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Efficient Traffic Management Algorithms for the Core Network using Device-to-Device Communication and Edge Caching

Hessam Yousefi, *The University of Western Ontario*

Supervisor: Wang, Xianbin, *The University of Western Ontario*
Co-Supervisor: Rahman, Quazi, *The University of Western Ontario*

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Abstract

Exponentially growing number of communicating devices and the need for faster, more reliable and secure communication are becoming major challenges for current mobile communication architecture. More number of connected devices means more bandwidth and a need for higher Quality of Service (QoS) requirements, which bring new challenges in terms of resource and traffic management. Traffic offload to the edge has been introduced to tackle this demand-explosion that let the core network offload some of the contents to the edge to reduce the traffic congestion. Device-to-Device (D2D) communication and edge caching, has been proposed as promising solutions for offloading data. D2D communication refers to the communication infrastructure where the users in proximity communicate with each other directly. D2D communication improves overall spectral efficiency, however, it introduces additional interference in the system. To enable D2D communication, efficient resource allocation must be introduced in order to minimize the interference in the system and this benefits the system in terms of bandwidth efficiency. In the first part of this thesis, low complexity resource allocation algorithm using stable matching is proposed to optimally assign appropriate uplink resources to the devices in order to minimize interference among D2D and cellular users.

Edge caching has recently been introduced as a modification of the caching scheme in the core network, which enables a cellular Base Station (BS) to keep copies of the contents in order to better serve users and enhance Quality of Experience (QoE). However, enabling BSs to cache data on the edge of the network brings new challenges especially on deciding on which and how the contents should be cached. Since users in the same cell may share similar content-needs, we can exploit this temporal-spatial correlation in the favor of caching system which is referred to local content popularity. Content popularity is the most important factor in the caching scheme which helps the BSs to cache appropriate data in order to serve the users more efficiently. In the edge caching scheme, the BS does not know the users request-pattern in advance. To overcome this bottleneck, a content popularity prediction using Markov Decision Process (MDP) is proposed in the second part of this thesis to let the BS know which data should be cached in each time-slot. By using the proposed scheme, core network access request can be significantly reduced, and it works better than caching based on historical data in both stable and unstable content popularity.

Keywords: Device-to-Device communication, edge caching, resource allocation, uplink, content popularity

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Table of Contents

List of Tables

List of Figures

List of Abbreviations

3GPP	Third Generation Partnership Project
4G	Fourth Generation of Mobile Communication
5G	Fifth Generation of Mobile Communication
BS	Base Station
CDF	Cumulative Distribution Function
CDN	Content Delivery Network
CQI	Channel Quality Information
CSI	Channel State Information
D2D	Device-to-Device Communication
FDD	Frequency Division Duplexing
HetNet	Heterogeneous Network
ICN	Information-Centric Network
LOS	Line of Sight
LTE	Long-term Evolution
LTE-A	LTE Advanced
MCC	Mobile Cloud Computing
MDP	Markov Decision Process

MEC	Mobile Edge Computing
Non-LOS	non-Line of Sight
NFC	Near-Field Communication
OFDMA	Orthogonal Frequency Division Multiple Access
PDF	Probability Distribution Function
QoE	Quality of Experience
QoS	Quality of Service
RAN	Radio Access Network
Rx	Receiver
SC-FDMA	Single Carrier Frequency Division Multiple Access
SINR	Signal to Interference plus Noise Ratio
Tx	Transmitter
V2V	Vehicle-to-Vehicle Communication
Wi-Fi	Wireless Fidelity

Chapter 1

1 Introduction

To cope with the proliferation of devices to support the future fifth generation of mobile communication systems (5G), and the associated congestion in the core network due to the exponential increase in the content-demand, many new wireless technologies have been introduced. To provide better Quality of Experience (QoE) for users, Device-to-Device (D2D) communication and edge caching are considered to be the key solutions to offload huge data demand. By allowing D2D communication to be established, mobile devices can connect to each other directly without going through the Base Station (BS) by using licensed or unlicensed spectrum. Although using dedicated spectrum has no additional interference, but it comes with a cost of inefficient spectrum usage. Coexistence of D2D communication and conventional cellular communication in a shared spectrum results in a higher spectral efficiency. However, it generates additional interference which may degrade the performance of either connection. To ensure cellular and D2D users received acceptable service threshold, advance resource allocation algorithms should be considered to minimize the performance degradation. The first part of this thesis is dedicated to designing an efficient and low-complexity resource allocation method in order to minimize additional intra-cell interference while maintaining service threshold.

As another promising solution to offload the traffic from the core network, edge caching has been introduced. According to a forecast by Cisco [1], video contents will be accounted for over 82% percent of the traffic by 2021. This exponential increase will challenge current content delivery mechanism

On the caching side, edge caching will provide low-delay and fast access to the available contents for users in the cell by keeping the copies of most popular contents at the BS, however determining which data to cache has become challenging due to the existence of high mobility devices and unknown content popularity distribution. In the second part of this thesis, we have provided a robust caching policy optimization using content popularity distribution learning to cache most popular data on the edge.

1.1 Motivation

Unlike traditional cellular communication which users should communicate with each other through an intermediate entity called the Base Station (BS), the introduction of direct communication under the name of D2D communication provide an architecture under which devices are allowed to communicate with each other directly. According to Third Generation Partnership Project (3GPP), Device-to-Device communication has one of the key roles in future mobile generations due to the fact that the number of connected users is increasing exponentially. Increasing number of devices generates higher data traffic which eventually dominates current mobile networks paradigm. Therefore, choice of offloading some of the burdens on devices should be considered as a solution. The reasons D2D communication can be considered as one option are: first, providing higher data rate due to the proximity of connected devices, second, increasing spectral efficiency since the cellular spectrum will be reused within the cell rather than further cells like the case in conventional communication, finally, there is a potential of increasing cell coverage by implementing multi-hop communication through connected devices.

Direct communication is feasible either in licensed (in-band) or unlicensed (out-band) spectrum. The in-band connection will be further divided into underlay and overlay communication in terms of dedication of the spectrum. The D2D communication underlying cellular network has attracted attention lately since it provides significant advantages to the network in terms of spectral efficiency while generating additional interference due to the fact that resources are not orthogonal. Advanced interference management techniques need to be proposed in order to efficiently allocate resource to the cellular users and D2D users.

D2D communication can facilitate local proximity services which are highly demanding because of wide usage of social networks, therefore users seek information that is more relevant timely and spatially. However existing methods like Wi-Fi, ZigBee, and Bluetooth which operates in the unlicensed band, cannot achieve desirable goals due to the uncontrolled connection. Hence, the D2D connection under the supervision of BS can provide a stable and reliable solution.

To further address offloading traffic from backhaul, caching systems has been proposed. According to a study, video contents are responsible for over 82% of traffic [1]. Even by considering advance content delivery architectures, high data traffic imposes significant latency on the end users. This rapid increase in content-request with increasing number of devices challenges current content distribution schemes.

Trying to address the issue, researchers have come up with content delivery networks (CDN) as a short-term solution. However, the problem of CDN is that with increasing traffic in the backhaul, the network architecture is not scalable. to solve the scalability issue, information centric network (ICN) has been proposed in the literature where contents have their own address irrespective of the location. The introduction of caching not only benefits the content providers by decreasing traffic but also benefits users by decreasing latency. By distributing replication of popular content intelligently around the network, users can request contents from closer locations other than going all the way to the core network. Although caching can benefit each party, it has many issues that need to be addressed in term of cache placement, content popularity and caching policy. In the second part of this thesis, we provide a comprehensive review of the challenges and propose a solution.

1.2 Research Objectives

So far, we have introduced two different solutions to deal with increasing traffic demand. Introducing D2D communication will provide significant interference problem that needs to be addressed. On the other hand, keeping copies of the popular contents is not feasible unless we know which contents should be cached. Therefore, the research objective is to design a low-complexity resource allocation algorithm for D2D and cellular devices, as well as design an efficient content popularity prediction technique at the edge of the network to learn local user preference in order to minimize core network access requests.

Low Complexity Resource Allocation Algorithm: In order to reduce additional interference, D2D users should reuse the cellular spectrum of a cellular user which has the maximum distance from the D2D pair. According to Shannon Capacity Law with Rayleigh fading channel, the higher distance between transmitter and interference victim results in better SINR, so we aim to match D2D pairs with cellular users while maximizing the sum distance between them. In order to formulate Shannon Capacity, all Channel State Information (CSI) is needed which induce significant overhead on the communication side. To reduce overhead, we should avoid transmitting redundant information by utilizing distributed allocation mechanism. By considering all the above notes, we aim to maximize the cell sum-rate while minimizing the overall interference by introducing distributed allocation technique.

Content Popularity Distribution Learning: increasing caching efficiency can be achieved by knowing which contents should be cached in the cell which directly relates to user's behavior and it is referred to local content popularity in the literature. Since content popularity is unknown to the BS in advance and it is changing because of random user activity. The objective is to learn local content popularity by observing past users request and intelligently cache contents. The challenge that needs to be addressed is although we assume a model for content popularity, users' requests do not follow the same model in each time slot, hence there may be noisy requests which degrade the performance of caching algorithm. We aim to increase the cache hit by designing robust content popularity learning algorithm.

1.3 Contributions

The main contribution of this thesis is summarized below:

- In chapter 2 and 3, we provide a comprehensive review of the device-to-device communication architecture and challenges. The focus is on the most important challenge of D2D communication which is interference management. We have proposed a low complexity interference management technique with distributed channel state (CSI) reporting to reduce communication overhead resulting from channel state reporting. As a result of utilizing the proposed scheme, resources can be efficiently allocated to the users trying to communicate directly and system sum-rate outperforms current methods.

- In chapter 4 and 5, edge caching is investigated with all benefits and challenges it brings to the network. We propose a learning mechanism for edge caching in order to learn local content popularity in a cell to increase the cache hit. We address fast-changing environment and random user activities which have not been considered in most of the previous works. By utilizing similar content-needs among users in the cell, the BS can serve users by caching popular contents. As a result, proposed learning algorithm outperforms conventional edge caching methods in terms of cache hit and core network access request.

1.4 Thesis Outline

The rest of the thesis is organized as follows: in chapter 2 we do an extensive literature survey on theory and applications of D2D network and current challenges that need to be addressed. In chapter 3, we provided our solution to the additional interference issue which arises in D2D-enabled networks. Then in chapter 4, existing methods and challenges of caching techniques are investigated and we showed that the main issue is what content to cache (content popularity). In chapter 5, we provide a solution on how to know what content should be cached by utilizing Markov Decision Process (MDP) and modeling content requests with Zipf law. Finally, we conclude our work and discuss future works in chapter 6.

Chapter 2

2 Introduction to Device-To-Device Communication

2.1 Direct Communication in LTE Networks

With increasing the number of devices, the need for faster communication push the limits of the current generation of mobile communication. Enabling devices to connect directly rather than going through BS has been introduced as a significant part of the evolution toward Fifth Generation of cellular communication (5G) which provide very high-speed communication among connected devices. There are several technologies trying to utilize direct communication between devices such as Wi-Fi-Direct, ZigBee, Bluetooth, NFC etc. detail comparison of current technologies in terms of standardization, frequency band, transmission distance and the data rate is provided in Table 1.

2.2 Types of D2D Communication

Device-to-Device communication can be classified into two different categories: In-band and out-band communication

In-band Communication: in this category, users are using the licensed spectrum for their direct connection. High control over interference and ability to manage additional interference more efficiently in this kind of communication is counted as an advantage of this category. There are two sub-categories for in-band communication, namely, underlay and overlay communication. In underlay direct communication, D2D users share cellular spectrum with mobile users which are better to deploy since cellular spectrum is under full control of the BS. In contrast, D2D devices have their dedicated spectrum in overlay communication which may result in inefficiency of using available bandwidth.

Table 1: Comparison of Various Technologies

Name	D2D	Wi-Fi Direct	NFC	ZigBee	Bluetooth	UWB
Standardization	3GPPLTE-A	802.11	ISO 13157	802.1504	Bluetooth SIG	802.1503a
Frequency Band	Licensed band for LTE-A	2.4, 5 GHz	13.56 MHz	868/915 MHz 2.4 GHz	2.4 GHz	3.1 10.6 GHz
Max Transmission Distance	1000 m	200 m	0.2 m	10 – 100 m	10 - 100 m	10 m
Max Data Rate	1Gbps	250 Mbps	424 Kbps	250 Kbps	24 Mbps	480 Mbps
Application	Offload Traffic, Public Safety, Context Sharing, Cellular Relay	Context Sharing, Group Gamming, Device	Contactless Payment	Home Entertainment and Control	Object Exchange, Peripheral Connection	Wireless USB, High Definition Video, Tracking System
Infrastructure	Licensed Band	Unlicensed Band	Unlicensed Band	Unlicensed Band	Unlicensed Band	Unlicensed Band

The drawback of using in-band D2D communication is the possibility of wasting the spectrum in overlay mode as well as complex interference management between cellular and D2D users in underlay mode. Most power control and interference management techniques will result in high complexity methods which induce a significant amount of overhead. Additionally, in underlay mode users cannot have simultaneous D2D and cellular communication. Researchers have been tending to overcome challenges of using in-band D2D connection because they believe it will provide higher spectral efficiency.

Out-band Communication: The direct communication under this category is established using unlicensed spectrum such as Wi-Fi Direct, Bluetooth or ZigBee. To tackle with complex power and interference management techniques out-band has been proposed to completely separate itself from cellular spectrum but new issues like interference between Wi-Fi devices will arise. There are two subcategories for out-band communication which are controlled and autonomous connection.

In the controlled mode, cellular network will control the establishing all communication in cellular spectrum and unlicensed band whereas in autonomous mode, D2D users initiate and establish their own communication under any standard like Wi-Fi, Bluetooth, and Zigbee, so there is no interference with cellular domain and they can have both D2D and cellular connection simultaneously.

2.3 D2D Connection Benefits for 5G Networks

Connecting directly to the other users to exchange content will benefit the overall system in many ways which are:

1) The user can gain high data rates as well as low delay and low power consumption because they are near each other [2] [3].

2) Like what we get by reusing cellular spectrum several times in different cells, we can benefit by reusing spectrum inside the cell more than one which means increasing the reuse factor.

3) Unlike the case of cellular connection, in D2D communication there is no need to use separate uplink and downlink resource.

2.4 D2D Design Aspects

2.4.1 Modulation

Under current LTE standard, users use single carrier FDMA (SC-FDMA) in uplink and OFDMA in the downlink. The same modulation format can be used for the case of D2D communication.

2.4.2 Frame Structure

Figure 1 shows framing for D2D communication. Assuming frequency division duplexing (FDD), the D2D connection will take place in FDD uplink because downlink traffic load is heavier than uplink spectrum, so this makes it a suitable candidate for D2D connection. The other reason is the amount of interference appears in downlink resource in comparison to the uplink spectrum which is significantly higher. For establishing communication in BS-controlled modes, there should be a signaling between BS and D2D user which is considered as a cellular connection and takes place in the downlink frame.

