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Game Theory Based Resource Allocation in D2D Communication with Traffic Aware Beam Selection in 5G Networks

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Abstract: Device to Device (D2D) communication is an advanced technology to increase cellular network efficiency, improving factors such as spectral efficiency, battery life, and coverage. The foundation of the 5G cellular network, striving for a network availability of 99.999%, relies heavily on D2D communication. When multiple D2D pairs connect to various base stations, the complexities of resource allocation for D2D links become apparent. In this paper, a resource allocation strategy based on game theory is introduced, with special focus on resource block (RB) sharing between multi-cell mobile phone networks involving D2D and handset users. In this approach, D2D user pairs engage in strategic games with nearby base stations, aiming to optimize their utility by thoughtfully distributing their initially allocated resources. Interuser interference may arise from side lobes in the antenna array. To address this challenge, the paper presents a traffic-aware beam configuration method combined with game theory-based resource allocation. This approach optimizes the allocation of beams across all Resource Blocks (RBs) to efficiently meet the traffic demands of User Equipment (UE). Each intercell D2D player simultaneously participates in a game with the base stations. The study reveals that by introducing an additional penalty factor for swift adherence, the duration of penalties for players deviating from the optimal strategy can be minimized. Additionally, the research identifies the ideal number of initial RBs that should be orthogonal and allocates them to both Device to Device (D2D) and cellular users. Evaluate the proposed approach compared to existing methods like multicast content sharing-based resource allocation (MCSRA), Quality of Experience-aware resource allocation (QoERA), and Mobile Edge Computing-based resource allocation (MECRA), showcases substantial improvements in resource utilization, throughput, and traffic demand management across the entire system. According to experimental analysis, the proposed system achieves a remarkable 96% increase in resource utilization, a 95% increase in throughput, and effectively addresses 97% of traffic demands.

Keywords: *D2D links, resource utilization, beam configuration, Game theory, resource block, throughput.*

1. Introduction

The rapid advancements in data communication have sparked a profound transformation within wireless networks. As anticipated, the proliferation of wireless devices continues to surge exponentially. In the foreseeable future, we envision a society becoming even more mobile and interconnected. This shift is characterized by a significant increase in connectivity, traffic, and a wide range of usage scenarios. The surge in data traffic is poised to be truly remarkable, with global data traffic projected to increase by over twenty thousand times between 2010 and 2030. While smartphones are expected to maintain their status as the most popular personal devices, other device categories, such as wearables and smart devices, are also poised for growth. Consequently, the widespread adoption of the 5G cellular communication system is imperative to meet the previous generation systems were unable to meet changing needs. [1,2].

The 5G network encompasses a myriad of technologies, including the IoT, SDN, D2D communications, vehicular networking, M2M communications, UAV's, CRAN's, mobile edge MEC, and cloud computing. These technologies aim to evolve traditional communication networks into a network of interconnected everything [3,4]. To keep up with the pace necessary to meet this immense demand, cutting-edge technologies must enhance the substantial cellular capacity Imagined within the highly regarded 5G cellular network framework [5].

One of the key features of 5G networks includes the integration of wireless fabrics, which can provide higher spectral efficiency and greater bandwidth than current cellular networks. This achievement is achieved through the deployment of multiple antenna elements and frequency reuse. These advancements are indispensable to facilitate the transfer of massive volumes of data, with speeds reaching up to 100 Gbps/km2, all while ensuring improved mobility. To support such high-speed and efficient data transfer, these systems demand the implementation of more efficient and pervasive radio access technologies (RATs) and an integrated programming model [6,7].

Resource allocation stands out as a pivotal aspect of D2D communication, necessitating the efficient allocation of licensed spectrum blocks for D2D transmissions. However, resource block sharing with cellular users introduces

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significant cross-tier interferences in such communication scenarios. Research has categorized interference mitigation techniques a classification of methods into centralized, distributed, and semi-distributed ones. In this study, we focus Our approach centers on centralized interference management, coupled with a resource-sharing algorithm where neighboring base stations work together to determine a subset of RBs allocated to D2D links.

