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ORIGINAL

Optimizing Energy Consumption in 5G HetNets: A Coordinated Approach for Multi-Level Picocell Sleep Mode with Q-Learning

Optimización del consumo de energía en redes de área extensa 5G: Un enfoque coordinado para el modo de reposo multinivel de picocélulas con Q-Learning

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ABSTRACT

Cell standby, particularly picocell sleep mode (SM), is a prominent strategy for reducing energy consumption in 5G networks. The emergence of multi-state sleep states necessitates new optimization approaches. This paper proposes a novel energy optimization strategy for 5G heterogeneous networks (HetNets) that leverages macrocell-picocell coordination and machine learning. The proposed strategy focuses on managing the four available picocell sleep states. The picocell manages the first three states using the Q-learning algorithm, an efficient reinforcement learning technique. The associated macrocell based on picocell energy efficiency controls the final, deeper sleep state. This hierarchical approach leverages localized and network-wide control strengths for optimal energy savings. By capitalizing on macrocell-picocell coordination and machine learning, this work presents a promising solution for achieving significant energy reduction in 5G HetNets while maintaining network performance.

Keywords: 5G; Hetnets; Energy Consumption; Energy Modeling; Sleep Mode; Machine Learning.

RESUMEN

El modo de espera de la célula, en particular el modo de reposo (SM) de la picocélula, es una estrategia destacada para reducir el consumo de energía en las redes 5G. La aparición de estados de reposo multiestado requiere nuevos enfoques de optimización. Este artículo propone una nueva estrategia de optimización energética para redes heterogéneas 5G (HetNets) que aprovecha la coordinación macrocelda-picocelda y el aprendizaje automático. La estrategia propuesta se centra en la gestión de los cuatro estados de reposo disponibles de la picocélula. La picocélula gestiona los tres primeros estados mediante el algoritmo Q-learning, una eficiente técnica de aprendizaje por refuerzo. La macrocélula asociada, basada en la eficiencia energética de la picocélula, controla el último estado de sueño, más profundo. Este enfoque jerárquico aprovecha las ventajas del control localizado y de la red para conseguir un ahorro energético óptimo. Aprovechando la coordinación macrocélula-picocélula y el aprendizaje automático, este trabajo presenta una solución prometedora para lograr una reducción significativa de la energía en redes 5G HetNets, manteniendo al mismo tiempo el rendimiento de la red.

Palabras clave: 5G; Hetnets; Consumo Energético; Modelado Energético; Modo Reposo; Aprendizaje Automático.

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INTRODUCTION

The combination of 5G and different types of networks has helped meet the increasing need for mobile data and fast data speeds. However, this improvement makes networks more complicated and uses much energy. In the future, mobile networks will become even more diverse because more devices will be used, more data will be transferred, and high-frequency networks with limited reach will be deployed more often.

While HetNets can handle more data, they also make it harder to manage energy. Some methods, like making small cells sleep when they're not needed (sleep mode), have shown promise in saving energy. But it's tricky to ensure these methods don't affect service quality. Moving from simple sleep modes to more advanced ones with different states of sleep needs a better way to determine how much energy each state uses. This is important for deciding when it's worth putting cells to sleep and when it's not. We also want to use machine learning to control sleep modes as best as possible.

Current methods for sleep mode have trouble managing energy well when there are different sleep states in HetNets. It's hard to save energy while keeping service quality high. Also, focusing only on small cells might not use energy as efficiently as possible in networks where different types of cells work together.

This study introduces a new way to save energy in 5G HetNets. It looks at how big and small cells can work together to decide when small cells should sleep. It also uses energy efficiency rules to pick the best sleep states. Machine learning techniques adjust sleep modes based on what's happening in the network.

This work contributes to the field of energy-efficient HetNet design by proposing a novel approach that leverages macrocell-picocell coordination and ML for optimal picocell sleep state control. This strategy has the potential to significantly reduce energy consumption while maintaining acceptable QoS levels in 5G networks.

