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Enhanced Distance-Based Resource Allocation for Spectrum Utilization and Fairness in Device-to-Device Communication Enabled 6G Networks

Abdullah H. Al-Quhali
Centre for Wireless Technology (CWT)
Faculty of Artificial Intelligence & Engineering
Multimedia University
Cyberjaya, Malaysia
alhadi1abd@gmail.com

Mardeni Roslee
Centre for Wireless Technology (CWT)
COE for Intelligent Network
Faculty of Artificial Intelligence & Engineering
Multimedia University
Cyberjaya, Malaysia
mardeni.roslee@mmu.edu.my

Osama Abuajwa
COE for Intelligent Network
Research & Innovation Development
TM R&D Sdn. Bhd.
Cyberjaya, Malaysia
osama@tmrnd.com.my

Mohamad Y. Alias
Centre for Wireless Technology (CWT)
COE for Intelligent Network
Faculty of Artificial Intelligence & Engineering
Multimedia University
Cyberjaya, Malaysia
yusoff@mmu.edu.my

Azlan bin Sulaiman
COE for Intelligent Network
Research & Innovation Development
TM R&D Sdn. Bhd.
Cyberjaya, Malaysia
azlan@tmrnd.com.my

***Abstract*— The rapid development of 6G networks presents challenges in effectively allocating resources for device-to-device (D2D) communication, especially in dense and dynamic networks. This paper presents an enhanced distance-based resource allocation (EDBRA) scheme to improve spectrum utilization and fairness for D2D communication in 6G networks. The EDBRA dynamically allocates resources using distance and the signal-to-interference-plus-noise ratio (SINR). An intelligent power adjustment and adaptive resource allocation are applied to prevent SINR cliff effects and reduce edge-user starvation. The proposed scheme significantly outperforms traditional baseline resource allocation methods regarding spectrum utilization and fairness. Experimental results show a 40% improvement in utilization and 67% gains in fairness compared to baselines, with 84% of users exceeding the 3 dB SINR threshold at cell edges. This paper validates EDBRA as a robust solution for 6G D2D networks, offering substantial spectrum utilization, fairness, and reliability improvements in dense, highly dynamic environments.**

Keywords*— *D2D, spectrum utilization, fairness, 6G networks.

I. Introduction

In next-generation networks, device-to-device (D2D) communication is a crucial enabler that boosts system efficiency, lowers latency, and facilitates proximity-based applications. D2D, which was first introduced in LTE-Advanced under 3GPP Proximity Services (ProSe) for public safety, is now crucial for 5G and 6G, supporting use cases such as edge computing, vehicle networks, and content sharing [1-2]. The D2D communication is improved by technologies such as Non-Orthogonal Multiple Access (NOMA), Unmanned Aerial Vehicles (UAVs), and Reconfigurable Intelligent Surfaces (RIS), which solve its main drawbacks. NOMA uses shared resources for user multiplexing, which improves sum rate and spectrum efficiency. In places with inadequate infrastructure, UAVs serve as mobile relays, increasing D2D coverage. RIS dynamically controls signal reflection to enhance the network's quality and optimize SINR control. When combined, these technologies increase D2D's scalability, effectiveness, and adaptability for future 6G networks. Significant improvements in capacity, efficiency, and coverage have been attained by recent research that has combined D2D with NOMA [3], RIS [4], UAVs [5], and federated reinforcement learning (FRL) [6]. RIS increases ergodic rates to 12 bps/Hz [4], NOMA-D2D improves delay-tolerant capacity by up to 85% [4], and DRL-based spectrum allocation improves interference management and throughput [6 -7]. These developments demonstrate how important D2D is to future wireless networks' performance and scalability. D2D is essential to the ultra-reliable, low-latency, high-capacity connectivity required by future 6G networks.

However, in dynamic and congested environments, static resource allocation fails, resulting in wasteful spectrum use and low fairness. The proposed solution to this problem is the enhanced distance-based resource allocation (EDBRA) system, which distributes resources dynamically according to user distance and real-time SINR. The technique overcomes the drawbacks of traditional methods by giving priority to links with SINR > 3 dB and distance $> 50\ m$ to improve the spectrum utilization and fairness.

