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RESEARCH ARTICLE

# Towards Sustainable 5G Networks: A Proposed Coordination Solution for Macro and Pico Cells to Optimize Energy Efficiency

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**ABSTRACT** The 5th generation of mobile communications, currently being rolled out, aims to improve network performance and efficiency over the older generations. With mmWaves, densified cell deployment is necessary for 5G networks, increasing capacity and improving network coverage. This imposes a considerable increase in the energy consumption of the 5G stations, which not only increases operating expenses for operators but also burdens the environment. Optimizing the energy consumption of 5G networks would be necessary to curb the energy curve. In this context, this paper presents a new algorithm called Energy Consumption Optimization Algorithm (ECOA), which combines cell selection and standby techniques to optimize energy consumption while preserving network performance. A comparison is conducted between ECOA and standard cell selection modes to evaluate the performance of the conventional approach. Our algorithm exhibits good performance, particularly in high-density, high-load scenarios. For instance, in a site with 25 Pico base stations serving 500 users, our algorithm achieves an average throughput of 23 Mb/s per user while consuming 1750.75 W of energy. This represents a 2.44% increase in energy consumption compared to the optimal solution.

**INDEX TERMS** 5G, cell selection, ecology, energy consumption, energy efficiency, hetnet, optimization, UE-BS association.

## I. INTRODUCTION

The strong growth of users and volumes of data exchanged has led to increased energy expenditure in mobile networks. One of the objectives of 5G is to significantly improve energy efficiency to slow down the evolution of the energy curve observed generation after generation within networks. The ''green domain'' is a new development stage focusing on protecting the environment through energy-efficient wireless networks. Radio networks consume about 80% of energy, with base stations alone accounting for over 50% of the total energy usage [1], [2]. Numerous studies have focused on optimizing base station design to improve energy efficiency. Some studies have proposed algorithms for task offloading in mobile edge computing networks and resource allocation schemes in 5G ultra-dense networks to optimize energy consumption. However, excessive use of edge computing resources may increase energy consumption, necessitating solutions to reduce the energy consumption of these resources. Other studies have proposed massive MIMO, lean carrier design, advanced idle modes, and artificial intelligence capabilities for maximizing both spectral efficiency (SE) and energy efficiency (EE) in 5G networks [3].

In [4], researchers propose a new model to accurately evaluate and optimize 5G base stations (BSs) power consumption. The model uses machine learning and data collected from a large-scale campaign. The proposed model is expected to be

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a fundamental tool for optimizing network energy efficiency and understanding the power consumption of 5G BSs.

These studies demonstrate promising approaches to improving energy efficiency in 5G networks, particularly in base stations and radio interfaces.

5G deployments consist mainly of macro stations associated with pico or femto base stations. One of the critical solutions to the energy consumption problem is associating mobile users with a Macro, a Pico, or a Femto base station, especially controlling this choice's impact on the base stations' energy consumption.

Various association strategies are based on cell selection or load balancing algorithms; however, the problem of conventional load balancing should only arise when the network is heavily loaded or overloaded [5]; otherwise, even if it remains essential, energy efficiency must also be taken into consideration by the 5G optimization algorithms. Ideally, these two issues should be combined to define algorithms that simultaneously consider these constraints and contextually prioritize one over the other.

The main objective of this article is to study the impact of the UE-BS association strategy or cell selection on energy consumption and thus propose a low-complexity UE-BS association algorithm that takes this constraint into account.

The originality of our approach lies in the fact that we want to offer a low-complexity algorithm that can be implemented autonomously to optimize energy consumption without degrading other metrics.

Our solution uses a cell selection algorithm based on the energy efficiency of UE-BS association and cell load to reduce the transmit power of active and standby base stations, leading to higher energy efficiency and network capacity.

The rest of this paper is organized as follows. Section II presents several related works on cell selection algorithms that aim to improve network performance and optimize energy efficiency. Section III introduces the main problem of this article and provides a modeling of 5G cells' energy consumption, demonstrating the impact of cell load and UE-BS association constraints on energy efficiency optimization. Section IV presents our new low-complexity algorithm for optimizing energy consumption in 5G networks. Section V provides the scenarios and parameters used in the simulations and details the results, including analysis and comparison of the newly developed algorithm's performance with those in the literature. Finally, the last section summarizes the work's findings and provides a conclusion.

## II. RELATED WORK

The "green domain" concept refers to a new stage of development that seeks to protect the environment by optimizing energy consumption. In light of this, there is a growing demand for energy-efficient wireless networks that aim to reduce operating expenses and minimize power usage in the telecommunications infrastructure. Studies show that radio networks account for around 80% of energy consumption, making it critical to focus on reducing energy consumption in this area. It is also a general consensus that base stations (BSs) consume substantial energy, making up over 50% of the total energy usage in a cellular network [2]. As such, optimizing power usage in BSs with a focus on environmental considerations is necessary.

Numerous researchers have dedicated significant efforts to studying BS design problems in cellular networks, with a substantial amount of published work focused on optimizing performance and energy efficiency. In [6], the authors present an algorithm for dependent task offloading in mobile edge computing networks that optimizes the tradeoff between energy consumption and task latency. The algorithm uses subtask-dependent graphs (SDGs) to model general task topologies with dependencies among subtasks and considers execution constraints of special subtasks. By jointly optimizing the task latency and energy consumption of devices using a weighted sum, the proposed algorithm optimizes the scheduling sequence and decision of subtasks while ensuring logical dependence of subtasks. The simulation results show that with the proposed algorithm, it is possible to reduce latency from 0.75 ms to 0.5 ms with a 10% increase in energy consumption due to parallel task processing at the edge. In [7], the authors propose a mobile edge computing (MEC) based task offloading and resource allocation scheme in 5G ultra-dense networks (UDN). The algorithm aims to address the high computing demand for new-generation mobile applications while attempting to reduce energy consumption. The results show that the algorithm effectively increases users' quality of service (QoS). However, the algorithm's efficiency in optimizing energy consumption decreases as the number of users in the cell increases.

While these methods focus on improving users' QoS, it is essential to note that excessive use of edge computing resources may increase QoS at the cost of increased energy consumption. Therefore, it is essential to propose solutions to reduce the energy consumption of these edge resources.

In [8], the authors propose a load balancing-based, software-defined, multi-objective optimization routing protocol to optimize energy consumption in 5G mobile access networks. The protocol enhances security by classifying data using deep belief Boltzmann neural network. The proposed technique achieved a high throughput of 92%, a packet delivery ratio of 88%, and high network routing energy efficiency. However, it is essential to note that this technique optimizes energy consumption only in the routing part of the access network and does not present energy optimization solutions in the Radio Base Station part, constituting the greatest energy consumption in the access network. Therefore, the Radio Base Station part needs additional energy optimization solutions to achieve overall energy efficiency in 5G mobile access networks.

