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RESEARCH ARTICLE

Optimizing 5G Power Allocation With Device-to-Device Communication: A Gale-Shapley Algorithm Approach

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ABSTRACT Creating innovative strategies for optimizing network resources is paramount in response to the growing demand for fast and reliable data transmission. This study delves into a unique method to enhance power allocation and throughput in 5G cellular systems. We aim to conserve resources and ensure top-tier communication through direct terminal connections using the Device-to-Device protocol and a modified Gale-Shapley algorithm. Our approach's robustness is tested in two scenarios: firstly, in standard 5G operations that focus on minimizing energy use while maximizing signal reliability, evaluating parameters like losses, gain, proximity of transmitters to receivers, and capacity using the Gale-Shapley algorithm. Second, we simulate a disaster-induced network disruption in which D2D devices autonomously establish connections without functional base stations. Our findings from detailed MATLAB simulations highlight that D2D communications within the Millimeter Wave frequency band consistently maintain reliable relationships, achieving network capacity rates between 150 and 180 Mbps under regular conditions and 110 to 140 Mbps during disaster scenarios. This underscores our approach's potential to significantly enhance 5G system performance and reliability.

INDEX TERMS Device-to-device (D2D), Gale-Shapley matching theory, non-orthogonal multiple access (NOMA), power allocation, 5G.

I. INTRODUCTION

With the swift progression of wireless communication methodologies, Device-to-Device (D2D) communication stands out as a transformative approach. It promises to bolster the capabilities of wireless networks, especially in the realms of 5G and subsequent cellular systems. D2D fosters a mechanism where nearby devices can interact directly, bypassing the traditional base station or central control. This strategy not only optimizes the use of the spectrum but also paves the way for innovative applications such as vehicular networking, ensuring public safety, and the expansive realm of the Internet of Things (IoT) [1], [2], [3].

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In the context of 5G networks, Non-Orthogonal Multiple Access (NOMA) is being championed as a pivotal technology. It addresses the growing demands for high-speed data transfers and expansive connectivity. Diverging from traditional orthogonal multiple access (OMA) paradigms, NOMA allows simultaneous access of resources by various entities, amplifying spectral efficiency through sophisticated decoding strategies, notably successive interference cancellation (SIC) [4], [5], [6], [7].

The intricacies of power distribution within NOMA frameworks, especially when synergized with D2D communication, are multifaceted. As NOMA solidifies its position as a foundational element for 5G and its successors, it allows multiple users to tap into the same time-frequency resources, thus enhancing spectral efficiency. However, the challenge

emerges in astutely distributing power among users, given the myriad variables, such as user density, individual channel dynamics, and the overarching system blueprint [8].

The nuances of the power distribution directly affect the pivotal metrics of the system within the confines of NOMA. For example, throughput, which quantifies the volume of data relayed successfully across the network within a stipulated timeframe, is intrinsically tied to the dynamics of the power distribution. A strategically devised power distribution paradigm can elevate throughput, ensuring optimal resource utilization and an enriched user experience [9].

Ensuring equitable access to resources is another metric intrinsically tied to power distribution. Crafting this equilibrium within NOMA can be intricate, given the inherent power differentials among users. A meticulously devised power distribution paradigm ensures that all users, irrespective of their position within the network or channel dynamics, are granted a balanced share of resources. Furthermore, energy efficiency, quantified as the ratio of pertinent information relayed to the aggregate energy expended, is also influenced by power distribution strategies. With the escalating demands for accelerated data transmissions and expansive connectivity, the emphasis on energy efficiency is paramount. A reasonable power distribution strategy can harmonize energy conservation with peak system performance, ensuring network longevity [10].

While prior research has provided a robust foundation on the merits of D2D within 5G frameworks, specific dimensions still need to be explored. These encompass deploying the Gale-Shapley algorithm and exploring the millimeter-wave (mmW) frequency spectrum in power distribution paradigms. This manuscript introduces a pioneering power distribution framework for NOMA anchored in D2D communication. This paradigm integrates a refined Gale-Shapley algorithm with path loss models and Mixed Integer Non-Linear Programming (MINLP) optimization strategies. This amalgamation promises to redefine power distribution in D2D communication within NOMA frameworks, showcasing resilience across diverse network scenarios. The robust nature of this paradigm makes it apt for emerging applications such as urban intelligent grids and industrial automation [11].

The evolution of 5G networks has brought forth many opportunities but also presents challenges. The exponential growth in traffic and service demands and the need for higher data rates and more efficient resource utilization have strained the current network infrastructure. D2D communication, as an integral component of the 5G architecture, promises improvements in energy efficiency, spectral efficiency, overall system capacity, and higher data rates. However, the full potential of D2D in 5G networks can only be realized by addressing significant challenges, such as interference management, resource allocation, and ensuring Quality of Service (QoS) [9]. NOMA further increases D2D capabilities by allowing multiple users to share the same frequency resources, thus enhancing spectral efficiency and

accommodating more users. D2D and NOMA present a formidable solution to many challenges faced by current 5G networks [12].

The subsequent sections of this manuscript are structured as follows. Section II offers a panoramic view of recent research endeavors on power distribution in NOMA, anchored in D2D communication and the deployment of the Gale-Shapley algorithm. This is succeeded by a section detailing the objectives of this research, the methodologies used, and the specific purposes. The subsequent section delves into the implementation methodology, elucidating the refinements to the Gale-Shapley algorithm and its deployment to address the power distribution challenge in NOMA, anchored in D2D communication. The penultimate section presents the outcomes of simulations, offering a quantitative assessment of the efficacy of our proposed methodology. The manuscript concludes with a recapitulation of critical insights and potential trajectories for future exploration.

In light of the transformative potential of D2D communication within the 5G architecture, this paper seeks to provide a substantive contribution to the domain by addressing the critical challenge of power allocation. We are motivated by the necessity to enhance network performance while ensuring energy efficiency—a crucial consideration as the proliferation of 5G technology accelerates. Our innovative contributions include applying a modified Gale-Shapley algorithm to power distribution in NOMA frameworks, comprehensively exploring the mmW frequency spectrum, and integrating MINLP optimization techniques. These advancements collectively promise to advance theoretical understanding and deliver tangible improvements in the operation of real-world 5G networks. The subsequent sections will elucidate our systematic approach, detail the novel methodologies employed, and demonstrate the efficacy of our strategies through rigorous simulation-based validation.

II. RECENT STUDIES

In the realm of D2D communication synergized with NOMA, extensive research has been carried out, each study paving the way for further innovation in this field. Our research draws upon these foundational studies, extending their concepts and addressing the gaps they have identified.

The study titled “*Energy-Efficient Matching for Resource Allocation in D2D-Enabled Cellular Networks*” [13] utilizes a matching algorithm to fine-tune resource allocation with a focus on energy efficiency. This approach is particularly relevant to our work as it highlights the importance of efficient power usage in D2D networks, a key consideration in our algorithm’s design.

In “*Resource Allocation for NOMA-Enhanced D2D Communications with Energy Harvesting*” [14], the authors present a dual-layer optimization framework that incorporates energy harvesting. This research is closely related to our approach, emphasizing the need for sustainable energy solutions within D2D and NOMA frameworks, a challenge our algorithm aims to address.

The work “*Non-Orthogonal Multiple Access for Unicast and Multicast D2D*” [15] focuses on optimizing both unicast and multicast D2D communications through a multi-objective optimization framework. Our research builds upon this by exploring how the Gale-Shapley algorithm can be adapted to achieve similar goals more efficiently and equitably.

“*An Efficient Resource Allocation Algorithm for Device-to-Device Communications*” [16] introduces a novel algorithm specifically designed for D2D communications. Our study extends these findings by comparing the Gale-Shapley algorithm’s performance in similar network environments.

Another pivotal study, “*Resource Allocation for Downlink NOMA in Joint Transmission Coordinated Multi-Point Networks*” [17], explores joint optimization strategies in NOMA networks. Our research contributes to this area by applying the Gale-Shapley algorithm to optimize power distribution in complex network scenarios, such as those encountered in 5G D2D communication.

