Optimizing Spectral and Energy Efficiency of Massive MIMO Networks Using MVO and API Algorithms

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Abstract — Wireless communication, especially that relying on 5G technology, plays a crucial role in modern networks. The use of massive multiple-input, multiple-output (MIMO) systems is one of the key advancements in this area, as it improves energy efficiency (EE) and spectral efficiency (SE), making such a technique critical for future communication networks. This article focuses on optimizing EE and SE using a new metaheuristic multiverse optimization algorithm (MVO), and compares the results obtained with those achieved with the use of the Pachycondyla Apicalis algorithm (API) and other methods. Furthermore, the study explores the best values for factors such as coherence time, power amplifier efficiency, and hardware power in each user, with all of them playing a critical role in maximizing EE. The authors also examine the correlation between EE and SE in the downlink direction. The results show that the MVO approach achieves better performance in fewer iterations compared to API and other methods, demonstrating its potential for improving wireless communication systems.

Keywords — 5G, energy efficiency, massive MIMO, multiverse optimizer, Pachycondyla Apicalis algorithm, spectral efficiency

1. Introduction

In recent years, the number of electronic devices connected to the Internet has grown quite rapidly. The fact that mobile phones, machines, cars, drones, and many other devices are connected to the web creates several challenges. We face such issues as higher amounts of interference, poor power efficiency, high propagation losses, and low communication efficiency [1], [2]. Traditional antennas are not capable of handling this massive increase in the number of devices they serve. Therefore, it is crucial to improve antennas and adopt new technologies that can manage such large numbers of connections.

Technologies such as massive multiple input multiple output (MIMO), beamforming, and precoding are key solutions [3]. These advances are part of new radio (NR) systems which are designed to support the growing number of users. They are capable of providing high data rates and improving spectral efficiency by at least ten times [4].

This paper focuses on using the massive MIMO technology to address the challenges faced. In a communication system relying on massive MIMO, the base station (BS) and the users interact in a way that utilizes many antennas in the BS to improve signal quality and efficiency [5]. When a user sends a request or data, the base station uses its large number of antennas to transmit the data to the user. These antennas work together to simultaneously send multiple signals to different users or even the same user, but using different channels or frequencies [6], [7]. This process is called "beamforming", where the BS can direct its signal, in a focused manner, to a specific user, thus improving the strength of the signal and reducing interference from other users [8].

On the user's side, a device like a smartphone has its own antennas, and when it receives the BS signal, it decodes the data. Communication occurs in such a way that the BS can serve many users simultaneously, each with a dedicated and stronger signal. Such a mode of operation improves network efficiency, ensures faster data speeds and offers more reliable connections [9].

The trade-off between spectral efficiency (SE) and energy efficiency (EE) is an important factor we focus on in this study. An increase in SE affects EE. In this paper, we aim to find the optimal balance between SE and EE. Specifically, we want to identify the ideal combination between the number of users and antennas and the transmission power to achieve the best values of both SE and EE. High SE and high EE are critical for the success of 5G networks, as they ensure faster data rates and lower energy consumption, improving overall network performance.

The proposed approach uses two different metaheuristic algorithms, i.e. multiverse optimization and Apicalis Pachycondyla, to enhance both SE and EE. We analyze how different parameters, such as power amplifier efficiency, coherence time, and hardware power at each user, affect EE. By examining the relationship between SE and EE, we aim to find the critical point that gives the highest values for both factors. Finally, the EE-SE trade-off is derived in a closed form, reducing computational complexity by expressing the essential derivatives in terms of power, thus making it easier to find the optimal solution.

This paper is organized as follows. Section 2 reviews related articles, summarizes their main ideas, and describes the methods used. Section 3 provides an overview of the key aspects of massive MIMO. In Section 4, we explain the functioning of two metaheuristic algorithms: the multiverse optimizer (MVO) and Pachycondyla APIcalis (API). Section 5 presents the simulation results and compares the performance of MVO and API with other methods. Finally, Section 6 concludes the article.

2. Related Works

Numerous studies have been dedicated to improving energy efficiency in massive MIMO systems. For example, article [10] explores hybrid systems that combine massive MIMO with other technologies to improve EE. Similarly, paper [11] proposed two energy efficient beamforming algorithms for multi-user downlink systems, aiming to improve EE while meeting SINR constraints. The methods investigated showed better results than traditional beamforming techniques and pointed out the need to study the effect of circuit power further. In addition, in articles [12], [13], the authors did not look at spectral efficiency (SE).

On the other hand, some research focused solely on improving SE. For example, [14] studied how massive multiuser MIMO systems perform during uplink transmission, when the base station is equipped with many antennas and each user has just one. They created methods to improve SE. In addition, in [15], the goal is to improve the number of users that may connect and communicate efficiently within a given network. The researcher proposes a new design that groups users by location or similar characteristics and serves each group with the best-suited method. This approach reduces the required number of antennas, while still achieving high efficiency and providing better performance compared to older methods [16]. This article aims to reduce power usage in massive MIMO systems by using low-resolution (2-bit) ADCs. It studies how these ADCs affect spectral efficiency of the system's uplink under different conditions, such as perfect and imperfect knowledge of the communication channel. The proposed method involves mathematical modeling and formulas to predict SE performance, showing that even with low-cost ADCs, good results can be achieved in massive MIMO systems. All this work achieves good results, but does not take into account.

