BULGARIAN ACADEMY OF SCIENCES

CYBERNETICS AND INFORMATION TECHNOLOGIES • Volume **23**, No 3
Sofia • 2023 Print ISSN: 1311-9702; Online ISSN: 1314-4081
DOI: 10.2478/cait-2023-0025

Dual-Step Hybrid Mechanism for Energy Efficiency Maximization in Wireless Network

Pundalik Chavan[1], *Neelam Malyadri*[1], *Husna Tabassum*[2], *Supreeth S.*[1], *Bhaskar Reddy P. V.*[1], *Gururaj Murtugudde*[1], *Rohith S.*[3], *Manjunath S. R.*[4], *Ramaprasad H. C.*[1]

[1]*School of Computer Science and Engineering, REVA University, Bengaluru, India*
[2]*Department of Computer Science and Engineering, HKBK College of Engineering, Bengaluru, India*
[3]*Department Of ECE, Nagarjuna College of Engineering and Technology, Bengaluru, India*
[4]*School of Computing and Information Technology, REVA University, Bengaluru, India*
E-mails: pundalik.chavan29@gmail.com malyadri1978@gmail.com husna.tabbu78@gmail.com supreeth1588@gmail.com bhaskarreddy.pv@reva.edu.in gururajmurtu@gmail.com rohithvjp2006@gmail.com manjunathsr.sr@reva.edu.in ramaprasad.hc@reva.edu.in

Abstract: *Wireless networks have become essential in daily life, with a growing number of base stations and connected devices. However, increasing traffic and energy consumption pose challenges. This research proposes a Dual Step Hybrid Mechanism (DSHM) for energy optimization, incorporating MIMO technologies. The first step introduces an optimal algorithm that iteratively updates the probability distribution to achieve the best solution. The second step focuses on reducing energy consumption while maximizing energy efficiency, using specific techniques and strategies to minimize usage without compromising energy maximization. The proposed approach is evaluated using parameter settings, including block length, path loss, hardware impairments, and bandwidth. The research investigates the impact of hardware impairments on energy efficiency and analyzes performance under different SINR constraints. The study also examines energy efficiency in active user density and base station density, highlighting the superior energy efficiency achieved by MIMO configurations.*

Keywords: *Wireless network, Energy efficiency, DSHM, QOS, SINR, Multimedia services.*

1. Introduction

Significant growth has been witnessed in the development of wireless communication systems, particularly in the realm of fifth-Generation (5G) networks and beyond. These advancements aim to achieve higher data rates while maintaining sufficient Quality of Service (QoS), all while minimizing energy consumption. Although consuming less power to achieve high data rates may initially seem contradictory, it is indeed possible. One potential solution to achieve high data rates is network densification. However, this approach faces challenges in terms of increased interference at bottlenecks, which subsequently leads to higher power consumption. Consequently, the key question that arises is how to increase data rates in the network while simultaneously achieving optimal energy efficiency. This question has been a focal point for both industries and academia. Unfortunately, the realization of energy-efficient wireless networks remains a challenge. The telecommunications sector is grappling with the dual objectives of reducing energy consumption and accommodating the growing demand for data transmission. In order to address this challenge, tailored, efficient, and flexible operations within the telecommunication network are required. This will enable industries, individuals, governments, and businesses to enhance their energy efficiency while simultaneously reducing overall energy consumption. Below are listed some key observations that have been highlighted as [2-5].

- Data usage is increasing rapidly, requiring more sophisticated networks to deliver high reliability, large volumes, and low latency. By 2030, connected devices will reach nearly 100 billion, with wireless networks supporting ten times more data than 4G networks in 2018. Addressing these growing demands is crucial for achieving energy consumption and efficiency targets.
- Mobile Network Operators (MNOs) aim to reduce energy bills by 40% by 2030 by meeting increasing traffic demands and reducing greenhouse gas emissions. The Third Generation Partnership Project (3GPP) aims to reduce energy consumption in 3GPP New Radio (NR) by 90% compared to LTE 3GPP. However, realizing these energy savings requires new specifications focusing on energy efficiency and individual network site performance. The deployment and operation of the network are crucial for achieving these gains. Intelligent network usage is essential to support wireless connectivity growth and reduce energy consumption per bit, requiring adaptations and optimizations at every network level to achieve a holistic effect.
- Mobile Network Operators (MNOs) must adopt new approaches in network deployment, optimization, planning, and management to achieve efficient energy consumption and meet targets. Research shows that wireless networks could use 140% more energy than 4G networks if energy efficiency is not prioritized. This is due to factors like higher density of antennas, base stations, user equipment, and cloud infrastructure. To address this issue, MNOs must implement energy-efficient practices and technologies across all network aspects, considering the deployment and density of network elements and optimizing energy consumption to minimize unnecessary usage.
- To tackle energy consumption in wireless networks, MNOs must analyze and report on the most energy-consuming components, particularly the base station within the Radio Access Network (RAN). The RAN is projected to contribute to 50.6% of the network's energy consumption by 2025. To reduce energy consumption, MNOs must re-evaluate the existing network's architectures and paradigms, which are considered unsustainable. Failure to do so will result in energy constraints with significant environmental and economic implications. By understanding energy consumption patterns, MNOs can develop strategies and implement technologies that

optimize energy usage, improve efficiency, and minimize the environmental impact of wireless networks.

- Environmental Concerns: Wireless communication systems, driven by carbon-based energy sources, currently account for 5% of global carbon dioxide emissions [2, 3]. The rapid increase of connected devices is a result of the growing number of devices.
- Economic concerns arise from the current network design, which aims to maximize capacity by scaling up transmit powers. However, increasing device count does not accommodate this approach, as higher energy usage increases communication capacity, leading to operational costs. Current wireless communication techniques are unable to provide the necessary increase in capacity by increasing transmit powers [9, 10].
- Moreover, considering the impact of energy efficiency, MIMO (Multiple Input, Multiple Output) has been one of the key technologies in increasing the speed of multimedia transmission, such as video or audio transmission, which requires special attention; hence, it is required to develop mechanisms to reduce the energy consumption [30-32].

1.1. Motivation and contribution

To combat the energy crisis in wireless networks, a new approach is needed for operation and design. The primary focus is to increase capacity by 1000 times while maintaining power consumption. This requires increasing the efficiency of every energy joule used for information transmission by a factor of 1000 or higher. This research work presents an energy-efficient maximization scheme for multimedia transmission, optimizing energy allocation and utilization to ensure efficient and effective transmission of multimedia data.

