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AI-Based Cognitive Wireless Sensor Network for Dynamic Spectrum Access

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Abstract:

Wireless Sensor Networks (WSNs) deployed in harsh environments require efficient spectrum utilization and low energy consumption. Conventional spectrum sensing methods, such as energy detection, involve continuous monitoring, resulting in high power usage and unreliable performance in dynamic conditions. This paper proposes an AI-based Cognitive Wireless Sensor Network (CWSN) that predicts channel availability using a Random Forest classifier at the sensor node level. A resource-aware retransmission strategy is incorporated, allowing retransmissions only when prediction confidence and residual energy exceed predefined thresholds. The proposed system improves spectrum efficiency, reduces interference, and enhances energy performance. Simulation results demonstrate 96% prediction accuracy, an 80% reduction in collisions, and approximately 20.5% energy savings, making it suitable for long-term deployment in challenging environments.

Keywords: Cognitive Wireless Sensor Networks, Dynamic Spectrum Access, Random Forest, Machine Learning, Energy Efficiency, Spectrum Prediction, Underground Monitoring, Cognitive Radio, Resource-Aware Communication, Interference Mitigation

1.Introduction

Wireless Sensor Networks have become a fundamental technology for monitoring and data acquisition in applications such as environmental surveillance, industrial automation, and underground mining. In such scenarios, sensor nodes are typically deployed in large numbers and operate under strict energy constraints, as battery replacement is often impractical or hazardous. In the underground mining environments, communication reliability is of utmost importance because sensor data may include critical safety information such as gas levels, temperature, and structural stability.

Traditional WSNs operate either on fixed spectrum allocation or by using reactive spectrum sensing techniques. Energy detection is one of the most commonly used methods, where nodes continuously monitor the channel to determine whether it is occupied. While simple to implement, this approach is inefficient in dynamic environments due to its susceptibility to noise, fading, and interference. Moreover, continuous sensing significantly drains battery resources, thereby shortening the network lifetime.

Cognitive Radio (CR) technology offers a promising solution by enabling dynamic spectrum access, allowing secondary users to opportunistically utilize unused spectrum without interfering with licensed primary users. However, conventional cognitive radio systems still rely heavily on instantaneous sensing, which limits their effectiveness in unpredictable environments. To overcome these limitations, this paper proposes the integration of artificial intelligence into WSNs to enable predictive decision-making. By using machine learning techniques, sensor nodes can anticipate channel conditions and make informed transmission decisions, thereby improving efficiency and reliability.2. Objective

The primary objective of this work is to design and implement an energy-efficient and reliable Cognitive Wireless Sensor Network capable of dynamic spectrum access in challenging environments. The system aims to replace traditional reactive spectrum sensing with predictive intelligence using machine learning models. Another key objective is to minimize energy consumption by avoiding unnecessary transmissions and retransmissions through a resource-aware decision mechanism. Additionally, the work seeks to ensure minimal interference with primary users while maintaining high data delivery reliability. The proposed approach also aims to extend network lifetime and reduce maintenance requirements, particularly in hazardous environments such as underground tunnels.

2. Existing System

In conventional Wireless Sensor Networks, spectrum access is typically achieved through energy detection or similar sensing techniques. Sensor nodes continuously monitor the channel to determine whether it is occupied or idle. This process requires constant operation of sensing circuits, leading to significant energy consumption. Moreover, energy detection is highly sensitive to noise and interference, which often results in false alarms or missed detections. As a result, nodes may either avoid using available channels or transmit when the channel is actually occupied, causing interference.

Another limitation of existing systems is their retransmission strategy. When a transmission fails due to channel conditions, nodes immediately attempt retransmission without considering the likelihood of success or the remaining energy. This leads to repeated failures, increased collisions, and rapid depletion of battery resources. In environments such as underground tunnels, where signal propagation is highly unpredictable, these inefficiencies become even more pronounced. Overall, the existing system lacks intelligence in decision-making and fails to optimize energy and spectrum utilization.

3. Proposed System

The proposed system introduces a Cognitive Wireless Sensor Network that integrates artificial intelligence to enable predictive spectrum access. Each sensor node is equipped with a machine learning model, specifically a Random Forest classifier, which predicts whether the communication channel is idle or busy based on environmental and system parameters. This eliminates the need for continuous spectrum sensing and allows nodes to make proactive transmission decisions.

