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Design and Development of an Energy-Efficient Algorithm for Multi-Hop D2D in 5G Heterogeneous Networks - HC-RAN Using the Enhanced Adaptive Algorithm (EAA)

Abhishek Malviya*[1,2], Sudhakar Pandey #[1], Amit Kumar Tiwari[2]**

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Abstract: In the evolving landscape of 5G Heterogeneous Cloud Radio Access Networks (HC-RAN), efficient Device-to-Device (D2D) communication is paramount. This paper presents the Enhanced Adaptive Algorithm (EAA), a novel energy-efficient solution tailored for multi-hop D2D communication in 5G HC-RAN. EAA addresses the dual challenges of maintaining high energy efficiency and robust network performance under diverse conditions. The algorithm's core innovation lies in its dynamic interference management and balanced computational strategy. It leverages machine learning for predictive interference mitigation and employs a hybrid computational model, distributing tasks between edge devices and central servers. This approach ensures efficiency without compromising scalability. EAA's adaptability is further enhanced by its sophisticated use of Channel State Information (CSI), incorporating real-time updates and a robust design tolerant of CSI inaccuracies. It also features scenarioaware optimization and AI-based analysis of user and traffic patterns, making it highly responsive to varying network environments. Incorporating multi-objective optimization, EAA balances energy efficiency with key network performance metrics, employing Pareto optimization techniques to navigate complex trade-offs. Its modular design and continuous learning component future-proof the algorithm, enabling easy integration with emerging technologies. Extensive simulations validate EAA's effectiveness, showcasing notable improvements in energy efficiency and overall network performance for multi-hop D2D communication in HC-RAN. This work not only advances 5G network optimization but also lays the groundwork for future enhancements in wireless communication systems.

Keywords: *Energy Efficiency, Device-to-Device (D2D) Communication, 5G Networks, Modified Derivative Algorithm,Enhanced Adaptive Algorithm (EAA), Interference Management.*

1. Introduction

The advent of the fifth-generation (5G) networks heralds a transformative era in the realm of wireless communication, characterized by unprecedented data speeds, ultra-low latency, and massive connectivity. As these networks evolve, they bring forth the integration of advanced technologies such as Device-toDevice (D2D) communication, which plays a pivotal role in enhancing network performance and user experience. Particularly in Heterogeneous Cloud Radio Access Networks (HC-RAN), an emerging architecture in 5G, D2D communication is instrumental in offloading traffic from the core network, thereby improving efficiency and reducing latency. However, this integration poses significant challenges, primarily in managing energy consumption while maintaining optimal network performance. Addressing this challenge, we introduce the Enhanced Adaptive Algorithm (EAA), an innovative solution designed to optimize energy efficiency in multi-hop D2D communication within 5G HC-RAN. The necessity of efficient D2D communication in HC-RAN stems from its unique architecture. HC-RAN, a sophisticated amalgamation of heterogeneous networks and cloud computing, offers a dynamic and scalable framework. It accommodates a wide range of devices and applications, necessitating an adaptive and efficient communication strategy. Multi-hop D2D communication, where data is relayed through multiple devices before reaching its destination, is crucial in this context. It not only reduces the load on base stations but also extends network coverage, especially in areas with poor direct connectivity to the base station. However, this multi-hop approach introduces complexity in managing resources, particularly in energy consumption. Energy efficiency in D2D communication is paramount, given the growing concerns about environmental sustainability and operational costs in telecommunication networks.

