Study on Negotiation between OTT and TSP for Integrated Service Delivery

Thesis

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By

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CERTIFICATE

This is to certify that the dissertation entitled **"Study on Negotiation between OTT and TSP for Integrated Service Delivery"** has been carried out by SANNIBHA PANDE (University Registration No.: 163486 of 2022-2023) under my guidance and supervision and be accepted as partial fulfilment of the requirement for the Degree of Master in Electrical Engineering. The research results presented in the thesis have not been included in any other paper submitted for the award of any degree to any other University or Institute.

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CERTIFICATE OF APPROVAL*

The forgoing thesis is hereby approved as a creditable study of an engineering subject and presented in a manner satisfactory to warrant acceptance as prerequisite to the degree for which it has been submitted. It is understood that by this approval the undersigned do not necessarily endorse or approve any statement made, opinion expressed or conclusion drawn there in but approve the thesis only for which it is submitted.

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DECLARATION OF ORIGINALITY AND COMPLIANCEOF ACADEMIC THESIS

I hereby declare that this thesis entitled **"Study on Negotiation between OTT and TSP for Integrated Service Delivery"** contains literature survey and original research work by the undersigned candidate, as part of his Degree of Master in Electrical Engineering. All information here have been obtained and presented in accordance with academic rules and ethical conduct. It is hereby declared that, as required by these rules and conduct, all materials and results that are not original to this work have been properly cited and referenced.

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Abstract

In contemporary times, the popularity and usage of Over the Top (OTT) platforms are increasing rapidly. This can be credited to their convenience, accessibility, affordability and diverse content offerings that can be customized according to the preferences of the customers. But in order to satisfy and for customer retention, the OTT platforms have to provide better Quality of Service (QoS) along with better Quality of Experience (QoE), which they are unable to provide independently to the customers. As a result of this, OTT platforms collaborate with Telecom Service Providers (TSP) networks for getting the leverage of the infrastructure of TSP networks for providing better QoS and QoE and expanding their audience base. On the other hand, TSP companies can also improve customer retention and satisfaction by partnering with OTT platforms to offer diverse and appealing content packages. Thus, for the collaboration between the OTT platforms and TSP networks, the process of negotiation takes place in order to reach an agreement for the finalized deals of the collaboration. In order to achieve better deals for agreement for the interests of the individual companies, both the companies deploy machine learning agents instead of human agents.

Two machine learning techniques have been used for the process of negotiation: Bayesian Learning and Reinforcement Learning. The Quality of Service (QoS) has been used as the utility value required by OTT and TSP agents for the process of negotiation. The QoS has been calculated with respect to network parameters like Delay Rate, Packet Loss Rate, Throughput Rate and Jitter. Utility values after varying the number of offers for both the agents obtained after the process of negotiation is studied. Variations of learning rates for both the agents have also been done to study the effect of variation of learning rates in both the learnings. Variation of time taken for the process of negotiation with respect to number of rounds of offers has also been investigated.

After comparing both the techniques used for the process of negotiation, it can be inferred that the Reinforcement Learning provides better utility values to both the agents while being compared to Bayesian Learning especially with low number of offers. While comparing with respect to time, Bayesian Learning method is faster than Reinforcement Learning. Again, the utility values obtained for both the agents after Reinforcement Learning is independent of the learning rate of any agent. As a result, the agents don’t have to worry about the learning rate of the opponent during the process of negotiation.

Hence, from the results obtained, we can say that for getting better deals from the negotiation process required for the collaboration between OTT and TSP companies, the OTT and TSP companies deploy machine learning agents using reinforcement learning as they give better utility values compared to Bayesian Learning. Besides, the agents don’t have to worry about the learning rate of the opponent during the process of negotiation.

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List of Acronyms

OTT	Over The Top
TSP	Telecom Service Provider
IPTV	Internet Protocol Television
VoIP	Voice Over Internet Protocol
STB	Set Top Box
ARPU	Average Revenue Per User
VR	Virtual Reality
CDN	Content Delivery Network
DRM	Digital Right Management
GDPR	General Data Protection Regulation
CCPA	California Consumer Privacy Act
AI	Artificial Intelligence
IoT	Internet of Things
DDoS	Distributed Denial of Service
SDN	Software Defined Networks
JV	Joint Venture
CLV	Customer Lifetime Value-based
MPC	Most Profitable Customers
SC	Standard Customer
SLA	Service Level Agreement
PARQUE	Pricing and Regulating Quality of Experience

LZ	Location Zone
SR	Surrogate Server
IP	Internet Protocol
REST	Representational State Transfer
RTT	Round Trip Time
NFV	Network Function Virtualization
vCDN	Virtual Content Delivery Network
PDH	Provisioning Delivery Hysteresis
RTP	Real-time Transport Protocol
MOS	Mean Opinion Score
uMOS	Utility Mean Opinion Score
HAS	HTTP Adaptive Streaming
ML	Machine Learning
ELA	Experience Level Agreement
SLO	Service Level Objective
QoBiz	Quality of Business
EFSM	Extended Finite State Machine
FSM	Functional State Machine
NB	Negotiation Broker
DLT	Distributed Ledger Technologies
IOTA	Internet of Things Application
IPFS	Inter Planetary File System
CM	Contract Management
SME	Small and Medium Enterprise
B2B	Business to Business

DSS	Decision Support System
MAS	Multi-agent System
WWW	World Wide Web
B2C	Business to Customer
ITU	International Telecommunication Union
BLBN	Bayesian Learning Based Negotiation
RLBN	Reinforcement Learning Based Negotiation

List of Notations and Symbols

QoS	Quality of Service
QoE	Quality of Experience
x_k	Network influencing factor
N	Number of network influencing factors
w_k	Corresponding weight of the network influencing factor
$f_k(.)$	Mapping function
JI	Jitter of the network
DL	Network Packet Delay
LR	Packet Loss Rate
TH	Throughput Rate
A^j_i	Acceptance of offer σ_j of session i
σ_j	jth offer of a session
w_i	Weightage of session i
w_{ij}	Weightage of offer σ_j of session i
w_{max}	Maximum weight
w_{min}	Minimum weight
K	Total number of offers in each session
$p(accept \mid \sigma_{OTT}^j)$	Probability of acceptance given that the offer was proposed to the opponent
p(accept)	Probability of acceptance of an offer

$p(\sigma_{OTT}^{j} \mid accept)$	Probability of selecting or making offer σ_{OTT}^{j} given that either it will be accepted
$p(\sigma_{OTT}^{j} \mid reject)$	Probability of rejection given that the offer was proposed to the opponent
p(reject)	Probability of rejection of an offer
$U(\sigma_{OTT}^{j})$	Utility Value of the offer
θ	Learning Rate of the Bayesian Learning
$U'(\sigma_{OTT}^{j})$	Final Preference Value
η	Learning Rate of the Reinforcement Learning

Contents

Chapter 1

Introduction

1.1 Background

Since the early 2000s, there has been an emergence of internet-based platforms that provide streaming media content directly to the customers. In the early 2000s, the concept of streaming video content over the internet began to take shape with the launch of services like Netflix, Hulu. These platforms initially focused on providing on-demand access to movies and TV shows, delivered over broadband internet connections.

According to the Ericsson Global Mobile Data Traffic 2027 Report [1], 60% of the mobile data traffic will pass through fifth generation (5G) networks in 2027 from 10% of the mobile data traffic in 2099. The report predicted fifth generation to 90% in North America in 2027. The report mentioned that the global average monthly traffic usage to be 15 GB and is expected to be twice or thrice in 2027. In India, Bhutan and Nepal, the report mentioned the average monthly traffic usage to 20 GB and will rise to 50 GB. Hence, fifth generation network will or has become very important for the mobile communications network.

Fifth generation communications will be benefited from the Over-The-Top (OTT) services for enhancing both technological advancements and user adoption. [2] The reasons why 5G communications need OTT services are:

i) **Content Demand**: OTT services like video content, online gaming and live streaming demand high data throughput. The widespread use of these services drives the need for faster and more reliable 5G networks, justifying investments in 5G infrastructure. [3]

ii) **Revenue Generation**: The popularity of OTT services can drive higher data usage, leading to increased revenues for Telecom Service Providers (TSP) through data plans and partnerships with OTT providers.

iii) **Quality of Service (QoS)**: By ensuring smooth and high-quality OTT content delivery, 5G can enhance user experience, leading to more customer satisfaction and increased adoption of 5G services.

iv) **Innovative Services**: OTT platforms can offer innovative services like interactive live events, cloud gaming and personalized content, attracting more users to 5G networks.

v) **Bandwidth Utilization**: The high bandwidth offered by 5G is ideal for data-heavy OTT services, ensuring efficient utilization of network resources.

vi) **Network Slicing**: 5G allows for network slicing, which can dedicate portions of the network to specific OTT services, optimizing performance and service delivery. [4]

vii) **Market Penetration**: By supporting popular OTT services, 5G can penetrate markets more effectively, appealing to a greater audience interested in high-quality delivery.

viii) **Demand for Mobility**: Consumers expect to access high-quality content on the go. 5G enables seamless mobile access to OTT services, meeting the demand for mobile content consumption.

ix) **Attracting Subscribers**: OTT services are often a key selling point for consumers while deciding to upgrade to 5G communication. The ability for streaming high-quality video, playing cloud-based games and usage of other heavy data applications without buffering or delays encourages users for adopting to 5G networks.

x) **Internet of Things (IoT) and Smart Cities**: 5G communication is designed for connecting a vast number of devices simultaneously, making it ideal for supporting Internet of Things (IoT) applications. Many of these smart applications, like home automation, health monitoring and smart city infrastructure, rely on OTT services for data processing, analytics and user interaction. [5]

xi) **Global Reach**: OTT Services can reach global audiences without the need for traditional broadcasting infrastructure. 5G networks can help these services to distribute content more efficiently across different regions, enabling providers to tap into new markets and reach a broader audience.

xii) **Partnerships and Revenue Streams**: Telecom Service Providers (TSPs) can partner with OTT providers to offer bundled services, creating new revenue streams. For example, 5G carriers might offer exclusive access to certain OTT content as part of their service plans, which can attract more subscribers and increase customer loyalty.

xiii) **Differentiation in the Market**: Telecom Service Providers (TSPs) can differentiate their 5G offerings by providing exclusive or premium OTT services, creating a competitive edge in the market. By integrating OTT services with 5G, operators can offer unique value propositions to consumers.

1.2 Over the Top (OTT)

Over the Top (OTT) is the means of providing television and film content over the internet to suit the requirements of the individual customer.

Since the mid-1990s, delivering television content through Internet Protocol (IPTV) has become a popular method for offering TV services to customers. This usually involves a TV subscription, a contract, a set-top box, and the assistance of a technician to set up the necessary hardware with high-speed internet in the customer's home.

OTT has revolutionized the way of consumption of media. By providing media services and content by internet, hence traditional cables, satellites and broadcast television platforms have been bypassed. Because of this bypassing, there has been a dramatic change in the content industry, thus empowering the viewers with greater control and choice regarding the access of the content. [6]

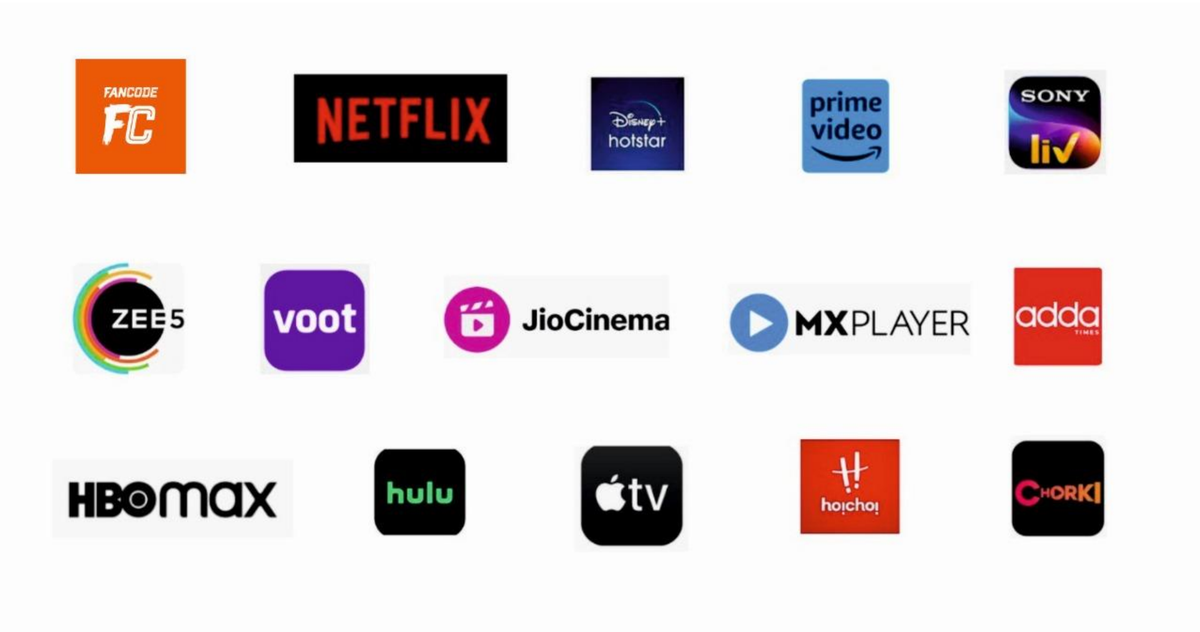

Fig 1.1: Examples of OTT Platforms

1.2.1 OTT Services Available

There are many types of OTT services available. They are:

i) **OTT Television:** Television is the most popular service available in the Internet. By this service, television content is directly offered to the users via the Internet bypassing cable, broadcast and satellite television platforms.

ii) **OTT Messaging:** OTT Messaging refers to instant messaging or online chat services offered by third-party providers, serving as an alternative to the traditional text messaging services provided by telecom operators.

iii) **OTT Voice Calling**: OTT Voice Calling, also called VoIP (Voice Over Internet Protocol) is a calling platform where the users can call their friends with the help of internet by using any devices, including mobile phones.

1.2.2 Reasons for growth of OTT platforms

Following are the reasons for growth of OTT platforms:

i) **Convenience**: OTT platforms offer on-demand content that can be accessed by users at anytime, anywhere and on any device with an internet connection. This feature is quite attractive to the customers as it offers flexibility in their viewing habits.

ii) **Variety of content**: OTT platforms provide a vast array of content across different genres, languages and formats catering to diverse audience preferences. This extensive library of movies, TV shows, documentaries and original shows ensures there is something for everyone.

iii) **Personalization**: OTT platforms use sophisticated algorithms for analysing user preferences and viewing habits, thus offering the users their personalized recommendations. This personalized experience enhances user satisfaction and encourages continued engagement with the platform.

iv) **Cost-effectiveness**: Multiple OTT platforms offer subscription plans at competitive prices, often with no long-term commitments or contracts. Compared to traditional cable or satellite TV subscriptions, OTT services can be more affordable, especially considering the wide range of content available.

v) **Accessibility**: With OTT platforms having global reach, users can access content regardless of their geographical location. This accessibility has facilitated the expansion of these platforms into international markets, reaching audiences worldwide.

vi) **Technological Advancements**: Advancements in streaming technology, including improved internet speeds and the proliferation of smart devices, have made it easier for users to stream high-quality content seamlessly. Additionally, the development of features like offline viewing and simultaneous streaming on multiple devices enhances the user experience.

vii) **Disruption of Traditional TV**: OTT platforms have disrupted the traditional TV industry by offering an alternative model that bypasses the need for cable or satellite subscriptions. This disruption has led to cord-cutting, with many customers opting to cancel their traditional TV services in favour of OTT options.

viii) **Original content**: OTT platforms invest heavily in original content, including exclusive series and films. These productions often feature high production values and top-tier talent, attracting subscribers who are drawn to unique and premium content not available elsewhere.

ix) **Global Pandemic**: The global pandemic further accelerated the growth of OTT platforms as lockdowns and social distancing measures prompted increase in demand for home entertainment.

x) **Widespread Connectivity**: The global increase in internet access, particularly with the advent of 4G and then 5G networks, has made it easier for people to access OTT contents. The improved speed and reliability of internet connections have enabled smooth streaming of high-definition video, contributing to the growth of OTT platforms.

xi) **User-Friendly Interfaces**: OTT platforms typically offer intuitive, easy-to-navigate interfaces with features like multiple device support, offline viewing and customizable subtitles. These features enhance the overall user experience, making OTT services more attractable to consumers.

xii) **Cultural Exchange**: OTT platforms have played a significant role in the globalization of content, allowing viewers to access foreign films, shows, and documentaries that were previously unavailable through traditional media. This cross-cultural exchange has broadened the appeal of OTT services.

1.2.3 Benefits of OTT to customers

OTT services offer customers a wide range of options right at their fingertips. Content can be accessed on various devices, including computers, Smart TVs, mobile phones, laptops, tablets, and gaming consoles. Additionally, users can switch between different apps to access content from multiple providers, giving them greater control over what to purchase and watch.

While both IPTV and OTT use IP technology, IPTV is delivered over a private cable network, whereas OTT content is delivered over the internet. OTT systems address the limitations of the single-operator set-top box (STB) required by IPTV. Unlike IPTV, OTT content is only delivered when requested. Each device has a unique connection to the content source via the internet, making it a "unicast" system—providing a single stream to a single device.

Some of the benefits are as follows:

i) **It is economical**: When compared to the cost of a traditional cable or satellite TV subscription, OTT services are a great value. OTT services are quite cheaper than the TV cable.

ii) **It offers Contents of a Diverse Nature**: OTT have greater channel options, material quality and diversity in comparison to standard cable packages.

iii) **It is Independent of the Devices**: Media services are available on OTT platforms whenever and wherever they are needed. OTT platforms can be accessed on any devices be it smart TV, laptops, computers, tablets or mobiles.

iv) **It offers Better Connectivity**: OTT broadcasting services are very user-friendly. A good internet connection and a suitable view device (smart TV, laptops, etc.) are all needed. In exchange for a subscription fee, the viewer receives internet service from the network provider and may tailor that service to his own needs.

v) **It has Added Convenience**: OTT services provide the users their freedom to watch their favourite shows whenever, wherever they want. Accessing content on OTT platforms is convenient on any device if the internet is widely available. On the contrary, conventional cable networks restrict the users to locations where cables may be laid. This mobility greatly facilitates the accessibility of the preferred streaming content of the users. They may access their account remotely and begin streaming immediately.

1.2.4 Importance of Good Quality of Services

In the study conducted in [7], quality and pricing are important causes for a user to become churner. Presently, the satisfaction of the users regarding the service plays an important role for the company to grow in market share and it has high cross correlation in the prediction of user's churn as well. In [8], the authors have proposed utility functions to model QoE by using Sigmoid function to model user satisfaction as a function of QoS parameters for Internet Protocol Television (IPTV). In [9], the authors also proposed a user churn model in terms of QoE of the user for the collaboration between OTT and TSP by using Sigmoid Function. Better the QoE, higher is the user retention and greater the attraction of new users and hence more revenue.

Following is the list of importances of Good QoS:

i) **Customer Retention and Loyalty**: High-quality services contribute to customer satisfaction and loyalty. When users have a positive experience with an OTT platform, they are more likely to continue using it and recommend it to others. This helps in increasing customer retention and reducing churn rate.

ii) **Brand Reputation**: Consistently delivering excellent QoS builds a positive brand image for an OTT platform. Customers associate high-quality service with reliability and professionalism, enhancing the platform's reputation in the market.

iii) **Competitive Edge**: Consistently delivering excellent QoS builds a positive brand image for an OTT platform. Customers associate high-quality service with reliability and professionalism, enhancing the platform's reputation in the market.

iv) **Differentiation and Competitiveness**: With the increasing competition in the OTT industry, good quality services can differentiate a platform from its competitors. By offering superior services such as faster streaming, better content recommendations, and personalized experiences, a platform can stand out in the crowded market.

v) **Revenue Generation**: Good QoS directly impacts revenue generation for OTT platforms. Satisfied customers are more likely to engage with content, leading to increased viewership, ad revenue, and subscription renewals.

vi) **Reduced Operational Costs**: By proactively monitoring and optimizing QoS, OTT platforms can minimize technical issues, downtime, and customer complaints. This results in cost savings associated with troubleshooting and customer support efforts.

vii) **Data-Driven Decision Making**: Implementing robust QoS monitoring tools provides valuable insights into network performance, user behaviour, and content delivery efficiency. This data enables informed decision-making to enhance overall service quality.

viii) **Regulatory Compliance**: Some countries have specific regulations regarding video streaming quality standards. Maintaining good QoS ensures compliance with these regulations, avoiding potential legal issues or penalties.

ix) **User Experience**: Providing a seamless and high-quality user experience is vital for retaining existing users and attracting new ones. A well-functioning platform with smooth streaming, high-resolution content, and user-friendly interface enhances the overall user experience.

x) **Content Delivery**: OTT platforms rely on delivering content efficiently to users. Good quality services ensure that content is delivered in a timely manner without interruptions such as buffering or playback issues. This enhances the user's viewing experience and satisfaction.

xi) **Reliability and Availability**: Users expect OTT platforms to be reliable and available whenever they want to access content. Good quality services help in maintaining platform uptime, minimizing downtime, and ensuring that users can access the platform anytime, anywhere.

xii) **Data Security and Privacy**: OTT platforms handle a large amount of user data, including personal information and viewing preferences. Ensuring data security and privacy through good quality services is essential for building trust with users and complying with data protection regulations.

1.2.5 Necessity of OTT in present scenario

In recent years, OTT platforms have given consumers more control over their entertainment options, freeing them from the constraints of traditional satellite cable services. Channel surfing is becoming obsolete, as users can now make informed choices about what to watch. These platforms offer a high degree of personalization, enabling them to predict what content a user is likely to enjoy. As the OTT market continues to grow, it is gradually disrupting the traditional TV industry, with early leaders in this space poised to dominate.

