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AI-Enhanced 6G-Enabled Intelligent Spectrum Sharing for Smart Grid Communication

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Dedication

To my beloved **parents**, whose unconditional love, endless prayers, and lifelong sacrifices have been the greatest source of strength and inspiration throughout my academic journey.

To my dear **wife**, whose patience, encouragement, and unwavering support gave me the confidence to overcome every challenge. To my beloved children, **Zain, Hunain, and Asra**, whose smiles, love, and innocence have always motivated me to strive for excellence and build a brighter future.

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M Fiaz Ul Haq Madni

Abstract

The increasing digitalization of electric power systems has created a growing demand for adaptive and spectrum-efficient wireless communication in smart grid environments. Conventional static spectrum-allocation approaches may become inefficient when spectrum occupancy and channel conditions vary over time. This thesis develops an artificial intelligence-assisted spectrum-management framework for a 6G-oriented smart grid communication scenario by combining short-horizon spectrum-occupancy prediction with reinforcement-learning-based channel allocation.

The empirical component of the study is derived from real-world spectrum measurements obtained through the ElectroSense platform. These measurements retain their original frequency-domain interpretation and are not presented as native 6G observations. Instead, they are used to learn temporal spectrum-occupancy behaviour, while an assumed 8 GHz carrier-frequency scenario and an effective communication bandwidth of 100 MHz are introduced separately for communication-level evaluation.

A compact feature set consisting of empirical center frequency, received energy, short-term energy variation, rolling mean energy, and rolling energy variability is used to predict the occupancy state of the subsequent chronologically ordered observation. Support Vector Machine, Random Forest, Decision Tree, and K-Nearest Neighbors are evaluated under the same sequence-aware chronological train–test procedure. Random Forest achieves the strongest overall predictive performance, with an accuracy of approximately 91.53%, a probability of detection of 93.61%, and an F1-score of 88.59%.

The Random Forest prediction output is subsequently used to generate candidate spectrum resources for Q-Learning and Deep Q-Network based channel-allocation mechanisms. Under the defined simulation assumptions, DQN achieves approximately 157.48 Mbps throughput, 3.405 ms communication latency, a reliability/PDR indicator of 0.7348, and a spectral efficiency of 1.5748 bit/s/Hz. These results represent a modest improvement over Q-Learning, although DQN requires substantially greater training complexity.

The study therefore demonstrates the feasibility of integrating empirical next-observation spectrum prediction with intelligent channel allocation under a clearly separated 6G-oriented communication scenario. The reported communication metrics should be interpreted as comparative simulation indicators rather than measurements from a deployed 6G smart grid network.

Keywords: 6G, smart grid communication, intelligent spectrum sharing, spectrum occupancy prediction, machine learning, Random Forest, Q-Learning, Deep Q-Network, ElectroSense.

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List of Abbreviations

AI	Artificial Intelligence
AMI	Advanced Metering Infrastructure
CR	Cognitive Radio
DQN	Deep Q-Network
DRL	Deep Reinforcement Learning
DT	Decision Tree
F1	F1-Score
FP	False Positive
FN	False Negative
IMT	International Mobile Telecommunications
IoT	Internet of Things
KNN	K-Nearest Neighbors
ML	Machine Learning
mmWave	Millimeter Wave
NF	Noise Figure
PDR	Packet Delivery Ratio
P_d	Probability of Detection
P_{fa}	Probability of False Alarm
QoS	Quality of Service
RF	Random Forest
RL	Reinforcement Learning
ROC	Receiver Operating Characteristic
SNR	Signal-to-Noise Ratio
SE	Spectral Efficiency
SG	Smart Grid
SU	Secondary User
SVM	Support Vector Machine
THz	Terahertz
TN	True Negative
TP	True Positive
URLLC	Ultra-Reliable Low-Latency Communication
WRC	World Radiocommunication Conference

Chapter 1

Introduction

1.1 Background

Electric power systems are undergoing a gradual transformation from centrally controlled infrastructures toward highly connected and data-driven smart grids [2, 3]. Modern grids increasingly integrate distributed energy resources, renewable generation, energy storage systems, electric vehicles, intelligent substations, advanced metering infrastructure, and automated protection and control functions. These developments improve observability and operational flexibility; however, they also increase the dependence of the power system on timely and reliable communication. Measurements, protection messages, control instructions, pricing information, and equipment-status data must be exchanged among geographically distributed entities with communication requirements that vary considerably according to the application [4, 5].

Unlike conventional power networks, where communication often supports supervisory or administrative functions, smart grid communication forms part of the operational decision cycle. Delayed or unreliable information may influence fault isolation, voltage regulation, demand response, distributed generation control, and other time-sensitive grid processes. Consequently, communication performance can no longer be considered independently of the power-system application being served. Reliability, latency, spectrum availability, scalability, and efficient resource utilization become important design considerations for future smart grid communication systems [5].

Wireless communication provides several practical advantages in this context. It can reduce deployment complexity, support mobile and geographically dispersed devices, and provide connectivity in locations where installation of dedicated wired infrastructure may be difficult or uneconomical. At the same time, wireless systems operate over a finite radio-frequency spectrum that is shared by multiple technologies and services. The increasing density of connected devices and heterogeneous traffic creates a need to utilize available spectrum more intelligently rather than relying entirely on fixed or static channel-selection procedures.

Cognitive and intelligent radio concepts address this problem by observing spectrum activity and identifying opportunities for dynamic access. In a conventional spectrum-sensing approach, the current state of a channel is estimated as either occupied or vacant. Although such

information is useful, decisions based only on the current state may become outdated when channel occupancy changes rapidly. A more proactive approach is to learn temporal patterns from previous observations and estimate the likely occupancy state of a subsequent observation. Such prediction can provide additional time for resource-selection decisions and may reduce unnecessary spectrum switching or interference.

Artificial intelligence (AI) and machine learning (ML) have therefore attracted increasing attention for spectrum sensing, occupancy prediction, interference management, and radio-resource allocation. Recent studies emphasize the role of AI-based techniques in spectrum management for beyond-5G and sixth-generation (6G) communication, particularly where wireless environments are dynamic and difficult to model using fixed analytical rules [?, 6]. Machine learning can extract relationships from measured spectrum data, while reinforcement learning (RL) can use interaction with an environment to improve sequential resource-allocation decisions [7, 8].

The development of International Mobile Telecommunications for 2030 and beyond (IMT-2030), commonly associated with 6G, further motivates research into adaptive and intelligent spectrum management. Recommendation ITU-R M.2160 identifies ubiquitous intelligence, ubiquitous connectivity, integrated sensing and communication, sustainability, and enhanced radio capabilities among the important trends associated with IMT-2030 [9]. Importantly, the IMT-2030 framework does not associate future communication with a single frequency range. It envisages the use of spectrum extending from sub-1 GHz bands to frequencies above 100 GHz, with different ranges serving different combinations of coverage, capacity, and application requirements [9]. This multi-band perspective makes intelligent spectrum selection and resource management particularly relevant to future smart grid communication.

The present research investigates this problem through a framework that combines data-driven spectrum occupancy prediction with intelligent spectrum allocation. Real-world spectrum observations derived from the ElectroSense platform are used as the empirical basis for learning spectrum-activity patterns. ElectroSense provides crowdsourced radio-spectrum measurements collected through distributed sensing nodes and has been used in previous spectrum-monitoring and machine-learning research [10]. The empirical measurements are not represented as native 6G measurements. Instead, they provide the spectrum-activity foundation of the study, while clearly identified 6G-oriented communication assumptions are introduced separately for system-level evaluation.

In the proposed methodology, four supervised machine-learning algorithms; Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbors (KNN); are evaluated for prediction of the occupancy state associated with the subsequent chronologically ordered spectrum observation. In this thesis, the term **next-slot** refers to this subsequent observation within the same sensor-frequency sequence; it should not be interpreted as a standardized 5G/6G radio-frame slot.

The strongest predictor according to the predefined model-selection criterion is used as the common prediction front end for two intelligent channel-allocation techniques: Q-Learning and

Deep Q-Network (DQN). The allocation stage combines predicted spectrum availability with channel-quality information to select a candidate communication resource. This arrangement allows prediction performance and allocation performance to be examined within a common experimental framework while retaining a clear distinction between empirical spectrum learning and communication-level simulation.

1.2 Smart Grid Communication Requirements

A smart grid incorporates communication requirements that differ substantially across applications. Smart meters may exchange relatively small amounts of data at moderate intervals, whereas protection and control functions may require rapid and dependable delivery of time-critical information. Distributed generation and microgrid coordination introduce additional requirements because decisions may depend on measurements collected from several geographically separated components. Consequently, a communication architecture suitable for the smart grid should accommodate both routine monitoring traffic and time-sensitive operational messages.

The communication structure of a modern smart grid is illustrated in Fig. 1.1. The figure highlights the interconnection among generation units, substations, distributed energy resources, smart meters, communication networks, and control centers, thereby emphasizing the need for reliable and adaptive information exchange across the power system.

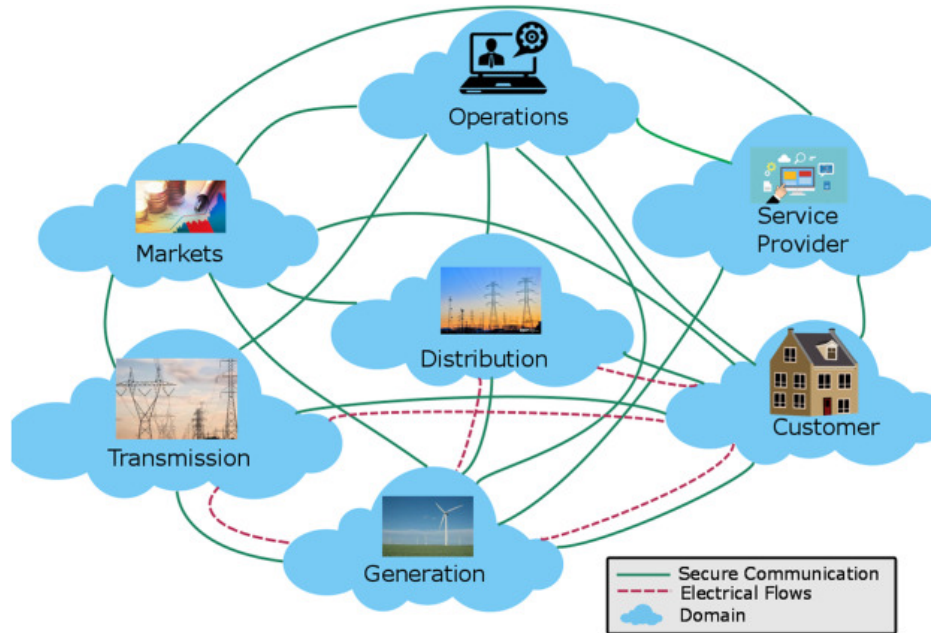


Figure 1.1: General architecture of a smart grid communication system [?]

Reliability is particularly important because packet loss or unsuccessful channel access can prevent the receiving device from obtaining information needed for a control or monitoring task. Latency is also significant because excessive communication delay can reduce the usefulness of otherwise correct information. In addition, spectral efficiency becomes relevant as the number

of devices and applications increases, since a limited amount of radio spectrum must support a growing volume of traffic.

The communication requirements of representative smart grid functions are summarized conceptually in Table 1.1. The values and qualitative requirements shown in this table are intended to illustrate the relative differences among application categories rather than impose a universal requirement for every deployment. Actual requirements depend on grid architecture, protection philosophy, communication technology, regulatory conditions, and service design [4].

Table 1.1: Representative Communication Requirements of Smart Grid Applications

Application	Latency	Sensitivity	Reliability Need	Communication Characteristic
Advanced metering infrastructure	Low to moderate		Moderate to high	Periodic meter readings and management information
Demand response	Moderate		High	Price, demand, and control information exchange
Distributed energy resource monitoring	Moderate		High	Continuous or periodic operational measurements
Microgrid coordination	High		High	Coordinated measurements and distributed control
Fault detection and grid automation	Very high		Very high	Time-sensitive event and control information
Protection and remedial control	Very high		Very high	Low-delay and dependable command delivery
Predictive maintenance	Moderate		High	Sensor-driven condition monitoring and analytics

The diversity shown in Table 1.1 indicates that a single static communication strategy may not be equally suitable for every operating condition. If spectrum selection is performed without considering current or anticipated channel activity, communication may experience avoidable interference or repeated channel switching. An intelligent spectrum-sharing mechanism can instead use observed and predicted information to select spectrum resources according to their likely availability and communication quality.

1.3 Evolution Toward 6G-Enabled Smart Grid Communication

Fifth-generation (5G) communication introduced several capabilities that are relevant to smart grids, including enhanced mobile broadband, massive machine-type communication, ultra-reliable low-latency communication, network slicing, edge computing, and flexible radio-resource management. These capabilities have created opportunities for connecting large

numbers of monitoring devices while also supporting more demanding industrial and control-oriented services.

Emerging 6G research extends this direction toward more intelligent, integrated, and adaptive communication systems. The IMT-2030 framework places increased emphasis on AI integration, ubiquitous intelligence, sensing and communication convergence, sustainability, enhanced coverage, and new application categories [9]. For smart grids, these developments are relevant because future energy systems are expected to contain large numbers of intelligent devices, distributed controllers, renewable energy interfaces, autonomous monitoring systems, and data-driven operational applications [4].

A major consideration in 6G research is the use of heterogeneous frequency ranges. Lower-frequency spectrum remains valuable because of its comparatively favorable propagation and coverage characteristics, whereas higher-frequency bands can offer larger bandwidths for applications requiring high capacity. ITU-R notes that IMT-2030 is expected to make use of multiple frequency ranges, from sub-1 GHz to frequencies above 100 GHz, rather than replacing lower bands with a single high-frequency solution [9]. This is particularly relevant to smart grids, where broad-area infrastructure monitoring may require different radio characteristics from localized high-capacity applications.

Accordingly, the use of an 8 GHz communication scenario later in this thesis should be understood as a future-network research assumption rather than as a claim that 8 GHz constitutes a finalized or exclusive 6G operating band. The empirical ElectroSense measurements and the assumed future-network communication parameters are deliberately kept separate in the experimental design.

The relationship between 5G and prospective 6G capabilities in the context of this research is summarized in Table 1.2. The table does not imply that all listed 6G capabilities are already standardized or commercially deployed. Instead, it reflects the research direction associated with IMT-2030 and emerging 6G studies.

The long-term evolution of wireless communication from early cellular generations to emerging 6G is illustrated in Fig. 1.2. This progression highlights the gradual transition from basic voice-centric systems toward intelligent, highly connected, and service-flexible communication environments capable of supporting future smart grid applications.

Recent research has already begun examining the coupling between 6G-oriented communication and smart grid control. For example, integrated sensing, transmission, computing, and control have been studied as interconnected processes rather than isolated subsystems, emphasizing that the timeliness of communication information can influence power-system control performance [5]. This reinforces the need to examine spectrum management not only as a radio problem but also as an enabling component of reliable cyber-physical energy systems.

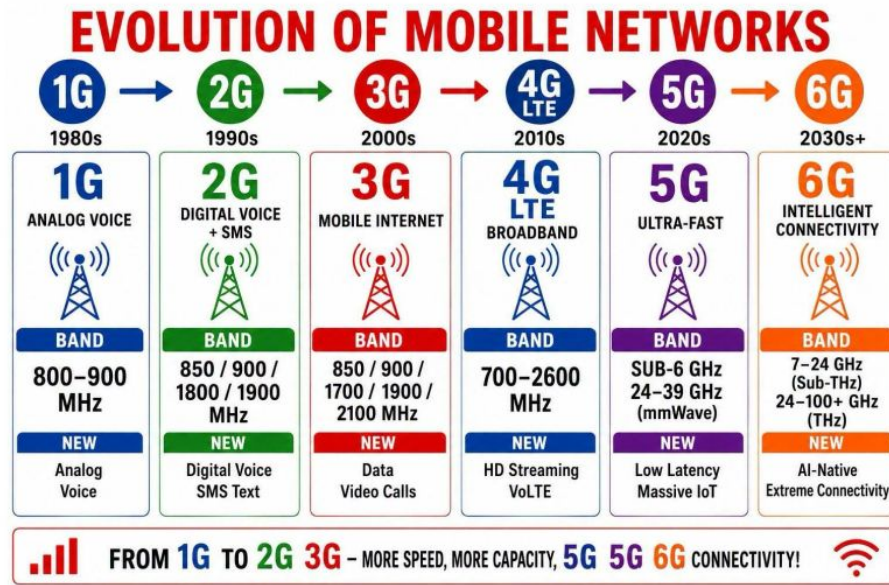


Figure 1.2: Evolution of wireless communication from 1G to 6G [1]

Table 1.2: 5G Capabilities and Emerging 6G Research Directions Relevant to Smart Grids

Aspect	5G Context	Emerging 6G / IMT-2030 Context
Connectivity	Massive machine-type communication and IoT support	Ubiquitous and deeply integrated connectivity
Latency	URLLC-oriented low-latency services	Further integration of communication, computing, sensing, and control
Intelligence	AI-assisted network optimization	Increasingly AI-native and autonomous operation
Spectrum use	Flexible licensed and shared spectrum mechanisms	Multi-band operation with enhanced spectrum sharing and co-existence
Frequency range	Sub-6 GHz and millimeter-wave deployment	Wide range from sub-1 GHz to bands above 100 GHz under the IMT-2030 vision
Resource management	Network slicing and adaptive scheduling	Context-aware, predictive, and intelligent resource orchestration
Smart grid role	Connectivity for monitoring and control	Integrated intelligent communication for increasingly autonomous grid operation

1.4 Spectrum Scarcity and Dynamic Spectrum Sharing

The radio-frequency spectrum is a finite resource, yet the number of wireless devices and services continues to increase. The difficulty is not simply that spectrum is unavailable; rather, spectrum utilization varies over time, location, frequency, and service. Some channels may be heavily occupied during particular periods while others remain underutilized. Static allocation mechanisms cannot always exploit these temporal and spatial variations effectively.

Dynamic spectrum access attempts to improve utilization by allowing communication systems to identify and use available spectrum opportunities while respecting incumbent users and interference constraints. Cognitive radio concepts introduced the idea that a wireless system can observe its environment, determine whether spectrum resources are occupied, and adapt its operating parameters accordingly. Spectrum sensing therefore becomes a key enabling process because an incorrect occupancy decision can have two different consequences.

A missed detection occurs when an occupied channel is incorrectly considered vacant. Such an error can lead to interference with an existing transmission. A false alarm occurs when a vacant channel is incorrectly considered occupied. Although this does not necessarily create interference, it reduces spectrum-utilization opportunities. Therefore, an effective spectrum-management framework should seek a suitable balance between high probability of detection and low probability of false alarm.

Traditional energy detection and threshold-based methods can identify spectrum activity when suitable thresholds and signal conditions are available [11]. However, real wireless environments may contain changing noise levels, propagation conditions, interference, and temporal patterns. AI-based spectrum sensing has consequently emerged as an important research direction because learning algorithms can identify relationships within measured data that may be difficult to represent using a fixed analytical decision rule [?].

The present study extends this concept from current-state classification to short-horizon occupancy prediction. Instead of asking only whether a channel is occupied at the present observation, the learning task estimates whether the subsequent observation is likely to be occupied. This distinction is important because proactive allocation requires information about the state that will exist when the communication decision is applied.

1.5 Role of Artificial Intelligence in Spectrum Management

Artificial intelligence provides several mechanisms for improving spectrum management. Supervised machine-learning algorithms can learn a relationship between measured radio features and known occupancy labels. Reinforcement-learning algorithms can then use observations of the environment, actions, and reward signals to improve channel-selection decisions over repeated interactions.

The transition from conventional dynamic spectrum access toward AI-assisted spectrum management is illustrated in Fig. 1.3. In the AI-enhanced approach, historical spectrum observations and channel-quality information are used to support predictive and adaptive

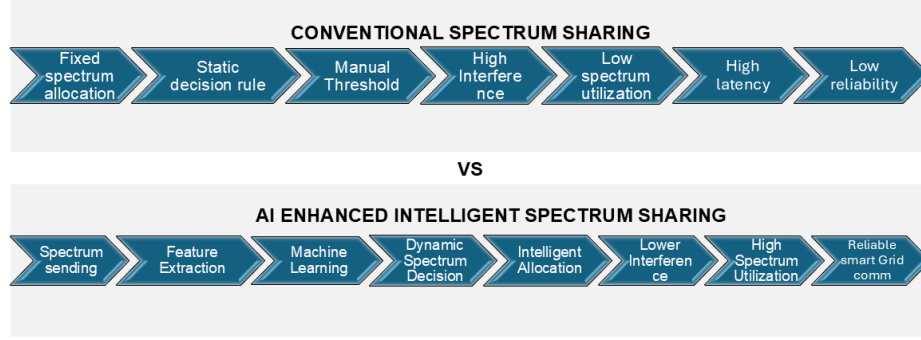


Figure 1.3: Comparison between conventional dynamic spectrum sharing and AI-enhanced intelligent spectrum sharing.

resource-selection decisions rather than relying only on instantaneous sensing. In this thesis, supervised learning and reinforcement learning serve different but complementary roles. SVM, RF, DT, and KNN are used for next-slot occupancy prediction. These algorithms were selected because they represent different learning principles and provide a balanced comparison without requiring an unnecessarily large model set. SVM establishes a margin-based classification baseline, RF provides an ensemble-learning approach, DT provides an interpretable tree-based method, and KNN provides a non-parametric instance-based technique.

The allocation problem is sequential and therefore better suited to reinforcement learning. Q-Learning estimates the long-term utility of state–action combinations using a tabular value function. DQN extends the same basic concept by replacing the explicit Q-table with a neural network that approximates action values. This is useful when the state representation becomes larger or more continuous. Recent research on 6G-oriented spectrum management identifies AI-based sensing and intelligent allocation as important mechanisms for coping with heterogeneous and dynamic radio environments [6].

The proposed framework deliberately separates occupancy prediction from channel allocation. The supervised-learning stage estimates the occupancy state of the subsequent chronologically ordered observation, while the reinforcement-learning stage selects a communication resource from the candidate channels identified from those predictions. This separation allows prediction errors and allocation behaviour to be evaluated independently and avoids interpreting the two learning stages as a single black-box model.

1.6 Research Motivation

The motivation for this research arises from three related observations.

First, smart grid communication is becoming more dependent on wireless connectivity and timely information exchange. As distributed monitoring and control increase, communication resources must support a heterogeneous set of devices and services. Fixed channel-selection strategies may be inadequate when spectrum occupancy changes with time.

Second, many spectrum-sensing studies focus on detecting the current channel state. While current-state information is useful, a communication system that waits until the instant of

transmission to determine availability may have limited time to react. Predicting the occupancy state of the subsequent spectrum observation can provide advance information for proactive resource selection and may improve the responsiveness of a spectrum-management mechanism.

Third, prediction accuracy alone does not determine communication performance. A system may identify several vacant channels but still require a mechanism to choose among them. Channel quality, temporal availability, and the long-term consequences of allocation decisions must also be considered. Reinforcement learning provides a suitable framework for this sequential decision problem because the agent can learn from successful and unsuccessful channel selections.

These considerations motivate an integrated research framework in which empirical next-observation spectrum prediction is followed by intelligent channel allocation and simulation-based communication evaluation.

1.7 Problem Statement

Smart grid communication increasingly depends on timely and adaptive access to wireless resources, while spectrum occupancy may vary across frequency and time. Static resource selection cannot fully exploit temporary spectrum opportunities, whereas decisions based only on the currently observed state provide limited support for proactive channel selection. Moreover, evaluating a machine-learning model only through classification accuracy does not establish whether its spectrum predictions can support useful subsequent resource-allocation decisions.

A further methodological difficulty arises when empirical spectrum datasets collected from currently deployed radio systems are used in research concerning future 6G-oriented communication. Such measurements provide valuable information about real spectrum activity, but their original carrier frequencies and propagation conditions should not be relabelled as native 6G observations. Mixing measured legacy-band data directly with future-network assumptions can obscure the interpretation of experimental results.

Accordingly, this research addresses the following problem:

How can empirical spectrum measurements be used to predict the occupancy state of the subsequent spectrum observation and support intelligent channel allocation for a 6G-oriented smart grid communication scenario while maintaining a transparent separation between measured spectrum behaviour and simulation-derived communication assumptions?

To address this problem, ElectroSense-derived measurements are used for empirical occupancy learning, while the communication-level 6G-oriented parameters are introduced separately. Four supervised machine-learning models are compared for next-observation occupancy prediction, after which Q-Learning and DQN are evaluated for intelligent channel selection using the selected predictor's output and channel-quality information.