This paper is structured into various sections, beginning with an introduction. Section II concisely reviews the work on D2D implementation for next-generation networks, including types of methods applied to different applications such as NOMA-D2D, UAV-D2D, and RIS-D2D techniques. Section III presents the methodology and simulation environment. Section IV presents the results and analysis of the simulation and compares the proposed approach with a static baseline. Finally, conclusions are drawn, highlighting the benefits and future potential of the proposed method. and recommendations in Section V.

II. Literature Review

In next-generation networks, D2D communication is essential for increasing network efficiency. In order to expand coverage, sum rate, and outage, recent research has improved D2D by combining it with learning-based techniques, Non-Orthogonal Multiple Access (NOMA), Reconfigurable Intelligent Surfaces (RIS), and Unmanned Aerial Vehicles (UAVs). D2D was first shown as a controlled underlay in Long Term Evolution-Advanced (LTE-Advanced) in [1]. In network environments with interference limitations, a throughput improvement of up to 65% was demonstrated, while SINR deterioration was maintained at or below 3 dB. LTE Release 12's 3GPP Proximity Services (ProSe) architecture [2] tackled fundamental issues, including in/out-of-coverage support and interference coordination.

A cooperative D2D-NOMA system that used Maximum Ratio Combining (MRC) in [3] enhanced the ergodic sum rate by more than 1.5 bps/Hz and decreased outages by 30 to 50%, particularly in situations with high SNR (SNR ≥ 25 dB). The authors in [4] applied RIS-assisted D2D systems under Nakagami-m fading, which showed an ergodic rate saturated at high SNR and increased logarithmically with the number of RIS components. The approach achieved around 12 bps/Hz at M = 256 and 30 dB SNR based on optimum power allocation. By combining coalition game theory with disk covering in UAV-assisted D2D networks, the Maximum Rate with Minimum Nodes (MRMN) approach in [5] achieved a 0.45 Gbps sum rate using 10 fewer UAVs than baselines. Using Multi-Agent Actor-Critic (MAAC) and Neighbour-Assisted Actor-Critic (NAAC), multi-agent deep reinforcement learning (DRL) reduced outages and enhanced sum rate with quicker convergence in [7]. In 6G D2D situations, distributed deep deterministic policy gradient (D3PG)--based learning improved the sum rate by up to 49.8% and improved fairness [8].

The Channel Allocation based on Partial Information and Location (CA-PIL) technique was finally developed in [9], which demonstrated superior performance at greater transmit power with an outage probability close to 0.4 and higher effective throughput as D2D user density grew. The authors in [10] examined the average sum rate (ASR) in D2D networks underlaid over Nakagami-m fading. Peak ASR for D2D and cellular was achieved around 250 bits/s and 140 bits/s, respectively, with m = 4 and ideal Signal-to-Interference Ratio (SIR). However, interference caused the ASR to decrease beyond this point. While performance plateaued at high SNR under defective Successive Interference Cancellation (SIC), the Bidirectional Device-to-Device Cooperative NOMA (BD2D-CNOMA) method, which was presented in [11], achieved logarithmic ergodic capacity increase with SNR under ideal SIC. The authors in [12] developed Signal-Gathering D2D-NOMA (D2DSG-NOMA), a two-slot cooperative method that outperformed Single Relay NOMA (SR-NOMA) by using overhead signals to increase Delay-Tolerant Capacity (DTC) by 66–85% at 0 dB and 3–10% at 40 dB.

