Enhancing Converged Optical and Millimeter Wave Radio Networks with Resource Management Games

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PROEFSCHRIFT

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“Do you not know you are in Heaven now? Or know the heavens are holy everywhere, and all that here is done is done from zeal?”

Dante Alighieri

Summary

Three convergent processes are likely to shape the future of the internet beyond-5G: the convergence of optical and millimeter wave (mmWave) radio networks to boost mobile internet capacity, the convergence of machine learning solutions and communication technologies, and the convergence of virtualized and programmable network management mechanisms towards fully integrated autonomic network resource management. Aiming to enhance the joint optical and radio transport, this thesis provides game theory-based distributed network control capability to optimize resource allocation in the C-RAN and fronthaul segments of converged wireless and optical networks. In addition, an external stakeholders vs. network game is designed to extend distributed decision-making to service providers and network users.

Autonomic network resource management concept brings dynamic network reconfiguration with learning and predicting the behavior of network entities. On the other hand, game theory-based resource management is studied for rational, autonomous and distributed decision-making among entities, as centralized optimization is challenging in a multi-stakeholder network environment. The focus is placed on these two approaches to design resource allocation solutions inside a distributed and autonomous management framework perspective. Autonomic networking requires control loops to monitor the network status and adapt network management by making use of observations from the monitoring stage. After presenting the challenges of autonomic networking, a management framework with monitoring and measurement, analysis and decision-making, and learning stages is introduced. In such a framework, game theoretic models are promising solutions to define the interactions between network stakeholders and to handle network management operations. This framework sets the foundation for the resource management contributions.

In light of the presented autonomic network management perspective, a systematic literature review is carried out as an initial step to the resource management contributions. The review is done to analyze how resource management solutions have dealt with optimizing millimeter wave radio and optical resources, understand the dimensions of the relationship between resource allocation methods and mmWave 5G and FiWi fronthaul, and identify the current trends in resource allocation. The results of this review is used to decide on the performance metrics and the evaluation criteria in the games designed in this dissertation for distributed decision-making. Based on the outcomes of the review, two experiments are designed to enhance control capabilities of the network. The first experiment creates the control interaction between fronthaul and access, whereas the second experiment regulates the interaction between service providers and the transport network represented by the infrastructure provider.

For joint access and fronthaul optimization, access — fronthaul interaction is defined as a coalition game for aggregate demand on the access side. By observing this demand, the transport network is able to distribute the available resources or reject the offer if it exceeds the total available bandwidth. When the offer is rejected, a bankruptcy game is used to distribute fronthaul resources to RRHs. On the access side, RRH utilization is improved by cooperative resource sharing. Different user distributions and service requirements bring dynamicity to the network demands. The target is to provide a game model that achieves dynamic bandwidth allocation with no fixed commitment of fronthaul resources and adapting to dynamic user load.

Infrastructure sharing is made possible with the help of virtualization technologies, and this fact transformed the network architecture into a novel stakeholder called the infrastructure provider. Even though profit generation was always a factor in performance optimization for network operators, the shift in the architecture with network virtualization makes dynamic revenue gains an apparent performance criteria for resource allocation. The second experiment considers virtualized optical network resources from this profit generation perspective with a game, in which providers bid to share the optical transport network and the infrastructure provider applies a Vickery – Clarke – Groves (VCG) auctioning mechanism to provide a social-welfare maximizing outcome, while users have the switching option between service providers for user utility maximization. The outcomes of user decision-making with blind search and guided search algorithms are also presented for this switching option.

The ultimate objective of this thesis is to provide a realistic guideline to optimize mmWave transport and radio resource use so that mmWave network implementations can be deployed in a cost-efficient manner. The presented experiments and results contribute to understanding how autonomous and distributed decision-making can improve network resource management and how network solutions for capacity enhancement can be exploited in an optimal way with game-theoretical algorithms.

Samenvatting

Drie convergente processen zullen waarschijnlijk de toekomst van het internet na 5G vormgeven: de convergentie van optische en millimetergolf (mmWave) radionetwerken om de mobiele internetcapaciteit te vergroten, de convergentie van machine learning oplossingen en communicatie technologieën, en de convergentie van gevirtualiseerde en programmeerbare netwerkbeheer mechanismen voor volledig geïntegreerd autonoom netwerk resourcebeheer. Met als doel het geïntegreerde optische en radiotransport te verbeteren, biedt dit werk op speltheorie gebaseerde gedistribueerde netwerkcontrole vermogen om de toewijzing van bronnen in de C-RAN en fronthaul-segmenten van de draadloze en optische netwerken te optimaliseren. Daarnaast wordt een spel tussen externe belanghebbenden en het netwerk ontwikkeld om het gedistribueerde besluitvormingsproces uit te breiden naar serviceproviders en netwerkgebruikers.

Het concept van autonoom beheer van netwerkbronnen maakt dynamische netwerk herconfiguratie mogelijk door het leren en voorspellen van het gedrag van netwerk entiteiten. Aan de andere kant wordt resourcebeheer op basis van speltheorie bestudeerd voor rationele, autonome en gedistribueerde besluitvorming tussen entiteiten, aangezien gecentraliseerde optimalisatie een uitdaging is in een netwerkomgeving met meerdere belanghebbenden. De focus van het proefschrift ligt op deze twee concepten om oplossingen te ontwikkelen voor de toewijzing van bronnen binnen een gedistribueerd en autonoom managementkader. Autonoom netwerken vereist terugkoppeling om de netwerkstatus te bewaken en het netwerkbeheer aan te passen door gebruik te maken van observaties uit de monitoringfase. Na het presenteren van de uitdagingen van autonoom netwerken, wordt een managementkader met monitoring en meting, analyse en besluitvorming, en leerfasen geïntroduceerd. De speltheoretische modellen zijn veelbelovende oplossingen in dit kader om de interacties tussen de belanghebbenden van het netwerk te definiëren en het netwerk te beheren. Dit kader vormt de basis voor de bijdragen aan resourcemanagement.

Met het oog op het gepresenteerde perspectief van autonoom netwerkbeheer wordt een systematisch literatuuronderzoek uitgevoerd. Het onderzoek analyseert hoe resourcebeheer oplossingen zijn omgegaan met het optimaliseren van

mmWave -radio en optische bronnen, vormt begrip van de dimensies van brontoewijzingsmethoden in de mmWave 5G en FiWi fronthaul, en identificeert de huidige trends in brontoewijzing. De resultaten van dit onderzoekworden gebruikt om te beslissen over de prestatiestatistieken en de evaluatiecriteria in de spellen die in dit proefschrift zijn ontworpen voor gedistribueerde besluitvorming. Op basis van de resultaten van het onderzoek zijn twee experimenten ontworpen om de controlemogelijkheden van het netwerk te verbeteren. Het eerste experiment creëert de besturingsinteractie tussen fronthaul en toegang , terwijl het tweede experiment de interactie tussen serviceproviders en het transportnetwerk (gerepresenteerd door de infrastructuurprovider) reguleert.

Voor de gezamenlijke optimalisatie van toegang en fronthaul wordt de interactie tussen beide gedefinieerd als een coalitiespel voor de totale vraag aan de toegangszijde. Door de vraag van te observeren, kan het transportnetwerk de beschikbare middelen toewijzen of het aanbod afwijzen als het de totale beschikbare bandbreedte overschrijdt. Wanneer het aanbod wordt afgewezen, wordt een faillissementsspel gebruikt om fronthaul-bronnen aan RRH's te verdelen. Aan de toegangszijde wordt het RRH-gebruik verbeterd door het gezamenlijk delen van bronnen. Verschillende gebruikersdistributies en servicevereisten resulteren in een dynamische ontwikkeling van netwerkvereisten. Het doel is om een spelmodel te bieden dat dynamische bandbreedtetoewijzing bereikt zonder vaste inzet van fronthaul-bronnen en dat zich aanpast aan dynamische gebruikersbelasting.

Het delen van infrastructuur wordt mogelijk gemaakt met behulp van virtualisatietechnologieën, en dit feit transformeerde de netwerkarchitectuur in een nieuwe belanghebbende genaamd de infrastructuurprovider. Hoewel het genereren van winst altijd een factor was bij prestatie optimalisatie voor netwerkoperatoren, maakt de verandering in de architectuur met netwerkvirtualisatie dynamische inkomstenwinsten een duidelijk prestatiecriterium voor de toewijzing van bronnen. Het tweede experiment bekijkt de bronnen van het gevirtualiseerde optisch netwerk vanuit het perspectief van winst maken met een spel, waarin de serviceproviders bieden op een deel van het optische transportnetwerk. De infrastructuuraanbieder past een veilingmechanisme van Vickery-Clarke-Groves (VCG) toe om sociaal welzijn te maximaliseren, terwijl gebruikers de mogelijkheid hebben om tussen serviceproviders te schakelen om hun nut te maximaliseren. De resultaten van de besluitvormingsprocessen van gebruikers met blinde en begeleide zoekalgoritmen worden ook gepresenteerd voor deze schakeloptie.

Het uiteindelijke doel van dit proefschrift is om een realistische richtlijn te bieden voor het optimaliseren van mmWave-transport en het gebruik van radiobronnen, zodat mmWave-netwerkimplementaties op een kostenefficiënte manier kunnen worden geïmplementeerd. De gepresenteerde experimenten en resultaten helpen te begrijpen hoe autonome en gedistribueerde besluitvorming het beheer van netwerkbronnen kan verbeteren en hoe netwerkoplossingen voor capaciteitsverbetering op een optimale manier kunnen worden benut met speltheoretische algoritmen.

Zusammenfassung

Drei zusammenlaufende Prozesse werden die Zukunft des Internets jenseits von 5G gestalten: Die Annäherung von optischen und millimeterwellen Funknetzen, um die Kapazität des mobilen Internets zu erhöhen, die Annäherung von maschinellem Lernen und Kommunikationstechnologien sowie die Annäherung der virtualisierten und programmierbaren Netzverwaltung für eine vollständig integrierte autonome Verwaltung der Netzressourcen. Mit dem Ziel, den integrierten optischen und funktechnischen Transport zu verbessern, bietet diese Arbeit eine auf der Spieltheorie basierende verteilte Netzwerksteuerung zur Optimierung der Ressourcenzuweisung in den C-RAN- und Fronthaul-Segmenten drahtloser und optischer Netzwerke. Darüber hinaus wird ein Spiel zwischen externen Akteuren und dem Netzwerk entwickelt, um die verteilte Entscheidungsverfahren auf Dienstanbieter und Netzwerknutzer auszuweiten.

Das Konzept der autonomen Verwaltung der Netzwerkressourcen ermöglicht eine dynamische Umgestaltung des Netzwerks durch Lernen und Vorhersage des Netzwerkzustands. Außerdem bietet das auf der Spieltheorie basierende Ressourcenmanagement die Möglichkeit eines rationalen, autonomen und verteilten Entscheidungsverfahrens zwischen den Akteuren, um die Herausforderung der zentralisierten Optimierung mit mehreren Akteuren zu überwinden. Der Schwerpunkt der Dissertation liegt auf diesen beiden Konzepten, um Lösungen für die Zuweisung der Ressourcen innerhalb eines verteilten und autonomen Managementrahmens zu entwickeln. Autonome Netzwerke erfordern Regelkreise zur Überwachung des Netzwerkstatus und zur Anpassung des Netzwerkmanagements unter Verwendung der Überwachungsdaten. Nach der Darstellung der Herausforderungen der autonomen Vernetzung wird ein Verwaltungsrahmen mit Überwachung und Messung, Analyse, und Lernphasen vorgestellt. Die spieltheoretischen Modelle sind vielversprechende Lösungen in diesem Rahmen, um die Interaktionen zwischen den Akteuren des Netzes zu definieren und die Operationen der Netzverwaltung zu steuern.

Angesichts der vorgestellten Perspektive des autonomen Netzwerkmanagements wird eine systematische Literaturanalyse durchgeführt. Dabei wird analysiert, wie Ressourcenmanagementlösungen mit der Optimierung von mmWave funk- und optischen Ressourcen umgegangen sind, werden die Ressourcenzuweisungsmeth-

oden von den mmWave C-RAN- und Fronthaul verstanden und die aktuellen Trends in der Ressourcenzuweisung identifiziert. Die Ergebnisse dieser Analyse werden genutzt, um die Leistungs- und Bewertungskriterien für die Spiele zu verteilten Entscheidungsverfahren in dieser Dissertation zu definieren. Basierend auf den Ergebnissen der Analyse werden zwei Experimente entwickelt, um die Steuerungsmöglichkeiten des Netzes zu verbessern. Das erste Experiment schafft die Steuerungsinteraktion zwischen Fronthaul- und Funknetz, während das zweite Experiment die Interaktion zwischen Dienstanbietern und den Infrastrukturanbieter regelt.

Für die gemeinsame Optimierung von Funknetz und Fronthaul wird die Interaktion zwischen den beiden als ein Koalitionsspiel definiert. Durch Beobachtung der Funknetzanforderung kann das Transportnetz die verfügbaren Ressourcen verteilen oder Anfragen ablehnen, wenn die gesamte verfügbare Bandbreite überstiegen wird. Wird die Anfrage abgelehnt, werden die Fronthaul-Ressourcen mit Hilfe eines Bankruptcy Game an die RRHs verteilt. Unterschiedliche Nutzerverteilungen und Dienstanforderungen bringen eine dynamische Entwicklung der Netzanforderungen. Ziel ist es, ein Spielmodell bereitzustellen, das eine dynamische Bandbreitenzuweisung ohne feste Bindung von Fronthaul-Ressourcen erreicht und sich an die dynamische Nutzerlast anpasst.

Die gemeinsame Nutzung von Infrastrukturen wird mit Hilfe von Virtualisierungstechnologien ermöglicht, und diese Tatsache hat der Netzarchitektur einen neuen Akteur, den Infrastrukturanbieter, hinzugefügt. Obwohl die Gewinnerzielung schon immer ein Faktor bei der Leistungsoptimierung von Netzbetreibern war, macht die Architekturveränderung mit der Virtualisierung dynamische Umsätze zu einem Leistungskriterium für die Ressourcenzuweisung. Das zweite Experiment betrachtet die Ressourcen des virtualisierten Netzwerks aus der Perspektive der Gewinnerzielung mit einem Spiel, bei dem die Diensteanbieter ihre Gebote für die gemeinsame Nutzung des optischen Transportnetzwerks abgeben. Der Infrastrukturanbieter wendet einen Vickery-Clarke-Groves (VCG)-Auktionsmechanismus an, um ein die soziale Wohlfahrt maximierendes Ergebnis zu erzielen. Außerdem haben die Nutzer die Möglichkeit, zwischen den Diensteanbietern zu wechseln, um ihren Nutzen zu maximieren. Die Ergebnisse der Entscheidungsverfahren der Nutzer mit blinder Suche und geführten Suchalgorithmen werden ebenfalls für diese Wechseloption vorgestellt.

Das Hauptziel dieser Dissertation ist es, ein realistisches Framework zur Optimierung der Vergabe von mmWave-Funkressourcen zu erstellen, damit mmWave-Netzwerke kostengünstig implementiert werden können. Die vorgestellten Experimente und Ergebnisse tragen dazu bei, zu verstehen, wie autonome und verteilte Entscheidungsverfahren die Verwaltung von Netzressourcen verbessern können und wie Netzlösungen zur Kapazitätserweiterung mit spieltheoretischen Algorithmen optimal genutzt werden können.

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CHAPTER 1

Introduction

The growth trend expected for beyond-5G and 6G networks is likely to transform wireless networks from a facilitator of person to person communications to the provider of connectivity among everything, by which ever means and everywhere [1], forming the basis of future societies [2]. Ericsson Mobility Report expects 5G subscriptions to reach from 1 billion by the end of 2022 to 4.4 billion in 2027, and total mobile subscriptions is expected to surpass 9 billion in 2027 [3]. The Mobile Economy 2022 report by GSMA Intelligence [4] expects the number of unique mobile subscribers worldwide to increase from 5.3 billion in 2021 to 5.7 billion in 2025, the number of licensed cellular Internet of Things (IoT) connections with machine-to-machine (M2M) communication capability is going to increase from 2.1 billion in 2021 to 4.1 billion in 2025, and the mobile data traffic to increase from 11.4 billion GB per month in 2021 to 41 billion GB per month in 2027. The increase in the numbers are also displayed in Figure 1.1.

Categorized under enhanced mobile broadband (eMBB), ultra-reliable low-latency communications (URLLC), and massive machine-type communications (mMTC) by ITU-R [5], many services and concepts were envisioned for 5G. Ambitious targets were set for 5G by the research initiatives, such as the 1000x challenge set by METIS [6] and the target set by 5GPPP [7] to establish up to a million connections per km^2, to realize the ever-increasing number of services such as smart cities [8], Industry 4.0 [9], digital twins [10], IoT [11], and autonomous driving [12]. Not being able to reach all the technological targets simultaneously forced the industry and the research initiatives to postpone the realization of these concepts to beyond-5G and 6G networks era. In addition, the creation of new verticals with multiple services and applications in domains such as entertainment, healthcare, education, and industry widened the need for physical and virtual network resources, and customization of these utilized resources [1].

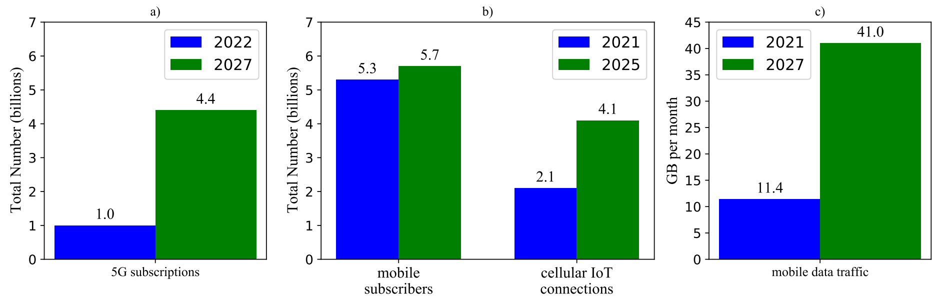


Figure 1.1: The growth trend predictions of Ericsson [3] and GSMA Intelligence [4] for wireless communications. a) shows the expected increase in 5G subscriptions from 2022 to 2027[3], b) shows the expected increase in the number of mobile subscribers and cellular IoT connections from 2021 to 2025[4], c) shows the expected increase in monthly mobile data traffic from 2021 to 2027 [4]

Beyond-5G and 6G networks are envisioned to enable rich interactions to transfer large amounts of data among heterogeneous entities, ranging from simple sensing devices to complex robotic devices and from autonomous service agents to human actors. This explains why more and more industry and research efforts emerge to define the use cases, driving characteristics, performance targets, and technical requirements of beyond-5G and 6G networks [1], [13]–[15]. Example 6G use cases, grouped in Figure 1.2, require a 6G network communication infrastructure that is able to respond to the key performance indicators (KPIs) of these use cases. For example, collective perception of environment use case of Vehicle-to-everything (V2X) requires peak data rates of 1 Gbps for all the vehicles involved in the use case [16], and streaming light field video for holographic communications require data rates ranging from 100 Gbps to 2 Tbps [17]. In general, user experience rate is set to 1 Gbps and peak data rate is expected to be over 1 Tbps in 6G networks [14]. The emphasis on ultra-low latency also increases with the challenging URLLC requirements of the use cases [18], defined as the "1 ms challenge" for delay sensitive applications, such as tactile internet [19] and augmented/virtual reality.

1.1 Motivation

The novel KPI targets of 6G networks can be translated as a remarkable increase in the demand for network resources. For this reason, network architectures providing resource expansion, the shift towards reconfigurable network architectures to manage these resources, and the increased use of artificial intelligence (AI) and machine learning (ML) techniques extracting knowledge from the increased communication data are expected to become three main pillars of beyond-5G/6G

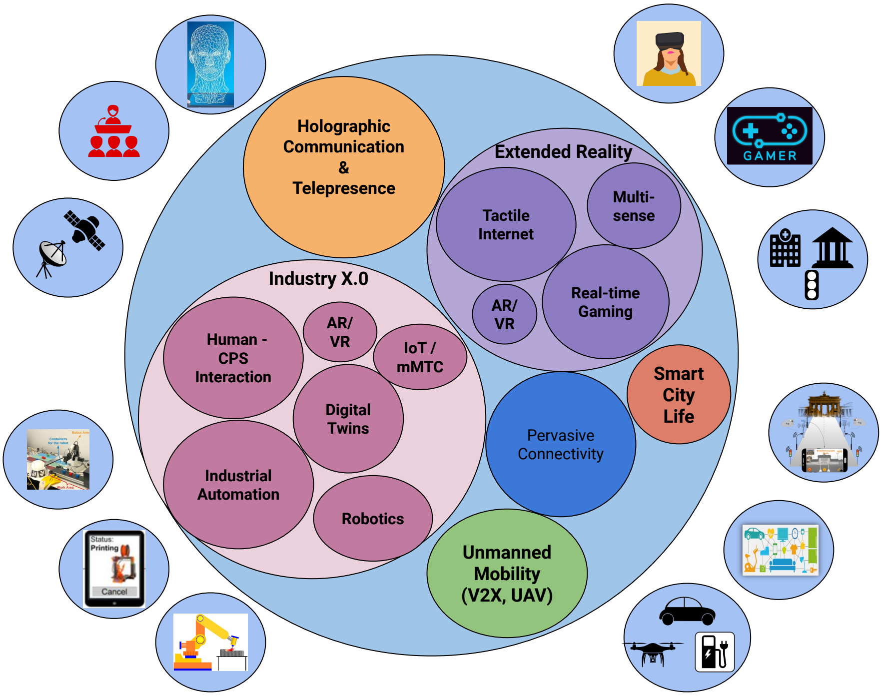


Figure 1.2: Envisioned 6G use cases [1], [13]–[15]

networks. An important step towards realizing these networks is to discuss the relations between autonomic reconfiguration, the management issues of wireless resource enhancement techniques, and the potential solutions provided by AI-based learning algorithms.

1.1.1 Wireless Network Capacity Expansion with Millimeter Wave

An essential source for capacity enhancement in dense networks is the use of millimeter wave (mmWave) spectrum bands around 28 GHz, 38 GHz, 71 GHz to 76 GHz, and 81 GHz to 86 GHz frequencies [20]. A total of 16 GHz bandwidth is available to use in these spectrum regions. In spite of the availability of large bandwidth, these bands were not used in cellular networks due to the high power consumption of the devices utilizing these bands [21] and the challenging propagation characteristics due to high path loss, poor signal penetration and reflection, the sensitivity to blockage from various objects outdoors and the high Doppler effect observed in frequency bands deployed until long term evolution (LTE) technology [22].

Extensive studies are carried out in order to understand whether mmWave spectrum bands can be used in dense networks despite these challenging characteristics [20]–[33]. A list of some of the key challenges that are addressed by the resource management solutions in the selected studies are as follows: In order to reach the extreme data rates, beamforming with adaptive antenna arrays and highly directional transmissions are required for narrow beam operations [23], [25], bringing in the problem of dynamic adjustment of antenna elements in analog beamforming to support multiple directed beams with massive Multiple-input and multiple-output (MIMO) [29], [31]. Synchronization and broadcasting should also be designed properly for these directional transmissions [32], as narrow beams can cause loss of connectivity in mmWave mobile networks when they are misaligned [27]. In addition, efficient beam-tracking and alternative directed spatial channels need to be provided to users in case of blockage [25] or outage [26] – one probable solution can be to serve a user at the same time over several access points (APs) [20].

Integration of capacity enhancement techniques, namely the use of mmWave and massive MIMO is also complementary to the small cell evolution [31]. In addition to this, utilizing higher frequency spectrum bands for capacity gains drives toward use of more small cells, as the propagation characteristics of mmWave signals lead to higher attenuation and reduced coverage area, requiring the deployment of more APs. Ultra-dense networks (UDN) is an attractive technology to boost the capacity in a coverage area [33], as increasing the number of access nodes enables radio frequency (RF) reuse in a certain coverage area. To unfold the added capacity provided by UDN, end-to-end network management has to deal with increased dynamics of radio access due to the complexity of the architecture with increasing number of nodes, massive data generation, and dynamic topology changes requiring quicker network reconfiguration.

The introduction of mmWave frequency bands for wireless access with dense deployments also leads to a major increase in fronthaul capacity, and fiber network solutions can provide the required data rates for this fronthaul. Radio-over-fiber (RoF) implementations for mmWave have long been considered to distribute mmWave radio signals to dense APs from a central station [34], [35]. Multiple wireless services can thus share the huge amount of bandwidth in the same optical fronthaul network, achieving optical-wireless convergence [36].

1.1.2 Autonomic Network Management Concept

Compared to existing wireless networks, a much more dynamic environment is foreseen due to mmWave propagation characteristics and massive deployments of small cells, leading to a dynamically changing large scale network topology. Furthermore, the changing network demand characteristics, such as the increase in traffic, the increased number of mobile users, heterogeneous user types ranging from humans to complex devices, and fluctuation in data traffic make dynamic user behavior an integral part of network management. As a natural result of this, providing a stable network communication that is able to withstand varying network conditions will become more complex, pushing any human dependent network management approach out of the equation. Predefined rules will also not be suitable for the dynamic environment of beyond-5G networks, and the lack of a management approach that is generic enough to capture the dynamics of most network technologies and user types prevents dynamic adaptation, both for additional resource provisioning and for avoiding over-provisioning, depending on the use case.

A number of approaches to transfer the intelligence to mobile networks have been around for many years from auto-configuration of network entities [37] to self-optimization of network operations [38], leading to the autonomic network management (ANM) paradigm for anticipating and diagnosing impairments in networks driven by operations and maintenance (O&M) layer goals [39]. At the same time, the emergence of software-defined networking (SDN) contributed to network optimization efforts by offering programmability and network system reconfigurability to 5G networks by decoupling the control plane from data plane [40]. Today, with the support of network function virtualization (NFV), cloud technologies, and SDN, softwarization and programmability are considered as the main enabling technologies to manage the dynamic topologies in a responsive way and achieve 5G and beyond traffic requirements [41]. In addition, the developments in the network elements with hardware support for dynamic reconfiguration introduce a lot more capabilities for autonomic network management.

An autonomic networking framework for 5G and beyond requires translating of high level O&M goals into low-level technical parameters and then monitoring the network to adapt the network status by making use of observations from the monitoring stage [J1]. The management paradigm shifts towards avoiding the rigid properties and the limitations arising from the difficulties in modeling the entire state space beforehand. The type of data to be collected for monitoring, the possible actions and control rules, the learning algorithms and data analytics functions should also be defined properly, resulting in a control loop through which multiple stakeholders can become involved in decision-making inside a hierarchical functional decomposition.

1.1.3 Learning-based Solutions for Network Resource Management

Mobile wireless networks have been commercially available for decades, and a lot of management challenges have been addressed by learning methods for optimization, diagnosis, and prediction. Probabilistic models, game theoretic models and ML models provided different solutions in application areas such as mobility management, call admission control, link optimization, load balancing, and resource sharing [J1]. Implementing self-organizing networks (SON) functionality with learning algorithms also enabled network elements to explore their environments, respond to the stochastic changes in the network environment, and to cooperate with other network elements [42].

