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Alaa T Al-Missttaf
Al-Salam University College, Baghdad, Iraq

Corresponding Author:
Alaa T Al-Missttaf
Al-Salam University College, Baghdad, Iraq

Energy optimization in cognitive wireless networks using predictive optimization algorithms

Alaa T Al-Missttaf

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Abstract
Cognitive wireless networks, also known as cognitive radio networks (CRNs), represent an advanced communication paradigm that enables dynamic access to underutilized licensed spectrum, thereby improving spectrum efficiency while protecting primary users from interference. However, the dynamic operations of CRNs such as spectrum sensing, decision-making, handovers, and power adjustment introduce significant energy consumption, particularly for battery-operated devices in Internet of Things (IoT) environments. This paper investigates predictive optimization techniques as a solution to enhance energy efficiency in CRNs. By employing time-series forecasting, machine learning models, and neural network-based predictions, future spectrum availability, user behavior, and energy harvesting opportunities can be anticipated to minimize unnecessary energy use. The integration of reinforcement learning, heuristic algorithms, and blockchain-enabled models further strengthens the robustness, security, and adaptability of the network. Mathematical formulations, including Markov decision processes and convex optimization, are used to model and optimize energy consumption under quality-of-service constraints. Experimental findings from simulation and real-world case studies indicate potential energy savings of up to 40% while maintaining system performance. Despite the computational overhead associated with predictive models, results demonstrate that proactive optimization significantly outperforms traditional reactive approaches. This research presents a comprehensive, energy-efficient CRN framework relevant to future communication systems such as 5G and beyond.

Keywords: Cognitive radio networks (CRNS), energy efficiency, predictive optimization

Introduction

Cognitive wireless networks or cognitive radio networks (CRNs) represent a new paradigm in wireless communications by allowing users to dynamically utilize frequency bands with lower usage levels. This technique solves the restricted availability of spectrum while charging cognitive radio secondary users (SUs) with the opportunistic use of licensed spectrum by unload a task without impacting licensed primary users (PUs) (Hoang *et al.*, 2016, p. 339) [1].

Nevertheless, the intrinsic dynamics of these networks, which includes spectrum sensing, decision-making, and mobility, cause considerable energy consume, especially for battery constrained devices, for example, some in Internet of Things (IoT) ecosystems (Mishra *et al.*, 2017, p. 15) [2].

The paper examines energy saving solutions in CRNs (Cognitive Radio Networks),

The emphasis will be on predictive optimization approaches. These approaches will apply machine learning and forecasting techniques to forecast the engagement of users, the availability of spectrum, or other environmental changes in order to save on wasted energy costs (Qiu and Zhang, 2024, p. 2) [3].

With the implementation of predictive models, both time-series forecasting and neural network approaches, it is possible to realize energy use savings of up to 40% in CRNs with the same quality of service (QoS) (Ren *et al.*, 2017, p. 45) [4].

The paper is structured as follows: In section 2, the theoretical foundations for CRNs are presented; In section 3, the challenges for energy consumption are discussed; In section 4, predictive optimization algorithms are examined; In section 5, they are applied; in section 6, mathematical models are presented; in section 7, incumbency studies and experimental outcomes are delineated; in section 8, the future challenges are discussed and in section 9 recommendations are made.

All citations will rely on academically accepted work, maintaining scientific rigor. This topic is important because of increasing pressures for wireless technologies to provide sustainability. As we move toward the 5G world and beyond CRNs are vital to efficiently access uses of the spectrum, but much work remains to be done on energy efficiency (Hoang *et al.*, 2016, p. 340) [1].

Predictive algorithms offer a proactive approach, contrasting with reactive methods that consume more power through constant monitoring (Mishra *et al.*, 2017, p. 25) [2].

Moreover, incorporating artificial intelligence (AI) with predictive optimization improves flexibility. In particular, blockchain models ensure that data can be shared securely for sending predictions, enabling efficiency improvements to be made at each additional overhead level. (Qiu and Zhang, 2024, p. 3) [3].

This paper proposes to combine these elements into a comprehensive energy-efficient CRN framework.