The proposed approach for energy efficiency maximization is called DSHM (Dual Step Hybrid Mechanism). DSHM is a two-step mechanism that integrates two distinct algorithms to maximize energy utilization in wireless networks.

- In the first step, an extended algorithm is introduced that aims to generate a closed-form solution for optimality. This algorithm considers various constraints**,** such as computation of the lower and upper bounds, given average spectral efficiency, and optimal energy consumption. By obtaining a closed-form solution, it allows for efficient optimization of energy utilization in the network.
- In the second step, another algorithm is introduced, which focuses on reducing energy consumption while still aiming for energy maximization. This algorithm further enhances the energy efficiency of the network by implementing specific techniques or strategies to minimize energy consumption without compromising on the desired energy maximization goal.
- To evaluate the effectiveness of DSHM, simulations are performed. These simulations consider different constraints and scenarios, such as computing the lower bound and upper bound, achieving a given average spectral efficiency, optimizing energy consumption, and obtaining the optimality of the system. Through these simulations, the performance and efficiency of DSHM can be assessed and compared with other existing mechanisms or approaches.

Overall, DSHM offers a dual-step approach to maximize energy utilization in wireless networks, combining closed-form optimization and energy reduction techniques. By evaluating DSHM through simulations, its effectiveness in achieving energy efficiency and optimization can be analyzed.

This particular research is organized in the following way; first section starts with the development and background of wireless networks and recent developments for multimedia transmission; the further importance of energy efficiency is broadly discussed with the motivation and contribution of this research work. The second section solely focuses on the different existing approaches developed for reducing energy consumption. The third section develops the DSHM for optimality generation with variables and reduction in energy with an algorithm and mathematical formulation. The Fourth section evaluates the DSHM with different constraints.

2. Related work

In [11], a scheme combining load-aware association and Maximum Energy Efficiency (MaxEE) is proposed. In [11, 12], a combined User Equipment (UE) association and power-based allocation scheme for heterogeneous tier networks is proposed. In [13] power allocation and UE association for large-scale wireless network scenarios is investigated. In [14], the UE association problem and resource allocation in energy-constrained HetNets are studied, along with a proposed algorithm for backhaul UE association. In [15], the focus is on downlink performance in access radio cloud networks and analysis is done of two coding schemes. A key distinction between the aforementioned works [11-14] and the proposed paper lies in the consideration of Coordinated MultiPoint (CoMP) scenarios, where UEs can access multiple base stations simultaneously. However, CoMP adoption increases system complexity. The effectiveness of CoMP technology for improving energy efficiency systems is highlighted in [16]. Studies [17-20] emphasize on Simultaneous Wireless Information and Power Transfer (SWIPT). [17] addresses EE and SWIPT problems in HetNet wireless networks. An energy concept pattern aided by SWIPT is proposed in [18]. In [19], the information and power transfer problem in SWIPT is investigated. [20] focuses on SWIPT relay problems in wireless networks for multiuser forwarding and channel decoding. It is worth noting that the studies mentioned above do not consider the recovery of electromagnetic energy from the environment at large-scale wireless network base stations using SWIPT technology. The proposed paper, however, investigates the deployment of recovery energy systems in large-scale wireless network base stations to take advantage of the massive number of antennas and reduce power consumption. Numerous research studies have also addressed resource allocation and energy efficiency [21-29]. In [22], an EE problem and a power-efficient Quality of Service (QoS)-driven allocation scheme are proposed for 5G networks. In [23] algorithms for hybrid network energy optimization in 5G networks are introduced. [24] analyzes overall performance based on chunk subcarrier allocation, considering average error rate constraints in the downlink of frequency division multiplexing for multiple users. In [21] a resource allocation scheme based on chunk allocation for maximum throughput with power transmission constraints is proposed. [25] proposes a resource allocation scheme considering different packet types and their bit error rate requirements in a single data stream. In [26] the focus is on interference problems in Ultra-Dense Networks (UDNs) between macro cell UEs and femtocell UEs. Table 1 compares the characteristics of the existing approaches.

Table 1. Comparison table of the characteristics of the existing approaches

Refe-rence	Topology	Initiation	Control overhead	Dependency	Mainte-nance	Periodic control message	Routing approach
[11]	Massive MIMO systems	Joint power allocation and User association Optimization	Mode-rate	Power allocation and User association	Low	Yes	Optimization-based
[12]	HetNets	Backhaul-aware user association and resource allocation	Low	Backhaul and Resource allocation	Low	No	Optimization-based
[13]	MISO heteroge-neous cellular networks	Energy efficient beamforming	Low	Beamforming	Low	No	Heuristic-based
[16]	Two-tier heteroge-neous network	Energy efficient joint user association and power allocation	Low	User association and Power allocation	Low	No	Optimization-based
[17]	Wirelessly powered communications	Analog spatial cancellation	Low	Spatial cancellation	Low	No	Heuristic-based
[19]	Green 5G mobile wireless networks	Statistical-QoS driven energy-efficiency optimization	Low	QoS and Energy efficiency	Low	No	Optimization-based
[20]	5G radio frequency chain systems	Energy efficiency optimization	Low	Radio frequency chain optimization	Low	No	Optimization-based
[21]	Millimeter wave cellular systems	Channel estimation and hybrid precoding	Low	Channel estimation and precoding	Low	No	Heuristic-based
[22]	OFDMA systems	Chunk allocation	Low	Chunk allocation	Low	No	Heuristic-based
[23]	OFDMA systems	Joint chunk, power, and bit allocation	Low	Chunk, power, and bit allocation	Low	No	Optimization-based
[24]	OFDMA systems	Radio resource allocation in high speed environments	Low	Resource allocation	Low	No	Optimization-based
[25]	mmWave massive MIMO systems	Machine learning-inspired energy-efficient hybrid precoding	Low	Hybrid precoding	Low	No	Machine learning-based
[26]	MQAM/OFDM systems under fast fading channels	Power and rate adaptation	Low	Adaptation	Low	No	Heuristic-based

The works reviewed propose a scheme combining load-aware association and Maximum Energy Efficiency (MaxEE), user equipment association, and power-based allocation for heterogeneous tier networks. They also investigate power allocation and UE association in energy-constrained HetNets, downlink performance in access radio cloud networks, and the deployment of recovery energy systems in large-scale wireless networks. The existing work also addresses resource allocation and energy efficiency in 5G networks, focusing on interference problems in Ultra-Dense Networks. But fails to take into consideration multiple QoS parameters while proposing the approaches.