The following are the reasons necessary for having OTT services in present scenario:

i) **Diverse Content**: OTT services provide wide range of content from movies, web series, TV to documentaries, original content, live streaming and shows. Thus, they provide diverse tastes and preferences to the users.

ii) **Global Access**: OTT platforms supply global content thus breaking down geographical barriers and allowing users for accessing international content easily.

iii) **Direct to Customer**: OTT services enable content creators to bypass traditional distribution channels and reach their audience directly, fostering a close connection between creators and consumers.

iv) **E-Learning**: OTT platforms are increasingly used for educational purposes, offering e-learning content and courses that can be accessible to a wide audience which can be accessed anytime and anywhere according to the convenience of the customers.

v) **News and Information**: Many OTT services provide access to news and informational content, allowing users to stay informed about current events in real time.

vi) **Reduced Physical Media**: The shift to a digital streaming reduces the need for physical media and distribution, which has a positive environmental impact by reducing waste and resource consumption.

1.2.6 Benefits to OTT platforms after Good Quality of Service

By providing good quality of service, OTT companies can retent not only large proportion of their customers, but also attract new customers. Old customers after being satisfied with the service can convince their friends to use this service who even after being satisfied with the service can convince their friends to use the service. Thus, the OTT companies will gain more customers by the chain of these events. More the customers more the revenue, hence more the profit. Along with this, the reputation of the company will also be enhanced and can attract more customers in the market. Following are the benefits to OTT platforms after good Quality of Service:

i) Improved User Experience

(I) Reduced Buffering and Latency:

(A) **Faster Loading Times:** Content loads more quickly, reducing the waiting time for users.

(B) **Smooth Playback:** Minimizes interruptions and buffering, providing a seamless viewing experience.

(II) Higher Video and Audio Quality:

(A) **Enhanced Visuals:** High-definition (HD) and Ultra HD (4K) streams are more reliable, offering better picture quality.

(B) **Clear Audio:** Improved audio quality enhances the overall experience, especially for content with high production values.

ii) Increased User Engagement and Retention

(I) Higher Satisfaction:

(A) **Positive User Experience:** A consistent and high-quality streaming experience leads to higher user satisfaction.

(B) **Longer Viewing Sessions:** Users are more likely to watch content for longer periods without frustration from technical issues.

(II) Loyalty and Retention:

(A) **Reduced Churn Rate:** Satisfied users are less likely to cancel their subscriptions or switch to competitors.

(B) **Increased Subscriptions:** Happy customers are more likely to recommend the service to others, boosting subscriber growth.

iii) Competitive Advantage

(I) Market Differentiation

(A) **Standout Service:** Superior QoS helps an OTT platform distinguish itself from competitors.

(B) **Brand Reputation:** High quality of service enhances the platform's reputation, making it a preferred choice for new users.

(II) Content Partnerships

(A) **Attractive to Creators:** Content creators and distributors prefer platforms with reliable QoS to ensure their content is showcased optimally.

(B) **Exclusive Deals:** Better QoS can lead to exclusive content deals, further enhancing the platform's appeal.

iv) Operational Efficiency

(I) Optimized Bandwidth Usage

(A) **Efficient Streaming:** Better QoS means more efficient use of bandwidth, reducing costs associated with data transfer.

(B) **Network Management:** Improved QoS allows for better traffic management and reduced strain on the network infrastructure.

(II) Lower Support Costs

(A) **Fewer Complaints:** Higher quality service results in fewer user complaints and technical issues.

(B) **Reduced Support Load:** Lower demand on customer support services can reduce operational costs.

v) Revenue Growth

(I) Advertisement Revenues

(A) **Better Ad Delivery:** For ad-supported models, high QoS ensures ads are delivered smoothly, increasing ad viewability and effectiveness.

(B) **Premium Pricing:** Platforms can charge premium rates for ad placements on a high-quality service.

(II) Subscription Revenues

(A) **Higher Average Revenue Per User (ARPU):** Satisfied users are more likely to opt for higher-tier subscription plans.

(B) **Upselling Opportunities:** Good QoS enables platforms to effectively upsell additional services and features.

vi) Future Proofing

(I) Scalability

(A) **Handle Growth:** Robust QoS ensures the platform can handle increasing numbers of users and higher traffic without degradation in service.

(B) **Adaptability:** Better QoS allows for smoother integration of new technologies and services, such as 4K streaming and Virtual Reality (VR) content.

(II) Regulatory Compliance

(A) **Meet Standards:** Ensuring high QoS can help platforms comply with regulatory requirements and avoid potential fines or sanctions.

(B) **Data Protection:** Good QoS often includes secure data transmission, helping to protect user data and comply with privacy regulations.

1.2.7 Challenges faced by OTT Platforms

OTT platforms are facing various challenges. Following are the list of challenges faced by OTT Platforms:

i) **Content Acquisition Costs**: Acquiring and licensing content is extremely expensive. With the increase in competitive market, platforms need to invest heavily in original content or secure rights in popular shows and movies.

ii) **Competition**: OTT market is highly competitive, with several platforms are desperate for the attention of the subscribers. The saturation in the market makes it challenging for newer or smaller platforms to survive.

iii) **User Retention**: OTT platforms need to attract new customers continuously while retaining the existing ones. This requires a balance of competitive pricing, offering compelling content and a seamless user experience.

iv) **Quality of Service**: Delivering high-quality streaming experiences require robust infrastructure and technology. Thus, there is need for investment in scalable servers, content delivery networks (CDNs) and adaptive bitrate streaming to ensure smooth playback across devices and regions.

v) **Piracy and Content Security**: Protecting content from piracy is a constant challenge for OTT platforms. Implementing effective digital rights management (DRM) systems and anti-piracy measures is essential to safeguard revenue and maintain relationship with content creators.

vi) **Regulatory Compliance**: OTT platforms must adhere to various regulations, including content license agreements, copyright laws, and data protection regulations like General Data Protection Regulation (GDPR) and California Consumer Privacy Act (CCPA). Navigating these legal landscapes can be complex, especially on a global scale.

vii) **Global Experience and Localization**: Expanding into international markets requires navigating diverse cultures, languages and regulations. Customizing content and user experiences for different regions can be both costly and challenging.

viii) **Overwhelming Choices**: With vast libraries of content, ensuring that users can easily find out what they want to watch is a challenge. Effective content discovery tools and algorithms are crucial, but they are not always fool proof. Poor user experience in this regard can lead to subscriber churn.

ix) **Content Preferences**: Consumer tastes and viewing habits are constantly evolving. OTT platforms need to be agile in adapting to these changes, whether it is the shift to mobile viewing, the demand for short-term content, or the growing interest in specific genres or formats.

x) **Live Streaming and Event Broadcasting**: Live streaming events, such as sports or concerts, require real-time delivery without delays. Any failure in this area, such as lag or poor-quality streaming, can lead to negative user experience and damage the reputation of the platform.

xi) **Device Compatibility**: Ensuring that an OTT platform works seamlessly across a variety of devices (smartphones, tablets, smart TVs, laptops, computers, gaming consoles, etc.) can be challenging. Inconsistent performance or lack of compatibility on certain devices can alienate potential users.

xii) **Content Ownership Disputes**: OTT platforms must navigate complex intellectual property landscapes, including issues related to copyright, trademarks and licensing. Disputes over content ownership or the unauthorized use of intellectual property can lead to legal battles and reputational damage.

1.3 Telecom Service Provider (TSP)

Telecom Service Provider (TSP) is a company that provides access to the internet to individuals and organizations. A TSP has the equipment and the telecommunication line access required to have a point of presence on the internet for the geographic area served.

TSP companies are liable for the operation and upkeep of telephone and related products and services. The industry spans over multiple regions and thus has huge number of customer bases, requiring maximum up-time. Uptime is the time in which the network devices can be operated without facing any problems.

TSP make data transmission fast across large geographical areas possible whether it is via wires or wireless. At the core of their operations, TSP build and maintained the infrastructure required for communication and data flow, including towers, cables and data centers.

TSPs compete among themselves in the competitive market, striving to make themselves best through innovative offers, better Quality of Service (QoS) and better customer experience. Thus, they made heavy investments in research, development and deployment of state of the art technologies to ensure efficient and reliable connectivity.

Fig 1.2: Examples of TSP

1.3.1 Benefits of Telecom Service Providers

The Benefits of Telecom Service Providers are as follows:

i) **Global Connectivity**: Telecom service providers enable individuals and organizations for communicating across large distances, enhancing global connectivity and collaboration. Be it through voice calls, messaging or internet access, telecom service providers facilitate seamless communication regardless of geographical boundaries.

ii) **Access to Information**: Telecom service providers help users access to a treasure of information and resources available online by providing internet access and data services. This access is revolutionary in education, research and accessing critical services such as healthcare and government information.

iii) **Business Efficiency**: Telecom service providers enhance business efficiency by enabling real-time communication, data exchange and collaboration among employees, partners and customers. Business can streamline operations, improve decision-making and reach markets more effectively with the help of telecom infrastructure.

iv) **Economic Growth**: Telecom infrastructure serves as a catalyst for economic development by driving innovation, entrepreneurship and job creation. Access to reliable communication networks attracts investment spurring productivity and facilitates the growth of industries such as e-commerce, finance and technology.

v) **Social Inclusion**: Telecom service providers play a vital role in promoting social inclusion by expanding access to communication services, particularly in remote or geographically hazardous areas. Access to affordable voice and internet services empowers individuals, communities and societies as whole, bridging the digital divide and enabling their participation in the digital economy.

vi) **Emergency Communication**: During emergencies and natural disasters, telecom service providers serve as lifelines for accessing critical information, coordinating rescue efforts and providing assistance to affected populations. Reliable communication infrastructure is essential for ensuring public safety and minimizing the impact of disasters.

vii) **Healthcare and Education**: Telecommunication service providers facilitate the delivery of telemedicine and remote education, allowing healthcare providers and educators to reach patients and students in remote or rural areas. Telemedical services enable remote consultations, medical diagnosis and monitoring, while distance learning platforms provide access to educational resources and opportunities.

viii) **Innovation and Technological Advancement**: Telecom service providers drive innovation in telecommunications technology, constantly upgrading infrastructure and introducing new services to meet evolving customer needs. Advancements such as 5G networks, fiber-optic broadband and Internet of Things (IoT) connectivity open up new possibilities for industries ranging from transportation and manufacturing to entertainment and agriculture.

ix) **Job Creation**: The Telecom sector creates jobs, both directly in telecommunications companies and indirectly through businesses that depend on telecom infrastructure.

x) **Digital Economy**: Telecom Service Providers are the backbone of the digital economy, supporting e-commerce, online banking and other internet-based services that drive economic growth.

xi) **Internet Services**: Telecom Service Providers enable access to the internet, offering individuals and organizations vast resources for education, research and entertainment.

xii) **5G and Future Technologies**: Telecom Service Providers are key players in the development and deployment of new technologies, including 5G, which offers faster speeds, lower latency and better connectivity for IoT and Artificial Intelligence (AI) applications.

xiii) **Smart Cities**: The infrastructure provided by Telecom Service Providers is crucial in developing smart cities, with services such as connected devices, traffic management, and smart grids.

xiv) **Bridging the Digital Divide**: Telecom Service Providers help bridge the digital divide by expanding network infrastructure to undeveloped and rural areas, ensuring that more people have access to communication technologies.

xv) **Disaster Response**: During natural disasters and emergencies, telecom service providers enable governments, organizations and individuals to coordinate and communicate efficiently.

1.3.2 Role of TSP in providing Good Quality of Experience (QoE)

TSP provides the required internet access to the customers. Thus, for OTT to provide good quality of service to its customers, it needs TSP's help for the access of the network. TSP thus provides the network to the OTTs and the customers hence the customers are benefitting from the good QoS.

The following are the list of ways how TSP can provide good QoE:

i) **5G Deployment**: The rollout of 5G technology is a significant factor in improving QoE, as it provides higher data speeds, lower latency and increased capacity. This enables more seamless and high-quality streaming, gaming and real-time applications.

ii) **Network Slicing**: Utilizing network slicing to create virtual networks for specific OTT services ensures that these services receive the necessary bandwidth and low latency performance, regardless of overall network traffic.

iii) **High-Speed Networks**: Telecom service providers invest in robust and high-speed network infrastructures, including 5G networks for supporting the bandwidth-intensive requirements of OTT services. This ensures fast and reliable internet connections essential for streaming high-definition content.

iv) **Low Latency**: By reducing latency through advanced network technologies and edge computing, telecom service providers enhance real-time applications such as live streaming, gaming and video conferencing, ensuring smooth and responsive experiences.

v) **Network Uptime:** Telecom Service Providers strive to maintain high network availability, minimizing downtime to ensure continuous access to communication services.

vi) **Quality of Service (QoS) Management**: Implementing QoS policies to prioritize traffic for OTT services can help manage network resources efficiently, reducing congestion and ensuring consistent performance during peak usage times.

vii) **Content Delivery Network (CDN) Integration**: Collaborating with or providing Content Delivery Network (CDN) services helps cache content creator closer to the end-users, reducing load times and buffering issues. The geographical proximity to content servers improves the overall streaming experience.

viii) **Edge Computing**: Deploying edge computing solutions processes data closer to users, which reduces latency and improves the performance of real-time applications, including interactive and immersive content.

ix) **Traffic Management**: Telecom Service Providers (TSPs) manage network traffic to prevent congestion, ensuring users can enjoy uninterrupted services, especially during peak hours.

x) **Adaptive Bitrate Streaming**: Telecom Service Providers (TSPs) implement adaptive bitrate streaming techniques for media services, adjusting the quality of the stream based on the user's network conditions to avoid buffering and maintain a smooth viewing experience.

xi) **Proactive Problem Detection**: Many Telecom Service Providers (TSPs) use network monitoring tools to identify and resolve issues before they impact the user, improving QoE by minimizing service disruptions.

xii) **Voice over Long-Term Evolution (LTE) (VoLTE)**: With Voice over Long-Term Evolution (VoLTE), Telecom Service Providers (TSPs) deliver higher quality voice calls over 4G networks, ensuring better clarity and connection stability.

xiii) **Data Plans and Services**: Telecom Service Providers (TSPs) offer flexible data plans, allowing users to choose services tailored to their specific needs, such as unlimited data for streaming or enhanced mobile plans for business users.

xiv) **Service Bundles**: Many Telecom Service Providers (TSPs) provide bundled services (e.g., internet, TV and phone) that enhance user experience by offering convenience and cost savings.

xv) **Feedback Mechanisms**: Telecom Service Providers (TSPs) actively gather user feedback to identify areas for improvement, ensuring that services evolve to meet changing customer needs.

1.3.3 Challenges Facing Telecom Service Providers

Telecom Service Providers are facing some challenges while providing internet access to customers. They are:

i) **Infrastructure Investment:** Building, maintaining and upgrading telecommunication infrastructure, including cables, towers and data centers, require substantial capital investment, often with long payback periods. Telecom Service Providers must balance the need for expansion with financial sustainability.

ii) **Cybersecurity Threats:** In recent years, there has been a surge of cybersecurity attacks on telecommunication service providers. These include hacking, data breaches, malware, distributed denial-of-service (DDoS) and ransomware attacks. Safeguarding network infrastructure, sensitive information and customer data from cyber-attacks is crucial for maintaining trust and credibility of telecommunication service providers. These require robust cybersecurity measures and continuous monitoring.

iii) **Regulatory Compliance:** Compliance with evolving regulatory requirements poses challenges for telecommunication service providers, particularly in areas such as data privacy, net neutrality and spectrum allocation.

iv) **Customer Expectations:** As days are progressing, customers are demanding faster speeds, greater reliability and seamless connectivity. In other words, customers are expecting better Quality of Experience from telecom service providers. Hence telecom service providers must continually enhance their offerings and customer service to meet these expectations.

v) **Technological Disruption:** Rapid advancements in telecommunications technology, such as the transition to 5G networks, fiber-optic broadband, and software-defined networking (SDN), present both opportunities and challenges for telecommunication service providers. Keeping pace with technological developments and deploying new infrastructure while ensuring compatibility with existing systems can be daunting and costly.

vi) **Competition:** The telecommunication industry is highly competitive, with multiple providers vying for market share and customer loyalty. Intense competition can lead to pricing pressures, margin erosion and the need for aggressive marketing and promotional strategies to attract and retain customers.

vii) **Network Congestion and Capacity Management:** With the increasing surge of connected devices, streaming devices and bandwidth-intensive applications, telecommunication networks are experiencing increasing levels of congestion and strain on capacity. Managing network congestion, optimizing bandwidth allocation, and ensuring good Quality of Service (QoS) during peak usage periods are ongoing challenges for telecommunication service providers.

viii) **Spectrum Availability and Allocation:** Spectrum, the radio frequencies used for wireless communication, is a finite and valuable resource controlled by regulatory authorities. Securing access to sufficient spectrum and efficiently managing its allocation to support growing demand for mobile broadband services pose challenges for telecom providers, particularly in densely populated urban areas.

ix) **Customer Churn:** High user churn rates or the rate at which customers switch between telecommunication service providers can negatively impact revenue and profitability. Addressing the root causes of user churn, such as dissatisfaction with poor Quality of Experience (QoE), pricing or customer support requires proactive measures to improve customer retention and loyalty.

x) **Data Privacy and Security Regulations**: TSPs must comply with rigorous regulations on data protection and privacy (e.g., General Data Protection Regulation (GDPR), California Consumer Privacy Act (CCPA)), which require robust security measures and frequent audits.

xi) **Spectrum Licensing**: The process of acquiring and renewing spectrum licenses can be costly and complex, often involving government actions and compliance with various national and international regulations.

xii) **Energy Consumption**: Telecom networks consume significant amount of energy, leading to high operational costs and environmental impact. Telecom Service Providers (TSPs) are under pressure to adopt more sustainable practices.

xiii) **Rising Data Demand**: The rapid growth in data consumption, driven by video streaming, online gaming, and Internet of Things (IoT) devices, creating significant pressure on telecom service providers.

xiv) **Peak Traffic**: Managing network traffic during peak times, such as live events or emergency situations, is a challenge, as network congestion can lead to poor service quality and user dissatisfaction.

xv) **High Costs**: Rolling out 5G networks is complex, as it requires regulatory approvals, site acquisition, and addressing health concerns raised by the public regarding 5G towers.

xvi) **Shift from Traditional Revenue Streams**: Telecom Service Providers (TSPs) face declining revenues from traditional services like voice and SMS due to the rise of the Over-The-Top (OTT) platforms (e.g., WhatsApp, Skype) that offer free messaging and voice services.

xvii) **Digital Transformation**: Adapting to digital transformation and offering value-added services such as cloud computing, data analytics and Internet of Things (IoT) solutions requires significant restructuring and investment in new technologies.

xviii) **Demand for High-Quality Service**: Customers expect high-quality, uninterrupted service, especially for bandwidth-intensive applications like streaming and gaming, which places stress on network performance.

xix) **Keeping Pace with Innovation**: Telecom Service Providers (TSPs) must continuously innovate and upgrade their networks to keep up with emerging technologies like 5G, Artificial Intelligence (AI) and Internet of Things (IoT), which requires significant Research and Development (R&D) investments.

xx) **Expanding Coverage**: Providing telecom services in rural or remote areas is often not economically viable due to the costs of infrastructure development and maintenance compared to the low return on investment.

xxi) **Legacy Systems**: Many Telecom Service Providers (TSPs) operate on legacy infrastructure that may not be compatible with new technologies, requiring costly updates and integration efforts.

xxii) **Unclear Business Models**: While 5G and IoT promise new revenue streams, many Telecom Service Providers (TSPs) face challenging in monetizing these technologies, especially in Business-to-Business (B2B) markets where customer demands and use cases vary widely.

xxiii) **Long-Term Return of Investment (ROI)**: The return on investment (ROI) for 5G and IoT infrastructure is uncertain, as the mass adoption of these technologies may take years.

xxiv) **Limited Spectrum Availability**: Spectrum is a finite resource, and acquiring license for new spectrum bands can not only be expensive but also competitive in nature.

xxv) **Spectrum Efficiency**: Telecom Service Providers (TSPs) must optimize spectrum usage to deliver high-quality services, which requires advanced technologies and regulatory cooperation.

1.4 Reason for OTT/TSP Collaboration

OTT providers and TSP providers have differing views on managing QoE, shaped largely by their respective roles in the service delivery process. As the network owner, the TSP facilitates customer access to the Internet and enables subscriptions to OTT services.

Currently, users are seeking higher quality, which places a challenging burden on TSPs to manage the vast amount of traffic generated by OTT services in order to deliver adequate QoE. Despite this, TSPs maintain a network-centric perspective on the quality they provide.

TSPs and OTT platforms have distinct views on QoE management, shaped largely by their respective roles in the service delivery process. As the network owners, TSPs enable their customers to access the Internet and subscribe to OTT services. With users now demanding higher quality, TSPs face the challenging task of managing the vast amount of traffic generated by OTT services, particularly multimedia content, to ensure they deliver satisfactory QoE to their users.

