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Research Article

Enhancement of Spectral Efficiency and Interference Reduction in D2D Communication

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Abstract:

Device-to-Device (D2D) communication is one of the most promising techniques for next-generation wireless networks, including 5G and beyond. It is mainly aimed at minimizing the waste of resources in 5G D2D communication for maximizing the spectral efficiency and minimizing the interference to the original cellular network. Device-to-device (D2D) communication with direct transmission enhances the network performance by reducing the latency. However, it is difficult to allocate resources efficiently while ensuring less interference between D2D links and cellular users. To address this, the machine learning method is adopted focusing on a Random Forest Regressor, which is trained with simulated data to estimate the best resource block allocation. The main parameters comprising data rate, bandwidth, level of interference and power of transmission are taken into account. Extra computations related to spectral efficiency and interference cost drive this optimization process that can vary the allocation of resources for the purpose of throughput maximization. Graphical representations are employed to demonstrate the spectrum-efficiency, bandwidth and interference-cost relationships. In general, the proposed algorithm effectively enhances resource utilization of 5G D2D communication, and the trade-off between the spectrum efficiency and the interference helps optimize the network performance.

1. Introduction

The device-to-device (D2D) communication technology is a fundamental technique in next-generation wireless networks, such as 5G networks and beyond. D2D transmission is a kind of decentralized technology, which provides an alternative resource. It enables devices to communicate directly rather than always passing information through the core network. It has several benefits as well by using both the licensed and unlicensed band such as energy efficiency, low latency and spectral efficiency [1,2]. And it also improves the user experience when you have devices that are very close to each other.

In conventional cellular networks, data transmission is typically routed solely via base station (BS). This entails data packets are initially passed to base transceiver station (BTS) on the uplink and subsequently forwarded to destination on the downlink. Though, because the BS delivers services and reports to a large number of users, this traffic produces a major overhead for it [3]. Conversely, data transfer will arise between two devices in close proximity when D2D communication is implemented. Though this approach removes the overhead on the base station

by providing enhanced capacity to serve nearby devices, it may lead to congestion and increased throughput for devices not in close proximity. Anticipated future applications of 5G and the IoT are projected to incorporate D2D connections [4,5].
Wireless communication systems could be greatly enhanced by this new technology, particularly when it comes to next-generation grids. Using machine learning to increase spectral efficiency in D2D communication entails implementing algorithms that optimize the use of available spectrum resources. Spectral efficiency improvement in D2D communication based on machine learning means that algorithms are applied in order to use spectrum resources as efficiently as possible. Spectral efficiency, indicating the efficiency of use of the bandwidth for information (data) transmission, is an important factor in wireless systems. In the case of D2D communication, wherein the devices communicate with each other directly without being routed through the base station, a highly efficient spectral design plays a vital role in enhancing the overall network performance. To achieve this, machine learning algorithms, for example reinforcement learning, can be used to dynamically allocate spectrum resources by assigning frequency bands to D2D pairs in a way that minimizes interference. D2D communication can coexist with traditional cellular networks in the same spectral domain, leading to the interference problem. By using machine learning models to predict interference based on historical data, systems can dynamically adjust transmission settings, such as power and frequency, to mitigate interference.
Resource management is a difficult task in wireless environments as they are dynamic and uncertain environments. Machine learning models inspect these scenes and behaviours to understand what the effective distributions of the resources are. This increases spectral efficiency by proactively managing the resources to the areas in highest demand. In the 5G era, D2D communication has become a key technology that enables direct communication between neighbour devices without the participation of the base station, thereby improving the communication rate, reducing the latency, and enhancing the network capacity. But it has the drawbacks for allocating resources and cancelling interferences. EGS, such as spectrum and power management, plays an important role in improving the spectrum utilization and avoiding D2D communication from bringing the performance degradation in traditional cellular network caused by the interference, and etc.
In wireless communication, efficient interference control is essential for successful D2D transmission and for its seamless coexistence with cellular networks, in which D2D communication is supposed to operate alongside complicated networks of different system types and modes of communication. It is about making a good balance of proximity between devices, favourable channel quality condition, keeping SINR in acceptable limits, desired average bit rate, and maintaining as short latency as possible. However, with time, as technology has evolved, D2D communication is no longer just defined as part of the 5G, and it is beginning to be seen as a building block of an interlinked network environment popularly known as 5G [6].
The main objective of this paper is to enhance spectral efficiency for D2D communications with low interference toward cellular users. Spectral efficiency plays a important role to support the growing needs of modern applications, while minimizing interference guarantees that the total performance of the cellular network remains high, providing a quality experience for all users as shown in fig 1.