3. Proposed methodology

This research work proposes a network energy optimization approach for multimedia networks, specifically focusing on a Base Station (BS) equipped with a large number of antennas to serve multiple users simultaneously. The paper addresses system modeling and network optimization aspects. It proposes models for wireless networks, wave channel systems, and energy-optimized networks. The efficiency of energy utilization is discussed in detail, and the paper presents a mathematical formulation for energy efficiency. The focus of this proposed work is on the Radio Frequency (RF) chains in 5G networks. In general, the RF chains in a 5G network comprise two separate frequency bands.

3.1. Wireless network system model

The base station equipped with this model has M antennas and uses L radio frequency chains in the 5G network. Considering the downlink of the wireless network, a single antenna J is active along with the high-speed transfer of data, which is termed a data stream. The model has a total of Jdata streams at the base stations. The communication and maximum throughput of the system are achieved due to the constraints on the count of the radio frequency chain's by the data stream $\leq$ radio frequency chains $\leq$ number of antennas $[J \leq L \leq M]$. The transmission vector r at the base station is concentrated on the network optimized A of RF chains and the total data streams. The radio frequency optimizer E is of radio frequency chain's as well as the number of antennas. The network optimizer allows modification of phase and amplitude for the multimedia signal. The modification of only phase can be performed by the radio frequency optimizer. Assuming that every radio frequency optimizer E has amplitude of one unit, the energy network optimizer A has been designed for limited power transmission. Assuming the presence of a fading channel in a medium of the multi-media, the received signal at the J-th mobile station is given in the equation below,

$$x_j = g_j EAr + m_j . \tag{1}$$

Considering the above equation r represents the transmission vector where $r = [r_1, r_2, \ldots, r_J]^s$ which belongs to $B^{J\times 1}$. Here the transmission vector contains every signal of all mobile stations. The single channel coefficient of the J-th mobile station is given by the equation below,

(2) $$\mathbb{Z}_J = g_J E .$$

The signal that is produced at the *J*-th mobile station is given in the equation below, where the digital energy network optimization matrix is denoted a_J ,

(3) $$\hat{r}_J = \mathbb{Z}_J a_J r_J + \sum_{h=1}^{J} \mathbb{Z}_J a_h r_h + m_j .$$

From the above equation, the interference and the noise which is attenuated in the signal is added to the equation. From the above equation,

(4) Interference is given as $\sum_{h=1}^{J} \mathbb{Z}_J a_h r_h$,

Noise is stated as m_j .

The efficiency is evaluated using the equation below, while assuming modulated formulation is Gaussian. In the equation below, $\mathrm{Sin}Q_J$ is the interference signal to the ratio of noise of *J*-th mobile station,

(5) $$Q = \sum_{j=1}^{J} \log_2 \left(\left| 1 + \mathrm{Sin}Q_J \right| \right),$$

(6) $\mathrm{Sin}Q_J$ is defined as $\mathrm{Sin}Q_J = \dfrac{\mathbb{Z}_J a_J r_J}{\sum_{h=1}^{J} \mathbb{Z}_J a_h r_h + m_j}$.

3.2. Multi-media channel model

The channel in the multimedia network obeys conventional fading, since the characteristics that are present in it with regard to various propagations are different when compared to channels of low frequency. A clustered model of the network channel illustrates the scattering feature that is limited in the channel. The network channel downlink that is normalized for the *J*-th mobile station is constructed as a summation of the paths for propagation that are scattered into clusters M_B in which each of the clusters, is involved in the total paths that is denoted as M_O . This is given in the equation below, where $f_{b,o}^{j}$ is used to denoted the complex network channel gain of *o*-th path and the *b*-th cluster,

(7) $$g_J = \left(\frac{1}{M_B M_O} \right)^{1/2} \sum_{b=1}^{M_B} \sum_{o=1}^{M_O} f_{b,o}^{J} z_{AR} \left(\vartheta_{b,o}^{J} \right) .$$

Considering Equation (7), for the given network channel the departure angle is denoted as $\vartheta_{b,o}^{J}$, the response array vector during transmission is denoted as $z_{AR}(\vartheta_{(b,o)}^{J})$ during which the dimension of elevation is ignored. The angle of departure has been distributed for a specific range for every cluster. Considering the base station and the mobile station array; ignoring the generality loss, a linear uniform array is deployed for modelling. Consider an antenna array M, the response array vector is denoted as $z_{AR}(\vartheta^{J}_{(b,o)})$ is given by the equation stated below,

(8) $$z_{AR}\left(\vartheta^{J}_{b,o}\right)=\left(N\right)^{-1/2}\left[1,e^{i2\pi c\sin\left(\vartheta^{J}_{b,o}\right)/\partial},\ \ldots,e^{i2\pi(M-1)c\sin\left(\vartheta^{J}_{b,o}\right)/\partial}\right]^{S}.$$

The wavelength of the network is denoted as ∂ for a particular carrier frequency, whereas the distance between antennas that are adjacent is denoted as c. Considering the half wavelength of an antenna, the response array vector can be obtained using Equation (8). This equation can also be applied to antennas of various wavelength patterns. The methodology proposed can be applied directly to random antenna arrays.

