Federated Learning Framework for Content Caching in D2D Wireless Networks

By

Nimra Mubeen

(Registration No: 00000363024)

Department of Electrical Engineering

A thesis submitted in partial fulfillment of the requirements for the degree of Masters in Electrical Engineering (MSEE)

In

Military College of Signals (MCS)

National University of Sciences and Technology (NUST)

Islamabad, Pakistan

December 2024

THESIS ACCEPTANCE CERTIFICATE

Certified that final copy of MS thesis written by Ms. **NS Nimra Mubeen,** Registration No. **00000363024** of **Military College of Signals** has been vetted by undersigned, found complete in all respect as per NUST Statutes/Regulations, is free of plagiarism, errors and mistakes and is accepted as partial, fulfillment for award of MS/MPhil degree. It is further certified that necessary amendments as pointed out by GEC members of the student have been also incorporated in the said thesis.

Signature: ______________

Name of Supervisor **Asst Prof Abdul Wakeel, PhD**

Date: 23/12/2024

Signature (HoD): ______________

Date: 23/12/2024

Signature (Dean): ______________
Dean, MCS (NUST)
(Adil Masood Siddiqui, PhD)

Date: 23/12/2024

Form TH-4

NATIONAL UNIVERSITY OF SCIENCES & TECHNOLOGY

MASTER THESIS WORK

We hereby recommend that the thesis prepared under our supervision by **NS Nimra Mubeen, MSEE-27 Course** Regn No **00000363024** Titled: **"Federated Learning Framework for Content Caching in D2D Wireless Networks"** be accepted in partial fulfillment of the requirements for the award of **MS Electrical Engineering** degree.

Examination Committee Members

1. **Brig Faisal Akram, PhD** Signature: ____________

2. **Assoc Prof Muhammad Imran, PhD** Signature: ____________

Co-Supervisor: **Assoc Prof Ayaz Ahmad, PhD** Signature: ____________

Supervisor: **Asst Prof Abdul Wakeel, PhD** Signature: ____________

Date: 23/12/2024

____
Head of Department

23/12/2024
Date

COUNTERSIGNED

Date: 23/12/2024

Brig
Dean, MCS (NUST)
(Adil Masood Siddiqui, PhD)
____
Dean

CERTIFICATE OF APPROVAL

This is to certify that the research work presented in this thesis, entitled "**Federated Learning Framework for Content Caching in D2D Wireless Networks**" was conducted by **NS Nimra Mubeen** under the supervision of **Asst Prof Abdul Wakeel, PhD**. No part of this thesis has been submitted anywhere else for any other degree. This thesis is submitted to **Military College of Signals, National University of Sciences and Technology - Electrical Engineering Department** in partial fulfillment of the requirements for the degree of Master of Science in Field of **Electrical Engineering** Department of Electrical Engineering, National University of Sciences and Technology, Islamabad.

Student Name: **NS Nimra Mubeen** Signature: Nimra.M

Examination Committee

a) GEC Examiner 1: **Brig Faisal Akram, PhD** Signature: Faisal

b) GEC Examiner 2: **Assoc Prof Muhammad Imran, PhD** Signature:

Name of Co-Supervisor: **Assoc Prof Ayaz Ahmad, PhD** Signature:

Name of Supervisor: **Asst Prof Abdul Wakeel, PhD** Signature:

Name of Dean/HOD: **Brig Adil Masood Siddiqui, PhD** Signature:

Brig
Dean, MCS (NUST)
(Adil Masood Siddiqui, PhD)

AUTHOR'S DECLARATION

I, **NS Nimra Mubeen** hereby state that my MS thesis titled "**Federated Learning Framework for Content Caching in D2D Wireless Networks**" is my own work and has not been submitted previously by me for taking any degree from National University of Sciences and Technology, Islamabad or anywhere else in the country/ world. At any time if my statement is found to be incorrect even after I graduate, the university has the right to withdraw my MS degree.

Student Signature: Nimra.M

Name: **NS Nimra Mubeen**

Date: Dec, 3rd 2024

PLAGIARISM UNDERTAKING

I solemnly declare that research work presented in the thesis titled "**Federated Learning Framework for Content Caching in D2D Wireless Networks**" is solely my research work with no significant contribution from any other person. Small contribution/ help wherever taken has been duly acknowledged and that complete thesis has been written by me.

I understand the zero tolerance policy of the HEC and National University of Sciences and Technology (NUST), Islamabad towards plagiarism. Therefore, I as an author of the above titled thesis declare that no portion of my thesis has been plagiarized and any material used as reference is properly referred/cited.

I undertake that if I am found guilty of any formal plagiarism in the above titled thesis even after award of MS degree, the University reserves the rights to withdraw/revoke my MS degree and that HEC and NUST, Islamabad has the right to publish my name on the HEC/University website on which names of students are placed who submitted plagiarized thesis.

Student Signature: Nimra-M

Name: **NS Nimra Mubeen**

Date: Dec, 3rd 2024

DEDICATION

This thesis is dedicated to

MY BELOVED FAMILY, HONORABLE TEACHERS

AND DEAR FRIENDS,

for their invaluable support and encouragement.

ACKNOWLEDGEMENTS

I extend my sincere gratitude to the Almighty, whose blessings have guided me through the successful completion of this research endeavor. My heartfelt thanks go to my esteemed supervisors, Assistant Professor Abdul Wakeel, PhD, and Associate Professor Ayaz Ahmad, PhD, whose unwavering support and guidance were instrumental in accomplishing my MS Degree. Their constant availability for mentorship and assistance significantly enriched my academic journey.

I am also grateful for the support and valuable suggestions generously offered by Brig. Faisal Akram, PhD and Assoc Prof Muhammad Imran, PhD, which greatly enhanced the quality of my research work.

Last but not least, I would like to express my deepest appreciation to my parents for their enduring care, love, and unwavering support throughout my pursuit of a master's degree. Their encouragement has been a source of strength and motivation in this academic endeavor.

Abstract

Caching in device-to-device (D2D) communication networks is complicated due to the dynamic and unpredictable nature of wireless environments. Limited bandwidth, high latency, and disruptions make effective content caching and timely user request fulfillment challenging in D2D wireless networks. This manuscript proposes a federated learning framework for edge caching in D2D wireless networks that can enhance the efficiency of content caching and balance the trade-off between cache hit ratio and memory use. The proposed methodology clusters devices based on their content similarity using the K-means algorithm while accounting for user ratings and Euclidean distance. Within the cluster, there is the master user equipment (MUE) and several pieces of slave user equipment (SUE). The MUE is selected based on factors such as willingness, signal-to-noise ratio, and battery percentage, with incentives offered by the cellular operator. SUE devices share raw data based on content popularity and usage patterns. The local model uses a graph convolutional gated recurrent unit that predicts content caching through its ability to handle complex dependencies based on the spatio-temporal features of the user devices. Federated learning facilitates global model training without centralization of the raw data, which enhances scalability. A proximal policy optimization algorithm determines the optimal content caching for each device, allowing dynamic D2D environments to be effectively handled. Simulation results demonstrate that the proposed solution yields strong caching performance by reducing the average delay and improving the overall offloading probability.

Keywords: Device-to-Device (D2D) Communication, Proactive Edge Caching, Content Caching, Federated Learning,Machine Learning Methods, Deep Reinforcement Learning.

Contents

ABSTRACT **VIII**

LIST OF TABLES **XII**

LIST OF FIGURES **XIII**

LIST OF ABBREVIATIONS AND ACRONYMS **XIV**

1 Introduction **1**
1.1 D2D Wireless Networks 1
1.1.1 Overview of Device-to-Device (D2D) communication 1
1.1.2 Importance of D2D Networks in Enhancing Communication Efficiency and Network Capacity 1
1.1.3 Challenges in D2D wireless network 2
1.2 Content Caching in D2D Wireless Networks 2
1.2.1 Challenges of Content Caching in Wireless Networks 2
1.3 Device-Level Caching Strategies in D2D Wireless Networks 4
1.3.1 Proactive Content Caching 4
1.3.2 Edge Caching 5
1.3.3 Two-Layered Edge Network Approach 5
1.4 Challenges and Limitations of Traditional Caching Approaches in Dynamic Wireless Environments 6
1.5 Federated Learning Strategies 7
1.5.1 Machine Learning Techniques in Federated Learning 7
1.5.2 Machine Learning Techniques in Layer-2 Challenges 7
1.6 Advanced Techniques and Strategies 8
1.7 Gaps and Challenges in Existing Content Caching Techniques in D2D Networks 9

1.7.1 Analyzing Geographical Factors 9
1.7.2 Social Dynamics in Content Distribution 10
1.8 Motivation for Research 10
1.9 Objectives of the Research 11
1.10 Thesis Structure 13

2 Literature Review 15
2.1 Related Work 15
2.2 Chapter Summary 19

3 Research Methodology 21
3.1 Clustering of Devices 22
3.2 MUE Selection 23
3.2.1 Willingness Factor (WF) 23
3.2.2 Signal-to-Noise Ratio (SNR) 23
3.2.3 Battery Percentage (BP) 24
3.2.4 MUE Selection Process 24
3.3 Data Sharing Process 25
3.3.1 Current Content Popularity Sharing 25
3.3.2 Historical Usage Data Sharing 25
3.4 GC-GRU Model Parameters and Values Explanation 26
3.5 Utilizing GC-GRU Model for Content Caching Optimization 28
3.5.1 Spatial Analysis using Graph Convolutional Layer 28
3.5.2 Temporal Analysis via Gated Recurrent Unit (GRU) 28
3.5.3 Prediction of Caching Probability 29
3.6 Leveraging Federated Learning for GC-GRU Output Integration 31
3.6.1 GC-GRU Output Preparation 31
3.6.2 Federated Learning Initialization 32
3.6.3 Federated Learning Iterations 32
3.7 Utilizing PPO for Refinement of Global Model from Federated Learning 32
3.7.1 Initial Policy Determination 32
3.7.2 PPO Training 33
3.7.3 Policy Update 33

4 Results and Disscussions **34**
4.1 Simulation Parameters and Dataset 34
4.2 Training vs Testing 35
4.3 Average Delay Analysis vs Content Size 36
4.4 Delay Comparison with Existing Techniques 37
4.5 Average Delay Analysis vs Storage Capacity 39
4.6 Offloading probability vs Content Size 40
4.7 Offloading Probability vs Storage Capacity 41
4.8 Comparison of Offloading Probabilities with Different Zipf Coefficients 43
4.9 Comparison of Throughput vs Number of Clusters 44
4.10 Comparison of Average Delay with Number of Clusters 46
4.11 Convergence of Rewards on Different Schemes 47
4.12 Comparison of MSE, MAPE, RMSE 48

5 CONCLUSIONS AND FUTURE RECOMMENDATION **50**
5.1 Limitations 50
5.2 Future Direction 51

BIBLIOGRAPHY **53**

List of Tables

3.1 GC-GRU Model Parameters and Values 26

4.1 Simulation Parameters and Values 35

List of Figures

3.1 Network Architecture for Caching in D2D Wireless Networks 21

3.2 The Federated learning model for Caching in D2D Networks: where local data from MUE is processed using the GC-GRU model for spatio-temporal feature extraction. These features are integrated into a global model at the BS, and PPO is employed for refining the global model through iterative policy updates 31

4.1 Training and testing dynamics of the clustering model 36

4.2 Comparative Analysis of Average Delays between GC-GRU and Baseline Model 37

4.3 Comparative Analysis of Average Delays for Different Caching Models across Varying Content Size 38

4.4 Comparative Analysis of Average Delays for Different Caching Models across Varied Storage Capacities 40

4.5 Comparative Analysis of Offloading Probabilities for Different Caching Models across Varied Content Sizes 41

4.6 Offloading Probabilities for Different Caching Models across Varied Storage Capacities 42

4.7 Offloading Probability Comparison under Different Zipf Coefficients for GC-GRU, MP, SLR, RD, and DQ 43

4.8 Comparative Analysis of Throughput for Different Caching Models across Varying Number of Clusters 45

4.9 Average Delay Dynamics for Different Caching Models across Varied Numbers of Clusters 46

4.10 Dynamics of Reward Convergence for Various Caching Schemes over Episodes, illustrating distinct convergence points and learning trajectories. 48

4.11 Comparative Analysis of Performance Metrics (MSE, MAPE, RMSE) for Different Caching Models 49

LIST OF ABBREVIATIONS AND ACRONYMS

D2D	Device-to-Device
Wi-Fi	Wireless Fidelity
IoT	Internet of Things
LTE	Long Term Evolution
QoE	Quality of Experience
AR	Augmented Reality
RL	Reinforcement Learning
DSA	Dynamic Spectrum Access
SON	Self-Organizing Networks
RNN	Recurrent Neural Networks
SIC	Successive Interference Cancellation
QoS	Quality of Service
P2P	Peer-to-Peer
ML	Machine Learning
DT	Decision Tree

RanF	Random Forest
LRU	Least Recently Used
LFU	Least Frequently Used
IU	Important User
FL	Federated Learning
FedAvg	Federated Averaging
UE	User Equipment
DDQN	Double Deep Q-learning Network
LSTM	Long Short-Term Memory
MOS	Mean Opinion Scores
UD	User Devices
MUE	Master User Equipment
SUE	Slave User Equipment
WF	Willingness Factor
SNR	Signal-to-Noise Ratio
BP	Battery Percentage
GC-GRU	Graph Convolutional Gated Recurrent Unit
CP	Caching Probabilities
GC-GRU_Out	GC-GRU outputs
PPO	Proximal Policy Optimization

SLR	Social-aware LRU caching
SMP	Social-aware Most Popular Caching
RD	Random Decision-based caching
DQ	Deep Q-Network
FL_Out	Federated Learning Output
ZIPF	Zipfian Distribution

Chapter 1

Introduction

The advancement of mobile communication, driven by the widespread use of smartphones, has significantly changed user experiences. The prevalence of these devices has led to a digital age marked by a remarkable increase in network data usage. As consumer demand for diverse and data-heavy experiences grows, network infrastructure is put under increasing strain, which emphasizes innovation to meet the changes in need [1].

1.1 D2D Wireless Networks

Device-to-device (D2D) communication has also become a promising technology for leveraging near-device resources to enhance the efficiency of future cellular networks.

1.1.1 Overview of Device-to-Device (D2D) communication

D2D communication directly transfers data between neighbouring devices, eliminating the requirement of a central network infrastructure such as cellular towers [2].The smartphones, other tablets, and IoT devices will directly communicate with each other using short-range wireless technologies such as Bluetooth or Wi-Fi Direct. D2D communication provides various latency and reliability benefits which are quite different from the traditional network- based communication systems.

1.1.2 Importance of D2D Networks in Enhancing Communication Efficiency and Network Capacity

D2D networks are prime additions to the efficiency of the network's communication. They allow direct communication between devices and relieve pressure on the central infrastructure by incorporating improved resource utilization and minimizing congestion. D2D also allows for improved localized data transfer at incredible speeds with great energy efficiency, especially in high-density population areas or sparsely covered areas.

1.1.3 Challenges in D2D wireless network

Interference management is probably one of the main issues emerging in D2D wireless networks. Here, signals are interfered with by devices with each other because of proximity. In principle, this would compromise the quality of communication and throughput. Another complicated task is resource allocation regarding spectrum, power, and bandwidth along D2D links by fairness. Security is another consideration where D2D communication introduces new vulnerabilities, such as eavesdropping and data leaks. Such risks demand the use of strong encryption and authentication protocols. Such risks must be mitigated by using strong encryption and authentication protocols. The dynamic nature of D2D networks, wherein devices are in constant motion, further complicates handover management and location tracking and thus demands more advanced algorithms for smooth transitions. These problems must be resolved if D2D wireless networks require growth in modern communications systems.

1.2 Content Caching in D2D Wireless Networks

Content caching is important in enhancing network performance and the quality of experience of a D2D wireless network. As time goes by with the extensive inclusion of D2D communication into classical wireless network structures, the demand for real-time services and higher data consumption continues to rise [3]. Direct communication between mobile devices reduces reliance on centralized base stations; its data rates and latency can be improved. Current practice: Route communications through the base station even when close to one another, inefficiencies, particularly for real-time applications.

To counter such challenges and increase spectral efficiency in future cellular networks, good content caching strategies will be adopted to have a centralized reduction in loads on central base stations while generally boosting the total network performance.

1.2.1 Challenges of Content Caching in Wireless Networks

Yet today, mobile operators face many difficulties, especially in increasing demand for data- heavy services caused by the wide spread of smartphones and multimedia content. The ever- changing and unpredictable user behaviour patterns add another layer of complexity to service optimization. In this environment, where user expectations are high and resources are limited, striking the right balance between service quality and limited resources is crucial. Below are the key challenges related to content caching in wireless networks:

- **Collisions of Instantaneous Responses and Resource Limitations**

  This need for fast answers often clashes with the scarcity of bandwidth, processing power, and sheer network infrastructure. This is bound to put significant operational pressure on the mobile operator's financial nervous system and increase pressure on all stakeholders to meet the growing expectations of users. Additionally, there will be a million-fold increase in the number of connected devices, resulting in an exponentially high increase in the volume of data traffic.

