approaches, considering their performance, scalability, adaptability, and computational complexity, are discussed.

Literature search refers to relevant peer reviewed publications from within the selected review time period. Digital infrastructure for smart-campus, which integrates a variety of wireless and connected services, offers an important application context for search [7]. Another core research line investigated in the review is the intelligent spectrum management based on reinforcement learning [8]. Search strings include terms like "intelligent spectrum management," "dynamic spectrum access," "cognitive radio," "AI-based spectrum allocation," "machine learning spectrum sensing," "campus wireless networks," "Wi-Fi," "IoT connectivity" and "smart library networks. Some ML-based cooperative spectrum-sensing studies are captured to obtain intelligent sensing progress advancements [9]. IEEE Xplore, Scopus, Web of Science, ScienceDirect, SpringerLink, and Google Scholar are used for literature search. The results of the search are increasingly limited in scope based on the relevance of the search to the formulated research questions and research scope.

Items eligible for this call for papers are peer-reviewed journal articles and conference papers that discuss intelligent spectrum management, cognitive radio, dynamic spectrum access, AI/ML-based spectrum decisions, Wi-Fi, IoT, campus networks, or smart-library connectivity. A deep reinforcement learning based adaptive spectrum access is also incorporated for its significance as an adaptive spectrum access technique [10]. The contribution of recent research and current technical difficulties are also included in the modern research of spectrum-sensing using cognitive radio, which is considered in [11]. The studies that apply deep reinforcement learning to the dynamic spectrum access problem give evidence for autonomous spectrum decisions as well [12]. To showcase the application and deployment needs of connected academic spaces, smart-campus IoT research is included. Duplicate publications, work outside the wireless spectrum range, too vague papers and non-relevant articles are not included. Study selection includes first identification, duplicate removal, title/abstract screening, full text eligibility screening and final inclusion.

Information is gathered and classified for the selected study including key findings, limitations reported, performance measures, evaluation method, network environment, intelligence technique, spectrum-management method and wireless technology. The adaptive cognitive-radio network management (RANM) is studied with the consideration of reinforcement learning-based dynamic spectrum allocation [14]. Then, compared with what is evaluated are the use of the spectrum, the efficiency of the use, throughput, latency, interference management, quality of service, energy efficiency, scalability, adaptability and computational complexity. In smart-campus applications, the practical connectivity and service

demands are also taken into account for wireless IoT applications [15]. This approach allows for the uniform comparison of intelligent spectrum-management approaches, and their applicability in real-world campus and smart-library wireless information services.

3. Evolution And Intelligent Spectrum Management Technologies

3.1 Conventional and Static Spectrum Management

The conventional spectrum management is based on fixed spectrum allocation: Fixed frequency bands or channels are allocated to a certain wireless technology or service. In campus interior networks, access points are typically configured as a static network of channels that do not change willy-nilly until manually or centrally reconfigured. These types of arrangements are easy to implement and convey predictable resource control, so they are adequate for considerably steady wireless environments. Centralized management can also ensure that channel assignments, transmission parameters and configurations of access points are coordinated between several locations.

However, the fixed allocation is not sufficiently suitable to cope with the highly variable traffic condition existent in modern universities. The density of users varies significantly across classrooms, laboratories, libraries, hostels and common areas and at different times of the day or year, creating varying spectrum demands at different locations and times of day and year. Lightly-used channels could be heavily congested in other sections of the network. It is therefore possible for the spectrum to be underutilized as well as for there to be a deficiency of resources in certain areas due to static assignments.

In the presence of Wi-Fi devices, IoT nodes, RFID systems, multimedia service and other wireless applications, these limitations are more profound. Centralized traditional solutions can detect congestion, but typically do not offer much intelligence for inferring spectrum utilization, or for dynamically fine-tuning allocation based on evolving network conditions. In such traffic conditions, therefore, interference, latency, throughput loss and non-uniform quality of service may result. The lack of these features has prompted the shift away from static spectrum allocation and towards technologies involving dynamic use, cognitive resource management and learning, which can capture network conditions and adjust spectrum resources according to current network needs for connectivity.

3.2 Dynamic Spectrum Access and Cognitive Radio

Dynamic Spectrum Access (DSA) is a technique that is more flexible than static spectrum allocation, which enables wireless systems to detect and make use of spectrum resources as the network requirements change at runtime. DSA allocates channel opportunities dynamically rather than reserving spectrum for permanent use, and hence makes better use of the spectrum in scenarios where the number of users and traffic demand varies over time. Cognitive Radio (CR) extends this capability by adding sensing, decision making and reconfigurable communication capabilities into wireless devices so they can intelligently adapt to changes in the spectrum environment around them.

