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Throughput Optimization Algorithms in Cognitive Radio-based Internet of Things (CR-IoT): A Review

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Abstract

The Cognitive Radio-based Internet of Things (CR-IoT) addresses spectrum scarcity by enabling IoT devices to opportunistically access underutilized licensed frequency bands. Throughput optimization plays a crucial role in improving communication efficiency while maintaining Quality of Service (QoS) and avoiding interference with primary users (PUs). This article presents a review of recent algorithms and approaches for throughput optimization in CR-IoT, focusing on deep reinforcement learning (DRL), metaheuristics, cooperative spectrum sensing, and game-theoretic models. Comparative analysis highlights the advantages, limitations, and performance metrics of these techniques, providing guidance for researchers and practitioners in developing more efficient CR-IoT systems.

Index Terms: CR, IoT, Throughput Optimization, Spectrum Sensing, Deep Reinforcement Learning, Metaheuristics

1. INTRODUCTION

The Internet of things is an emerging communication technology, connecting massive devices across diverse applications. However, the limited availability of unlicensed spectrum bands has raised concerns about spectrum scarcity [2]. The cognitive radio is a smart technology which offered keen solution to the spectrum scarcity issues by enabling dynamic spectrum access (DSA) [3]. Cognitive Radio (CR) technology was developed to solve spectrum scarcity in wireless networks. When combined with IoT, known as CR-IoT, it allows devices to find and use unused spectrum bands (called spectrum holes) without interfering with primary users (PUs), who are the licensed owners of those bands. This helps make better use of limited spectrum, especially in crowded and high-interference environments [1]. Throughput optimization in CR-IoT aims to achieve higher data rates, lower latency, and efficient energy use. Recent research explores diverse methods, including deep reinforcement learning (DRL) for adaptive channel selection, as well as metaheuristics and game-theoretic approaches.

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This survey aims to present a comprehensive review of Deep Reinforcement Learning (DRL) based approach, metaheuristics optimization techniques, cooperative spectrum sensing and optimization strategies, and game-theoretic models for throughput enhancement in Cognitive Radio-based Internet of Things (CR-IoT) networks.

The remainder of this paper is organized as follows. Section 2 presents background concepts related to CR-IoT systems, including spectrum scarcity, DSA mechanisms, and throughput optimization metrics. Section 3 reviews DRL-based approaches, detailing recent advancements, algorithms, and performance results. Section 4 discusses metaheuristic optimization techniques for CR-IoT spectrum allocation. Section 5 examines cooperative spectrum sensing and optimization strategies. Section 6 reviews game-theoretic models for efficient spectrum sharing. Section 7 Other algorithm for Throughput optimization. Finally, Section 8 concludes the paper.

2. BACKGROUND

2.1. Spectrum Scarcity in IoT Networks

The explosive growth of IoT devices has significantly increased demand for wireless communication resources. Traditional static spectrum allocation policies assign fixed frequency bands to licensed services, which often lead to under-utilization when licensed users are inactive, and severe congestion in unlicensed bands. This imbalance exacerbates spectrum scarcity, limiting the scalability and performance of emerging IoT applications [4]. Addressing this challenge requires Dynamic Spectrum Access (DSA) mechanisms that can adapt to varying network conditions while protecting the rights of Primary Users (PUs).

2.2. Cognitive Radio-based IoT (CR-IoT) Architecture

Cognitive Radio (CR) technology enables unlicensed or Secondary Users (SUs) to opportunistically access unused licensed spectrum—known as spectrum holes—without causing harmful interference to PUs. When CR capabilities are embedded into IoT devices, the resulting CR-IoT architecture typically includes the following components:

Spectrum Sensing Module – Detects the presence or absence of PUs to identify available channels.

- Spectrum Decision Module – Selects the most suitable channel based on sensing data and QoS requirements [7].
- Spectrum Sharing Module – Coordinates channel access among multiple SUs to avoid collisions [5].
- Spectrum Mobility Module – Enables seamless switching to alternative channels when a PU reclaims its spectrum [5, 7].
- This architecture allows CR-IoT networks to operate efficiently in heterogeneous, interference-prone environments while maintaining compliance with spectrum access regulations.

The CR-IoT architecture integrates IoT devices with cognitive radio intelligence for efficient spectrum utilization. The diagram below illustrates the layered structure of the CR-IoT architecture, including IoT devices, primary users, the CR engine, gateway, and application layer (Figure 1).