Following are the list of reasons for OTT/TSP Collaboration:

i) **Improved Quality of Service (QoS):** Telecom Service Providers (TSPs) can prioritize traffic for OTT services, reducing latency and buffering issues, which results in smothering experience and better user experience.

ii) **Optimizing Content Delivery:** By integrating with Content Delivery Networks (CDNs) and utilizing edge computing, TSPs can ensure that OTT content is delivered more efficiently, closer to the end-user, minimizing load times and improving performance.

iii) **Bundled Offerings:** Collaborations allow TSPs to offer bundled packages that combine data plans with OTT subscriptions. This not only provides added value to customers but also generates additional revenue for both parties.

iv) **Shared Revenue Models:** TSPs and OTT providers can engage in revenue-sharing agreements, where a portion of the subscription fees or ad revenues is shared, benefitting both entities financially.

v) **Subscriber Growth:** TSPs can leverage the popular content provided by the OTT platforms to attract new subscribers and reduce churn among existing users.

vi) **New Audience Segment:** OTT services can access a wider audience by being marketed directly to the extensive customer base of TSPs, including in regions where OTT platforms might not have a strong presence.

vii) **Reduced Infrastructure Costs:** By collaborating with TSPs, OTT providers can reduce the costs associated with delivering content, as TSPs manage the network infrastructure.

viii) **Shared Technology Investments:** Both parties can share the costs of implementing new technologies, such as 5G and edge computing, which are essential for delivering high-quality OTT content.

ix) **User Behaviour Analytics:** Collaborative efforts allow both parties to gain deeper insights into user behaviour and preferences, enabling more effective personalization and targeted marketing strategies.

x) **Regulatory Support:** TSPs often have established relationship with regulators, which can help OTT providers navigate local regulations more effectively.

xi) **Integrated Customer Solutions:** TSPs can offer integrated customer support for OTT services, providing a single point of contact for users and improving overall customer satisfaction.

xii) **Comprehensive Support Solutions:** Combining the support of both the resources of both the entities ensures quicker resolution of technical issues and better service reliability.

xiii) **Targeted Promotions:** Using demographic and geographic data, TSPs can assist in promoting OTT content that is tailored to specific user groups, increasing the effectiveness of marketing campaigns.

1.5 Integration of OTT/TSP Collaboration

One important factor which must be considered while studying the dynamics between TSPs and OTTs is the Network Neutrality principle. Network Neutrality principle states that the end users must equal access to all the content available in the Internet in order to preserve the openness of the Internet, and the TSP should be prohibited from discriminating or blocking the content from any of the application providers [17]. In this principle, the network must deliver traffic in the best effort as possible, but lower levels of violation regarding neutrality can be accepted as blocking of illegal content.

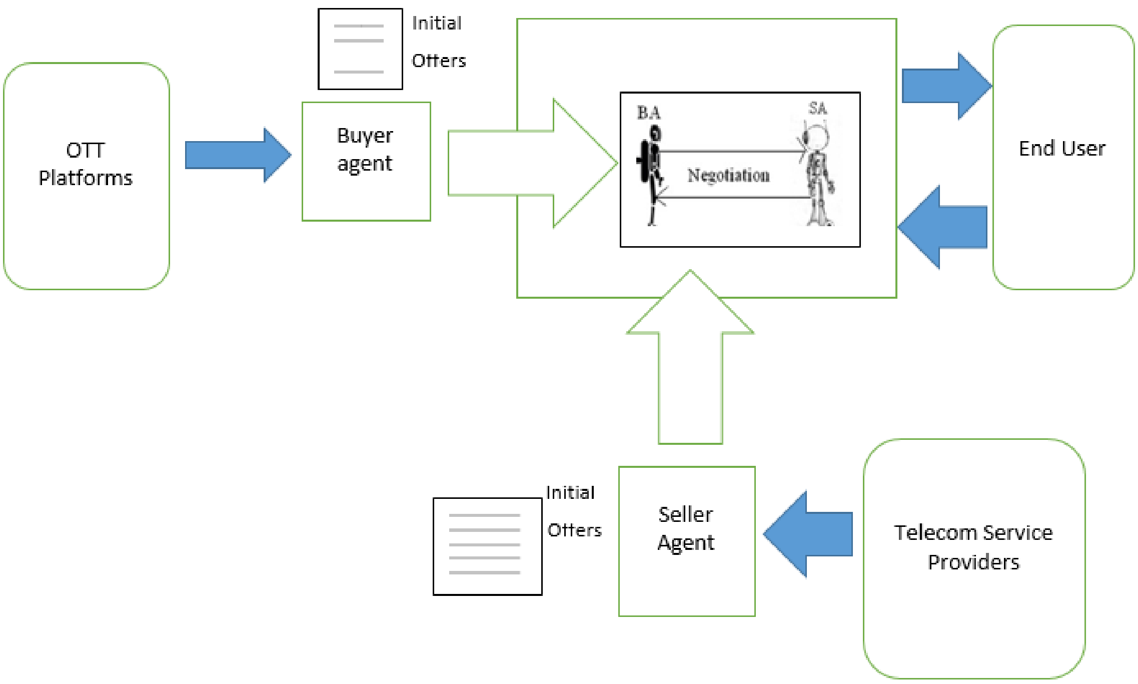

Fig 1.3: OTT/TSP Negotiation Architecture

Some papers have suggested some architectures regarding collaboration between OTT and TSP. In [9], the authors have proposed QoE-centered approach for collaboration. This model considers many important factors like user churn, pricing, marketing and revenue maximization. In [10], the authors have proposed three models for collaboration namely Joint-Venture (JV), Customer Lifetime Value-based (CLV) and QoE fairness based. Joint-Venture model proposed in [11] aims to maximize the revenue by providing better QoE to customers who pay more. CLV model aims to maximize the profit by providing better QoE to Most Profitable Customers (MPCs). QoE-fairness based model aims to maximize QoE and QoE fairness among all customers. In terms of profit, the CLV based model gives the best results, followed by JV model and the QoE-fairness based model.

1.5.1 Joint-Ventured Model

The QoE-centered approach model for collaboration [10] has three modelling: Revenue Modelling, Churn Modelling and Revenue Maximization.

1.5.1.1 **Revenue Modelling**

Revenue Modelling is driven by the maximization of the revenue for both TSP and OTTs. Paris Metro Pricing concept is used for the pricing of the Internet proposed in [12].

Studies conducted in [13] showed that the companies gain their customers mostly by proper marketing strategies and campaigns.

1.5.1.2 **Churn Modelling:**

The satisfaction of users regarding the service plays a crucial role in the reputation of any service provider in the market. Lowering the QoE may result in the high level of user churn, i.e., reduction of the number of active users. One of the major barrier is to predict the user churn model in terms of QoE. In [8], the authors have proposed the model in terms of Sigmoid function of QoE.

1.5.1.3 **Revenue Maximization**

After modelling revenue and user churn, we will have to model the maximum revenue from the revenue maximization.

The OTT is able to know the expectations of the user's QoE and to measure the QoE delivered, while the TSP supports the OTT by providing the needed network services to achieve the required QoE.

1.5.2 CLV-based approach

CLV is a metric used to identify the most profitable customers (MPCs), meaning those customers who hold greater value for providers compared to others. Customers who do not fall into the MPC category are referred to as standard customers (SCs).

CLV can depend on various factors, including the length of customer loyalty, the revenue they generate, and the profit margins they contribute. Additionally, customer characteristics like the likelihood to churn (e.g., passive customers) or frequent changes in subscriptions can influence CLV; for instance, passive customers might have a lower CLV, while those frequently changing subscriptions might have a higher CLV. Customers with the highest CLV are deemed the most valuable and should be targeted for retention efforts. This is because acquiring new customers is generally more expensive than retaining existing ones [14], and maintaining relationships with high-CLV customers is even more advantageous.

TSPs and OTTs likely have their own distinct methods for calculating CLV, which can vary between companies. However, they typically provide only normalized CLV data to ensure that exact figures remain confidential, while still allowing for effective collaboration.

1.5.3 QoE-fairness based approach

The previous two models focus on maximizing profit by enhancing QoE for high-paying or more profitable customers. However, future objectives in multimedia services aim to ensure fair, user-centric quality, meaning that all users across the network receive the best possible QoE. According to the fairness metric outlined in [15], a system is considered perfectly fair if every user gets the same QoE. The goal of the proposed collaboration scenario is to enhance both QoE and fairness for all customers shared by TSPs and OTTs. Specifically, while customers who pay more naturally expect better quality, the focus is on maximizing QoE for every individual customer [8].

OTTs lack control over the network infrastructure, which significantly impacts QoE and is used by various OTT services. Therefore, collaborating with OTTs to share the computed QoE data enables TSPs to manage the network more effectively, aiming for both overall QoE improvement and fairness. The relevance factor p is determined through agreements between the ISP and the OTTs.

1.6 Problem Description

In this thesis, we are going to create a negotiation model between OTT and TSP by using machine learning techniques like Bayesian Learning and Reinforcement Learning (or Q-Learning) so that the best QoE is supplied to the customers and also maximum profit is earned by OTT and TSP.

1.7 Motivation and Our Contribution

In the existing literature, there has been very limited work on negotiation tools being applied between OTT agents and TSP agents for the collaboration between them in e-marketplace. The works have been done regarding pricing and quality of traffic. While establishing them in 5G wireless network environment, there is some gap and network parameters have not been addressed. As a result of this gap, there has been some significant problem which must be addressed. Hence, we were motivated for this work to create a scenario of negotiation between both these agents enhancing the collaboration of these agents. We have considered multiple network parameters like latency, throughput, delay rate and jitter creating multiple issue negotiation scenario between OTT and TSP in e-marketplace which has been missing in the existing literature.

In this thesis, we have created a scenario of negotiation between OTT and TSP agents in e-marketplace by negotiation techniques. We have used two machine learning techniques like Bayesian Learning and Reinforcement Learning (also known as Q-Learning) for carrying out the negotiation between these two agents in e-marketplace. We have applied this negotiation technique with multiple issues like latency, delay rate, throughput and jitter resulting in the acceptance of an offer dealing with multiple network parameters of latency, delay rate, throughput and jitter.

1.8 Organization of Thesis

Chapter 1 is the Introduction, where have discussed about OTT and TSP, reason for their collaborations and some examples of architectures of collaboration between OTT and TSP present in the literature. Chapter 2 is the literature survey where we have surveyed the models of collaboration between OTT and TSP present in the literature along with the models of QoE management proposed in the literature, cloud computing and Service Level Agreements (SLA) and negotiation tools discussed in the literature. Chapter 3 is the Problem Formulation where we have formulated the problem. Chapter 4 is the Solution Methodology where we have discussed the methodologies used in our solution for solving the problem. Chapter 5 is the Performance Analysis where we have discussed the results of simulation formed after solving the problem. We have compared the results of simulation with respect to two methods Bayesian Learning Based Negotiation (BLBN) and Reinforcement Learning Based Negotiation (RLBN). We have also varied the learning rate to study the effects of learning rate for both methods of negotiation, i.e., Bayesian learning and Reinforcement Learning. Chapter 6 is the Conclusion where we have drawn the conclusion after obtaining the results of simulation for the process of negotiation.

1.9 Summary

In this chapter, we have started with brief discussion about OTTs and TSPs. Then we discussed about their benefits and importance of good Quality of Service (QoS) in present scenario. Then we have discussed the reasons for collaboration between OTTs and TSPs. After that, we have discussed about the architectures of collaboration between OTTs and TSPs discussed in the literature. We have concluded the chapter with the problem description of our thesis, motivation and our contribution in the thesis.

Chapter 2

Literature Survey

2.0 Introduction

There has been some works present in the literature regarding collaboration between OTT and TSP, works regarding management of QoE, works regarding cloud SLA (Service Level Agreement) management and works regarding negotiation techniques. In this chapter, we will survey the works present in the literature present in the literature and we will have a brief discussion about the works mentioned while surveying them.

2.1 Work-Related to OTT-TSP Collaboration

In [9], the authors have proposed an architecture for the collaboration of QoE management between OTTs and TSPs. In the model, many important factors have been included like revenue modeling, user churn modeling and revenue maximization. The user-churn, which is being affected by QoE has been modeled by using the Sigmoid function. In [8], the authors have used Sigmoid function for modelling user satisfaction as a function of QoS parameters for Internet Protocol Television (IPTV).

In [10], the authors have proposed three different approaches for collaboration between OTTs and TSPs, namely Joint Venture (JV), Customer Lifetime Value based (CLV) and QoE fairness based. Joint venture model aims to maximize the revenue generation by providing better QoE to customers paying more. Customer lifetime value-based model aims to maximize the profit by providing better QoE to the most profitable customers (MPCs). The QoE-fairness based model aims to maximize QoE fairness among all customers. The authors have found that CLV-based and JV approaches provide better QoE to Premium and Standard users, respectively. The price to subscribe to the Premium Service is higher than that for the Standard service. The QoE-fairness based approach provides a higher degree of QoE fairness among the users of the same Classes of Services (CoS), as well as on the network level. The CLV-based approach provides the highest profit, followed by the JV approach and the QoE fairness-based approach. Unfortunately, the authors could not evaluate the impact of frequency on exchange of information among the OTTs and TSP on the network load, as well as on the amount of data and the cost of data storage.

In [18], the authors have investigated the impact of different pricing strategies between TSP and OTT or directly between the TSP and the users. As a result, the TSP may sell QoS to users at a lower price than when QoS is sold to the OTT. In [19], a pricing mechanism has been proposed integrated with QoE aspects, called PARQUE (Pricing and Regulating Quality of Experience). Two different types of applications, web traffic and video traffic have been considered in PARQUE, implying higher QoS requirements for video traffic than for the web traffic. By simulating results, it has been demonstrated that integrating QoE aspects in traffic classification enhances overall user utility. Unfortunately, these works do not consider the user churn nor the collaboration between TSPs and OTTs.

In the study referenced as [20], the researchers introduced strategies for collaboration between OTTs and TSPs that prioritize Quality of Experience (QoE) while aiming to maximize profits. These strategies focus on reducing user churn among the Most Profitable Customers (MPCs), identified based on their Customer Lifetime Value (CLV). The authors enhanced service delivery by strategically placing Surrogate Servers (SRs) closer to Location Zones (LZs) with a high concentration of MPCs. The simulation results demonstrated that this approach significantly decreased MPC churn, leading to higher user retention and, consequently, increased profits.

In the study referenced as [21], the researchers introduced a new QoE fairness index, denoted as F, to measure and define fairness in Quality of Experience. They demonstrated that this index satisfies several essential properties that Jain's fairness index [37] does not. The authors also proposed that this QoE fairness index could be utilized to compare QoE fairness across different systems and applications, making it a valuable benchmark for optimizing QoE management and system performance.

In the study cited as [14], the authors introduced a zero-rated QoE approach, incorporating a context-aware QoE-based network resource allocation algorithm. This algorithm takes into account the user's Class of Service (CoS), device resolution, and video characteristics. Through simulations, the researchers compared their zero-rated QoE approach with a traditional zero-rated data rate approach across various metrics, including QoE delivered, fairness in QoE among users, video quality, profit growth over time, and network resource utilization. The findings demonstrated that their approach outperformed the zero-rated data rate method across all these metrics, resulting in more efficient QoE-aware network resource management.

Traffic within TSP networks is on the rise, increasingly driven by a few large OTTs that connect at multiple locations. At the same time, these networks are becoming more adaptable in terms of routing, OTT user mapping, and Internet Protocol (IP) topology, thanks to new optical technologies that allow for flexible reconfiguration. In [37], the researchers explored the potential benefits of these reconfigurable capabilities. Their concept involves making the OTT-TSP infrastructure responsive to demand, allowing it to be re-optimized according to evolving end-user needs over time. They developed an optimization framework and conducted a thorough evaluation using data from a major European TSP. The study revealed that such reconfigurable infrastructure holds significant promise, as it can substantially enhance the efficiency of both TSP networks and OTTs by taking advantage of spatial and diurnal traffic patterns.

In [38], the authors introduced a communication mechanism between OTTs and their associated TSPs, where the TSPs could act as relays with neighbouring TSPs to extend service directly to the user premises, ultimately improving QoS for both the OTT and the user while alleviating some of the TSPs' load. They also proposed a Representational State Transfer (REST) interface specifically designed for scenarios where enforced Round Trip Time (RTT) is adjusted by reducing available bandwidth in exchange. The authors laid out a framework for a collaborative approach between OTTs and TSPs, aimed at enhancing QoS by exchanging and balancing connection parameters. This collaboration allows OTTs to offer better services to their customers at a reduced cost or even for free, while TSPs improve the QoE for users by adjusting parts of their Service Level Agreements (SLA). As a result, customers experience a more seamless service with fewer issues.

In [40], the authors addressed the challenge of finding efficient and equitable methods to ensure high-quality services for end users during collaborations between OTTs and TSPs. They proposed a new model where content delivery stakeholders collaborate over a Virtualized Infrastructure, allowing for a fair distribution of the generated revenue. The authors identified key challenges and highlighted new technical opportunities to overcome them, including the deployment of a distributed Network Function Virtualization (NFV) platform at the edge of the Internet Service Provider's network, where a virtual Content Delivery Network (vCDN) could be implemented. They also applied a game-theoretic approach to analyze various TSP-OTT collaboration models and determine the optimal conditions for the proposed OTT as a Virtual Network Function model. Additionally, the authors designed a TSP NFV platform that enables OTTs to execute their delivery functions and proposed both technical and business solutions to address the limitations of current collaboration models. They modelled the TSP-OTT collaboration as a game and explored the optimality conditions using practical estimates.

2.2 Work-Related to QoE Management

In [48], the authors explored how issues in provisioning and delivery due to limited resources impact QoE, leading to what they termed the QoE provisioning-delivery hysteresis (QoE-PDH). They illustrated this effect for Voice-Over IP, Live Streaming, and web browsing using existing measurement data. Their findings emphasized the importance of actively managing quality to avoid uncontrollable factors, such as packet loss from congestion, that can degrade QoE.

In [22], the authors introduced a versatile QoE management framework that can be applied across various systems. They showcased an implementation of this framework as a network access point management system for RTP-based video. The authors placed particular emphasis on the QoE management component, illustrating how data gathered from the network can be processed into insights about the quality experienced by users, and how to implement corrective actions when needed.

In [23], the authors introduced a comprehensive model that integrates QoE and user behaviour, offering a framework that unifies various existing modelling approaches. This framework is designed to consider the perspectives of service provider benefits, user well-being, and technical system performance. The authors also examined a wide range of influence factors, particularly focusing on user and contextual issues, and illustrated their approach through several related use cases. Their novel framework jointly models QoE and user behaviour, treating user behaviour as one of the key dimensions alongside system performance and user state.

QoE management stands out as a key practical application of effective QoE models, as predicting how users perceive service quality enables service providers to optimize delivery based on various criteria. In [14], the authors expanded on these concepts by introducing the ideas of QoE fairness (in contrast to QoS fairness) and user diversity. They explored how the choice of measurement metrics, the significance of fairness, and the differences among users can influence optimal QoE management strategies for service providers. Through illustrative numerical examples, the authors demonstrated that selecting different metrics for quality estimation leads to system optimization tailored to different user types. They also analyzed how varying levels of user score diversity impact QoE management outcomes when different metrics are applied.

Mean Opinion Scores (MOS) are widely used as the results of subjective tests for the research of QoE. Thus, the performance of QoE management process actually depends heavily on QoE. However, the rationality of MOS for QoE management is not yet technically proven in the literature. The authors in [16] prove that subject homogeneity is implicitly assumed for obtaining MOS by modeling the arithmetic averaging process from a systematic viewpoint. The authors have proposed a utility-based averaging method (uMOS) which improves the performance of QoE management. The authors have investigated the implicit assumptions behind the arithmetic averaging of subjective ratings, namely MOS. It has been discovered that the arithmetic averaging of MOS based QoE could lead to unfairness which severely degrade the performance of QoE management. Finally, an alternative with utility-based averaging uMOS is proposed which could avoid the extreme unfairness.

In [25], the authors offer a tutorial and an extensive survey of QoE management solutions for both current and future networks. They begin with an overview of QoE management for multimedia services, which encompasses QoE modelling, monitoring, and optimization. The discussion then covers HTTP Adaptive Streaming (HAS) as the primary method for streaming video over the best-effort Internet. The authors also summarize key aspects of

Softwire Defined Networks (SDN) and Network Function Virtualization (NFV). Their survey categorizes the latest QoE management techniques into three main groups: a) QoE-aware or QoE-driven strategies using SDN and/or NFV; b) QoE-aware or QoE-driven methods for adaptive streaming in emerging architectures like multi-access edge computing, cloud/fog computing, and information-centric networking; and c) advanced QoE management approaches in new areas such as immersive augmented and virtual reality, as well as multimedia and video gaming applications.

The authors in [39] explores a shift towards utilizing machine learning (ML) techniques for developing QoE prediction models, which are closely tied to the personalized experiences of end-users. The authors analyze application-oriented ML-based QoE prediction models aimed at managing QoE for multimedia services. They review cutting-edge ML-based QoE predictive models, innovative methods, and challenges related to assessing multimedia quality, with a particular focus on extended reality and video gaming applications. The survey defines QoE in the context of multimedia services and offers a comprehensive analysis of the factors influencing QoE. It includes a detailed review of significant quality metrics, both subjective and objective, as well as methods for evaluating performance and mathematical models linking QoS parameters to QoE. The authors also examine the unique QoE aspects in extended reality and video gaming, highlighting how these emerging technologies differ from traditional video streaming services. Additionally, they provide an in-depth analysis of the quality factors impacting extended reality and video gaming applications.

In [45], the authors proposed that introducing an Experience Level Agreement (ELA) could serve as a QoE-focused alternative to traditional QoS-based Service Level Agreements (SLAs). They argue that ELAs would be a significant step forward in offering service quality directly to users. The authors explored various approaches to leverage QoE awareness to enhance SLAs, including improving internal aspects like Service Level Objectives (SLOs) and developing entirely new ELA definitions that explicitly define QoE. They also addressed key issues and challenges associated with this transition. The goal of ELAs is to support new business models by providing distinct QoE guarantees for users of online services.

In [46], the authors introduced a framework for assessing QoE as a service, incorporating both functional and non-functional requirements. Non-functional requirements are divided into three categories: objective, subjective, and business parameters, which influence Quality of Service (QoS), Quality of Experience (QoE), and Quality of Business (QoBiz) respectively. Given the interdependence of these metrics, the authors explored how to evaluate the QoE of a web-based OTT service by considering these various parameters. They used an Extended Finite State Machine (EFSM) to describe the functional behaviour of the service, tracking non-functional parameters through context variables and updating functions. This model enables the evaluation of QoE by monitoring user-service interactions and integrating objective, subjective, and business parameters. The authors demonstrated that the EFSM framework allows for tracking how user decisions affect QoE and provides insights for service providers on critical transitions and potential improvements to enhance user satisfaction.