The increase in data traffic and the number of users, devices and network components lead to a huge increase in data which can be analyzed with ML techniques for optimization in user quality of service (QoS), network management, and service provisioning. At the same time, the increasing number of unknowns in the system expands the interest in the use of learning techniques in network management. It is expected that the convergence of learning solutions and communication technologies will improve significantly in beyond-5G/6G networks era, with a special focus on AI/ML-assisted approaches for channel measurements, estimation, data-driven localization [43], AI-enabled new applications that transfer processing and knowledge creation to diverse network elements such as smartphones [44], creating a collective AI for 6G [15].

All these ANM framework requirements and the increasing interest in AI/ML-assisted approaches to resource orchestration and optimization led to the efforts of ITU-T [45], ETSI [46], and 3GPP [47] to define the architectural framework for integrating ML solutions to 5G and beyond networks, whereas exploiting AI solutions in every network segment possible to learn and adapt to network dynamics is conceptualized as the 'AI Everywhere' principle for networks [48], [49]. 3GPP has introduced the network data analytics function (NWDAF) and the management data analytics function (MDAF) for core services [50] that can be used for centralized optimization of the network resources. On the other hand, the 5G radio access network (RAN) data analytics function (DAF) is proposed for radio resource management [51], which targets managing ML and AI solutions in the RAN with open interfaces inside the O-RAN project [41]. RAN DAF can also be extended with local monitoring lightweight data analytics capabilities for decision-making at different types of RAN nodes inside a distributed and hierarchical framework [52], allowing local and distributed resource management optimizations to take place inside the network.

1.2 Research Objectives and Dissertation Overview

In this section, the research questions covered in the dissertation, the contributions of the author, and the dissertation structure are presented.

1.2.1 Research Questions

Resource management mechanisms are required to offer solutions that keep the network performance at a level that maintains a seamless and robust connection for network end users. Taking all these changes towards beyond-5G/6G networks into account, we can reformulate the resource management problem with the following research question:

How can a resource management composition be created for a converged optical and mmWave radio network architecture? How can multiple stakeholders get involved in decision-making process to maximize their utilities?

To provide a well-defined framework to answer the main research question, the dissertation is extended with the following sub research questions:

- What are the enabling concepts of autonomic network management? What are the challenges ahead for achieving the technology agnostic autonomic network management framework? What are the design goals of ANM for converged optical and mmWave radio networks?

- How should an ANM architecture be defined to implement learning capabilities for network management and enable network stakeholder interaction in a concrete structure?

- What aspects are relevant for classification of resource management solutions from the point of view of autonomic network management? In what ways do the solutions in the literature consider autonomic networking to optimize millimeter wave radio and optical resource management?

- How should the interactions and possible actions among the stakeholders that control radio and transport networks be defined in case of limited resources to reach optimized dynamic bandwidth allocation in converged optical and mmWave radio networks?

- Can a balanced profit and social welfare trade-off be achieved in converged optical and mmWave radio networks infrastructure sharing scenario with distributed decision making?

1.2.2 Contributions

In this section, a brief summary of the independent contributions of the thesis is provided to readers.

- Based on the ANM framework proposed in [J1], an analysis is presented on how this concept and its principles can be applied to organize the management of 5G use-cases and converged mmWave radio and transport networks. The separate characteristics of the use cases and the challenges of mmWave networks are identified to emphasize the need for an ANM framework that defines the the degree of information about the network to be collected for monitoring, and the possible actions of the stakeholders that take part in the decision-making mechanism. A separate section is dedicated to discuss how game-theoretic learning can be used to model the interaction between network stakeholders.

- A literature survey is presented to understand the key concepts and the key network state parameters used to evaluate the performance of AI-based network optimization algorithms, to identify the future demands and to analyze the options for novel contributions and the limitations of resource management in converged optical and mmWave radio networks. This survey aims at identifying the main features, objectives, and the resource allocation solution methods in mmWave networks by also considering the relationship between the use of optimization algorithms for virtualized resource allocation and the use of the ANM technological enablers in the 5G and beyond-5G network architecture.

- In light of the network management model principles, the objectives, and performance metrics that came into prominence in the previous contribution, a bankruptcy game is created for cooperative bandwidth allocation in a converged mmWave radio and optical network. Jain's fairness index is used to determine the outcomes of the division rules, and user satisfaction are measured to determine the efficiency of resource allocation. The simulation presents the effectiveness of simple strategic algorithm implementation over pre-defined rules to optimize resource allocation.

- Even though profit generation was always a factor in performance optimization for network operators, the shift in the architecture with network virtualization makes dynamic revenue gains an apparent performance criteria for resource allocation. In order to investigate this dimension of resource allocation, a dynamic fronthaul path allocation game simulation is created. The game aims to validate the hypothesis that auctioning games with VCG outcomes and distributed learning help in providing maximized profit and social welfare in sharing network resources. The results can be exploited during a pre-deployment phase in which different fronthaul topology options can be simulated to reach a desired market solution.

1.2.3 Dissertation Overview

After introducing the motivation, research questions, and the contributions, in Chapter 1, the remainder of the thesis is divided into five chapters, which are structured as follows:

- In **Chapter 2**, the autonomic network management concept is introduced together with the evolution of management in radio network and transport layers. The enablers of autonomic management for beyond-5G and 6G networks are presented with concrete examples from the expected use cases. The design goals and functional decomposition that can achieve seamless management of the converged optical and radio mmWave networks are clarified. Finally, a literature survey on game theory-based resource allocation is provided for autonomous management and distributed decision-making in multi-stakeholder network environments. The definition and enabling concepts of autonomous network management are provided in [J1] and examples of use case—network management mapping are presented in [J2], [C1], [C2].

- In **Chapter 3**, a converged optical and mmWave radio architecture is defined for beyond-5G/6G networks. The main performance metrics and optimization objectives of the architecture are classified under throughput maximization, delay minimization, and energy-efficiency targets. As the paradigm shift with network softwarization leads to the abstraction of network resources, virtual resource allocation is also classified as a separate category. Based on these targets, a review is presented to explain how existing resource management solutions deal with optimizing mmWave radio and optical resources from an autonomic network management perspective. The methodology and the outcomes of this review is first published in [J3].

- Dynamic bandwidth allocation for a multi-user environment is presented in **Chapter 4**. mmWave radio network units cooperate with a coalition in a bankruptcy game between transport network and RRHs played to achieve fairness for radio acesss and quality of experience (QoE) maximization for users. The results of applying different division rules for the Bankruptcy game for resource scarcity and demand increase scenarios are presented. Furthermore, users have different service subscription categories in order to analyze the impact of demand heterogeneity.

- **Chapter 5** focuses on a distributed network management paradigm, in which infrastructure provider and service provider profits are optimized in a setting that considers social welfare pursuing outcomes with a descending Vickrey-Dutch auction. A dynamic fronthaul path allocation game is designed for service providers that lease the resources from the infrastructure provider. This chapter considers optical network resource allocation from a profit generation perspective with an auctioning game, in which providers bid to lease space division multiplexing-enabled (SDM) fronthaul paths. The game aims to distribute fronthaul resources with a social-welfare maximizing outcome. The results of this experiment are presented in [C3].

- **Chapter 6** concludes the thesis by summarizing the findings and contributions with final remarks. This chapter also provides an in-depth discussion for future research.

CHAPTER 2

Autonomic Management of Beyond-5G/6G Networks

Network management consists of the activities, methods, and tools used for administration, maintenance, and provisioning tasks of networked systems [53]. 5G brings the newest step in the evolution of mobile network management, bringing programmability, SDN-based flow control and on-demand network slices tailored for various verticals into the big picture. Besides, the increase in data traffic, number of devices and the proliferation of service types escalate the performance requirements that 5G networks will have to support, motivating all actors to come up with innovative KPI optimization solutions, leading to the integration of artificial intelligence into network management. All these novel technologies introduce the next paradigm shift to network management, leading to an urge for the dynamic reconfiguration of networks. The new challenge in network management is therefore to design an autonomic network management mechanism that predicts network load, learns the behavior of different network domains, and enables coordination between those domains to optimally adapt to the system-wide objectives. In this chapter, the driving factors of ANM, ANM design goals for future networks, and the game theory-based distributed decision-making mechanisms with multiple network stakeholder involvement are presented.

2.1 Driving Factors of Autonomic Network Management

In mobile networks, network management must offer solutions to reduce the complexity of the system and keep the network performance at a level that meets the ever increasing capacity optimization, coverage expansion, QoS and energy-efficiency demands from users, services and operators. The process of controlling

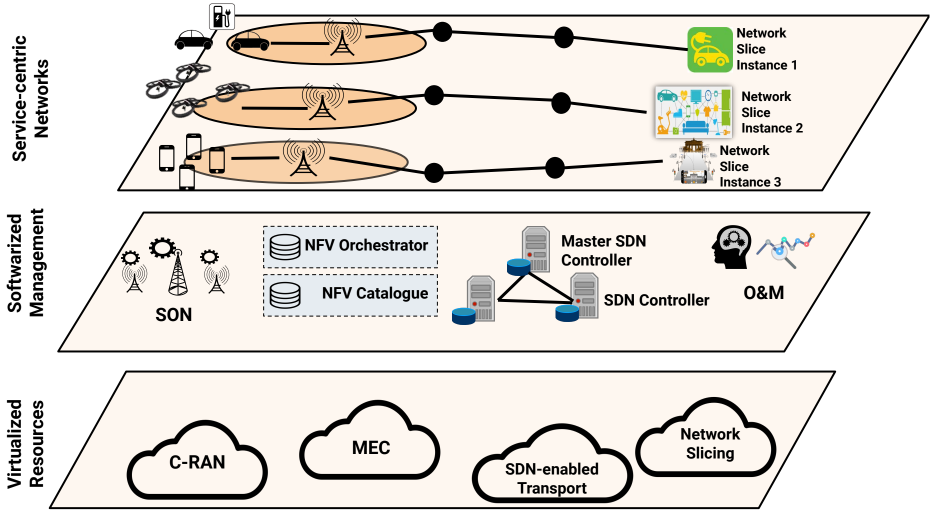


Figure 2.1: 5G/Beyond-5G software-centric network management overview

a complex mobile network to maximize its efficiency and the pressure to cut costs shifted mobile network management from human-centric to softwarized solutions with simple network policies, and the next step is to move to autonomous solutions with global policies. This section presents network management technologies that should be considered as evolution milestones towards ANM and discusses their impact on 5G and beyond-5G network management. A high level picture that presents the driving factors of ANM is depicted in Figure 2.1.

2.1.1 Self-organizing Networks

Self-organization is a term that is inspired from the nature and it means autonomously adapting to the changes in the environment to achieve a certain objective [38]. Used in various scientific branches from economics to computer science, self-organized systems in general aim to reach a global equilibrium via the distributed interaction of system elements. This equilibrium can be achieved with the ability to remain in a stable state and quickly responding to changes. In mobile networks, SON defines a concept that enables the network elements to explore their environment, cooperate with other network elements, and respond to changes without human involvement to reach a mobile network objective such as load balancing or interference management [42]. SON functionalities for network O&M procedures are grouped under self-configuration, self-optimization, and self-healing categories.

The benefits of self-organizing functions to solve these problems were firstly discussed for LTE systems. 3GPP defined use of SON [54] by emphasizing the need to reduce complexity, improve operability and minimize operational effort with addition of self-configuration and self-optimization functions to LTE systems. Based on the 3GPP definition, NGMN [55] defined SON use-cases and categorized them under planning, deployment, organization and maintenance. The prominent SON functions defined by 3GPP for LTE [56] include obtaining information from neighbor BSs, interference mitigation, mobility robustness optimization (MRO) to manage handovers and radio link failures, and mobility load balancing (MLB). With the introduction of small cells in heterogeneous networks, SON functions need modifications with the variety of handover and interference types [57].

A much more dynamic environment is foreseen for 5G and beyond-5G in comparison to LTE and LTE-A; creating the need to follow policies and objective functions more dynamically for SON functions. For this reason, it is necessary to define new use-cases for self-organization functions whereas existing self-organization functions should be modified to react faster and to involve conceptual changes foreseen for 5G. For example, transmission power adjustment in a small cell environment is more likely to require AI-based solutions [58]. Furthermore, backhauling and transport networks in general is not defined as a SON use-case for LTE systems; however, the massive deployment of small cells leads to the proliferation of massive fronthaul and expansion of front-/mid-/backhaul splits; therefore defining specific transport network use cases is of key importance to an operational 5G. In addition to this, antenna parameter adjustment has to be redefined as a self-optimization function as MIMO needs to be integrated to cellular networks and highly directional antennas and adaptive beamforming is required to exploit mmWave spectrum. Knowledge extraction with cognitive radio is an attractive idea where self-organizing functions learn over the extracted knowledge from spectrum sensing and small cells can dynamically adapt to the environment, minimizing interference towards other users. Finally, network management optimization with SON is a challenging issue as conflicts exist between single optimization targets. For this reason, optimization targets for network management with self-optimization algorithms require coordination mechanisms. Fuzzy classification techniques are applied in [59] to classify network management targets in a self-coordination framework to solve these conflicts.

SON allows collection of radio layer data from the environment and adapts to changes at the right time, allowing policy enforcement with specific parameter configurations in network elements [J1]. SON is therefore an important step towards ANM and distributed decision-making in wireless networks. However, when compared to ANM, SON should be considered as a use case confined to the management and control of cellular networks, targeting at keeping the network stable and operating, reducing the O&M costs, and optimize the overall network performance.

2.1.2 Software-Defined Networking

In the dynamic environment foreseen for 5G and beyond-5G networks, networks do not only have to deal with massive mobile device connections and the expansion of data traffic, but they also have to sustain operation under load variations, leading to higher temporal and spatial traffic fluctuations. Efficient management of these complex networks cannot easily be taken care of with traditional network solutions. For this reason, there has been a paradigm shift from hardware-centric to software-centric management to reconfigure the network and enforce new policies to different services in a dynamic way, owing to enabling technologies such as SDN and NFV.

SDN concept addresses the ossification problem of networks by decoupling the data plane from control plane, and makes it possible to configure network devices at setup and update them on-the-fly order to modify the data plane behavior and provide dynamic responses to changing network requirements [40]. This reconfiguration is much needed and novel architectures exist for 5G networks that deploy SDN [60], [61] as a technological enabler to shift towards flexible, software-based and reconfigurable solutions. The centralization of control knowledge enables controlling multiple flows, leading to consistent network management decisions and agile transport and access networks. Programmability and reconfigurability features of SDN make it possible to configure the network components dynamically in 5G networks. SDN can change the network behavior for services by sending control messages to the devices (routers, switches) without interrupting the end-users data flow. The northbound interface can be used for several management applications such as interference mitigation, centralized transmission power control, mobility management, elastic bandwidth provisioning, vendor agnostic transport networking, and energy efficiency. These applications can implement different policies to respond to the QoS/QoE requirements of services and users.

Kreutz et al. [62] define four pillars of SDN as decoupling of control and data planes, flexibility with match and action based forwarding decisions, logically centralized abstract view of SDN controller and programmable network applications. SDN creates abstractions in networking and enables addition of new services such as load balancing and energy efficiency as programmable applications that can enforce new policies and reconfigure the network based on the logically centralized controller view. SDN also makes it possible to use high level programming languages while modifying network applications for policy enforcement. Decoupling of data and control planes keeps applications in the abstracted level of the control layer, and gives them the opportunity to reconfigure forwarding paths regardless of their geographical location.

SDN-based architectural approaches transform network designs of next generation wireless architecture. Design options based on network virtualization, SDN and NFV exist for several RAN architectures; however centralized radio access network (C-RAN) architecture can benefit greatly from SDN as processing is centralized at the central office that contains Baseband unit (BBU) pool. With SDN and C-RAN approach, BBU pool is tasked with both data forwarding and a level of radio control functionalities [63]. Besides, a programmable fronthaul design for C-RAN can reduce the required number of BBUs with a switching element that establishes the links dynamically for Remote radio head (RRH)-BBU mappings computed by SDN [64]. An SDN resource manager is also presented for dynamic path management between small cells and the backhaul in a similar fashion in [65]. In dual-connectivity and HetNet use cases, coordinated handovers can be managed by SDN in an architecture that separates control signaling and data traffic between the macrocell and microcells [66]. Coordinating and optimizing RAN traffic with SDN can also be used to distribute the traffic in congested radio nodes, with applications that monitor QoE with a network status database for decision-making [67]. Regarding the optical networks, SDN can be responsible for lightpath establishment and provisioning. Physical layer parameter tuning is possible with SDN controllers, such as modifying the amplitude and phase of the generated optical signal or changing the modulation format [63].

SDN controller architecture plays an essential role in resource management; however, a very commonly known challenge is SDN's scalability due to its characteristic of a logically centralized controller. Distributed SDN controllers can also be an attractive design option for beyond-5G/6G architectures, as distributed controllers can be deployed at the edge, and this architecture potentially enables improved performance for edge services with lower delay, while consuming less amount of radio and computational resources [68]. Distributed SDN architecture involves multiple inter-connected network domains, each managed by a master SDN controller in a hierarchical structure. In [69], the controller placement problem in distributed SDN networks is discussed. The synchronization problem among controllers is investigated in [70] to enable efficient intra-domain routing. Joint delay and overhead optimization in distributed SDN networks is considered in [71].

2.1.3 Network Function Virtualization

NFV transforms the hardware-centric management to software-centric management by running softwarized network functions on general-purpose hardware instead of hardware dedicated to the network function [72]. ETSI defines NFV as decoupling network functions' software from the computation, storage, and networking resources [73], in order to deploy new network services rapidly and support multiple services on a single hardware with multi-tenancy. This gives the network operator the flexibility to customize data flows of services with chained virtual network function (VNF) middleboxes to optimize their QoS with customized data processing, as introduced in [74]. Chaining network functions that have different operations with virtual links is a step towards the network slicing concept explained in Section 2.1.4. NFV also has the potential to reduce capital expenditure and operational expenses [73], [75].

The reference architecture used for NFV Management and Orchestration (MANO) is the ETSI framework [73] demonstrated in Figure 2.2. NFV-MANO framework consists of three main components, namely network function virtualiza-

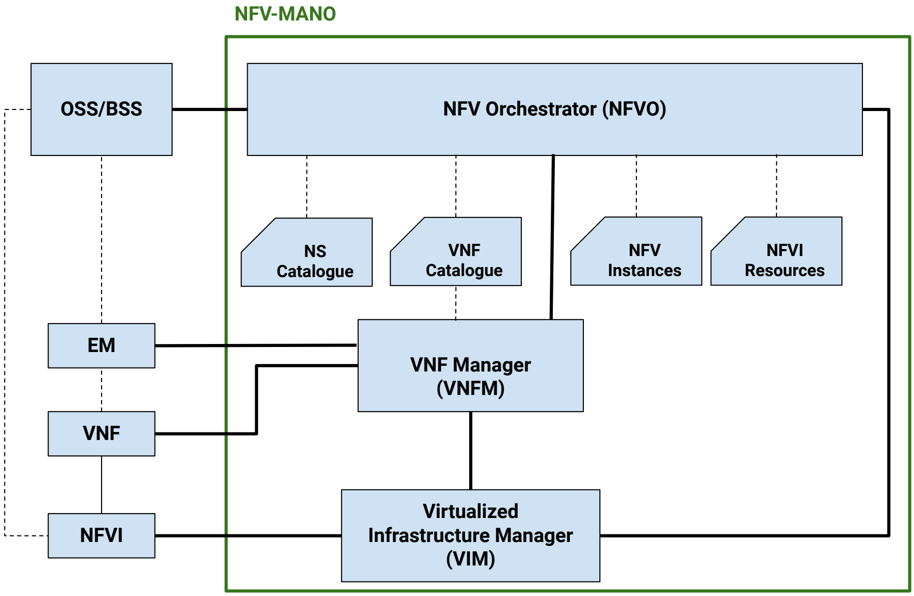


Figure 2.2: ETSI NFV-MANO framework [73]

tion orchestrator (NFVO), VNF Manager, and virtualized infrastructure manager (VIM). NFVO orchestrates network function virtualization infrastructure (NFVI) resources and is responsible for the lifecycle management of network services. It is also connected to external entities such as Operations Support System/Business Support System (OSS/BSS). The VNF manager is responsible for the lifecycle management of VNFs, and the VIM is responsible for controlling and managing the virtualized compute, storage and networking resources of the NFVI. NFVI is responsible for the abstraction of storage, compute and processing resources by using servers and a network hypervisor that runs virtual machines. In conclusion, ETSI framework provides an end-to-end perspective to service management and resource orchestration [76].

The orchestration of VNF deployments in SDN/ NFV architectures is challenging as the unique kernel and software container needs of a VNF have to be considered during the resource allocation process [77]. OpenStack [78] is an open source cloud computing platform that provides various tools and technologies to hide the complexity of the underlying infrastructure by abstracting virtual and physical network resources. OpenStack provides virtual machines and containers, and it offers various ready-to-use applications to manage those resources. Openstack manages large pools of compute, storage and networking resources throughout a datacenter, all managed and provisioned through APIs. Resource monitoring is also possible through OpenStack APIs and its applications. Designed according to

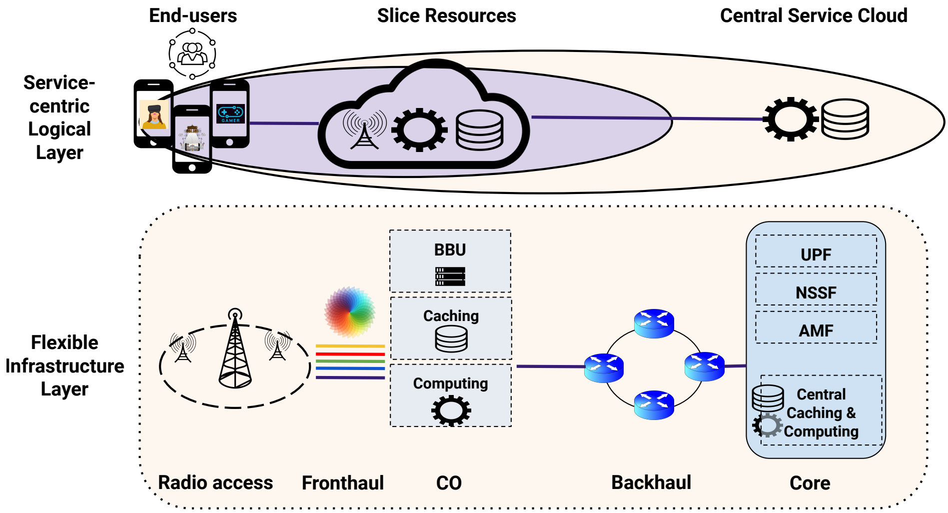


Figure 2.3: A two layered approach to network slice formation [J2]

ETSI MANO architectural framework, Openstack NFV orchestrator Tacker also aims at creating a Generic VNF Manager and NVF Orchestrator in order to install VNFs and network services on an NFV platform.

NFV and SDN are associated with network softwarization technologies. A service-oriented approach for NFV orchestration involves using SDN-based routing to compute an optimal flow for a service. This removes the constraint to pass through the VNF node as the network orchestrator can decide to replace the node on which the VNF server is implemented to get a better bandwidth for multiple services using this VNF. On the other hand, SDN functions and applications can run in virtual machines provided by the NFV MANO. Creating integrated NFV/SDN architectures is investigated in the literature [77], with VNF performance, VNF Scheduling and Placement, high-level policy definitions, traffic management based on network behavior, and the overall orchestration still remaining as the main challenges of such an integrated architecture.

2.1.4 Network Slicing

Network slicing is a technique for flexible service-specific resource provisioning [79], and one of the key technological enablers of the paradigm shift towards software-centric network management. The emerging use cases and applications introduced in Chapter 1 for beyond-5G networks require dedicated network resources that can be virtually provided over customized logical networks called slices. To simplify service development, Service Layer Agreements (SLAs) define the service specific requirements such as coverage area, capacity, and QoS [80]. Network slicing provides different slices to services with different QoS levels over short or long term SLA contracts. Network operators provision infrastructure level, network function level, and application level resources to the services to satisfy these requirements and create an end-to-end chain for each slice, which is conrtolled by an NFV-MANO framework. Different slices should be managed simultaneously, as the infrastructure provider supports simultaneous data transmissions with different QoS classes over the same physical infrastructure. To achieve this management goal, the infrastructure provider should be able to provide slice isolation to the dedicated bandwidth, processing, and storage resources [81]. As dynamic slice creation and deletion are required in 5G, network slice selection function (NSSF) is added to the 5G core in order to retrieve the network slice information during session establishment and to subscribe, unsubscribe or notify service procedures [82].

SDN and NFV play the enabler role in network slicing, as NFV functions required in a slice are deployed on physical nodes with network function placement, and the virtual links that connect virtual network functions are mapped to physical resources with the path computation engine of the SDN topology manager. The connected virtual links and nodes create a network slice on top of the physical infrastructure dedicated to the communication service, which is named as a tenant of the network. Virtual Network Embedding (VNE) problem deals with dynamic mapping of virtual nodes and links to the physical hardware to maximize the benefit gained from existing hardware [83].

A virtualized 5G architecture is controlled by a network slice manager, NFV orchestrator, and SDN controllers. The interactions among all these network management components should be defined with well-defined interfaces for information exchange, dynamic reconfiguration, and efficient slice management. The creation and customization of a network slice for a service by forming an end-to-end service-specific virtual network connecting users' devices and cloud-based resources are demonstrated in Figure 2.3.

Network slice management is responsible for on-demand resource provisioning, i.e., associating the services with a particular network slice including a set of network functions and network resources. The physical infrastructure contains radio access resources (spectrum bands and beams), optical network resources, and computing resources with multi-access edge computing (MEC) [84], and a network slice manager is responsible to allocate all these resources to slices and compute all the routes that link these resources in a cost-effective way by taking all resource constraints into account. In conclusion, network slice management can be considered as an optimization problem with multi-objectives from the infrastructure provider/network operator side.

A network slice manager manages the lifecycle of network slices by dynamically translating their QoS requirements. Depending on the service type and QoS requirements, a service may require data updates over the traffic capacity, network coverage area and user density, degree of isolation, mobility management, connection priorities, service availability, and service reliability [85]. All these data can be used by the service with learning algorithms to maximize their objective functions.

Depending on the service type, services can cooperate or compete with each other to exploit the common physical infrastructure. The fact that different network stakeholders have different objectives in creating slices, network slicing opens the way for decision-making with the interrelation of stakeholders. Through this interrelation, services can adjust their preferences depending on the QoS requirements and manage their resources autonomously by replacing the static partitioning of resources. The roles related to network slicing management can also be extended to end-users and third-party VNF / MEC providers that lease their services to and/or from network operators during slice creation. These stakeholders have different and sometimes conflicting objectives; therefore defining the interactions between the stakeholders in network slicing with QoS, cost, and revenue aspects is a challenging task. Table 2.1 shows the categories of potential stakeholders, objective functions, and learning parameters in a network slicing scenario. There exist network slicing games with auctioning [86], [87] and market models [88] in the literature. Under appropriate conditions, the game associated with the strategic decision-making of services converges to a Nash equilibrium [88].

Table 2.1: Objective functions of stakeholders during slice formation

Network Stakeholder	**Objective Function**	**Learning Parameters**
Network Operator	maximize revenue fair resource allocation optimal utilization	service demand user demand resource availability
Service Provider	maximize revenue availability at all times maximize user QoE	user QoE degree of isolation service priority slice costs
3rd Party Computing	maximize revenue energy-efficiency	server price service costs
End Users	maximize QoE reduce costs	user satisfaction service cost connection quality

2.1.5 Use Cases with Proposed Approaches

Before closing this section, two high-level use-cases are presented to demonstrate how these novel solutions can help in realizing network applications in 5G and beyond era.

