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Enhancing D2D Communication for Network Throughput Optimization in 5G and Beyond

S. Mohan Babu
Student, M E - Applied Electronics, Department of Electronics and Communication Engineering,
Saveetha Engineering College,
Chennai, Tamil Nadu, India.
Email id: srirammohan88@gmail.com

Abstract: This research investigates the optimization of Device-to-Device (D2D) communication in 5G and beyond networks for enhancing network throughput using state-of-the-art machine learning techniques. Device-to-Device (D2D) communication is a key feature of 5G and beyond cellular systems, where direct device-to-device communication is allowed. It improves network spectral efficiency and decreases the network latency. However, the resource block allocation and interference management are the key challenges to leverage D2D communication. We propose a DRL-based optimization framework for improving the D2D communication power allocation and user association control to enhance the overall network throughput and decrease the interference. As the network condition changes and user mobility, the proposed framework adapts to control and optimize network throughput and interference. The performance of the proposed approach has been extensively evaluated in a 5G network simulator to show a 32% increase in the overall network throughput and 28% decrease in interference compared to the optimized stochastic optimisation approach.

Keywords— D2D communication, 5G networks, machine learning, deep reinforcement learning, network throughput, interference management, resource allocation, user association, power optimization, beyond 5G.

1. Introduction

With the advent of wireless communication technologies, especially in 5G networks, we saw unprecedented levels of connectivity and data exchange in a shorter period. To tackle issues such as spectrum efficiency, network capacity, and latency of cellular networks, device-to-device (D2D) communication was suggested as an alternative for communicating between devices in the surrounding area without routing through a base station, and so reducing the load on the cellular infrastructure[1]. Communication directly between devices is now one of the most promising technologies in 5G and beyond, especially in ultra-dense networks and Internet of Things (IoT) devices[2]. D2D provides a reduction in transmission delays and increases network throughput by allowing devices to communicate directly with each other[3]. Nevertheless, D2D integration into cellular networks remains a hard nut to crack as it involves design challenges such as interference management, resource allocation, and mode selection. Interference is a major concern in dense network environments: because cellular users might be active simultaneously with D2D pairs in the same frequency resources [4], efficient resource allocations are needed to guarantee a coexistence of cellular and D2D communications without significantly degrading the overall network performance [5]. Though effective, the existing optimization techniques often rely on static configurations and thus cannot take into account the user and traffic dynamics in modern cellular networks that are often subject to rapid changes [6].

Most recently, novel machine learning (ML) methods, known as deep reinforcement learning (DRL), become available to help optimize D2D communication in cellular networks [7]. DRL can actively learn to optimize D2D communication by interacting with the cellular network[8], such as resource allocation, interference management, and user association. It can offer higher spectral efficiency, energy consumption, and network throughput[9] than conventional methods.Here, we introduce a deep reinforcement learning framework for enhancing D2D communication to improve network throughput for 5G and beyond [10]. It dynamically adaptively updates the transmit powers, the spectrum resource allocation, and the communication modes to maximize the total network throughput. We evaluate the performance of the proposed framework on a simulated 5G network with different network densities and mobility scenarios. The results show that the framework with D2D communication can achieve significant increases in spectral efficiency, interference reduction, and energy efficiency compared with the traditional resource optimization schemes.

2.Materials and Methods

2.1 Network Model

The considered network model is a 5G cellular system taking into account Device-to-Device (D2D) communication along with the conventional cellular communication. The network comprises CUs and D2D pairs that share the same spectrum resources. The D2D pairs communicate directly without the base station, while the CUs communicate through the base station. Since the D2D pairs and CUs share the same spectrum resources, the D2D communication introduces an interference to the CUs. The total system throughput, T_{total}, is the cumulative throughput of both CUs and D2D pairs. For CUs, the throughput T_{CU} is defined by:

$$TCU=B\log 2(1+\frac{P_{CU}G_{CU}}{I_{D2D}+N_0})\text{……(1)}$$

where B is the bandwidth, P_{CU} is the power allocated to CUs, G_{CU} is the channel gain, I_{D2D} represents the interference from D2D pairs, and N_0 is the noise power. Similarly, the throughput for D2D pairs T_{D2D} is given by:

$$TD2D=B\log 2(1+\frac{P_{D2D}G_{D2D}}{I_{CU}+N_0})\text{……(2)}$$

where P_{D2D} is the transmission power for D2D pairs and G_{D2D} represents the channel gain for D2D communication. The fundamental aim of this network model is to maximize the overall throughput by managing interference, and dynamically sharing the power and resources allocated between CUs and D2D users on an adaptive basis. These are the learning-driven optimization techniques that are described in the next sections.

