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Non-ideal Data Problems in Cooperative Spectrum Sensing

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Abstract. In recent years, as the development of wireless communication technologies and the increase in smart devices rapidly, the shortage of spectrum resources has become the important issue for future wireless communication systems. Cognitive Radio (CR) enabled spectrum utilization through Dynamic Spectrum Access (DSA) which allowing unlicensed users to access licensed spectrum without interference. Cooperative Spectrum Sensing (CSS) which is an important part of cognitive radio systems to improve the sensing reliability by allowing multiple nodes shared sensing results and made a joint decision. In practical scenarios, CSS systems always faced several non-ideal data issues which include noise uncertainty, data missing, transmission errors, hardware impairments, and synchronization problems. These problems will distort sensing statistics, to reduce the detection probability, increase false alarm probability, and reduce the benefit of gain from cooperative. Therefore, this paper investigates how non-ideal data affects CSS systems and reviews several representative methods, including adaptive threshold detection, robust detection methods, data recovery techniques, synchronization correction, and uncertainty-aware fusion. The comparison results indicate that robust and intelligent cooperative methods can provide better sensing performance than traditional energy detection method under practical non-ideal conditions, especially in terms of detection probability, false alarm control, and overall system robustness. In addition, this paper discusses potential future research directions for intelligent cooperative sensing and explores the emerging technology such as potential influence of 6G networks and IoT, which may influence the development of CSS system.

Keywords: cooperative spectrum sensing, cognitive radio, non-ideal data, noise uncertainty, false alarm probability

1. Introduction

With the rapid development of wireless communication technologies and the increasing number of smart devices, the less of spectrum resources has gradually become a critical challenge for future wireless communication systems. Studies have shown that although most spectrum bands have already licensed, the significant portion of them remain underutilized. The average range of utilization rate is between 15% and 85%, and some spectrum bands remain unused for extended periods [1, 2].

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Cognitive Radio (CR), as the spectrum-sharing technology which enable the unlicensed users to access these spectrum bands while avoiding interference with licensed users to improve the spectrum efficiency. Spectrum sensing is the key component of cognitive radio systems, allowing cognitive users to detect the presence of licensed users in real time. However, in real practical wireless environments, various factors which will affect the reliability of spectrum sensing.

To solve these problems, Cooperative Spectrum Sensing (CSS) enabled multiple cognitive users to collaborate and exchange the sensing information. By utilizing spatial diversity gain, CSS can improve sensing performance and become an important technology in cognitive radio system.

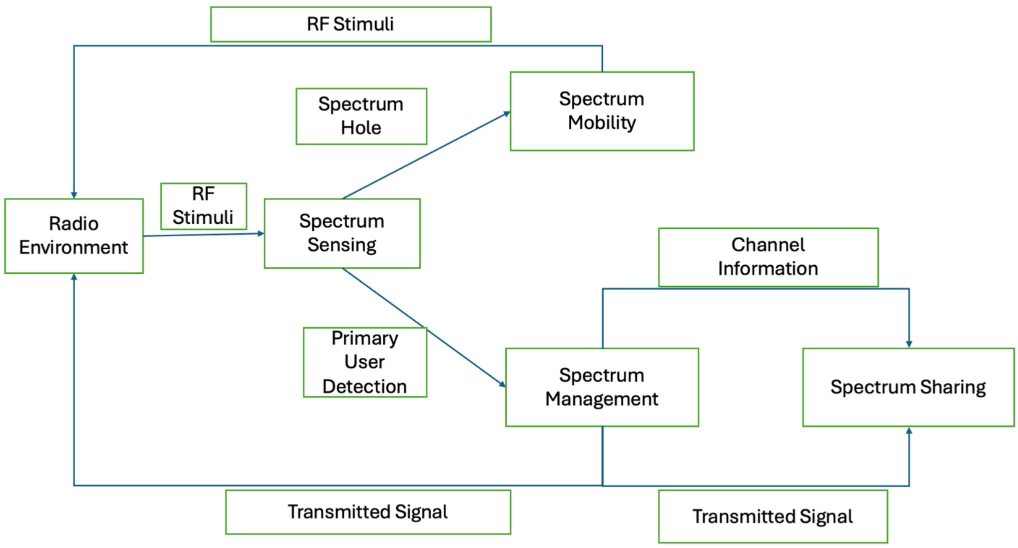

Figure 1. Basic cognitive radio process

Figure 1 shows that the basic progress of cognitive radio. This process allows secondary users to access available spectrum while preventing harmful interference with primary users.