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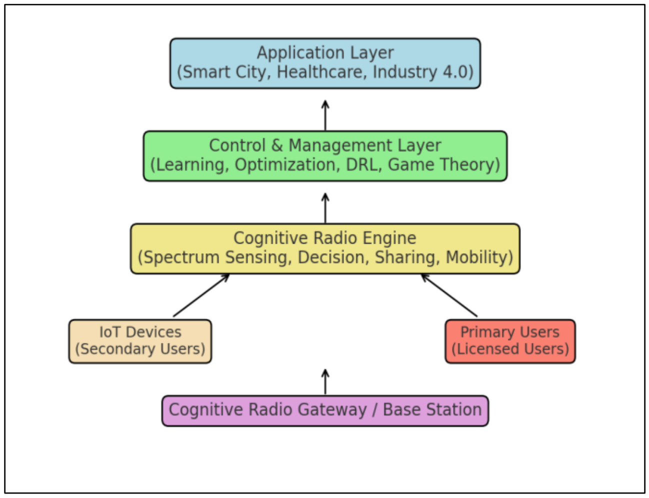

Figure 1 CRIoT Architecture

Note:

- IoT Devices (Secondary Users):
  - Opportunistically access spectrum.
- Primary Users (Licensed Users)
  - Hold spectrum priority.
- Cognitive Radio Engine:
  - Handles sensing, decision, sharing, and mobility.
- Gateway/Base Station:
  - Aggregates traffic and coordinates access.
- Control Layer:
-
  - Optimization and learning (e.g., DRL).
- Application Layer:
  - Supports IoT services such as healthcare, industry, and smart cities.

2.3. Throughput Optimization in CR-IoT

Throughput optimization in CR-IoT refers to maximizing the successful data delivery rate per unit time while considering additional objectives such as minimizing latency, improving energy efficiency, and ensuring PU protection [8]. The optimization process involves several factors:

- Channel Availability Prediction: Forecasting spectrum hole occurrences using statistical or machine learning methods.
- Adaptive Channel Selection: Dynamically assigning channels to SUs based on real-time conditions and predicted availability.
- Transmission Power Control: Adjusting transmission power to balance interference avoidance and communication reliability.
- Multi-user Coordination: Ensuring fair and efficient spectrum sharing in dense IoT deployments.

These objectives formulate a complex multi-objective optimization problem that demands intelligent decision-making. Consequently, recent studies have increasingly investigated Deep Reinforcement Learning, metaheuristic algorithms, and game-theoretic models to devise effective solutions (Figure 2).

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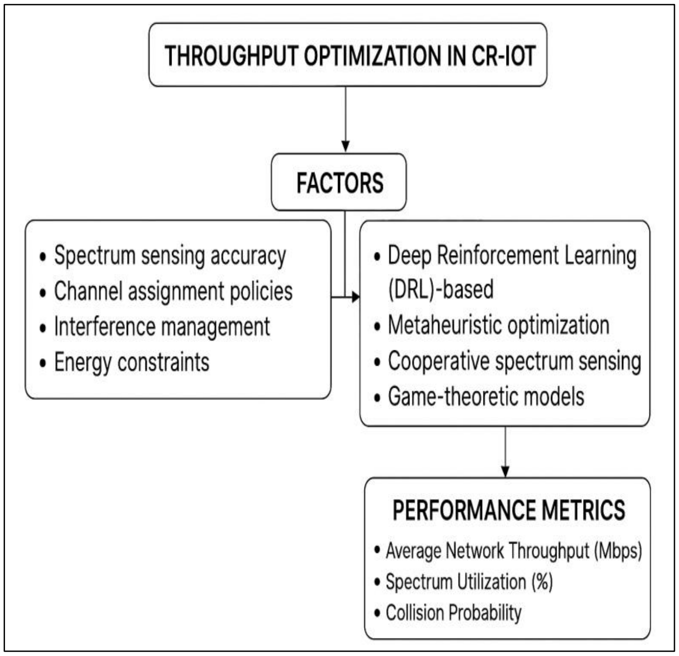

Figure 2 Throughput Optimization in CRIoT

3. DEEP REINFORCEMENT LEARNING-BASED APPROACHES

Deep Reinforcement Learning (DRL) has emerged as a promising paradigm for throughput optimization in CR-IoT, enabling devices to autonomously learn and adapt spectrum access strategies in dynamic and uncertain environments. By combining reinforcement learning with deep neural networks, DRL agents can approximate complex value functions, capture temporal dependencies, and make near-optimal channel access decisions without explicit modeling of the wireless environment (Figure 3).

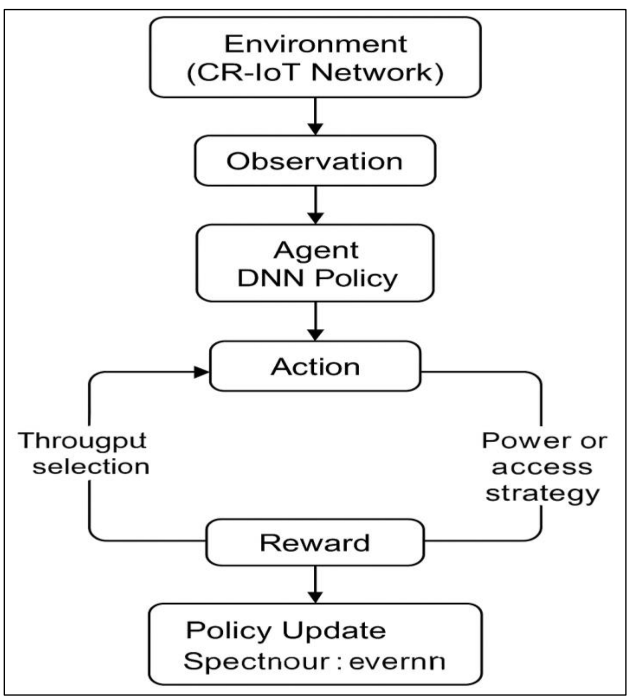

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Figure 3 flowchart of the Deep Reinforcement Learning (DRL) working process in CRIoT