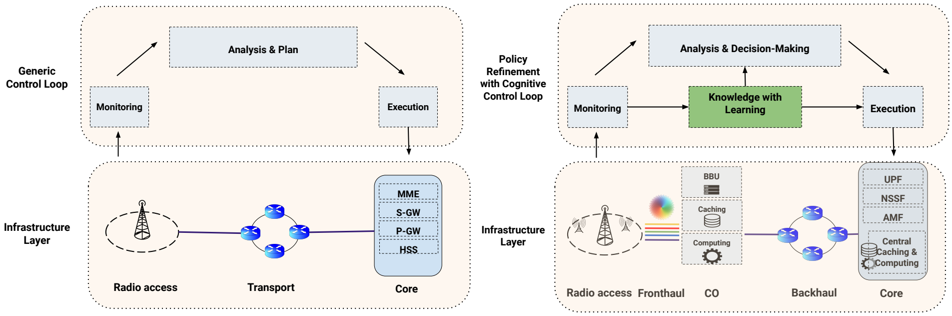
Smart Home Application

A high-level approach to form a network slice for a smart home application is presented in [J2]. For a beyond 5G community, radio resources are made available by small cells, while storage and processing resources are provided by a MEC. The envisioned flexible infrastructure layer for a smart home application shortens the bit pipe bringing the access point closer to the user or by directing the data traffic between users via device-to-device communication. Self-organization of device layer parameters (transmission power, sub-carrier spacing, etc.) deals with the trade-off between energy efficiency and spectral efficiency. Moreover, integration of MEC to this architecture enables applications running at the edge with low latency, and at the same time reduces backhaul and core traffic of the network. Pushing the on-demand service close to the last mile requires SDN control over the content layer instead of the switch-based topology of current control systems, bringing the idea of merging information-centric networking (ICN) with SDN. The ICN paradigm offers a new distribution method in networks by decoupling information and location with named data objects that correspond to the role of IP in the traditional network [89]. When ICN and SDN concepts are merged, SDN controllers should detect ICN requests and reroute the traffic for ICN request-response pairs instead of finding IP servers. ICN domain creates a form of smart traffic, in which closer communication between the demanding user and the content provider can be established with offloading, and the traffic can be cached closer to demand so that the user is not obliged to go through the content servers.

Smart City Application

A smart city platform is presented in [C2]. The platform is a multi-agent system based service-oriented middleware, on which IoT services operate their tasks. The interaction between IoT services and network devices are managed through a network layer, which is composed of three essential blocks: network management application (NMA), network agent, and OpenStack tools. The NMA provides a generic concept to orchestrate the underlying network resources. The NMA orchestrator is responsible for network resource distribution in the smart city network. It also optimizes resource management by using Network Analyzer, Network Monitoring with OpenStack Ceilometer, and Strategy Planner components. Infrastructure manager allocates nodes and links in the physical network to network slices, VNF servers and Fog servers. VNFs are deployed to requested nodes by using OpenStack Tacker. When a VNF server is deployed, then this server is added to the VNF Server Catalog so that smart city services can decide whether to add them to their network slices. Network agents establish a bi-directional communication between service-layer and network layer. Each smart city service can communicate with network agents to manage their network slices.

Forming a new network slice with a specific QoS class, the measurement of users' quality of experience, and the direct interaction with NMA to obtain the



(a) Generic control loop (b) Cognitive control loop

Figure 2.4: A generic control loop and a cognitive control loop example for mobile networks [J1]

available network resources are all carried out through agents. The interaction flow of these components from network slice request to its optimization can be explained as follows: Each smart city service requests a network slice with a QoS class (excellent, good, fair) based on some parameters such as bandwidth, latency, and price. Smart city service also sends its VNF and Fog server requests. The extracted values from the requested QoS class are then shared with the NMA. NMA first searches for suitable VNF and Fog servers with respect to the given network parameters and send a list of available servers to the smart city service agent. Service agent selects the suitable VNF and Fog servers based on its utility function, and then sends this information back to the NMA. Once the orchestrator inside the NMA gets this message, it initiates the creation of a new network slice and then binds the servers to the slice with OpenStack Tacker. OpenStack Tacker creates the network slice and establishes the data flow channels through an SDN Controller. The created network slice and the VNFs are continuously monitored by OpenStack Ceilometer.

2.2 ANM Design Goals for Beyond-5G/6G Networks

Managing the paradigm shifts listed in Section 2.1 in beyond-5G/6G networks requires an evolution towards autonomic networking. Autonomic networking targets implementing intelligent behavior in network management systems. The term is inspired by the concept of autonomic computing, presented by IBM in 2001 [90]. This section presents ANM design goals and challenges and the proposed ANM framework in [J1] that aims to respond to ANM design challenges.

2.2.1 ANM Challenges and Evolution

Beyond-5G/6G networks will differ significantly from previous standards in terms of achievable throughput, minimized delay and the massive number of devices that need to be served. As a consequence, mobile network operators are facing challenges to evolve their large scale network deployments to fulfill the foreseen requirements of beyond-5G/6G networks. One major challenge in this regard is the instatement of a self-x network management paradigm that enables autonomic behavior at all levels of the network management hierarchy, from element management level up to the business management level.

Policy-based management is one of the earliest approaches to implement autonomic behavior to network control. In 2001, IETF defined policy-based networking as a mechanism that can merge using software abstractions for network monitoring and control with programmable control for configuring and operating the network [91]. This mechanism is used to convert network management into an SLA-driven and autonomous approach by separating the network behavior governing rules from their functionality [92]. By applying the concept of policy refinement, the high-level goals of these SLAs are translated to control device level network resources. An example framework for this hierarchical translation can be seen in the policy continuum approach introduced by FOCALE project [93].

ANM evolved from policy-based network management with control loops. Autonomic networking requires control loops to monitor the network status and adapt network management by making use of observations from the monitoring stage. MAPE-K control loop proposed by IBM defines the first stage of autonomic network management with Monitor – Analyze – Plan – Execute – Knowledge stages [94]. In this proposal, it is stated that an intelligent control loop is formed when the stages of "information collection from the system", "analysis of information to decide for changes in the system", and "creation of a plan for a sequence of actions" are automated. The use of policies allows high level expression of business goals independently from network element level control and configuration. The layers are connected by the policy refinement stage, in which a control loop autonomously enforces adaptivity of the network to the changing environment by translating policy goals into conflict-free local network control functions, in line with the ANM design goal of closing the gap between business and network layers with mechanisms that convert business level policies to concrete actions on different network elements.

The network paradigm shift with SDN, NFV, and network slicing is expected to divide mobile networks into chains of high-level services using functionalities provided by lower-levels network services, with each layer managed by the respective service provider. In addition to the flexibility enabled by these technologies, the increase in the complexity of the networks require a novel approach to policy refinement in ANM that overcomes the functional rigidity, avoiding simple rule-based solutions and a single management layer that controls all network entities.

Another challenge of ANM is to create the right abstraction layer that fits the network environment and different network stakeholders [J1].

In addition to the intelligent control loop proposed with MAPE-K, control loops are required to be enhanced for beyond-5G networks so that they respond to the problem of not being able to solve issues that are not defined by an existing policy. Cognitive modeling is a promising method to solve this problem. Cognitive modeling aims to simulate human problem solving skills and mental tasks in computer science area [95]. Use of cognitive modeling can enhance control loops for dynamic network management by making management processes compatible with the architectural changes in future networks and thus define the second stage in autonomic network management after MAPE-K, as visualized in Figure 2.4b. As the stages of the cognitive control loop are learning-enabled, cognitive control loops are able to anticipate the changes in a network and answer the challenge of achieving a robust adaptation mechanism.

2.2.2 Control Loop Stages

In order to extend the autonomous management framework to control network entities, the following control loop requirements must be satisfied [J1]:

- *Defining the type of data to be collected for QoS monitoring:* A reasonable method for this is to define utility functions to different stakeholders and create a decision-making logic that make use of the monitored data.
- *Defining the possible actions and control rules of the decision-making mechanism of users:* Game theory-based models are a promising alternative to concretely define these actions and control rules and to distribute these rules to different stakeholders.
- *Designing learning algorithms for decision-making and improving the QoS:* Implementing learning algorithms have the advantage of adapting or replacing the decision logic without requiring a substantial change in management design.

These three requirements can be mapped to the three main control loop stages, namely monitoring & measurement, analysis & decision-making, and learning. Before presenting the architecture of the proposed framework, these control loop stages should be explained in more detail:

- *Monitoring:* Samaan – Karmouch [39] classify monitoring methods as active vs. passive, and centralized vs. distributed. Methods with different monitoring granularity, i.e., measurement at byte, packet, flow or aggregated traffic level, different monitoring timing and and different level of monitoring programmability indicate the level of scalability and flexibility required in these systems. In order to provide useful data to the control loop, all these aspects have to be considered during the design phase of a monitoring system. With the convergence of wireless technologies, increasing number of nodes and introduction of novel applications, mobile networks demand more scalability and flexibility at all layers, and network monitoring is no exception. For this reason, the paradigm in monitoring systems shifts towards cloud-based systems, and Openstack [78] is a widespread cloud-based monitoring service.

- *Analysis and decision-making:* This stage aims to adapt the network environment by making use of the observations obtained by monitoring the network status. The possible actions and control rules of the decision-making mechanism define the policy execution step in network management. Converting this mechanism from a reactive rule-based decision-making to proactive decision-making that is able to respond to previously unknown problems is one of the main targets of ANM [J1].The aim of introducing the learning step is to modify this rigid structure to proactive decision-making.

- *Learning:* The learning mechanisms are used for inference and anticipatory decision-making. Through these mechanisms, control loops are enhanced with autonomous behavior, so that they respond to the problem of not being able to solve issues that are not defined by an existing policy, bringing in the requirement for self-x characteristics. Autonomic behavior in a management system is achieved by implementing learning approaches; therefore a learning stage with AI/ML techniques is added to the control loop structure of beyond-5G/6G networks to manage the unknowns in the envisioned management framework.

2.2.3 Proposed ANM Framework

As part of the autonomic networking concept, a cognitive control loop framework is proposed in [J1] to organize control decisions and adaptation with monitoring, decision-making and learning steps at each layer. The hierarchical structure of the framework aims to provide a mechanism that concretely decomposes different network domains into functional components, and the interactions between those components and the external stakeholders should be clearly defined. In the proposed framework, the segmentation of mobile networks remains unchanged, and each domain is controlled with a separate cognitive control loop, as shown in Figure 2.5.

Another motivation in the design of this management framework hierarchy is to contain different abstraction levels of functionality. In order to achieve a framework that is agnostic to underlying heterogeneous technologies, the objective functions are distributed from global to local domain within the network. The main objective functions of mobile networks are presented in Section 2.2.4. The cognitive loop of each layer is able to interact with the other layers in the hierarchy, and global policy execution is handled at the operator layer. As adjusting each

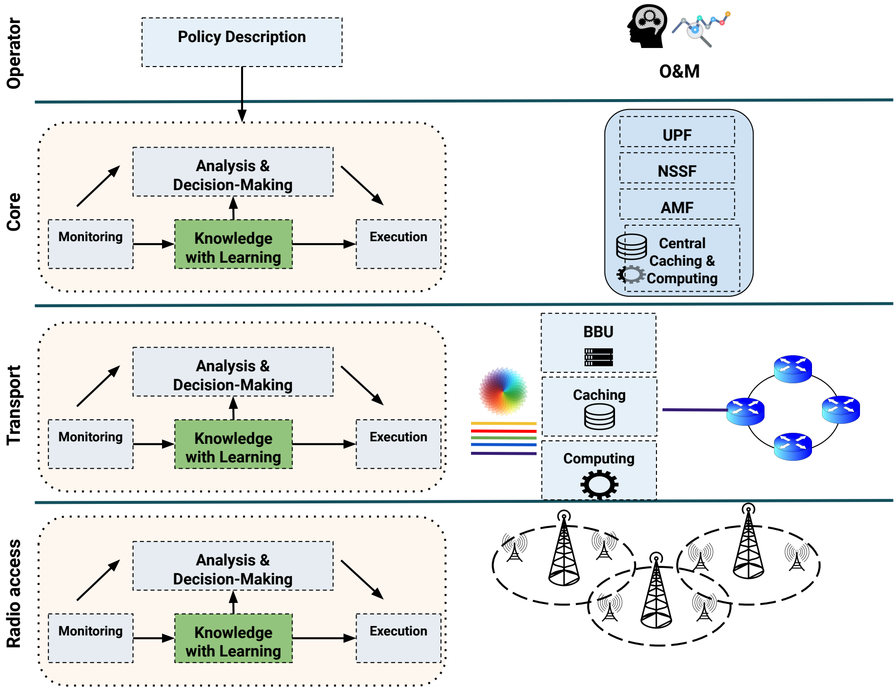


Figure 2.5: Hierarchical autonomic networking framework defined in [J1]

individual parameter from the operator level creates a scalability issue, the aim of the hierarchical framework is to avoid concrete specification of low-level behavior with an abstraction based on sending key aggregate values to upper layers. Learning based on aggregate values at higher layers can speed up predictions for future network states and replace rule based policies to reduce complexity.

The objective functions of external stakeholders such as users and service providers are independent from the framework, creating a distributed learning framework with self-evolving characteristics. To give an example, the objective functions of network and external stakeholders can be mapped to the proposed ANM framework as follows: Global policies of reducing operational costs of a service and increasing the satisfied users are defined in the operator layer. The management of the aggregated flows of service users, the required core network functionalities, and sparing core and transport network resources for this service without affecting other services are the issues to be planned at the cluster layer. The local objective functions of load balancing, congestion avoidance, call admission control, handover optimization, and link adaptation come into play at the radio layer. To optimize these objective functions, learning algorithms are implemented at radio, transport and core layers that adjust the controlling parameters, and control each network element to effectively manage end-to-end QoS. The users can define their own objectives such as throughput maximization to experience the best possible service, and optimizing the mean opinion score (MOS), which is a direct indicator of the overall satisfaction of the users. The functionalities at each layer and the interactions between them should be clearly defined in order to provide concrete management solutions to network operations.

2.2.4 Mobile Network Objective Functions

Before closing this section, the main network management objective functions that can exploit this ANM framework in different network domains and use cases are presented.

Load Balancing

Load balancing encompasses the approaches that address system overload issues when exposed to increasing requests and demand. Load balancing solutions are typically designed in such a way that system components under load can horizontally be scaled by instantiating additional resources and distributing load inside the resource pool. Load balancing is therefore a common local objective function in most network domains, i.e., radio, transport, and core networks, both in data and control layers. The load balancing solution approach influences the selection of monitoring points in the system. After capturing the required information via monitoring, this information is processed by the learning approaches.

In dense mmWave networks, the high density of users may lead to load balancing issues for RU, DU, and CU, especially if one of the units forms a bottleneck with one-to-many connections. If the density of users in a zone is very high and all the antennas in the zone are connected to a single BBU, the load on the BBU will become very high [96]. Load distributions also show a different pattern in mmWave networks, as obstacles that cause blocking in a region lead to different loads due to mmWave propagation characteristics [97].

Handover Optimization

Network management is supposed to cope with dynamics in access and user layers, which often include user mobility and resource relocation among others. The transfer of state information from one component to the next due to changes in locations or outcomes of load balancing decision is called a handover, and the mechanisms that aim to ensure QoS of mobile users by providing session and call continuity are grouped under the handover optimization objective function.

Creating an autonomous handover optimization framework at the network edge is required to make the best use of the capacity enhancement provided by mmWave deployments. As adjusting each parameter in a centralized way creates a scalability issue, in this optimization framework, each stakeholder takes part in management decisions with their learning rules created according to their informational and computational requirements.

Route Optimization

Route optimization deals with solution approaches that implement efficient routing in the core and transport network topology for avoiding congestion and meeting application QoS requirements. The main route management issues arise in guaranteeing fair allocation of network resources to services in order to meet their QoS requirements defined in SLAs. For example, in an overloaded network traffic situation, when less capacity is allocated to a service than indicated in certain SLA, punishment mechanisms may discourage resource under-allocation between the infrastructure provider and service provider. However, from service provider's perspective, compensation is not as important as guaranteed network performance. Autonomic management approaches resolve those issues by dynamically reconfiguring the virtual network topology, taking into account current and future service demands.

Resource Sharing

This is the local objective function that deals with approaches for network resource sharing, which may belong to any network segment of the end-to-end network stretch, e.g., resources at core, transport, and radio. The measurements and control parameters are specific to the implemented resource sharing approach and the resource allocation SLA agreement between the infrastructure provider and the service provider. Radio resource sharing has the potential to increase capacity in future networks without any infrastructural expenditures, as in the case of using millimeter wave for data transmission. As this objective function is also considered as a capacity enhancement technique for mmWave networks, the details of relevant use cases are presented under the title spectrum sharing in Section 3.1.4.

Link Adaptation

Link adaptation is a local objective function that adapts the links of end-to-end data transmission partially in network domains or completely with a global network view to optimize resource utilization. Selecting modulation schemes, frequencies, waveforms, or beam direction are all covered by link adaptation functions. Interference mitigation techniques can also become part of link adaptation by using frequency assignment and power control schemes.

For future networks, maintaining a seamless and robust connection for users with link adaptation is likely to be more challenging. Firstly, introduction of millimeter wave bands to mobile networks brings more dynamic channel conditions. In future networks, mmWave transmissions require pencil beam transmission channels created by beamforming with multiple antennas [23]. To overcome propagation issues, learning methods can be used for link adaptation on the base station side by adjusting the angles of the base station on a per user basis to form optimal beamwidth and optimize signal to interference plus noise ratio (SINR) of pencil-beam channels. Autonomic reconfiguration of modulation parameters according to different network scenarios is likely to be part of link adaptation in future self-organizing network management systems. Instead of a single pre-defined sub-carrier spacing with a single numerology like LTE, a tilting concept that adjusts radio frames based on user specific subcarrier spacing schemes, frame design and adjustable TTI length for different network scenarios is proposed in [98].

With 5G NR, service specific objectives can be achieved by adapting transmission parameters thanks to key link adaptation technologies such as flexible numerology [99]. The choice of the appropriate numerology can be made with ML frameworks, according to energy requirements of a mMTC service, whereas URLLC services are given priority with innovative puncturing techniques [100]. 5G NR also has a new frame structure in which a subframe is formed by adjacent slots with 7 or 14 OFDM symbols. OFDM symbols can be assigned as flexible, and then can be adapted for both downlink and uplink transmissions.

2.3 Game Theory-based Learning

As mentioned several times throughout this dissertation, creating a decision-making structure in which multiple stakeholders can interact is one of the most important design goals of ANM. Game theoretic models are an alternative to define the network stakeholder interaction as game theory provides methods to define a group of rational players, who make decisions strategically and the interactions among this group [101], and the concepts used in this explanation are defined as follows:

- *Group* defines the set of players in any game, in which each player is considered as a decision-maker.
- *Interaction* among players directly affects other players, and the action of any one individual player affects at least one other player in the *group*.
- *Strategic* decisions are taken when an individual player is able to learn the environment and the interdependence to actions of other players when deciding for her action.
- *Rational* choices are made when each player in the group chooses her best action by taking this interdependence into consideration. The best action of a decision-maker is at least as good as every other available action.

A strategic game therefore consists of a set of players $N = \{1, \ldots, n\}$, a set of actions a_i for each player i, and preferences u over the set of action profiles a for each player [102]. John Nash introduces the solution concept of equilibrium to game theory in [103]. A strategic game has a Nash equilibrium for the action profile $a*$, if no player i can do better by choosing an action different from $a*_i$, given that every other player j chooses $a*_j$. If a player attains a probability distribution over her set of actions, this is defined as a mixed strategy, whereas assigning a probability of 1 to a single action is called a pure strategy. A game can have a single Nash equlilbrium, many Nash equilibria or no Nash equilibrium for pure strategies, depending on the game type.

In strategic games, the players choose their action simultaneously and the event occurs only once. To examine the effect of past behaviour of other players, repeated games are considered [101]. In finitely repeated games, a strategic game is repeated t times, therefore the effect of cooperation or learning can be observed in such games. The behavior of network stakeholders can be defined in several different game models, such as auctions, coalition formation games, evolutionary games to observe population dynamics, or Stackelberg games where follower acts sequentially after the leader's action. Several examples of these game theoretic models are provided in Section 2.3.1. Player behavior may change based on the type of game that they are playing with other players (cooperation game, non-cooperative game, evolutionary game, etc.).

Learning in games is studied in the literature as the concept of equilibrium brings to question of how the players in a game can reach an equilibrium state. Learning model in a game is defined by Fudenberg and Levine [104] as any model that defines the learning rules of players and studies the interaction when the game is played in a repeated fashion. In order to consider game theory-based learning, the game should be repeated so that the players can learn by making observations from the history of the game and updating their knowledge in a distributed way.

For learning in games, three dynamic adjustment processes have received the most attention, namely best response dynamics, fictitious play, and replicator dynamics [104]. Best response dynamics occur if the player plays her best response to the other players' actions in the previous period [102]. The game converges to a pure Nash equilibrium if an action profile remains the same from period to period. In best response dynamics, the players' actions change from period to period and each player believes that other players' actions are pure strategies. In fictitious play, players think they are facing a distribution of opponents strategies as realization of a mixed strategy, and they consider actions in all the previous periods when forming a belief about their opponents' strategies.

Replicator dynamics is considered mostly in population games, in which a strategy is used by a higher proportion of the population if the current payoff of the strategy is higher than other available strategies [104]. Players take part in an evolutionary game and they are able to imitate other players' strategies with replicator dynamics to maximize their payoffs. A strategy is called an evolutionarily stable strategy, if the equilibrium is able to "repel invaders", meaning that any small group of invaders using another strategy will eventually die off over multiple generations. An evolutionarily stable strategy is a refinement of Nash equilibrium.

2.3.1 Network Stakeholder Interaction Modeling with Games

This section presents the existing game theory-based approaches in for multi-party decision making. The categorization for network stakeholder interaction in [105] is used as an example for this section.

Network vs. Network Interactions

Table 2.2: Mobile network games between network components

Ref.	**Stakeholder Interaction**	**Game Model**	**Objective**
[106]	AP vs. AP	Coalition Formation Game	Computational Resource Allocation
[107]	AP vs. AP	Non-cooperative game	Frequency assignment
[108]	AP vs. AP	Network Formation Game	Energy Efficient Route Optimization
[109]	AP vs. AP	Non-Cooperative Symmetric Game	Energy Efficient Mobility Management
[110]	ONU vs. ONU (Transport)	Bidding Game	Load Balancing and Bandwidth Allocation
[111]	Controller vs. Controller	Trial and Error Learning	Route Optimization
[112]	Radio Domain vs. Transport Domain	Replicator Dynamics	Backhaul Resource Allocation
[113]	Network Operator vs. Network Operator	Multi-leader and Follower Game	Network Selection
[114]	Network Operator vs. Network Operator	Cooperative Game	Handover Minimization & Load Balancing

Network vs. network games can define the hierarchical structure and the inter-domain interactions inside the ANM framework proposed in Section 2.2.3. For example, radio network and transport network inter-domain interactions are defined with a game in [112], in which resource allocation is optimized with replicator dynamics. On the other hand, network operators that serve users in the same region can define the interactions between them in a game model to compete in providing network resources to the users [113], or to cooperate to minimize handovers and balance the load [114].

As seen from Table 2.2, the increase in the number of network nodes with dense deployments make centralized optimization challenging and game-based distributed decision-making among the AP nodes are used to achieve different objectives with inner-domain interactions. Depending on the use case, both cooperative and non-cooperative games are studied among small cells [106]–[109]. As the supporting transport nodes also increase to provide the required bandwidth to dense networks, bandwidth allocation and load balancing games are proposed for the optical network units (ONUs) in the transport domain [110] for efficient resource allocation. For the core network domain with distributed network controllers, route optimization games are introduced between these network controllers [111]. In Chapter 4, a cooperative game among RRHs is introduced to solve a fronthaul bandwidth allocation problem with a bankruptcy game.

External Stakeholder vs. Network Interactions

Table 2.3: Mobile network games between external stakeholders and network components

Ref.	Stakeholder Interaction	Game Model	Objective
[115]	User vs. Network	Non-Cooperative Strategic Game	Handover Optimization
[116]	User vs. Network	Non-cooperative Game	Power Control with Price Setting
[117]	User vs. Network	Non-cooperative Game	Transmission Power Allocation
[118]	User vs. Network	Stackelberg Game	Bandwidth Allocation
[119]	User vs. Network	Two sequential non-cooperative games	Bandwidth Allocation
[120]	Service vs. Network	Hierarchical Game	Virtual Resource Allocation
[121]	Service vs. Network	Stackelberg game	Price-based Resource Optimization

The games between users and networks are used to optimize different mobile network objective functions, such as handover optimization [115], link adaptation [116], [117], and bandwidth allocation [118]. Most games are designed as non-cooperative games, in which users aim to maximize their own utility function and networks optimize resource allocation or their profit by setting prices based on observing user's behavior in the game. The virtualization of networks and network slicing concepts introduce novel games to network managment, such as the games between service providers and network operators, which are also defined as infrastructure providers depending on the use case. Hierarchical games are preferred between services and networks in [120], [121], in which networks and services make decisions sequentially. In [120], physical resources of small cells are virtualized to provide customized service to virtual resource requesters on a price-based mechanism. A similar price adjustment mechanism is used in a Stackelberg game in [121] to lease MEC computing resources of a virtualized network. The network acts as the data center operator that sets the prices and services are the followers that compete to obtain computing resources.

External Stakeholder vs. External Stakeholder Interactions

Table 2.4: Mobile network games between external stakeholders

Ref.	Stakeholder Interaction	Game Model	Objective
[122]	Service vs. Service	Non-cooperative Game	Resource Allocation
[87]	Service vs. Service	Vickrey-Dutch Auction	Path Allocation
[88]	Service vs. Service	Fisher Market Model	Resource Sharing
[87]	Service vs. User	Matching Game	Path Allocation
[123]	Service vs. User	Stackelberg Game	Bandwidth Allocation
[124]	Service vs. User	Stackelberg Game	Pricing
[124]	User vs. User	Replicator Dynamics	Path Allocation
[125]	User vs. User	Vickrey-Clarke-Groves Auction	Bandwidth Allocation
[126]	User vs. User	Cooperative Bargaining	Bandwidth Allocation
[127]	User vs. User	Non-cooperative Poisson Game	Spectrum Sharing
[128]	User vs. User	Non-cooperative Game	Cloud Resource Allocation

Allocating network resources in a distributed fashion with games that define the interaction between external stakeholders is a common method game theory-based network management researches. Users or services that demand resources from the network have their own utility functions that take into consideration the QoS requirements and the cost of leasing or allocating the network resources. In user vs. user games, selfish users can be modelled in non-cooperative games in which users optimize their utility function, i.e., minimize their cost for bandwidth allocation or maximize their throughput in spectrum sharing scenarios [127] while competing with other network users. Alternatively, cooperative games are modelled between users in which excess resources are distributed to other users [126]. Besides, users a of network can be modelled inside a population game, and users in a population imitate evolutionary stable strategy of the population with replicator dynamics [124]. Finally, in virtualized networks, computational resources are allocated with non-cooperative games between users, in which users decide to rent MEC services based on a pricing strategy [128].