The study by Yoganathan et al. [18] focuses on optimizing Multihop-D2D (M-D2D) connections in cellular networks to enhance spectrum-sharing efficiency. It emphasizes QoS and energy efficiency in M-D2D communications, a method that facilitates data transmission across multiple D2D links without relying on a central base station. This approach benefits 5G networks, improving efficiency and supporting high-speed communications in dense areas. The study employs advanced optimization techniques, including the Hungarian method, Harris Hawks, and red fox algorithms, providing sophisticated solutions for M-D2D complexities. This research aligns with our work’s emphasis on advanced resource allocation strategies to boost network efficiency and user experience in 5G environments.

Finally, the investigation into resource allocation in D2D-supported V2V communication systems [19] examines the intricate balance of resource block allocation and power optimization. Our research aligns with this study by offering innovative solutions for resource distribution in 5G D2D networks, aiming to optimize overall network performance.

By integrating and building upon these diverse yet interconnected studies, our research contributes a novel perspective to the field of telecommunications. We aim to advance the understanding of power allocation strategies in D2D communication within NOMA frameworks, offering solutions that promise to optimize network performance and energy efficiency.

III. OBJECTIVE AND METHODS

The evolution of 5G has ushered in a new era of wireless communication, teeming with possibilities yet riddled with complexities. Central to this intricate web is the challenge of power allocation, a pivotal aspect that can make or break the efficiency of data transmission. Our research’s objective is clear-cut: to devise a power allocation scheme tailor-made for D2D communication within the framework of NOMA.

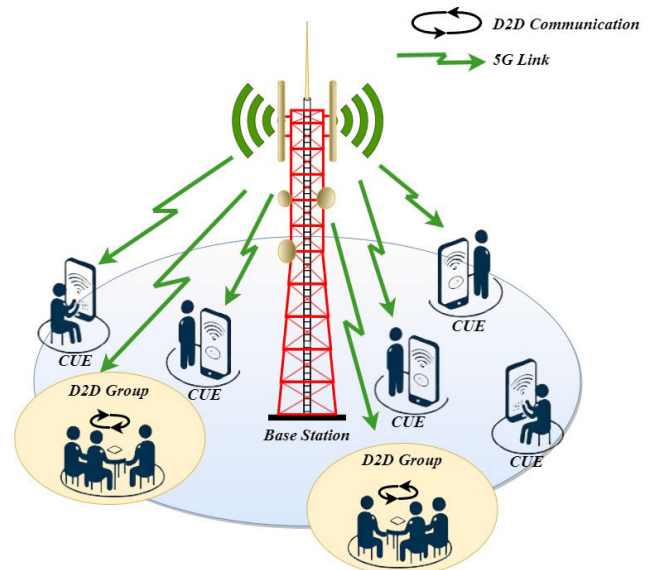


FIGURE 1. Enhanced underlay D2D communication system model, showcasing the integration of cellular and direct links.

To navigate this challenge, we have harnessed the power of the modified Gale-Shapley algorithm. This algorithm, renowned for its precision, has been fine-tuned to cater to the nuances of D2D communication, ensuring optimal resource distribution in environments where demand often outstrips supply.

But theory alone is not enough. To truly gauge the efficacy of our approach, we have put it to the test in two distinct scenarios:

- **Standard 5G Operations:** In this scenario, we explore the algorithm’s performance under ideal conditions, where base stations and network infrastructures operate at their peak. This provides a benchmark, showcasing the algorithm’s potential in a well-optimized environment.
- **Sub-Optimal Base Station Performance:** Real-world situations aren’t always ideal. There are instances where base stations might face challenges, be it due to technical glitches, environmental factors, or other unforeseen circumstances. In this scenario, we test the algorithm’s resilience and adaptability, ensuring that efficient power allocation remains uncompromised even in less-than-perfect conditions.

IV. D2D NETWORK ESSENTIALS

Our research delves into the intricacies of a D2D cognitive network, elucidating the components of the system and their sophisticated interactions. This enhanced system is visually represented in the diagram *D2D Underlay Communication System Model*.

At the nucleus of this network stands the Base Station (BS), a critical entity that provides uplink service via OMA. The BS is connected to the D2D transmitters (DT) through dedicated

links typically designed for downlink communication in a full-duplex mode, allowing simultaneous transmission and reception of signals.

Cellular User Equipment (CUE) represents the mobile devices used by the cellular subscribers within the network. It is shown in the diagram to indicate its role in communication with BS and D2D receivers (DRs) through cellular links. These links are established using the cellular network infrastructure, enabling connectivity and data exchange between the CUE and other network nodes.

The system encompasses M cellular users, denoted as $CUE = [cue_1, cue_2, \dots, cue_M]$, serving the individual communication needs of these users. The CUEs are essential as they communicate with the BS and potentially serve as relays or participants in the D2D communication, depending on the network configuration.

Inter-device communication establishes a direct link between D2D Receivers (DRs), allowing for a half-duplex communication mode, where devices take turns transmitting and receiving signals to avoid self-interference.

The network houses two DRs on the receiving end, DR_1 and DR_2 . Notably, DR_1 employs SIC to counteract any interference from DR_2 . This technique is particularly crucial in a NOMA network, where signals are superimposed at different power levels and decoded sequentially at the receivers.

The channel model used in this network is typically a fading model, which considers various factors, such as path loss, shadowing, and multipath fading, that affect signal quality. These models are crucial for estimating the performance of wireless links under different environmental conditions and designing robust communication strategies.

The details of the SIC process and the pivotal role of the channels, such as H_{DT_1} and H_{DT_2} , are further expounded in the subsequent sections, highlighting their contribution to the network's efficiency and reliability.

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A. REVERSE TRANSMISSION DYNAMICS IN D2D COMMUNICATION

While the primary focus of our study has been on scenarios where D2D transmitters (DTs) transmit signals to D2D receivers (DRs), the reverse transmission scenario, where DRs act as transmitters, is an integral aspect of a comprehensive D2D communication model. In this subsection, we explore the dynamics when DR_1 and DR_2 assume the

role of transmitters and their implications on the network performance.

In reverse transmission, DR_1 and DR_2 transition from mere signal recipients to active transmitters. This role reversal necessitates reconfiguring the network's resource allocation and signal processing strategies. For example, when DR_1 and DR_2 transmit, the base station (BS) and the CUEs can assume the role of receivers, altering the traditional communication flow within the network.

Furthermore, the network must adapt to manage this transmission mode, especially concerning interference management and signal quality assurance. SIC techniques and NOMA protocols must be re-evaluated and adjusted to cater to the reversed signal flow. The network's ability to maintain efficient communication under this scenario is a testament to its flexibility and robustness.

The impact of reverse transmission on network performance is multifaceted. It affects parameters such as signal-to-interference-plus-noise ratios (SINRs), overall network capacity, and resource utilization efficiency. The network's architecture must handle these changes to ensure seamless communication irrespective of the transmission direction.

In summary, including reverse transmission dynamics in the D2D cognitive network model adds a layer of complexity and versatility to the system. It underscores the need for adaptive network protocols capable of handling various communication scenarios, thereby enhancing the overall resilience and efficiency of 5G networks.

B. COGNITIVE ASPECTS OF D2D COMMUNICATION

With the rapid advancement of wireless communication technologies, cognitive D2D communication has emerged as a critical area of interest. It involves employing cognitive strategies within D2D networks, enhancing efficiency and adaptability. Integrating cognitive processes in D2D communication allows for more intelligent and efficient use of the wireless spectrum and network resources.

The cognitive cycle in D2D communication encompasses several phases, including spectrum detection, decision-making, and adaptation. This cycle enables D2D devices to analyze their environment intelligently, make informed decisions about spectrum usage, and adapt their communication strategies accordingly. This is particularly crucial in congested network environments or scenarios where dynamic spectrum access is essential.

Cognitive D2D communication is relevant in various applications, especially in scenarios where network efficiency and spectrum utilization are critical. It paves the way for more innovative and responsive communication methods in next-generation wireless networks.

For an in-depth understanding of cognitive D2D communication, we refer to the work of A. Iqbal et al., which provides comprehensive insights into this field [20].

C. INTEGRATION OF D2D IN STANDARD 5G SYSTEMS

D2D communication within 5G networks can be integrated through a centralized system managed by the base station or autonomous connections between devices. The base station orchestrates D2D connections centrally, managing resources and ensuring optimal network performance. However, this method may introduce additional latency and overhead. On the other hand, an autonomous approach allows devices to establish direct connections independently, enhancing network flexibility and reducing latency. However, it poses challenges in terms of interference management and resource distribution.