Spectrum sensing is a key element in cognitive radio, and is employed to detect the occupation of channels, the strength of the interference signals and the opportunities to use the spectrum. Cooperative or cooperative/individual sensing mechanisms can be used to help identify appropriate channels prior to transmission. Based on the result of sensing, the decision of the spectrum is made by evaluating the available channels based on certain parameters like bandwidth, interference, signal quality, traffic demand, quality of service etc. The chosen bandwidth resources can then be allocated to users or services based on network requirements.

When more than one user, device or wireless service uses the same resources, they must share them with one another (coordinate access). The right sharing methods can prevent interferences and ensure a fair distribution while maintaining a connection between different heterogeneous applications. Spectrum mobility additionally enables an active connection to be moved from one channel to another if there is an increase of interference, poor channel quality, or if a channel is no longer available. The features are very important for the dense-campus or smart-library environments, where spectrum needs can change rapidly due to the presence of Wi-Fi, IoT, RFID, mobile and multimedia services. Nevertheless, there are challenges in terms of sensing accuracy, decision latency, coordination overheads, and regular switching of the spectrum, which is a driving factor for the development of more intelligent spectrum management approaches by employing AI- and ML-assisted methodologies.

3.3 AI and Machine Learning-Based Spectrum Management

The combination of artificial intelligence (AI) and machine learning (ML) technologies improves spectrum management by allowing wireless systems to learn from the past and current network condition, which goes beyond simply following existing allocation rules. Combining labeled observations of channel occupancies, traffic and interference patterns, supervised learning techniques can be applied to classify the states of spectrum usage and to predict

suitable spectrum resources for communication. When network conditions and user behavior differ significantly from campus environment to campus environment, unsupervised learning can help discover hidden patterns or clusters within the spectrum measurements without needing the use of predefined labels.

Occupancy prediction is a crucial ML-enabled function in which previously used spectrum is monitored and information about traffic and spectrum use is used to estimate future spectrum availability. By predicting accurately, the network controllers can foresee congestion and allocate channels before the quality of the service gets affected. Learned information on signal quality, channel availability, interference and traffic demand also is used by intelligent channel selection to determine appropriate communication channels to support various users and applications. Such adaptive selection can help achieve better utilization of the available resources than if only fixed selection or strict sensing-based selection was used.

Machine learning can also play a role in interference prediction by discovering associations between the activity in the network, device density, channel usage and measured interference. In the event that channel interference is possible, it is possible to plan ahead for interference events and optimize the resources accordingly, potentially enhancing throughput, latency, and connection quality. These features are beneficial in wireless campus and smart library applications where wireless access points, IoT devices, RFID systems and mobile users are in the vicinity. However, ML-based spectrum management still requires training data to represent the network, the accuracy of the model, computational power in the system, and the ability to adapt to new network changes, and further research and development of the deep learning and reinforcement learning technologies are needed.

3.4 Deep Learning and Reinforcement Learning

Deep learning (DL) takes intelligent spectrum management one step further by learning complex relationships between spectrum occupancy, traffic behavior, signal conditions and interference patterns. Deep Neural Networks (DNNs) can be used for modelling the non-linear relationship between network observations and spectrum decisions, and Convolutional Neural Networks (CNNs) can be used to extract relevant features from spectrum measurements and time-frequency representations. Recurrent Neural Networks (RNNs) have been proven to be well suited for sequential spectrum analysis and predicting temporal variations of channel utilization. These methods can be used in dynamic wireless environments for spectrum sensing, interference classification, traffic prediction and adaptive channel selection.

Another way is reinforcement learning (RL), which continuously interacts with the wireless environment to learn better decisions for spectrum management. Q-Learning allows an agent to make a channel or spectrum resource selection based on network observations and rewards received for past actions. Reward functions may include the use of the spectrum, the throughput, the interference level, latency or quality of service requirements. With a large number of network states and potential spectral choices however, conventional Q-learning becomes challenging.

Deep Reinforcement Learning (DRL) is an extension of deep neural networks and reinforcement learning that assists in decision making for larger and more complex spectrum environments. It does not need to explicitly model all possible network conditions, and can learn adaptive allocation policies. Multi-Agent Reinforcement Learning (MARL) also allows multiple access points, users, or network controllers to multi-agently coordinate spectrum decisions in distributed environments. This is useful in large campus networks, smart libraries with many devices interacting through wireless technology. While the DL and RL approaches offer great promise, there are challenges with training, computational burden, convergence, explanation, coordination of agents, and reliable deployment in real-time.