Game theory-based resource allocation in virtualized networks and network slicing concept convert service providers into active decision-makers with dynamic resource provisioning. Network operators can use auctioning or different market models as games that lease network resources to external stakeholders. Applying Vickrey-Clarke-Groves (VCG) auctioning for leasing provides a social-welfare maximizing outcome for resource allocation among self-interested players; therefore it is used both for modeling service vs. service [87] and user vs. user [127] games. Alternatively, Fisher market model is used in [88] to increase network slice utility and provide isolation between network slices. Games between services and users are also found in the literature, examples can be found in [123] and [124]. In these papers, service vs. user games are interlinked with games among services for pricing as a second step of resource optimization. In [87], users have the option to choose the service that they expect to bring the highest utility after services form their network slices with auctioning. In Chapter 5, an auctioning game is presented to distribute fronthaul resources by distributing decision-making among external stakeholders, namely service providers and users.

2.4 Summary

Network capacity enhancement solutions and the remarkable shift towards reconfigurable network management architectures are expected to become two pillars of beyond-5G/6G networks. For this reason, an important step towards designing future networks is to discuss the relations between technological enablers of autonomic reconfiguration techniques and management issues of beyond-5G/6G networks. As a consequence, this chapter aims to provide answers to the following research questions:

What are the enabling concepts of autonomic network management? What are the challenges ahead for achieving the technology agnostic autonomic network management framework? What are the design goals of ANM for converged optical and mmWave radio networks? How should an ANM architecture be defined to implement learning capabilities for network management and enable network stakeholder interaction in a concrete structure?

The chapter first describes the driving factors that lead to radical breakthroughs from existing management approaches towards software-centric solutions in the 5G era, and shows conceptual examples of how these solutions can be applied to novel network applications. Policy-making with specific network parameter configurations with SON, controlling the network with a globally centralized logical view and enforcing new policies with applications over SDN, and the integration of NFV to abstract network policy implementation replace the existing hardware-centric management in previous generations. Network slicing exploits all these technological developments to replace static resource partitioning and offer a dynamic service-centric management framework that enables decision-making with the interrelation of stakeholders. To sum up, an ANM framework should be able to handle the flexibility enabled by these technologies, allow autonomic behavior of stakeholders and network domains, and provide policy refinement options to overcome the functional rigidity.

The evolution of network management approaches from a simple management layer to policy based approaches with self-x network management requires device layer abstraction, learning mechanisms to analyze network behavior, and programmability to dynamically respond to changes. Having identified the challenges of creating such a mechanism, an ANM Framework that is based on cognitive control loops is presented in this chapter. Monitoring and measurement, analysis and decision-making, and learning are introduced as cognitive control loop stages of this framework. Through this framework, mobile networks are divided into chains of high-level services and network domains, with each network managed by the respective cognitive control loop, and services implement their own decision logic independently. The functionalities at each layer and the interactions between them should be clearly defined in order to provide concrete management solutions to network operations. Finally, network management objective functions are briefly described to explain why these functions require an ANM based approach. However, it should be stated that most of the network management problems are interrelated and conflicts occur if one of the problems are singled out without defining network optimization inside a structured framework.

The final section presents the existing game theory-based approaches for multi-party decision making with common or conflicting interests. The existing researches are classified based on the stakeholder interaction that they model in the game. The state-of-the-art shows that game theory is a viable approach for stakeholder interaction definition for network performance optimization in terms of utility function maximization and is widely used to deliver network policy making mechanisms in a distributed way. Furthermore, it can be seen that the impact of virtualization, increasing number of nodes in the network, and the architectural changes in network domains are reflected in recent network game research. In conclusion, game theory-based learning approaches are implemented as part of this study to involve multiple network stakeholders in decision-making and to maximize their utilities.

CHAPTER 3

Resource Management in Converged Optical and mmWave Radio Networks

The key objective of this chapter is to reveal how the use of mmWave spectrum bands and the supplementary capacity enhancement techniques have changed the 5G network architecture and the resource management targets. The first section examines 5G capacity enhancement techniques and the resource management issues that they introduce. Then, the following section provides a state-of-the-art on the 5G resource management solutions for converged optical and mmWave radio networks, classified under throughput optimization, delay minimization, energy-efficiency, and virtual resource allocation targets. The outcomes of this review are used to select the utility function parameters, the learning algorithms, and the game models presented in Chapter 4 and Chapter 5.

3.1 Converged Optical and mmWave Radio Networks

The expected increase in the performance indicators such as data volume per area, number of devices, and user experienced data rates determined the targets of 5G initiatives and organizations in years 2014 and 2015, as seen in Table 3.1. These targets are directly translated into the need for a substantial increase in capacity for 5G networks. The wireless network capacity of a single cell is found by multiplying the spectral efficiency and the spectrum used by the AP [129]. The wireless network capacity in a coverage area is then proportional to the multiplication of the capacity of a single AP to the number of total cells in the area. The capacity can therefore be increased either by utilizing more spectrum bands, by deploying technologies to increase the spectral efficiency (bps/Hz) or by increasing the number of APs in the coverage area.

Table 3.1: 5G targets of 5G initiatives and companies for several performance indicators between 2014 and 2015

5G Initiative or Company	**Data Volume per Area**	**Number of Connected Devices**	**Data Rate**
NGMN [130]	1000x LTE	2000 users per km^2 200000 M2M connections per km^2	Peak: 1 Gbps
5GPPP [7]	1000x LTE	1000x LTE	Guaranteed: 50 Mbps Peak: 10 Gbps
DOCOMO [131]	1000x LTE per km^2	100x LTE	Peak: 1 Gbps
ITU-R / IMT-2020 [132]	10 Tbps per km^2	1 million per km^2	User Experienced: 1 Gbps Peak: 10 Gbps
SAMSUNG [133]	-	1 million per km^2	Peak: 6 Gbps
NOKIA [134]	1000x LTE	10 to 100x	Guaranteed: 100 Mbps Peak: 10 Gbps

Capacity enhancement techniques for 5G networks do not exclude each other. On the contrary, dense deployments and use of massive MIMO are considered as pre-requisites to wide range use of mmWave radio networks due to the characteristics of mmWave. Furthermore, the transport network implementations have to respond to the capacity expansion at the radio network, with fiber transport network solutions expected to provide feasible data rates [36]. Thus, many 5G resource management solutions aim to implement multiple capacity enhancement techniques inside a converged optical and mmWave radio network architecture. Use of mmWave spectrum bands, network densification, massive MIMO, resource sharing, and fiber-wireless integration are presented as the promising capacity enhancement options in the following subsections.

3.1.1 Utilizing mmWave Bands for Radio Access Networks

An essential source for capacity enhancement is the use of mmWave frequency bands in cellular communication, especially for use cases with challenging capacity demands, reflected in Table 3.1 for 5G and demonstrated in Figure 1.2 for beyond-5G/6G. Despite the fact that the channel propagation challenges at mmWave frequencies require fundamental changes in the network architecture, mmWave propagation models are investigated both for outdoor urban street scenarios such as V2I connections [135], and indoor scenarios such as smart factories [136]. This is obviously due to the fact that mmWave bands offer huge spectrum bands between 20 GHz and 90 GHz, as shown in Figure 3.1. Data rates are expected to scale with the increased utilization of the available mmWave spectrum bands [137],

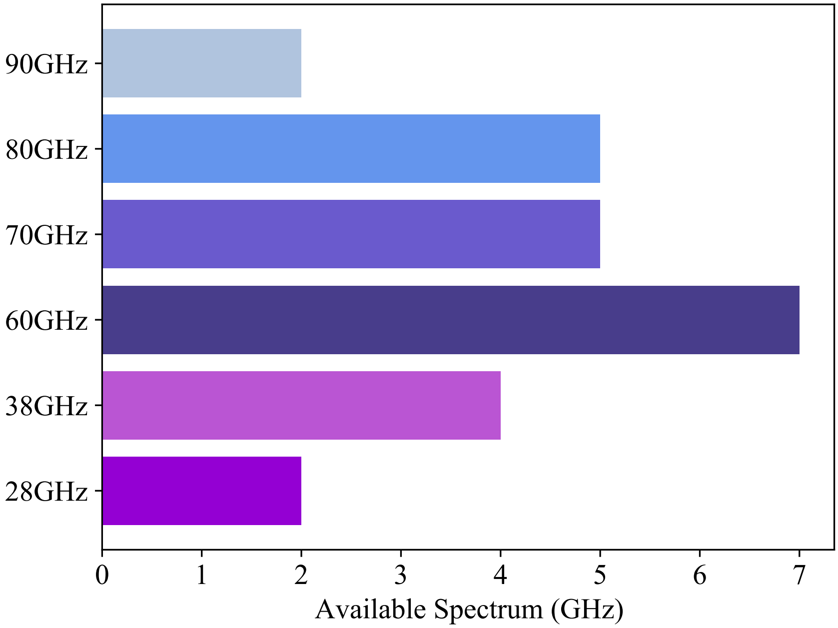


Figure 3.1: Available spectrum in mmWave bands between 20 GHz and 90 GHz [20]

and providing dense deployments and massive MIMO as technological enablers to overcome the challenges of the propagation characteristics.

The channel characteristics and the existence of line-of-sight (LOS) path between the antennas play a more important role in mmWave radio networks than the legacy cellular networks at lower frequencies due to the path loss, signal penetration and reflection of the signals at mmWave frequencies. Friis transmission equation [138] in Eq. (3.1) shows that the free space path loss increases with the square of the transmission frequency, and it can only be compensated by the increase in the transmit power or antenna gains. Besides that, in mmWave frequencies, natural changes such as rain attenuation and oxygen absorption [139], and blockage from dynamic obstacles impact the path loss and limit the communication distance. The path loss exponents at mmWave transmisison frequencies and the impact of rain attenuation and oxygen absorption at 200 m are listed in Table 3.2.

$$\frac{P_{\mathrm{RX}}}{P_{\mathrm{TX}}} = G_{\mathrm{TX}} G_{\mathrm{RX}} \left(\frac{c}{4\pi f_c R} \right)^2 \tag{3.1}$$

Channel measurements are carried out to analyze whether these unfavourable characteristics can be overcome by the increases in antenna gain and by adjusting the transmitter – receive distance. The path loss measurements at 28 GHz and 73 GHz in [30] show that the omnidirectional path loss is approximately 20 dB to 25 dB higher in mmWave when compared to 700 MHz-2.6 GHz bands; however, this path loss can be compensated by increases in antenna gain, and a hypothetical 1 GHz bandwidth mmWave system with a 100 m cell radius can provide 25 times greater cell throughput than an LTE system, when the users are able to receive multiple antenna transmissions. Another measurement at 28 GHz [26] demonstrates that inside a coverage area of 200 meters, atmospheric absorption does not create additional path loss. 73 GHz bands indicate comparable path loss behavior with 28 GHz bands when directional and high-gain antenna arrays are used, according to [32]. Based on the path loss measurements in [140], operational ranges of 200 and 100 meters can be maintained in LOS worst case for 35 and 60 GHz, respectively.

Table 3.2: The propagation characteristics of mmWave spectrum bands [25]

Frequency Band (GHz)	**Path Loss Exponent**		**Rain attenuation (@200m)**		**Oxygen absorption (@200m)**
	LOS	NLOS	5 mm/h(dB)	25 mm/h(dB)	(dB)
28	1.8-1.9	4.5-4.6	0.18	0.9	0.04
38	1.9-2.0	2.7-3.8	0.26	1.4	0.03
60	2.23	4.19	0.44	2	3.2
73	2	2.45-2.69	0.6	2.4	0.09

Contrary to the legacy cellular networks, penetration losses that occur due to buildings also pose a threat to mmWave radio network communications [141]. The effect of penetration losses at 28 Ghz are observed in [26], and the results show that building penetration provides high isolation between outdoor and indoor networks. The inability of penetration of mmWave signals from outdoor to indoor requires additional network solutions such as relaying or finding alternative directed spatial channels to extend coverage to all users. Dynamic obstacles such as blockage by a human [142] also impacts the mmWave communications negatively, therefore finding alternative directed spatial channels in case of blockage as quick as possible and with minimum overhead in a proactive way is a challenging mmWave network management problem [23]. Finally, with beamforming and directivity of transmission signals, the negative impact of interference can be mitigated, but still has to be considered for dense network scenarios when many LOS users are connected to a single AP or when APs have significant LOS coverage overlaps [140].

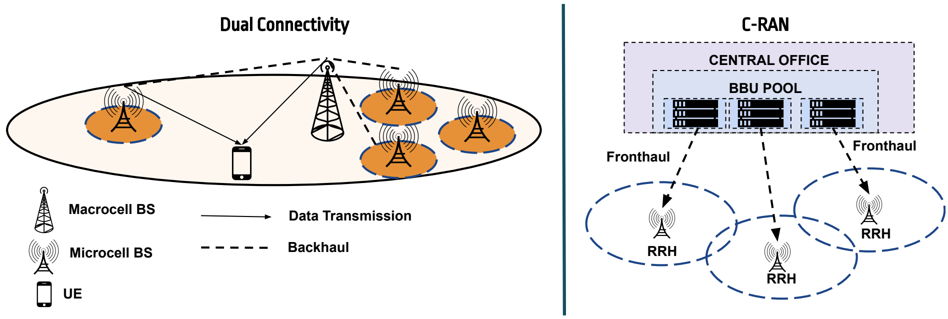


Figure 3.2: Dense radio access network architecture options

3.1.2 Dense Radio Access Network Deployments

Network densification enhances spatial reuse in a certain area with macrocell-microcell heterogeneous networks (HetNets) and or small cell only deployments, and is the key enabler for capacity gains in future networks [143]. Spatial reuse has a theoretical limit of a single access point serving a single user, until that point new access points can be introduced for densification. Small cell densification also brings access points closer to the user, thus improves channel propagation conditions [144]. UDN is therefore an attractive technology to boost the capacity in a coverage area. Utilizing higher frequency spectrum bands for capacity gains in future wireless network systems also drives toward the use of more small cells, as the propagation characteristics of millimeter-wave signals lead to higher attenuation and reduced coverage area, requiring the deployment of more access points. As a consequence, small cells and their challenges have a significant impact on mmWave radio networks.

It is obvious that dense deployments create new challenges to network management. The complexity of the architecture with increasing number of nodes, massive data generation, and dynamic topology changes in future dense networks require quicker network reconfiguration. Handovers occur more frequently due to small cell radius and increased traffic has to be handled via novel solutions for the transport network [143]. Finally, the rise in the number of network nodes is going to increase energy consumption in cellular networks, threatening energy-efficiency of the network if a smart network management architecture with sleep modes is not provided. To unfold the added capacity provided by UDN, end-to-end network management has to deal with increased dynamics and the unknowns in the radio access network (RAN), while at the same time guaranteeing network operation aligned with business objectives.

The data rate demands of beyond-5G networks push towards small cells from being the additional capacity providers to macro cells to ultra-dense networks, in which small cells are the main capacity providers. This transformation can be achieved with the integration of mmWave transmissions, novel adaptive waveforms and massive MIMO solutions. However, mmWave systems have a highly dynamic channel quality, and providing rapid solutions to service unavailability means an alternative path for a seamless connection is required for mmWave cells to meet the ultra-low latency target of 5G networks [145]. Macro cells are highlighted as anchor points that provide an alternative data path to overcome the fluctuating channel characteristic of mmWave cells [146]. Regarding the role of macro cell and small cells in dense networks, when mmWave networks encounter no channel quality problems, splitting control decisions and data forwarding issues between macro cells and small cells is considered for more efficient data transmission.

With dual-connectivity, loss of quality in a link can be solved by switching to macrocell overlay when mmWave cells are in an outage, a handover from a mmWave cell to another mmWave, or by changing the steering direction for transmission without changing the serving mmWave cell. In [145]–[147], a dual-connectivity framework for adapting beams in a mmWave network is explained. The framework uses periodic measurement reports to track the channel quality and steering directions for data transmission. Due to the highly directional transmissions in mmWave, mmWave cells and UEs will utilize directional phase arrays. This brings the requirement to track each direction between the UE and mmWave small cell, and then to decide for one of the transmission directions. A control loop needs to monitor the received signal strength (RSS) on each possible direction for possible links and build report tables based on channel quality in the beam acquisition phase. Both users and base stations in the Non-Standalone (NSA) architecture have a predefined codebook of directions that cover the whole angular space [148], and the user selects beam with the maximum signal-to-noise ratio(SNR) above a predefined threshold during the 5G NR synchronization procedure of the downlink transmission. During the uplink transmission synchronization, each Next Generation Node Base Station (gNB) sends the information on the received beams to a central controller, which selects the best beam pair. To sum up, the optimal density for small cells, their placement into a macro cell region for dual connectivity and task division between the macro cell and small cells are the three main deployment issues for these types of networks.

C-RAN is also considered as an enabler for dense small cell deployments. C-RAN offers the following solutions to dense networks [J2]: It reduces signaling load of RRHs by support of BBU pool for spectral efficiency and the use of the BBU pool for signal processing for many small cells to reduce processing delays. With the inclusion of many access points, the complexity of the system is going to increase; therefore there will be more need for cooperation between network elements. C-RAN also enables centralized and cooperative network management solutions over a centralized controller interacting with the BBU pool. For example, a programmable fronthaul design for C-RAN can reduce the required number of BBUs when compared with traditional one-to-one RRH BBU mapping, which brings flexible one-to-many mappings between the RRHs and BBUs [64]. Regarding the energy-efficiency, circuit power consumption is reduced in C-RAN compared to the traditional RAN architectures as processing is carried to BBU data centers. Dual-connectivity and C-RAN architecture options are demonstrated in Figure 3.2.

3.1.3 Massive MIMO

Massive MIMO is defined in [149] as systems that use antenna arrays to simultaneously serve multiple users within the same time-frequency resource. Massive MIMO systems can operate with less RF power than current technology, bringing much needed energy efficiency to cellular systems. In addition, MIMO systems can be built with inexpensive, low-power components. These systems are more robust than traditional systems against noise, fading, and antenna failures as signals from a large number of antennas are added up constructively at the locations of the intended terminals, resulting in huge gains in spectral efficiency.

Propagation characteristics of mmWave bands require the use of large-scale antenna arrays; therefore MIMO can be deployed as a solution method to overcome the fragile propagation characteristics of mmWave. For this reason, signal processing issues of massive MIMO deployments with mmWave are analyzed in [140] and pilot contamination, loss of channel orthogonality and interference during simultaneous transmission to LOS users that are close to each other are considered as the main challenges. Large antenna arrays also make channel estimation a challenging problem due to large-scale fading over the array and small-scale signal statistics [149]. UDN scenarios with massive MIMO also require load information [150] that can quickly vary in use cases with high-mobility, in addition to challenging channel conditions.

AI-solutions with massive training data are taken into consideration to solve these problems. An example channel estimation solution for mmWave massive MIMO with deep learning that uses a large number of channel matrices as training data is provided in [151]. Authors of [43] suggest creating a generalized ML-based channel estimation scheme built over a massive amount of communication data to be able to use massive MIMO without further training as a beyond-5G/6G solution.

3.1.4 Spectrum Sharing

Network operators use licensed frequency bands to control the interference within their licensed spectrum band and ensure QoS for their users. This; however, leads to an underutilized spectrum which is undesired when the increase in the demand for capacity is considered. Spectrum sharing aims to increase spectrum utilization by allowing secondary users to use these licensed frequency bands when the band is not utilized by the owner [129].

If a spectrum band is licensed to a user but remains idle at a location for a certain amount of time, then this spectrum band is defined as a spectrum hole [152]. Cognitive radio is proposed as a method for secondary users to detect these spectrum holes and transmit data through these holes. An ideal cognitive radio is

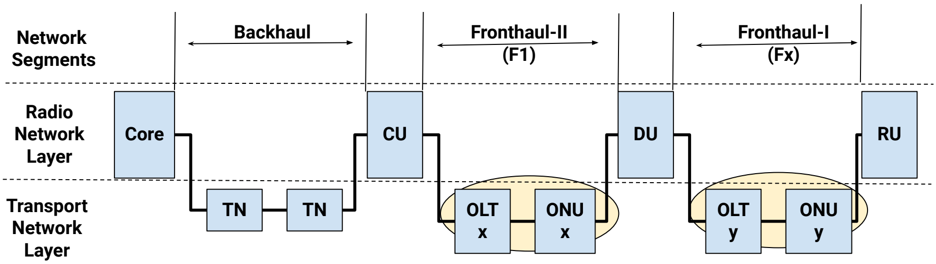


Figure 3.3: Layered 5G transport and radio network architecture with point-to-point fiber backhaul and PON fronthaul [155]

able to learn transmission power, carrier frequency and other required parameters and optimizes its performance based on these parameters by performing machine learning solutions. The detection of spectrum holes by cognitive radios is called spectrum sensing. As a result, microcells with cognitive radio capabilities can utilize the spectrum more effectively.

Coordination mechanisms are required between dense RAN elements to exchange information and share the available spectrum. Information exchange between network elements can occur by a direct communication interface in a distributed way or over a centralized element, such as the macrocell [153]. In both distributed and centralized cases, a network resource management architecture with spectrum sharing has substantial benefits to network operators. An example resource management solution is provided in [154], in which the network operators with separate RANs in the same region play a non-cooperative game (e.g., without access to other operator's spectrum information). The results obviously reveal that operators provide higher data rates under high instantaneous load or high interference with a coordination mechanism for spectrum sharing.

3.1.5 Fiber-Wireless Integration for mmWave Networks

The use of mmWave spectrum bands, network densification and the architectural changes in 5G such as CU/DU/RU wireless systems and C-RAN require higher bandwidth utilization and different architectural designs on the transport networks, as shown in Figure 3.3. Creating an efficient beyond-5G/6G transport network structure is highly dependent on capturing the key technological advancements in the optical networks that provide high-capacity solutions.

The capacity increase in the transport network mainly relies on fiber-optical communication systems. Fiber-optical systems are deployed from radio networks to the core as they offer the required bandwidth for the expected data rates with a good bit error rate performance [156], and each new generation of optical systems provide longer transmission distances between the radio network and the core with higher bit rates [157]. For the beyond-5G/6G era, photonics-assisted

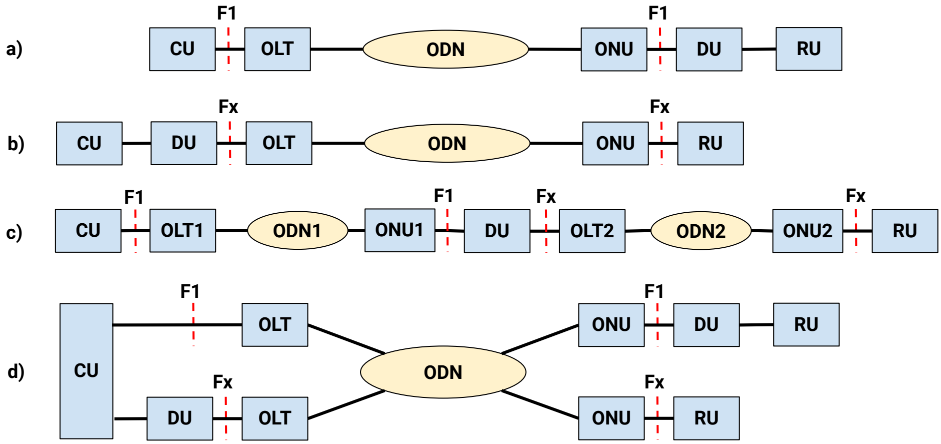


Figure 3.4: ITU-T PON fronthaul architecture options for different functional splits a)high-layer split, b) low layer split, c)cascaded split, d)parallel split [162]

mm-wave generation is expected to provide mmWave transmissions over 40 Gbps data rates [158], and ultra-Dense WDM network is another capacity enhancement solution to support dense radio networks, with dedicated wavelength-to-the-user scenarios and flexible wavelength allocation providing an aggregate bandwidth of over 100 Gbps [159].

A fiber-wireless (FiWi) network consists of the optical fronthaul and the wireless frontend, with an optical unit (ONU) connecting the wireless frontend and the backhaul [160]. Passive Optical Networks (PON) are considered as the optical backhaul for 5G mmWave wireless frontend, as it is widely deployed and its point-to-multipoint topology with an optical line terminal (OLT) at the centralized unit and ONUs as the radio network interface provides efficient use of fiber resources [155]. Different PON architectures for the fifth generation new radio (5G NR) and different functional split options are displayed in Figure 3.4. mmWave radio network supported with a PON backhaul is a commonly used system model for C-RAN architectures [110], [112], [161]. This C-RAN architecture can further be supported with analog radio-over-fiber (ARoF) as it centralizes the digital to analog and analog to digital conversion stages with analog transport of the baseband signals from BBU to the RRH [36].

Optical-wireless convergence should be inherent to network resource management decisions to provide the required bandwidth to multiple beyond-5G/6G applications [36], as an efficient resource allocation for 5G mmWave radio networks can only be achieved by joint spectral and spatial resource management approaches for optical transport networks. With the help of an SDN controller, wavelength and spatial dimension selection can be supported for WDM and SDM, respectively. In addition, optical network elements can be put to sleep modes in order to minimize overall energy consumption with network status monitoring and providing paths in a dynamic manager by using network topology information [163]. Elastic optical networking is also considered to improve fixed-grid optical networks with the adaptive modulation format use and multiplexing spectrum in a flexible frequency grid [164], and introducing SDM on multiple fiber cores or modes during the optical transmission can further expand the overall transport network capacity in a cost-effective way [165]. However, flexible control of spatial resources is also a new challenge towards optical network control in beyond-5G/6G networks, as it requires flexible switching solutions and an additional dimension of control on different network nodes and amplifiers, which should be considered in network slicing and virtualization solutions [166].

3.2 Resource Management Targets of Converged Optical and mmWave Radio Networks

Aiming to understand the relationship between resource management, virtualization, and the dense 5G fronthaul with an emphasis on converged radio and optical communication, this section presents a review of how resource management solutions have dealt with optimizing mmWave radio and optical resources from an autonomic network management perspective. The extended version of this review is published in [J3].

3.2.1 Research Method

This section introduces the method employed for finding and selecting articles to be included in the study and subsequently provides information on the data extracted from the selected articles. Before presenting the works, this subsection explains the research method of the review based on the research steps given in [167]. The selection procedure is also illustrated in Figure 3.5.

For the selection of the papers, database searches were conducted in the Association for Computing Machinery (ACM), Elsevier/Science Direct, Institute of Electrical and Electronics Engineers (IEEE), Institution of Engineering and Technology (IET), Multidisciplinary Digital Publishing Institute (MDPI), Optical Society (OSA)/Optica, Springer, Taylor & Francis, and Wiley online library databases with keywords *"resource allocation AND converged mmWave fiber wireless"*, *"resource management AND converged mmWave fiber wireless"*, and *"resource allocation AND converged fiber wireless"*. The searches in all databases were completed in May 2021. The resulting collection was screened to exclude non-scientific texts, book chapters, out of context papers, and survey papers. The full list of papers can be found in [J3].

