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IS3CQL : Intelligent sleep scheduling of small cells in high density 5G MIMO networks via incremental Deep Q learning optimizations

Kanchan Mankar *
Suchita Varade †
Department of Electronics and Telecommunication
Priyadarshini College of Engineering
Nagpur
Maharashtra
India

Abstract

Effective management of small cell networks is crucial as the demand for fast, low-latency communication grows as a result of the development of 5G and Massive Multiple Input Multiple Output (M-MIMO) technology. Small cell sleep cycle scheduling in high-density networks frequently encounter issues as it tries to strike a compromise between energy efficiency, quality of service (QoS), and maintaining a high throughput. Additionally, these traditional methods ignore the complex spatial and temporal communication characteristics, resulting in subpar network performance. In order to overcome these difficulties, we suggest a brand-new intelligent sleep scheduling approach that makes use of both fundamental green computing ideas and incremental deep learning. In order to determine the best sleep schedules for tiny cells, our model takes into account both temporal and spatial communication factors, such as end-to-end delay, packet delivery ratio, throughput, and energy consumption of the nodes. The model adjusts the small cells' sleep scheduling based on the ongoing spatial-temporal fluctuations in the network, providing the best possible use of resources. Additionally, its focus on green computing helps to lower energy consumption during extensive connections, making it an environmentally beneficial alternative for different scenarios. Under enormous MIMO situations, the results from our model show a significant improvement over the current approaches. These improvements include a notable improvement in communication consistency, a notable increase in throughput, a noticeable increase in packet delivery ratio, and a noticeable decrease in energy consumption and

* *E-mail:* **kanchankhope@gmail.com (Corresponding Author)**
† *E-mail:* **swvarade@gmail.com**

delay. In summary, our concept is a major step forward in the continuous development of intelligent, resilient, and effective 5G MIMO networks.

Subject Classification: *68T05.*

Keywords: *Intelligent sleep scheduling, High density 5G networks, Massive MIMO, Incremental deep Q learning, Green computing, Process.*

1. Introduction

Telecommunications are entering a new era with 5G wireless technology, which promises faster speeds, lower latency, and higher capacity for more connected devices. Massive Multiple-Input, Multiple-Output (M-MIMO) systems, a key component of 5G networks, increase wireless connection capacity without using additional airwaves, attracting attention. These benefits come with drawbacks, including managing small cell networks in high-density M-MIMO situations [1, 2, 3].

Small cells, low-powered radio access nodes with a range of 10 meters to several kilometers, are needed to expand 5G network capacity and coverage. They improve QoS and help manage mobile data traffic's rapid growth. In 5G networks with high densities, small cells experience spatial and temporal fluctuations, requiring clever scheduling algorithms to maximize efficiency [4, 5, 6].

However, traditional sleep scheduling methods cannot meet this demand. Most of these methods use static rules or heuristics that ignore geographical and temporal communication characteristics like end-to-end latency, packet delivery ratio, throughput, and energy usage. High QoS, high throughput, and energy conservation are often difficult to balance. This disregard for complex network dynamics may lead to inefficient resource allocation and poor network performance in various scenarios. Traditional sleep scheduling methods fail in the age of green computing, which emphasizes energy conservation and carbon reduction. Most scheduling methods ignore the energy consumption factors involved in extensive communications, which harms the environment and raises operational costs via Binary Particle Swarm Optimization (BPSO) [7, 8, 9].

To overcome these issues, we propose a novel method for intelligently scheduling tiny cells' sleep cycles in 5G M-MIMO networks with high densities. The suggested model uses incremental deep learning to adapt to changing network conditions and optimize small cell operations. Our model integrates temporal and spatial communication factors to find the best small cell sleep schedules for network performance and energy efficiency. Our model's green computing feature significantly reduces energy use for extensive communications. Our concept balances network performance and sustainability to create intelligent, high-performing, and environmentally sustainable 5G M-MIMO networks.