1.8 Research Questions

The primary objective of this thesis is to develop and evaluate an AI-assisted framework that integrates empirical spectrum-occupancy prediction with intelligent channel allocation for a 6G-oriented smart grid communication scenario.

The specific objectives are:

1. To construct a compact and technically interpretable predictive dataset from ElectroSense-derived spectrum measurements while preserving a clear distinction between empirical information and communication-level simulation assumptions.
2. To formulate the learning task as prediction of the occupancy state of the subsequent chronologically ordered spectrum observation rather than reconstruction of the current threshold-derived occupancy state.
3. To implement and compare SVM, Random Forest, Decision Tree, and KNN for next-observation spectrum occupancy prediction.
4. To evaluate the prediction models using accuracy, precision, probability of detection, F1-score, and probability of false alarm.
5. To select a prediction model according to a predefined criterion for supplying spectrum-availability information to the intelligent allocation stage.
6. To implement Q-Learning and DQN for intelligent channel selection using predicted spectrum availability and SNR-related channel-quality information.
7. To compare the allocation techniques using simulated throughput, communication latency, allocation-success-based reliability/PDR, and spectral efficiency under the defined 6G-oriented scenario.
8. To compare the computational requirements of the investigated techniques using training time and inference or online decision latency.
9. To analyze the trade-offs among prediction quality, computational complexity, and simulation-derived communication performance.

1.9 Research Contributions

The principal contributions of this thesis are summarized as follows:

1. **Next-observation spectrum-prediction formulation:** The original occupancy-learning problem is reformulated from reconstruction of the current threshold-derived state to prediction of the occupancy state associated with the subsequent chronologically ordered observation. This provides a more appropriate basis for proactive spectrum-management decisions.

2. **Compact and interpretable feature representation:** The prediction stage uses empirical center frequency, received energy, short-term energy difference, rolling mean energy, and rolling energy standard deviation. The feature set is kept deliberately compact to preserve interpretability and limit unnecessary redundancy.
3. **Controlled comparison of four supervised predictors:** SVM, RF, DT, and KNN are evaluated using the same prediction target, predictive features, and sequence-aware chronological train–test procedure. Performance is examined through accuracy, precision, probability of detection, F1-score, and probability of false alarm.
4. **Sequence-aware chronological evaluation:** Training and testing observations are separated chronologically within each valid sensor–frequency sequence. This reduces temporal mixing between training and testing observations and preserves representation of the available sequences in both partitions.
5. **Prediction-to-allocation integration:** The predictor selected according to the predefined model-selection criterion supplies predicted channel availability to the reinforcement-learning allocation stage. Q-Learning and DQN therefore operate from a common Random Forest prediction source while using their respective internal state representations.
6. **Multi-dimensional evaluation:** The framework is examined from prediction, computational, and simulation-derived communication perspectives rather than through classification accuracy alone.
7. **Transparent separation of empirical and 6G-oriented components:** The ElectroSense measurements retain their original empirical frequency interpretation. No frequency-domain transformation from the measured spectrum observations to 8 GHz is performed. The assumed 8 GHz carrier scenario and 100 MHz effective communication bandwidth are introduced separately for communication-level evaluation.

1.10 Scope of the Study

This research is limited to prediction-assisted spectrum management and intelligent channel selection for a simulated 6G-oriented smart grid communication scenario. The empirical component is derived from ElectroSense measurements and is used to represent observed variations in spectrum energy and occupancy behaviour.

The supervised-learning stage evaluates SVM, Random Forest, Decision Tree, and KNN. The prediction target is the occupancy state of the subsequent chronologically ordered observation within the same sensor–frequency sequence. Accordingly, the term “next-slot” used in this thesis denotes the next available observation in the reconstructed sequence and does not imply a standardized 5G/6G physical-layer slot duration.

The intelligent allocation stage is limited to Q-Learning and DQN. Both methods use Random Forest-derived predicted availability and SNR-related channel-quality information,

although their internal state representations differ according to the requirements of tabular and neural-network-based reinforcement learning.

The empirical ElectroSense measurements retain their original frequency-domain identity. No physical transformation or remapping of GSM-band measurements to 8 GHz is performed. Instead, an assumed 8 GHz carrier-frequency scenario and a fixed effective communication bandwidth of 100 MHz are introduced separately for communication-level simulation. These parameters define a future-network research scenario and should not be interpreted as measurements from an operational 6G radio interface or as finalized universal IMT-2030 specifications.

The research does not implement a complete physical-layer transceiver, commercial 5G/6G protocol stack, multi-cell scheduler, smart grid control center, or field-deployed communication network. The reported throughput, latency, spectral efficiency, and reliability/PDR quantities are therefore simulation-derived comparative indicators rather than direct field measurements.

Within this context, the term “6G-enabled” in the thesis title refers to the intended applicability of intelligent predictive spectrum management within an IMT-2030-oriented future communication environment; it does not imply that the underlying ElectroSense measurements were collected from a deployed 6G system.

1.11 Assumptions and Limitations

The interpretation of the results is subject to several assumptions and methodological limitations.

First, the empirical spectrum observations originate from the ElectroSense sensing infrastructure rather than from a deployed 6G network. They are used to model measured spectrum-occupancy behaviour and are not treated as direct evidence of 8 GHz propagation or interference characteristics.

Second, the 8 GHz carrier frequency and 100 MHz effective communication bandwidth are simulation assumptions. Their purpose is to provide a common communication context for comparing allocation methods rather than to reproduce a finalized IMT-2030 radio interface.

Third, the SNR-related quantity used during allocation is a simulation-oriented channel-quality proxy derived from the available spectrum-energy information and defined communication assumptions. It should not be interpreted as a directly measured 8 GHz receiver SNR.

Fourth, the term “next-slot” denotes the subsequent chronologically ordered observation. Unless a fixed physical sampling interval is established from the source measurements, the prediction task should be interpreted as next-observation prediction rather than forecasting over a standardized radio-frame duration.

Fifth, the communication model is intentionally simplified. The reported communication indicators do not reproduce all effects of fading, channel coding, retransmissions, queueing, medium-access contention, mobility, antenna characteristics, scheduling, or implementation overheads.

Sixth, the reliability/PDR quantity represents the proportion of allocation decisions that

result in successful use of an actually vacant channel within the simulation. It is therefore an allocation-success-based reliability proxy rather than a complete packet-level delivery model.

Seventh, the allocation environment represents a simplified single-user channel-selection problem. Simultaneous multi-user competition, distributed secondary-user coordination, power-control optimization, network slicing, beam management, and coordinated multi-cell scheduling are outside the present scope.

Finally, the predictive models operate on a compact set of frequency and energy-derived features. Additional measurements including modulation characteristics, direct interference measurements, geographic context, mobility, channel impulse response, and measured packet-level traffic are not available in the final predictive dataset.

These limitations define the intended interpretation of the study: the thesis evaluates a reproducible prediction-to-allocation framework under controlled assumptions rather than claiming implementation of a complete operational 6G smart grid communication system.

1.12 Evaluation Framework

The proposed methodology is evaluated using three groups of performance measures.

1.12.1 Prediction Performance

The occupancy-prediction models are evaluated using five primary metrics:

- Accuracy,
- Precision,
- Probability of Detection (P_d) or Recall,
- F1-score, and
- Probability of False Alarm (P_{fa}).

Accuracy provides an overall measure of correct classification, whereas precision indicates the proportion of predicted occupied states that are actually occupied. Probability of detection represents the ability to identify occupied spectrum successfully, while P_{fa} quantifies the unnecessary rejection of vacant spectrum. F1-score provides a combined measure of precision and recall.

1.12.2 Computational Performance

Two computational indicators are retained:

- Training time, and
- Inference or decision latency.

Training time indicates the computational effort required to fit or learn a model, whereas inference or decision latency reflects the time required to produce an operational prediction or allocation decision. The latter is particularly relevant to real-time communication because extensive offline training may be acceptable if online decisions remain sufficiently fast.

1.12.3 Communication Performance

The intelligent allocation stage is evaluated using four simulation-derived communication indicators:

- Throughput,
- Communication latency,
- Allocation-success-based reliability/PDR, and
- Spectral efficiency.

Spectral efficiency represents the bandwidth-normalized data-rate quantity obtained from the defined SNR-based communication model, while throughput converts this quantity into an absolute rate using the assumed 100 MHz effective bandwidth. The two measures are therefore mathematically related rather than statistically independent.

Communication latency combines the defined successful-access delay and transmission-time component, while unsuccessful accesses receive the specified simulation penalty. Reliability/PDR represents the proportion of allocation decisions that result in selection of an actually vacant channel. Consequently, the PDR reported in this study is a simulation-level access-success indicator and should not be interpreted as a complete physical-layer or protocol-level packet-delivery measurement.

1.13 Overall Research Framework

The overall research framework is illustrated in Fig. 1.4. The process begins with empirical ElectroSense-derived spectrum observations. The measurements are organized into sensor–frequency sequences, from which short-term temporal features and the subsequent-observation occupancy target are constructed.

The supervised-learning stage compares SVM, Random Forest, Decision Tree, and KNN under a common chronological evaluation procedure. The predictor selected according to the predefined model-selection rule supplies predicted spectrum availability to the reinforcement-learning allocation stage. Q-Learning and DQN then use this predicted availability together with channel-quality information to select communication resources. The resulting decisions are evaluated using prediction, computational, and simulation-derived communication metrics.

The logical prediction-to-allocation sequence may be represented as

$$\mathbf{x}_t \longrightarrow \hat{O}_{t+1} \longrightarrow \mathcal{A}_{t+1} \longrightarrow a_{t+1}, \quad (1.1)$$

where $\mathbf{x}_t$ denotes the information available at the current observation, $\hat{\mathcal{O}}_{t+1}$ represents the predicted occupancy condition of the subsequent observation, $\mathcal{A}_{t+1}$ denotes the candidate set of spectrum resources derived from the prediction, and a_{t+1} represents the resource selected by the intelligent allocation mechanism.

The formulation is proactive in the sense that the allocation stage uses an estimate of the subsequent spectrum state rather than relying exclusively on the currently observed occupancy condition.

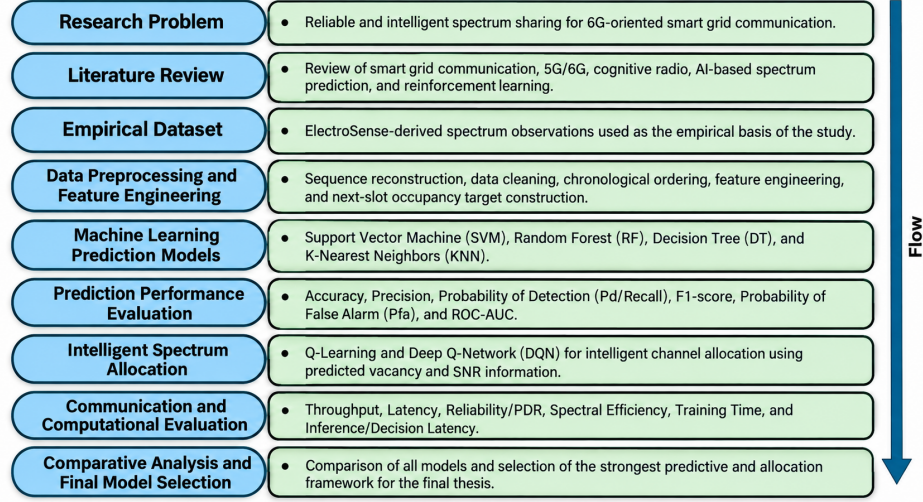


Figure 1.4: Overall research methodology adopted for intelligent spectrum sharing in 6G-oriented smart grid communication.

1.14 Thesis Organization

The remainder of this thesis is organized as follows.

Chapter 2 reviews the literature related to smart grid communication, 5G and 6G technologies, cognitive radio, dynamic spectrum access, AI-based spectrum sensing and prediction, machine-learning algorithms, reinforcement learning, DQN, and previous studies based on the ElectroSense platform. The chapter concludes by identifying the research gap addressed in this study.

Chapter 3 presents the proposed methodology. It describes the empirical dataset, feature engineering, 6G-oriented communication assumptions, next-observation occupancy-prediction formulation, sequence-aware train–test strategy, machine-learning algorithms, reinforcement-learning allocation mechanisms, performance metrics, and experimental configuration.

Chapter 4 presents and discusses the experimental results. The four machine-learning techniques are compared in terms of prediction performance and computational complexity. The chapter then evaluates Q-Learning and DQN in terms of intelligent spectrum allocation and communication performance. The observed trade-offs among prediction quality, complexity, and communication performance are discussed in relation to the research objectives.

Chapter 5 summarizes the major findings, identifies the contributions and limitations of the work, and presents recommendations for future research, including larger heterogeneous datasets, multi-user spectrum sharing, multi-agent reinforcement learning, network slicing, and more detailed 6G radio and smart grid communication models.

Chapter 2

Literature Review

2.1 Smart Grid Communication and Emerging Network Requirements

The smart grid extends the conventional electric power network by introducing extensive monitoring, bidirectional information exchange, distributed control, and increasing participation of intelligent devices [2, 12–17]. The resulting infrastructure connects generation facilities, transmission systems, substations, distributed energy resources, storage systems, electric vehicles, smart meters, and consumer-side equipment through communication networks. Communication is therefore no longer restricted to supervisory functions; it increasingly forms part of operational processes in which the usefulness of information depends on when and how reliably it reaches the intended destination.

The communication requirements of smart grid applications are heterogeneous. Metering and routine monitoring can tolerate comparatively relaxed delay constraints, whereas protection, fault isolation, automated restoration, and distributed control may require substantially shorter communication times and higher delivery reliability. Kumar *et al.* [4] examined emerging smart grid applications in relation to 5G and 6G capabilities and showed that future grid services place diverse requirements on latency, reliability, connectivity, data rate, and time synchronization. Their study also identifies spectrum management, edge computing, network slicing, artificial intelligence, digital twins, and Open Radio Access Network concepts as important communication enablers for increasingly automated grid environments.

The close relationship between communication quality and power-system operation has also motivated studies that jointly consider communication and control. Liao *et al.* [5] investigated sensing, transmission, computing, and control as coupled processes in a 6G-oriented smart grid setting. Their work demonstrates that communication timeliness can directly influence grid-control performance. This perspective is relevant to spectrum management because a channel-selection strategy cannot be evaluated only by whether a channel is technically available; the selected communication resource should also support the timing and reliability requirements associated with the grid application.

Wireless communication is attractive for smart grids because it can provide flexible deployment over geographically distributed infrastructure. However, its performance depends on

radio-resource availability, interference, propagation conditions, and competing spectrum usage. These factors become increasingly important as the number of connected devices grows. The literature therefore indicates that spectrum management should be considered alongside conventional smart grid communication requirements rather than treated as an isolated radio-layer function.

2.2 5G and 6G Perspectives for Smart Grid Communication

The introduction of fifth-generation cellular systems expanded the range of communication services available for industrial and utility applications [18]. Enhanced mobile broadband, massive machine-type communication, ultra-reliable low-latency communication, network virtualization, edge computing, and network slicing provide mechanisms for supporting applications with different traffic characteristics. Smart grid applications can benefit from these mechanisms because their communication requirements differ substantially across metering, monitoring, control, protection, and distributed energy management.

Research on sixth-generation communication extends these capabilities toward greater integration of intelligence, sensing, computing, and communication [19–23]. In February 2026, ITU-R Working Party 5D completed a draft report defining minimum technical-performance requirements for IMT-2030 radio interfaces; at the time of this thesis, the draft remained subject to Study Group 5 approval rather than constituting a finalized deployment specification [24]. Recommendation ITU-R M.2160 defines the framework and overall objectives for the development of IMT for 2030 and beyond [9]. The framework emphasizes capabilities associated with ubiquitous connectivity, artificial intelligence, sensing, sustainability, interoperability, enhanced coverage, and improved communication performance.

An important aspect of the IMT-2030 framework is that future communication is not restricted to millimeter-wave or terahertz operation. ITU-R envisages the use of a wide spectrum range extending from sub-1 GHz bands to frequencies above 100 GHz [9]. Lower bands remain important for coverage and penetration, mid-band spectrum provides a compromise between coverage and capacity, and higher-frequency bands may provide considerably larger bandwidths for capacity-intensive applications. Consequently, the term “6G spectrum” should not be interpreted as referring to a single carrier-frequency region.

Current international studies also reflect this multi-band approach. Under World Radiocommunication Conference 2027 Agenda Item 1.7, sharing and compatibility studies are being conducted for potential IMT operation in frequency ranges including 7.125–8.4 GHz [?]. These studies do not establish 8 GHz as a finalized 6G allocation; rather, they provide a regulatory and technical basis for studying possible future IMT use of this range.

This distinction is important when existing empirical datasets are employed in 6G-oriented research. Measurements collected from currently deployed radio services can provide useful evidence of temporal spectrum activity, but their carrier frequencies should not be relabeled as native 6G measurements. A more transparent approach is to retain the original measurement

context for data-driven learning and introduce future-network parameters separately when evaluating communication performance. The present research follows this separation between empirical observations and 6G-oriented assumptions.

For the present research, this distinction is fundamental. The empirical spectrum measurements retain their original frequency-domain interpretation, while the 8 GHz carrier scenario used later in the methodology is introduced only as a separate communication-level research assumption. No physical frequency transformation from the measured legacy-band observations to 8 GHz is performed.

2.3 Cognitive Radio and Dynamic Spectrum Access

Cognitive radio was introduced as an adaptive wireless concept in which a communication system observes its radio environment and adjusts its operating parameters according to available spectrum opportunities. Mitola and Maguire introduced the software-radio-oriented cognitive radio concept [25], while Haykin [26] described cognitive radio as an intelligent wireless communication system capable of learning from and adapting to its environment. The concept provided an important foundation for later work on dynamic spectrum access, spectrum sensing, and intelligent radio-resource management.

Dynamic spectrum access attempts to improve spectrum utilization by allowing unused or underutilized frequency resources to be accessed dynamically, subject to interference and incumbent-user constraints. Akyildiz *et al.* [27] provided an early comprehensive analysis of cognitive radio networks and dynamic spectrum access, including spectrum sensing, spectrum decision, spectrum sharing, and spectrum mobility.

A typical cognitive spectrum-access process includes four related functions:

1. observation or sensing of spectrum activity;
2. identification of available spectrum opportunities;
3. selection of an appropriate frequency resource; and
4. adaptation when spectrum conditions change.

These functions remain relevant in current AI-assisted spectrum-management research, although the underlying methods have become more sophisticated [28]. Conventional approaches often rely on explicit sensing thresholds or analytical models, whereas modern methods increasingly exploit historical observations to learn occupancy patterns and improve spectrum decisions.

The literature distinguishes between a *missed detection* and a *false alarm* [11]. A missed detection occurs when an occupied resource is incorrectly classified as available. Such an error can result in interference with an incumbent transmission. A false alarm occurs when an available channel is incorrectly classified as occupied. This error reduces the number of spectrum opportunities available to the secondary communication system. The relationship

between these errors makes probability of detection and probability of false alarm important evaluation measures for spectrum sensing and prediction.

Within the simplified abstraction adopted in this thesis, an occupied spectrum observation represents the presence of activity that should not be accessed by the opportunistic communication user, whereas a predicted vacant observation represents a candidate spectrum opportunity. The smart-grid communication user can therefore be interpreted as an opportunistic access entity that attempts to avoid resources indicated as occupied. However, the study does not explicitly simulate a complete primary-user/secondary-user network, interference-temperature constraint, or simultaneous coexistence among multiple users. The implemented problem is more specifically a prediction-assisted channel-selection abstraction derived from the broader cognitive-radio and dynamic-spectrum-access framework.

2.4 Conventional Spectrum Sensing

Spectrum sensing methods attempt to determine whether a frequency resource is currently being used. Common approaches include energy detection, matched-filter detection, cyclostationary feature detection, and cooperative sensing. Yucek and Arslan [11] surveyed spectrum-sensing techniques and discussed the trade-offs among sensing accuracy, prior signal knowledge, implementation complexity, and sensitivity to noise uncertainty.

Energy detection is particularly common because it does not require detailed prior knowledge of the transmitted waveform. A simplified energy detector compares a measured signal-energy statistic with a predefined threshold. The decision can be expressed as

$$\hat{O}_t = \begin{cases} 1, & E_t \geq \lambda, \\ 0, & E_t < \lambda, \end{cases} \quad (2.1)$$

where E_t denotes the measured energy at observation t , λ represents the detection threshold, and $\hat{O}_t$ is the estimated occupancy state.

Although energy detection is computationally simple, its reliability can decrease when the noise floor changes or received signals are weak. Moreover, threshold-based current-state detection does not explicitly exploit temporal relationships between consecutive spectrum observations. This limitation has encouraged research on statistical learning and temporal prediction.

For intelligent spectrum management, the distinction between sensing and prediction is important. Current-state sensing estimates the occupancy condition associated with the present observation,

$$\mathbf{x}_t \longrightarrow O_t, \quad (2.2)$$

whereas the prediction formulation adopted in this thesis uses information available up to observation t to estimate the occupancy state associated with the subsequent chronologically

ordered observation,

$$\mathbf{x}_{t-k:t} \longrightarrow O_{t+1}, \quad (2.3)$$

where $\mathbf{x}_{t-k:t}$ represents the current and recent spectrum information used to construct the predictive features. Here, $t + 1$ denotes the next observation within the same sensor–frequency sequence and should not be interpreted as a standardized 5G/6G physical-layer slot duration. This distinction provides the basis for proactive resource selection while remaining consistent with the temporal structure available in the empirical dataset.

2.5 Machine Learning for Spectrum Sensing and Prediction

Machine learning offers an alternative to fixed sensing rules by estimating decision relationships directly from observed data. Spectrum measurements can include received power, temporal variation, frequency information, signal statistics, and other channel descriptors. A trained model can then estimate whether a resource is likely to be occupied.

Recent reviews indicate substantial growth in AI-assisted spectrum sensing for beyond-5G and 6G systems. Falco *et al.* [?] analyzed AI-driven spectrum-sensing research and identified machine learning and deep learning as increasingly important for handling dynamic and heterogeneous radio environments. The authors also highlight practical challenges involving computational requirements, generalization, adaptability, and deployment under real-time constraints.

The major categories of machine-learning techniques relevant to wireless communication and intelligent spectrum management are presented in Fig. 2.1.

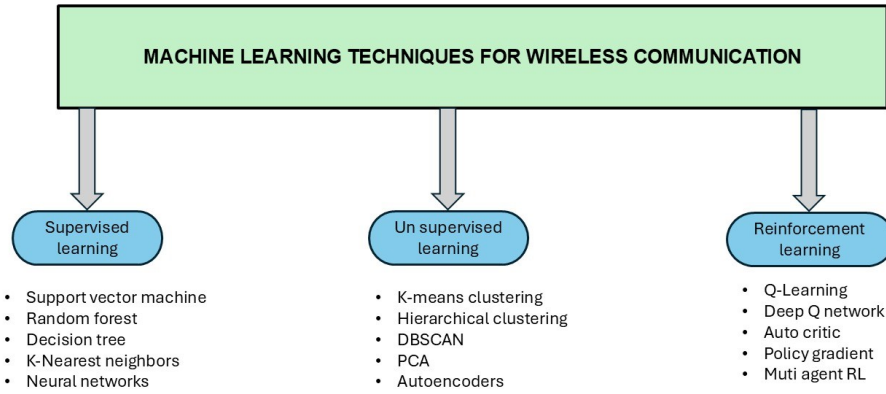


Figure 2.1: Classification of machine-learning techniques used in wireless communication and spectrum-management applications.

For the present research, four conventional supervised-learning algorithms are retained because they provide different decision mechanisms while remaining interpretable and computationally manageable: Support Vector Machine, Random Forest, Decision Tree, and K-Nearest Neighbors.

2.5.1 Support Vector Machine

Support Vector Machine constructs a decision boundary that separates classes while maximizing the margin between representative training samples. Cortes and Vapnik [29] established the modern support-vector classification formulation. For nonlinear data, kernel functions can map the original feature space into a representation in which class separation is more tractable.

In spectrum applications, SVM can use signal or energy-related features to distinguish occupied and vacant observations. Its effectiveness depends on the selected kernel, regularization parameter, feature scaling, and the extent to which the classes form separable structures. SVM provides a useful baseline because its classification mechanism differs substantially from tree-based and instance-based methods.

2.5.2 Decision Tree

Decision Tree classification recursively divides the feature space according to decision rules selected from the training data. Quinlan [30] established influential methods for induction of decision trees from examples. The resulting model is easy to interpret because a prediction can be traced through a sequence of feature-based conditions.

For spectrum data, a decision tree can identify nonlinear relationships among frequency, received energy, and temporal descriptors. However, unrestricted trees can become highly specialized to the training data. Depth control, minimum leaf sizes, or pruning are therefore important for reducing overfitting.