In [47], the authors proposed an OpenFlow-assisted QoE Fairness Framework designed to enhance the QoE for multiple competing clients within a shared network environment. Utilizing Software Defined Networking (SDN) technology, such as OpenFlow, they provided a control plane to manage this functionality. Their approach, evaluated in a home networking scenario, focuses on user-level fairness and network stability, demonstrating how QoE can be optimized across various devices in the network.

2.3 Work-Related to Cloud Service Level Agreement (SLA) Modelling

Cloud computing offers a valuable technology where infrastructure, development platforms, software, and storage are provided as services. As the number of cloud service providers grows, selecting the most reliable ones becomes crucial. In [26], the authors introduced a Service Level Agreement (SLA) platform that uses metrics to help compare different cloud service providers, aiding consumers in choosing the most dependable options. They proposed a Reputation System to assess provider reliability and a SLA template pool to make the negotiation process between providers and consumers more fair, transparent, and efficient. By evaluating providers' reputations and feedback recorded in the Reputation System, consumers can identify the most trustworthy providers. The reliability of these reputations is reinforced by the extensive data provided by users.

In [27], the authors outlined the key criteria to consider when designing Service Level Agreements (SLAs) in cloud computing. They also explored negotiation strategies between cloud providers and consumers, and proposed a method to uphold trust and reliability throughout the negotiation process between the parties involved.

Proving a Service Level Agreement (SLA) violation can be challenging for cloud consumers, especially when using services from multiple providers with different monitoring policies. To assist consumers in monitoring SLAs and detecting violations, the authors in [28] introduced a new semantic SLA modelling approach for cloud computing. Their method helps consumers track SLA documents and identify breaches by interpreting the semantic meaning of SLA concepts and utilizing reasoning techniques. This approach ensures reliable QoS and adherence to SLA parameters. The authors demonstrated the effectiveness of their method through simulations and case studies. Similarly, in [29], the authors proposed a solution for monitoring web services, allowing users to verify service functionality against the metrics specified in their SLA contracts.

In the emerging digital markets for trading cloud resources, such as computational services, the typical approach is akin to a supermarket model, where consumers purchase services based on fixed functional and non-functional characteristics without any negotiation. In [62], the authors proposed a new, generic service market ecosystem from which strategies for bilateral negotiations are developed. They categorized these strategies according to various stages of the negotiation process. Their analysis revealed two distinct groups: one that operates under the assumption of complete information during negotiations, and another that deals with incomplete information.

In [63], the authors introduced an innovative Trusted Negotiation Broker (NB) framework designed for adaptive and intelligent bilateral negotiations of SLAs between service providers and consumers, based on each party's high-level business needs. They developed mathematical models to translate business-level requirements into detailed parameters for the decision function, which adds complexity to the system. Additionally, they proposed an algorithm for adjusting decision functions during negotiations to align with an opponent's offers or updated consumer preferences. The NB employs intelligent agents to manage negotiations locally, choosing the most appropriate time-based decision functions. It also enables the negotiating parties to provide feedback to their agents during the negotiation process, aiding critical decision-making. The authors implemented three time-based decision functions—exponential, polynomial, and sigmoid—and used a utility-function-based cost-benefit model to assess consumer satisfaction with negotiation offers.

Blockchain and Distributed Ledger Technologies (DLT) offer features like immutability and transparency, which can benefit the telecommunication industry by facilitating service exchanges through smart contracts. This enables various stakeholders in a sixth generation (6G) network to participate in a marketplace for inter-provider agreements, whether as service providers or consumers. A blockchain-based 6G network can support administrative domains in sharing resources such as virtual network functions, services, or slices. However, this dynamic environment necessitates rigorous SLA monitoring and management. In [64], the authors explored a use case involving smart contract-based inter-provider agreements. They employed innovative solutions such as IOTA Tangle for transactions, the InterPlanetary File System (IPFS) for storing hashes of use case data files, and Chainlink for accessing off-chain data feeds to monitor SLAs. These solutions aim to reduce costs and enhance transparency. The authors presented a conceptual framework designed to improve SLA management and advance QoS assurance for 6G use cases, particularly in inter-provider agreements.

In managing Cloud Services, Contract Management is crucial and requires effective software solutions to handle the provision of applications, infrastructure, or services by third parties. Cloud contracts must address a range of international legal, financial, technical, and operational aspects concisely to drive business while minimizing disputes in case of issues. They need to cover various scenarios, from standard situations like email and web hosting for smaller companies to highly customized cases for governments, large enterprises, and strategic clients with specific needs. Throughout the entire lifecycle of a contract—from creation to execution and completion—software support is vital. In [66], the authors introduced a process model and an information model designed to form the basis for a Contract Management (CM) tool for Cloud Services. These models were validated through a focus group of Small and Medium Enterprises (SMEs).

As e-business environments become increasingly widespread and dynamic, the frequency of negotiations between companies is rising. Despite the potential benefits and advancements in research, the adoption of negotiation systems has been slow. According to the authors in [68], one reason for this is the insufficient focus on process management aspects like design, description, and deployment. Negotiations should be viewed through the lens of process management since they occur within corporate processes such as procurement or sales. The authors explored system support and automation for business-to-business (B2B) negotiations from a process management perspective. They proposed a Web Services-enabled marketplace architecture for managing negotiation processes and enhanced it by incorporating pattern-based process composition. Additionally, they introduced a pattern-based negotiation process composition tool to facilitate the creation and modification of flexible negotiation processes, addressing challenges in managing ad hoc business activities such as negotiations.

Many existing decision support systems (DSSs) struggle to adapt to new working practices and organizational environments. As decision-making becomes more varied and less hierarchical, driven more by the nature of the evidence and confrontation rather than corporate rank, DSSs with negotiation capabilities become essential. Intelligent negotiation agents, which can interact and negotiate with users and among themselves, are well-suited for modelling various decision-making tasks. The emerging constraint agent technology offers a promising solution for these negotiation agents. In [69], the authors proposed a model using constraint negotiation agents for DSSs. They defined an object-oriented constraint language for modelling these agents, enabling them to reason collaboratively with users or other agents. The model treats negotiations as interactive constraint satisfaction processes and includes effective algorithms for implementing negotiation-oriented constraint satisfaction. Given the rising costs of manpower and increased negotiation workload, future DSSs are expected to play a crucial role in the negotiation process.

2.4 Work-Related to Negotiation Techniques

In [30], the authors proposed using Bayesian learning as a technique for agent negotiations in e-marketplaces. Their study demonstrated that probabilistic negotiation agents, which leverage knowledge discovery mechanisms, are more effective and efficient compared to Pareto optimal agents in realistic negotiation scenarios.

In [31], the authors aimed to enhance and unify the understanding of opponent models in bilateral negotiations by offering a thorough survey of existing models. They explored various methods of opponent modelling that have been utilized to benefit agents, and introduced a taxonomy of these models based on their underlying learning techniques. Additionally, the authors outlined methods for evaluating the success of opponent models and provided guidelines for selecting suitable performance measures for each type within their taxonomy.

In [32], the authors explored methods for generating offers in automated negotiations involving multiple issues, even when the utility function of the opponent is unknown. They demonstrated that using an alternating projection strategy, it is feasible to reach an agreement in multi-attribute negotiations where agents have nonlinear utility functions and lack information about each other's utility functions. The authors also showed that rational agents have no incentive to deviate from this proposed strategy. Through simulations, they illustrated that their algorithm's solutions are closely aligned with the Nash bargaining solution, which maximizes the joint utility of the agents.

In [33], the authors introduced an innovative bilateral negotiation model using Bayesian learning, which allows self-interested agents to dynamically adjust their negotiation strategies throughout the process. The model proves effective in helping agents learn about the potential range of their opponent’s private information and adapt their concession strategies accordingly, leading to improved negotiation outcomes.

In [34], the authors conducted a survey that consolidates research on multi-attribute negotiation. They proposed a general framework for automated multi-attribute negotiation, introducing two new mechanisms designed to tackle challenges related to incomplete information, Pareto optimality, and tractability.

In [35], the authors explored how new cellular system architectures and advanced spectrum management techniques can help meet the rapidly growing demand for mobile data capacity. They introduced an intelligent case-based Q-learning approach for dynamic spectrum access (DSA), which enhances and stabilizes the performance of cognitive cellular systems with changing topologies.

In [36], the authors examine Automatic Negotiation and analyze a framework for a Negotiation Model using Multi-Agent technology. They employed a Q-learning algorithm within an Artificial Intelligence and multi-agent system (MAS) simulation platform.

In [49], the authors explored algorithms for learning and updating user profiles to identify interesting World Wide Web (WWW) sites on specific topics. They described the use of a naïve Bayesian classifier, demonstrating its ability to incrementally learn from user feedback about their interest in websites. The Bayesian classifier can also be easily adapted to revise user profiles. Compared to more computationally intensive methods, the Bayesian classifier consistently performed well across various domains. The authors also empirically assessed how providing the classifier with background knowledge from user-defined profiles and utilizing lexical knowledge can significantly enhance prediction accuracy.

In [50], the authors developed a genetic algorithm designed to solve multiparty, multi-objective negotiation problems. This approach aligns well with the complexities of real-world negotiations, making it suitable for more realistic scenarios. They introduced a trade operator to improve the search process, which mimics the concessions that negotiators might make. When compared to traditional genetic algorithms that use crossover, reproduction, and mutation, the genetic algorithm with the trade operator demonstrated superior performance in experimental results.

In [51], the authors introduced a computational prototype to model negotiation behaviour under various conditions: (i) agents use different matching tactics, (ii) agents lack knowledge of opponents' preferences, (iii) agents face costs for delaying settlements, (iv) agents have varying levels of goal difficulty and initial offer sizes, and (v) demands and counteroffers are evaluated based on how well they match the opponent's concessions. Their study investigates how these different agent behaviours influence negotiation outcomes. Simulations demonstrated that the prototype effectively exhibits key negotiation patterns and validates the effectiveness of traditional strategies, such as setting ambitious goals and employing aggressive concession-matching tactics.

In [52], the authors introduced a novel model for multi-issue negotiations under time constraints and incomplete information. This model applies to scenarios involving either single or multiple services. The agenda-based approach they proposed determines the sequence of issues to be negotiated and the agreements reached as part of the bargaining equilibrium. The authors identified conditions under which agents either have aligned or conflicting preferences regarding the negotiation process. They demonstrated that an equilibrium can exist even when agents possess uncertain and private information about each other. Additionally, the authors explored the properties of the equilibrium solution, including when it is unique, symmetric, and Pareto-optimal.

In [53], the authors outline the key parameters that influence automated negotiation processes. They demonstrate the usefulness of their classification framework by applying it to a representative selection of notable negotiation models from the literature. This framework is designed specifically for automated negotiations in e-commerce contexts. The authors use their classification scheme to analyze a variety of well-known negotiation models, illustrating its application and effectiveness.

In [54], the authors introduced a formal heuristic computational model for trade-off strategies, demonstrating its potential to enhance the overall social welfare of the system. They developed a new linear algorithm that allows software agents to make trade-offs in the context of distributed resource allocation for multi-dimensional goods. This novel hill-climbing algorithm is designed to handle both qualitative and quantitative decision variables in multi-dimensional negotiations. The authors conducted a theoretical analysis of the algorithm and found that its average complexity scales linearly with the number of negotiation variables involved.

In [55], the authors investigated how negotiations focusing on interests versus values are affected by different levels of time pressure. Their experiments revealed four key findings. First, individuals were more likely to reach early deadlocks under low time pressure compared to high time pressure. Second, when early deadlocks occurred, negotiators exhibited a shift from low to high integrative behaviour later in the negotiation, but this was more pronounced when negotiating interests rather than values. Third, negotiations focused on interests resulted in better joint outcomes than those focused on values, particularly under low time pressure. Fourth, there was a notable increase in integrative behaviour when there was low time pressure and a conflict of interest.

In [56], the authors addressed the challenge of finding association rules among items within extensive sales transaction databases. They introduced two algorithms, Apriori and AprioriTid, designed to identify all significant association rules within such large datasets.

In [61], the authors reviewed the latest developments in agent-mediated e-commerce, focusing on both business-to-consumer (B2C) and business-to-business (B2B) contexts. They examined how agents are used in B2C activities, such as identifying needs, brokering products, forming buyer coalitions, and negotiating with merchants. In the B2B sector, the paper explored how agents are involved in partnership formation, brokering, and negotiation through a B2B transaction model.

In [65], the authors examined whether the preferences encoded in electronic negotiation support systems are truly reflected in negotiators' behaviour and the outcomes of negotiations. Their empirical findings reveal that aspects of negotiation behaviour, such as initial offers and the extent of concessions, generally align with individual preferences. However, the influence of these preferences on achieving an agreement or the efficiency of the compromise was found to be relatively minimal.

The study by the authors in [67] introduced several protocols for scheduling meetings among agents that represent their users' interests. They examined four protocols:

(i) **Full Information Protocol**: All agents share their preference profiles and availability.

(ii) **Approval Protocol**: Agents only share their preference profiles.

(iii) **Voting Protocol**: Agents only share their available times.

(iv) **Suggestion Protocol**: Agents do not share either their preferences or availability.

The authors used a unique metric to evaluate these protocols, aiming to both maximize average preferences and minimize preference differences among agents. The Full Information and Approval Protocols were found to be optimal, providing the best solutions. The Suggestion Protocol was identified as coalition-free, meaning it does not facilitate agents forming coalitions to negotiate against non-coalition members.

The authors in [70] introduced adaptive negotiation agents enhanced by robust evolutionary learning techniques to handle complex and evolving negotiation scenarios. Their experiments demonstrated that these genetic algorithm-based agents outperformed a theoretically optimal negotiation mechanism that ensures Pareto optimality. The agents utilize effective evolutionary learning to gradually understand their opponents' preferences and adapt to changing negotiation contexts. These agents meet practical negotiation system needs by simulating diverse negotiation attitudes, finding near-optimal solutions with limited information, and continuously adjusting to new contexts. Furthermore, their approach, which considers time pressure, improves negotiation outcomes, such as joint payoffs and success rates, in various agent encounters.

In [71], the author demonstrated how a system of artificial adaptive agents, utilizing a genetic algorithm-based learning approach, can effectively learn strategies for conventional business negotiations. The learned negotiation policies were assessed across various dimensions, including joint outcomes, proximity to the efficient frontier, and alignment with human negotiation results. These findings are valuable for integrating such agents into practical e-commerce systems. Although enhancements to the genetic algorithm, like improved crossover techniques and better diversity management, could further boost effectiveness, the basic performance of these agents is commendable. Systematic, statistical comparisons with human negotiators reveal that these artificial adaptive agents can perform on par with, or even exceed, human capabilities.

2.5 Chapter Summary

However, none of the works have considered a negotiation scenario between OTT and TSP networks. Our work deals with the practical problem that is most likely to be faced by OTT and TSP agents during negotiation in e-marketplace. Hence, to the best of our knowledge, this work is unique.

Chapter 3

Problem Formulation

3.1 Background

Since the early 2000s, there has been an emergence of internet-based platforms that provide streaming media content directly to the customers. In the early 2000s, the concept of streaming video content over the internet began to take shape with the launch of services like Netflix, Hulu. These platforms initially focused on providing on-demand access to movies and TV shows, delivered over broadband internet connections.

According to the Ericsson Global Mobile Data Traffic 2027 Report [1], 60% of the mobile data traffic will pass through fifth generation (5G) networks in 2027 from 10% of the mobile data traffic in 2099. The report predicted fifth generation to 90% in North America in 2027. The report mentioned that the global average monthly traffic usage to be 15 GB and is expected to be twice or thrice in 2027. In India, Bhutan and Nepal, the report mentioned the average monthly traffic usage to 20 GB and will rise to 50 GB. Hence, fifth generation network will or has become very important for the mobile communications network.

OTT and TSP have different perspectives with respect to management of QoE, which are mainly influenced by their roles in the service delivery chain. TSP, being the owner of the network, allows its customers to connect to the Internet as well as to subscribe to OTT services.

Presently, users are demanding better quality and hence TSP has difficult role to manage the huge traffic generated by OTT services to provide sufficient QoE to the users. Although, TSP has a network-centric view of the quality provided, TSPs and OTT providers have distinct viewpoints on managing Quality of Experience (QoE), largely shaped by their positions in the service delivery chain. TSPs own the networks that enable their customers to access the Internet and subscribe to OTT services. With users increasingly demanding high-quality experiences, TSPs face the challenging task of managing the vast traffic generated by OTT services, particularly multimedia content, to ensure a satisfactory QoE for their users.

n 1994, the International Telecommunication Union (ITU) described Quality of Service (QoS) as a thorough assessment of performance across mobile telecommunications, computer networks, and other digital transmission systems. Many commercial multimedia services now utilize QoS-focused optimization methods to manage data flow effectively for real-time applications, including IPTV [41], VoIP, multiplayer online games, online meetings, and more.

A general assessment of QoS is done by a linear mapping method. The design of linear mapping function is [42]

$$QoS = \sum_{k=1}^{N} w_k . f_k(x_k) \qquad \text{———————————— (3.1)}$$

where,

x_k = Network influencing factor

N = Number of network influencing factor

w_k = Corresponding weight of the network influencing factor

$f_k(.)$ represents the mapping function

The linear mapping method has certain limitations. It overlooks the "marginal effect" of certain network parameters, meaning it doesn't fully capture the relationship between these parameters and the QoS score.

Quality of Experience (QoE) is the user's assessment of the network service experience under the overall network environment. Generally, subjective evaluation–MOS(Mean Opinion Score) is used for quantifying QoE. MOS denotes the ratings of the user's experience and can be represented by a single number for rating in the range of 1 to 5 as mentioned in the table below.

Table 3.1: QoE Rating

Experience	Excellent	Good	Average	Poor	Bad
Score	5	4	3	2	1

However, using subjective evaluation for obtaining QoE is quite complex, time-consuming and costly. Markus et al. [43] have obtained a relationship between QoE and QoS by the following equation

$$\frac{\delta QoE}{\delta QoS} = -(QoE - \gamma) \qquad \text{———————— (3.2)}$$

Solving the differential equation (3.2), we get

$$\frac{\delta QoE}{\delta QoS} = -(QoE - \gamma)$$

or, $\int \frac{\delta QoE}{QoE - \gamma} = -\int \delta QoS$

or, ln (QoE–γ) = –QoS

or, QoE = $e^{-QoS} + \gamma$

or, QoE = $\alpha e^{-\beta QoS} + \gamma$ —————————— (3.3)

Where, α and β are arbitrary constants.

The relationship between QoE and jitter is [44]

$$QoE = -0.4(JI)^{\frac{1}{2}} + 5 \quad \text{—————————————— (3.4)}$$

where,

JI is the jitter of the network.

From (3.3), we get

QoE = $\alpha e^{-\beta QoS} + \gamma$

or, $\alpha e^{-\beta QoS}$ = QoE–γ

or, $e^{-\beta QoS} = \frac{QoE-\gamma}{\alpha} = \frac{5 - \gamma - 0.4(JI)^{\frac{1}{2}}}{\alpha}$ [From (4)]

or, $-\beta QoS = \log\left[\frac{5 - \gamma - 0.4(JI)^{\frac{1}{2}}}{\alpha}\right]$

or, $QoS = (-1/\beta).\log\left[\frac{5 - \gamma - 0.4(JI)^{\frac{1}{2}}}{\alpha}\right]$ ———————————— (3.5)

In order to solve the problem of the linear mapping function $f_k(.)$, the relations between QoS and network parameters are considered separately.

For the network packet delay (DL), the experimental data obtained in [42] is

QoS(DL) = $ae^{bDL} + \phi_1$ —————————— (3.6)

For the packet loss rate (LR), the experimental data obtained in [42]

QoS(LR) = $\frac{c}{LR+d} + \phi_2$ —————————— (3.7)

For the throughput rate (TH), the experimental data obtained in [42]

QoS(TH) = p log TH + ϕ_3 —————————— (3.8)

For the jitter, JI

$$QoS(JI) = (-1/\beta).\log\left[\frac{5-\gamma-0.4(JI)^{\frac{1}{2}}}{\alpha}\right] + \phi_4 \qquad \text{———————————— (3.9)}$$

After merging and combining the network influencing factors, we get

QoS = QoS(DL) + QoS(LR) + QoS(TH) + QoS(JI)

$$= ae^{bDL} + \frac{c}{LR+d} + p\log TH + (-1/\beta).\log\left[\frac{5-\gamma-0.4(JI)^{\frac{1}{2}}}{\alpha}\right] + q \qquad \text{————————— (3.10)}$$

Where,

$q = \phi_1 + \phi_2 + \phi_3 + \phi_4$

And

α, β and γ are arbitrary constants.

a,b,c,d,p and q are parameters whose values vary for different types of network services.

3.2 Formulation of the Objective Function

Utility function of an offer is the term that is used to quantify an agent's preference of the offer during the process of negotiation.

Here, the quality of service is actually the utility function for both the agents.

3.2.1 Buyer's Utility

The utility function of the buyer agent may be expressed as

$$U = a_1e^{b_1DL} + \frac{c_1}{LR+d_1} + p_1logTH + \left(-\frac{1}{\beta_1}\right)log\left[\frac{5-\gamma_1-0.4(JI)^{\frac{1}{2}}}{\alpha_1}\right] \qquad \text{————————————— (3.21)}$$

3.2.2 Seller's Utility

The utility function of the seller agent may be expressed as

$$V = a_2 e^{b_2 DL} + \frac{c_2}{LR+d_2} + p_2 logTH + \left(-\frac{1}{\beta_2}\right) log\left[\frac{5-\gamma_2-0.4(JI)^{\frac{1}{2}}}{\alpha_2}\right] \quad \text{———————————— (3.99)}$$

The buyer and seller have different perspectives on each of the same network parameters, hence the arbitrary constants will be different for different agents.