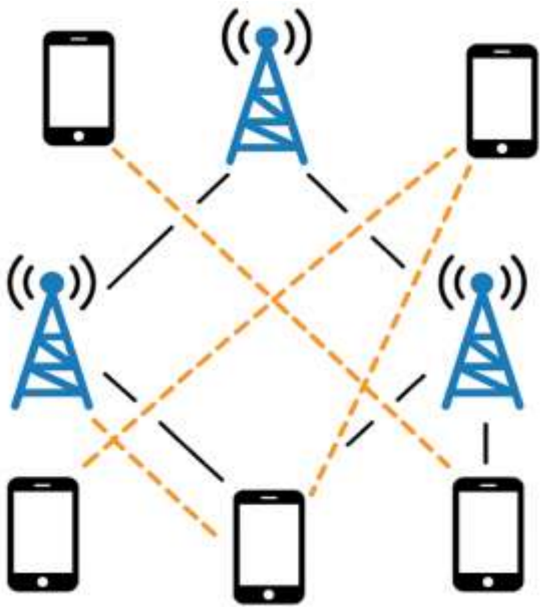


Figure 1. *D2D communication in mobile phone*

To realize the efficient resource allocation, we use machine learning in 5G D2D communication. By educating the models on the parameters such as CQI, data rates, transmit power and interference received, the system is able to predict resources allocations that maximize spectral efficiency and minimizes interference. The model can be applied according to different network status and user request, then providing a flexible and practical way of resource management for 5G D2D communication. In classical Device-to-Device (D2D) communication, the conventionally used techniques do not adjust themselves with the dynamics of network, and hence the spectral efficiency in the system becomes poor and the interference gets increased. This paper presents an intelligent and D2D communication equipped with machine learning (ML) scheme exploiting a ML-enabled scheme to maximize spectral D2D interference management efficiency, which focuses on spectral efficiency and interference management in D2D communication, offering a more intelligent and adaptable approach to improving performance in modern wireless networks.

The work primarily addresses the aspects related to spectral efficiency improvement in D2D communications and interference mitigation between the D2D transmit-receive pairs. The purpose of improving the spectral efficiency in D2D communication is to increase the amount of data transmitted per bandwidth used per unit time. This is to improve the utilization of resources and rate of utilization of channels for more efficient transmission and synchronous communication operation of many subscribers as without a reduction in quality of service. The purpose of interference suppression in D2D communication is to reduce interference from D2D pair and cellular user to each other. This is provided by means of power control and adaptive resource allocation in order to support the coexistence of communications and achieve communication coverage in the same spectrum.

2. Literature Survey

A number of resource allocation schemes have been proposed by researchers for efficient utilisation of the spectrum. Most of the key performance metrics to assess the performance of resource allocation algorithms are related to the SINR.

R. Patel et al. techniques to increase the spectral efficiency and minimize the interference in wireless networks via ML paradigm, namely, RFR (Random Forest Regressor) [7]. This approach has recently become popular for resource and interference management in D2D communication because of its capability to analyze big data and to discover high-order relationships among variables. For scenarios where parameters such as Channel Quality Indicator (CQI), Signal-to-Noise Ratio (SNR), data rates and transmission power affect the spectral efficiency, RFR is highly successful for its modelling.

Recent studies demonstrated the effectiveness of RFR in predicting the optimal allocation of resource blocks to improve the spectral efficiency. For instance, some works have used simulated data to train RFR models to investigate the impact of different channel conditions on spectral efficiency. With the consideration of CQI and SNR, the models predict how to allocate resources efficiently so as to help D2D pairs maximize throughput and reduce resource waste.