- **Financial Implications and Service Costs**

  Delivering services under such high quality and due to the rising demand will create significant financial repercussions. All these expenditures to maintain and modernize network infrastructure, invest in new technologies, and respond to the needs of an ever-more sophisticated user base create enormous operational costs. These points lead to the need to find novel ways to lower service costs while increasing the efficiency of content delivery.

- **Untapped Potential of Modern Smartphones**

  With all these challenges there would still lie tremendous potential in the present advanced storage and processing capability of modern smartphones. Smartphone is an essential creature of today's life that stores underutilized features that can be tapped by changing content distribution when accessed through the computing power of smartphones. That would usher in new prospects toward easing resource constraints in service delivery with a new future for mobile communication.

- **Revolutionizing Content Distribution Strategies**

  The powerful storage, processing capabilities, and ease of connection characterize the modern smartphone. Based on their integration into network infrastructures, they can open new accessions. The result will be a redefining concept of content distribution models that the smartphone will no longer just be a receiver of passive content but an active contributor with the most efficient data transmission and retrieval.

- **Addressing the Evolving Challenges of the Digital Age**

  With such a progressive scenario, the landscape of challenges undergoes constant metamorphosis due to technology marches and shifts in user behavior, so innovation must be sought. Properly integrated into content distribution systems, key features of the modern smartphone could prove to be a promising solution to age-old challenges of the digital age. The integration thus opens up avenues for better services and mobilizes mobile networks to deal with the rising bandwidth of an increasingly interconnected world.

1.3 Device-Level Caching Strategies in D2D Wireless Networks

D2D wireless networks promise exciting development on the challenges of content distribution in mobile networks, based on caching strategies at the device level. Device-level strategies for content delivery are considered: location, social interactions, user preferences, and conditions under which the network operates. Using powerful smartphones with storage capacity may enhance efficiency in transmitting data, reduce congestion in the network, and provide a generally better experience for the users [4].

1.3.1 Proactive Content Caching

With increasing demands in the fast-evolving field of mobile communication, proactive content caching is the new direction needed to meet those demands. This section will study the strategic placement of caches at either Base Stations or User Equipment and further would explore how proactive approaches benefit further. Proactive content caching is a network approach that anticipates its contents and pre-loads them before users ask for those contents. This reduces latency and provides a better user experience with the storing of such frequently accessed or expected content close to the end-users, thereby reducing the time it takes for such content downloads from remote servers [5]-[7].

- **Strategic Positioning at Base Stations and User Equipment**

  Proactive content caching also focuses on the strategic location of caches at the Base Stations or within the User Equipment. This is much more efficient for networks, reducing latency in fetching content that is closer to users and more beneficial to user experience. It also reduces pressure on core network infrastructure because it keeps all the frequently accessed data at the network's edge, where the users are.

- **Enhancing Energy Efficiency and Throughput**

  This strategic use of proactive content caching brings several key benefits, especially concerning the amelioration of energy efficiency in network infrastructure. Proactive caching helps reduce overall energy consumption by reducing unnecessary data transfers and shortening the distance data needs to travel. On the other hand, proactive content caching boosts network throughput alleviates bandwidth resource pressure and improves overall network performance. [8].

1.3.2 Edge Caching

Edge caching supports the development of proactive content caching. It allows user equipment processing once content is pulled into the network, thus resulting in the reduction of latency by directly accessing content that is stored locally. Furthermore, the approach enhances the efficiency of network resource utilization, thus resulting in overall optimization of content delivery [9]. This method is truly shifting in the way of content distribution strategies as it resembles content delivery through anticipatory principles. Since network edge dynamic reprocessing content qualifies as a new evolution of delivery, in itself, this will bring a significant improvement in QoE for mobile users.

1.3.3 Two-Layered Edge Network Approach

The use of the two-edge layer network is considered as a core strategic framework [10]. to be used to optimize content caching and delivery. Here, this section deepens to put out an intensive investigation of the approach, focusing on the complexities of Layer-1 caching, concerned with an effort to enhance cache hit ratios, and the distinct challenges of Layer-2 wireless networks.

- **Layer-1 Caching for Cache Hit Ratio Maximization**

  Layer-1 caching is a basic principle of content distribution policies. Content must be placed in Layer 1, with emphasis always on high cache-hit rates. This chapter deals with the underlying principles and schemes of Layer-1 caching by focusing on the proactive placement of content to improve user satisfaction and proper use of networking facilities. Key techniques such as prefetching and intelligent caching policies are discussed as the current best means of achieving these goals.

- **Layer-2 Solutions for Wireless Network Challenges**

  Whereas Layer-1 is optimized to improve cache hit ratios, Layer-2 focuses on specifically targeting the challenges unique to wireless. The section explores the challenges presented in the wireless environment, such as low bandwidth, latency, and interference [11]. Layer-2 techniques work to push even further the limits of good content delivery in poor conditions. Two of the techniques are high-accuracy error correction and adaptive bitrate streaming.

- **Content Placement Dynamics in Layer-2**

  One of the salient features of Layer-2 is dynamic content placement management. Real-time network conditions, user demand patterns, scalability for future expansion, and factors and algorithms that influence the optimal placement of content in the wireless network are evaluated. These are critical factors and algorithms that ensure efficient content distribution, minimal latency, and effective use of network resources.

1.4 Challenges and Limitations of Traditional Caching Approaches in Dynamic Wireless Environments

TThis is where the challenges and limitations of traditional caching come into play, with resource constraints, network conditions' fluctuations, and the need to adapt to the dynamic nature of changing user demand within dynamic wireless environments [12]. Therefore, innovative caching strategies that could adapt dynamically to the unique characteristics of the wireless network, including mobility of the users, varying channel conditions, and shifting user behaviors must be sought after in greater numbers.

- **Optimal Content Placement Dilemma**

  In proactive content caching, one has to detect the best distribution of the contents. It involves "the fine balance between request patterns and cache capacity". With dynamic users' demands and a small available space in the cache, an adaptive and agile approach becomes essentially more significant. To achieve the optimal balance between the pattern of the user's requested content and the stored ones requires continuous refinement and the application of advanced algorithms.

- **Geographical and Social Factors**

  Geographical and social factors play into optimizing content caching in this section. It will be clear that at numerous points in the discussion of placement, several considerations are at play, both geographically and socially driven dynamics involved in the process of caching are highlighted here.

- **Social Dynamics in Content Distribution**

  Besides geographical differences, social network characteristics among users also influence the nature of a caching strategy. Most users who live within proximity have almost identical preferences about content, which leaves scope for even more focused cache strategies. This subsection discusses how social network differences affect the optimization of content delivery and cache hit ratios.

- **Challenges in Content Delivery**

  Proactive caching of content does have several potential benefits, however, the delivery of content poses various challenges at times. This challenge is sometimes caused by D2D communication or the cellular downlink at times of peak congestion. Many of these difficulties demand sophisticated solutions to ensure that there are smooth transitions among these diverse forms of communication, but only when based on continuous content delivery as the premise behind the complexity and challenges in effectively executing a proactive content caching strategy.

1.5 Federated Learning Strategies

Federated Learning is an approach to distributed model training that does not necessarily rely on centralized raw data. This chapter stresses the deployment of FL methods within a two-layered network architecture considering their extensibility and flexibility to optimize content caching. A privacy-preserving technique, FL enables distributed devices to collaboratively train a shared machine-learning model using local data, with user data being stored on the devices thus preserving privacy. FL has recently shown great performance in applications like next-word prediction, fault detection, and analysis of sensitive medical data.

1.5.1 Machine Learning Techniques in Federated Learning

WithinFL, the integration of various machine learning techniques enhances model training. This subsubsection provides insights into the machine learning algorithms employed inFL for content caching optimization in Layer-1 and Layer-2.

1.5.2 Machine Learning Techniques in Layer-2 Challenges

To navigate the wireless network-specific challenges addressed in Layer-2, a suite of machine learning techniques proves invaluable. This subsection explores how Machine Learning algorithms contribute to real-time decision-making, mitigating the impact of limited bandwidth, high latency, and disruptions. In the subsequent sections, we delve deeper into the applications of the two-layered edge network approach, exploring real-world implementations, case studies, and the evolving landscape of content caching optimization.

1.6 Advanced Techniques and Strategies

Pursuing optimal content caching in dynamic wireless environments requires further investigation into the application of advanced techniques and strategies. This section discusses the advanced methodologies that utilize recent technologies and strategies to enhance the efficiency of content caching.

- **Graph Convolutional Gated Recurrent Unit (GC-GRU) Models**

  The GC-GRU models present a novel approach towards content caching prediction. This subsection describes the architecture and prominent features of GC-GRU models and considers complex dependencies involved in dynamic D2D communication [13], [14].

- **Proximal Policy Optimization (PPO) Algorithm**

  As one of the tools to optimize content caching on individual devices within a dynamic D2D environment, PPO is more critical [15]. The principles and applications of PPO are briefly described next, including its ability to adapt the content caching strategy to the dynamic changes in the network conditions.

- **Dynamic Adaptation in PPO**

  Another major strength of the PPO algorithm is dynamic adaptability. This subsection explores how PPO iteratively adjusts content caching policies in response to real-time data, ensuring that it remains flexible and responsive to the unpredictable nature of wireless environments [16].

- **Augmented Reality (AR) Integration**

  The integration of Augmented Reality (AR) introduces an additional layer of real-world context to content caching. This subsection explores how AR technologies enhance content caching accuracy by considering factors such as the physical environment, user movements, and environmental changes [17].

- **Reinforcement Learning for Device-Level Adaptability**

  In the context of device-level adaptability, Reinforcement Learning (RL) algorithms play a vital role. This subsection examines the application of RL techniques in developing personalized content caching strategies at the device level, customized to individual user preferences and usage patterns [18].

- **Dynamic Spectrum Access (DSA) for Enhanced Connectivity**

  To address the challenges posed by limited bandwidth, Dynamic Spectrum Access (DSA) emerges as a strategic solution. This subsection explores how DSA technologies optimize content delivery by dynamically allocating spectrum resources based on real-time demand [19].

- **Adaptive Spectrum Allocation Strategies**

  In the realm of Dynamic Spectrum Access (DSA), the development of adaptive spectrum allocation strategies is critical. This subsection examines the machine learning-based algorithms employed in DSA to optimize spectrum utilization for content caching in dynamic wireless networks [20].

- **Self-Organizing Networks (SON) for Autonomic Optimization**

  he adoption of Self-Organizing Networks (SON) introduces autonomous optimization capabilities. This subsection explores how SON technologies automatically adjust content caching parameters based on network feedback, enhancing the overall system efficiency.

- **Learning Mechanisms in SON for Efficient Content Caching**

  A comprehensive understanding of the learning mechanisms within Self-Organizing Networks (SON) is crucial for optimizing content caching. This subsection investigates how SON incorporates machine learning algorithms to adaptively refine content caching strategies in response to evolving network dynamics. The subsequent sections will present case studies, practical applications, and an analysis of the broader implications of these advanced techniques on content caching in wireless networks [21].

1.7 Gaps and Challenges in Existing Content Caching Techniques in D2D Networks

Identifying the limitations and challenges of current content caching techniques on D2D networks is essential for understanding the deficiencies of existing methods and promoting further development with more effective solutions. This Research contributes to exploring and analyzing these gaps, such as spectrum allocation, adaptive resource management, and learning mechanisms.

1.7.1 Analyzing Geographical Factors

Geographical context adds another layer of complexity to optimizing content caching. The spatial distribution of users at different locations directly influences the effectiveness of the cache [22]. This subsection discusses challenges and strategies involving geographical factors to improve effective content placement.

1.7.2 Social Dynamics in Content Distribution

Besides the above geographical influences, social dynamics between users influence the design of cache content strategies more intensely than the other aspects. Users in tightly knitted social circles share similar interests in content and, hence, have scope for focusing and efficient caching. This subsection looks at how social dynamics can be used to optimize content distribution and, hence, improve cache hit ratios.

1.8 Motivation for Research

The motivation behind this Research stems from the ever-growing demand for more efficient and reliable strategies for caching content in D2D wireless networks. While data volumes continue to grow and the number of connected devices increases, traditional centralized content caching methods are reaching limits concerning resource efficiency and scalability. The increasing challenges call for developing alternative approaches, and FL is one of them. FL is a promising solution that will distribute the learning process across edge devices to improve content caching in a decentralized manner, utilizing collective device capabilities. The next section lists the central motivations driving this Research:

- **Nuanced Approach to Content Placement**

  Addressing the challenge of optimal content placement demands a sophisticated and multi-faceted approach. The integration of machine learning algorithms, predictive analytics, and real-time monitoring is crucial for navigating this complex domain. By analyzing patterns in user behavior, content preferences, and network dynamics, a proactive content caching system can adapt dynamically, ensuring that the most relevant and frequently requested content is efficiently stored and made readily available within the cache.

- **Effective Content Placement Strategies**

  Achieving an optimal equilibrium between geographical and social factors requires the design of carefully crafted content placement strategies. This section delves into the complexities of developing approaches that incorporate both geographic and social data, ensuring that cached content is effectively aligned with the preferences of users within specific regions and social networks.

- **Alleviating Backhaul Congestion**

  A key objective of integrating geographical and social factors into content caching is to mitigate backhaul congestion. By strategically placing content caches in accordance with user distribution and social connections, the strain on central network backhauls is significantly reduced. This section explores how thoughtful content placement can improve both the distribution and robustness of network architecture.

1.9 Objectives of the Research

The foundation of this research is rooted in addressing the intricate and complex challenges posed by dynamic D2D communication within wireless networks. This section articulates in detail the specific objectives that guide the investigation, along with the overarching motivation driving the pursuit of these objectives. The research objectives of this study include developing aFL framework for content caching in D2D wireless networks, exploring the integration of augmented reality. The primary objectives of this research are delineated to provide a structured framework for exploration. These objectives encompass:

- **Optimizing Content Caching Efficiency**

  The core objective is to optimize content caching efficiency within D2D networks. This involves enhancing cache hit ratios, minimizing latency, and strategically placing content to balance space utilization and caching effectiveness. Additionally, the goal is to leverage FL techniques to enable collaborative intelligence among devices in the network, improving overall caching performance.

- **Addressing Trade-offs in Cache Hit Ratio and Space Utilization**

  A key focus is on addressing the trade-off between cache hit ratio and space utilization. Balancing these factors is crucial for ensuring an efficient and sustainable content caching strategy in dynamic wireless environments.

- **Integrating Machine Learning Algorithms for Dynamic Adaptation**

  The primary objective in addressing the dynamic aspects of Device-to-Device (D2D) communication is to integrate machine learning algorithms that facilitate the adaptive optimization of content caching strategies. This approach enables real-time adjustments that respond to shifts in user behaviors and fluctuations in network conditions.

- **Intricacies of D2D Communication**

  The dynamic and unpredictable nature of Device-to-Device (D2D) communication presents considerable challenges. A comprehensive understanding of these challenges is essential for developing robust content caching strategies capable of adapting to the ever-changing conditions of the wireless environment.

- **Optimizing User Experience**

  The main motivation behind this research is to improve user experiences in response to the increasing demand for multimedia, gaming, and social interactions on smartphones. Proactive content caching plays a vital role in ensuring fast and efficient content delivery, ultimately enhancing overall user satisfaction.

- **Efficiency Gains Through Advanced Techniques**

  The integration of advanced techniques, including Federated Learning (FL), Graph Convolutional Gated Recurrent Unit (GC-GRU) models, and Proximal Policy Optimization (PPO) algorithms, holds significant promise for enhancing efficiency. The goal is to utilize these technologies to overcome the limitations of traditional content caching methods, offering more effective and adaptable solutions.

- **Contribution to the Wireless Networking Landscape**

  This research seeks to offer meaningful insights and strategies that contribute to the evolution of wireless networking. By addressing key challenges in content caching, the study aims to drive innovations that extend beyond individual use cases, ultimately aiding in the broader advancement of wireless communication frameworks. The subsequent sections outline the methodology employed in this study, with a particular focus on the use of machine learning algorithms, Federated Learning (FL), and other state-of-the-art techniques to enhance content caching in Device-to-Device (D2D) wireless networks. The proposed framework is designed to address the inherent complexities of content caching in dynamic wireless environments, leveraging machine learning-driven adaptive strategies for improved performance.

1.10 Thesis Structure

The organization of the thesis is as follows:

- **Chapter 1: Introduction**

  Chapter 1 serves as a comprehensive introduction to the research. It delves into the intricate landscape of D2D communication in wireless networks, emphasizing the dynamic and unpredictable nature of wireless environments. The challenges posed by limited bandwidth, high latency, and disruptions are explored. The chapter outlines the exploration of machine learning-based methods, FL, and edge caching to address the efficiency of content caching in D2D wireless networks. It sets the stage by presenting the research objectives, questions, and the contextual significance of the study.

- **Chapter 2: Literature Review**

  In Chapter 2, a thorough literature review is presented, encompassing existing studies on edge caching, FL, and machine learning techniques in wireless communication scenarios. The critical analysis identifies gaps and limitations in the current body of knowledge, establishing the theoretical foundation for the proposed research. Relevant methodologies and findings from prior works inform the development of the approach to optimizing content caching in D2D wireless networks.

- **Chapter 3: Methodology**

  Chapter 3 provides a detailed exposition of the methodology employed in the research. It elucidates the experimental setup, data collection process, simulation scenarios, and the metrics used for performance evaluation. The chapter offers insights into the execution of experiments designed to validate the proposed approach for enhancing content caching efficiency in D2D networks.