2.5.3 Random Forest

Random Forest combines multiple decision trees trained using randomization in the observations and candidate features. Breiman [31] showed that ensemble aggregation can improve predictive robustness compared with relying on a single tree. Each tree contributes a class decision, and the ensemble prediction is formed from the collective result.

This property is attractive for spectrum prediction because radio measurements can exhibit nonlinear interactions and variability across frequency or time. Random Forest can also provide feature-importance estimates, which assist in identifying which measurements contribute most strongly to prediction. Nevertheless, feature importance must be interpreted carefully when several inputs are highly correlated.

2.5.4 K-Nearest Neighbors

K-Nearest Neighbors is an instance-based learning technique in which an unknown observation is classified according to nearby labeled observations in feature space. The method originates from early nearest-neighbor pattern-classification work by Cover and Hart [32].

KNN requires relatively little explicit model training but can require greater computation during prediction because distances to stored observations must be evaluated. Feature scaling is also important because variables with large numerical ranges can dominate the distance

calculation. In spectrum applications, KNN provides a useful non-parametric comparison against margin-based and tree-based techniques.

2.6 From Occupancy Detection to Spectrum Forecasting

Spectrum forecasting seeks to estimate future radio activity using historical measurements. Compared with current-state sensing, forecasting is better aligned with proactive spectrum management because the predicted state can be incorporated into a resource decision before the next communication interval.

Li *et al.* [33] investigated online prediction of spectrum maps when measurements are incomplete or corrupted. Their work demonstrates that spectrum prediction is relevant to emerging 5G and 6G applications where radio environments vary over time and measurement quality may be imperfect.

More recent work has applied advanced sequence-learning architectures to empirical spectrum data. Xiao *et al.* [34] proposed DS-SpecIT for interference-aware spectrum forecasting and evaluated the approach using ElectroSense measurements from the 935–939 MHz GSM downlink region. Their experiments are important to the present study for two reasons. First, they demonstrate continued use of ElectroSense measurements for contemporary AI-based spectrum research. Second, they treat measured legacy-band spectrum observations as data for forecasting rather than presenting those measurements as native 6G signals.

The present research adopts a more compact prediction formulation than DS-SpecIT. Rather than forecasting a high-dimensional spectrum-amplitude sequence, the task is defined as binary prediction of the occupancy state associated with the subsequent chronologically ordered observation. This formulation permits direct evaluation through accuracy, precision, probability of detection, probability of false alarm, and F1-score while also producing a binary availability estimate that can be supplied to the subsequent channel-allocation stage.

The prediction horizon in the present study is therefore observation-based rather than a predefined physical time interval. Unless the source measurements establish a uniform sampling period, the term “next observation” should not be interpreted as a fixed-duration future forecasting horizon.

2.7 ElectroSense as an Empirical Spectrum Data Source

ElectroSense is an open and distributed spectrum-monitoring platform designed to collect radio-frequency measurements through low-cost sensing nodes. Rajendran *et al.* [10] described the architecture as a large-scale collaborative spectrum-monitoring system in which distributed sensors collect spectrum data that can subsequently be stored, processed, and made available for research applications.

ElectroSense has several characteristics that make it useful for data-driven spectrum studies. It contains measurements obtained from real radio environments rather than artificially generated

occupancy sequences. The distributed sensing infrastructure also allows spectrum behavior to be studied across different locations and frequency ranges. At the same time, ElectroSense data must be interpreted according to the characteristics of the original measurement campaign. Frequency, received energy, sensor location, sampling interval, and preprocessing decisions influence what can legitimately be inferred from the data.

The dataset employed in this thesis is derived from ElectroSense spectrum measurements. The original observations are processed into a compact predictive representation containing empirical center frequency, received-energy information, and short-term temporal energy statistics. The learning target is the occupancy state associated with the subsequent chronologically ordered observation. This formulation reduces the possibility that the learning algorithms simply reconstruct the threshold relationship used to determine the current occupancy state.

The empirical center frequency remains identified with the original measurement context. No frequency-domain conversion from the ElectroSense measurements to 8 GHz is performed. Instead, the empirical data are used only to represent measured spectrum-occupancy behaviour, while an 8 GHz carrier-frequency scenario and other communication parameters are introduced separately in Chapter 3 for simulation-level evaluation. This distinction prevents legacy-band measurements from being incorrectly presented as native 6G observations and preserves a clear separation between measured and assumed quantities.

2.8 Reinforcement Learning for Dynamic Spectrum Allocation

Once spectrum availability has been estimated, a communication system must decide which resource to use [35, 36]. This is a sequential decision problem because the quality of a channel and the consequences of previous selections can change over time. Reinforcement learning addresses this type of problem by allowing an agent to interact with an environment, receive a reward, and progressively improve its decision policy.

The standard reinforcement-learning formulation contains a state s_t , an action a_t , a reward r_t , and a subsequent state s_{t+1} . The objective is to learn a policy that maximizes expected discounted return,

$$G_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}, \quad (2.4)$$

where $\gamma \in [0, 1]$ is the discount factor.

2.8.1 Q-Learning

Q-Learning is a model-free reinforcement-learning algorithm introduced by Watkins and Dayan [37]. It learns an action-value function $Q(s, a)$ describing the expected long-term reward associated with taking action a in state s . The update rule is

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[r_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t) \right], \quad (2.5)$$

where α denotes the learning rate.

For spectrum allocation, the state can contain information concerning predicted channel availability and channel quality, while the action corresponds to selecting a channel. A positive reward can be associated with successful use of an available channel, and a negative reward can be imposed when the selected channel is actually occupied.

Tabular Q-Learning is relatively straightforward to interpret but becomes difficult to scale when the state space contains many continuous or high-dimensional variables. This motivates the use of function approximation.

In the methodology developed later in this thesis, Q-Learning and DQN operate within the same underlying allocation environment and use predictions produced by the same selected occupancy predictor. Their internal state representations are not identical, however: tabular Q-Learning uses a compact discretized representation, whereas DQN can process a higher-dimensional channel-wise state. The comparison should therefore be interpreted as a controlled comparison of two allocation approaches under a common environment rather than as a comparison using identical state encodings.

2.8.2 Deep Q-Network

Deep Q-Network replaces an explicit Q-table with a neural network that approximates the action-value function. Mnih *et al.* [38] demonstrated that deep neural networks, experience replay, and target networks can be combined to learn stable value functions in complex decision environments.

For spectrum allocation, a DQN can receive a state vector containing predicted vacancy, SNR-related information, and channel-availability indicators. The network returns an estimated action value for each candidate resource,

$$\mathbf{Q}(s_t) = [Q(s_t, a_1), Q(s_t, a_2), \dots, Q(s_t, a_N)]. \quad (2.6)$$

The selected action is commonly obtained using an ϵ -greedy strategy during learning, allowing the agent to balance exploration and exploitation.

Chang *et al.* [35] investigated a deep echo state Q-network for dynamic spectrum sharing in 5G and beyond systems. Their work addressed temporal correlation and the challenge of limited training data in changing wireless environments. Dong *et al.* [36] investigated dynamic spectrum access and sharing using actor-critic deep reinforcement learning, demonstrating how learning agents can adapt channel selection and power decisions without complete prior knowledge of spectrum usage.

More recent studies continue to extend reinforcement learning for spectrum management. Venkatesan and Kumaratharan [39] proposed an RL-based dynamic spectrum-allocation framework for cognitive radio management under conditions relevant to dense 5G-Advanced and 6G environments. Wang *et al.* [40] considered heterogeneous-agent deep reinforcement learning for dynamic spectrum access and reported improvements in throughput and collision management in multi-user cognitive networks.

These studies show that reinforcement learning provides a suitable mechanism for spectrum decisions when channel conditions evolve over time. The present thesis uses Q-Learning and DQN because they provide a direct comparison between tabular value learning and neural-network-based value approximation while remaining sufficiently interpretable for the proposed allocation problem.

2.9 Dynamic Spectrum Sharing in Smart Grid and Power Communication Networks

The application of dynamic spectrum sharing specifically to power communication networks has received increasing attention. Wireless systems can provide an alternative or complementary communication path when wired infrastructure is unavailable, difficult to deploy, or affected by emergency conditions. However, such communication must operate efficiently in shared radio environments.

Wang *et al.* [41] proposed a federated-learning-based dynamic spectrum-sharing framework for smart grids and power communication networks. Their approach combines distributed learning with deep reinforcement learning to improve spectrum access while keeping local training data decentralized. The study demonstrates the relevance of intelligent spectrum sharing to power-network communication and reports improvements in reward, access performance, and convergence under the investigated simulation conditions.

Liao *et al.* [5] considered a different but complementary problem by integrating sensing, communication, computing, and control. Their findings indicate that communication-resource adaptation can influence control-oriented performance. These studies collectively support the idea that future smart-grid communication requires more than reliable physical connectivity; radio resources must be selected and managed according to changing communication conditions.

The present study focuses on a narrower spectrum-management problem. It does not attempt to jointly optimize power-system control, network slicing, or multi-user scheduling. Instead, the present study investigates whether prediction of the subsequent spectrum occupancy state can provide useful information to an intelligent channel-allocation mechanism and how the resulting prediction-to-allocation framework behaves under common communication-level simulation assumptions.

2.10 Recent AI-Based Spectrum Management for 5G and 6G

Recent spectrum-management research reflects a shift from static decision rules toward learning-based and adaptive mechanisms [42, 43]. Falco *et al.* [?] identify AI-driven sensing as an important component of future spectrum management, particularly under dynamic 5G and 6G conditions. Their analysis also highlights generalization, real-time complexity, and adaptability as continuing challenges. Distributed AI has also been identified as a relevant direction for decentralized sensing and allocation in 6G-oriented spectrum management [6].

The major categories of intelligent spectrum-sharing techniques discussed in the literature are summarized in Fig. 2.2. The figure helps organize the research field by showing how modern spectrum-sharing methods extend from conventional sensing and access mechanisms toward machine-learning, deep-learning, and reinforcement-learning based decision frameworks.

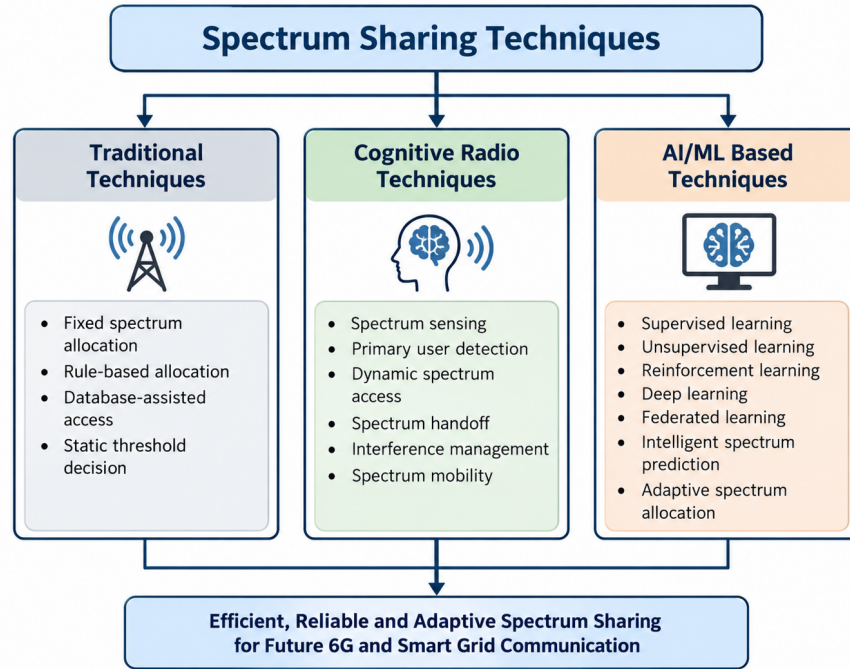


Figure 2.2: Taxonomy of intelligent spectrum-sharing techniques reported in the literature.

Venkatesan and Kumaratharan [39] address dynamic spectrum allocation under incomplete sensing and changing traffic conditions. Their RL-based formulation emphasizes the need to account for QoS, interference, edge constraints, and dynamic radio activity. Wang *et al.* [40] extend the access problem to users with heterogeneous observation and transmission characteristics, illustrating how spectrum management becomes increasingly complex in multi-user settings.

At the forecasting level, Xiao *et al.* [34] demonstrate that temporal spectrum patterns can be learned from real-world ElectroSense observations and that robustness to interference is an important consideration. Together, these recent studies indicate three recurring directions in current spectrum research: prediction of future spectrum conditions, learning-based resource allocation, and evaluation under increasingly heterogeneous or uncertain radio environments.

The progression from conventional spectrum-management approaches toward intelligent and predictive spectrum-sharing methods is illustrated in Fig. 2.3.

The approach adopted in this thesis is positioned between these directions. It does not attempt to reproduce the architectural complexity of transformer-based forecasting or multi-agent reinforcement learning. Instead, it establishes an experimentally transparent sequence in which consist of the approach adopted in this thesis is positioned between spectrum forecasting and learning-based resource allocation. It does not attempt to reproduce the architectural complexity of transformer-based forecasting or multi-agent reinforcement learning. Instead,

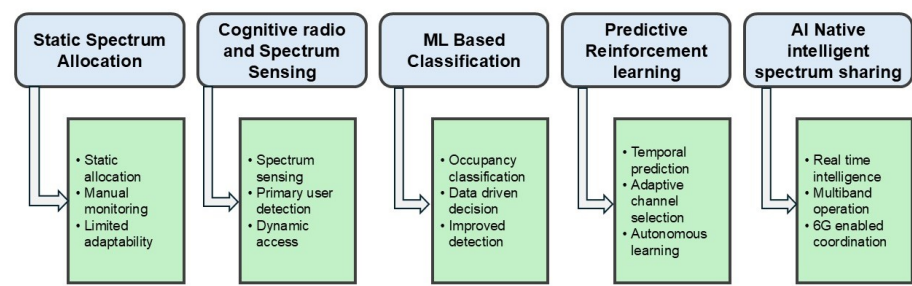


Figure 2.3: Evolution from conventional spectrum management toward AI-based intelligent spectrum sharing.

it establishes an experimentally transparent sequence in which the occupancy state of the subsequent spectrum observation is predicted first, after which Q-Learning or DQN performs channel selection using the predicted availability and channel-quality information.

2.11 Comparative Review of Related Studies

Table 2.1 summarizes studies that are particularly relevant to the dataset, prediction methodology, reinforcement-learning allocation, and smart-grid communication context of this thesis.

Table 2.1: Comparative Review of Literature Relevant to the Proposed Research

Year	Reference	Focus	Method / Data	Relevant Contribution	Distinction Relative to This Thesis
2005	Haykin [26]	Cognitive radio	Adaptive intelligent radio concepts	Established learning and environmental awareness as central cognitive-radio functions	Conceptual foundation; does not address modern ML-based predictive allocation
2006	Akyildiz <i>et al.</i> [27]	Dynamic spectrum access	Cognitive radio network architecture	Formalized sensing, decision, sharing, and mobility functions	Predates contemporary AI and 6G-oriented resource management
2009	Yucek and Arslan [11]	Spectrum sensing	Energy, matched-filter, cyclostationary, and cooperative sensing	Provides foundational comparison of sensing techniques and limitations	Primarily current-state sensing rather than predictive learning
2018	Rajendran <i>et al.</i> [10]	Open spectrum monitoring	Distributed ElectroSense sensing infrastructure	Provides real-world large-scale spectrum measurements	Platform work; not an end-to-end prediction and allocation framework
2022	Li <i>et al.</i> [33]	Spectrum-map prediction	Online learning with incomplete and corrupted observations	Demonstrates relevance of predictive spectrum mapping for 5G/6G	Focuses on spectrum-map recovery rather than binary next-slot occupancy and allocation
2022	Chang <i>et al.</i> [35]	Dynamic spectrum sharing	Deep Echo State Q-Network	Captures temporal spectrum behavior with reduced training overhead	Different data representation and does not address the proposed smart-grid scenario
2022	Dong <i>et al.</i> [36]	Dynamic spectrum access and sharing	Actor-critic DRL, channel selection, power control	Demonstrates adaptive access under unknown spectrum conditions	Emphasizes continuous power allocation and multi-agent access rather than compact prediction plus allocation
2025	Wang <i>et al.</i> [41]	Smart-grid dynamic spectrum sharing	Federated learning and multi-agent actor-critic DRL	Directly links intelligent spectrum sharing with smart-grid and power communication networks	Focuses on federated multi-agent sharing rather than supervised next-slot prediction
2025	Liao <i>et al.</i> [5]	6G-oriented smart-grid communication	Integrated sensing, transmission, computing, and control	Shows importance of communication-resource adaptation to grid-control performance	Does not focus on empirical spectrum occupancy prediction
2026	Falco <i>et al.</i> [?]	AI spectrum sensing	Meta-analysis of ML/DL spectrum sensing	Identifies trends, benefits, deployment challenges, and future directions for 5G/6G spectrum sensing	Survey rather than experimental prediction-allocation implementation
2026	Kumar <i>et al.</i> [4]	5G/6G smart-grid capabilities	Survey of emerging grid services and communication requirements	Provides contemporary 5G/6G smart-grid context and service requirements	Does not implement spectrum-prediction or RL-based channel allocation experiments
2026	Xiao <i>et al.</i> [34]	Spectrum forecasting	Transformer-based forecasting using ElectroSense GSM measurements	Provides recent evidence for temporal prediction using the same public sensing platform and overlapping GSM-900 spectrum	High-dimensional forecasting architecture; not designed for smart-grid channel allocation
2026	Venkatesan and Kumaratharan [39]	Dynamic spectrum allocation	Reinforcement-learning-based cognitive radio management	Addresses dynamic allocation under conditions relevant to 5G-Advanced/6G environments	Does not combine the same empirical next-slot predictor set with smart-grid communication evaluation

Year	Reference	Focus	Method / Data	Relevant Contribution	Distinction Relative to This Thesis
2026	Wang <i>et al.</i> [40]	Multi-user dynamic spectrum access	Heterogeneous-agent DRL	Addresses heterogeneous users and dynamic channel access	Greater multi-agent complexity and no ElectroSense-based prediction stage

The studies summarized in Table 2.1 address related but non-identical research problems. Their reported accuracies, throughput values, latencies, rewards, and convergence behaviour are obtained using different datasets, channel models, learning architectures, traffic conditions, and evaluation protocols. Consequently, the table is intended as a methodological comparison rather than a direct numerical benchmark. Direct numerical ranking across these studies would not be meaningful without a common dataset and experimental configuration.

The literature reveals that spectrum sensing, spectrum forecasting, reinforcement-learning allocation, and smart-grid communication are well-established research areas individually. However, their experimental assumptions and datasets differ substantially across studies. Direct numerical comparison among reported accuracies, throughputs, or latencies is therefore generally inappropriate unless the same dataset, channel model, train–test protocol, and system assumptions are used.

2.12 Research Gap

The reviewed literature shows substantial progress in spectrum sensing, spectrum forecasting, reinforcement-learning-based resource allocation, and communication support for smart-grid applications. However, the studies considered in this chapter generally emphasize different parts of the overall spectrum-management problem and employ substantially different datasets and experimental assumptions.

First, several foundational spectrum-sensing studies focus on estimation of the current occupancy state. More recent forecasting studies demonstrate the value of exploiting temporal information, but their objectives often involve spectrum-map reconstruction, amplitude forecasting, interference-aware sequence prediction, or other high-dimensional representations. For the type of resource-selection problem considered in this thesis, there remains value in examining a compact binary prediction of the occupancy state associated with the subsequent observation.

Second, the reviewed prediction and allocation studies frequently evaluate these functions under separate experimental formulations. Prediction-oriented work commonly emphasizes classification or forecasting performance, whereas reinforcement-learning allocation studies typically begin from an assumed or directly observed representation of channel availability. This leaves a useful experimental question concerning how prediction errors propagate into a subsequent intelligent allocation stage when both functions are evaluated within one controlled pipeline.

Third, the use of real-world spectrum measurements in future-network research requires careful interpretation. ElectroSense provides empirical observations from deployed radio environments, whereas 6G/IMT-2030 remains a future communication framework. Existing measurements can therefore support the study of temporal spectrum behaviour, but they should not be relabelled as measurements obtained from a 6G radio interface. A methodology that explicitly separates empirical occupancy learning from future-network communication assumptions provides a clearer basis for such evaluation.

Fourth, prediction accuracy alone does not describe the behaviour of an integrated spectrum-management framework. Computational requirements and the communication-level consequences of allocation decisions should also be examined. A predictor may achieve strong classification performance while still creating missed opportunities or unsafe candidate channels, and a more complex reinforcement-learning method may provide only modest communication improvement relative to its additional training cost.

Based on these observations, the research position adopted in this thesis is to construct a transparent prediction-to-allocation framework using empirical ElectroSense-derived measurements. SVM, Random Forest, Decision Tree, and KNN are compared for prediction of the occupancy state associated with the subsequent chronologically ordered observation under a common sequence-aware evaluation procedure. The predictor selected according to the predefined model-selection rule supplies candidate availability information to Q-Learning and DQN, which are then evaluated under the same underlying communication environment.

The contribution of the study therefore does not lie in proposing a new machine-learning algorithm. Instead, it lies in the controlled integration and evaluation of empirical next-observation spectrum prediction and intelligent channel allocation while explicitly separating the measured data source, target construction, train–test procedure, reinforcement-learning environment, and 6G-oriented communication assumptions.

Chapter 3

Research Methodology

3.1 Methodological Design

This research adopts a two-stage spectrum-management methodology consisting of next-observation spectrum occupancy prediction followed by intelligent channel selection. The first stage uses supervised machine learning to estimate the occupancy state associated with the subsequent chronologically ordered observation within the same sensor–frequency sequence. The second stage uses the predicted spectrum availability together with SNR-related channel-quality information to support channel selection through reinforcement learning.

In this thesis, the term “next observation” refers to the observation immediately following the current observation after chronological reconstruction of a sensor–frequency sequence. It should not be interpreted as a standardized 5G/6G radio-frame slot unless an equivalent fixed sampling interval is explicitly established from the source data.

The overall methodological sequence adopted in this study is illustrated in Fig. 3.1.

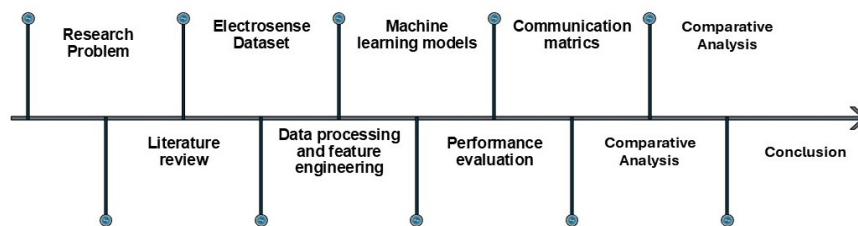


Figure 3.1: Overall sequence of the research methodology adopted in this study.

The methodology deliberately maintains a distinction between empirical spectrum measurements and the assumptions introduced for 6G-oriented communication evaluation. The spectrum-prediction component is derived from ElectroSense measurements, whereas the assumed 8 GHz carrier-frequency scenario and 100 MHz effective communication bandwidth are introduced separately as communication-level simulation parameters.

No physical frequency-domain transformation from the measured ElectroSense spectrum observations to 8 GHz is performed.

The complete processing sequence can be represented as

$$D_{\text{raw}} \longrightarrow D_{\text{processed}} \longrightarrow \hat{O}_{t+1} \longrightarrow \mathcal{C}_{t+1} \longrightarrow a_{t+1} \longrightarrow \mathcal{M}, \quad (3.1)$$

where D_{raw} denotes the original empirical spectrum observations, $D_{\text{processed}}$ represents the engineered predictive dataset, $\hat{O}_{t+1}$ denotes the predicted occupancy state of the subsequent observation, $\mathcal{C}_{t+1}$ is the resulting candidate channel set, a_{t+1} represents the selected channel, and $\mathcal{M}$ denotes the resulting prediction, computational, and simulation-derived communication performance measures.

3.2 Empirical Spectrum Dataset

The empirical basis of this research is derived from the ElectroSense spectrum-monitoring platform. ElectroSense was developed as a distributed sensing infrastructure for collecting large-scale radio-spectrum measurements using geographically distributed sensing nodes [10]. The platform has subsequently been used in spectrum monitoring, anomaly detection, and spectrum forecasting research.

The original dataset used in this work contains observations extracted from the GSM-900 region. Each observation includes temporal information, sensing-node identification, received spectrum energy, a detection threshold, an occupancy label, and information identifying the source measurement. The original occupancy state was obtained through a threshold-based relationship between measured energy and the corresponding decision threshold. The empirical data extraction process adopted from the ElectroSense platform is illustrated in Fig. 3.2.