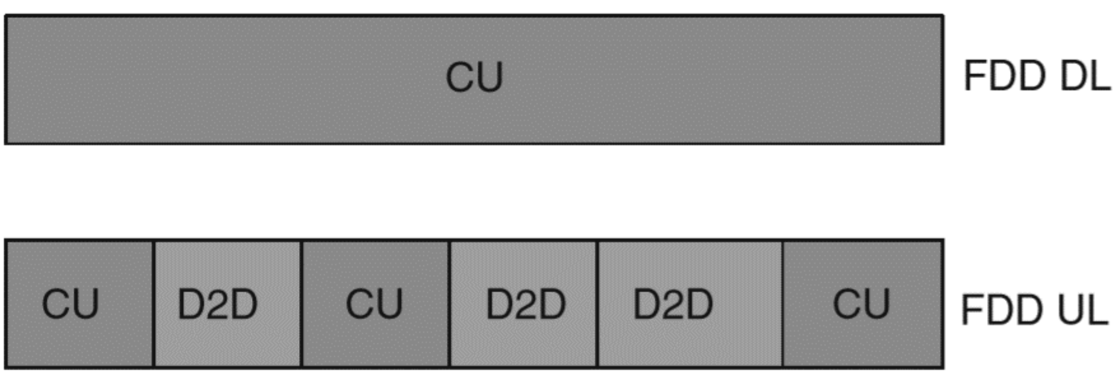


Figure 1: Frame Structure

2.4.3 Signaling

To let BS informs D2D users which time slot and frequency they should use, a couple of signaling between BS and D2D users should occur. There is no limitation on the signaling between D2D transmitter and receiver, so they can communicate with each other and initiate the connection whenever they want.

2.4.4 Synchronization

In the network-assisted D2D scenario, there is an important need for synchronization of time-slots and frequency. To maintain the synchronization both in time and frequency, D2D users use reference signals similar to what LTE does in the downlink.

2.4.5 Channel Measurement

One the important part of design aspect in D2D connection is how users can measure the channel and take proper action based on the channel state. For instance, measurement of received signal strength transmitted by users in downlink resource can be used to estimate the amount of interference they cause. For the D2D communications, the BS can obtain the channel status of D2D links between transmitter and receiver by taking periodic or aperiodic Channel Quality Indication (CQI) reports from both of them.

2.4.6 Power Control

Researchers have been investigating power control as a solution to the interference management problem between D2D users and cellular users. There are fixed SNR target and fix power schemes which D2D communication can exploit. The drawback of using fixed TX-power scheme is that although it is quite simple to use, it does not work well due to the large dynamic range of D2D SINR. The overall dynamic range is relating directly to the interference management scheme. In the worst case which is random resource allocation, dynamic range is large whereas when D2D users are using their own dedicated spectrum, they have lower dynamic range, so they can use fixed power scheme. In fixed SNR target, we must choose appropriate TX power in order to reach desired SINR target. The higher the SINR target is, the higher TX power needed which increase D2D users final SINR while imposing significant interference on the other cellular users.

2.5 D2D Uses Cases and Applications

There are three main use cases for D2D connection. D2D can serve simple exchanging data between sender and receiver or act as a relay to forward data to or from the other users.

- **Local Data Services**

  There are a couple of local services which can benefit from the D2D connection which are: information sharing, mobile multiplayer gaming, mobile advertising, streaming services and social networking. By using D2D, one can facilitate the connection between users, sensors, and devices in proximity. However, D2D technologies offer benefits that exploit the physical proximity of the communicating sides in terms of latency. Irrespective of the underlying technology, we foresee the need for D2D communication technology containing functions such as mobility control, user data routing, proximity detection, and security management.

- **Public Safety**

  Recently 3GPP defined the most important role of D2D connection which is public safety services. From the deployment perspective, public safety services can be categorized into within network coverage and outside coverage [4].

- **Data Security**

  The other benefit comes with D2D service is data security which results from a direct route between sender and receiver and avoids passing through cloud entity which can prevent advance authentication methods.

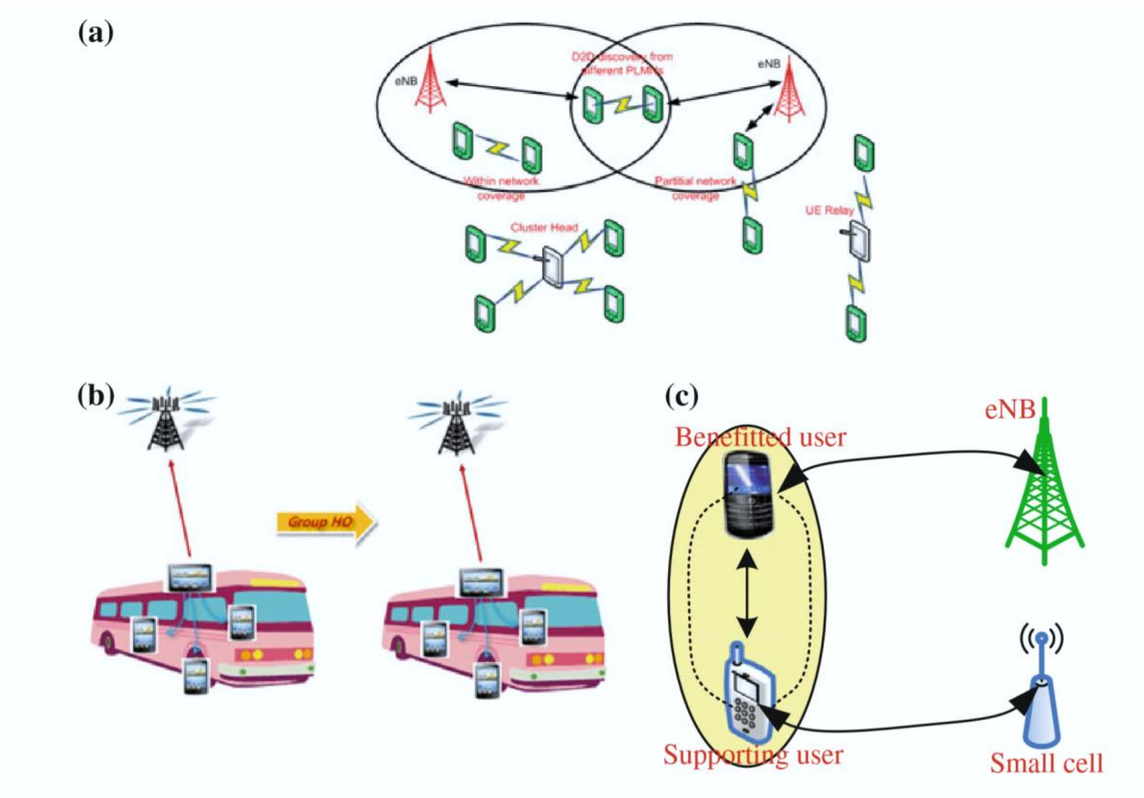


Figure 2: D2D Use Cases

2.5.1 Vehicle to Vehicle Communication (V2V)

There has been a strict need for low-delay communication in the vehicular network in order to send or receive traffic information. For example, for collision systems, it is crucial to send signals on low latency protocols to coordinate braking system. Without V2V connection, vehicles need to detect if any car in near distance is braking in order to avoid a collision. Additionally, the Additionally, V2V connection can provide extensive and reliable information about traffic stream to all the vehicles which could be useful to maintain a safe distance.

2.6 D2D Communication Background

D2D communication refers to short-range communication between users without going through the BS. Apart from the Bluetooth and Wi-Fi connection, in-band type of communication does not utilize unlicensed spectrum and it takes place in cellular spectrum and guarantees QoS. The first step in D2D communication is peer discovery which is manually operated by devices without any network intervention. Unlike the case of cognitive radio in which there are two types of users (primary and secondary), in the case of D2D connection cellular users known as primary users are allowed to establish this type of connection as well so it is not just limited to secondary users. Since the role of BS is eliminated, significant processing power can be saved, and shared usage of the cellular spectrum may lead to spectrum efficiency.

In the literature D2D connection is categorized into two major class:

1. D2D in-band underlay which shares cellular spectrum between cellular and D2D users

2. D2D in-band overlay in which D2D users are only allowed to use the cellular spectrum when it is empty.

There is an extensive comparison of these two approaches in [5] with respect to throughput. The most important problem which must be addressed in both approaches is efficient interference management. To deal with this, [4] [6] [7] recommends the use of uplink spectrum due to its underutilized feature. Moreover, in the case of using uplink additional interference will be imposed on the BS which is equipped with high-performance receivers and antenna. The other victim of this additional interference is a D2D receiver. Considering the current advances in standardization toward ultra-dense cells such as microcell and small cell, the amount of interference from devices in proximity to the D2D receiver is not negligible and requires extensive investigation to find efficient ways for controlling intercell interference.

Researchers have been approaching to the interference mitigation problem mainly in the context of resource allocation and power control schemes provided in [8] [9] [10] [11] by gathering required information from users and D2D devices, BS tries to allocate appropriate spectrum and power level to devices to minimize intracell interference. to reduce overhead, different techniques have been proposed in order to inform BS about channel state information (CSI) such as periodic reporting [10] [12] [13]. However, reporting all the information to the BS requires network resources and even with accurate information, the problem of resource allocation and power control is NP-Hard.

The other aspect of D2D communication which considered as a first step is peer discovery. Peer discovery means finding out whether devices are close enough to initiate reliable and high data rate connection. There are two major approaches to this problem: centralized and decentralized approach. Researchers tend to use decentralized algorithms since it requires less signaling and operates at the local level. However, finding devices in proximity without the intervention of the BS may lead to unauthorized use of the licensed band, hence centralized algorithms introduced to overcome this drawback. Recent efforts in implementing D2D connection has been done by Qualcomm as FlashLinq which includes: a) timing and frequency synchronization b) link management c) distributed power allocation and scheduling [14].

The idea of mode selection which is a strong basis of many papers in the literature first introduced in [15] [16] which shows D2D connection can be used for network performance optimization while the problem of connection loss during switching between cellular and the D2D connection should be addressed carefully.

2.7 Proposed System Model in 3GPP for D2D Connection

In the system model, the BS is responsible for controlling D2D connection which means:

1. Resource allocation and power control

2. The peer discovery step.

All devices in the cell are equipped with D2D connection requirement. In this scenario, D2D devices request resources from the base station, then the BS runs peer discovery algorithm to find the best match from devices in proximity. When BS found a candidate, the process of resource allocation and power control will be begun and inform D2D transmitter and receiver their specific resource, power level and timing. In order to give each D2D devices a unique identity in the peer discovery process, one can use IP address which requires the intervention of the core network since IP information is not available at the local level. The new identity generated during the first access of the devices to the network. Moreover, D2D transmitter knows the identity of its target device so it can be reported to the BS. D2D connection procedure can be summarized as follow:

1. D2D devices identity generated during the first access at the BS.
2. D2D transmitter initiated connection and request spectrum in order to establish direct communication. Target D2D receiver can be specified or detected by the BS.
3. After receiving spectrum request, the BS runs peer discovery procedure if applicable.
4. The BS informs D2D users of their allocated spectrum and power level which minimize the intracell interference between the D2D system and cellular users.
5. The D2D transmitter tunes itself to the allocated spectrum and synchronized its communication window, then start to transmit its data where the receiver is tuned to the same communication window in order to receive data as well.
6. The D2D receiver acknowledges the reception of the data by sending acknowledgment signal and they end the connection.

2.8 Interference Management Techniques for D2D Communication

Because of coexistence of D2D and cellular communication, additional harmful interference on the cellular users is generated which significantly decrease QoS. This additional interference results in performance degradation of the cellular nodes [17] [18] [19]. An efficient interference management technique should be introduced to address this problem. As the priority is given to the cellular nodes, most interference management's objectives are to protect cellular nodes performance. The impact of power control is investigated in [16] [10] [20] [21] [22]. Doppler *et* al showed that controlling the D2D transmit power could result in an increase in overall system throughput ref [16] [22] while Yu *et* al guarantee SINR level for cellular users and showed there is an acceptable level of SINR for D2D users as well. Moreover, Gu *et* al introduced dynamic power allocation to decrease the amount of interference by the cellular users [21]. The author in [23] considered a multi-cell scenario to minimize overall transmission power in the cellular network. The problem of resource sharing, power allocation, and mode selection are formulated as a linear programming problem which is NP-Hard. Trying to reduce the complexity, they considered only single cell scenario. A heuristic approach to the problem showed a significant gain in power efficiency over traditional cellular communication. In [24] the problem of power allocation and mode selection has been discussed. In their proposed algorithm, first power efficiency is calculated which is a function of transmission rate and power consumption for the different users in different modes (D2D and cellular). Therefore, each user uses the mode in which it gains the maximum power efficiency. There is a comprehensive comparison of different power control schemes in [20] which shows this approach is able to manage additional interference.

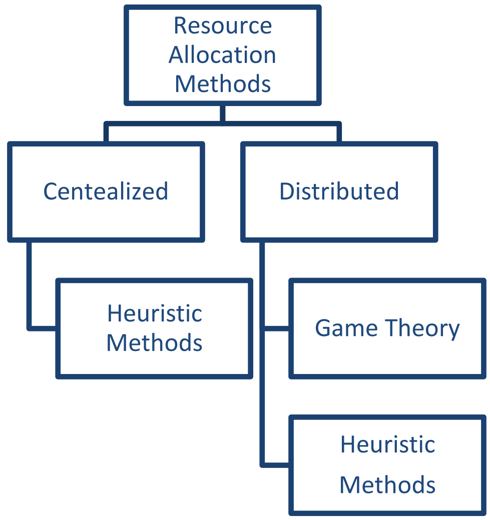
The second approach is resource allocation to overcome harmful interference [5] [25] [26]. Depends on whether the D2D connection is going to take place in underlay or overlay mode, the BS shares part of the cellular spectrum or dedicates an empty part of the cellular spectrum to the D2D user respectively [25]. In case of overlay connection, additional interference can be eliminated while decreasing reuse factor and results in spectrum inefficiency. Yu *et* al formulated resource allocation problem into power constrained problem [5]. They have shown that, by jointly optimize resource allocation and power allocation, the D2D connection can reach significant performance over conventional cellular communication. Note that, by limiting transmit power or resources of the D2D users, there is a possibility to get a quite unreliable connection and critical performance loss. Therefore, many works have been done in order to enhance throughput of cellular and D2D connection [27] [8] [28] [29]. Janic *et* al proposed resource allocation in order to maximize overall system performance where there are multiple D2D and cellular users exist [8]. Furthermore, a power efficient scheme is proposed to jointly optimize power level and resource allocation in [24]. Since optimizing resource allocation for multiple cells is an NP-Hard problem, Feng *et* al adopted three-step optimization technique to solve the problem [27]. Until now, the BS only utilized channel state information in order to allocate power or resources. Wang *et* al show by considering location information of users in the cell, there could be a significant performance gain, but this information is not always available.

The most important category we must look at is In-band Underlay communication since resources are shared in this category. In [30] uplink resources are shared between D2D and cellular users. To tackle the additional interference imposed on cellular users, D2D users monitor received signal strength (RSS) of the downlink control signal to estimate the path loss effect on the signal coming from BS. This allows D2D users to control the transmit power and maintain it below a specific threshold to decrease the amount of interference on the cellular users. The mode selection in this algorithm allows the D2D user to establish a direct connection if the transmit power required by the D2D users is less than the threshold. Routing among D2D users using multi-hop connection known as Dynamic Source Routing is proposed in [31] as well. Through simulation, the author claimed that probability of establishing direct communication increases when path loss effect is stronger. The reason for this is the stronger path loss, the weaker interference at the BS causing by the D2D user. In [32], D2D users read control channel to avoid using same resources as cellular users in proximity. The authors propose to allocate a dedicated control channel for D2D users. Cellular users can listen to this control channel and measure the SINR. If the SINR is higher than a threshold, cellular users send a report to the BS. Based on these reports, BS reschedule cellular users and avoid using resource blocks that are currently occupied by D2D users. In each time slot, location information of users and their allocated spectrum is broadcasted by the BS, therefore, D2D users avoid using recourse blocks that cause interference on the cellular users in proximity.