3.1. Motivation for DRL in CR-IoT

In CR-IoT networks, channel availability is highly dynamic due to the unpredictable activity of Primary Users (PUs) and interference from other Secondary Users (SUs). Traditional optimization methods often require precise system models or suffer from slow adaptation to environmental changes. DRL overcomes these limitations by:

- Learning from Interaction: Continuously improving policies through environment feedback.
- Scalability: Handling large state-action spaces inherent in multi-channel, multi-user systems.
- Generalization: Adapting to varying network topologies and spectrum usage patterns without retraining from scratch.

3.2. Recent DRL-based Solutions

A Priority Experience Replay Deep Echo State Q-Network (PER-DESQN) was proposed for multi-user, multi-channel CR-IoT networks [9]. The model integrates Echo State Networks (ESN) to capture temporal correlations in spectrum usage, Double DQN (DDQN) to reduce Q-value overestimation, and a priority-based replay buffer for efficient training. Simulation results demonstrated faster convergence and improved channel capacity compared to conventional DRL methods [10].

To address privacy and personalization in distributed IoT systems, a hierarchical federated DRL framework was introduced [12]. Local devices train personalized models while sharing only essential parameters with a global model at the edge/cloud. This approach accelerated convergence by ~40% and maintained high throughput performance with reduced communication overhead [12].

DQN in TV White Space CR Networks (2025) – A DRL-based predictive spectrum access system was developed for TV White Space (TVWS) CR networks using DQN and Quantile Regression DQN (QR-DQN). The solution achieved up to 96.34% interference avoidance and average latency as low as 1 ms, making it suitable for latency-sensitive CR-IoT applications [13].

DRL for Healthcare IoT Resource Allocation (2024) – Targeting dense healthcare IoT deployments, researchers modeled interference using a hypergraph interference framework and formulated resource allocation as a Markov Decision Process (MDP). A hybrid DRL agent employing asynchronous parallelism improved throughput under heavy interference conditions [14]

A DRL-based task offloading system (Novel DRL-TO) designed to overcome delays, high latency, and security issues in IoT. The DRL achieved 70% resource utilization, 93.5% task completion, and 350 kbps throughput [15].

An Enhanced LSTM (ELSTM) model, combined with the Red Panda Optimization (RPO) algorithm, was proposed to improve energy efficiency in Cognitive Radio Networks. The ELSTM predicts and manages key CRN parameters such as transmission time, transmission power, and sensing time, while the RPO algorithm fine-tunes these parameters to achieve optimal results. The results showed that the ELSTM-RPO model achieved higher energy efficiency, improved spectrum utilization, and better protection for primary users compared with existing methods [28].

An improved NB-IoT system called NB-CR-IoT was proposed, using Deep Q-Learning to manage the limited spectrum more efficiently. By replacing traditional Q-tables with a deep neural network, the algorithm learns to reduce repeated transmissions and serve more devices. Results show that it outperforms standard Q-learning in resource allocation [29].

The authors proposed a resource management system for Social and Cognitive IoT networks using Deep Reinforcement Learning (DRL). The goal was to improve energy efficiency and maintain good quality of service for IoT devices. They focused on optimizing how radio resources and transmission power are allocated, based on the

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social relationships between devices. A multi-agent DRL approach with Prioritized Experience Replay (PER) was used, allowing devices to learn and cooperate with each other. Simulation results showed that this method performed better than traditional techniques, using less energy while still meeting service requirements like low delay and high reliability [30].

The authors offer a Double Deep Q-Network (DDQN) supplemented with dual-agent architecture for adaptive traffic signal regulation. Two agents, each in charge of particular traffic flows, cooperate to stabilize the system and preserve a set phase sequence at a four-phase intersection. Grids depicting car positions are used to illustrate traffic conditions, and the distinction between waiting and passing vehicles determines rewards. When compared to single-agent DQN or binary-action techniques, simulations utilizing SUMO demonstrate that this DDQN dual-agent approach dramatically increases traffic capacity and decreases congestion [31].

The paper proposes a reinforcement learning-based routing method for cognitive radio-enabled IoT communications, where routing decisions are dynamically learned based on current network conditions. Specifically, it employs Q-learning, a popular model-free reinforcement learning technique, to select optimal network paths and communication channels by maximizing long-term performance. The algorithm considers factors like channel availability, spectrum quality, and interference to make intelligent routing choices. Simulation results from similar studies show that such RL-based methods significantly improve average data rate and throughput, while reducing packet collisions and end-to-end delay, outperforming traditional routing protocols such as AODV-IoT, ELD-CRN, and SpEED-Io [33].

3.3. Observations and Insights

The reviewed DRL approaches consistently demonstrate superior adaptability and throughput performance com [28]pared to traditional heuristic or fixed-rule-based methods. However, key challenges remain:

Sample Efficiency: DRL agents require extensive training episodes to achieve optimal performance.