Resource allocation becomes less complex and Minimizing interference is straightforward when both a Device to Device (D2D) transmitter and receiver are within the similar cell. However, complications arise when these components are located in separate cells. The sharing of resource blocks (RBs) across cells introduces the potential for inter-cell interference, which is particularly problematic for user equipment (UE) at the cell boundaries. Thus, creating a D2D link necessitates collaboration among neighboring base stations to collectively reduce interference, as highlighted in references [8,9].

Due to its strong concepts and methods for decision-making, game theory has become a well-known instrument for developing future wireless networks. The repeating game is a form of non-cooperative gameplay that occurs iteratively over time, as encountered in various game types explored in the existing literature. With each successive round of the game, players acquire valuable insights into the actions of their peers, which prompts them to adapt their strategies to maximize their individual advantages. In this context, short-term gains for any player are discouraged, as they can reduce long-term payoffs. Players benefit most by cooperating with one another [10,11].

In this paper, an integer programming model have been formulated for efficient resource allocation by game theory and the demands of downlink traffic by the traffic aware scheduling mechanism are combined to maximize the throughput effectively. This is a simple method that aims to approximate the best beam arrangement and resource distribution.

The contributions of this paper are:

- To integrate the game theory and traffic aware for resource allocation and efficient beam scheduling and to obtain the increased throughput.
- To compare the throughput and resource utilization with the existing system like multicast content sharing based resource allocation (MCSRA), QoE aware resource allocation (QoERA) and MECRA.

The paper organizational structure is as follows: Section-2 presents a synopsis of relevant research. In Section-3, we elaborate on the proposed methodology. Section-4 is dedicated to presenting the results and engaging in discussions, while Section-5 delivers the concluding remarks.

2. Related Research

In a prior study [12], the primary goal was to enhance the overall system data rate by efficiently managing the allocation of uplink and downlink resources, all while ensuring QoS for both CUE's and DUE's. To tackle the challenge of formulating this optimization problem, which falls under the category of MINLP with known NP-hard complexities, the study took into account the allocation of uplink and downlink subcarrier resources for DUEs. The simulation results underscored the substantial performance gains achieved by this algorithm.

Another innovative approach introduces strategies that combine AC and RRA [13] to provide continuous Quality of Service (QoS) support for cellular and Device-to-Device (D2D) communications. The AC algorithm optimizes service provider profits while adhering to QoS constraints, effectively determining the most favorable configuration of cellular and D2D connections. Numerical data demonstrated the effectiveness of this integrated AC and RRA technique, significantly improved satisfaction by 40% cellular and D2D links, along with a noteworthy reduction in energy consumption exceeding 50%.

In order to address the intricate challenge of allocating resources among mmWave and cellular bands for numerous Device-to-Device (D2D) pairs, a separate research study employed game theory as its approach. [14]. Specifically, They utilize a coalition formation game to maximize the average total system rate. This game rapidly converged to a Nash-stable equilibrium, yielding solutions closely aligned with the ideal. Compared with several other practical methods, this scheme shows superior performance in terms of total system rate.

[15] A resource allocation optimization problem was tackled concerning D2D communication spectrum allocation across multiple microwave and mm-wave bands in Heterogeneous Cellular Networks (HCNs). To increase system transmission rate while taking into account the heuristic method is proposed that produces highly accurate results based on different propagation conditions in two frequency bands. Simulations confirm the effectiveness and efficiency of this method.

[16] An algorithm is developed for joint allocation of sub-channels and power for device-to-device D2D communication using NOMA. The aim of this algorithm was maximizing energy efficiency and throughput in mobile communication systems for uplink transmission. It utilized the KM technique for channel allocation and implemented the KKT criteria to formulate an optimal power allocation problem. Simulations consistently demonstrate that our algorithm outperforms state-of-the-art methods in terms of

energy efficiency and throughput across a variety of network configurations.