3.5 Edge and Software-Defined Spectrum Intelligence

SDN/edge-assisted networking methods continue the concept of intelligent spectrum management by decoupling the intelligence from baseline hardware configuration, allowing flexible control of wireless resources. With Software-Defined Radio (SDR) functions like modulation, channel selection, filtering and even spectrum sensing can be changed by software, rather than hardware changes. The flexibility is useful in campus settings with different spectrum conditions in classrooms, laboratories, libraries, hostels, and common areas, as well as different requirements for the services provided. Software-Defined Networking (SDN) is another feature that complements SDR and gives the network a central view and network control programmability. The SDN controller will be able to gather network-state data, orchestrate access points, control traffic flows, and make dynamic spectrum decisions based on traffic, channel occupancy and interference.

With the introduction of edge-assisted spectrum intelligence, sensing analysis and decision making have come closer to users and wireless access points. The edge nodes benefit from lower communication delay when it comes to processing spectrum occupancy, interference, traffic demand and QoS information. It

has special importance for smart-library services, the campus Internet of Things (IoT), multimedia services and other services with latency requirements. Distributed spectrum intelligence also allows for multiple access points, edge nodes or wireless agents to be involved in decisions about the resources allocated via these approaches, which reduces reliance on a single central controller and enhances responsiveness. But there are still some challenges to consider, such as implementation overhead, synchronisation, consistent decisions among controllers and controller security.

The steps from traditional static allocation to dynamic spectrum access, cognitive radio, and AI/ML, and deep or reinforcement learning, are briefly explained in Figure 1. Development of more predictive, adaptive and autonomous spectrum-management mechanisms as illustrated in the taxonomy. Edge and software-defined intelligence further propel this evolution by adding programmable and distributed intelligence, which can enable real-time spectrum decisions near the network user.

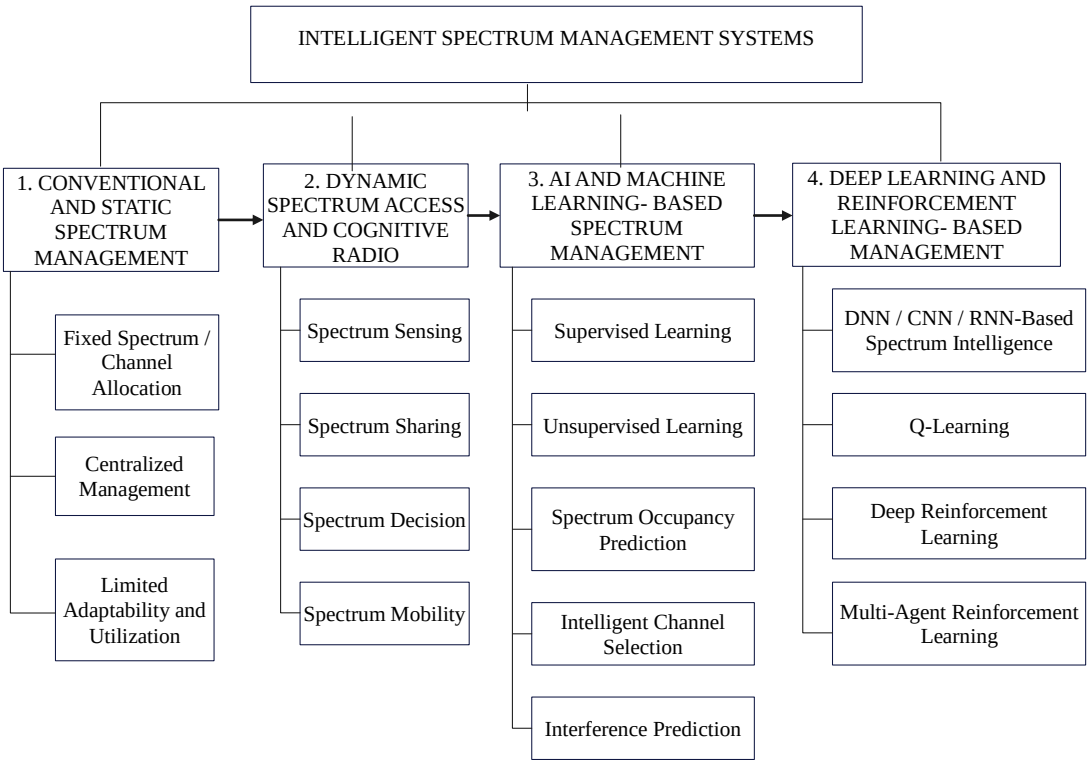


Fig. 1. Taxonomy and Evolution of Intelligent Spectrum Management Systems

The approaches vary significantly in terms of sensing capability, decision mechanism, adaptability, implementation complexity, advantages and limitations, although the technological evolution is presented in Figure 1. These characteristics are comparatively summarized in Table 1.