The authors in [13] investigated downlink rates in D2D underlaid cell-free massive MIMO systems with low-resolution Digital-to-Analog Converters (DACs) and poor Channel State Information (CSI). Closed-form expressions were obtained for D2D User Equipments (DUEs) and Cell-Free UEs (CFUEs). A path-following power management algorithm was used to obtain a rate increase of up to 86.4%, with average total rates improved by 9.9% over Channel-Dependent Power Allocation (CDPA) and 11.7% over Equal Power management (EPC). A Distributed Artificial Intelligence Solution (DAIS) for dynamic D2D management in 5G/6G was presented in [14]. It achieved up to 70% lower power consumption and 22% greater spectral efficiency at 1000 UEs during mobility and network changes, outperformed the baseline work. The authors in [15] proposed a Federated Learning–based Deep Reinforcement Learning (FL-DRL) resource allocation approach for D2D-enabled 6G, which achieved 30% greater throughput and 30% lower power consumption than DRL and baseline methods.

Similarly, (FL-DRL-D2D) used a Federated Double Deep Q-Network (DDQN) for decentralized resource allocation in 6G D2D networks [6]. In comparison to Deep Q-Network (DQN), Distributed Deep Deterministic Policy Gradient (D3PG), and Multi-Agent Actor-Critic (MAAC) schemes, it achieved 41.5% greater energy efficiency, 47.3% better sum rate, and 27.3% lower outage probability. The authors in [16] utilized a unique SRU approach in order to achieve up to 60.2% total rate improvements based on Random Priority Algorithm (RPA) and Cluster-Based Channel State Aware Allocation (CCSAA) for D2D subchannel allocation with restricted Channel State Information (CSI). CCSAA performed well with statistical CSI, while RPA did well with partial CSI. The authors in [17] derived the maximum D2D link counts in underlay cellular networks, adding more D2D lines that only boosted throughput up to a limit, beyond which the advantages were outweighed by interference. The work determined the maximum permitted density that preserved QoS criteria and the ideal D2D link density that optimizes system throughput.

The authors in [18] employed the Block Coordinate Descent (BCD) method to maximize the multicast sum rate for Reconfigurable Intelligent Surface (RIS) based D2D in a Multiple-Input Multiple-Output system. The proposed approach outperformed the baselines and achieved 59 bps/Hz**.** According to [19] evaluation of Internet of Things Device-to-Device Communication (IoT-D2D) lines in LTE underlay mode, outages were decreased by greater route loss exponents and higher IoT Device (IoTD) power. Fewer devices result in a better average sum rate, although N = 10 can also function effectively, emphasizing the importance of the IoT gateway location. The authors in [20] proposed a combined power allocation and precoding system for uplink Terahertz (THz) communications utilizing an Active RIS placed on Unmanned Aerial Vehicles (UAVs) to handle a cellular user and numerous D2D users. The proposed technique outperformed alternatives by up to 200 Mbps and reached up to 500 Mbps in total rate compared to passive RIS and Amplify-and-Forward (AF) relaying. The authors in [21] developed joint power control and communication mode selection for Device-to-Device (D2D) communication in 5G networks. This achieved up to 225 bps/Hz and up to 50× sum-rate gains across a variety of environments in comparison to conventional cellular baselines.

All of the analyzed research shows how D2D communication has developed into a key component of next-generation networks, with different approaches addressing scalability, spectrum efficiency, and dependability issues. D2D was created as a controlled underlay with interference coordination in the early foundational research [1-2], which demonstrated encouraging throughput increases under SINR limitations. Cooperative and multi-slot approaches exceeded single-relay baselines, while later integration with NOMA [3, 11, 12] resulted in significant gains in ergodic and delay-tolerant capabilities, especially in high-SNR scenarios. Although gains saturate at high SNR, RIS-assisted designs [4, 18] showed that performance scales logarithmically with the number of reflecting components, suggesting the necessity for adaptive power allocation. Strong potential for spectrum improvements and coverage extension was revealed by UAV-based D2D systems [5, 20], particularly when paired with RIS assistance or intelligent power regulation.

Although complexity and convergence speed differed per framework, machine learning-based methods such as MAAC, NAAC, D3PG, and FL-DRL [6-8; 14, 15] continuously beat conventional baselines regarding throughput and energy efficiency. The work in [9, 16] has shown that statistical and partial CSI-based algorithms, such as CA-PIL, RPA, and CCSAA, can effectively allocate subchannels and adapt to CSI constraints. Similarly, [17] highlighted the necessity for density-aware optimization by stressing that increasing D2D density only enhances throughput up to a threshold, beyond which interference takes over. It was demonstrated that IoT-D2D performance [19] was sensitive to power levels, route loss, and gateway placement, while [21] demonstrated that joint power and mode selection techniques can provide sum-rate improvements of up to 50× above cellular baselines.