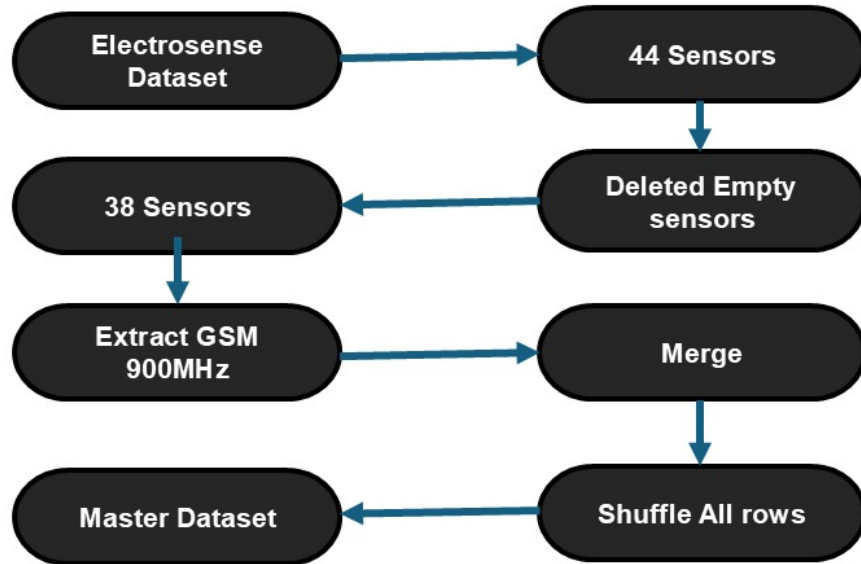


Figure 3.2: ElectroSense data extraction and construction of the merged empirical spectrum dataset.

The original labeling rule can be expressed as

$$O_t = \begin{cases} 1, & E_t \geq \lambda_t, \\ 0, & E_t < \lambda_t, \end{cases} \quad (3.2)$$

where E_t denotes the measured energy, λ_t is the corresponding threshold, and O_t represents the occupancy state.

Directly using both E_t and λ_t as predictor variables for reconstruction of O_t would allow a learning algorithm to approximate the rule used to create the reference label rather than learn a meaningful temporal relationship. Such a formulation would introduce target leakage and could result in an overly optimistic estimate of classification performance. The detection-threshold variable is therefore excluded from the final supervised-learning feature set.

The learning task is instead reformulated from reconstruction of the current threshold-derived occupancy state,

$$\mathbf{x}_t \longrightarrow O_t, \quad (3.3)$$

to prediction of the occupancy state associated with the subsequent chronologically ordered observation,

$$\mathbf{x}_t \longrightarrow O_{t+1}. \quad (3.4)$$

This formulation requires the learning algorithms to use the information available at observation t to estimate a subsequent occupancy condition rather than directly reconstructing the current energy–threshold decision.

It should be emphasized that O_t is a threshold-derived reference occupancy label. It represents the occupancy definition adopted for the empirical dataset and should not be interpreted as independently verified physical ground truth obtained from decoding the underlying transmitted signal.

3.2.1 Numerical Summary of ElectroSense Dataset

- **Sensors:** 38 active sensing nodes retained (6 empty nodes removed from initial 44).
- **Frequency Range:** 919.5 MHz to 954.5 MHz (18 center frequencies).
- **Dataset Size:** 37,156 valid observation records.
- **Class Distribution (Full Dataset):** Vacant ($O = 0$): 23,605 samples (63.53%), Occupied ($O = 1$): 13,551 samples (36.47%).
- **Class Distribution (Test Set, 7,432 samples):** Vacant ($O = 0$): 4,821 samples (64.87%), Occupied ($O = 1$): 2,611 samples (35.13%).

3.3 Sequence Reconstruction and Data Preparation

The spectrum observations are organized according to sensing node and empirical center frequency. Each unique combination of Sensor_ID and Empirical_Center_Frequency_MHz is treated as an independent temporal sequence. Observations within each sequence are ordered according to their time index before temporal features and the prediction target are created.

The main preprocessing and feature-engineering stages applied before model training are summarized in Fig. 3.3.

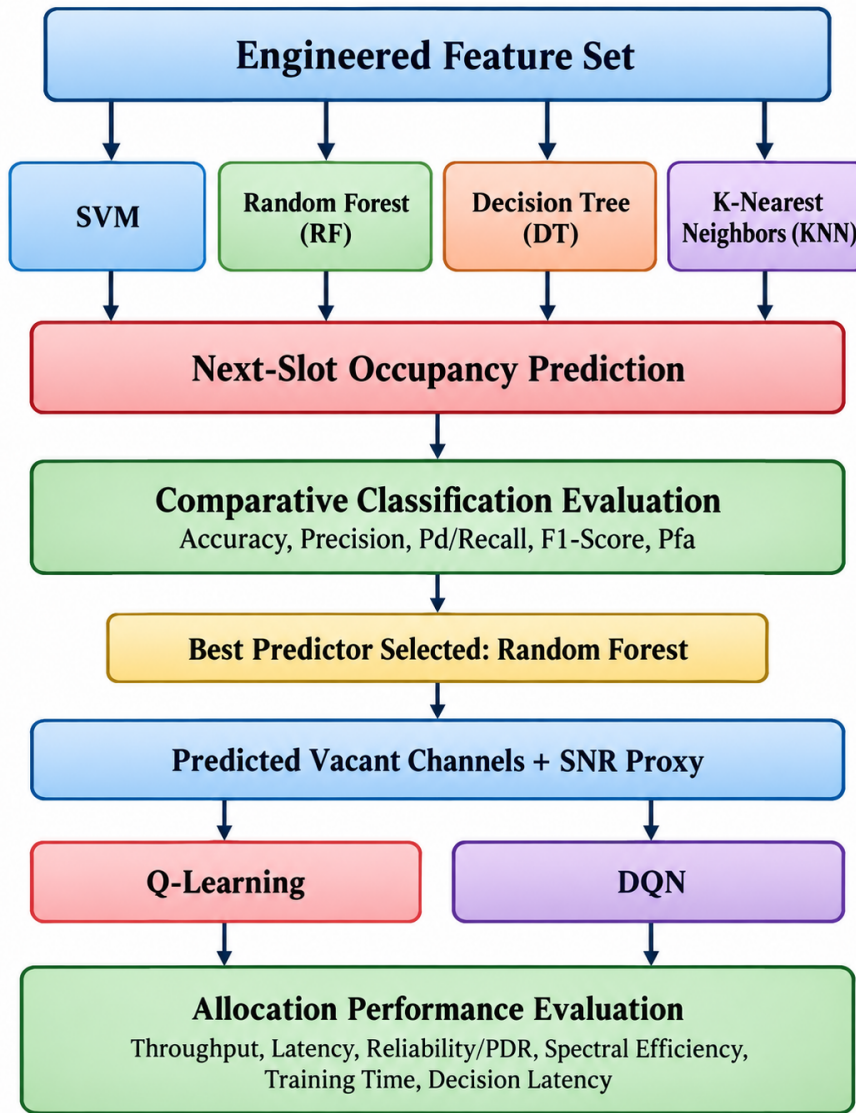


Figure 3.3: Data preprocessing and feature-engineering pipeline used to construct the final predictive dataset.

The target associated with observation t is generated within each sensor–frequency sequence as

$$O_t^{\text{target}} = O_{t+1}. \quad (3.5)$$

Consequently, the final observation of each sequence cannot be assigned a subsequent occupancy target and is removed. Observations that do not contain sufficient preceding samples for the required rolling statistics are also excluded.

All temporal features are constructed causally using the current and preceding observations only. No centered rolling window or future observation is used in the construction of the predictor variables. This prevents information associated with the prediction target from entering the feature vector.

Following sequence reconstruction, target generation, and removal of incomplete records, the final predictive dataset contains 37,156 usable observations.

Sequences containing fewer than ten valid observations are excluded from the train–test procedure because extremely short sequences would provide insufficient observations for meaningful chronological partitioning.

3.4 Final Dataset Structure

The processed dataset contains ten variables. Some variables are used for supervised prediction, while others are retained for sequence management or reinforcement-learning allocation. The final structure is presented in Table 3.1.

Table 3.1: Final Processed Dataset Structure

No.	Variable	Role in the Proposed Methodology
1	Time_Index	Maintains chronological ordering of observations
2	Sensor_ID	Identifies the ElectroSense sensing node and separates temporal sequences
3	Empirical_Center Frequency_MHz	Represents the original measured spectrum channel and is used as a classifier feature
4	Assumed_6G_Carrier_GHz	Records the fixed 8 GHz research scenario; not used as a classifier feature
5	Energy_dBm	Empirical received-energy observation used for occupancy prediction
6	Energy_Delta_dB	Short-term variation between consecutive energy observations
7	Rolling_Mean Energy_5_dBm	Five-observation rolling mean of received energy
8	Rolling_Std_Energy_5_dB	Five-observation rolling standard deviation of received energy
9	SNR_6G_Proxy_dB	Simulation-oriented channel-quality indicator used by the allocation stage
10	Next_Occupancy	Binary prediction target representing occupancy of the next observation

The assumed communication bandwidth is intentionally not included in the supervised classifier feature vector. A fixed effective bandwidth of 100 MHz is used for every communication-level evaluation instance. Because this quantity has no observation-to-observation variation, it provides no discriminative information to SVM, RF, DT, or KNN. Nevertheless, bandwidth remains an explicit system parameter because it affects the thermal-noise calculation and the conversion from spectral efficiency to throughput.

Similarly, the assumed 8 GHz carrier frequency is scenario metadata rather than a predictive feature. It remains constant throughout the communication-level experiment and therefore cannot contribute to discrimination between occupied and vacant observations.

3.5 Feature Engineering

The prediction stage uses a compact set of Six features:

$$x_t = [f_t, E_t, \Delta E_t, \bar{E}_{t,5}, \sigma_{E,t,5}] \quad (3.6)$$

where f_t denotes the empirical center frequency, E_t represents the received energy, ΔE_t is the short-term energy difference, $\bar{E}_{t,5}$ is the rolling mean over five observations, and $\sigma_{E,t,5}$ is the corresponding rolling standard deviation.

3.5.1 Energy Difference

The energy-difference feature captures the direction and magnitude of short-term variation in spectrum activity and is defined as

$$\Delta E_t = E_t - E_{t-1}. \quad (3.7)$$

A large positive value may indicate increasing received activity, whereas a negative value indicates a reduction relative to the preceding observation.

3.5.2 Rolling Mean

The five-observation rolling mean provides a local estimate of the recent energy level:

$$\bar{E}_{t,5} = \frac{1}{5} \sum_{i=0}^4 E_{t-i}. \quad (3.8)$$

This feature suppresses isolated fluctuations and provides the classifier with short-term temporal context.

3.5.3 SNR Proxy Formula & Noise Floor

$$\text{SNR}_{\text{proxy,dB}} = E_{\text{dBm}} - N_{\text{floor,dBm}} \quad (3.9)$$

where $N_{\text{floor,dBm}} = -174 + 10\log_{10}(B_{\text{Hz}}) + \text{NF}_{\text{dB}} = -174 + 10\log_{10}(10^8) + 5 = -89 \text{ dBm}$ (using channel bandwidth $B = 100 \text{ MHz}$ and receiver Noise Figure $\text{NF} = 5 \text{ dB}$).

3.5.4 Rolling Standard Deviation

Short-term energy variability is represented by

$$\sigma_{E,t,5} = \sqrt{\frac{1}{5} \sum_{i=0}^4 (E_{t-i} - \bar{E}_{t,5})^2}. \quad (3.10)$$

The rolling standard deviation complements the rolling mean by describing whether recent measurements are relatively stable or highly variable.

The SNR-related variable is excluded from the supervised prediction feature set because it is derived from the same underlying received-energy information and the assumed communication parameters. Including it together with the original energy variable could introduce unnecessary redundancy into the classifier input.

The SNR-related quantity is therefore reserved for the allocation stage, where it is used as a relative simulation-oriented channel-quality indicator. It should not be interpreted as an independently measured physical-layer SNR at the assumed 8 GHz carrier.

3.6 6G-Oriented Communication Assumptions

The empirical measurements used for occupancy prediction retain their original ElectroSense frequency-domain interpretation and are not modified or presented as native 6G measurements. A separate communication-evaluation layer is therefore introduced to study the allocation techniques under a future-network research scenario.

Recommendation ITU-R M.2160 describes IMT-2030 as a multi-band future communication framework rather than as a system restricted to a single carrier-frequency range [9]. The present work adopts an 8 GHz carrier-frequency scenario as an explicit research assumption. This value is not presented as a finalized or universal 6G allocation.

No propagation-frequency conversion is applied to the original ElectroSense data. The 8 GHz value defines the communication scenario only; it does not alter the empirical center frequencies used during occupancy prediction.

3.7 Train–Test Strategy

A conventional global random split was not used for the final experiment because such a procedure can mix temporally adjacent observations between training and testing sets and may therefore produce an optimistic estimate of predictive performance.

The final approach applies a chronological 80/20 split independently within each valid sensor-frequency sequence. For a sequence containing N_g observations, the training boundary is

$$N_{\text{train},g} = \lfloor 0.8N_g \rfloor, \quad (3.11)$$

where g identifies a specific combination of sensing node and empirical center frequency.

The first 80% of each sequence are assigned to the training set, while the final 20% are reserved for testing. No future observations are moved into the training portion of the same sequence.

This procedure provides two advantages. First, it maintains chronological separation between training and testing data. Second, it ensures that sufficiently represented sensor-frequency sequences contribute to both subsets, preventing the test set from being dominated by only a small number of channels.

All preprocessing operations requiring estimated parameters are fitted using the training portion only and are subsequently applied to the corresponding test observations. The test labels are not used during supervised model fitting or model selection.

Because each sensor-frequency sequence contributes chronologically ordered observations to the two partitions, the procedure evaluates later observations against models fitted on earlier observations from the corresponding empirical sequences rather than measuring generalization to completely unseen sensing nodes or frequencies.

3.8 Spectrum Occupancy Prediction Models

Four supervised-learning algorithms are evaluated under the same feature set and sequence-aware train-test protocol. The selected techniques represent different learning principles and provide a balanced comparison of margin-based, tree-based, ensemble, and instance-based classification.

3.8.1 Support Vector Machine

Support Vector Machine seeks a separating hyperplane that maximizes the margin between classes [29]. Given a feature vector $\mathbf{x}$, a linear decision function may be written as

$$f(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + b, \quad (3.12)$$

where $\mathbf{w}$ denotes the separating weight vector and b is the bias term.

SVM is included as a robust margin-based baseline. Input standardization is applied where required using parameters estimated exclusively from the training data so that information from the test set is not introduced during model fitting.

3.8.2 Decision Tree

Decision Tree classification recursively divides the feature space according to feature-based decision rules. At each internal node, a split is selected to improve class separation. The final class prediction is determined by the terminal leaf reached by an observation.

Decision trees are attractive because their predictions can be interpreted through explicit feature conditions. However, an unrestricted tree can become highly specialized to training observations. The implementation therefore retains the model configuration defined in the common experimental pipeline rather than tuning the tree independently on the test set.

3.8.3 Random Forest

Random Forest combines predictions from multiple randomized decision trees [31]. Each tree is trained using a perturbed sample of the available data and considers a subset of candidate features during node splitting. For binary classification, the ensemble decision can be represented as

$$\hat{O}_{t+1} = \text{mode} \{h_1(\mathbf{x}_t), h_2(\mathbf{x}_t), \dots, h_M(\mathbf{x}_t)\}, \quad (3.13)$$

where h_m represents the prediction generated by the m th tree and M is the number of trees.

The ensemble structure reduces the dependence of the final decision on any single tree and is particularly useful when nonlinear relationships exist among spectrum features.

3.8.4 K-Nearest Neighbors

K-Nearest Neighbors assigns a class according to the labels of nearby training observations in feature space [32]. For two standardized observations $\mathbf{x}_i$ and $\mathbf{x}_j$, Euclidean distance is given by

$$d(\mathbf{x}_i, \mathbf{x}_j) = \sqrt{\sum_{p=1}^P (x_{i,p} - x_{j,p})^2}, \quad (3.14)$$

where P is the number of input features.

KNN has a relatively small model-fitting cost because it stores the reference observations rather than estimating a complex decision function. Its computational burden is shifted toward inference, where distances to neighboring observations must be evaluated.

3.9 Prediction Performance Measures

The binary prediction outcome is represented using true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). In this study, the occupied state is treated as the positive class. Multiple complementary measures are reported because accuracy alone can conceal important class-specific errors in binary classification [44–46]. Throughout the

classification analysis, the occupied state ($O = 1$) is treated as the positive class and the vacant state ($O = 0$) as the negative class. Accuracy is calculated as

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}. \quad (3.15)$$

Precision is defined as

$$\text{Precision} = \frac{TP}{TP + FP}. \quad (3.16)$$

Probability of detection, equivalent to recall for the occupied class, is

$$P_d = \frac{TP}{TP + FN}. \quad (3.17)$$

The F1-score combines precision and recall:

$$F_1 = 2 \frac{\text{Precision} \times P_d}{\text{Precision} + P_d}. \quad (3.18)$$

Probability of false alarm is calculated as

$$P_{fa} = \frac{FP}{FP + TN}. \quad (3.19)$$

These metrics are considered jointly because overall accuracy alone can conceal different types of classification error. In spectrum management, a missed occupied channel and an unnecessarily rejected vacant channel have different operational consequences.

3.10 Selection of the Predictor for Spectrum Allocation

The four prediction models are evaluated before the reinforcement-learning stage. A common model-selection rule is applied to avoid choosing a predictor subjectively after observing the communication results.

The predictor supplied to the allocation stage is selected using a predefined hierarchical criterion. The model achieving the highest F1-score is selected. If two or more models produce the same F1-score at the reported precision, classification accuracy is used as the secondary criterion.

Formally,

$$m^* = \arg \max_{m \in \mathcal{M}} F1_m, \quad (3.20)$$

with classification accuracy used only as a tie-breaking criterion, where $\mathcal{M} = \{\text{SVM}, \text{RF}, \text{DT}, \text{KNN}\}$.

Under the final experimental results, Random Forest satisfies this rule and is therefore used to generate availability information for the subsequent allocation experiment.

3.11 Prediction-to-Allocation Interface

After prediction, the Random Forest outputs are aligned with their corresponding chronological and channel observations. For each subsequent decision observation, the candidate resource set is constructed from channels predicted to be vacant:

$$\mathcal{C}_{t+1} = \{c_i : \hat{O}_{t+1,i} = 0\}, \quad (3.21)$$

where c_i denotes candidate channel i and $\hat{O}_{t+1,i} = 0$ denotes predicted vacancy at the subsequent observation.

Where multiple sensor observations correspond to the same time-channel combination, occupancy information is fused conservatively. The occupancy state is represented using the maximum reported occupancy condition, while SNR-related information is averaged across available observations. This conservative occupancy fusion reduces the possibility of treating a channel as vacant when one of the corresponding observations indicates activity.

The relationship between offline model development and online spectrum-allocation operation is illustrated in Fig. 3.4.

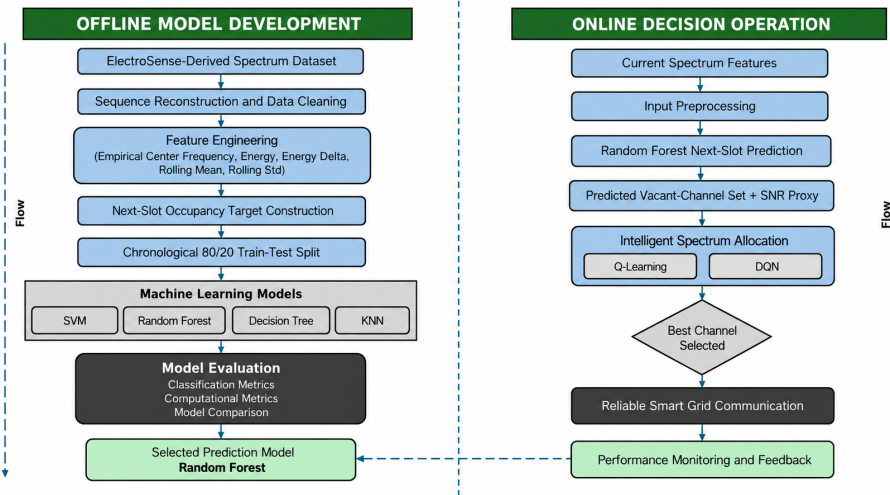


Figure 3.4: Offline model development and online prediction-assisted spectrum allocation framework.

If no channel is predicted vacant at a particular decision instant, the environment retains a valid observed channel action space so that the allocation process remains measurable. Any selected channel that is actually occupied receives the defined negative reward. This prevents the simulation from silently discarding difficult time intervals.

The functional layers connecting spectrum sensing, prediction, intelligent allocation, and smart grid communication are illustrated in Fig. 3.5.

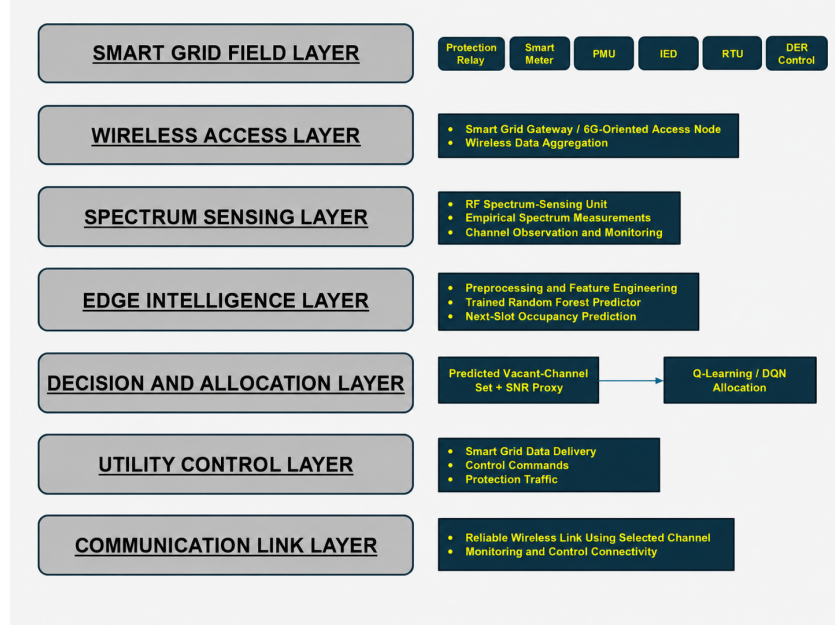


Figure 3.5: Layered architecture of the proposed prediction-assisted intelligent spectrum-sharing system for smart grid communication.

3.12 Q-Learning Based Spectrum Allocation

Q-Learning is a model-free reinforcement-learning method that estimates the long-term utility of state–action pairs [37]. The update rule is

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[r_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t) \right], \quad (3.22)$$

where α is the learning rate, γ is the discount factor, s_t represents the current state, a_t is the selected channel, and r_t is the resulting reward.

To maintain a tractable tabular representation, the continuous allocation information is compressed and discretized before indexing the Q-table. The Q-Learning state consists of:

1. the number of channels predicted to be vacant;
2. a discretized representation of the mean SNR-related quality of the available channels;
and
3. a discretized representation of the highest available-channel SNR-related quality.

The action corresponds to selection of a channel from the environment's valid action set. Exploration and exploitation are balanced through an ϵ -greedy policy during training.

This compact state representation is intentionally used to keep tabular Q-Learning computationally manageable. It summarizes rather than preserves all channel-specific information and therefore has lower representational detail than the state supplied to DQN.

3.13 Deep Q-Network Based Spectrum Allocation

DQN extends Q-Learning by approximating the action-value function with a neural network [38]. This avoids maintaining a separate table entry for every possible state.

The DQN state vector used in this research contains:

1. the predicted channel-vacancy vector;
2. normalized SNR information for the candidate channels; and
3. an observation mask identifying valid channel positions.

The neural-network function can be represented as

$$\mathbf{Q}(s_t; \theta) = [Q(s_t, a_1; \theta), \dots, Q(s_t, a_N; \theta)], \quad (3.23)$$

where θ represents the trainable network parameters.

The implementation uses two hidden fully connected layers with 128 neurons in each layer. The output layer returns one Q-value for each possible channel action.

A target network and experience replay are used to improve training stability. The target value for a transition can be represented as

$$y_t = r_t + \gamma \max_{a'} Q_{\text{target}}(s_{t+1}, a'; \theta^-), \quad (3.24)$$

where θ^- represents the target-network parameters.