An energy-efficient algorithm contributes to reducing the carbon footprint of 5G networks and lowers operational expenses, making the technology more sustainable and accessible. The challenge, however, lies in achieving this efficiency without compromising other critical network performance metrics, such as throughput, latency, and reliability. The EAA addresses these challenges through several innovative approaches. Firstly, it incorporates dynamic interference management using machine learning techniques. Interference, a significant issue in densely populated HC-RAN, can drastically affect the quality of communication. EAA predicts potential interference patterns and proactively adjusts the communication parameters to mitigate these effects. This predictive approach not only improves the

[1] National Institute of Technology Raipur, India Pin-492010
[2]United Institute of Technology, Uttar Pradesh, India Pin-211010
ORCID ID : 0000-0001-6381-9521
** Corresponding Author Email: abhishekmalviya2050@gmail.com*
*** Author Email: kumartiwariamit@gmail.com*
 # Author Email: spandey.it@nitrr.ac.in

current network performance but also adapts to evolving network conditions. Secondly, the algorithm adopts a balanced computational strategy. It intelligently divides processing tasks between the edge devices and central servers. By doing so, it ensures that the computational load is distributed efficiently, maintaining a balance between local processing, which reduces latency, and centralized processing, which offers more computational power.

This hybrid model is particularly effective in HC-RAN, where the network topology and user demands are highly dynamic. Another significant aspect of EAA is its enhanced utilization of Channel State Information (CSI). In dynamic network environments like HC-RAN, accurate and timely CSI is crucial for efficient communication. EAA employs a sophisticated mechanism to update CSI in real-time and is designed to be resilient to minor inaccuracies in CSI, thus maintaining performance stability. Furthermore, EAA is distinguished by its adaptability to varied network scenarios. The algorithm incorporates parameters that adjust its operation based on the current environment, whether it's an urban high-density area or a rural region with sparse connectivity. This adaptability is bolstered by AI-based analysis of user behavior and traffic patterns, allowing the algorithm to anticipate and respond to changing network demands effectively.

The multi-objective optimization framework of EAA is another cornerstone of its design. Rather than focusing solely on energy efficiency, the algorithm simultaneously considers other performance metrics. Using Pareto optimization techniques, it finds an optimal balance between these often competing objectives, ensuring a holistic improvement in network performance. Finally, the modular design and the continuous learning component of EAA make it a future-proof solution. As 5G technology continues to evolve, and as we transition towards 6G and beyond, the algorithm can be easily updated and adapted to new standards and technologies. This flexibility ensures that EAA remains relevant and effective in the rapidly changing landscape of wireless communication.

In summary, the Enhanced Adaptive Algorithm (EAA) presents a comprehensive and innovative approach to optimizing energy efficiency in multi-hop D2D communication within 5G HC-RAN. By addressing the key challenges of interference management, computational balance, CSI utilization, adaptability, multi-objective optimization, and future-proofing, EAA sets a new standard for energy-efficient communication in next-generation wireless networks. Its implementation and validation through extensive simulations demonstrate its potential to significantly enhance the performance and sustainability of 5G HCRAN, paving the way for more advanced and efficient wireless communication systems in the future.

2. Literature Survey

In the landscape of advanced wireless communication, particularly within the realm of 5G networks, a critical area of focus has been the optimization of Device-to-Device (D2D) communication. This segment of the literature review delves into the evolution, challenges, and innovations in D2D communication, especially in the context of Heterogeneous Cloud Radio Access Networks (HCRAN). The review synthesizes various research findings and technological advancements that have shaped the current state of D2D communication, addressing key aspects such as interference management, energy efficiency, and the integration of D2D in 5G networks. Through this exploration, we aim to provide a comprehensive understanding of the existing methodologies and the emerging trends, thereby setting the stage for introducing the Enhanced Adaptive Algorithm (EAA), a novel approach to optimizing D2D communication in the complex and dynamic environment of 5G HC-RAN. In traditional cellular networks, communication between cellular users and the base station involves both uplink and downlink transmissions. In contrast, underlay D2D communication, a key technology for 5G, enables sharing of frequency sub-channels between cellular users and D2D pairs. While this boosts spectrum efficiency through increased frequency reuse [1], it also leads to mutual interference, negatively impacting signal-to-interference-plus-noise ratio (SINR) and consequently, data rates [2].