Although cooperative spectrum sensing can enhance sensing performance, its practical performance in real wireless environments is often lower than expected. This is mainly because sensing data collected in practical environments are affected by non-ideal conditions. In theoretical models, noise power is assumed to keep stable, received samples are assumed complete, and all sensing nodes are perfectly synchronized. However, those assumptions are difficult to maintain in the real practical systems. In CSS systems, large amount of non-ideal data issues will occur. First, noise uncertainty can cause the actual noise power problems over time. Traditional energy detection methods are usually depending on an accurate detection threshold. When noise power changes, the detection of threshold may become inaccurate, which will result the incorrect sensing decisions. Under low signal-to-noise ratio (SNR) conditions, this issue will become more serious and may lead to the SNR wall problem [3].

Second, missing data may occur either the signal sampling or during the data transmission. For example, some samples may be lost because of the hardware failure or the overflow of buffer during this process. When sensing results are transmitted from local nodes to the fusion center, the packet loss and the bit errors may also occur because of channel fading or limited bandwidth. As result, the fusion center may receive incomplete or corrupted sensing information.

Third, hardware imperfections and synchronization problem lowered correlation among sensing data collected by different nodes. Analog-to-digital converters would suffer from the saturation or

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quantization errors. Sensing nodes may also suffer from timing offsets as well as frequency offsets, and phase errors. Those issuess can distort received signals and reduce the benefit of cooperation.

Therefore, a practical CSS system should not only achieve the good perform which not only under ideal assumptions, but also maintain reliable performance when noise uncertainty, missing data, transmission errors, and synchronization problems exist.

The primary innovations and contributions of this work are as follows:

• This paper systematically investigates the effect of non-ideal data conditions on cooperative spectrum sensing such as noise uncertainty, missing data, transmission errors, hardware impairments, and synchronization errors. It provides an analysis of how those factors influence the reliability and the performance.

• This paper establishes the comparison framework for representative CSS methods which combined by both qualitative and quantitative. The proposed framework enables the comprehensive evaluation of detection performance, robustness, computational complexity, and applicability under practical non-ideal wireless environments.

2. Related work

2.1. Fundamentals of Cooperative Spectrum Sensing

Basic idea of Cooperative Spectrum Sensing (CSS) is to allow the multiple cognitive users observe from the same spectrum environment and user can combined their sensing results to improve their spatial diversity reliability through the same environment [4]. Compared to the single-node spectrum sensing, the CSS system can solve problems effectively such as multipath fading, shadowing effects, and the hidden terminal. Therefore, CSS system helped to improves the reliability of primary user detection and has become one of the most important key technologies in radio systems.

2.1.1. Centralized and distributed CSS

Cooperative spectrum sensing system can be divided into two different mode which is centralized CSS and distributed CSS.

In centralized CSS, each user performs their local sensing and sends those sensing results to the fusion center, then fusion center needs to collect all information to make the final decision. This architecture is relatively easy to manage because the decision process is controlled by the central node. It also facilitates global optimization since all sensing information are available at the fusion center.

However, centralized CSS also has some disadvantages. Since all nodes need to send their information to the fusion center, the communication overhead will become higher. If the number of sensing nodes is large, the reporting channel may become congested. In addition, the fusion center is a single point of failure. If the fusion center fails or is attacked, the entire sensing system will be affected.

In distributed CSS, it doesn't need the fusion center. Therefore, each node will exchange their information with their own neighbor nodes so that gradually reaches a common decision. This architecture is more flexible because it doesn't rely on the single fusion center. It is suitable for ad hoc networks, vehicular networks, and large-scale IoT systems.

However, distributed CSS also have several disadvantages. Because each nodes need to be communicated with their neighbor nodes lots of times, so the fusion process will become complex and slower. Consensus algorithms may require several iterations to reach the stable decision.

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Therefore, distributed CSS needs the balance robustness, communication cost, and convergence speed.

