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Machine learning-based spectrum occupancy prediction: a comprehensive survey

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In cognitive radio (CR) systems, efficient spectrum utilization depends on the ability to predict spectrum opportunities. Traditional statistical methods for spectrum occupancy prediction (SOP) are insufficient for addressing the non-stationary nature of spectrum occupancy, especially with UEs' increased mobility and diversity in the sixth-generation and beyond wireless networks. This survey provides a comprehensive overview of machine learning (ML)-based SOP methods that address these challenges. The paper begins with a brief discussion of problem definition and traditional statistical methods before delving into a detailed survey of ML-based methods. Various aspects of SOP are analyzed from a CR perspective, highlighting the multidimensional correlations in spectrum usage across time, frequency, space, etc. Key challenges and enabling methods for effective prediction are reviewed, focusing on deep learning methods that exploit these multidimensional correlations. The survey also covers dataset generation techniques for SOP. Additionally, the paper discusses CR threats that impair spectrum utilization and reviews ML methods for detecting these threats. The future directions for ML-based SOP are also given.

KEYWORDS

6G, cognitive radio, deep learning, machine learning, multi-dimensions, spectrum occupancy prediction

1 Introduction

Accommodating exploding data traffic is one of the most critical challenges for communication systems in the sixth generation (6G) and beyond (Zhang and Zhu, 2020; Guo et al., 2021). In 6G networks, data rates are expected to exceed 1 terabit per second, and end-to-end delays will be reduced to less than 0.1 milliseconds. Additionally, 6G will provide access to powerful edge intelligence with processing delays below 10 nanoseconds and network reliability exceeding 99.99999%. The extreme connection density of over 10 million devices per square kilometer will support the Internet of everything (De Alwis et al., 2021). Thus, there is an intrinsic gap with the limited spectrum available due to the ever-demanding nature of higher-rate communications (Amjad et al., 2018).

One potential solution to this gap is the recent integration of communication and sensing capabilities in 6G networks (Bazzi and Chafii, 2023; Chowdary et al., 2024), which aim to optimize the use of limited spectrum resources. However, this solution is limited to the integration of sensing and communication tasks. A more general and flexible approach to addressing the spectrum demand is the use of cognitive radio (CR) systems (Ivanov et al., 2021), which dynamically allocate spectrum based on the environment's needs.

CR systems rely on accurate spectrum sensing and prediction to identify and exploit "spectrum holes" efficiently. Traditional statistical methods, such as autoregressive methods and Bayesian inference, have been widely used for spectrum occupancy prediction (SOP) (Wen et al., 2008; Xing et al., 2013b). However, these methods often struggle to cope with the non-stationary nature of spectrum occupancy, which is increasingly influenced by the mobility and diversity of users (UE)s in modern wireless communication networks. Machine learning (ML) methods are proposed as a robust alternative to SOP to address these challenges.

ML methods, ranging from shallow neural networks (NN)s to advanced deep learning (DL) methods, offer significant improvements in prediction accuracy by leveraging the complex temporal and spatial correlations in spectrum data (Tumuluru et al., 2012; Eltholth, 2016; Selim et al., 2017). In particular, DL methods such as convolutional neural networks (CNN)s and long short-term memory (LSTM) networks have been particularly useful, as CNNs excel at extracting spatial patterns, while LSTMs effectively capture temporal dependencies, both of which enhance the reliability of spectrum predictions (Yu et al., 2017; Omotere et al., 2018).

Despite the successes of ML-based methods, several challenges remain. The need for large labeled datasets, the adaptability of methods to changing environments, the interpretability of predictions, the computational cost and energy consumption, how to use multidimensional correlations for higher accuracy, and data privacy are critical issues that should be addressed for efficient ML usage. Additionally, the presence of CR threats, such as jamming and primary UE (PU) emulation attack (PUEA), necessitates the development of robust security measures to ensure the integrity of SOP (Fragkiadakis et al., 2013). Therefore, ML-based SOP methods should be investigated thoroughly. Along with this line, a comprehensive survey is required to highlight and address these challenges, discussing different ML-based SOP methods.

1.1 Related work

Numerous studies have investigated SOP. While some of these studies solely focus on traditional methods, some of them discuss ML-based methods. Miao et al. (2009) reviews spectrum measurement campaigns and introduces interference maps as spectrum analysis and management tools. The paper highlights how these maps characterize spectrum use by defining the level of interference over specific areas and frequency bands. López-Benítez and Casadevall (2011) gives an overview of the existing SOP methods that characterize the spectrum usage patterns of licensed systems in the time, frequency, and space dimensions. Xing et al. (2013a) gives an overview of the problem of spectrum assignment in CR network (CRN), presenting the literature, analyzing the criteria for selecting the most suitable portion of the spectrum, and showing the most common methods used to solve the spectrum assignment problem. Tragos et al. (2013) surveys the state-of-the-art spectrum prediction in CRNs. They summarize the main spectrum prediction methods, illustrate their applications, and present the relevant open research challenges. Chen and Oh (2014) focuses on various SOP methods based on real-world measurements, highlighting their importance for CR systems. Chen and Oh (2014) studies the various SOP methods used in diverse locations by research campaigns worldwide. The detailed analyses of the empirical results in different measurement scenarios were compared. Ding et al. (2017) provides a comprehensive survey and tutorial on spectrum inference. Eltom et al. (2018) categorizes various spectrum prediction methods, including single memoryless source, Markov-based, and linear statistical regression methods. It comprehensively reviews current spectrum prediction methods and their applications in dynamic spectrum access. Agarwal et al. (2018) investigates the practical prowess of various time-series modeling and the ML methods for predicting spectrum occupancy based on a spectrum measurement campaign conducted in India. In Tidjani and Hammoudi (2019), spectral prediction methods are meanly divided into four categories: linear, pattern mining, Markov model, and ML-based methods. Naikwadi and Patil (2020) delves into applying artificial NNs (ANN)s for SOP. It discusses how these methods can improve spectrum efficiency by predicting spectrum bands' occupied or free status from existing measurement data. Okorie et al. (2022) analyzes the use of ANNs to identify vacant portions of the spectrum in CR systems. Several ANN topologies are considered, including CNNs, LSTM networks, and hybrid combinations. Radhakrishnan (2022) performs spectrum prediction in the temporal domain using a DL method. It also compares different ML-based SOP methods in a multi-UE cooperative radio environment. Cullen et al. (2023) takes a comprehensive method for dynamic spectrum allocation, covering measurement of spectrum usage, prediction methods, and system deployment. It emphasizes the holistic nature of these systems and the importance of accurate spectrum usage predictions. Li et al. (2024) provides insights into SOP methods, emphasizing data-driven methods. Although these works investigated several challenges for SOP and methods used to predict spectrum occupancies, a more comprehensive survey is still required to investigate ML-based SOP methods and their challenges, including research directions.

1.2 Contributions of the paper

The contributions of this paper to the literature are itemized as follows.

- To the best of the authors' knowledge, this paper is the first to comprehensively analyze ML-based SOP methods.
- Several scenarios are provided to enable an easier understanding of the dataset generation process.
- This paper introduces interpretable ML methods specifically tailored for SOP.
- The attacks on CR systems are defined, their consequences are highlighted, and solutions for these security weaknesses are provided by leveraging diverse domains.
- Future research directions for ML-based SOP methods are outlined to guide further advancements in the field.

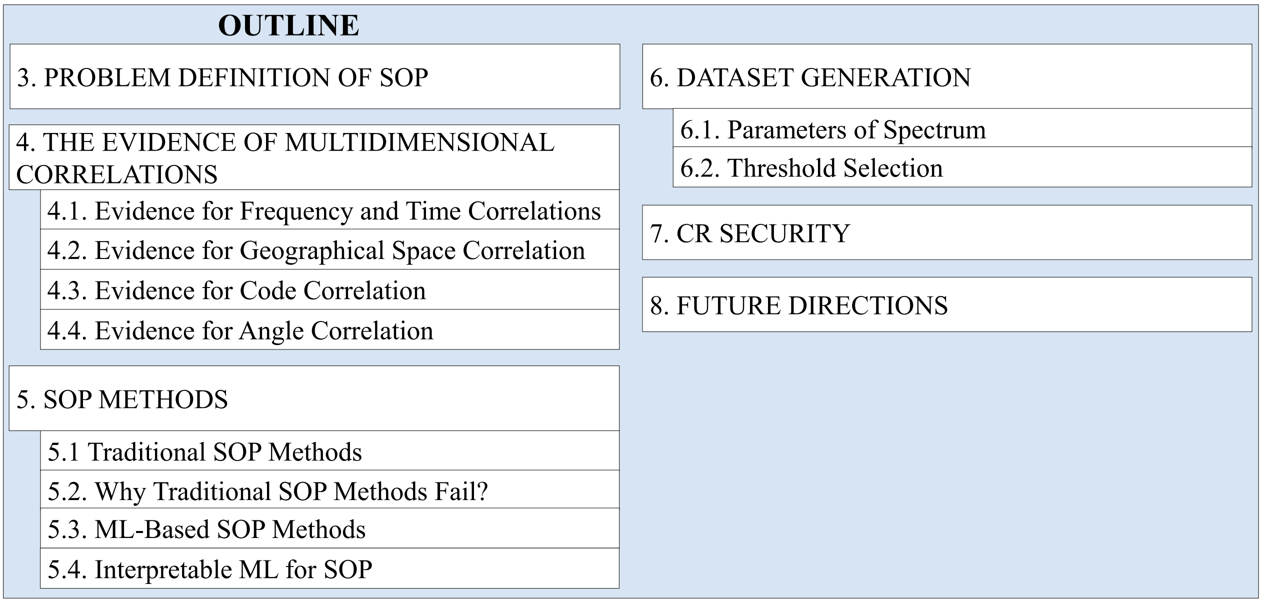

FIGURE 1
Structure of this survey.

2 Structure of the survey

As illustrated in Figure 1, the structure of this survey is as follows. The problem definition of SOP is covered in Section 3. Section 4 delves into the evidence for leveraging multidimensional correlations in SOP, highlighting their significance in improving prediction accuracy. Section 5 explores state-of-the-art SOP methods, offering a critical comparison of various algorithms. The process of dataset generation, crucial for training and validating SOP models, is covered in Section 6. Section 7 investigates CR threats and discusses potential protection methods to mitigate security risks. Section 8 discusses the key challenges faced in advancing ML-based SOP methods and discusses future research directions to address these challenges Finally, Section 9 concludes the paper, summarizing the key contributions and findings.