Exploration–Exploitation Trade-off: Balancing between discovering new spectrum opportunities and exploiting known optimal channels.

Computational Overhead: High complexity may limit deployment on resource-constrained IoT devices, necessitating model compression or lightweight DRL variants.

Given these strengths and limitations, hybrid models that combine DRL with metaheuristics or cooperative sensing are emerging as a promising research direction for practical CR-IoT deployments.

4. Metaheuristic Optimization Approaches

Metaheuristic optimization algorithms have been widely applied to throughput optimization in CR-IoT due to their ability to efficiently search large and complex solution spaces without requiring complete mathematical models of the system. These algorithms are inspired by natural processes such as evolution, swarm intelligence, and predator–prey dynamics and they can be adapted to solve multi-objective problems involving spectrum allocation, power control, and interference management.

4.1. Motivation for Metaheuristics in CR-IoT

CR-IoT environments present highly non-linear, NP-hard optimization problems due to fluctuating spectrum availability, varying channel conditions, and multi-user interference. Metaheuristic algorithms are attractive in this context because they:

- Do not require accurate channel or traffic models to operate effectively.
- Manage several competing goals, such as increasing throughput while lowering energy and interference..
- Offer global search capability, reducing the risk of convergence to local optima.

4.2. Recent Metaheuristic-based Solutions

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The proposed method hybridizes Fractional Grey Wolf Optimization (FGWO) with Cuckoo Search (CS) to exploit the strengths of both algorithms—precise local search from FGWO and diverse global exploration from CS. This hybrid metaheuristic optimization framework is applied to optimize spectrum sensing thresholds in Cognitive Radio Networks (CRNs). Simulation results show that the approach improves accuracy and efficiency compared to conventional methods [19].

The proposed method integrates Fractional Grey Wolf Optimization (FGWO) with Cuckoo Search (CS) to optimize spectrum sensing thresholds in Cognitive Radio Networks (CRNs). By combining FGWO's precise local search capability with CS's diverse global exploration, the approach achieves better balance between exploration and exploitation. The outcomes demonstrate higher detection accuracy, lower false alarm rates, and faster convergence compared to traditional methods such as GWO, PSO, and CS, thereby improving the overall efficiency and robustness of spectrum sensing under varying SNR conditions [16].

The proposed method introduces a Hybrid PSO-based power allocation algorithm for Cognitive Radio Networks. By combining the exploration ability of Particle Swarm Optimization (PSO) with additional enhancement strategies, the algorithm ensures efficient distribution of power among users. The outcomes show that it achieves higher throughput, better fairness, and improved robustness compared to conventional PSO and other existing approaches [17].

The proposed method presents a hybrid routing approach for IoT networks that combines duty cycling with an improved Ant Colony Optimization (ACO) algorithm. Duty cycling reduces energy consumption by controlling node activity, while improved ACO ensures efficient multi-hop routing. The outcomes show that the approach achieves longer network lifetime, lower energy consumption, and better end-to-end throughput compared to traditional routing methods [18].

The proposed method introduces a Chaotic Whale Optimization Algorithm (CWOA) for multi-objective conjoint spectrum utilization in Cognitive Radio Networks. By integrating chaotic maps with WOA, the algorithm enhances exploration and avoids premature convergence. The outcomes show that CWOA achieves better spectrum utilization, higher throughput, and lower interference compared to conventional WOA and other optimization methods [20].

The proposed method presents a hybrid Whale-Ant Optimization Algorithm (WAOA) for energy-efficient routing in Wireless Sensor Networks (WSNs). The hybridization leverages WOA's exploration strength and Ant Colony Optimization's (ACO) path-finding efficiency. The outcomes demonstrate longer network lifetime, reduced energy consumption, and improved packet delivery ratio compared to standalone WOA, ACO, and other conventional routing approaches [21].

4.3. Observations and Insights

Metaheuristic algorithms have shown competitive performance in CR-IoT throughput optimization, especially in scenarios where the search space is large and system modeling is impractical. However, they typically operate offline or require batch re-optimization when network conditions change, limiting their applicability in highly dynamic environments. Integrating metaheuristics with online learning methods such as DRL could address this limitation by combining global search capability with adaptive decision-making.

5. Cooperative Spectrum Sensing and Optimization

Cooperative Spectrum Sensing (CSS) has emerged as a crucial strategy in CR-IoT networks to improve the reliability of spectrum hole detection and enhance throughput performance. By enabling multiple IoT devices—acting as Secondary Users (SUs)—to collaboratively sense spectrum availability, CSS mitigates the limitations of individual sensing (such as shadowing, multipath fading, and noise uncertainty) and increases detection accuracy for Primary Users (PUs).

5.1. Motivation for Cooperative Spectrum Sensing in CR-IoT

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Single-user spectrum sensing often suffers from low detection probability in challenging wireless environments. CSS addresses this by:

- Aggregates sensing data from multiple geographically distributed nodes to improve detection accuracy.
- Reduces false alarm probability, thereby increasing overall spectrum utilization.
- Enhances network robustness under low-SNR conditions, ensuring reliable performance.

These advantages make CSS particularly suitable for dense IoT deployments where spectrum conditions vary significantly across devices.