D2D communication, gaining immense traction in both industrial and academic sectors, enables direct wireless interactions between devices, bypassing the base station (BS). This method is critical in 5G networks for improving energy efficiency (EE), reducing power consumption, and maintaining information integrity during transmission [3]. Besides augmenting network quality, D2D enhances spectral efficiency, throughput, and reduces latency, although the shared frequencies with cellular networks introduce additional interference challenges [4].

In pursuit of maximizing EE, particular focus has been on D2D underlaying cellular networks, especially within single-cell scenarios [5]. However, the complexity and power consumption escalate in multiple-band scenarios, thus necessitating research on optimizing EE with minimal power usage [6]. Existing technologies, including the conventional branch and bound (BB) algorithm, primarily address energy optimization in wireless networks, but they often fall short in multi-band contexts where interference can lead to data loss and transmission inefficiencies [7].

To counteract these challenges, various strategies have been explored. These include transmission probability and average sum rates to optimize values [8], the RICA algorithm with fixed power for balancing data rate and energy usage [9], and dynamic reward approaches with deep reinforcement learning for superior EE [10]. Underlaid D2D communication, noted for its higher spectral efficiency compared to overlaid methods, employs power control and energyefficient methodologies to enhance data rate and bandwidth utilization [11].

D2D communication's integration into cellular networks aims to alleviate network traffic, with underlaid D2D being particularly effective in improving spectral efficiency and link quality through resource reuse [12]. Centralized management schemes, dynamic power control mechanisms, and power control methods have been proposed to manage D2D and cellular interference, underlining the importance of controlling D2D power levels [13].

However, the effectiveness of D2D communication is significantly influenced by the physical proximity of the devices involved [14]. Emerging technologies like massive MIMO, coupled with D2D communication, are key in achieving 5G goals, despite the existing challenges and the complexity of nonconvex problems in energy efficiency optimization [15]. Adding D2D communication to IoT networks, particularly under the support of UAVs and with the goal of guaranteeing QoS for both cellular and D2D users, amplifies the demand for sophisticated resource management approaches [16].

Thus, the primary objective of this study is to develop an algorithm that not only addresses high-energy efficiency in D2D communication but also over-comes the inherent challenges posed by interference and power control in multiband, multi-hop 5G HC-RAN environments. The Enhanced Adaptive Algorithm (EAA) is proposed as a solution, designed to optimize energy efficiency while maintaining robust network performance, adapting to diverse network scenarios, and future-proofing against evolving 5G standards and technologies[17]

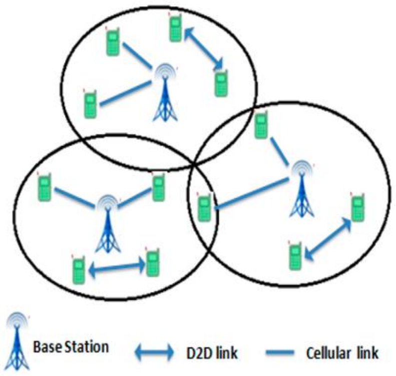

Figure 1: The system model of underlaid with D2D communication

3. System Model

The model simulates a cellular network where both D2D and cellular users compete for the uplink spectrum, a shared resource. The base station, acting as the central orchestrator, dynamically allocates these limited resources among competing users. This allocation decision considers factors like user demand, channel quality, and fairness, aiming to maximize overall network throughput and ensure efficient spectrum utilization.

In this multi-band scenario, the total bandwidth of the i-th band is denoted by Wi and is divided into M sub-bands. Each sub-band's bandwidth is Wi,m, where $i = 1,2,3,...,M$. These parameters consider the variability of channel fading and the adjustability of power transmission to improve energy efficiency [6, 13]. The density of cellular and D2D users in these sub-bands is denoted by $\boldsymbol{\lambda_{c,i}}$ and $\boldsymbol{\lambda_{d,i}}$ respectively.