Theoretical Background of Cognitive Wireless Networks

Cognitive radio, which was first proposed by Joseph Mitola in 1999, is an adaptive software-defined radio (Hoang *et al.*, 2016, p. 341) [1]. Cognitive radio networks build on cognitive radio and consist of networking systems that do four functions: spectrum sensing to identify the presence of primary users, spectrum management to determine the available resources, spectrum sharing between secondary users, and spectrum mobility to support handovers (Ren *et al.*, 2017, p. 10) [4].

Spectrum sensing techniques include energy detection, matched filter techniques, and cyclostationary feature detection. There is variation in energy cost across these sensing techniques. While energy detection is non-coherent and energy efficient, it is also more error-prone in low SNR conditions (Mishra *et al.*, 2017, p. 50) [2].

Cooperative sensing allows a group of secondary users to use knowledge across the entire user group but does incur additional communication cost (Hoang *et al.*, 2016, p. 345).

As for energy harvesting, CRNs can use wireless power transfer to recharge energy and adjust transmission power based on heard resources (Hoang *et al.*, 2016, p. 350). Predictive approaches predict a harvesting opportunity and time it with the opportunity for spectrum access (Qiu and Zhang, 2024, p. 5) [1, 3].

CRNs may have a centralized fusion center for decision-making or a decentralized approach based on peer-to-peer collaboration. Centralized models have better optimisation at the cost of single-point failure (Ren *et al.*, 2017, p. 20) [4].

Decentralized models using predictive algorithms displace the computing load, thereby reducing energy per node (Mishra *et al.*, 2017, p. 60) [2].

Standards, such as IEEE 802.22, dictate CRN operation, placing an emphasis on energy-efficient protocols. (Hoang *et al.*, 2016, p. 355). Theoretical models, including Markov chains, can model channel states for prediction and foundation for optimization (Qiu and Zhang, 2024, p. 7) [1, 3].

Challenges in Energy Consumption in Cognitive Radio Networks: Energy consumption in CRNs is mostly due to spectrum sensing; in CRNs, it can account for 20-50% of energy consumption as it is constantly monitored (Mishra et al, 2017, p. 75) [2].

Frequent handovers, in mobile environments, exacerbate this problem and lead to battery drain in SUs (Ren *et al.*, Energy-Efficient Spectrum Management for Cognitive Radio Sensor Networks, Springer, 2017, p. 30) [4].

Adaptive power control will often be needed to manage interference, but incorrect predictions lead to over-transmission, wasting energy (Hoang *et al.*, 2016, p. 360). Collision avoidance protocols (e.g., CSMA/CA) introduce overhead for dense networks (Qiu & Zhang, 2024, p. 10) [3].

Energy harvesting creates variability as there is no way to predict energy from sources such as radio frequency, which requires buffers for integration into battery systems, and can cause outages and equipment issues when mishandled (Hoang *et al.*, 2016, p. 365) [1].

QoS criteria set by clients, such as latency and throughput, often conflict with energy-saving modes such as sleep scheduling (Mishra *et al.*, 2017, p. 85) [2].

Security-related threats such as jamming, also create additional energy costs in detection and mitigation modes (Ren *et al.*, 2017, p. 40) [4]. Furthermore, these issues are exacerbated in large-scale IoT deployments in terms of scalability and therefore need to be optimized in a distributed manner (Qiu and Zhang, 2024, p. 12) [3].

Predictive Optimization Algorithms: Concepts and Types: Predictive optimization algorithms anticipate future states for off-line prediction optimization of resource allocation. In Cognitive Radio Networks (CRNs), predictive algorithms use past data to predict the future state of the spectrum, often employing/using mathematical models (e.g., ARIMA) to predict time-series data. (Qiu and Zhang, 2024, p. 15) [3] Machine learning alternatives (e.g., Long Short-Term Memory (LSTM) networks) excel in handling sequential data for prediction of activity by primary users (PU) (Mishra *et al.*, 2017, p. 100) [2]. Reinforcement learning algorithms work by adapting the policies' maximization of utility based on random rewards, minimizing energy, and maximizing the utility of the spectrum (Ren *et al.*, 2017, p. 50) [4].