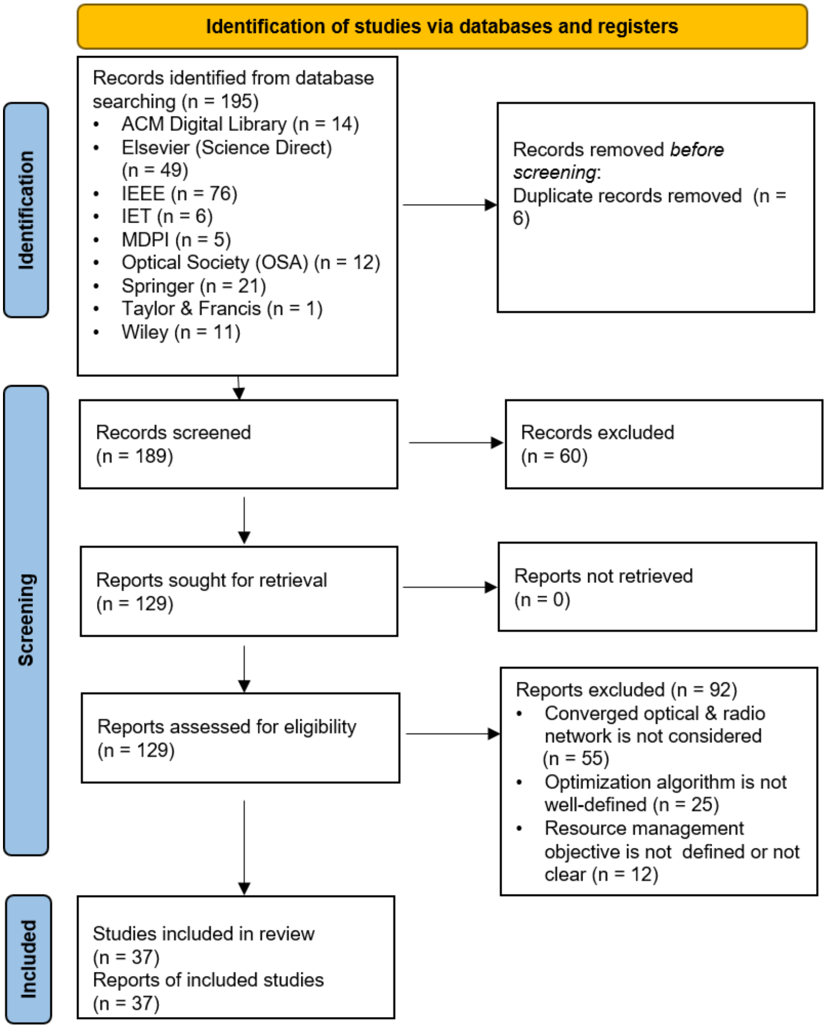


Figure 3.5: Paper selection phases of the review [J3]

Among the remaining 189 papers found in the database search, the selection criteria was created to present the works that are most relevant to the target network architecture, providing novel implementation solutions to the requirements of the optimization objective. The criteria selected for the eligibility step can be summarized as follows:

- The study provided a sound research approach and published after a scholarly review process;

- The study had a resource management optimization objective for mmWave networks;
- The study explained the system model and proposed a well-defined optimization algorithm;
- The effects of the algorithm on a performance metric was reported and the different aspects of the performance metric were analyzed with different evaluation criteria.

This review is limited to the focus scope on converged optical and mmWave radio network solutions and to the databases taken into consideration. The prioritization of the works that address a well-defined optimization algorithm led to the omission of relevant papers during the screening phase. After the screening, 37 papers are identified that focused on at least one of the resource management objectives of throughput maximization (Section 3.2.3), delay minimization (Section 3.2.4), energy-efficiency (Section 3.2.5), and virtualized resource allocation (Section 3.2.6). The papers that have joint objectives are classified under their main optimization focus of that paper. As one of the targets is to understand the recent optimization techniques used in resource allocation for converged optical fronthaul and radio mmWave access network implementations, this review focuses on the works completed in the five years between 2016 and 2021 (both included), and approximately 95 % of the selected papers fit in this category.

3.2.2 Overview of Data Collected from Selected Papers

The overview of the data collected on the current trends in the algorithms for optimizing the performance of mmWave optical and radio networks is presented to understand the key network state parameters. Performance evaluation criteria of the presented algorithms are also identified. The questions to be answered in this section can be listed as follows:

- Question 1: Which algorithms are used more often in performance optimization in converged mmWave networks?
- Question 2: Which performance metrics are determined to show that the optimization method achieves the objective?
- Question 3: Which criteria are used to evaluate the solution method?

Regarding the first question, Figure 3.6 shows the distribution of the optimization algorithms used by the selected papers. Heuristic and iterative algorithms are frequently used in the literature, due to the fact that many optimization problems in this field are non-deterministic polynomial time hard (NP-hard) and thus require decomposition and simplification to create sub-optimal solutions which can then be solved with heuristic algorithms.

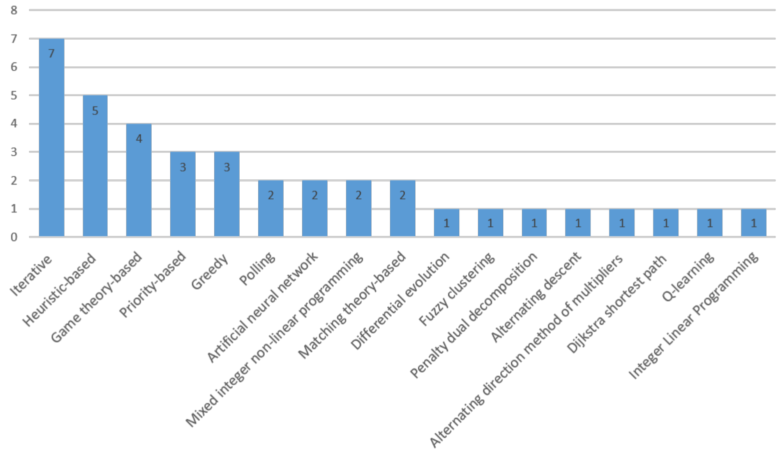


Figure 3.6: Distribution of optimization algorithms for converged optical and mmWave radio resource management

Game theory and matching theory-based solutions are also attractive for distributed decision-making among entities, as centralized optimization is challenging in multi-stakeholder environments [87], [107], [110], [112], [117], [119]. Finally, AI-based models (artificial neural network (ANN) [18], [168], Q-learning [169]) are utilized for resource management optimization problems. The distribution of the main performance metrics according to the resource optimization objectives is given in Table 3.3. In conclusion, the evaluation criteria to test the performances of the selected papers are grouped in Table 3.4, which shows how many times each criterion is used together with how many of the resource management objectives use the relevant criterion.

3.2.3 Throughput Maximization and Resource Allocation Algorithms

Higher throughput requirements of novel services defined under the eMBB category are one of the main drivers of creating resource allocation solutions with learning algorithms for throughput maximization. The learning methods for throughput optimization in mmWave radio and optical networks are presented in this section. The existing solutions to throughput maximization problems are given in Figure 3.7. The list of selected papers can be found in Table 3.5. Finally, it is discussed that the potential improvements of applying existing AI-ML solutions, which are not parts of the existing literature for converged optical and radio networks.

Table 3.3: Distribution of the main performance metrics depending on optimization objectives

Objective	Performance Metric	Total Papers
Throughput Maximization	Throughput / Sum rate (Bits/s)	7
	Spectrum efficiency (bits/s/Hz)	2
	Quality of Service (QoS)	2
	Fairness	2
	Bandwidth Utilization	1
Delay Minimization	Delay	3
	Average response time	2
	End-to-end delay	1
	Maximum delay	1
Energy Efficiency (EE)	EE gain	5
	Power consumption	3
	Achievable EE	1
	Revenue	1
Virtualized Resource Allocation	Virtual Network (VN) acceptance ratio	4
	Resource utility / pooling gain	3
	Revenue / Profit	3
	Average Operator Quality of Experience (QoE)	1

Selected Papers

Regarding the technical challenges of converged optical and mmWave radio networks, the selected papers in Table 3.5 focus on solving the beamforming optimization and interference mitigation for throughput maximization. From the ANM perspective, the selected throughput optimization algorithms reveal that both centralized and distributed management systems are used in solving dynamic bandwidth allocation (DBA) problems. However, there is a shift towards distributed throughput optimization solutions, especially with the involvement of different network stakeholders in management decisions. The integration of massive MIMO and beamforming solutions for throughput optimization in optical and mmWave radio networks lead to solving the multiple objective resource allocation algorithms joint with power allocation [161] or beam selection [170] optimization solutions. In [161], an algorithm called volume adjustable backhaul constrained water-filling dynamic programming method is developed to maximize the downlink throughput in a FiWi mmWave network. In [170], the downlink data arrival rate is maximized for a mmWave small cell C-RAN with free space optical fronthaul between RRHs and BBUs. A resource optimization solution with Lagrangian dual

Table 3.4: Distribution of evaluation criteria

Four objectives		Three objectives		Two objectives		One objective	
Number of users	10	Transmit power	4	Coverage radius	3	Antenna number	3
Traffic load	9	Delay	3	Bandwidth	3	Queue length	1
Number of APs	8	User location	3	Rate of requests	3	Operator number	1
				Requested service class	2	Channel estimation error	1
				Service number	2	Flow arrival rate	1
				Computing capacity	2	Offload probability	1
						Fairness	1
						Rate demand	1
						VN size	1

decomposition is proposed in which the sub-problems are iteratively solved with a combination of separate optical fronthaul beam selection, fronthaul link selection, access link power allocation, and UE-RRH association algorithms.

Interference reduction is a common objective for throughput maximization in mmWave networks, and ML-based beamforming is used in [171], [172] to solve the traditional interference reduction problems. A hybrid beamforming design based on joint spatial division and multiplexing and fuzzy c-means clustering is proposed in [172]. Fuzzy c-means gives membership grades to UEs so that they can belong to several clusters. Dual-connectivity with a macro cell and mmWave cells is also considered as an alternative architecture for fair scheduling in the presence of interference in [171] with approximation algorithms based on the fractional weighted vertex coloring of conflict graphs method are used for throughput optimization under mutual interference.

Different stakeholders get involved in the decision-making framework of converged optical and radio mmWave networks, such as competing network operators in [112], network services with different QoS demands in [173], and users in [174]. The interactions among these stakeholders are defined by distributed cooperative and competitive models depending on their relation. Evolutionary game theory is used to model the interactions among the BSs and the PON for DBA in [112] and BSs change their strategies based on replicator dynamics. Three algorithms are developed in [173] to assign appropriate bandwidth to each service with priority based differentiation of the QoS demands of different services. A user and network sub-channel resource allocation problem is analyzed in a joint algorithm in [174] and the interactions are defined with an optimal algorithm based on Lagrange duality and a greedy algorithm based sub-optimal solution. Distributed resource allocation methods are used not only to define the interactions between

Table 3.5: Analysis of resource allocation papers with throughput maximization objective

Ref.	Objective	Solution Method	Optimization Algorithm
[112]	optical resource allocation in two BSs from competing operators	evolutionary game theory for BS-PON interactions	BSs change strategy based on replicator dynamics
[161]	maximize the downlink throughput	power allocation & caching with mixed integer nonlinear programming	volume adjustable water filling-dynamic programming
[173]	DBA responds to service demand with fairness	different service models are created for NS3 simulations	QoS parameter tuning for services
[175]	maximize spectral efficiency	guarantees the 5G/WiFi users coexistence on 60GHz	joint beam selection and resource allocation
[176]	improve performance by distributing DBA tasks	access nodes exchange control information for DBA	interleaved polling with adaptive DBA scheme
[110]	optimal mapping of ONUs to available channels	game-based bandwidth distribution	game based stochastic DBA
[170]	maximize the downlink aggregate data arrival rate in mmWave C-RAN	joint fronthaul and access optimization solved by Lagrangian dual decomposition	iterative algorithm to determine QoS aware data arrival rate
[171]	design a scheduler to optimize backhaul efficiency	schedule-oriented optimization with matching theory	three approximation algorithms are created
[174]	maximize the weighted sum rate of all users in downlink transmission	jointly optimizing user association, RRH channel selection and power allocation	Lagrange duality-based algorithm and greedy search-based heuristic
[177]	maximizing the mmWave C-RAN fronthaul capacity	jointly optimizing UE and RRH power sharing factors	differential evolution algorithm
[172]	reduce interference to achieve data rate gains	hybrid beamforming with unsupervised ML	user selection strategy based on fuzzy clustering

the stakeholders as in [112], but also to enable information exchange at the network edge [110], [176]. In [176], a distributed control plane shifts control tasks to FiWi access nodes with interleaved polling with adaptive cycle time DBA scheme. The nodes are able to exchange control information such as queue states and transmission needs with each other. In [110], a load balancing game and a bandwidth allocation game based on a bidding system are designed to overcome the problem of mapping the channels to ONUs in a PON for different traffic scenarios.

Throughput maximization for eMBB is a two-sided problem for mmWave radio and optical networks, as priority based QoS-aware solutions are discussed [173] to realize such services with QoS guarantees, whereas minimum throughput targets for other services are also considered by applying fair scheduling [171]. Among the existing works, centralized management decisions are mainly used to respond to the throughput maximization - resource allocation fairness trade-off. The optimization

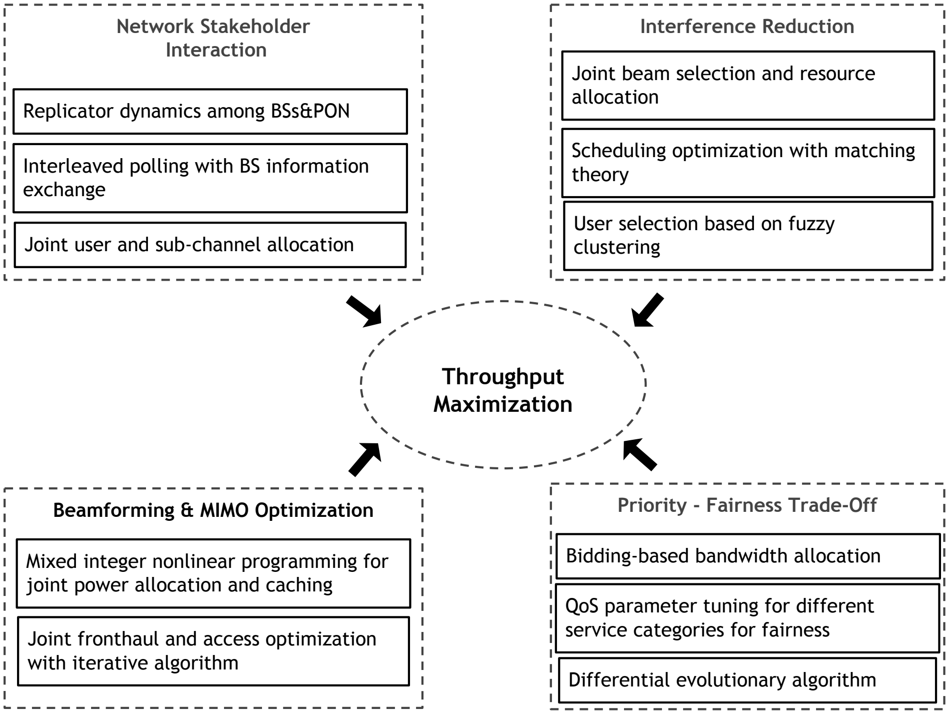


Figure 3.7: Existing resource allocation optimization solutions to throughput maximization issues

solution in [110] has a centralized regulator, as the OLT acts as the resource manager to keep optimal fairness values. Another centralized solution is provided in [177] for solving the UE-RRH and RRH-BBU uplink sum-rate optimization problem with a differential evolutionary algorithm. Apart from this general trade-off discussion, the problem of translating eMBB application specific requirements to mmWave radio and optical resource allocation is not discussed in detail in the existing scientific and technical researches.

Discussion

The increasing number of external stakeholders and the need for information exchange among the mmWave radio and optical networks are already reflected in several works [110], [112], [173], [174], [176]. Considering the expanding level of information with the increasing number of users, nodes, antennas in massive MIMO mmWave networks, distributed federated learning approaches provide a novel optimization solution on top of the existing beamforming and DBA solutions. Among the joint optimization algorithms for radio and optical access and transport resources, no federated learning models were detected. This might be due to the fact that federated learning is considered a bandwidth-consuming method with the model updates requiring the transmission of many parameters that scale with the size of the access node deployments [178]. However, the capacity boost provided by the optical transport network for massive UDN deployments can overcome this limitation, thus providing a future research direction for resource optimization in radio and optical mmWave networks.

Regarding interference mitigation, predictive analytics can further help in interference handling by monitoring channel quality and traffic load variation in the mmWave radio and optical networks [51]. However, the computational cost of learning from inter-channel information to mitigate inter-cell interference at the access nodes of dense massive MIMO systems should also be considered for throughput maximization [179]. A future research direction for throughput maximization might therefore be creating a multi-layer learning framework [J1] to adjust fronthaul resources by learning the aggregate radio access node interference behavior.

The evaluation criteria in Table 3.4 show that the number of users are monitored frequently in throughput maximization solutions, bringing the integration of user demand-driven ML solutions such as the deep reinforcement learning throughput maximization algorithm used to achieve a minimum throughput target of 1 Mbit/s for 50 users [180]. The throughput scales well above 1 Mbit/s with the available bandwidth in mmWave frequencies, dense deployments and the use of MIMO; making eMBB applications such as V2X and mobile augmented reality, the use case targets of mmWave radio and optical networks. For this reason, reinterpreting such ML solutions should be considered carefully as mmWave radio and optical network deployments aim to achieve significantly higher the throughput targets, e.g., 1 Gbit/s for eMBB use cases such as V2X collective perception [181].

Due to the scaling up of the network elements and the dependent increase in the amount of information, ML applications were discussed for massive MIMO, cognitive radios, heterogeneous networks and small cells at an early phase of the convergence of AI-ML methods and communications technologies [182]. The number of access nodes and antennas are also taken into account as evaluation parameters in the selected papers [170], [175], [177]. These parameters should be considered not only in the operations and management phases, but also during the cost-effective planning and pre-deployment phases of mmWave access and transport networks. Finally, the communication-efficient methods to push training processes of AI models to edge nodes [183] should also be regarded to increase the distributed network control capability and make use of the increasing amount of information at the edge.

3.2.4 Delay Minimization and Resource Allocation Algorithms

Minimizing the delay caused by congestion or increased traffic has been a common management target throughout the evolution of mobile networks. However,

Table 3.6: Analysis of resource allocation papers with delay minimization objective

Ref.	Objective	Solution Method	Optimization Algorithm
[184]	maximize utility for all users while meeting the delay restrictions	decompose resource optimization with Lagrange duality theory	a distributed iterative algorithm & broadcasting of the Lagrange multipliers
[185]	reduce the delay of the high QoS class traffic	a priority based resource allocation scheme is created	QoS class with higher priority transmissions precede lower priority packets
[186]	beamforming design to minimize the secure transmission delay	a two-phase fronthaul and maximum access transmission delay minimization	two separate iterative algorithms to solve the divided optimization problem
[187]	minimize the maximum system delay of mmWave MEC system	a joint hybrid beamforming and resource allocation algorithm for mmWave MEC	distributed algorithm based on the penalty dual decomposition framework
[188]	guarantee low end-to-end latency for FiWi access network	user-driven computation offloading approach to help reduce the workload of APs	TDMA based polling scheme for resource management
[189]	minimize the average response time for mobile users	distributed cooperative offloading between UE, cloud and MEC	users and MEC servers iteratively set offloading probabilities until convergence
[18]	minimize end-to-end delay	decentralized cooperative dynamic bandwidth allocation for FiWi	an ANN method (multilayer perceptron) is used to forecast the samples

the emphasis on latency increased with the challenging URLLC requirements [18], due to the "1 ms challenge" of the delay sensitive applications such as tactile internet [19] and augmented/virtual reality. The optimization methods, used to reach these delay targets in converged optical and mmWave radio networks, are summarized in this section. The existing solutions to delay minimization problems are shown in Figure 3.8, and the list of selected papers can be found in Table 3.6. The potential research directions for delay minimization in converged optical and radio networks with AI-ML solutions are also discussed.

Selected Papers

Among the technological enablers of ANM, MEC is heavily adopted in the selected works as it contributes to delay minimization [188], [189] and offloading. In [188], a FiWi enhanced two-level edge computing concept is developed to guarantee low end-to-end latency with offloading capabilities. The UEs send their computation offloading tasks to their associated ONU-APs in this the user-driven approach. [189] introduces a cooperative offloading strategy that allows users and MEC servers to iterate backhaul and user offloading probabilities until the mini-

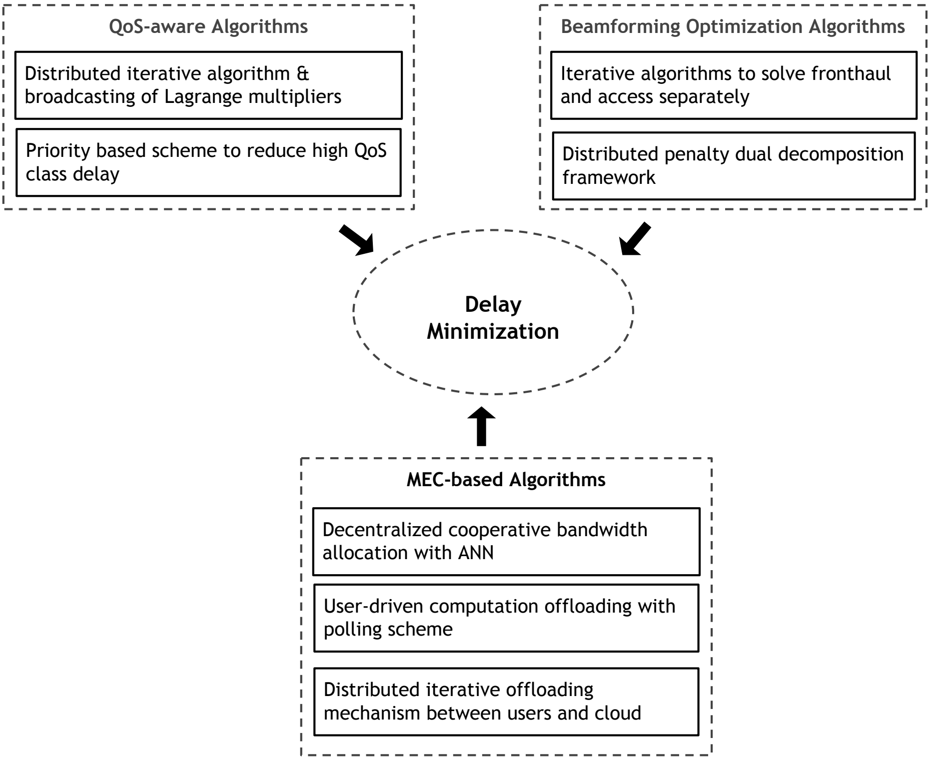


Figure 3.8: Existing resource allocation optimization solutions to delay minimization issues

mized delay converges to a near-optimal solution. MEC is also seen as an enabler to reach URLLC target of 1 ms end-to-end delay for a tactile internet application in [18], and an artificial neural network is used at the network edge to minimize delay together with the offloading scheme used in [189].

Delay minimization in optical and mmWave radio networks is also considered in the scope of QoS restrictions in [184], [185]. The delay restrictions of different services are used as constraint in the optimization problem in [184]. The problem is decomposed using Lagrange duality theory and solved with a distributed iterative algorithm to maximize the utility of all users and to provide a better average response time. A resource management scheme for FiWi fronthaul is presented in [185] in which time slots are allocated in a way that the packets of a QoS class with higher priority are sent using more time slots to reduce the delay of the high QoS traffic.

In order to realize an optical and mmWave radio network, the relation between delay and beamforming is studied in the literature [186], [187]. An iterative algorithm is proposed for the beamforming at the central processor and the RRHs to minimize the fronthaul transmission delay for mmWave C-RAN in [186]. The computational capabilities of MEC can be used for beamforming as well, such as the joint beamforming and resource allocation algorithm presented in [187] for system delay minimization. The proposed dual decomposition-based distributed algorithm also has an information exchange mechanism between the system components. Another work that investigates the relation between delay and the use of beamforming is [186], in which a two-phase fronthaul and access transmission delay minimization method is proposed.

Discussion

As seen in Table 3.6, several works consider traffic level and UE number as an evaluation criteria for delay minimization. To achieve the delay minimization objective, AI/ML-based traffic forecasting methods are highly relevant to exploit the data collected from monitoring. A forecasting example that uses neural networks for delay minimization is provided for FiWi networks in [18]. By taking the optimal training time and forecast accuracy trade-off into account, different neural networks approaches can also be used to detect patterns and forecast the network traffic characteristics, such as the traffic forecasting with long-short term memory method in [190].

Regarding the deployment of MEC solutions, deep reinforcement learning based delay minimization solutions [191] and edge caching [192] can achieve significant QoS improvements for applications such as video streaming. However, the impact of integrating these application-based decision-making mechanisms to optical and mmWave radio networks has not been studied in the existing papers, providing a novel research direction for delay minimization.

In delay optimization papers, users [184], network services [185], and cloud servers [189] are involved in decision-making as external stakeholders. MEC servers could also be third party stakeholders who lease their computing resource blocks to process or store for dynamic function placement, providing AI-as-a-Service [48] or Security-as-a-Service to other network stakeholders and making service providers an external decision-maker in network management for service-specific decisions.

3.2.5 Energy Efficiency and Resource Allocation Algorithms

The objective of energy efficiency is defined as maximizing the amount of data transferred per unit energy consumed by the system [199]. This section presents the selected papers given in Table 3.7, which provide EE solutions to converged optical and radio networks with AI-based techniques. The existing solutions are grouped in terms of EE problems in Figure 3.9. Finally, a discussion on the future challenges and potential research directions are provided in this section.