3.3. Network energy optimizer

The energy network discussed in this study is fully connected to every antenna through radio frequency adders as well as shifters of variable degree, which is done for performance improvement and unconstrained maximization. There are constrains that are present in the network optimizer where every element has a shift applied to it which is given as

(9) $$\kappa^{(o,p)}\in\left\{1,e^{i2\pi/2^{A}},\ldots,e^{i2\pi\left(2^{A}-1\right)/2^{A}}\right\}.$$

In the above equation $\kappa^{(o,p)}$ is at the o-th and p-th entry of E. Most of the algorithms that are considered in these studies pertaining to network optimization breakdown the problem into an analog and digital approach. The maximization of the sum rate of channels that is predefined is used for the selection of an analog network optimizer E, considering that the work proposed focuses on multimedia communication. The digital network optimizer A is used to omit any interference that occurs among the radio frequency chains. This complexity is reduced by changing this fully connected network structure into a semi-connected network structure in which the chains of radio frequency are linked to only a degree P which varies wherein $P=\frac{M}{L}$. The radio frequency of the optimized network format is written in the following equation, as shown below:

(10) $$E=\begin{bmatrix} e_1 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & e_l \end{bmatrix}.$$

In that equation e_l is used to indicate the analog optimization vector of the l-th radio frequency chain, which has a size of $P\times 1$ and every element that is not zero should be in the 8-th set. The above stated equations and their complexity can be further simplified by replacing the phase shifters with radio frequency switches and a single inverter. This, however, fails to perform due to the on-off nature of the connection. The optimization performed on the network is a crucial methodology that results in maximum energy efficiency. The energy optimization matrix combined with the problems relating to optimization are non-coherent. The optimization matrix is not possible to trace even by using exhaust searching, whereas the restrictions that are imposed on the optimizer have been managed. Considering completely digital wireless network systems, it requires massive effort to obtain energy efficiency using a local optimizer.

3.4. Network energy optimizer for energy efficiency

Consider the proposed work consists of a large count of antennas, an appropriate design of network energy optimizer has an array gain. There are two constraints that have to be met simultaneously – firstly, the channel that is equivalent has to be maintained well for efficient transmission of the data streams. Secondly, the radio frequency chain that are not useful are closed along with the antennas. Due to this efficiency, the energy is made as large as possible. The modelling of the design and mathematical formulation of the network energy optimizer is performed. The proposed algorithm framework, along with the generation of radio frequency chains, and the selection algorithm of the radio frequency chains is evaluated in this section.

Consider the power consumed by the network to be denoted as O and the sum rate to be denoted as Q, then the efficiency of energy is given by the equation stated below,

$$D(E,A) \triangleq \frac{Q(E,A)}{O(E,A)}. \tag{11}$$

In that equation Q which is the sum rate is given in Hz per 1 bit per 1 s and the consumed power O is in watt. The power consumption that is stated in this proposed work is given in the equation stated below,

$$O = O_{\mathrm{AA}} + M_{\mathrm{R}} O_{\mathrm{QEB}} + M_{\mathrm{R}} O_{\mathrm{CZB}} + M_{\mathrm{AR}} O_{\mathrm{OZ}} + M_{\mathrm{AR}} O_{\mathrm{OR}}, \tag{12}$$

where: M_{AR} as well as M_{R} is the number of the antennas that are active and radio frequency chains, respectively: $O_{\mathrm{OZ}}, O_{\mathrm{OR}}, O_{\mathrm{QEB}}$ and O_{CZB} are the power of the amplifiers OR, QE and CZB, respectively. Power of the signal that is digital during processing is denoted as O_{AA}. The value of each of the powers consumed in the above equation is as given,

$$O_{\mathrm{AA}} = 4,\ O_{\mathrm{CZB}} = 200\ \mathrm{mW},\ O_{\mathrm{QEB}} = 30\ \mathrm{mW},\ O_{\mathrm{OR}} = 30\ \mathrm{mW},\ O_{\mathrm{OZ}} = 20\ \mathrm{mW}.$$

The difference in a fully connected network that requires more power can be easily noticed in the above equation which shows the power consumed by O_{AA} is lesser which is a semi-connected network structure and also the radio frequency adders is excluded.

3.4.1. Analog energy network optimization

The efficiency of the energy consumed is optimized by turning off the unnecessary antennas of the base station. This results is a small portion of the total energy efficiency. Here, the effective selection of the antennas that have to be shut down is important. The antenna selection process is performed by adding an extra state termed as 0 indicating that the particular antenna is off, and the antennas that do not a have 0 values determine the phase of the antenna that is active. The rate of information for the network is high when the number of active antennas increases, but the power used by these active antennas is also high. The value calculated for E is as given in the equation below:

(13) $$E^{(o,p)} \text{ belongs to} \left\{ 0, 1, e^{\frac{i2\pi}{2^A}}, \ldots, e^{\frac{i2\pi\left(2^A-1\right)}{2^A}} \right\}.$$

We consider a semi-connected network structure in this proposed work, to show the energy efficiency that is produced through network optimization with E and A.

(14) $$\left(E, A\right) = \max_{E,A} D\left(E, A\right) = \max_{E,A} \frac{\sum_{J=1}^{J} \log_2\left(1+\rho_J\right)}{O\left(E, A\right)}.$$

We consider, $\mathbb{E}$ is the possibility of the analog network optimizers of a matrix satisfying Equations (10) and (13, and for the above Equation (14).

(15) $$\left\|EA\right\|_E^2 = J,$$

where $E \in \mathbb{E}$.

The equivalent of the network baseband channel is as given in the next equation:

(16) $$G_{\text{equivalent}} = [g_1^S \ldots g_J^S]^S E.$$

SINQ is the interference signal to the ratio of noise of J-th mobile station user ρ_J is as calculated below,

(17) $$\rho_J = \frac{\left\|g_J^S E a_J\right\|_E^2}{\varnothing_J^2 + \sum_{h \neq J} \left\|g_J^S E a_J\right\|_E^2}.$$

Considering the above Equation (17), a_J is the J-th column in the digital network optimizer A where the hybrid optimization is to model E under the given constrains. An exhaust search is used in this process where there are M non zero elements present in E in which every element has $2^A - 1$ values hence stating that that there are $\left(2^A - 1\right)^M$ possibilities. While considering wireless network systems, the configuration of these systems is potentially large; therefore**,** maintaining the restrictions that are dependent on the radio frequency optimizer is questionable. Hence, the proposed work focuses on optimization by producing a minimum cost function and generating tests that reach the near optimum. This is performed as follows.

Step 1. Initialization of the equal optimized matrix O^1. If the possibility of the k-th phase of the m-th element which is not of zero value in E in which

1 is lesser than or equal to k lesser than or equal to $2^A - 1$, and

1 is lesser than or equal to m lesser than or equal to M.

Step 2. Consider power consumed of O^l, in which the iteration is represented as l and in E^R the random generation is denoted by R for every individual E to which A^R which is corresponding, in which

1 lesser than or equal to r lesser than or equal to R.

Step 3. Evaluating the efficiency of energy D^R using Equation (11) in the order $\{D_1, D_2, \ldots, D_R\}$. In this case a target is picked as the selected batch.