3 Problem definition of SOP

The problem definition of SOP is to make spectrum occupancy state predictions over a given frequency range according to previous occupancies. Spectrum access is modeled using the heterogeneous spectrum access model (Khalfi et al., 2018). This model divides the spectrum into k contiguous frequency sub-bands. The presence of a PU signal indicates signal occupancy, while the absence of such a signal indicates a spectrum hole. Hypotheses ($\mathcal{H}_0$ and $\mathcal{H}_1$) denote these scenarios scenarios, as in Equation 1

$$\boldsymbol{r} = \begin{cases} \boldsymbol{n}, & \mathcal{H}_0\text{: There is no PU.} \\ \boldsymbol{Hs} + \boldsymbol{n}, & \mathcal{H}_1\text{: A PU is exist,} \end{cases} \tag{1}$$

where $\boldsymbol{r}$, $\boldsymbol{s}$, $\boldsymbol{H}$, and $\boldsymbol{n}$ represent received signal, transmitted signal, channel matrix, and noise realization, respectively.

The primary system model that is considered for SOP is demonstrated in Figures 2A, B. Here, Figure 2A illustrates the real occupancies while predicted occupancies are given in Figure 2B. As shown in these figures, when the occupied band is predicted to be a hole, SU uses that band, creating interference. On the other hand, when the band is vacant and is predicted as occupied, its usage opportunity is lost, so spectral efficiency is decreased. Besides that, it should be predicted promptly so there will be enough time to allocate holes to the SUs efficiently. Thus, spectrum occupancies should be predicted with low complexity and high accuracy.

4 The evidence of multidimensional correlations

4.1 Evidence for frequency and time correlations

To show the frequency and time correlations, the following test is carried out. First, 10 min of the spectrum was recorded between 832 and 862 megahertz. (Note that 832–862 megahertz is just an example frequency range, and similar analyses can be applied to other frequency bands as well. We focused on the frequency range of 832–862 MHz because it corresponds to the private uplink bands of the top three telecom operators in Turkey: Türk Telekom, Vodafone, and Turkcell.) Then, the plot of the block-correlation pattern is given in Figure 3A to show the correlation coefficients in frequency. This figure indicates a high correlation in the neighboring frequency bands for each operator. This shows the correlation in frequency.

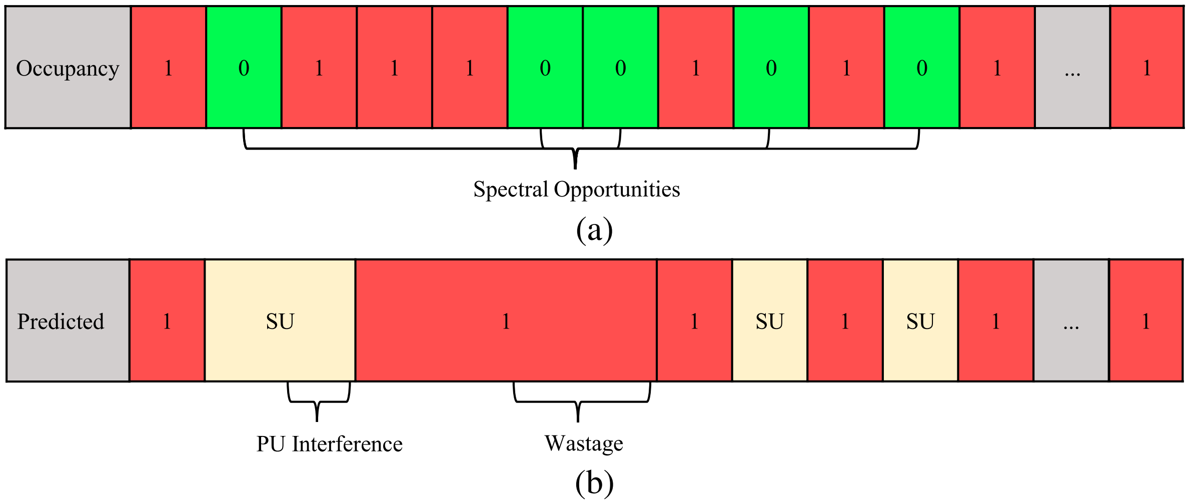

FIGURE 2
Modeling the **(A)** true and **(B)** predicted occupancies and usage of sub-band spectrum units.

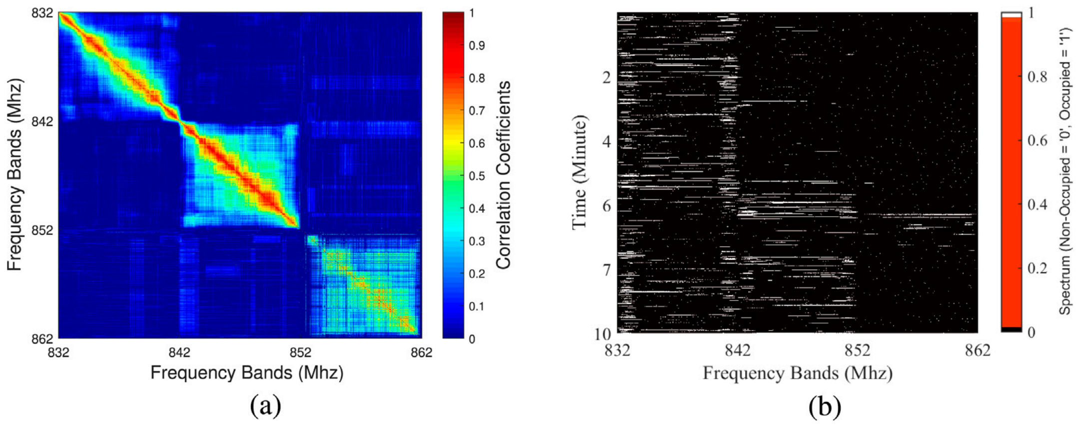

FIGURE 3
Illustration of channel **(A)** correlation and **(B)** occupancy distributions.

The channel occupancy distribution is computed for all time instants and frequency sub-bands for each frequency point in Figure 3B. The spectrum occupancy state representing frequency and time correlations is illustrated in this figure by the color bar (black indicates the spectrum is not occupied, while white indicates the spectrum is occupied). In other words, the correlation in time is illustrated by the vertical lines, while the horizontal lines show the correlation in frequency. This figure shows the correlation across frequency and time since the occupied accumulates in one place.

4.2 Evidence for geographical space correlation

The exploitation of spatial correlation is advantageous for the SOP problem, as demonstrated in Figure 4. Here, BS_1 is the base station (BS) on which the SOP will be made. This figure shows that when BS_1 is trained without prior information from neighboring BSs, it decides on the future spectrum as vacant. On the other hand, BS_2 and BS_3 are full, and the UE of BS_2 and BS_3 can occupy the spectrum of the BS_1 for the upcoming intervals, so the number of occupied bands will increase for BS_1. Along with this line, more accurate predictions of spectrum occupancy can be made by utilizing the data from the space dimension.

4.3 Evidence for code correlation

In the code domain, the spectrum can be correlated through orthogonal codes, which allow simultaneous transmissions without interference. This correlation occurs because different UEs or services can use different orthogonal codes to share the same frequency band. Figure 5 illustrates an example of opportunistic code domain usage. In this scenario, if a secondary UE (SU) can

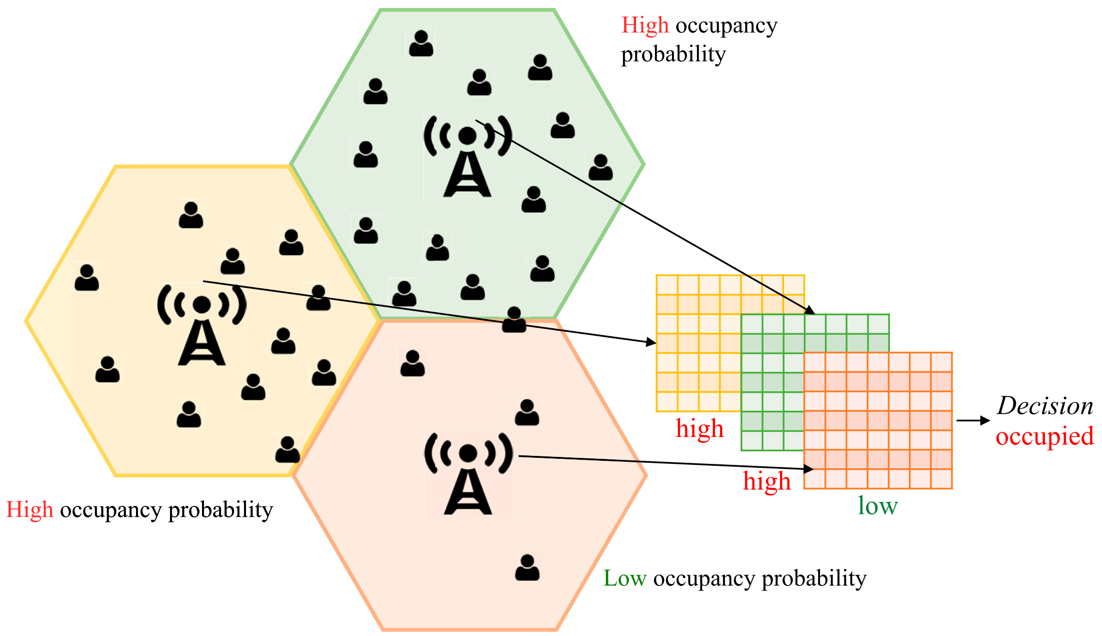

FIGURE 4
The proposed method-training stage.

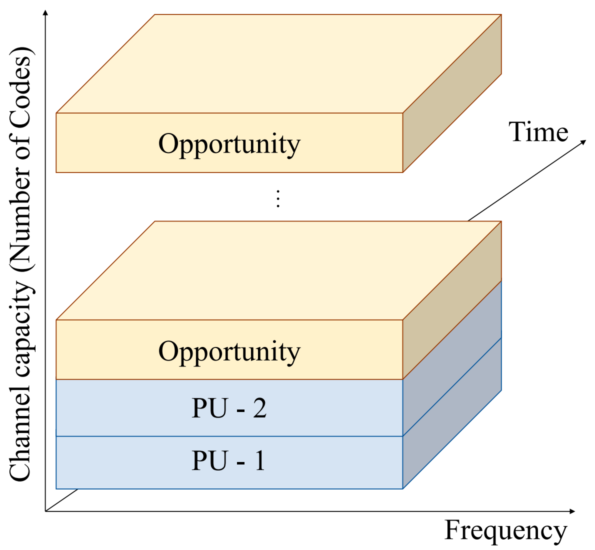

FIGURE 5
Opportunistic code domain usage.

identify which codes are currently being utilized by PUs, they can select an orthogonal code for their transmission.