- **Chapter 4: Results and Discussions**

  In Chapter 4, the research unfolds with the presentation of experiment results and their in-depth analysis. The proposed approach's performance is scrutinized and compared against existing methods, unraveling insights into the factors influencing caching efficiency. The findings are discussed in alignment with the research objectives, showcasing the efficacy of the proposed methodology.

- **Chapter 5: Conclusion**

  The concluding chapter, Chapter 5, encapsulates the essence of the research. It summarizes the main findings, draws conclusive insights from the results and analyses, and underscores the contributions of the study. Implications for content caching optimization in D2D wireless networks are discussed, paving the way for potential future research directions. This chapter serves as a succinct and conclusive endpoint to the thesis.

Chapter 2

Literature Review

This chapter delves deeply into the application of a FL framework for content caching in D2D wireless networks. A comprehensive review of pertinent literature in this domain is undertaken to provide readers with a thorough understanding of prior research and advancements. The primary objective of this literature review is to establish a strong foundation for the proposed FL approach in optimizing content caching within D2D wireless networks. The chapter begins with an exploration of the pivotal role that optimized edge caching plays in the context of wireless communication systems, diving into the existing challenges hindering efficient edge caching while emphasizing the importance of addressing these obstacles. Further, it underlines the far-reaching impacts and relevance of the use of FL algorithms in boosting caching performance within the unique dynamics of D2D wireless networks and their future benefits.

2.1 Related Work

Caching is the most crucial process, which involves storing frequently accessed data in a local cache, thus reducing access times and offloading network congestion. In the dynamic context of D2D communication, caching becomes even more significant, and therefore plays a vital role in improving overall performance as well as betterment of communication efficiency. The highlight of this contribution was that Zhu et al, proposed a machine learning-based novel resource reuse scheme designed for D2D communication within cellular networks [23]. This novel scheme addresses the co-channel interference challenge with cellular users by distributing orthogonal subcarriers very smartly. By maximizing the throughput of cellular users, the scheme then permits D2D pairs to reuse various subcarriers which then improve their throughput without deteriorating the performance of cellular users. The architectural elegance of the proposed solution is in the exploitation of a low complexity pointer network which makes use of two Recurrent Neural Networks (RNN)—one to act as an encoder and the other as a decoder. This sophisticated model not only achieves quite satisfactory performance metrics but it is also able to shine in scenarios characterized by low computational complexity networks, which often demonstrate its versatility and efficiency within dynamic D2D environments.

The study in [24],[25] aim is to increase sum rate while considering the decoding constraint in Successive Interference Cancelation (SIC) and maintaining the Quality of Service (QoS) for D2D and cellular users. In today's wireless networks, the demand for higher data rates and improved quality of service is ever-increasing. The communication between mobile users in the network is performed by making groups. This communication can be peer-to peer (P2P) and the grouping that is done by two or more than two mobile user is called clustering [26]. There are several types of clusters depend on the user in that cluster. There are heterogenous networks that consist of different types of cellular devices using diverse technologies, such as 5G, LTE, and Wi-Fi. [27]. Micro cell, homogeneous networks, and macro cell are some of the other types of clusters that exist in cellular network architecture. Users in a network can be employed uniformly, stochastically, or randomly [28].

In a notable exploration of enhancing caching strategies within D2D networks, Prerna et al, delved into the complexities of node classification and cache location determination, as documented in [29]. Their approach is based on detailed classification of nodes into clusters using a trust factor, which will be the most crucial factor in reliability and efficiency in D2D communication networks. Based on the power of Machine Learning, researchers used the classifiers of the Decision Tree (DT) and Random Forest (RanF) models to identify prime locations for the cache inside the network architecture. Remarkably, these models perceive the trust factor as the main parameter in the mutual connections between users and they portray dynamic interpersonal connections between them, within the network. Interestingly, the experimental results unveiled the superiority of the RanF model in accuracy, with the evidence of effectiveness in making more accurate cache location predictions. However, in spite of its virtues, the RanF algorithm had a significant flaw—a potential delay in convergence from the use of cached data based on the gateway. This subtle insight into the limitation of the algorithm, notwithstanding its otherwise commendable performance, certainly adds a layer of practical consideration and therefore offers valuable insights into further fine-tuning within the context of D2D caching strategies.

In [5], new community detection and attention-weighted FL-based proactive edge caching is proposed by Li et al, The authors ranked the contents of the users based on LRU and LFU. However, the drawbacks of the proposed strategy is that the performance of Important User (IU) or prioritized user will degrade with time because of it limited battery power.

As far as advanced D2D network innovations are concerned, Zhang et al, proposed a foundational FL framework in [30] particularly named D2D-FedAvg, which was designed exclusively for application in mobile edge networks. This new idea concentrates on the design of a more advanced model of two-tier learning selectively engineered to reduce communication costs with no loss of the desired learning performance, precisely like that associated with the classic Federated Averaging model, FedAvg. This is achieved by natively integrating the D2D communication in the learning process, including D2D grouping, master user equipment (UE) selection, and D2D exit, resulting in the design of a strong D2D-assisted federated averaging algorithm. The empirical results underline well the algorithm's strength in significantly reduced communication cost as compared with its traditional federated averaging counterpart within cellular networks. Authors introduced, in parallel research of trailblazers, a double-layer Blockchain-Based Deep Reinforcement Federated Learning (BDRFL) scheme in [31].The new framework aims at improving the data security and caching efficiency in D2D networks. Under exhaustive evaluation with comprehensive failure scenarios such as crash, omission, and Byzantine failure, the scheme based on BDRFL was very robust. Simulation results illustrated a strong reduction in download latency, mainly under different types of attacks, making this two-layered blockchain-infused solution capable of enhancing a network's security along with the effectiveness of caching content in D2D. This juxtaposition of approaches brings to light the dynamic landscape of D2D research, exhibiting diverse methodologies to tackle key challenges in communication networks.

Xiao et al, designed an optimization algorithm considering task completion delay and energy consumption [32]. Their work employed the improved BPSO algorithm to optimize the content caching, and the iMOB algorithm was used to find task offloading. The experimental results also showed the superiority of their approach compared with several benchmark algorithms because it can optimize the performance of D2D-aided MEC networks. The authors, Li et al, developed the CAFLPC algorithm incorporating Attention Weighted Federated Learning with a Bidirectional Long Short-Term Memory network, named it AWFL BiLSTM in the domain of proactive edge caching [1]. This is to predict content popularity without losing users' privacy effectively. An LRU and LFU are used for content in this algorithm. This strategy introduces the problem of the mobility of high- priority users, typically mobile devices whose performance might be jeopardized due to low battery power. An essential challenge for maintaining the success of this proactive edge caching framework requires choosing and replacing Important Users (IUs) in the cluster.

Yu et al, [33] came up with a new joint approach that takes care of cache placement and content recommendation to improve edge caching performance in opportunistic mobile networks. Extensive experiments by the proposed algorithms demonstrated better performance in various scenarios than baseline methods. Meanwhile, Li et al, presented a proactive edge caching scheme that adopted D2D-assisted wireless networks, while focusing on learning from user preference [34]. This new scheme aggregates the prediction of users' future demands via machine learning and at the network's edge, strategically caches it. This user preference is dynamically learned from historical behaviors and provides real-time adaptivity to dynamic network conditions. Simulation results emphasize the efficiency of this scheme, dictating higher hit ratios and lower average access delay than existing approaches. This marks a very important stride in advancing the caching efficiency of D2D-assisted wireless networks.

Bai et al, introduced a social-aware D2D caching scheme that intricately integrates social incentives and recommendations into the decision-making process of D2D caching [13]. Employing FL, the scheme predicts social relationships in a privacy-preserving manner and employs deep reinforcement learning to make optimal D2D caching decisions based on these predicted social relationships. The overarching optimization objective is to maximize the data offloading probability, formulated as a Markov decision process and effectively solved using a double deep Q-learning network (DDQN) algorithm. Simulation results underscore the efficacy of the proposed scheme, showcasing commendable performance in prediction accuracy and convergence while leading to reduced average delay and improved offloading probability. In a related context, Khan et al, delved into the strategic utilization of caching at the network edge to enhance service quality, particularly in mitigating transmission costs and network congestion during surges in network traffic, facilitated by D2D communication [35]. Their proposed approach involves clustering D2D users with similar interests through a hierarchical agglomerative clustering algorithm, subsequently optimizing the cache hit probability for each cluster. Additionally, the authors put forth a monetary incentive-based mechanism designed to incentivize user participation in D2D communication by rewarding users with a favorable content-providing history. Simulation results underscore the significant potential of these methods, showcasing an impressive improvement in cache hit rates by over 40% in D2D networks.

Nowadays the majority of researchers studied interaction behavior of user and then extract their preferences. This is proven by vast research that the prediction of network by using users preferences is an intelligent way [36]-[39]. For example, Meng et al, designed a methodology for social networks by using LSTM network combined network embedding [36]. Xia et al, explored a prediction model for dynamic social networks, focusing on learning dynamic graph representations [37]. Nevertheless, the aspect of privacy remains a significant concern in social prediction. In prior research, Xiao et al, presented security measures utilizing reinforcement learning techniques to ensure secure offloading to edge nodes, particularly in the context of safeguarding against jamming attacks [40]. Several studies combined FL with graph representation learning using private factors of users [41]. For example, the study in [42] exhibited that the federated graph neural network is effective and protected computationally.

2.2 Chapter Summary

This chapter delves into the contemporary research landscape on applying Federated Learning (FL) frameworks for content caching in D2D wireless networks. Our investigation has identified a few relevant findings and some knowledge gaps of interesting nature. There is a research gap with regards to optimization of content caching in D2D wireless networks- scanty scalable, and efficient solutions abound. FL seemed promising, in addition to the improvements in cache hit ratios and latency reduction, few systemic studies have been carried out so far concerning the high computational complexity and scalability issues prevalent in large-scale networks.

In spite of the research body on FL content-caching in D2D wireless networks, an obvious gap lies in the investigation of the infusion of other machine learning algorithms or methods. This is pointed out in this paper. While the previous sections have established benefits of coupling deep reinforcement learning with FL to optimize caching, much more needs to be explored on how all the benefits of unsupervised learning methods could attach and improve the intelligence of these content caching systems significantly. Techniques such as clustering algorithms or generative models are bound to reveal inherent patterns or hierarchies in the data. This bridging opens new avenues for novel approaches to integrate diverse machine learning methodologies into order to achieve more advanced and adaptive content caching solutions for D2D wireless networks. What follows is a variety of machine learning approaches and their implications for improving cache efficiency, scalability, and privacy that call for further research, respectively.

The inspection done brings along with it several important findings and methodologies connected to content caching in D2D wireless networks, especially on FL techniques. Key findings of this work include:

- A notable approach for content distribution and caching selection difficulty is the application of multi-stage techniques of FL, as well as reinforcement learning. Another salient approach is multi-agent systems enabling mobile users to make context-aware caching decisions sensitive to their dynamic operating conditions.
- Cooperative caching techniques, combining learning automata-based Q-learning, demonstrate the potential to enhance Mean Opinion Scores (MOS) for participating users. These strategies, by considering anticipated user locations and content interests, surpass non-cooperative and random caching approaches.
- The fusion of FL holds the promise of efficient and privacy-preserving content caching solutions. FL enables accurate estimation of user preferences and content caching algorithms independently, optimizing caching decisions while safeguarding user privacy.

- Scalability emerges as a pivotal consideration in the design of content caching systems. Adaptive algorithms and multi-layered structures, present promising results in developing scalable content caching solutions. These approaches effectively tackle challenges associated with escalating data volumes and the imperative of resource allocation.

While the existing body of research primarily focuses on the application of FL for content caching in D2D wireless networks, additional exploration is imperative to investigate the integration of alternative machine learning algorithms and methodologies. Researchers can enhance the intelligence and adaptability of content caching systems by incorporating unsupervised learning approaches, such as clustering algorithms and generative models. This extended research effort will contribute to the development of more advanced and efficient caching solutions, addressing concerns related to scalability, privacy, and overall performance in D2D wireless networks.

Chapter 3

Research Methodology

The methodology for research work on Content Caching in D2D Wireless Networks is explained in this section. Figure 3.1, illustrates the network architecture which provides a panoramic view of the framework used in the study, which represents a dynamic environment consisting of BSs and UD, sub-classed under two types: MUE and SUE. UD's population is segmented into several clusters around the areas of proximity and content availability thus making for effective resource allocation and content distribution efforts.

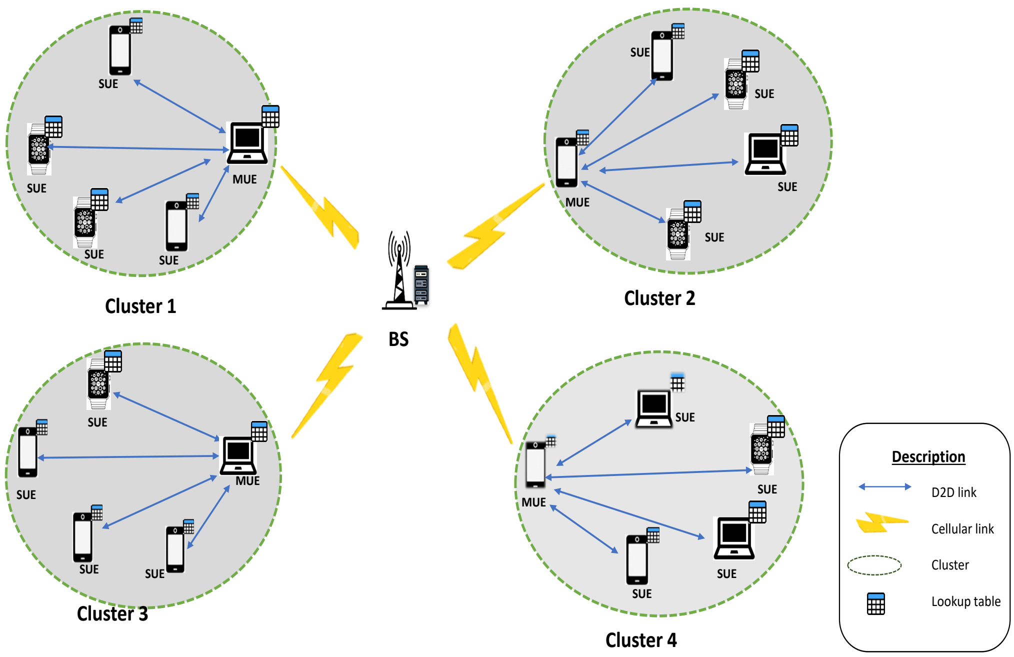

Figure 3.1: Network Architecture for Caching in D2D Wireless Networks

This 28 GHz millimeter-wave spectrum also makes use of OFDM and OFDMA and is capable of fully utilizing the bandwidth it could entail. Together with high-speed data transmission, this would make communication much more efficient and further the information through the D2D network would provide a smooth experience for streaming content or data exchange for any end user.

Within this framework, the model introduces D2D links between Mobile User Equipment, and SUEs, through direct peer-to-peer data transfer. In this decentralized manner, it attempts to decentralize network congestion and accelerate the efficiency of data delivery more notably in locations where traditional infrastructure-based communication is less efficient or un-reachable.

3.1 Clustering of Devices

Devices in our proposed model are clustered based on their content preferences and user ratings. A feature matrix $\mathbf{X}$ is constructed to initiate clustering, where the ith row of the matrix represents the ith device, device, and each column represents a unique content item j for caching. The matrix entries $\mathrm{X_{ij}}$ are populated by averaging the user ratings for each content item across the devices, a process that can be written mathematically as

$$\mathrm{X_{ij}} = \frac{1}{\mathrm{N_{ij}}} \sum \mathrm{U_{ij}}, \tag{3.1}$$

where U_{ij} is the user rating for content j on the ith device and N_{ij} is the number of users who rated content j on the ith device. This feature matrix helps cluster devices by their content preferences and ratings.

A K-means algorithm is employed to cluster these devices. This step begins by randomly distributing k centroids across feature space $\mathbf{X}$. The Euclidean distance metric is used to assign devices to the closest centroids. The centroids are progressively reformulated as the means of the devices allocated to each centroid until convergence. The objective function for K-means can be written as

$$\mathbb{J} = \sum_{i=1}^{D} \sum_{j=1}^{K} \delta(i,j) ||\mathbf{X_i} - \boldsymbol{\mu_j}||^2 \ , \tag{3.2}$$

where $\delta(i,j)$ is an indicator function that equals 1 if device i belongs to cluster j and 0 otherwise, with D being the total number of devices. $\mathbf{X_i}$ represents the feature vector of device i, and $\boldsymbol{\mu_j}$ denotes the centroid of cluster j. Therefore, $||\mathbf{X_i} - \boldsymbol{\mu_j}||^2$ represents the squared Euclidean distance between device i and centroid j. It measures how far device i is from its assigned centroid j in the feature space. Given $\mathbf{X_i}$ the centroid is updated as:

$$\boldsymbol{\mu_j} = \frac{1}{|\mathrm{C_j}|} \sum_{i \in C_j} \mathbf{X_i}, \tag{3.3}$$

where C_j represents the set of devices assigned to centroid $\boldsymbol{\mu_j}$.