Step 4. The probability distribution of the network for the energy efficiency is

(18) $$\mathbb{P}\left(O^l\right) = \sum_{s=1}^{S} v_s \sum_{m=1}^{M} \sum_{k=1}^{2^A-1} \sigma_{s,m,k}^l \ln o_{m,k}^l .$$

In that equation, the indicator for the binary activity is indicated by $\sigma_{s,m,k}^l$. The selected batch weight is given by the next equation:

(19) $$\mathrm{weight}_s = \frac{\left|Q_s - Q_S\right|}{\sum_{s=1}^{S} \left|Q_s - Q_S\right|} .$$

Step 5. The matrix of probability is improvised as follows

(20) $$O^{l+1} = \min_{O^l} \mathbb{P}(O^l) .$$

This can be further simplified as follows: Minimum $[\mathbb{P}(O^l)]$ is

(21) $$\sum_{k=1}^{2^A-1} O_{m,k}^l = 1 \text{ in which } m = 1, \ldots, M .$$

To further simplify the above equation, we use multipliers γ_m where $m = 1, \ldots, M$ the function pertaining to the optimization of the power is given as

(22) $$\mathfrak{l}\left(O^l, \gamma_1, \ldots, \gamma_m\right) = \sum_{s=1}^{S} \mathrm{weight}_s \sum_{m=1}^{M} \sum_{k=1}^{2^A-1} \sigma_{s,m,k}^l \ln o_{m,k}^l - \sum_{q=1}^{M} \gamma_q \left(\sum_{k=1}^{2^A-1} o_{m,k} - 1 \right).$$

After solving the above equation, we obtain

(23) $$\mathfrak{l}\left(O^l, \gamma_1, \ldots, \gamma_m\right) = 0 ,$$

$$M \geq q \geq 1,\ M \geq m \geq 1,\ 2^A - 1 \geq k \geq 1 .$$

The final result after computation of the following equations is

(24) $$O_{m,k}^{l+1} = \frac{\sum_{s=1}^{S} \mathrm{weight}_s \sigma_{d,m,k}^l}{\sum_{s=1}^{S} \sum_{k=1}^{2^A-1} \mathrm{weight}_s \sigma_{d,m,k}^l}$$

in which $M \geq m \geq 1,\ 2^A - 1 \geq k \geq 1$.

Step 6. Consider $l \leftarrow l+1$ after which the loop has to be restarted from the second step until the weight of the selected batch is equal to 0 or it has reached the maximum iterations. Therefore, we obtain the output E^{output} and A^{output} having the highest D^{output}. The algorithm that is proposed has the weight of the selected batch weight_s creates an unfairness for every selection which provides a criterion that has a simple ending as in Step 6.

Algorithm 1. Proposed Hybrid Energy Network Optimization Algorithm

Input: G, ρ^2

Output: E, A and D

Step 1. Loop

Step 2. for r where $r = 1, ..., R$

Step 3. E^R is generated according to $\mathbb{P}^l$

Step 4. A^R is evaluated by using Equation (27)

Step 5. D^R is evaluated using Equation (11)

Step 6. end for

Step 7. for s where $s = 1, ..., S$

Step 8. Evaluate weight_s using Equation (19)

Step 9. end for

Step 10. Check merging

Step 11. for m where $m = 1, \dots, M$

Step 12. for k where $k = 1, ..., 2^A + 1$

Step 13. Updating of O_m^{l+1}, using Equation (24)

Step 14. end for

Step 15. end for

Step 16. $l \leftarrow l + 1$

Step 17. end Loop

Step 18. return the output $E^{\text{output}}, A^{\text{output}}$ and D^{output}

3.4.2. Selection of radio frequency chain

In this section, we evaluate the selection of the radio frequency chain which we obtain from the Equation (16) by calculating $G_{\text{equivalent}}$.

Algorithm 2. Proposed Selection of Radio Frequency Chain Algorithm

Input: $G_{\text{equivalent}}$

Output: A

Step 1. Initialization of $G = G_{\text{equivalent}}\, 7_{h,i+j}, 7 = H_M$,

Step 2. Decompose: $G = PQ$ where $Q = [Q_J B]$

Step 3. while h, i where in $|Q - 1\ \text{JB}|_{h,i} > 1$

Step 4. Updating: $= G_{\text{equivalent}}\, 7_{h,i+j}$

Step 5. Decompose: $G = PQ$ where $Q = [Q_J B]$

Step 6. end while

Step 7. evaluate A using Equation (27)

Step 8. return A

For selection of the radio frequency chain, we calculate the matrix for permutation as follows

$$G_{\text{equivalent}} 7 = \left[G_1 G_2 \right]. \tag{25}$$

Considering Equation (25), G_1 has L columns that are independent which implies to condition one of $G_{\text{equivalent}}$. G_1 has a best combination with G_2 such that $\left\| G_1 - G_2 \right\|$ is very small which implies to condition 2. Therefore, the conclusion that is obtained to performing permutation of the matrix is as follows. Where $Q = Q7_{h,i}$, using which, the determinant ratio is as given.

$$\frac{\left| \text{derterminant}\left(\bar{Q} \right) \right|}{\left| \text{determinant}\left(Q \right) \right|} = \left| \frac{B}{Q_J} \right|_{h,i}. \tag{26}$$

In the above Equation (26), only the h-th and i-th column of the Equation (26) holds a greater threshold. In the proposed work, increase in the determinant causes an increase in the magnitude; therefore, the final optimization calculation is as shown below

$$A = \frac{\left(J \right)^{-1/2} \left(G_1 \right)^G \left(G_1 \left(G_1 \right)^G \right)^{-1}}{\left\| E (G_1)^G \left(G_1 \left(G_1 \right)^G \right)^{-1} \right\|_E^2}. \tag{27}$$

The optimization selection of the radio frequency chains is explained in detail in Algorithm 2.

4. Performance evaluation

Energy efficiency is the amount of energy used to achieve a task, particularly in wireless communication. Defined as the number of bits reliably transmitted per unit of energy consumed, energy efficiency is crucial for optimizing resource utilization, reducing energy consumption, and enhancing network performance. However, achieving high energy efficiency in wireless networks presents significant challenges due to their complexity and variability. To maximize energy efficiency and improve user experience, it is essential to consider the unique characteristics and demands of wireless communication systems when developing energy-efficient mechanisms and strategies.