Table 1. Classification of Intelligent Spectrum Management Approach

Approach	Spectrum Sensing	Decision Mechanism	Adaptability	Complexity	Major Advantage	Limitation
Conventional/static allocation	Limited or none	Predefined channel assignment	Low	Low	Simple implementation and predictable control	Inefficient under dynamic traffic and congestion
Dynamic Spectrum Access	Yes	Availability-based channel selection	Moderate	Moderate	Improves spectrum utilization	Depends on reliable sensing and coordination
Cognitive Radio	Yes	Context-aware spectrum decision	High	Moderate to high	Supports sensing, sharing, mobility, and adaptation	Sensing errors and switching overhead

AI/ML-based management	Yes	Data-driven prediction and classification	High	Moderate to high	Enables occupancy and interference prediction	Requires representative training data
Deep learning-based management	Yes	Learned nonlinear decision model	Very high	High	Handles complex spectrum patterns	High computational and training requirements
Reinforcement learning-based management	Yes	Reward-based adaptive decision	Very high	High	Learns dynamic spectrum-allocation policies	Convergence and exploration challenges
SDR/SDN-based management	Yes	Programmable centralized control	High	Moderate to high	Flexible reconfiguration and network-wide coordination	Controller dependence and integration complexity
Edge/distributed intelligence	Yes	Local or cooperative decision-making	Very high	High	Low latency and improved scalability	Coordination, synchronization, and security issues

4. Intelligent Spectrum Management For Campus Networks And Smart Libraries

4.1 Campus Wireless Environment and Spectrum Challenges

A university campus is a wireless environment of great dynamism where many users and many devices access the network in many classrooms, laboratories, libraries, hostels, administrative buildings and common spaces. High-density connectivity is further charged with constant user mobility as the students and staffs are constantly moving from one place to the other in relation to different access points. Campus networks are consequently required to support the different types of smartphones, laptops, tablets, IoT nodes, sensors, laboratory equipment and institutional devices all communicating differently and having varying traffic patterns.

Also, there is significant variation in wireless demand based on academic schedules, type of applications, etc. The load on the learning platform as well as video conferencing, multimedia streaming, cloud applications, digital library services, administrative services and IoT-based campus services can produce very dynamic load patterns. Generally, in such environments as high traffic areas, high density deployment of access points is necessary to ensure coverage and capacity; however, high density deployment of access points can cause co-channel and adjacent-channel interference problems if spectrum resources are not managed properly. This large-scale simultaneous device access can then result in channel congestion, throughput decrease, latency, and poor service quality.

Spectrum demand also is very time dependent. Peak network usage can occur during lecture periods and examinations, during times of institutional events, or during the peak hours when the library is open, or during shared laboratory sessions, but not during other times of the day. Static channel assignments are thus unable to have a responsive reaction to the changing spatial/temporal demand. There is need for intelligent use of the spectrum to observe channel conditions, identify interference and congestion, and dynamically allocate wireless resources, based on real-time requirements. Dynamic channel allocation and interference-aware decision making can better utilize spectrum, alleviate local congestion, and help provide for more reliable connectivity when multiple technologies are deployed in a heterogenous campus environment.

4.2 Heterogeneous Connectivity and Smart Library Services

Most campus environments will use the Wi-Fi as the main access infrastructure for the campus, offering academic platforms, administrative applications, digital resources and Internet access. At present, campus settings are becoming more complex and heterogeneous communication spaces that include not just Wi-Fi, but other IOT technologies such as cell phones and numerous other innovations. The integration of other 6G capabilities and 5G will further enable high capacity and low latency, context-aware campus services. In the smart classroom and smart lab, the deployed IoT sensors can be used to monitor sensors, detect the occupancy, sense environment and control

automatically, and the wireless building-management system can be used to control the lights, energy management, security and building automation.

Smart libraries constitute one of the most significant aspects of this complex landscape, as information services rely more and more on the need for continuous wireless access. Users need access to information services (electronic journals, digital repository, institutional databases, e-books, cloud-based library platform and remote information services). The use of these high bandwidth applications, such as multimedia learning resources, video content, virtual collaboration and others can significantly affect network demand, especially at high library occupancy. This is because reliable availability of the spectrum is essential in order to ensure acceptable information-access performance and continuity of service.

Wireless technologies can also facilitate the management of the smart-library resources in the physical world. Circulation systems are enhanced by RFID technology to aid with identification, borrowing, return and inventory operations, smart shelves assist with resource control and asset track and wireless systems make it easier to keep track of resources. Environmental IoT Sensor can perform continuous monitoring of temperature, humidity, light, occupancy and other conditions in the buildings. Users have multiple devices, access points, RFID infrastructure, IoT sensors, cell phone services and cloud-connected applications running simultaneously, thus presenting a variety of requirements for the spectrum and QOS. There is, therefore, a need for coordinated intelligent spectrum management, to minimize the interference problem, to allocate resources as per the demand for such service, and to ensure reliable connectivity between services of a heterogeneous campus and smart-library.