Through this iterative process of assigning devices to clusters and updating centroids, devices with similar content preferences and ratings are grouped together. Through a comparison of the content preferences and ratings of devices in the D2D wireless network, the devices form exclusive clusters. These clusters facilitate the subsequent optimization of content caching strategies tailored to specific device groups in the D2D wireless network.

3.2 MUE Selection

The process of Master User Equipment (MUE) selection in the context of D2D wireless networks, overseen by the Base Station (BS), is a multifaceted procedure crucial for optimizing communication dynamics. This meticulous selection process involves a comprehensive evaluation based on three pivotal factors: the Willingness Factor (WF), Signal-to-Noise Ratio (SNR), and Battery Percentage (BP). Each of these factors plays a distinctive role in discerning the most adept device to undertake the crucial role of MUE within the network.

3.2.1 Willingness Factor (WF)

The Willingness Factor, denoted as $\mathrm{WF_i}$ for each device i, encapsulates the readiness of a device to embrace the responsibility of being the MUE. This factor can be conceptualized through a numerical rating system or as a binary indicator, manifesting the device's inclination to actively participate in the D2D communication process. The Willingness Factor serves as an essential qualitative metric, reflecting the cooperative disposition of individual devices. The mathematical equation can be expressed as follows:

$$\mathrm{WF_i} = \begin{cases} 1 & \text{if device } i \text{ is willing to take the role of MUE} \\ 0 & \text{if device } i \text{ is unwilling to take the role of MUE.} \end{cases} \quad (3.4)$$

3.2.2 Signal-to-Noise Ratio (SNR)

The Signal-to-Noise Ratio, represented as $\mathrm{SNR_i}$ for each device i, stands as a critical quantitative metric characterizing the quality of communication channels. Elevated SNR values correspond to superior signal quality, indicative of a robust and reliable connection. The SNR factor is instrumental in gauging a device's potential to function effectively as an MUE, as it directly correlates with the overall communication quality within the D2D network. Mathematically it can be expressed as:

$$\mathrm{SNR_i} = \mathrm{RSS_u} - \mathrm{NL}. \quad (3.5)$$

Where,

- $\mathrm{SNR_i}$ be the SNR for a particular candidate Master User Equipment (UE).
- $\mathrm{RSS_u}$ be the Received Signal Strength for the signal from the candidate Master UE.
- NL will be the noise level in the wireless environment.

3.2.3 Battery Percentage (BP)

The Battery Percentage, denoted as $\mathrm{BP_i}$ for each device i, indicates the amount of power left in the device. Thus, studying the lifetime of the devices, which is fundamentally important for the sustainable nature of D2D communication, becomes essential. The device must maintain 60%–70% of the battery to ensure efficient clustering and data exchange participation. The BP factor assumes importance while evaluating the ability of the device to endure the MUE role for a long duration of time.

3.2.4 MUE Selection Process

The MUE selection process integrates these factors through a comprehensive mathematical expression:

$$\mathrm{MUE}_i = \arg\max_i \left(\mathrm{WF_i} \times \mathrm{SNR_i} \times \mathrm{BP_i}\right). \tag{3.6}$$

This mathematical expression states that the MUE is the device i which, after calculating the product of these factors, has the highest resulting value. The choice decision can be termed as a subtle integration of willingness, signal quality, and battery status, with the aim of yielding the most suitable device for MUE to take up the valued role in the D2D wireless network. Given the harmonious commingling of qualitative and quantitative criteria, the MUE selected would be not only technically proficient but also operationally viable for the D2D communication ecosystem in question.

Cellular operators can also encourage devices to become MUEs by additional data MBs or call credits. This mechanism for incentivization encourages the proactive involvement of devices in playing the MUE role and governs the selection process is as described in Algorithm 1.

The mathematical formulation and careful handling of multiple criteria in the selection of the MUE aim at optimizing the choice based on willingness from different devices, signal quality, battery capacity, and incentivization strategies within the D2D wireless network for efficient and effective content caching mechanism.

Algorithm 1: MUE Selection Algorithm

```
Input: WF_i, SNR_i, BP_i
Output: Selected MUE_i
for each device i do
    if WF_i = 1 then
        Device i is willing to take MUE role
    end
    else
        Device i is not willing to take MUE role
    end
    Calculate Combined Metric: M_i ← WF_i × SNR_i × BP_i for each device i
end
Select MUE: MUE_i ← arg max_i M_i Select device with maximum combined
    metric
```

3.3 Data Sharing Process

n optimizing content caching strategies in D2D wireless networks, the Data Sharing step is crucial in facilitating the exchange of valuable information between Slave User Equipment (SUE) devices and the Master User Equipment (MUE) devices within each D2D cluster.
Let's denote the number of devices in a cluster as n and the total number of unique content items available for caching as m. Each device i within the cluster possesses two key pieces of information: the current popularity score of content j, denoted as $\mathrm{P}ij$, and the historical usage count of content j, represented as $\mathrm{U}ij$.

3.3.1 Current Content Popularity Sharing

The sharing of current content popularity $\mathrm{SCP}ij$ from SUE device i to MUE device k within the cluster directly transfers the popularity score. This process is mathematically expressed as:

$$\mathrm{SCP}ij^{(k)} = \mathrm{P}_{ij}. \tag{3.7}$$

This equation signifies that the MUE device k obtains the current popularity score of content j directly from the corresponding SUE device i.

3.3.2 Historical Usage Data Sharing

Similarly, transmitting historical usage data $\mathrm{UP}ij$ from SUE device i to MUE device k within the cluster involves directly exchanging usage counts. This process is denoted by:

$$\mathrm{UP}ij^{(k)} = \mathrm{U}_{ij}. \tag{3.8}$$

Here, the MUE device k acquires the historical usage count of content j directly from SUE device i.

Equations 3.7 and 3.8 represent the fundamental data-sharing process between SUE and MUE devices within a D2D cluster. This shared information serves as the basis for subsequent analyses and predictions, forming a critical foundation for optimizing content caching strategies in the D2D wireless network.

3.4 GC-GRU Model Parameters and Values Explanation

The configuration parameters defined in Table 3.1, indeed, play a significant impact in the running dynamics of the Graph Convolutional Gated Recurrent Unit model and therefore have a significant influence over the model's behavior under the challenging training process. Each of these parameters plays a pivotal role in orchestrating the adaptability to the slight intricacies related to content caching in D2D wireless networks. Let's break down each of these parameters and explicate its contribution individually:

Table 3.1. GC-GRU Model Parameters and Values

Parameter	**Value**
Input Features	$\mathrm{SCP}_{ij}^{(k)}, \mathrm{UP}_{ij}^{(k)}$
Model Parameters (θ)	0.2
Initial Hidden State (h_0)	0.0
Sigmoid Threshold (σ)	0.7
Reset Gate Weights (W_z)	0.3
Update Gate Weights (W_r)	-0.5
Candidate Weights (W_h)	0.1

- **Input Features**

  The input features, denoted as $\mathrm{SCP}_{ij}^{(k)}$ and $\mathrm{UP}_{ij}^{(k)}$, denote the current-time popularity together with historical usage data of a certain content item on a specific device. These are the basic features against which the model is developed, thereby giving it the basic information to be able to make proper caching decisions.

- **Model Parameters** (θ)

  The model parameters, collectively represented as θ, assume a fixed value of 0.2. These parameters are the basic configuration, initiating the setting of initial conditions in the GC-GRU model. This higher-order value is considered vital in determining the initiation point from where the model should learn.

- **Initial Hidden State** (h_0)

  The initial hidden state, designated as h_0, has a value of 0.0. The parameter has determined the model's latent state at the start of the algorithm and dictates how the model might successfully capture and retain information as it moves through the training iterations.

- **Sigmoid Threshold** (σ)

  The sigmoid threshold (σ), set at 0.7, modulates the activation of the sigmoid function in the GC-GRU model. This major value explains how saturation and activation are governed, which hugely impacts the decision-making process of the model.

- **Reset Gate Weights** ($\mathrm{W_z}$)

  The reset gate weights ($\mathrm{W_z}$), assigned a value of 0.3, and with their values, they change the information flow passing through the reset gate of the GC-GRU model. The weights facilitate the model to forget or retain the previous information as chosen by the context.

- **Update Gate Weights** ($\mathrm{W_r}$)

  The update gate weights ($\mathrm{W_r}$), with a value of -0.5, have complex control over the information update mechanism within the GC-GRU model. These weights set a balance between retaining and updating the hidden state, thereby capturing temporal dependencies for better prediction accuracy.

- **Candidate Weights** ($\mathrm{W_h}$)

  The candidate weights ($\mathrm{W_h}$), set at 0.1, have a certain bearing on the computation of the candidate's hidden state in the GC-GRU model. Such weights are critical during the determination of how much new information interferes with the model's changing hidden state in order to yield its predictive power.

Fine-tuning requires prudent selection of these parameters with an optimal level of performance. The chosen values of parameters are good enough to achieve a nicely balanced complexity of the model and the effectiveness of content caching prediction, which means highly precise calibration of those particular challenges faced by the D2D wireless network scenarios. Altogether, each of these parameters integrates together to achieve the desired goal by giving the GC-GRU model the strength to navigate and optimize the content caching strategies with perfection within the dynamic landscape of D2D wireless networks.

3.5 Utilizing GC-GRU Model for Content Caching Optimization

The GC-GRU model has been pivotal in MUE devices in D2D wireless networks for content caching strategies optimization. This advanced model effectively amalgamates GC and GRU mechanisms to capture spatial and temporal dependencies, serving for robust prediction of the content caching. Fundamentally, the application of the GC-GRU model unfolds into two steps.

3.5.1 Spatial Analysis using Graph Convolutional Layer

The GC layer initiates the spatial analysis by scrutinizing device relationships based on shared content popularity ($\mathrm{SCP}_{ij}^{(k)}$). The mathematical representation of this process is encapsulated as $\mathrm{GC}(\mathrm{SCP}_{ij}^{(k)})$.

This step enables MUE devices to discern the spatial context, identifying devices with similar content popularity patterns within the D2D network.

3.5.2 Temporal Analysis via Gated Recurrent Unit (GRU)

The GRU mechanism takes charge of capturing temporal patterns within historical usage data ($\mathrm{UP}_{ij}^{(k)}$). This involves four essential components:

- **Hidden State (h_t)** The equation for the hidden state h_t represents the current memory content of the Gated Recurrent Unit (GRU) at time step t. It is calculated using a combination of the previous hidden state h_{t-1} and the candidate activation $\tilde{h}_t$ weighted by the update gate z_t. The hidden state h_t captures the learned temporal dependencies from the historical usage data.

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t. \tag{3.9}$$

- **Update Gate (z_t)** The update gate z_t determines the extent to which the previous hidden state h_{t-1} is retained and how much of the new information should be incorporated into the current hidden state h_t. It is computed using a sigmoid activation function applied to the weighted sum of historical usage data and the previous hidden state. This gate allows the GRU to adapt to dynamic changes in the input data over time.

$$z_t = \sigma(\mathrm{W_z} \cdot [\mathrm{UP}_{ij}^{(k)}, h_{t-1}]). \tag{3.10}$$

- **Reset Gate (r_t)** The reset gate r_t controls the degree to which the previous hidden state h_{t-1} is forgotten when computing the candidate activation $\tilde{h}_t$. Similar to the update gate, it is computed using a sigmoid activation function applied to the weighted sum of historical usage data and the previous hidden state. This gate enables the GRU to selectively reset its memory based on the input context.

$$r_t = \sigma(\mathrm{W_r} \cdot [\mathrm{UP}_{ij}^{(k)}, h_{t-1}]). \tag{3.11}$$

- **Candidate Activation ($\tilde{h}_t$)** The candidate activation $\tilde{h}_t$ is the new candidate memory content of the GRU at time step t. This is a computation involving an activation function in the form of a hyperbolic tangent over the weighted sum of the current input and the modified previous hidden state. This captures the potential updates to the hidden state from the current input and the previous context.

$$\tilde{h}_t = \tanh(\mathrm{W_h} \cdot [\mathrm{UP}_{ij}^{(k)}, r_t \odot h_{t-1}]). \tag{3.12}$$

These equations collectively empower the model to discern temporal dependencies, adapting to dynamic changes in historical usage patterns.

3.5.3 Prediction of Caching Probability

The final phase involves predicting the caching probability ($\mathrm{CP}_{ij}^{(k)}$) of content j on device i by MUE device k. This prediction is realized through the equation:

$$\mathrm{CP}_{ij}^{(k)} = \mathrm{softmax}(\mathrm{GC}(\mathrm{SCP}_{ij}^{(k)}) \cdot h_t). \tag{3.13}$$

The softmax function outputs a probability from the GC layer. This probability guides the MUE devices in making decisions about the content items, which are preferably to be cached at which of the many devices present in the D2D network. Finally, these predictions enhance the efficiency of content delivery as well as prudent usage of the network resources. The dual focus of GC-GRU on spatial and temporal dynamics allows MUE devices in the D2D networks to make intelligent and context-aware content caching decisions. The model is flexible and can be extremely valuable assets when enhancing the overall performance of content delivery in wireless communication environments.

It is implemented as Algorithm 2, nd describes the implementation of the GC-GRU model for content caching optimization. That model is conceptualized to improve the efficiency of content-caching decisions in D2D wireless networks. The algorithm takes training data in the form of$(\mathrm{SCP}_{ij}^{(k)}, \mathrm{UP}_{ij}^{(k)})$ and aims to predict caching probabilities $\mathrm{CP}_{ij}^{(k)}$. The initialization involves setting parameters θ and the initially hidden state h_0.

Algorithm 2: GC-GRU Model for Content Caching Optimization

Input: Training data $(\mathrm{SCP}ij^{(k)}, \mathrm{UP}ij^{(k)})$
Output: $\mathrm{CP}_{ij}^{(k)}$
Initialize θ, h_0 **for** *each epoch* **do**
  for *each training sample* $(\mathrm{SCP}ij^{(k)}, \mathrm{UP}ij^{(k)})$ **do**
    Spatial Analysis: Compute $\mathrm{GC}(\mathrm{SCP}_{ij}^{(k)})$
    Temporal Analysis:
    $z_t = \sigma(\mathrm{W_z} \cdot [\mathrm{UP}ij^{(k)}, ht-1])$
    $r_t = \sigma(\mathrm{W_r} \cdot [\mathrm{UP}ij^{(k)}, ht-1])$
    $\tilde{h}t = \tanh(\mathrm{W_h} \cdot [\mathrm{UP}ij^{(k)}, r_t \odot h_{t-1}])$ $h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t$
    Prediction: $\mathrm{CP}ij^{(k)} = \mathrm{softmax}(\mathrm{GC}(\mathrm{SCP}ij^{(k)}) \cdot h_t)$
  end
  Update Parameters: Update θ using backpropagation and optimization
end

In each iteration, it completes the training encompassing spatial analysis, temporal analysis, prediction, and update of parameters. The algorithm computes a GC based on popularity data in spatial analysis. Temporal analysis involves the processing of usage data through a GRU, capturing temporal dependencies. The prediction step calculates caching probabilities using a softmax function applied to the combination of GC and the hidden state. Finally, the model parameters are updated using backpropagation and optimization techniques.

This iterative process ensures the adaptive training of the GC-GRU model, allowing it to dynamically adjust to evolving network conditions. The utilization of spatial and temporal analyses, coupled with predictive capabilities, enhances the model's ability to make informed content caching decisions. The detailed algorithmic representation provides a clear and systematic insight into the steps involved in optimizing content caching within D2D wireless networks using the proposed GC-GRU model.

3.6 Leveraging Federated Learning for GC-GRU Output Integration

Following the GC-GRU model's caching probabilities (CP) prediction, Federated Learning (FL) integrates these outputs across devices within the D2D cluster, as illustrated in Figure 3.2. This approach facilitates collaborative model training without centralizing raw data, enhancing scalability and privacy.