4.1. Parameter settings

The DSHM (Dual Step Hybrid Mechanism) is evaluated for energy efficiency maximization by adjusting parameter settings. The evaluation includes the following parameter values: Block Length of 400, path loss of 3.76, and varying levels of hardware impairments with a bandwidth of 20 MHz and more details are listed in Table 2. These settings are utilized to assess the performance and energy efficiency achieved by the DSHM mechanism.

Table 2. Simulation parameters

Parameters	Values
Simulator	Matlab
Simulation time	300 s
Node movement	Random Direction
Pausetime	0/50/ 150 ms
Traffic	UDP
Packet size	512 KB
Transmission rate	4/s
Mobility speed	20/50 ms

4.2. Computation of lower bound and upper bound

A lower bound on a problem represents a big Omega bound on the worst-case running time of any algorithm that solves the problem. For example, it is known that any comparison-based sorting routine takes Ω (*n*log*n*) time. Fig. 1 illustrates the energy efficiency as a function of base density, considering other optimized variables, and with three different Signal-to-Interference-plus Noise Ratio (SINR) values: 1, 3, and 7. The figure provides a visual representation of how energy efficiency varies with different base densities and SINR values. An upper bound for a function *f* is a number *U* so that: for all *x*, we have $f(x) \leq U$.

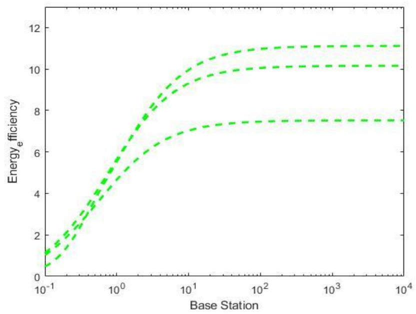

Fig. 1. Lower bound energy efficiency

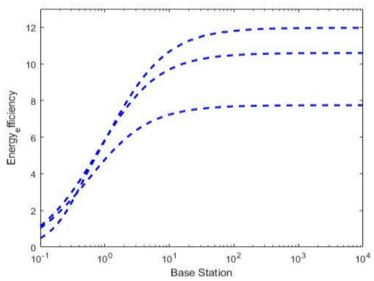

Fig. 2. Upper bound energy efficiency

Fig. 2 shows the upper bound with three different SINR values. Through Figs 1 and 2, it is observed that there is only a slight difference between the upper and lower bounds and curves seem to behave in a similar way, which validates the optimality.

4.3. Optimal energy consumption

Fig. 3 shows the optimal energy efficiency with a 3D diagram; moreover, the aim is to project the global optimum. In order to evaluate, the initialization point is set and it is observed that for certain Base stations and user equipment's, optimality is observed.

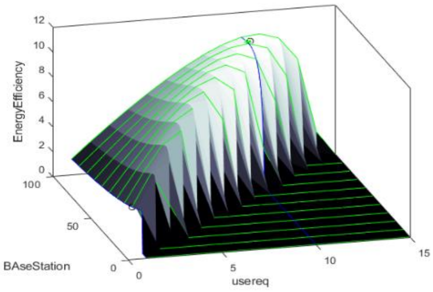

Fig. 3. Energy efficiency

4.4. Hardware impairments

Additionally, when considering hardware impairments as constraints, we evaluate the DSHM mechanism with three SINR constraints. It is noted that hardware impairments have a marginal impact on energy efficiency. The evaluation reveals that as the SINR constraints increase, the energy efficiency performance of the DSHM mechanism decreases. This observation suggests that higher SINR constraints result in lower energy efficiency in the system.

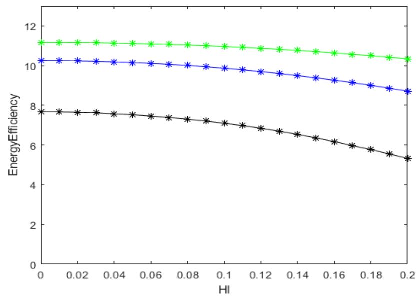

Fig. 4. Energy efficiency over hardware impairments

4.5. Energy efficient v/s active users

Fig. 5 illustrates the energy efficiency of active user density at a SINR level of 3. It also depicts energy efficiency as a function of user equipment density.

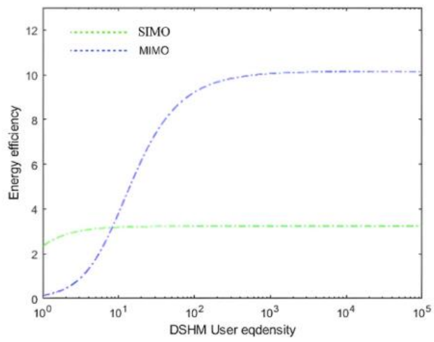

Fig. 5. Energy Efficiency over user equipment density

The figure includes two reference curves: the green curve represents the energy efficiency of a single-user system with a single input and multiple outputs, while the blue curve represents the energy efficiency of a multiple-input and multiple-output system. Both of these curves are considered optimal references in the analysis.

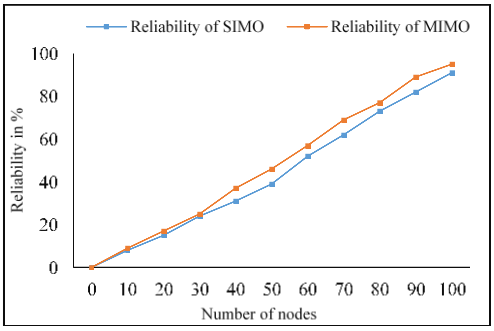

Fig. 6. Performance evaluation by number of nodes v/s reliability

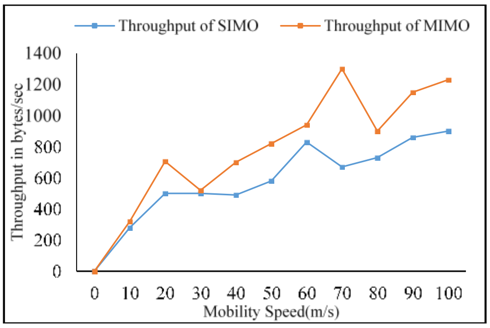

Fig. 7. Performance evaluation of mobility speed v/s throughput

4.6. Discussions

Wireless networks are one step towards achieving high energy utilization in wireless networks, which can be attained through deploying either a large number of base stations or base station antennas. In order to obtain the optimal configuration, the DSHM is proposed. Through the dual-step mechanism, an average lower bound on spectral efficiency is made tractable, and energy efficiency is maximized with respect to base station density and transmission capability. Moreover, optimality is achieved by considering optimal variables, hardware characteristics, and the respective environment through performance evaluation. The following observations can be made:

- Energy efficiency can be maximized by increasing base station density. As the density of base stations increases, energy resources are utilized more efficiently, resulting in improved energy efficiency in the network.
- Energy efficiency decreases with an increase in the Signal-to-Interference-plus-Noise Ratio (SINR) constraint. When the SINR constraint becomes more stringent, more energy is required to achieve the desired level of performance, leading to decreased energy efficiency.