Mode selection which means determining the mode in which users should work is discussed in [25]. In this work, users perform channel measurement and then achievable channel transmission rate in each mode is calculated. Based on the achievable rate, each user chooses the mode which results in higher transmission rate. Simulation results have shown wisely choosing the mode for D2D communication can significantly increase system throughput.

Downlink resource sharing among cellular users and D2D pairs is considered in [33], [34], [35]. Sum-rate optimization using Game Theory is proposed in a work by Xu *et* al [35]. They exploited Auction Theory to design combinatorial auction game trying to manage available resources. In this game, the spectrum resources are considered as bidders while D2D links are goods to be sold. The upside of their algorithm is less complexity in comparison with traditional schemes since they have used the distributed method. Simulations have been done under WINNER II channel and showed 13% of performance upgrade. Sequential second price auction algorithm is used in [33] to iteratively match D2D pairs with available resource blocks, where the goal was to minimize the interference between shared users. Islam *et* al In [34] proposed a polynomial-time matching algorithm for the resource allocation problem to maximize the sum-rate by assuming the location information of all the devices in the cell, which is not always available at the BS. In [36], a two-phase auction-based algorithm is used to share

Figure 3: Different Resource Allocation Methods



uplink spectrum. The authors assumed that all the channel information was calculated at the BS and broadcasted to users in a timely manner.

Table 2: Taxonomy of Different Approaches to The Resource Allocation in D2D Communication

Reference	Spectrum	Metric
[18]	UL/DL	Sum Throughput
[37]	UL/DL	Energy Efficiency
[38]	UL/DL	QoS
[39]	UL/DL	SINR
[40]	UL	Cell Throughput
[41]	UL/DL	Sum-rate
[42]	UL	Cell throughput

[43]	UL	Power efficiency
[42]	UL	SINR CDF
[14]	UL	Cellular rate
[44]	UL/DL	Rate Gain
[45]	UL	SINR
[46]	UL	Sum-rate
[47]	UL/DL	SINR CDF
[48]	UL	Mean System Capacity
[49]	UL	Outage Probability

2.8.1 Interference Channels

In order to compare the use of uplink and downlink spectrum for the D2D connection, we consider a single cell scenario consists of single BS and single cellular user and single D2D pair as depicted in Figure 4.

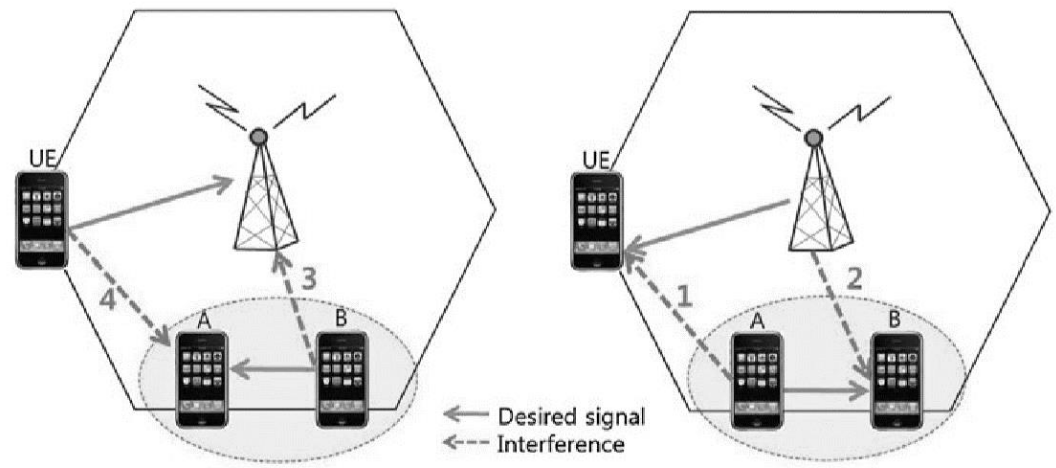


Figure 4: a Single Cell Scenario in Which D2D Pairs Share the Cellular Spectrum with Cellular Users

In this figure, we consider users are equipped with a single antenna, so they are able to operate in one mode (cellular or D2D) at the same time.

In Figure 4, D2D pair A and B are in close proximity and therefore they have initiated to connect directly. While increasing spectrum efficiency by reusing the cellular spectrum, additional harmful interference will be imposed in the cellular network. Below we elaborate more on how using uplink and downlink resource may impact on connections.

Uplink: in this case, the coexistence of D2D and cellular connection generates two kinds of interference. The D2D transmitter generates interference to the BS during transmitting data to the D2D receiver and cellular user imposes harmful interference on the D2D receiver during its uplink period. Therefore, the overall system performance will be degraded resulting this phenomenon.

Downlink: in downlink period, victims of additional interference are a D2D receiver and cellular users. In downlink period the BS stations impose interference on the D2D receiver which will degrade its performance significantly due to the fact that the BS has powerful SINR. The cellular users suffer from receiving signals from D2D transmitter which makes it a victim in downlink scenario. In Table 2 we summarized victims and aggressors for each scenario.

Table 2: Different Scenarios of Interference

Scenario	Period	Aggressor	Victim
1	Downlink	D2D Transmitter	Cellular User
2	Downlink	Cellular BS	D2D Receiver
3	Uplink	D2D Transmitter	Cellular BS
4	Uplink	Cellular User	D2d Receiver

Since the cellular user has always a higher priority, it is always necessary to guarantee the QoS of the cellular users, so in the case of 1 and 3, the interference from D2D communication should be suppressed. This can be achieved by two means: controlling transmit power or interference aware resource allocation. By pursuing either of them, limited performance gain for the D2D connection could be achieved.

2.9 Chapter Summary

In this chapter, we provided a comprehensive literature review of D2D communication from emergence and competitors to D2D communication use cases and the classification of D2D connection as underlay and overlay. we have seen pros and cons of each category and elaborated on why researchers tend to use underlay and that is because of the fact that it gives better spectral efficiency. In-band and out-band connection have been discussed and related works in each area have been provided. We have discussed several design issues associating with a D2D connection such as synchronization modulation and signaling. Then we focused on the main problem of D2D connection which is generating additional harmful interference due to shared resources. To address this issue, we have provided a comprehensive comparison between two main methods namely power control and resource allocation. In the end, we provided interference scenario considering a single cell scenario with single cellular users and single D2D pair to illustrate interference victims in each downlink and uplink period.

Chapter 3

3 Delay-tolerant Resource Allocation for Device-to-Device Communication Using Matching Theory

3.1 Introduction

To deal with the increasing demand for data communication with limited radio resources, D2D communication has been proposed as a key aspect of Long Term Evolution (LTE) networks. D2D communication allows users to communicate with each other directly rather than going through the BS [50]. Establishing direct communication in the underlying cellular networks increases system spectral efficiency and provides additional service for new users while maintaining the minimum Quality of Service (QoS) for cellular users [50]. Although D2D brings benefit to the network, it generates unwanted interference on the existing cellular users, which needs to be addressed efficiently. Thus, efficient interference management techniques must be designed to make D2D communication in the underlying cellular network feasible to implement [27].

In this chapter, we propose a resource allocation algorithm to share uplink resources based on stable matching with distributed CSI. Stable Matching is a well-known algorithm, which helps us match between any two finite sets of entities with low complexity. This algorithm has been defined in detail in [51]. Our proposed resource allocation scheme has three significant parts, which address unresolved problems in the previous works in terms of distributed CSI gathering, time of the request and delay-rate trade-off. These three parts and the corresponding contributions are elaborated below. Most previous works [9]– [34], [36] have assumed full CSI scenario and utilized a centralized algorithm which is not practical due to an uncontrolled overhead [52]. They are unable to address the challenge of the distributed CSI collection, and simply assume that all the CSI is known at the BS. In order to deal with this challenge in a practical manner, we propose a procedure to collect the required CSI information from the distributed sources while minimizing the overhead. All types of needed CSI for an uplink resource sharing for D2D communication is summarized in Table 3. The second problem, which has not been addressed in the literature, is the time of the D2D request. After D2D pairs find each other in the cell, which is known as peer discovery phase, they should seek spectrum resources to exchange their data. Because of the continuity and probabilistic nature of the request, it has virtually zero probability that a BS receives two or more number of requests at the same time. Most of the existing works have proposed an algorithm to allocate resources to the users without addressing how BS collects D2D requests and process them. To address this problem, we propose a framed structure for requesting D2D communication for the LTE networks. The last contribution of this work in designing practical structure for allocating spectrum is to exploit the concept of delay-tolerant networks in D2D infrastructures which means the D2D pair can wait for a specific time-interval to get the spectrum, and this waiting time may vary based on the D2D's application-level requirements. Because of the frequently changing channel characteristics due to the relative motions of the devices, channel response may vary from time to time during the D2D communications, and in this case, we can exploit this natural phenomenon to serve the users without violating their delay limit. In this work, we find the probability of meeting the minimum data-rate threshold for cellular users and relate it to the time delay needed for the D2D pairs to get the service. The rest of this paper is organized as follows: in Section 3.2 we provide system model and mathematical problem formulation in obtaining the expected data-rate pdf. In Section 3.4, a brief explanation of the Stable Matching algorithm, and its modified version are provided. The CSI gathering procedure from the distributed resources, time of the request frame and the detailed procedure to allocate resources are discussed in Section 3.5. Simulation results and conclusion are provided in Sections 3.3 and 3.6, respectively.

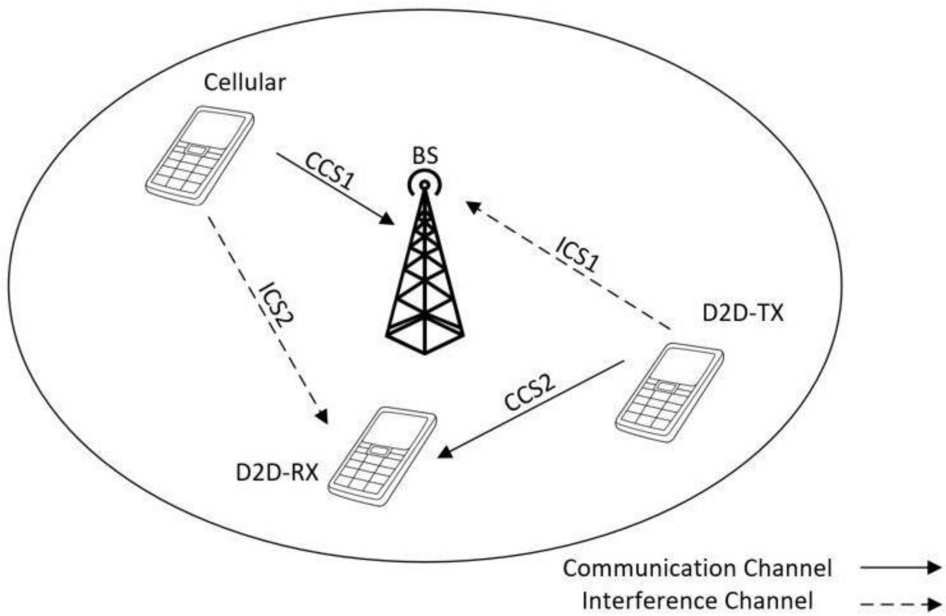


Figure 5: Network Model with One Cellular User and D2D Pairs to Show Available Channels

3.2 System Model

To analyze the proposed resource allocation algorithm, we have considered a single cell scenario with multiple numbers of D2D pairs and conventional cellular users who want to share the uplink spectrum. The main concern in this scenario is the interference between the shared users who must be dealt efficiently in order to achieve maximum sum-rate. It has been assumed that the cellular users and D2D pairs are distributed uniformly around the cell. D2D pairs are composed of D2DTx and D2D-Rx, and the distance l between a D2D pair should be less than a threshold l_{Th} in order to establish a direct communication between them. Direct communication is only allowed when the BS is under heavy load and all of its resource blocks are occupied, otherwise, conventional communication via BS would be established. The mathematical optimization problem is provided below whose objective is to maximize the system weighted sum-rate.

3.2.1 Problem Formulation

Let us denote a set of D2D pairs by $d \in D$ and a set of cellular users by $c \in C$. The optimization problem to maximize the z as the system weighted sum-rate becomes:

$$\max z = \sum_{c}^{C}\sum_{d}^{D}\gamma_d^c R_d^{UL} + W_c \sum_{c}^{C} R_c^{UL} \tag{3.1}$$

$$R_c^{UL} \geq R_{\mathrm{C},Th}^{UL} \tag{3.2}$$

$$R_d^{UL} \geq R_{\mathrm{D},Th}^{UL} \tag{3.3}$$

$$\gamma_d^c \in \{0,1\} \; \forall c \in C, \forall d \in D \tag{3.4}$$

Where R_c^{UL} and R_d^{UL} are cellular user and D2D user data-rate. The objective is to maximize the system sum-rate while providing additional service for the D2D pairs. In (3.2) and (3.3) it is shown that the final resource allocation should meet the minimum threshold for data-rate $R_{UL}{}^{c}{}_{,\mathrm{Th}}$ and $R_{UL}{}^{d}{}_{,Th}$ for each cellular user and D2D pairs, respectively. The parameter γ_c d is defined by the resource allocation method, which shows whether cellular resource block $c \in C$ is shared with D2D pair $d \in D$. We emphasize on the importance of the cellular users and their sum-rate by adding a weight of W_C. In this problem, we consider sharing only one resource block between cellular and a D2D pair which means each D2D pair can access only one resource block. After $\gamma_c{}^d$ is determined by the Stable Matching algorithm, the consistency with optimization problem constraints should be checked before announcing the assigned resources to the users. Based on the information that will be gathered during the CSI gathering step (Section 3.5.1), achievable data-rate after resource allocation can be calculated using the following expression:

$$\mathrm{R}_c^{UL} = W\log_2\left(1+\frac{p_c H^{c,BS}}{N_0 W+\sum_d^D \gamma_d^c p_d H^{d,BS}}\right)\forall c\in C,\forall d\in D \tag{3.5}$$

$$\mathrm{R}_d^{UL} = W\log_2\left(1+\frac{p_d H^{\mathrm{d}}}{N_0 W+\sum_c^C \gamma_d^c p_c H^{c,d}}\right)\forall c\in C,\forall d\in D \tag{3.6}$$

$$p_c = p_c^{Tr} - 128.1 + 37.6\log_{10}\left(d[km]\right) \tag{3.7}$$

$$p_d = p_d^{Tr} - 148 + 40\log_{10}\left(d[km]\right) \tag{3.8}$$

In the above equations, W is the bandwidth of each resource block and N_0 is the Gaussian noise power spectral density. p_c and p_d are the received powers in the BS and D2D-Rx, respectively where p_c^{Tr} and p_d^{Tr} are cellular user and D2D-Tx transmit powers. These received powers have been calculated based on the path-loss model outlined in [53]. Since we have considered Rayleigh fading channel in our analysis, in equations (3.5) and (3.6) $H^{i,j}$ represents the magnitude of the complex Gaussian random variable *CN(0,1)* that characterizes the fading effect on the channel between user *i* and user *j*, and h_d represents the channel between D2D-Tx and D2D-Rx.