Related work

SM is a technique used in mobile networks to reduce base station energy consumption significantly. By temporarily turning off non-essential functions during low-traffic periods, SM allows energy usage to adapt to real-time cell load, minimizing the amount of wasted power.[1] This approach is particularly relevant in today's context, driven by both environmental concerns and economic factors. Studies show that base stations account for a substantial portion (60-80 %) of a mobile network's energy consumption.[2]

However, a key challenge lies in the inherent energy draw of base stations, even during low-load periods. Estimates suggest that a base station can still consume 50-60 % of its maximum power under no-load or low-load conditions.[3] This highlights the need for a consumption model that dynamically adapts to cell load variations. Among various proposed solutions, SM stands out for its effectiveness. It offers a simple and readily implementable method for reducing energy consumption without requiring extensive modifications to the existing network architecture.[4] The concept of cell sleep mode was first introduced by Micallef et al.[1], who combined it with "cell size breathing" - a mechanism for dynamically adjusting cell coverage area. Advancements followed the[5] and[6], where researchers proposed putting specific resources on standby based on traffic load, ensuring minimal impact on quality of service (QoS). The emergence of heterogeneous networks (HetNets) opened new possibilities for SM. With macrocells providing full coverage, cellular monitoring could be applied at the picocell level, as explored in some studies. For instance, Frenger et al.[7] introduced Cell Discontinuous Transmission (DTX), where the radio transmitter is switched off when there's no data or reference signal to transmit.

Beyond the initial binary (on/off) sleep mode, research has focused on more granular control. The concept of Advanced Sleep Mode (ASM) with multiple sleep states emerged, facilitated by the more extended (160ms) discontinuous transmission duration introduced in 5G compared to 4G's 1ms limit.[7] Building on this concept, Debaillie et al.[8] proposed a system with four distinct sleep states, each characterized by unique activation, deactivation times, and minimum sleep durations. While multi-state sleep mode (MSSM) strategies, as proposed Saker et al.[9], offer significant energy savings at low traffic loads, they often come at the cost-of-service quality. Finding the optimal balance between energy consumption and QoS becomes crucial. As MSSM systems become more complex, choosing the ideal sleep level presents a growing challenge. Machine learning emerges as a promising solution for optimizing sleep state selection. Several studies have explored this approach. Pervaiz et al.[10] proposed an MDP-based (Markov Decision Process) control mechanism for heterogeneous networks, considering both cell load and user equipment (UE) location. Similarly, Salem et al.[11] and Masoudi et al.[12] leverage Q-learning algorithms to determine optimal sleep durations for minimizing energy consumption while respecting latency and QoS constraints. Notably, Amine et al.[13] incorporates co-channel interference into their HetNet Q-learning solution.

However, current MSSM algorithms primarily focus on optimizing sleep modes at the individual small-cell level, neglecting the overlapping coverage areas within HetNets. This is where the concept of "energy profitability" introduced by Fall et al.[14] becomes relevant. It defines a threshold below which offloading traffic to the macrocell becomes more energy-efficient for the network, considering resource availability. Ultimately, effective energy optimization strategies require maintaining QoS. As highlighted throughout these studies, robust coordination between macrocells and picocells remains essential for achieving this goal.

METHODOLOGY

Good coordination between macrocells and picocells is essential for an effective SM system. Thus, we introduced a coordinated multi-state SM mechanism, where the picocell manages the first 3 states of a picocell, and the associated macrocell manages the 4th state.

Macrocell - Picocell coordination principle

A base station must wake up periodically to send signaling bursts to communicate with the mobile terminals. The article[8] introduced 4 states of sleep: SM1, SM2, SM3 and SM4 (Table 1):

- SM1: represents the shortest SM, with a transition time of 71 μ s corresponding to an OFDM symbol. In this mode, only the power amplifier and some processing components are disabled.
- SM2: corresponds to an intermediate sleep with a transition time of 1 ms equivalent to a subframe. We have more disabled processing components here.
- SM3 corresponds to a sleep state with a transition time of 10 ms (one frame) in which all essential or processing components and the power amplifier are disabled.
- SM4: corresponds to BSM where only the wake-up functions are retained. This is the deepest sleep and requires a transition duration of 1s.

Table 1. Characteristics relating to sleep states

Sleep state	Activation time	Deactivation time	Minimal sleep time
SM1	35,5 μs	35,5 μs	71 μs
SM2	0,5ms	0,5ms	1ms
SM3	5ms	5ms	10ms
SM4	0,5s	0,5s	1 sec

Salem et al.[15] present a detailed table of the different components disabled at each state (Table 2).