4.3 QoS-Aware Intelligent Spectrum Management

However, in campus and smart-library networks there are significantly different communication requirements of different applications requiring Quality-of-Service (QoS) aware spectrum management. Resources in spectrum should thus be assigned based Though high throughput is important for data-intensive services like multimedia streaming, digital repositories, cloud-based learning platforms and video conferencing, it is perhaps low latency and stable connectivity that are key factors for interactive applications and real-time institutional services. on application type, traffic level and service priority, and not uniformly assigned to a channel.

Reliable communication and continuous service availability is also essential for applications such as IoT monitoring, tracking and tracing (RFID), building automation and security.

In addition to assisting high bandwidth applications, the QOS-aware management needs to ensure fairness between users and devices, and avoid any single application using up so much bandwidth that it consumes a disproportionate share of the spectrum. Delay-sensitive and institutionally critical services can get higher priority for traffic prioritization, and channel selection that considers interference can minimize co-channel and adjacent-channel conflicts in systems that are densely deploy with access-points. These adaptive channel allocation methods can then allocate channels, bandwidth or transmission opportunities in response to the congestion level, the application's requirements, and the current level of the spectra. These capabilities are especially useful during high-demand learning time when classrooms, labs, common spaces and libraries can be subject to heavy wireless traffic.

AI- and ML-driven solutions complement QoS-aware spectrum control by forecasting when congestion may occur, when channels are available, interference and traffic patterns, and when degradation could occur before it does. These forecasts can help in channel reassignment and resource allocation (before the problem even starts), rather than just managing it reactively after it has occurred. But with more intelligence also comes computational and signaling overhead which makes it necessary to also consider the service performance of a system and the complexity of the decision to be made along with the efficiency of the system for the purposes of the use of the spectrum. The interdependency of campus applications, smart-library services, intelligent spectrum control, heterogeneous wireless technologies, and network infrastructure is demonstrated in Figure 2. Its architecture focuses on the key functions of architecture, namely spectrum monitoring, interference detection, channel selection, dynamic channel allocation, and QOS-aware decision making.

Campus and smart-library applications have different demands and quality of service priorities; thus, they must be considered individually. Table 2 lists examples of the common services and gives an overview of their connectivity features, the main spectrum issues, and the associated QoS needs.