Some studies have explored the balance between spectral efficiency (SE) and energy efficiency (EE) in massive MIMO systems. For example, in [17], the researchers used deterministic and analytical methods focusing on power allocation and selection of access points (AP) through closed form derivations and system constraints. However, they did not use metaheuristic algorithms, relying instead on structured optimization techniques to enhance energy efficiency in cell-free massive MIMO systems. Similarly, in [4], the authors addressed the challenge of optimizing resource efficiency (RE) in a single-cell massive MIMO downlink transmission. Their work considered statistical channel state information at the transmitter (CSIT) to find a balance between SE and EE using mathematical optimization and algorithmic design.

In study [5], the trade-off between SE and EE is analyzed by solving a multi-objective optimization problem. The paper investigates how transmit power and the number of antennas impact this trade-off by examining their first derivatives. In the same context, article [18] used geometric programming to optimize SE and EE in a unified massive cell-free MIMO system with simultaneous wireless information and power transfer (SWIPT). Like the remaining studies mentioned, the work did not employ metaheuristic algorithms.

Although these studies contributed valuable information about SE and EE optimization, they all relied on structured or mathematical methods rather than metaheuristic algorithms. In contrast, our work introduces two novel metaheuristic algorithms in this field: the multiverse optimization (MVO) algorithm, which has not been applied to massive MIMO systems before, and the Pachycondyla Apicalis (API) algorithm. We compare the performance of these algorithms to determine which one achieves better results.

3. Massive MIMO

Massive MIMO is a fundamental innovation in modern wireless communication systems [19], [20]. It addresses the growing demand for high-speed data and reliable connections, i.e. challenges that traditional single-input single-output (SISO) systems were not capable of overcoming due to their limited data rates and inability to support multiple users simultaneously [21].

To overcome the limitations of SISO, advanced MIMO technologies, such as single-user MIMO (SU-MIMO) [22], multiuser MIMO (MU-MIMO) [23], and network MIMO [24], were developed. These technologies improved capacity but struggled with the exponential growth in wireless users and data demands. With billions of connected devices, including devices connected to the Internet of Things (IoT) in smart homes, healthcare, and energy systems, more efficient solutions have become essential [19].

Massive MIMO extends traditional MIMO by deploying hundreds or even thousands of antennas at the base station [25], [26]. This setup improves wireless performance by better focusing energy into smaller spatial regions, thus enhancing spectral efficiency and throughput. Narrowing and directing beams to target users also reduces interference and improves connectivity.

Massive MIMO operates efficiently using time division duplexing (TDD) which divides communication into three main phases during a coherence interval [27]. In the first phase, called channel estimation, users send unique pilot sequences to the base station (BS). The BS estimates the channel state information (CSI) using these pilots. Accurate CSI enables

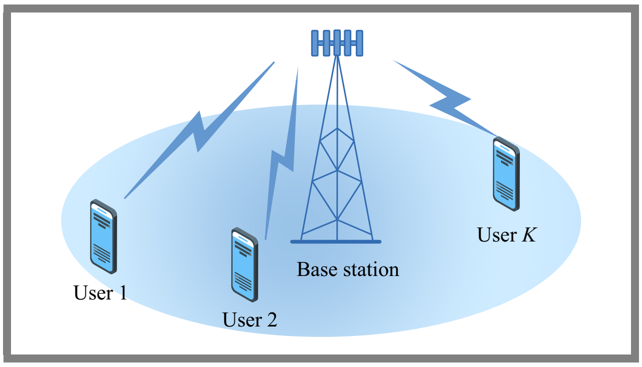

Fig. 1. Massive MIMO transmission concept.

precise signal precoding for the downlink phase. During downlink transmission, the BS uses channel estimates and user-specific data to create pre-coded signals that are transmitted through multiple antennas to all users in the same time-frequency resource. This process improves communication efficiency and reliability by using channel information to reduce interference and optimize energy usage.

Massive MIMO offers several key advantages over traditional MIMO systems. It provides higher spectral efficiency by reusing time-frequency resources for multiple users. It also improves energy efficiency by focusing beams to reduce power wastage and interference. Additionally, it improves reliability by supporting more users with stable connections. These advantages make massive MIMO indispensable for 5G and future networks [19], [20].

Figure 1 illustrates the downlink transmission in a massive MIMO setup. The BS in a cell transmits the downlink signal x_l as follows:

$$x_l = \sum_{k=1}^{K} w_{kl}\, q_k \,, \tag{1}$$

where $q_k \sim CN(0, \rho_{kl})$ represents the data signal intended for user equipment (UE) k in cell l, and $w_{kl} \in C^M$ is the precoding vector directing the signal. The precoding vector satisfies $E[\,|w_{kl}|^2] = 1$, ensuring $E[\,|x_l|^2] = \rho_{kl}$, which corresponds to the transmit power for UE k. The received signal y_{ik} at UE k in cell i is:

$$y_{ik} = h_{iilk}^H\, w_{kl}\, q_k + \sum_{l \neq i} \sum_{j=1}^{K} h_{iilk}^H\, w_{jl}\, q_j + n_{ik} \,, \tag{2}$$

where h_{iilk} denotes the channel between BS l and UE k in cell i, and $n_{ik} \sim CN(0, \sigma^2)$ represents additive noise. The received signal consists of the desired signal, interference between cells, and noise [27].

3.1. Energy Efficiency in Wireless Networks

Energy efficiency (EE) is a key feature in modern wireless networks, especially after the introduction of the 5G technology. EE measures how much data can be transmitted using a certain amount of energy [28], [29]. It is calculated as:

$$EE = \frac{\text{Throughput [bit/s/cell]}}{\text{Power consumption [W/cell]}} \,. \tag{3}$$

This ratio, expressed in bits per Joule, helps reduce costs and environmental impact. Improving EE involves techniques such as setting base stations to sleep mode when traffic is low, using renewable energy, and optimizing resources such as antennas, spectrum, and power.