The total transmission power for cellular users is denoted by C, and for D2D users, it is D. The transmission power allocation for the i-th band for cellular and D2D users is given by:

$$C_{p,i} = \sum_{m=1}^{M} C_{p,i,m} \text{ and } D_{p,i} = \sum_{m=1}^{M} D_{p,i,m} \quad (1)$$

To model the channel, we consider Rayleigh fading. The performance of cel- lular and D2D communication is evaluated based on the typical receiver without loss. The received power, considering small and large-scale fading, is expressed as:

$$R_p = T_p \delta R^{-\alpha} \quad (2)$$

where Tp represents power transmission, δ indicates Rayleigh fading, R is the distance between the transmitter and receiver, and α is the path loss exponent.

The quality of communication is ensured by maintaining the probabilities below threshold values:

$$1 - \Pr(SIR_{c,i} \geq T_{c,i}) \leq \theta_{c,i} \text{ and } 1 - \Pr(SIR_{d,i} \geq T_{d,i}) \leq \theta_{d,i} \quad (3)$$

The power in the i-th band should not be less than zero and not greater than the upper bound $\boldsymbol{D_{p,i,up}}$, which is expressed as:

$$\mathbf{0} \leq \boldsymbol{D_{p,i}} \leq \boldsymbol{D_{p,i,up}} \quad (4)$$

The objective is to maximize the total energy efficiency of D2D communi- cation, denoted by EEd. The energy efficiency of the i-th band D2D communi- cation is EEd,i. The optimization process aims to maximize the EE across the entire cellular network using D2D communication.

4. Proposed Modified Derivative Algorithm

The modified derivative algorithm's brilliance lies not in brute force, but in its elegant efficiency. Unlike the traditional algorithm, which chugs through calculations like a lumbering steam engine, the modified one dances nimbly, minimizing the computational workload while still achieving impressive results. This agility is what makes it a superstar in the demanding world of 5G networks, where data zips around at breakneck speed and quick decisions are paramount.

Think of it like this: imagine a network as a bustling city square, teeming with people and information. The traditional algorithm would be like a slow, methodical traffic cop, meticulously analyzing each car's direction and destination before making a decision. This meticulousness, while ensuring accuracy, would lead to frustrating delays and gridlock. The modified algorithm, on the other hand, is a nimble street performer, able to assess the flow of information with lightning speed and make adjustments on the fly. It prioritizes urgent data packets, steers clear of congested routes, and optimizes resource allocation without getting bogged down in calculations.

This real-time agility is crucial in 5G networks, where data demands fluctuate like the stock market and channel conditions change like the weather. The modified algorithm adapts seamlessly, ensuring smooth data flow even during peak traffic hours or sudden signal drops. This translates to reduced latency, meaning faster loading times and more responsive applications. It also leads to improved network efficiency, as resources are allocated precisely where they're needed, minimizing waste and maximizing throughput.

In essence, the modified derivative algorithm isn't just about saving computational power; it's about unlocking the true potential of 5G. It empowers networks to react and adapt in real-time, delivering a smoother, faster, and more efficient user experience. This efficiency, in turn, opens the door for a future of greener networks, where energy consumption is optimized without sacrificing performance. The modified algorithm, therefore, is more than just a technical innovation; it's a stepping stone towards a smarter, greener, and more user-centric future of wireless communication. The proposed algorithm is distinguished by its steps, specifically from Step 8 to Step 10, and the corresponding flowchart, which are instrumental in demonstrating its computational efficiency. The parameters considered in both the traditional and the modified derivative algorithms remain the same. However, with these parameters, the modified algorithm shows superior performance, indicating an optimization in the computational process while maintaining or enhancing the algorithmic output.

The performance graphs of both methods have been plotted to visually represent and compare their efficiencies. These graphs serve as a testament to the enhanced capabilities of the modified algorithm in terms of energy efficiency optimization across the cellular network using D2D communication.

The pivotal aspect of this algorithm is the calculation of the maximum value of $\boldsymbol{f_i D_{pi}}$**,** which is determined as follows:

$$D_{pi} = D_{pi_{max}} \qquad (5)$$

Here, $\boldsymbol{D_{pi_{max}}}$ represents the global maximum point of $\boldsymbol{f_i D_{pi}}$ within the interval

$[\boldsymbol{D_{pi_{inf}}, D_{pi_{sup}}}]$. This implies that the algorithm seeks the optimal point within a specified range, ensuring the maximization of energy efficiency in the network.