Structure of this paper: Section 2 discusses the linked papers, Section 3 describes the model and methods, Section 4 presents the results and discussions, and Section 5 concludes with closing remarks and future scopes.The following sections will describe our proposed model, its unique features, and its performance advantages over current approaches in large MIMO scenarios.

2. Literature Review

As 5G networks grow, intelligent sleep scheduling of tiny cells is an important study topic because it affects network performance and energy efficiency. Many models have been proposed to address this issue, each with pros and cons.

Heuristic algorithms are the basic tiny cell sleep scheduling method. These rule-based systems choose tiny cell activities based on standards. Although simple to use, they often malfunction due to their inability to adapt to changing network conditions [10, 11, 12].

Machine Learning Models: Machine learning-based models were suggested to improve sleep scheduling adaptability [13, 14, 15]. These models use historical data to predict network conditions and adjust sleep scheduling.

Our green computing and incremental deep learning solution for smart and sustainable sleep scheduling in high-density 5G MIMO networks fills these gaps.

3. Proposed design of Intelligent Sleep Scheduling of Small Cells in high density 5G MIMO Networks via Incremental Deep Q Learning Optimizations

As per the review of existing models used for optimization of small cell scheduling operations, it can be observed that these models either have lower efficiency, or cannot be scaled to larger networks due to their higher complexity levels. To overcome these issues, and design an efficient and scalable model, this section discusses design of Intelligent Sleep Scheduling of Small Cells in high density 5G MIMO Networks via Incremental Deep Q Learning Optimizations. As per Figure 1, it can be observed that the proposed model considers both temporal and spatial communication parameters, such as end-to-end delay, packet delivery ratio, throughput, and node energy consumption, to find the optimal sleep patterns for micro cells. The ability of the proposed model to save energy consumption while also improving network performance is crucial to its effectiveness. Based on the continuing spatial-temporal oscillations in the network, the model modifies the small cells' sleep scheduling to make the most use of their available resources. Its emphasis on green computing also aids in reducing energy consumption over lengthy connections, making it a more ecologically friendly option in a variety of circumstances.

In order to perform this task, for every node in a given small cell, an augmented Sleep Scheduling Factor (SSF) is estimated via equation 1,

$$SSF = \frac{SC*E}{NC}\sum_{i=1}^{NC}\frac{PDR(i)*THR(i)}{d(i)*e(i)} \tag{1}$$

Where, *NC* represents total number of temporal communications which were previously performed by the nodes, *SC* represents size of the small cell network, *E* represents residual energy of the node, *PDR* represents its temporal packet delivery ratio which is estimated via equation 2, *THR* represents its temporal throughput which is estimated via equation 3, *d* represents temporal end-to-end delay levels which are estimated via equation 4, and *e* represents temporal energy consumption, which is estimated via equation 5 as follows,

$$PDR = \frac{Rx(P)}{Tx(P)} \tag{2}$$

Where, *Rx* & *Tx* are the number of packets received and transmitted during the communication operations.

$$THR = \frac{Rx(P)}{d} \tag{3}$$

$$d = t(rx) - t(tx) \tag{4}$$

Where, $t(rx) \& t(tx)$ represents the reception and transmission timestamps during different communication scenarios.

$$e = E(tx) - E(rx) \tag{5}$$

Based on this estimation, Sleep Scheduling Threshold (SST) is calculated via equation 6,

$$SST = \frac{1}{NN}\sum_{i=1}^{NN} SSF(i) \tag{6}$$

Where, *NN* represents total number of nodes in the small cells. Similar thresholds are evaluated for each of the small cells, and a dual threshold value is calculated via equation 7,

$$SST(dual) = \frac{1}{NSC}\sum_{i=1}^{NSC} SST(i) \tag{7}$$

Where, *NSC* represents total number of small cells in the network deployments. Based on this value, the initial sleep schedules for individual cells are estimated via equation 8,