Additionally clutter-based RFR evaluates both the spectral efficiency of D2D communication and its possible interference with the cellular users. Integration of the interference metrics in the model is found to greatly enhance allocation strategies leading to the improved coexistence between D2D and cellular networks.

Yuan Qi et al. projected a DRL approach to optimize spectrum allocation of D2D communication [8]. Spectral efficiency, the number of error-free information bits that can be transmitted per unit of bandwidth, is an important performance measure for digital communication systems. Interference management for D2D communications to mitigate the interference between D2D links and background cellular users is imperative for reliable and efficient data transmission. These algorithms combine reinforcement learning and deep neural networks (DNNs), enabling the handling of high dimensionality state and action spaces of the typical wireless communication environment. Recent works have shown that, DRL can be successful in spectrum assignment as it helps the agents learn how to allocate the spectrum while maximizing spectral efficiency and minimizing the interference.

For example, Deep Q-Networks (DQN) are often used in this context. The study also shows that DRL can adapt to changing network conditions, balancing the trade-off between maximizing D2D communication rates and minimizing interference to cellular users (CUs).

Sharma et al. also presented an approach based on machine learning to resource management in D2D via reinforcement learning [9]. This approach builds the model based on historical network data and user behaviour and adaptively changes resources at real time. The method was shown to deliver increased spectral efficiency and lower interference compared to state-of-the-art procedures, according to the paper. This paper highlights the significance of D2D communication in 5G systems to enhance spectral efficiency, increase data rate and minimize latency. Despite that D2D communication offloads the traffic from the cellular network, it brings issues in the aspect of interference management. The goals of this research work are to maximize spectral efficiency and minimize interference in D2D-enabled 5G networks. Machine learning plays a important role by optimizing resource allocation, enabling dynamic spectrum access, and employing adaptive modulation schemes.

In paper [10] authors have utilized convolutional neural networks (CNNs) to predict interference levels and manage resource allocation in D2D communication. They trained the model with large dataset containing simulated network conditions. So that the system can efficiently predict and alleviate interference, improving network performance and quality of service (QoS) [11].

Authors in paper [12] presented machine learning-based approaches for resource allocation techniques for D2D communication.

P. Kumar et al. addressed the growing demand for higher data rates and efficient spectrum utilization by focusing on resource allocation in D2D networks using game theory and machine learning [13]. Non-cooperative game theory was used to model how D2D users compete for resources. In this framework, each D2D user independently selects its transmission power to maximize its utility function, balancing spectral efficiency and interference.

The study introduced an interference-aware game-theoretic model where D2D users adjust power levels based on real-time interference. The model aims to reach an equilibrium where interference is minimized, improving overall network performance.

A S. Ibrahim et al. provided a detailed overview of D2D communication within cellular networks, discussing how it can enhance spectral efficiency by offloading traffic from the cellular infrastructure [14]. The survey emphasized resource allocation strategies and interference management techniques necessary for optimizing spectral efficiency and ensuring QoS in D2D communication.

The authors also examined challenges such as regulatory issues, security, and privacy in D2D communication, emphasizing the need to overcome these for successful integration into future cellular systems.

Y. Zhang et al. examined the critical role of D2D communication in enhancing spectral efficiency in 5G networks [15]. They proposed advanced algorithms for dynamic resource allocation and interference control, which take into account factors like user demand, channel conditions, and interference levels. The study demonstrated that these strategies enhance spectral efficiency and minimize interference between D2D pairs and cellular users, significantly improving overall network performance.