Table 3: Types of Interference Channels

Type of Channel	Abbreviation	status
Communication channel state between BS and cellular user	CCS1	Known at the Base Station
Communication channel state between D2D-Tx and D2D-Rx	CCS2	Known at the D2D-Rx
Interference channel state between D2D-Tx and BS	ICS1	Unknown
Interference channel state between cellular user and D2D-Rx	ICS2	Unknown

3.2.2 Data-Rate and Delay Threshold Model

In this work, we exploit the concept of delay-tolerant networks in D2D communication, which means each D2D pair can wait for a specific amount of time to get the spectrum and start to communicate. This specific amount of time is determined by the required application-level scenario of each D2D pair, and the service it needs. On the other hand, cellular users rate is probabilistic due to the probabilistic nature of the channel, and according to the optimization problem, cellular user data-rate is one of the constraints, which should be met by the allocation algorithm. Therefore, finding the probability of meeting the minimum data-rate threshold and relate it to the D2D pair's delay threshold helps us to find how many time slots are approximately needed to reach the threshold. Now that $H^{i,j}$ is a Rayleigh distributed random variable, we can calculate the pdf for R_{UL}^{c}, and then we can find the probability of the minimum data-rate threshold that will be met after resource allocation. Let's introduce new variables *x* and *y* as follows:

$$\begin{cases} x = H^{c,BS} \\ y = H^{d,BS} \end{cases}, \begin{cases} \exists d \in D \Rightarrow \gamma_d^c = 1 \\ N_0 B \ll 1 \end{cases} \tag{3.8}$$

We can write:

$$w = \frac{p_c x}{N_0 B + \sum_{d}^{D} \gamma_d^c p_d y} \simeq \frac{p_c x}{p_d y} \tag{3.9}$$

Since we have two random variables *x* and *y* here, first we need to find their joint *pdf* and then we need to evaluate the marginal *pdf* for *w* which is introduced in equation (3.10) as a function of variables *x* and *y*. Here, we introduce a new variable *z*, and then construct *Jacobian matrix J* as:

$$\Rightarrow \begin{cases} x = z = h_1(x,y) \\ y = \dfrac{p_c z}{p_d w} = h_2(x,y) \end{cases} \tag{3.10}$$

$$J = \begin{pmatrix} \dfrac{\partial h_1}{\partial z} & \dfrac{\partial h_1}{\partial w} \\ \dfrac{\partial h_2}{\partial z} & \dfrac{\partial h_2}{\partial w} \end{pmatrix} = -\frac{p_c p_d z}{p_d w^2} \tag{3.11}$$

$$\Rightarrow f_{z,w}(z,w) = f_{x,y}\left(h_1(x,y), h_2(x,y)\right) | J | \tag{3.12}$$

Due to the fact that $H_{c,BS}$ and $H_{d,BS}$ are independent random variables, their joint *pdf* is

$$f_{x,y}(x,y) = f_x(x)\, f_y(y) \tag{3.13}$$

Then we can calculate marginal pdf of w from expression (3.12). Since z is always positive according to expression (3.10), we can write:

$$f_w(w) = \int_0^{+\infty} f_x(z)\, f_y\left(\frac{p_c z}{p_d w}\right) \frac{p_c p_d z}{p_d w^2}\, dz \tag{3.14}$$

where $f_w(w)$ is the *pdf* of Signal to Interference and Noise Ratio (SINR). Then expression (15) can be written as:

$$\begin{aligned} &\Pr[R_c^{UL} \geq R_{c,Th}^{UL}] = \Pr[w \geq 2^{\frac{R_{c,Th}^{UL}}{B}} - 1] \\ &\Rightarrow \int_{2^{\frac{R_{c,Th}^{UL}}{B}} - 1}^{+\infty} f_w(w) dw \end{aligned} \tag{3.15}$$

Since $H^{c,BS}$ and $H^{d,BS}$ are Rayleigh distributed random variables, equation(3.15) can be evaluated numerically. After we find this probability, we can relate it with the delay threshold which is requested by a D2D pair and see whether it has any significant chance to get the spectrum in the desired time or not. This new concept helps us to have an approximate guess on the time duration a D2D pair should wait to get the spectrum.

3.3 Stable Matching

The problem of matching arises when we have two finite population that want to be matched. These two populations have relative preference over each other. The definition of preference relation is as follows:

In set X, binary relation > satisfies the following properties:

- Every two members of X is comparable
- If x > y and y > z, the x > z which means the relation is transitive

The simple form of the Stable Matching algorithm is when we have two finite sets with an equal number of members. In order to match between two sets, one should follow steps below to reach the stable matching. For simplicity, we use the example of two groups of men and women who want to be matched based on their preference relation with each other. The algorithm is as follows:

1- Every man stands in fronts of the woman he prefers most.

2- We ask every woman to choose the man she most prefers to stay and dismiss others

3- Every dismissed man stands in front of the woman he most prefers who has never dismissed him

4- Check if there is only one man in front of each woman and if not go to step 2

By following above algorithm, we reach a matching which is stable. Stable means there is not any pair that both prefer each other but they are not already together.

3.4 Modified Stable Matching Theory

In a formal Stable Matching algorithm, there are two finite sets, which are equal in size. Every individual member of each of these sets has preference over the members of the other set which is called preference relations. In the modified version of the Stable

Matching approach, which we employed in our work, sets are resource blocks and D2D pairs, and the numbers of two sets are not equal, and yet we have those preference relations for the members of each set by the other one. In order to solve this problem with the assumption that the number of D2D pairs is less than the cellular users i.e. $C > D$, we need $(C - D)$ dummy D2D pairs to change the problem to the formal Stable Matching definition. These dummy D2D pairs do not change anything in the final matching scenario because they are least preferred pairs as seen by the cellular users. Formal Stable Matching has two well-known approaches called women courtship and men courtship [51]. The former one is better from the perspective of the women while the latter one is the best for men. Here, we assume the cellular users and the D2D pairs play the roles of men and women, respectively, and our matching approach is men courtship; therefore, cellular users as men receive better matching based on their preference.

3.5 Resource Allocation Procedure

3.5.1 Channel States Gathering

CSI is one of the important parts of any resource allocation problem. In this work, we assume distributed CSI to avoid reporting all the information to the BS. Based on the consideration that the uplink resources are shared among the D2D pairs and the cellular users, we have four types of channels that are summarized in Table 3. Essentially, we need all this information in order to solve the maximizing sum-rate optimization problem but gathering this information in one place requires overhead because it is distributed in different locations. Unlike the centralized algorithm, we try to use distributed algorithm to avoid gathering all the information at the BS. Each of these four types of channels will be obtained as follows: CCS1 information is already known at the BS during conventional communication between BS and the cellular user. During the activation process, when D2D pairs are identifying each other, they can estimate the channel between them. Therefore, CCS2 information is also known at the D2D pairs. In order to estimate the ICS1, we know that during direct communication request, D2D-Tx should communicate with the BS. Therefore, the BS can estimate the channel quality and keep this information for future use. The next step is to identify the ICS2. During each scheduling interval, the BS broadcasts the information of C available resource blocks, so after pairing process and before requesting direct communication, D2D-Rx starts listening to the available channels and calculate the Received Signal Strength (RSS) from each $c \in C$ cellular users and then determines respective distances [11]. By using this information, each D2D-Rx can make its own $1{\times}C$ array representing its preference on cellular users in descending order. By following the above procedure, all the required information for calculating the system sum-rate is gathered. The frequency to update this information is based on the mobility of devices.

3.5.2 Time of the Request for D2D Communication

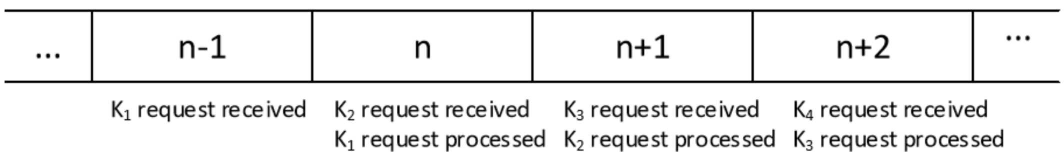


Figure 6: Frame Structure for D2D

One of the missing parts in previous works, discussed briefly in Section 3.1, is the time of the D2D request. Each D2D pair requests data, based on the pdf. According to the probability theory, two or more continuous events cannot happen at the same time; therefore, only one request to be processed is received at any time by the BS. Processing one request at a time decreases the efficiency of the resource allocation method because of the probable decrease in the solution region of the optimization problem, which results from the fact that it omits some possible solutions. To solve this problem, we consider a time-frame structure for requesting the D2D communication from the BS, so that every D2D requests in the *n-th* frame is processed in the *(n + 1)-th* time slot. This frame structure can be matched with the LTE frame structure, or it can be an independent frame structure. Figure 6 shows the frame structure for collecting D2D communication request.

3.5.3 Stable Matching Procedure

In this step, preference matrix is already generated at the BS, which was reported by each D2D-Rx in section 3.5.1, and it is ready to find the final allocated spectrum using Stable Matching approach. Our proposed algorithm has two phases: find the allocated spectrum based on *preference* matrix, and then checks the threshold constraints. The first phase is shown in Algorithm 1 on the next page. In line 1, the Preference matrix is used as an input and the Allocation matrix is initialized to store each iteration of the matching algorithm. In each iteration, the most preferred D2D pair from the cellular user ci is chosen as *Pref* and checked whether it is dismissed in any previous iteration or not in line 6. Then in line 9, *Pref* is written under d_i. Then every D2D pair asks the cellular user whom it most prefers among all the cellular users under its column. In this case, if there is any preferred cellular user for a D2D pair, it waits by dismissing all the other users in line 11. This process continues until one cellular user is available in each column. The algorithm returns this as a *Final Allocation* in line 15. In Algorithm 2, *Final Allocation* is used as an input and Rate, Rate Threshold vectors are initialized. Then in lines 2 and 5, achievable data-rate after spectrum-allocation is calculated for cellular users and D2D pairs respectively. In line 8 consistency with optimization constraint is checked, and the final decision is announced in line 9 or 11. If, in any case, the algorithm cannot satisfy the minimum threshold requirement, the BS waits for a coherence time and then runs Algorithm 2 again in order to utilize the variation of the fading channel, which results in different channel coefficients during the consecutive coherence time interval. The important part, which must be addressed here, is the maximum delay tolerance each D2D has, to get its resource block. This information is available at the BS along with the preference vector which is reported by each D2D-Rx. Delay for each D2D pair is incremented in line 12 and then the BS checks whether it can wait for another coherence time interval or not. Algorithm 2 is terminated with the announcement of the Final Allocation or with the report that the D2D pair could not reach the minimum requirement due D2D-Tx’s close proximity to the BS and the resultant intolerable interference.

Algorithm 1 Stable Matching between $C = \{c_1, c_2, ..., c_C\}$ and $D = \{d_1, d_2, ..., d_D\}$

Get the $Preference$ *matrix from Section IV-A and initialize* $Allocation$ *matrix*
Initialize $Dismissed_i$ *vector for each* c_i
while until eliminate all zeros from the first row of *Allocation* matrix **do**
  for $c_i \in C$ **do**
    $Pref \leftarrow$ *the most preferred* $d_i \in D$
    while $Pref \in Dismissed_i$ **do**
      $Pref \leftarrow$ *the next most preferred* $d_i \in D$
    end while
    put $Pref$ *under the* d_i *in the* $Allocation$ *matrix*
  end for
  for $d_i \in D$ **do**
    choose the most preferred c_i *and dismiss others*
  end for
end while
$FinalAllocation \leftarrow$ *First row of* $Allocation$ *matrix*

Figure 7: Algorithm 1

Algorithm 2 Calculate achieved rate after allocation and check whether the allocation meets the minimum constraint

Initialize the $Rate$ *and* $Rate_{Threshold}$ *vector*
Get *DelayHolder*
for $c_i \in C$ **do**
  $Rate_i \leftarrow$ *Uplink data-rate between* c_i *and BS*
end for
for $d_i \in D$ **do**
  $Rate_{i+C} \leftarrow$ *Uplink data-rate at* d_i *receiver*
end for
if $Rate \geq Rate_{Threshold}$ **then**
  return $FinalAllocation$
else
  Increment each *D2D pair delay holder*
  if $DelayHolder_i \geq Delay_{Threshold}$ **then**
    return Minimum Threshold for delay was not met
  end if
end if

Figure 8: Algorithm 2

3.6 Simulation Results

Simulation parameters are listed in **Error! Reference source not found.**. For the s imulation, we have considered single cell scenario, where simulations have been carried out using MATLAB simulation software, under the path-loss model and Rayleigh fading channel for both cellular and D2D users. For the simplicity of the simulation, we have considered equal delay thresholds for all the D2D pairs, also we have assumed W_C to be 2 to show that the cellular user's data rate is twice as important than the D2D pairs data-rat

Table 3: Simulation Results

Cell radius	500m
Maximum distance between D2D pairs (l_{Th})	50 m
Transmit Power for the cellular user	25 dBm
Transmit Power for D2D-Tx	25 dBm
Noise Power	-174 dBm/Hz
Fading Model	Rayleigh fading channel
Path-loss model	Given in 3.5 and 3.6
Minimum rate threshold for the cellular user	2 bit/s/Hz
Delay constraint for D2D pairs	10 time-slots
Cellular user's sum-rate weight (W_C)	2

3.6.1 Effect of the Number of D2D Pairs on Weighted System Sum-Rate

In Figure 9, we compare the proposed resource allocation algorithm with random allocation and forced cellular communication. In random allocation strategy, D2D pairs are randomly matched with the cellular users as long as they satisfy the data-rate threshold by not paying attention to the degree of interference being imposed on the other users. The forced cellular communication strategy does not allow any direct communication to take place. As shown in the figure, we observe that an increase in the number of D2D pairs increases system's sum-rate, and in this case, the proposed algorithm outperforms the other two strategies in terms of sum-rate. Also, it is clear from the figure that by allowing direct communication to be established, the cell can have more sum-rate.

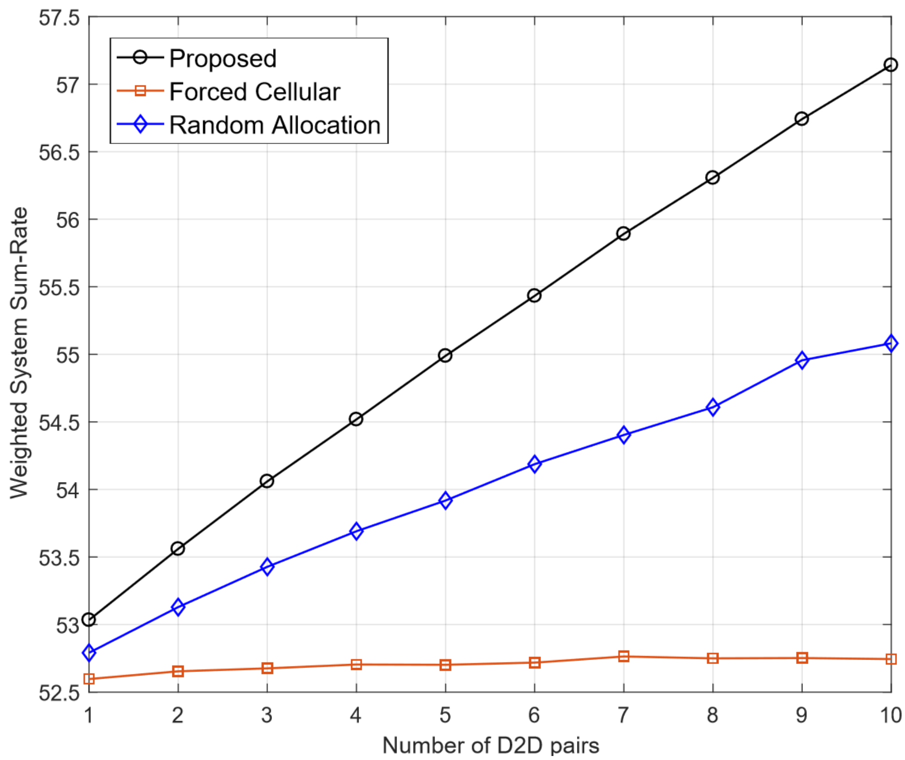


Figure 9: Effect of Number of D2D pairs on System Sum-rate

3.6.2 Effect of Number of Available Resource Blocks on Weighted System Sum-Rate

Figure 10 illustrates the effect of available resource blocks, which are cellular users. When the number of resource blocks increases, the possibility of getting farther resource blocks for each D2D pair increases, so we have less interference, and that results in a better system sum-rate. In this situation, the superiority of the proposed algorithm is clear over random allocation.