Thus, the objective of the work is to:

$$\text{Maximize } [U + V] = a_1 e^{b_1 DL} + \frac{c_1}{LR+d_1} + p_1 logTH + \left(-\frac{1}{\beta_1}\right) log\left[\frac{5-\gamma_1-0.4(JI)^{\frac{1}{2}}}{\alpha_1}\right] + a_2 e^{b_2 DL} + \frac{c_2}{LR+d_2} + p_2 logTH + \left(-\frac{1}{\beta_2}\right) log\left[\frac{5-\gamma_2-0.4(JI)^{\frac{1}{2}}}{\alpha_2}\right] \quad \text{———————————— (3.23)}$$

where, for buyer agent

$0<DL<0.5$,

$0<LR<0.01$

$25<TH<35$ MBPS

$0<JI<30$ ms

And for seller agent

$0.2<DL<0.7$

$0.003<LR<0.015$

$30<TH<40$ MBPS

$10<JI<45$ ms

The constraints for the objective function is mentioned in the table below:

Table 3.2: Constraints of the Parameters

Parameter	**Values**
Delay Rate for OTT	0 to 0.5
Delay Rate for TSP	0.2 to 0.7
Packet Loss Rate for OTT	0% to 1%
Packet Loss Rate for TSP	0.3% to 1.5%
Throughput for OTT	25 MBPS to 35 MBPS
Throughput for TSP	30 MBPS to 40 MBPS
Jitter for OTT	0 ms to 30 ms
Jitter for TSP	10 ms to 45 ms

It is quite clear from the equation that the goal or objective of the work is to maximize the surplus utility. The reason behind this consideration is that the surplus utility gets distributed between the agents. Hence, higher surplus utility, the chance of receiving more utility or benefit increases to both the agents.

3.3 Chapter Summary

In this chapter, we have formulated the problem required for the process of negotiation between OTT and TSP agents. The QoS and QoE with respect to various network parameters are evaluated. We have also got a relationship between QoS and QoE to assist in finding the QoS and QoE with respect to various network parameters. The utility functions for both the OTT and the TSP agents are evaluated which are essential for solving the process of negotiation.

Chapter 4

Solution Methodology

4.1 Bayesian Learning

Bayesian learning is done based on the data from past negotiation history. The negotiation history has values of parameters in each offer of every past session. Along with that, the information regarding whether the offer has been accepted or rejected is present. In each session, certain number of offers has been made. Notations i and j have been used which indicate session number and offer number of that particular session respectively. Offers are denoted by σ, where σ_j denotes the jth offer of the corresponding session. Acceptance of offer σ_j of session i is denoted by A_i^j [58]. If the offer σ_j of the session i has been accepted by the opponent or the offer has been offered by the opponent, then A_i^j = 1. If the offer of the session has been rejected by the opponent, then A_i^j = 0.

A sample table of negotiation history is presented below. In this negotiation history, four offers in four sessions are shown. The values of parameters of each offer, whether the offers were accepted by the opponent or not and the weight of the offer is shown.

Table 4.1: Sample Negotiation History

Session	**Offer**	**Delay Rate**	**Throughput (in MBPS)**	**Packet Loss Rate (in %)**	**Jitter (in ms)**	**Acceptance by opponent (A_i^j)**	**Weight**
1	σ_1	0.2	32	0.05	15	Yes	100
1	σ_2	0.45	27	0.01	24	No	75
1	σ_3	0.25	28.5	0.1	27	Yes	50
1	σ_4	0.3	33	0.65	16	No	25
2	σ_1	0.25	34	0.74	14	Yes	267
2	σ_2	0.15	26.5	0.87	11	No	995
2	σ_3	0.13	69.5	0.89	5	No	183
2	σ_4	0.99	30.5	0.69	7	Yes	142
3	σ_1	0.05	31	0.45	9	No	433
3	σ_2	0.16	33.5	0.54	12	No	392
3	σ_3	0.24	34.5	0.56	28	No	350
3	σ_4	0.26	30	0.78	23	No	308
4	σ_1	0.34	26	0.43	18	No	600
4	σ_2	0.45	27.5	0.34	4	No	558
4	σ_3	0.4	28	0.5	3	No	517
4	σ_4	0.34	69	0.4	21	Yes	475

In the negotiation table, to each offer weight has been assigned. The chance of acceptance of any offer is indicated by its weight. An offer's weight is calculated in two stages.

Weightage of a session i, w_i is determined by the equation [58]

$$w_i = w_{max} - step \times \frac{w_{max} - w_{min}}{S-1} \quad \text{----------------------} \ (4.1)$$

Here, S = Number of past sessions considered at the time of current transaction.

step = Sequence of the session and it varies from 0 to S – 1. For example, the step value of the most current negotiation session is 0, and the second most current session is 1, and so on.

Here, w_i is the highest weight assigned to a particular negotiation session i. The terms $w_{max} > 0$ and $w_{min} > 0$ represent the maximum and the minimum weights assigned for valuating all the negotiation sessions respectively.

The weight of each offer or counter-offer within a session i of the negotiation process vary. For example, a counter-offer proposed by the opponent at the earlier stage is more preferable for the opponent than the one proposal at a later stage.

The weight of each offer σ_j of session i is evaluated from the equation [58]

$$w_{ij} = w_i - (j-1) \times \frac{w_i - w_{i-1}}{K} \quad \text{---------------------} \ (4.2)$$

where, K = Total number of offers in each session.

Initially, the value of w_{i-1} is assumed to be zero.

Considering σ_{OTT}^j be the jth offer of OTT agent, the probability of acceptance of offer σ_{OTT}^j has been computed as per Bayesian theorem below:

$$p(accept|\sigma_{OTT}^j) = \frac{p(accept) \times p(\sigma_{OTT}^j|accept)}{p(accept) \times p\left(\sigma_{OTT}^j \middle| accept\right) + p(reject) \times p(\sigma_{OTT}^j|reject)} = p^j_{\mathbf{OTT}} \quad \text{----------} \ (4.3)\ [58]$$

where,

$$p(accept) = \frac{\sum i \sum j (w_{ij}|A_i^j = 1)}{\sum i \sum j w_{ij}} \quad \text{---------------------} \ (4.4)$$

$$p(reject) = \frac{\sum i \sum j (w_{ij}|A_i^j = 0)}{\sum i \sum j w_{ij}} \quad \text{---------------------} \ (4.5)$$

$$p(\sigma_{OTT}^j\ |accept) = \frac{\sum i (w_{ij}|A_i^j = 1)}{\sum i \sum j (w_{ij}|A_i^j = 1)} \quad \text{---------------------} \ (4.6)$$

$$p(\sigma_{OTT}^j|reject) = \frac{\sum i (w_{ij}|A_i^j = 0)}{\sum i \sum j (w_{ij}|A_i^j = 0)} \quad \text{---------------------} \ (4.7)$$

where,

p(accept) and p(reject) are the probabilities of an offer to be offered and rejected respectively.

$p(accept|\sigma_{OTT}^{j})$ refers to the probability of acceptance given that the offer was proposed to the opponent.

$p(\sigma_{OTT}^{j}|accept)$ and $p(\sigma_{OTT}^{j}|reject)$ refer to the probabilities of selecting or making offer σ_{OTT}^{j} given that either it will be accepted or rejected respectively. In other words, $p(\sigma_{OTT}^{j}|accept)$ and $p(\sigma_{OTT}^{j}|reject)$ are the ratios between the weightage of offer (σ_{OTT}^{j}) when offer (σ_{OTT}^{j}) is accepted or rejected respectively in previous sessions and sum of weightage of all the accepted offers in previous sessions.

The final preference value of each offer is calculated as [57]

$$U'(\sigma_{OTT}^{j}) = [U(\sigma_{OTT}^{j})]^{\theta} \times [p(\sigma_{OTT}^{j})]^{1-\theta} \qquad \text{------------------------ (4.8)}$$

where $U(\sigma_{OTT}^{j})$ is the utility function of the offer σ_{OTT}^{j} with respect to OTT agent.

and θ is the learning rate or trade off factor.

If $\theta = 0$ is set, the negotiation agent is a strictly benevolent agent or kindly agent. If $\theta = 1$ is set, the negotiation agent is a strictly self-interested agent. [57]

The initial value of the learning rate or trade-off factor is generally provided by the user. However if the value of the learning rate or trade-off factor is not provided, then the value of the learning rate or trade-off factor will be taken as 0.5 as default.

$U'(\sigma_{OTT}^{j})$ is the final preference value of the offer σ_{OTT}^{j} with respect to OTT agent.

The final preference values of offers are sorted and their corresponding offers are stored in the set $\Omega_{BA} = \{\sigma_{OTT}^{1}, \sigma_{OTT}^{2}, \sigma_{OTT}^{3}, ..., \sigma_{OTT}^{K}\}$ such $U'(\sigma_{OTT}^{1}) > U'(\sigma_{OTT}^{2}) > U'(\sigma_{OTT}^{3}) ... > U'(\sigma_{OTT}^{K})$.

4.2 Algorithm for Bayesian Learning

4.2.1 Algorithm

Pseudocode for OTT agent

1) **Formation of History Table**

1.1) Input S = Total Number of past sessions

1.2) Input K = Total Number of offers

1.3) Values of parameters of each offer in all the past sessions are recorded.

1.4) The parameters in each offer are Delay Rate, Packet Loss Rate, Throughput and Jitter.

1.5) Utility value of each offer is calculated from the equation (3.21).

1.6) In each offer, whether the offer was accepted or rejected is recorded.

1.7) From this record, p(accept) and p(reject) were calculated.

2) **Initialization**

2.1) Arbitrary values are assigned to w_{max} and w_{min} such that w_{min} is always greater than w_{min}.

2.2) Assign $w_0 = 0$

3) **Calculation of weights**

3.1) for i = 1 to S

3.2) Calculate w_i from the equation (4.1)

3.3) End i

3.4) for i = 1 to S

3.5) for j = 1 to K

3.6) Calculate w_{ij} from equation (4.2)

3.7) End j

3.8) End i

4) **Calculation of the Probabilities**

4.1) for j = 1 to K

4.2) Calculate $p(\sigma_{OTT}^j/\text{accept})$ and $p(\sigma_{OTT}^j/\text{reject})$ from the equations (4.6) and (4.7) respectively

4.3) End j

4.4) for j = 1 to K

4.5) Calculate $p^j_{\mathbf{OTT}}$ from the equation (4.3)

4.6) End j

5) **Sorting of Offers**

5.1) Calculate the final preference value $U' (\sigma_{OTT}^j)$ from the equation (4.8)

5.2) Sort the offers in decreasing orders of final preference values in Ω_{OTT}

Pseudocode for TSP agent

1) **Formation of History Table**

1.1) Input S = Total Number of past sessions

1.2) Input K = Total Number of offers

1.3) Values of parameters of each offers in all the past sessions are recorded.

1.4) The parameters in each offer are Delay Rate, Packet Loss Rate, Throughput and Jitter.

1.5) Utility value of each offer is calculated from the equation (3.99).

1.6) In each offer, whether the offer was accepted or rejected is recorded.

1.7) From this record, p(accept) and p(reject) were calculated.

2) **Initialization**

2.1) Arbitrary values are assigned to w_{max} and w_{min} such that w_{max} is always greater than w_{min}.

2.2) Assign $w_0 = 0$

3) **Calculation of weights**

3.1) for i = 1 to S

3.2) Calculate w_i from the equation (4.1)

3.3) End i

3.4) for i = 1 to S

3.5) for j = 1 to K

3.6) Calculate w_{ij} from the equation (4.2)

3.7) End j

3.8) End i

4) **Calculation of the Probabilities**

4.1) for j = 1 to K

4.2) Calculate $p(\sigma_{TSP}^j/accept)$ and $p(\sigma_{TSP}^j/reject)$ from the equations (4.6) and (4.7) respectively

4.3) End j

4.4) for j = 1 to K

4.5) Calculate $p^j_{\mathbf{TSP}}$ from the equation (4.3)

4.6) End j

5) **Sorting of Offers**

5.1) Final Preference value U′ (σ_{TSP}^{j}) is computed from equation (4.8)

5.2) Sort the offers in decreasing orders of final preference values in Ω_{OTT}

Pseudocode for Negotiation Process

Negotiation Process:

1.1) for j = 1 to K

1.2) TSP offers (σ_{TSP}^{j}) to OTT

1.3) If U(σ_{TSP}^{j}) > U((σ_{OTT}^{j})

1.4) Display Success and print the parameters in the Offer σ_{TSP}^{j} as Output

1.5) Break away from the loop

1.6) Else

1.7) OTT offers (σ_{OTT}^{j}) to TSP

1.8) If V(σ_{OTT}^{j}) > V(σ_{TSP}^{j})

1.8) Display Success and print the parameters in the Offer σ_{OTT}^{j} as Output

1.9) Break away from the loop

1.10) End j

1.11) If j = K

1.12) Display Failure

4.2.2 Explanation

The Bayesian Learning Based Negotiation is divided into three parts. They are

i) Bayesian Learning Algorithm for OTT agent
ii) Bayesian Learning Algorithm for TSP agent
iii) Bayesian Learning Based Negotiation Process Algorithm

4.2.2.1 Bayesian Learning Algorithm for OTT agent

This algorithm is run by OTT agent for prioritizing multiple offers of the TSP agent. First of all, the records of the past negotiation history are recorded. The number of past sessions, that is S, and the number of offers in each session K, are initialised. From the past history, p(accept) and p(reject) are computed from the equations (4.4) and (4.5) respectively.

The range of weightage of each offer is specified by assigning random value to maximum weightage (w_{max}) and minimum weightage (w_{min}) such that $w_{max} > w_{min}$. The weightage of each session i is calculated from the equation (4.1). The weightage of offer j in each session i are calculated from the equation (4.2).

The values of $p(\sigma_{OTT}^{j}/accept)$ and $p(\sigma_{OTT}^{j}/reject)$ are calculated from the equations (4.6) and (4.7) respectively. From the equation (4.3), p^{j}_{OTT} is calculated.

From the equation (4.8), the preference value of each offer is calculated. After calculating the preference value of each offer, the offers are sorted according to the decreasing order of the preference values of the offers.

4.2.2.2 Bayesian Learning Algorithm for TSP agent

This algorithm is run by TSP agent for prioritizing multiple offers of the OTT agent. First of all, the records of the past negotiation history are recorded. The number of past sessions, that is S, and the number of offers in each session K, are initialised. From the past history, p(accept) and p(reject) are computed from the equations (4.4) and (4.5) respectively.

The range of weightage of each offer is specified by assigning random value to maximum weightage (w_{max}) and minimum weightage (w_{min}) such that $w_{max} > w_{min}$. The weightage of each session i is calculated from the equation (4.1). The weightage of offer j in each session i are calculated from the equation (4.2).

The values of $p(\sigma_{TSP}^{j}/accept)$ and $p(\sigma_{TSP}^{j}/reject)$ are calculated from the equations (4.6) and (4.7) respectively. From the equation (4.3), $p^{j}_{\mathbf{TSP}}$ is calculated.

From the equation (4.8), the preference value of each offer is calculated. After calculating the preference value of each offer, the offers are sorted according to the decreasing order of the preference values of the offers.

4.2.2.3 Bayesian Learning Based Negotiation Process Algorithm

After prioritizing the offers by the OTT and the TSP agents, the process of negotiation starts between OTT and TSP agents. At the start of the process of negotiation, the TSP agent offers its jth offer (σ_{TSP}^{j}) (at first, j = 1) to the OTT agent. If the utility value of the offer σ_{TSP}^{j} for the OTT agent ($U(\sigma_{TSP}^{j})$) is more than the utility value with its own jth offer ($U(\sigma_{OTT}^{j})$), then the OTT agent accepts the offer and the success is reported with the final output as σ_{TSP}^{j}. Else, OTT agent makes a return offer σ_{OTT}^{j} to the TSP agent. If the utility value of the offer σ_{OTT}^{j} for TSP agent ($V(\sigma_{OTT}^{j})$) is more than the utility with its own jth offer ($V(\sigma_{TSP}^{j})$), then the TSP agent accepts the offer the success is reported with the final output as σ_{OTT}^{j}. Otherwise, the TSP agent offers the next best offer to the OTT agent. Then, the value of j is increased. This process of offer and counter-offer continues for all the K number of offers. If none of the offers is accepted then, the negotiation process will be declared as failure.

4.3 Reinforcement Learning based Negotiation

Reinforcement Learning is an unsupervised, trial-and-error-based technique where an agent interacts with a dynamic environment and selects actions from a set of available options to maximize its objective. The agent observes its state in the environment and receives a reinforcement signal or reward based on the action taken. In choosing actions, the agent must balance between immediate rewards and the long-term expected outcomes.

The negotiation between OTT and TSP regarding the collaboration with respect to various network parameters has been mapped using reinforcement learning. Q-learning technique has been employed for implementing the reinforcement learning mechanism. In Q-learning technique, the desirability of any action at a particular state is quantified by a numerical value called Q-value [60]. For each state-action pair, the Q-value is computed. For solving our problem, all the offers are considered as states of the agents. Again, action of agents can be of two types: acceptance of opponent's offer and preparation of counter-offer. For example, actions of OTT agents would be acceptance of TSP agent's offer σ_{OTT}^{j} selecting the next counter-offer σ_{OTT}^{m}. Here, $\sigma_{OTT}^{m} \in \Omega_{OTT}$ refers to those offers that have been accepted previously or came as a counter-offer from the opponent in the past encounters of negotiation. Thus, the Q-value of state-action pair $\sigma_{OTT}^{j}, \sigma_{OTT}^{j} \rightarrow \sigma_{OTT}^{m}$ quantifies the benefit of the OTT agent for moving to offer σ_{OTT}^{m} from its current offer or state σ_{OTT}^{j}.

In the process of negotiation using reinforcement learning, both the agents separately compute the Q-values of their offers. Here, the Q-value of $(\sigma_{OTT}^{j}, \sigma_{OTT}^{j} \rightarrow \sigma_{OTT}^{m})$ is defined as: [58]

$$Q(\sigma_{OTT}^{j}, \sigma_{OTT}^{j} \rightarrow \sigma_{OTT}^{m}) = \eta \times [U(\sigma_{OTT}^{m}) - U(\sigma_{OTT}^{j}) + (1 - \eta) \times \{\chi - Ed(\sigma_{OTT}^{j}, \sigma_{OTT}^{m})\}] \qquad \text{———————— (4.9)}$$

Again,

$$Ed(\sigma_{OTT}^{j}, \sigma_{OTT}^{m}) = \sum_{i=1}^{4} \sqrt{(\sigma_{OTT}^{ji} - \sigma_{OTT}^{mi})^2} \qquad \text{————— (4.10)}$$

Equation (4.9) denotes the Q-value of state and action to move from σ_{OTT}^{j} to σ_{OTT}^{m} (denoted by $\sigma_{OTT}^{j} \rightarrow \sigma_{OTT}^{m}$). The symbol η denotes the learning rate of the reinforcement learning. The Q-value consists of two parts:

(i) short-term reward in terms of increase in utility value for moving to state σ_{OTT}^m from state σ_{OTT}^j.

(ii) Potential benefit at state σ_{OTT}^m subject to the required changes in system parameters.

$Ed(\sigma_{OTT}^j, \sigma_{OTT}^m)$ is the Euclidean distance between two offers indicated in the equation which indicates the required changes [58]. In the equation refers to the pth attribute or element in the offer. The Euclidean distance between two offers is determined by computing distance of the individual issues from one offer to another. Less Euclidean distance signifies better acceptability of the target offer. In the equation, a constant χ is introduced such that less value of $Ed(\sigma_{OTT}^j, \sigma_{OTT}^m)$ increases the Q-value of the offer-action pair. This constant is always greater than the Euclidean distance between the two offers.

4.4 Algorithm of Reinforcement Learning

4.4.1 Algorithm

Algorithm for OTT agent

1) **Formation of History Table**

1.1) Input S = Total Number of past sessions

1.2) Input K = Total Number of offers

1.3) Values of parameters of each offer in all the past sessions are recorded.

1.4) The parameters in each offer are Delay Rate, Packet Loss Rate, Throughput and Jitter.

1.5) Utility value of each offer is calculated from the equation (3.21).

1.6) In each offer, whether the offer was accepted or rejected is recorded.

1.7) Define σ_{TSP}^j as the jth offer of TSP agent.

1.8) Initialize index set of accepted offers I_i = NULL $\forall i = 1$ to S

1.9) Initialize f = 0

2) **Iteration**

2.1) for i = 1 to S

2.2) for j = 1 to K

2.3) if offer σ_{TSP}^j in session i is accepted by the opponent

2.4) $J_i = J_i \cup \{\sigma_{TSP}^j\}$

2.5) End j

2.6) End i

3) **Computation**

3.1) Define a set

3.2) Assign Q(σ_{TSP}^{j}, $\sigma_{TSP}^{j} \rightarrow \sigma_{TSP}^{m}$) = 0 ∀i, ∀f ∈ $\hat{J}$

4) **Updating Q-values**

4.1) for j = K to 1

4.2) if if (∀f ∈ $\hat{J}$) and U (σ_{OTT}^{f}) > U (σ_{OTT}^{j})

4.3) Update Q(σ_{OTT}^{j}, $\sigma_{OTT}^{j} \rightarrow \sigma_{OTT}^{f}$) from equation (4.9)

4.4) End j

Algorithm for TSP agent

1) **Formation of History Table**

1.1) Input S = Total Number of past sessions

1.2) Input K = Total Number of offers

1.3) Values of parameters of each offer in all the past sessions are recorded.

1.4) The parameters in each offer are Delay Rate, Packet Loss Rate, Throughput and Jitter.

1.5) Utility value of each offer is calculated from the equation (3.21).

1.6) In each offer, whether the offer was accepted or rejected is recorded.

1.7) Define σ_{OTT}^{j} as the jth offer of OTT agent.