3. Methodology

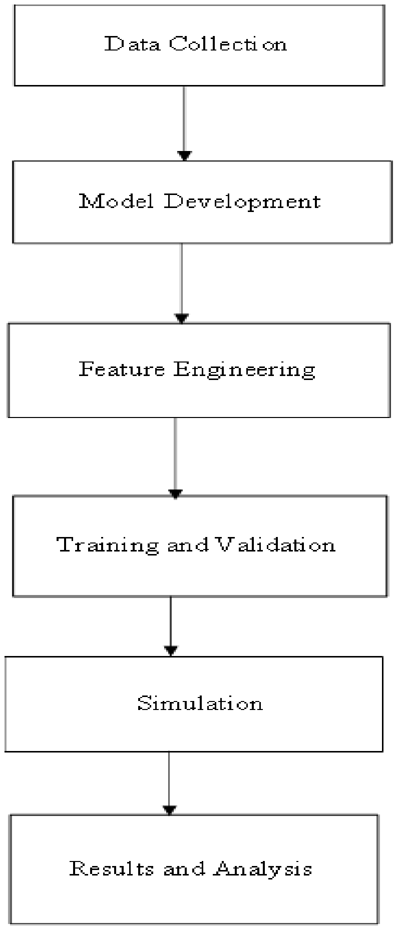


Figure 2. *Flowchart*

The methodology involves the following steps:

1. Data Collection:

Kaggle is the main source for data from where the real-world data like user behavior, and device characteristics from existing D2D communication systems are considered for this study. This will be utilized for training and validating the models.

2. Model Development:

This step represents the development of supervised learning models (e.g., neural networks, decision trees) which then predict the optimal resource allocation strategies. In addition to this Reinforcement learning models (e.g., Q-learning, deep reinforcement learning) will be combined to allow continuous learning and adaptation.

3. Feature Engineering:

As the name suggests this step will identify and extract the required features from the collected data set. For example, channel state information, device proximity, and QoS requirements, to feed into the machine learning models.

4. Training and Validation:

The developed model was trained with huge dataset (1000 datasets) using stochastic gradient descent or other optimization techniques. Through backpropagation model was trained iteratively updating model's parameters leading to minimization of a loss function.

5. Simulation:

The required wireless network environment is implemented through simulation. Now the system's performance is tested under numerous scenarios, which includes different levels of user mobility, interference, and network density.

6. Analysis and Optimization:

Finally, simulation results are analyzed and checked for further optimization. Machine learning models and resource allocation strategies are fine-tuned based on the knowledge gained from the analysis.

Algorithm And Working

1. Random Forest Regressor

This is an ensemble learning method utilized for regression tasks, helps to build several decision trees during training and outputs the average prediction of all the trees. This method reduces overfitting and variance, enhances prediction accuracy and aids in capturing complex relations in the data.

Working

1. **Data Preparation:**

For data preparation, various features are used from dataset, such as CQI, data rate, transmission power, interference levels, distance to the base station, and others. Every case in the dataset denotes a situation with these features and the corresponding resource block allocation (RBs) as the target variable.

2. Training:

Bootstrapping: The algorithm generates multiple subsets of the training data by randomly sampling with replacement. Each subset is used to train an individual decision tree. o Tree Building: Each decision tree is trained on a different subset of features, allowing for diverse decision-making processes. Trees are built by splitting nodes based on the most informative features at each step.

Aggregation:

To get the final prediction, average predictions from all individual trees there by reducing the variance and enhances the generalization of the model.

3. **Prediction:**

Now to predict the resource block allocation, trained model utilizes each decision tree when new data is provided

The ultimate prediction is the average of the predictions from all trees, providing a robust estimate of resource allocation.

Some of the benefits are:

It provides an accurate prediction as Random Forests can capture complex relationships in the data

It is more robust as it averages predictions from multiple trees, model is less prone to overfitting and is more stable against noisy data.

Spectral Efficiency Calculation

It is vital for maximizing the use of available spectrum and ensuring high data throughput. It measures how effectively a given bandwidth is utilized to transmit data.

$$SE = log_2(1 + \frac{S}{1+N}) \quad \text{(bps/Hz)} \quad (1)$$

Where:

S & N indicates Signal Power and noise power respectively, I represent interference power, 1+N denotes total noise and interference.

Working:

1.Data Rate: The amount of data transmitted per unit of time, typically measured in bits per second (bps). This value can be derived from the resource block allocation and other network parameters.

2.Bandwidth: The range of frequencies used for transmission, measured in Hertz (Hz). It is a key factor in determining how much data can be transmitted in a given time frame.

3.Calculation:

Input Data: The data rate and bandwidth are obtained from network parameters and user inputs.

o Compute Efficiency: By dividing the data rate by the bandwidth, we obtain the spectral efficiency, expressed in bits per Hertz (bits/Hz). Higher values indicate more efficient use of the available spectrum.