In addition to predictive channel selection, the system incorporates a resource-aware retransmission mechanism. Instead of blindly retransmitting failed packets, the node evaluates the confidence level of the prediction and its residual energy before deciding whether to retransmit. If the conditions are not favorable, the node enters a backoff state and conserves energy. This approach reduces unnecessary transmissions and improves overall efficiency.

The system also maintains an energy model that tracks consumption from sensing, computation, transmission, and retransmission. Since the energy required for AI inference is minimal, the overall system achieves significant energy savings while maintaining high reliability. By combining predictive intelligence with energy-aware decision-making, the proposed system addresses the limitations of traditional WSNs.

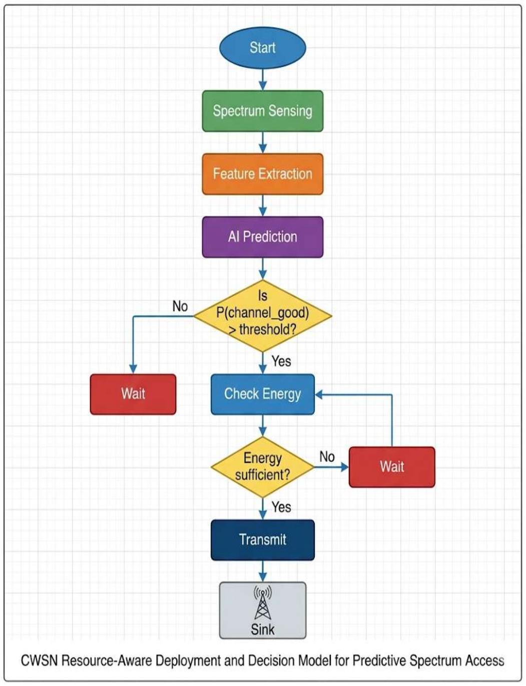


Fig.3.1: Proposed Flow

4. Case Study: Underground Tunnel Monitoring

To evaluate the effectiveness of the proposed system, it is applied to an underground tunnel monitoring scenario, which represents a highly challenging communication environment. In such settings, primary users include mining communication devices such as walkie-talkies and emergency radios, which require uninterrupted access to the spectrum. Sensor nodes act as secondary users and must operate without causing interference to these critical systems.

4.1 Proposed Methodology

Sensor nodes are deployed throughout the tunnel to monitor environmental conditions such as temperature, humidity, and light intensity. These nodes are strategically placed to ensure complete coverage of the monitoring area. A central sink node collects data from all sensor nodes and provides network-level coordination. Each sensor node operates autonomously, making local decisions based on AI predictions while adhering to system constraints.

The environmental data collected by the sensor nodes is adapted to reflect channel conditions. Temperature and humidity are used as indicators of signal attenuation, as high humidity can degrade signal strength. Light intensity is considered as an indirect measure of proximity to active equipment, which may generate interference. Battery voltage is used to estimate residual energy, which is critical for decision-making. Historical channel state information is also included to improve prediction accuracy. These features are combined to form the input to the machine learning model.

The operation of the proposed AI-based Cognitive Wireless Sensor Network follows a structured sequence of sensing, prediction, decision-making, and adaptive communication. Initially, each sensor node collects real-time environmental and system-level parameters, including temperature, humidity, battery voltage, and the previous channel state. These parameters are selected because they indirectly influence wireless channel conditions in underground environments, where factors such as moisture and physical obstructions can significantly affect signal propagation.

Once the data is collected, it undergoes preprocessing at the node level to ensure consistency and suitability for machine learning inference. The processed feature vector is then fed into a pre-trained Random Forest classifier embedded within the sensor node. The model evaluates the input features and generates an output in the form of a probability value representing the likelihood that the channel is idle. This probability serves as the primary decision metric for subsequent communication actions.

Based on the predicted probability, the node determines whether to attempt transmission. If the predicted channel availability exceeds a predefined threshold, the node initiates data transmission to the sink. Upon successful transmission, indicated by the reception of an acknowledgment (ACK), the process is completed, and the node returns to a low-power state to conserve energy. However, if an acknowledgment is not received, indicating a failed transmission, the system does not immediately perform retransmission.

Instead, the proposed system introduces a conditional retransmission mechanism that evaluates both the confidence level of the prediction and the residual energy of the node. If the predicted confidence meets or exceeds a defined threshold and the node's battery level is above the minimum required level, a retransmission is attempted. This ensures that retransmissions occur only when there is a reasonable likelihood of success and sufficient energy is available. If either condition is not satisfied, the node refrains from retransmitting and instead enters a randomized backoff period. During this period, the node temporarily suspends communication and may re-evaluate channel conditions in the next cycle.