In [9], the authors present a framework for maximizing spectral efficiency (SE) and energy efficiency (EE) using ultra-dense in-building small cells for 5G and beyond mobile systems. The framework exploits the four most interconnected domains for SE and EE: power, time, frequency, and space. The paper describes the framework and derives system-level performance metrics for SE and EE. An algorithm is developed, and an extensive performance evaluation is carried out to show the impact of each domain on SE and EE. The paper also defines an upper limit for reusing the same spectrum in a building in terms of horizontal spatial reuse of the spectrum. Depending on the environment and building profiles of a particular area, horizontal, vertical, or both spatial reuse of spectrum can be exploited to achieve both SE and EE targets. Overall, this framework offers a promising approach to achieve both SE and EE targets in ultra-dense in-building small cells for 5G and beyond mobile systems. It's important to note that this technique can offer a specific solution for ultra-dense in-building small cells and does not provide a general solution for the entire 5G access network.

Other research work primarily focuses on reducing energy consumption in base stations, especially in the radio interface. Research in [10] and [11] has researched optimizing energy efficiency for service transmissions with heterogeneous latency requirements in the flexible 2-dimensional resource allocation of 5G wireless technology. They have proposed a sliding window-based algorithm that utilizes frequency-selective resource allocation and an ''on-off'' operation of the power amplifier to maximize energy efficiency while meeting varying quality of service requirements. Their findings indicate that this proposed algorithm can achieve up to a 16.7% reduction in power consumption compared to other baseline systems. This research provides valuable insights into improving energy efficiency for various 5G wireless technology service transmission requirements. In [11], the authors introduce a novel approach to enhance MU-MIMO systems' energy efficiency and capacity rate. The proposed system, which employs norm-based user and antenna selection, outperforms existing user-based systems by 43% in sum rate and 19% in energy efficiency for 100 users. This study presents a promising solution for enhancing MU-MIMO systems' energy efficiency and capacity rate.

The study in [2] proposes a modified Real-coded Genetic Algorithm (RGA) for optimizing the positioning of 5G base stations to achieve optimal coverage while minimizing power consumption. The study's results demonstrate the potential of the modified RGA method to significantly improve the energy efficiency and coverage of 5G networks. However, it is essential to note that the study does not consider the practical challenges associated with the constrained positioning of cells in real-world scenarios. Despite this limitation, the study's findings offer valuable insights into the role of location intelligence and green communications in designing and deploying 5G networks, with potential implications for reducing operating expenses and minimizing power usage in the telecommunications infrastructure.

In [12], researchers investigate various energy optimization techniques and focus on the potential of massive MIMO (mMIMO) as a solution for improving energy efficiency in future wireless networks. The article discusses the architecture, operation, and requirements of mMIMO and evaluates its performance using different precoding algorithms. Furthermore, the article explores using machine learning to switch off underused mMIMO arrays and minimize energy usage. Finally, the article highlights open research issues in mMIMO and machine learning for future research and implementation in next-generation wireless networks.

In [13], the authors discuss the challenges posed by deploying 5G Ultra-Dense Networks (UDNs) and explore the potential of using reinforcement learning to optimize energy consumption. They propose a sleep mode management system based on State-Action-Reward-State-Action (SARSA) that uses specific metrics to find the best tradeoff between energy reduction and QoS constraints. Simulations show that in low-traffic load scenarios, energy savings of up to 80% can be achieved with a minimal impact on latency if a reduction in energy consumption is preferred over QoS. However, if QoS is preferred, the maximum energy savings reach only up to 5% with a minimal impact on latency. The study highlights the significant role of AI and machine learning in developing next-generation mobile networks that prioritize energy efficiency. However, implementing reinforcement learning requires significant amounts of data and real-world scenarios, and the complexity of the model and training can be challenging.

One technique widely studied for optimizing energy consumption in radio access networks is the association between the base station (BS) and users. Previous studies have proposed various algorithms or methods of UE-BS association with the primary objective of load balancing, quality of service, spectral efficiency, and moderate energy efficiency [14], [15]. However, in heterogeneous networks, traditional association techniques such as Max-SINR or maximum achievable throughput, which rely mainly on the power received by the mobile, are no longer suitable due to the differences in transmission power between macrocells and small cells. This often results in most associations being made with macrocells [16]. To address this issue, authors in [17] proposed a cell selection heuristic algorithm that maximizes energy efficiency based on network metrics. In addition, [18] developed an association method that minimizes power consumption through a heuristic algorithm on a generalized quadratic assignment problem.

Similarly, the authors in [19] based their energy optimization algorithm on defining a cost function that assigns a weight to each user based on the available BS [20]. While these proposed algorithms offer energy efficiency, they can also lead to the degradation of other performance metrics, such as latency and achievable throughput. Furthermore, the complexity of these algorithms may increase implementation difficulties and impact the network load. In the table below, you will find a summary of the strengths and weaknesses of the techniques discussed.

Based on previous research, our work focuses on proposing a low-complexity algorithm to optimize energy consumption in 5G networks. The algorithm is based on cellular cell selection and association techniques and also incorporates the ''standby'' state of underloaded cells while ensuring the QoS of mobile users.

## III. SYSTEM MODEL AND PROBLEM FORMULATION METHODOLOGY

### A. PROBLEMATIC

The ecological footprint of mobile networks has placed energy issues at the heart of 5G research, particularly those aimed at defining cell selection algorithms. Energy efficiency has thus become a significant issue in cell selection. The algorithms used in the first generations had signal strength as their primary metric. With the advent of heterogeneous networks and power disparities between macrocells and small cells, they have become increasingly complex, integrating new metrics such as quality of service, spectral efficiency, energy efficiency, and latency.

Our work focuses on proposing a low-complexity algorithm to optimize energy consumption in 5G networks. To do this, we make a model of the energy consumption of a base station to expose the different constraints of associations present in 5G. Then we introduce two new concepts, the energy break-even point, and the load index. Finally, we give a detailed presentation of our new proposed algorithm.

### B. ENERGY CONSUMPTION MODELING

The consumption of a base station can be modeled using an affine function, with the station load as a variable.

$$C(x) = Ax + B \tag{1}$$

where C is the power consumed by the base station, and A is the load factor of the base station. B is the zero-load power, and x is the percentage of charge.

The authors of [21] highlight the impact of base station loading on power consumption for each 4G cell type. This research shows that the energy consumption of BS Macrocells is more sensitive to load than BS Picocells. This is explained by the size of the Macrocells and the transmission power required for that cell type. Table 2 details the energy costs of base stations for Macrocells and Picocells related to 4G.

We can thus model the energy consumption for any cell through the following formulas:

$$C_m(c) = C_{o_m} + F_m \times c \tag{2}$$
$$C_p(c) = C_{o_p} + F_p \times c \tag{3}$$

where $C_m$ *and* $C_p$ represent respectively the power consumed by the BS of the Macrocell and the Picocell, $C_{o_m}$ *and* $C_{o_p}$ represent respectively for each type of cell the power consumed at zero loads, and $c$ represents the charge percentage.