D. CONTROL FUNCTIONS IN D2D-ONLY SCENARIOS

In scenarios where D2D communication operates independently of the base station, several key control functions come into play:

Device Discovery: Devices identify and discover each other in a D2D-only scenario through specific protocols or technologies, allowing efficient and direct communication without central coordination.

Mode Selection: Devices decide whether to communicate directly (D2D mode) or through the base station (cellular mode) based on various factors, such as signal strength, proximity, and network conditions.

Resource and Power Allocation: Without a central coordinating authority, D2D devices allocate resources (such as spectrum and channels) and power among themselves using algorithms or strategies designed for efficient and fair distribution.

E. SCENARIO OVERVIEW

Our study assesses the D2D protocol's effectiveness within 5G networks through two meticulously defined operational scenarios:

- 1) **Standard 5G System:** This scenario models a conventional 5G network architecture comprising a central base station, Cellular User Equipment (CUE), and D2D users. The key characteristics of this setup include:
 - Seamless integration of D2D links into the existing network infrastructure.
 - Independent transmission of signals by D2D transmitters, designed to minimize reliance on the central base station.
 - Focused examination of how D2D communication impacts latency and overall system capacity, including the management of network traffic and resource allocation efficiencies.
 - Exploration of scenarios where D2D communication occurs without initial base station interaction, highlighting direct device connections and their influence on network dynamics.

This scenario is critical for evaluating the D2D protocol's role in enhancing traditional 5G networks,

particularly optimizing system capacity and response times.

- 2) **Urban 5G Environment with High Device Density:**

The second scenario delves into a more complex urban setting characterized by high device density and diverse user behaviors. This scenario aims to simulate real-world challenges in urban 5G networks, such as:

- High user density increases network demand and potential interference issues.
- Varied user mobility patterns impacting network stability and D2D communication reliability.
- The effectiveness of D2D communication in managing network congestion and maintaining QoS under challenging urban conditions.
- Evaluation of the D2D protocol's capacity to sustain high data rates and consistent connectivity in densely populated areas.

The focus here is on understanding the scalability of the D2D protocol in dynamic urban environments and its potential to improve user experience and network efficiency.

Each scenario is tailored to illustrate the D2D protocol's practicality and performance under different network conditions, providing comprehensive insights into its applicability and benefits in 5G telecommunications.

1) SIGNAL DYNAMICS

In the D2D cognitive network, signals at the cellular user (CUE) and decoding relays, represented as CUE , y_{DR1} , and y_{DR2} , are shaped by direct links, relayed signals, interference, and noise. Their rates are ascertained using signal-to-interference-plus-noise ratios (SINRs). The system uses the SINR metric for flow rates and power levels and employs the Gale-Shapley technique for pairing DTm and CUE. Path loss, influenced by transmitter-receiver distances and frequency, categorizes communication channels into Line of Sight (LOS) and Non-Line of Sight (NLOS). Antenna gain, crucial for SINR, is optimized when signals are directed between the main lobes of the transmitter and receiver.

2) OPTIMIZATION PROBLEM

The signals at the cellular user (CUE) and decoding relays, represented as y_{CUE} , y_{DR1} , and y_{DR2} , are influenced by various factors such as direct links, relayed signals, interference, and noise. The performance of these entities is gauged using their respective signal-to-interference-plus-noise ratios (SINRs) [21].

The term $\frac{s}{N+I}$ represents the signal-to-interference-plus-noise ratio (SINR), where:

- s is the signal power.
- N is the noise power.
- I is the interference power.

This SINR metric is pivotal in determining the achievable rates of communication entities. It aids in computing flow

rates, designating power levels, and pairing devices using the Gale-Shapley technique.

The system, in this context, refers to the D2D cognitive network. It is designed to optimize power allocation in D2D communication using NOMA technologies. The primary goal is to enhance system performance, ensuring resilience under diverse network conditions, making it suitable for applications like smart cities and industrial automation [21].

3) ANTENNA DYNAMICS

The effective aperture of the antenna, A_e , related to the antenna gain (G) and the signal wavelength (λ), impacts the received signal power, influencing achievable rates and SINRs.

$$A_e = \frac{\lambda^2}{4\pi} \cdot G \quad (1)$$

This relationship offers insights into system performance, especially for D2D pairs and cellular users engaged in signal transmission and reception.

4) PATH LOSS CALCULATION MODELS

Path loss is a critical parameter in wireless communication, determining the strength and quality of the received signal. In the D2D cognitive network, the path loss is influenced by the distance between devices and the transmitted signal's frequency [22].

The path loss between two devices, DTm and DRn , is given by:

$$PL_{D2D} = 12 \log_{10}(d) + 12 \log_{10}(fc) + 19.45 \quad (2)$$

where d represents the distance between the devices, and fc denotes the frequency. This formula is applicable when the distance d is less than a specific threshold [22].

Interference from traditional communication users, especially concerning the DRn device, introduces additional complexities. The interference at the receiver can be represented by two distinct cases:

Case 1: Short Distances - When the distance d between the devices is less than a certain threshold, the path loss due to interference is given by:

$$PL_{INTF_{short}} = 20 \log_{10}(d) + 20 \log_{10}(fc) + 32.45 \quad (3)$$

This equation captures the path loss dynamics for shorter distances, where the interference effects are more pronounced due to the proximity of devices [22].

Case 2: Long Distances - For scenarios where the distance d exceeds the threshold, the path loss due to interference is represented by:

$$PL_{INTF_{long}} = 34 \log_{10}(d) + 34 \log_{10}(fc) + 64.9 \quad (4)$$

In this case, the path loss is influenced by the extended distance between devices, which can decrease signal strength and increase susceptibility to interference from other distant sources [22].

By understanding these two cases and accurately calculating the path loss, one can make informed decisions regarding transmission power or frequency selection, ensuring optimal communication quality [22].

The equations (5) to (9) provided offer insights into calculating path loss based on distance and frequency, differentiating between Line of Sight (LOS) and Non-Line of Sight (NLOS) scenarios.

For LOS links, the equation, derived from [22] and [23], can be simplified to be dependent only on distance:

$$PL(d)[dB] = \delta + \beta 10 \log_{10}(d) \quad (5)$$

In this equation:

- δ (delta) is the floating intercept, a parameter that adjusts the path loss equation based on specific environmental conditions or system configurations.
- β represents the path loss exponent, indicating the rate at which the path loss increases with distance.

For NLOS communication, the equation introduces the shadowing effect, which captures the variability in path loss due to obstacles and other environmental factors:

$$PL(d)[dB] = \delta + \beta 10 \log_{10}(d) + \xi, \xi \sim N(0, \sigma^2) \quad (6)$$

Here, ξ represents the shadowing effect and follows a normal distribution with mean 0 and variance σ^2 . The term σ (sigma) denotes the standard deviation of the shadowing effect.

Depending on the environment, the path loss is further categorized into urban (denoted by u) and highway (denoted by h):

Urban LOS

$$PL_{LoS}^u(d) = 16.7 \log(d) + 18.2 \log(fc) + 38.77 + \xi \quad (7)$$

Highway LOS

$$PL_{LoS}^h(d) = 20 \log(d) + 20 \log(fc) + 32.4 + \xi \quad (8)$$

NLOS

$$PL_{NLoS}(d) = 30 \log(d) + 18.9 \log(fc) + 36.85 + \xi \quad (9)$$

V. SIMULATION PARAMETERS

Before presenting the results, we summarize the key parameters used in our simulations.

VI. IMPLEMENTATION METHODOLOGY

In the pursuit of optimizing 5G networks, this research meticulously navigates through the complexities of power allocation, mainly focusing on D2D communication within the NOMA framework. The methodology hinges on the modified Gale-Shapley algorithm, renowned for its precision and adaptability. It has been fine-tuned to cater to the nuanced demands of D2D communication, ensuring optimal resource distribution in environments where network demands are perpetually evolving. Two distinct scenarios are explored to validate the methodology: Standard 5G Operations, which provides a benchmark by exploring the algorithm's performance under ideal conditions, and Sub-Optimal Base Station

TABLE 1. Summary of key simulation parameters.