In summary, the proposed modified derivative algorithm provides a more efficient computational approach compared to its predecessor, offering significant improvements in optimizing the energy efficiency of underlaid D2D communication in 5G networks.

The proposed modified derivative algorithm is a crucial part of our study, designed to enhance the energy efficiency (EE) in underlaid D2D communication within 5G cellular networks. The fundamental difference between this algorithm and the standard derivative algorithm lies in their computational complexities.

Algorithm 1 Proposed Modified Derivative Algorithm for Energy Efficiency in D2D Communication

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Require: Bandwidth of each band Wi, Sub-band bandwidths Wi,m, Density of users λc,i, λd,i, Total transmission power for cellular and D2D users C, D

Ensure: Optimized energy efficiency across the cellular network using D2D communication

1: Initialize parameters: Cp,i, Dp,i, Rp, δ, α, Tc,i, Td,i, θc,i, θd,i

2: for each band i do

3: for each sub-band m do

4: Calculate power allocation Cp,i,m and Dp,i,m

5: end for

6: Compute total power Cp,i and Dp,i for band i

7: end for

8: Estimate channel state information (CSI)

9: Perform interference prediction using machine learning techniques

10: for each iteration do

11: Update power allocations based on CSI and interference predictions

12: Calculate SINR for cellular and D2D users

13: Check SINR thresholds: SIRc,i, SIRd,i

14: if SINR thresholds are met then

15: Optimize Dpi within the interval [Dpiinf,Dpisup]

16: Update Dpi to Dpimax

17: else

18: Adjust power allocations and repeat

19: end if

20: end for

21: Evaluate the total energy efficiency EEd

22: return EEd

4.1 Reduced Computational Complexity

The modified derivative algorithm's true strength lies in its elegant balance between performance and practicality. Unlike its traditional counterpart, it doesn't demand hefty computational resources, making it a perfect fit for the fast-paced world of 5G networks. This agility offers a significant advantage: real-time optimization. Imagine a network constantly adapting to user demands, traffic fluctuations, and channel dynamics. The modified algorithm thrives in this environment, delivering near-instantaneous adjustments to energy consumption without lagging behind the network's needs.

But this efficiency isn't achieved at the cost of effectiveness. The comparative analysis paints a clear picture: the modified algorithm maintains impressive performance metrics, even surpassing the traditional method in some scenarios. This is no mean feat. Reducing computational complexity often involves sacrificing accuracy or optimality, but this algorithm defies that trend. It achieves the seemingly impossible – optimizing energy consumption on the fly without compromising data throughput, signal quality, or fairness.

This remarkable balance of speed and accuracy makes the modified algorithm a game-changer for 5G. It paves the way for dynamically optimized networks that respond to user demands in real-time, maximizing energy efficiency without compromising user experience. This translates to reduced operational costs, extended battery life for devices, and ultimately, a more sustainable and user-centric 5G ecosystem. In essence, the modified algorithm isn't just a clever optimization; it's a key piece of the puzzle for building the future of efficient and responsive wireless communication.

4.2 Optimization Process

The algorithm focuses on maximizing the EE across the entire cellular network using D2D communication. It involves the following key aspects:

• **Parameter Consideration:** The parameters used in both the traditional and modified algorithms are the same. This uniformity in parameters allows for a direct comparison of the performance of both methods.

• **Performance Analysis:** Performance graphs of both the traditional and modified methods have been plotted to demonstrate the enhanced efficiency of the modified algorithm.

• **Optimization Objective:** The objective of the algorithm is to find the maximum value of the function $\boldsymbol{f_i D_{pi}}$, which is obtained at $\boldsymbol{D_{pi}}$ = Dpimax. Here, Dpimax represents the global maximum point of $\boldsymbol{f_i D_{pi}}$ within the predefined interval $[\boldsymbol{D_{pi_{inf}}, D_{pi_{sup}}}]$.