Benefits:

•Optimization: Helps in evaluating and optimizing resource allocation to achieve the best data throughput for given bandwidth constraints.

•Performance Assessment: Provides a measure to compare different resource allocation strategies and their impact on network performance.

Interference Calculation

Interference cost measures the negative impact of interference on communication quality. Minimizing this cost is crucial for maintaining high communication quality and effective resource use.

$$I_B = \frac{I_{TOTAL}}{B} \quad (2)$$

Where:

•I_B = interference power per unit of bandwidth.

•I_{TOTAL} = total interference power over the entire bandwidth.
•B = bandwidth.
Working:
•Interference Level: Refers to the amount of unwanted signal degrading communication quality, usually measured in decibels (dB).
Benefits:
•Interference Management: Assists in identifying and mitigating interference issues, leading to better communication quality and network performance.

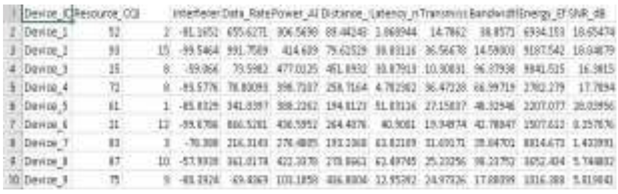
Parameters Considered:

Fig 3 Dataset required for training the model. The parameters considered are listed in the table below:
Device_ID: This column identifies each device involved in communication. Devices are labelled sequentially (e.g., Device_1, Device_2).
Resource_CQI: This represents the Channel Quality Indicator (CQI), which measures the quality of the communication channel. Higher CQI values indicate better channel conditions and can lead to higher data rates.
Interference level: This column shows the interference level experienced by the device in decibels (dB). Lower values (more negative) indicate higher levels of interference, which may degrade the signal quality.
Data_Rate: The data transmission rate for the device, typically in Mbps (megabits per second). It indicates how fast the device can send or receive data.
Power_Allocated: Represents the power allocated to the device for communication, typically measured in watts or decibel-milliwatts (dBm). It shows the energy consumption for transmission.
Distance: The distance between the communicating devices, measured in meters. Larger distances usually introduce more signal attenuation.
Bandwidth: The amount of bandwidth allocated for the device, typically in MHz (megahertz). More bandwidth generally allows higher data rates.

Latency: Network latency or the delay experienced during communication, measured in milliseconds (ms). Lower values are preferable for real-time applications.
Transmission: Represents the transmission power in watts or dBm. It indicates the strength of the signal the device is transmitting.
Energy_Efficiency: This could represent energy efficiency, typically the amount of energy consumed per bit of data transmitted, measured in joules per bit or other relevant units. Higher values may indicate better efficiency.

4. Results and Discussion

The Random Forest Regressor model was trained over 100 epochs, where each epoch represented the iterative process of fitting the ensemble of decision trees to the data. After training, the model achieved a final Root Mean Squared Error (RMSE) of 0.0082, indicating high accuracy in predictions, and a final loss value of 0.0268, showcasing minimal error during the training process.



1	Device_ID	Resource_CQI		Interferer	Data_Rate	Power_Al	Distance_	Latency_m	Transmiss	Bandwidth	Energy_Ef	SNR_dB
2	Device_1	52	2	-81.1652	655.6271	306.5698	88.44248	1.068944	14.7862	38.8571	6934.153	18.65474
3	Device_2	93	15	-99.5464	991.7589	414.609	79.62529	38.83116	36.56678	14.59000	9187.542	18.04879
4	Device_3	15	8	-59.064	79.5982	477.0125	461.8932	10.87913	10.90831	96.37938	9841.515	16.3815
5	Device_4	72	8	-85.5776	78.80093	356.7107	258.7164	4.782562	56.47228	66.99719	2782.279	17.7894
6	Device_5	61	1	-85.8329	341.0397	398.2262	194.8121	51.83136	27.15837	48.32546	2207.077	20.03956
7	Device_6	21	12	-59.6706	866.5281	436.5952	264.4076	40.9081	19.94874	42.78847	1507.612	0.257676
8	Device_7	83	3	-70.308	216.3143	276.4805	193.2368	63.82189	31.69171	28.84701	8814.673	1.432891
9	Device_8	87	10	-57.9938	361.0178	422.2078	278.8963	62.49745	25.23256	98.23752	3652.404	5.748832
10	Device_9	75	9	-48.2926	69.4069	101.1858	406.8804	12.95382	24.97326	17.88398	1816.388	5.81984