[17] This research focuses on resource allocation in communication mode selection for Device-to-Device (D2D) communication. The research methodology involved clustering D2D users based on their geographical locations and then selecting communication modes based on the priority of their communication needs. In order to improve resource allocation efficiency, the signal-to-noise ratio of the orthogonal mode, multi-mode and cellular mode of the algorithm was evaluated. Through simulation analyses conducted in a multi-user scenario within a single cell, the study consistently demonstrated that the algorithm effectively allocated the most suitable communication mode and resources to maximize throughput.

[18] Introducing a unique sharing paradigm known as the "pure D2D model," this approach enabled DUE’s to share resources independently of CUE’s, thereby increasing flexibility. To optimize the number of supported links in the network, an optimization problem was formulated, leading to the proposal of a DRAPC framework. Simulation results consistently indicated that DRAPC improved network performance and ensured fairness among links. [19] Resource allocation between D2D communications between devices paired and regular mobile phone users within a vehicular network was addressed using Stable Matching Theory. This heuristic-based algorithm consistently provided nearly optimal results with significantly reduced complexity, outperforming existing solutions in terms of performance. [20] In a MIMO-NOMA cellular network, resource allocation planning for D2D communication is introduced to improve spectral efficiency. An optimization problem was formulated to achieve this objective. Simulations consistently demonstrated that this technique outperformed traditional D2D communication methods in mmWave-underlying MIMO-NOMA cellular networks. [21] Effective D2MD groups for content sharing in cellular networks were developed using a multicast content sharing context (MCSRA) that took into consideration the social characteristics of mobile users. The power and channel distribution among D2MD clusters was adjusted using this method, which significantly increased throughput in 5G cellular networks.

[22] A QoE-aware model was introduced for dynamic resource allocation in Industrial Internet of Things (IIoT) applications. Middleware, such as fog computing, was highlighted for allocating resources based on QoS/QoE requirements. Empirical results underscored the impact of this QoE-aware resource allocation model, particularly in the context of the Tactile Internet.

[23] Based on the differential evolution algorithm, an effective method for job offloading and channel resource allocation was put forth. This scheme reduced energy consumption and demonstrated good convergence. It also addressed task offloading and resource allocation for heterogeneous UDN’s with Multiple Mobile User Equipment (MUE) and Single User Equipment (SUE). This approach optimized energy consumption and exhibited strong convergence properties while considering varying network conditions.

3. Proposed Methodology

The system model presents a challenge centered on maximizing throughput for the entire system, with a specific focus on D2D communication within the LTE-A system architecture, as illustrated in Figure 1. Within this framework, we find a three-cell LTE-A system that integrates D2D connectivity between cells. Device-to-device (D2D) transmitters and receivers are distributed across multiple cells and are connected via the PC5 interface. Furthermore, the base station eNB forms a connection to the core network via the X2 using interface. The S1-U and S1-MME interface.

An app server, found in both Device-to-Device (D2D) devices and the core network, manages a range of functions, it includes all aspects of resource allocation, power control, control signaling, and Device-to-Device (D2D) communication. From the user's perspective, application functionality establishes connectivity with the Evolved Packet Core (EPC) server via the PC1 interface. This traffic-aware beam-sharing game-theoretic resource-sharing system is implemented within the application server, which holds control over all software operations on both the EPC and D2D devices. The core network oversees these functions while also communicating with the eNBs through the S1-MME interface.