Parameter	Value
Monte Carlo Repetitions iterations	2000
Number of CUE Devices	50
Number of D2D Pairs	25
Minimum Power for D2D	25
Maximum Power for D2D	$10^{(20/10-3)} W$
Total Power for D2D	$10^{(24/10-3)} W$
Total Power for Interferers	$10^{(35/10-3)} W$
Cell Radius	$10^{(34/10-3)} W$
Bandwidth	200 meters
Frequency for Path Loss (First Scenario)	0.5 GHz
Frequency for Path Loss (Second Scenario)	2GHz (microwave band)
	28GHz (microwave band)

Performance, which tests the algorithm's resilience and adaptability in less-than-perfect conditions. This approach ensures efficient power allocation and provides a robust framework that maintains reliable communication despite unforeseen network challenges [24].

A. COMPARATIVE ANALYSIS OF THE ADAPTED GALE-SHAPLEY ALGORITHM IN D2D COMMUNICATION

The Gale-Shapley algorithm, initially effective in solving the stable marriage problem, has been innovatively adapted in our study. This adaptation addresses the complex resource allocation challenges within D2D communication in 5G networks. We have conducted an extensive analysis comparing the performance of our adapted Gale-Shapley algorithm with other established algorithms in this field.

The effectiveness of our modified Gale-Shapley algorithm is evaluated on three major fronts:

- **Efficiency:** The algorithm performs better in pairing devices, optimizing overall network throughput and reducing latency. This improvement is notable when compared to other prevalent algorithms, such as the Hungarian method or traditional auction-based approaches.
- **Fairness:** A critical aspect of our algorithm is its ability to ensure equitable resource distribution among D2D pairs. This is a distinct advantage over other algorithms, which may not prioritize network users as evenly.
- **Adaptability:** Our algorithm exhibits remarkable flexibility, efficiently accommodating changes in network topology and user demand. This adaptability is a marked improvement over more static or predetermined matching approaches that are commonly used.

1) KEY MODIFICATIONS

The enhancements made to the Gale-Shapley algorithm to suit D2D communication are as follows:

- **Determining Preferences:** Unlike traditional criteria based on singular preference lists, our algorithm considers signal strength, proximity, and data rate potential to define preferences in the D2D context. This approach is more aligned with the dynamic nature of 5G networks.

- **Matching Process:** We have refined the matching process to emphasize network efficiency metrics, such as minimizing interference. This step goes beyond the original algorithm's scope, primarily focusing on mutual preferences without considering the broader implications on system-wide performance.
- **Algorithm Execution:** Tailored for real-time operations, our execution strategy is uniquely designed to adapt to the ever-changing dynamics of network conditions. This contrasts with some existing algorithms, which may not offer the same level of responsiveness in real-time scenarios.

2) EMPIRICAL EVIDENCE AND CONTRIBUTIONS

Our enhancements to the Gale-Shapley algorithm enable it to outperform specific existing algorithms regarding throughput, fairness, and adaptability. This makes it a robust candidate for resource allocation in D2D communication within 5G networks. The subsequent sections of this paper will present empirical evidence to support these claims, further highlighting our work's significant contributions to the telecommunications field.

B. IMPLEMENTATION ENVIRONMENT

We utilized MATLAB for software implementation due to its efficient management of multi-dimensional arrays and strong signal and image processing computational capabilities. The simulation uses a standard toolbox without relying on external libraries. We base the simulation on two D2D communication programs, which will be discussed in subsequent sections.

C. FOUNDATIONAL SCRIPTS

This section elaborates on the two primary scripts underpinning our simulation, emphasizing the integral components during the implementation phase.

1) RESOURCE ALLOCATION USING MATCHING THEORY FOR D2D UNDERLAY

This script configures a system comprising D2D users, CUE, and a central BS. Its primary objective is to optimally pair D2D users with CUEs to maximize the flow rate across dual connections. The algorithm considers shadowing, attenuation, and device interference, integrating intra-cell device distances. These distances are determined using the Euclidean equation:

$$d(p, q) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2} \quad (10)$$

After this, power allocation is carried out for DT_m and CUE devices, predicated on anticipated throughput after ascertaining distance and gain. The system leverages the SINR metric to deduce flow rates and designates apt power levels.

The Gale-Shapley algorithm, originally designed to solve the stable marriage problem, optimally pairs DT_m and CUE

optimally. In this context, D2D users (or DT_m) and CUEs rank each other based on preferences, which factors like signal strength, proximity, or potential data rates can influence. The algorithm then finds a stable pairing where no two devices would prefer to be paired with each other over their current partners, ensuring efficient resource utilization.

2) D2D COMMUNICATIONS IN THE MILLIMETER WAVE BAND: A NOVEL DISTRIBUTED MECHANISM

Inspired by the research of Bahadori et al. [25], this scenario illustrates a D2D-enabled, multi-cell cellular network. In this context, devices equipped with MIMO antennas send out detection signals, which are specific signals to identify and establish communication links with other devices. Depending on the environmental conditions and the presence of a Line-of-Sight (LOS) link, these devices can communicate over either the micro-Wave (μW) or mmW band.

The significance of this mechanism lies in its ability to harness the high-frequency mmW band, which offers substantial bandwidth and can support higher data rates, making it crucial for 5G and beyond. However, the mmW band is also characterized by its susceptibility to blockages and high path loss. By enabling D2D communication in this band, devices can achieve direct, short-range communications, mitigating some of the challenges associated with mmW transmissions.

During the simulation, a DR is strategically positioned at the center of the axes, with a transmitter located 50m away. This setup is surrounded by square-shaped structures generated using a Poisson Point Process (PPP) distribution. The primary transmission medium is air, which inherently has uniform free space losses. The system precedes the mmW band (28GHz) for LOS connections. The positions of potential interfering devices, structures, and DR(s) are adjusted with each simulation iteration and epoch.

Devices in this scenario construct the Angle of Arrival (AoA) spectrum. This spectrum assists devices in locating peer D2D devices, identifying available LOS links, and subsequently aligning their communication beams for optimal transmission. The performance metrics, crucial for evaluating the efficiency and reliability of this mechanism, are derived using the SINR metric and the equation for direct antenna gain at the receiver.

D. SIMULATION CODE IMPLEMENTATION

Our simulation code demonstrates D2D communication within 5G networks, incorporating mobile and D2D users and a base station. The code focuses on enhancing overall network performance by fine-tuning the allocation of energy resources within two distinct scenarios. The first scenario depicts the network in a standard operational mode, aiming to reduce energy consumption while increasing signal reliability. In this context, the simulation evaluates various parameters such as losses, gain, proximity of the closest transmitter to each receiver, and overall network capacity. The Gale-Shapley algorithm is employed for comparative analysis in this scenario. Conversely, the second scenario

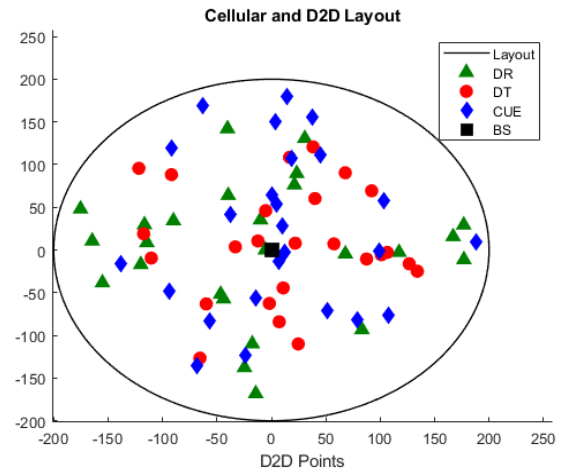


FIGURE 2. Cellular and D2D layout.

simulates a network disruption induced by a disaster, wherein D2D devices establish connections autonomously. The simulation for each scenario is executed over 50 epochs, encompassing 2,000 Monte Carlo iterations, cumulatively resulting in 100,000 iterations for the entire simulation. This comprehensive approach ensures a robust evaluation of the network's performance under varying conditions. Additionally, two distinct power distribution scenarios are considered, creating seven different usage scenarios to be explored in the simulations.