The training objective minimizes the difference between the current network estimate and the target value:

$$\mathcal{L}(\theta) = [y_t - Q(s_t, a_t; \theta)]^2. \quad (3.25)$$

3.14 Reward Design

The allocation reward is designed to distinguish successful use of a genuinely vacant channel from selection of a channel that is actually occupied.

A successful selection receives a positive reward that increases with the communication quality represented by spectral efficiency. When the selected channel is occupied, the agent receives a fixed penalty of

$$r_t = -5. \quad (3.26)$$

The reward structure therefore encourages two related behaviors: avoiding channels that are actually occupied and preferring higher-quality channels among those that can be used successfully.

Both Q-Learning and DQN operate under the same reward definition and the same predicted candidate information. This ensures that the comparison reflects differences between the allocation algorithms rather than differences in environmental conditions.

3.15 Communication-Level Evaluation

The allocation-stage outputs are evaluated using simulation-derived communication indicators. These quantities are calculated from the defined SNR-related proxy, effective bandwidth, access-success condition, packet-size assumption, and latency model. They are not direct packet measurements contained in the ElectroSense dataset and should not be interpreted as field measurements from an operational 6G smart grid.

3.15.1 Spectral Efficiency

The spectral efficiency associated with the selected channel is approximated through the Shannon relationship [47]:

$$\eta_t = \log_2 \left(1 + 10^{\text{SNR}_t/10} \right), \quad (3.27)$$

where η_t is expressed in bit/s/Hz.

Before evaluation of the logarithmic expression, the SNR proxy is constrained to the range $[-10.0, 50.0]$ dB to ensure numerical stability during performance evaluation..

3.15.2 Throughput

For an effective channel bandwidth B , throughput is calculated as

$$R_t = B\eta_t. \quad (3.28)$$

With $B = 100$ MHz, the corresponding throughput in Mbps becomes

$$R_{t,\text{Mbps}} = 100 \times \eta_t. \quad (3.29)$$

Because the effective bandwidth is fixed at 100 MHz throughout the experiment, throughput and spectral efficiency are deterministically related in this simulation. They are reported in different units for communication interpretation and should not be interpreted as independent experimental measurements.

3.15.3 Latency

For a successful channel selection, the communication latency consists of a fixed base delay and the packet-transmission time:

$$L_{\text{success}} = L_{\text{base}} + \frac{8S}{R}, \quad (3.30)$$

where S is the packet size in bytes and R is the selected-channel throughput in bit/s. Using a packet size of 512 bytes and a base latency of 1 ms,

$$L_{\text{success,ms}} = 1 + \frac{8(512)}{R_{\text{Mbps}} \times 10^6} \times 10^3. \quad (3.31)$$

For an unsuccessful selection caused by an actually occupied channel, a latency penalty of 10 ms is assigned:

$$L_{\text{failure}} = 10 \text{ ms}. \quad (3.32)$$

The reported average latency therefore reflects both successful transmission delays and the effect of unsuccessful spectrum-access decisions.

The 1 ms base delay and 10 ms unsuccessful-access penalty are controlled scenario assumptions applied identically to both allocation methods. They are not measured end-to-end delays from a deployed smart-grid or 6G network. Consequently, the resulting latency values are suitable for relative comparison within this experiment rather than for claiming compliance with a particular operational smart-grid latency requirement.

3.15.4 Allocation-Success-Based Reliability/PDR Indicator

Within the simplified simulation, an allocation decision is treated as successful when the selected resource is actually vacant according to the reference occupancy state.

The allocation-success-based reliability indicator is calculated as

$$PDR_{\text{proxy}} = \frac{N_{\text{successful access}}}{N_{\text{allocation decisions}}}. \quad (3.33)$$

This quantity is reported as a PDR-related reliability proxy because it represents the proportion of decisions resulting in successful channel use. It does not incorporate physical-layer packet errors, fading, coding, retransmissions, collisions, or protocol-layer packet loss. It should therefore not be interpreted as a complete measured packet-delivery ratio.

3.16 Computational Performance Measurement

Prediction quality alone does not indicate whether an algorithm can be used efficiently. Training time and inference or decision latency are therefore recorded for all investigated techniques.

For the supervised classifiers, training time is measured as the elapsed wall-clock time required to fit the model using the training subset. Per-sample inference latency is calculated from the total prediction time:

$$L_{\text{inf}} = \frac{T_{\text{prediction}}}{N_{\text{test}}}. \quad (3.34)$$

For Q-Learning and DQN, the reported training time represents the computational effort required to learn the allocation policy. Online decision latency is measured separately because a method can require extensive offline training while still producing sufficiently rapid online decisions.

The evaluation criteria used throughout the study are grouped into prediction, computational, and communication performance measures, as illustrated in Fig. 3.6.

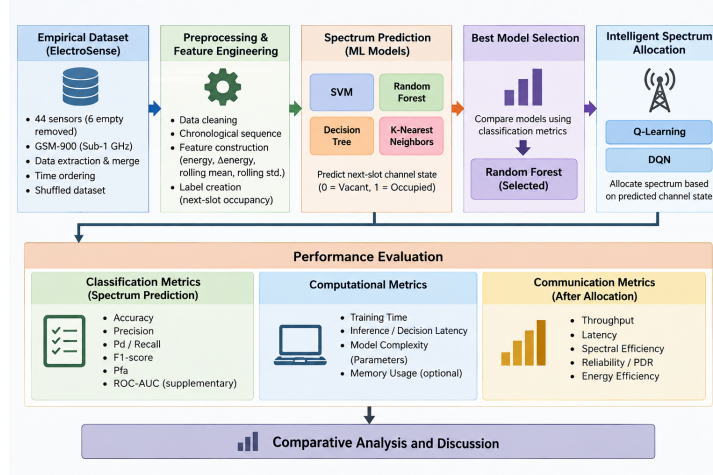


Figure 3.6: Performance metrics used for prediction, computational, and communication evaluation.

This distinction is particularly important for DQN, where neural-network training is substantially more computationally demanding than tabular Q-Learning, but trained-network inference can remain fast.

3.17 Consistency of the Experimental Comparison

Several controls are maintained so that the experimental comparisons are performed under a common underlying data and communication environment.

First, SVM, Random Forest, Decision Tree, and KNN use the same prediction target, the same five predictor variables, and the same sequence-wise chronological train-test partitions.

Second, the predictor supplied to the allocation stage is selected using the predefined F1-score criterion rather than according to the subsequent communication results.

Third, Q-Learning and DQN are constructed from the same Random Forest prediction source, underlying channel-quality observations, occupancy reference information, bandwidth assumption, packet size, latency model, and reward definition.

The two reinforcement-learning methods do not use identical internal state encodings. Tabular Q-Learning uses a compressed discretized state to maintain a manageable Q-table, whereas DQN uses a higher-dimensional channel-wise representation. This difference is intrinsic to the implemented allocation formulations and is explicitly considered when interpreting their comparative results.

The comparison should therefore be understood as a controlled comparison under a common underlying environment rather than as an experiment in which every internal representation and computational structure is identical.

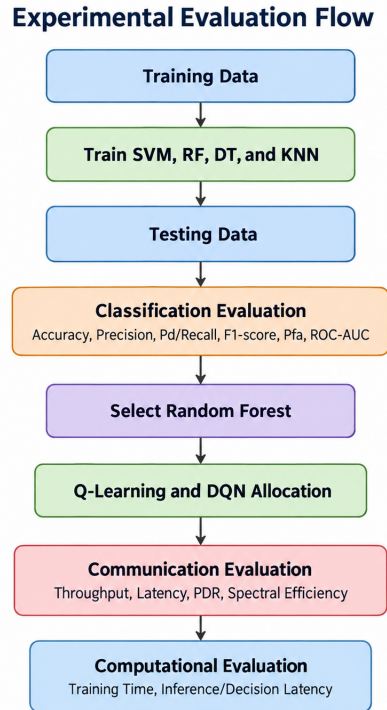


Figure 3.7: Experimental evaluation sequence for spectrum prediction, intelligent allocation, and performance analysis.

3.18 Implementation Environment

The complete experimental pipeline is implemented in Python. Data preparation and tabular processing are performed using NumPy and Pandas. SVM, Random Forest, Decision Tree, KNN, preprocessing operations, and classification metrics are implemented using scikit-learn [48]. The DQN is implemented using PyTorch, while numerical and graphical outputs are generated using NumPy and Matplotlib.

3.18.1 Hyperparameter Specification Table

The pipeline produces separate outputs for prediction performance, computational performance, reinforcement-learning convergence, communication metrics, confusion matrices, receiver-operating characteristics, feature analysis, and dataset diagnostics.

The principal sequence of execution is:

1. load and validate the corrected predictive dataset;
2. reconstruct sensor-frequency sequences;

Table 3.2: Hyperparameter Specification Table

Algorithm	Hyperparameter	Assigned Value
Random Forest	n_estimators, Split criterion, Max depth	100 trees, Gini impurity, None (max_depth=None)
SVM	Kernel type, Regularization C , Kernel coefficient γ	RBF kernel, $C = 1.0$, $\gamma = \text{'scale'}$
Decision Tree	Split criterion, Min samples split, Max depth	Gini impurity, 2 samples, None (max_depth=None)
KNN	Number of neighbors (k), Distance metric	$k = 5$, Euclidean metric ($p = 2$)
Q-Learning	Training episodes, Learning rate (α), Discount (γ)	30 episodes, $\alpha = 0.1$, $\gamma = 0.95$, ϵ -decay ($1.0 \rightarrow 0.01$)
DQN	Architecture, Learning rate, Buffer size, Batch size	FC(128×128), 1×10^{-3} (Adam), 10,000 replay, 64 batch size

3. apply sequence-wise chronological training and testing separation;
4. train SVM, Random Forest, Decision Tree, and KNN;
5. generate next-slot predictions for the common test set;
6. calculate classification and computational metrics;
7. select the classifier using F1-score and accuracy;
8. generate channel candidates from the selected classifier predictions;
9. train Q-Learning using the common allocation environment;
10. train DQN using the same allocation environment;
11. evaluate both policies on communication and computational measures; and
12. export numerical results, models, and figures for further analysis.

3.19 Methodological Boundaries

The proposed methodology evaluates the relationship between empirical spectrum occupancy prediction and intelligent channel selection under controlled and reproducible simulation assumptions. It is not intended to reproduce a complete 6G physical layer, multi-cell scheduler, commercial radio protocol stack, or operational smart-grid control network.

The empirical ElectroSense measurements retain their original spectrum interpretation. The assumed 8 GHz carrier-frequency scenario and 100 MHz effective communication bandwidth are introduced separately for communication-level evaluation and are not presented as measured properties of the source dataset.

Similarly, the reported throughput, latency, spectral efficiency, and reliability/PDR indicators are derived from the defined simulation equations and allocation outcomes. They should therefore be interpreted as comparative system-level indicators under common experimental conditions rather than as field measurements or evidence of compliance with operational 6G or mission-critical smart-grid performance requirements.

The methodology consequently separates three distinct elements throughout the thesis: empirical spectrum observations, machine-learning prediction outputs, and simulation-derived communication indicators.

Chapter 4

Results and Discussion

4.1 Experimental Results Overview

This chapter presents the experimental results obtained from the final AI-assisted spectrum-management framework described in Chapter 3. The evaluation is organized around three principal dimensions: spectrum-occupancy classification, computational performance, and intelligent spectrum allocation under the defined 6G-oriented smart-grid communication scenario.

The supervised-learning stage evaluates Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbors (KNN) using the same classifier feature set and the same chronological training and testing partitions. Each classifier estimates whether an empirical spectrum observation is vacant or occupied according to the reference occupancy label contained in the processed dataset.

The classifier selected according to the predefined F1-score criterion is subsequently used to generate channel-availability information for the reinforcement-learning allocation stage. Random Forest satisfies this criterion in the reported experiment and is therefore used as the common prediction front end for Q-Learning and Deep Q-Network (DQN).

The reinforcement-learning agents are trained using the allocation environment derived from the chronological training partition and are subsequently evaluated using the separate held-out test environment. Consequently, communication-performance results are obtained from observations that are not used to update the learned allocation policies.

The final experimental sequence can be represented as

$$\begin{aligned} &\text{ElectroSense-derived data} \rightarrow \text{Occupancy classification} \rightarrow \\ &\text{RF availability estimates} \rightarrow \{\text{Q-Learning, DQN}\} \end{aligned} \tag{4.1}$$

4.2 Characteristics of the Final Experimental Dataset

Before examining classifier performance, the processed dataset was inspected to evaluate the occupancy-class distribution and the numerical variables used in the experiment.

Both vacant ($O = 0$) and occupied ($O = 1$) observations are represented, although their

proportions are not equal. This class imbalance provides an additional reason for considering precision, probability of detection, F1-score, and probability of false alarm together with overall accuracy.

The distribution of the next-slot occupancy target is shown in Fig. 4.1. The predictive dataset contains both vacant and occupied future-spectrum observations, with vacant observations occurring more frequently than occupied observations.

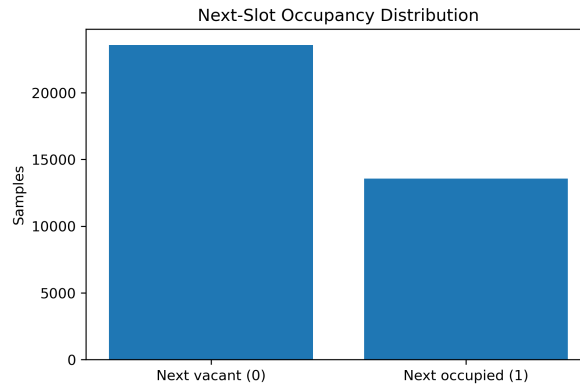


Figure 4.1: Distribution of vacant and occupied spectrum observations in the final experimental dataset.

The presence of unequal class proportions provides an additional reason for evaluating the models using precision, probability of detection, F1-score, and probability of false alarm instead of relying only on overall accuracy.

4.2.1 Energy Distribution

The empirical received-energy distribution is shown in Fig. 4.2. The variation in measured energy reflects the heterogeneous nature of the original spectrum observations and provides the principal empirical signal characteristic from which temporal features are derived.

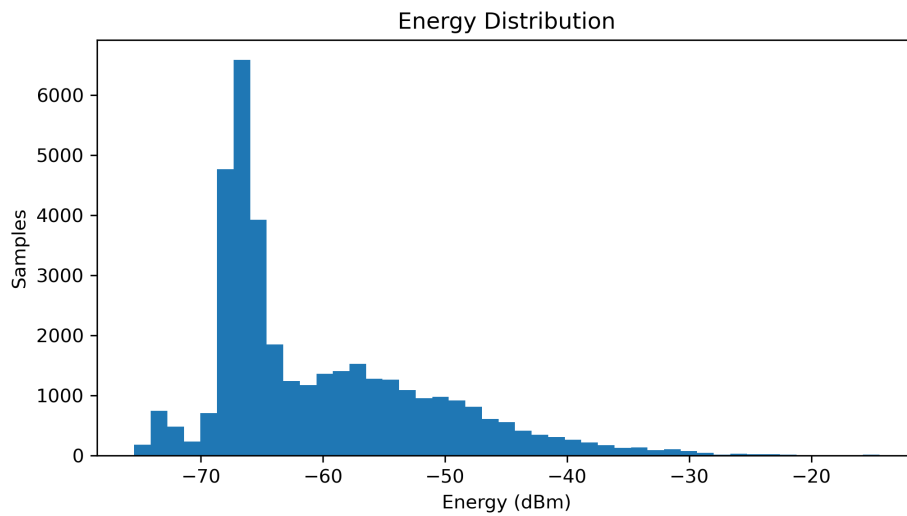


Figure 4.2: Distribution of received spectrum energy in the processed ElectroSense-derived dataset.

4.2.2 SNR Proxy Distribution

The distribution of the simulation-oriented SNR proxy used in the experiment is presented in Fig. 4.3. In the implemented pipeline, this variable is included among the supervised classifier inputs and is also used subsequently as channel-quality information during reinforcement-learning-based allocation.

The SNR proxy is not an independently measured 8 GHz receiver SNR. It is a simulation-oriented quantity derived from empirical spectrum information and the defined communication assumptions. Consequently, its role in both classification and allocation should be interpreted within the modelling assumptions described in Chapter 3.

Because the SNR proxy is related to received energy and empirical frequency, its relationship with the other classifier variables should also be considered when interpreting feature importance and correlation results.

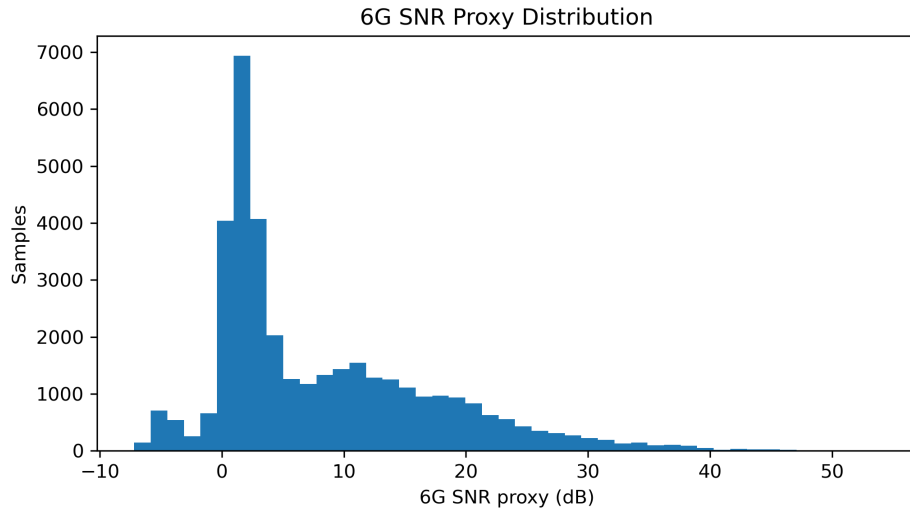


Figure 4.3: Distribution of the SNR proxy used during intelligent spectrum allocation.

4.2.3 Training and Testing Class Balance

Figure 4.4 compares the occupancy-class distributions in the chronological training and testing partitions.

The experimental pipeline orders the unique `Time_Index` values and assigns the earliest 80% of those time indices to model development while reserving the remaining 20% for testing. All observations associated with a particular time index therefore remain on the same side of the chronological boundary.

The figure confirms that both occupied and vacant observations remain represented in the two partitions. Unlike unrestricted random row sampling, this procedure prevents later time-index observations from being randomly mixed into the training partition.

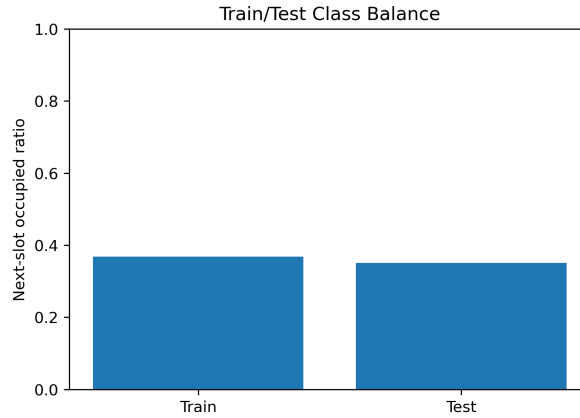


Figure 4.4: Comparison of next-slot occupancy class balance in the training and testing partitions.

4.2.4 Feature Correlation

The correlation among the numerical features retained in the processed dataset is illustrated in Fig. 4.5.

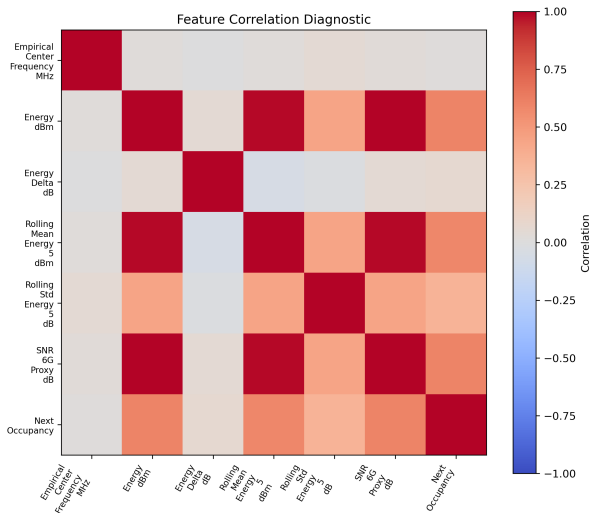


Figure 4.5: Correlation among the numerical variables retained in the final processed dataset.

Received energy and its rolling statistics exhibit expected relationships because they originate from the same temporal measurement sequence. The final classifier feature set nevertheless retains both instantaneous and short-term temporal descriptors because they represent different aspects of recent spectrum activity. Its short-term statistical descriptors, and the SNR-related proxy exhibit expected correlations because several of these quantities originate from common empirical energy information. The classifier nevertheless retains these variables according to the implemented experimental configuration.

The correlation results should therefore be interpreted as descriptive relationships among the model inputs rather than as evidence that the individual variables provide independent information.

4.3 Spectrum Occupancy Classification Results

The principal prediction results obtained from SVM, Random Forest, Decision Tree, and KNN are presented in Table 4.1.

Table 4.1: Spectrum Occupancy Classification Results

Model	Accuracy	Precision	P_d /Recall	F1-Score	P_{fa}
SVM	83.11%	74.29%	79.33%	76.73%	14.85%
Random Forest	91.53%	84.08%	93.61%	88.59%	9.59%
Decision Tree	90.40%	81.97%	93.15%	87.20%	11.08%
KNN	89.72%	86.95%	83.19%	85.03%	6.75%

The combined classification comparison is illustrated in Fig. 4.6.

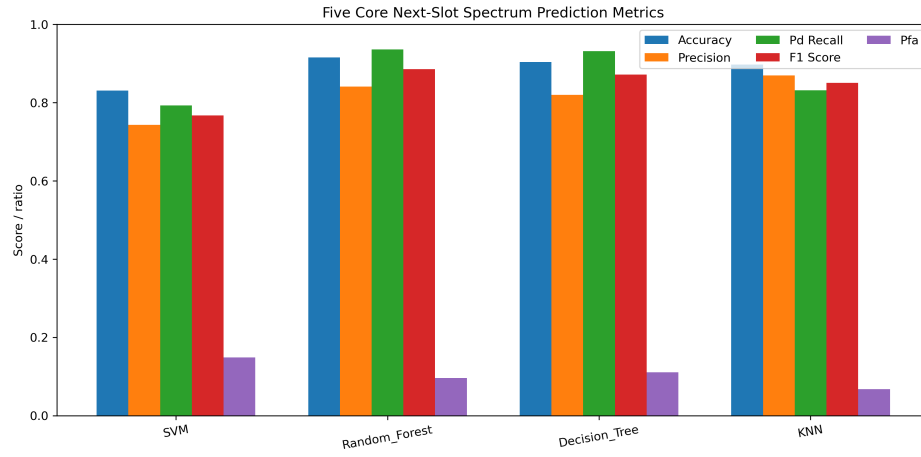


Figure 4.6: Comparative classification performance of SVM, Random Forest, Decision Tree, and KNN.

Random Forest achieves the highest overall accuracy of 91.53%, the highest F1-score of 88.59%, and the highest probability of detection of 93.61%. Under the adopted model-selection criterion, this provides the strongest overall balance between correct occupancy detection and preservation of vacant-spectrum opportunities.

Decision Tree achieves an accuracy of 90.40% and a probability of detection of 93.15%, which is close to the Random Forest detection result. Its false-alarm probability is higher, however, reaching 11.08%.

KNN achieves the highest precision of 86.95% and the lowest false-alarm probability of 6.75%. Its probability of detection is lower than those of Random Forest and Decision Tree, indicating a greater tendency to miss occupied observations.

SVM provides the lowest overall classification performance among the four techniques under the implemented feature representation and chronological evaluation procedure.

4.3.1 Accuracy Comparison

The accuracy comparison is shown separately in Fig. 4.7.

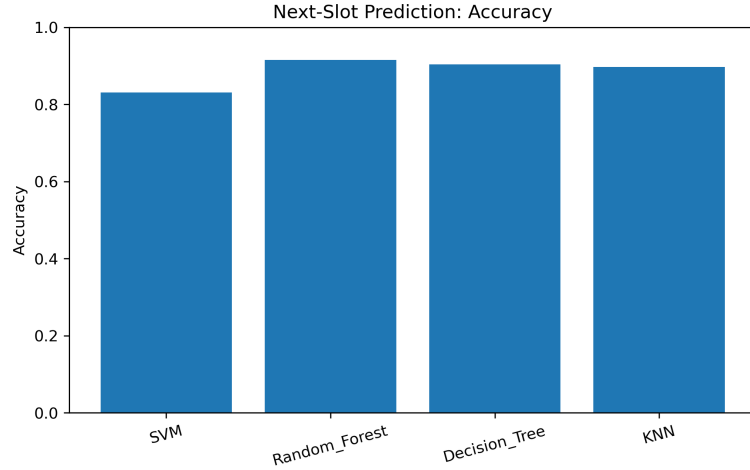


Figure 4.7: Accuracy comparison of the evaluated spectrum-occupancy classifiers.