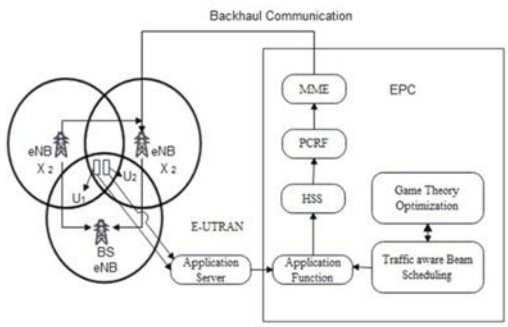

Fig. 1. LTE-A Architecture for 5G Communication

The goal is to increase the overall system throughput by efficiently allocating resource blocks (RBs) to base stations for downlink transmissions and Device-to-Device (D2D) pairs. These RBs are jointly utilized by mobile users and Device-to-Device (D2D) users, the structure of the optimization problem is as follows:

In this approach, a collaborative resource-sharing scheme is employed, where a Device-to-Device (D2D) pair shares resources with its neighboring BS, and conversely, a BS shares resources with a Device-to-Device (D2D) pair. Equation (1) represents the constraint, which represents the total number of RBs used by a BS or D2D pair in the entire system.

$$max_{N_B} \sum_{i\in(B\cup D)} \sum_{k\in N_i} r_k^i \quad (1)$$

Equation (2) This suggests that each D2D pair employs the shared resource blocks (RBs) from one or more of its adjacent base stations (BSs).

$$|\sum_{k\in N_i} r_k^i - R_{req}^i| \leq \Delta \quad (2)$$

$$\gamma_k^i \geq \gamma_{th}, (\forall k \in N_i) \quad (3)$$

In this case, a small positive value that is very close to zero is represents as Δ. Sets "B" and "D" is denoted within each element as a "Node". Ni represents the total number of accessible orthogonal resource blocks in the system. The Signal-to-Interference-Plus-Noise-Ratio (SINR) threshold (denoted as γ_th) ensures successful transmission by minimum rate guaranteed for each RB.

Each node aims to improve throughput by taking additional shared RBs from other nodes. The throughput achieved by a particular node, denoted as "i," should closely align with its rate demand, R_req^i, with only a small margin, as indicated in equation (3). The most important thing is to ensure that the channel Signal-to-Interference-Plus-Noise-Ratio (SINR) of all RBs used in BS and Device-to-Device (D2D) pairs exceeds the threshold γ_th. To achieve these goals, we introduce a game-theoretic framework in which a pair of D2D users acts as one player and adjacent base stations collectively constitute the other players in the game. The goal is to maximize each player's utility by optimizing the initial orthogonal RB assignments for D2D and cellular users.

In game theory, repeated games fall into two primary categories: (i) games with limited repetitions and (ii) a game that repeats endlessly over time. Infinite repetition games apply to scenarios where players cannot predict how many rounds the game will last until equilibrium is reached, while finite games model situations with a predetermined number of repetitions.

In this study, focus on having participants replay the game indefinitely without knowing the total number of stages until the game ends. If the game time is known in advance, players may not be able to fully cooperate during the game, thereby reducing the overall reward. Hence, we utilize a finite game, often referred to as a stage game, to illustrate player strategies at each step.

A single shot game is, expressed as: G = {i, s, u}, comprises the following elements:

"i" represents the set of players, with D_i forming The first player and its neighboring eNB (B n Di) together constitute another player.

"s" covers a range of strategies used by players, focusing on increasing RB numbers.

"u" comprises the set of player's utility functions, representing the difference between a player's benefit and cost. In our proposed game, a player's benefit equates to its throughput, which increases as the number of used RBs grows. The cost is related to the interference that occurs when the same RB is reused by another player.

The utility function of the ith participant is defined as:

$$u_i = \begin{cases} \sum_{k\in N_i} r_k^i \ when\ D_i\ is\ the\ ith\ player \\ \sum_{j\in B_{D_i}^n} \sum_{k\in N_i} r_k^j\ when\ D_i\ is\ the\ iB_{D_i}^n\ player \end{cases} \quad (4)$$

In this context, Ni represents the total count of RB's allocated to the ith player. It's important to highlight that all base stations (BSs) within the intersection of B and Di also employ Ni RBs. In this scenario, the optimization of the utility function involves increasing the number of Nis for the players until the data traffic demand is fully met. Sharing the kth RB with an opponent leads to a reduction in the SINR, resulting in a diminished achievable throughput for the kth RB, denoted as r_k^i, compared to when the RB is not shared.