- From Figs 4 and 5, it is observed that energy efficiency becomes independent when the density is large. In Fig. 6, it is observed that a single user requires nearly ten times higher base station density, which reduces energy efficiency.
- From Figs 6 and 7, it is observed that the proposed DSHM gives better performance than SIMO in terms of reliability and throughput.

By considering these observations and optimizing various factors, the proposed DSHM aims to achieve optimal energy efficiency in wireless networks.

5. Conclusions

Wireless networks have undergone rapid evolution in the past decade due to the high demand for multimedia services, such as video and audio transmission. Energy efficiency has become a crucial performance indicator for both present and future wireless networks, but it remains a challenging phenomenon to achieve. This research work focuses on designing and developing the Dual Step Hybrid Mechanism (DSHM) for energy-efficient maximization. The performance analysis conducted in this study demonstrates that decreasing cell size can lead to higher energy efficiency. Additionally, the addition of base stations increases the number of equipment per cell. While this paper aims to achieve a balance between energy efficiency and spectral efficiency, it also considers economic factors and deployment costs. Although this research work presents an algorithm to achieve energy-efficient maximization, it is important to acknowledge that there are numerous constraints that need to be considered based on the specific services being provided. These constraints should be taken into account in order to optimize energy efficiency effectively.

Conflict of interest: There is no conflict of interest.

Acknowledgment: Authors acknowledge the support from REVA University for the facilities provided to carry out the research.

References

1. Gupta, A., A. Trivedi, B. Prasad. B-GWO Based Multi-UAV Deployment and Power Allocation in NOMA Assisted Wireless Networks. – Wirel. Networks, Vol. **28**, 2022, No 7, pp. 3199-3211. DOI: 10.1007/s11276-022-03045-2.
2. Khan, W. U., F. Jameel, X. Li, M. Bilal, T. A. Tsiftsis. Joint Spectrum and Energy Optimization of NOMA-Enabled Small-Cell Networks with QoS Guarantee. – IEEE Trans. Veh. Technol., Vol. **70**, 2021, No 8, pp. 8337-8342. DOI: 10.1109/TVT.2021.3095955.
3. Kułacz, Ł., A. Kliks, P. Kryszkiewicz. Dynamic Transmit Profile Selection in Dense Wireless Networks. 2021.
4. Mehta, R. Trade-Off between Spectral Efficiency and Normalized Energy in Ad-hoc Wireless Networks. – Wirel. Networks, Vol. **27**, 2021, No 4, pp. 2615-2627. DOI: 10.1007/s11276-021-02610-5.
5. Gui, J., X. Dai, N. N. Xiong. Design and Analysis of Network Behaviors for Optimizing Network Energy Efficiency in 5G Mmwave Systems. – IEEE Trans. Netw. Sci. Eng., Vol. **8**, 2021, No 2, pp. 1842-1861. DOI: 10.1109/TNSE.2021.3074362.
6. V p, S. 3rd Generation Partnership Project; Technical Specification Group Radio Access Network; Evolved Universal Terrestrial Radio Access (E-UTRA); Further Advancements for E-UTRA Physical Layer Aspects. Release 9. Accessed: 04 March 2023 (Online).