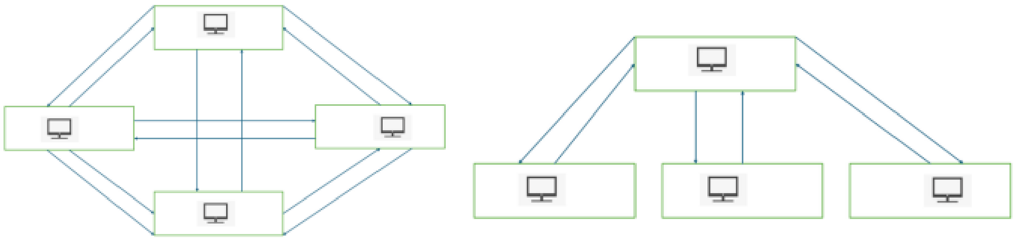

Figure 2. Centralized and distributed cooperative sensing architectures

Figure 2 compares the centralized and the distributed cooperative sensing architectures. In the centralized model, nodes transmit their results to the fusion center and wait for the final decision. In the distributed model, nodes exchange information directly with their neighbor nodes.

Table 1. Comparison of CSS architectures

Type	Features	advantages	disadvantages
centralized	node uploads the detection results to the center	Unified Management	High communication overhead high risk of single point of failure
Distributed	Nodes exchange information	High robustness, adaptive	Complex integration Complex integration, slow convergence

Note: Table 1 summarizes the major differences between centralized and distributed CSS.

2.1.2. Hard decision and soft decision fusion

At the fusion level, CSS can also be classified into two decision which is hard decision fusion and soft decision fusion.

In hard decision fusion, each node only sends a one-bit decision to the fusion center. The fusion center then makes the final decision based on rules such as AND, OR, or majority voting.

Hard decision fusion has lower communication overhead, because each node only transmits one bit of the whole information. It is suitable for bandwidth-limited systems and energy-constrained devices. However, this approach will lose detailed sensing information. If one of the local decisions is incorrect or missing, the fusion center may not have enough information to correct it.

In soft decision fusion, each node sends their own sensing information to the fusion center, such as their own received energy and likelihood ratios. After all nodes send their information, the fusion center will use information to make an accurate decision. Compared to the hard decision fusion, this will provide a better detection performance.

Soft decision fusion needs higher bandwidth and more resources. It's also more sensitive to reporting channel errors because of large amount of data needs to be transmitted. Therefore, choices between hard and soft decision fusion were depended on the system requirements, channel condition, and available resources.

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2.2. Non-ideal data

Under ideal conditions, cooperative spectrum sensing use multi-node information fusion to improve detection performance. However, in practical wireless environments, CSS systems are affected by various non-ideal factors. These factors may introduce the deviations in the observed sensing data and reduce the reliability of cooperative spectrum sensing systems. The main challenges include noise uncertainty, incomplete data, and hardware and synchronization imperfections.

2.2.1. Uncertainly noise

Noise uncertainly is one of the most common non-ideal factors in CSS system. In practical wireless examples, background noise changed will be affected by many factors such as environmental changes and temperature increase or decrease and different kind of hardware problems. As a result, detectors may have difficulty accurately estimating noise variance, which will lead to deviations in the detection threshold.

Traditional energy detection methods assume that noise power remains constant or keep the same level. When noise levels change, the probability of false detection also changed. This problem becomes more serious under low signal-to-noise ratio (SNR) conditions and leads to the SNR Wall. In such situations, even if the number of cooperative nodes or sampling points increases, the detection performance cannot exceed a certain SNR threshold.

2.2.2. Data incompleteness

Data incompleteness refers to the missing samples, packet loss, and bit errors. Missing samples are caused by hardware failures, unstable sampling rates and buffer overflow. Packet loss happens when the sensing results are transmitted through control channels with fading or interference effects. Also, bit errors can also happen under low SNR or limited bandwidth conditions.

Consequently, the fusion center may receive incomplete or corrupted information, and it will reduce the accuracy of the final sensing decision.

2.2.3. Hardware and synchronization non-idealities

Hardware and imperfections of synchronization are common problems in CSS systems. ADC saturation, quantization errors, and timing mismatches can distort received signals. Frequency offset and phase error will also reduce the consistency of signals.

These issues will weaken the gain of cooperative in CSS system and reduce the reliability of the final fusion decision.

3. Cooperative spectrum sensing methods

3.1. Classical methods

3.1.1. Energy detection

Energy detection is one of the most used spectrum sensing methods in CSS systems [5]. Basic idea of this is to check if this system has a primary user, which through measuring the energy of received signal. Since it doesn't require knowledge of the signal structure, this method has advantage about simple implementation and low computational complexity.