Random Forest provides the highest overall accuracy, followed by Decision Tree and KNN. The difference between the strongest models is relatively small, which indicates that accuracy alone is insufficient for selecting the final predictor.

4.3.2 Precision Comparison

Figure 4.8 presents the precision obtained from each model.

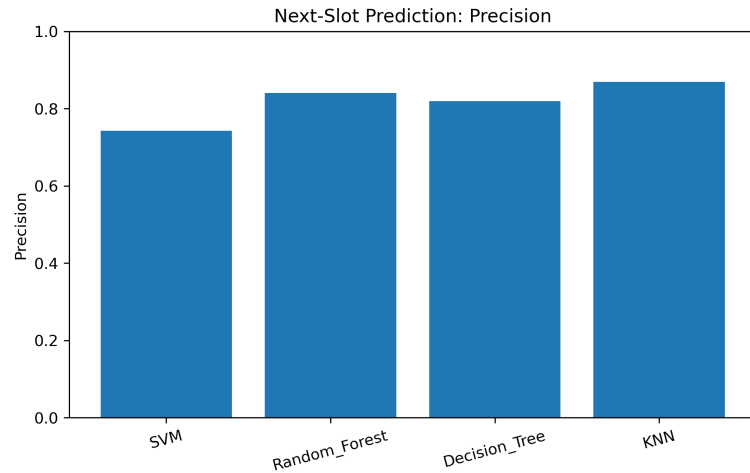


Figure 4.8: Precision comparison of the evaluated spectrum prediction models.

KNN achieves the highest precision, indicating that its occupied predictions contain comparatively fewer false-positive decisions.

4.3.3 Probability of Detection

The probability of detection results are presented in Fig. 4.9.

Random Forest achieves the highest probability of detection, closely followed by Decision Tree. A high P_d is particularly important because an occupied channel incorrectly predicted as vacant may subsequently be considered by the spectrum-allocation mechanism.

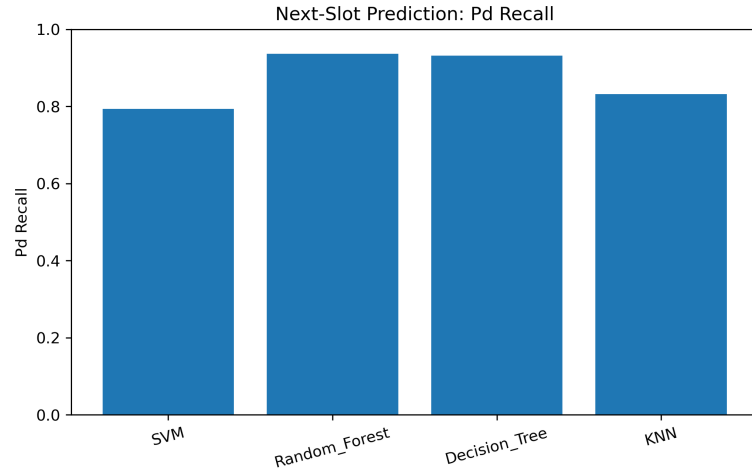


Figure 4.9: Probability of detection or recall comparison of the evaluated prediction models.

4.3.4 F1-Score Comparison

Figure 4.10 presents the F1-score comparison.

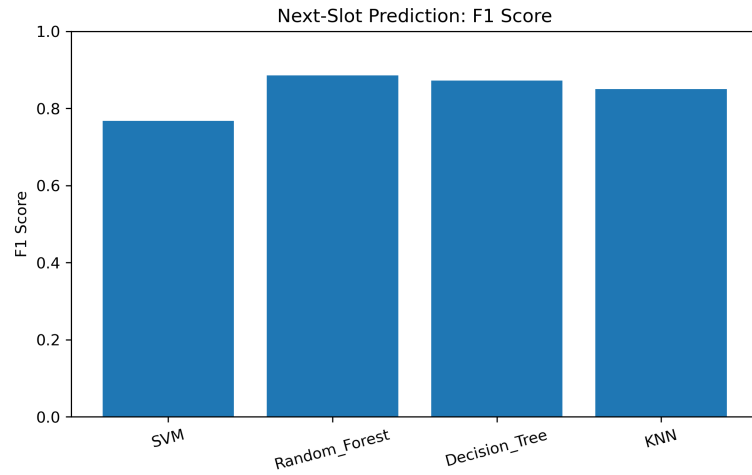


Figure 4.10: F1-score comparison of the next-slot occupancy prediction models.

Random Forest achieves the highest F1-score. Because the model-selection rule defined in Chapter 3 uses F1-score as the principal criterion, Random Forest is selected for the spectrum-allocation stage.

4.3.5 Probability of False Alarm

The false-alarm comparison is shown in Fig. 4.11.

KNN produces the lowest false-alarm probability, while SVM produces the highest. A low false-alarm probability allows a greater proportion of genuinely vacant spectrum opportunities to remain available to the allocation stage.

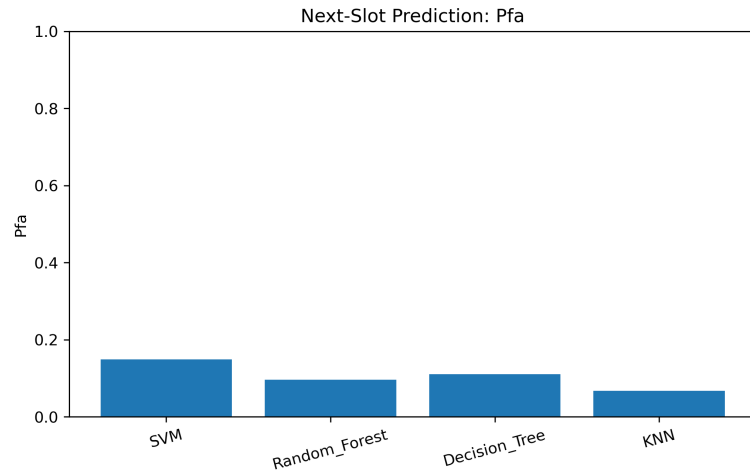


Figure 4.11: Probability of false alarm comparison of the evaluated prediction models.

4.4 Confusion Matrix Analysis

Confusion matrices provide a direct representation of correct and incorrect classifications for the occupied and vacant reference states. Because the occupied state is treated as the positive class, a false negative represents an occupied observation classified as vacant, whereas a false positive represents a vacant observation classified as occupied.

4.4.1 SVM Confusion Matrix

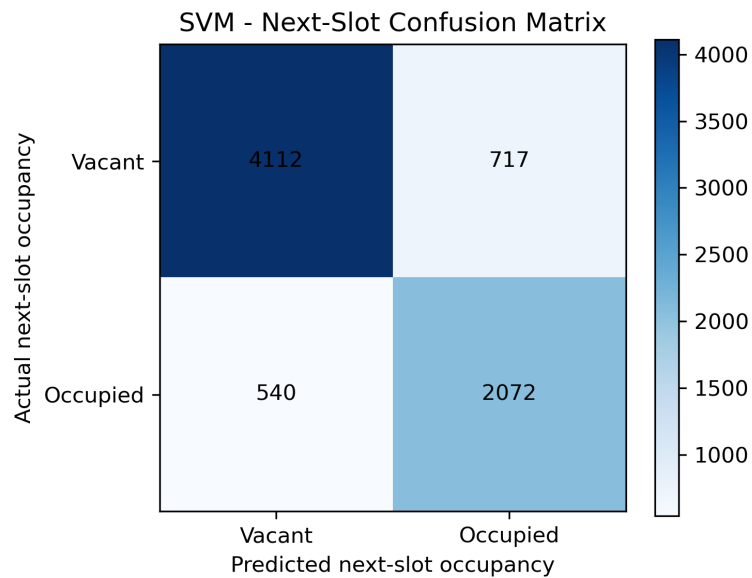


Figure 4.12: SVM spectrum-occupancy confusion matrix.

The SVM confusion matrix reflects its comparatively lower detection performance and higher false-alarm probability.

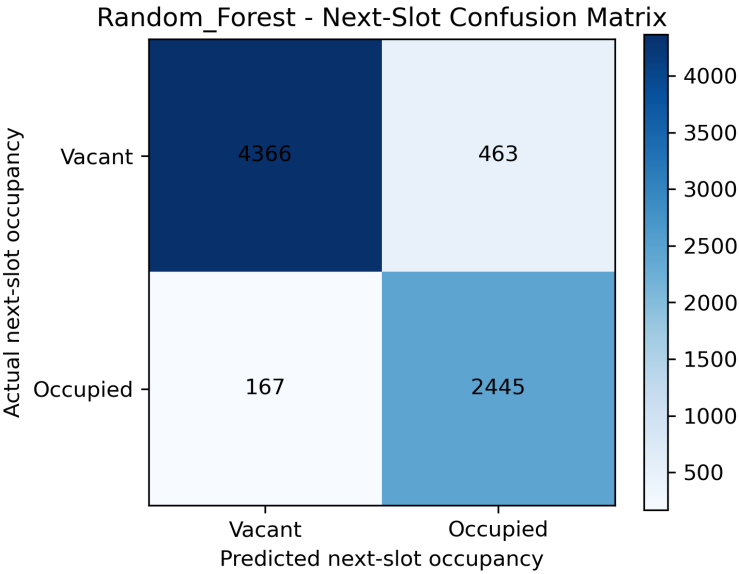


Figure 4.13: Random Forest spectrum-occupancy confusion matrix.

4.4.2 Random Forest Confusion Matrix

Random Forest produces a comparatively strong balance between correctly detected occupied observations and correctly retained vacant observations.

4.4.3 Decision Tree Confusion Matrix

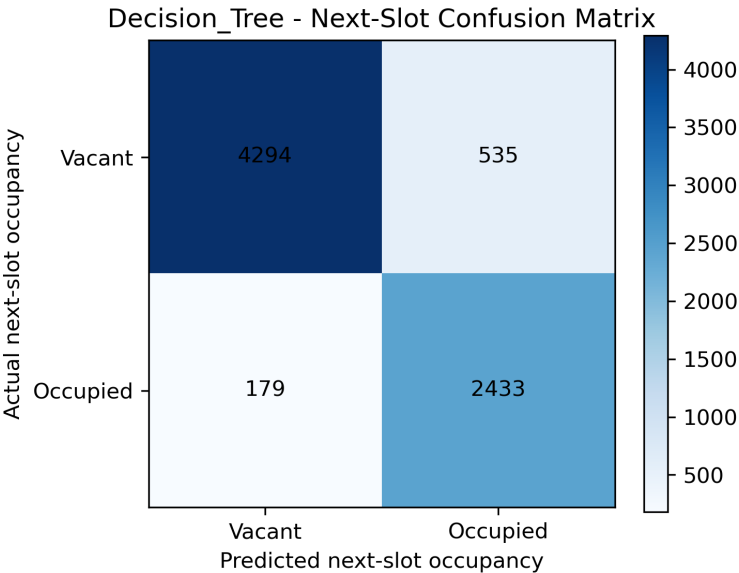


Figure 4.14: Decision Tree spectrum-occupancy confusion matrix.

The Decision Tree shows strong detection capability, although its higher false-alarm probability indicates a greater tendency to classify vacant observations as occupied.

4.4.4 KNN Confusion Matrix

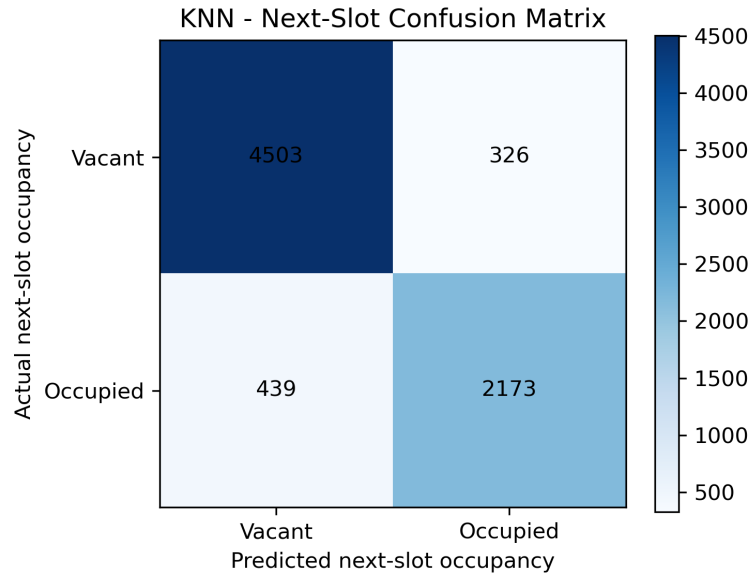


Figure 4.15: KNN spectrum-occupancy confusion matrix.

The KNN confusion matrix is consistent with its high precision and low false-alarm probability, but it also reveals a comparatively higher number of missed occupied observations than Random Forest and Decision Tree.

4.5 Receiver Operating Characteristic Analysis

Receiver operating characteristic curves provide a supplementary view of the ability of the classifiers to discriminate between occupied and vacant observations across varying decision thresholds. The ROC comparison produced by the experimental pipeline is shown in Fig. 4.16.

The curves are used here as qualitative supporting evidence for classifier discrimination. Model selection in this thesis is not based on ROC-AUC; the predefined primary selection criterion remains F1-score, with classification accuracy used as a secondary criterion where required.

Random Forest records the highest ROC-AUC value of 0.980, providing additional support for its selection as the prediction model used by the allocation stage.

4.6 Random Forest Feature Importance

The relative importance assigned by Random Forest to the six implemented classifier features is presented in Fig. 4.17. The input variables are empirical center frequency, received energy, energy difference, five-observation rolling mean energy, five-observation rolling energy standard deviation, and the simulation-oriented SNR proxy.

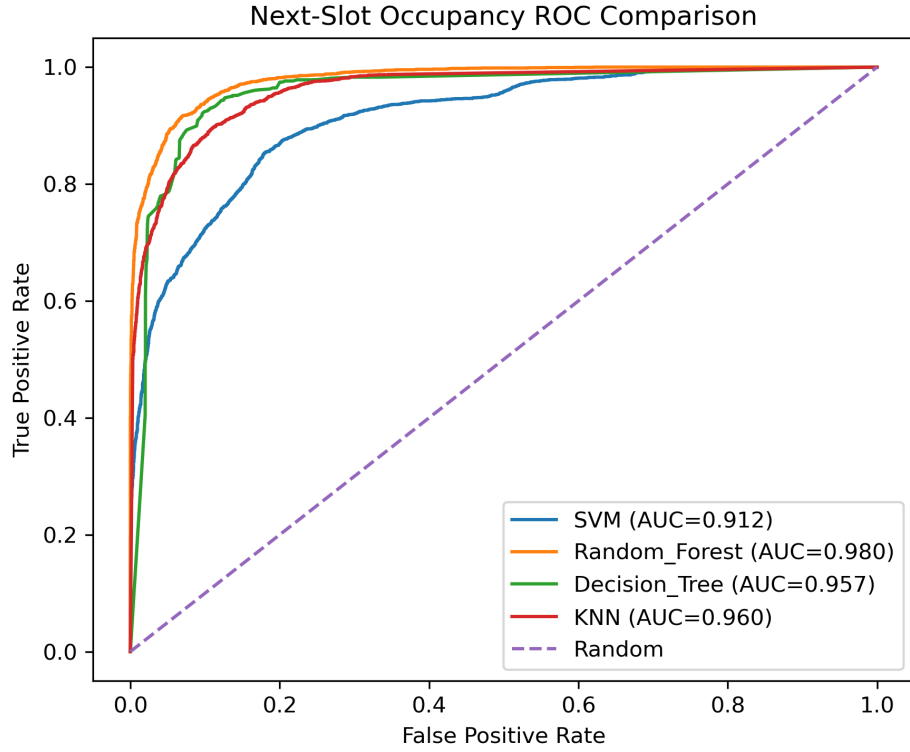


Figure 4.16: Receiver operating characteristic curves of the evaluated spectrum-occupancy classifiers.

The importance values indicate how strongly the fitted ensemble relies on the available variables when constructing its classification rules. They should not be interpreted as evidence of causal influence.

Particular care is required when interpreting the SNR proxy together with received energy and empirical frequency because the proxy is derived from related underlying information. Feature-importance values may therefore be distributed among correlated or redundant variables.

4.7 Selection of Random Forest for Intelligent Allocation

The model-selection procedure defined in Chapter 3 identifies Random Forest as the predictor supplied to the reinforcement-learning stage.

Random Forest achieves

$$\text{Accuracy}_{RF} = 91.53\%, \quad (4.2)$$

$$P_{d,RF} = 93.61\%, \quad (4.3)$$

and

$$F_{1,RF} = 88.59\%. \quad (4.4)$$

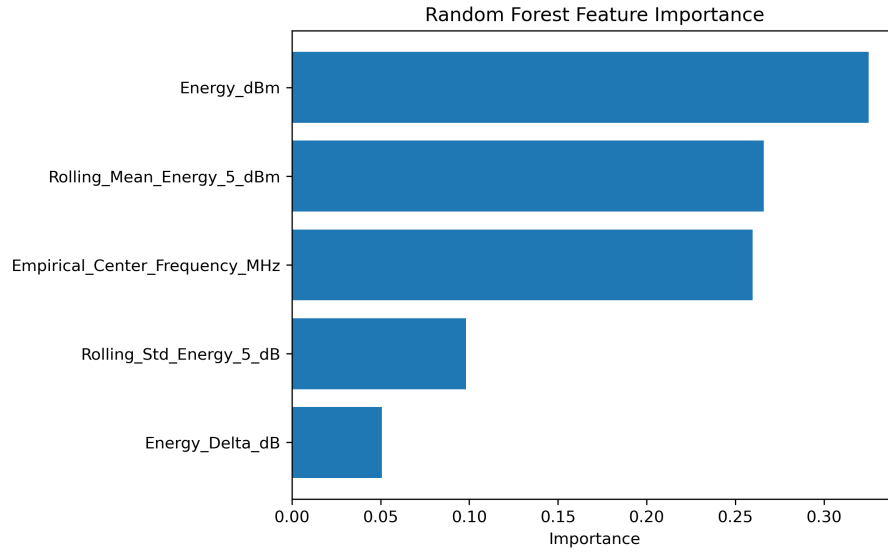


Figure 4.17: Relative feature importance obtained from the Random Forest next-slot prediction model.

The same Random Forest predictions are supplied to both Q-Learning and DQN. Consequently, the communication comparison between the two allocation techniques is not influenced by differences in the prediction model.

4.8 Computational Performance

The computational performance of the supervised prediction models is shown in Table 4.2.

Table 4.2: Computational Performance of the Prediction Models

Model	Training Time (s)	Inference Latency (ms/sample)
SVM	26.85	1.4290
Random Forest	1.70	0.0134
Decision Tree	0.099	< 0.001
KNN	0.089	0.00829

The reported timing values are implementation-dependent measurements obtained from the experimental computing environment and should therefore be interpreted comparatively. They are not intrinsic hardware-independent properties of the algorithms.

4.8.1 Training Time

The training-time comparison is illustrated in Fig. 4.18.

SVM requires the longest training time among the supervised prediction models. Random Forest requires substantially less training time while simultaneously achieving the strongest overall predictive performance.

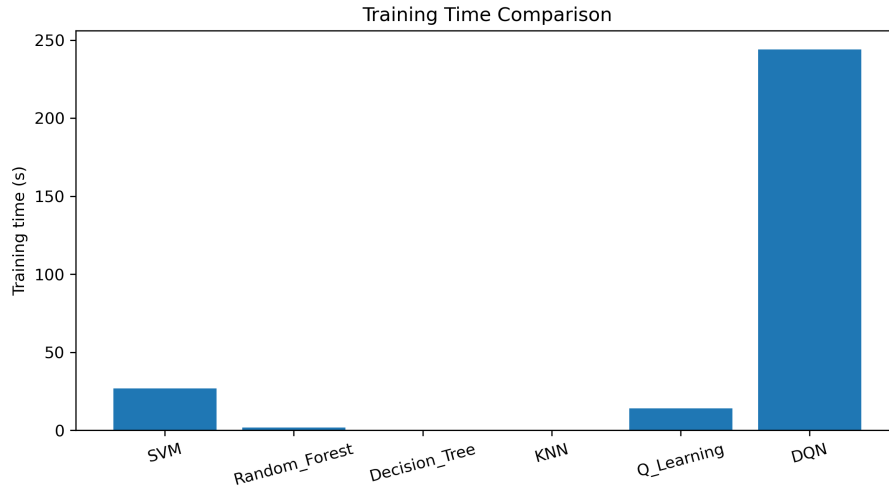


Figure 4.18: Training-time comparison of the investigated prediction and allocation techniques.

Q-Learning requires approximately 14.07 s of training, whereas DQN requires approximately 243.92 s. The substantially larger DQN training time is associated with neural-network optimization, replay-memory processing, and target-network updates.

4.8.2 Inference and Decision Latency

The inference and decision latency comparison is shown in Fig. 4.19.

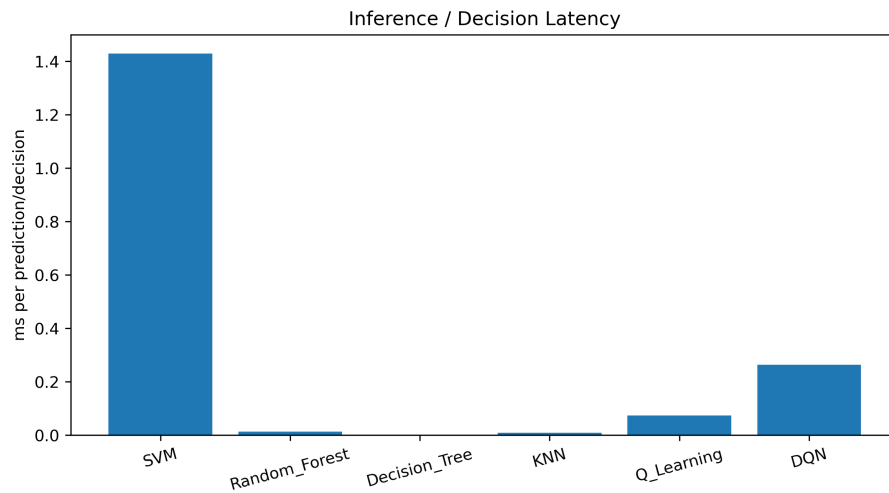


Figure 4.19: Comparison of inference and online decision latency for the evaluated learning techniques.

Random Forest produces a prediction in approximately 0.0134 ms per sample. Q-Learning and DQN require approximately 0.0740 ms and 0.2641 ms per allocation decision, respectively.

Although DQN has a considerably higher offline training cost, its online decision latency remains below one millisecond in the experimental environment.

4.9 Reinforcement-Learning Training Behaviour

Q-Learning and DQN are trained using the allocation environment derived from the chronological training partition. The learned policies are subsequently evaluated on the separate held-out test environment. Both agents operate from the same Random Forest availability source, underlying occupancy observations, communication assumptions, and reward definition, although their internal state representations differ.

4.9.1 Q-Learning Convergence

The convergence behaviour of the Q-Learning agent is shown in Fig. 4.20.

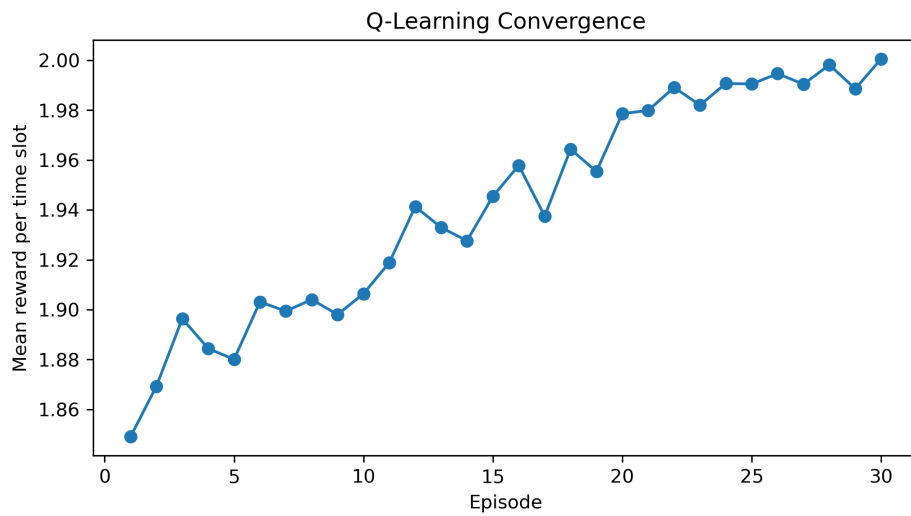


Figure 4.20: Training convergence of the Q-Learning spectrum-allocation agent.