The MIMO technology is a major contributor to improving EE, as it increases spectral efficiency. This means that more data can be sent using the same amount of energy, making networks more energy efficient [22], [30]–[32].

To model and calculate EE, we use the following objective function [33]:

$$EE = \frac{N * AUR}{P_{tot}} \,, \tag{4}$$

where N is the number of active antennas, AUR is the average user rate, and P_{tot} is the total power consumption. These values are defined using the following specific equations.

The average user rate represents the average data rate for each user, influenced by factors such as the number of antennas and the transmitting power. It is calculated as [33]:

$$AUR = R_{avg} = \omega \left(1 - \frac{N}{\omega_c \cdot t_c}\right) \log_2 \left(1 + \frac{\frac{p_t}{N}(M - N)}{p_n^2 \Psi_1 + p_t \Psi_2}\right) . \tag{5}$$

Total power consumption includes all sources of power used in the network, such as transmission, hardware, and processing. It is given by [33]:

$$P_{tot} = \frac{p_t}{\eta} + M p_c^M + N p_c^N + \frac{FP}{\eta_c} + p_s \,. \tag{6}$$

Floating point processes represent the computational load of the system, calculated as [33]:

$$FP = 3\, N^2 M \frac{\omega}{\omega_c\, t_c} \,. \tag{7}$$

Several parameters influence EE and overall system performance:

- M_{max} – maximum number of antennas at the base station, which determines the capacity of the system. More antennas mean better beamforming and spectral efficiency,
- ω – transmission bandwidth, defining the range of frequencies for communication. A wider bandwidth supports higher data rates,
- p_n^2 – average noise power, which affects signal quality and SNR.
- Ψ_1 and Ψ_2 – these represent channel conditions and intercell interference. Good channel conditions Ψ_1 and lower interference Ψ_2 lead to higher efficiency.
- η – power amplifier efficiency, which impacts energy consumption during transmission.
- p_s – static hardware power, representing the baseline energy used by such components as cooling systems.
- η_c – computational efficiency, indicating how effectively the system processes tasks.
- ω_c and t_c – coherence bandwidth and time, critical for stable communication and efficient resource allocation.

By integrating advanced technologies, such as massive MIMO and carefully optimizing the above parameters, we can significantly improve EE in wireless networks. This not only reduces energy consumption, but also enhances network performance, making future communication systems more sustainable.

3.2. Spectral Efficiency

Spectral efficiency (SE) measures how efficiently a wireless system uses its available frequency spectrum. It is expressed in bits per second per Hertz (bps/Hz). In massive MIMO systems, the use of large-scale antenna arrays greatly improves SE. The mathematical expression for SE is:

$$SE = \log_2(1 + SINR) \,, \tag{8}$$

where $SINR$ is the signal-to-interference plus noise ratio. Adding more antennas increases $SINR$, leading to higher spectral efficiency [29], [34].

To further improve SE in wireless networks, several techniques can be used. An increased in the number of antennas in a massive MIMO systems enhances spatial multiplexing and reduces interference, improving SINR. Optimizing beamforming techniques also focuses the signal more effectively towards intended users, reducing interference, and boosting SE. Advanced modulation and coding schemes allow more bits to be transmitted per Hertz, additionally increasing SE. Furthermore, advanced interference management methods, such as interference cancellation and coordination between base stations, can improve SE, especially in dense networks [35].

In this work, we use the following objective function to model SE:

$$SE = \frac{N * AUR}{\omega} \,. \tag{9}$$

4. Algorithm Description and Methodology

4.1. Multi-Verse Optimizer Algorithm

In this paper, the multiverse optimizer (MVO) is used, inspired by three key concepts: white holes, black holes, and wormholes. These ideas are integrated into the algorithm's key steps and equations.

White holes help in the exploration process. In cosmology, the Big Bang is considered a white hole, and in the multiverse theory, collisions between universes can create white holes, acting as gateways between them. Universes with high inflation rates are more likely to have white holes that transport objects outwards, unlike black holes that pull things in [36], [37].

Black holes have strong gravitational pulls, trapping objects, including light. They are more common in universes with low inflation rates and can receive objects from white holes. This exchange between white holes and black holes allows to transfer variables between universes [38], [39]. The mechanism is outlined as follows:

$$x_i^j = \begin{cases} x_k^j & r_1 < NI(Ui) \\ x_i^j & r_1 \geqslant NI(Ui) \end{cases} \,. \tag{10}$$

Wormholes act as tunnels, allowing objects to move between different parts of a universe or between universes. In MVO, wormholes randomly transport objects between a universe and the best universe found so far. The probability of a wormhole appearing and the distance at which it moves objects are controlled by two factors [37], [39].