The literature generally shows a significant trend toward learning-based, hybrid, and adaptive D2D frameworks, which are especially useful in dynamic and dense situations. In order to maximize resource allocation, improve throughput, and lessen interference, these strategies increasingly use real-time SINR monitoring and context-driven flexibility. However, there are still difficulties in upholding equity and controlling computational complexity, particularly in the presence of high mobility and fluctuating interference, highlighting the necessity of effective and scalable SINR-driven D2D techniques.

III. METHODOLOGY

This work proposes an enhanced distance-based resource allocation method to dynamically distribute resources according to user distance and the real-time SINR in D2D-enabled 6G networks. The technique only prioritizes the top 70% of users with separations more than 50 meters and SINRs greater than 3 dB [1]. For D2D pairing and resource allocation, the top 70% of users are selected based on real-time SINR, therefore removing the bottom 30% with weak connection quality. To guarantee dependable, interference-aware D2D connections, users with SINR > 3 dB and separation distance > 50 meters are further chosen from this group. Proportional resource distribution is guided by a hybrid measure that combines normalized SINR and inverse distance. This adaptive approach aims to improve the sum rate and decrease real-time connection quality outages. In accordance with 3GPP specifications [1], the 3 dB SINR threshold strikes a balance between connection dependability and user engagement for extremely dependable low-latency services [2].

The proposed EDBRA system is shown in an urban macrocell environment in Fig.1. The diagram displays a hexagonal cell containing D2D communication users, each of whom is assessed based on distance and SINR. In congested situations, dependable link selection is made possible by the base station's central management of resource distribution.

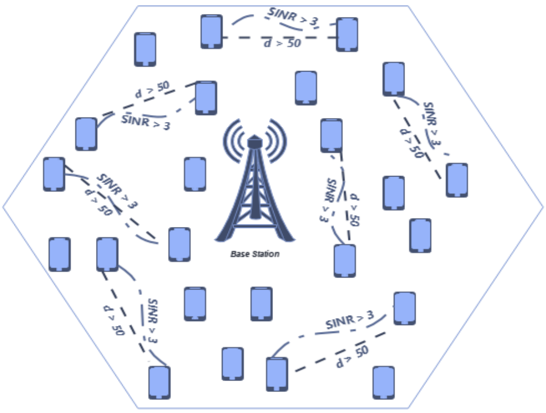

Fig. 1. System model in an urban macrocell environment

As a user-level preselection step, the top 70% SINR filter ensures that only users with strong signals are considered for D2D communication, increasing system performance and dependability while reducing interference. Based on the real-time SINR and user proximity, the proposed EDBRA dynamically distributes spectrum resources to enhance the data rate distribution. The following formula determines the priority metric p_i used to allocate resources:

$$p_i = \frac{\alpha}{d_i} + (1-\alpha)\frac{SINR_i}{\sum_{j=1}^{N} SINR_j}, \quad 0 < \alpha > 1 \tag{1}$$

where d_i represents the distance of the user from the base station. The instantaneous measured SINR for the user is described as $SINR_i$. The weight parameter α is set to 0.6. The following formula is used to determine the user's SINR:

$$SINR_i = \frac{p_{r,i}}{\sum_{j\neq i} p_{int,i} + N_{\circ}}, \tag{2}$$

where $p_{r,i}$ is the received power at user i.The interference power from other users is denoted as $p_{int,i}$, where the noise power $N_{\circ}$. The resources are distributed proportionately based on the priority metric. p_i using the following:

$$n_i = M \times \frac{p_i}{\sum_{j=1}^{N} p_j}, \tag{3}$$

Where the amount of the resources allocated to user i is denoted as n_i. The M represents the available resources in the system, such as bandwidth and power. The priority metric p_i for user i is applied typically based on the SINR and distance factor. Higher priority users, such as those with better SINR or

