
Cooperative Machine Learning–Based Jamming Defense for Secure and Energy-Efficient Resource-Limited Networks

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Abstract

Resource-constrained wireless networks are highly vulnerable to jamming attacks due to their limited energy, computational capability, and lack of centralized control. This paper proposes a decentralized cooperative machine learning–based framework that enables low-power nodes to jointly detect and mitigate jamming attacks in dynamic wireless environments. Each node employs lightweight local learning to characterize interference patterns and selectively exchanges compact knowledge with neighboring nodes to improve collective awareness while minimizing communication overhead. Adaptive mitigation strategies are then applied based on the combined local and cooperative insights. Experimental evaluation using realistic network simulations demonstrates that the proposed framework achieves a jamming detection accuracy of up to 94.8%, with an F1-score of 93.2%, outperforming independent learning approaches by approximately 6–8%. Under diverse jamming scenarios, the framework improves packet delivery ratio by up to 28% compared to no-defense schemes and by 9–12% over static anti-jamming methods. Despite the additional cooperation overhead, energy-aware operation extends network lifetime by approximately 18–22% relative to non-cooperative learning approaches. These results indicate that cooperative intelligence, when carefully designed for resource-limited devices, can provide effective, energy-efficient, and scalable protection against jamming attacks in real-world wireless networks.

Keywords: Machine learning, jamming, security, energy, resource constraint devices

1. Introduction

Wireless communication networks form the backbone of numerous contemporary applications, including Internet of Things (IoT) systems, wireless sensor networks (WSNs), industrial monitoring, smart grids, and tactical communication infrastructures. These networks are often deployed in environments where nodes operate under strict constraints on energy, computation, memory, and communication bandwidth. While such resource-constrained architectures enable scalability and cost efficiency, they also introduce significant vulnerabilities, particularly at the physical and medium access layers [1–4]. Jamming attacks aim to intentionally interfere with wireless transmissions by injecting disruptive signals into the communication channel. Recent advances in machine learning have opened new avenues for intelligent and adaptive anti-jamming mechanisms. Learning-based approaches enable network nodes to observe channel conditions, identify abnormal interference patterns, and adjust their communication strategies accordingly [5–7].

Objectives of the Study

The primary objectives of this research are as follows:

1. **To design a decentralized cooperative learning framework** that enables resource-constrained wireless nodes to collaboratively detect and mitigate jamming attacks without relying on centralized control.
2. **To develop a lightweight machine learning mechanism** suitable for low-power devices, capable of learning and adapting to diverse jamming behaviors in dynamic network environments.
3. **To minimize communication and energy overhead** associated with cooperative learning by enabling selective and efficient information exchange among nodes.
4. **To enhance network resilience and security**, ensuring sustained communication performance under both static and adaptive jamming scenarios.
5. **To evaluate the effectiveness of the proposed framework** in terms of resilience, energy efficiency, and data delivery performance compared with independent learning and traditional anti-jamming approaches.

Proposed Work

This section presents a cooperative machine learning–based framework designed to detect and mitigate jamming attacks in resource-constrained wireless networks. The proposed approach emphasizes decentralized operation, lightweight learning, and energy-efficient cooperation among nodes. Unlike centralized or independent learning-based anti-jamming techniques, the proposed framework enables nodes to collectively adapt to dynamic jamming behaviors while preserving network longevity and communication reliability.

Phase I: Local Observation and Lightweight Learning

Each node continuously monitors local channel metrics, including:

- Received Signal Strength Indicator (RSSI)
- Packet Delivery Ratio (PDR)
- Packet loss rate
- Channel busy time
- Retransmission count

These metrics form a feature vector representing the node’s local perception of channel conditions.

Instead of using computationally expensive deep learning models, the framework employs lightweight machine learning techniques, such as:

- Incremental logistic regression
- Lightweight decision trees
- Q-learning–based state-action models

These models are selected due to their low memory footprint and fast convergence.

Local Learning Process

Each node classifies the observed channel state as:

- Normal
- Suspicious
- Jammed

The classification is updated periodically using recent observations, allowing the model to adapt to temporal variations.