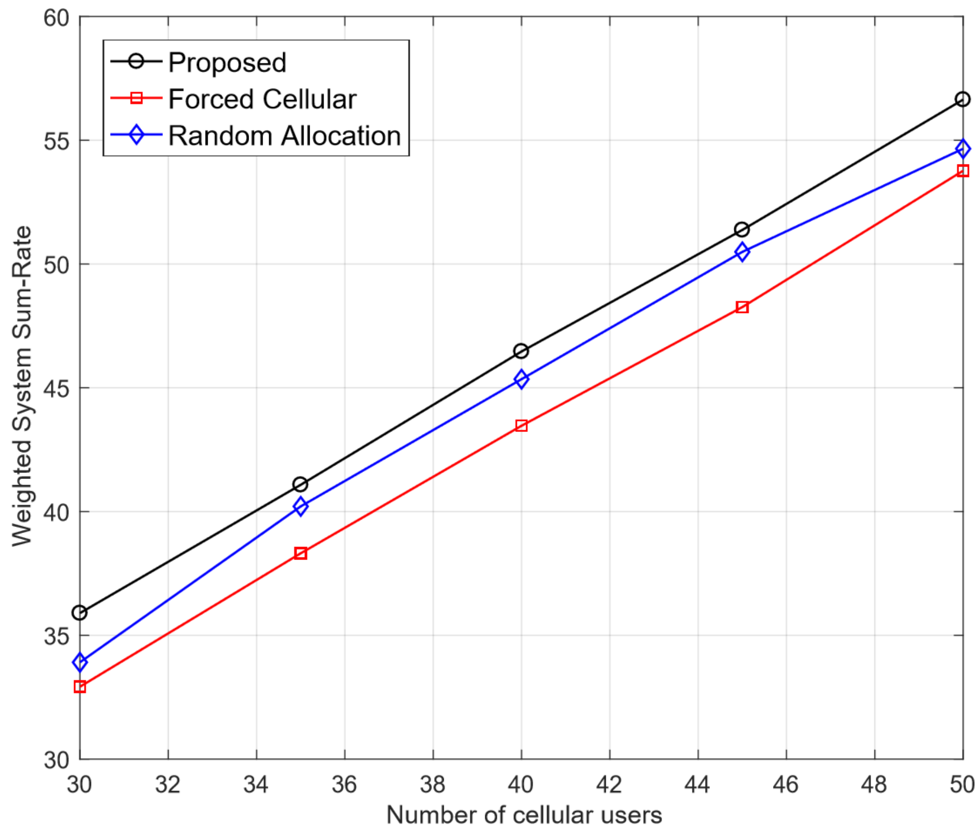


Figure 10: Effect of Number of Available Resources on the System Sum-rate

3.6.3 Proposed Matching Scheme vs. Exhaustive search

In Figure 11, we compare the proposed algorithm with the Exhaustive search and random allocation strategies. Exhaustive search strategy tries to find the allocation for the D2D which has the maximum sum distance between matched pairs, and this strategy provides an optimal solution to the resource allocation problem. Figure 11 illustrates the fact that proposed algorithm and the Exhaustive search strategy show close performance for a fewer number of D2D pairs. The reason behind providing a separate Figure for comparing these two allocation strategies is that the Ex-search cannot be generalized to a large number of cellular users. The limitation arises from the fact that with a large number of cellular users, it leads to an extremely large ordered algorithm and in turn deems to be impractical for LTE networks.

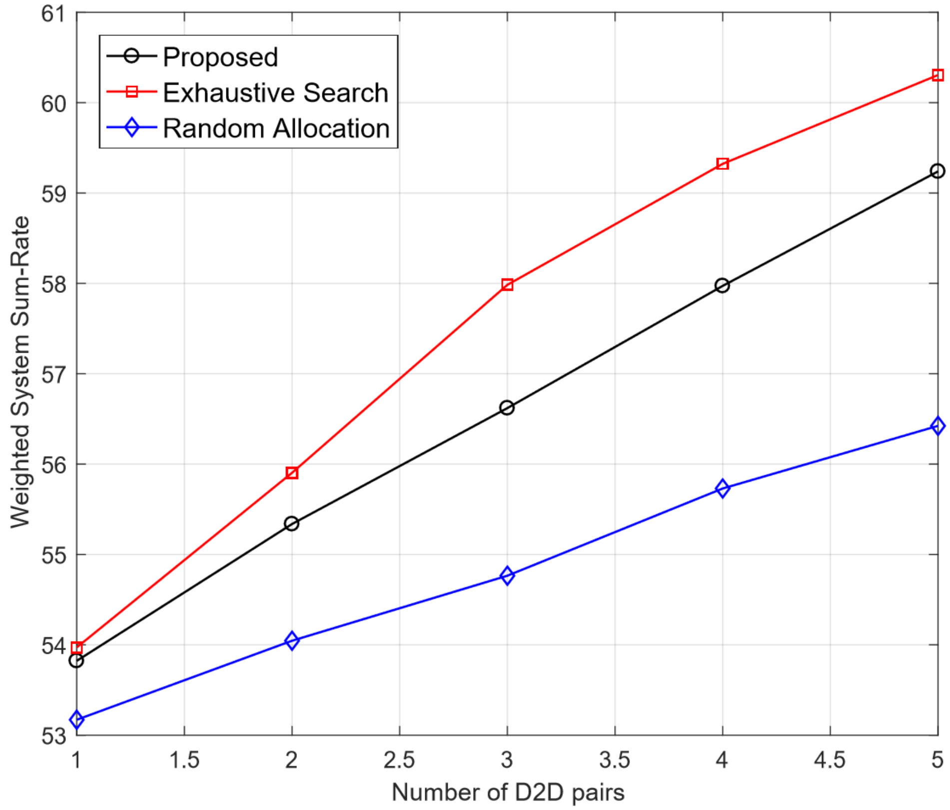


Figure 11: Comparison with Ex-search

3.7 Chapter summary

In this chapter, we have proposed a delay-tolerant resource allocation mechanism for D2D communication based on the Stable Matching algorithm to maximize the system sum-rate in a single cell scenario to share uplink resources. A distributed CSI gathering procedure has been proposed in order to minimize the overheads from the reporting CSI to the BS. We have calculated date-rate pdf to have an approximate guess on whether a D2D pair will be assigned any resource or not. A concept of delay-tolerant request has been exploited in D2D communication to show that D2D pairs satisfy application level requirements and take advantage of user's mobility as well as channel variation. An explicit request structure has been proposed to address how BS receives direct communication request. Simulation results show better performance of the proposed algorithm in comparison to both random allocation and forced-cellular strategies, and it has been demonstrated that when there is a fewer number of D2D pairs, the proposed algorithm gets close to the optimal performance shown by the Exhaustive search strategy.

Chapter 4

4 Introduction to the Edge Caching

Due to an exponential growth of smart devices and new applications, there is a significant traffic congestion in the core network. The conventional network architecture cannot serve users well because of high congestion in the backhaul which induces significant delay. In order to serve users better and guarantee Quality of Experience (QoE), mobile edge computing and caching have been proposed recently. In this chapter, a comprehensive literature review in the area of caching have been provided to show some important challenges in the area.

4.1 Evolution of Caching in the Network

Consistent evolution of mobile communication systems from voice to data leads to significant improvement in data rate and capacity as well as developing low delay systems by a great enhancement in physical aspects such as OFDMA, MIMO, … also in the network layer by introducing heterogeneous networks (HetNets) and cloud radio access network. Besides, great improvement in mobile computing capabilities and the emergence of sensors and wearable devices result in a new era called machine-to-machine connection (M2M). While bringing a wide range of application, the M2M connection has challenges described in [54] such as a large number of connected device, low latency communication, and high data rates. Researchers have been dealing with these challenges through the introduction of 2-level communication between servers and clients also known as cloud and users.

Introduction of cloud computing brings a new area of research called mobile cloud computing (MCC) that mainly deals with mobile-related factors. There are comprehensive surveys discuss several aspects of MCC. [55] [56] provided a deep insight into MCC architecture and implementation as well as technical challenges and applications. The author in [57] provided comprehensive taxonomy on the effect of communication entities on offloading decisions and presented latest cloud applications.

In order to summarize all the merits of using cloud computing, following benefits can be named:

- MCC can provide flexible additional resources for mobile users.
- Cost of managing MCC is low due to the centralized management of the network.
- Due to the flexibility of the network, MCC can accommodate different platforms in the cloud.

below a schematic of a cloud network is provided in Figure 12.

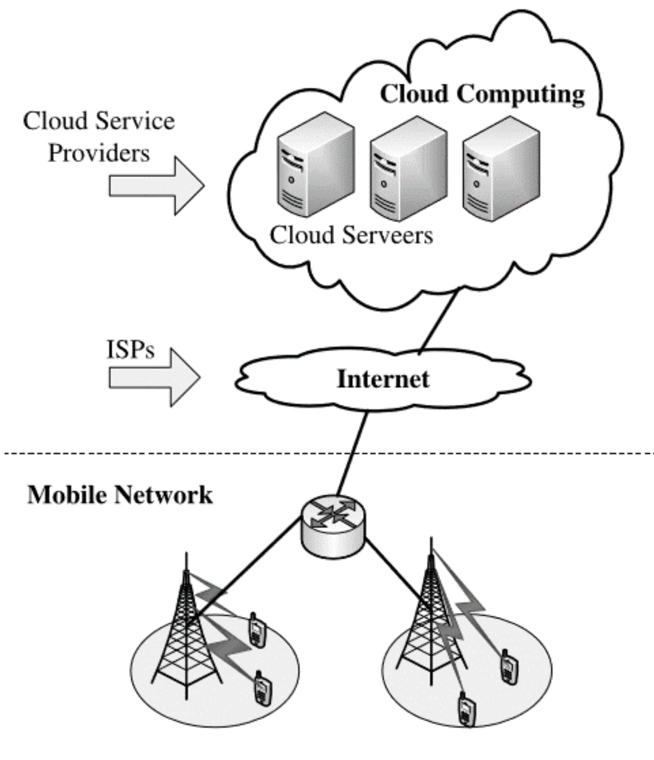


Figure 12: Cloud Architecture

Cloud computing provides additional service to the end users; however, it has inevitable latency and backhaul congestion. To tackle with these problems mobile edge computing (MEC) has been introduced which deploys cloud architecture on the edge which is the BS. Deploying cloud at the BS benefits end users due to the fact that the communication occurs in the shorter range, it has lower latency higher bandwidth and location awareness. Recently, MEC has been accepted a promising technology for Fifth Generation of mobile networks (5G) by 5GPPP. It can provide benefits for each contributing party, for the network users low latency and high data rate connection can be provided as well as providing user-related information for application providers.

4.2 Caching Applications

4.2.1 Content Delivery Network

Providing distributed intermediate entities as content providers in the network can be named as content delivery networks (CDN). The goal of using these intermediate entities is to store the copies of most popular contents in order to serve users on behalf of the core network.

Due to the fact that these caching entities are distributed in the network, they can benefit the overall network efficiency for a couple of reasons. Firstly, since users are closer to these entities than the core network, the required latency to get the requested content will be reduced significantly which improves throughput as well. Moreover, CDNs can provide economic advantages because operators can provide contents for their own users through caching systems more cost-effectively.

4.2.2 Information-Centric Networks

The content delivery network has already provided content aware protocols to serve users, however, the lack of infrastructure prevents this kind of networking to evolve. To solve this, researchers have been thinking of new structure of the internet which is based on user-content traffic pattern. As a result of this effort, information-centric networks (ICN) architecture have been proposed [CCN, NDN, COMET].

Each architecture has its own features and implementations properties, but they share some common aspects described below:

a) **Request Response Model:** each user issue content specific request which will be routed to the appropriate entity and will be replied to the requested content.

b) **Location Independence**: in an ICN, content names do not include the location where content is stored. In most aforementioned ICN architectures content names have specific information about the routing.

c) **Content Authenticity**: in the traditional content delivery network, security of delivery guaranteed by securing content information and routing channel, however in an ICN, content can be validated regardless of the serving node and the route.

4.3 Mobile Edge Network

The idea of mobile edge network comes from moving communication resources such as computing resources and storage closer to the users. Three different edge computing schemes are considered in the literature: MEC, Fog Computing, and Cloudlet which is briefly discussed here, but the main focus of this section is on edge caching architecture as apart of edge computing implementation. MEC first introduced in [58] which was based on a virtual platform in order to enable applications to run at the edge. By introducing small cells, edge infrastructure has been moved to the small BSs to further decrease communication latency.

Fog Computing is another architecture of edge computing which mainly used in IoT applications [59]. While the fog is closer than clouds to the people, the terminology is used to refer to an infrastructure which is closer than cloud to the end users.

Cloudlet first introduced by a team in Carnegie Mellon University [60]. Cloudlet can be used in both licensed and unlicensed band. They claim that cloudlet can work for near-real-time applications and provide better handoff when users move between cells.

4.3.1 Edge Caching

Due to the deployment of different mobile networks in an area in future communication standards, moving toward edge caching proved to be beneficial for this kind of heterogeneous networks which is the main focus of this chapter. Conventionally, contents requested by users were fetched through core network which was not necessarily near end users, thus significant request time was expected by end users until they receive what they requested. With decreasing cost of deployment of high-performance BSs as well as cheap storage, caching at the BS and small BSs has become feasible. Additionally, by exploiting D2D communication, caching can be done even closer to the users to enable content sharing among neighboring users in proximity. Figure 13 illustrates connections in the network architecture.

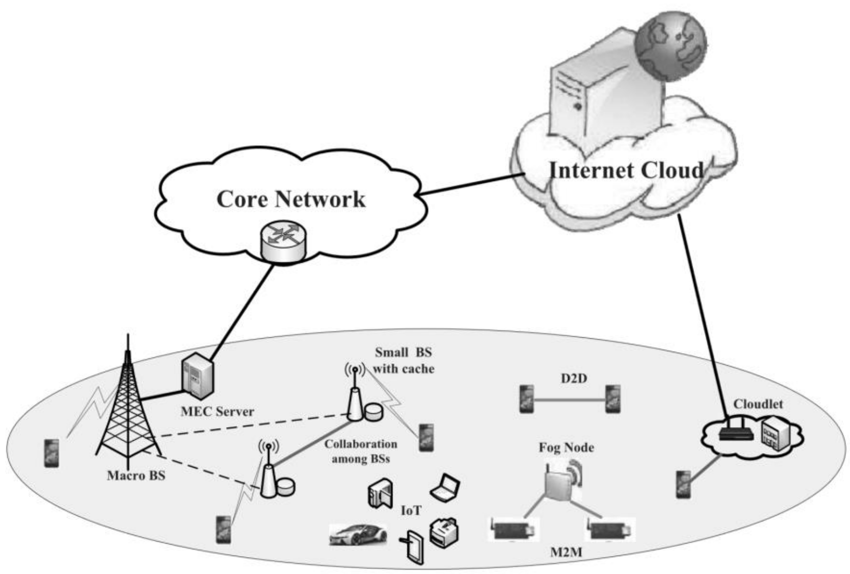


Figure 13: Architecture of Mobile Edge Networks

As discussed above, caching on the edge can provide advantages to the network. Below a brief explanation of each advantage is provided to give a better insight of different aspects of caching systems.