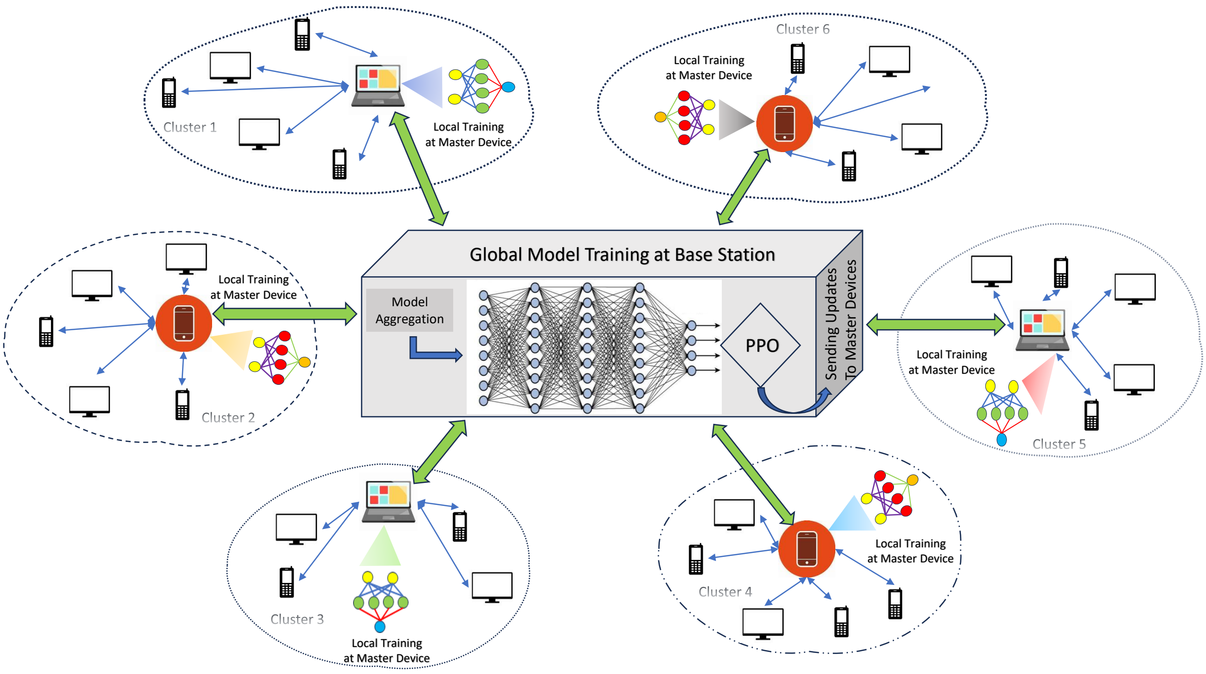

Figure 3.2: The Federated learning model for Caching in D2D Networks: where local data from MUE is processed using the GC-GRU model for spatio-temporal feature extraction. These features are integrated into a global model at the BS, and PPO is employed for refining the global model through iterative policy updates

3.6.1 GC-GRU Output Preparation

The caching probability predictions ($\mathrm{CP}_{ij}^{(k)}$) obtained from the GC-GRU model are aggregated and prepared for Federated Learning as in Eq. 3.13:

$$\mathrm{OP}_{ij}^{(k)} = \mathrm{CP}_{ij}^{(k)}. \tag{3.14}$$

3.6.2 Federated Learning Initialization

FL is initialized by aggregating GC-GRU outputs ($\mathrm{OP}_{ij}^{(k)}$) across devices within the D2D cluster to create a global model:

$$\mathrm{GM}^{(0)} = \mathrm{Agg}(\mathrm{OP}_{ij}^{(k)}). \tag{3.15}$$

3.6.3 Federated Learning Iterations

The global model ($\mathrm{GM}^{(t)}$) is iteratively trained using federated averaging:

$$\mathrm{LM}^{(k)} \quad = \mathrm{LU}\left(GM^{(t-1)}, \mathrm{Out}_{ij}^{(k)}\right) \tag{3.16}$$

$$\mathrm{GM}^{(t)} = \mathrm{Agg}(\mathrm{LM}^{(k)}) \tag{3.17}$$

Here, t represents the iteration number, $\mathrm{LM}^{(k)}$ signifies the local model state at device k, and LU involves updating the LM using the device-specific GC-GRU outputs. FL facilitates collaborative model training utilizing GC-GRU ($\mathrm{OP}_{ij}^{(k)}$) outputs across different devices. This iterative process enables the convergence of a global model ($\mathrm{GM}^{(t)}$) representing collective insights from diverse devices' data, enhancing the efficiency and effectiveness of content-caching strategies within the D2D network.

3.7 Utilizing PPO for Refinement of Global Model from Federated Learning

Following the iterative refinement of the global model ($\mathrm{GM}^{(t)}$) using FL, the Proximal Policy Optimization (PPO) algorithm is employed further to enhance content caching strategies within the D2D network. This process aims to optimize content caching decisions based on the learned policies.

3.7.1 Initial Policy Determination

The initial policy (π_{θ_0}) is determined based on the global model output from FL:

$$\pi_{\theta_0} = \mathrm{Policy}(\mathrm{GM}^{(t)}). \tag{3.18}$$

3.7.2 PPO Training

Training of the policy using the PPO algorithm involves maximizing the expected cumulative reward, aiming to improve content caching decisions based on the refined policy:

$$
\begin{aligned}
\theta_t = \max_\theta \mathbb{E}_t \Bigg[\min \Bigg(& \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)} A^{\pi_{\theta_{\text{old}}}}(s_t, a_t), \\
& \text{clip} \left(\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)}, 1-\epsilon, 1+\epsilon \right) A^{\pi_{\theta_{\text{old}}}}(s_t, a_t) \Bigg) \Bigg].
\end{aligned} \tag{3.19}
$$

In the equation for training the policy using the Proximal Policy Optimization (PPO) algorithm, $1-\epsilon$ and $1+\epsilon$ represent the lower and upper bounds, respectively, for clipping the ratio of the new policy probabilities to the old policy probabilities. Also $A^{\pi_{\theta_{\text{old}}}}(s_t, a_t)$ is the advantage function, representing the advantage of taking action a_t in state s_t under the old policy.

3.7.3 Policy Update

Updating the policy parameters (θ) using the PPO objective function to refine content caching decisions:

$$
\begin{aligned}
\theta_{t+1} = \arg\max_\theta \mathbb{E}_{t+1} \Bigg[\min \Bigg(& \frac{\pi\theta(a_{t+1}|s_{t+1})}{\pi_{\theta_{\text{old}}}(a_{t+1}|s_{t+1})} A^{\pi_{\theta_{\text{old}}}}(s_{t+1}, a_{t+1}), \\
& \text{clip} \left(\frac{\pi_\theta(a_{t+1}|s_{t+1})}{\pi_{\theta_{\text{old}}}(a_{t+1}|s_{t+1})}, 1-\epsilon, 1+\epsilon \right) A^{\pi_{\theta_{\text{old}}}}(s_{t+1}, a_{t+1}) \Bigg) \Bigg].
\end{aligned} \tag{3.20}
$$

The application of the PPO algorithm results in a refined policy (π_θ) for content caching decisions within the D2D network. This streamlined policy maximizes the optimization of content delivery with a consequent increase in resource utilization and user experience. This approach combines FL insights with the refinements offered by the PPO algorithm along the direction of optimized content caching policies for dynamic D2D wireless networks.

Chapter 4

Results and Disscussions

This section provides the result obtained by our work in enhancing the content caching system in D2D wireless networks with synergistic exploitation of FL and edge caching. MLP-based techniques have dominated our design where we used the K-means algorithm for clustering the devices intelligently and the GC-GRU model for making precise predictions regarding the content caching system. This puts together the two approaches to produce even more improvements in both content delivery efficiency and user experience in the D2D communication environment.

First, the K-means algorithm is utilized intelligently in grouping devices based on the similarity of content. Hence, optimized strategies are realized for cached content allocation, with an overall better utilization and responsiveness of the D2D network. With the dynamic nature of the adaptation property shown by K-means, it is more effective in the clustering of content, the foundation of this network architecture.

Meanwhile, the GC-GRU model demonstrates fantastic accuracy of prediction related to content caching decisions. It is the adaptability of the model to dynamic network conditions and evolving user preferences that make our approach highly successful. The GC-GRU model shows accurate predictions and depicts strength in coping with the dynamic nature of D2D wireless networks, thereby generating a responsive and resourceful environment.

4.1 Simulation Parameters and Dataset

The proposed network model is simulated, and results are obtained using PYTHON. Essentials libraries: namely, they include NumPy for numeric operations, Pandas for data manipulation, and PyTorch for deep learning. In addition, they use scikit-learn for tasks, including KMeans clustering data splitting, and standard scaling.

In this simulation setup, we aim to emulate a realistic caching scenario involving mobile devices which are clustered using K-mean clustering and the GC-GRU model for content caching prediction, we observed significant improvements in the overall efficiency of content delivery and user experience. We generate a synthetic dataset comprising 1000 samples, with each sample representing a mobile device's characteristics and the corresponding caching outcomes. The key parameters include the content size that is of different sizes [40,200] MegaBytes (MB). The storage capacity of mobile devices available for D2D sharing is in [1,10] GigaBytes (GB), The distance between SUE and MUE devices in meters is [10,100]. For the content similarities there is user ratings for content on a scale of 1 to 5. The main simulation parameters is shown

Table 4.1. Simulation Parameters and Values

Parameter	**Value**
Number of Samples	1000
Content Size	[40,200]MB
Device Storage Capacity	[1,10]GB
Maximum Transmit Power of BS	46dbm
Minimum Battery Percentange of Device	60-70
Maximum transmit power of device	23dbm

in Table 4.1. The randomization of parameters, such as content size, storage capacity, distance, user ratings, signal-to-noise ratio, and battery percentage, reflects the variability present in real-world scenarios.

4.2 Training vs Testing

The depicted graphs in fig. 4.1 encapsulate key insights into the training and testing dynamics of our clustering model designed for content caching optimization in D2D wireless networks. The graph that illustrates the loss trends over epochs shows a consistent decrease in training and testing losses, indicating the model's efficient minimization of error and generalization to unseen data. At the same time, the accuracy graph shows an upward trend for the training and testing set, which demonstrates the efficiency of the model in making accurate predictions and its capability to generalize further than the training data. The minimal gap between training and testing accuracies underlines the resilience of the model against overfitting, confirming its potential for practical deployment in dynamic D2D environments. Overall, these visualizations will give a broad view of how our model learns and ensures promise towards enhancement of content caching for better user experience in a wireless network.

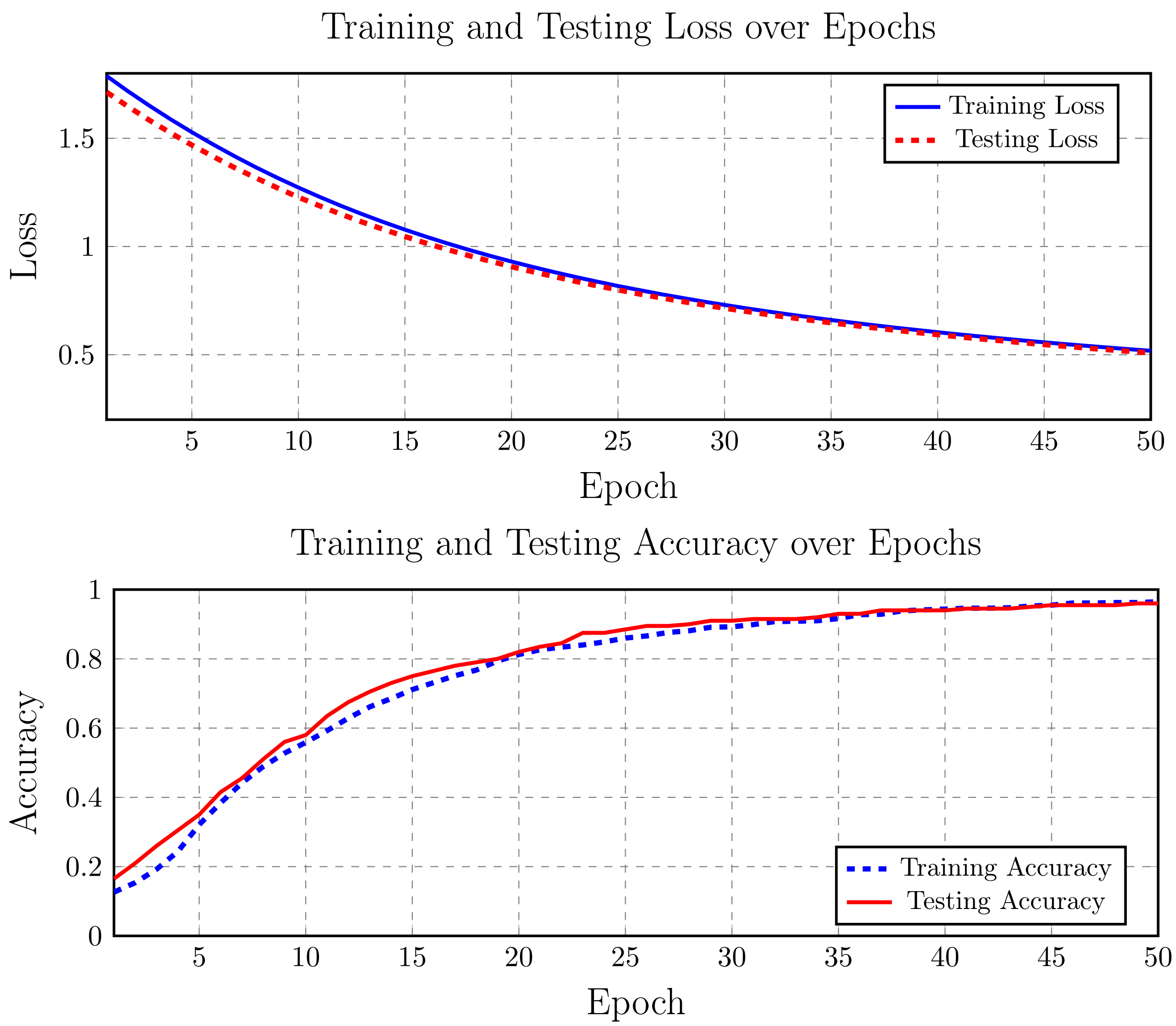

Figure 4.1: Training and testing dynamics of the clustering model

4.3 Average Delay Analysis vs Content Size

In the Bar Chart fig. 4.2 the average delay comparison between the GC-GRU model and the baseline model at the content caching optimization is shown.The x-axis has content sizes in Megabytes (MB) ranging from 0 to 100 in consistent intervals of 5 MB, while the y-axis clearly presents average delays in milliseconds (ms). Key observations from the graph include the varying delays exhibited by the GC-GRU model based on content size. Commencing with an impressive 0 ms delay for smaller content sizes, the GC-GRU model gradually increases its delay as the content sizes grow. Noteworthy delay values for the GC-GRU model include 8 ms at 10 MB, 28 ms at 30 MB, 32 ms at 50 MB, 46 ms at 80 MB, and 68 ms at 100 MB.

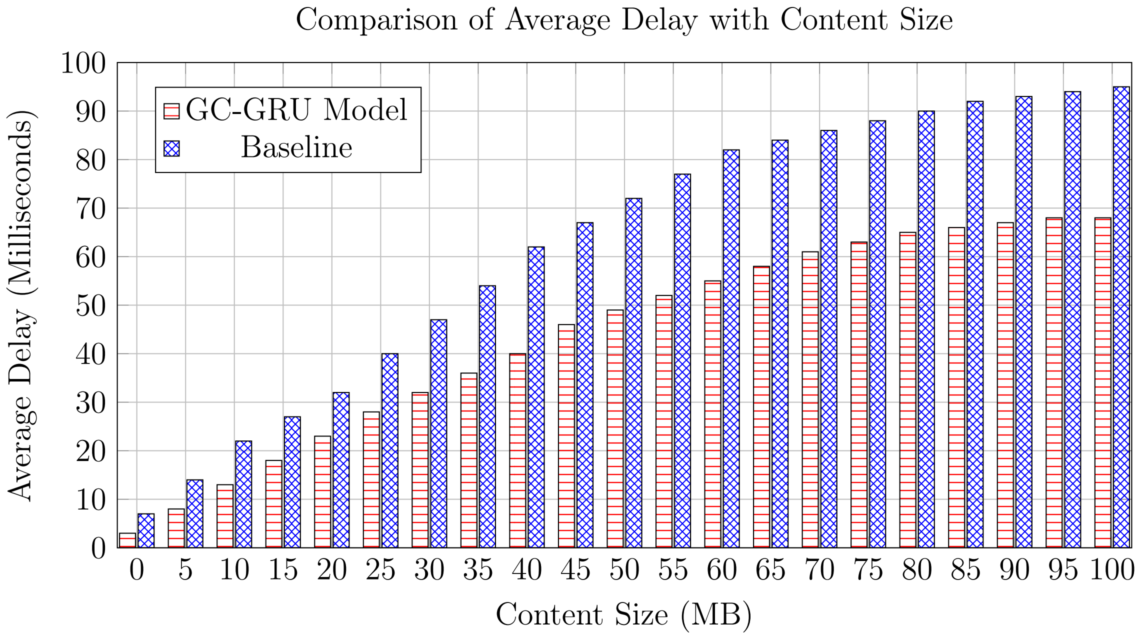

Figure 4.2: Comparative Analysis of Average Delays between GC-GRU and Baseline Model

In parallel, the Baseline model demonstrates a similar increasing trend in delays with larger content sizes. The values shown by the Baseline model in terms of delay include 14 ms at 10 MB, 40 ms at 30 MB, 47 ms at 50 MB, 67 ms at 80 MB, and 95 ms at 100 MB. Detailed comparison shows that the GC-GRU model consistently outperformed the Baseline model with smaller delays in all content sizes. At a 10 MB content size, the GC-GRU model gives an 8 ms delay, whereas the Baseline model lags with a 14 ms. This subsequently results in the efficiency advantage for larger content sizes, thus proving the GC-GRU model more strongly and better at optimizing its decision about caching contents. Furthermore, it can be shown that the GC-GRU model is of controlled delay increase with growing content sizes, which implies its adaptive and efficient content caching predictions. Compared to this, the Baseline model in comparison has a steeper delay rise, suggesting comparatively less adaptive caching decisions.