**TABLE 1. Summary of techniques for energy consumption optimization in mobile wireless networks.**

| Ref. | Technique | Strengths | Weaknesses |
|---|---|---|---|
| [6] | Dependent task offloading in mobile edge computing networks | Optimizes tradeoff between energy consumption and task latency | May increase energy consumption due to excessive use of edge computing resources |
| [7] | MEC-based task offloading and resource allocation scheme in 5G UDN | Increases QoS of users | Efficiency decreases as the number of users in the cell increases |
| [9] | Framework for maximizing SE and EE in ultra-dense in-building small cells for 5G and beyond mobile systems | Exploits power, time, frequency, and space domains for SE and EE | Offers a specific solution for ultra-dense in-building small cells (not suitable for any network) |
| [8] | Load balancing-based, software-defined, multi-objective optimization routing protocol in 5G mobile access networks | Enhances security and achieves high network routing energy efficiency | Does not present energy optimization solutions in the Radio Base Station part. |
| [10] | Sliding window-based algorithm for energy efficiency in service transmissions with heterogeneous latency requirements in the flexible 2-dimensional resource allocation of 5G wireless technology | Maximizes energy efficiency while meeting varying quality of service requirements | It only optimizes the radio amplifier and doesn't consider the optimization of all the resources of the base station, including the power supply and computational units. |
| [11] | Norm-based user and antenna selection for enhancing energy efficiency and capacity rate in MU-MIMO systems | Outperforms existing user-based systems in terms of sum rate and energy efficiency | Specific to MU-MIMO systems |
| [2] | Modified Real-coded Genetic Algorithm for optimizing 5G base station positioning | Achieves optimal coverage while minimizing power consumption | Limited to optimizing the positioning of 5G base stations |
| [12] | Massive MIMO and machine learning | Incorporates machine learning to switch off underused arrays and minimize energy usage | Requires significant infrastructure investment and May not be suitable for all network scenarios |
| [13] | Reinforcement learning-based sleep mode management system | Uses specific metrics to find the best tradeoff between energy reduction and QoS constraints | Implementation requires significant amounts of data and real-world scenarios, and also the complexity of the model and training can be a challenge |
| [18,19] | UE-BS association algorithms (Cell selection heuristic algorithm) | Maximizes energy efficiency based on network metrics Assigns weight to each user based on the available BS | This may lead to the degradation of other performance metrics; increased complexity may impact implementation difficulties. |

**TABLE 2.** Power consumption of 4G Macro and Pico BS.

| Type of base station | Maximum number of UEs | Energy cost (W) | | Load factor (W) |
|---|---|---|---|---|
| | | Zero load | Standby state | |
| Macro | 800 | 260 | 150 | 188 |
| Pico | 32 | 13,6 | 8,6 | 1 |

The study [22] published in the Huawei 5G white paper shows that the average power consumption of a BS 5G is about 300% to 350% greater than that of 4G BS. This study used field data from a Chinese operator to compare the average energy consumption between a 4G BS and a 5G BS at different load levels. Table 3 compares the average power consumed by the 5G BS with the 4G BS at different load levels.

**TABLE 3.** Comparison of the average power consumption of a 4G and 5G base station.

| Traffic load | 4G | 5G | 4G/5G Energy Consumption Ration |
|---|---|---|---|
| 100% | 1044.72W | 3674.85W | 5G/4G = 3.5 |
| 50% | 995.06W | 2969.97W | 5G/4G = 3 |
| 30% | 949.22W | 2579.83W | 5G/4G = 2.7 |
| 0% | 837.21 | 2192.57W | 5G/4G = 2.6 |

The levels of data collection on the energy consumption of 5G base stations do not make it possible to establish an exact model considering the capacity and the different specificities of 5G. However, the studies' results suggest an average consumption multiplied by 3. This justifies the energy consumption table of a 5G BS, which we use in our simulations (Table 4).

**TABLE 4.** Energy consumption of BS Macro and Pico 5G.

| Type of base station | Maximum number of UEs | Energy cost (W) | | Load factor (W) |
|---|---|---|---|---|
| | | Zero load | Standby state | |
| Macro | 800 | 780 | 450 | 564 |
| Pico | 32 | 40,8 | 25,8 | 3 |

### C. UE-BS ASSOCIATION CONSTRAINTS

In heterogeneous 5G networks, we cannot turn off the BS of the Macrocells, and only the Picocells can see their base station turned off. Several optimization constraints can be noted based on the energy consumption models of the BS of Macrocells and Microcells.

The unit energy cost relative to the association with a UE is more critical for a Macrocell than a Picocell. It is, therefore, appropriate to associate a new UE with a Picocell. Only a Picocell can be powered off, unlike a Macrocell. Therefore, in the next part of this section, the UE and BS Picocell associations allow only optimization of energy consumption from a certain number of UEs, called the energy break-even point.

Regarding energy, the optimal states of the Picocells are the off, the standby, or the saturated state. In other words, as soon as you turn on a Picocell, transferring as many UEs as possible without altering the UEs QoS is better.

A UE associated with the BS of the Macrocell costs much more energy than being associated with a Picocell. This unit energy cost makes it preferable to associate the UEs with the BS of the Picocells, from an energy point of view, considering direct consumption.

As the picocells can be put on standby, the energy cost at zero charges is associated with the UEs of the Picocells. A Picocell is only energy-efficient from a certain number of associated UEs, called the energy break-even point. We have:

$$C_{u_m} \times S_{re} = C_{u_p} \times S_{re} + C_{o_p} - C_{mv} \tag{4}$$

where $C_{u_m}$ and $C_{u_p}$ represent the unit energy cost of a UE-BS combination for the Macrocell and the Picocell. $C_{mv}$ represents the energy consumption of a standby picocell. $S_{re}$ represents the energy break-even point of the Picocell, which means that the number of associated UEs at which the energy cost of the whole would be less than if the whole were associated with a Macrocell.

$$\begin{aligned} C_{u_m} \times S_{re} - C_{u_p} \times S_{re} &= C_{o_p} - C_{mv} \\ S_{re}(C_{u_m} - C_{u_p}) &= C_{o_p} - C_{mv} \\ S_{re} &= \frac{C_{o_p} - C_{mv}}{C_{u_m} - C_{u_p}} \end{aligned} \tag{5}$$

The energy efficiency of a small cell is thus defined as the ability to serve the user equipment while consuming less energy compared to the association with the Macrocell.

In an initial configuration, only the BS of the Macrocells needs to be active, with the BS of the Picocells being put to sleep. It is necessary to monitor the level of charge of the Macro BS. The first UEs thus be directly associated with Macrocells.