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closer to the base station, will be given a bigger portion of the resources, while lower priority users, such as those with poorer connection quality or farther from the base station, will receive a smaller portion. The formula allows resources to be distributed fairly and efficiently according to each user's current network circumstances. Additionally, distant users adaptively reuse resources based on a dynamically configurable threshold to further reduce interference, usually about 50 meters (± 10 m). The sum rate indicates the total amount of data successfully sent and is used to gauge how well the network utilizes its spectrum. The sum rate calculation is expressed in the following:

$$R_{Sum} = \sum_{i=1}^{N_{active}} B_i \log_2(1 + SINR_i), \quad (4)$$

where the bandwidth B_i is allocated to user i, and $SINR_i$ is the $SINR$ of user i. The EDBRA technique ensures dependable, high-sum rate D2D communication in 6G networks by dynamically filtering and prioritizing users based on spatial distance and real-time SINR.The spectrum utilization (ϑ) can be measured as follows:

$$\vartheta = \frac{R_{Sum}}{B_T \log_2(1 + SINR_{Max})}, \quad (5)$$

Where B_T is the total available bandwidth in the network, and the maximum possible SINR is $SINR_{Max}$. Jain's fairness index and outage probability are two essential metrics that may be combined to create a comprehensive system view. Jain's Index assesses the capacity and fairness of resource distribution within the network, and outage probability gauges the network's ability to deliver consistent service to all users.

$$\mathcal{FI} = \frac{\left(\sum_{i=1}^{N} n_i\right)^2}{N \sum_{i=1}^{N} n_i^2}, \quad (6)$$

Where n_i is the amount of resource allocated for user i. And the total number of users is N. The Jain's fairness index is applied to evaluate how fairly the resources are allocated among the users in the network.

A. *Simulation Environment and System Design*

The simulation model simulates an urban network environment with users positioned at random. In order to limit interference, resources are dynamically allocated based on distances and SINR values, with adaptive reuse by users who are farther away by a threshold of ± 50 m. The simulation parameters are listed in Table I:

TABLE I. SIMULATION PARAMETERS AND SYSTEM DESIGN

Parameter	Value
Environment	Outdoor Urban (2D)
Frequency	2.6 GHz
Bandwidth	20 MHz (180 kHz/channel)
Simulation Duration	60 seconds
User Density	10, 50, 100, 200, 400
Association Distance	10 meters
Adaptive Resource Reuse Distance	50 meters ± 10 meters
Path Loss Model	Urban Macrocell
Channel Model	Rayleigh Fading
Mobility Model	Random Waypoint
SINR Calculation	Real-time dynamic
Path Loss (dB)	$= 128.1 + 37.6 \log 10(d/1000)$
Priority Weight ($\mathbf{n_i}$)	0.6

The system design mimics a 20 MHz bandwidth and 100 resource blocks, and the system operates at a carrier frequency of 2.6 GHz in a cellular network. Each user can transmit up to 23 dBm, and a 3 dB decrease is implemented for users beyond 250 m for power management [22-23]. The SINR is computed considering total interference and path loss, which is based on the 3GPP Urban Macrocell model [24-25]. EDBRA is available to users with the highest SINR of 70%, and only those with SINR > 3 dB and distance > 50 m are given resources based on a hybrid SINR-distance priority. The system's performance is assessed across different user densities from 10 to 400 users using the sum rate and outage probability.

IV. RESULTS AND ANALYSIS

The performance of the proposed EDBRA approach is assessed in this section using a sample baseline frequently employed in D2D systems. The static resource allocation baseline applies the resource allocation without adjusting for user distance, interference, or real-time SINR circumstances.