1.8) Initialize index set of accepted offers J_i = NULL ∀i = 1 to S

1.9) Initialize f = 0

2) **Iteration**

2.1) for i = 1 to S

2.2) for j = 1 to K

2.3) if offer σ_{OTT}^{j} in session i is accepted by the opponent

2.4) $I_i = I_i \cup \{\sigma_{OTT}^{j}\}$

2.5) End j

2.6) End i

3) **Computation**

3.1) Define

3.2) Assign Q($\sigma^{j}_{OTT}, \sigma^{j}_{OTT} \rightarrow \sigma^{f'}_{OTT}$) = 0 ∀i, ∀f′ ∈ $\hat{I}$

4) **Updating Q-values**

4.1) for j = K to 1

4.2) if (∀f′ ∈ $\hat{I}$) and V ($\sigma^{f'}_{TSP}$) > V (σ^{j}_{TSP})

4.3) Update Q($\sigma^{j}_{TSP}, \sigma^{j}_{TSP} \rightarrow \sigma^{f'}_{TSP}$) from equation (4.9)

4.4) End j

Algorithm for Negotiation

1.1) for j = 1 to K

1.2) SA offers σ^{j}_{TSP} to BA

1.3) if Q($\sigma^{j}_{TSP}, \sigma^{j}_{TSP} \rightarrow \sigma^{f}_{OTT}$) = 0 ∀f ∈$\hat{J}$

1.4) Report Success

1.5) Display offer σ^{j}_{TSP}

1.6) else

1.7) Assign $\sigma^{j}_{OTT} \leftarrow \sigma^{f}_{TSP}$ such that Q($\sigma^{j}_{TSP}, \sigma^{j}_{TSP} \rightarrow \sigma^{f}_{OTT}$) is maximum at f.

1.8) Generate offer σ^{j}_{OTT} which is σ^{f}_{OTT}

1.9) BA offers σ^{f}_{OTT} to SA

1.10) if Q($\sigma^{j}_{OTT}, \sigma^{j}_{OTT} \rightarrow \sigma^{f}_{TSP}$) = 0 ∀f′∈$\hat{I}$

1.11) Report success

1.12) Display offer σ^{j}_{OTT}

1.13) else

1.14) Assign $\sigma^{j}_{TSP} \leftarrow \sigma^{f}_{OTT}$ such that Q($\sigma^{j}_{OTT}, \sigma^{j}_{OTT} \rightarrow \sigma^{f'}_{TSP}$) is maximum at f′.

1.15) Generate offer σ^{j}_{TSP} which is $\sigma^{f'}_{TSP}$

1.16) End j

4.4.2 Explaination

The Reinforcement Learning Based Negotiation is divided into three parts. They are

i) Reinforcement Learning Algorithm for OTT agent
ii) Reinforcement Learning Algorithm for TSP agent
iii) Reinforcement Learning Based Negotiation Process Algorithm

4.4.2.1 Reinforcement Learning Algorithm for OTT agent

In the Reinforcement Learning Algorithm for OTT agent, the Q-values are computed for the OTT agent.

At first, the number of past negotiation sessions (S) and the number of offers in each session (K) are initialized. The offers that were accepted by the opponent at session i are stored in index set J_i. $\hat{J}$ set is defined as a superset of J_i. Notation f is employed for identifying the element of set $\hat{J}$. The Q-values of offers Q($\sigma_{OTT}^{j}, \sigma_{OTT}^{j} \rightarrow \sigma_{OTT}^{f}$) for all the offers are initialized to zero.

Suppose the OTT agent chooses an offer σ_{OTT}^{j}. In every session i, the utility value of offer σ_{OTT}^{j} is compared with the utility values of previously accepted offers, i.e., σ_{OTT}^{f}, f $\in \hat{J}$.

If the utility value of offer σ_{OTT}^{f} is greater than that of σ_{OTT}^{j}, the corresponding Q-value of ($\sigma_{OTT}^{j}, \sigma_{OTT}^{j} \rightarrow \sigma_{OTT}^{f}$) is updated using the equation (4.9). The Euclidean distance between the two offers is calculated from the equation (4.10). This process of comparing the utility values of each offer and updating the Q-values of the two offers is continued for each other.

4.4.2.2 Reinforcement Learning Algorithm for TSP agent

In the Reinforcement Learning Algorithm for TSP agent, the Q-values are computed for the TSP agent.

At first, the number of past negotiation sessions (S) and the number of offers in each session (K) are initialized. The offers that were accepted by the opponent at session i are stored in index set I_i. $\hat{I}$ set is defined as a superset of I_i. Notation f' is employed for identifying the element of set $\hat{I}$. The Q-values of offers Q($\sigma_{TSP}^{j}, \sigma_{TSP}^{j} \rightarrow \sigma_{TSP}^{f'}$) for all the offers are initialized to zero.

Suppose the TSP agent chooses an offer σ_{TSP}^{j}. In every session i, the utility value of offer σ_{TSP}^{j} is compared with the utility values of previously accepted offers, i.e., $\sigma_{TSP}^{f'}$, f′ ∈ $\hat{I}$.

If the utility value of offer $\sigma_{TSP}^{f'}$ is greater than that of σ_{TSP}^{j}, the corresponding Q-value of ($\sigma_{OTT}^{j}, \sigma_{OTT}^{j} \rightarrow \sigma_{OTT}^{f}$) is updated using the equation (4.9). The Euclidean distance between the two offers is calculated from the equation (4.10). This process of comparing the utility values of each offer and updating the Q-values of the two offers is continued for each other.

4.4.2.3 Reinforcement Learning Based Negotiation Process Algorithm

After the updating Q-values of all offers by both the OTT and the TSP agents is done, the process of negotiation between the OTT and the TSP agents starts.

Suppose the TSP agent makes the first move with the offer σ_{TSP}^{j}, which has the highest utility value with respect to the TSP agent. After receiving the offer, the OTT agent considers itself to be at a state of offer σ_{TSP}^{j}. Then, the OTT agent computes the Q-value of the state action pair ($\sigma_{TSP}^{j}, \sigma_{TSP}^{j} \rightarrow \sigma_{OTT}^{f}$) for all f ∈ $\hat{J}$. If the value of Q($\sigma_{TSP}^{j}, \sigma_{TSP}^{j} \rightarrow \sigma_{OTT}^{f}$) is equal to zero, then we can say that there is no better offer available to the OTT agent in comparison with the recent offer of TSP agent σ_{TSP}^{j}. As a consequence of this, the OTT agent accepts the offer σ_{TSP}^{j} and the success is reported thus completing the process of negotiation with the output as the offer σ_{TSP}^{j}. But, if better offers are available to OTT agent compared to σ_{TSP}^{j} then, the OTT agent selects the offer σ_{OTT}^{f} that corresponds to maximum Q($\sigma_{TSP}^{j}, \sigma_{TSP}^{j} \rightarrow \sigma_{OTT}^{f}$). Then, σ_{OTT}^{f} is designated as σ_{OTT}^{j} and the OTT agent sends a counter offer σ_{OTT}^{j} to the TSP agent.

After receiving the counter offer σ_{OTT}^{j} from the OTT agent, the TSP agent considers itself to be at a state of offer σ_{OTT}^{j}. Then, the TSP agent computes the Q-value of the state action pair ($\sigma_{OTT}^{j}, \sigma_{OTT}^{j} \rightarrow \sigma_{TSP}^{f'}$) for all f′ ∈ $\hat{I}$. If the value of Q($\sigma_{OTT}^{j}, \sigma_{OTT}^{j} \rightarrow \sigma_{TSP}^{f'}$) is equal to zero, then we can say that there is no better offer available to the TSP agent in comparison with the recent offer of TSP agent σ_{OTT}^{j}. As a consequence of this, the TSP agent accepts the offer σ_{OTT}^{j} and the success is reported thus completing the process of negotiation with the output as the offer σ_{OTT}^{j}. But, if better offers available to TSP agent compared to σ_{OTT}^{j} then, the TSP agent selects the offer $\sigma_{TSP}^{f'}$ that corresponds to maximum Q($\sigma_{OTT}^{j}, \sigma_{OTT}^{j} \rightarrow \sigma_{TSP}^{f'}$). Then, $\sigma_{TSP}^{f'}$ is designated as σ_{TSP}^{j} and the TSP agent sends a counter offer σ_{TSP}^{j} to the OTT agent.

This process of offer and counter-offer continues for all the K number of offers. If none of the offers is accepted then, the negotiation process will be declared as failure.

4.5 Parameter Setting

Table 4.2: Parameter Setting

Parameter	Values
w_{max}	600
w_{min}	100
Delay Rate for OTT	0 to 0.5
Delay Rate for TSP	0.2 to 0.7
Packet Loss Rate for OTT	0% to 1%
Packet Loss Rate for TSP	0.3% to 1.5%
Throughput for OTT	25 MBPS to 35 MBPS
Throughput for TSP	30 MBPS to 40 MBPS
Jitter for OTT	0 ms to 30 ms
Jitter for TSP	10 ms to 45 ms

Table 4.3: Arbitrary Constants and Values

Constant	Value
w_{max}	600
w_{min}	100
χ	10
θ	0.5
η	0.5

4.6 Chapter Summary

In this chapter, we have discussed about the two techniques to be employed for solving the process of negotiation between OTT agents and TSP agents, namely BLBN (Bayesian Learning Based Negotiation) and RLBN (Reinforcement Learning Based Negotiation). Bayesian Learning is primarily based on the past negotiation history and the probability of accepting an offer, while on the other hand, Reinforcement Learning is primarily based on selecting a counter-offer to the opponent by comparing the offer with respect to the offers available to the agent.

Chapter 5

Performance Analysis

In this chapter, we have shown the results of simulation obtained after implementing both the Bayesian Learning and Reinforcement Learning techniques. Both these techniques have been implemented in MATLAB version 9.4.0.802882.

The points (depicted in bold) in the simulation results in this chapter is the average result of running the test 100 times. The initial parameter settings are listed in Table (). The learning rate for both Bayesian Learning and Reinforcement Learning techniques is chosen to be 0.5. The reason for this choice is that the value chosen signifies equal weightage of immediate reward and long-term reward for the Reinforcement Learning technique. In case of Bayesian Learning technique, the chosen value signifies equal weightage of maximizing the payoff between the agent and its opponent. Here, a 'round' refers to a pair of offers (i.e., an offer and a counteroffer) in a particular session of negotiation.

Table 5.1: Parameter Setting

Parameter	**Values**
w_{max}	600
w_{min}	100
Delay Rate for OTT	0 to 0.5
Delay Rate for TSP	0.2 to 0.7
Packet Loss Rate for OTT	0% to 1%
Packet Loss Rate for TSP	0.3% to 1.5%
Throughput for OTT	25 MBPS to 35 MBPS
Throughput for TSP	30 MBPS to 40 MBPS
Jitter for OTT	0 ms to 30 ms
Jitter for TSP	10 ms to 45 ms

Table 5.2: Arbitrary Constants and Values

Constant	**Value**
w_{max}	600
w_{min}	100
χ	10
θ	0.5
η	0.5

5.1 Buyer Utility vs Number of Rounds of Offers

The plot of Buyer Utility vs Number of Rounds of Offers in Bayesian Learning is shown below:

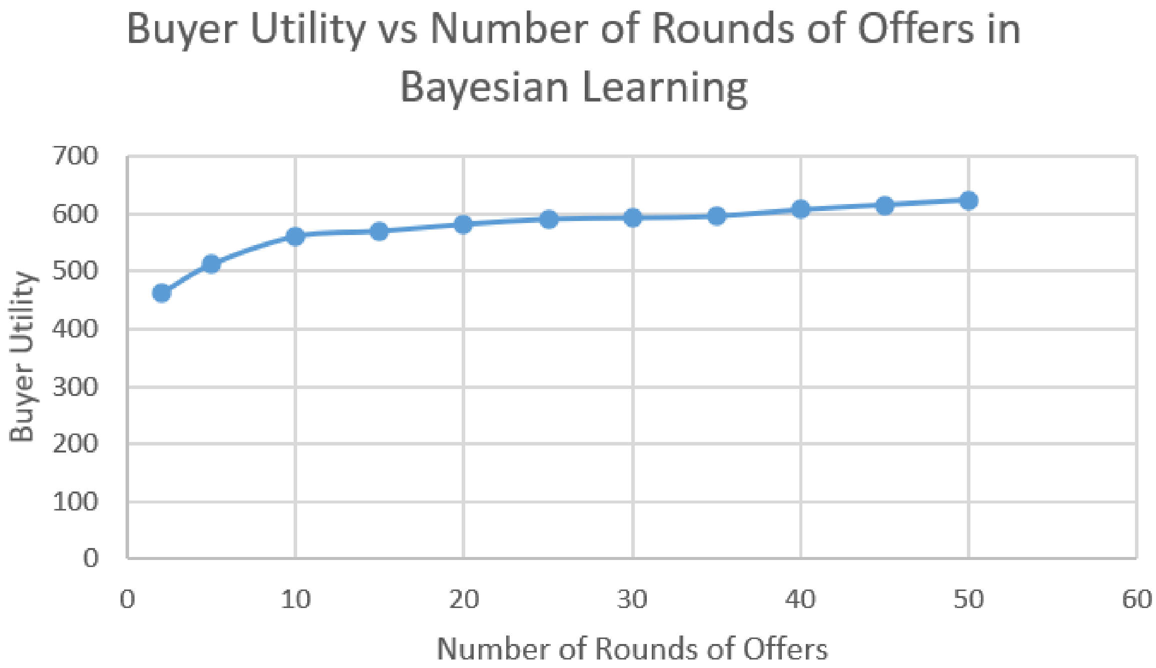

Fig 5.1: Plot of Buyer Utility vs Number of Rounds of Offers in Bayesian Learning

Initially the buyer utility is less when there is a smaller number of offers. The Buyer Utility increases with the increase in number of offers. The Buyer utility increases until it reaches its maximum value. The buyer agents and the seller agents have their own preferences regarding the network parameters. The process of negotiation ends with both the agents agreeing on the region of overlapping of the preferences of both the agents. Initially due to lack of number of offers, the buyer agent has to settle with comparatively less utility because the opponent didn't gave better offer or the offer has been rejected by the opponent. But as the number of offers increases, the buyer agent gets better offers from the opponent and hence the buyer utility becomes greater after the process of negotiation.

The plot of Buyer Utility vs Number of Rounds of Offers in Reinforcement Learning is shown below:

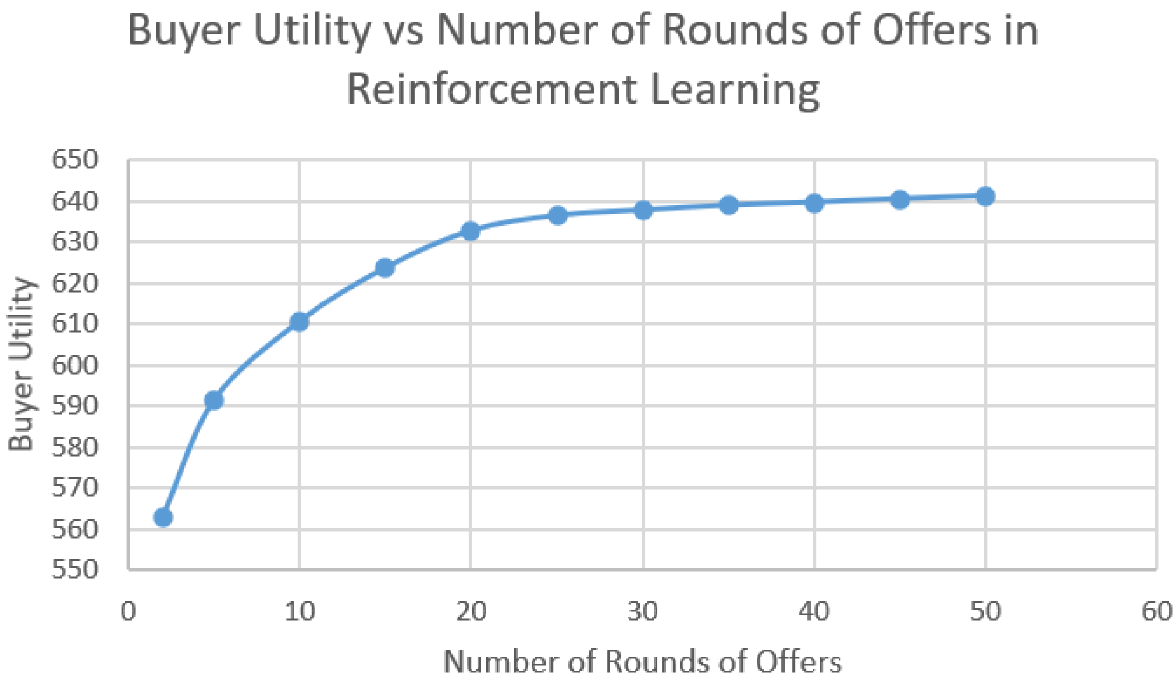

Fig 5.2: Plot of Buyer Utility vs Number of Rounds of Offers in Reinforcement Learning

The plot is quite similar to that of in Bayesian Learning. The difference being that the buyer utility of reinforcement learning is greater than that of the buyer utility in Bayesian Learning. This is because in reinforcement learning, the buyer agent compares its utility gain (or in other words increase in Q-value) of accepting the offer of seller agent with each of the offers available to the agent. But in the case of Bayesian Learning, probabilities of acceptance of the offer are considered during the process of negotiation.

Talking about the plot, initially the buyer utility is less when there is a smaller number of offers. The Buyer Utility increases with the increase in number of offers. The Buyer utility increases until it reaches its maximum value. The buyer agents and the seller agents have their own preferences regarding the network parameters. The process of negotiation ends with both the agents agreeing on the region of overlapping of the preferences of both the agents. Initially due to lack of number of offers, the buyer agent has to settle with comparatively less utility because the opponent didn't gave better offer or the offer has been rejected by the opponent. But as the number of offers increases, the buyer agent gets better offers from the opponent and hence the buyer utility becomes greater after the process of negotiation.

The plot of comparison of Buyer Utilities for Both Buyer Utilities vs Number of Rounds of Offers in both Bayesian Learning and Reinforcement Learning is shown below:

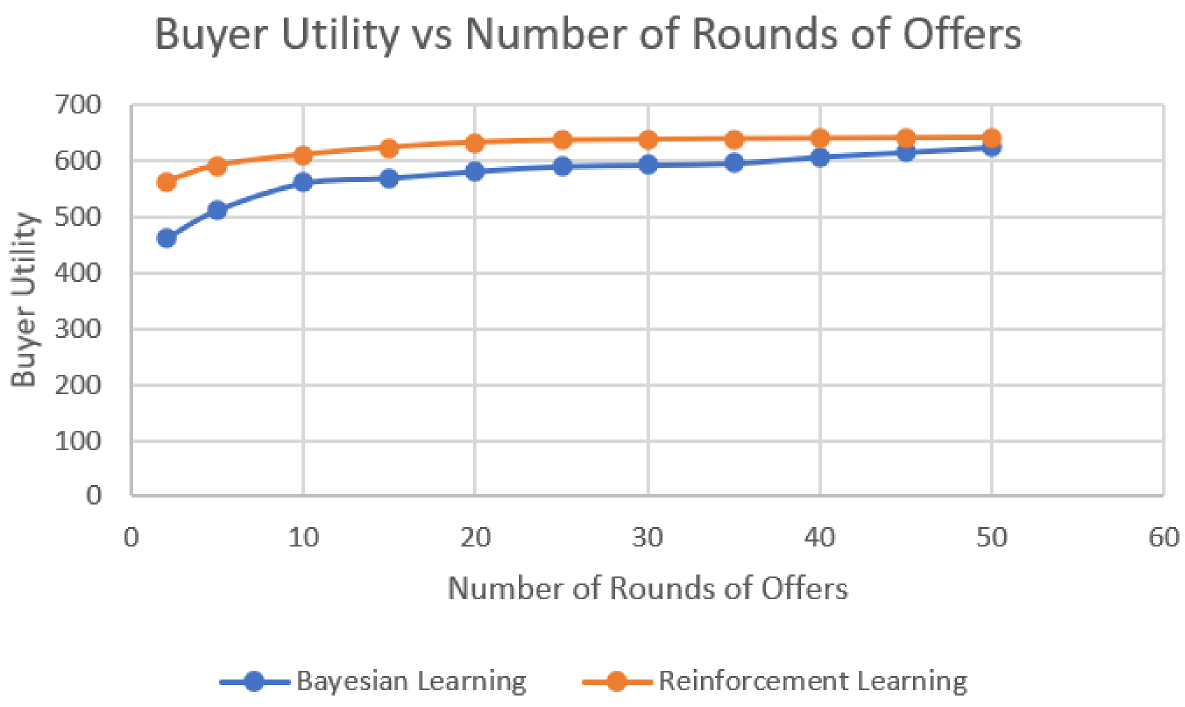

Fig 5.3: Comparison of Buyer Utilities vs Number of Rounds of Offers in both Bayesian Learning and Reinforcement Learning

5.2 Seller Utility vs Number of Rounds of Offers

The plot of Seller Utility vs Number of Rounds of Offers in Bayesian Learning is shown below:

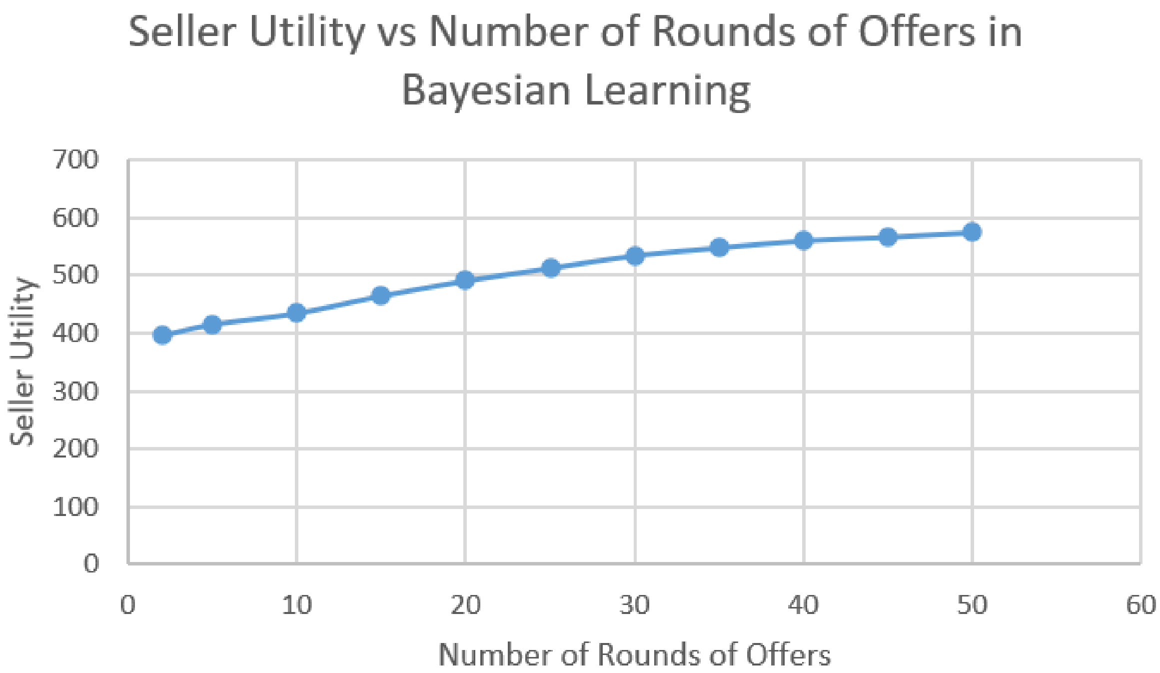

Fig 5.4: Plot of Seller Utility vs Number of Rounds of Offers in Bayesian Learning

Initially the seller utility is less when there is a smaller number of offers. The Seller Utility increases with the increase in number of offers. The Seller utility increases until it reaches its maximum value. The seller agents and the buyer agents have their own preferences regarding the network parameters. The process of negotiation ends with both the agents agreeing on the region of overlapping of the preferences of both the agents. Initially due to lack of number of offers, the seller agent has to settle with comparatively less utility because the opponent didn't gave better offer or the offer has been rejected by the opponent. But as the number of offers increases, the seller agent gets better offers from the opponent and hence the seller utility becomes greater after the process of negotiation.