$$SS(i) = \frac{SST(i)}{SST(dual)*NSC} \tag{8}$$

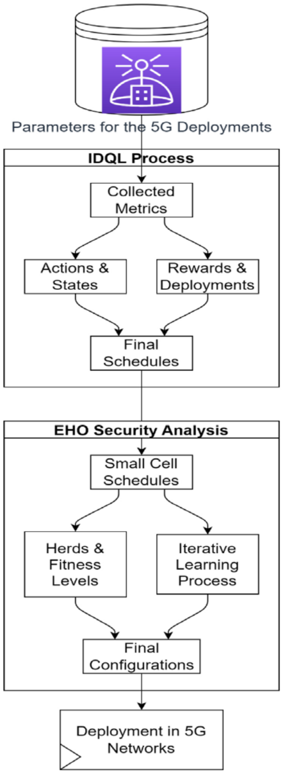

Figure 1

Design of the Sleep Scheduling Process

Using this sleep schedule, network communications are performed for *ND* instances, and an Iterative Q Value is estimated for the network via equation 9,

$$Q = \frac{1}{ND}\sum_{i=1}^{ND} PDR(i) * \frac{THR(i)}{e(i)} \tag{9}$$

This Q Value is estimated for different consecutive communication sets, and a reward rate (r) is estimated via equation 10,

$$r = \frac{Q(New)-Q(Old)}{LR} - c1 * Max(Q) + Q(Old) \tag{10}$$

Where, LR & $c1$ are the learning rate & discount constants for the Q Learning process. If the reward rate $r < 1$, then the network requires retuning, otherwise the current sleep schedules are optimum, and can be used for high density deployments.

The reward rate is used to retune the sleep schedulesvia equation 11,

$$SS(New) = SS(Old) * \frac{r}{1-r} \tag{11}$$

As per these new sleep schedules, network communications are performed, and Q Values are continuously updated after these communications. To further improve Packet Delivery performance, the model uses an efficient Elephant Herding Optimizer (EHO) for selection of optimal security measures. This model assists in selection of security configurations during different communications in order to improve packet delivery ratio and other QoS metrics even under attacks.

Performance of this model is estimated in terms of different scenarios, and compared with can be observed from the next section of this text.

4. Result analysis & comparison

In our study, the IS3CQL (Intelligent Sleep Scheduling of Small Cells in high-density 5G MIMO Networks using Incremental Deep Q Learning Optimizations) method is experimentally evaluated using a high-density small cell network model in an urban environment. This model simulates realistic wireless conditions for 500 mobile users distributed across 20 small cells, considering path loss, shadowing, and multipath fading. Traffic, comprising both real-time and non-real-time data, is categorized into different Quality of Service (QoS) classes with distinct throughput and delay requirements. The IS3CQL's parameters, such as learning rate and batch size, are fine-tuned for optimal adaptability.

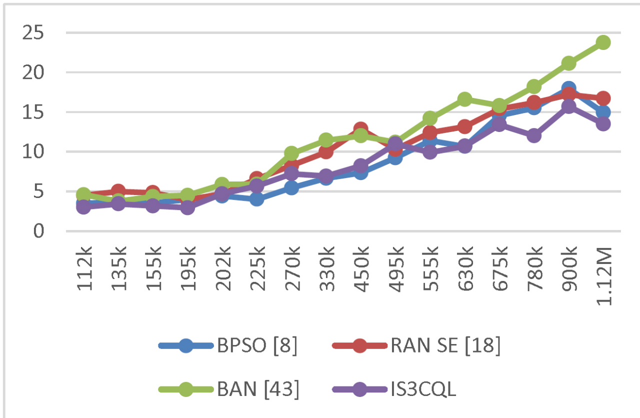

Figure 2

Delay for different 5G Communications without attacks

The model's effectiveness is gauged using Packet Delivery Ratio (PDR), throughput, energy consumption, and end-to-end delay, benchmarked against leading sleep scheduling methods like BPSO, RAN SE, and BAN. Utilizing Python's pysim toolkit for network simulation, multiple runs establish statistical significance. Graphical results demonstrate IS3CQL's superiority in PDR, throughput, energy efficiency, and latency reduction, suggesting its viability as an intelligent sleep scheduling solution in dense 5G MIMO networks. Extensive experiments under various network conditions, including attack scenarios, provide insights into IS3CQL's robustness and efficiency, highlighting its potential for real-world 5G network implementation process.