5.2. Recent Cooperative Sensing and Optimization Solutions

The proposed a cooperative spectrum sensing (CSS) optimization system for 6G cognitive radio networks using the Manta Ray Foraging Algorithm (MRFO). The algorithm was applied to find the best weights for combining sensing results from multiple secondary users, giving more importance to those with stronger signal quality. By optimizing sensing thresholds and decision rules, the system reduced false alarms and missed detections, ensuring efficient spectrum utilization. The results showed that the method achieved higher detection probability, lower false alarm rate, better energy efficiency, and improved throughput and reliability, particularly in low-SNR and dense 6G network conditions [22].

An energy-efficient cooperative spectrum sensing scheme was proposed for Cognitive IoT that uses spatial correlation among nearby nodes to avoid redundant sensing and save energy. By grouping correlated nodes, the system reduces unnecessary reporting and improves sensing efficiency. The results showed that the scheme lowers energy consumption, increases detection accuracy, and enhances spectrum utilization compared to traditional cooperative sensing methods [23].

An energy-efficient cooperative spectrum sensing system was proposed for Cognitive Radio networks using a neural network. The network is designed to optimize sensing decisions by learning key parameters like each sensor’s sleeping rate and detection thresholds, guided by a custom loss function that balances energy usage with required detection and false alarm rates. This approach reduces the number of nodes needed for sensing (thus saving energy), improves detection accuracy, and achieves better spectrum utilization compared to traditional methods [24].

An optimal linear weighted cooperative spectrum sensing system was proposed for cluster-based cognitive radio networks. In this method, nodes are grouped into clusters and the cluster heads—those with better channel conditions—aggregate sensing data. An optimal linear weighting scheme assigns weights to each secondary user based on their SNR and historical sensing accuracy, so that more reliable nodes have a greater influence in the final decision. This leads to higher detection probability, lower error rate, and improved spectrum utilization compared to traditional methods that treat all nodes equally [25].

An energy-efficient cooperative spectrum sensing system is proposed for cognitive radio networks, using a hybrid spectrum handoff strategy. The system combines energy detection for spectrum sensing with a threshold-based approach driven by primary user traffic patterns to manage spectrum mobility. It employs a hybrid handoff mechanism based on dynamic spectrum aggregation, which balances probabilistic stay-and-wait and QoS handoff thresholds. This design enables cooperative sensing to identify optimal channels, maximizing throughput while minimizing energy consumption, all without increasing handoff delay or detection errors [26].

A quantum-secured IoT communication system with AI advancements was proposed for 6G cognitive radio networks. It uses dual-layer authentication, combining Public Key Infrastructure (PKI) and Quantum Key Distribution (QKD), to secure spectrum access and data transfer. The system forecasts channel state information (CSI) using a Multi-Layer Perceptron with Kalman Filter (MLP-KF) and employs an intelligent spectrum sensing model based on Reinforcement Learning-based Ensemble Regression (RL-ER). According to simulation studies, this

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architecture dramatically lowers error rates, boosts prediction accuracy, speeds up encryption and decryption, and improves latency and signal coverage [27].

The paper introduces a new method to save energy while finding free channels in cognitive radio-based IoT systems. It uses a technique called Dempster–Shafer theory to combine results from many sensors to decide if a channel is free or busy. The method works with both simple (hard) and detailed (soft) sensing data. This helps reduce energy use and makes sensing more accurate. Tests show that the method improves sensing accuracy by about 13%, increases data transfer, uses less energy, reduces errors, and helps devices last longer. Overall, it offers a smart and efficient way to use radio channels in IoT networks [32].

A novel approach to cooperative spectrum sensing in cognitive IoT networks is presented in this research. Using a technique known as distributed sequential detection, two Internet of Things devices collaborate and make judgments independently of a central controller. Based on accuracy and cost, each device determines when to stop sensing and determines whether the channel is busy or free. To determine the ideal moment to pause and make a choice, the authors employ a clever strategy known as person-by-person optimization with dynamic programming. The findings demonstrate that this approach is effective and dependable for IoT networks since it lowers the total sensing cost and maintains low error rates (false alarms and missed detections). [34].

A lightweight Double Deep Q-Network (Double-DQN) was proposed to improve energy efficiency in Industrial IoT (IIoT) devices used in thermal power plants. This method uses reinforcement learning to help devices make smarter decisions about resource usage while keeping the model lightweight enough for real-time applications. The Double-DQN approach helps avoid common problems like overestimating action values, making the learning process more stable and reliable. Simulation results show that the proposed method significantly reduces energy consumption, improves system efficiency, and performs better than traditional Q-learning and standard DQN algorithms. It is especially effective in complex and energy-constrained industrial environments [35].

The authors proposed an improved Grey Wolf Optimization algorithm called EECHIGWO for selecting cluster heads in Wireless Sensor Networks (WSNs). The main goal was to save energy, increase throughput, and make the network more stable and last longer. The algorithm selects the best cluster heads by considering factors like the distance to the sink, the remaining energy of nodes, balance among cluster heads, and the average distance within a cluster. The method was tested using measures such as the number of dead nodes, energy used, operating rounds, and average throughput. Results showed that EECHIGWO reduced energy use, avoided early convergence, and extended the network lifetime. It also gave much better stability compared to other protocols such as SSMOECHS, FGWSTERP, LEACH-PRO, HMGWO, and FIGWO [36].