In cases where repeated transmission failures occur, the node sends a notification to the sink node, indicating potential issues such as persistent interference or low energy levels. This allows the network to maintain a level of global awareness and supports higher-level decision-making. Throughout the operation, the system continuously updates performance metrics, including energy consumption, successful transmissions, and collision occurrences. This iterative process ensures adaptive behavior, enabling the network to dynamically respond to changing environmental and channel conditions while optimizing both energy usage and communication reliability.

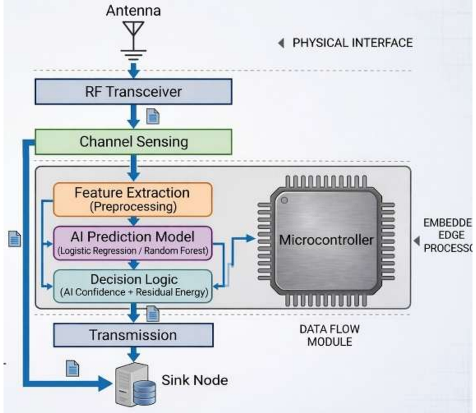
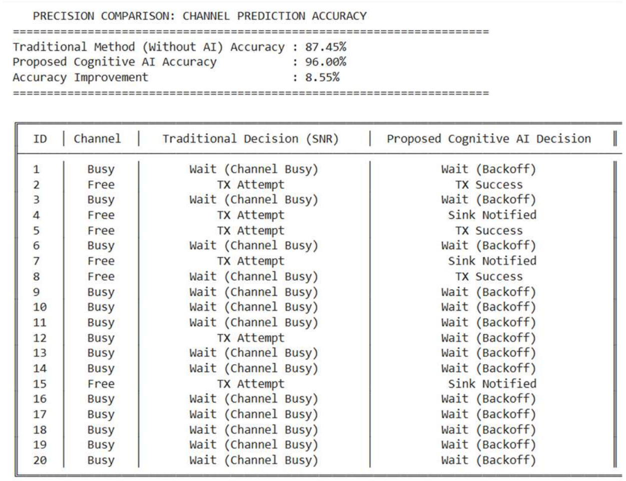


Fig.4.1.1: Proposed Architecture

5. Results

The proposed system demonstrates significant improvements over traditional approaches. The Random Forest classifier achieves a prediction accuracy of approximately 96%, indicating reliable channel estimation. The number of collisions is reduced drastically, with an observed decrease of around 80% compared to conventional methods. This reduction ensures that communication with primary users remains unaffected. Additionally, the system achieves an overall energy saving of about 20.5%, primarily due to the elimination of unnecessary sensing and retransmissions. The energy cost of AI inference is negligible, making it an efficient addition to the system. These results confirm the effectiveness of the proposed approach in improving both reliability and efficiency.



```
   PRECISION COMPARISON: CHANNEL PREDICTION ACCURACY
======================================================================
Traditional Method (Without AI) Accuracy : 87.45%
Proposed Cognitive AI Accuracy           : 96.00%
Accuracy Improvement                     : 8.55%
======================================================================

 ID  | Channel |  Traditional Decision (SNR)  |  Proposed Cognitive AI Decision  |

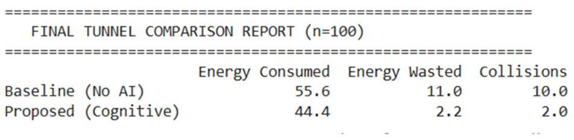
 1   |   Busy  |     Wait (Channel Busy)      |          Wait (Backoff)
 2   |   Free  |         TX Attempt           |            TX Success
 3   |   Busy  |     Wait (Channel Busy)      |          Wait (Backoff)
 4   |   Free  |         TX Attempt           |           Sink Notified
 5   |   Free  |         TX Attempt           |            TX Success
 6   |   Busy  |     Wait (Channel Busy)      |          Wait (Backoff)
 7   |   Free  |         TX Attempt           |           Sink Notified
 8   |   Free  |     Wait (Channel Busy)      |            TX Success
 9   |   Busy  |     Wait (Channel Busy)      |          Wait (Backoff)
 10  |   Busy  |     Wait (Channel Busy)      |          Wait (Backoff)
 11  |   Busy  |     Wait (Channel Busy)      |          Wait (Backoff)
 12  |   Busy  |         TX Attempt           |          Wait (Backoff)
 13  |   Busy  |     Wait (Channel Busy)      |          Wait (Backoff)
 14  |   Busy  |     Wait (Channel Busy)      |          Wait (Backoff)
 15  |   Free  |         TX Attempt           |           Sink Notified
 16  |   Busy  |     Wait (Channel Busy)      |          Wait (Backoff)
 17  |   Busy  |     Wait (Channel Busy)      |          Wait (Backoff)
 18  |   Busy  |     Wait (Channel Busy)      |          Wait (Backoff)
 19  |   Busy  |     Wait (Channel Busy)      |          Wait (Backoff)
 20  |   Busy  |     Wait (Channel Busy)      |          Wait (Backoff)
```