At the outset of the game, each player is initially endowed with a fixed number of non-overlapping RBs, N_i. If a player chooses to work with his opponent, his opponent will have access to a portion of his initially allocated RBs. The selection of these RBs is based on favorable channel conditions to minimize overall interference.

In situations where neither player cooperates, player payout factor i is expressed as:

$$p_0^i = \sum_{k\in N_i^{initial}} r_k^i\, , N_i^{shared} = \varphi, \forall_i \in i \quad (5)$$

It's important to highlight that r_k^i, which stands for the cumulative achieved throughput across all base stations (BSs) within the intersection of B and Di, pertains to the ith player, as outlined in equation (5).

In this particular context:

u_(c,c)^i represents the payout to the i-th player when both players are playing in cooperative mode.

u_(nc,c)^i indicates the reward obtained by the i-th player when operating in cooperative mode, while another player is also in cooperative mode, thus sharing RB.

u_(nc,nc)^i signifies the benefit when neither player participates in co-operative mode.

Lastly, u_(c,nc)^ i represents the reward when the i-th player cooperates, even if the other player does not.

These associated payoffs are defined as follows:

$$u_{c,c}^{i}=p_{1}^{i}+p_{2}^{i} \quad (6)$$

$$u_{nc,c}^{i}=p_{0}^{i}+p_{2}^{i} \quad (7)$$

$$u_{nc,nc}^{i}=p_{0}^{i} \quad (8)$$

$$u_{c,nc}^{i}=p_{1}^{i} \quad (9)$$

The payoffs on the above can be more specifically given as follows:

$$p_{1}^{i}=\sum_{k\in N_{i}^{initial}} r_{k}^{i} \quad N_{i}^{shared} \neq \varphi, \exists_{i} \in i \quad (10)$$

$$p_{1}^{i}=\sum_{k\in N_{i}^{shared}} r_{k}^{i} \; j\in I, and \; i\neq j \quad (11)$$

In this context, p_1^i signifies the highest attainable throughput for the ith player when using the RBs initially designated to it. This encompasses the situation where the ith player collaboratively shares its RBs with the jth player, permitting the jth player send part of the content to ith player's RBs. Conversely, p_1^i represents the throughput reached by the ith player when opportunity arises to submit additional information, mj RBs allocated from the jth player.

3.1. Traffic aware scheduling mechanism:

This design places a strong emphasis on taking users' traffic demands into account to optimize beam selection. Initially, the "Max-demand allocation" approach was introduced to enhance spectrum utilization by considering user traffic demands. However, this approach overlooks inter-user interference and might lead to the selection of beams that suffer from significant interference issues. Consequently, the design underwent refinement, incorporating the "top-K demand allocation" method, it takes into account the combination of user requirements and side lobe interference.

It is important to note that a base station (BS) can only configure a specific set of beams at any time. While a User Equipment (UE) can maintain acceptable signal quality even with a non-optimal beam, it achieves the highest receiving power when served using its ideal beam.

UEs assigned to Resource Blocks within the same time slot in 5G NR, which employs OFDMA and different subcarriers are allocated to different UEs, will share the same set of beams. However, not all UEs within those RBs may find these beams ideal.

To simplify this discussion, we classify the users served by the best beams as "primary users." Conversely, if the beam providing the service is not optimal, the user becomes a "secondary user" of that beam. Therefore, all primary users of beam θ are collected into a set called Vθ, and all remaining users are considered as secondary users of beam θ, expressed as the set Sθ = V/V_θ.

In this architectural framework, RBs are assigned to the relevant primary users after selecting an appropriate subset of beams. If the modest demands of primary users do not fully utilize all RBs, the surplus RBs are allocated to secondary users to maximize spectrum utilization.

Traditional game theory-based resource allocation methods usually prioritize a set of beams to maximize the UE's SINR, regardless of traffic demand. However, assigning RBs to more primary users, who are served by their best beams due to higher traffic demands, may prove to be a more efficient approach. Nonetheless, maximizing the potential data rate of allocated RBs by choosing beams with fewer primary users and lower traffic demands may result in lower spectrum efficiency and underutilization of RBs.