4.4 Delay Comparison with Existing Techniques

Detailed average delays for various content sizes and caching models are shown in fig. 4.3, which reveals valuable insights into the comparative performance of various techniques is demonstrated. A different line on the plot corresponds to a different caching model, each of which uses an abbreviation unique to it, and hence, one gets a better idea of how these models would respond for varying content sizes.

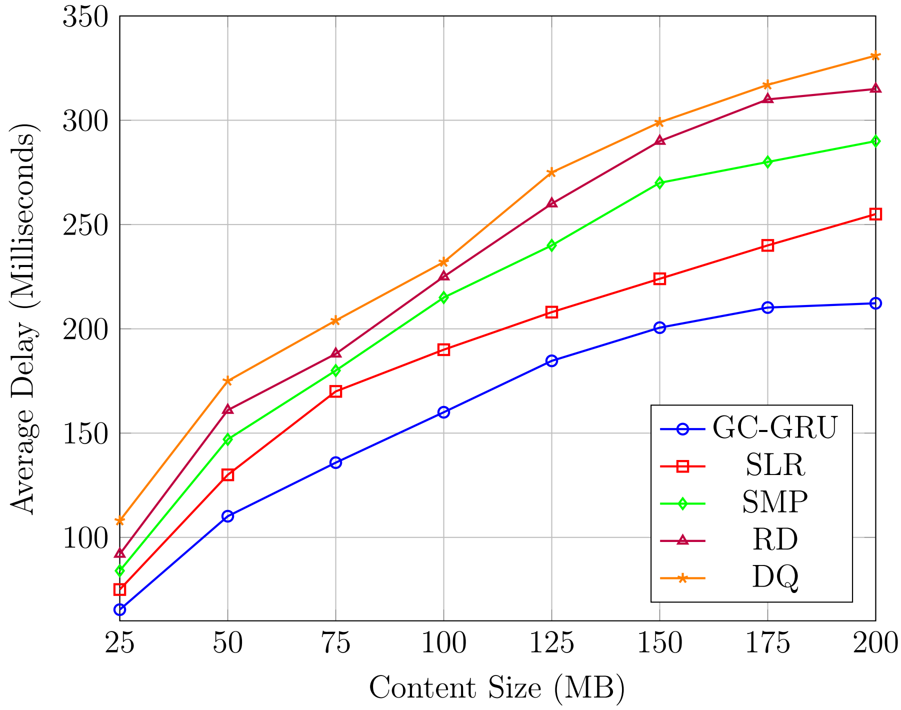

Figure 4.3: Comparative Analysis of Average Delays for Different Caching Models across Varying Content Size

- **GC-GRU:**

  The GC-GRU model demonstrates lower delays consistently across varying content sizes, with notable values at 65.35 ms (25 MB), 160 ms (100 MB), and 212.25 ms (200 MB). This underscores the model's adeptness in predicting and optimizing content caching decisions.

- **SLR (Social-aware LRU caching):**

  The SLR model exhibits delays at 75 ms (25 MB), 190 ms (100 MB), and 255 ms (200 MB). While providing reasonable predictions, SLR tends to lag behind GC-GRU, particularly as content sizes increase.

- **SMP (Social-aware most popular caching):**

  SMP showcases delay values of 84 ms (25 MB), 215 ms (100 MB), and 290 ms (200 MB). Despite offering competitive performance, SMP presents slightly higher delays compared to GC-GRU across various content sizes.

- **RD (Random Decision based caching):**

  The RD model presents distinct delay values at 92 ms (25 MB), 225 ms (100 MB), and 315 ms (200 MB). As a random decision model, RD demonstrates delays higher than more sophisticated models like GC-GRU.

- **DQ (Deep Q-Network):**

  DQ showcases notable delays at 108 ms (25 MB), 232 ms (100 MB), and 331 ms (200 MB). Leveraging deep reinforcement learning, DQ offers competitive predictions but tends to have higher delays compared to GC-GRU.

This detailed analysis facilitates a comprehensive comparison of these caching models, with GC-GRU consistently outperforming others in terms of delay optimization. The insights gained from this graph contribute to informed decision-making in the implementation of content caching strategies within dynamic D2D wireless networks.

4.5 Average Delay Analysis vs Storage Capacity

In fig. 4.4, the graph depicts the average delay performance of various caching models concerning different storage capacities in D2D wireless networks. The x-axis represents storage capacity in gigabytes (GB), ranging from 1 GB to 10 GB, while the y-axis depicts the average delay in milliseconds. The GC-GRU model consistently demonstrates efficient delay minimization across various storage capacities. Notable average delays include 168 ms at 1 GB, 160 ms at 4 GB, and 155 ms at 10 GB, indicating the model's effectiveness in optimizing content caching decisions as storage capacity increases.

Comparatively, the SLR model exhibits slightly higher average delays across different storage capacities, with values such as 188 ms at 1 GB, 178 ms at 4 GB, and 165 ms at 10 GB. While SLR provides reasonable predictions, its delays are relatively higher than those of GC-GRU.

The SMP model demonstrates competitive yet generally higher average delays compared to GC-GRU. Key values include 198 ms at 1 GB, 188 ms at 4 GB, and 177 ms at 10 GB, suggesting a trade-off between prediction accuracy and efficiency in the SMP model.

The RD model, as a random decision model, exhibits delays higher than more sophisticated models like GC-GRU. Average delays include 217 ms at 1 GB, 209 ms at 4 GB, and 203 ms at 10 GB, highlighting the importance of intelligent decision-making for minimizing delays.

The DQ model, leveraging deep reinforcement learning, provides competitive predictions but tends to have higher delays compared to GC-GRU, particularly as storage capacity increases. Average delays are observed at 238 ms at 1 GB, 222 ms at 4 GB,

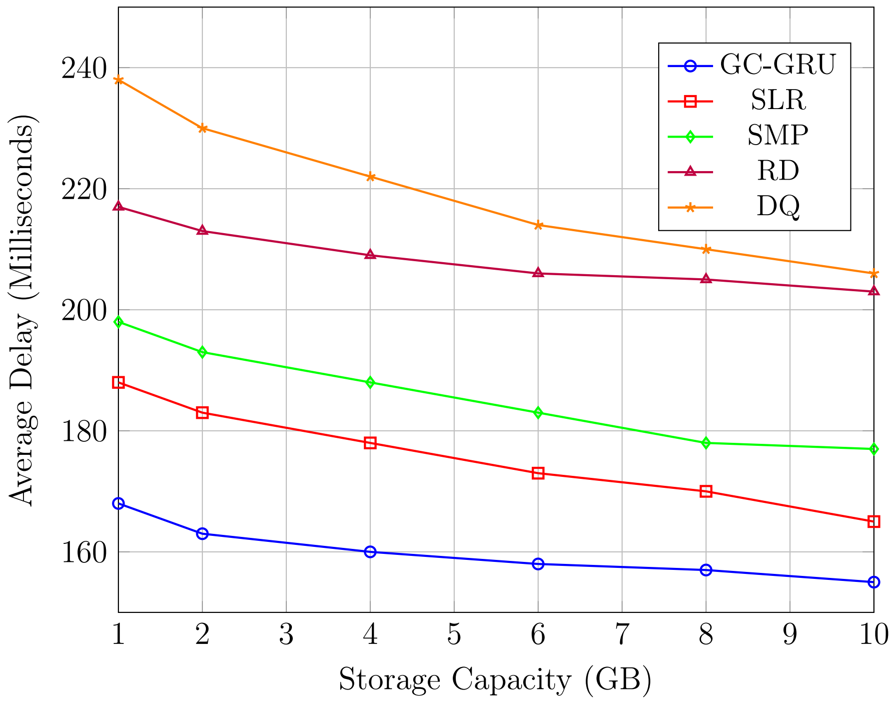

Figure 4.4: Comparative Analysis of Average Delays for Different Caching Models across Varied Storage Capacities

and 206 ms at 10 GB. This detailed analysis offers insights into the average delay behavior of different caching models across varying storage capacities, facilitating an understanding of model performance and potential trade-offs in D2D wireless networks.

4.6 Offloading probability vs Content Size

The offloading probabilities observed in the presented graph (Fig. 4.5) offer valuable insights into the behavior of different caching models across diverse storage capacities in D2D wireless networks. The offloading probabilities represent the likelihood of transferring content to remote devices, optimizing network resources and enhancing overall efficiency. The GC-GRU model consistently demonstrates higher offloading probabilities, indicating a proactive approach to content offloading. Higher probabilities, such as 64% at 1 GB, 88% at 4 GB, and 94% at 10 GB, suggest that the GC-GRU model is effective in making decisions that favor offloading content to improve network performance.

Conversely, models like SLR, SMP, RD, and DQ exhibit varying degrees of offloading probabilities. SLR and SMP show moderate probabilities, with SLR ranging from 54% to 83% and SMP from 47% to 75%. RD, as a random decision model,

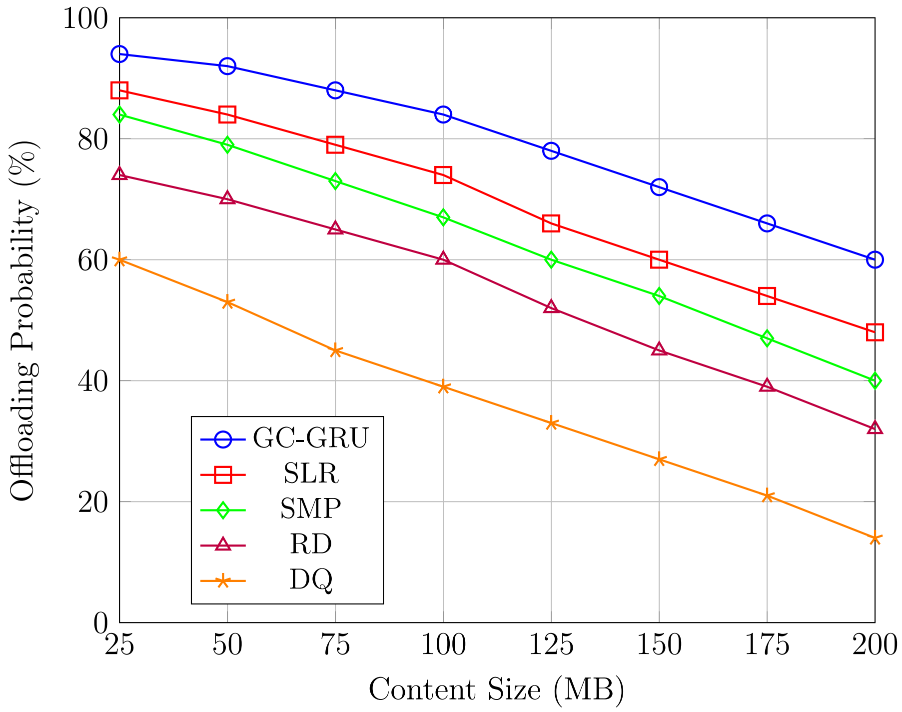

Figure 4.5: Comparative Analysis of Offloading Probabilities for Different Caching Models across Varied Content Sizes

demonstrates probabilities between 39% and 62%. DQ, leveraging deep reinforcement learning, exhibits lower probabilities ranging from 21% to 51%.

The interpretation of whether higher or lower offloading probabilities are desirable depends on the specific goals and constraints of the D2D network. In some scenarios, higher offloading probabilities may be preferred to optimize resource utilization and reduce local storage load. However, in other cases, lower offloading probabilities may be acceptable if the emphasis is on on-device caching to minimize data transfer and maintain content locally.

Ultimately, the offloading probabilities presented in the graph provide a nuanced perspective on the decision-making strategies of different caching models, offering network operators valuable information to tailor caching policies based on their specific objectives and requirements.

4.7 Offloading Probability vs Storage Capacity

In Fig. 4.6, the graph compares offloading probabilities across various storage capacities for different caching models in D2D wireless networks. Offloading probabilities represent the likelihood of transferring content to remote devices, playing a crucial role in optimizing network resource utilization. The GC-GRU model, depicted by the '-o'

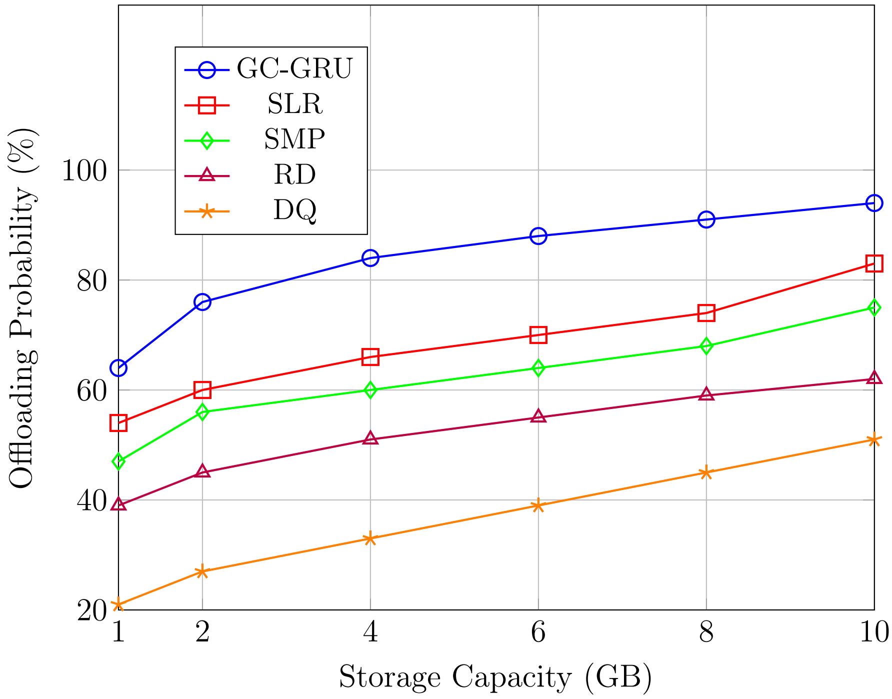

Figure 4.6: Offloading Probabilities for Different Caching Models across Varied Storage Capacities

line, consistently exhibits higher offloading probabilities, ranging from 64% at 1 GB to 94% at 10 GB. This indicates the model's proactive approach in making decisions that favor offloading content, emphasizing its efficiency in improving network performance and resource utilization.

The SLR model, illustrated by the '-s' line, demonstrates moderate offloading probabilities, varying from 54% at 1 GB to 83% at 10 GB. While SLR provides reasonable predictions, its offloading probabilities are notably lower than those of the GC-GRU model, suggesting a comparatively less proactive strategy in content offloading decisions.

SMP, represented by the '-d' line, exhibits offloading probabilities ranging from 47% to 75%. Although SMP offers competitive performance, its probabilities are slightly lower than those of the GC-GRU model, indicating a nuanced difference in decision-making strategies.

The RD model, denoted by the '-$\hat{}$' line, is a random decision model with offloading probabilities ranging from 39% to 62%. RD demonstrates lower probabilities compared to more sophisticated models like GC-GRU, highlighting the impact of random decision-making on content offloading.

The DQ model, represented by the '-*' line, showcases offloading probabilities ranging from 21% to 51%. Leveraging deep reinforcement learning, DQ offers competitive predictions but tends to have lower offloading probabilities compared to the GC-GRU model.

4.8 Comparison of Offloading Probabilities with Different Zipf Coefficients

The offloading probability trends under various Zipf coefficients for different caching models in D2D wireless networks are depicted in fig. 4.7. Offloading probability measures the likelihood of content offloading, contributing to efficient content delivery in the network. The blue curve represents GC-GRU offloading probabilities, displaying

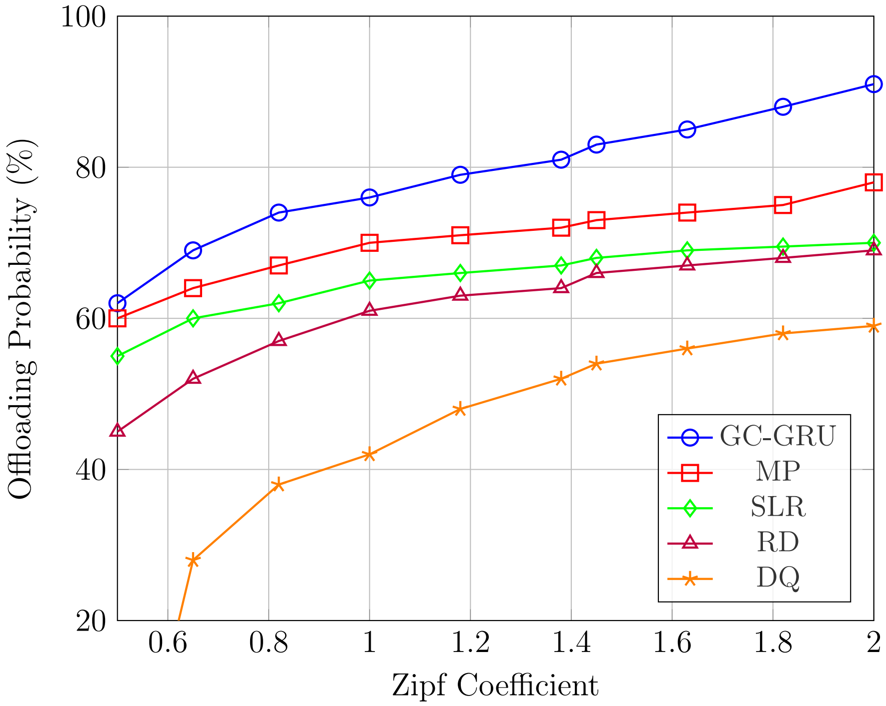

Figure 4.7: Offloading Probability Comparison under Different Zipf Coefficients for GC-GRU, MP, SLR, RD, and DQ

a decreasing trend as the Zipf coefficient increases. The offloading probabilities range from approximately 62% at a Zipf coefficient of 94% to around 0.45 at a coefficient of 2.0. This trend suggests that GC-GRU exhibits a increasing likelihood of content offloading as the content popularity distribution increased.