4.4 Evidence for angle correlation

In wireless communications, signals propagate differently depending on their transmission angle, which is influenced by factors like antenna directivity, terrain, and obstacles. These characteristics create an angular correlation that can be exploited to predict spectrum occupancy more accurately. The angle correlation becomes particularly useful in scenarios involving directional antennas or beamforming, where the transmission power is concentrated in specific directions, leaving other angles with lower signal levels.

Consider a PU transmitting in a particular direction. Due to the directional nature of the antenna, the energy radiated is stronger along the intended path, while signals in other directions are weaker due to factors like path loss, scattering, and obstacles. This leads to an occupancy pattern that correlates with angle: when a PU transmits in one direction, the likelihood of significant spectrum usage in other directions decreases. This phenomenon arises from directional beam patterns, suggesting that SUs can opportunistically utilize the angular information to access the spectrum more effectively. For example, if an SU can determine that a PU is transmitting toward the north, it may choose to transmit in the east or west directions, where the signal strength from the PU is lower, thus minimizing interference and enhancing spectrum utilization.

5 SOP methods

This section begins by reviewing several traditional methods and examining the limitations of traditional SOP methods. Next, ML-based SOP methods are explored, highlighting their advantages. Finally, the importance of interpretable ML in SOP is emphasized, underscoring the critical need for transparency and explainability in prediction methods.

5.1 Traditional SOP methods

5.1.1 Prediction with autoregressive method

The autoregressive (AR) method is a widely used linear predictor in time series analysis. It operates by expressing the predicted state of a future time instant as a weighted sum of past observations and a noise term, as in Equation 2:

$$\hat{s}_t = \sum_{i=1}^{r} \varphi_i y_{t-i} + \omega_t, \tag{2}$$

where r represents the model order, φ_i $(i = 1, 2, \ldots, r)$ are the model parameters, $\hat{s}_t$ denotes the predicted state at time t, ω_t represents white noise at time t, and y_{t-i} are the past observations at time instants $t-i$.

The AR model requires careful tuning of its parameters to provide accurate predictions. This tuning can be done using various methods, such as the Yule-Walker equations, which solve a system of linear equations derived from the data's autocorrelation, or through maximum likelihood estimation, which seeks parameters that maximize the likelihood of observing the historical data. Once the model parameters are determined, the AR model leverages the historical data and these parameters to predict future states of the system. This method is particularly useful when the spectrum occupancy patterns exhibit linear dependencies over time. The effectiveness of the AR method has been demonstrated in Wen et al. (2008), Gorcin et al. (2011).

5.1.2 Prediction with moving average

Moving average (MA)-based prediction is a straightforward technique for smoothing and forecasting trends within a sequence of observations (Bütün et al., 2010). In this approach, the next predicted value is computed as the average of the last k observed values, where k is the order of the MA. This simple method is effective for filtering out short-term fluctuations and highlighting longer-term trends in spectrum occupancy.

To improve responsiveness to recent changes, the exponential MA (EMA) assigns exponentially decreasing weights to older values, placing more emphasis on recent observations (Lin et al., 2009). This makes the EMA more sensitive to sudden changes in the spectrum, which can be advantageous in dynamic environments where occupancy patterns shift rapidly. Both techniques are valuable when dealing with noisy data and are commonly used to smooth short-term variations while retaining meaningful trends.

5.1.3 Prediction with time series analysis using ARIMA

The AR integrated MA (ARIMA) model is a powerful traditional time series forecasting technique that can be employed for SOP. The ARIMA model combines three components: AR, differencing, and MA. It is particularly useful for time series data that exhibit trends and require transformation to achieve stationarity. Wang and Salous (2011) applies ARIMA to SOP.

By analyzing past occupancy data, the ARIMA model can capture both the AR and MA components, providing a robust framework for predicting future spectrum occupancy. The model parameters can be identified through techniques like the Box-Jenkins methodology, which involves examining the autocorrelation and partial autocorrelation functions of the time series data. ARIMA is especially effective when past occupancy states are indicative of future states, making it suitable for scenarios where temporal correlations are strong.

5.1.4 Prediction with hidden Markov model

The hidden Markov model (HMM) is a probabilistic framework that extends the Markov chain by introducing hidden states, which are not directly observable. In the context of CRNs, the true spectrum occupancy states are hidden from UEs, who can only observe the spectrum usage indirectly. The HMM consists of two processes (Saad et al., 2016): a hidden state process, where transitions between states (e.g., idle or busy) follow a Markov process, and an observation process, where the observations depend probabilistically on the hidden states.

Define the hidden state space as $X = x_1, x_2$, where $x_1 = 0$ represents an idle channel and $x_2 = 1$ represents a busy channel. The corresponding observation space is defined as $Y = y_1, y_2$, where $y_1 = 0$ indicates an idle spectrum and $y_2 = 1$ indicates a busy spectrum. The channel's hidden state at time slot n is denoted by q_n, and the corresponding spectrum prediction result is q. The HMM is parameterized by $\Lambda = (\pi, A, B)$, where π is the initial state distribution, A is the state transition probability matrix, and B is the emission probability matrix, which links the hidden states to the observations. The HMM's ability to model the uncertainty in spectrum states makes it a powerful tool for SOP in dynamic environments (Chatziantoniou et al., 2013).

5.1.5 Prediction with Bayesian inference

Bayesian inference is a probabilistic method that updates the distribution of a hypothesis based on observed evidence. In the context of SOP, Bayesian inference allows CR UEs to update their belief about the spectrum occupancy state based on newly acquired observations (Jacob et al., 2014). The method applies Bayes' rule to compute the posterior probability of the spectrum state s given the observed data $\boldsymbol{y}$, as given in Equation 3:

$$P(s|\boldsymbol{y}) = \frac{P(\boldsymbol{y}|s) \cdot P(s)}{P(\boldsymbol{y})}, \tag{3}$$

where $P(s)$ is the prior probability of the state, $P(\boldsymbol{y}|s)$ is the likelihood of the data given the state, and $P(\boldsymbol{y})$ is the marginal likelihood of the data.

Bayesian inference-based method is particularly useful when the spectrum occupancy pattern is uncertain or when prior knowledge about the spectrum environment is available. By continuously updating the posterior probability as new evidence becomes available, Bayesian inference provides a dynamic and adaptive approach to SOP, enabling more accurate predictions in real-time scenarios. Bayesian inference-based method is applied to spectrum prediction in Xing et al. (2013a).

5.2 Why traditional SOP methods fail?

Traditional SOP methods have served as the foundation for spectrum management and optimization strategies in wireless communication for decades. However, as wireless systems evolve and the demand for spectrum resources intensifies, particularly in dense urban environments, these traditional techniques encounter significant limitations. Many of these methods rely heavily on linear models and static assumptions, which do not adequately capture the complexities and dynamic nature of real-world scenarios.

One primary challenge with traditional SOP methods is their reliance on the assumption that the spectrum environment is stationary. This means that historical data is used to forecast future occupancy patterns without adequately accounting for time-varying factors such as UE mobility, interference from neighboring systems, or sudden fluctuations in network traffic. For instance, traditional techniques may use historical occupancy data from the previous week to make predictions, failing to consider that external events—like concerts, sporting events, or public gatherings—can drastically alter UE behavior and spectrum demand. Moreover, traditional approaches often employ simplified statistical models, such as Markov Chain or ARIMA models, which may overlook the intricate, multidimensional correlations among various factors, including frequency, time, geographic space, code, and angle. These correlations are critical for accurately predicting spectrum opportunities, as they can reveal underlying patterns that influence channel usage in ways that simplistic models cannot grasp.

Consider a bustling metropolitan city during a major festival, where numerous wireless services compete for limited spectrum resources. Network operators deploy a traditional Markov Chain model to predict spectrum occupancy based on historical data. However, this model assumes constant transition probabilities and fails to account for the surge in UE demand or the exclusive use of certain channels by emergency services. As thousands of attendees flood the area, drastically increasing mobile data demand for activities like live streaming and social media, the model inaccurately predicts spectrum availability, leading to unanticipated channel congestion. Additionally, it overlooks multidimensional correlations such as the interplay between time, location, user behavior, and external factors like emergency services. This one-dimensional approach results in severe delays, dropped connections, and slow data speeds, frustrating attendees and causing negative feedback. The model's failure to adapt to real-time changes and complex factors highlights the need for more advanced spectrum prediction techniques that incorporate real-time analytics and consider the dynamic nature of modern wireless environments.

This is where ML approaches provide a transformative solution. ML models can process large-scale, complex data and identify non-linear relationships that traditional models often miss. By leveraging real-time data from multiple dimensions, ML models can dynamically adapt to changing spectrum conditions. These models learn from patterns across various datasets and improve prediction accuracy over time, enabling proactive spectrum management. In the case of the festival scenario, an ML-based model can learn from historical data as well as real-time inputs to predict and react to the surge in UE demand. Rather than relying on static assumptions, ML techniques allow the network to adapt to congestion, reallocate spectrum resources, and prioritize channels based on real-time usage patterns. This can result in more efficient spectrum utilization, minimized disruptions, and an overall improved UE experience during high-demand events. Thus, ML offers a path forward by enabling more dynamic, data-driven approaches for SOP, capable of handling the complexities of modern wireless communication environments. These techniques empower network operators to make more accurate predictions and real-time decisions, addressing the limitations of traditional models and improving spectrum efficiency in a fast-evolving wireless landscape.

5.3 ML-based SOP methods

5.3.1 Support vector machines

Support vector machines (SVM)s are supervised learning models used for classification and regression tasks (Suthaharan and Suthaharan, 2016). In the context of SOP, SVM can be used to identify spectrum availability by learning decision boundaries between spectrum usage states (occupied or free) based on features such as signal strength, interference levels, or historical spectrum usage patterns. SVM aims to find the optimal hyperplane that separates classes with the maximum margin, ensuring robust predictions. Panchal et al. (2018), Azmat et al. (2015), Kyeremateng-Boateng et al. (2020) utilize SVM for SOP.

SVM's ability to handle high-dimensional feature spaces and work well with non-linear data makes it a valuable tool for spectrum prediction tasks. SVM achieves this by employing the kernel trick, which maps input data into a higher-dimensional space to make it linearly separable. Common kernels include the radial basis function and polynomial kernels.

5.3.2 Decision trees

Decision trees (DT)s are a non-parametric, interpretable ML method used for classification and regression tasks Mienye and Jere (2024). For SOP, a decision tree can predict the availability of a frequency band based on a series of binary decisions derived from input features such as signal strength, UE traffic, and interference levels.