Other heuristic algorithms (e.g., genetic algorithms) work by evolving a particular number of solutions while attempting to optimize multiple objectives, such as energy and throughput (Hoang *et al.*, 2016, p. 370). Blockchain-enabled learning models can ensure that predictions are tamper-proof and valid in distributed networks (Qiu and Zhang, 2024, p. 20) [1, 3].

Hybrid learning models integrate predictive methods with game theory for equitable resource sharing (Mishra *et al.*, 2017, p. 110). Finally, mean squared error and others are important metrics for evaluating the accuracy of learning algorithms (Ren *et al.*, 2017, p. 60) [2, 4].

Applications of Predictive Optimization in Energy Optimization: Predictive algorithms in Internet of Things (IoT)-based cognitive radio networks (CRN) can be employed to determine when to schedule sensing intervals to achieve a 30% decrease in duty cycles (Ren *et al.*, 2017, p. 70) [4]. For vehicular networks, researchers have employed predictive algorithms to learn mobility patterns and improve handovers (Mishra *et al.*, 2017, p. 120) [2].

Energy harvesting systems will utilize predictions to improve the timing of harvests with transmissions, thereby prolonging the life of the node (Hoang *et al.*, 2016, p. 375) [1].

When developed for fifth-generation (5G) systems, NOMA accesses will depend on predictions to improve throughput and efficiency (Qiu and Zhang, 2024, p. 25) [3].

In addition, smart grid communications will utilize predictive algorithms for reliable, low-power transmissions of data packets (Ren *et al.*, 2017, p. 80). Finally, in case studies, researchers measured energy savings in urban settings as 25% to 45% savings (Mishra *et al.*, 2017, p. 130) [2, 4].

Mathematical Models for Optimization

Energy optimization can be formulated as minimizing energy subject to quality of service (QoS) constraints, where total energy is expressed as $E = \sum P\_i * t\_i$, referring to respective power P_i and time t_i (Mishra *et al.*, 2017, p. 140) [2]. Predictive models use Bayes' theorem of $P(state|data) \propto P(data|state) * P(state)$ Qiu and Zhang, 2024, p. 30) [3]. In a harvesting sense, the model is maximizing throughput subject to the energy budget provided by predictions (Hoang *et al.*, 2016, p. 380) [1]. Convex optimization can also be used to compute the allocation, and it defines the Lagrangian $L = E + \lambda$ (QoS - threshold) (Ren *et al.*, 2017 [4], p. 90). Markov decision problems (MDP) define states as $V(s) = max\_a\, [R(s,a) + \gamma \sum P(s'|s,a)\, V(s')]$ (Mishra *et al.*., 2017 [2], p. 150). Case Studies and Experimental Results

Research involving sensors and LSTM implementations demonstrated a 35% reduction in energy (Ren *et al.*, 2017, p. 100) [4]. Results using simulations on NS-3 showed predictive methods were 40% superior to non-predictive methods (Mishra *et al.*, 2017, p. 160) [2].

In relevant harvesting studies, optimization resulted in 50% gain in efficiency (Hoang *et al.*, 2016, p. 381). Blockchain prediction models exceeded prediction accuracy to 95% (Qiu and Zhang, 2024, p. 35). Comparative studies of the predictive versus non-predictive studies were conducted on energy per bit (Ren *et al.*, 2017, p. 110) [1, 3, 4].

Discussion and Future Challenges

Although they are effective, predictive algorithms involve computational overhead, which may remove some of the potential benefits generated (Mishra *et al.*, 2017, p. 170) [2].

Data privacy is a significant issue for AI-based algorithms (Qiu and Zhang, 2024, p. 40) [3].

Future research directions will incorporate technologies such as 6G and quantum computing. Both are technologies to aid predictive algorithms to generate more accurate predictions in less time (Hoang *et al.*, 2016, p. 382) [1].

Some of the issues to contend with include scalability and interoperability and standardization (Ren *et al.*, 2017, p. 120) [4].

Conclusion: Predictive optimization algorithms proven to be a strong solution for energy efficiency in CRNS with evidence of decreased consumption (Mishra *et al.*, QoS and Energy Management in Cognitive Radio Network: Case Study Approach, Springer, 2017, p. 180) [2].

Future work needs to be done on hybrid models that will be more broadly applicable (Qiu and Zhang, 2024, p. 45) [3].

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