For a given Macrocell, the UEs of its coverage area are associated with it as long as it can satisfy them without the quality of service degradation. This decision is managed by the load index based on the BS's capacity to meet the UEs' demand. This index named $I_c$ must meet the following requirements:

$$I_c = 0,5 \quad when\ r_{EU} = d_{EU} \tag{6}$$

$$I_c = 1 \quad when\ r_{EU} = 0 \tag{7}$$

$$I_c = 0 \quad when\ r_{EU} = \infty \tag{8}$$

With $d_{EU}$ the bit rate request of the UE and $r_{EU}$ *is* the possible response defined by the BS.

These different requirements allow us to define the load index as a function with values between 0 and 1 and inversely proportional to the UE requests. This allows us to define the load index as follows:

$$I_c = \frac{d_{EU}}{d_{EU} + r_{EU}} \tag{9}$$

The index $I_c$ is defined to measure the satisfaction of the speed request made by the User Equipments (UEs) in the 5G enhanced Mobile Broadband (eMBB) case. It serves as a metric to assess how well our proposed algorithm meets the speed requirements of the UEs. It is important to note that while the current formulation of the index focuses on the eMBB use case, it can be adapted and extended to accommodate other 5G use cases, such as Massive Machine-Type Communications (mMTC) or ultra-reliable low latency communications (URLLC).

## IV. PROPOSED SOLUTION

The algorithm we propose aims at minimizing the energy consumption of the base stations, BS Macrocell (BSm) and BS Picocell (BSp), through a cellular association based on the energy efficiency of BSp and the load of BSm. Figure 1 shows the diagram of our proposed algorithm.

When a UE solicits an association in each Macrocell, the first step is to analyze the UE metrics, especially bandwidth demand in the EMBB case, to find a cost-effective BSp that can serve it. If such a BSp, the UE shall associate with it; otherwise, the BSm load index is evaluated. If it is greater than the defined threshold, a Picocell wake-up algorithm is executed to release the resources of the BS Macro by a downward transfer of the users. This involves scanning the metrics of the UEs connected to the BSmin to choose the BSp to wake up and perform a downlink transfer of the UEs. But If there is no BSp available, the UE joins the BSm.

We also offer optimization functions to keep overall consumption at or near optimal levels. Figure 2 shows the diagram of our energy consumption optimization Algorithm.

The energy optimization algorithm, which can be run periodically, scans the BSps of a Macrocell to identify those below the defined break-even point. An assessment of the impact of an up transfer of the US of this BSp Is then carried out to be able to put it on hold. All the UEs are transferred to the BSm if the load index $I_c$ is below the defined threshold; otherwise, the transfer is impossible.

$$I_c = \frac{d_{EUs}}{d_{EUs} + r_{EUs}} \tag{10}$$

where $d_{EUs}$ *and* $r_{EUs}$ represent respectively the overall demand of the UEs to be transferred, and $r_{EUs}$ the overall response of the BS.

When a BSp sees its load fall less than Sre, an up transfer of the UEs can be made if the calculated load index does not exceed the defined threshold.

In this way, we want to measure the impact of the UE-BS association mode on BS's energy consumption. We have two expressions of energy consumption depending on the selection algorithm: when BSps can be put to sleep and when they cannot be.

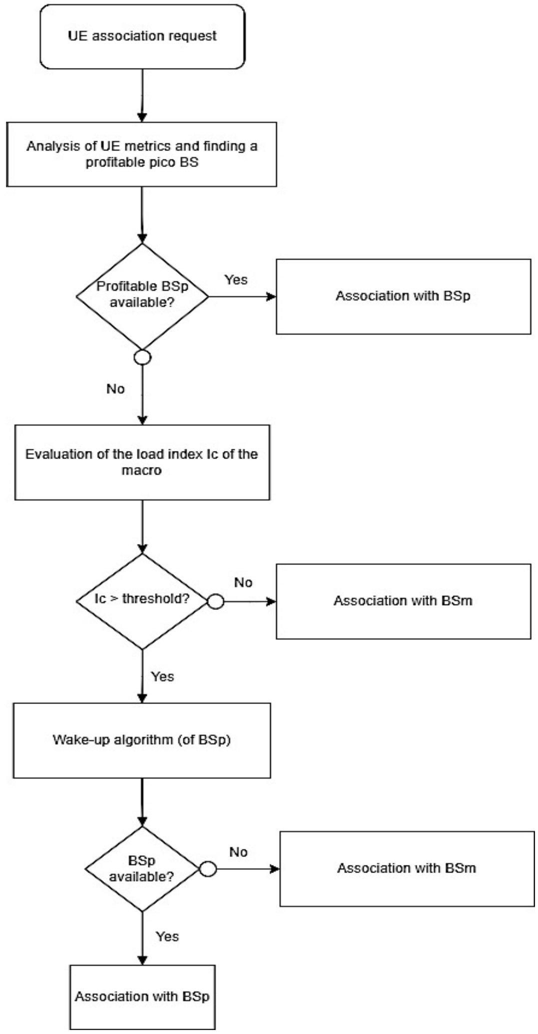


**FIGURE 1. Cell selection algorithm.**

For the latter, we have the energy consumption C, which is defined as follows:

$$C = \sum_{i=1}^{n} C_{mi} + \sum_{j=1}^{m} C_{pj} \tag{11}$$

where *n and m* represents the number of Macrocells and the number of Picocells, respectively.

$$C = \sum_{i=1}^{n} (C_{o_m} + F_m \times c_i) + \sum_{j=1}^{m} (C_{o_p} + F_p \times c_j) \tag{12}$$

$$C = n \cdot C_{o_m} + F_m \cdot \sum_{i=1}^{n} c_i + m \cdot C_{o_p} + F_p \cdot \sum_{j=1}^{m} c_j \tag{13}$$

When the picocells can be put to sleep, the following expression is used:

$$C = \sum_{i=1}^{n} C_{mi} + \sum_{j=1}^{m} C_{pj} \sum_{k=1}^{p} C_{pk} \tag{14}$$

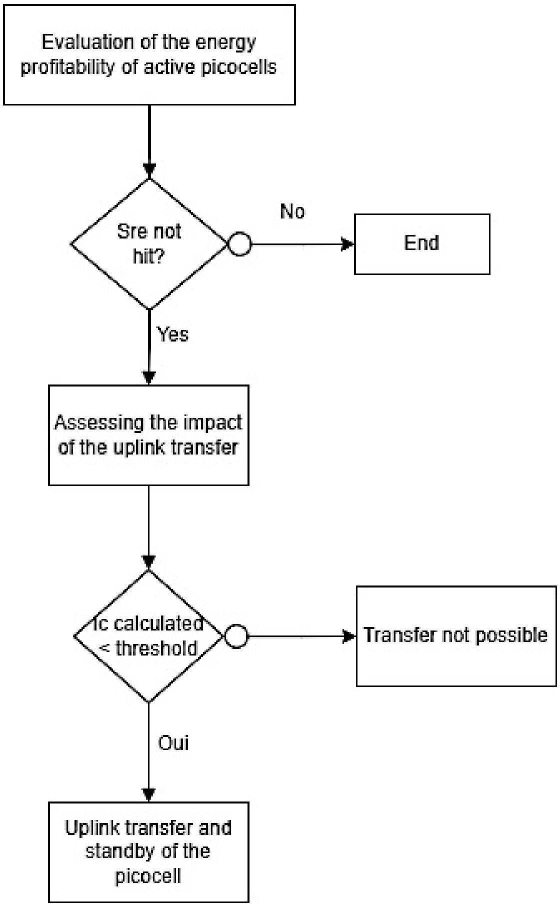


**FIGURE 2.** Energy consumption optimization algorithm.

where $n, m$ *and* $p$ represent the number of Macrocells, the number of active Picocells, and the number of Picocells in the standby state, respectively.