The tree splits the feature space into regions based on decision rules learned during training. Each internal node represents a feature, and each leaf node corresponds to a prediction (e.g., spectrum available or unavailable). Azmat et al. (2015), Panchal et al. (2018), Zhao et al. (2018) applies DT to SOP. The simplicity and interpretability of these algorithms make them appealing for real-time SOP tasks Zhao et al. (2018), but they tend to overfit the training data if not properly pruned. Despite this, they serve as the basis for more sophisticated ensemble methods like random forests.

5.3.3 Random forest

Random forest is an ensemble learning method that builds multiple decision trees during training and merges their predictions to improve accuracy and robustness (Rigatti, 2017). For SOP, random forest can predict whether a spectrum band will be available by leveraging multiple historical and environmental features (Baddour et al., 2018). It is less prone to overfitting compared to individual decision trees due to their ensemble nature, which aggregates multiple independent predictions. Moreover, it provides feature importance measures, helping network operators understand which factors most influence spectrum availability. Accordingly, random forest algorithm is used in SOP in Baddour et al. (2018). However, random forests can be computationally intensive when dealing with very large datasets or high-dimensional features.

5.3.4 k-nearest neighbors

The k-nearest neighbors (k-NN) algorithm is a simple, non-parametric method that can be used for SOP prediction (Ghazizadeh et al., 2016). In this context, k-NN identifies the k-nearest historical instances of spectrum usage to a current observation and assigns a label based on the majority vote among its neighbors.

The advantage of k-NN lies in its simplicity and interpretability, as predictions are based directly on historical data points rather than complex models (Syriopoulos et al, 2023). This makes k-NN suitable for scenarios where spectrum patterns exhibit strong local correlations. Along with this line, k-NN is used in SOP (Panchal et al., 2018). However, its performance can degrade with increasing data dimensionality or volume, leading to high computational costs, especially in large-scale SOP systems. Additionally, k-NN is sensitive to the choice of distance metrics and can be affected by noisy data.

5.3.5 Prediction with linear regression

Linear regression provides a robust and interpretable approach for predicting spectrum occupancy (Uyanik et al., 2012). In SOP, it is often essential to estimate how different variables—such as time, frequency, and space—influence the likelihood of spectrum availability. Linear regression allows for modeling the relationship between these variables and spectrum occupancy, making it easier to analyze and interpret trends that may follow linear patterns.

One of the key advantages of linear regression in this context is its simplicity and ease of implementation, which makes it suitable for environments where transparency and interpretability are crucial. Additionally, its ability to handle continuous variables and provide a straightforward estimation of their contributions to spectrum occupancy makes it a practical choice for predicting spectrum availability in diverse scenarios. Along with this line, linear regression usage is analyzed for SOP in Azmat et al. (2015).

5.3.6 Naive Bayes

Naive Bayes (NB) is a probabilistic classifier that applies Bayes' theorem under the assumption that features are conditionally independent given the class label. While this assumption is often unrealistic, NB performs well in many real-world scenarios. In SOP prediction, NB can estimate the probability that a given frequency band is free (Mishra and Vijaykumar, 2018), according to features such as prior usage patterns, signal strength, or interference levels.

The NB classifier is computationally efficient and works well with small datasets or when the independence assumption roughly holds (Rish et al., 2001). It is also easy to implement and interpret, making it a suitable choice for real-time spectrum management in resource-constrained environments. Panchal et al. (2018), Bolat and Kelek (2020) are the examples of NB usage in SOP. However, NB may struggle with highly correlated features, which is common in dynamic spectrum environments, limiting its prediction accuracy compared to more complex models.

5.3.7 Prediction with multilayer perceptron NN

A multilayer perceptron (MLP) is a widely used feedforward NN technique for supervised learning tasks, mapping input data onto the corresponding outputs by learning complex patterns through hidden layers (Aran and Alpaydın, 2003). In SOP prediction, MLP leverages past observations to predict future system performance. The key advantage of MLP is its ability to approximate any continuous function, making it highly adaptable to various prediction problems, including those in dynamic and non-linear systems (Tumuluru et al, 2010; Tumuluru et al., 2012).

An MLP consists of at least three layers: an input layer, one or more hidden layers, and an output layer. Each neuron in the hidden layers is connected to every neuron in the subsequent layer, forming a fully connected directed graph. The neurons process input by calculating a weighted sum and applying an activation function such as sigmoid and rectified linear unit, which introduces non-linearity to the network. This non-linearity is essential in capturing complex dependencies in the input data, enabling the MLP to perform tasks that linear models cannot handle.

The MLP's training process is iterative, involving forward and backward passes through the network. During the forward pass, the network produces predictions based on the current weights. The error is computed as the difference between predicted and actual outputs using a loss function like mean squared error (MSE). In the backward pass, the network uses the error to adjust the weights via gradient descent and backpropagation, minimizing the loss. Over multiple epochs, the model improves its predictive performance. Once trained, the MLP can generalize to unseen data by making predictions based on newly observed inputs.

There are several examples of NN usage in SOP, such as Tumuluru et al. (2010), Tumuluru et al. (2012), Eltholth (2016), Das et al. (2018), Mohammadjafari et al. (2019), Fan et al. (2019), Ajiboye et al. (2021), Chirov and Kandaurova (2023), Kandaurova and Chirov (2023), Enwere et al. (2023). On the other hand, recent literature views that spectrum occupancy is a non-stationary process (Ding et al., 2017). Nevertheless, the methods above may not always be capable of addressing this issue. This incapacity has become more visible since more UE mobility and various UE types are anticipated in 6G and beyond. Thus, thanks to multiple hidden layers, DL methods, such as deep NN (DNN), CNN, and LSTM networks, which can capture complex temporal and spatial correlations in spectrum data, have been proposed as an advanced SOP framework for addressing this non-stationarity. For example, Cao et al. (2021) proposes a type of DNN that combines residual network, channel and spatial attention modules, and gated recurrent unit network.

5.3.8 Prediction with CNN

One-dimensional CNN (1D-CNN) are commonly used for tasks that involve sequential or temporal data, such as time-series prediction. A 1D-CNN has a simpler architecture compared to two-dimensional CNNs (2D-CNN)s, making it suitable for real-time and low-cost applications (Kiranyaz et al., 2019). The process is composed of two stages: the training stage and the testing stage.

During the training stage, the 1D-CNN model adjusts the convolutional layers. The core operation of the convolutional layer is to slide a filter over the input sequence and compute the dot product between the filter and the input sequence. The result of this operation is known as the convolved feature map, and it can be expressed mathematically as

$$o = \sum_{p=1}^{u} w_p \cdot \boldsymbol{x}_k [p - 1],$$

where w_p represents the element at the p-th row of the $u \times 1$ filter vector, and $\boldsymbol{x}_k$ denotes the elements of the input feature vector being convolved with the filter.

After convolution, the feature map is typically passed through an activation function (such as rectified linear unit) to introduce non-linearity, followed by pooling layers to reduce the dimensionality and retain the most important features. This process helps the model capture local patterns in the input sequence.

During the testing stage, the trained 1D-CNN model uses the learned filters to process new input data by convolving the filters with the input sequence, generating a feature map that highlights the most relevant information. The final output is then used to predict the next sequence or value, depending on the specific task at hand.

While 1D-CNN uses one-dimensional data, 2D-CNN processes two-dimensional input, such as images or matrices. 2D-CNN is also composed of two stages: the training stage and the testing stage. During the training stage, the convolutional layers are adjusted based on the input data. A feature map is generated by convolving the input feature vector with a set of filters. The operation can be expressed mathematically as

$$o = \sum_{p=1}^{u} w_p \cdot \boldsymbol{x}_k[p-1] \cdot \boldsymbol{y}_k[r-1],$$

where $\boldsymbol{y}_k$ represents the elements of the input feature vector convolved by w_p, and r is the corresponding element in the second dimension of the feature map. The other processes are the same as the 1D-CNN. CNNs have been particularly effective in detecting the presence of radar signals by analyzing the phase and amplitude differences in data (Selim et al., 2017; Sun et al., 2019). In Ambika et al. (2021), a deep CNN method is used to classify the occupancy state of PU.

5.3.9 Prediction with LSTM

LSTM networks are a type of recurrent NN (RNN) designed to handle sequential data with long-term dependencies. Standard RNNs struggle to retain information over long sequences due to the vanishing gradient problem. LSTM mitigates this issue using memory cells that maintain information over time, allowing the model to capture both short-term and long-term dependencies (Yu et al., 2019).

The LSTM architecture consists of a series of gates that control the flow of information: the input gate $\boldsymbol{i}_t$, the forget gate $\boldsymbol{f}_t$, and the output gate $\boldsymbol{o}_t$. These gates are regulated by the current input $\boldsymbol{x}_t$ and the previous hidden state $\boldsymbol{h}_{t-1}$. The memory cell $\boldsymbol{c}_t$ stores information, and the hidden state $\boldsymbol{h}_t$ is computed based on the cell's output.

The mathematical operations within an LSTM cell are as follows.

- Forget Gate: The forget gate determines how much of the previous cell state $\boldsymbol{c}_{t-1}$ should be forgotten. It is computed as

$$\boldsymbol{f}_t = \sigma\left(\boldsymbol{W}_f \cdot [\boldsymbol{h}_{t-1}, \boldsymbol{x}_t] + \boldsymbol{b}_f\right),$$

where $\boldsymbol{W}_f$ are the weights, $[\boldsymbol{h}_{t-1}, \boldsymbol{x}_t]$ is the concatenation of the previous hidden state and the current input, $\boldsymbol{b}_f$ is the bias, and σ is the sigmoid activation function. The output $\boldsymbol{f}_t$ is a vector with values between 0 and 1, controlling the amount of forgetting.

- Input Gate: The input gate controls how much new information is added to the cell state. It is computed as

$$\boldsymbol{i}_t = \sigma(\boldsymbol{W}_i \cdot [\boldsymbol{h}_{t-1}, \boldsymbol{x}_t] + \boldsymbol{b}_i).$$

Simultaneously, a candidate cell state $\tilde{\boldsymbol{c}}_t$ is generated using a tanh activation function as follows.

$$\tilde{\boldsymbol{c}}_t = \tanh(\boldsymbol{W}_c \cdot [\boldsymbol{h}_{t-1}, \boldsymbol{x}_t] + \boldsymbol{b}_c).$$

The new cell state $\boldsymbol{c}_t$ is updated by combining the forget gate and input gate is

$$\boldsymbol{c}_t = \boldsymbol{f}_t \odot \boldsymbol{c}_{t-1} + \boldsymbol{i}_t \odot \tilde{\boldsymbol{c}}_t,$$

where, $\odot$ represents element-wise multiplication.