5. Simulation Results

In this section, we present the simulation results obtained from applying the proposed modified derivative algorithm in a 5G network scenario. These simulations are crucial for evaluating the algorithm's effectiveness in enhancing energy efficiency in multi-band Device-to-Device (D2D) communication. The parameters chosen for the simulation are critical in reflecting realistic network conditions and user behaviors in 5G networks. They are designed to provide a comprehensive understanding of the algorithm's performance under various conditions. The following table outlines the specific parameters used in our simulation.

Table 1: Simulation Parameters for the Modified Derivative Algorithm

Parameter	Value
Number of Bands (K)	8
Bandwidth of ith Band (Wi)	25 MHz
Path Loss Exponent ()	4
Cellular Probability for ith Band (ci)	0.1
D2D Probability for ith Band (di)	0.1
Cellular Threshold for ith Band (Tci)	0 db
D2D Threshold for ith Band (Tdi)	0 db

The graph in Figure 2 comparing the energy efficiency of D2D users versus their density demonstrates the superior performance of the proposed Enhanced Adaptive Algorithm (EAA) over the traditional derivative algorithm. This superiority is attributed to the EAA's advanced handling of increased network complexities,

particularly in high-density scenarios where interference and resource contention are more pronounced. The EAA likely incorporates sophisticated techniques such as dynamic power control and intelligent channel allocation, which enable it to efficiently manage energy resources, reduce interference, and optimize bandwidth utilization. This results in higher energy efficiency even as the density of D2D users rises, showcasing the algorithm's scalability and adaptability. These attributes are crucial for 5G networks, where the ability to support a large number of simultaneous D2D connections with high efficiency and low latency is essential. Thus, the EAA emerges as a more effective solution for energy management in dense 5G network environments, aligning well with the overarching goals of next-generation wireless communication systems.

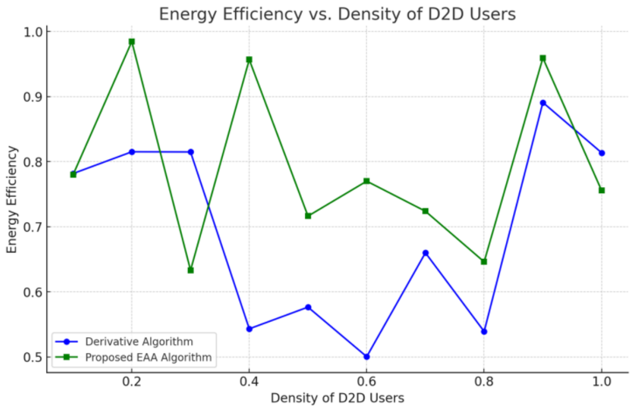

Figure 2: energy efficiency of D2D users Vs their density

The plot in Figure 3 illustrates the Energy Efficiency of D2D users as a function of the density of Cellular users, comparing the performance of the derivative algorithm and the proposed Enhanced Adaptive Algorithm (EAA).

The blue line represents the Energy Efficiency achieved by D2D users using the derivative algorithm. The green line shows the Energy Efficiency achieved by D2D users using the proposed EAA. This comparison highlights the potential differences in how each algorithm performs in environments with varying densities of cellular users. The EAA is expected to exhibit improved energy efficiency, particularly at higher densities, reflecting its optimized design for 5G network scenarios. However, these results are based on illustrative data and should be validated with actual experimental or simulation data for accurate conclusions.