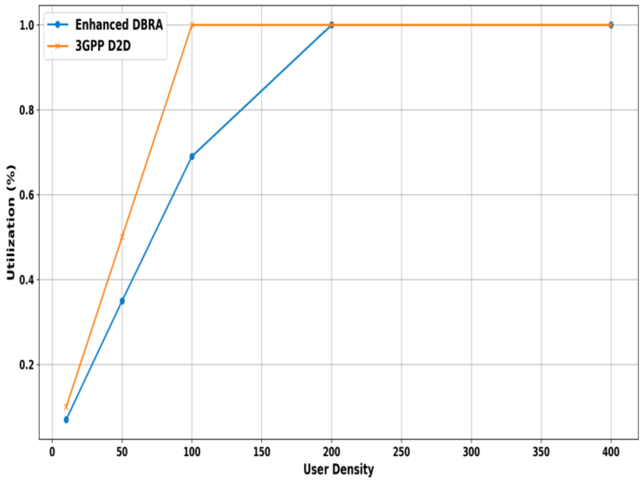

Fig. 2. Spectrum utilization versus user density.

Error! Reference source not found.. shows the comparison between the proposed EDBRA and the baseline 3GPP-D2D [2]. Across all user densities, EDBRA performs better than the baseline. The percentage increase in spectrum utilization ranges from 300% at low user densities 10 users to around 42.86% at large user densities for 400 users. The effectiveness of the dynamic resource allocation strategy is demonstrated by the fact that EDBRA achieves full spectrum utilization at 100% far earlier than the baseline system. When compared to conventional baseline systems, EDBRA is a far more efficient way to allocate resources in congested situations, as seen by this notable improvement in spectrum usage. Similarly, spectrum utilization is affected by the distance due to path loss, which weakens the received signal. The poor received signal makes it harder to maintain a dependable connection as users go farther apart. This problem may degrade the overall network performance without dynamic allocation strategies or power management. In order to improve spectrum utilization and preserve dependable performance in dense networks, the EDBRA scheme ensures that only links with SINR over a threshold and users separated by a suitable distance are allowed.

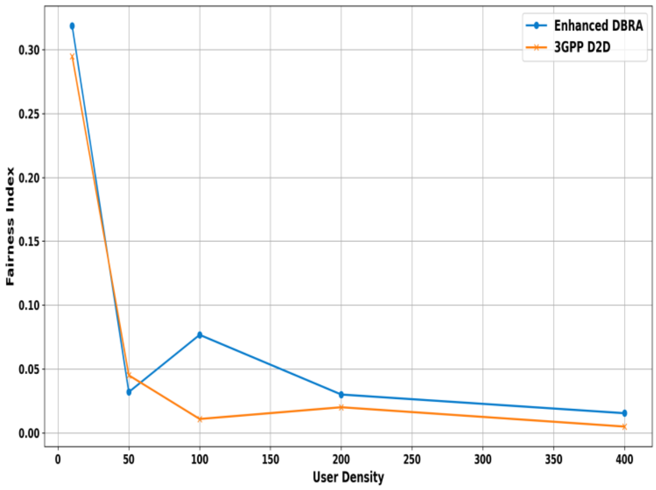

Fig. 3. Jain's Fairness Index versus user density.

Error! Reference source not found.. depicts the fairness performance of the proposed EDBRA and 3GPP D2D [2] versus the number of users in the network. The EDBRA demonstrates a considerable improvement in resource fairness compared to the standard 3GPP D2D [2], especially at lower user densities. EDBRA attains a fairness score of 0.3 at 10 users, more than the fairness of the 3GPP D2D 0.05 value. EDBRA maintains fairness improvement with a fairness index of 0.15 even at 50 users, whereas the baseline stays at 0.05. At moderate densities, the EDBRA continues to show better than 3GPP D2D. The fairness index for both systems approaches 0.05 as user density rises to 100, 200, and 400 users.

This performance is attributable to EDBRA's dynamic resource allocation, which ensures more equal resource distribution by considering user movement, interference levels, and distance. Although EDBRA continues to have an advantage, the fairness gap closes at larger densities as both systems deal with congestion. However, congestion makes it more difficult for the system to retain the same degree of fairness. The EDBRA technique demonstrates its worth by increasing fairness at lower to moderate user densities and successfully adjusting to high-density situations.