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For the i cooperative node, the energy statistic of the received signal within the observation window can be expressed as:

$$T_i(y) = \frac{1}{N} \Sigma |y_i(n)|^2 \quad (1)$$

where yi(n) represents the n-th sample received by the i-th node and N is the number of samples. When the statistic Ti(y) is greater than a predefined detection threshold, the system determines that the primary user exists; otherwise, the spectrum is considered idle.

In CSS systems, energy statistics from different nodes can be transmitted to the fusion center for global decision making. However, energy detection is highly sensitive to noise uncertainty. Under low SNR or unstable noise conditions, threshold mismatch may occur and lead to the SNR wall problem.

3.1.2. Matched filter detection

Matched filter detection achieves optimal detection performance when the structure of the primary user signal is known. From the perspective of statistical detection theory, matched filtering can maximize the output signal-to-noise ratio under additive white Gaussian noise conditions.

In cooperative spectrum sensing systems, if cognitive nodes can obtain the signal template or prior information of the main user, they can use matched filters to process the received signals. The detection results are then transmitted to the center for cooperative decision. Compared with energy detection, matched filter detection can maintain higher detection probability under low SNR conditions.

However, this method strongly depends on knowledge of the signal structure. In real cognitive radio systems, it is difficult to obtain accurate of the primary user signals. In addition, different channel conditions and synchronization errors among nodes also reduce the performance advantage of matched filter detection. Therefore, this method is mainly suitable for scenarios where the primary signal structure is stable and known [6].

3.1.3. Cyclisation feature detection

Cyclostationary feature detection uses the periodic characteristics of communication signals caused by modulation, coding, and carrier structures. By using these periodic statistical features, this method can distinguish primary user signals from noise.

Compared with energy detection, cyclostationary detection does not rely heavily on accurate noise estimation, so it has better robustness under noise uncertainty. However, it usually requires complex feature extraction and accurate synchronization among nodes. Therefore, its computational cost is high, which limits its application in resource-constrained devices.

3.2. State-of-the-Art solutions under non-ideal data conditions

To solve the challenges caused by non-ideal data, many robust CSS solutions have been proposed. These approaches mainly include robust detection algorithms, data recovery and compensation techniques, synchronization correction mechanisms, and communication-sensing co-design strategies.

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3.2.1. Robust detection algorithms

Robust detection algorithms are designed to maintain stable detection performance under noise uncertainty or changing channel conditions. Adaptive threshold energy detection is a typical method. This method is not relied on the fixed threshold. However, it estimates the current noise power and dynamically adjusts the detection threshold to improves the robustness of energy detection under fluctuating noise conditions.

Another approach is robust statistics-based detection, and this method will use robust estimators such as median estimators to reduce the impact of abnormal data. This method is useful when noise uncertainty and data contamination occur simultaneously.

The robust detection method can be expressed through the minimization of a cost function:

$$\lambda = \alpha \cdot \sigma_n^2 \tag{2}$$

Studies show that when noise uncertainty and data contamination happened at same time, the detection probability of this method can higher 15%–25% than the traditional energy detection.

3.2.2. Data recovery and compensation techniques

Missing data and transmission errors can significantly affect CSS performance. Matrix completion is a common method for recovering missing data. It represents the observations of cooperative nodes as a low-rank matrix and reconstructs missing elements through optimization.

Deep learning-based interpolation can also be used when missing data patterns are complex. Models such as convolutional autoencoders or Transformer networks can learn time-frequency features and repair incomplete data. In addition, error-resilient coding can reduce the influence of bit errors during sensing result transmission.

3.2.3. Synchronization alignment

Different sensing nodes may be synchronized in real CSS systems environment. During cooperative sensing system some problems will happened such as timing mismatch, frequency offset, and phase difference. Those problems will affect the consistency of received signals and reduce the benefit obtained from cooperation

One of the common correction methods is use pilot signals so that estimate the clock and frequency to reduce synchronization errors. The sensing nodes will compare the received information to estimate timing and frequency differences. After that, all the differences can be corrected to improve the consistency of signals between cooperative nodes.

cross-correlation peak detection and cyclostationary feature-based synchronization is also used to improve the synchronization accuracy. Studies show that those techniques can improve synchronization accuracy to approximately 40%.