Table 2. Components disabled in each mode[15]

Components	Subcomponents	SM1	SM2	SM3	SM4
Power amplifier		X	X	X	X
Baseband unit	Prewarp			X	X
	Filtering	X	X	X	X
	FFT/IFFT	X	X	X	X
	MIMO precoding	X	X	X	X
	Synchronization	X	X	X	X
	Channel estimation	X	X	X	X
	Calculation of the Equalizer	X	X	X	X
	Equalization	X	X	X	X
	OFDM Mod/ Demod	X	X	X	X
	Mapping/ Demapping	X	X	X	X
	Channel coding	X	X	X	X
Control unit	Control				
	Backhaul				
	Network				
Analog receiver	LNA	X	X	X	X
	LNA2	X	X	X	X
	Frequency synthesis		X	X	X
	Blender	X	X	X	X
	VGA	X	X	X	X
	Clock				X
	ADC			X	X

Analog transmitter	Modulator	X	X	X	X
	Buffer	X	X	X	X
	Frequency synthesis		X	X	X
	VCO Feedback		X	X	X
	Blender	X	X	X	X
	Clock				X
	DAC		X	X	X
	DAC feedback			X	X
Energy source	AC DC				
	DC/DC				
	Air conditioner				

In 5G, the CRS reference signal is no longer necessary, and synchronization signals can be transmitted with a periodicity of 5, 10, 20, 40, 80, or 160ms.[16] Based on these values, Amine et al.[17] declared that SM4 could not be used and limited their work to the first 3 states.

SM4, for its part, can be compared to the sleep state in binary mode. In the scheme proposed, this state is controlled by the macrocell, which can put the picocells to sleep (SM4) or wake them up. Amine et al.[17] would thus perfectly complement the previous work presented by Fall et al.[14] to have a complete mechanism for handling a 4-state SM: "coordinated multi-state SM." The picocells control the first 3 states (SM1, SM2, and SM3) and can transit between them autonomously. The SM4 state, on the other hand, is controlled by the macrocell, which decides which picocells to activate or deactivate. Therefore, this state is assimilated into the base station's inactive state. From the macrocell perspective, there are only two states at the picocell level, either active or in SM4 (inactive).

The defined management mechanism is based on coordination between the macrocell and the picocells. The macrocell is based on the energy profitability threshold Sre[14] to activate and put a small cell into SM4. When a small one is active, it can manage internal transitions between the active state and the SMs SM1, SM2, and SM3 through a learning algorithm that decides at each cycle (Table 3).

Table 3. State management of a small cell

	Managed States					**Transition**
	Active	**SM1**	**SM2**	**SM3**	**SM4**	
Macrocell	X				X	Safe
Small cell	X	X	X	X		Reinforced learning

Macrocell management based on energy profitability

The macrocell integrates algorithms for optimizing energy consumption based on energy profitability for deactivating unprofitable picocells or activating picocells in sleep mode (Figure 1).

At each SM4 cycle, corresponding to the minimum sleep duration for the state considered and equal to 1s, the deactivation algorithm is executed for all the picocells. It is based on the profitability threshold of picocells to decide whether to put them on standby (SM4). This evaluation frequency (1s) can be increased if traffic fluctuates slightly. Regarding picocells in SM4, their activation will depend on the charge or saturation level of the macrocell. These different parameters are grouped around the concept of load index I_c presented Fall et al.[14].

Integrating the multi-state SM at the SB of picocells can save significant energy savings. Lähdekorpi et al.[18] highlighted these savings as up to 92 % at low load or 15 % at 40 %. The following figure illustrates this new consumption curve:

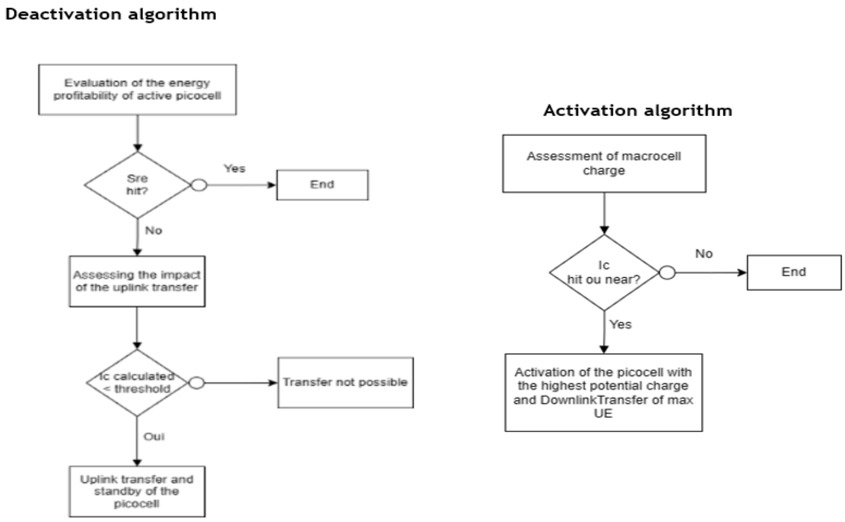

Figure 1. Picocell management algorithms

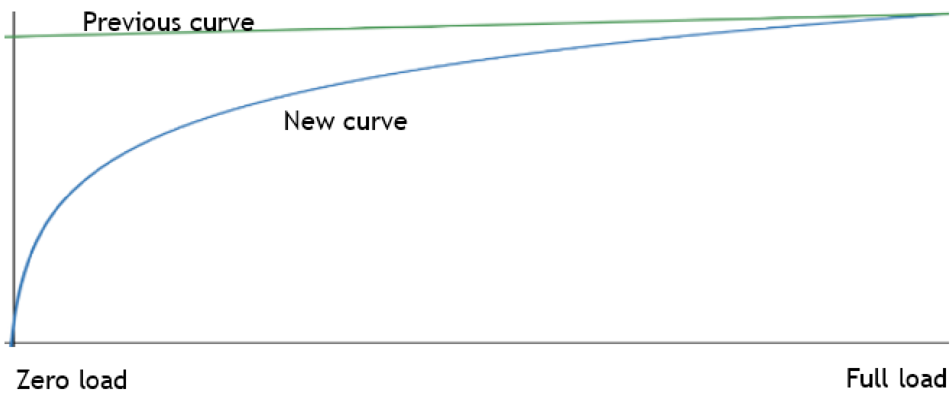

Figure 2. Picocell energy consumption curve

The new consumption curve looks like a logarithmic function, which we have modeled as follows:

$$C_p(x) = A_p \log_y(a_p x + b_p) + C_{p0} \qquad (1)$$

Where C_p represents the power consumed by the base station; A_p represents the coefficient of the logarithm function; b_p is a horizontal translation value of the energy curve; C_{p0} represents the fixed component of the power; And x represents the percentage of chargeBased on our curvature estimates, we have used the base 2 logarithm:

$$C_p(x) = A_p \log_2(a_p x + b_p) + C_{p0} \qquad (2)$$

We, therefore, need to re-evaluate the break-even point, materialized by the equality between the consumption of the macrocell C_{xm} (induced by the UEs) and that of the pico-cell C_{xp} induced by the same number of UEs.

$$C_{xm}\left(\frac{S_{re}}{N_p}\right) = C_{xp}\left(\frac{S_{re}}{N_p}\right) \qquad (3)$$

Where N_p represents the total number of UEs supported by the picocell, so we have the following equation to find S_{re}:

$$A_m \frac{S_{re}}{N_p} = A_p \log_2 \left(a_p \frac{S_{re}}{N_p} + b_p \right) + C_{p0} - C_p(0) \qquad (4)$$

Picocell management based on reinforced learning

Each picocell SB autonomously manages 3 other sleep states through a reinforced learning policy, adapted to decision problems. We have chosen the Q-learning algorithm, based on the evaluation of a state-value function Q, which links a state S to an action A, and which is updated at each iteration.[19]

Our work is thus associated with that presented by Amine et al.[17] who proposed a Q- learning algorithm which is presented as follows:

Algorithm 1 : Online Interference-Aware BS Sleeping

procedure Training ($Q_m^T(s,a)$)
Initialize the positions of the users and $q_m(s,a) = 0, \forall m \in \mathcal{M}, \forall s \in \mathcal{S}$ and $\forall a \in \mathcal{A}$.
Set the weight w, and the average user velocity.
while Learning **do**
    for $m \in \mathcal{M}$ **do**
        Visit state s_m.
        Select an action a_m using ϵ-greedy rule in (12).
        Calculate the cost c_m.
        Observe next state s'_m.
        Update the Q-value $q_m(s,a)$ from (11).
    end for
end while
end procedure

procedure Online
for $u \in$ cluster of SBSs **do**
    if $r_{MBS,u'} \geq R^{min}$ **then**
        Offload u to the MBS.
    end if
end for
for $m \in \mathcal{M}$ **do**
    $Q_m(s,a) = Q_m^T(s,a)$
    Run Q-Learning.
end for
end procedure