Adaptive wormhole existence probability (WEP) represents the likelihood of wormholes appearing within universes during an optimization process.

$$WEP = min + l \times \frac{max - min}{L} \,. \tag{11}$$

Adaptive traveling distance rate (TDR) controls how far the variables can move from the best solution when using wormholes.

$$TDR = 1 - \frac{l^{\frac{1}{p}}}{L^{\frac{1}{p}}} \,, \tag{12}$$

$$x_i^j = \begin{cases} \begin{cases} x_j + TDR \times \big((ub_j - lb_j) \times r_4 + lb_j\big) \\ r_3 < 0.5 \\ x_j - TDR \times \big((ub_j - lb_j) \times r_4 + lb_j\big) \\ r_3 \geqslant 0.5 \end{cases} & r_2 < \text{WEP} \\ \\ x_i^j & r_2 \geqslant \text{WEP} \end{cases} \tag{13}$$

The general steps of the MVO algorithm are the following:

Initialization. The algorithm starts by defining key parameters for the MVO, such as white hole exploration probability (WEP), travel distance rate (TDR), and the number of universes p. These parameters control the exploration and exploitation during optimization. A random initialization of the universes is performed, where each universe represents a potential solution to the problem.

Normalization. Once the universes have been initialized, they are sorted based on their fitness values (a measure of how good the solution is). The inflation rates of all universes are then normalized to create a probabilistic model, where better universes (higher fitness) are more likely to influence others.

Fitness evaluation. For each universe in the population, the fitness function is evaluated. This function quantifies the quality of the solution represented by the universe, guiding the optimization process.

Loop start. The algorithm enters a loop to iterate through all universes. It starts with $i = 1$, representing the first universe, and processes each one sequentially to update its properties.

Update parameters. WEP and TDR parameters are dynamically updated during the iteration. This adjustment balances exploration (searching new areas) and exploitation (refining known good solutions). The blackhole index, representing the best universe, is identified based on the highest fitness value.

Inner loop. A nested loop begins with $j = 1$, representing the first object (variable) within the universe. The algorithm will iterate through all objects in the universe for potential updates.

Generate random value. A random number r is generated between 0 and 1. This random value determines whether an object in the current universe will be replaced based on white hole probabilities.

Check the probability of a white hole. If the random number r is less than WEP, the object is replaced using a roulette wheel selection mechanism, where objects from better universes (white holes) are more likely to be chosen. Otherwise, the object remains unchanged.

Increment object index. The index j is incremented to process the next object within the universe. If all objects have been processed ($j >$ number of objects), the algorithm proceeds to the next step.

Check universe completion. Index i is incremented to process the next universe. If all universes have been processed ($i >$ number of universes), the algorithm moves to check the stopping criteria.

Check stopping criteria. The algorithm evaluates whether the stopping criteria, such as reaching the maximum number of iterations or convergence to an optimal solution, are met. If the criteria are satisfied, the algorithm finishes to operate. Otherwise, it restarts the loop for the next iteration.

End. The algorithm concludes by outputting the best universe, representing the optimal solution to the problem.

4.2. Pachycondyla Apicalis Algorithm

The API algorithm, inspired by the foraging behavior of Pachycondyla Apicalis ants, efficiently balances exploration and exploitation to solve optimization problems. Each ant operates individually, performing local searches around hunting sites and dynamically updating its strategies based on results. These ants collectively contribute to the search process through implicit and explicit cooperation. Implicitly, their independent exploration diversifies the search, while explicit recruitment allows ants to share high-quality solutions, fostering global optimization [32], [42].

The robustness of the approach is enhanced by a heterogeneous population of ants with varying amplitudes of exploration, A_{local} and A_{site}, which improves adaptability to diverse problem landscapes. Periodic nest movement, acting as a dynamic restart mechanism, prevents stagnation in suboptimal solutions and allows ants to refocus their search efforts on the most promising areas.

Additionally, success-based memory prioritizes productive hunting sites while forgetting unproductive ones, ensuring efficiency. Key functions, such as defining the search space, global exploration O_{rand}, local refinement O_{explo}, and nest movement work together to maximize the objective function, integrating local exploitation with global exploration [40], [41].

The main equations governing the algorithm are described below:

- Random initialization (global search): The nest location N is initialized randomly in the search space S using:

$$x_i = b_i + U[0,1] \times (B_i - b_i) \,, \tag{14}$$

  where b_i and B_i are the bounds of the i-th dimension in S, and $U[0,1]$ is a uniform random value.

- Local exploration (neighborhood search): Around a hunting site s, ants refine their search using:

$$x_i' = x_i + U[-0.5,\ 0.5] \times A \times (B_i - b_i) \,, \tag{15}$$

  where A is the exploration amplitude.

- Global and local exploration parameters:

$$A_{site}(i) = x_i \times 0.01 \,, \tag{16}$$

$$A_{local}(i) = \frac{A_{site}(i)}{10} \,. \tag{17}$$

  These parameters govern the range of global and local exploration, respectively.

- Relocation of the nest. The nest is moved to the best solution s^* found after T iterations:

$$N = s^* . \tag{18}$$

- Recruitment (cooperation).

  Two ants compare their best sites. If $f(site_i) < f(site_j)$, replace $site_j$ with $site_i$.

Building on these principles, the API algorithm follows a structured sequence of steps to achieve optimization, as outlined below [43], [44]:

1) Initialization – place the nest in the search area. Set the number of ants, hunting sites, and exploration range.
2) Hunting site exploration – ants search around their hunting sites. If they find a better result, they update the site. If not, they choose a new site.
3) Recruitment (optional) – compare the results of two ants. The weaker site is replaced with the stronger one.
4) Nest movement – move the nest to the best location found after a set number of attempts. Start the search again near the new nest.
5) Stopping criterion – stop when the maximum number of attempts is reached or a good enough result is found.