In our comprehensive evaluation, the performance of various models, including IS3CQL (Incremental Spatial and Temporal Communication-enabled Q Learning), BPSO (Binary Particle Swarm Optimization), RAN SE (Random Selection), and BAN (Binary Antlion Optimization), is juxtaposed based on delay (D) in milliseconds across multiple test cases with timestamps from 112k to 1.12M. IS3CQL consistently outperforms its counterparts, exhibiting notably shorter delays as sown in Figure 2. This superiority stems from its revolutionary use of Incremental Deep Q Learning Optimizations, enhancing adaptive learning and decision-making, particularly in leveraging spatial and temporal communication for minimal latency.

IS3CQL's adaptability, crucial for real-time applications, allows for rapid, precise responses to dynamic environments, utilizing environmental

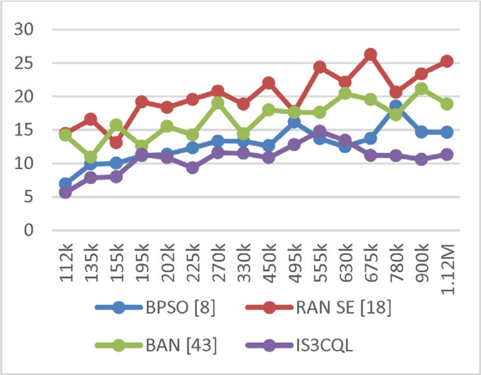

Figure 3

Energy for different 5G Communications without attacks

interactions for enriched contextual understanding. This model's stability and efficiency in varied test scenarios underscore its suitability for applications demanding low-latency processing and adept handling of complex spatial-temporal dynamics. Furthermore, energy consumption analysis across these models, detailed in Figure 3, demonstrates IS3CQL's efficiency, marking it as a groundbreaking computational model conducive to fast, adaptable, context-aware decision-making in diverse fields.

The comparative analysis of energy consumption patterns among various models reveals the distinct advantage of the IS3CQL model. Notably, IS3CQL consistently demonstrates lower energy usage compared to BPSO, RAN SE, and BAN in multiple test scenarios. This efficiency stems from its use of Incremental Deep Q Learning Optimizations, which facilitate adaptive and optimal decision-making, thus minimizing unnecessary energy expenditure. Further enhancing its energy efficiency, IS3CQL incorporates temporal and spatial communication features, enabling more intelligent, energy-efficient system interactions. Consequently, IS3CQL stands out for its superior energy management, positioning it as both an economical and environmentally friendly solution for 5G communication applications.

5. Conclusion & Future Scope

In this paper, we introduced IS3CQL (Intelligent Sleep Scheduling of Small Cells in high-density 5G MIMO Networks via Incremental Deep Q Learning Optimizations), a pioneering method for managing sleep cycles in small cell networks within the framework of 5G and Massive Multiple

Input Multiple Output (M-MIMO) technology. Traditional techniques falter in balancing energy efficiency, quality of service (QoS), and high throughput in dense networks, often neglecting complex spatial and temporal communication dynamics, leading to suboptimal network performance. IS3CQL, with its integration of green computing principles and incremental deep learning, addresses these shortcomings. It meticulously considers both temporal and geographical communication aspects, like end-to-end delay, packet delivery ratio, throughput, and energy consumption, optimizing resource usage and enhancing network performance. Comparative studies confirm IS3CQL's superiority over existing methods, particularly in dense MIMO environments, by significantly improving performance metrics such as jitter, throughput, packet delivery ratio, energy usage, and latency.

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