- Output Gate: The output gate determines the next hidden state based on the current cell state $\boldsymbol{c}_t$. It is computed as

$$\boldsymbol{o}_t = \sigma(\boldsymbol{W}_o \cdot [\boldsymbol{h}_{t-1}, \boldsymbol{x}_t] + \boldsymbol{b}_o).$$

The hidden state $\boldsymbol{h}_t$ is then updated as

$$\boldsymbol{h}_t = \boldsymbol{o}_t \odot \tanh(\boldsymbol{c}_t).$$

In these equations, $\boldsymbol{W}_f, \boldsymbol{W}_i, \boldsymbol{W}_c, \boldsymbol{W}_o$ are weight matrices, and $\boldsymbol{b}_f, \boldsymbol{b}_i, \boldsymbol{b}_c, \boldsymbol{b}_o$ are bias vectors associated with the forget gate, input gate, candidate cell state, and output gate, respectively. The sigmoid function $\sigma(z) = \frac{1}{1+e^{-z}}$ ensures that the gate values are between 0 and 1, while the tanh function constrains the candidate cell state values between -1 and 1.

The flow of information through the gates allows the LSTM to retain relevant information and discard irrelevant data over time. This structure enables LSTMs to model long-term dependencies effectively, making them ideal for time-series SOP predictions. Along with this line, in SOP, spectral and temporal correlations were used with LSTM methods (Shawel et al., 2018). Furthermore, the spectrum in a frequency hopping communication was predicted by an LSTM network (Yu et al., 2017). This work was extended using the Taguchi method (Yu et al., 2018). In Radhakrishnan et al. (2021), different hard and soft fusion methods perform cooperative SOP in a CR environment with trained LSTM-based local predictors. Feng et al. (2020) proposes a bidirectional LSTM-based spectrum prediction scheme performed in two stages. Notably, in the first stage, the historical spectrum data is pre-processed. In the second stage, the pre-processed data is sent to the bidirectional LSTM method, which performs training and generates the optimized hyperparameters. Pan et al. (2024) proposes a multichannel multi-step spectrum prediction method using a transformer and stacked bidirectional LSTM. Li et al. (2019) proposed an LSTM-based method by analyzing the relationships between frequency and time of historical spectrum data for IoT. Besides that, frequency and time correlations were exploited to predict spectrum occupancy over real-world measurements via 2D-LSTM Aygül et al. (2020b). To improve duty cycle prediction after block averaging, LSTM, and gated recurrent units are selected and enhanced using data features, such as the variance of duty cycle data and duty cycle data themselves (Al-Tahmeesschi et al., 2021). Tusha et al. (2022) designs a hierarchical SOP method, taking advantage of the RNN focusing on the gated recurrent unit. Nandakumar et al. (2023) also proposes an LSTM-based method to predict the radio spectrum state for two time slots simultaneously. Besides the use of DL methods individually, Zhang and Jia (2021) proposed a method that adopts the joint CNN and LSTM in a combined manner. Furthermore, Omotere et al. (2018) designed DNNs, LSTM, and CNN-based and compared their capabilities in SOP.

5.3.10 Prediction with convolutional LSTM

Convolutional LSTM (ConvLSTM) networks integrate the strengths of LSTMs and CNNs by applying convolutional operations within the LSTM architecture. This allows ConvLSTM to capture both spatial and temporal dependencies in the input data, making them ideal for tasks that involve spatio-temporal dynamics, such as SOP prediction in multi-dimensional systems.

In ConvLSTM, the convolutional structure is applied during both input-to-state and state-to-state transitions, which allows the model to extract spatial features at each time step. The state transition within a ConvLSTM cell can be expressed, as in Equation 4.

$$o = \sum_{p=1}^{u} w_p \boldsymbol{x}_k [p-1], \tag{4}$$

where the convolution operations capture spatial correlations while the LSTM structure handles temporal dependencies. ConvLSTMs are particularly useful in applications where system states are represented as multidimensional grids, allowing for the simultaneous prediction of multiple SOP metrics over time. Accordingly, Shawel et al. (2019); Wang L. et al. (2024) propose a method that uses ConvLSTM for spectrum prediction.

5.3.11 Prediction with reinforcement learning

Reinforcement learning (RL) provides a framework for agents to learn optimal behaviors through interactions with their environment. In the context of SOP prediction, RL agents are trained to make decisions that maximize long-term performance by taking actions based on current system states and receiving rewards or penalties as feedback. The agent's goal is to learn a policy that maps states to actions in a way that maximizes cumulative rewards over time (Kaelbling et al., 1996).

The RL process consists of several steps. First, the agent observes the current state of the system and selects an action based on a policy, which can be either a deterministic function or a probability distribution over actions. The agent then receives feedback from the environment in the form of rewards or penalties, which is used to update its policy. Over time, the agent improves its decision-making by maximizing the expected cumulative reward, enabling it to predict and optimize future system performance dynamically.

Despite the successes of the supervised learning-based methods (such as LSTM and CNN), they require a large set of labeled data points, which prevents them from being fully independent solutions. Furthermore, even with the availability of such a dataset, these methods do not inherently adapt to the environment where they are operated. Therefore, RL is proposed to predict spectrum occupancies without requiring prior training overhead while working in a standalone fashion, i.e., with minimized human dependency (Jalil et al., 2021; Peng et al., 2022; Aygül et al., 2022c).

5.3.12 Prediction with tensor-based method

Despite the methods above helping analyze numerous cases, they consider correlations only one or two of time, frequency, and space domains. On the other hand, these dimensions do not provide a detailed analysis of the wireless signals' non-stationary characteristics and multidimensional attributes (Hisham and Arslan, 2008). Jointly exploiting multidimensional correlations provides a promising perspective for spectrum prediction. Tensor analysis is used to utilize multidimensional correlations for spectrum prediction. Along with this line, Sun et al. (2018) converted spectrum prediction into a third-order tensor completion problem. This method achieved one-day-long forecasts with a reasonable error margin. Another study examines combining LSTM with CANDECOMP/PARAFAC tensor decomposition for prediction (Alkhouri et al., 2020). Moreover, multidimensional correlations were utilized jointly with ConvLSTM for a long-term temporal prediction (Shawel et al., 2019).

Despite tensor methods providing a robust and rich representation of a three-dimensional (3D) dataset, they require high processing time (Ioannidou et al., 2017; Gezawa et al., 2020) and assume 3D data can be provided at any time. On the other hand, sometimes, getting information from all of the BSs is not easy. For instance, in the case of CR security threats [PUEA and jamming attack (Fragkiadakis et al., 2013)], accurate information about spectrum occupancy cannot be provided from BSs. Besides that, in the case of a natural disaster, the information flow of some BSs can be cut. Thus, such an assumption is not always accurate or practical. To compensate for the effects above, Aygül et al. (2020a) proposed using composite 2D-LSTM methods to divide the 3D SOP problem into smaller sub-problems while exploiting multidimensional correlations. Experimental results indicate that the composite 2D-LSTM method can predict spectrum occupancies with less complexity and slight performance loss compared to tensor-based methods.

5.3.13 Federated learning

One of the critical challenges in SOP is ensuring data privacy, while maintaining high performance. The collection of vast amounts of data for SOP can expose sensitive information about UEs, devices, and their behaviors. In shared spectrum environments, data from different UEs or systems can inadvertently reveal private details, such as location, communication patterns, or operational frequencies, raising serious privacy concerns. With increasing regulatory oversight and the rise of privacy regulations, addressing these privacy issues becomes imperative. To mitigate these concerns, federated learning (FL) has emerged as a promising solution to ensure data privacy in ML-based SOP systems (Kułacz and Kliks, 2023). In traditional centralized learning, raw data must be transferred to a central server for model training, which risks exposing sensitive information during transmission or storage. FL, however, enables models to be trained directly on decentralized devices (e.g., spectrum sensors, UE devices) without the need to share raw data. Only model updates or gradients are shared with the central server, ensuring that the underlying data remains private and secure. This approach significantly reduces the risk of privacy breaches, as the sensitive data does not leave the local device. Moreover, FL also improves data security by distributing the model training process, making it harder for attackers to compromise the entire system. Ensuring that only aggregated model updates are shared prevents malicious entities from inferring sensitive information about individual UEs or devices.

This decentralized approach also aligns well with the dynamic nature of CRNs, where data is often generated in real-time and across a distributed infrastructure. FL can adapt to these environments, ensuring both privacy and performance are maintained.

However, despite its advantages, FL introduces new challenges that need to be addressed. The communication overhead associated with sharing model updates across decentralized nodes can become a bottleneck, especially in resource-constrained environments. Furthermore, ensuring that the models trained locally on heterogeneous devices converge to a global solution requires careful consideration of factors such as model synchronization, data heterogeneity, and local computational limitations. Future research should focus on optimizing these aspects to fully leverage the privacy benefits of FL in SOP applications.

Additionally, privacy-preserving techniques like differential privacy can be incorporated within the FL framework to provide even stronger privacy guarantees. Differential privacy ensures that the model updates shared with the central server are randomized in such a way that it becomes statistically impossible to infer information about any single data point in the dataset. This combination of FL and differential privacy can offer robust protection against privacy threats while still enabling effective ML-based spectrum prediction.

5.4 Interpretable ML for SOP

Numerous ML-based SOP methods have demonstrated superiority over traditional model-based methods, as discussed in this paper. However, the increasing reliance on ML raises several critical questions that go beyond mere performance metrics: What exactly have these ML models learned from the data? Why do they outperform traditional methods in complex wireless environments? What unique insights do they uncover that traditional model-based methods, grounded in expert-designed heuristics, might have overlooked? Furthermore, can wireless engineers fully trust these ML models to predict spectrum occupancy outcomes accurately, especially in critical scenarios where communication efficiency and security are at stake?

The crux of these questions is understanding the underlying decision-making processes of ML models, which is pivotal for their deployment in real-world wireless systems. Trusting ML to act as more than a black-box predictor—transforming it into a tool for actionable intelligence—requires clear, interpretable insights into why certain predictions are made. Along these lines, interpretable ML has already gained traction in domains like medical imaging, where its predictions are relatively easy for humans to cross-check and verify (Salahuddin et al., 2022; Fuhrman et al., 2022; Wang A. Q. et al., 2024). Recently, interpretable ML has also been explored in wireless communication applications such as channel estimation (Gizzini et al., 2023), modulation classification (Xu et al., 2024), and resource management (Khan et al., 2023), but its potential within the domain of SOP remains under-explored.