1) FIRST SIMULATION SCENARIO: RESOURCE ALLOCATION IN D2D UNDERLAY

This scenario envisions a 5G network operating within a distinct cell with a radius $R = 200 m$, with the base station strategically positioned at its center. The setup comprises 30 D2D receivers (DR_n), 30 D2D transmitters (DT_m), and 20 mobile users (CUEs) randomly dispersed within the cell.

a: SIMULATION SETUP

The D2D pairs are identified based on minimal distance, calculated using MATLAB with the base station facilitating distance measurement for each receiver. A Throughput Power Allocation (TPA) strategy is implemented to optimize system throughput. The optimization problem is maximizing the sum of the logarithmic function of one plus the SINR for each device. Critical parameters in this formulation include the power allocation vector (\mathbf{P}), channel gain (h_i), noise power (σ^2), and interference (I_i). The Rayleigh fading model is applied to represent realistic signal propagation in urban environments characterized by multiple signal paths and varying signal amplitudes.

Figure 2 depicts the D2D pairs, determined based on the minimal distance between transmitter and receiver. MATLAB calculates these distances with the base station's assistance, identifying the shortest distance for each receiver.

TPA strategy maximizes system throughput by allocating power to devices or users. The optimization problem for TPA is expressed as:

$$\max_{\mathbf{P}} \sum_{i=1}^N \log_2 \left(1 + \frac{P_i h_i}{\sigma^2 + I_i} \right) \quad (11)$$

where:

- \mathbf{P} : Power allocation vector.
- P_i : Power allocated to the i -th device or user.
- h_i : Channel gain for the i -th user.
- σ^2 : Noise power.
- I_i : Interference experienced by the i -th user.

The Rayleigh fading model is applied to simulate real-world wireless communication environments. In this model, the amplitude varies rapidly, causing the received signal strength to fluctuate. This fluctuation is due to multiple signal paths' constructive and destructive interference. The Rayleigh fading model is particularly suitable for urban environments with many obstructions, and the signal can take various paths to reach the receiver. The channel coefficient is a complex Gaussian random variable with zero mean and variance equivalent to the path loss. From this, we derive the channel gain, represented by $h_{i,j}$ [23].

b: SIMPLIFIED EXAMPLE CALCULATION

Consider a scenario with 10 D2D pairs in a cell and a total bandwidth of 20 MHz. The bandwidth allocation per D2D pair would be $\frac{20 \text{ MHz}}{10} = 2 \text{ MHz}$. This illustrates an equal distribution of resources among the D2D pairs in the underlay scenario.

2) SECOND SIMULATION SCENARIO: AUTONOMOUS D2D COMMUNICATION IN POST-SEISMIC ENVIRONMENTS

In this scenario, we design an autonomous network capable of operating even when the central base station is compromised, making it particularly suitable for environments affected by post-seismic vibrations, such as aftershocks following an earthquake. The network operates within the FR2 (Frequency Range 2) frequency range, which spans from 24.25 GHz to 52.6 GHz, focusing on the 28 GHz frequency and a bandwidth of $BW = 0.5 \text{ GHz}$.

a: SIMULATION LAYOUT

The simulated cell includes randomly distributed obstacles based on Poisson Point Processes, with about 35 barriers per simulation. The algorithm identifies the closest $DR_n - DT_m$ pairs from an initial set of 30 D2D devices and computes path loss using parameters like floating intercept (δ), signal slope (β), and log-normal shadowing (σ). Channel gains are then estimated for resource management.

Figure 3 illustrates the cell layout with obstacles distributed based on the Poisson Point Processes (PPPs). On average, 35 square-shaped barriers are introduced during the simulation, simplifying comparisons by correlating the coordinates of their corners to the universal network users' coordinates.

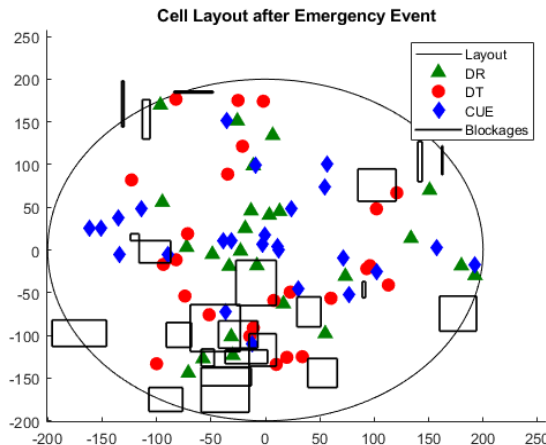


FIGURE 3. Cell layout in challenging environments.

For D2D communication, optimal connections are typically within a 200m range. However, interference can impact receivers even from greater distances. The system identifies the nearest $DR_n - DT_m$ pairs, reducing the original set of 30 D2D devices to a smaller subset, N' .

The algorithm uses the recorded distances to compute the path loss for each communication channel. The parameters include:

- δ : Floating intercept, representing the path loss at a reference distance.
- β : Signal slope, indicating the rate at which the path loss increases with distance.
- σ : Log-normal shadowing, capturing the variability in path loss due to obstacles and terrain.

After categorizing the channels, channel gains are estimated using the system's channel coefficients.

Resource management simplifies power distribution for optimal throughput across conventional and D2D channels based on each channel's path loss. The base station evaluates and aggregates each link's loss to determine the total power distribution.

The final SINR is calculated as:

$$SINR = \frac{\text{Signal}}{\text{Noise} + \text{Interference}} \quad (12)$$

This SINR metric is then used to compute the channel capacity:

$$C = W \log(1 + SINR) \quad (13)$$

b: SIMPLIFIED EXAMPLE CALCULATION

For a D2D pair at a distance of 100m, with a path loss exponent of 3, the path loss would be $10 \times 3 \times \log_{10}(100) = 60 \text{ dB}$. This calculation highlights the consideration of distance in resource allocation in post-seismic scenarios.

E. DESCRIPTION OF POWER ALLOCATION SCHEMES

Our study evaluates three distinct power allocation schemes: Random, Path Loss, and Gale-Shapley. Each scheme

optimizes resource allocation in D2D communication within 5G networks.

1) RANDOM POWER ALLOCATION

This scheme allocates power to devices randomly without considering network conditions or specific device needs. While simple, it can lead to inefficient network performance due to its non-strategic nature.

2) PATH LOSS-BASED POWER ALLOCATION

This more systematic approach adjusts power levels according to the estimated path loss, ensuring adequate signal strength while minimizing interference. It's designed to improve signal reliability and overall network efficiency.

3) GALE-SHAPLEY POWER ALLOCATION

Adapting the Gale-Shapley matching algorithm, this scheme optimizes resource allocation by efficiently pairing transmitters and receivers. It considers factors like signal strength, device proximity, and potential data rates for an efficient distribution of resources.

Each power allocation scheme offers unique benefits and impacts network performance differently in 5G D2D communication. The study aims to identify the most effective method for enhancing network efficiency and user experience by comparing these diverse allocation strategies.

VII. SIMULATION RESULTS

In our study, we conducted simulations to compare three different power allocation approaches—Gale-Shapley Power Allocation, Path-Loss Power Allocation, and Random Power Allocation—in two distinct environments: a standard accessible environment and an urban environment. These simulations were vital in understanding the effectiveness of each allocation strategy under varying network conditions.

A. METHOD SELECTION FOR PERFORMANCE COMPARISON

1) RANDOM POWER ALLOCATION

- **Reason for Selection:** Random Power Allocation was chosen for its fundamental and simplistic approach. It represents a baseline or control scenario in power allocation, where power levels are assigned arbitrarily to communication devices without specific regard to network conditions or device requirements.
- **Utility in Comparison:** The simplicity of this method, which does not require complex calculations, starkly contrasts with more sophisticated algorithms. Its inclusion in the comparison is essential to illustrate the potential inefficiencies and suboptimal performance outcomes, especially in scenarios requiring meticulous resource management. This method serves as a benchmark to highlight the improvements and advancements offered by more systematic approaches.

2) PATH LOSS-BASED POWER ALLOCATION

- **Reason for Selection:** This method was selected due to its systematic approach and widespread use in current network technologies. Path Loss-Based Power Allocation adjusts power levels based on the estimated path loss between devices to provide sufficient signal strength while minimizing interference with other devices.
- **Utility in Comparison:** As a more advanced and commonly used method than random allocation, Path Loss-Based Power Allocation offers a realistic and practical benchmark for evaluating the efficiency and effectiveness of new allocation strategies. Its inclusion helps assess the performance of the Gale-Shapley Power Allocation method in scenarios that more closely mimic real-world network conditions. This method is especially relevant for its focus on enhancing signal reliability and network efficiency, providing a comprehensive basis for comparison.