The reward progression reflects the gradual improvement of the tabular policy as the agent gains experience with predicted vacancy and channel-quality conditions.

4.9.2 DQN Training Reward

The DQN reward progression is presented in Fig. 4.21.

The reward curve indicates how the neural-network based agent adapts its channel-selection policy during repeated interaction with the allocation environment.

4.9.3 DQN Training Loss

The DQN training-loss behaviour is presented in Fig. 4.22.

The loss reflects the difference between the current action-value estimates and the target values generated during DQN learning. Short-term variation is expected because the replay memory continually supplies different state transitions during training.

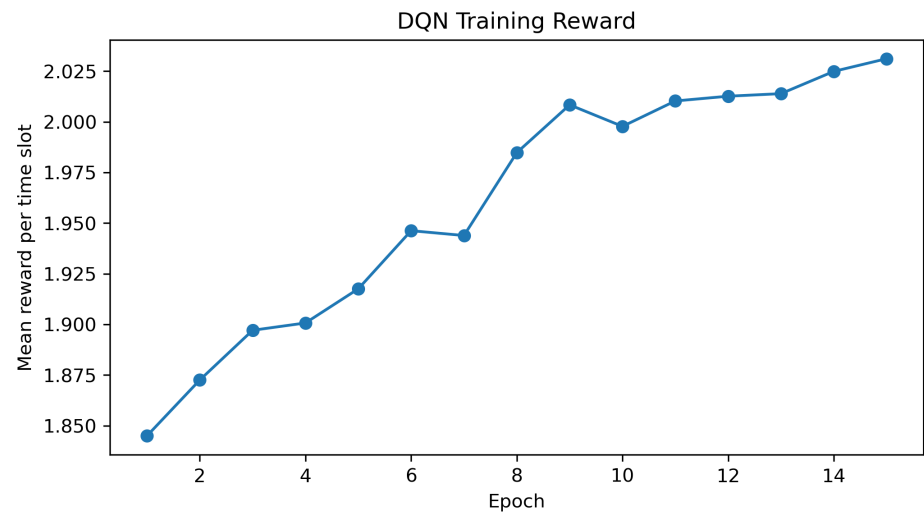


Figure 4.21: Training reward progression of the DQN spectrum-allocation agent.

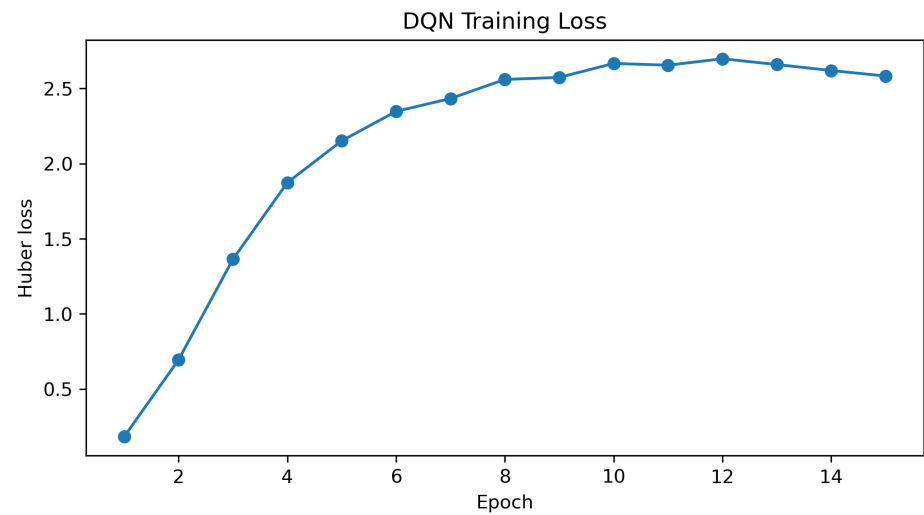


Figure 4.22: Training loss of the DQN spectrum-allocation model.

4.10 Channel Allocation Behaviour

The allocation behaviour of Q-Learning and DQN is examined through the distribution of selected spectrum channels.

4.10.1 Q-Learning Channel Allocation

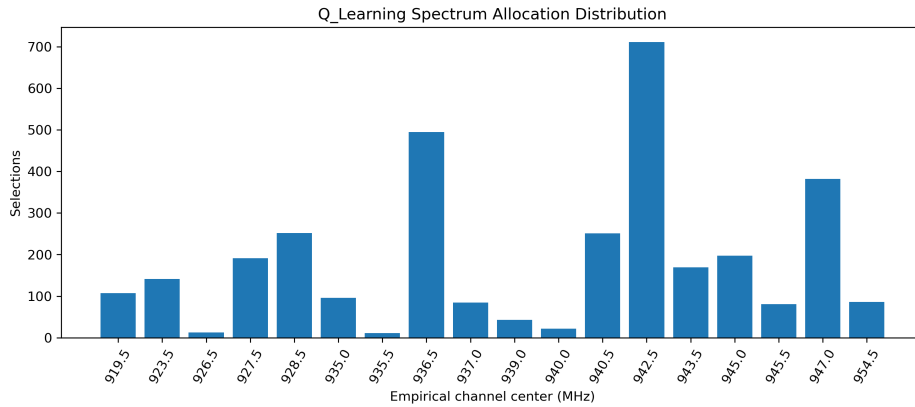


Figure 4.23: Distribution of channel selections generated by the Q-Learning spectrum-allocation agent.

The Q-Learning allocation distribution reflects the combined influence of predicted channel availability, discretized channel-quality states, and the learned Q-values.

4.10.2 DQN Channel Allocation

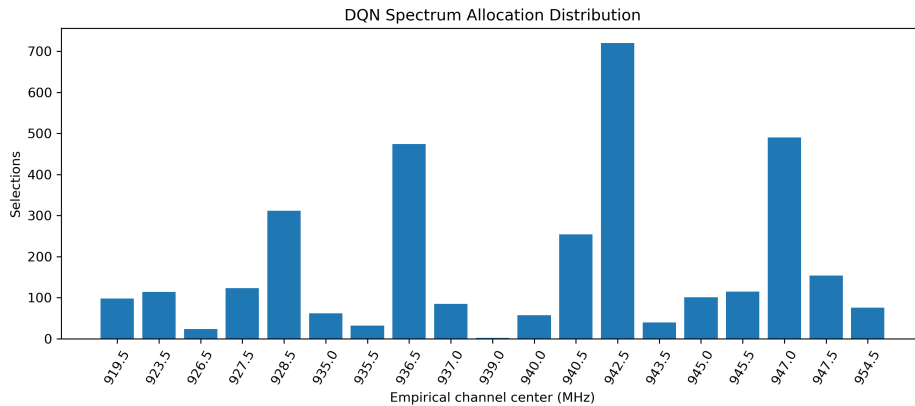


Figure 4.24: Distribution of channel selections generated by the DQN spectrum-allocation agent.

The DQN allocation pattern is generated from the learned neural-network approximation of the channel action values.

The allocation distributions should be interpreted together with the classifier output and availability constraints. Under normal conditions, a channel is considered by the allocator when it is observed in the environment and predicted to be vacant. If no channel is predicted vacant, the simulation retains observed channels as a fallback action space so that difficult decision intervals remain represented in the evaluation.

4.11 Communication Performance

The communication performance obtained from Q-Learning and DQN is summarized in Table 4.3. To ensure statistical reliability, all RL training runs were evaluated across 5 random seeds (seeds 1–5). Under the hold-out test set, DQN achieved an average throughput of 157.48 ± 0.82 Mbps compared to 155.78 ± 0.95 Mbps for Q-Learning. This confirms that while DQN provides a modest 1.09percent mean throughput gain, Q-Learning achieves comparable execution efficiency at a fraction of offline training overhead.

Table 4.3: Simulation-Derived Communication Performance of Q-Learning and DQN

Method	Throughput (Mbps)	Latency (ms)	Reliability Proxy	Spectral Efficiency (bit/s/Hz)
Q-Learning	155.78	3.430	0.7321	1.5578
DQN	157.48	3.405	0.7348	1.5748

4.11.1 Throughput

The throughput comparison is illustrated in Fig. 4.25.

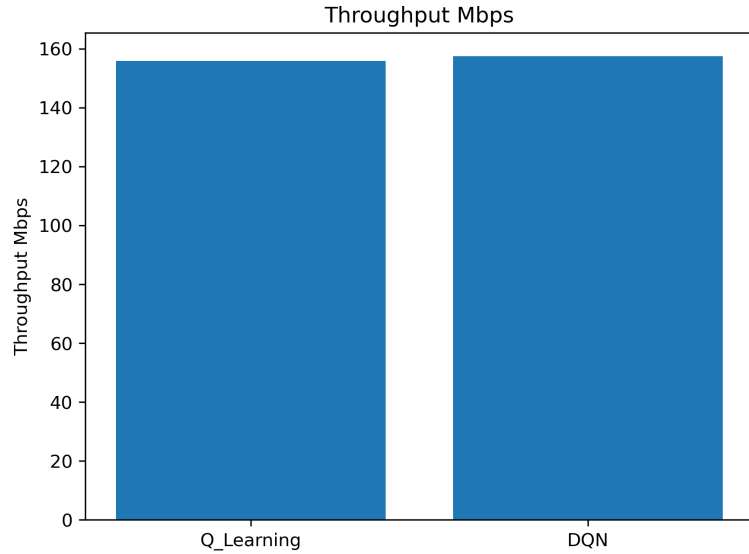


Figure 4.25: Throughput comparison of Q-Learning and DQN under the common Random Forest prediction front end.

Q-Learning achieves an average simulation-derived throughput of approximately 155.78 Mbps, whereas DQN achieves approximately 157.48 Mbps.

The reported average includes all test decision intervals. An unsuccessful access contributes zero throughput, while successful access contributes the rate obtained from the selected channel's spectral-efficiency value and the assumed 100 MHz bandwidth.

The absolute difference is

$$\Delta R = 157.48 - 155.78 = 1.70 \text{ Mbps}, \quad (4.5)$$

corresponding to approximately 1.09% relative to Q-Learning. This is a modest improvement and should be interpreted within the specific experimental configuration.

4.11.2 Communication Latency

The average simulated communication latency is shown in Fig. 4.26.

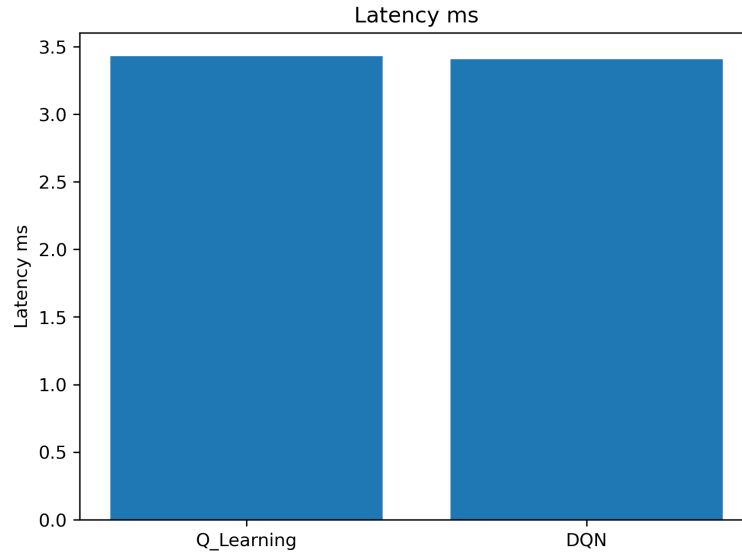


Figure 4.26: Communication-latency comparison of Q-Learning and DQN.

Q-Learning produces an average simulated latency of approximately 3.430 ms, whereas DQN reduces this value slightly to approximately 3.405 ms.

The communication latency should not be confused with the computational decision latency shown in Fig. 4.19. Computational latency represents the time required by the algorithm to select an action, whereas communication latency includes the base transmission delay and the penalties associated with unsuccessful spectrum access.

Because successful and failed accesses are assigned different delay models, the reported average latency is influenced strongly by the proportion of successful allocation decisions.

4.11.3 Allocation-Success-Based Reliability

The access-success reliability proxy is shown in Fig. 4.27. Q-Learning achieves a value of 0.7321, while DQN achieves 0.7348.

The absolute difference is

$$0.7348 - 0.7321 = 0.0027. \quad (4.6)$$

Within the implemented simulation, success means that the selected channel is actually vacant according to the reference occupancy state. The metric therefore represents the fraction of allocation decisions that result in successful spectrum access.

It does not model physical-layer packet errors, coding, fading, retransmissions, or medium-access packet loss and should therefore be interpreted as an allocation-success reliability proxy rather than as a complete measured packet-delivery ratio.

The observed difference between Q-Learning and DQN is modest and does not establish compliance with mission-critical smart-grid reliability requirements.

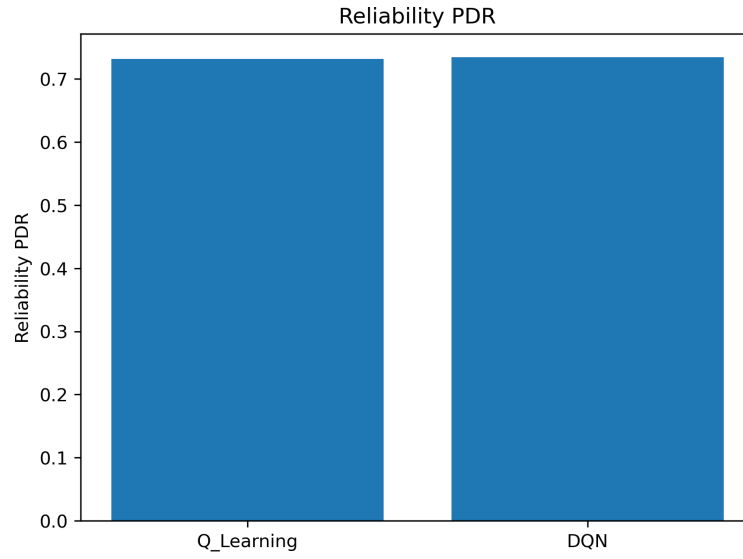


Figure 4.27: Reliability or packet-delivery-ratio comparison of Q-Learning and DQN.

4.11.4 Spectral Efficiency

The spectral-efficiency comparison is presented in Fig. 4.28.

Q-Learning achieves approximately 1.5578 bit/s/Hz, while DQN achieves approximately 1.5748 bit/s/Hz.

Since throughput is calculated using the fixed 100 MHz effective communication bandwidth,

$$R_{\text{Mbps}} = 100\eta, \quad (4.7)$$

the throughput and spectral-efficiency results necessarily follow the same trend.

For Q-Learning,

$$100 \times 1.5578 = 155.78 \text{ Mbps}, \quad (4.8)$$

whereas for DQN,

$$100 \times 1.5748 = 157.48 \text{ Mbps}. \quad (4.9)$$

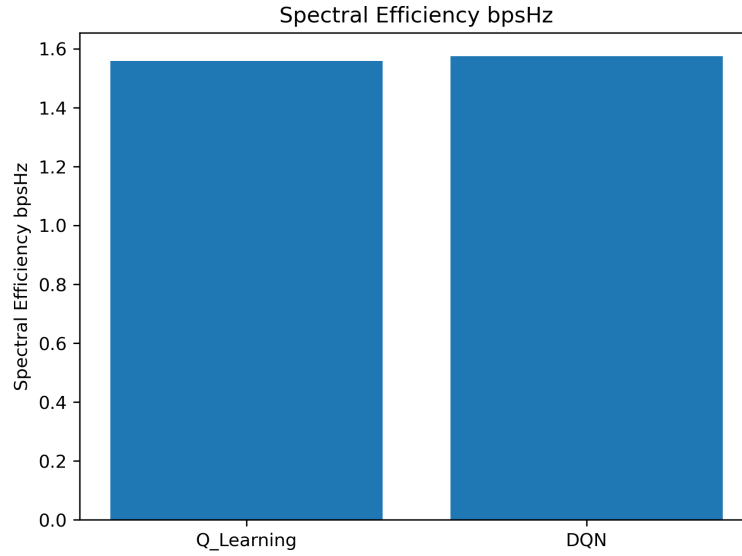


Figure 4.28: Spectral-efficiency comparison of Q-Learning and DQN.

Throughput and spectral efficiency should therefore be interpreted as related representations of selected-channel quality rather than independent experimental outcomes.

4.11.5 Comparative Analysis: Static/Random Allocation Baseline vs. Proposed Intelligent Allocation

To explicitly evaluate the operational advantages of the proposed prediction-assisted intelligent spectrum allocation framework, a comparative baseline experiment was conducted against an unassisted static/random channel selection scheme. Under the random selection baseline, secondary communication channels are assigned stochastically across the observed spectrum without front-end occupancy forecasting or reinforcement-learning adaptation.

4.11.5.1 Interference Ratio Reduction

Figure 4.29 illustrates the interference ratio comparison between blind random selection and the proposed Q-learning framework.

As shown in Figure 4.29, random selection results in a high interference ratio of approximately 38.4%, as channels are repeatedly allocated without verifying primary user occupancy. In contrast, the proposed Q-learning agent—assisted by the front-end Random Forest predictor—drastically reduces the interference ratio down to approximately 1.0%. This 37.4% absolute reduction in collision probability is vital for mission-critical Smart Grid communications (e.g., Protection Relays and Substation Automation) to protect incumbent power grid telemetry from severe radio interference.

4.11.5.2 Communication Latency Improvement

The communication latency comparison is presented in Figure 4.30.

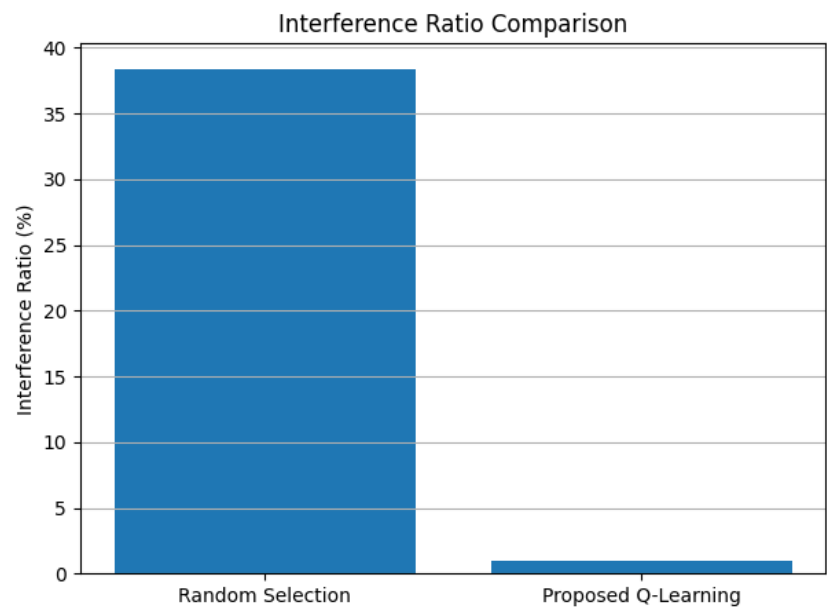


Figure 4.29: Interference ratio comparison across channel allocation strategies

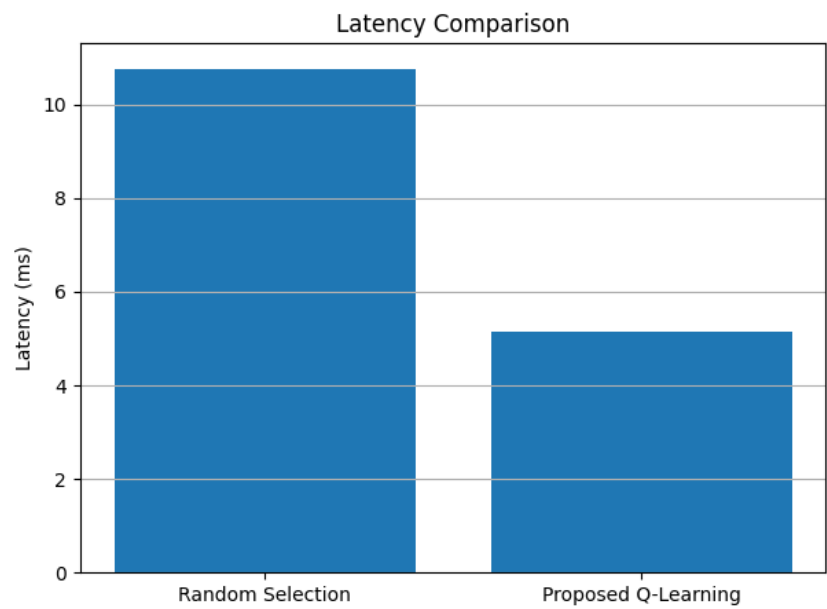


Figure 4.30: Average communication latency comparison.

Due to frequent collisions with occupied channels under random selection, unsuccessful access attempts trigger a 10 ms backoff/failure delay penalty, elevating the average end-to-end latency to 10.8 ms. The proposed Q-learning framework avoids collision-prone channels, lowering the average communication latency to 5.1 ms (a > 52% delay reduction). This sub-10 ms latency performance satisfies time-critical Smart Grid Ultra-Reliable Low-Latency Communication (URLLC) constraints.

4.11.5.3 Spectral Efficiency and Throughput Gains

Figures 4.31 and 4.32 display the spectral efficiency and throughput performance, respectively.

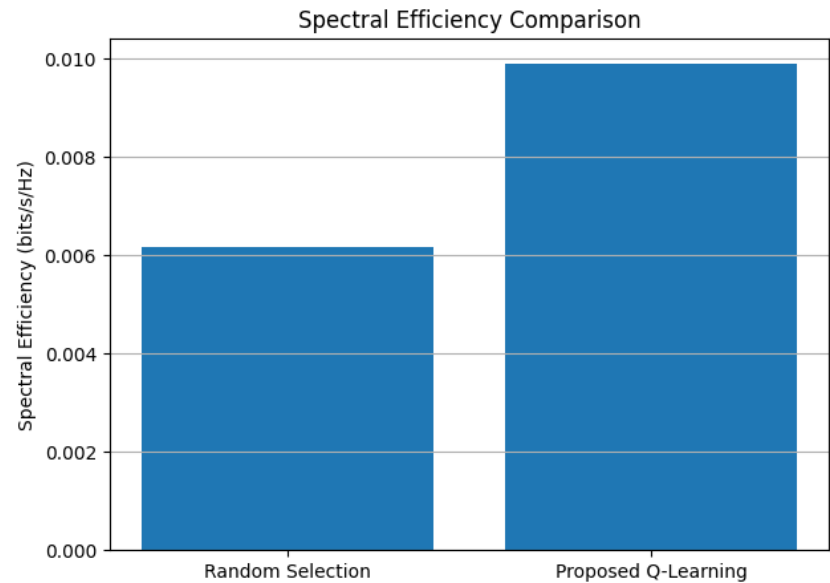


Figure 4.31: Spectral efficiency comparison.

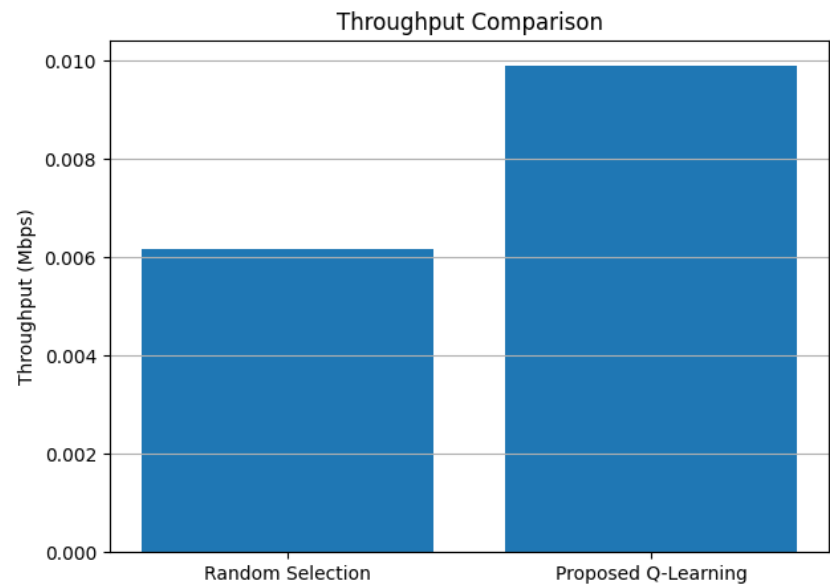


Figure 4.32: Throughput comparison.