Integrating interpretable ML techniques into SOP modeling can provide valuable insights into the internal workings of these complex algorithms. For instance, understanding why an ML model classifies a specific spectrum band as occupied or vacant is essential for engineers to validate the reliability of these predictions. This level of understanding ensures that ML decisions align with known characteristics of radio frequency (RF) behavior, offering engineers a clearer picture of the factors influencing these outcomes. Techniques such as feature attribution, which highlights the most relevant aspects of the spectrum data the model is focusing on, can help engineers pinpoint how temporal, spatial, and frequency-domain correlations contribute to the model's final decision. This transparency helps demystify the black-box nature of many advanced models, enabling engineers to make more informed decisions based on the model's interpretations.

Additionally, interpretable ML plays a critical role in identifying potential biases embedded within spectrum data, which may stem from environmental conditions or hardware-related inconsistencies. Such biases, if left unchecked, can lead to flawed predictions, which can compromise the reliability of SOP systems. By offering clear, human-readable explanations for each decision, interpretable ML empowers engineers to verify the influence of various input features—such as PSD, interference levels, and noise figures—on the model's output. This insight is especially crucial in CR systems, where the accuracy and robustness of spectrum predictions are directly tied to network performance, spectrum efficiency, and the security of communication links. In this context, interpretable ML not only enhances the transparency and accountability of SOP models but also enables engineers to detect and correct any underlying biases or model weaknesses before they propagate through the network.

Furthermore, interpretable ML can facilitate collaboration between wireless engineers and ML practitioners by bridging the knowledge gap between these two domains. It can translate complex algorithmic decisions into understandable terms that align with engineers' domain expertise, ensuring that the model's behavior is not only statistically sound but also practically relevant for real-world deployment. This collaboration can lead to the development of hybrid models where domain-specific knowledge is integrated with data-driven insights, ultimately improving both performance and trustworthiness. As SOP evolves within increasingly complex and dynamic wireless environments, the role of interpretable ML becomes indispensable in fostering confidence in these systems, ensuring that they can be safely and efficiently deployed in diverse applications, from commercial networks to mission-critical systems.

6 Dataset generation

It is also important to explore various dataset generation methods and real-world datasets used for SOP (Naikwadi and Patil, 2020; Agarwal et al., 2018). These datasets are crucial for training and validating ML methods, ensuring they generalize well to real-world scenarios. Therefore, parameters of the spectrum and threshold selection mechanism should be investigated to use the ML methods efficiently.

6.1 Parameters of spectrum

Spectrum usage can be predicted using several key parameters, each of which provides valuable information about the current state and future occupancy of frequency bands. The most common parameters include power spectral density (PSD) and received signal strength indicator (RSSI). Beyond these, additional parameters such as duty cycle, interference level, historical usage patterns, UE mobility patterns, network traffic load, geolocation data, device type and capability, environmental factors, and quality of service (QoS) requirements are also critical features for SOP. Each of these parameters captures different aspects of the radio environment, contributing to a more comprehensive understanding of spectrum occupancy patterns.

6.1.1 PSD

PSD quantifies the distribution of power across a signal's frequency spectrum. It is typically expressed in watts per hertz and provides a direct measure of the power level at each frequency. PSD analysis is crucial for understanding how much power is being transmitted within a given frequency band, which directly correlates to the level of spectrum utilization. For example, in heavily congested areas, the PSD across multiple bands may be high, indicating significant spectrum usage. By evaluating PSD trends over time, it is possible to predict future spectrum occupancy and identify underutilized bands that can be better managed for efficient spectrum allocation. Additionally, PSD provides insights into signal interference and noise, which are key factors in determining spectrum availability.

6.1.2 RSSI

RSSI is a measure of the strength of a received signal and reflects how well a receiver can "hear" the transmission. It is usually measured in decibels relative to one milliwatt. RSSI plays an important role in determining the quality of a wireless connection, and higher values indicate stronger signals. In SOP, RSSI data can reveal which frequency bands are actively being used and by how many devices. For example, a consistently high RSSI value across a particular frequency band suggests that the channel is occupied by multiple transmitters. By analyzing the variations in RSSI over time, the future load on that frequency band can be anticipated.

6.1.3 Duty cycle

The duty cycle is the proportion of time a frequency band or channel is actively being used compared to the total available time. It is expressed as a percentage, where a higher duty cycle indicates that the spectrum is heavily utilized. Duty cycle analysis is particularly important in time-varying environments where spectrum usage fluctuates throughout the day. For instance, during peak hours, a channel may exhibit a high duty cycle, signaling continuous usage, whereas off-peak hours might show a lower duty cycle. By analyzing these patterns, it is possible to forecast when a channel will be in use and when it might become available for other applications.

6.1.4 Interference level

Interference refers to the presence of unwanted signals in the frequency band that degrade communication quality. Measuring the interference level helps in understanding how crowded the spectrum is and how multiple devices interact with each other in a shared environment. High interference levels generally indicate high spectrum occupancy, as many devices or services may be competing for the same frequency bands. Furthermore, interference analysis can identify problematic areas in the spectrum where noise or cross-talk between devices is prevalent. This information is essential for improving spectrum efficiency and for predicting when and where future interference might occur.

6.1.5 Historical usage patterns

Analyzing historical spectrum usage data provides valuable insights into recurring trends and patterns that can be used for future predictions. This includes identifying peak usage times (such as during business hours or specific seasons) and low-traffic periods. By aggregating long-term usage data, it is possible to predict with reasonable accuracy when a frequency band will be in high demand. Historical patterns can also highlight emerging trends, such as increased spectrum usage due to the deployment of new services or technologies.

6.1.6 UE mobility patterns

The mobility of UE, such as smartphones or Internet of things (IoT) devices, plays a significant role in spectrum occupancy. For instance, if a large number of UEs are moving toward a specific geographic area, it is likely that spectrum usage in that region will increase. Mobility patterns can be tracked using geolocation data and movement models, which in turn provide a dynamic forecast of spectrum occupancy. This is especially important in urban areas where UE density and mobility are high, leading to frequent handovers and spectrum reallocation between BSs.

6.1.7 Network traffic load

Network traffic load is a measure of the total demand placed on the network by active UEs. This load is closely correlated with spectrum usage, as high traffic demands typically require more spectrum resources to meet the QoS requirements. Monitoring current traffic loads can provide real-time data on spectrum utilization, while long-term traffic patterns can help in predicting future demand. For example, during major events or festivals, network traffic may surge, requiring careful spectrum planning to avoid congestion.

6.1.8 Geolocation data

Geolocation data provides insights into where spectrum demand is highest. By mapping UE density and usage patterns to specific geographic locations, network operators can optimize spectrum allocation based on real-world usage. For example, urban centers with high UE density may require more spectrum resources, while rural areas might have more available bandwidth. Incorporating geolocation data into spectrum prediction models allows for location-specific forecasting, enabling more efficient resource management.

6.1.9 Device type and capability

Different types of devices, such as smartphones, IoT devices, or laptops, have varying spectrum needs and capabilities. IoT devices, for example, typically require less bandwidth compared to video-streaming applications on smartphones. Understanding the mix of devices on the network helps in predicting future spectrum needs and allocating resources appropriately. Device capabilities, such as multi-band support or advanced modulation schemes, can also influence how spectrum is used and managed.

TABLE 1 Comparisons of fixed threshold selection methods.

Method	Advantages	Disadvantages	Use case
Empirical Methods	Simple, based on historical data	Non-adaptive, accuracy depends on past data	Stable environments
Statistical Methods	Considers variability, customizable	Requires understanding of signal distribution	Environments with known distributions
Fixed Value Thresholds	Extremely simple and easy	Not flexible, non-responsive to changes	General applications, industry standards
SNR-Based Thresholds	Relates to signal quality	Requires accurate noise estimation	Moderate variability environments
ED Methods	Widely used, straightforward	Fixed thresholds may not handle low SNR well	Practical applications with consistent noise levels

6.1.10 Environmental factors

Environmental conditions, such as weather, terrain, and physical obstructions, significantly affect signal propagation. For example, rain or heavy fog can attenuate wireless signals, reducing the effective range and increasing the likelihood of interference. Understanding these environmental factors allows for more accurate predictions of spectrum occupancy under different conditions. Spectrum prediction models that account for weather-related effects can help optimize frequency allocations during adverse conditions.

6.1.11 QoS requirements

Different applications and services have varying QoS requirements. For instance, real-time applications like voice or video calls require low latency and stable connections, which translate to specific spectrum demands. By understanding the QoS requirements of different services, it is possible to predict which parts of the spectrum will be most in demand at any given time. Applications with high QoS requirements may need to be prioritized in spectrum allocation to ensure uninterrupted service.

6.2 Threshold selection

Threshold selection is essential for efficient SOP. This work categorizes threshold selection into two groups: fixed threshold and adaptive threshold selections.

6.2.1 Fixed threshold selection

Fixed threshold selection involves setting a predetermined, constant threshold value that does not change over time or with varying conditions. This method is simple and easy to implement. The threshold value is usually chosen based on historical data or specific requirements of the spectrum occupancy environment. It provides a consistent decision criterion and often relies on historical data or empirical observations to determine the threshold. However, it may not adapt well to changing conditions, leading to potential inaccuracies in SOP. Below are the methods used for fixed threshold selection for SOP, and Table 1 compares these methods.

- Empirical Thresholds: This method uses historical data and empirical observations to set a threshold. The threshold is chosen based on past measurements of signal presence and absence. It is simple to implement and does not require complex calculations. However, it may not be adaptable to changing conditions, and performance depends on the accuracy of historical data.
- Statistical Methods: Mean and standard deviation is one of the examples of statistical methods. In this method, we set the threshold based on the mean signal power plus a multiple of the standard deviation. It takes into account the variability of the signal. However, it requires a good understanding of the signal distribution and may not be suitable for highly variable environments.
- Percentile-Based Thresholds: It sets the threshold at a specific noise or signal power distribution percentile. It can be tailored to specific requirements (e.g., setting at the 95th percentile to minimize false positives). However, it may still be static and not responsive to real-time changes.
- Fixed Value Thresholds: A fixed value (e.g., −90 decibel-milliwatts) is chosen based on general industry standards or specific application requirements. It is simple and easy to implement but does not account for environmental or temporal noise or signal strength variations.
- SNR-Based Thresholds: A fixed SNR threshold is set to distinguish between signal and noise. It is more accurate than simple power-based thresholds directly related to signal quality. Still, it requires precise noise power estimation and may not adapt well to rapid changes in the environment.
- ED Method: A threshold is set based on the energy detected in the frequency band. If the detected energy exceeds the threshold, the band is considered occupied. It is widely used in practical applications and is straightforward to implement. However, fixed energy thresholds may perform poorly in low SNR conditions or fluctuating noise levels.

6.2.2 Adaptive threshold selection

Adaptive threshold selection involves dynamically adjusting the threshold value based on real-time data and changing conditions. This method aims to improve prediction accuracy by responding to variations in the spectrum environment. However, it is more complex to implement compared to fixed thresholds. Adaptive threshold selection methods for SOP are detailed below, and comparisons between them are given in Table 2.