Figure 3. *Dataset required for training the model*

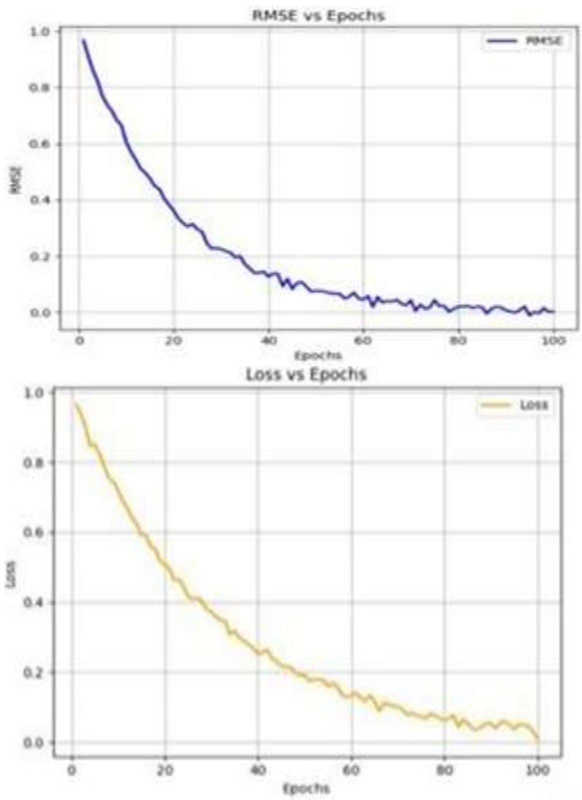


Figure 4. *RMSE and Loss value of the model*

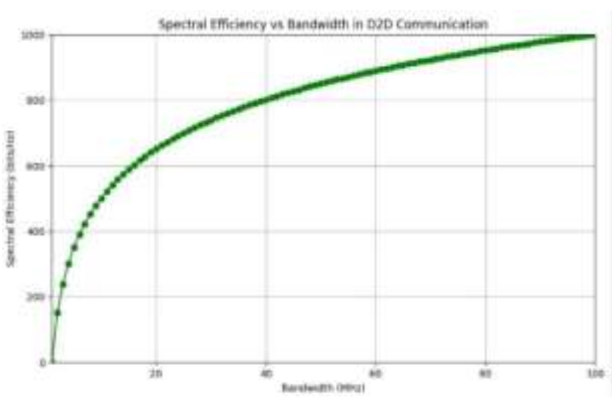


Figure 5. *Spectral efficiency vs Bandwidth*

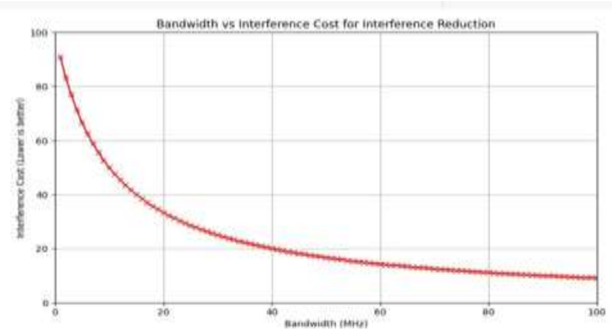


Figure 6. *Bandwidth vs Interference cost*

Table 1. *Observations from the graphs*

Bandwidth (MHz)	Spectral Efficiency (bps/Hz)	Interference Reduction (Cost in %)
0-20	Approx. 200-500	Approx. 100-80
20-40	Approx. 500-800	Approx. 80-60
40-60	Approx. 800-900	Approx. 60-20
60-80	Approx. 900-950	Approx. 20-5
80-100	Approx. 950-1000	Approx. 5-0