Table 3.7: Analysis of resource allocation papers with energy-efficiency objective

Ref.	Objective	Solution Method	Optimization Algorithm
[108]	routing with sleep and active modes	formation of groups among mesh nodes	a heuristic imitating far-sighted network formation
[119]	maximizing the sum rate and EE of the network	one-to-many user and sub-carrier matching game	two-sided stable matching
[193]	improve downlink energy efficiency	an iterative algorithm with Dinkelbach method	joint access and fronthaul allocation
[194]	SDN-based routing of traffic flows	demand based sleep mode regulation	an SDN application controls sleeping modes
[117]	increasing EE by decreasing path loss	joint spectrum resource and power allocation of	a water filling operator and price-based iterative algorithm
[195]	minimize total consumed power	joint user association and power allocation	alternating descent algorithm
[107]	joint EE and SE maximization	two layered game with frequency assignment and multi-objective optimization	small cells select the combination of frequencies maximizing user sum rate
[196]	minimize total power consumption for user association	joint user association and sleep mode optimization	a matching heuristic and a user reallocation heuristic
[197]	maximize EE performance	joint resource allocation with fractional programming	iterative Lagrangian dual decomposition
[168]	Avoid frequent lightpath deactivation and reactivation	training ANN model to optimize traffic prediction weights	Adaptive ant colony optimization based optimization
[198]	minimize energy consumption for joint caching and bandwidth allocation	energy consumption and network usage are combined with weights	alternating direction method of multipliers

Selected Papers

Resource allocation algorithms for EE optimization take into account the trade-off between EE and bandwidth utilization. Thus, joint optical and radio resource and transmission power allocation algorithms are used to minimize the total consumed power in the entire network. For instance, in [117], the NP-hard problem of the joint uplink resource allocation of small cells, spectrum resources, and transmission power is decomposed into a potential game for small cell selection and a non-cooperative game for power allocation. The EE maximization problem is formulated in [195] in terms of number of bits delivered per Joule subject to the QoS rate threshold for each user, and an alternating descent algorithm is applied to separate the energy efficiency optimization problem into two sub-problems of EE maximization problem and user throughput fairness. In [197], the EE maxi-

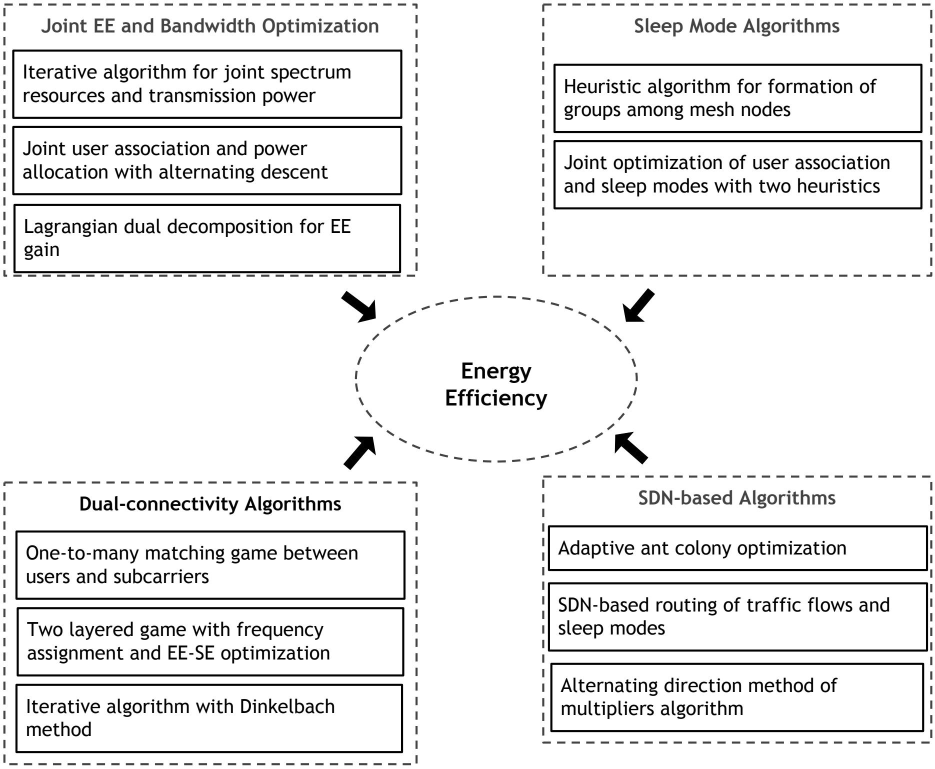


Figure 3.9: Existing resource allocation optimization solutions to energy efficiency issues

mization problem is modeled as a class of optimization problems called fractional programming to minimize the total power consumption of the entire system.

With the increased use of dense small cell deployments due to mmWave characteristics, activating and deactivating these small cells with sleep modes based on different parameters such as the number of APs and network loads [108], flow arrival rates [194], under the presence of a macro cell [196] has become a frequently used energy saving method. In [108], the system to optimize transmission and sleep periods is modeled with a network formation game, in which every AP is a player, establishing connections with its neighbors to create energy efficient routes. The minimization of the total power consumption in user association is modeled as a capacitated facility location problem and solved with the selection and repetition based heuristic algorithms for sleep mode decisions in [196].

Dual-connectivity network architectures with both macro cell and mmWave small cell options are also considered for the trade-off analysis of joint energy efficiency and throughput gain maximization under varying number of users [107], [119], [193]. The coexistence of microwave and mmWave leads to a better performance in terms of both sum rate and EE when compared to mmWave and microwave only networks with a one-to-many matching game for frequency band selection in [119]. Downlink resource allocation is investigated for a non-standalone network with macrocell and small cells in [107], and a two layered hierarchical game approach is used for modeling the problem. A non-cooperative frequency assignment game is designed for small cells in the first layer and a power and subcarrier allocation via joint maximization of the revenue per cost based EE and spectral efficiency (SE) in the second layer. In [193], a joint access and fronthaul radio resource allocation method is proposed for downlink dual connectivity mode of a power domain non orthogonal multiple access-based C-RAN system with mmWave and microwave carriers.

The network paradigm shift towards softwarized solutions provides novel options to implement EE algorithms in the optical and radio networks, as seen from the SDN-based solutions proposed in [168], [194], [198]. An SDN application called energy management and monitoring application, and a power consumption optimizer is developed in [194] to optimize the energy consumption of a C-RAN infrastructure with energy consumption estimation based on flow rates. An SDN controller-based power control framework with an adaptive ant colony optimization algorithm is proposed in [168] to avoid the frequent deactivation and reactivation of the lightpaths when new traffic request arrives, thus saving switching power. Finally, a joint caching, computing, and bandwidth resource allocation is designed for SDN in [198] to minimize the energy consumption consumed by content caching, data computing and traffic transmission.

Discussion

There are several network EE issues that should be taken into consideration for management in optical and mmWave radio networks. The massive small cell deployments increase the signalling cost as mmWave bands have smaller coverage radii. In addition, antenna processing for massive MIMO antenna systems consumes extra power [200]. The selected papers in Table 3.7 reveal that the use of sleep modes and information exchange among small cells are some of the methods to respond to EE requirements of mmWave UDN deployments. The EE optimization methods identified for optical and mmWave radio networks can be enhanced with cognitive networking methods, where each node seeks to "minimize its energy" by minimizing the cumulative neighborhood energy function, as in [201]. Adapting cluster-based protocols used to harvest energy utilization for wireless sensor networks [202] for UDN deployments can also provide a novel research direction for converged optical and radio networks.

Apart from these operation and maintenance level for EE such as the sleep modes, the reduction of energy related costs should be a target during the planning and pre-deployment phases [203], which can be optimized by selecting the optimal AP density and distribution. The relationship between the transmit power and the AP density is defined as a function with the use of stochastic geometry in [204],

Table 3.8: Analysis of virtualized resource allocation papers

Ref.	Objective	Solution Method	Optimization Algorithm
[86]	achieve social welfare with C-RAN resource sharing	operators bid for C-RAN resources in an auction	an approximation algorithm for dissected graphs
[207]	guarantee service connection during fog node failure	cross radio, optical and fog layer protection scheme to guarantee the QoS	Dijkstra algorithm for path accommodation and spectrum allocation
[169]	maximize InP revenue with virtual FiWi resource embedding	Use VNE algorithms to embed the VNs of services	traffic prediction with Q-Learning
[87]	InP slices mmWave BSs to improve operator QoE	a heuristic three-phase framework to price slices and operator allocation	slice allocation with VCG distributed auction
[208]	allocate FiWi resources to the VNs with sleep modes	collaborative sleep of nodes with a re-embedding mechanism for VNs	QoS-aware priority based energy-saving algorithm
[209]	maximize the total profit and bandwidth utilization	centralize control and allocate networking and computing resources	revenue-based VNE with two greedy approaches
[210]	C-RAN resource pooling gain for mmWave optical network	centralized resource orchestration scheme for RoF fronthaul and BBU	a resource pooling algorithm using user location
[211]	maximizing InP profit in FiWi access network	integer linear programming model for QoS-aware VNE	breadth first search channel allocation

and solving this non-linear function gives the unique transmit power and density that maximizes the energy efficiency. At the same time, modeling the energy performance of APs and optical transport network together should be considered in the planning phase [205] to increase the overall EE of the network.

Finally, creating SDN applications that aim to achieve energy minimization as the one in [194] can be considered as strategy to overcome EE issues. However, the architectural changes for network management by implementing SDN can at the same time increase power consumption as it introduces new components with controllers and SDN switches. To analyze the power consumption impact of the architectural changes in the C-RAN fronthaul, [206] measures the power consumption of SDN switches, RRHs, optical transceivers and control components, and the results show that this architecture increases the total power consumption of the network by about 20 %. The optimal EE solution therefore requires planning of the power consumption of the SDN components in the pre-deployment phase.

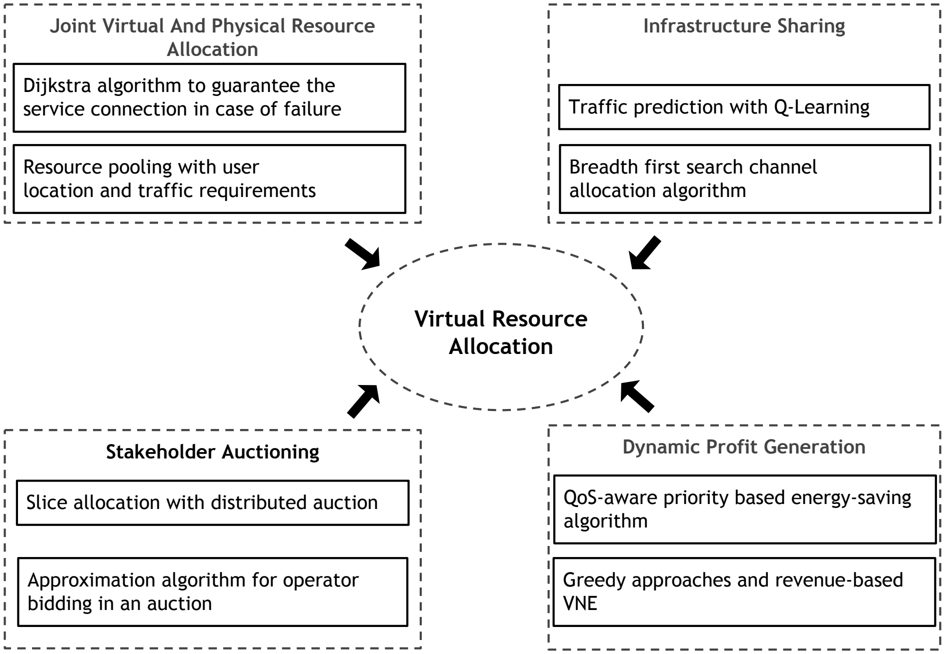


Figure 3.10: Existing solutions to virtual resource allocation optimization issues

3.2.6 Virtual Resource Allocation Algorithms

The paradigm shift with network softwarization leads to the abstraction of network resources and makes it possible to dynamically allocate computation and storage resources. This section is composed of the selected virtual resource management optimization solutions for converged optical and radio networks. The existing solutions to virtualized resource allocation optimization issues are grouped in Figure 3.10. The selected papers are also listed in Table 3.8. This section also concerns how these solutions can be enriched with network slicing and the use of agents for distributed decision-making.

Selected Papers

Infrastructure sharing is made possible with the help of virtualization technologies, and this fact transformed the network architecture itself into a novel stakeholder called the infrastructure provider (InP) [169], [211]. InP is considered as part of the infrastructure as a service (IaaS) concept, with the main objective of on-demand provisioning of virtual infrastructure and computing resources with Service Level Agreements (SLAs) [212]. To maximize InP profit in FiWi access networks, [211] proposes resource allocation in both wireless and optical subnetworks with a wireless channel allocation algorithm based on breadth first search and a DBA algorithm in FiWi for both radio and virtual resources. A revenue based bandwidth resource allocation is provided in [169] to map the idle resources of a virtualized FiWi access network architecture to the service provider requests. The InP uses Q-learning to predict idle bandwidth resource and the traffic load on each physical link. This algorithm enables InPs to accept more VN requests and obtain higher revenue.

Virtualized network resources pave the way for dynamic resource allocation between the InPs and the network operators over auctioning algorithms. An infrastructure sharing scenario is created for mmWave radio networks in [87], in which the operators use a distributed auction mechanism (Vickrey-Clarke-Groves) to allocate mmWave AP resources by obtaining the slices. The results show that applying these algorithms after the auction provides payoff gains to the network operators. Another resource allocation scheme based on auctioning is discussed in [86]. In this scheme, operators submit bids to capacitate a C-RAN subnetwork, and the infrastructure owner (auctioneer) aims to maximize the aggregate social welfare, defined as the sum of the aggregate operators' utility and the C-RAN's revenue.

Even though profit generation is always a factor in performance optimization for network operators, the shift in the architecture with network virtualization makes dynamic revenue gains an apparent performance criteria for resource allocation. This shift transforms the network into a market interaction between different stakeholders that aim to profit from the available physical and virtual resources in a dynamic way [208], [209]. In [209], a VNE problem is analyzed for FiWi hybrid nodes that have abstracted physical optical and wireless resources. The main objective is to maximize profit by considering the gains of service requests and costs of the physical plane including networking and edge computing servers' resources. Virtual resource allocation in a FiWi network is combined with an energy saving perspective in [208]. FiWi network resources are monitored globally to put the low-load devices to sleep mode. The results show that the algorithm manages to provide low energy consumption, high network service profit and high network link utilization.

The integration of network virtualization technologies creates the incentive to dynamically reconfigure both the physical and virtual resources of converged optical and radio networks. For this reason, the joint optimization of both radio, optical and virtual resources is studied in the literature. The radio, optical and fog resources are controlled with SDN in a cross-layer architecture for a fog-computing-based radio over fiber network in [207], in which the controller selects MEC nodes and establishes paths with spectrum and modulated radio frequency allocation. A mmWave 5G C-RAN pooling gain solution over an ARoF fronthaul design is presented in [210], in which both virtual and physical resources are allocated with a resource pooling algorithm.

Discussion

The softwarization of network functions with NFV and their live migration thanks to the technological enablers such as SDN and MEC make it possible to dynamically allocate computation and storage resources. Physical layer abstraction is required for both optical and radio resources of the converged network to achieve joint optimization of physical and virtual network resources at the NFV orchestrator level. Achieving the abstraction of all physical resources is a step towards achieving end-to-end network slicing and translating high-level O&M goals to technical parameters in beyond-5G networks, as seen in the efforts such as [84], [163]

As seen from Table 3.8, the addition of the infrastructure provider to the increasing number of the stakeholders in 5G networks is also taken into account in several studies. In addition to the abstraction of all physical and virtual resources of the network, the common abstraction at the network management framework is required between these stakeholders. A well-known abstraction for the design and implementation of intelligent stakeholders in a distributed fashion is the use of intelligent agents [J1]. The collaboration, cooperation and negotiation of multiple agents to achieve a common goal creates a multi-agent system, which is an ideal candidate to solve complex resource management problems between multiple stakeholders in a distributed fashion.

3.3 Summary

The aim of this chapter is to provide answers to the following research questions:

How can a resource management composition be created for a converged optical and mmWave radio network architecture? In what ways can multiple stakeholders get involved in decision-making to maximize their utilities?

Section 3.1 clarifies the changes that the utilization of mmWave spectrum and the enabling technologies in 5G networks brought to the resource management problem. As the capacity boosts with mmWave frequencies, dense radio networks, massive MIMO and spectrum resource sharing also necessitate a parallel capacity boost in the transport network, it was decided to focus on the converged mmWave radio and optical networks. After identifying the technological advancements and the resources to be managed in the whole architecture, the novel management issues these technologies bring to converged mmWave radio and optical networks are emphasized.

Enhancing the capacity of 5G networks is essential but not enough to meet the requirements of the novel applications and societal goals. Smart resource management solutions are needed to complement the radio and optical network technologies to generate a network architecture that optimizes the use of the resources provided to the external stakeholders. For this reason, AI-based resource optimization techniques and dynamic management enablers are heavily investigated in the literature.

In Section 3.2 of this chapter, example methods from the literature are provided to explain how technological enablers can play their role in reaching the network management targets of throughput maximization, delay minimization, energy-efficiency, and virtual resource allocation. The key concepts and the key network state parameters used to evaluate the performance of AI-based network optimization algorithms are identified. The limitations of resource management in converged optical and mmWave radio networks are also analyzed. Furthermore, dedicated discussions are provided for each resource management objective to identify the gaps in the existing literature and to provide potential directions for future research.

Section 3.2 can be expanded upon with further research on the resource optimization algorithms. The researches that do not present a concrete optimization algorithm were excluded from the study; however it is well-known that many conceptual papers also provide a basis for solving resource management problems. It should also be emphasized that AI-ML solutions presented in the discussion subsections do not directly include a converged optical and mmWave radio architecture; therefore the re-interpretation of their results might be costly for some specific optimization algorithms. Despite the limitations, the contributions of this state-of-the-art review add value to the discussion with respect to integrating ML-based data analytics solutions with converged optical and mmWave radio networks, and motivate further research towards the autonomic resource management for 5G and beyond-5G performance optimization.

CHAPTER 4

Cooperative Bandwidth Allocation for Converged mmWave Networks

This chapter describes the experimental results of strategic cooperative learning behavior to improve resource allocation under dynamic network conditions. An application of cooperative game theory to the fronthaul bandwidth allocation problem is presented with a bankruptcy game. Bankruptcy games model situations in which the total demand from players claiming a resource exceeds the available resources. In converged photonic and wireless mmWave networks, this situation can occur when extra RRHs are turned into active mode after sleep modes, flexible functional split decisions increase the fronthaul bandwidth demand, or when user traffic demand reaches a sudden peak. In order to take full advantage of the provided fronthaul capacity, the available fronthaul resources are utilized by cooperative sharing among the RRHs with several division rules in this game. Different user distributions and QoS requirements bring dynamicity to the problem, giving the transport network the opportunity to adapt to the dynamic load based on user utility and C-RAN bandwidth allocation outcomes. The outcomes of applying the selected division rules are evaluated in terms of fairness, total data rate, and user satisfaction.

4.1 Bankruptcy Games

For network elements that are part of the infrastructure of the same network operator, allowing cooperation between these elements by coalition formation is a feasible solution for resource allocation, and studied in various works such as [106], [108], and [114]. In such cooperative network games, the overall network architecture is treated as an actor with a global objective of maximizing its users' utility,

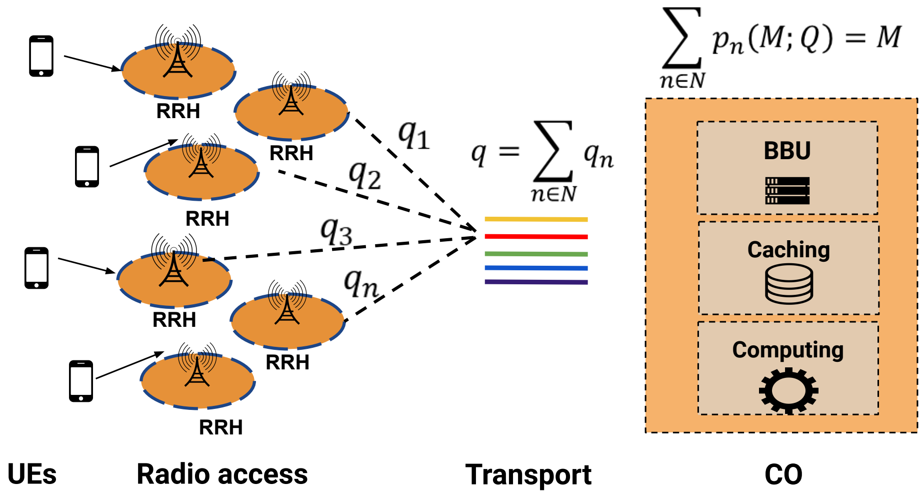


Figure 4.1: Bankruptcy game between C-RAN radio access and transport networks

and network cooperation helps to reach network operator's global objective of network resource use optimization under varying user traffic demand and load.

The interaction between the transport network and RRHs can be turned into a cooperative game to adapt to varying aggregate user load in a dynamic way in a mmWave C-RAN architecture. As each RRH has a separate demand based on the current traffic load, the aggregate demand is sent to the transport network side in the form of a demand matrix. After sending the aggregate bandwidth demand of the RRHs to the transport side, the demands of RRHs are satisfied according to the demand matrix if the total demand is below the maximum capacity of transport network. If the aggregated demand is over the capacity, the problem can be formulated as a bankruptcy game for allocating the aggregate demand of the RRHs.

A bankruptcy problem is used to model cases in which the total claims of the agents on a certain resource is more than the total available resources [213]. N-player cooperative games that arise from the bankruptcy problems are called bankruptcy games. In situations where the total available fronthaul bandwidth is less than the sum of RRH bandwidth demands, dynamic fronthaul resource allocation can be achieved with a bankruptcy game designed for multiple RRHs with fronthaul network capacity constraints. A resource allocation example with bankruptcy games for C-RAN architecture is demonstrated in Figure 4.1.

The game is formally defined with (N, M, Q), where $N = \{1, \ldots, n\}$ represents the set of players, M the total value of resources, and $Q = \{q_1, \ldots, q_n\}$ the demand vector of the agents. In the dynamic bandwidth allocation game, N is the set of RRHs with n being the total number of RRHs, M is the total available fronthaul bandwidth, and Q is the set of bandwidth demands of all RRHs. The bankruptcy problem conditions are met when $0 \leq q_1 \leq q_2 \leq \ldots \leq q_n$, and $0 \leq M \leq \sum_{n=1}^{N} q_n = \Theta$, where Θ indicates the total demand of RRHs. It should be noted that the ordering of the demands in this description does not limit the generality of the description. The total available fronthaul bandwidth M is distributed among the RRHs based on the total demand of RRHs indicated with Θ, and the solution to this problem is given as $\sum_{n=1}^{N} x_n = M$, with x_n denoting the amount of bandwidth assigned to RRH_n [214], also called the payoff of the player.

If $\Theta > M$, then each RRH's demand impacts other RRHs directly, creating an interdependence among the RRHs while obtaining the fronthaul bandwidth. The RRHs take this interdependence into consideration when deciding for their actions as players of the game. In a cooperative game, this interdependence is used to form coalitions between the players. Forming a coalition with other players is considered as a rational action on the player side, as the players have the option to improve the outcome of their individual RRH demands being rejected by the transport network by accepting the payoff obtained after forming a coalition. In cooperative games, a *coalition* S defines any subset of the player set $N = \{1, \ldots, n\}$, whereas the *grand coalition* defines the set N of all players [215].

Bankruptcy games are expressed with the characteristic function form [213], defined by an ordered pair (N, v), with $v : 2^N \rightarrow \mathbf{R}$ being the characteristic function that maps each coalition S to the value of the coalition, denoted as $v(S)$. An outcome of a characteristic function game consists of the partition of players into coalitions, called the coalition structure; and the payoff vector, which distributes the value of the coalition among its members [215]. The question of how to divide coalitional value is dependent on the importance of each player to the cooperation, and the expected payoff of the player from the coalition. The Shapley value [216] is based on the intuition that the payment each agent receives should be proportional to her contribution to the coalition.

As the total value of resources is insufficient to meet all the claims in a bankruptcy problem, the problem of dividing the available resources among all agents is solved with a division rule p. The division rule should satisfy the condition that no player gets more than their claim or less than zero, and the total available resources are totally divided among the agents, which are denoted as follows:

$$0 \leq p_n(M; Q) \leq q_n, \forall n \in N \tag{4.1}$$

$$\sum_{n=1}^{N} p_n(M; Q) = M \tag{4.2}$$

The straightforward way to calculate the bandwidth shares of the RRHs is to use proportional division (PD) and divide the total resources in proportion to each RRH's claim. The main advantages of this method as the division rule is that it is effective in distributing all the available resources, and it is considered as strategy-proof as the players have no incentive to form coalitions with this division rule [217]. With this method, each player gets a payoff $x_n = \frac{M}{\Theta} \cdot q_n$.

Two other division rules are introduced in [218], which are favorable to players with smaller demands and players with larger demands, respectively. Constrained equal awards (CEA) rule assigns to player $\min(\alpha, q_n)$, where $\alpha \in [0, q_n]$ is considered as a minimal right for all players. The α value has to satisfy $\sum_{n=1}^{N} CEA_n(M; q_n) = M$. On the other hand, constrained equal losses (CEL) rule assigns to player n as payoff $\max(q_n - \beta, 0)$, where β is considered as a maximal loss for all players and no player ends up with a negative payoff. The β value also has to satisfy $\sum_{n=1}^{N} CEL_n(M; q_n) = M$.

By making use of the proportional division method and the minimal right concept, the authors in [213] propose the adjusted proportional method (APM), which consists of two steps. In the first step, each player n receives her minimal right α_n, given that $\sum \alpha_n \leq M$. In the second step, a new total resource $M' = M - \sum \alpha_n$, and a new demand vector with demands $q'_n = q_n - \alpha_n$ are created, and M' is divided proportional to the new demand vector q'. The minimal right α_n is set to $\min(q_n)$ for each RRH in the simulations.

In [214], contested garment (CG) principle is introduced as a division rule. The rule first explained for a 2-player case with players n and n', in which the payoff x_n of the player for $(M - q_n) \geq 0$ and $(M - q'_n) \geq 0$ is given as:

$$x_n = \frac{M - (M - q_n) - (M - q'_n)}{2} + (M - q'_n) \tag{4.3}$$

The rule is extended from 2 players to n-players with a coalitional procedure. The coalitional procedure of the contested garment rule is given in [214] as follows:

- Divide M between $\{1\}$ and $\{2, \ldots, n\}$ according to consistent garment solution of the 2-player problem $(M; q_1, q_2 + \ldots + q_n)$, and use the $n-1$ person rule by dividing $\{2, \ldots, n\}$ among its members. This rule is applied when $n \cdot q_1/2 \leq M \leq q - (n \cdot q_1/2)$. If the player demand q_1 or the sum of other players' demands $q_2 + \ldots + q_n$ is more than the total available resources M, the demand is truncated to the total available amount of resources.

- Assign equal awards to all players with CEA rule, when $M \leq n \cdot q_1/2$

- Assign equal losses to all players with CEL rule, when $M \geq q - (n \cdot q_1/2)$

Recursive completion (RC) method is proposed as a division rule in [217], which produces as payoff the Shapley value of the cooperative game corresponding to the bankruptcy problem. The division problem is solved by listing all possible orders of arrival for the players and calculating the payoff each player would receive, and then by taking the average payoff value of all possible orders of arrival for every player. If a player demand q_n is more than the total resources, the demand is truncated to the total available amount of resources. For a given coalition S, the characteristic function of the game is defined as:

$$v(S) = \max(M - \sum_{n \in N-S} q_n, 0) \; for \; S \subseteq N \tag{4.4}$$

With $s = |S|$, the Shapley value of the game for player n is calculated as:

$$\phi_n = \sum_{n \in S} \frac{(s-1)!(n-s)!}{n!}(v(S) - v(S - \{n\})) \tag{4.5}$$

$$v(S) - v(S - \{n\}) = \begin{cases} q_n & \text{if} \quad M - \sum_{j \in N-S}(q_j) \geq q_n \\ M - \sum_{j \in N-S}(q_j) & \text{if} \quad q_n \geq M - \sum_{j \in N-S}(q_j) \geq 0 \\ 0 & \text{if} \quad 0 \geq M - \sum_{j \in N-S}(q_j) \end{cases} \tag{4.6}$$

Evaluating the fairness of the division rules in allocating resources is a factor in deciding for the rule that appropriately fits the requirements of the players of the game as the players claim different proportions of the total resources.

4.2 System Model

The network simulation setup and system evaluation parameters considered for the bankruptcy game for dynamic fronthaul bandwidth allocation is explained in this section.

4.2.1 Network User Distribution

Users in set $I = \{1, ..., i\}$ are scattered inside a $400\,\mathrm{m}^2$ open square area. Ten mmWave RRHs with center frequency $f_c = 28\,\mathrm{GHz}$ are distributed randomly inside this area first by using a Poisson point process [219], and then by adjusting these positions to ensure that the maximum distance between the RRHs is less than 150 m and the minimum distance is more than 30 m. The users are connected to the closest mmWave RRH.