- Noise Level Estimation: It adjusts the threshold based on real-time measurements of the noise level in the spectrum. MA and median filtering are the widely used methods. MA calculates the average of recent noise measurements to estimate current noise levels. Median filtering uses the median of recent noise measurements to reduce the impact of outliers. It is simple and effective in environments with varying noise levels. However,

TABLE 2 Comparisons of adaptive threshold selection methods.

Method	Advantages	Disadvantages	Use case
Noise Level Estimation	Simple, effective in varying noise levels	Requires frequent updates, sensitive to window size	Environments with varying noise
SNR-Based Methods	Accurate detection considering signal and noise	Requires accurate estimation of signal and noise	Environments with varying SNR
Statistical Methods	Robust performance in varying conditions	Computationally intensive, requires accurate models	Dynamic statistical environments
ML-Based Methods	Highly flexible, adapts to complex environments	Requires extensive training data, computationally heavy	Complex and non-linear environments
Bayesian Methods	Probabilistic framework for adjustment	Computationally intensive requires accurate prior models	Environments with well-defined priors

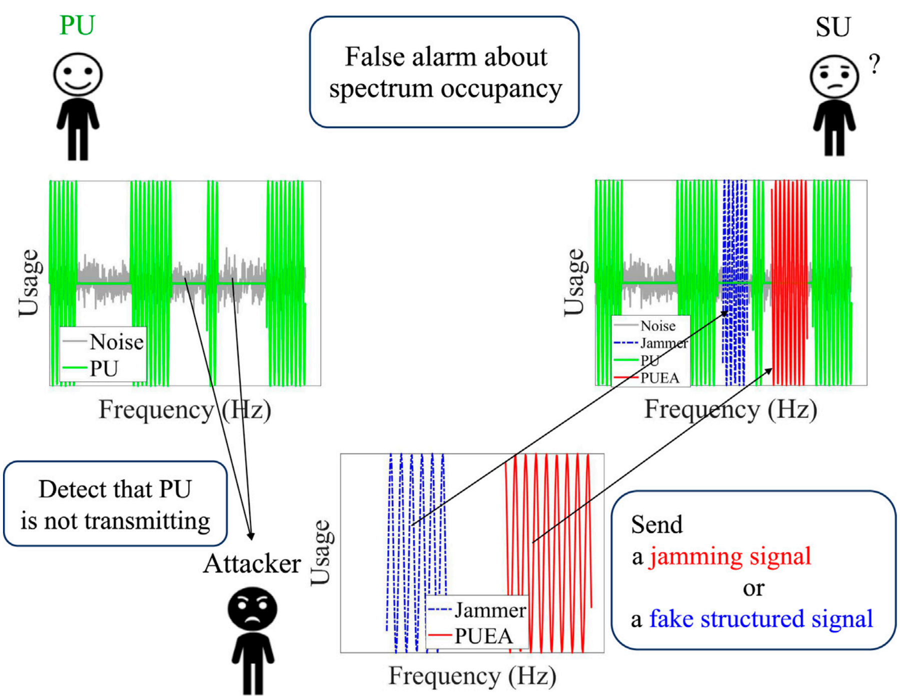

FIGURE 6
An example that shows a noise, an attacker, and a PU.

it may require frequent updates and is sensitive to the choice of window size for averaging or filtering.

- SNR-Based Methods: It dynamically adjusts the threshold based on the estimated SNR. The adaptive SNR thresholding method is widely used to continuously update the threshold to maintain a desired SNR level. It provides more accurate detection by considering both signal and noise, but it requires an accurate estimation of both signal and noise levels.
- Statistical Methods: It utilizes statistical properties of the received signal to adjust the threshold. Variance-based thresholding and probability density function (PDF) estimation are widely used methods. Variance-based thresholding adjusts the threshold based on the variance of the received signal. PDF estimation uses the estimated PDF of the noise and signal to set adaptive thresholds. It can provide robust performance in varying conditions. However, it is computationally intensive and requires accurate statistical methods.
- ML-Based Methods: It employs ML methods to predict and adjust the threshold based on historical and real-time data. It is highly flexible and can adapt to complex and non-linear environments, but it requires extensive training data and computational resources.
- Bayesian Methods: It uses Bayesian inference to adjust the threshold based on prior and observed data. In other words, it models the relationship between signal, noise, and threshold and updates based on observed data. It provides a probabilistic framework for threshold adjustment. However, it is computationally intensive and requires accurate prior models.

7 CR security

Jamming and PUEA may mislead spectrum prediction (Fragkiadakis et al., 2013), as illustrated in Figure 6. A PU emulator can emulate the transmission characteristics of the PU, while a jammer can generate intentional interference. In both cases, the consequences of the attacks result in an incorrect inference on the spectrum occupancy. Thus, there should be methods to identify these attacks.

The formal objective of these methods is to distinguish between the following hypotheses, as in Equation 5.

$$\boldsymbol{y} = \begin{cases} \boldsymbol{n}, & \mathcal{H}_0: \text{ there is no PU} \\ \boldsymbol{h}_{PU}\boldsymbol{x}_s + \boldsymbol{n}, & \mathcal{H}_1: \text{ A PU is exist} \\ \boldsymbol{h}_i\boldsymbol{x}_s + \boldsymbol{n}, & \mathcal{H}_2: \text{ A PU emulator is exist} \\ \boldsymbol{h}_i\boldsymbol{x}_n + \boldsymbol{n}, & \mathcal{H}_3: \text{ A jammer is exist,} \end{cases} \tag{5}$$

where $\boldsymbol{y}$, $\boldsymbol{h}_{PU}$, $\boldsymbol{h}_i$, $\boldsymbol{x}_s$, and $\boldsymbol{x}_n$ represent the received signal, the channel corresponding to the legitimate PU, the channel corresponding to PUEA or jammer, the structured signal, and the jamming signal, respectively. After these attacks are identified, they can be preventable, and the spectrum can be predicted more accurately.

Traditional methods to identify jamming and PU emulation include cryptography-based methods. On the other hand, these methods suffer from key management and distribution issues in heterogeneous wireless communication networks (Wang et al., 2016). To solve these issues, an ED-based method (Jin et al., 2015) is proposed for identifying legitimate PUs. Another method uses a Markov random field-based belief propagation framework based on ED for PUEA detection (Yuan et al., 2012). Although ED-based methods are simple, they tend to create high false alarm rates (Fragkiadakis et al., 2013). Another detection method category is based on exploiting physical layer characteristics. Although these methods effectively detect CR security threats, more intelligent and robust methods are still required to support diverse services in various scenarios (Wu et al., 2018).

Recent literature considers using ML methods to detect JAs and PUEAs. This usage is based on training a machine to identify such attacks, where training is conducted over features extracted from received signals (Pu and Wyglinski, 2014). In Pourranjbar et al. (2021), an anti-jamming strategy is proposed based on deceiving the jammer into attacking a victim channel while maintaining the communications of legitimate UEs in safe channels. Since the jammer's channel information is unknown to the UEs, an optimal channel selection scheme and a sub-optimal power allocation method are proposed using an RL method. Kihei et al. (2021) demonstrates a supervised ML method that can detect and classify the jamming attack with high accuracy. tu Zahra et al. (2024) proposes an LSTM-based method for jamming detection that uses parameters from multiple layers. Liu et al. (2021) models the attack and defense strategies optimization using single-channel jamming, multiple-channel jamming, single-channel sensor, and multiple-channel sensor DNNs for channel jamming attacks. Besides that, it extends the design to the scenario where the intelligent jammer can launch a hybrid mode jamming attack and propose a DNN Stackelberg game-based defense scheme. Ullah et al. (2023) proposes a hybrid learning framework for jamming detection and path loss predictions based on the successive usage of multiple DNN blocks.

Kasturi et al. (2020) proposes an ML-based classification technique for different types of jamming attacks. Hachimi et al. (2020) focuses on deploying a multi-stage ML-based intrusion detection that can detect and classify four types of jamming attacks: random, constant, reactive, and deceptive jamming. Lee et al. (2023) proposes a jammer classification and effective defense method to classify jamming attack types using ML. Different multi-output multiclass ML methods are trained with global positioning system-specific sample datasets obtained from exhaustive feature extraction and data collection routines that followed a set of realistic experimentations of attack scenarios (Alkhatib et al., 2024). Reda et al. (2024) uses a DL-based method to detect two specific kinds of jammers: continuous wave jammers and chirp jammers.

Shi and Sagduyu (2022) investigates how to launch over-the-air jamming attacks to disrupt the FL process when executed over a wireless network. A federated deep RL-based anti-jamming technique is proposed (Sharma et al., 2022). Meftah et al. (2023) proposes an FL-based jammer detection and waveform classification method for distributed tactical wireless networks. Also, Abou El Houda et al. (2024) combines FL with deep RL for efficient jamming attack detection. Meftah et al. (2024) presents a FL method, named Aggregated and Augmented Training Federated, tailored for stochastic, distributed, tactical terrestrial and non-terrestrial network environments to address jammer detection through convolutional variational autoencoders within the FL framework.

Shafique et al. (2021) proposed a support vector machine-based method signal spoofing attack in unmanned aerial vehicles (UAV)s. Pawlak et al. (2021) proposes an ML method to detect and classify jamming attacks on UAVs. Jasim et al. (2022) proposes an intelligent security system for UAVs that harnesses ML to detect spoofing and jamming attacks. An ML method is proposed to detect and classify jamming attacks against orthogonal frequency division multiplexing receivers with applications to unmanned aerial vehicles UAVs (Li et al., 2022). Mensi et al. (2023) uses ML-based methods for detecting jamming attacks in UAVs. Zagrouba and Alhajri (2021) focuses on proposing low-power consumption ML methods for detecting IoT botnet attacks using random forest as an ML-based detection method and describing common IoT attacks with their countermeasures. Hussain et al. (2022) proposes an ML method for jamming detection in IoT wireless networks. Saheed et al. (2022) proposes an ML-based intrusion detection system for detecting IoT network attacks. Jayabalan and Pugazendi (2022) proposes a DL method for detecting jamming attacks in low-power and lossy wireless networks. Latif et al. (2020) proposes a lightweight random NN-based prediction method for industrial IoT networks. A RL-based method is proposed for based jamming-detection in vehicular *ad hoc* networks (Shetty and Manjaiah, 2021). Bousalem et al. (2023) proposes a DL-based method to detect radio jamming attacks on vehicle-to-network and vehicle-to-infrastructure communications interfaces using a dataset collected from a vehicular-to-everything testbed. In Zhou et al. (2021), an intelligent anti-jamming communication method is investigated for wireless sensor networks. The stochastic game framework is introduced to model and analyze the multi-UE anti-jamming problem, and a joint multi-agent anti-jamming method is proposed to obtain the optimal anti-jamming strategy. The proposed method adopts multi-agent RL to make online channel selections in an intelligent multichannel blocking jamming environment. This can tackle external malicious jamming and avoid internal mutual interference among sensor nodes. Bensalem et al. (2019) proposes an ML method to detect and prevent jamming attacks in optical networks. Asif et al. (2021)

uses a CNN method for anti-jamming in safety-critical aeronautical communications.