5. Numerical Results and Discussion

Building 5G networks is challenging because we need to balance several goals: service for fast-moving users, high network capacity, and efficient power usage. These goals often conflict with each other, so we rely on multi-objective optimization techniques to find the best possible solutions. In our research, we apply two metaheuristic algorithms: multiverse optimizer (MVO) and Pachycondyla Apicalis (API), using Matlab. We tested different numbers of users, antennas, and transmission power levels to identify the ideal setup. This approach helps us design 5G networks that deliver excellent performance:

$$X = \begin{cases} & 1 \leqslant N \leqslant \frac{M}{2} \\ [NMP_t]^T & 2 \leqslant M \leqslant M_{max} \\ & 0 \leqslant p \leqslant MP_t^{max} \end{cases}$$

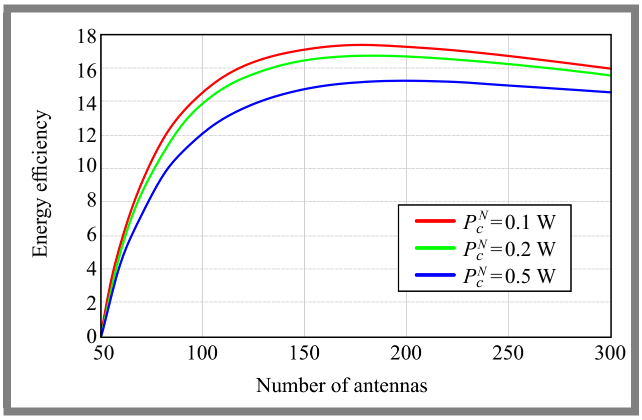

Fig. 2. EE performance versus the number of BS antennas M for different hardware power at each p_c^N .

In this study, we wanted to see how parameter p_c^N affects energy efficiency in a massive MIMO system. We tested three different values: $p_c^N = 0.5$ W, $p_c^N = 0.2$ W, and $p_c^N = 0.1$ W. The value $p_c^N = 0.5$ W represents older hardware, which is less energy efficient. The value $p_c^N = 0.2$ W represents more modern and efficient hardware, while $p_c^N = 0.1$ W represents highly optimized hardware with excellent power efficiency. Our goal was to observe how these values impact energy efficiency as the number of antennas continues to grow.

From the results shown in Fig. 2, we observed that energy efficiency improves significantly as the number of antennas increases, but it eventually reaches a peak and then decreases slightly. Lower values of $p_c^N = 0.1$ W result in higher energy efficiency compared to higher values of 0.5 W. This is the case because more efficient hardware reduces power losses, leading to better overall energy performance. However, after a certain point, adding more antennas starts to increase power consumption without providing significant gains in energy efficiency. In conclusion, using modern, low-power hardware is essential for achieving high energy efficiency in massive MIMO systems, but there is also a limit to how much increasing the number of antennas can improve performance.

In our previous analysis, we studied how p_c^N affects energy efficiency in massive MIMO systems. Now, we want to see how EE is affected by parameter η (Fig. 3). We tested three different values: $\eta = 0.25, 0.35$, and 0.45. The value $\eta = 0.25$ represents older systems, which are less efficient. The value $\eta = 0.45$ represents modern systems with better efficiency. We also introduced an intermediate value, $\eta = 0.35$, to explore a balanced setup. Our goal is to understand how these values influence energy efficiency as the number of antennas increases.

From the results, we observed that energy efficiency improves as the number of antennas increases, similarly to our findings regarding hardware power at each user. However, the efficiency reaches a peak and then starts to decline slightly. Higher values of $\eta = 0.45$ result in better energy efficiency, because they represent more advanced systems with optimized performance. The intermediate value of $\eta = 0.35$ shows ranks between older and modern systems, indicating a balanced trade-off. In conclusion, modern systems with higher η values perform better in terms of energy efficiency, but increasing the number of antennas beyond a certain point does not bring significant improvements and may even slightly reduce efficiency. These findings, combined with our previous analysis of p_c^N, highlight the importance of both hardware efficiency and system parameters in designing energy efficient massive MIMO networks.

After we found the best values of p_c^N and η for energy efficiency in massive MIMO systems, we wanted to see how the coherence time t_C impacts EE – see Fig. 4. We tested three different values: $t_C = 3$ ms, 5 ms, and 7 ms. The value $t_C = 3$ ms represents scenarios with fast-moving users, where the channel conditions change quickly. The value $t_C = 7$ ms represents low mobility scenarios, where the channel remains stable for a longer time. We also tested an intermediate value of $t_C = 3$ ms, to find a balance between these two situations. Our goal is to understand how these coherence time values influence energy efficiency as the number of antennas increases.

From the results, we observed that energy efficiency improves as the number of antennas increases, similarly to our findings concerning p_c^N and η. However, the efficiency eventually reaches a peak and then decreases slightly. Higher values of $t_C = 7$ ms result in better energy efficiency, because more stable channel conditions allow better data transmission with fewer updates. On the other hand, lower values (e.g.,

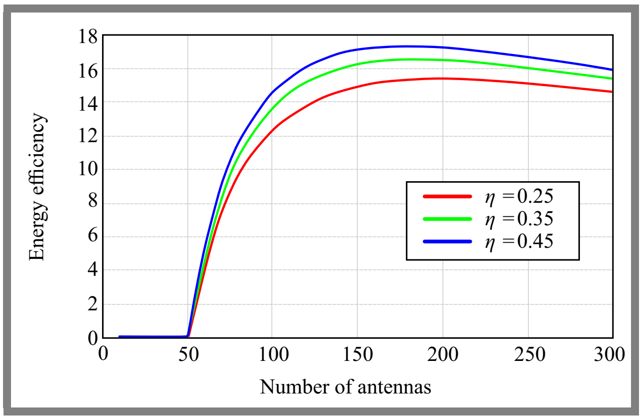

Fig. 3. Impact of power amplifier efficiency η on the corresponding energy efficiency.