The proposed method combines beam selection and resource allocation while taking user traffic requirements into account to improve spectrum efficiency and maximize beam utilization. It is designed specifically for downlink scenarios with a predefined number of packets in the buffer. The main purpose of this algorithm is to prioritize beam selection in descending order based on the traffic needs of the primary users. In this case, the total load θ on the beam can be expressed mathematically as follows:

$$D_{\theta}=\sum_{u\in v_{\theta}} d_{u} \quad (12)$$

In every time period, the Base Station (BS) proceeds to select the top-N demanded beams, Denoted as the set θ = {θ_1, θ_2, … θ_N}, provide downstream links User Equipments (UEs). Each Resource Block (RB) can accommodate a maximum of N UEs, each of which belongs to the primary UE set V_(θ_i) served along beam θ_i, where 1 ≤ i ≤ N. A similar sorting process is applied to UEs within V_(θ_i) Based on the traffic request, RBs are allocated to the UE request to sort in descending order. This approach maximizes spectrum utilization, increasing the likelihood of full RB utilization by primary users during the current time period. When the beams are configured, SINR_u, f denotes the Signal to Interference Noise Ratio (SINR) of UE u on subcarrier f from this, the data rate that UE u can achieve on subcarrier f is determined.

$$r_{u,f}=W(1+log\frac{P_{u,f,\theta}}{\sum_{\theta\prime\in\ominus\theta\prime\neq\theta} P_{u,f,\theta^{\prime}}+N_{0}} \quad (13)$$

RB allocation continues for subcarrier "f" until it can fulfill its traffic demands or until all the available Resource Blocks within this time slot are allocated to User Equipment (UE) "u." The allocation process for primary UEs is concluded once the requirements of a specific beam have been entirely satisfied. This repetition of the process occurs in each time slot. Before resource allocation takes place, the demand database is updated and sorted for each time slot. It is important to note that UEs with higher SINR can take advantage of higher-order MCS, thereby achieving higher transmission rates. Therefore, the number of RBs required by a UE is not linearly proportional to its traffic demand (number of bits).Therefore, UEs are ranked in descending order of RB requirement, rather than achievable rate divided by initial traffic demand.

The max-demand algorithm places significant emphasis on user traffic demands but may not consider the potential influence of achievable (SINR) Signal-to-Interference-plus-Noise Ratio for users. In a beamforming system, steering the beam in a particular direction θ may cause side lobes to appear in unintended directions ≠ θ. Although the UE benefits from service from its ideal beam, it is also susceptible to interference from the side lobes of other beams θ ∈ θ. As a result, while the purpose of maximum demand allocation is to optimize beam utilization based on traffic considerations, it may inadvertently create beam patterns in which selected beams cause significant interference with each other.

To address this issue, the algorithm has been enhanced to take into account the trade-off between traffic requirements and achievable data rates. Rather than simply selecting the N beams with the highest demand, this approach identifies K beams (K ≥ N) from the top K traffic demands. These K beams form the candidate set θtop-K, from which N beams are selected to maximize the data rate among the beams with the greatest demand. The selection process involves a comprehensive search across K beams to calculate the cumulative capacity. By setting K slightly larger than N, the search complexity remains reasonably manageable.