Different ML types are used to detect PUEA. A semi-supervised ML method is proposed to detect and prevent PUEA (Srinivasan et al., 2019). Support vector machine detects PUEA (Arul Selvi and Sundararajan, 2016; Cadena Munoz et al., 2020; Ambhika, 2024). In Muñoz et al. (2022), K-nearest neighbors, random forest, and support vector machine are implemented to detect the PUEA. An RL method is used to detect PUEA (Sureka and Gunaseelan, 2022). Camana et al. (2022) uses a decision tree method to detect PUEA. Furqan et al. (2020) uses the convergence patterns of sparse coding as features for ML-based classification to identify jamming and PUEA. A DL-based method is proposed to detect the PUEA and jamming without explicit feature extraction (Aygül et al., 2020).

Besides the technical papers, Villain et al. (2022) surveys ML methods for jamming detection in electromagnetic communication. Also, Šimon and Götthans (2022) surveys the use of DL methods for UAV jamming and deception. Teeda et al. (2023) propose and evaluate experimentally the use of ML to detect the presence of a jammer attack in next-generation wireless fidelity networks.

8 Future directions

Although there are promising existing works for ML-based SOP, as investigated in this paper, several areas still need to be studied.

- Data Augmentation and Synthetic Data Generation: The challenge of acquiring large-scale, high-quality, and labeled datasets is particularly acute in the context of SOP prediction, where spectrum dynamics vary across different environments and applications. Future research can address this by leveraging advanced data augmentation techniques and synthetic data generation methods. Specifically, generative adversarial networks (GAN)s can be employed to create realistic spectrum usage scenarios that mimic real-world conditions. GANs can help simulate a variety of interference patterns, UE behaviors, and environmental conditions, providing diverse datasets that are invaluable for training ML models. Beyond GANs, variational autoencoders and diffusion models can also generate synthetic data that enhances the training process by introducing controlled variations in spectrum characteristics. These techniques can be combined with domain adaptation approaches, where synthetic data is fine-tuned to better reflect real-world conditions, further improving model generalization and reducing the reliance on manually collected data.
- Interpretable ML and Model Interpretability: As SOP prediction methods become increasingly reliant on complex DL architectures, there is a growing need for model interpretability to foster trust and ensure reliable deployment. Interpretable ML methods should focus on enhancing transparency at multiple levels: feature attribution, decision explanation, and system transparency. Tools like SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) can be used to provide detailed insights into which input features most influence the predictions. This helps both engineers and end-UEs understand why a model made a specific decision and whether that decision aligns with expected spectrum usage patterns. Furthermore, counterfactual analysis can be introduced, where the ML model generates "what-if" scenarios to show how small changes in input (e.g., signal strength, interference levels) can affect the prediction. In the context of SOP, this is valuable as it can highlight sensitive features and parameters that need more precise monitoring. Visual tools that map the learned patterns from the model to interpretable visualizations, such as spectrum heatmaps, can also make the decision-making process more accessible to practitioners. Therefore, integrating these interpretable features into real-time systems will be key for adoption in practical CRNs, as it will allow for both monitoring and dynamic model adjustments in response to live spectrum conditions.
- Integration of Multidimensional Correlations: Current SOP methods typically exploit correlations in time, frequency, and space simultaneously; however, the spectrum environment involves a broader range of dimensions, and expanding the utilization of additional dimensions simultaneously can enhance prediction capabilities. While prior works have considered domains such as angle and code, future research should aim to integrate these dimensions more comprehensively.
- Advanced ML Methods: While certain DL techniques have already demonstrated impressive results in SOP, future advancements in ML are likely to focus on more sophisticated architectures capable of representing complex relationships in wireless communication networks. These advanced methods can be particularly promising for capturing the intricate interactions between multiple entities, such as UEs, BSs, and spectrum resources, enabling more effective modeling of the spatial dependencies in wireless communication networks. Additionally, architectures designed to handle long-range dependencies and large-scale sequence data hold great promise for modeling time-varying spectrum dynamics. By combining multiple techniques, these hybrid architectures can unlock the potential for capturing intricate relationships across spatial, temporal, and frequency domains, resulting in more accurate and robust SOP predictions.
- Robustness Against Adversarial Attacks: As CRNs become more prevalent, security threats pose significant challenges to ML-based SOP methods. Therefore, enhancing the robustness of these methods against such threats is critical. One approach to address adversarial attacks, where malicious entities attempt to manipulate the SOP model's predictions, is adversarial training. This involves generating adversarial examples during training to expose the model to potential attacks, allowing the model to better withstand such manipulations. Additionally, integrating anomaly detection methods, such as autoencoders and one-class SVMs, can help detect suspicious spectrum activity that deviates from normal usage patterns, potentially signaling a threat before it affects SOP predictions. Defensive techniques like gradient masking and defensive distillation can also mitigate adversarial attacks by reducing the information attackers can exploit. However, despite these promising approaches, more research is required to develop comprehensive solutions that can fully protect ML

models in CRN environments. Ensuring the robustness of these models remains a priority for their reliable deployment, and future work should focus on advancing these defense mechanisms.

- Real-World Implementation and Standardization: For ML-based SOP methods to be effective in practice, extensive real-world validation is essential. Future research should focus on collaborative field trials with industry stakeholders, leveraging actual CRN deployments to gather real-world performance data. Additionally, edge-computing-based deployment can be explored, allowing SOP models to operate in a distributed fashion, closer to the spectrum sensing nodes, thus reducing latency and improving real-time decision-making. The development of standardized protocols, interfaces, and frameworks is also vital for ensuring the interoperability of SOP methods across different platforms and hardware implementations. Establishing benchmarks and performance metrics, such as spectrum efficiency, latency, and energy consumption, will facilitate fair comparisons between various SOP methods, driving further innovation and enabling regulatory bodies to evaluate the performance and compliance of these models.
- Green CRNs: Energy efficiency is a crucial consideration for the deployment of ML-based SOP methods in CRNs, as SOP is often a resource-intensive task. Future research should focus on developing energy-efficient algorithms that balance prediction accuracy with reduced energy consumption. This involves exploring the use of low-power ML models, such as those optimized through model compression techniques like pruning and quantization. Furthermore, energy-harvesting technologies, which enable CR nodes to generate power from ambient sources (e.g., solar or RF energy), can be integrated into SOP systems. By incorporating energy awareness into the model training and operation processes, ML-based SOP systems can minimize their energy footprint, making them more sustainable for large-scale CRN deployments.
- Cross-Layer Optimization: The performance of SOP models can be significantly enhanced by adopting a cross-layer optimization approach, where interactions between different layers of the communication protocol stack (physical, MAC, and network) are considered. Accordingly, future research should explore joint optimization techniques that holistically consider constraints and opportunities at multiple layers. Additionally, RL-based cross-layer strategies allow SOP systems to dynamically adapt to real-time changes in the network environment, learning optimal policies for spectrum management while accounting for UE behavior, interference, and energy consumption. By optimizing across layers, SOP models can achieve higher accuracy, better QoS, and improved spectrum efficiency.
- Ethical AI and Fairness in SOP: As ML models become more pervasive in SOP, it is essential to ensure that these systems operate in a fair and unbiased manner. Future research should focus on investigating potential biases in SOP predictions, which may arise from the underlying training data or model design. These biases can disproportionately affect certain UEs or regions, leading to unfair spectrum allocation or access. Techniques such as fairness-aware ML or adversarial debiasing can be explored to mitigate these risks. Additionally, incorporating ethical AI principles into the development of SOP systems helps ensure that these technologies are not only efficient but also equitable and just in their deployment.
- Context-Aware SOP: The integration of contextual information, such as UE behavior, environmental factors, and network load conditions, into SOP models remains an open research direction. Context-aware SOP can leverage additional data sources, such as IoT devices or environmental sensors, to improve the accuracy of predictions. By incorporating real-time contextual data, SOP models can become more adaptive and responsive to dynamic network conditions, such as sudden increases in traffic or changes in UE mobility.
- Comparative Analysis of ML Models for SOP: Although several comparative studies have been conducted on ML models for SOP, a truly systematic and fair comparison remains an open research challenge. One of the key issues is the inconsistency in hyperparameter selection, where the chosen parameters might be optimal for one model but not for others, potentially leading to biased results. Ensuring that each model is evaluated with its best possible configuration requires rigorous optimization techniques and fair evaluation protocols. Without such measures, comparisons can favor certain architectures simply because they were better tuned, rather than because they are inherently more effective. Additionally, most existing studies tend to focus primarily on accuracy, neglecting other critical factors such as model complexity, computational efficiency, energy consumption, and even data privacy. For example, while one model may achieve higher accuracy, it could come at the cost of significantly higher computational requirements or power consumption, making it impractical for real-world applications. Similarly, some models may have higher privacy risks due to their data processing style. Future research should thus aim to provide a more holistic comparison, incorporating these aspects alongside accuracy, to offer a clearer understanding of each model's trade-offs and suitability for different deployment scenarios.

9 Conclusion

This survey comprehensively reviewed ML-based methods for SOP in 6G and beyond wireless networks, highlighting their superiority over traditional statistical methods in addressing the non-stationary nature of spectrum usage. These methods effectively capture complex temporal and spatial correlations by leveraging advanced ML methods, such as CNN and LSTM networks, enhancing prediction accuracy. The paper also emphasized the importance of interpretable ML in ensuring the interpretability and trustworthiness of these ML methods, which is crucial for practical applications in CR systems. Additionally, the survey addressed vital challenges, such as dataset generation and CR threats. Future research directions were outlined, focusing on improving ML methods' robustness, adaptability, and transparency and exploring new multidimensional correlations to achieve more efficient and secure spectrum utilization in dynamic and complex wireless environments.

Author contributions

MA: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Resources, Validation, Visualization, Writing–original draft, Writing–review and editing. HC: Conceptualization, Formal Analysis, Investigation, Methodology, Resources, Supervision, Validation, Writing–review and editing. HA: Conceptualization, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Writing–review and editing.

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Conflict of interest

Author MA was employed by the company Vestel.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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