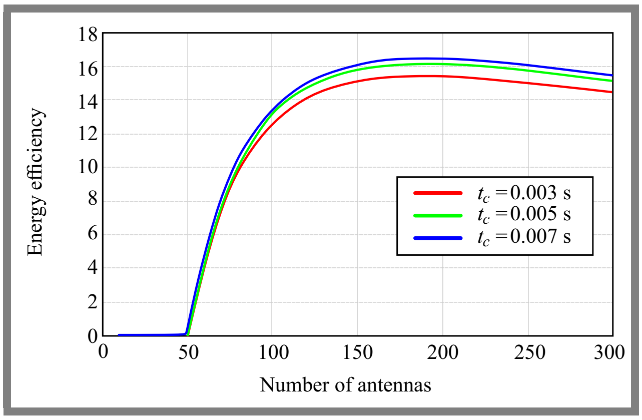

Fig. 4. Energy efficiency as a function of the number of antennas at different coherence times t_C.

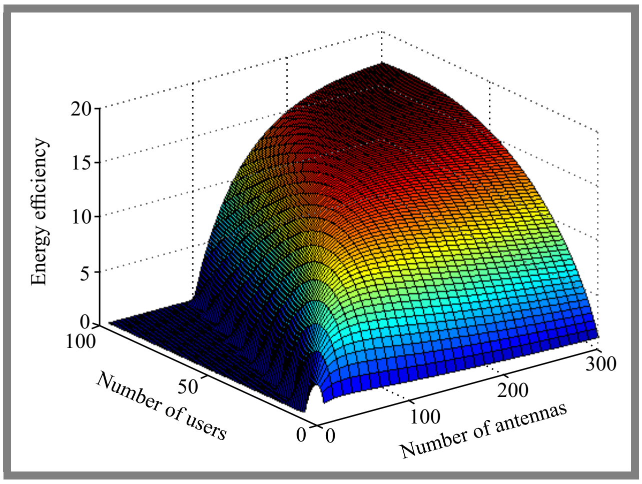

Fig. 5. Energy efficiency as a function of the number of antennas and users in massive MIMO systems.

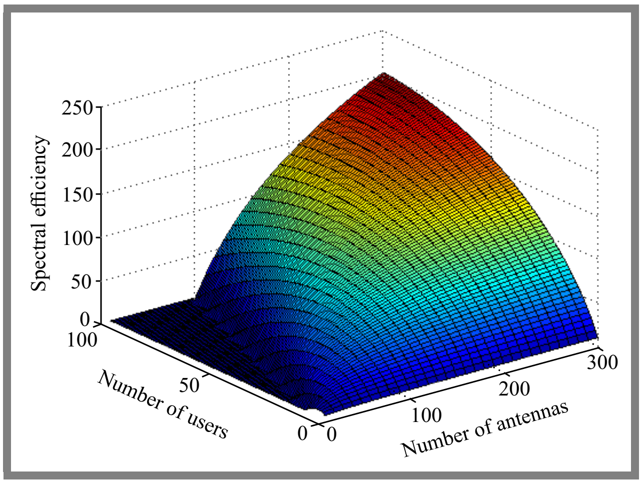

Fig. 6. Spectral efficiency as a function of the number of antennas and users in massive MIMO systems.

3 ms) are characterized by reduced efficiency due to frequent updates and higher overhead. The intermediate value of $t_C =$ 5 ms offers a balanced performance ranking between the two extremes.

Table 1 summarizes all the values that we used.

After testing different hardware power per user p_c^N, power amplifier efficiency η, and coherence time t_C values, we selected the best value. Here, we observe how energy efficiency and spectral efficiency change simultaneously as a function of two parameters: number of users N and number of antennas M.

Figure 5 shows how energy efficiency changes with the number of antennas M and the number of users N. When both M and N increase, energy efficiency improves and reaches its highest point. For example, when there are 300 antennas and 100 users, the EE value is 17.01, confirming very good efficiency in a large system. However, with fewer antennas and users, e.g. 20 antennas and 4 users, EE drops to 4.578, showing poor efficiency due to limited resources. In a medium range, with 110 antennas and 37 users, EE reaches 14.49, showing a good balance, but not the highest efficiency. This pattern shows that there is an optimal point where the balance between antennas and users gives the best energy efficiency. Adding more antennas or users after this point does not significantly improve and may even reduce efficiency levels.

Tab. 1. Set of parameters defining the system model.

Parameter	Name	Value
M_{max}	Maximum number of antennas	300
ω	Transmitting bandwidth	10 MHz
p_n^2	Average noise power	10^{-13} W
Ψ_1	Inverse channel loss	$1.72 \cdot 10^9$
Ψ_2	Intercell interference strength	0.540
p_c^N	Hardware power at each user	0.2 W
p_s	Static hardware power	10 W
η_c	Typical computational efficiency	12.8 Gflops/W
ω_C	Bandwidth of coherence	200 kHz
t_C	Coherence time	7 ms
η	The power amplifier's efficiency	0.45
P_C^M	Hardware power consumption	0.5 W

The 3D graph shown in Fig. 6 illustrates how spectral efficiency changes with the number of antennas M and the number of users N.

When both M and N increase, SE improves. For example, at 300 antennas and 100 users, SE reaches 201, showing very good use of the available bandwidth. But with fewer antennas and users, e.g. 20 antennas and 7 users, SE drops to 14.05, showing poor performance due to limited resources.