3.2.4. Communication-sensing co-design

Communication-sensing co-design consider the balance between communication bandwidth, and energy consumption. In load-adaptive reporting, each nodes decide different kind of information and all decision are based on channel quality. When the channel condition is stable, nodes can transmit more detailed information, however if the channel condition is weak and unstable, nodes change to transmit hard decisions or key features.

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In uncertainty-aware fusion, not all sensing nodes are treated equally in the fusion center. Instead, each node estimated their reliability through contribution. Nodes have more reliable sensing results will receive higher weights, while less reliable nodes will receive less weights.

4. Experiment result and analysis

4.1. Performance evaluation metrics

Four methods are used to evaluate CSS performance under non-ideal data conditions which is detection probability, false alarm probability, cooperative gain, and robustness.

4.1.1. Detection probability

Detection probability always means how often the system identifies the presence of the primary user signal, which means higher Pd candidate higher sensing performance. It can be defined as:

$$P_d = P(Decision = H1 \mid H1) \tag{3}$$

Detection probability reflects the ability of a spectrum sensing algorithm to correctly identify the existence of a primary user signal.

4.1.2. False alarm probability

False alarm probability represents the probability that system incorrectly decides that a primary user signal exists when it is absent. It can be expressed as:

$$P_{fa} = P(Decision = H1 \mid H0) \tag{4}$$

A lower false alarm probability indicates that the algorithm can better resist noise interference and avoid incorrect detection.

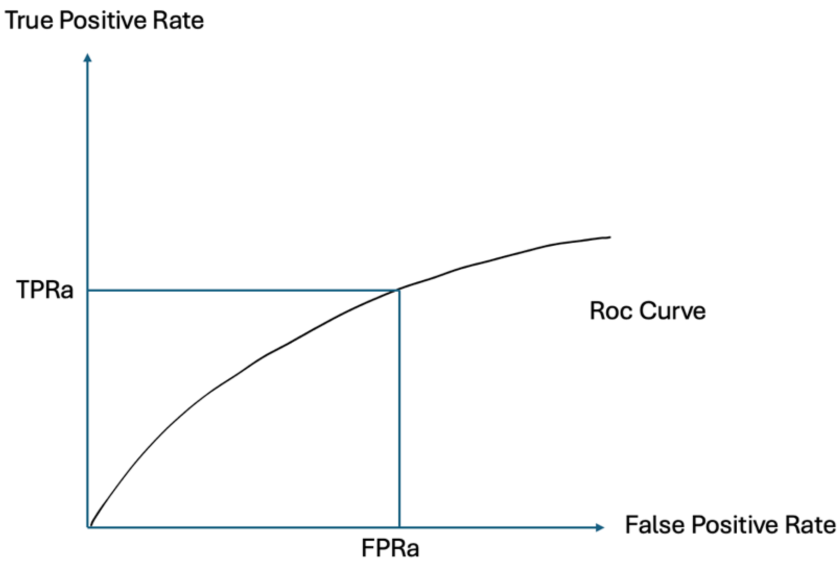

Figure 3. Roc curve

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Figure 3 shows the relationship between detection probability and false alarm probability. A better sensing algorithm should achieve higher detection probability while maintaining lower false alarm probability.

4.2. Cooperative gain and robustness

$$G_{coop} = \frac{P_d^{coop} - P_d^{single}}{P_d^{single}} \quad (5)$$

Cooperative gain measures the performance improvement achieved by multi-node cooperative detection compared with single-node detection. Robustness reflects how an algorithm maintains the performance under non-ideal conditions which include uncertainty noise, missing data, and synchronization errors.

4.3. Results comparison

To compare the performance of different methods under non-ideal data conditions to performs both qualitative and quantitative analysis.

Before the comparison, a five-level evaluation standard is defined for qualitative analysis.

In this study, qualitative performance is using a five-level rating scale: Excellent, Good, Moderate, Poor, and Very Poor.

Excellent rating indicates strong robustness against non-ideal conditions. Good represents the ability to effectively handle the corresponding problem. Moderate suggests that additional adaptability is required to maintain satisfactory performance. Poor indicates that the method's performance is noticeably affected. Very Poor denotes high sensitivity to the corresponding issue.