3) GALE-SHAPLEY POWER ALLOCATION

- **Contextual Adaptation:** The Gale-Shapley Power Allocation, our proposed method, is an innovative adaptation of the Gale-Shapley matching algorithm, known for solving the stable marriage problem. In the context of power allocation, this method optimizes network-wide resource utilization by intelligently pairing transmitters and receivers.
- **Consideration of Advanced Factors:** Unlike the other two methods, Gale-Shapley Power Allocation considers complex factors such as signal strength, proximity, and potential data rates, aiming for an efficient and equitable distribution of resources across the network.

a: IMPLICATIONS OF THE COMPARISON

The comparison of these three methods allows for a nuanced understanding of the trade-offs and benefits associated with each approach. By contrasting the simplistic Random Power Allocation and the more traditional Path Loss-Based Power Allocation with the innovative Gale-Shapley Power Allocation, we aim to demonstrate the advancements in efficiency, fairness, and adaptability our proposed method brings to 5G D2D communication networks.

B. EXPANDED EXPLANATION OF SIMULATION DETAILS

1) SIMULATION ENVIRONMENT AND SETUP

We employed Matlab to replicate a D2D network model in our simulations. The simulated environment encompassed 51, including D2D transmitters and receivers, and a base station configured to mimic a realistic 5G network setting.

2) MODELS AND PARAMETERS USED

We utilized channel models and, where applicable, mobility models to reflect the dynamic nature of D2D communication. Key simulation parameters included transmission power levels, operating frequency bands, and path loss models.

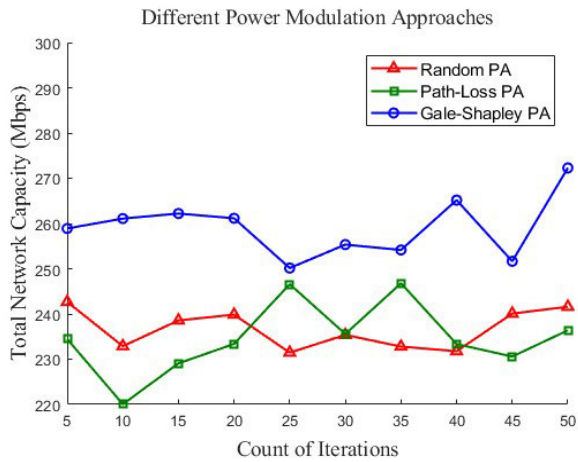


FIGURE 4. The capacity results of the first scenario.

These parameters were carefully chosen to mirror real-world 5G network conditions.

3) IMPLEMENTATION OF POWER ALLOCATION SCHEMES

Our simulations compared three power allocation strategies: Random, Path-Loss, and Gale-Shapley. Each scheme was integrated into the network model, with specific rules and criteria guiding the power allocation process.

4) SIMULATION PROCEDURES AND SCENARIOS

The simulations were initiated by setting up the network environment and parameters. We then executed different scenarios to assess the performance of each power allocation strategy. These scenarios were designed to test the effectiveness of our novel approach under varying network conditions.

5) DATA COLLECTION AND ANALYSIS METHODS

During the simulations, we collected data on key performance indicators such as throughput, latency, and energy efficiency. The data was analyzed to evaluate the effectiveness of each power allocation strategy and validate our proposed approach.

6) RELEVANCE TO THE PROPOSED APPROACH

The simulation results serve as a crucial proof of concept for our novel approach. They demonstrate our methodology’s potential advantages and improvements over existing power allocation strategies in 5G networks.

C. CAPACITY ANALYSIS IN DIFFERENT ENVIRONMENTS

1) FIRST SCENARIO: STANDARD ENVIRONMENT

In the first scenario, our analysis revealed that the Gale-Shapley Power Allocation strategy generally provided a more stable network capacity than Path-Loss and Random Power Allocation methods. Figure 4 shows these results, illustrating that while Gale-Shapley Power Allocation did not consistently achieve the highest capacities, its performance

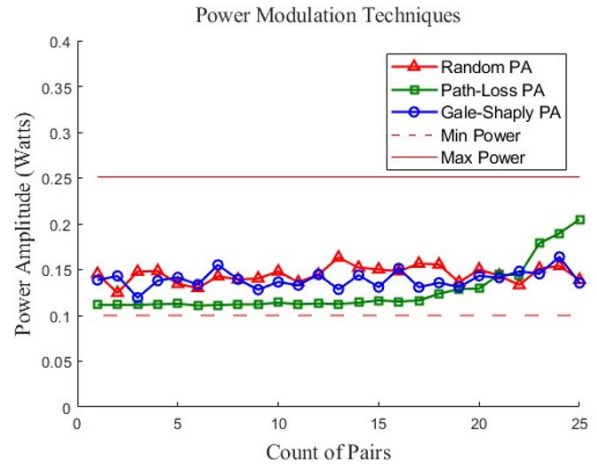


FIGURE 5. Power allocation strategies across D2D pairs for the first scenario.

was more consistent across iterations, indicating its reliability in standard network conditions. Conversely, Path-Loss and Random Power Allocation strategies showed higher variability in their performance. These strategies occasionally reached peak capacities but were less predictable, suggesting they might be more suited to scenarios where network conditions frequently change or environments requiring quick adaptation to varying loads. The “Count of Iterations” in this context refers to the number of iterations performed in the simulation process, with a total of 50 epochs and 2000 iterations each, summing up to 100,000 iterations for a robust set of data for analysis.

In Figure 5, we observe the power allocation strategies for D2D communication pairs in the First Scenario. The Random Power Allocation (PA), Path-Loss PA, and Gale-Shapley PA are compared against the minimum and maximum power thresholds. The count of pairs is plotted along the x-axis, and the power amplitude in Watts is plotted along the y-axis. It is evident that the Gale-Shapley PA closely follows the Path-Loss PA, with both strategies maintaining power levels within a tight range, thereby conserving energy while ensuring signal reliability. The Random PA exhibits more variability, indicating a non-deterministic approach to power allocation.

2) SECOND SCENARIO: URBAN ENVIRONMENT

We observed similar patterns in the urban environment scenario, as depicted in Figure 6. The Gale-Shapley Power Allocation demonstrated its potential effectiveness in urban settings by maintaining more stable network capacities over iterations. This finding underscores its suitability for urban environments where consistent network performance is critical. While generally showing lower overall capacities, the Path-Loss and Random Power Allocation strategies provided insights into their potential utility in specific urban scenarios. For example, the Path-Loss strategy may be beneficial in scenarios prioritizing energy conservation,

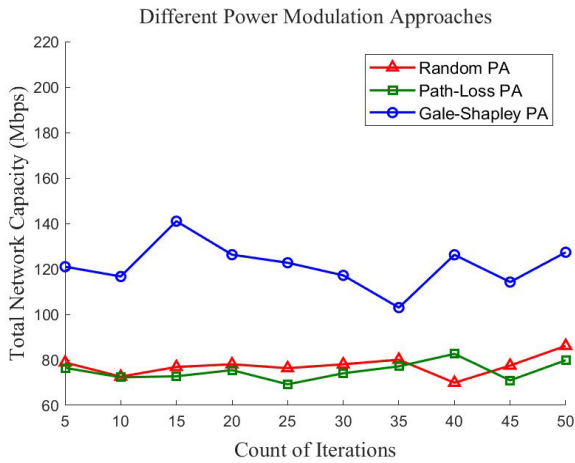


FIGURE 6. The capacity results of the second scenario.