$$C = \sum_{i=1}^{n} (C_{o_m} + F_m \times c_i) + \sum_{j=1}^{m} (C_{o_p} + F_p \times c_j) + p \cdot C_{v_p} \tag{15}$$

$$C = n \cdot C_{o_m} + F_m \cdot \sum_{i=1}^{n} c_i + m \cdot C_{o_p} + F_p \cdot \sum_{j=1}^{m} c_j + p \cdot C_{v_p} \tag{16}$$

## V. RESULTS AND DISCUSSION

For our simulations, we used the Vienna 5G Link Level Simulator, a powerful simulation tool used to evaluate the performance of 5G wireless communication systems. This software package models the physical layer of the 5G network, including the channel, antenna, modulation and coding schemes, and propagation effects. The simulator is based on the MATLAB programming language and provides a flexible and customizable environment for conducting link-level simulations [23]. In our simulations, we consider a dimension 500m × 500m surface with a BSm in the center (0.0) and 25 BSp distributed according to a Poisson distribution. BS transmits on a frequency of 2GHz. There are 500 users, 80% indoors with a speed of 0.3m/s and 20% outdoors with a speed of 10m/s.

The different deployment scenarios are inspired by the "Urban Dense" architecture of [24] while strengthening the density of small cells and remaining on the low-frequency bands to highlight further the problem of cell selection in this heterogeneous architecture and also to comply more closely with the first 5G deployment forecasts.

The calculated break-even point is as follows:

$$S_{re} = \frac{C_{o_p} - C_{mv}}{C_{u_m} - C_{u_p}} \tag{17}$$

$$S_{re} = \frac{40,8 - 25,8}{\frac{564}{800} - \frac{3}{32}} \tag{18}$$

$$S_{re} = 24,540 \tag{19}$$

A picocell is, therefore, only energy-efficient from 25 UEs. Below, consumption would be lower if the UEs are associated with the Macrocell. Table 4 provides the simulation parameters for our simulation scenarios [25].

**TABLE 5.** Simulation parameters.

| Parameter | Value |
|---|---|
| Simulation surface | 500m x 500m |
| Number of BSm | 01 |
| Transmission power | 43 dBm |
| Number of BSp | 25 |
| Transmission power | 23 dBm |
| Bias (CRE) | 6 dB |
| Frequency of BSm | 2 GHz |
| Frequency of BSp | 3.6 GHz |
| Bandwidth | 20 MHz |
| Path-loss model | UMa3D and UMi3D |
| Break-even point | 25 |

4G mainly uses pairing methods based on signal strength, such as "Max-SINR," and introduces the concept of extending cellular coverage. Max-SINR [26] is a standard association technique based, as its name suggests, on the power ratio between the received signal and the sum of noise and interference.

Cell Range Expansion (CRE) [27] extends the cellular coverage of small cells by adding a bias to the signal received by the UE. Applied to BSp and combined with Max-SINR, it allows BSp to offer a higher signal strength than BSm over a wider area around the BSp station (extension of coverage) and, thus, more UEs connected to the latter. This technique allows a better load balancing between BSm and BSp.

As far as 5G is concerned, one of the significant integrations in this area is the adoption of cellular standby in the basic specifications found in [28], [29], and [30]. Therefore, it is a question of selectively turning "Off" "One" or more equipment in the absence of traffic.

We compared our energy consumption optimization algorithm (ECOA) to the calculated minimum consumption (Optimum), which is an optimal theoretical limit from the point of view of energy consumption, and to the two modes of the association presented above, "Max-SINR" and "CRE." Moreover, we have integrated the possibility of putting unloaded BSp on standby. We compare 6 techniques:

- The Max-SINR "SMV" (without standby),
- The Max-SINR "AMV" (with standby),
- The CRE "SMV" (without standby), with a bias of 6 dB,
- The CRE "AMV" (with standby), with a bias of 6 dB,

The "Urban Dense" model defines a base of 10 UEs per antenna, up to 20, at a very high load. We have thus defined a situation of a low load with 100 UEs and a high load with 500 UEs.

First, we compared the different algorithms for many UEs of 500 (scenario 1) and 100 (scenario 2) to analyze the level of energy consumption induced by each algorithm in situations of high and low load.

Next, we varied this number from 10 to 500 (scenario 3) to analyze the energy consumption for each algorithm according to the number of users. This scenario allows us to measure the evolution of the consumption of each algorithm from a low load level to a high level and to compare them.

Subsequently, we compared the energy consumption induced by our algorithm to the optimum by varying the number of Picocells, always in high with 500 UEs (scenario 4.a) and low loads with 100 UEs (scenario 4.b), to evaluate the impact of BSp density on this energy consumption. Considering our simulation area (500m × 500m) and estimating the radius of a BSp between 50m and 100m, we can see that it takes between 30 and 50 BSp to cover the simulation area in a regular distribution entirely. Thus, we have retained two key density values about the simulation area: 5 BSp for a low density and 30 BSp for a high density.

Finally, we compared the data rates per user versus the total UE number for each algorithm to analyze the impact of cell selection on user throughput (scenario 5).

In the following, we present the results of the simulation scenarios.

In scenario 1, figure 3 shows the average energy consumption for each algorithm, with a UE number of 500.

The minimum energy consumption (Optimum) would be obtained when the 15 BSp were saturated, 480 UEs associated with BSp, and the remaining 20 below-break-even would be associated with BSm.

In a real situation, the probability of having an optimum is almost zero because it requires a particular distribution of UEs on the Macrocell.