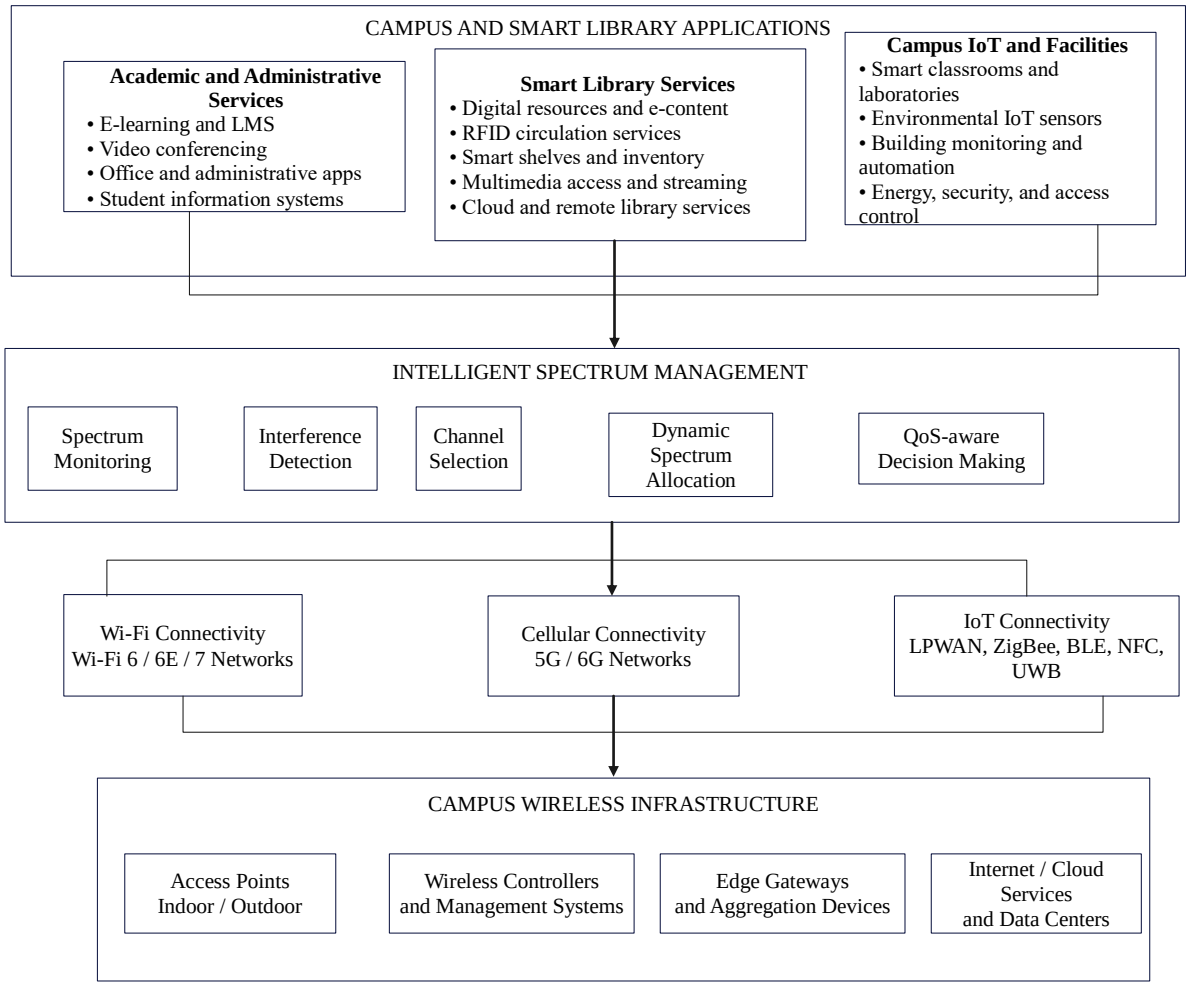


Fig. 2. Intelligent Spectrum Management for Campus and Smart Library Networks

Table 2. Wireless Campus and Smart Library Applications with Spectrum and QoS Requirements

Application / Service	Wireless Technology	Traffic Requirement	Major Spectrum Challenge	Primary QoS Requirement	Suitable Spectrum Management
E-learning and LMS access	Wi-Fi 6/6E/7	Moderate and continuous data traffic	High concurrent user density	Reliability and throughput	Load-aware dynamic channel allocation
Video conferencing and virtual classrooms	Wi-Fi / 5G	High-bandwidth interactive traffic	Congestion and interference	Low latency and high throughput	QoS-aware interference-sensitive allocation
Smart classrooms and laboratories	Wi-Fi / IoT / 5G	Mixed sensor and application traffic	Heterogeneous device coexistence	Reliability and adaptability	Context-aware spectrum coordination
Digital library resources	Wi-Fi	Moderate-to-high data access	Peak-hour congestion	Throughput and availability	Demand-responsive channel allocation
Multimedia and cloud library services	Wi-Fi / 5G	High-volume multimedia traffic	Bandwidth competition	High throughput and low delay	Traffic-priority-based spectrum allocation
RFID circulation and smart shelves	RFID / NFC	Low-volume periodic traffic	Coexistence with nearby wireless systems	Reliable connectivity	Interference-aware resource coordination
Environmental monitoring	IoT / BLE / ZigBee / LPWAN	Low-rate periodic sensing	Large numbers of connected sensors	Energy efficiency and reliability	Lightweight adaptive spectrum access
Building automation and security	IoT / Wi-Fi / Cellular	Periodic and event-driven traffic	Interference and service contention	Low latency and service continuity	Priority-aware spectrum management
Wireless asset tracking	BLE / UWB / RFID	Frequent short-range transmissions	Dense device interaction	Reliability and positioning continuity	Dynamic interference-aware channel selection

Administrative and institutional services	Wi-Fi / Cellular	Moderate transactional traffic	Variable campus-wide demand	Availability and fairness	Adaptive QoS-based resource allocation

Compared to bandwidth intensive services, which typically demand throughput oriented management, IoT, RFID, and security services are more focused on reliability and/or latency or energy efficiency. Automation services are more focused on reliability and/or latency or energy efficiency. So intelligent spectrum management should not optimize a single spectrum metric; rather, it should adjust resources based on the differences in the QoS requirements of campus applications and smart-library applications.