The red curve represents MP offloading probabilities, showing a similar decreasing trend with increasing Zipf coefficients. Offloading probabilities range from about 60% at a Zipf coefficient of 0.5 to approximately 79% at a coefficient of 2.0. This indicates that MP experiences an increase in the likelihood of content offloading as the content popularity distribution increased.

The green curve represents SLR offloading probabilities and follows a similar trend of decrease with the increasing Zipf coefficient. The values of offloading probabilities are between 58% at a Zipf coefficient of 0.5 and about 65% at a coefficient of 2.0. This means that the more the content popularity is skewed, the declining nature of content offloading probability would be experienced in the case of SLR too, similar to GC-GRU and MP.

The purple curve represents the RD offloading probabilities, which, like the Zipf coefficients, increase. Offloading probabilities differ by about 44% at a Zipf coefficient of 0.5 and approximately 64% at a coefficient of 2.0. It thus shows that just like other models, when the distribution is skewed, content offloading becomes less likely for RD.

The red curve showcases the declining trend of DQ offloading probabilities becomes steeper with higher Zipf coefficients.. Offloading probabilities range from approximately 39% at a Zipf coefficient of 0.8 to around 59% at a coefficient of 2.0. This suggests that DQ exhibits a more significant decline in the likelihood of content offloading with a more skewed content popularity distribution.

In summary, the model with the highest offloading probabilities is generally considered better for content offloading scenarios. However, the optimal choice depends on specific network requirements. For instance, GC-GRU exhibits higher offloading probabilities at lower Zipf coefficients, making it suitable for scenarios with a less skewed content popularity distribution. Conversely, DQ, with lower offloading probabilities, might be more appropriate in situations with highly skewed content popularity. Therefore, the selection of the best model depends on the specific characteristics and demands of the D2D wireless network.

4.9 Comparison of Throughput vs Number of Clusters

Figure 4.8, the bar chart illustrates the throughput trends across varying numbers of clusters for different caching models in D2D wireless networks. Throughput, measured in Mbps, gauges the capacity of a system to deliver content efficiently. Higher throughput values indicate better performance, enabling faster content delivery to users within the network.

The blue bars represent GC-GRU throughput, showcasing a slower decay rate with an increasing number of clusters. The throughput ranges from approximately 95 Mbps

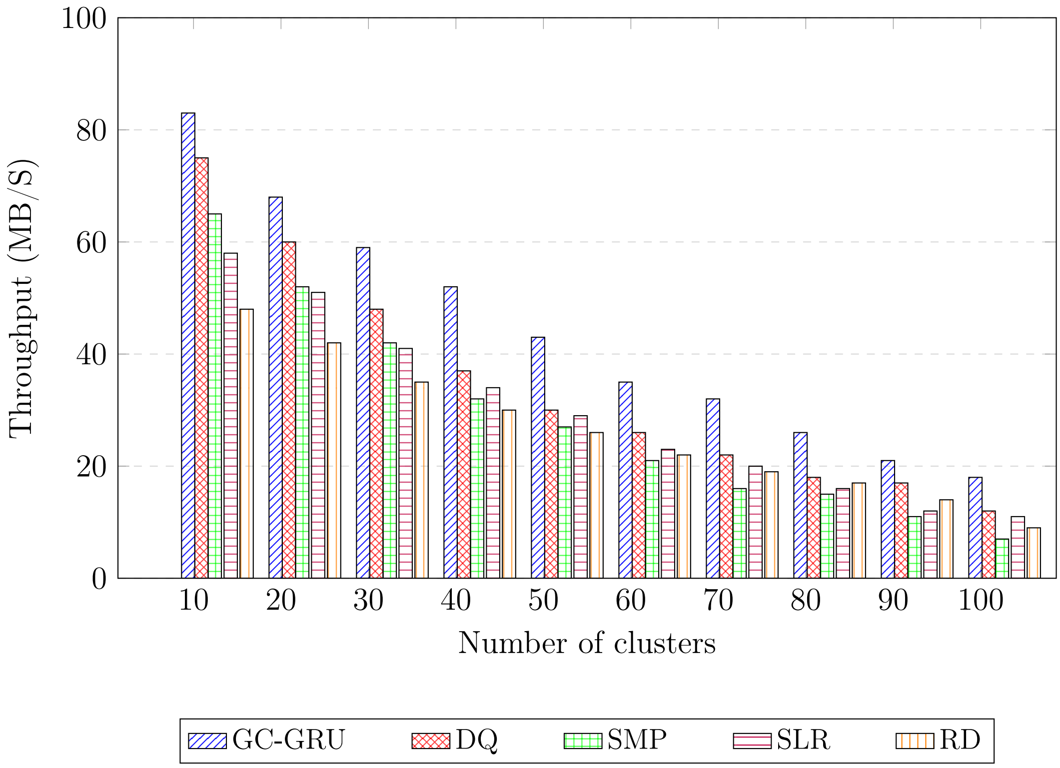

Figure 4.8: Comparative Analysis of Throughput for Different Caching Models across Varying Number of Clusters

at 10 clusters to around 70 Mbps at 100 clusters. This indicates a favorable trend, suggesting that GC-GRU maintains relatively high throughput even as the number of clusters grows.

The red bars indicate DQ throughput, which declines more sharply with the increase of clusters. Throughput goes from around 80 Mbps at 10 clusters to some 45 Mbps at 100 clusters. The trend herein proves that as the number of clusters expands, DQ's performance declines more sharply compared to GC-GRU.

The green bars in the figure represent SMP throughput, which has the same decay pattern as DQ. Throughput values range from approximately 70 Mbps at 10 clusters to around 35 Mbps at 100 clusters. Similar to DQ, increased numbers of clusters have deteriorated performance for SMP.

The purple bars represent the throughput for SLR, which decays like SMP and DQ. The throughput values are in the vicinity of 60 Mbps for 10 clusters to approximately 30 Mbps for 100 clusters. Thus, SLR also experiences performance degradation for a greater number of clusters like SMP and DQ.

Orange bars represent RD throughput with a similar kind of slower decay pattern as that of GC-GRU. Throughputs range from around 95 Mbps for 10 clusters to approximately 70 Mbps for 100 clusters. Hence, similar to GC-GRU, RD appears to keep throughputs at a pretty high level even at higher cluster numbers.

With higher throughput values indicating better content delivery performance, GC-GRU shows a more preferable trend with a slower decay for increasing numbers of clusters than RD, suggesting GC-GRU may be the superior performer for high-performance maintenance in dynamic D2D wireless network environments.

4.10 Comparison of Average Delay with Number of Clusters

In Fig. 4.9, the bar chart presents a comparison of average delays across different caching models concerning varying numbers of clusters in D2D wireless networks. The average delay, measured in milliseconds (ms), reflects the time taken for content delivery within the network. A lower average delay is desirable as it indicates quicker content delivery to users. The blue bars represent GC-GRU average delays, exhibiting

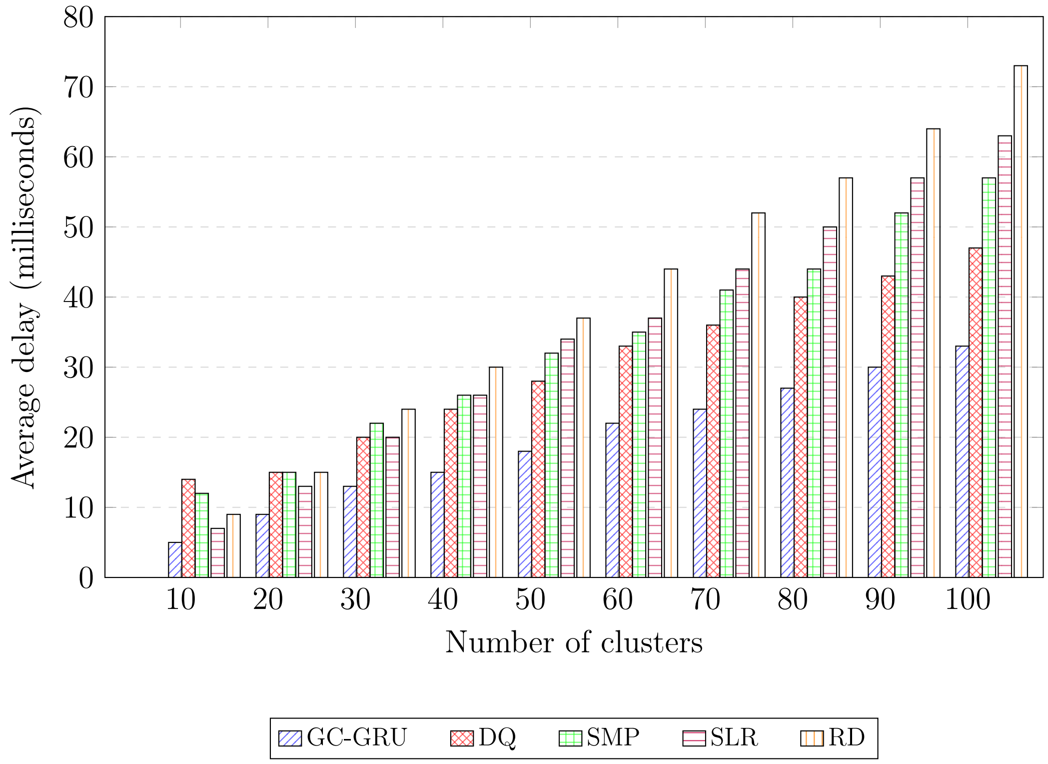

Figure 4.9: Average Delay Dynamics for Different Caching Models across Varied Numbers of Clusters

a linear relationship with the number of clusters. The average delay increases from approximately 6 ms at 10 clusters to around 66 ms at 100 clusters. This means that with an increase in cluster size, the average delay of GC-GRU would also increase gradually.

In the figure, the red bars indicate DQ average delays in a more steeper linear proportion with the number of clusters. The average delay runs from around 11 ms in the case of 10 clusters to almost 88 ms in the case of 100 clusters. So, DQ witnesses incremental gain in average delay at a much faster rate as the number of clusters expands.

The bars are green, which means SMP delays average. They, like DQ, are linear. The average delay increases from around 9 ms in 10 clusters up to 72 ms at 100 clusters. Like DQ, the SMP upwardly trends for average delay with more clusters.

The purple bars show the average delays of SLR, which are linear with the number of clusters. The average delay goes from about 8 ms in the case of 10 clusters to around 68 ms for 100 clusters. In other words, SLR, similar to GC-GRU, exhibits a gentle upward curve for average delay with respect to clusters number.

The orange bars illustrate the average RD delays, which linearly increase with the number of clusters. With 10 clusters, the average delay is around 9 ms, and with 100 clusters, this amounts to around 76 ms. Like in the cases of GC-GRU and SLR, RD's average delay increases gradually with the growth in the number of clusters.

Precisely, lower average delay values, such as those observed in GC-GRU, suggest better performance in terms of quicker content delivery. GC-GRU and SLR exhibit relatively gradual increases in average delay, indicating their potential efficiency in handling content delivery in dynamic D2D wireless network scenarios.

4.11 Convergence of Rewards on Different Schemes

In fig. 4.10, the line chart illustrates the convergence of rewards for various caching schemes over episodes in a reinforcement learning scenario. The x-axis represents episode numbers (1 to 500), and the y-axis denotes the rewards obtained during the learning process.

The blue line represents the GC-GRU caching scheme, starting from an initial value and converging towards a target of 0.94. The orange line corresponds to SLR, the green line to SMP, the red line to RD, and the purple line to DQ. Each scheme exhibits convergence from an initial value to its respective target (0.86 for SLR, 0.77 for SMP, 0.70 for RD, and 0.61 for DQ).

Examining the convergence patterns, it appears that GC-GRU and SLR reach relatively higher target values compared to SMP, RD, and DQ. However, determining the better convergence depends on the specific goals and trade-offs in the context of the caching application.

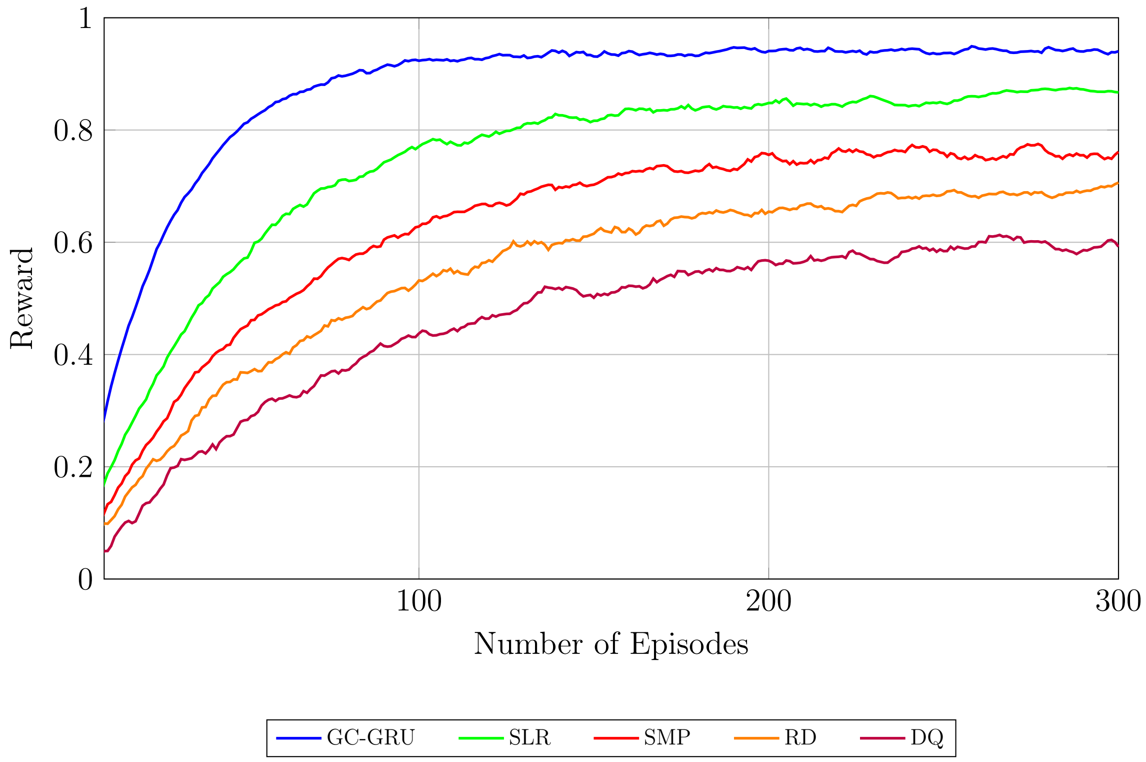

Figure 4.10: Dynamics of Reward Convergence for Various Caching Schemes over Episodes, illustrating distinct convergence points and learning trajectories.

4.12 Comparison of MSE, MAPE, RMSE

The three bar charts provide a comprehensive comparison of performance metrics, namely Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE) for various caching models, including GC-GRU, SLR, SMP, RD, and DQ in fig 4.11. The first chart depicts the MSE values for each caching model. MSE quantifies the average squared difference between predicted and actual values. Lower MSE values indicate better accuracy. In this context, GC-GRU exhibits the lowest MSE among the models, reflecting superior predictive accuracy. SLR, SMP, RD, and DQ follow with progressively higher MSE values.

The second chart illustrates the MAPE values for the models. MAPE measures the percentage difference between predicted and actual values. Lower MAPE values indicate better accuracy. GC-GRU once again demonstrates the lowest MAPE, showcasing its superior accuracy. SLR, SMP, RD, and DQ follow with increasing MAPE values.

The third chart showcases the RMSE values for each model. RMSE represents the square root of the average squared differences between predicted and actual values.