4.3.2 Advantages of Edge Caching

As compared to conventional content access, caching can provide various advantages.

4.3.2.1 Low Latency

Due to the shorter range of communication, users can benefit from low latency communication for delay-constrained application such as video streaming. As demonstrated in [61] by using joint cloud and edge, packet delay can be reduced significantly. Another study shows experimental result of the 4G-LTE network which illustrates latency can be improved by 51% by using edge caching compared to cloud caching.

4.3.2.2 Energy Efficiency

In [62] demonstrated that in a real environment by caching on the edge, energy can be saved in both Wi-Fi and LTE networks.

4.3.2.3 Proximity Services

As discussed in Chapter 2, D2D communication can provide many benefits to the network. By considering edge caching on devices in proximity one can achieve great advantages in terms of traffic load reduction in the core network [63].

4.3.2.4 Context Information

Device specific context information can be utilized by the application providers as well as the network provider in order to model users' behavior. By exploiting caching on the edge, the network can obtain context information in each cell [63] and can provide better QoE by allocating appropriate spectrum, power etc.

Like every other new technology, there is a tradeoff between benefits of exploiting a technology and additional drawbacks it brings to the network. In the next section, we provide comprehensive challenges that caching at the edge will face and provide an insight into the main challenges going to be addressed in this thesis.

4.4 Edge caching Challenges

Researchers have been studied several issues related to edge caching. Three main question which should be answered clearly is:

1. Where to cache? (cache placement)

2. What to cache? (content popularity)
3. How to cache? (caching policy)

A detailed explanation of each question is provided below.

4.4.1 Cache Placement

To answer this question first we must consider the feasibility of caching in a different location. Three possible places to cache data are the core network, BS, and cellular users. Although contents can be cached in each of these places, the scope of this chapter is to cache contents at the BS due to several advantage it brings to the network. Caching at the BS can be further classified into two subgroups which are: cell caching and small cell caching.

Generally, content can be cached proactively or reactively. Proactive caching refers to the techniques in which the cache entity tries to store popular data based on historical information during the off-peak period and periodically repeat this placement. Many algorithms have been proposed to optimize cache placement with different objectives outlined in [64] [65] [66] [67]. On the other hand, in reactive caching, content will be cached irrespective of historical data. One of the important reactive caching strategies is “Leave a Copy Everywhere” (LCE) which leaves a copy of the content in every node that the content may pass to reach the end user which obviously generate significant redundancy issue. To solve redundancy issue, some efforts have been made to cache the content only in a subset of nodes in the delivery path such as “Leave Copy Down” (LCD) and “Cache Less for More”.

Proactive caching has more complex mechanism but allows users to reach higher QoE. Providing new caching mechanism comes at the cost of less robustness to the change in users incoming traffic where any random request pattern leads to lower cache hit until the caching entity updates itself. Secondly, proactive caching requires historical data from the core network and content provider which may be hard to obtain due to the fact that these two are separate networks.

Cell Caching: According to [68] caching at the cell results in a higher cache hit due to the fact that a cell has more coverage and includes more number of users. Gu *et* al in [69] provided a mathematical formulation of multicell caching which turns to become NP-hard, so they have come up with a heuristic method to solve it.

Small Cell Caching: In the next generation of mobile networks, each cell consists of multiple small cells because of the dense deployment of users. Therefore, caching at the edge can be further pushed forward to the small cell BSs which is widely investigated in [70] [71] [72] [73] [74].

4.4.2 Content Popularity

The most important problem that should be addressed in order to maximize caching efficiency is the popularity of each content in the cell. there are two main models that are considered in the literature: static and dynamic models

Static Models: Most often researchers use static models in the literature due to the fact that it can be formulated easily. One of the most popular models is Zipf Law [75] which considers requests of each user is an independent Poisson Process with a variable parameter which follows the power law. This model works well for many scenarios unless we have a fast-changing environment. In that case, we can assume the model parameter will be updated frequently to model the changing environment which will be discussed in the next chapter of this thesis.

Dynamic models: The time-varying characteristics of content popularity cannot be reflected by using static models. Recently, Shot Noise Model (SNM) has been introduced in [76] as a dynamic model for content popularity which utilizes two parameters of Dirac function to model each content’s popularity: length of each Delta function illustrates the life span of each content and the heights shows the instantaneous popularity. One example of dynamic content popularity is provided in [77] where the author demonstrated through simulation that SNM model can model video contents in a dynamic environment well.

4.4.3 Caching policy

There are various caching policies developed by researchers. Some of them tried to use a modified version of caching policies in the core network at the edge, while others trying to exploit recent advances in machine learning algorithms in order to come up with new caching policies. Below a taxonomy of caching policies at the wireless edge has been provided.

Table 4: Caching Policy Taxonomy

Work Area	Reference	Focus
Conventional Caching Policies	[78] [79]	Least Frequency Used (LFU) Least Recently Used (LRU) Most Popular Video (MPV)
User Based Policies	[80]	Local popularity
Learning-Based Policies	[81] [82]	Utilizing reinforcement learning Q-learning caching
Non-cooperative Caching	[80] [82]	Single cell caching scenario Markov decision process modeling
Cooperative Caching	[83] [84] [85] [86] [74] [87]	Cooperative policy among different BSs Bandwidth efficiency Joint caching and routing design

4.4.3.1 Conventional Caching Policy

Traditional methods such as LRU and LFU which have been used in the core network caching were adopted by [78] [79] in order to come up with an edge caching policy. Authors in [79] derived a closed form for cache hit ratio per content. Since the previous method for analyzing multi-content caching are time-consuming, the proposed method can be efficiently used to analyze multiple caches. Although conventional caching policies are simple, they are highly dependent on the size of the content. To this end, researchers utilize MPV policy in order to cache video content based on global distribution [80].

4.4.3.2 Learning-Based Policies

Learning policies let the caching entity to track changes in the local content popularity and try to predict future request in order proactively cache contents. To deal with unknown popularity, the BS should be able to predict the most popular contents and cache them accordingly. Popularity prediction is a well-known problem in many real-world sentiment classification problems such as predicting the popularity of a product or a movie. Researchers have been utilizing recent advances in machine learning to tackle the prediction problems as outlined in [88] [89] [90] [91] [92]. Authors in [88] have proposed a caching policy for video contents using Moving Average (MA) filter and Auto Regression, based on past observation of requests for the individual video. They have shown that AR model works better than MA in predicting popularity and provides more accurate results. Multi-arm bandit technique has been widely used in the literature to address the prediction of the popularity issue by caching entity. The method used in [89] increases cache hit by 14% by exploiting past data and taking into account user's specific context such as personal characteristic in order to let proposed model learn context-specific popularity. The authors have shown that utilizing context information may result in a better caching performance. To generalize caching scheme further, multicell caching has been considered in [90]. Based on the assumption that the content sharing among BSs provides better QoE, multi-arm bandit algorithm has been used to predict the most popular data in each cell. In order to reduce the complexity, the multicell formulation has been changed to several single cell formulations with acceptable performance in the simulation. The drawback in this proposed scheme is the assumption of stable popularity. Small cell popularity prediction based on user's instantaneous demand, has been discussed in [91]. The authors in [91] have shown that the number of users, number of files, and distribution skewness have a significant effect on the performance of any proposed algorithm. In [92], Gue *et* al claimed that prior knowledge of cached data would make an incentive for users to request those contents in order to get higher data rate and reduced latency. To further push users, to request cached contents more than the other contents, a concept of recommendation has been introduced assuming that the content popularity is unknown but stable. They have exploited the Q-learning formulation to learn user-arrival behavior to maximize average long-term reward. Most of the previous works considered stable content popularity which is not always the case. In the next chapter, we propose a robust Markov Decision Process (MDP) based caching policy optimization algorithm by learning unknown content popularity distribution

4.4.3.3 User-Based Policies

determine user-specific content popularity can significantly improve cache hit. In [80], it can be observed that user-specific preferences are different with global popularity distribution for a video content so that it may lead to a better performance in terms of cache utilization and decrease traffic in the core network.

4.4.3.4 Non-Cooperative Caching Policies

Due to users' random behavior, content needs among users can be less correlated among different cells. In [82], caching policy is modeled as a Q-learning algorithm in order to intelligently cache most popular contents. The authors demonstrated that this method can work better than conventional methods such as LRU and LFU.

4.4.3.5 Cooperative Caching Policies

It can be shown that content popularity among users in the neighboring cells is somewhat correlated, so one can use this correlation in favor of increasing caching efficiency in a cell. In [67], light-weight cooperative cache management algorithms aimed at maximizing the traffic volume served from cache and minimizing the bandwidth cost is proposed and demonstrated through simulation that the proposed scheme works in a guaranteed distance from optimal policy even in worst case scenario. While in [84], they developed the optimal cooperative content caching and delivery policy, for which BSs and cellular users are all engaged in local content caching. The caching problem is formulated as an integer linear programming problem and use hierarchical primal-dual decomposition method to decouple the problem into two-level optimization problems, which are solved by using the sub-gradient method. Simulation results have shown that cooperation among small BSc can result in performance improvement. Wang *et* al in [85] proposed a distributed caching scheme considering the tradeoff between the diversity and redundancy of BSs' cached contents. Their goal was to minimize the transmission cost both in RAN and core network, therefore the caching policy is formulated as an optimal redundancy caching problem. Results show that the optimal redundancy ratio is mainly influenced by two parameters, which are the core network to RAN unit cost ratio and the skewness of file popularity distribution. Under typical file request pattern, the reduction amount can be up to 57%. Cooperation among users and BS is investigated in [86].

4.5 Chapter summary

In this chapter, we have discussed a fundamental technique to provide better QoE for users by reducing traffic in the core network and request latency. We have discussed that caching can be done both in the core network and the edge. The edge caching technique refers to leave a copy of most popular contents at the BS to better serve users. In order to implement edge caching, three main questions must be answered in order reach optimal caching policy. Those there are what, where and how to cache contents. In each section, we provided a description and brief literature review on existing methods for each challenge and provided comprehensive taxonomy on content popularity models which are the main focus of second part of this thesis. Lastly, we outlined the problem that should be solved which is learning content popularity in a fast-changing environment. In the next chapter, we propose a robust approach to learn content popularity in order to come up with an efficient caching policy at the edge.

Chapter 5

5 Robust Edge Caching Based on Unstable Popularity Distribution Learning Using MDP

5.1 Abstract

Proactive caching in wireless edge network has been proposed as a promising approach to reduce traffic burden in the core network. Neighboring devices in the same cell with similar content needs can benefit from edge caching performance. However, unknown content popularity distribution may lead to ineffective caching. In order to overcome this difficulty, an efficient learning algorithm is proposed to accurately predict local content popularity among neighboring users in a cell, based on Markov Decision Process (MDP). A single cell scenario consisting of multiple users has been formulated as a Markov Process in which the reward received by the base station (BS) is determined depending on the cached contents and user requests. To tackle this changing environment, two new parameters used in MDP have been introduced and optimized. It has been demonstrated that the proposed caching scheme using the proposed popularity prediction outperforms random caching and history caching schemes in terms of the number of requests for accessing the core network. Additionally, simulation results confirm that the proposed scheme works better than the other schemes in the case of unstable content popularity. Finally, the effect of two newly introduced parameters on the learning rate has been investigated through simulation.

5.2 Introduction

Rapidly growing demand for data, which stems from increasing number of connected devices, has been imposing a significant amount of latency due to the increasing traffic in the core networks. To cope with the demand-explosion and provide a better quality of experience (QoE), edge caching has been proposed recently as a solution in 5G networks to bring multimedia contents (especially large contents like video) closer to the users in order to offload the traffic of the backhaul. Since users in the same cell may share similar interest regarding content needs, by saving the copies of most popular contents at the base station (BS), traffic imposed to the core network can be reduced, also users might be served at a faster rate in the cell. According to [1], video contents will be responsible for over 82% of traffic by 2021. Now that the content popularity in a specific cell is unknown and unstable due to users' random movement, the problem that should be addressed is how to know which content should be cached. To deal with unknown popularity, the BS should be able to predict the most popular contents and cache them accordingly. Popularity prediction is a well-known problem in many real-world sentiment classification problems such as predicting the popularity of a product or a movie. Researchers have been utilizing recent advances in machine learning to tackle the prediction problems.

Most of the previous works considered stable content popularity which is not always the case. In this section, we propose a robust Markov Decision Process (MDP) based caching policy optimization algorithm by learning unknown content popularity distribution. In order to make the proposed algorithm robust to the changing environment and make it more efficient to track the change in the popularity, two new parameters have been introduced, and these are *Remember-Value* and *Step-Effect*, which will be defined later. these two additional parameters have been exploited to control the effect of noisy

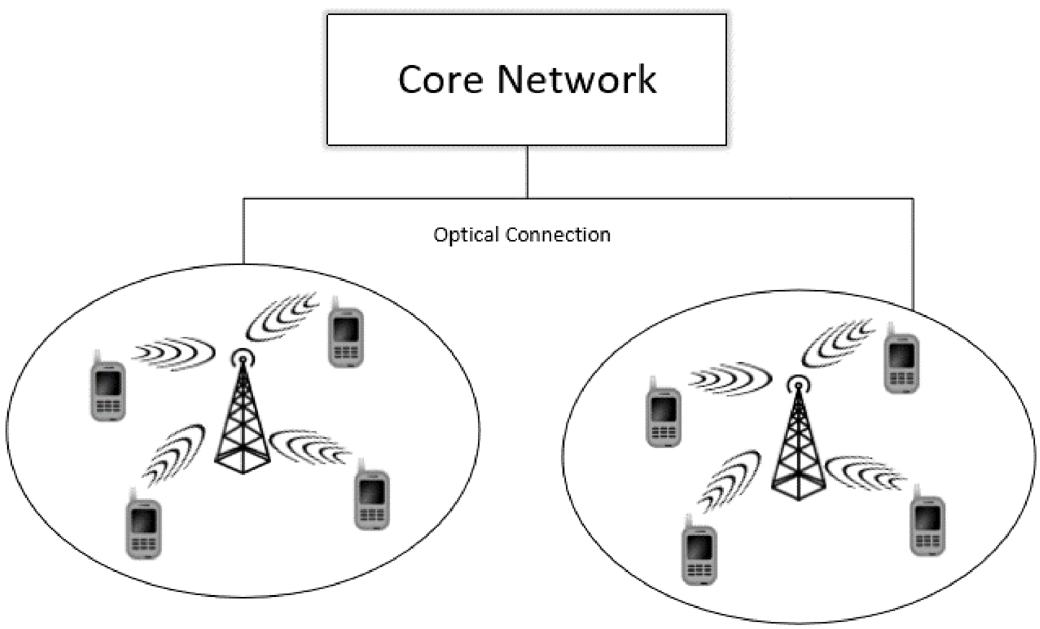


Figure 14: Connection Among Multiple Cells and Core Network via Fiber Optics

requests that are coming from the users and the learning rate. The rest of this section is organized as follows: in section 5.3 content popularity distribution is discussed and the mathematical formulation for the caching policy is proposed. In addition, section 5.3.2 provides a brief introduction to MDP. In section 5.4 the algorithm is proposed to learn how to predict popularity distribution in order to come up with an efficient caching policy. Finally, simulation results and conclusion are provided in sections 5.5 and 5.6, respectively.