Table 3. Qualitative comparison of different CSS methods

Method	Uncertainty noise	Missing data	Synchronization error	Computational complexity	Overall performance
Traditional Energy Detection [5, 6]	Poor	Poor	Moderate	Good	Moderate
Matrix Completion [7]	Moderate	Good	Moderate	Moderate	Good
Deep Learning Interpolation [8]	Good	Good	Good	Poor	Good
Adaptive Energy Detection [9]	Good	Moderate	Moderate	Good	Good
Federated Learning CSS [10]	Good	Good	Good	Good	Excellent

Note: Table 3 summarizes the qualitative performance of different CSS methods under non-ideal data conditions. The comparison is based on the characteristics and limitations discussed in the related studies.

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Table 4. Summary of representative CSS methods under non-ideal data conditions

Source	Method	Non-ideal problem	Main contribution	Limitation
Digham et al. [5]	Energy detection	Noise and fading	Basic detection model	Sensitive to noise
Yucek and Arslan [6]	Spectrum sensing survey	Practical sensing issues	Reviews major methods	Not a specific solution
Meng et al. [7]	Matrix completion	Missing observations	Recovers missing data	Needs low-rank structure
Zheng et al. [8]	Deep learning-based sensing	Complex signal features	Improves classification	Needs training data
Srisomboon et al. [9]	Adaptive multi-criteria thresholding	Shadowing effect	Adjusts sensing threshold	Depends on reliability
Chen et al. [10]	Federated learning-based CSS	Privacy concern	Reduces raw data sharing	Needs training rounds

Note: Table 4 summarizes representative CSS methods and their main contributions under different non-ideal data conditions.

5. Future research directions and perspectives

With the increasing complexity of wireless communication systems, CSS will face more dynamic, multidimensional, and heterogeneous environments in future networks such as 6G, IoT, and V2X systems. Although current methods can reduce the influence of non-ideal data to some extent, challenges remain in dynamic adaptation, privacy protection, and secure cooperation.

5.1. Dynamic environment-adaptive sensing

Future wireless networks will operate in two different types of environments which is dynamic and distributed environments. Many traditional CSS algorithms assume that channel conditions and noise characteristics are stable. In real environment, this assumption can't happen because of user mobility, dense device deployment, and heterogeneous networks. Those problems can cause interference and channel conditions, and those conditions will also change over time and across different locations.

Cooperation between sensing nodes and cloud platforms will also cause different transmission delays, so the results will not arrive at the same time, and the result may also be incorrect because of delay. when the environment changes algorithms that are based on fixed models or static parameters will respond slower. This will also cause to increase the detection delay; the raise of false alarm rate and reduce the efficiency of resource usage.

In rapidly changing environments, adaptive sensing methods are necessary for CSS systems. Machine learning techniques could also help the system to adjust its sensing strategy when channel changes or when the interference conditions changes.

5.2. Privacy-Preserving cooperative mechanisms

Cooperative spectrum sensing requires multiple users to share local data or sensing features for fusion detection. However, sending signal samples directly or statistical information directly may expose private information, such as user location, device identity, and traffic patterns.

In cloud-based sensing systems, data sharing will create new privacy and security risks. One of the possible solutions is using privacy-preserving learning methods. This method will help users cooperate without sending their original data to keep user's privacy information.

For example, federated learning allows each node to train its own local model, sharing only parameters, not data, between nodes. In addition, differential privacy and blockchain can also be used to improve security. Both methods not only protect user privacy but also maintain performance.

Future research should consider different direction such as balance between privacy and communication efficiency, and balance between cost and efficiency. How to keep that balance should become an important for applying CSS system for next generation.

6. Conclusion

This paper shows that the whole CSS system will be affected by all non-ideal data conditions. Non-ideal problems including noise uncertainty, missing data, transmission errors, hardware limitations, and synchronization problems, and those non-ideal problems will reduce reliability in real wireless environment. Although the cognitive and CSS can improve spectrum utilization, but they performance are still mainly depends on how to solve those non-ideal conditions problems.

Results show that different non-ideal factors can affect the performance of CSS systems in many ways. Traditional sensing methods are still work and useful, but when noise, missing data, or synchronization problems happen, traditional sensing methods still have some limitations. Therefore, methods like robust detection, data recovery, and synchronization correction can help to improve sensing performance when traditional methods are not working very well.

Compared to the traditional methods, robust cooperative sensing method usually provide better detection results, fewer false alarms, and more stable performance. In future 6G, IoT, and vehicular networks, CSS should further combine adaptive learning, privacy protection, and secure cooperation to improve practical sensing performance.

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