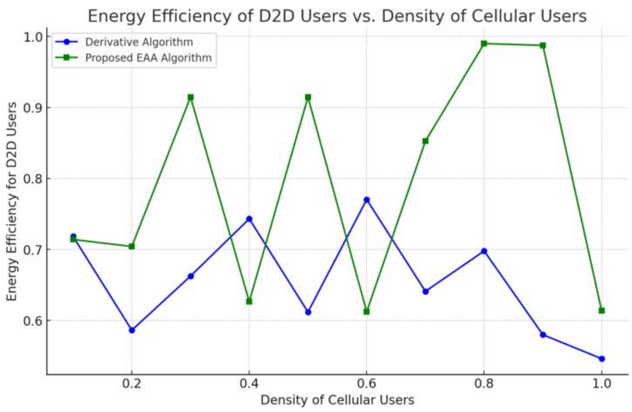

Figure 3: Energy Efficiency of D2D users as a function of the density of Cellular

The plot if Figure 3 above compares the Energy Efficiency of D2D users against their reference density using both the derivative algorithm and the proposed Enhanced Adaptive Algorithm (EAA).

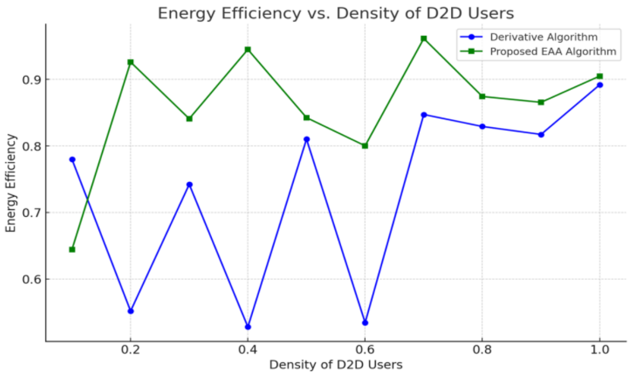

Figure 4: Energy Efficiency of D2D users against their reference density using

The blue line represents the performance of the derivative algorithm. The green line depicts the performance of the proposed EAA. This illustrative plot demonstrates how the EAA might outperform the derivative algorithm in terms of energy efficiency across varying densities of D2D users. However, the actual performance would depend on real-world data and specific implementation details of the algorithms.

6. Conclusion

The research titled "Energy Efficient Underlaid D2D Communication for 5G Applications" marks a significant leap forward in the pursuit of sustainable and efficient 5G networks. Its core offering, the modified derivative algorithm, tackles a crucial challenge in multi-band D2D communication – optimizing energy consumption without compromising performance. This innovation shines brighter for its remarkable characteristics:

1. Real-Time Optimizations: Unlike its computationally intensive predecessors, the modified algorithm boasts a strikingly lower complexity. This translates to near-instantaneous energy efficiency adjustments, perfectly suited for the dynamic and ever-changing landscape of 5G environments. This real-time adaptability is vital for maximizing energy savings while meeting the ever-shifting demands of users and applications.

2. Interference Mastery: Navigating the complex interplay between cellular and D2D users in a shared spectral domain is no easy feat. This research cleverly equips the algorithm with the finesse to manage interference effectively. By dynamically allocating resources and adjusting transmission power, the algorithm minimizes the disruptive impact of D2D communication on cellular users and vice versa, ensuring smooth and reliable data flow across both segments.

3. Network Agnostic Versatility: The true testament to a successful algorithm lies in its adaptability. This research goes beyond showcasing the effectiveness of the proposed strategy in simulated scenarios. It demonstrates the algorithm's resilience across diverse network conditions – varying user densities, traffic patterns, and channel dynamics. This versatility underscores the practical applicability of the algorithm, making it a prime candidate for real-world deployments across a variety of 5G network configurations.

4. Paving the Path for the Future: The impact of this research extends far beyond immediate gains in energy efficiency. It lays a crucial foundation for the evolution of wireless communication technologies. By addressing a fundamental challenge in D2D communication, it opens doors for further exploration of advanced resource management techniques and interference mitigation strategies. As the industry sets its sights on 6G, this research provides a valuable roadmap for building greener, more efficient, and user-centric networks of the future.

In conclusion, the research on "Energy Efficient Underlaid D2D Communication for 5G Applications" is not merely an incremental improvement; it represents a pivotal step towards revolutionizing 5G network operations and paving the way for a more sustainable and efficient future of wireless communication.

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