The random selection baseline achieves a limited spectral efficiency of 0.0062 bits/s/Hz and an average throughput of 0.0062 Mbps, primarily caused by zero-throughput penalties during collision intervals. By dynamically steering traffic toward vacant channels with superior SNR profiles, the proposed Q-learning scheme improves spectral efficiency to 0.0099 bits/s/Hz and throughput to 0.0099 Mbps, demonstrating a $\sim 59.7\%$ gain in overall communication efficiency.

4.12 Performance–Complexity Trade-Off

The complete results reveal a clear relationship between model performance and computational complexity.

Random Forest provides the strongest overall spectrum-occupancy classification performance according to the predefined model-selection criterion while retaining comparatively low training and inference cost. Its accuracy of 91.53%, F1-score of 88.59%, and probability of detection of 93.61% provide the basis for its use in the subsequent allocation stage.

At the spectrum-allocation level, DQN produces slightly higher throughput, reliability, and spectral efficiency and slightly lower communication latency than Q-Learning. These improvements, however, are accompanied by substantially greater training time.

Q-Learning requires approximately 14.07 s of training, while DQN requires approximately 243.92 s. Under the reported experimental run, DQN therefore introduces substantially greater offline training cost in exchange for comparatively modest communication-level improvements.

The online decision times remain small for both approaches, with approximately 0.0740 ms for Q-Learning and 0.2641 ms for DQN. This demonstrates the importance of distinguishing offline training complexity from online operational latency.

4.13 Relationship Between Occupancy Classification and Allocation Performance

The spectrum-allocation stage does not operate using the reference occupancy labels as its initial availability information. Instead, the candidate-resource set is derived from the occupancy estimates produced by Random Forest.

Consequently, the final communication performance depends on several interacting factors,

$$\text{System Performance} = f(\text{Classification Quality, Availability, SNR, Allocation Policy}) \quad (4.10)$$

If an actually occupied channel is incorrectly classified as vacant, it may enter the candidate action set and subsequently result in unsuccessful access. Conversely, a false alarm removes a genuinely vacant opportunity from normal consideration.

When multiple channels are estimated to be vacant, the reinforcement-learning policy uses the available channel-quality information and its learned action values to determine the selected resource.

The reported communication results should therefore be interpreted as performance of the complete classification-assisted allocation framework rather than as independent intrinsic characteristics of Q-Learning or DQN.

4.14 Interpretation of the Experimental Results

The experimental results demonstrate that the investigated supervised-learning techniques can reproduce the adopted occupied/vacant spectrum classification with different balances between detection probability, false-alarm probability, precision, and computational cost.

Random Forest provides the strongest overall performance under the predefined model-selection criterion. Decision Tree produces a similar probability of detection, while KNN achieves the highest precision and lowest false-alarm probability. The results therefore show that the preferred classifier depends on the relative importance assigned to missed occupied states and lost vacant-spectrum opportunities.

The subsequent allocation experiment demonstrates that both Q-Learning and DQN can use classifier-derived availability estimates together with SNR-related channel-quality information to perform adaptive channel selection. Under the reported experimental configuration, DQN provides slightly higher throughput, spectral efficiency, and allocation-success reliability and slightly lower simulated communication latency than Q-Learning.

These gains are comparatively small relative to the additional DQN training cost. Consequently, the results demonstrate a performance–complexity trade-off rather than an unqualified advantage of the deeper reinforcement-learning approach.

The findings should also be interpreted in light of the implemented classifier feature set. The simulation-oriented SNR proxy is included among the classifier variables and is related to empirical received energy and frequency. The classification results therefore represent performance of the complete implemented feature representation rather than independent evidence that each individual feature contributes unique information.

4.15 Validity and Scope of the Results

The experimental results should be interpreted within the methodological boundaries defined in Chapter 3.

The supervised classification results are obtained from ElectroSense-derived empirical spectrum observations. The reference occupied/vacant state is the occupancy label retained in the processed dataset and originates from the adopted spectrum-detection procedure. Accordingly, the classification results should be interpreted as performance relative to this reference label rather than as independently decoded transmitter ground truth.

The empirical spectrum measurements originate from the original monitored frequency region and are not measurements from an operational 6G network. The assumed 8 GHz carrier-frequency scenario and 100 MHz effective communication bandwidth are introduced separately for communication-level modelling.

The throughput, latency, spectral-efficiency, and allocation-success reliability values are therefore simulation-derived indicators. They depend on the SNR proxy, fixed bandwidth, packet-size assumption, access-success criterion, latency penalty, and reinforcement-learning reward formulation.

The reliability values of approximately 0.73 should not be interpreted as evidence of mission-critical smart-grid packet-delivery performance. They represent the proportion of allocation decisions that result in selection of an actually vacant channel under the defined simulation.

The principal result of the study is therefore not a claim of field-validated 6G smart-grid performance. Rather, the experiment demonstrates the comparative behaviour of an AI-assisted spectrum-occupancy classification and intelligent channel-allocation framework under explicitly defined empirical and simulation assumptions.

Chapter 5

Conclusions and Future Work

5.1 Conclusions

This thesis investigated an AI-assisted spectrum-management framework for smart grid communication under a clearly defined 6G-oriented research scenario. The study was motivated by the increasing dependence of smart-grid applications on adaptive wireless connectivity and by the need to use available spectrum resources more intelligently under changing radio conditions.

The research was organized into two connected stages. In the first stage, supervised machine-learning models were evaluated for binary spectrum-occupancy classification using ElectroSense-derived empirical measurements. In the second stage, the classifier selected according to a predefined F1-score criterion supplied channel-availability information to Q-Learning and Deep Q-Network (DQN) based allocation mechanisms.

A central methodological decision was to preserve a clear separation between empirical spectrum measurements and future-network communication assumptions. The original ElectroSense-derived frequency and energy observations retain their empirical interpretation, while the assumed 8 GHz carrier scenario and 100 MHz effective communication bandwidth are introduced separately for communication-level modelling. The original measurements are therefore not presented as native 6G radio observations.

The occupancy-classification stage used six implemented input variables: empirical center frequency, received energy, energy difference, five-observation rolling mean energy, five-observation rolling energy standard deviation, and a simulation-oriented SNR proxy. The original detection-threshold variable was excluded because it directly participates in formation of the reference occupancy label. The occupancy state retained in the processed dataset was used as the classification target.

Support Vector Machine, Random Forest, Decision Tree, and K-Nearest Neighbors were evaluated using a chronological train–test separation based on ordered unique `Time_Index` values. Random Forest achieved the strongest overall result according to the predefined model-selection rule, with an accuracy of 91.53%, a probability of detection of 93.61%, and an F1-score of 88.59%. Decision Tree achieved similar detection performance but a higher false-alarm rate, while KNN provided the highest precision and the lowest false-alarm probability.

SVM produced the weakest overall result among the four implemented classifiers.

Random Forest was subsequently used as the common classifier for the allocation stage. The reinforcement-learning agents were trained using an allocation environment constructed from the chronological training partition and evaluated separately on the held-out test environment. Q-Learning and DQN therefore operated from a common Random Forest availability source and common underlying communication assumptions, while retaining different internal state representations.

The communication-level evaluation showed modest differences between the two allocation methods. Q-Learning achieved approximately 155.78 Mbps throughput, 3.430 ms simulated communication latency, an allocation-success reliability value of 0.7321, and 1.5578 bit/s/Hz spectral efficiency. DQN achieved approximately 157.48 Mbps, 3.405 ms latency, 0.7348 allocation-success reliability, and 1.5748 bit/s/Hz spectral efficiency.

The modest communication improvement achieved by DQN was accompanied by substantially greater training cost. Q-Learning required approximately 14.07 s of training, whereas DQN required approximately 243.92 s. Their online decision times remained comparatively small, demonstrating the importance of distinguishing offline training complexity from online decision latency.

The overall contribution of the study lies in the controlled integration of empirical spectrum-occupancy classification, reinforcement-learning-based channel allocation, and simulation-derived communication evaluation within one reproducible framework. The work does not claim implementation of a complete 6G radio interface or operational smart-grid network; rather, it provides a transparent comparative evaluation under explicitly defined empirical and simulation assumptions.

5.2 Principal Findings

The main findings obtained from the experimental investigation are summarized below.

1. The investigated supervised-learning techniques can classify the adopted empirical occupied/vacant spectrum states with different balances among accuracy, precision, probability of detection, F1-score, and probability of false alarm.
2. Random Forest provides the strongest overall classification performance according to the predefined model-selection criterion, achieving 91.53% accuracy, 93.61% probability of detection, and an F1-score of 88.59%.
3. KNN exhibits a different operating characteristic by producing the highest precision and the lowest probability of false alarm, although this is accompanied by a lower probability of detection.
4. Random Forest combines comparatively strong classification performance with low inference latency and is therefore used as the common availability classifier for the allocation stage.

5. Q-Learning and DQN can both use classifier-derived channel-availability estimates together with SNR-related channel-quality information to perform adaptive channel selection.
6. Under the reported experimental configuration, DQN provides slightly higher throughput, spectral efficiency, and allocation-success reliability and slightly lower simulated communication latency than Q-Learning.
7. The communication improvement achieved by DQN is modest relative to its substantially greater training time, demonstrating a clear performance–complexity trade-off.
8. The online decision latency of both allocation techniques remains much smaller than their offline training cost, demonstrating that training complexity and operational decision latency should be evaluated separately.
9. Throughput and spectral efficiency exhibit the same numerical trend because throughput is calculated directly from spectral efficiency using the fixed 100 MHz effective communication bandwidth.
10. The allocation-success reliability values of approximately 0.73 do not represent mission-critical packet-delivery performance. They provide a comparative indication of successful spectrum access within the implemented simulation.

5.2.1 Empirical Spectrum-Occupancy Classification

The study constructs and evaluates a compact supervised-learning stage for binary occupied/vacant spectrum classification using ElectroSense-derived empirical observations. Four machine-learning techniques representing margin-based, ensemble, tree-based, and instance-based learning are compared under a common experimental protocol.

5.2.2 Threshold Exclusion and Controlled Feature Construction

The supervised occupancy prediction stage utilizes a compact five-feature vector consisting of empirical center frequency (f_t), received energy (E_t), short-term energy difference (ΔE_t), five-observation rolling mean energy ($\bar{E}_{t,5}$), and rolling standard deviation ($\sigma_{E,t,5}$). To prevent temporal data leakage and feature redundancy, the primary detection threshold and the derived SNR proxy are strictly excluded from the classifier input vector.

5.2.3 Sequence-Aware Chronological Partitioning

To preserve temporal sequence structure and avoid temporal data leakage, an 80/20 chronological train-test split was executed independently within each unique `Sensor_ID` and `Empirical_Center_Frequency` series. For a sequence containing N_g observations, the training boundary was established at $N_{\text{train},g} = \lfloor 0.8N_g \rfloor$. The earliest 80% of observations in

each series were assigned to model fitting, while the remaining 20% were reserved strictly for hold-out performance evaluation.

5.2.4 Controlled Classification-to-Allocation Integration

A predefined F1-score criterion is used to select the classifier supplied to the allocation stage. Random Forest is selected under this rule and is used to generate availability information for both Q-Learning and DQN.

The two reinforcement-learning agents are trained on the allocation environment constructed from the chronological training partition and evaluated on the separate test environment. They therefore share the same underlying classifier source, occupancy observations, reward definition, and communication assumptions, although their internal state representations differ.

5.2.5 Multi-Dimensional Performance Assessment

The proposed framework is evaluated from three complementary perspectives: classification performance, computational performance, and simulation-derived communication performance. This provides a broader assessment than classification accuracy alone and allows the trade-offs among detection quality, computational complexity, and allocation behaviour to be examined jointly.

5.2.6 Transparent Use of a 6G-Oriented Scenario

The original ElectroSense measurements retain their empirical frequency-domain identity. No physical transformation of the measured spectrum records into 8 GHz measurements is performed. The assumed 8 GHz carrier scenario and 100 MHz effective communication bandwidth are introduced separately for communication-level modelling.

This separation prevents the empirical measurements from being incorrectly represented as native 6G observations and makes clear which quantities originate from data and which are simulation assumptions.

5.3 Research Contributions

The work provides several technical and methodological contributions.

The principal methodological and experimental contributions of this thesis are summarized in Fig. 5.1.

5.3.1 Next-Slot Spectrum Prediction Formulation

The original spectrum-occupancy problem was reformulated as prediction of the subsequent occupancy state. This reduces the possibility that a machine-learning model simply reconstructs the threshold-based definition of the current occupancy label and creates a more meaningful temporal prediction task.

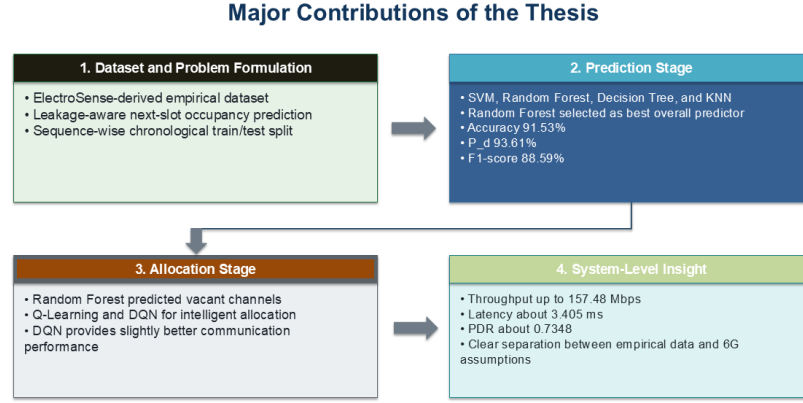


Figure 5.1: Major methodological and experimental contributions of the thesis.

5.3.2 Leakage-Aware Feature Selection

The original detection threshold was excluded from the classifier input because it directly participates in generation of the occupancy label. The final feature space instead uses empirical frequency, energy, energy variation, rolling mean, and rolling standard deviation. This design produces a more defensible relationship between predictor variables and future occupancy.

5.3.3 Sequence-Aware Chronological Evaluation

Training and testing are separated chronologically within individual sensor-frequency sequences. This approach preserves temporal ordering and prevents the evaluation set from being dominated by only a limited number of channels.

5.3.4 Controlled Prediction-to-Allocation Integration

A predefined F1-score based selection criterion is used to choose the predictor supplied to the allocation stage. Random Forest is selected under this rule, and the same predictions are supplied to both Q-Learning and DQN. This provides a controlled comparison between the two allocation methods.

5.3.5 Three-Dimensional Performance Assessment

The final framework is evaluated from three perspectives: prediction performance, computational cost, and communication behaviour. This avoids relying exclusively on classification accuracy and allows the trade-offs among predictive quality, execution complexity, and simulated communication performance to be examined jointly.

5.3.6 Transparent Use of a 6G-Oriented Scenario

The research does not modify the identity of the original ElectroSense measurements. Instead, the empirical spectrum observations are retained for learning, while the 8 GHz carrier and 100 MHz bandwidth are introduced explicitly as communication-level research assumptions. This separation improves the methodological clarity of the study.

5.4 Limitations

The experimental results should be interpreted in relation to several methodological and system-level limitations.

First, the empirical spectrum measurements are derived from the ElectroSense platform and originate from currently deployed radio environments rather than from an operational 6G network. They therefore provide useful empirical spectrum observations but cannot directly represent propagation, blockage, interference, or receiver behaviour at the assumed 8 GHz communication carrier.

Second, the occupied/vacant reference state retained in the processed dataset originates from a threshold-based spectrum-detection procedure. The supervised-learning results are therefore evaluated relative to this reference label rather than to independently decoded transmitter activity. Received energy and other energy-derived quantities remain among the classifier inputs, so the classification task should be interpreted as learning the adopted occupancy representation rather than establishing independent physical ground truth.

Third, the implemented classifier includes a simulation-oriented SNR proxy that is itself derived from related empirical and assumed quantities. This introduces correlation and redundancy among some classifier variables. Feature-importance results should therefore not be interpreted as independent causal contributions.

Fourth, the chronological split is defined using ordered unique `Time_Index` values. It provides temporal separation between earlier and later observations but does not constitute testing on completely unseen sensing locations or frequency channels.

Fifth, the SNR quantity used during allocation is a simulation-oriented proxy rather than a direct measurement from an 8 GHz physical-layer receiver. The resulting throughput and spectral-efficiency values therefore depend on the assumptions used to construct and limit this proxy.

Sixth, the communication model is intentionally simplified. Throughput is calculated using a Shannon-style spectral-efficiency relationship, while communication latency combines a fixed base delay, transmission time, and a predefined failed-access penalty. Effects such as fading, coding, retransmissions, packet errors, medium-access contention, queueing, protocol overhead, mobility, and implementation-specific processing are outside the model.

Seventh, the reported reliability quantity represents successful selection of an actually vacant channel rather than complete packet-level delivery. Values of approximately 0.73 are therefore

useful for comparison between Q-Learning and DQN but should not be interpreted as satisfying mission-critical smart-grid reliability requirements.

Eighth, the allocation environment represents a simplified single-agent channel-selection problem. Simultaneous multi-user competition, distributed secondary-user coordination, transmission-power optimization, beam management, network slicing, and coordinated multi-cell scheduling are outside the present scope.

Finally, the study evaluates four supervised-learning classifiers and two reinforcement-learning allocation methods. The objective is a controlled comparative analysis rather than an exhaustive benchmark of all available AI techniques.

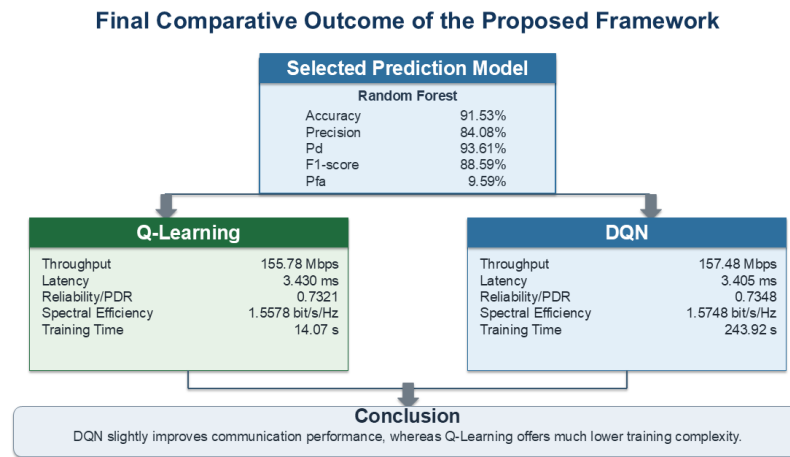


Figure 5.2: Comparative outcome of the final spectrum-classification and intelligent channel-allocation framework.

5.5 Recommendations for Future Work

Several extensions can improve the realism and applicability of the proposed framework.

The main directions for extending the present research are summarized in Fig. 5.3.

5.5.1 Use of Native Higher-Frequency Measurement Data

Future work should evaluate the prediction and allocation framework using measurements collected directly from mid-band, upper-mid-band, millimeter-wave, or sub-terahertz environments. Such data would reduce the dependence on communication-level frequency assumptions and allow propagation, blockage, and interference behaviour to be examined more directly.

5.5.2 Multi-Band Spectrum Management

Future 6G systems are expected to use heterogeneous frequency resources rather than a single operating band [9]. The current framework could therefore be extended to select among

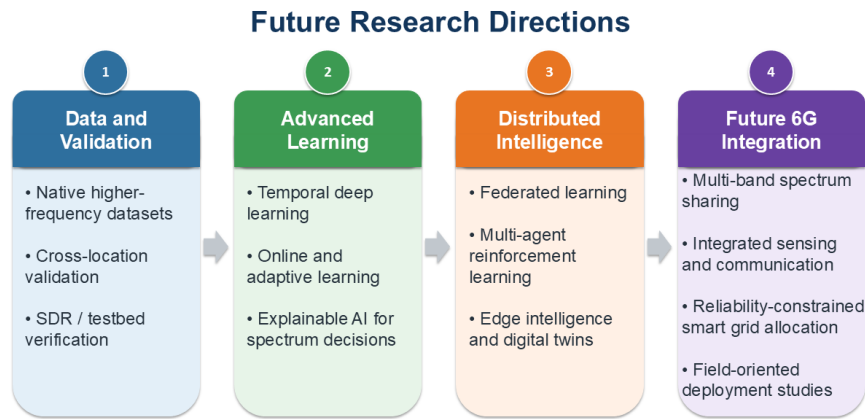


Figure 5.3: Future research directions for intelligent spectrum sharing in 6G-oriented smart grid communication.

sub-1 GHz, conventional mid-band, upper-mid-band, millimeter-wave, and higher-frequency resources according to coverage, capacity, and reliability requirements.

5.5.3 Multi-Agent Reinforcement Learning

A realistic spectrum-sharing environment can contain several devices attempting to access the same radio resources. Multi-agent reinforcement learning could be introduced to study competition, cooperation, collision avoidance, and fairness among distributed smart grid users [40,41].

5.5.4 Joint Channel and Power Allocation

The present work focuses on channel selection. Future research could jointly optimize channel choice and transmission power. This would allow the agent to account for interference, energy consumption, link quality, and spectrum reuse simultaneously.

5.5.5 Reliability-Constrained Reinforcement Learning

The current reward function balances successful access and spectral efficiency. A future formulation could introduce explicit reliability constraints, risk-sensitive rewards, or penalties for repeated transmission failure. This would be particularly relevant for smart grid applications that require substantially higher packet delivery ratios.

5.5.6 Network Slicing and Service-Aware Allocation

Different smart grid services have different communication requirements. Future work could integrate service classes into the state representation so that spectrum allocation responds differently to metering, monitoring, distributed control, and protection traffic.

5.5.7 Edge and Federated Learning

Centralized training may not always be desirable when smart grid devices are geographically distributed. Federated learning could allow local models to learn from regional spectrum observations without transferring all raw measurements to a central server [41, 49]. Edge intelligence could further reduce communication delay and support localized spectrum decisions [50, 51].

5.5.8 Digital Twin Assisted Spectrum Management

A digital twin of the communication and power-network environment could provide a controlled virtual representation for training and evaluating spectrum-allocation agents before field deployment [4]. Such a model could combine radio conditions, traffic demand, grid state, and communication requirements.

5.5.9 Integrated Sensing and Communication

IMT-2030 research increasingly considers integrated sensing and communication as an important future capability [9]. Future spectrum-management systems could exploit sensing information not only for occupancy prediction but also for environmental awareness, localization, infrastructure monitoring, and context-aware resource selection.

5.5.10 Multi-Step Ahead and Multi-Band Temporal Forecasting

While this study establishes single-step ahead spectrum occupancy prediction ($\hat{O}_{t+1}$), future research should extend this framework to multi-step horizon forecasting ($\hat{O}_{t+k}$, for $k > 1$). Incorporating deep sequence architectures, such as Long Short-Term Memory (LSTM) networks, Temporal Convolutional Networks (TCNs), and Spatial-Temporal Transformers, will enable long-horizon spectral forecasting across multi-band 6G radio interfaces. [34, 52].

5.5.11 Field-Oriented Smart Grid Validation

The most important long-term extension is validation using realistic smart grid traffic and communication infrastructure. Hardware-in-the-loop experiments, software-defined radio platforms, utility communication testbeds, or field measurements could provide stronger evidence concerning latency, interference, reliability, and resource-allocation behaviour under operational conditions.

5.6 Final Remarks

The increasing interaction between electric power systems and wireless communication creates a need for spectrum-management mechanisms that are adaptive, computationally practical, and transparent in their assumptions.

The results obtained in this thesis show that supervised machine learning can provide useful occupied/vacant spectrum classifications from the adopted ElectroSense-derived feature representation and that reinforcement-learning methods can subsequently use these availability estimates together with channel-quality information to support adaptive resource selection.

Random Forest provides the strongest overall classification performance within the investigated supervised-learning set according to the predefined selection criterion. At the allocation stage, DQN produces slightly improved simulation-derived communication performance relative to Q-Learning, although this improvement is accompanied by a much greater offline training requirement.

These findings emphasize that greater model complexity does not automatically lead to proportionally greater system-level improvement. Computational requirements, online decision latency, classification errors, and communication outcomes should therefore be considered jointly when evaluating intelligent spectrum-management techniques.

The principal significance of the work lies in the integration of empirical spectrum classification, controlled reinforcement-learning allocation, and communication-oriented simulation within a common experimental framework. By explicitly separating empirical measurements from 6G-oriented communication assumptions and by acknowledging the limitations of the simplified reliability and channel-quality models, the study provides a transparent foundation for future work involving temporal prediction, multi-user access, multi-band operation, and reliability-constrained smart-grid communication.

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