7. L o p e z-P e r e z, D., et al. A Survey on 5G Radio Access Network Energy Efficiency: Massive MIMO, Lean Carrier Design, Sleep Modes, and Machine Learning. – IEEE Commun. Surv. Tutorials, Vol. **24**, 2022, No 1, pp. 653-697. DOI: 10.1109/COMST.2022.3142532.
8. A l-Y a s i r, Y. I. A., et al. Green and Highly Efficient MIMO Transceiver System for 5G Heterogenous Networks. – IEEE Trans. Green Commun. Netw., Vol. **6**, March 2022, No 1, pp. 500-511. DOI: 10.1109/TGCN.2021.3100399.
9. B o r g e s, D., P. M o n t e z u m a, R. D i n i s, M. B e k o. Massive Mimo Techniques for 5G and Beyond – Opportunities and Challenges. – Electron., Vol. **10**, 2021, No 14, pp. 1-29. DOI: 10.3390/electronics10141667.
10. B u z z i, S., I. C h i h-L i n, T. E. K l e i n, H. V. P o o r, C. Y a n g, A. Z a p p o n e. A Survey of Energy-Efficient Techniques for 5G Networks and Challenges Ahead. – IEEE J. Sel. Areas Commun., Vol. **34**, April 2016, No 4, pp. 697-709. DOI: 10.1109/JSAC.2016.2550338.
11. V a n C h i e n, T., E. B j o r n s o n, E. G. L a r s s o n. Joint Power Allocation and User Association Optimization for Massive MIMO Systems. – IEEE Trans. Wirel. Commun., Vol. **15**, January 2016, No 9, pp. 6384-6399. DOI: 10.48550/arxiv.1601.02436.
12. H a n, Q., B. Y a n g, G. M i a o, C. C h e n, X. W a n g, X. G u a n. Backhaul-Aware User Association and Resource Allocation for Energy-Constrained HetNets. – IEEE Trans. Veh. Technol., Vol. **66**, January 2017, No 1, pp. 580-593. DOI: 10.1109/TVT.2016.2533559.
13. S h e n g, M., L. W a n g, X. W a n g, Y. Z h a n g, C. X u, J. L i. Energy Efficient Beamforming in MISO Heterogeneous Cellular Networks with Wireless Information and Power Transfer. – IEEE J. Sel. Areas Commun., Vol. **34**, April 2016, No 4, pp. 954-968. DOI: 10.1109/JSAC.2016.2544538.
14. Z h a n g, R., L. L. Y a n g, L. H a n z o. Energy Pattern Aided Simultaneous Wireless Information and Power Transfer. – IEEE J. Sel. Areas Commun., Vol. **33**, August 2015, No 8, pp. 1492-1504. DOI: 10.1109/JSAC.2015.2391551.
15. W a n g, N., E. H o s s a i n, V. K. B h a r g a v a. Joint Downlink Cell Association and Bandwidth Allocation for Wireless Backhauling in Two-Tier HetNets with Large-Scale Antenna Arrays. – IEEE Trans. Wirel. Commun., Vol. **15**, May 2016, No 5, pp. 3251-3268. DOI: 10.1109/TWC.2016.2519401.
16. Y e, G., H. Z h a n g, H. L i u, J. C h e n g, V. C. M. L e u n g. Energy Efficient Joint User Association and Power Allocation in a Two-Tier Heterogeneous Network. – In: 2016 IEEE Glob. Commun. Conf., 2016. DOI: 10.1109/GLOCOM.2016.7841794.
17. Z h u, G., K. H u a n g. Analog Spatial Cancellation for Tackling the Near-Far Problem in Wirelessly Powered Communications. – IEEE J. Sel. Areas Commun., Vol. **34**, December 2016, No 12, pp. 3566-3576. DOI: 10.1109/JSAC.2016.2611961.
18. B e n k h e l i f a, F., A. S. S a l e m, M. S. A l o u i n i. Sum-Rate Enhancement in Multiuser MIMO Decode-And-Forward Relay Broadcasting Channel with Energy Harvesting Relays. – IEEE J. Sel. Areas Commun., Vol. **34**, December 2016, No 12, pp. 3675-3684. DOI: 10.1109/JSAC.2016.2611878.
19. C h e n g, W., X. Z h a n g, H. Z h a n g. Statistical-QoS Driven Energy-Efficiency Optimization over Green 5G Mobile Wireless Networks. – IEEE J. Sel. Areas Commun., Vol. **34**, December 2016, No 12, pp. 3092-3107. DOI: 10.1109/JSAC.2016.2599980.
20. Z i, R., X. G e, J. T h o m p s o n, C. X. W a n g, H. W a n g, T. H a n. Energy Efficiency Optimization of 5G Radio Frequency Chain Systems. – IEEE J. Sel. Areas Commun., Vol. **34**, April 2016, No 4, pp. 758-771. DOI: 10.1109/JSAC.2016.2544579.
21. A l k h a t e e b, A., O. E l A y a c h, G. L e u s, R. W. H e a t h. Channel Estimation and Hybrid Precoding for Millimeter Wave Cellular Systems. – IEEE J. Sel. Top. Signal Process., Vol. **8**, October 2014, No 5, pp. 831-846. DOI: 10.1109/JSTSP.2014.2334278.
22. Z h u, H., J. W a n g. Chunk-Based Resource Allocation in OFDMA Systems – Part I: Chunk Allocation. – IEEE Trans. Commun., Vol. **57**, 2009, No 9, pp. 2734-2744. DOI: 10.1109/TCOMM.2009.09.080067.
23. Z h u, H., J. W a n g. Chunk-Based Resource Allocation in OFDMA Systems-Part II: Joint Chunk, Power and bit Allocation. – IEEE Trans. Commun., Vol. **60**, February 2012, No 2, pp. 499-509. DOI: 10.1109/TCOMM.2011.112811.110036.

24. Z h u, H. Radio Resource Allocation for OFDMA Systems in High Speed Environments. – IEEE J. Sel. Areas Commun., Vol. **30**, May 2012, No 4, pp. 748-759. DOI: 10.1109/JSAC.2012.120509.
25. G a o, X., L. D a i, Y. S u n, S. H a n, I. C h i h-L i n. Machine Learning Inspired Energy-Efficient Hybrid Precoding for mm Wave Massive MIMO Systems. – IEEE Int. Conf. Commun., July 2017. DOI: 10.1109/ICC.2017.7997065.
26. D o n g, Z., P. F a n, W. Z h o u, E. P a n a y i r c i. Power and Rate Adaptation for MQAM/OFDM Systems under Fast Fading Channels. – In: Proc. of IEEE Veh. Technol. Conf., 2012. DOI: 10.1109/VETECS.2012.6239931.
27. D o n g, Z., P. F a n, E. P a n a y i r c i, X. L e i. Conditional Power and Rate Adaptation for MQAM/OFDM Systems under CFO with Perfect and Imperfect Channel Estimation Errors. – IEEE Trans. Veh. Technol., Vol. **64**, November 2015, No 11, pp. 5042-5055. DOI: 10.1109/TVT.2014.2377153.
28. C h a v a n, P., K. S a t y a n a r a y a n R e d d y. Integrated Cross Layer Optimization Approach for Quality of Service Enhancement in Wireless Network. DOI: 10.21817/indjcse/2021/v12i4/211204074.
29. C h a v a n, P., K. S. R e d d y. QoS Aware Video Transmission in Wireless Network: Successful and Failure Existing Technique. – Int. J. Recent Technol. Eng., 2020, No 5, pp. 2277-3878. DOI: 10.35940/ijrte.E5071.018520.
30. M u n u s a m y, N., S. V i j a y a n, M. E z h i l a r a s i. Role of Clustering, Routing Protocols, MAC Protocols and Load Balancing in Wireless Sensor Networks: An Energy-Efficiency Perspective. – Cybernetics and Information Technologies, Vol. **21**, 2021, No 2, pp. 136-165.
31. V i j a y a n, S., N. M u n u s a m y. Deterministic Centroid Localization for Improving Energy Efficiency in Wireless Sensor Networks. – Cybernetics and Information Technologies, Vol. **22**, 2022, No 1, pp. 24-39.
32. B a l a m u r a l i, R., K. K a t h i r a v a n, T. K r i s h n a n. Mitigating Hotspot Issue in WSN Using Sensor Nodes with Varying Initial Energy Levels and Quantification Algorithm. – Cybernetics and Information Technologies, Vol. **19**, 2019, No 3, pp. 118-136.

Received: 05.05.2023; Second Version: 02.07.2023; Third Verion: 19.07.2023; Accepted: 28.07.2023 (fast track)