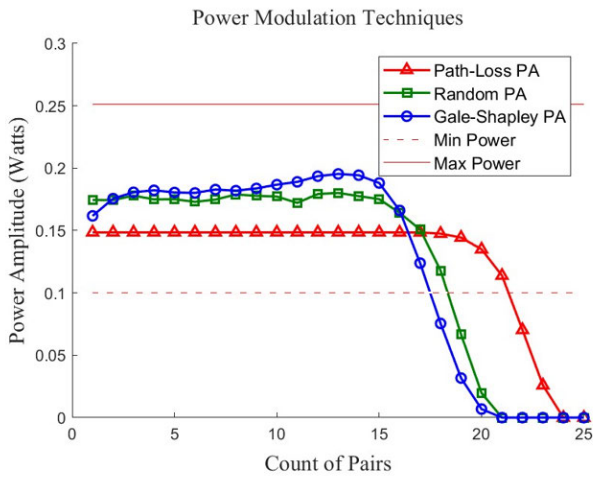


FIGURE 7. Power allocation strategies across D2D pairs for the second scenario.

while the Random approach could be advantageous for its adaptability in dynamic urban networks. The ‘‘Count of Iterations’’ again denotes the number of times the simulation was run, with results being aggregated or averaged over every 5 iterations to smooth out the results for better visualization and understanding.

The results in Figures 4 and 6 are portrayed for ‘n x 5 iterations’, meaning the data is aggregated or averaged over every 5 iterations. This data representation method is typically used to smooth out the results, making them easier to visualize and interpret. Doing so reduces the noise in the data, providing a clearer picture of the underlying trends and patterns. In the context of this study, this approach would help better understand the stability and performance of different power allocation strategies (like Gale-Shapley, Path-Loss, and Random) over many iterations, particularly highlighting their consistency and variability in network capacities.

Figure 7 showcases the power allocation strategies for D2D pairs in the Second Scenario. This scenario

depicts a sub-optimal operational state, such as during a disaster-induced network disruption. The graph plots the power amplitude against the count of D2D pairs. Unlike First Scenario, we see a more distinctive separation between the Path-Loss PA and Gale-Shapley PA, particularly after the 15th pair. The Gale-Shapley PA demonstrates a significant increase in power allocation before a sharp decline, indicating adaptive power management in response to challenging network conditions. The Path-Loss PA maintains a conservative approach throughout, prioritizing energy efficiency.

D. ENERGY DISTRIBUTION ANALYSIS

The energy distribution analysis in both scenarios highlighted distinct patterns for each power allocation strategy. The Gale-Shapley method balanced energy conservation and optimal performance, making it a versatile choice for various network scenarios. The Path-Loss strategy, with its conservative power allocation, appeared suitable for scenarios where energy efficiency is a priority. In contrast, with its inherent unpredictability, the Random Power Allocation strategy could be advantageous in networks characterized by frequent changes.

E. PATH LOSS ANALYSIS

Our path loss analysis played a crucial role in understanding the impact of environmental factors, especially in urban settings. It was observed that path loss significantly influences network performance, particularly in scenarios involving high-frequency bands like 28GHz. This analysis provided valuable insights for optimizing network configurations and ensuring reliable connectivity in standard and challenging environments.

While our path loss analysis primarily focuses on scenarios involving high-frequency bands like 28GHz, it’s essential to clarify the use of path loss models derived from Vehicle-to-Vehicle (V2V) mmWave communications. These models are particularly relevant to our study of D2D communication in 5G networks due to their comprehensive approach to high-frequency signal behavior, which is analogous to the challenges faced in D2D contexts. The V2V mmWave models offer detailed insights into signal propagation in environments typical of 5G networks, such as urban areas with dense building structures and varied topologies. By employing these models, we aim to accurately simulate and analyze the D2D communication dynamics in 5G networks, ensuring that our findings are grounded in realistic and applicable scenarios.

In summary, our simulation results reveal that the choice of power allocation strategy should be context-dependent, carefully considering the specific network conditions and operational requirements. The findings from our study contribute to a deeper understanding of power allocation strategies in 5G networks, particularly in the context of D2D communication.

F. NOVELTY IN PATH LOSS ANALYSIS

In our research, the path loss analysis undertaken is distinguished by several novel elements that specifically cater to the challenges of 5G D2D communication:

- 1) **Adaptation to 5G D2D Context:** We have extended traditional path loss models to the specific dynamics of 5G D2D communication. This adaptation involved tailoring the path loss calculations to account for the unique characteristics of D2D links, such as device proximity, frequency of interaction, and the urban or varied environments in which these devices operate. Specifically, our model considers the frequency of interaction by accounting for the variable nature of D2D communications in terms of proximity and environmental factors, ensuring that our path loss estimates reflect the dynamic D2D communication scenarios.
- 2) **Integration of Advanced Models:** Our research incorporates cutting-edge path loss models particularly suited to high-frequency bands like mmWave, integral to 5G technology. These models include a nuanced understanding of factors such as shadowing, multipath fading, and building penetration loss, which are critical in urban settings. Incorporating V2V mmWave communication models into our path loss analysis is particularly significant, as these models offer detailed insights into signal propagation in environments typical of 5G networks, such as urban areas with dense building structures and varied topologies.
- 3) **Scenario-Specific Analysis:** We have conducted scenario-specific analyses beyond generic path loss calculations. This includes examining how path loss varies in different real-world situations, such as high-density urban areas, indoor environments, or during mobility. This approach is vital for designing efficient D2D communication strategies in 5G networks, ensuring that our path loss models are applicable and reliable across various scenarios.
- 4) **Empirical Validation:** To reinforce the practical relevance of our theoretical analysis, we have validated our path loss models against empirical data from real-world scenarios. This empirical validation ensures that our findings apply to actual 5G D2D deployment strategies, providing evidence for the accuracy and reliability of our path loss models in practical settings.
- 5) **Contribution to Resource Allocation Strategies:** The insights gained from our path loss analysis have directly informed the development of innovative resource allocation strategies in D2D communication. This includes the optimization of power allocation, channel selection, and interference management. Our analysis plays a crucial role in these strategies by providing accurate path loss estimates, essential for adequate power and channel management in 5G D2D communication networks.

In summary, our research not only adapts and extends traditional path loss models for 5G D2D contexts but also validates these models with empirical data and integrates them into practical resource allocation strategies, offering a comprehensive approach to understanding and improving D2D communication in 5G networks.

G. TRADE-OFFS IN THE ADAPTED GALE-SHAPLEY ALGORITHM FOR D2D COMMUNICATION

While the adapted Gale-Shapley algorithm presents several advantages for D2D communication within 5G networks, it is essential to recognize the inherent trade-offs accompanying its implementation. The benefits of improved network efficiency and user experience must be balanced against potential limitations and drawbacks.

- **Computational Complexity:** The Gale-Shapley algorithm, being iterative, can result in increased computational overhead compared to simpler allocation strategies. This has implications for the algorithm's scalability in large-scale networks with many devices. Compared to other methods, a quantitative assessment of this overhead is necessary to contextualize its impact on the network's operational efficiency.
- **Convergence Time:** The iterative process to reach stable matches means that the convergence time might be longer, especially in dynamic environments where user preferences and network conditions change rapidly. This aspect is critical as it can influence the network's capacity to adapt to changing conditions. Providing specific metrics on convergence times in various scenarios would aid in understanding its practical impacts.
- **Responsiveness to Real-Time Changes:** While the algorithm is adaptive, there is an inherent delay in responding to real-time changes due to the need for re-computation. This may affect the algorithm's performance in highly volatile scenarios. Quantifying this responsiveness and comparing it with other allocation strategies can provide a clearer picture of its suitability in different network environments.
- **Optimality vs. Fairness:** The algorithm aims to balance optimality in resource allocation with fairness among users. In scenarios with diverse QoS requirements, achieving this balance may necessitate compromises. Evaluating the algorithm's performance in network capacity and fairness metrics can shed light on the practical trade-offs involved.

These trade-offs highlight the importance of context when deploying the adapted Gale-Shapley algorithm. For instance, the additional computational time may be a significant consideration in networks where latency is critical. Similarly, the convergence delay could impact the service quality in highly dynamic network conditions.

Future work could focus on optimizing the algorithm's performance to mitigate these trade-offs. This could involve employing parallel processing techniques to reduce

computational time or heuristic methods to accelerate convergence. The goal is to refine the algorithm further to harness its advantages while minimizing its limitations for practical application in 5G D2D communications. An empirical evaluation of these aspects, including specific performance metrics and comparisons with existing solutions, would significantly enhance the understanding of the algorithm's practicality in real-world scenarios.