5. Comparative Assessment And Future Outlook

The concept of intelligent spectrum management has progressed from a fixed spectrum allocation towards adaptive, predictive and distributed spectrum management. Static allocation is simple and efficient, but doesn't react well to variable traffic and interference. Dynamic Spectrum Access (DSA) provides channel reassignment to enhance the utilization; Cognitive Radio (CR) provides spectrum sensing, sharing, decision and mobility. Optimization based methods distribute the spectrum based on throughput, interference, power or QoS criteria. Machine Learning (ML) can be applied for spectrum prediction and intelligent channel selection while Deep Learning (DL) is for more complex spectrum patterns and requires more computational resource. On the one hand, Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) can be used for adaptive decision-making, and on the other hand, Multi-Agent Reinforcement Learning (MARL) can be used for cooperative spectrum allocation. Further decision latency reduction is achieved by Edge-assisted approaches featuring local processing.

The metrics for the estimation of performance should include spectrum utilization, spectral efficiency, throughput, latency, interference mitigation, packet delivery, and energy efficiency. For the actual deployment, computational demands, scalability, real-time requirements, device density and adaptability are additional. Learning based techniques tend to be more flexible; however, they bring overheads of training, processing and coordination. Table 3 represents some representative findings of the investigated approaches.

Table 3. Comparative Assessment of Intelligent Spectrum Management Studies

Study	Method	Network / Technology	Metrics	Reported Findings	Limitation	Applicability
Kaur and Kumar (2020)	RL	Cooperative CR	Spectral efficiency, throughput, utilization	Supports adaptive utilization of available spectrum	Learning and coordination requirements	High
Li et al. (2022)	DQN-based DSA	CR with FDMA/NOMA	Throughput, interference	DQN-NOMA provides better throughput and interference handling than DQN-FDMA	Training complexity	High
Usage-aware DSA (2022)	DRL	Interweave CR	Access success, interference	Traffic and channel-use patterns improve access decisions	Simulation-based	Moderate-High
Actor-Critic DSA (2022)	TD3-DRL	Cognitive spectrum sharing	Information rate, conflicts, power	Learns adaptive channel and power allocation	Processing complexity	High
Giri and Majumder (2023)	Multi-agent DRL	Distributed CR	Throughput, collisions	Reduces channel conflicts through distributed learning	Convergence complexity	High
Liu and Li (2023)	DRL	IoT with DSA/NOMA	Throughput, utilization	About **0.8 Mbps** improvement over FDMA and **0.5 Mbps** over NOMA	Simulation and learning overhead	Very High
Alauthman and Shraa (2025)	DQN/PPO	Wi-Fi 6/7	Throughput, latency, fairness	Supports adaptive allocation in dense Wi-Fi environments	Learning overhead	Very High
ESN-BEDQN (2026)	Ensemble DQN	Anti-jamming DSA	Reliability, adaptation	Supports adaptation under changing jamming conditions	Model complexity	Moderate

Table 3 demonstrates that the learning-assisted methods offer improved adaptability when changes in spectrum usage and interference occur. Dynamic channel and resource allocation are supported by DRL, and multi-agent approaches are showing promise for the distributed coordination. Notwithstanding,

comparison by direct numbers is still hard since the studies are conducted using different configurations, different Traffic and Evaluation Metrics.

The above mentioned methods are especially applicable to smart-library networks and campus networks. High density campus Wi-Fi environments need congestion awareness and interference-aware channel assignment, and smart classrooms involve multimedia, learning platforms, sensors and connected devices. Campus IoT focuses on dependable and efficient communication. Smart libraries also have digital resources, cloud services, multimedia access, RFID circulation, smart shelves and asset tracking. Heterogeneous traffic and diverse QoS demands, therefore, have to be accommodated by the management of the spectrum.

There are still several gaps in the research for campus-specific spectrum intelligence, coexistence, real-time spectrum prediction, mobility-aware allocation, scalability, QoS, fairness, security, privacy, and computational overhead for AI. To grasp automated spectrum decisions, there is a need for explainability. Most crucially, many traditional methods are still simulation-based, and few have been tested in real campus or "Smart Library" settings.

AI native spectrum management, federated learning, Explainable AI, MARL, and edge-assisted intelligence are areas that require further research. Heterogeneous campus connectivity can be facilitated through Wi-Fi 7, private 5G and future 6G networks; digital twins can help make predictions about the spectrum and plan for it. Apart from user density, mobility, application priority, channel conditions, and QoS, context-aware allocation can also take into account application characteristics, service types, etc. These future directions are summarized and related to the existing challenges in Figure 3.