Figure 3. Description of the Q- learning algorithm[17]

However, a buffer must be set up in each picocell to keep incoming connection requests that find the picocell in SM.[15,4] We propose the establishment of a buffer that would store the service requests and, depending on the depth of the sleep state and the phase in which the base station is, would decide between waiting for the base station to wake up and offloading requests to the macrocell. This offloading only concerns demand and not the UE as a whole.

RESULTS AND DISCUSSION

Simulation scenarios

For our simulations, we use the environment that we defined in our article Fall et al.[14] and which is inspired by the "Urban Dense" architecture of[20], namely:

A surface of dimension 500m x 500m with a Macro BS in the center (0,0) and 25 Pico BS distributed according to a Poisson law. The BS transmits at a frequency of 2GHz. There are 100 UEs for a low load, 500 for a medium load, or 1000 for a high load: 80 % indoors at a speed of 0,3m/s and 20 % outdoors at a speed of 10m/s.

We have the following parameters (Table 4):

Table 4. Simulation parameters

Setting	Value
Simulation surface	500m x 500m
Number of MBS	01
Transmission power	43 dBm

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Number of PBS	25
Transmission power	23dBm
Bias (CRE)	6dB
MBS frequency	2GHz
Frequency of PBS	3,6GHz
Bandwidth	20 MHz
Loss Model	UMa3D and UMi3D

In[14] we presented the table below, which describes the standard energy consumption model of 5G base stations (Table 5):

Table 5. Energy consumption of 5G macro and pico BS

Base station type	Max number of UEs	Energy cost (W)		Load factor (W)
		Zero load	Sleep state	
Macro	800	780	450	564
Pico	32	40,8	25,8	3

Evaluation of the break-even point

The break-even point S_{re} is defined by the following equation:

$$A_m \frac{S_{re}}{N_m} = A_p \log_2\left(a_p \frac{S_{re}}{N_p} + b_p\right) + C_{p0} - C_p(0) \qquad (5)$$

With $\begin{cases} A_m = 564 \\ N_p = 32 \end{cases}$

$$564 \; \frac{S_{re}}{800} = A_p \log_2\left(a_p \frac{S_{re}}{32} + b_p\right) + C_{p0} - C_p(0) \qquad (6)$$

Evaluation of A_p, a_p, b_p and C_{p0}

$$C_p(x) = A_p \log_y(a_p x + b_p) + C_{p0}$$

With 3 remarkable points:

$$C_p(0) = A_p \log_2(b_p) + C_{p0} = 8\%. C(0) = 3{,}264\, W \qquad (7)$$
$$C_p(0{,}4) = A_p \log_2(0{,}4. a_p + b_p) + C_{p0} = 15\%\,. C(0{,}4) = 85\%\,(40{,}8 + 3\, X\, 0{,}4) = 35{,}7\, W \qquad (8)$$
$$C_p(1) = A_p \log_2(a_p + b_p) + C_{p0} = C(1) = 43{,}8\, W \qquad (9)$$

Where C_p represents the consumption function of a picocell without multi-state SM. We have the following system of equations:

$$\begin{cases} A_p \log_2(b_p) + C_{p0} = 3{,}264 \\ A_p \log_2(0{,}4. a_p + b_p) + C_{p0} = 35{,}7 \\ A_p \log_2(a_p + b_p) + C_{p0} = 43{,}8 \end{cases} \qquad (10)$$