Compared to the optimum, the ECOA allows overconsumption of less than 3%, which constitutes a real performance compared to other algorithms that lead to more than 17% overconsumption. It offers, compared to other algorithms, the energy gains presented in the following table:

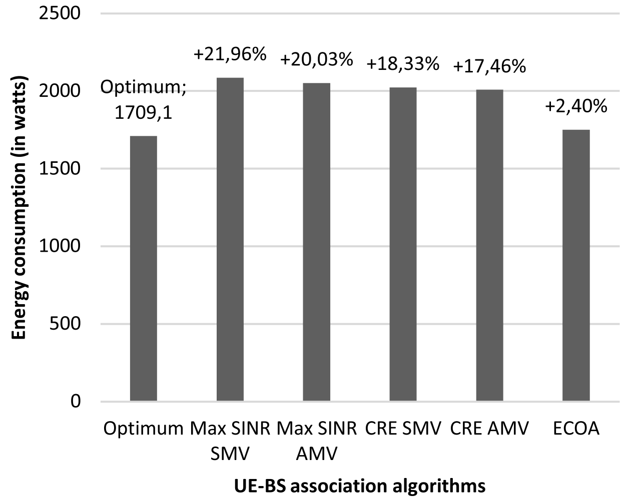


**FIGURE 3.** Energy consumption as a function of UE-BS association algorithms (500 UEs).

**TABLE 6.** Energy savings of ECOA compared to other BS association algorithms.

| | Max-SINR SMV | Max-SINR AMV | CRE SMV | CRE AMV |
|---|---|---|---|---|
| ECOA | 16,04% | 14,69% | 13,47% | 12,82% |

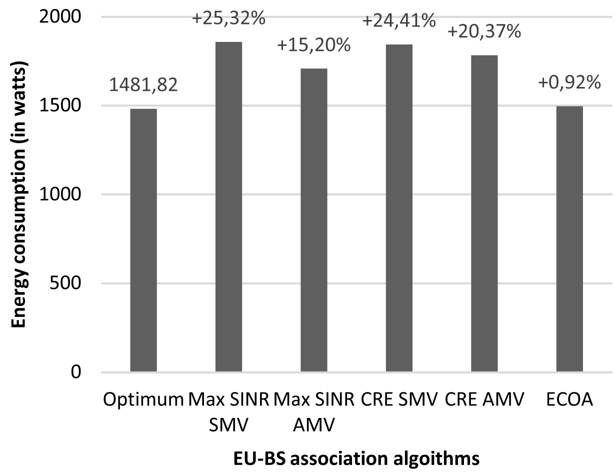


**FIGURE 4.** Energy consumption according to UE-BS association algorithms (100 UEs).

Also, we instead notice a low energy gain when introducing a standby of unloaded BSp for Max-SINR algorithms and CRE (1 to 2%). Thus, an effective strategy of standby of BSp must be accompanied by a policy of transfer of low-loaded BSp to BSm, as integrated by our ECOA algorithm.

In scenario 2, figure 4 also compares each algorithm's average energy consumption at a low load for 100 UEs.

At a low load (100 UEs), the ECOA offers overconsumption of less than 1%, compared to the optimum of

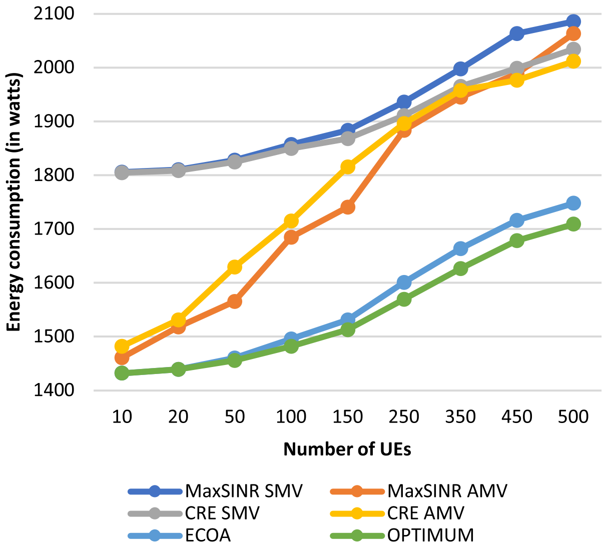


**FIGURE 5.** Average energy consumption by cell selection algorithm as a function of EU number.

1481.82 watts. It is very close to the optimum and thus allows a significant energy gain.

One of the significant lessons we can draw from this comparison is the lower impact of the standby of BSp for the case of CRE than for Max-SINR. This is explained by the fact that the added power bias promotes the association with BSp, however creating more BSp very low charged, far from the energy efficiency of these. At low loads, the power bias thus becomes counterproductive on an energy level.

Figure 5 shows the evolution of the average energy consumption as a function of the load for each algorithm (scenario 3).

From the various evolution curves, we can observe three distinct trends:

The Max-SINR SMV and CRE SMV algorithms do not optimize energy consumption. At low loads, as at high loads, they have consumption levels above the optimum.

The Max-SINR AMV and CRE AMV algorithms promote overconsumption as the cellular load increases, and their curve approach that of BSp's no-standby algorithms. This is explained by the fact that the more the load increases, the fewer empty cells we do not have. Consequently, the strategy of putting empty cells to sleep loses efficiency.

Our algorithm, ECOA, demonstrates remarkable efficacy in minimizing energy consumption, as evidenced by its ability to maintain proximity to the optimal solution even at high loads where the optimal configuration remains almost unaltered.

The two graphs below (Figures 6 and 7) compare the average energy consumption of the optimum solution and the ECOA with 500 UEs (scenario 4.a) and 100 UEs (scenario 4.b).

With a load of 500 UEs, the higher the number of BSp, the more difficult the optimum is to achieve; the probability of

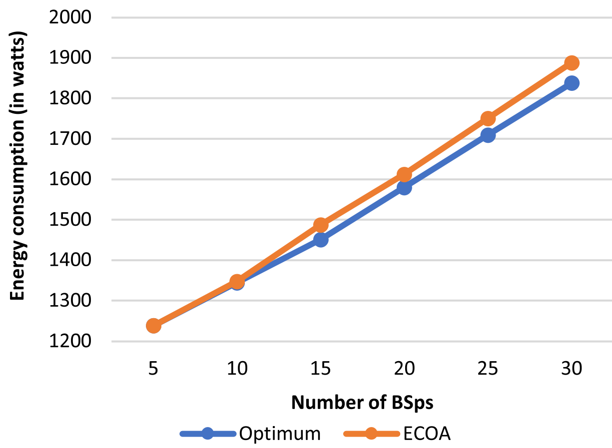


**FIGURE 6.** Average energy consumption as a function of the number of BSp per 500 UEs.

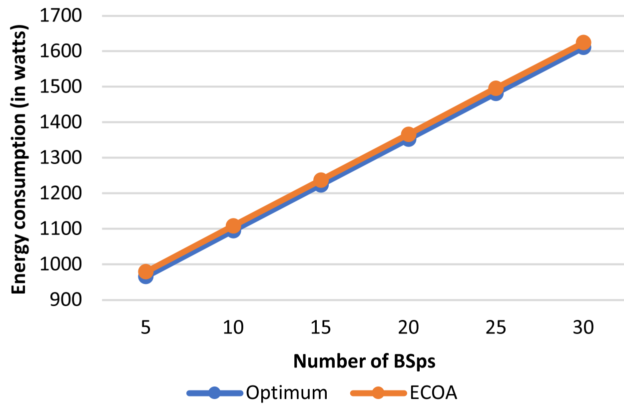


**FIGURE 7.** Average energy consumption as a function of the number of BSp per 100 UEs.

having the required UE distribution is almost zero. However, the algorithm remains very efficient with overconsumption of less than 3%, as shown in the following table:

**TABLE 7.** Average energy consumption by the number of BSp per 500 UEs.

| Number of BSp | 5 | 10 | 15 | 20 | 25 | 30 |
|---|---|---|---|---|---|---|
| Optimum | 1238,7 | 1344,9 | 1451,1 | 1580,1 | 1709,1 | 1838,1 |
| ECOA | 1238,7 | 1347.35 | 1487.35 | 1612,02 | 1750,75 | 1888,26 |
| Overconsumption of ECOA | +0.00% | +0.18% | +2.50% | +2.02% | +2.44% | +2.73% |

At a low load, the consumption for the ECOA is very close to the optimum, with very low overconsumption (less than 1%).

Figure 8 shows the average throughput per user as a function of the total UE number with a BSp of 25.

The analysis of this graph allows us to notice that the Optimum guarantees, by far, a better throughput than the other algorithms. This can be understood because it simulates an ideal situation where the BSp is associated with the maximum

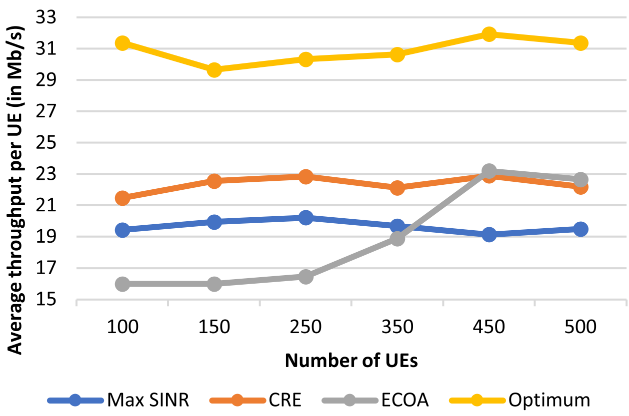


**FIGURE 8.** **Average throughput per UE as a function of the number of UE for 25 BSp.**

of UEs, guaranteeing them a better throughput. Also, the CRE algorithm offers better throughput than the Max SINR.

Analysis of the ECOA curve shows that it provides lower average throughput with a low number of UEs. This is because the UEs associated with the unprofitable BSp are transferred to the BSm, which provides a lower average throughput than a BSp.

However, evaluating the Macro load index ensures that the requested quality of service is maintained.

This trend is reversed from several UEs (about 370 onwards). Indeed, the large number of UEs means that several BSps can become profitable or be made profitable, and more transfers are made to BSps.

## VI. CONCLUSION

With the specifications and requirements of 5G, environmental issues have returned to the heart of research, including energy consumption, to slow down the observed generation-after-generation curve. The 5G specifications include the possibility of putting to sleep uncharged small base stations; however, our research has shown that cellular extension techniques become counterproductive from an energy point of view, mainly under low-load conditions due to the existence of several low load Picocells which induce overconsumption. More generally, research into the mode of cell selection in heterogeneous networks has shown the importance of cell selection in the network's energy consumption. We have thus proposed an algorithm to optimize this consumption.

Our algorithm demonstrates strong performance, especially in high user and base station density scenarios. In a site where 25 Pico base stations serve 500 users, our algorithm delivers an average throughput of 23 Mb/s per user with an energy consumption of 1750.75 W. This results in only a 2.44% increase compared to the optimal solution.

Regarding throughput, transfers at the BSm level mean that the ECOA offers a lower average when the number of UE is small. This trend was subsequently reversed. However, the evaluation of the Macrocell's load index $I_c$ guarantees the maintenance of the quality of service requested by the UE.

These two metrics ($I_c$ and $S_{re}$) are, therefore, essential for our optimization strategy. However, their expression can be adapted to other contexts or environments in the 5G networks.

As part of our future work, we aim to incorporate massive MIMO into our solution to mitigate interference, which is expected to enhance user throughput and decrease energy consumption.

## REFERENCES

[1] T. Han and N. Ansari, "Optimizing cell size for energy saving in cellular networks with hybrid energy supplies," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Anaheim, CA, USA, Dec. 2012, pp. 5189–5193, doi: 10.1109/GLOCOM.2012.6503944.

[2] R. Sachan, T. J. Choi, and C. W. Ahn, "A genetic algorithm with location intelligence method for energy optimization in 5G wireless networks," *Discrete Dyn. Nature Soc.*, vol. 2016, no. 3, Jan. 2016, Art. no. 5348203, doi: 10.1155/2016/5348203.

[3] D. López-Pérez, A. D. Domenico, N. Piovesan, G. Xinli, H. Bao, S. Qitao, and M. Debbah, "A survey on 5G radio access network energy efficiency: Massive MIMO, lean carrier design, sleep modes, and machine learning," *IEEE Commun. Surveys Tuts.*, vol. 24, no. 1, pp. 653–697, 1st Quart., 2022, doi: 10.1109/COMST.2022.3142532.

[4] N. Piovesan, D. López-Pérez, A. D. Domenico, X. Geng, H. Bao, and M. Debbah, "Machine learning and analytical power consumption models for 5G base stations," *IEEE Commun. Mag.*, vol. 60, no. 10, pp. 56–62, Oct. 2022, doi: 10.1109/MCOM.001.2200023.

[5] A. Mamane, M. Fattah, M. E. Ghazi, M. E. Bekkali, Y. Balboul, and S. Mazer, "Scheduling algorithms for 5G networks and beyond: Classification and survey," *IEEE Access*, vol. 10, pp. 51643–51661, 2022, doi: 10.1109/ACCESS.2022.3174579.

[6] B. Younes, M. Fattah, S. Mazer, and M. E. Bekkali, "5G uplink interference simulations, analysis and solutions: The case of pico cells dense deployment," *Int. J. Electr. Comput. Eng.*, vol. 11, no. 3, pp. 2245–2255, Jun. 2021, doi: 10.11591/ijece.v11i3.pp2245-2255.

[7] S.-E. Chafi, Y. Balboul, S. Mazer, M. Fattah, and M. E. Bekkali, "Resource placement strategy optimization for smart grid application using 5G wireless networks," *Int. J. Electr. Comput. Eng. (IJECE)*, vol. 12, no. 4, pp. 3932–3942, Aug. 2022, doi: 10.11591/ijece.v12i4.pp3932-3942.