The plot of Seller Utility vs Number of Rounds of Rounds of Offers in Reinforcement Learning is shown below:

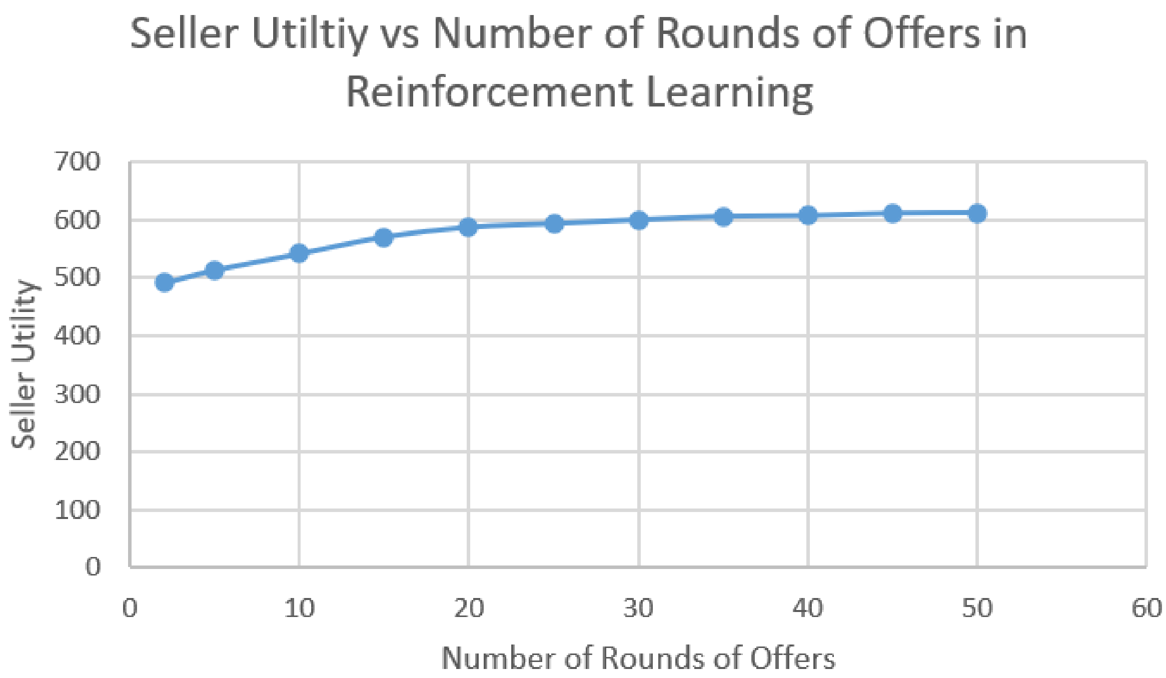

Fig 5.5: Plot of Seller Utility vs Number of Rounds of Offers in Reinforcement Learning

The plot is quite similar to that of in Bayesian Learning. The difference being that the seller utility of reinforcement learning is greater than that of the seller utility in Bayesian Learning. This is because in reinforcement learning, the seller agent compares its utility gain (or in other words increase in Q-value) of accepting the offer of buyer agent with each of the offers available to the agent. But in the case of Bayesian Learning, probabilities of acceptance of the offer are considered during the process of negotiation.

Discussing about the plot, initially the seller utility is less when there is a smaller number of offers. The Seller Utility increases with the increase in number of offers. The Seller utility increases until it reaches its maximum value. The seller agents and the buyer agents have their own preferences regarding the network parameters. The process of negotiation ends with both the agents agreeing on the region of overlapping of the preferences of both the agents. Initially due to lack of number of offers, the seller agent has to settle with comparatively less utility because the opponent didn't gave better offer or the offer has been rejected by the opponent. But as the number of offers increases, the seller agent gets better offers from the opponent and hence the seller utility becomes greater after the process of negotiation.

The comparison of Buyer Utilities and Seller Utilities vs Number of Rounds of Offers in both Bayesian Learning and Reinforcement Learning is shown below:

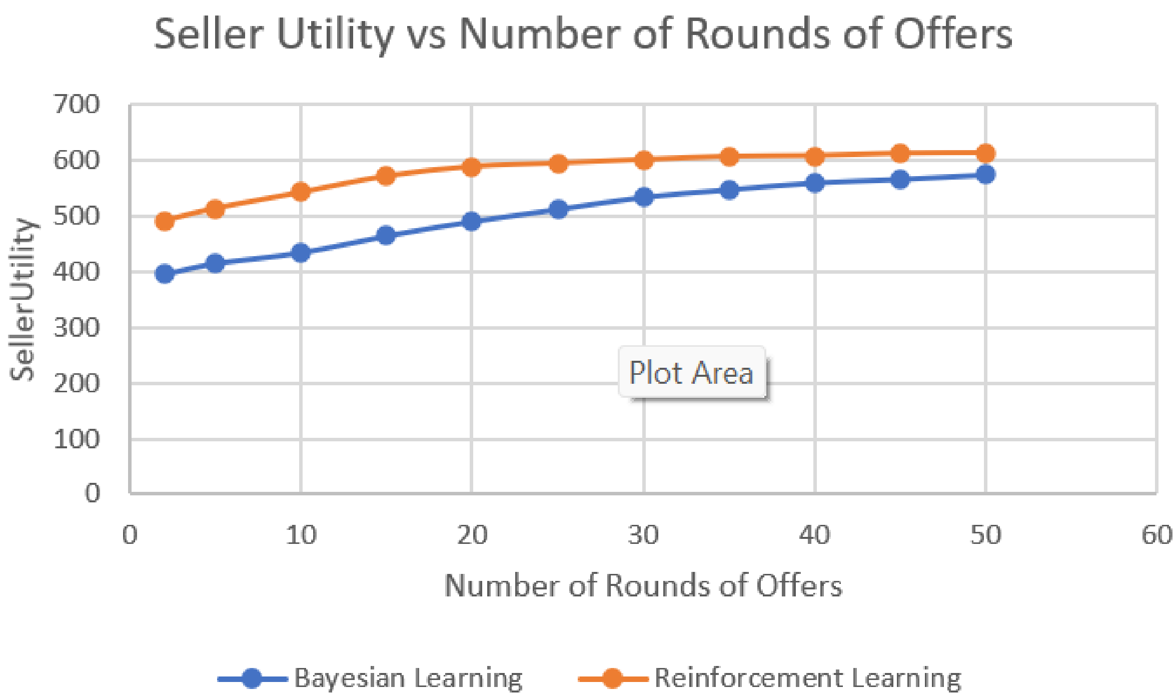

Fig 5.6: Comparison of Seller Utilities vs Number of Rounds of Offers in both Bayesian Learning and Reinforcement Learning

5.3 Sum of Buyer's and Seller's Utilities vs Number of Rounds of Offers

The plot of Sum of Buyer's and Seller's Utilities vs Number of Rounds of Offers in Bayesian Learning is shown below.

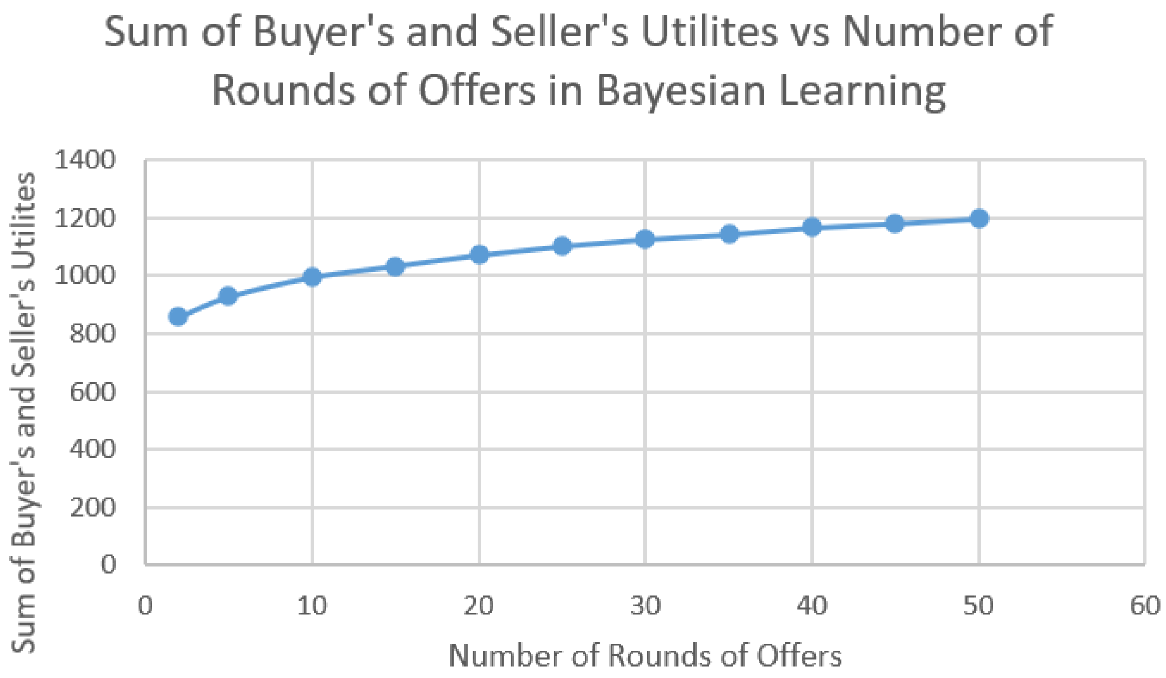

Fig 5.7: Plot of Sum of Utilities vs Number of Rounds of Offers in Bayesian Learning

Initially the sum of utilities is less when there is a smaller number of offers. The Sum of Utilities increases with the increase in number of offers. The Sum of Utilities increases with the increase in number of offers. Both the buyer agents and the seller agents have their own preferences regarding the network parameters. The process of negotiation ends with both the agents agreeing on the region of overlapping of the preferences of both the agents. Initially due to lack of number of offers, both the buyer agents and the seller agents have to settle with comparatively less utility because their opponents didn't gave better offer or the offer has been rejected by their respective opponents. But as the number of offers increases, both the buyer agent and the seller agent get better offers from the opponent and hence both the buyer utility and the seller utility become greater after the process of negotiation.

The plot of Sum of Utilities vs Number of Rounds of Offers in Reinforcement Learning is shown below:

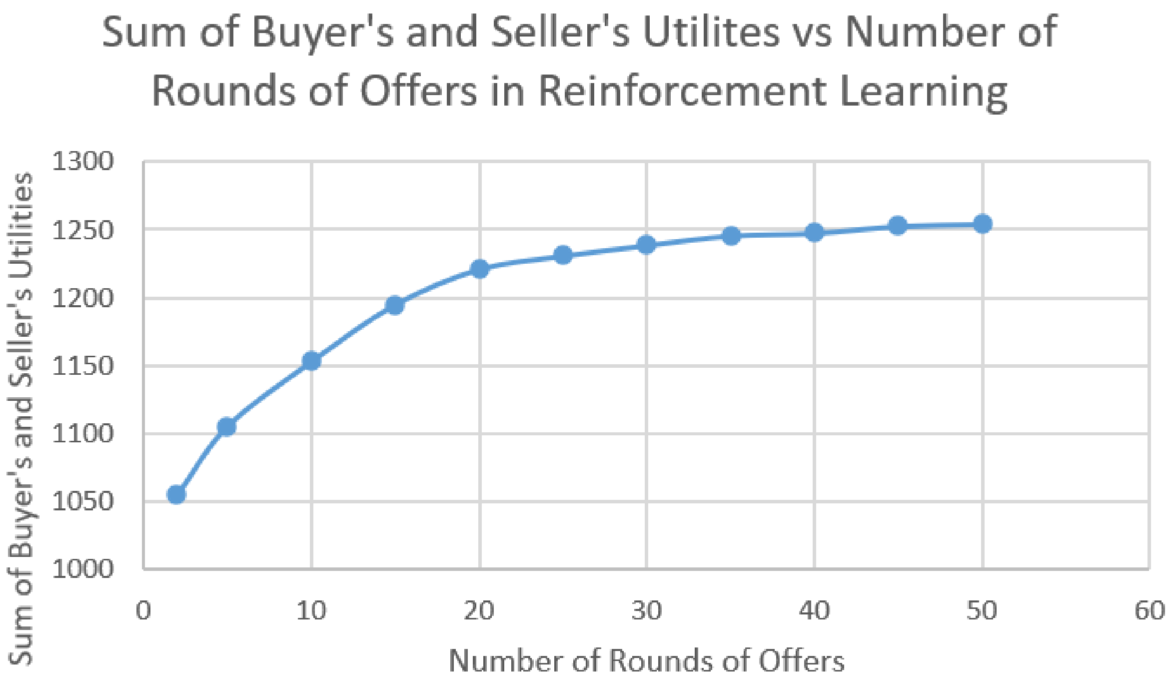

Fig 5.8: Plot of Sum of Utilities vs Number of Rounds of Offers in Reinforcement Learning

The plot is quite similar to that of in Bayesian Learning. The difference being that both the seller utility and the buyer utility of reinforcement learning is greater than that of both the seller utility and the buyer utility in Bayesian Learning. This is because in reinforcement learning, both the seller agent and the buyer agent compare their respective utility gains (or in other words increase in Q-value) of accepting the offer of their opponents with each of the offers available to them. But in the case of Bayesian Learning, probabilities of acceptance of the offer are considered during the process of negotiation.

Discussing about the plot, initially the sum of utilities is less when there is a smaller number of offers. The Sum of Utilities increases with the increase in number of offers. The Sum of Utilities increases with the increase in number of offers. Both the buyer agents and the seller agents have their own preferences regarding the network parameters. The process of negotiation ends with both the agents agreeing on the region of overlapping of the preferences of both the agents. Initially due to lack of number of offers, both the buyer agents and the seller agents have to settle with comparatively less utility because their opponents didn't gave better offer or the offer has been rejected by their respective opponents. But as the number of offers increases, both the buyer agent and the seller agent get better offers from the opponent and hence both the buyer utility and the seller utility become greater after the process of negotiation.

The plot of comparison between sum of buyer utilities and seller utilities vs number of rounds of offers in both Bayesian Learning and Reinforcement Learning is shown below.

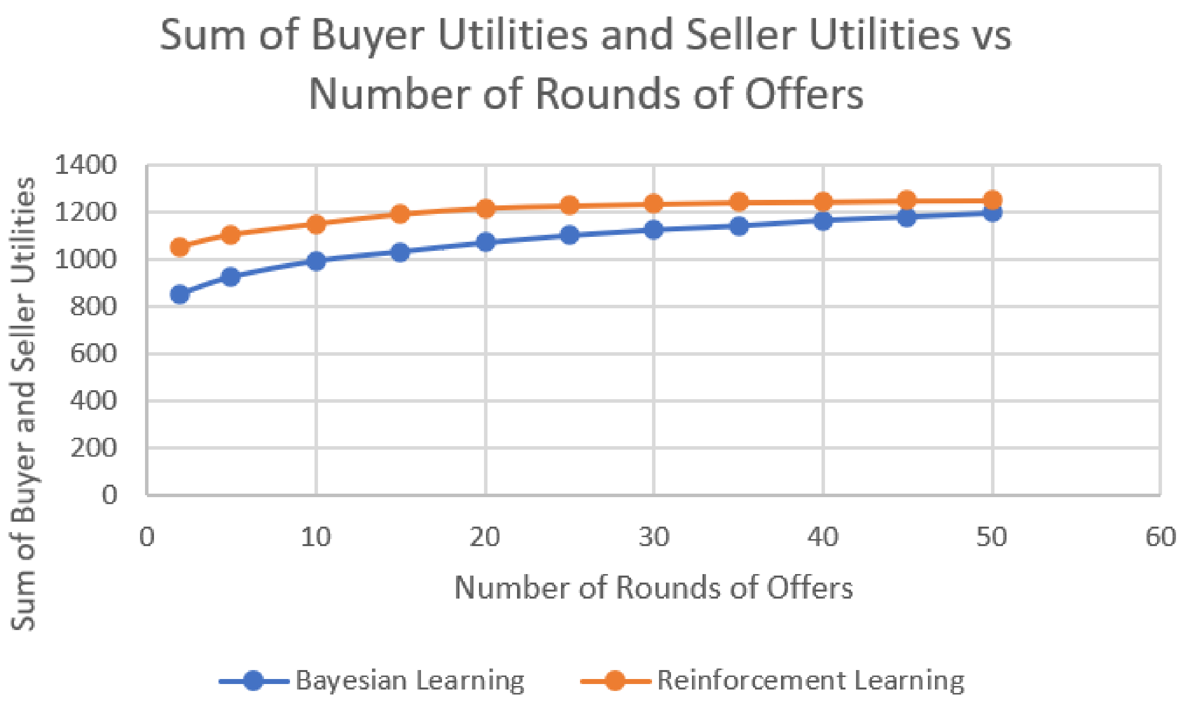

Fig 5.9: Comparison of Sum of Buyer Utilities and Seller Utilities vs Rounds of Offers in both Bayesian Learning and Reinforcement Learning

5.4 Time vs Number of Rounds of Offers

The plot of Time vs Number of Rounds of Offers in Bayesian Learning is shown below:

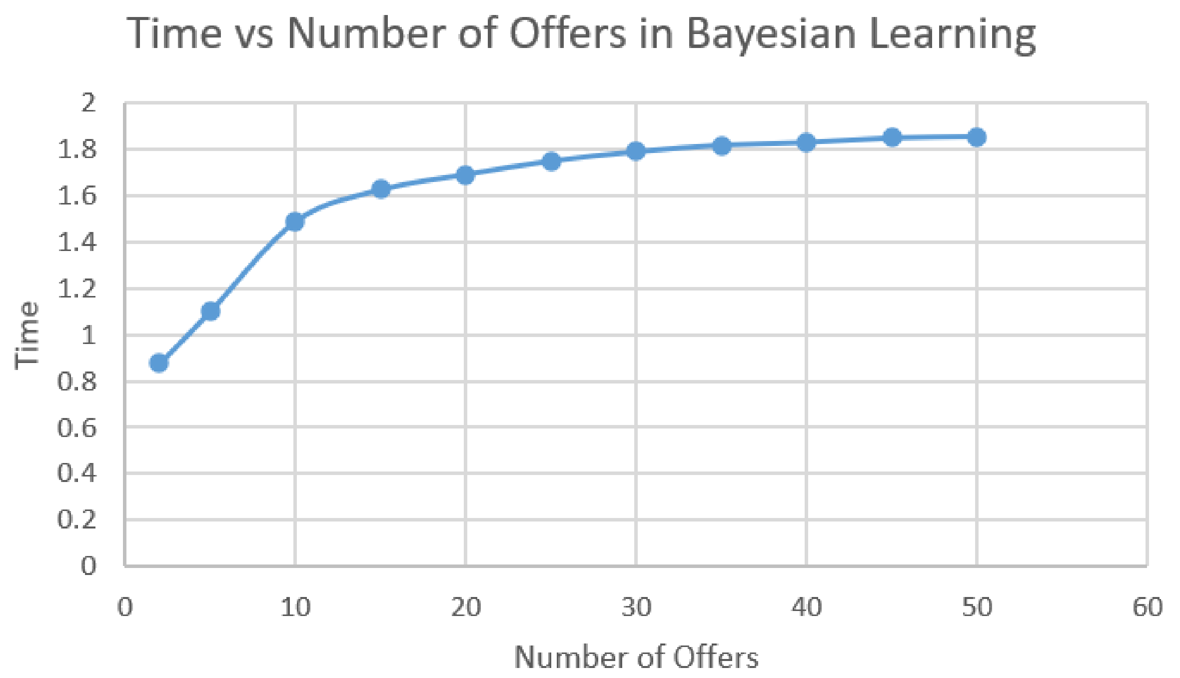

Fig 5.10: Plot of Time vs Number of Rounds of Offers in Bayesian Learning

From the graph, we can see that the time of process of negotiation increases with the number of rounds of offers in Bayesian Learning. After some certain number of rounds of offers, time taken for the process of negotiation increases at very slow rate or remains constant which is quite evident from the graph.