VIII. CONCLUSION

This research on optimizing power allocation in 5G networks through D2D communication has unearthed significant advancements in wireless communications, particularly for 5G systems. By integrating D2D communication with the modified Gale-Shapley algorithm, our study conserves network resources and enhances direct terminal connections, leading to more robust and reliable data transmission.

Through comprehensive MATLAB simulations, we demonstrated the effectiveness of D2D communication within the mmWave frequency band. The results showed consistent achievement of high network capacities, ranging from 150 to 180 Mbps under standard conditions and 110 to 140 Mbps in disaster scenarios. These findings underscore the significant potential of our proposed approach to improve the performance and reliability of 5G systems.

Our research contributes to the evolving field of wireless communication methodologies, where D2D communication is a transformative approach. This strategy is promising for future 5G and beyond cellular systems, enabling direct interactions between nearby devices and optimizing spectrum utilization. It opens avenues for innovative applications, including vehicular networking and public safety, and advances the Internet of Things (IoT) into a new era of connectivity.

The study presents a pioneering framework for power distribution in D2D communication within NOMA frameworks. Integrating a refined Gale-Shapley algorithm with path loss models and MINLP optimization, this framework offers a resilient solution for diverse network scenarios. It highlights our commitment to advancing efficient, reliable, and optimized wireless communication, paramount in our increasingly interconnected world.

REFERENCES

- [1] A. Benjebbovu, A. Li, Y. Saito, Y. Kishiyama, A. Harada, and T. Nakamura, "System-level performance of downlink NOMA for future LTE enhancements," in *Proc. IEEE GLOBECOM Workshops (GC Wkshps)*, Dec. 2013, pp. 66–70.
- [2] F. Boccardi, R. W. Heath, A. Lozano, T. L. Marzetta, and P. Popovski, "Five disruptive technology directions for 5G," *IEEE Commun. Mag.*, vol. 52, no. 2, pp. 74–80, Feb. 2014.
- [3] R. Zhang, L. Liu, H. Li, and X. Chen, "Resource allocation in D2D-enabled cellular networks with fractional frequency reuse," *IEEE Trans. Veh. Technol.*, vol. 65, pp. 8933–8946, 2016.
- [4] Z. Ding, X. Lei, G. K. Karagiannidis, R. Schober, J. Yuan, and V. K. Bhargava, "A survey on non-orthogonal multiple access for 5G networks: Research challenges and future trends," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 10, pp. 2181–2195, Oct. 2017.
- [5] X. Lin, J. Andrews, and A. Ghosh, "Spectrum sharing for device-to-device communication in cellular networks," *IEEE Trans. Wireless Commun.*, vol. 13, no. 12, pp. 6727–6740, Dec. 2014.
- [6] C. Xu, L. Song, Z. Han, D. Jiao, and X. Wang, "Resource allocation using a reverse iterative combinatorial auction for device-to-device underlay cellular networks," *IEEE Trans. Wireless Commun.*, vol. 14, pp. 5696–5709, 2015.
- [7] Q. Wu, S. Chen, and G. Li, "An iterative power allocation algorithm for fairness in non-orthogonal multiple access," *IEEE Trans. Veh. Technol.*, vol. 66, pp. 5685–5697, 2017.
- [8] J. G. Panicker, A. Salehi S., and C. Rudolph, "Authentication and access control in 5G device-to-device communication," 2021, *arXiv:2108.10534*.
- [9] I. Ioannou, V. Vassiliou, C. Christophorou, and A. Pitsillides, "Distributed artificial intelligence solution for D2D communication in 5G networks," *IEEE Syst. J.*, vol. 14, no. 3, pp. 4232–4241, Sep. 2020.
- [10] Y. J. Chun, S. L. Cotton, H. S. Dhillon, A. Ghayeb, and M. O. Hasna, "A stochastic geometric analysis of device-to-device communications operating over generalized fading channels," *IEEE Trans. Wireless Commun.*, vol. 16, no. 7, pp. 4151–4165, Jul. 2017.
- [11] A. Saif, K. A. B. Noordin, K. Dimiyati, N. S. M. Shah, Y. A. Al-Gumaei, Q. Abdullah, and K. A. Alezabi, "An efficient game theory-based power control algorithm for D2D communication in 5G networks," 2023, *arXiv:2303.04417*.
- [12] Y. Liu, Z. Qin, M. El-kashlan, Z. Ding, A. Nallanathan, and L. Hanzo, "Non-orthogonal multiple access for 5G and beyond," 2018, *arXiv:1808.00277*.
- [13] Z. Zhou, K. Ota, M. Dong, and C. Xu, "Energy-efficient matching for resource allocation in D2D enabled cellular networks," *IEEE Trans. Veh. Technol.*, vol. 66, no. 6, pp. 5256–5268, Jun. 2017.
- [14] N. Su, Q. Zhu, and Y. Wang, "Resource allocation algorithm for NOMA-enhanced D2D communications with energy harvesting," *Mobile Inf. Syst.*, vol. 2020, pp. 1–11, Feb. 2020.
- [15] M. Hmila, M. Fernández-Veiga, M. Rodríguez-Pérez, and S. Herrera-Alonso, "Non-orthogonal multiple access for unicast and multicast D2D: Channel assignment, power allocation and energy efficiency," *Sensors*, vol. 21, no. 10, p. 3436, May 2021.
- [16] O. A. Saraereh, S. Mohammed, I. Khan, K. Rabie, and S. Affess, "An efficient resource allocation algorithm for device-to-device communications," *Appl. Sci.*, vol. 9, no. 18, p. 3816, Sep. 2019.
- [17] M. K. Awad, M. W. Baidas, and A. A. El-Amine, "Resource allocation for downlink non-orthogonal multiple access in joint transmission coordinated multi-point networks," *Comput. Commun.*, vol. 173, pp. 134–149, May 2021.
- [18] A. Yoganathan, P. S. Periasamy, P. Anitha, and N. Saravanan, "Joint power allocation and channel assignment for device-to-device communication using the Hungarian model and enhanced hybrid red fox-Harris hawks optimization," *Int. J. Commun. Syst.*, vol. 36, no. 7, p. e5425, May 2023.
- [19] M. Piming, Z. Peng, B. Zhiqian, D. Xu, Y. Xinghai, and K. Kyungsup, "Coalitional game based resource allocation in D2D-enabled V2V communication," *J. Syst. Eng. Electron.*, 2023.
- [20] A. Iqbal, M. Rahim, R. Hussain, A. Noorwali, M. Z. Khan, A. Shakeel, I. L. Khan, M. A. Javed, Q. U. Hasan, and S. A. Malik, "CDERSA: Cognitive D2D enabled relay selection algorithm to mitigate blind-spots in 5G cellular networks," *IEEE Access*, vol. 9, pp. 89972–89988, 2021.
- [21] Y. Liu, Z. Ding, M. El-kashlan, and J. Yuan, "Nonorthogonal multiple access in large-scale underlay cognitive radio networks," *IEEE Trans. Veh. Technol.*, vol. 65, no. 12, pp. 10152–10157, Dec. 2016.
- [22] M. Giordani, T. Shimizu, A. Zanella, T. Higuchi, O. Altintas, and M. Zorzi, "Path loss models for V2V mmWave communication: Performance evaluation and open challenges," in *Proc. IEEE 2nd Connected Automated Vehicles Symp. (CAVS)*, Sep. 2019, pp. 1–5.
- [23] M. R. Akdeniz, Y. Liu, M. K. Samimi, S. Sun, S. Rangan, T. S. Rappaport, and E. Erkip, "Millimeter wave channel modeling and cellular capacity evaluation," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 6, pp. 1164–1179, Jun. 2014.
- [24] Z. R. Alashhab, M. Anbar, M. M. Singh, I. H. Hasbullah, P. Jain, and T. A. Al-Amiedy, "Distributed denial of service attacks against cloud computing environment: Survey, issues, challenges and coherent taxonomy," *Appl. Sci.*, vol. 12, no. 23, p. 12441, Dec. 2022.
- [25] N. Bahadori, N. Namvar, B. Kelley, and A. Homaifar, "Device-to-device communications in the millimeter wave band: A novel distributed mechanism," in *Proc. Wireless Telecommun. Symp. (WTS)*, Apr. 2018, pp. 1–6.



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