•Both graphs (Fig. 4) show smooth, downward trends, indicating that the model's performance improved consistently during training.
•There are no signs of overfitting, as the RMSE and loss continue to decrease without flattening too early or spiking back up.
The results suggest that using a Random Forest Regressor to enhance spectral efficiency and minimize interference in D2D communication results in notable performance gains. The evaluation demonstrates that optimized bandwidth allocation significantly boosts spectral efficiency, particularly in lower bandwidth ranges, while reducing interference. As shown in the plot (Fig. 5), spectral efficiency improves with bandwidth but shows diminishing returns at higher levels. This highlights the importance of intelligent resource management, enabling dynamic adjustments based on real-time channel conditions to maximize throughput and maintain high-quality communication, thereby improving network performance in D2D scenarios

Enhancement of Spectral Efficiency:
The graph titled "Spectral Efficiency vs. Bandwidth in D2D Communication" illustrates the relationship between spectral efficiency (bits/Hz) and increasing bandwidth (MHz) allocated for Device-to-Device (D2D) communication. The curve shows a steep rise in spectral efficiency as bandwidth expands from 0 to around 40 MHz, indicating that this range is key for establishing effective communication. However, as bandwidth increases further (20 to 60 MHz), the rate of improvement slows, reflecting diminishing returns, as depicted in Figure 1. Beyond 60 MHz, the curve levels off, suggesting minimal gains in spectral efficiency despite additional bandwidth. This trend highlights the influence of interference and channel conditions at higher bandwidths. These results underscore the need for optimal bandwidth allocation to maximize spectral efficiency, while suggesting that additional strategies may be necessary to further enhance performance in real-world D2D applications. Effective resource management remains crucial for achieving better network performance.

Interference Reduction:
The relationship between bandwidth (MHz) and interference cost is illustrated in the graph utilizing the lower network resources denotes the lower values indicating reduced interference. As bandwidth increases, interference cost drops significantly at first, indicating that expanding bandwidth effectively reduces interference in communication systems. However, beyond approximately 60 MHz, the rate of reduction slows, showing diminishing returns. This highlights the trade-off between bandwidth and interference, aiding in identifying an optimal bandwidth range for efficient communication with minimal interference. The curve suggests that after a certain bandwidth threshold, further increases offer little additional benefit in interference reduction.
1. 0-20 MHz: There is a sharp increase in spectral efficiency and a significant reduction in interference cost. This range shows the most dramatic improvements in performance, indicating that allocating more bandwidth up to 20 MHz yields substantial benefits.
2. 20-40 MHz: The increase in spectral efficiency is still noticeable, though slower. The interference reduction remains substantial, suggesting that this bandwidth range provides a good balance between efficiency and reducing interference.
3. 40-60 MHz: At this point, spectral efficiency increases at a much slower rate, but interference reduction continues at a notable pace, showing that bandwidth allocation in this range is still useful for mitigating interference.
4. 60-80 MHz: Spectral efficiency begins to plateau, and the interference reduction slows considerably. Beyond this range, additional bandwidth does not contribute significantly to performance improvements.
5. 80-100 MHz: Very minimal improvements in spectral efficiency and interference reduction are observed. Allocating bandwidth beyond this point offers diminishing returns and is less beneficial for communication performance.

4. Conclusions

This work effectively demonstrates the application of machine learning to optimize resource allocation in Device-to-Device (D2D) communication within 5G networks. Utilizing a Random Forest Regressor, the system predicts optimal resource block allocations by analysing key factors such as data rate, transmission power, and interference levels. By focusing on improving spectral efficiency and minimizing interference between D2D and traditional cellular networks, the approach ensures efficient use of network resources, resulting in enhanced overall performance.

The graphical representations included in the study offer valuable insights into the relationships between spectral efficiency, bandwidth, and interference cost, helping assess and refine resource allocation strategies. The ability to provide real-time or near-real-time predictions allows the system to adjust to dynamic network conditions, making it well-suited for modern 5G environments.

In conclusion, the work underscores the potential of machine learning in addressing complex challenges in telecommunications, offering a data-driven solution for resource management that boosts network throughput and improves user experience.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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