We consider C_{p0} it is to be the fixed component at zero load. So, we have:

$$\begin{cases} C_{p0} = 3{,}264 \\ \log_2(b_p) = 0 \rightarrow b_p = 1 \\ A_p \log_2(0{,}4.a_p + b_p) + C_{p0} = 35{,}7 \\ A_p \log_2(a_p + b_p) + C_{p0} = 43{,}8 \end{cases} \quad (11)$$

$$\begin{cases} C_{p0} = 3{,}264 \\ b_p = 1 \\ A_p \log_2(0{,}4.a_p + 1) = 32{,}436 \\ A_p \log_2(a_p + 1) = 40{,}536 \end{cases} \quad (12)$$

$$\frac{\log_2(0{,}4.a_p + 1)}{\log_2(a_p + 1)} = 0{,}80017762 \quad (13)$$

$$\begin{cases} C_{p0} = 3{,}264 \\ b_p = 1 \\ A_p = 6{,}239 \\ a_p = 89{,}294 \end{cases} \quad (14)$$

The equation becomes:

$$564\,\frac{S_{re}}{800} = A_p \log_2\left(a_p \frac{S_{re}}{32} + b_p\right) + C_{p0} - C_p(0) \quad (15)$$

$$0{,}113\, S_{re} = \log_2(2{,}790\, S_{re} + 1) \quad (16)$$

$$S_{re} = 66{,}818 \quad (17)$$

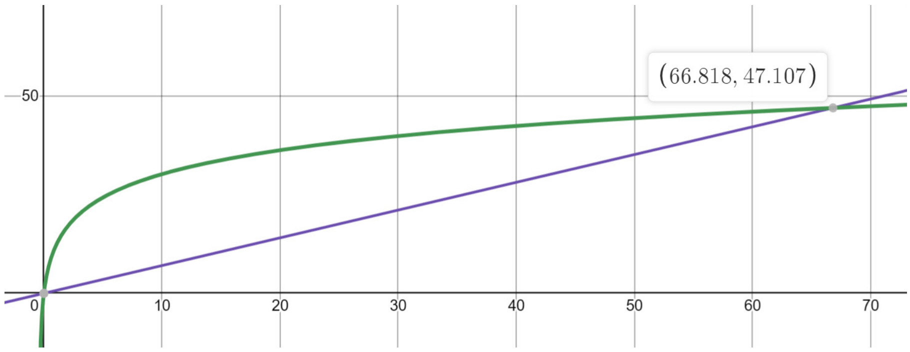

Figure 4. Evaluation of the energy profitability threshold

With BSM, the break-even point S_{re} was 25 UEs, while with ASM, it is 69. This is because ASM is more efficient, so most of the energy consumed by the picocell is associated with the UEs. In contrast, with BSM, the picocell consumed almost all of its maximum energy, even at zero load or in SM. The energy consumption per UE is very low: 0,705W for a microcell UE and 1,369W for a picocell UE.

Therefore, the main reasons for deploying picocells are not energy-related but are instead focused on improving throughput and capacity. For picocells to be energy-efficient, the energy consumption per UE (C_{up}) must be lower than that for the macro-cell (C_{um}).

We note this factor k:

$$k = \frac{C_{um}}{C_{up}} \quad (18)$$

Table 6. Break-even threshold values as a function of k

k	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
S_{re}	69	27,87	16,35	11,04	8,06	6,178	4,898	3,979	3,293	2,763	2,345	2,008	1,732	1,502	1,308	1,143	1,001	0,879	0,772	0,678

The main motivation for deploying picocells could be reducing energy consumption if we lower the factor k to 18, making S_{re} equal to 1. This would make picocells profitable regardless of their load. Even below this factor of 18, reducing energy consumption can still be a goal, considering the average load of picocells relative to the break-even threshold. If the average load of picocells is below this threshold, deploying picocells can be seen as aiming to reduce energy consumption.

Simulation results

Fall et al.[14] presented our energy consumption optimization algorithm (AOCE), compared to Max-SINR,[21] CRE (Cell Range Expansion)[22] and the energy optimum, which represents the theoretical minimum consumption. With this new coordination, integrating multi-state SM, we have AOCE2 which represents its version 2.

Introducing ASM, along with macrocell-picocell coordination, maximizes energy optimization. At low load, as shown in figure 5, the ECOA (ASM) aligns with the optimal (ASM) because all UEs are connected to the macrocell. This happens because the break-even threshold exceeds the maximum number of UEs a picocell can handle, making the UE-macrocell association more efficient than the UE-picocell association. For the same reason, the MaxSINR association mode is more economical than the CRE mode.