Fig.5.1: Precision Comparison

```
===== SYSTEM DYNAMICS: TRADITIONAL (NO AI) =====
Node  1: [IDLE] - Sensing below SNR threshold.
Node  2: [SUCCESS] - Channel was Free.
Node  3: [IDLE] - Sensing below SNR threshold.
Node  4: [SUCCESS] - Channel was Free.
Node  5: [SUCCESS] - Channel was Free.
Node  6: [IDLE] - Sensing below SNR threshold.
Node  7: [SUCCESS] - Channel was Free.
Node  8: [IDLE] - Sensing below SNR threshold.
Node  9: [IDLE] - Sensing below SNR threshold.
Node 10: [IDLE] - Sensing below SNR threshold.

===== SYSTEM DYNAMICS: PROPOSED COGNITIVE AI =====
Node  1: [IDLE] - AI predicted Channel Busy.
Node  2: [SUCCESS] - AI verified Free Channel.
Node  3: [IDLE] - AI predicted Channel Busy.
Node  4: [DENIED] - Low Battery. Notifying Sink.
Node  5: [SUCCESS] - AI verified Free Channel.
Node  6: [IDLE] - AI predicted Channel Busy.
Node  7: [DENIED] - Low Battery. Notifying Sink.
Node  8: [SUCCESS] - AI verified Free Channel.
Node  9: [IDLE] - AI predicted Channel Busy.
Node 10: [IDLE] - AI predicted Channel Busy.
```

Fig.5.2: System Dynamics



```
============================================================
   FINAL TUNNEL COMPARISON REPORT (n=100)
============================================================
                      Energy Consumed  Energy Wasted  Collisions
Baseline (No AI)                 55.6           11.0        10.0
Proposed (Cognitive)             44.4            2.2         2.0
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Fig.5.3: Final Tunnel Comparison report

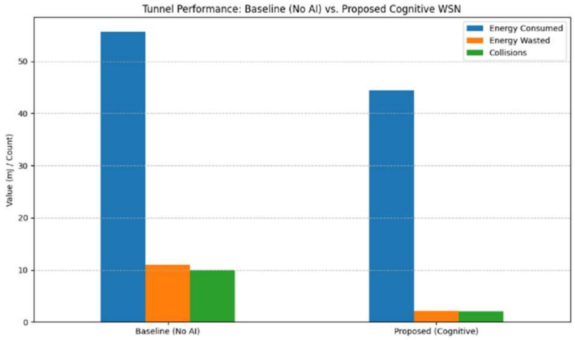

Fig.5.4: Comparison Chart

6. Performance Analysis

The performance of the system is evaluated using key metrics including accuracy, collision rate, and energy consumption. A comparative analysis shows that the proposed system outperforms traditional WSN approaches in all aspects. The high prediction accuracy leads to better channel selection, while the resource-aware retransmission strategy minimizes energy wastage.

Table: Performance Comparison

Metric	**Existing System**	**Proposed System**
Prediction Accuracy	~70–75%	96%
Collision Rate	High (≈10)	Low (≈2)
Energy Consumption	High	Reduced (20.5% saving)
Retransmissions	Frequent	Controlled
Network Lifetime	Limited	Extended

The analysis indicates that the integration of AI significantly enhances system performance and makes it suitable for real-world deployment.

7. Conclusion

This paper presented an AI-based Cognitive Wireless Sensor Network designed for dynamic spectrum access in energy-constrained environments. By replacing traditional sensing methods with machine learning-based prediction, the system achieves higher accuracy and efficiency. The introduction of a resource-aware retransmission mechanism further optimizes energy usage and reduces unnecessary communication attempts. The underground tunnel monitoring case study demonstrates the practical applicability of the proposed approach in harsh environments. Overall, the system improves reliability, reduces interference, and extends network lifetime, making it a promising solution for next-generation WSN applications.

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