5.3 System Model

We consider a single cell scenario with multiple numbers of users randomly requesting multimedia contents from the BS to analyze the performance of the proposed content popularity learning and to come up with a robust caching policy. The BS is connected to the core network via fiber optic, and any user can request the contents at any time. We consider that a set $F = \{f_1, f_2, ..., f_D\}$ is all contents that are available in the core network. According to [93], the correlation among requests which is content popularity follows *Zipf* Law, which means the probability of requesting any content with rank k in the cell is the following:

$$f(k) = \frac{\frac{1}{k^s}}{\sum_{i=1}^{D}(\frac{1}{i^s})} \tag{5.1}$$

where:

- D is the total number of files in set F
- k is the content rank
- s is the skewness of the distribution

The content popularity distribution describes the popularity of each content in the cell, which is directly related to users' preference, and can be obtained by the expression below:

$$f(k)=\lim_{T\to\infty}\frac{\sum_{\tau=1}^{T}N(\tau,k)}{\sum_{k=1}^{D}\sum_{\tau=1}^{T}N(\tau,\mathrm{k})} \tag{5.2}$$

Where *N(τ,i)* is the number of requests for content *i* in time slot *τ*. Depending on whether a specific content has been previously cached or not, two situations can happen after a user makes a request for a content. Firstly, if the requested content is not cached by the BS, it needs to be requested from the core network, which in turn will increase the core network traffic as well as the delay. Secondly, if the requested content already been cached, it will be delivered to the requesting user by the BS, which in turn enhance QoE.

5.3.1 Problem Formulation

We aim to design a learning mechanism in order to let BS intelligently predict and cache most popular contents based on content-requests made by different users randomly. We have formulated caching policy as an MDP process and defined reward function so that when a user requests for a specific content, the BS gets a reward based on whether it cached that specific content earlier or not. The performance of the proposed technique is highly dependent on how we utilize incoming data per content and predict the popularity of that content. By maximizing the long-term reward, the caching policy optimization can be formulated as:

$$\max E[\sum_{\tau=1}^{T}\sum_{i=1}^{D}N(\tau,i)\delta_{c,\mathrm{i}}(\tau)] \tag{5.3}$$

Where:

$$\delta_{c,i}(\tau)=\begin{cases}1 & i\in C\\ 0 & i\notin C\end{cases} \tag{5.4}$$

In the above formulation *C* is the cached contents in time slot *τ*, *N(τ,i)* is the number of requests for content *i* in time slot *τ*, *T* is the total number of time slots and *D* is the total number of contents in set *F*. BS expected long-term reward function, shown in equation (5.3) needs to be maximized by optimizing parameter (5.4). In other words, the BS gets the reward if it caches the requested contents, and this reward is equal to the number of requests of those specific contents. In order to solve the above optimization problem, we have to find the binary parameter $\delta_{c,i}(\tau)$, which shows whether content *i* is cached or not. The problem of predicting a parameter based on the real-time stream of data is in the category of online learning. In online Learning method, the agent tries to learn a pattern or a parameter without having labeled dataset unlike the case of supervised learning. The agent should interact with the environment and actively optimize its future action to reach the objective. One of the main elements in modeling a learning environment is MDP which will be briefly introduced in the next section.

5.3.2 Markov Decision Process

Markov Decision Process is a well-known framework to model decision-making problems in a random environment [94]. Each MDP can be defined by 4 elements:

- *S*: a finite set of states $S = \{s_1, s_2, \ldots\}$
- *A*: a set of actions the agent can take in each state
- $P_a(s', s)$: the probability of arriving to state s' from state *s* by taking action a
- $R_a(s', s)$: the reward the agent gets after transition from state s' to state *s* under action *a*.

The goal of MDP is to determine a set of actions $\pi(s)$ which indicates the proper action that should be taken in each state *s*, so by following π, the agent can maximize the reward.

5.3.3 Formulation of Popularity Prediction in the MDP Framework

In this section caching policy optimization problem is formulated as an MDP process. We define four parameters of MDP as follows:

$$S = \{1,2,3, \dots, T\} \tag{5.5}$$

$$A = \{All\ Combinations\ of\ size\ M\ of\ elements\ in\ F\} \tag{5.6}$$

$$P_a(s, s') = \begin{cases} 1 & s' = s+1 \\ 0 & s' \neq s+1 \end{cases} \rightarrow \tag{5.7}$$

$$\begin{bmatrix} 0 & 1 & 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 1 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$R_a(s, s') = \begin{cases} \sum_{i=1}^{D} N(\tau, i)\, \delta_{c,i}(\tau) & s' = s+1 \\ 0 & s' \neq s+1 \end{cases} \tag{5.8}$$

- In equation (5.5), set S includes all the available time-slots where each time-slot represents one state.

- As defined in equation (5.6), set F contains all the contents of the core network. In each time-slot (state) the BS saves M number of contents from F, so each action $a \in A$ chooses which contents to cache. Cached contents could be any combination of existing contents in F.

- By taking into account that the states are time-slots, $P_a(s',s)$ in equation (5.7) has been defined irrespective of action a. Figure 15 illustrates the transition matrix.

- As shown in optimization problem 5.3, reward function is the number of requests of cached contents in each time slot that can be formulated as $N(\tau,i)\delta_{c,i}(\tau)$.

Now the requesting procedure should be observed closely in order to predict content popularity so as to choose efficient caching policy. As discussed in 5.3, content popularity follows Zipf Law but it is unknown to the BS. Users request content based on *i.i.d* distribution in each time-slot. The goal is to capture the contents that are going to be requested most often and try to cache them. Since the requests are probabilistic, the BS needs to capture the effect of each time-slot in order to accurately predict the popularity and reduce the effect of noisy request on the final prediction. To do so, two parameters,

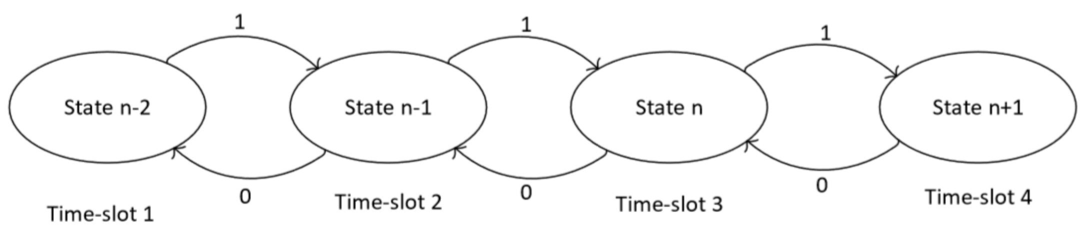


Figure 15: Transition Probability- in each time-slot (state), the probability of reaching the next time slot is 1 irrespective of what action is taken

the *Remember-Value* α, and the *Step-Effect* β are introduced. The *Remember-Value* determines the amount of information the BS should keep from previous steps. For instance, lower *Remember-Value* for BS results in shorter memory, which means the BS just remembers the effects of few steps back. In contrast, higher *Remember-Value* means longer memory for the BS. By tuning α, the robustness of the algorithm to the noisy effects can be determined. If users arrive in a cell more frequently, thus content popularity distribution changes faster, and in this case, α should be lower. On the other hand, in a slowly changing environment, the BS can exploit the information from several previous steps, resulting in higher α value. *Step-Effect* β determines how fast the algorithm can reach the optimal value. Smaller β value results in slower content popularity learning, and in this case, the BS should wait for more number of time-slots to find out which contents are a better candidate to be saved in BS memory, whereas larger β may result in faster learning. We start by writing $R(\tau)$ as a reward of BS in each time slot:

$$R(\tau) = \sum_{i=1}^{D} N(\tau)\Delta^{T}(\tau) \tag{5.9}$$

where $N(\tau)$ is the number of requests per content in time slot τ and $\Delta(\tau)$ is a matrix containing caching policy of $\delta(\tau,i)$ in each time slot. by assuming that we know the optimal policy $Y(\tau)$ we can find the loss function $J(\tau)$ of our caching policy in order to estimate how well we have predicted the popularity distribution. The loss function is defined as:

$$J(\tau) = \frac{1}{2}[R(\tau) - Y(\tau)]^2 \tag{5.10}$$

In order to minimize $J(\tau)$ we use gradient descent method with respect to variable Δ as outlined below:

$$\min \quad J(\tau): \frac{\partial J}{\partial \Delta} = N[R - Y] \Rightarrow \tag{5.11}$$

$$\Delta(\tau + 1) = \Delta(\tau) - k\frac{\partial J}{\partial \Delta} \tag{5.12}$$

$$k = \alpha^{\beta} \tag{5.13}$$

In the next time-slot, we update the caching policy with respect to the gradient $\partial J/ \partial\Delta$ and variable k which has been defined in equation (5.13) based on *Step-Effect* and *Remember-Value* parameter.

5.4 Caching Policy Optimization Algorithm

In the algorithm presented below, the BS initializes the cache memory of size M with random cached contents, in line 1-3. In each time-slot, users request for contents randomly, and these data items are collected and stored in the *Request array* (line 5). Then the first M most requested contents are selected as a candidate to be cached in the time slot τ. In line 7-8 the consistency of candidates with previous cached contents is checked to see whether they were previously cached or not. Since requests are generated randomly by users, there is a possibility that the most requested contents in current time-slot are not the most popular ones, so care must be taken to avoid noisy requests. In order to do so in line 9, cache probability of each content in the *Cached* will be updated so that popular contents' probability will be increased, this is how we capture the effect of each time-slot and propose caching policy based on content popularity prediction. The more time-slot we wait, the more accurate prediction we get. In line 10 the *Update* step is increased to help faster convergence of the algorithm. Finally caching policy is returned in line 13.

Algorithm 1 Optimizing BS caching policy based on content popularity learning at the BS with cache size M

1: *initialize the caching array, Cached, to uniformly random caching for all contents*
2: *initialize the request array, Request, to zero*
3: *initialize the $Candidate$ array to zero and parameter $Update$ to zero*
4: **while** Until reach the last time-slot **do**
5:     $Request \leftarrow$ number of requests received for each content in the time slot τ
6:     $Candidate \leftarrow$ *first M most requested contents*
7:     **for** each content in Candidate **do**
8:         **if** content $\notin$ First M highest caching probability in $Cached$ **then**
9:             $cached_i \leftarrow cached_i * \alpha^{Update}$
10:             $Update \leftarrow Update + \beta$
11:         **end if**
12:     **end for**
13:     **return** $Cached$ as final caching policy
14: **end while**

Figure 16: Algorithm 3

5.5 Simulation Results

Simulation parameters are listed in **Error! Reference source not found.**. In this case, a s ingle cell scenario has been considered where multiple users are trying to request contents from the BS. The BS is connected to the core network via the optical connection and equipped with a cache memory of size *M* to save popular data to decrease request delay. The core network has a library of *D* number of data items and users can request any of those items according to *i.i.d*. distribution. Content popularity follows Zipf Law with parameter s. For comparison purpose, in generating all the graphs, the optimal caching policy has been considered to set the upper bound. Optimal caching policy refers to the scenario when the popularity is known at the base station so in each time-slot the contents with the highest popularity will be cached. It is worth noting that, in a realistic environment, it is not possible to achieve this optimal scenario.

Table 5: Simulation Results

Cell Radius	500 m
Number of Users	100
Number of Time-slots (T)	1000 time-slots
Number of contents in library F	20
Step-Effect (β)	1, 2.5, 5
cache memory size (M)	5
Remember-Value (α)	0.1, 0.5, 0.9
Content popularity distribution skewness (s)	0.8

5.5.1 Expected Value of BS reward

In Figure 17 different caching policies are compared through simulation with the assumption that the popularity is unknown but stable. In random caching policy, the BS caches random contents irrespective of user's requests, resulting in a poor performance. In history caching, the BS looks at previous step's requests and cache the most requested contents. Although this policy shows improvement through time, it does not consider the effect of random requests in each time-slot. Note that the assumption of stable content popularity distribution in this environment is for overall time-slots so each time-slot does not necessarily follow the overall distribution in the cell. As shown in Figure 17, the proposed policy based on popularity prediction outperforms history and random caching due to the fact that it keeps valuable information from previous steps to increase the prediction accuracy.

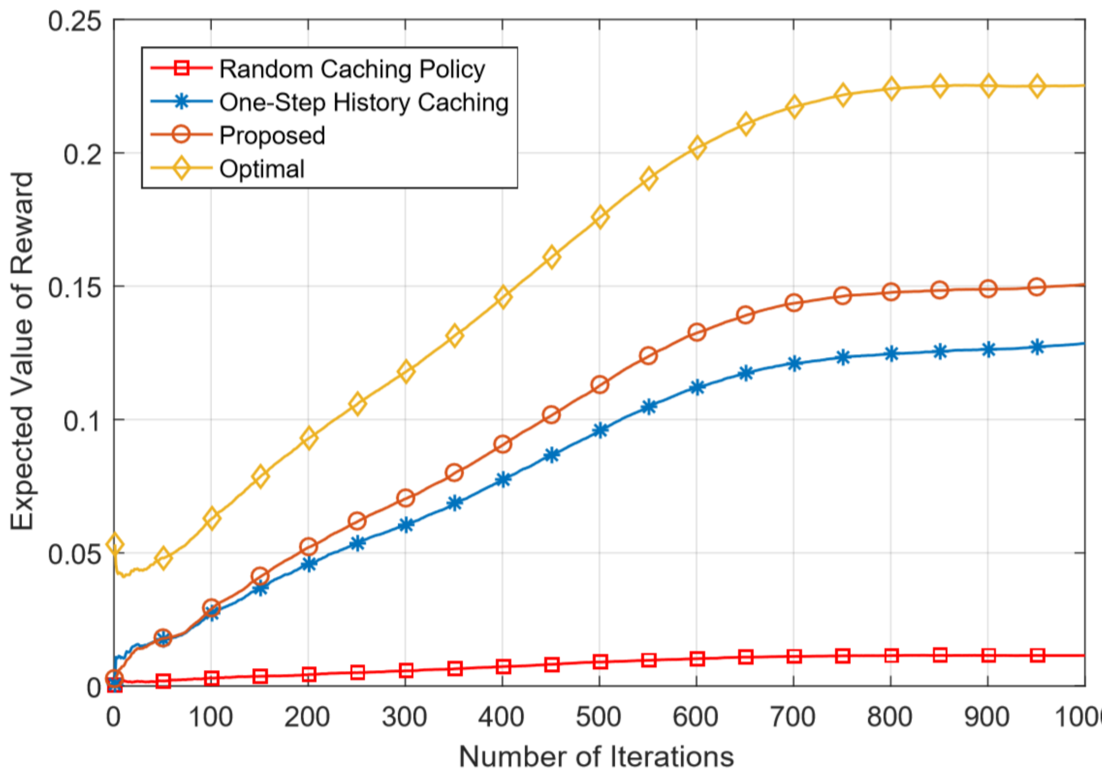


Figure 17: Comparison of Different Caching Policy

5.5.2 Effect of Remember-Value on the Expected Value of Reward

In Figure 18 the effect of different *Remember-Values* on the expected value of the reward has been shown. It can be inferred that higher *Remember-Value* corresponds to higher expected reward. But it is important to note that, increasing *Remember-Value* in a slow changing environment only, will result in this benefit because in this case, the algorithm keeps information from more previous steps. However, in a fast-changing environment higher *Remember-Value* results in performance degradation.