Resource sharing has an advantage only when u_(c,c)^i > u_(nc,nc)^i or (p_1^i + p_2^i) > p_0^i. By Applying this condition to each player's cooperative mode strategy, and replacing each period's utility value with player I's non-cooperation during Tp time, we can determine the penalty period (Tp) as follows:

$$\lim_{\delta\to 1} T_p > \lim_{\delta\to 1} T_p^{\delta} = \lim_{\delta\to 1} \max_i \frac{\delta . p_2^i}{\delta . p_2^i - (p_0^i - p_1^i)} \qquad (14)$$

When δ approaches 1, the minimum punishment period (T_min) can be expressed as:

$$T_{min} > \max_i \frac{p_2^i}{(p_1^i + p_2^i) - p_0^i} \qquad (15)$$

In cellular environments, the convergence time of resource allocation solutions is very important. To facilitate this convergence process, we introduce a penalty factor in the player's utility function, denoted as "α" [0<α]. Within the resource allocation algorithm, a player who deviates from cooperation mode experiences a substantial reduction in their utility during a defined punishment period. This serves as an incentive for the player to cooperate with others.

By decreasing the value of α, we can effectively shorten the punishment period, motivating players to return to cooperation more rapidly. In this case, if the i-th player refuses to share part of its resource block (RB) with an opponent player, it will be penalized, thereby reducing the additional throughput it gains. Simultaneously, the quantity of shared RBs between the opponent player and the uncooperative player is reduced. Consequently, the payout for the The ith player is represented as:

$$u_{nc,c}^i = p_0^i + \alpha p_2^i$$
(16)

The minimum punishment time T_{min} can be reduced to:

$$T_{min} > \max_i \frac{\alpha p_2^i}{(p_1^i + p_2^i) - p_0^i} \qquad (17)$$

Pseudo code: Resource allocation algorithm

Step1: Initialize Input NT, N_B,

Step2: Output: $u_{nc,c}^i$, T_{min}

Step 3: Initialization of n1,n2,N_i

Step 4: Distribute the active users and device to device pair

Step 5: Initialize initial RBs

Step 6: Calculate p_0^i

Step 7: Enhance spectrum efficiency and beam utilization

Step 8: Calculate total load of beam

Step 9: Set each time slot

Step 10: Configure beams, sub carriers

Step 11: Calculate minimum punishment period

Step 12: Calculate resource payoff

4. Result and Discussion

We propose game theory-based resource allocation for throughput and resource utilization using traffic-aware beam selection for existing systems such as multicast content sharing based resource allocation (MCSRA). QoE aware resource allocation (QoERA) and Mobile Edge Computing based Resource allocation (MECRA).

4.1. Resource Utilization

Table 1 describes comparison of the resource utilization with proposed Game theory based resource allocation with traffic aware beam selection with the existing system like multicast content sharing based resource allocation (MCSRA), QoE aware resource allocation (QoERA) and Mobile Edge Computing based Resource allocation (MECRA).

Table 1: Comparison of resource utilization with proposed system with MCSRA, QoERA and MECRA

Number of users	Resource Utilization (%)			
	MCSRA[21]	QoE RA [22]	MECRA [23]	Proposed
20	78	81	80	86
40	80	84	84	90
60	82	86	89	93
80	85	89	90	95
100	92	90	91	96

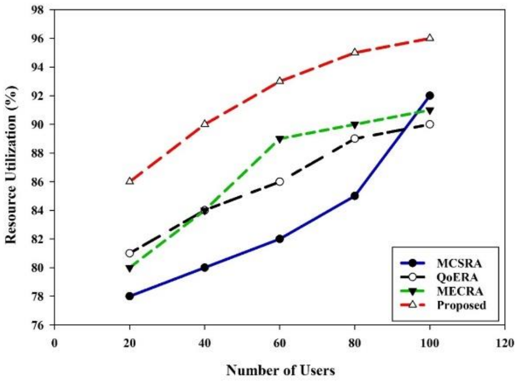

Fig 2: Comparison of Resource Utilization (RU)

In figure 2 the Resource Utilization (RU) comparison of the proposed system with MCSRA, QoERA and MECRA is represented. In this figure, red line represents the proposed system, blue line represents MCSRA, black line represents QoERA and green line denotes MECRA. From the analysis it is noted that proposed method achieves highest resource utilization.

4.2. Throughput Analysis:

Table 2 describes comparison of the throughput with proposed Game theory based resource allocation with traffic aware beam selection with the existing system like multicast content sharing based resource allocation (MCSRA), QoE aware resource allocation (QoERA) and Mobile Edge Computing based Resource allocation (MECRA).