The plot of Time vs Number of Offers in Reinforcement Learning is shown below:

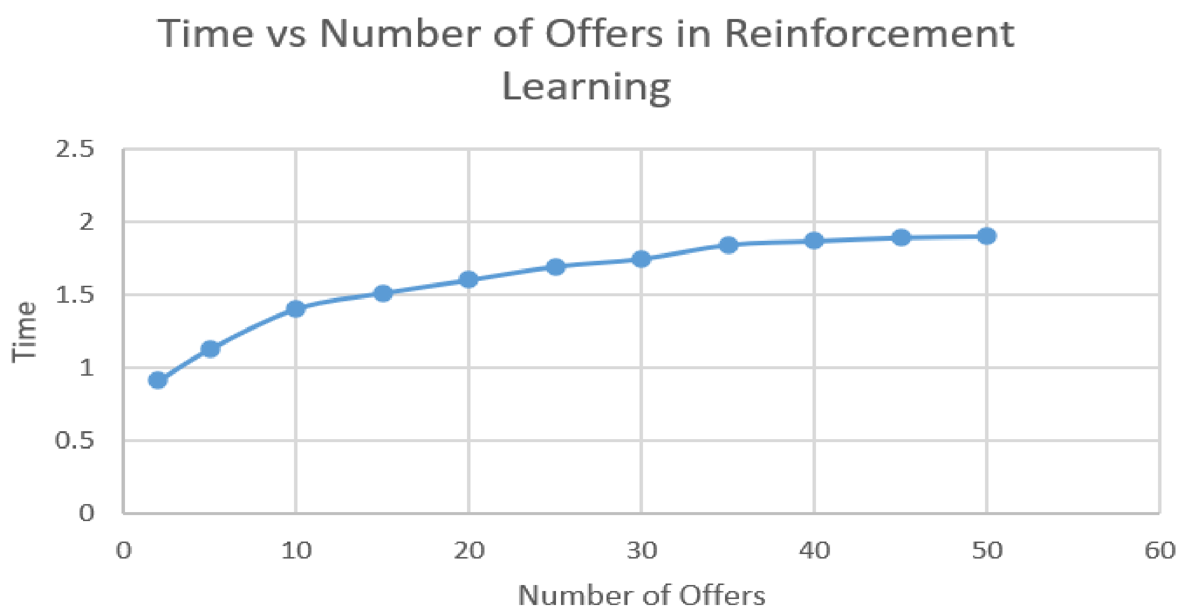

Fig 5.11: Plot of Time vs Number of Rounds of Offers in Reinforcement Learning

From the graph, we can see that the time of process of negotiation increases with the number of rounds of offers in Reinforcement Learning. After some certain number of rounds of offers, time taken for the process of negotiation increases at very slow rate or remains constant which is quite evident from the graph. But the time taken for the process of negotiation is more in Reinforcement Learning than in Bayesian Learning. This is due to the fact the offers are arranged in Bayesian Learning with respect to the final preference values once. But on the other hand, in Reinforcement Learning Q-value of one offer with respect to all other offers are computed and then the offer with maximum Q-value is taken as counter-offer. This process of choosing the counter-offer leads to longer amount of time in Reinforcement Learning than the Bayesian Learning.

The plot of comparison of time between Bayesian Learning and Reinforcement Learning is shown below:

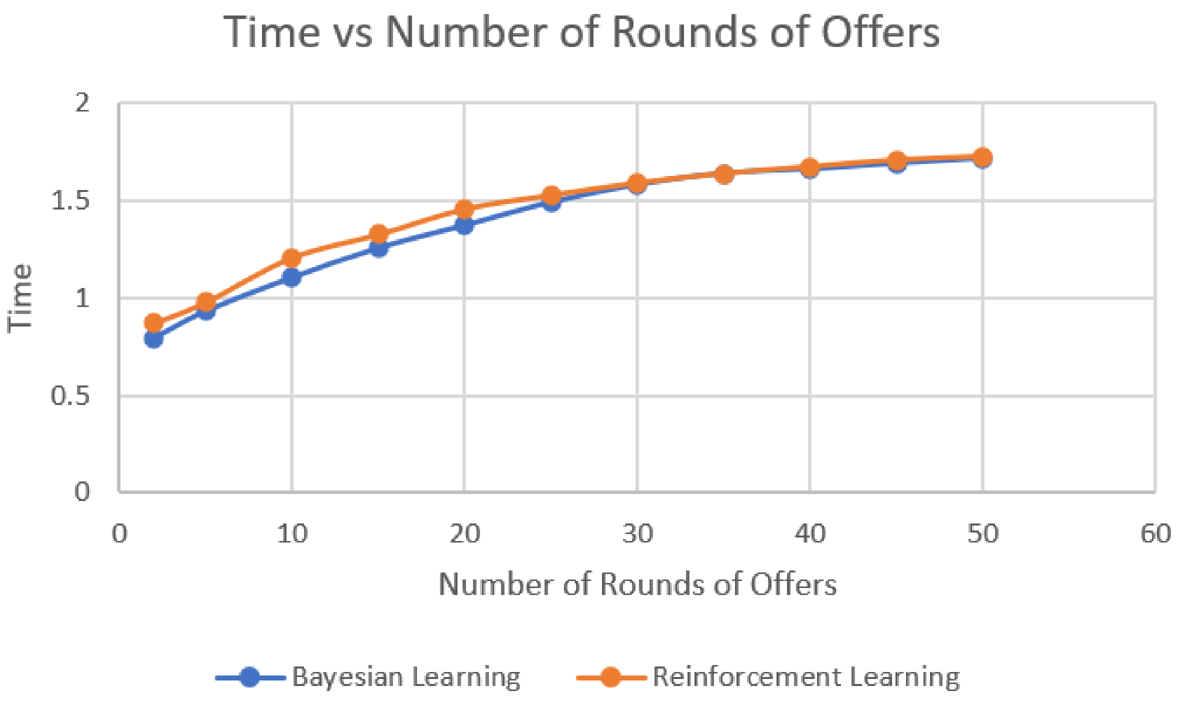

Fig 5.12: Comparison of Time vs Number of Rounds of Offers in both Bayesian Learning and Reinforcement Learning

5.5 Output with respect to Various Learning Rates

We have then seen the output values with respect to number of rounds of offers for both Bayesian Learning and Reinforcement Learning while varying the learning rate of the agents. While varying, it has been kept that the sum of learning rates for both the agents is 1. For example, if the learning rate of the buyer agent is 1, then the learning rate of the seller agent is 0. Again, if the learning rate of the buyer agent is 0, then the learning rate of the seller agent is 1. In all the graphs (both in buyer utility and the seller utility) mentioned below, the learning rate of the buyer agent is considered.

The graph of Buyer Utility vs Number of Rounds of Offers in Bayesian Learning is shown below:

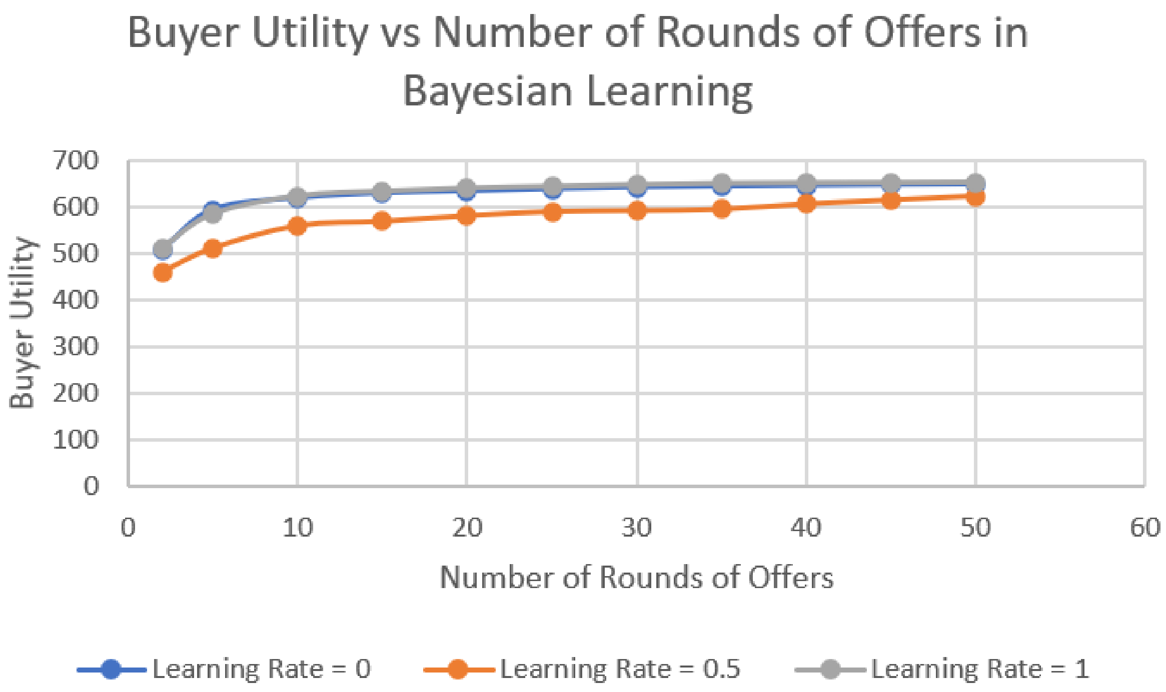

Fig 5.13: Buyer Utility vs Number of Rounds of Offers in Bayesian Learning with respect to various Learning Rates

From the graph, we can see that both the curve of the buyer agent in Bayesian Learning in both of the extreme learning rates converge. While on the other hand, in case of the learning rate to be moderate (i.e., learning rate = 0.5) give lesser value of buyer utilities with respect to both the extreme cases.

The graph of Buyer Utility vs Number of Rounds of Offers in Reinforcement Learning is shown below:

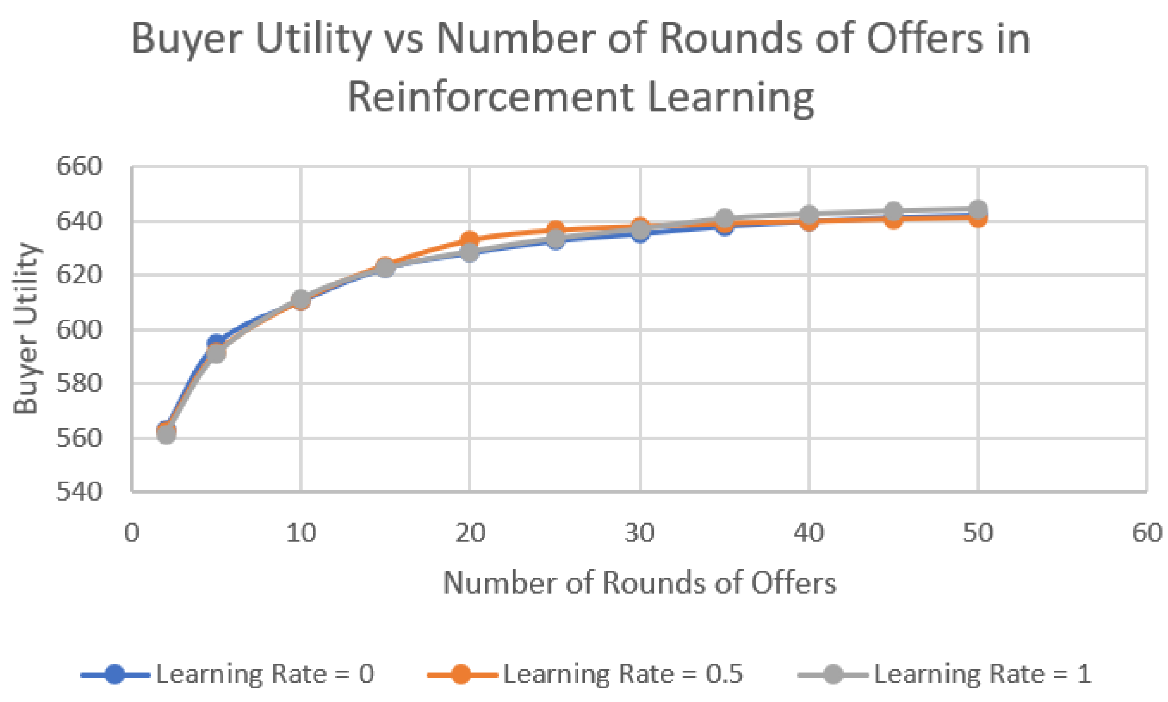

Fig 5.14: Buyer Utility vs Number of Rounds of Offers in Reinforcement Learning with respect to various Learning Rates

From the graph, we can see that all the three curves of buyer utility in Reinforcement Learning almost converge to provide similar results. This is due to the fact that the agents of Reinforcement Learning are quite independent of its learning rate which is quite evident from this result.

The graph of Seller Utility vs Number of Rounds of Offers in Bayesian Learning is shown below:

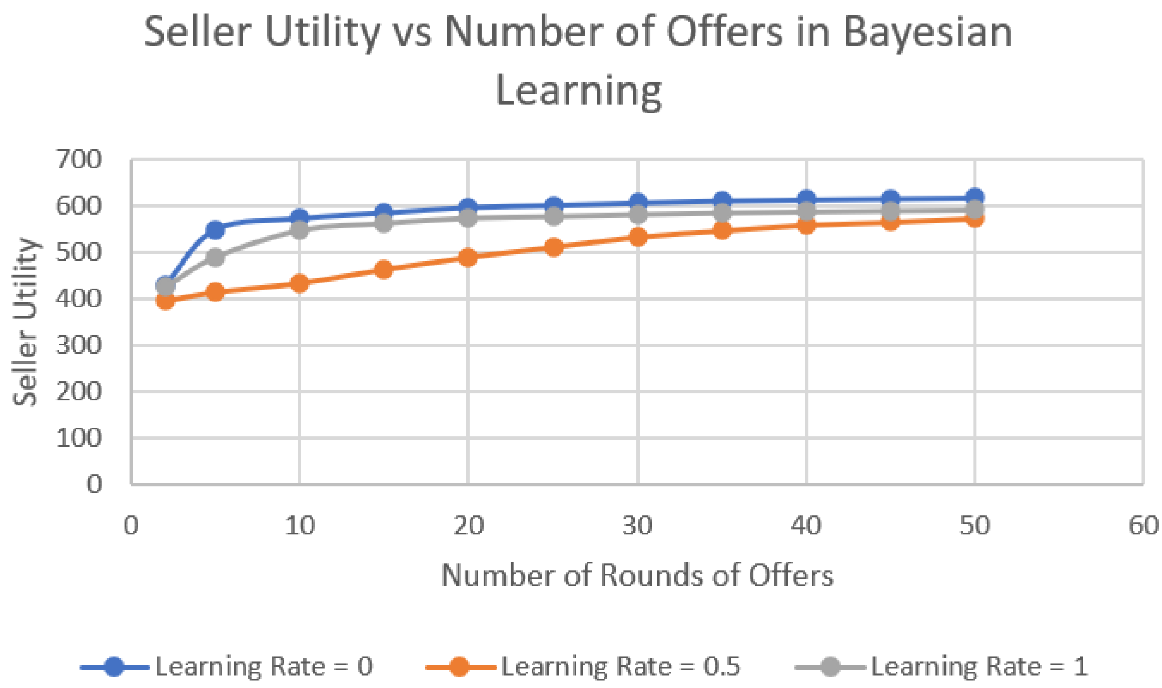

Fig 5.15: Seller Utility vs Number of Rounds of Offers in Bayesian Learning with respect to various Learning Rates

From the graph, we can see that when the learning rate of the buyer agent is 0 (which means that the learning rate of the seller agent is 1), the seller agent provides the best results, followed by the other extreme learning rate and followed by the moderate learning rate (learning rate = 0.5).

The graph of Seller Utility vs Number of Rounds of Offers in Reinforcement Learning is shown below:

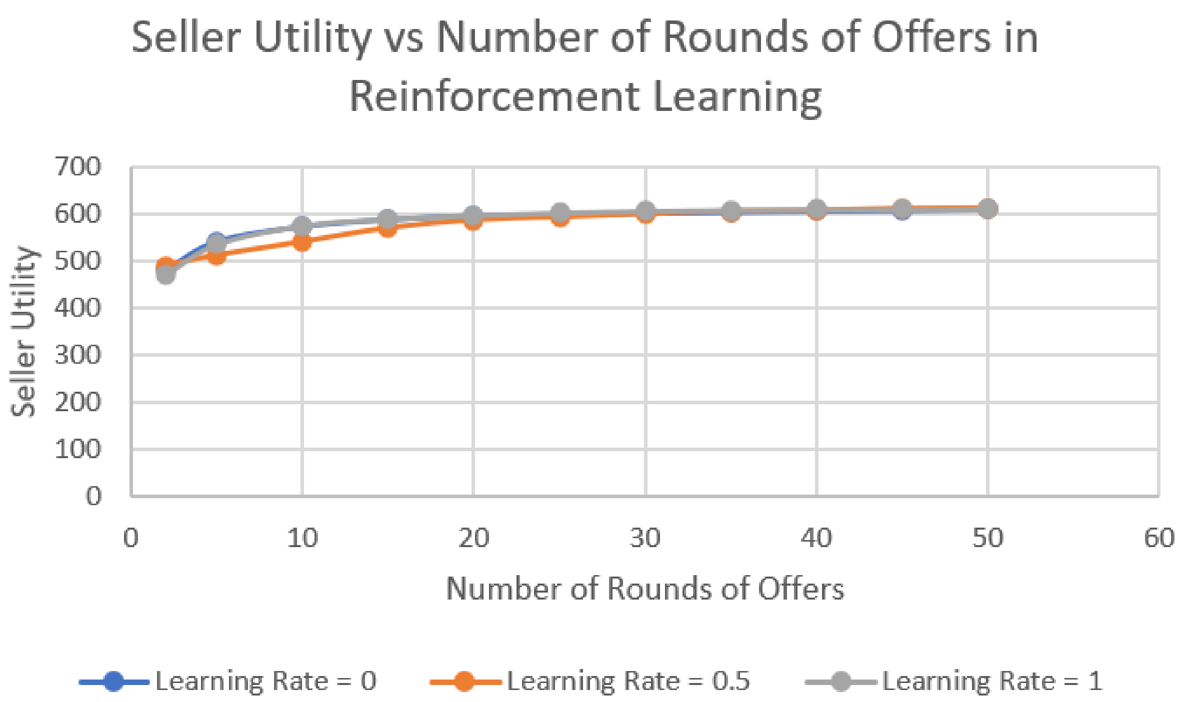

Fig 5.16: Seller Utility vs Number of Rounds of Offers in Reinforcement Learning with respect to various Learning Rates

From the graph, we can see that all the three curves of seller utility in Reinforcement Learning almost converge to provide similar results. This is due to the fact that the agents of Reinforcement Learning are quite independent of its learning rate which is quite evident from this result. Although there are some rounds of offers, where the utility in case of moderate learning rate is quite lower in case of extreme learning rates.

Thus, from the above graphs, we have seen that the Reinforcement Learning is quite independent of the learning rate of the agent. In case of Bayesian Learning rate, the extreme learning rates give the best values of utilities than that of moderate learning rates.

5.6 Chapter Summary

The simulation results performed confirm that both Bayesian Learning and Reinforcement Learning can effectively solve the multi-issue bilateral negotiation problem. The Reinforcement Learning techniques give better utility values in comparison to Bayesian Learning techniques. On the other hand, the Bayesian Learning techniques can solve the problem of multi-issue bilateral negotiation in less time compared to Reinforcement Learning techniques. Again, Reinforcement Learning is quite independent of learning rate of both the agents which is not possible in case of Bayesian Learning. The Bayesian Learning gives extreme values of utilities to the agents in extreme learning rates than that of the moderate learning rate.

Chapter 6
Conclusion

In our work, we have created a scenario of the process of negotiation between OTT agents and TSP agents for both the parties. Two machine learning algorithms have been proposed namely Bayesian Learning Based Negotiation (BLBN) and Reinforcement Learning Based Negotiation (RLBN). The objective of our work is to maximize the sum of utilities of the two agents.

6.1 Inference

From the results of simulation, we can say that the Reinforcement Learning provides better utility values while being compared to the Bayesian Learning. While comparing with respect to time, Bayesian Learning method is faster while being compared to the Reinforcement Learning. The Reinforcement Learning is independent of the learning rate of the agent. So, while performing Reinforcement Learning, the agents don’t have to worry about the learning rate of the agent of the opponent. Especially with low number of offers, Reinforcement Learning clearly outperforms the performance of the Bayesian Learning.

Thus, Reinforcement Learning can be used while getting the best deals or maximum profit from the process of negotiation. Talking about the collaboration between OTT agents and TSP agents, more profitable models like Joint Venture Model and Customer Lifetime Value will be benefitted from the Reinforcement Learning. Because these models give maximum profits to both of the agents when there is a collaboration between OTT agents and TSP agents. While Bayesian Learning can be used when the required time for the process of negotiation is small.

6.2 **Future Work**

In future work, other machine learning algorithms can be applied for the process of negotiation between OTT agents and TSP agents. Other machine learning algorithms include Supervised Learning, Unsupervised Learning and Game Theoretic Learning. The outputs after the process of negotiation can be compared among all these Machine Learning Algorithms along with Bayesian Learning and Reinforcement Learning. After comparing, which learning can give the best output and least time required for the process of negotiation.

6.3 Chapter Summary

Thus, we have solved the solution required for the process of Bayesian Learning and Reinforcement Learning required for the process of negotiation between OTT agents and TSP agents.

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