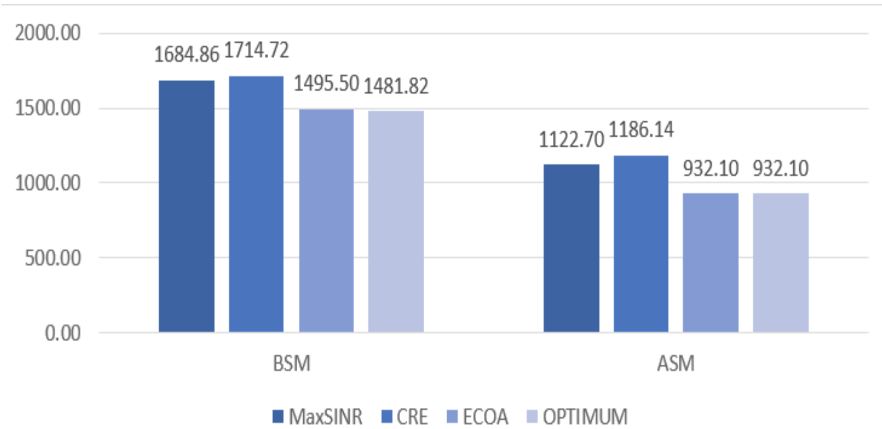

Figure 5. Energy consumption at low load

At high load, as shown in figure 6, the difference in energy consumption between BSM and ASM naturally decreases, and the likelihood of using SM is lower. There is a noticeable difference between the ECOA and the optimal scenario in ASM. The picocells become loaded with the number of UEs exceeding the macrocell's maximum capacity. In this situation, achieving an optimal configuration is nearly impossible due to the saturation of active picocells. However, the ECOA remains close to optimal, with only a 7,45 % increase in consumption.

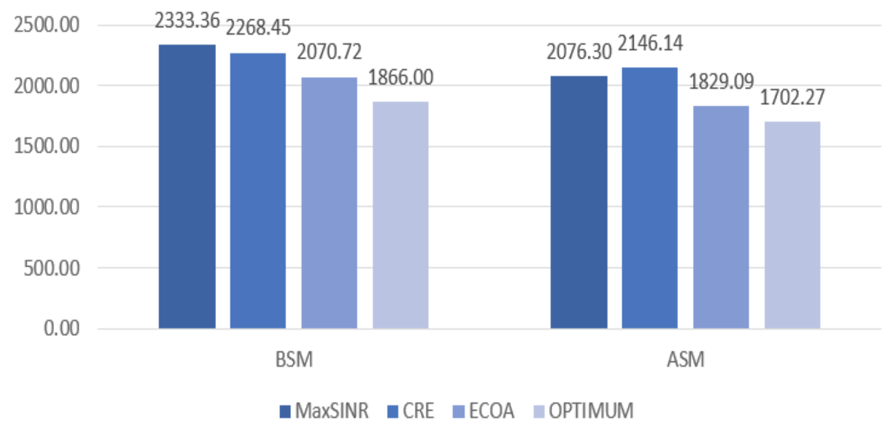

Figure 6. Energy consumption at high load

Coordination assessment

The new ECOA2 algorithm combines the benefits of ASM, limited to state 3 of SM, with the advantages of coordinated cellular association from our previous article, which extends to state 4. This allows for optimal use of picocell SM (see Table 7).

Table 7. Energy savings compared to MaxSINR BSM

	100 UEs	500 UEs	1000 UEs
ECOA 1	11,24 %	15,28 %	11,26 %
MaxSINR ASM	33,37 %	17,88 %	11,02 %
ECOA 2	44,68 %	41,15 %	21,61 %

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The algorithm can save up to 45 % energy compared to traditional cellular selection with BSM. Most of the savings come from ASM; a picocell can reduce energy consumption by 92 % at zero load. However, the impact of coordination is less significant due to the low number of UEs. As the load increases, the energy savings from ASM decrease because of the logarithmic nature of the consumption curve. At 40 % load, ASM savings drop from 92 % to 15 %. Conversely, as the load increases, the coordination between the macrocell and picocells becomes more crucial, leading to greater energy savings. The reduction mechanisms near their limits at high load levels, and potential savings become increasingly minimal.

Figure 7 illustrates the energy consumption at low, medium, and high loads. The ECOA ASM effectively optimizes energy consumption across these different loads. However, it's essential also to consider other metrics such as QoS and throughput.