In the middle range, with 170 antennas and 53 users, SE reaches 117.8, showing a good balance but not the best efficiency. At first, increasing the number of antennas greatly improves SE, but after a certain point, the improvement slows down and efficiency stops growing significantly.

It is important to note that if there are many users and few antennas, the system struggles to manage the users properly, leading to low SE. This happens because a small number of antennas cannot effectively handle many users through beamforming and spatial diversity.

The two graphs presented in Figs. 7 and 8 show how energy efficiency and spectral efficiency are related in a massive MIMO system.

In the 2D graph, as the number of users increases, EE also increases along with SE, but then starts to drop after reaching a peak point. For example, when $N = 60$, the peak occurs at SE = 120 and EE = 16. This happens because adding more users or increasing SE needs more energy and after a point, the system cannot remain efficient.

In the 3D graph, as the number of antennas increases, both SE and EE increase, but only up to a certain limit. After this peak, EE starts to drop, while SE continues to rise. For instance, when $M = 100$, SE = 150 and EE = 12. This shows that achieving a higher SE requires more energy, which limits EE.

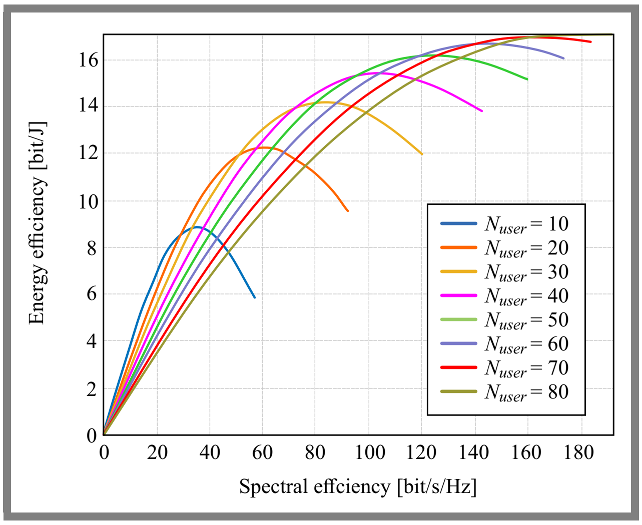

Fig. 7. 2D Energy efficiency vs spectral efficiency for different numbers of users.

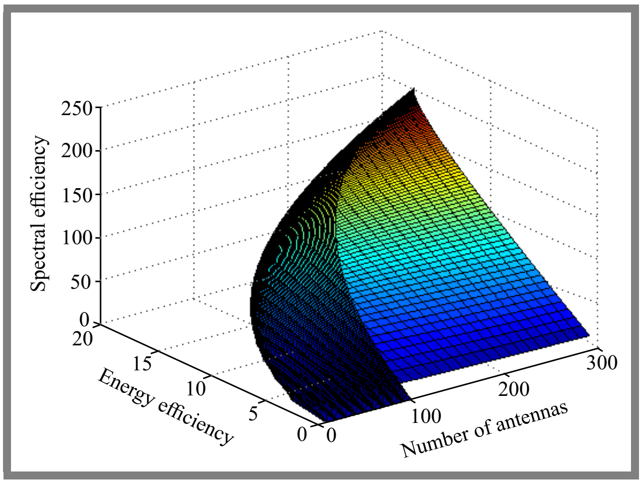

Fig. 8. 3D energy efficiency vs. spectral efficiency for different numbers of users.

This behavior proves that after a certain point, the increase in SE consumes too much power and reduces overall EE. To get the best results, it is important to find the right balance between the number of users and the number of antennas to avoid wasting energy.

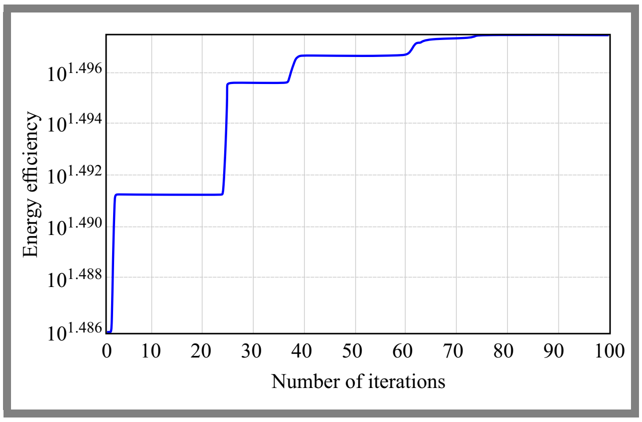

Fig. 9. Optimization of energy efficiency as a function of the number of iterations using the MVO algorithm.

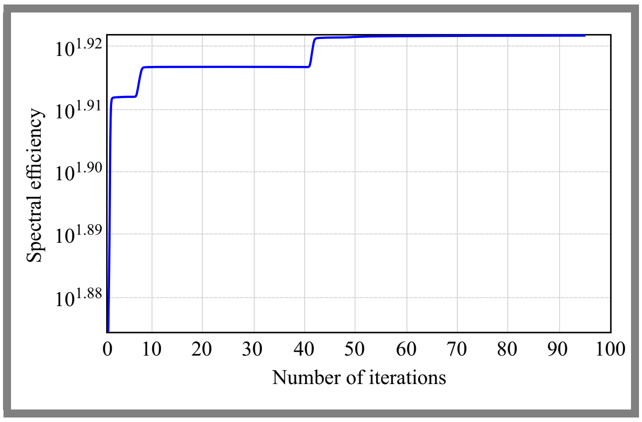

Fig. 10. Optimization of spectral efficiency as a function of the number of iterations using the MVO algorithm.