Table 2: Comparison of throughput with prosed system with MCSRA, QoERA and MECRA

Number of users	Throughput(mbps)			
	MCSRA[21]	QoE RA [22]	MECRA [23]	Proposed
20	75	81	80	86
40	79	84	84	90
60	80	86	89	93
80	82	89	90	95
100	92	90	91	96

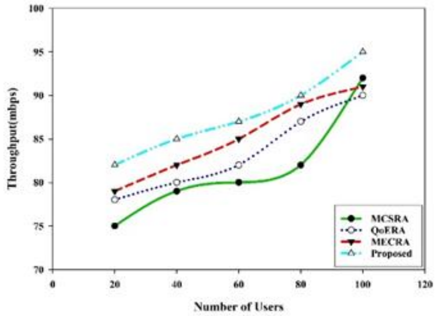

Fig 3: Comparison of Throughput

In figure 3 the throughput comparison of the proposed system with MCSRA, QoERA and MECRA is represented. In this figure, red line represents the proposed system, green line represents MCSRA, dotted violet line represents QoERA and red line denotes MECRA. From the analysis it is noted that proposed method achieves highest throughput.

4.3. Traffic Demands

Table 3 describes comparison of the traffic demands with proposed Game theory based resource allocation with traffic aware beam selection with the existing system like multicast content sharing based resource allocation (MCSRA), QoE aware resource allocation (QoERA) and Mobile Edge Computing based Resource allocation (MECRA).

Table 3: Comparison of traffic demands with prosed system with MCSRA, QoERA and MECRA

Arrival rate	Effective throughput			
	MCSRA[21]	QoE RA [22]	MCSRA[21]	Proposed
0.5	70	0.5	70	0.5
1	76	1	76	1
1.5	81	1.5	81	1.5
2	86	2	86	2
2.5	90	2.5	90	2.5

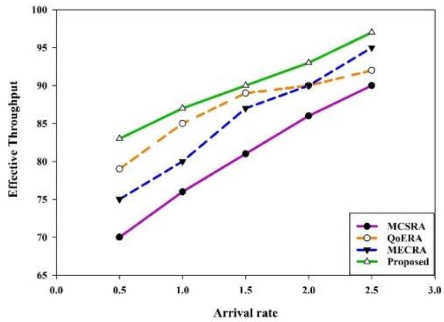

Fig 4: Comparison of Traffic demands

In figure 4 the traffic demand comparison of the proposed system with MCSRA, QoERA and MECRA is represented. In this figure, green line represents the proposed system, purple line represents MCSRA, orange line represents QoERA and blue line denotes MECRA. From the analysis it is noted that proposed method maintains the traffic demands effectively.

5. Conclusion

In this study, we introduce a Resource Block (RB) sharing policy for Device-To-Device (D2D) and cellular users in multi-cellular networks, employing principles from game theory. In this context, D2D user pairs engage in a game with neighboring base stations to enhance their utility by jointly utilizing a portion of the initially allocated resources. Potential interuser interference may arise from suboptimal antenna array beam patterns, leading to side lobes. To address this, the study proposes a traffic-aware beam configuration integrated with game theory-based resource allocation, which takes into account User Equipment (UE) traffic demands and optimizes beam usage across all RBs.

The results indicate that the proposed approach, named MCSRA (Multicast Content Sharing-based Resource Allocation), and surpasses resource allocation methods based on multicast content sharing. The incorporation of QoE aware resource allocation (QoERA) and Mobile Edge Computing-based Resource Allocation (MECRA) significantly enhances system resource utilization, throughput, and alignment with traffic requirements. Experimental findings demonstrate that the suggested system effectively manages 97% of traffic demands while increasing throughput by 95% and improving resource utilization by 96%. Future studies will focus on implementing effective strategies to accommodate the growing traffic demands and adjusting the arrival rate accordingly.

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