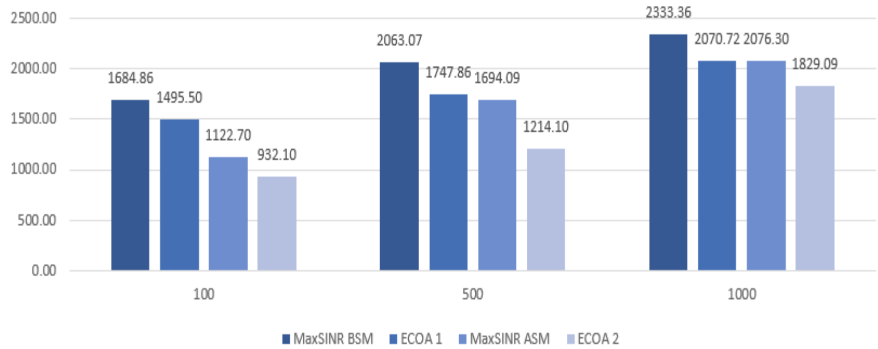

Figure 7. Energy consumption at 100, 500, and 1000 UEs

Figure 8 shows the average throughput per UE at low, medium, and high loads. ECOA ASM has a smaller average throughput at low load compared to ECOA BSM. Its throughput is notably lower at medium load because the UEs are associated with the macrocell, preventing the picocells from reaching their break-even point. ECOA ASM also has a lower average flow rate at high load, as the macrocell is fully utilized before the picocells are engaged. The high profitability threshold, which exceeds the picocell's maximum capacity, negatively impacts throughput and overall quality of service. Since picocells perform better than macrocells, the break-even point must be reduced to optimize energy and improve QoS. However, ECOA ensures QoS by allowing uplink transfers only when certain metric limits defined by the load index in the article, subject to compliance with certain metric limits defined through the load index present by Salem et al.[15], are met.

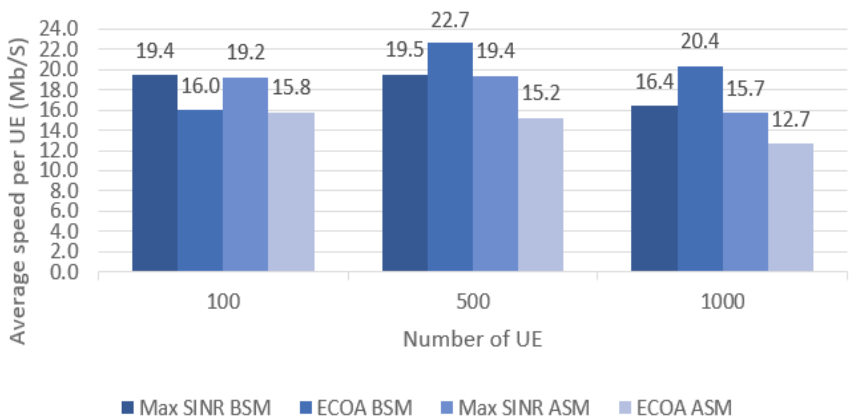

Figure 8. Average throughput per UE at various loads

CONCLUSION

This paper presented a novel approach to tackle the growing energy consumption challenge in 5G networks. Focusing on heterogeneous networks with macrocells and picocells, we proposed a coordinated multi-state sleep mode (SM) strategy that combines two established techniques: Advanced Sleep Mode (ASM) and macrocell-picocell coordination for cell selection.

We developed a new logarithmic energy consumption model for picocells to achieve this. This model and implementation of Q-learning, a machine learning algorithm, allowed for dynamic and efficient management of ASM states within picocells. Additionally, a new energy profitability threshold was calculated for picocells to guide macrocell coordination decisions. This comprehensive approach, named "coordinated multi-state SM," leverages the full potential of sleep states and macrocell-picocell collaboration, resulting in significant energy savings of up to 45 %.

While this work demonstrates the effectiveness of coordinated multi-state SM, further research holds promise for even more significant energy efficiency gains. One key area of focus lies in optimizing the hardware components within picocells. By exploring more energy-efficient hardware designs, we can further minimize the energy consumption associated with user equipment (UE)-base station links. This optimization would maximize the overall benefits achieved through macrocell-picocell coordination. Additionally, investigating more advanced coordination algorithms between macrocells and picocells has the potential to unlock even more significant energy savings.

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