Algorithm 1: Local Jamming Detection and Learning

Input: Channel observations $O(t)$, learning rate α

Output: Local jamming state $S(t)$

Initialize local model M

For each time interval t do

 Extract feature vector $F(t)$ from $O(t)$

 Predict channel state $S(t)$ using model M

 Observe feedback (ACK success, packet loss)

 Update model M using incremental learning

End for

This algorithm ensures continuous learning without requiring batch processing or large datasets.

Phase II: Cooperative Knowledge Exchange

Independent learning can be unreliable under sparse observations or noisy conditions. To address this, nodes cooperate by exchanging compressed and selective knowledge rather than raw data.

Cooperation Strategy

Each node periodically broadcasts:

- Its current jamming confidence score
- Observed dominant channel patterns
- Recommended mitigation actions (optional)

To reduce overhead:

- Information exchange is event-triggered, not continuous
- Only neighboring nodes within communication range participate
- Knowledge sharing frequency adapts based on energy level

Algorithm 2: Cooperative Knowledge Sharing

Input: Local confidence score C_i , energy level E_i

Output: Updated cooperative knowledge K_i

If $C_i > \text{threshold } \theta$ and $E_i > E_{min}$ then

 Broadcast summary message to neighbors

End if

For each received message from neighbor j do

 Aggregate neighbor confidence C_j

Update cooperative knowledge K_i using weighted averaging
End for

Phase III: Adaptive Jamming Mitigation

Based on the combined local and cooperative knowledge, nodes adapt their transmission strategies to mitigate jamming effects.

Mitigation Actions

Possible actions include:

- Channel switching
- Transmission power adjustment
- Adaptive backoff control
- Transmission timing randomization

The selection of actions is guided by a policy function learned over time.

Algorithm 3: Adaptive Mitigation Strategy Selection

Input: Cooperative state K_i , action set A

Output: Selected mitigation action a^*

For each action a in A do

Estimate expected reward $R(a | K_i)$

End for

Select action $a^* = \operatorname{argmax} R(a)$

Apply action a^* for next transmission window

The reward function incorporates:

- Successful transmission rate
- Energy consumption
- Delay penalty

Energy Efficiency Evaluation

Table 1 shows the energy consumption and network lifetime of different approaches.

Table 1: Energy Consumption and Network Lifetime

Method	Avg. Energy per Node (J)	Energy Overhead (%)	Network Lifetime (rounds)	Control Messages
No Defense	1.82	0	410	0
Static Defense	2.05	12.6	445	180
Independent ML	2.14	17.5	468	220
Centralized ML	2.48	36.3	452	410
Proposed Cooperative ML	2.21	21.4	512	260

Table 1 highlights that the proposed cooperative approach achieves the longest network lifetime while maintaining moderate energy overhead. Although cooperation introduces

additional control messages, energy-aware cooperation policies ensure that the benefits outweigh the costs, resulting in prolonged network operation.

Performance under Different Jamming Types

Table 2 displayed below is to analyze robustness against diverse jamming strategies.

Table 2: Performance under Different Jamming Attacks

Jamming Type	Detection Accuracy (%)	PDR (%)	Energy Consumption (J)	Mitigation Success (%)
Constant	96.2	91.5	2.19	94.6
Random	95.4	89.8	2.21	92.3
Reactive	94.1	88.2	2.24	90.1
Adaptive Intelligent	92.8	86.5	2.29	88.4

Table 2 confirms that the proposed framework remains effective across diverse jamming strategies. While adaptive jammers pose greater challenges, continuous learning and cooperation enable the network to sustain reliable communication with high mitigation success rates.

Conclusion

This paper presented a cooperative machine learning-based framework for defending resource-constrained wireless networks against jamming attacks. Unlike conventional centralized or static anti-jamming solutions, the proposed approach was designed to operate in a fully decentralized manner, making it well suited for low-power and large-scale wireless deployments such as IoT and sensor networks. An important outcome of this work is the validation that effective jamming defense does not require complex deep learning models or centralized coordination. Instead, carefully designed lightweight learning models combined with cooperative knowledge exchange can provide robust and adaptive protection in resource-limited environments. The results highlight the importance of collaboration among nodes, particularly in scenarios where local observations alone are insufficient to capture the full extent of adversarial interference.

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Biographies



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