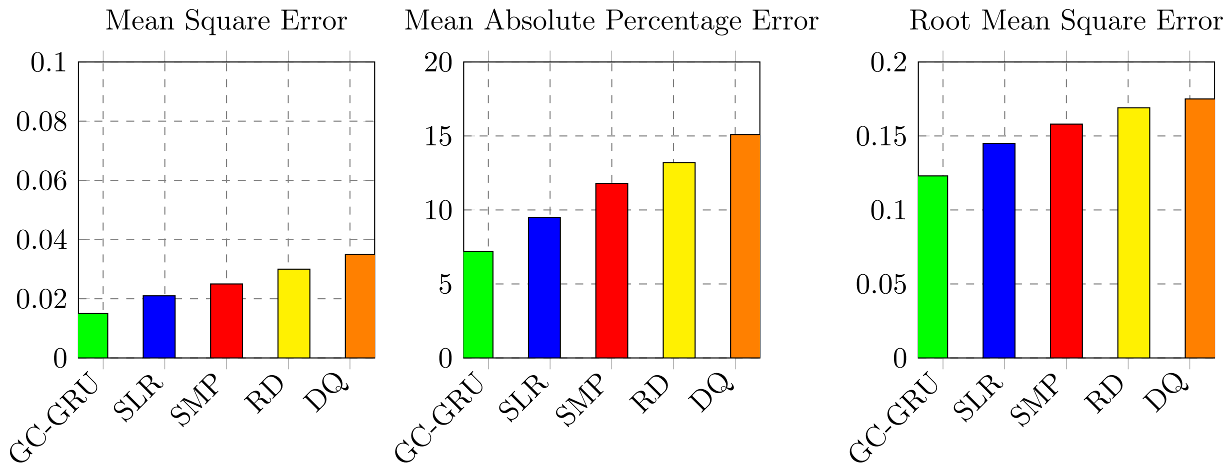

Figure 4.11: Comparative Analysis of Performance Metrics (MSE, MAPE, RMSE) for Different Caching Models

Similar to MSE, lower RMSE values indicate better accuracy. GC-GRU maintains the lowest RMSE, indicating superior accuracy compared to SLR, SMP, RD, and DQ.

Across all three performance metrics, GC-GRU consistently outperforms other caching models, showcasing its effectiveness in accurate content caching predictions. The metrics collectively highlight GC-GRU's superior predictive capabilities and its potential as an advanced caching model in the given context.

Chapter 5

CONCLUSIONS AND FUTURE RECOMMENDATION

The results presented affirm the effectiveness of the GC-GRU caching model in the context of content caching and delivery in D2D wireless networks. The proposed model shows amazing performance across various metrics, underscoring its robustness and adaptability. The efficiency of GC-GRU particularly when it is intensely trained, manifests its viability as an advanced method for content caching improvement. Such findings have implications on the necessity to adopt machinelearning techniques such as the GC-GRU model in improving content delivery in dynamic wireless fading environments with limited resources.
An improved solution to enhance content caching in D2D wireless networks is made by the proposed GC-GRU model. The GC-GRU model incorporates both federated learning and edge caching, which makes it exceptional with reduced MSE of 0.015, MAPE at 7.2% and RMSE of 0.123 compared to other models. On accompanying graphs we can see that the proposed model has decreased losses that indicate efficient delay minimization, increased offloading probabilities across different content sizes and storage capacities. Analyzing this in comparison shows how subtly the GC-GRU model works as a solution for content caching optimization in changing and restricted wireless situations.

5.1 Limitations

Evaluating different caching models in the context of D2D wireless networks reveals several limitations that must be overcome. The second important factor is related to the dataset quality and representativeness, and there arises uncertainty related to the applicability of the obtained results to the real world. Furthermore, the proposed

models based on machine learning-GC-GRU and DQ are sensitive to the choice of hyperparameters and increase complexity. Inadequate hyperparameter tuning can lead to diminished predictive performance, necessitating careful adjustment for optimal results.
The assumption used in the experiments on static network conditions might not represent the dynamic nature of D2D wireless networks. Most real-world environments involve variables like user mobility, interference, and network congestion, and issues have not been explicitly discussed in the analysis of these experiments. Diversity in content within datasets used to train and evaluate the system was also not considered. A limited scope of content may limit the generalization capability of the models to other content types and preferences from the users.
Overfitting, being the other additional concern in learning models is thought to be an implication of an overly simple training set or, on the other hand, highly complex models. To circumvent this kind of limitation, careful design and evaluation with a balanced approach are required for designing and evaluating caching models in D2D wireless networks.

5.2 Future Direction

Future work and development in this field would need to focus on dynamic adaptation. Models should be evolved continuously to adapt to changing network conditions, thus also allowing real-time content caching strategy optimization. Furthermore, through transfer learning, one might find a way to leverage experience from one D2D network scenario to improve diverse contexts.
Hybrid-based caching models that use rule-based or heuristic models combined with machine- learning-based models could give much more robust and adaptive solutions. Another area of work is the integration of caching models with some emerging technologies such as edge computing, which would improve content-delivery efficiency and lower latency. Real-world deployment studies are necessary to test their practical feasibility and precious insights into their performance under varied and dynamic environments. Ensuring privacy and security in cache-enabled D2D networks is a must. Methods that guarantee secure content delivery at the cost of user privacy, especially when dealing with sensitive or personal information, are worth investigating in future work. Energy-efficient strategies should also be targeted, especially when devices are restricted to limited power resources. Adjusting caching decisions to curtail energy consumption would be a critical step toward enhancing the sustainability of D2D wireless networks. Overcoming these limitations and searching for future directions of research will be crucial for further perfecting the effectiveness and practical applicability of the caching model in the dynamic landscape of D2D wireless networks. Further research and de-

velopment on the efficiency, adaptability, and security of content caching solutions will be important tasks in these dynamic communication environments.

Bibliography

[1] W. Li, C. Wang, D. Li, B. Hu, X. Wang,and, J. Ren, “Edge caching for D2D enabled hierarchical wireless networks with deep reinforcement learning," *Hindawi-Wireless Communications and Mobile Computing*, vol. 2019, 2019.

[2] Y. Wu, J. Chen, L. P. Qian, J. Huang, and, X. S. Shen, “ Energy- aware cooperative traffic offloading via device-to-device cooperations: An analytical approach," *IEEE Transactions on Mobile Computing*, vol. 16, no. 1, pp. 97–114, 2017.

[3] Y. Zhang, M. S. Hossain, A. Ghoneim, and, M. Guizani, “ Content-oriented caching on the mobile edge for wireless communications,” *IEEE Wireless Communications* , vol. 26, no. 3, pp. 26–31, 2019.

[4] L. Wang, C. Yang,and, R. Q. Hu, “Autonomous traffic offloading in heterogeneous ultra-dense networks using machine learning,” *IEEE Wireless Communications* , vol. 26, no. 4, pp. 102–109, 2019.

[5] D. Li, H. Zhang, T. Li, H. Ding,and, D. Yuan, “Community Detection and Attention-Weighted Federated Learning Based Proactive Edge Caching for D2D-Assisted Wireless Networks,” *IEEE Transactions on Wireless Communications* , vol. 22, no. 11, pp. 7287-7303, Nov. 2023, doi: 10.1109/TWC.2023.3249756.

[6] L. Li, Y. Xu, J. Yin, W. Liang, and,X. Li, “Deep Reinforcement Learning Approaches for Content Caching in Cache-Enabled D2D Networks,” *IEEE Internet of Things Journal* , vol. 7, no. 1, pp. 544-557, Jan. 2020, doi: 10.1109/JIOT.2019.2951509.

[7] A. Said, SWH. Shah, H. Farooq, AN. Mian, A. Imran,and, J. Crowcroft, “Proactive Caching at the Edge Leveraging Influential User Detection in Cellular D2D Networks.,” *Future Internet* , doi: 10.3390/FI10100093.

[8] Y. Qian, R. Wang, J. Wu, B. Tan, and H. Ren, “Reinforcement learning-based optimal computing and caching in mobile edge network,” *IEEE J. Sel. Areas Commun* , vol. 38, no. 10, pp. 2343–2355, Jun. 2020. learning techniques for caching

in next-generation edge net- works: A comprehensive survey," *Journal of Network and Computer Applications* , vol. 181, pp. 103005, 2021.

[9] J. Yao, T. Han, and,N. Ansari, "On mobile edge caching," *IEEE Communication Survey* , vol. 21, no. 3, pp. 2525–2553, Mar. 2019.

[10] J. Tang, T. Quek, T. Chang, and B. Shim, "Systematic resource allocation in cloud ran with caching as a service under two timescales," *IEEE Trans. Commun* , vol. 67, no. 11, pp. 7755–7770, Nov. 2019.

[11] L. Feng, Z. Yang, S. Guo, X. Qiu, W. Li, and P. Yu, "Two-Layered Blockchain Architecture for Federated Learning over Mobile Edge Network," *IEEE Network* , doi: 10.1109/MNET.011.2000339,2021.

[12] J. Shuja, K. Bilal, W. Alasmary, H. Sinky,and, E. Alanazi, "Applying machine learning techniques for caching in next-generation edge networks: A comprehensive survey." *Journal of Network and Computer Applications*, p.103005.

[13] Y. Bai, D. Wang, G. Huang and B. Song, "A Deep-Reinforcement- Learning-Based Social-Aware Cooperative Caching Scheme in D2D Communication Networks," in *IEEE Internet of Things Journal*, vol. 10, no. 11, pp. 9634-9645, 1 June1, 2023, doi: 10.1109/JIOT.2023.3234705.

[14] Z. Yang, Y. Liu, Y. Chen, and L. Jiao, "Learning automata based Q- learning for content placement in cooperative caching," *IEEE Trans. Commun* , vol. 68, no. 6, pp. 3667–3680, Jun. 2020.

[15] C. Zhang, Wu C. Wu, M. Lin, Y. Lin, W.Liu "Proximal Policy Optimization for Efficient D2D-Assisted Computation Offloading and Resource Allocation in Multi-Access Edge Computing", *Future Internet* 2024; 16(1):19, doi.org/10.3390/fi16010019.

[16] Z. Chen, B. Yin, H. Zhu, Y. Li, M. Tao and W. Zhang, "Mobile Communications, Computing, and Caching Resources Allocation for Diverse Services via Multi-Objective Proximal Policy Optimization," in *IEEE Transactions on Communications*, vol. 70, no. 7, pp. 4498-4512, July 2022, doi: 10.1109/TCOMM.2022.3173005.

[17] N. Dang, K. Kim, L. U. Khan, S. M. A. Kazmi, Z. Han and C. S. Hong, "On-Device Computational Caching-Enabled Augmented Reality for 5G and Beyond: A Contract-Theory-Based Incentive Mechanism," in *IEEE Internet of Things Journal*, vol. 8, no. 24, pp. 17382-17394, 15 Dec.15, 2021, doi: 10.1109/JIOT.2021.3080709.

[18] G. Chandrasekaran, N. Wang, M. Hassanpour, M. Xu and R. Tafazolli, "Mobility as a Service (MaaS): A D2D-Based Information Centric Network Architecture for

Edge-Controlled Content Distribution," in *IEEE Access*, vol. 6, pp. 2110-2129, 2018, doi: 10.1109/ACCESS.2017.2781736.

[19] Y. Wang, X. Li, P. Wan and R. Shao, "Intelligent Dynamic Spectrum Access Using Deep Reinforcement Learning for VANETs," in *IEEE Sensors Journal*, vol. 21, no. 14, pp. 15554-15563, 15 July15, 2021, doi: 10.1109/JSEN.2021.3056463.

[20] L. Zhang, M. Xiao, G. Wu and S. Li, "Efficient Scheduling and Power Allocation for D2D-Assisted Wireless Caching Networks," in *IEEE Transactions on Communications*, vol. 64, no. 6, pp. 2438-2452, June 2016, doi: 10.1109/TCOMM.2016.2552164.

[21] F. Hasna, M. Rihab, C. Lamia, J. Mohamed,"Comprehensive survey on self-organizing cellular network approaches applied to 5G networks",Computer Networks, Volume 199,2021,108435,ISSN 1389-1286,doi.org/10.1016/j.comnet.2021.108435.

[22] M. Gregori, J. G´omez-Vilardeb´o, J. Matamoros and D. G¨und¨uz, “. Wireless Content Caching for Small Cell and D2D Networks,” *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 5, pp. 1222- 1234, May 2016, doi: 10.1109/JSAC.2016.2545413.

[23] L. Zhu, C. Liu, J. Yuan, and G. Yu,“Machine Learning-Based Resource Optimization for D2D Communication Underlaying Networks," *IEEE 92nd Vehicular Technology Conference (VTC2020-Fall)*,Victoria, BC, Canada, 18 Nov - 16 Dec, 2020. doi: 10.1109/VTC2020-Fall49728.2020.9348830.

[24] R. Yin, C. Zhong, G. Yu, Z. Zhang, K. Wong, and X. Chen,“ Joint spectrum and power allocation for D2D communications underlaying cellular networks," *IEEE Trans. Veh. Technol* , vol. 65, no. 4, pp. 2182-2195, Apr. 2016.

[25] R. Wang, J. Zhang, S. H. Song, and K. B. Letaief, “Optimal QoS-aware channel assignment in D2D communications with partial CSI,” *IEEE Trans. Wireless Commun.*, vol. 15, no. 11, pp. 7594-7609, Nov. 2016.

[26] A. Rowstron and P. Druschel,“ : Scalable, decentralized object location, and routing for large-scale peer-to-peer systems,"in *IFIP/ACM International Conference on Distributed Systems Platforms and Open Distributed Processing* , pp. 329–350, Springer, 2001.

[27] C. Zhan and G. Yao,“ Optimizing caching placement for mobile users in heterogeneous wireless network," in 2017 *IEEE 42nd Conference on Local Computer Networks (LCN)*, pp. 175–178, IEEE, 2017.

[28] B. Bai, L. Wang, Z. Han, W. Chen, and T. Svensson,“ Caching based socially-aware d2d communications in wireless content delivery networks: A hypergraph framework," in 2017 *IEEE Wireless Communications*, vol. 23, no. 4, pp. 74–81, 2016.

[29] D. Prerna, R. Tekchandani, N. Kumar and S. Tanwar, “An Energy- Efficient Cache Localization Technique for D2D Communication in IoT Environment,” in *IEEE Internet of Things Journal*, vol. 8, no. 6, pp.4816-4829, 15 March15, 2021, doi: 10.1109/JIOT.2020.3029168.

[30] X. Zhang, Y. Liu, J. Liu, A. Argyriou and Y. Han, “D2D-Assisted Federated Learning in Mobile Edge Computing Networks,” 2021 *IEEE Wireless Communications and Networking Conference (WCNC), Nanjing, China*, 2021, pp. 1-7, doi: 10.1109/WCNC49053.2021.9417459.

[31] R. Cheng, Y. Sun, Y. Liu, L. Xia, D. Feng and M. A. Imran, “Blockchain- Empowered Federated Learning Approach for an Intelligent and Reliable D2D Caching Scheme,” in *IEEE Internet of Things Journal*, vol. 9, no. 11, pp. 7879-7890, 1 June1, 2022, doi: 10.1109/JIOT.2021.3103107.

[32] Z. Xiao et al,, “Multi-Objective Parallel Task Offloading and Content Caching in D2D-Aided MEC Networks,” in *IEEE Transactions on Mobile Computing*, vol. 22, no. 11, pp. 6599-6615, 1 Nov. 2023, doi:10.1109/TMC.2022.3199876.

[33] D. Yu, T. Wu, C. Liu and D. Wang, “Joint Content Caching and Recommendation in Opportunistic Mobile Networks Through Deep Reinforcement Learning and Broad Learning,” in *IEEE Transactions on Services Computing*, vol. 16, no. 4, pp. 2727-2741, 1 July-Aug. 2023, doi: 10.1109/TSC.2023.3247611.

[34] D. Li, H. Zhang, H. Ding, T. Li, D. Liang and D. Yuan, “User- Preference-Learning-Based Proactive Edge Caching for D2D-Assisted Wireless Networks,” in *IEEE Internet of Things Journal*, vol. 10, no. 13, pp. 11922-11937, 1 July1, 2023, doi: 10.1109/JIOT.2023.3244621.

[35] K. S. Khan, A. Naeem and A. Jamalipour, “Incentive-Based Caching and Communication in a Clustered D2D Network,” in *IEEE Internet of Things Journal*, vol. 9, no. 5, pp. 3313-3320, 1 March1, 2022, doi: 10.1109/JIOT.2021.3098003.

[36] Y. Meng, P. Wang, J. Xiao, and X. Zhou, “NeLSTM: A new model for temporal link prediction in social networks,” 2019 *IEEE 13th International Conference on Semantic Computing (ICSC)*, pp. 183–186, 2019.

[37] T. Xia, Y. Gu, and D. Yin, “Research on the link prediction model of dynamic multiplex social network based on improved graph representation learning,” *IEEE Access*, vol. 9, pp. 412–420, 2021.

[38] A. A. Samad, M. Qadir, and I. Nawaz, "Sam: a similarity measure for link prediction in social network," 2019 *13th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics (MACS)*, pp. 1–9, 2019.

[39] L. Zhu, D. Guo, J. Yin, G. Ver Steeg, and A. Galstyan, "Scalable temporal latent space inference for link prediction in dynamic social networks (extended abstract)," in *IEEE 33rd International Conference on Data Engineering (ICDE)*, 2017, pp. 57–58.

[40] L. Xiao, X. Wan, C. Dai, X. Du, X. Chen, and M. Guizani, "Security in mobile edge caching with reinforcement learning," *IEEE Wireless Communications*, vol. 25, no. 3, pp. 116–122, 2018.

[41] H. Zhang, T. Shen, F. Wu, M. Yin, H. Yang, and C. Wu, "Federated graph learning - a position paper," *ArXiv*, vol. abs/2105.11099, 2021.

[42] C. He, K. Balasubramanian, E. Ceyani, Y. Rong, P. Zhao, J. Huang, M. Annavaram, and S. Avestimehr, "FedGraphNN: A federated learning system and benchmark for graph neural networks," *ArXiv*, vol.abs/2104.07145, 2021.