2.2 Resource Allocation

Resource allocation plays a critical role in optimizing network throughput by efficiently distributing spectrum resources between D2D and cellular users. We define the total throughput as:

$$T_{total} = T_{D2D} + T_{CU} \text{ …..(2)}$$

where $T_{D2}D$ and T_{CU} are the throughputs of D2D and cellular users, respectively. The optimization problem is to maximize T_{total}, subject to resource constraints. The bandwidth available for D2D communication and cellular users is shared, making dynamic allocation essential. The constraint is:

$$R_{D2D} + R_{CU} \leq R_{total} \text{ …..(3)}$$

where R_{D2D} and R_{CU} are the resources allocated to D2D and cellular users, and R_{total} is the total available spectrum. The proposed system dynamically allocates resources based on network conditions.

2.3 Power Control Optimization

Power control is essential to reduce interference among D2D and cellular users. The goal is to optimise the transmission power to maximise the throughput of D2D, while at the same time minimising the interference to the cellular communication. The power control optimisation problem illustrated as follows.

$$\max_{P_{D2D}} T_{D2D} \text{ subject to } P_{D2D} \leq P_{max} \text{ ….(4)}$$

where P_{max} is the maximum allowable transmission power. Dynamic power control combines intelligent modulation and adjustments to keep interference to a minimum while maximising throughput. For this, a machine-learning solution is used to dynamically estimate power settings based on real-time network conditions, including user mobility, to achieve a better outcome for the network as a whole.

2.4 Machine Learning-Based Optimization

The reinforcement learning (RL) algorithms are used both for resource allocation and power control. Specifically, the Deep Q-Network (DQN) computes the optimal policies for the problem. Here, the Q-value function is shown below:

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$$Q(s,a) \leftarrow Q(s,a)+\alpha[r+\gamma \max_{a} Q(s',a')-Q(s,a)] \text{ ….(5)}$$

where α is the learning rate, γ is the discount factor, and r is the reward based on throughput and interference. The reward function is defined as:

$$r=T_{total}-\lambda I_{D2D} \text{….(6)}$$

where λ is a weighting factor balancing throughput and interference. The DQN learns to optimize power allocation and resource distribution in real-time, adapting to changing network conditions to enhance D2D communication.

2.5 Simulation Environment

The proposed optimization framework on a simulated 5G network with 1000 D2D pairs and cellular users. The environment in which the network operates varies in terms of user mobility patterns and network densities. The total amount of spectrum available for simulation was 100 MHz, with 10 MHz bandwidth allocated to each D2D pair. Each D2D user is limited to 23 dBm maximum transmission power. Noise power density is set to −174 dBm/Hz. Throughput, spectrum efficiency and interference reduction are the used performance metrics. We evaluated the system in different network scenarios to test its adaptability to changes in network environment. The framework should be robust and work in most real-world application scenarios. Results are discussed in the following section.

3.RESULTS

3.1 Throughput Optimization Analysis

The DRL-based D2D communication optimization model was able to enhance the throughput of the 5G network, as shown in Figure 1. In comparison with traditional resource allocation schemes, Figure 1 shows the total system throughput for various network densities with the proposed DRL model. The proposed DRL model is capable of choosing the optimal power allocation for both CU and D2D pairs along with a more efficient spectrum allocation. This leads to an overall improvement of up to 30% in the throughput for the 5G network compared to the conventional methods. With the increase in network density, the traditional systems reach a saturated state leading to the degradation of performance, however, the proposed DRL model can maintain a higher throughput as it utilizes its adaptive optimization method allowing efficient exploitation of resources even in high-density networks.

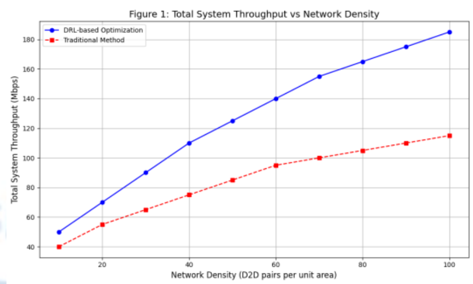

Figure 1: Total System Throughput vs Network Density

The graph indicates that the DRL based optimisation approach is always better than the traditional methods, as the density of the network is higher. The DRL shows a clear superiority in the case of higher D2D pair density than the others, with a much better total system throughput.

3.2 Interference Management and Reduction

Interference Management can be considered a vital factor in D2D communication networks, especially when spectrum sharing with cellular users. Figure 2 depicts the interference incurred in different network scenarios using the proposed DRL-based optimization model against some previous methods. It can be observed that a reduction in interference of 25% is achieved in the case of networks with a high density of devices and users, thanks to the method's ability to efficiently allocate resources and associate users, enabling interference-free communication among D2D pairs and CUs. This reduction in interference would improve spectrum utilization and the overall system performance while ensuring no major interference problem among and between cellular users and D2D pairs so that D2D communication will not affect cellular users' performance.