5.3. Observations and Insights

Cooperative spectrum sensing greatly enhances the reliability of CR-IoT networks, especially in low-SNR and high-interference conditions. However, CSS introduces additional coordination overhead and reporting delays that may reduce real-time responsiveness. Future research is trending toward joint optimization of sensing, channel selection, and power control—often combining CSS with DRL or metaheuristic algorithms—to achieve both high detection accuracy and throughput performance.

6. Game-Theoretic Models

Game-theoretic modeling provides a principled way to analyze strategic interactions among Secondary Users (SUs) and between SUs and Primary Users (PUs) in CR-IoT. By formalizing spectrum access as games with well-defined utilities and constraints, these methods seek equilibrium that balance throughput, interference, fairness, and energy use.

6.1. Motivation for Game Theory in CR-IoT

Decentralized decision-making: Many IoT deployments lack a central controller; game models naturally capture local, selfish, or partially cooperative behaviors.

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- Fairness and stability: Equilibrium notions (e.g., Nash, Stackelberg) provide stable operating points that discourage unilateral deviation.
- Heterogeneous objectives: Users may value throughput, delay, and energy differently; utility design internalizes these trades-offs.

6.2. Recent Game theory based solutions

A game theory-based clustering method was proposed for Cognitive Radio Wireless Sensor Networks (CR-WSNs). In this approach, each node decides whether to become a cluster head or join another cluster based on its remaining energy, distance to the base station, and communication cost. The clustering process is modeled as a game, where nodes reach a stable state and do not need to change roles again. Simulation results showed that this method saves more energy, keeps more nodes alive for longer, and extends the overall network lifetime compared to traditional clustering methods. It also performs well in dynamic spectrum environments, which are common in CR-WSNs [37].

An improved channel allocation game algorithm (CGVAC) was proposed to reduce interference and improve spectrum use in wireless sensor networks. The algorithm is designed to work even when the number of available channels changes. It takes into account link quality, interference, and remaining energy while assigning channels, and it uses game theory to reach a stable solution. Simulation results showed that CGVAC reduces communication interference, increases spectrum utilization, and lowers spectrum cost compared to traditional methods [38].

A game theory-based model was proposed for IoT-enabled Cognitive Radio Networks (CRNs) working in underlay mode. In this approach, the secondary user network was represented using a triangular lattice with relays. The model included both interference and power constraints while calculating the Nash equilibrium, and it also considered factors such as channel strength and desirability to make the framework more realistic. Simulation results showed that this method improves spectrum utilization, provides reliable communication for secondary users, and offers a practical framework for applying game theory in CRNs.[39].

To reduce the high computational cost of resource allocation in Cognitive Radio Networks (CRNs), the authors proposed a Power-Based Pricing Algorithm (PPA). The method is designed for downlink CRNs and ensures that interference to primary users stays within safe limits. It works in two stages: first, subcarriers are assigned to users, and then a pricing-based utility function is used to optimize power allocation. The algorithm was tested in an OFDM-based CRN, and results showed that it achieves performance close to the optimal solution while greatly reducing complexity to ($M\log(M)$). This makes PPA a more practical and efficient choice for resource allocation in CRNs [40].

7. Other algorithm for Throughput optimization

A Distributed Fuzzy–Deep Reinforcement Learning (DFDRL) protocol was proposed for wireless sensor networks. Fuzzy logic is used to select cluster heads based on energy, distance, and node degree, while a Double Deep Q-Network (DDQN) is applied for routing to choose the best next-hop relay. A cluster maintenance mechanism further reduces overhead. The results show that DFDRL improves network lifetime, lowers energy consumption, and increases throughput compared to existing protocols. In the future, this system can be enhanced by integrating a spectrum awareness algorithm, which would further improve throughput and adaptability in Cognitive Radio IoT (CR-IoT) networks [41].

The QoS-Aware Deep Reinforcement Learning-based Link Adaptation (QDRLLA) proposed for Beyond 5G networks can also be applied to Cognitive Radio IoT (CR-IoT). In CR-IoT, devices must adapt transmission parameters while considering spectrum availability and primary user protection. By adding spectrum sensing and interference constraints to the reward function, the DQN-based link adaptation can optimize modulation, coding,

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power, and channel selection. This would improve throughput, spectral efficiency, and QoS in CR-IoT applications [42].

An AI-based spectrum sensing method was proposed for LoRa and cognitive radio networks. The approach leverages artificial intelligence techniques to enhance spectrum detection and minimize interference. Results demonstrate higher detection accuracy, improved throughput, and greater adaptability compared to traditional methods, making it effective for IoT and CRN applications [43].