The simulation of the mmWave C-RAN scenario considers different users that demand different services inside the $400\,\mathrm{m}^2$ simulation area. Two user profiles are used for dense urban and massive IoT scenarios. For the dense urban user profile, target urban user data rate DR_{urban} value is chosen as 300 Mbps, in line with the 3GPP service requirements of the dense urban downlink scenario [220]. For each urban user connection request, RRH estimates the required fronthaul bandwidth that provides a 300 Mbps connection to a user at a 30 m 2D distance.

In order to reflect the impact of user mobility on the dynamic decision-making, the Random Waypoint Model (RWP) is selected for the simulation environment as the model reflects the fact that people habitually stay at some locations for a long time compared with other locations. In RWP, a user randomly selects a destination in a 2D-plane [221]. Then, the user moves with constant speed to reach the destination by following a straight line. Before selecting a new destination, the user pauses for a random amount of time. In addition, the users can move with angular directions and their speed can vary during each motion with this mobility model. After their movements are completed, the users may or may not change their RRH connection depending on their new position.

For the massive IoT scenario, target data rate value DR_{mIoT} is 1 Mbps, and the number of users in the $400\,\mathrm{m}^2$ open square area is equal to 400, as this value reflects the high connection density target of 1 million connections per km^2. For each mIoT connection request, RRH calculates a fronthaul bandwidth demand that provides the target DR_{mIoT} value to a user at a 30 m 2D distance. mIoT users are initially distributed inside the area with Poisson Point Process. These users are static; therefore they do not use a mobility model and they do not change their position at any iteration.

4.2.2 Path Loss Model

In order to capture an urban scenario, Urban Micro (UMi) LOS channel model of the street canyon scenario defined in 3GPP TR 38.901 [222] is used to create the path loss values of the RRHs. In the street canyon scenario, the RRHs are mounted below rooftop levels of surrounding buildings. In this scenario, two path loss calculations are used depending on the breakpoint distance d'_{BP} calculated by using Eq. (4.7), with h'_{BS} denoting base station height, h'_{UE} denoting user height. In addition, f_c denotes center frequency of the radio unit, and $c = 3x10^8 m/s$ denotes the propagation velocity in free space.

$$d'_{BP} = 4 \cdot h'_{BS} \cdot h'_{UE} \cdot \frac{f_c}{c} \tag{4.7}$$

A different path loss formula is applied depending on the 2D Euclidean distance d_{2D} between the RRH and the user, and the d'_{BP} in Eq. (4.7) is used as a threshold value, as shown in Eq. (4.8). The distances are given in meters with unit m.

$$PL_{\mathrm{UMi,LOS}} = \begin{cases} PL_{\mathrm{LOS},1} & 10\,\mathrm{m} \le d_{2D} \le d'_{BP} \\ PL_{\mathrm{LOS},2} & d'_{BP} \le d_{2D} \le 5000\,\mathrm{m} \end{cases} \tag{4.8}$$

The formulas to calculate $PL_{\mathrm{LOS},1}$ and $PL_{\mathrm{LOS},2}$ are given in Eq. (4.9) and Eq. (4.10), respectively. d_{3D} represents the 3D Euclidean distance between the user and the RRH in meters.

$$PL_{\mathrm{LOS},1} = 32.4 + 21\log_{10}(d_{3D}) + 20\log_{10}(f_c) \tag{4.9}$$

$$PL_{\mathrm{LOS},2} = 32.4 + 40\log_{10}(d_{3D}) + 20\log_{10}(f_c) - 9.5\log_{10}((d'_{BP})^2 + (h_{BS} - h_{UE})^2) \tag{4.10}$$

After obtaining the path loss value with the given equations, the RSS value of users is calculated with Eq. (4.11), in which the power of the transmitter P_{T_x} is assumed as 30 dBm according to the model described in [223]. The SNR value is obtained by subtracting the thermal noise T_{noise} from the calculated RSS value, as shown in Eq. (4.12). T_{noise} equation is displayed in Eq. (4.13).

$$RSS_{\mathrm{user}} = P_{T_x} - PL_{\mathrm{UMi,LOS}} \tag{4.11}$$

$$SNR_{\text{user}} = RSS_{\text{user}} - T_{noise} \tag{4.12}$$

$$T_{noise} = -174 + 10 \cdot \log_{10}(b_n) \tag{4.13}$$

4.2.3 User Data Rate and Satisfaction

The data rate of each user DR_i is calculated by using a simple user bandwidth to rate conversion model with overhead and loss factors OF and LF in Eq. (4.14) [224]. Both OF and LF take values between 0 and 1. User bandwidth b_i is a function of the fronthaul bandwidth allocated by the RRH k, the number of users connected to this RRH, and their bandwidth demands.

$$DR_i = (1 - OF) \cdot b_i \cdot \log_2(1 + (1 - LF) \cdot SNR) \tag{4.14}$$

The users aim to remain seamlessly connected to the network in a way that best suits their service demands, meaning that they demand at least the minimum data rate required for the service specific data transmission. In this scenario, the data rate of user i determines the user utility U_i based on the user utility function in [225], given in Eq. (4.15). DR_{min} value is the threshold to sustain 5G service use with acceptable quality, and γ value characterizes the user sensitivity to data rate. Service based data rate requirements are reflected with this utility function. Furthermore, the satisfaction parameter ρ_{DR_i} is specific to the user, and can be adjusted to reflect user specific behavior.

$$U_i(DR_i) = \begin{cases} 0 & \text{if} \quad DR_i < DR_{min} \\ \rho_{DR_i} \cdot (1 - e^{-\gamma(DR_i - DR_{min})}) & \text{if} \quad DR_{min} \leq DR_i \end{cases} \tag{4.15}$$

4.2.4 Radio Access and Transport Network Interaction

With the proposed approach, limited fronthaul bandwidth resources are shared among RRHs that demand bandwidth from the transport network based on the dynamic traffic requests of the users. All RRHs are connected to a common transport network path to reach the centralized controller and the total bandwidth in this path is divided among the RRHs. This transport network path with total bandwidth M is divided among N RRHs based on a specific pre-defined contract between the RRHs and the transport network, defined as the division rule of the bankruptcy game. The steps of the game is given in Figure 4.2, and can be summarized as follows:

- Step 1: The game begins with an initial user distribution and the users move or wait inside the given area for the period of an iteration and send their traffic requests to RRHs by indicating their service type w. RRH n receives the user connection requests and demands bandwidth from the transport network for the next period by calculating the demand as in Eq. (4.16),

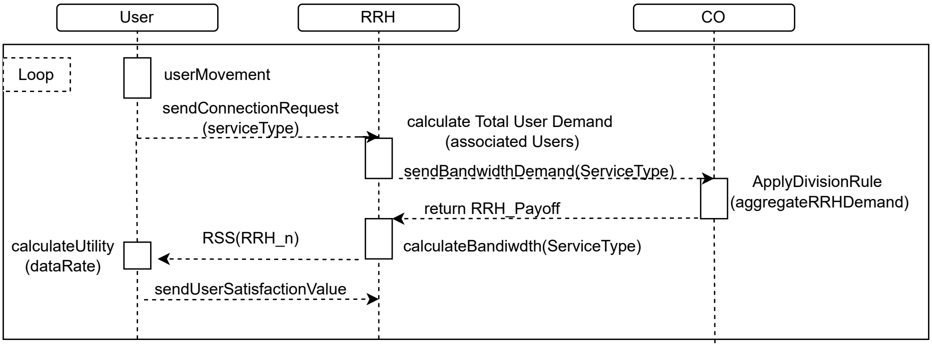


Figure 4.2: Sequence diagram of the demand allocation game between users, RRHs and CO

where w_i indicates the service type and DR_w denotes the data rate demand for the service type.

$$q_n = \sum_{i \in I} w_i \cdot DR_w \tag{4.16}$$

- Step 2: The centralized office retrieves all the requests in form of a demand matrix $Q = [q_1 ... q_n]$. It accepts the offers if the aggregate bandwidth demand is less than the maximum available bandwidth M, and offers the bankruptcy game solution to users if the aggregate demand is more than the maximum available bandwidth. The centralized office uses one of the division rules to solve the bankruptcy problem and provides the outcomes as payoffs to all RRHs.

- Step 3: The RRHs divide the obtained bandwidth among the user groups that request different services by using proportional division rule. The users that request traffic for the same service type obtain the same bandwidth, but the data rate may differ depending on the RRH-user distance. The users calculate their final utility from the two closest RRHs and send their user satisfaction value for the given iteration.

4.2.5 Resource Allocation Fairness

Evaluating the fairness of division rule payoffs is a factor in deciding for the rule that appropriately fits the requirements of allocating resources. The fairness in resource allocation can be measured with several measures, such as Jain's index, max-min fairness, proportional fairness, and α fairness [226]. Among these measurements, Jain's fairness index [227] is a special case of the family of functions that satisfy the axioms about fairness given in [228], and it is widely used in the resource allocation literature, with some examples also being provided in Chapter 3

Table 4.1: Simulation parameters

Urban user	$\gamma_{urban} = 0.000\,01$, $\rho_{DR,urban} = 1$, $DR_{target,urban} = 300\,\text{Mbps}$, $DR_{min,urban} = 50\,\text{Mbps}$
mIoT user	$\gamma_{mIoT} = 0.0022$, $\rho_{DR,mIoT} = 1.1$, $DR_{target,mIoT} = 1\,\text{Mbps}$, $DR_{min,mIoT} = 0.1\,\text{Mbps}$
RWP	$v_{min} = 0.1\,\text{m}$ per iteration, $v_{max} = 1.0\,\text{m}$ per iteration, $t_{wait} = 1\,iteration$
Rate	$LF = 0.5$, $OF = 0.2$

such as [110] and [173]. Jain's index uses a normalized square mean to evaluate fairness, as given in Eq. (4.17):

$$\gimel(x_1, \ldots, x_n) = \frac{(\sum_{n=1}^{N} x_n)^2}{N \cdot \sum_{n=1}^{N} x_n^2} \tag{4.17}$$

Instead of directly evaluating the fairness of the payoffs $\{x_1, \ldots, x_n\}$,the satisfaction of the RRHs from the payoffs are evaluated with an expectation index (EI), which is equal to the payoff divided by the demand for each RRH [229]:

$$EI_n = \frac{x_n}{q_n} \tag{4.18}$$

4.3 Results and Discussion

The simulation parameters of the bankruptcy game for dynamic bandwidth allocation are as follows: Dense urban users move inside the $400\,\text{m}^2$ open square area by using RWP. The code library by which the mobility model is generated can be found in [230]. According to this model, users are generated at a random 2D position inside the area. The velocity is chosen from a uniform distribution between 0.1 m to 1.0 m at each iteration, and the maximum waiting time is chosen as 1 iteration. DR_{min} threshold value in Eq. (4.15) is 50 Mbps for dense urban traffic, which is the expected experienced data rate for urban macro users according to 3GPP service requirements. DR_{min} threshold value for the massive IoT scenario is 100 Kbps. User sensitivity γ and the satisfaction parameter ρ_{DR} in Eq. (4.15) are given in Table 4.1.

To evaluate the performance of the division rules presented in Section 4.1, three experiments are designed. In the first experiment, the proportion of the total available bandwidth to total RRH demand is changed and the outcomes of the rules are observed. In the second experiment, the density of urban users is

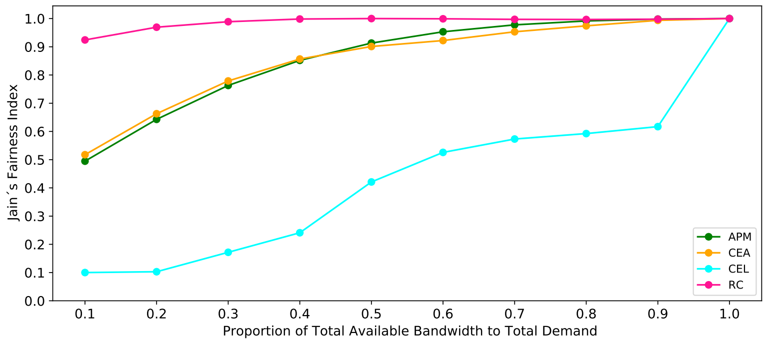


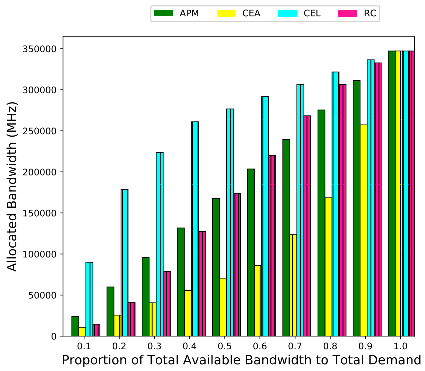
Figure 4.3: Jain's fairness index values of division rules for changing available total bandwidth

increased in the simulation area. The third experiment is carried out to evaluate the outcomes of the division rules while the user density increases only inside the coverage area of one RRH. As CG principle returns the same outcomes with the CEA rule in the experiments conducted, only the outcomes of CEA are presented. In addition, APM division rule with a minimal bandwidth right for all RRHs is preferred to the simple proportional division rule. For the RC rule, the payoffs are returned to RRHs by assuming that all RRHs form a grand coalition. Together with CEL rule, the outcomes of these four division rules are presented in the following subsections.

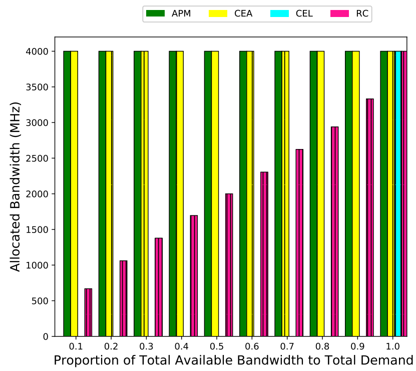
4.3.1 Division Rule Results for Increasing Total Available Bandwidth

In this experiment, the user distribution is adjusted to 400 mIoT users and urban user density is set to 0.025 per m^2 based on 3GPP service requirements [220], which corresponds to 10 urban users in 400 m^2 area. The user number is kept constant and the positions of the urban users change with RWP. All RRHs have mIoT users in their coverage area; however, not all RRHs serve a dense urban user at all iterations, creating low-demand and high-demand groups between RRHs. RRHs estimate bandwidth demand for an average user distance of 30 m; therefore the sum of RRH demands Θ does not change with user mobility during the simulation. The results are collected for 100 iterations with 10 different proportions of total available bandwidth M to Θ, the proportion ranging from 0.10 to 1.00.

The results reveal that the fairness and user satisfaction outcomes differ for the division rules for changing total available bandwidth M. Figure 4.3 shows that CEL is the least fair division rule for all $M < \Theta$. This result is due to the fact that the demand q_n of RRHs with mIoT users only are smaller than the β



(a) Bandwidth allocation for the RRH with the highest demand (both urban and mIoT users)

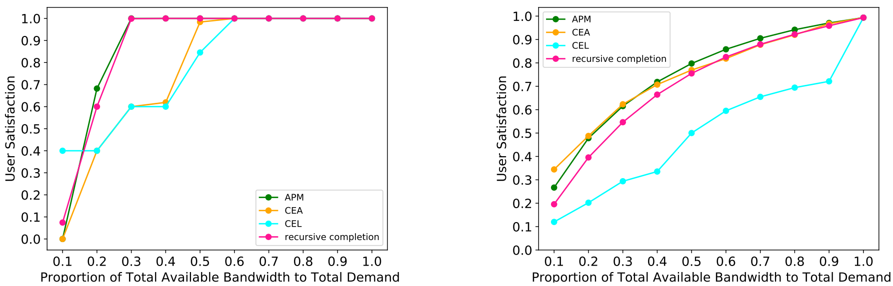


(b) Bandwidth allocation for an RRH with the lowest demand (only mIoT users)

Figure 4.4: Bandwidth allocation for RRHs with high and low demand with different division rules

value of CEL; therefore they are not allocated any bandwidth by CEL rule, as shown in Figure 4.4b. CEA and APM show similar outcomes in terms of overall Jain's fairness measurements; and Figure 4.4 shows that these methods provide a minimal right to RRHs with only mIoT users. As seen from Figure 4.3, all these three division rules are significantly less fair than RC when the total available bandwidth M is equal to or less than half of the total demand Θ. However, they converge to an index value of 1 for when the available bandwidth is high. Figure 4.4a demonstrates that CEA provides the least bandwidth to the RRH with the highest demand for all $M < \Theta$. APM provides more bandwidth than RC if the total available bandwidth proportion is less than 0.5, and RC provides more bandwidth than APM when the value is above 0.5.

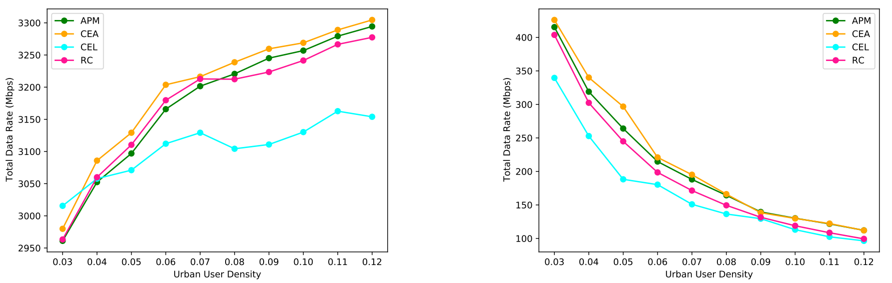
The average user satisfaction results for 100 iterations obtained by using Eq. (4.15) are shown in Figure 4.5. As seen from Figure 4.5b, CEL provides the lowest satisfaction value among mIoT users for all $M < \Theta$. On the urban user side in Figure 4.5a, only CEL can provide bandwidth resources to urban users for 0.1 available bandwidth proportion; however, CEL can only reach a 1.0 urban user satisfaction after $\frac{M}{\Theta} = 0.7$, as it fails to provide a satisfactory outcome to users connected to RRHs with both urban and mIoT demand, which do not have the highest bandwidth claim. APM and RC obtain the highest user satisfaction values for urban users and mIoT users, whereas CEA performs similar for mIoT users but provides lower urban user satisfaction values than APM and RC for $\frac{M}{\Theta} < 0.5$. For $\frac{M}{\Theta} > 0.5$, CEA also provides the highest urban user satisfaction.



(a) Urban user satisfaction results

(b) mIoT user satisfaction results

Figure 4.5: User satisfaction results for changing total available bandwidth



(a) Urban total data rate results

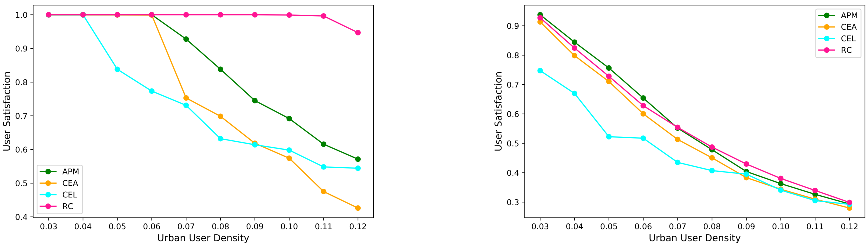
(b) mIoT total data rate results

Figure 4.6: Total data rate results for increasing urban user density

4.3.2 Division Rule Results with Increasing Urban User Density

The impact of urban user density on RRH demand distribution with the division rules are analyzed in this subsection. In this experiment, the total available bandwidth M remains constant matching a user demand estimation with 400 mIoT users and 10 urban users in $400\,\mathrm{m}^2$ area, which is equal to 0.025 per m^2 urban user density. On the user side, the results are obtained for different urban user densities between 0.030 per m^2 and 0.120 per m^2, i.e., between 12 and 44 urban users. All urban users move or wait inside the area with the RWP parameters given in Table 4.1.

The total data provided to urban users as the average of 100 iterations is demonstrated in Figure 4.6a, and mIoT user results are demonstrated in Figure 4.6b. As seen from Figure 4.6, all division rules provide more total data rate to urban users with increasing user density, contrary to the total data rate values of mIoT users. As in subsection 4.3.1, CEL provides less total data rate to



(a) Average urban user satisfaction results

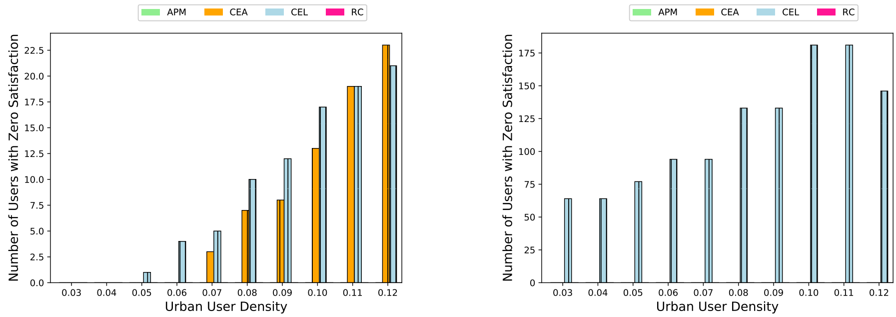
(b) Average mIoT user satisfaction results

Figure 4.7: Average user satisfaction results with increasing urban user density

urban users than other division rules when user density exceeds 0.03 per m^2. By allocating less bandwidth to RRHs with less demands, CEL division rule provides the least average mIoT total data rate. When the user satisfaction results are considered, it can be seen in Figure 4.7a that CEL provides a higher average user satisfaction value than CEA after 0.09 per m^2 urban user density. This results from CEL rule's support to RRHs that demand the most bandwidth. Nevertheless, urban users with zero satisfaction can be observed for CEL rule starting from 0.05 per m^2 urban user density, meaning that the data rate provided to urban users go below the 50 Mbps DR_{min} threshold value. The number of urban users with zero satisfaction value increases with increasing urban user density. Furthermore, CEL division rule provides the least average mIoT user satisfaction, and it is the only division rule that leads to mIoT users with zero satisfaction for urban user densities between 0.03 per m^2 and 0.12 per m^2, as shown in Figure 4.7b and Figure 4.8b.

CEA rule provides the most average total data rate to urban users from 0.04 per m^2 to 0.12 per m^2. However, Figure 4.7a shows that total data rate provided by CEA and CG principle does not directly increase the users' data rate satisfaction. This is due to the fact that the CEA rule and CG principle provide equal payoffs to all RRHs that demand bandwidth above the α threshold. Due to this equality in payoffs, the RRHs that serve more urban users end up providing less data rate to these users. Figure 4.8 depicts that the data rate provided to urban users go below the 50 Mbps DR_{min} threshold value for 3 urban users with CEA & CG principle rules when urban density is equal to 0.07 per m^2, hence these users have zero satisfaction value. The number of users with zero satisfaction keeps increasing with increasing user density, and 23 of the 44 dense users calculate zero satisfaction for 0.12 per m^2 urban user density.

AP method and RC algorithms provide similar outcomes in terms of total data rate both for urban and mIoT users, as seen from Figure 4.6. Their user satisfaction results are similar until urban user density reaches 0.07 per m^2; however RC outperforms AP when the user density exceeds this point, as depicted in Fig-



(a) Number of average urban users with zero satisfaction

(b) Number of average mIoT users with zero satisfaction

Figure 4.8: Average number of users with zero satisfaction for increasing urban user density

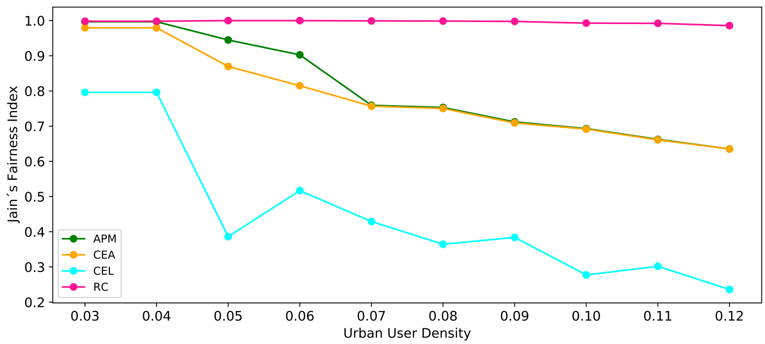
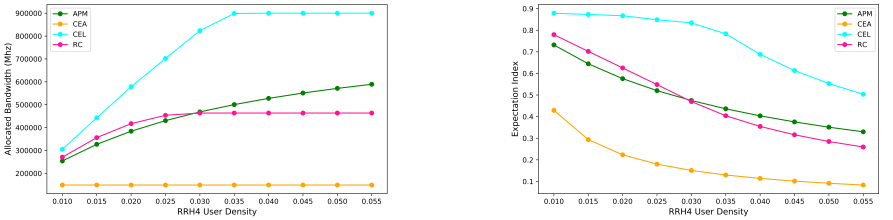


Figure 4.9: Jain's fairness index values of division rules for increasing urban user density

ure 4.7. The bandwidth allocation of these division rules does not result in any users with zero satisfaction between 0.03 per m^2 and 0.12 per m^2 urban user densities. AP method provides slightly higher total rates than RC for urban and mIoT users after the user density exceeds 0.08 per m^2. However, as in the CEA case, the increase in the total data rate does not lead to an increase in user satisfaction, as seen from Figure 4.7a. Jain's fairness index results in Figure 4.9 show that APM also differs from RC rule in terms of fairness after urban user density exceeds 0.05 per m^2.



(a) Bandwidth allocation of $RRH_{q_{max}}$ (b) Expectation index of $RRH_{q_{max}}$

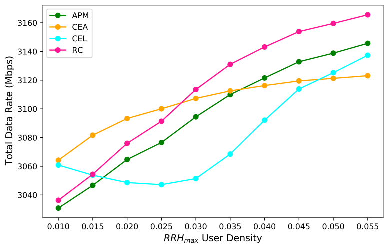
Figure 4.10: Bandwidth allocation and expectation index of $RRH_{q_{max}}$ for increasing $RRH_{q_{max}}$ urban user density

4.3.3 Division Rule Results with Increasing Urban User Density for RRH with Most Demand

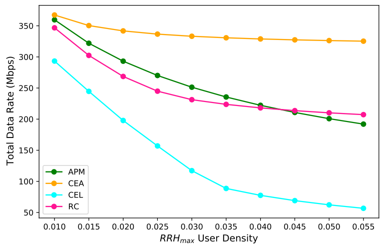
In this experiment, urban user density increase only happens inside the coverage area of a single RRH, while the user density in other areas remain the same at 0.025 per m^2. Urban users can move to the coverage areas of other RRHs for 100 iterations. The RRH, which is denoted as $RRH_{q_{max}}$, requests more of the total bandwidth with the increasing user density inside its coverage area, and the outcomes of the division rules are evaluated in terms of the allocated bandwidth, Jain's fairness index, and user satisfaction for increasing user density in the RRH area. As in subsection 4.3.2, the total available bandwidth M remains constant for a user distribution estimation with 400 mIoT users 10 urban users in 400 m^2 area, which is equal to 0.025 per m^2 urban user density. For this reason, 0.025 per m^2 provides a threshold user density value, as the user density inside the coverage area of $RRH_{q_{max}}$ is higher than the overall user density in the area after this threshold density value.