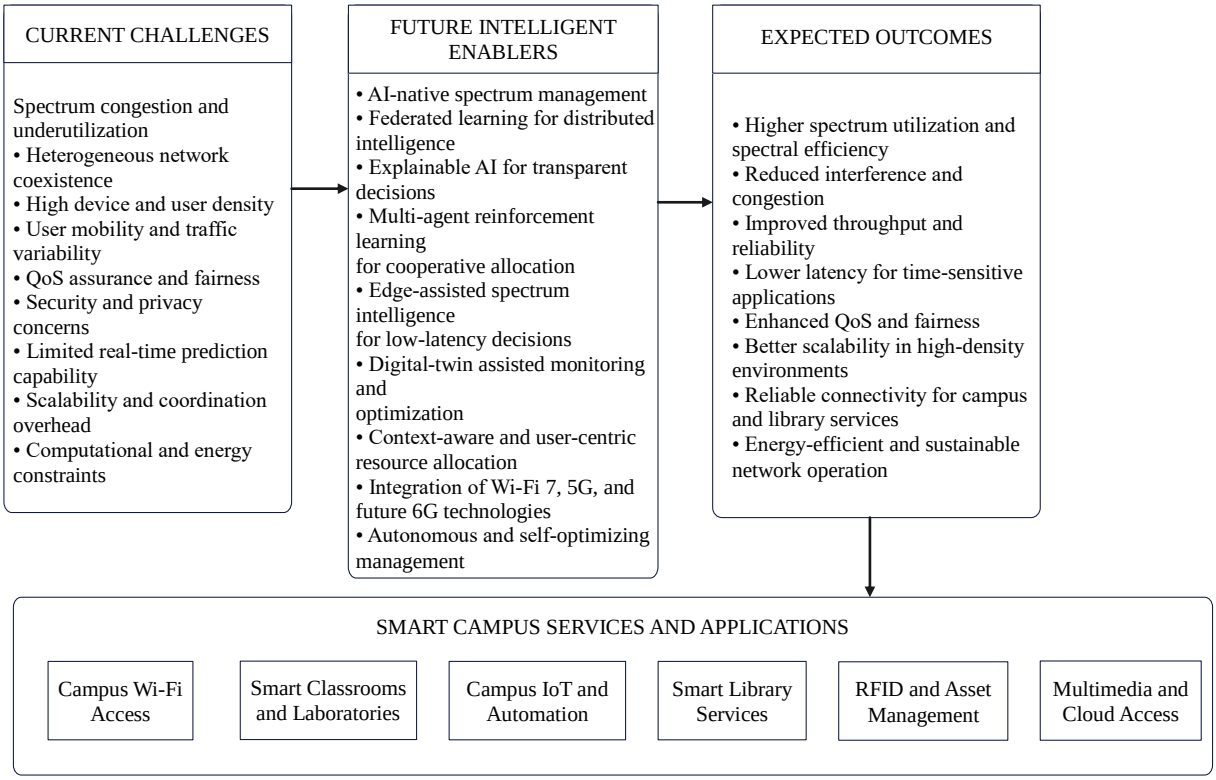


Fig. 3. Future Spectrum Management Framework for Smart Campus Networks

Distributed and context-based spectrum intelligence can be used to solve issues such as congestion, heterogeneous co-existence, mobility, scalability, security and processing limitations, as illustrated in the subsequent Figure 3. This would result in higher spectrum utilization, improved reduction of interference, increased throughput and reliability, reduced latency, better QoS and improved scalability across campus wireless, smart classrooms, IoT, smart-library, RFID, multimedia and cloud services. Real world campus validation and standardised performance evaluation are key issues that should be addressed by future studies.

6. Conclusion

This review explored the evolution of conventional Static Spectrum Allocation, Dynamic Spectrum Access, towards Cognitive/learning-based and Distributed Spectrum Intelligence. The comparative evaluations

indicates that traditional methods are simple and have low computational cost, but are not very suitable when wireless conditions change frequently. Unlike these, Machine Learning (ML), Deep Learning (DL), Reinforcement Learning (RL), Multi-Agent Reinforcement Learning (MARL), and edge-assisted approaches have more powerful spectrum prediction, intelligent channel selection, interference mitigation, and adaptive resource allocation capabilities. They can effectively address several key features of high-density campus networks with user mobility, multiple device types, and fluctuating traffic and QoS demands. Intelligent spectrum management can improve the connectivity of digital repositories, multimedia services, cloud platforms, RFID circulation, smart shelves, asset tracking and IoT monitoring for smart-library environments. The practical deployment is limited, however, due to the following aspects: (1) computational overhead, (2) scalability, (3) learning complexity, (4) security and privacy issues, (5) lack of explainability and (6) lack of real campus validation. However, future research should focus on scalable, secure, adaptive and explainable spectrum intelligence with realistic deployment studies. With the introduction of Wi-Fi 7, private 5G, the new 6G technology, federated learning, edge intelligence and digital twins, context-aware and autonomous decisions about the spectrum can be taken even more. This will contribute to the reliable, efficient and sustainable wireless connectivity for next-generation smart campus and intelligent library information services.

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