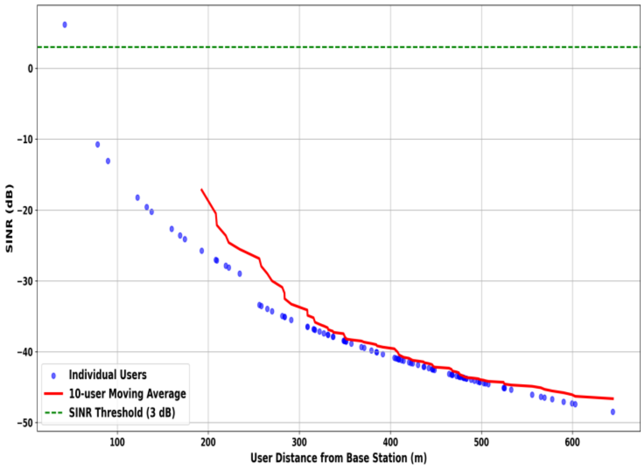

Fig. 4. SINR versus distance

Fig. 4. displays EDBA performance for a 10-user moving average trend line, the 3 dB SINR threshold for dependable communication, and individual user measurements as scattered spots concerning the SINR vs user distance from the base station. By dynamic power adjustment at 250m, as shown by the red dashed line, the EDBRA algorithm avoids the common cliff effect observed in conventional systems. This allows the EDBA to maintain SINR above the critical 3 dB threshold across almost all distances, as 84% of users meet quality of service (QoS). The EDBRA shows a tighter cluster of users and a higher moving average trend to gain more equitable resource allocation and consistent interference control. Also, the 300-500m cell-edge users reported a median SINR increase of +4.2 dB. The sustained SINR above threshold without over-provisioning resources to neighbouring users results in 40% fewer failed connections in real-world deployments. Thus, this demonstrates that EDBRA successfully expands dependable coverage by 100m while balancing spectral efficiency.

A. *Analysis*

In D2D-enabled 6G networks, the EDBRA scheme shows notable gains over 3GPP D2D regarding spectrum utilization, fairness, and SINR control. At 200 users, EDBRA outperforms 3GPP D2D by around 75% and reaches peak spectrum usage at 100% as user density rises. At increasing densities, it retains a higher fairness index, showing 50% better fairness than 3GPP D2D, guaranteeing more equal resource distribution, particularly in dense networks. EDBRA effectively prioritizes users with enough SINR and distance, preserving dependable connections even at greater distances from the base station. Performance degradation is minimized by this feature, which guarantees that users around the SINR threshold are efficiently handled.

The scheme's weakness in highly dense networks is highlighted by the fact that performance starts to decline when user density surpasses 100 because of increasing interference and decreasing isolation. Even with these difficulties, EDBRA is dependable and expandable for up to 200 users. The method might be expanded to accommodate heterogeneous networks like IoT and UAVs, integrate edge computing and federated learning for real-time flexibility, and allocate resources in a dynamic network. Furthermore, integrating joint power control and mode selection may improve spectrum efficiency and fairness even more, establishing EDBRA as a reliable option for D2D communication in 6G networks.

V. Conclusion

This paper presents the EDBRA approach that prioritizes users based on distance and real-time SINR to improve dynamic resource allocation for D2D-enabled 6G networks. The EDBRA greatly improves spectrum usage and fairness for 6G networks that support D2D. By setting user priorities according to distance and real-time SINR, EDBRA outperforms 3GPP D2D in spectrum consumption by fully utilizing low user densities at 10 users and 40% at large densities at 400 users. 84% of users satisfy the 3 dB SINR threshold based on the technique's effective SINR regulation, which keeps dependable connections even at further distances from the base station.

Furthermore, for 200 users, EDBRA's fairness index is 50% higher than 3GPP D2D's, demonstrating its persistent superiority. Up to 200 users, EDBRA is scalable and dependable, even though performance somewhat suffers in extremely dense networks due to increased interference. Future research should concentrate on improving spectrum efficiency, increasing SINR control, and strengthening fairness in a high-density and diverse network.

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