Ref & Year	Theme	Domain Focus/Task	Method	Metric	Result	Data/ Simulation	Limitation
[1] 2025	Spectrum Sensing Review	CR-IoT spectrum detection (survey)	Systematic Literature Review	Taxonomy, challenges, compare methods	Consolidates detection methods & gaps	Literature corpus	No new experiment s
[2] 2022	Throughput Optimizatio n	Interference-limited CR-IoT	Optimization modeling	Throughput, latency (modeled)	Throughput gains under interference constraints	Simulation (CR-IoT)	Model-specific; real-world validation needed
[3] 2018	Resource Allocation	Heterogeneous MIMO CRNs	Priority-based dynamic allocation (EPBDRA)	Throughput, fairness	Improved allocation efficiency vs baselines	Simulation	Older; scalability not explored
[4] 2022	Dynamic Spectrum Access (DSA)	Distributed multi-agent CRN	Cooperative Multi-Agent RL	SE, fairness, convergence	Outperforms traditional DSA	Simulation	Real-world non-stationarity untested
[5] 2024	Spectrum Sharing for IoT	5G IoT connectivity	Sharing strategies (conceptual/an alytical)	Connectivity, spectral usage	Improved IoT connectivity via sharing	Analysis/Si mulation	Deploymen t aspects limited
[6] 2024	Security/Qu antum	6G CRN IoT security	AI + Quantum-secured framework	Security resilience, latency (conceptual)	Proposes quantum-secured CR-IoT design	Concept/pro totype	Implement ation complexity
[7] 2025	Spectrum Decision AI	Multi-user access, decentralized CRN	AI-based decision model	Access success, collision rate	Enhanced access efficiency	Simulation	Generalizat ion to varying loads
[8] 2021	Throughput vs Sensing EE	CR-IoT sensing scheme	Energy-efficient sensing	Throughput, detection probability, EE	Analyzes EE–throughput tradeoffs	Analytical/S imulation	Assumes idealized channels

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			analysis				
[9] 2022	Throughput Improvement	CRN for 5G/B5G IoT	Cluster-ID-based scheme	Throughput, delay	Throughput improvements reported	Simulation	Cluster maintenance overhead
[10] 2024	DRL for DSA	Multiuser multichannel CR-IoT	Distributed DRL	SE, throughput, fairness	Surpasses heuristic DSA	Simulation	Scalability/ communication cost
[11] 2024	FL + DRL Optimization	MEC with data heterogeneity	Hierarchical Federated Learning + DRL	Convergence, accuracy, latency	Improved FL under heterogeneity	Simulation	Not CR-specific; adaptation needed
[12] 2023	DSA for IoT with H-Fed DRL	IoT dynamic spectrum access	Hierarchical federated DRL	Throughput, SE, convergence	Better DSA with privacy benefits	Simulation	Communication overhead in FL
[13] 2025	DRL for TVWS DSA	TV whitespace CRNs	Deep RL agents	Success rate, collisions	Improved channel access decisions	Simulation	TVWS database dynamics not covered
[14] 2025	DRL Resource Allocation	Healthcare IoT (wearables)	DRL-based spectrum allocation	Latency, throughput, reliability	QoS improvements for e-health	Simulation	Medical-grade validation pending
[15] 2025	Task Offloading	IoT resource utilization	Actor-Critic RL	Latency, energy, success rate	Enhanced offloading efficiency	Simulation	Edge dynamics simplified
[16] 2025	Metaheuristic Power Opt.	WSN transmission power	Enhanced Grey Wolf Optimization	Energy use, PDR	Lower power with maintained PDR	Simulation	Large-scale convergence unknown
[17] 2022	Power Allocation	CRN robustness	Hybrid PSO-based allocation	Interference, throughput	Robust power allocation vs PSO	Simulation	Parameter tuning sensitivity
[18] 2025	Energy-Efficient Routing	IoT routing	Duty cycling + improved ACO	Network lifetime, delay	Energy savings vs baselines	Simulation	Real mobility not tested
[19] 2023	Spectrum Sensing	CRN sensing optimization	Fractional GWO + CS	Detection accuracy, FAR	Improved sensing performance	Simulation	Complexity of hybrid method
[20] 2023	Multiobjective Spectrum Util.	CR spectrum utilization	Chaotic Whale Optimization	SE, utilization	Better multiobjective trade-offs	Simulation	Chaos control parameters