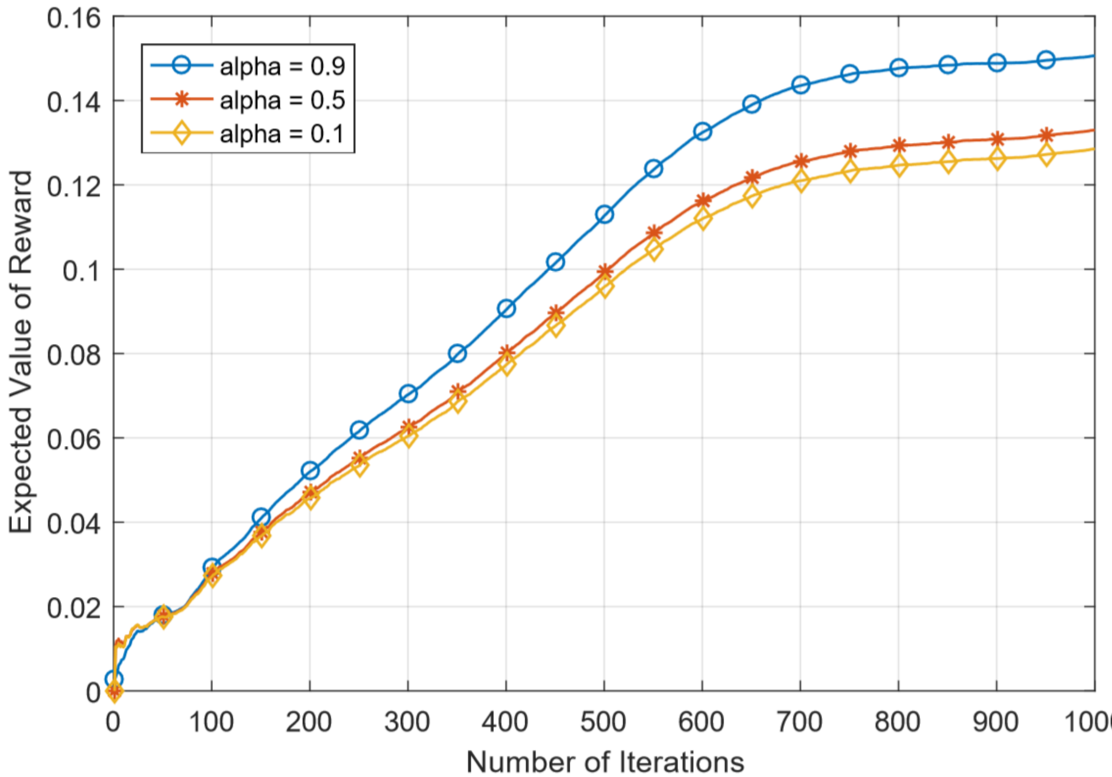


Figure 18: Effects of Popularity Change During Learning Process

5.5.3 Effect of Popularity Change

In generating Figure 19, the assumption of popularity stability has been relaxed to analyze the performance of the proposed algorithm in a fast-changing environment. In this case, it will be much harder for the learning algorithm to track the popularity change and adapt itself. It is demonstrated in this figure the proposed caching policy works better than random and history caching because of the introduction of the *Remember-Value* and *Step-Effect* parameters that control the robustness of the proposed scheme.

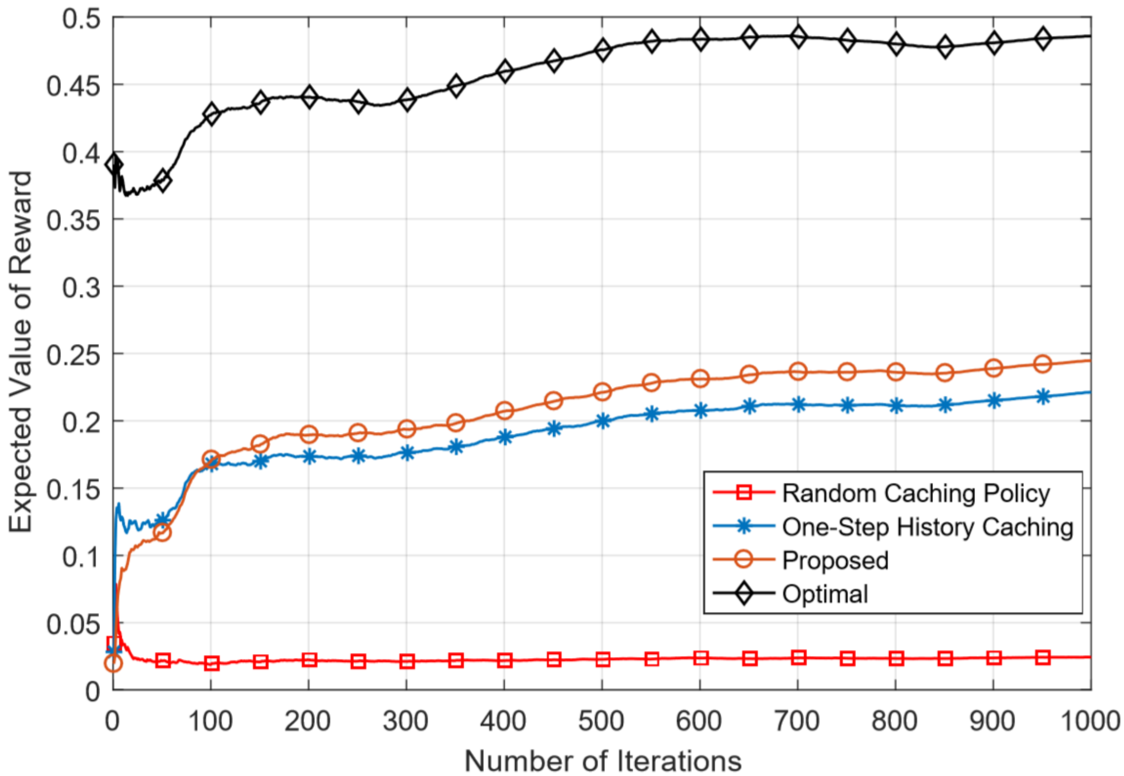


Figure 19: The Effect of Remember-Value on the Expected Value of Reward

5.5.4 Effect of Step-Effect parameter on the Learning Rate

In Figure 20 the effect of the *Step-Effect* parameter on the learning rate has been demonstrated. As discussed in section 5.3, the higher *Step-Effect* value contributes to faster learning when the popularity is constant. It can be shown that by increasing the *Step-Effect*, the algorithm approaches the final value much faster. The drawback of increasing the *Step-Effect* value is that it will dampen the effect of *Remember-Value* in the long run, so joint optimization of these two parameters is needed.

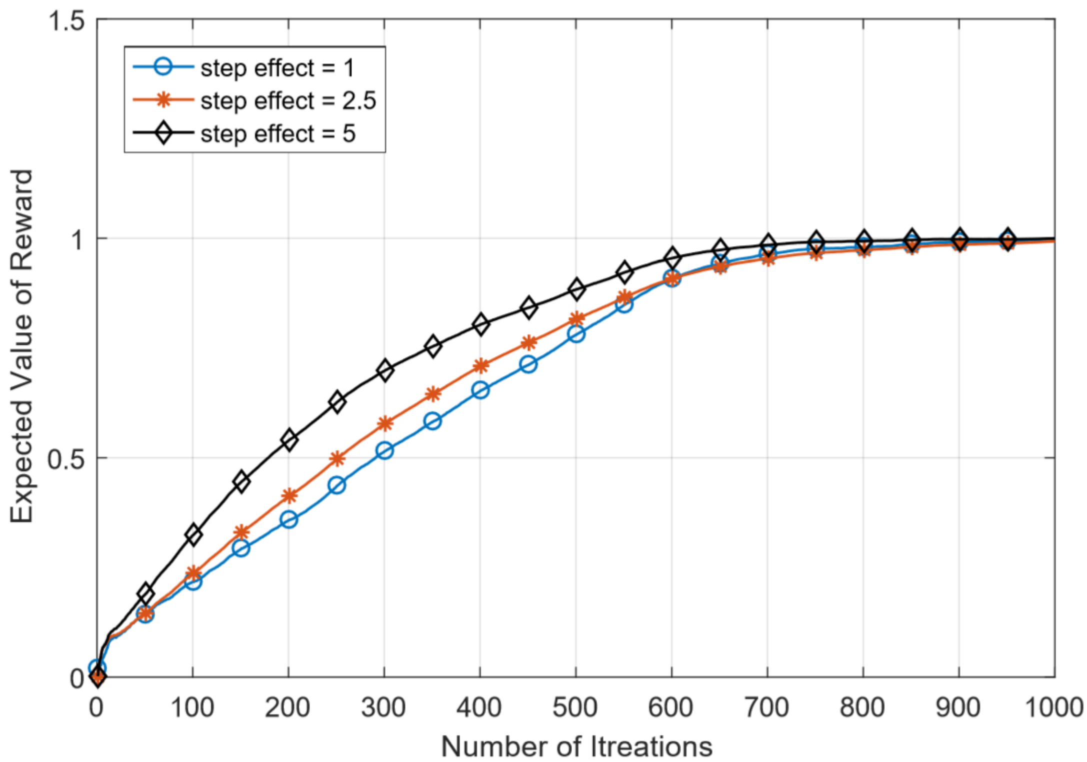


Figure 20: Effects of Step-Effect Parameter on the Learning Rate

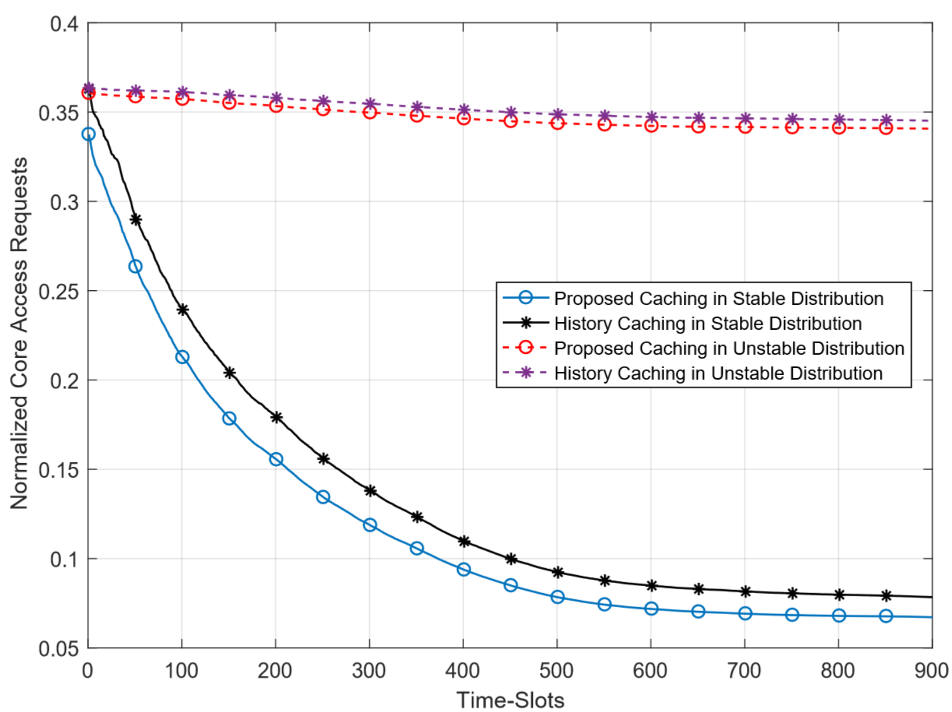


Figure 21: Effects of Proposed Caching Policy on the Core Network Traffic

5.5.5 Core Network Access Requests

As discussed previously, if the BS caches popular contents, it will enhance users' QoE significantly. In Figure 21 we have provided the normalized number of core access requests in both stable and unstable popularity in order to illustrate how caching will affect the traffic in the core network. It is shown through simulation that the proposed scheme works better than caching based on the previous step, so it will decrease the traffic in the backhaul by keeping the copies of popular contents at the BS rather than the core network to serve the users better.

5.6 Conclusion

In this section, we have proposed caching policy optimization method by predicting content popularity using MDP framework. Parameters α and β have been introduced in order to make the algorithm able to track changing environment as well as keeping useful information from previous steps and avoid noisy request. The problem is formulated as maximizing the long-term reward for the BS by observing number of requests per content in each time-slot. Simulation results show a significant performance improvement of the proposed algorithm in comparison to random caching and history caching in terms of the number of access requests to the core network which result in a great decrease in the backhaul traffic. Moreover, it has been demonstrated that by changing the *Remember-Value* α, the robustness of the algorithm can be adjusted. In a fast-changing environment where popularity changes frequently, the proposed algorithm outperforms the other two schemes. Lastly, it has been demonstrated through simulation that the convergence of the algorithm can be controlled by the *Step Effect*.

Chapter 6

6 Conclusion and Future Works

In this thesis, we investigated two promising solutions to the data traffic management in the core network which is Device-to-Device Communication and Edge Caching. Since the number of connected devices is increasing, introducing new content delivery paradigms is vital for the future generation of mobile networks.

The first focus of this thesis is on managing interference among shared users while maintaining minimum throughput threshold. We have formulated maximizing throughput by considering single cell scenario which consists of multiple cellular users and D2D pairs with Rayleigh fading channel. To further decrease communication overhead, distributed allocation mechanism has been utilized to match between D2D users and the farthest cellular user in order to minimize interference. Since application-level plays an important role in requesting content, we have taken into account application-level requirements to guarantee QoE threshold and increase the chance of getting spectrum through introducing delay-tolerant request. finally, extensive simulation results have shown significant performance improvement in term of system sum-rate by using proposed scheme.

The second focus of this is on deploying caching at the edge of the network in order to bring contents closer to the users. Since video contents are responsible for major part of the data request and this is directly related to user preference, knowing users behavior is vital in order to cache efficiently. User preference is unknown to the caching entity at the edge which is BS, we have proposed a robust mechanism in order to learn content popularity distribution to increase the cache hit and decrease core network access requests. By observing past request pattern, BS can predict incoming data stream and cache them in advance. Through simulation, we have shown that the proposed learning scheme will significantly decrease traffic in the backhaul and increase cache hit. The assumption of stable content popularity has been relaxed to show that the proposed algorithm can achieve acceptable performance in a fast-changing environment.

For future works, we aim to focus on combining caching at the edge with D2D communication and utilizing social ties between users in the cell to further push caching from the edge to the users.

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Curriculum Vitae

Name:	Hessam Yousefi
Post-secondary Education and Degrees:	Sharif University of Technology Tehran, Iran 2012-2016 B.S. The University of Western Ontario London, Ontario, Canada 2016-2018 M.E.Sc
Honours and Awards:	Western Graduate Scholarship 2016-2018 Western Tuition Fee Scholarship 2016-2018
Related Work Experience	Teaching Assistant The University of Western Ontario 2016-2018

Publications:

H. Yousefi, Q. Rahman and X. Wang, "Delay-Tolerant Resource Allocation for D2D Communication Using Matching Theory," *2017 IEEE 86th Vehicular Technology Conference (VTC-Fall),* Toronto, ON, 2017, pp. 1-6.

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