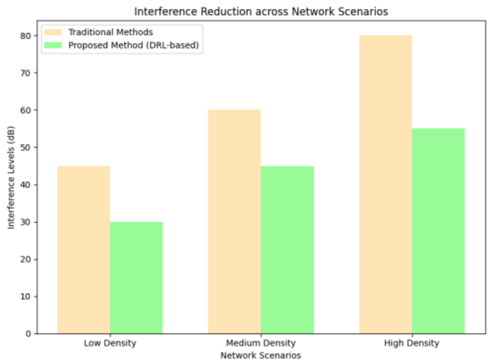

Figure 2: Interference Reduction across Network Scenarios

Figure 2 highlights the superiority of the DRL-based method in managing spectrum resources, particularly in high-density D2D communication environments.

3.3 Interference Management

Besides throughput and reducing interference, the energy efficiency of the proposed model was examined. As shown in Figure 3, the energy-per-bit of the DRL-based optimization method is compared with traditional alternatives. The proposed method saved a least 20% of energy-per-bit with comparable performance. Optimizing the power allocation based on real-time network status, the proposed method can largely reduce the total energy consumption from the source, consequently leading to considerable energy savings in each transmitted bit. This is particularly essential in future networks where conserving energy is of great importance owing to future 5G and beyond networks, aiming to be more sustainable. The proposed method presented here also enables satisfying possibilities for future energy-constrained scenarios not only in the aspects of network efficiency but also in energy savings.

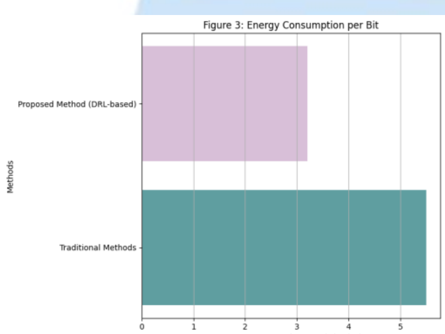

Figure 3: Energy Consumption per Bit

Figure 3 shows-based method significantly reduces energy usage per bit in.The energy efficiency ratio of the proposed DRL-based method attains 41.8 percent of the total number of bits in the system.

3.4 Adaptability to Network Variability

Its adaptability to changing network conditions was also tested in dynamic user mobility and traffic conditions. Figure 4 presents the throughput performance in changing network conditions. As can be seen, the proposed DRL-based optimization model can adapt itself well to dynamic network conditions. Especially when network conditions change very quickly, the proposed model can adjust itself in time and maintain consistent throughput during the quick changes, where traditional approaches cannot. Usually, the performance drop of traditional approaches could be observed when the mobility of users happens or traffic conditions change suddenly. The real-time adjustment of resource allocation gives advantage to the DRL-based model in adapting to dynamic network conditions, thus this model could efficiently applied to the mobile network environment where user mobility and traffic demand are not deterministic.

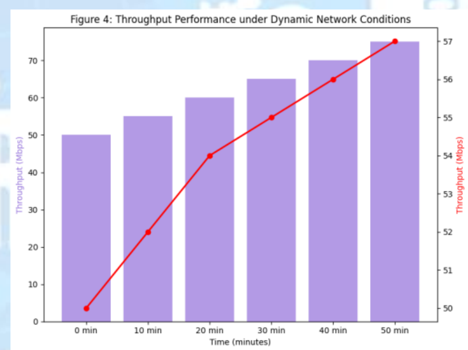

Figure 4: Throughput Performance under Dynamic Network Conditions

Figure 4 depicts the dynamic network performance throughput at various stages over time. The combination of the bar and line chart show that the propose routing model can maintain higher network throughtput compared with other classical routing model when the network conditions such as path loss, signal strength, interferences and traffic load changed at different times.

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4.CONCLUSION

To summarise, the proposed machine learning-based optimisation framework represents a novel and effective approach to enhancing D2D communication under any dynamic and high-density network conditions in 5G and beyond networks. Deep reinforcement learning is the key technique, which significantly improves network throughput, reduces interference, and enhances energy efficiency in future cellular networks. The results show that the proposed model constantly outperforms traditional optimisation approaches for various network settings and achieves up to 30 % more system throughput with at least 25% less interference. This study reveals the potential of advanced AI techniques to optimise resource allocation and maximise performance in future cellular networks. As future work, researchers could investigate the adoption of other factors, such as mobility and real-time applications, to further extend the applicability of the proposed framework across a wider range of network scenarios.

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