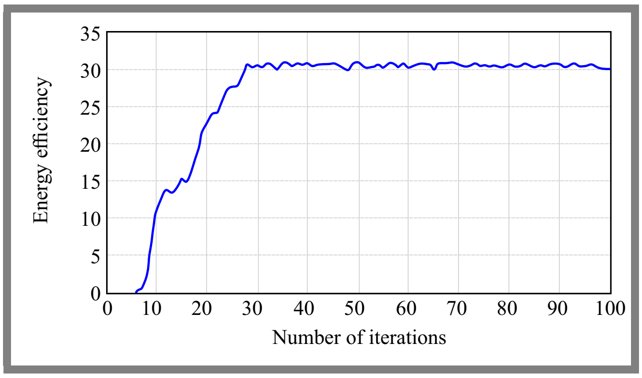

Fig. 11. Optimization of energy efficiency as a function of the number of iterations using the API algorithm.

A comparative analysis of two metaheuristic algorithms, i.e. MVO and API, was performed to evaluate spectral efficiency and energy efficiency. Both algorithms were tested under identical parameters, including the number of iterations set to 100, to ensure a fair comparison (Figs. 9–12). From the results, it is evident that the MVO algorithm outperforms the API in terms of both objectives. Ater 100 iterations, MVO achieved optimal values of SE = 83.55 and EE = 31.44, while API reached SE = 80 and EE = 30. This demonstrates the superior capability of MVO to optimize both spectral and energy efficiency in this scenario.

Fig. 12. Optimization of spectral efficiency as a function of the number of iterations using the API algorithm.

Tab. 2. Comparison between MVO and API algorithms for SE.

Criterion	MVO	API
Convergence speed	Faster	Slower
Stability	Stable after 50 iterations	Fluctuates significantly
Final value	~ 83.55	~ 78–80
Trend	Smooth growth	Irregular growth
Overall performance	Better	Moderate

Tab. 3. Comparison between MVO and API for EE.

Criterion	MVO	API
Convergence speed	Faster, distinct steps	Gradual, smooth rise
Stability	Perfectly stable after 70 iterations	Minor fluctuations persist
Final value	~ 31.44	~ 30–32
Trend	Step-like growth	Smooth growth
Overall performance	Slightly better	Good but less stable

5.1. Comparison of MVO and API

Tables 2–3 compare the performance of MVO and API in terms of spectral efficiency and energy efficiency. As far as SE is concerned, MVO is faster and more stable, achieving a higher final value of approx. 83.55. API is slower, with more fluctuations, and reaches a lower final value of 78 to 80. The growth trend for MVO is smooth, while API shows irregular growth. Overall, MVO performs better in terms of SE.

As far as EE is concerned, MVO also shows better results. It is faster with distinct steps and becomes perfectly stable after 70 iterations. API rises smoothly, but shows minor fluctuations. The final value of EE for MVO is approximately 31.44, which is slightly higher than the API range of 30 to 32. The growth trend for MVO is step-like, while API shows smooth growth. Overall, MVO is better, but API still remains good.

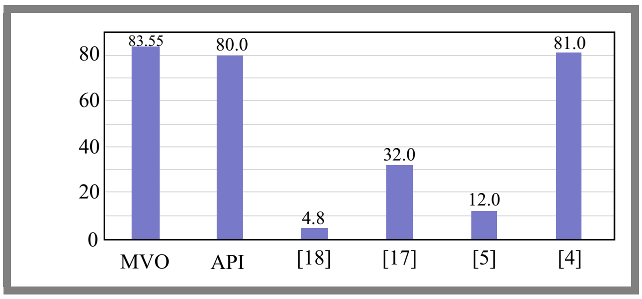

Fig. 13. Comparison of the spectral efficiency values (API and MVO) for the proposed algorithm and other papers.

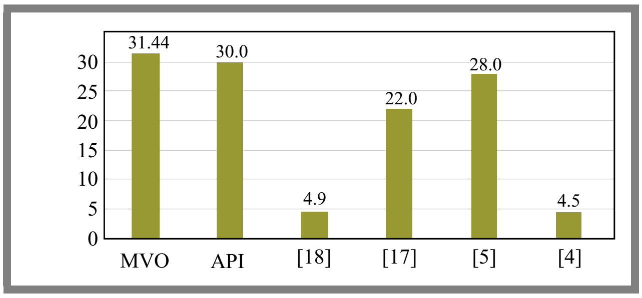

Fig. 14. Comparison of energy efficiency values (API and MVO) for the proposed algorithm and other papers.

6. Conclusions

In this work, we focused on optimizing spectral efficiency and energy efficiency using the massive MIMO technology in the downlink direction. By testing various hardware power, power amplifier efficiency, and coherence time values, we identified the best parameters to achieve an effective balance between SE and EE. Our results showed a trade-off between these two metrics, highlighting their interdependence.

We applied two metaheuristic algorithms, MVO and API, to analyze performance differences. Although both algorithms showed promising results, MVO consistently outperformed API by achieving higher SE and EE values in a shorter lead time. Finally, we compared our findings with previous works, further validating the superior efficiency and stability of the MVO algorithm (Figs. 13–14). This study confirms that MVO is a powerful tool for optimizing massive MIMO systems, offering significant improvements that may benefit modern wireless networks.

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