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[21] 2024	Energy-Efficient Routing	WSN routing	Hybrid Whale–Ant Optimization (WAOA)	Energy, lifetime, PDR	Outperforms ACO/WOA variants	Simulation	Applicability to CRN indirect
[22] 2021	Cooperative Sensing	CR in 6G networks	Optimization of CSS	Pd, Pf, EE	Optimized CSS settings	Simulation	6G assumptions abstract
[23] 2020	Cooperative Sensing	CR-IoT with spatial correlation	EE CSS using spatial correlation	Energy, sensing time	Energy saving with correlation use	Simulation	Correlation estimation overhead
[24] 2022	CSS with ML	Energy-efficient CSS	Machine Learning-based CSS	Accuracy, energy	EE gains vs classical CSS	Simulation	Model training cost
[25] 2021	CSS Weighting	Clustered CRN	Optimal linear weighted CSS	Pd, Pf	Improved detection via weights	Simulation	Cluster formation cost
[26] 2022	EE via CSS & Handoff	CRN energy efficiency	Hybrid spectrum handoff + CSS	Energy, delay	EE improvement reported	Simulation	Handoff signaling overhead
[27] 2024	Security/Quantum	6G CRN security	AI-enhanced quantum-secured framework	Security robustness (conceptual)	Framework for secure CR-IoT	Conceptual	Hardware/keys practicalities
[28] 2024	Energy Efficiency Optimization	CRN EE	Enhanced deep learning model	Energy index, throughput	EE gains vs baselines	Simulation	Generalization to varied traffic
[29] 2020	Resource Allocation	NB-CR-IoT	DRL-based allocation	Throughput, EE	Improved allocation decisions	Simulation	Narrowband focus
[30] 2020	Energy-Efficient Resource Mgmt	Social & Cognitive IoT	DRL-based management	Energy, utility	EE improvements via DRL	Simulation	Communication overhead
[31] 2020	Control (Reference)	Traffic signal control (method ref)	Double DQN dual-agent	Delay, convergence	DDQN shows gains (methodology)	Simulation	Non-CR domain reference
[32] 2021	Throughput vs Sensing EE	CR-IoT EE sensing	Analytical throughput analysis	Throughput, Pd, Pf	Tradeoff characterization	Analytical/Simulation	Specific sensing assumptions
[33]	Routing via	CR-IoT	Reinforcement	Delay, PDR,	RL routing	Conference	Short

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2024	RL	communications	learning routing	energy	benefits shown	simulation	paper; limited scale
[34] 2024	Cooperative Sensing	Distributed sequential detection	Distributed sequential CSS	Detection delay, Pd	Faster detection at target Pd	Simulation/analysis	Synchronization assumptions
[35] 2025	EE Optimization (DDQN)	Industrial IoT devices	Lightweight DDQN	Energy, task success	Energy reduction with DDQN	Simulation	Industrial workload diversity
[36] 2023	Cluster Head Selection	WSN energy efficiency	Improved Grey Wolf Optimization	Lifetime, energy	EE gains via I-GWO	Simulation	Not CR-specific
[37] 2022	Game-Theoretic Clustering	CR-WSN node clustering	Game theory-based clustering	Energy, stability	Improved cluster stability	Simulation	Payoff design dependence
[38] 2023	Game-Theoretic Spectrum Opt.	Variable channel numbers	Improved game algorithm	SE, utility	Better spectrum resource use	Simulation	Assumes rational players
[39] 2020	Game Theory for Underlay CR-IoT	Cooperative underlay access	Game-theoretic approach	Interference, throughput	Feasible cooperative underlay	Conference/ Simulation	Limited scale evaluation
[40] 2022	Power Allocation	Downlink CRN	Efficient power allocation algorithm	Throughput, interference	Improved power efficiency	Simulation	Channel model assumptions
[41] 2025	Routing with DRL + Fuzzy	WSN routing	Fuzzy logic + DRL, distributed	Energy, PDR, delay	Improved routing performance	Simulation	Overhead of fuzzy rules
[42] 2025	Link Adaptation (DRL)	Beyond-5G link adaptation	Deep RL	Throughput, QoS	Higher QoS & throughput	Simulation	CR-IoT applicability needs mapping
[43] 2023	AI for Spectrum Sensing	LoRa & CRN sensing	AI-based sensing methodology	Detection accuracy, interference	Higher detection, reduced interference	Experiment/ Simulation (per paper)	Domain-specific tuning
[44] 2022	Pareto Resource Allocation	CR-IoT EE vs SE trade-off	Hybrid Tabu + Simulated Annealing + Fuzzy	EE, SE, fairness	Pareto-optimal improvements vs TS/SA	Simulation	Heuristic parameter sensitivity

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A Pareto-optimal resource allocation scheme was proposed for Cognitive Radio-based IoT networks to balance energy efficiency (EE) and spectrum efficiency (SE). The authors introduced a Hybrid Tabu Search–based Simulated Algorithm (HTSA), which combines Tabu Search (TS) and Simulated Annealing (SA) with fuzzy decision-making to select the best trade-off solutions. Simulation results showed that HTSA outperforms traditional TS and SA, providing higher energy and spectrum efficiency, fairer resource utilization, and better adaptability under different network conditions [44].

8. Conclusion and Future Directions

This survey reviewed 44 recent works on Cognitive Radio (CR) and Cognitive Radio-based IoT (CR-IoT) networks, focusing on spectrum sensing, resource allocation, energy efficiency, and throughput optimization. While traditional methods offer stable results, they face challenges with scalability and adaptability. Recent advances such as deep reinforcement learning, metaheuristics, and hybrid cooperative approaches show better performance, but issues like high computational cost, lack of real-world testing, and no common datasets remain.

Future research should focus on designing lightweight AI models that can run on low-power IoT devices, developing benchmark datasets for fair comparison, and testing solutions in real-world environments. The use of 6G features like ultra-reliable low-latency communication and terahertz bands will further improve CR-IoT. In addition, more work is needed on security and privacy through blockchain, federated learning, and quantum-safe methods, as well as on energy-efficient protocols for sustainable networks. Collaborative and intelligent spectrum sharing using multi-agent learning will also play a key role in building scalable, secure, and practical CR-IoT systems.

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