[8] A. Mamane, M. Fattah, M. E. Ghazi, Y. Balboul, M. E. Bekkali, and S. Mazer, "Proportional fair buffer scheduling algorithm for 5G enhanced mobile broadband," *Int. J. Electr. Comput. Eng.*, vol. 11, no. 5, pp. 4165–4173, Oct. 2021, doi: 10.11591/ijece.v11i5.pp4165-4173.

[9] S. Corroy, L. Falconetti, and R. Mathar, "Dynamic cell association for downlink sum rate maximization in multi-cell heterogeneous networks," Presented at the IEEE Int. Conf. Commun. (ICC), Jun. 2012, doi: 10.1109/ICC.2012.6364568.

[10] Y. Zhang, J. Chen, Y. Zhou, L. Yang, B. He, and Y. Yang, "Dependent task offloading with energy-latency tradeoff in mobile edge computing," *IET Commun.*, vol. 16, no. 17, pp. 1993–2001, Oct. 2022, doi: 10.1049/cmu2.12454.

[11] X. Chen, Z. Liu, Y. Chen, and Z. Li, "Mobile edge computing based task offloading and resource allocation in 5G ultra-dense networks," *IEEE Access*, vol. 7, pp. 184172–184182, 2019, doi: 10.1109/ACCESS.2019.2960547.

[12] S. E. Nwachukwu, M. Chepkoech, A. A. Lysko, K. Awodele, J. Mwangama, and C. R. Burger, "Integration of massive MIMO and machine learning in the present and future of power consumption in wireless networks: A review," in *Proc. IEEE 7th Forum Res. Technol. Soc. Ind. Innov. (RTSI)*, Paris, France, Aug. 2022, pp. 154–160, doi: 10.1109/RTSI55261.2022.9905123.

[13] S. Malta, P. Pinto, and M. Fernández-Veiga, "Using reinforcement learning to reduce energy consumption of ultra-dense networks with 5G use cases requirements," *IEEE Access*, vol. 11, pp. 5417–5428, 2023, doi: 10.1109/ACCESS.2023.3236980.

[14] D. Paikaray, D. Chhabra, S. Sharma, S. Goswami, H. K. Shashikala, and P. G. Jethava, "Energy efficiency based load balancing optimization routing protocol in 5G wireless communication networks," *Int. J. Commun. Netw. Inf. Secur.*, vol. 14, no. 3, pp. 187–198, Dec. 2022, doi: 10.17762/ijcnis.v14i3.5605.

[15] R. K. Saha, "On maximizing energy and spectral efficiencies using small cells in 5G and beyond networks," *Sensors*, vol. 17, no. 6, p. 1676, Mar. 2020, doi: 10.3390/s20061676.
[16] W. Sui, X. Chen, S. Zhang, Z. Jiang, and S. Xu, "Energy-efficient resource allocation with flexible frame structure for heterogeneous services," in *Proc. Int. Conf. Internet Things (iThings), IEEE Green Comput. Commun. (GreenCom), IEEE Cyber, Phys. Social Comput. (CPSCom), IEEE Smart Data (SmartData)*, Jul. 2019, pp. 749–755, doi: 10.1109/iThings/GreenCom/CPSCom/SmartData.2019.00139.
[17] A. Taneja and N. Saluja, "A practical approach to improve product of energy efficiency and capacity rate in MU-MIMO systems," *Int. J. Pervasive Comput. Commun.*, vol. 16, no. 2, pp. 183–202, May 2020, doi: 10.1108/IJPCC-03-2019-0032.
[18] D. Liu, L. Wang, Y. Chen, M. Elkashlan, K.-K. Wong, R. Schober, and L. Hanzo, "User association in 5G networks: A survey and an outlook," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 2, pp. 1018–1044, 2nd Quart., 2016, doi: 10.1109/COMST.2016.2516538.
[19] S. Corroy, L. Falconetti, and R. Mathar, "Dynamic cell association for downlink sum rate maximization in multi-cell heterogeneous networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Ottawa, ON, Canada, Jun. 2012, pp. 2457–2461, doi: 10.1109/ICC.2012.6364568.
[20] R. Madan, J. Borran, A. Sampath, N. Bhushan, A. Khandekar, and T. Ji, "Cell association and interference coordination in heterogeneous LTE-A cellular networks," *IEEE J. Sel. Areas Commun.*, vol. 28, no. 9, pp. 1479–1489, Dec. 2010, doi: 10.1109/JSAC.2010.101209.
[21] A. Mesodiakaki, F. Adelantado, L. Alonso, and C. Verikoukis, "Energy-efficient context-aware user association for outdoor small cell heterogeneous networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Sydney, NSW, Australia, Jun. 2014, pp. 1614–1619, doi: 10.1109/ICC.2014.6883553.
[22] M. Javad-Kalbasi, Z. Naghsh, M. Mehrjoo, and S. Valaee, "A new heuristic algorithm for energy and spectrum efficient user association in 5G heterogeneous networks," in *Proc. IEEE 31st Annu. Int. Symp. Pers., Indoor Mobile Radio Commun.*, London, U.K., Aug./Sep. 2020, pp. 1–7, doi: 10.1109/PIMRC48278.2020.9217199.
[23] S. Pratschner, B. Tahir, L. Marijanovic, M. Mussbah, K. Kirev, R. Nissel, S. Schwarz, and M. Rupp, "Versatile mobile communications simulation: The Vienna 5G link level simulator," *EURASIP J. Wireless Commun. Netw.*, vol. 2018, p. 226, Sep. 2018, doi: 10.1186/s13638-018-1239-6.
[24] S. Achki, L. Aziz, F. Gharnati, and A. A. Ouahman, "User association strategy for energy efficiency and interference mitigation of heterogeneous networks," *Adv. Mater. Sci. Eng.*, vol. 2020, May 2020, Art. no. 7018727, doi: 10.1155/2020/7018727.
[25] *NR; Physical Channels and Modulation (Release 16)*, document 3GPP TS 38.211, Jul. 2020.
[26] N. Hassan and X. Fernando, "An optimum user association algorithm in heterogeneous 5G networks using standard deviation of the load," *Electronics*, vol. 9, no. 9, p. 1495, Sep. 2020, doi: 10.3390/electronics9091495.
[27] A. Choutri. (2016). *Gestion Des Ressources et de la Consommation Énergétique Dans les Réseaux Mobiles Hétérogénes*. [Online]. Available: https://theses.hal.science/tel-01472963
[28] Huawei. *5G Telecom Power Target Network—White Paper, 5th Global ICT Energy Efficiency Summit*. Accessed: Feb. 1, 2023. [Online]. Available: https://www.huawei.com/en/huaweitech/industry-insights/outlook/green-5g-white-paper
[29] *5G—Study on Scenarios and Requirements for Next Generation Access Technologies*, Standard ETSI TR 138 913, Version 14.3.0, 2017.
[30] *NR; Radio Resource Control (RRC); Protocol Specification (Release 15)*, document 3GPP TS 38.331, Jul. 2020.

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