$RRH_{q_{max}}$ bandwidth allocation and expectation index results in Figure 4.10a and Figure 4.10b show that RC provides a close amount of bandwidth to $RRH_{q_{max}}$ with APM until user density in RRH area reaches 0.030 per m^2, and then deviates from APM by providing less bandwidth payoff to $RRH_{q_{max}}$. CEL always provides the highest bandwidth payoff to $RRH_{q_{max}}$. This division rule displays an extreme case by providing all the available bandwidth to $RRH_{q_{max}}$ after user density exceeds 0.035 per m^2. On the other hand, CEA displays another extreme case by providing a constant bandwidth payoff value to $RRH_{q_{max}}$ despite the increasing urban user density in this RRH's region. Thus, CEA has the worst expectation index value for $RRH_{q_{max}}$, as seen in Figure 4.10b.

Regarding total data rate of urban users, RC rule provides the highest total data rate to users after the user density inside $RRH_{q_{max}}$ coverage area exceeds the overall user density, denoted with 0.030 per m^2 user density in Figure 4.11a. APM provides a similar total data rate curve; however, different from the results

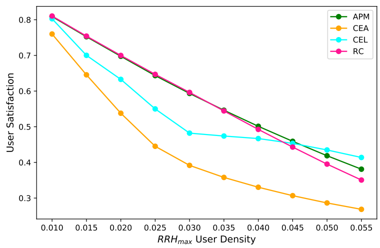


(a) Urban total data rate results

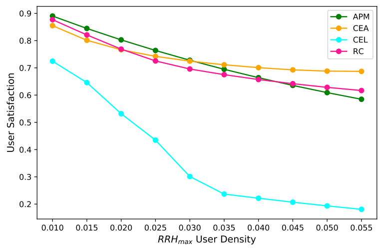


(b) mIoT total data rate results

Figure 4.11: Total data rate results for increasing $RRH_{q_{max}}$ urban user density



(a) Average urban user satisfaction results



(b) Average mIoT user satisfaction results

Figure 4.12: Average user satisfaction results with increasing $RRH_{q_{max}}$ urban user density

in Section 4.3.2, RC outperforms APM in terms of average urban total data rate for all user densities. Figure 4.11b shows that RC and APM results are similar for total data rate of mIoT users. The figure also shows that CEA provides the highest total data rate to mIoT users in all cases, and the opposite happens for CEL for all user densities. CEL also shows the worst total data rate performance in urban user case between 0.020 per m^2 and 0.045 per m^2 user densities, as this division rule neglects the urban user demands that come from the RRHs other than $RRH_{q_{max}}$.

User satisfaction values with increasing user density in $RRH_{q_{max}}$ coverage area are displayed in Figure 4.12. The highest urban user satisfaction values are provided by RC and APM until the $RRH_{q_{max}}$ user density reaches 0.055 per m^2, then CEL provides higher user satisfaction values than the two other division rules as it allocates all the available bandwidth to $RRH_{q_{max}}$. Figure 4.12b displays that mIoT user satisfaction results are also similar for RC and APM. As seen from Figure 4.12a, CEA rule has the lowest urban user satisfaction results, and the satisfaction values decreases with increasing user density inside $RRH_{q_{max}}$ coverage

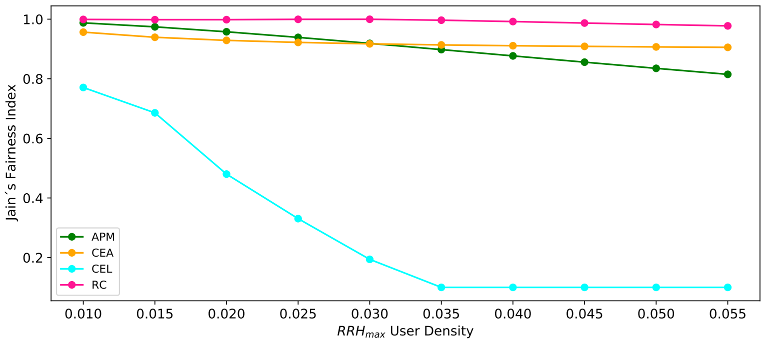


Figure 4.13: Jain's fairness index values of division rules for increasing $RRH_{q_{max}}$ urban user density

area, as CEA does not provide additional bandwidth to $RRH_{q_{max}}$. By doing the exact opposite, CEL rule obtains the lowest mIoT user satisfaction value for all user density values, as shown in Figure 4.12b.

Finally, Jain's fairness index values in Figure 4.13 show that CEL has the worst fairness values for the demand increase in a single RRH coverage area. RC provides the best Jain's fairness index results, which are almost equal to 1 in all $RRH_{q_{max}}$ urban user densities. AP method deviates from RC in terms of Jain's fairness measuremnets with increasing $RRH_{q_{max}}$ urban user densities. This is due to the fact that APM provides less bandwidth to RRHs with both urban and mIoT users, despite providing high expectation index values for the RRHs with only mIoT users. CEA provides an extreme case in Jain's fairness. The average value is high as it meets the expectations of all RRHs except the RRH with the highest demand. For this reason, the fairness index remains constant despite providing the lowest urban user satisfaction values, as seen in Figure 4.12a.

4.4 Summary

The aim of this chapter is to provide answers to the following research questions:

How should the interactions and possible actions among the stakeholders that control radio and transport networks be defined in case of limited resources to reach optimized dynamic bandwidth allocation in converged optical and mmWave radio networks?

Bankruptcy games deal with situations in which the total demand exceeds the available resources at that time interval, and division rules are used to solve the problem. The approach presented in this chapter compares the division rules that solve the bankruptcy problem and divide the limited fronthaul resources among

RRHs to improve resource utilization with cooperative sharing in a converged optical and mmWave radio access network scenario. The logic behind this cooperative approach is to optimize resource utilization and the data rate provided to the users to improve their satisfaction under increasing traffic demand.

Among the several division rules that solve the bankruptcy problem, recursive completion makes use of coalition formation and Shapley value calculation to provide fair allocation among the players. By forming a coalition consisting of a set of C-RAN RRHs, this method makes a bandwidth allocation viable by dividing the coalitional value among the members of the coalition. With this method, the interaction between the radio access elements and the transport network as a cooperative game, and the game can involve distributed agents that control the RRHs and make decisions on whether to join the a coalition or send its own demand without joining the coalition. A grand coalition is formed if all the RRHs join the coalition and send their sum demand to the transport network.

Recursive completion method is compared with the well-known division rules that solve the bankruptcy game, namely the adjusted proportional method, constrained equal awards, and constrained equal losses to observe their fairness and efficiency in providing the required data rate and satisfaction to network users under different conditions. The impact of heterogeneous users on the division rules is observed by adding dense urban users and mIoT users to the experiment, which have different characteristics and data rate requirements. As explained in Section 4.1, all the division rules allocate the total available bandwidth to RRHs, and there remains no leftover fronthaul capacity after the division rules are applied.

The division rules are compared in terms of Jain's fairness index, total data rate provided to different groups of users and user satisfaction, for changing proportions of the total available bandwidth to total RRH demand, increasing urban user density in the overall area, and inside the coverage area of one RRH. Recursive completion provides the highest Jain's fairness index measurements and the highest urban user satisfaction in all three experiments. Recursive completion also manages to keep all data rates above the minimum thresholds defined in these experiment for urban and mIoT users. Adjusted proportional method also provides similar outcomes to recursive completion; however it also shows no clear benefit on the RRH or user side, when these two methods are compared. Constrained equal awards rule provides the highest mIoT user satisfaction results by securing the minimal demand right of other RRHs, when the user demand increases extremely inside the coverage area of a single RRH. This minimal right concept can be considered as an SLA guarantee to a service provider under extreme traffic load increase. On the other hand, constrained equal losses return the lowest Jain's fairness index measurements and most RRHs would be expected to leave the coalition due to low returns if they are given the right to operate outside the scope of this rule. The only benefit it can provide is keeping user satisfaction high for the RRH with most demand under extreme traffic demand increases. The outcomes of these experiments can be used to adjust the available fronthaul bandwidth dynamically by monitoring the outcomes of the user satisfaction values or to negotiate SLAs with different service providers.

CHAPTER 5

Infrastructure Sharing with Auctioning Game

Different network sharing options have been discussed for next generation mobile networks. Infrastructure sharing is one these options, and it is divided into two categories of passive sharing and active sharing [231]. Passive sharing option considers sharing towers, sites and building premises among network operators, whereas active sharing encompasses sharing network elements of the RAN, transport and core networks. With the help of virtualization technologies, a physical network can be transformed into logical networks, and the resources of these network domains can be abstracted. Virtualization-based infrastructure sharing provides the opportunity to split these abstracted network resources between service providers (SPs) that provide different services to subscribers with the network slicing concept [232]. Additional resources can dynamically be added to these slices based on their users' demands.

This infrastructure sharing model redefines the network operator as the infrastructure provider (InP). The increasing number and diversity of service providers make slicing for shared fronthaul and radio resource allocation a complex problem for InPs. Furthermore, the dynamic demands of service providers from the InPs require a well-defined interaction and decision-making model between them. Beyond-5G and 6G networks necessitate a distributed network management paradigm that takes the objective functions of different stakeholders into account to solve this problem.

This chapter considers optical network resource allocation from a profit generation perspective with a game, in which providers bid to lease SDM-enabled fronthaul paths via Vickrey-Clarke-Groves (VCG) auctioning. Applying VCG auctioning for leasing provides a social-welfare maximizing outcome for resource allocation among self-interested services that demand fronthaul resources for their slices. InP also aims to maximize its revenue in this auctioning game. Another main target of the game is to include service providers and users in virtualized network resource allocation decisions. Service providers maximize their revenue by predicting user behavior and requesting bandwidth resources from the InP by bidding in the auction. Users have the option to switch between the service providers to maximize their utility. As a result, resource allocation decisions are distributed among the stakeholders such as the service providers, network operators and network users.

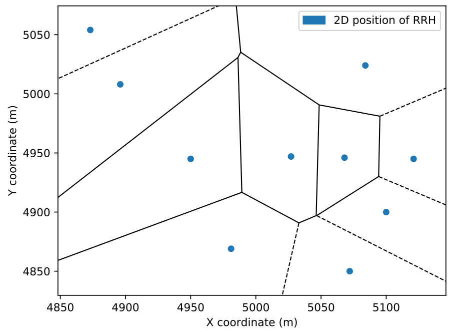
The rest of this chapter is structured as follows: The fundamental concepts of Vickrey-Dutch auction and VCG outcomes are presented in the background section. Then, the converged optical and mmWave radio network architecture, the game models between the service providers, InP, and users, and the utility functions of the stakeholders are introduced. Finally, the results of the experiments are presented and discussed.

5.1 System Model

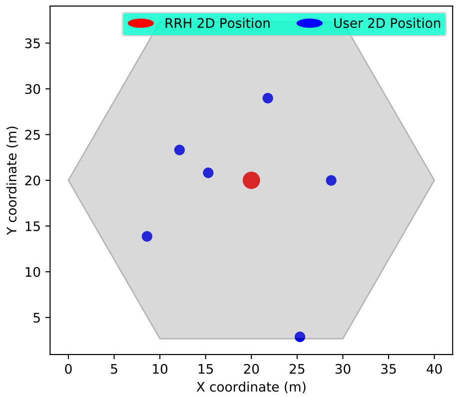
The main objective of this section is to present the overall network model and the stakeholders involved in the experiment. The utility functions of the stakeholders are also described in detail.

5.1.1 Network Model

The need for wireless network capacity expansion in mobile networks has transformed the traditional network architecture that consists of base stations and the backhaul to connect the core network to the mobile users. As C-RAN architecture is an option that addresses the capacity expansion, this study is based on an SDM-enabled C-RAN network architecture where many RRHs are connected with a centralized BBU pool [233]. BBU pool is connected to the backhaul segment to the core network, enabling end-to-end data transmission between the core network and mobile users. RRHs are simplified versions base stations that consist of the antenna units at the radio sites connecting mobile users to the cellular network, and the BBU pool is located at the central office (CO) is responsible for baseband processing. The centrally implemented BBUs are connected to RRHs over the fronthaul links. The use of ARoF technology in the fronthaul links increases centralization by removing digital to analog and analog to digital converters from the RRH and placing them to the central office (CO), and increases the fronthaul network capacity to support massive RRH deployments [234]. This centralization is a step towards more flexible routing and lightpath provisioning with an SDN controller [84]. The InP owns the RAN, transport and core parts of the network architecture.



(a) RRHs separated with Voronoi tessellation in open square area



(b) Scattered users inside a RRH coverage area

Figure 5.1: Simulation with C-RAN RRHs in an open square area

mmWave Radio Interface

In this study, 100 users are scattered inside an $400\,\mathrm{m}^2$ open square area using a Poisson point process [219]. Ten mmWave RRHs with center frequency $f_c = 28\,\mathrm{GHz}$ are distributed randomly inside this area, by ensuring that the maximum distance between the RRHs is less than 150 m and the minimum distance is more than 30 m. The coverage zones of RRHs are separated with Voronoi tessellation [235], as shown in Figure 5.1, and the users are connected to the closest RRH. The fifth generation channel model (5GCM) open square omnidirectional line-of-sight (LOS) urban microcell model in Eq. (5.1) is used to calculate the path loss, in which d_{3D} represents the 3D Euclidean distance between the user and the RRH in meters [141]. This equation uses the close-in free space model with a 1 m reference distance based on Friis' law.

$$PL_{\mathrm{LOS}} = 32.4 + 18.5 \cdot \log_{10}(d_{3D}) + 20 \cdot \log_{10}(f_c) \tag{5.1}$$

The RSS value of users is then calculated with Eq. (5.2), in which the power of the transmitter P_{T_x} is arranged as 30 dBm according to the model described in [223]. The SNR value is obtained by subtracting the thermal noise T_{noise} from the calculated RSS value, as shown in Eq. (5.3). T_{noise} equation is displayed in Eq. (5.4).

$$RSS_{\mathrm{user}} = P_{T_x} - PL_{LOS} \tag{5.2}$$

$$SNR_{\mathrm{user}} = RSS_{\mathrm{user}} - T_{noise} \tag{5.3}$$

$$T_{noise} = -174 + 10 \cdot \log_{10}(b_n) \tag{5.4}$$

Finally, the data rate of each user DR_n is calculated by using a simple user bandwidth to rate conversion model with overhead and loss factors OF and LF in

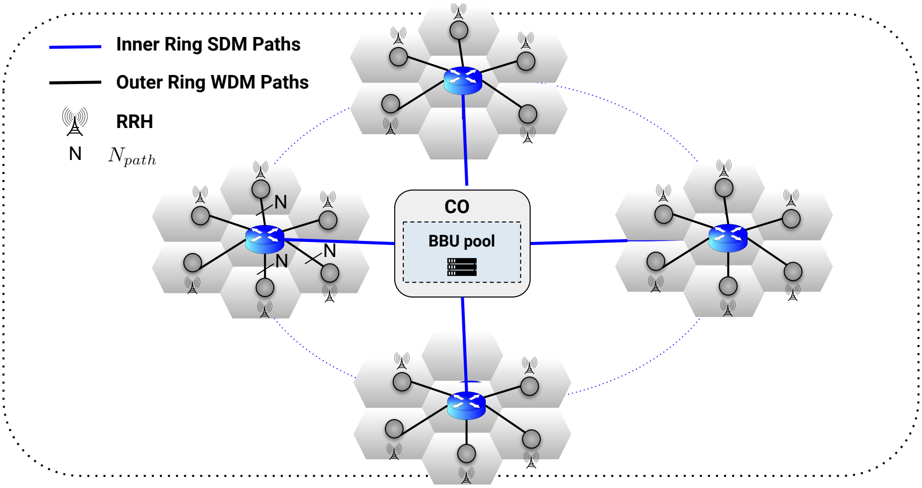


Figure 5.2: SDM-enabled C-RAN fronthaul topology with an SDM inner ring and a WDM outer ring

Eq. (5.5) [224]. Both OF and LF take values between 0 and 1. User bandwidth b_n is assumed to be distributed equally among all users connected to the RRH, before the service provider game begins. This data rate value is used in the utility calculation of the users, as given in Section 5.1.2.

$$DR_n = (1 - OF) \cdot b_n \cdot \log_2(1 + (1 - LF) \cdot SNR) \tag{5.5}$$

Fronthaul Topology

The fronthaul topology expands in both spatial and spectral dimensions, increasing the options for end user connectivity. Different spectral and spatial distribution options can be allocated separately to a number of RRHs, and the total number of supported RRHs is a product of the available spatial and spectral resources. In this study, a mixed-stage fronthaul topology design with both space and spectrum dimensions is taken into consideration to cover the increased fronthaul capacity requirement of dense C-RAN RRHs. A dual stage tree connection topology is created between the CO and the RRHs. The inner SDM tree provides the required capacity expansion in the paths from CO to the switch nodes and wavelength division multiplexing (WDM) paths reach from the switch nodes to the RRH [236]. The topology is depicted in Figure 5.2.

The fronthaul topology provides a number of optical paths per RRH, denoted with the set $I = \{1, ..., N_{\text{path}}\}$. The bidding takes place only for the WDM paths that reach the RRHs. The rest of the logical slice paths that connect CO to the RRH is provided automatically by the path computation element of the control

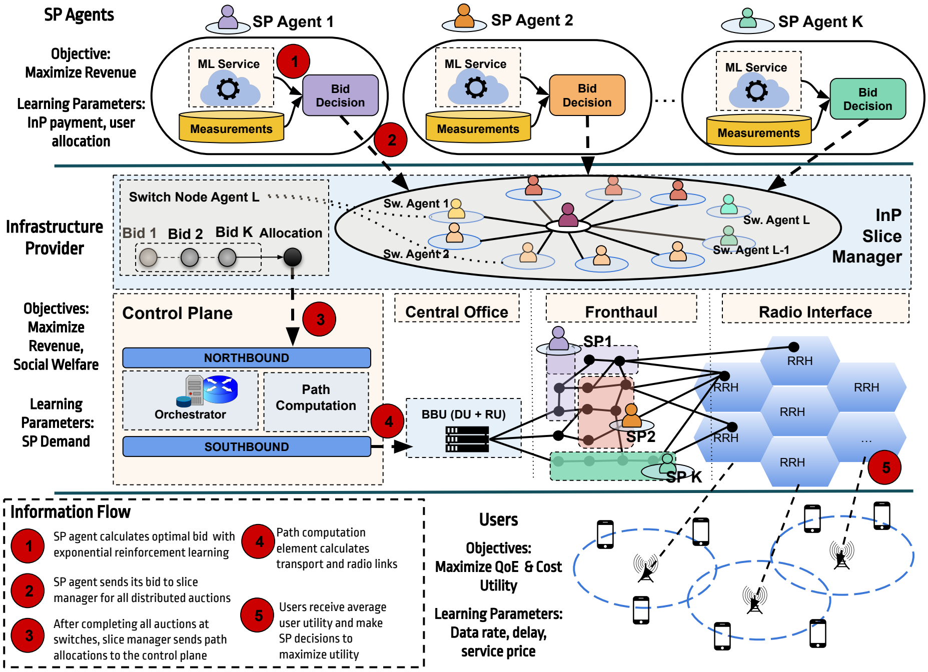


Figure 5.3: Stakeholder interactions and high level resource allocation architecture

plane. The losses of the network elements in optical paths and the splitting losses are neglected so that each wavelength channel has the same value in the auction.

5.1.2 Stakeholders and their Utility Functions

Before explaining the resource allocation model at the network edge, the stakeholders and their utility functions need to be clarified. The interactions between the network stakeholders and the distribution of the decision-making algorithms among stakeholders are depicted in Figure 5.3.

Infrastructure Provider (InP)

InP provides tailored network slices to service providers from the available network resources by means of an auctioning game. This auction design aims to provide a social-welfare maximizing outcome for resource allocation among different services demanding optical resources for their network slices. A network slice manager is responsible for creating slices for service providers and managing multi-tenancy [237]. This network slice manager on top of the NFVO creates end-to-end network slices and distributes these optical resources by running distributed auctions for each RRH. The slice manager obtains the required fronthaul topology and the optical resource information from the transport network SDN controller and NFV orchestration framework.

The fronthaul topology is divided into sub-graphs for these slices and the paths are leased with a descending auction. The descending auction is a non-cooperative game among service providers. InP is also self-interested and its objective is to reach a profit maximizing solution in this auctioning game; however, it is also bounded with the social welfare maximization condition of the auction. With a set of service providers B that make the payment C to lease fronthaul paths, the revenue function of InP in each game iteration i is given as:

$$U_{\text{InP},i} = \sum_{k \in B} C_{k,i} \tag{5.6}$$

When the auction for the fronthaul paths is finalized, the resulting service provider path allocation is forwarded to the control plane. The control plane keeps the virtual topology information and divides the network into sub-graphs to isolate service providers as tenants. The interaction between the service providers and the InP starts with a network slice request by the services registered to the InP slice manager.

Users

End users in set $H = \{1, ..., N_{\text{user}}\}$ want to maximize their utility by dynamically switching between the services and remaining connected to the service that best suits their demand at the given game iteration over the radio interface. Users subscribe to a service by paying the price set by the service provider and connecting to the slice dedicated to the service provider. Before the new game iteration, they compare their current utility to the average utility of all users, and switch their service provider based on a probabilistic function if they are below the average in that iteration. The probability to switch increases with the difference between user utility $U_{\text{user},n,i}$ and average user utility $\overline{U_i}$. If a user decides to switch from its service provider $SP_{n,i}$ at iteration i, then it has the option to randomly switch to the service providers that provide user utilities over the average user utility. The decision-making algorithm of users are given in Algorithm 1, where $SP_{n,i}$ indicates the service provider that the user is connected to at iteration i, $B_{-SP_{n,i}}$ is the set of all service providers other than $SP_{n,i}$, and $SP_\rho \in B_{-SP_{n,i}}$.

The utility of user n at iteration i is given in Eq. (5.7), where $DR_{n,i}$ represents user data rate, $d_{\text{user},n,i}$ is the transmission delay, and $p_{\text{user},n,i}$ is the price set by the service provider to the users [124].

$$U_{\text{user},n,i} = \ln(\alpha_1 \cdot DR_{n,i}) - \alpha_2 \cdot d_{\text{user},n,i} - \alpha_3 \cdot p_{\text{user},n,i} \tag{5.7}$$

As given in Eq. (5.5), data rate DR_n, i is a function of the user bandwidth $b_{n,i}$, calculated as $b_{n,i} = \frac{b_{k,i}}{n_{k,i}}$, where $b_{k,i}$ represents the fronthaul bandwidth allocated

Algorithm 1 User average utility comparison

Initialize: $i \leftarrow 0$;
repeat
  $i \leftarrow i + 1$
  for all User $n \in H$ **do simultaneously**
    calculate $U_{\text{user},n,i}$ using Eq. (5.7);
    retrieve $\overline{U_i}$ from InP;
    compare $U_{\text{user},n,i}$ with $\overline{U_i}$;
    if $U_{\text{user},n,i} < \overline{U_i}$ **then**
      $prob = |U_{\text{user},n,i} - \overline{U_i}| \div \overline{U}$
      $SP_{n,i} = \begin{cases} SP_{n,i-1} & \text{w.p. } prob \\ SP_\rho & \text{w.p. } 1 - prob \end{cases}$
    else
      $SP_{n,i} = SP_{n,i-1}$
    end if
  end for
until final iteration is reached.

to SP k, and $n_{k,i}$ is the number of users connected to this service provider. α_1, α_2, α_3 are the data rate, delay, and price weights of the utility function, respectively. These weights can be adjusted depending on the data rate and delay requirements of the service provided in the use case, and the cost requirements of the user. The logarithmic relationship between fronthaul bandwidth and the user utility in Eq. (5.7) shows that the users experience diminishing returns as user bandwidth increases [124].

Service Providers

Service providers use their intelligent agents that enable them to implement their policies based on their objective functions. The utility function of service provider SP_k at iteration i is given in Eq. (5.8).

$$U_{\text{SP},k,i} = \beta_1 \cdot p_{\text{user},n,i} \cdot n_{k,i} - \beta_2 \cdot C_{k,i} \tag{5.8}$$

where $p_{\text{user},n,i}$ is the price set by SP_k for users at iteration i, and $n_{k,i}$ is the number of users connected to SP_k. $p_{\text{user},n,i} \cdot n_{k,i}$ calculation gives the revenue of SP_k at iteration i, whereas $C_{k,i}$ is SP_k's total payment to InP for the allocated paths at the end of the auction. β_1 is the revenue weight and β_2 is the cost weight, and these weights can be adjusted according to the financial priorities of a service provider.

In the auction, service providers use exponential reinforcement learning to predict future utilities and make bids accordingly. The bid is calculated by using the utility $U_{SP,k,i}$, the total available paths in set I denoted with N_{path}, the total available bandwidth in the fronthaul paths BW_k, the bandwidth $b_{k,i}$ allocated to SP_k in iteration i, and the price set for users $p_{\text{user},n,i}$ [238]. The algorithm is distributed as all the values mentioned are locally available on the service side, and service providers do not need to know the topology of the system; hence the algorithm is also regarded as stateless [124]. Exponential reinforcement learning algorithm enables making bids in the auction by updating the marginal utility value for the next iteration. The marginal utility calculation is given as $w_k(\chi_k(m)) = \bigtriangledown_k U_{\text{SP},k,m}(\chi_k)$, where $\bigtriangledown_k(m)$ denotes the differentiation with respect to the fronthaul path allocation profile $\chi_k(m)$ at iteration m [238]. The following equations constitute the learning algorithm of services providers:

$$\widetilde{U}_{\text{SP},k,m} = \beta_1 \cdot p_{n,m} \cdot N_{\text{user}} \cdot \frac{\chi_k(m)}{N_{\text{path}}} \tag{5.9}$$

$$Z_k(m+1) = Z_k(m) + \gamma_m \cdot w_k(\chi_k(m)) \tag{5.10}$$

$$b_k(m+1) = BW_k \cdot \frac{e^{Z_k(m+1)}}{1 + e^{Z_k(m+1)}} \tag{5.11}$$

Eq. (5.9) defines the maximum revenue that SP_k can achieve with the user price and InP payments in iteration m of the association game between users and service providers. In this study, the association game iteration m is equal to the overall game iteration i, meaning that users make their association decisions in a single iteration. If $\widetilde{U}_{\text{SP},k,m} \leq 0$, then the service provider exits the game.

Eq. (5.10) predicts the optimal bids at the next auction, where k represents the k-th service provider in the set of service providers in the game $B = \{1, \ldots, N_{\text{SP}}\}$. $Z_k(m)$ represents the recursive score calculated by adding the marginal service provider utility $w_k(\chi_k(m))$ to the score at previous iteration, γ_m is the step size of the learning procedure, which is equal to $\gamma_m = \frac{1}{m}$. The calculated score for the next iteration $Z_k(m+1)$ is then used in a sigmoid function given in Eq. (5.11) to determine the optimal bandwidth request for the next auction iteration $b_k(m+1)$. This sigmoid function determines the proportion of the total available bandwidth BW_k for SP_k in all fronthaul paths in the auction, which is equal to $BW_k = N_{\text{path}} \cdot b_{max}$, and b_{max} represents the maximum available bandwidth in a single fronthaul path.

By using the score obtained from Eq. (5.10), Eq. (5.11) computes the path request of service provider k at the next iteration. BW_k is total available bandwidth per service provider, and a higher score resulting from a marginal utility means a higher proportion of the bandwidth is to be requested by the service provider at the next game iteration. This mechanism allows service providers to reach closer to the equilibrium in a distributed way, and the related algorithm is given in Algorithm 2. The algorithm terminates when the final iteration m_{final} is reached.

Algorithm 2 Exponential reinforcement learning for bidding [124]

Parameter: step-size sequence γ_m (default: $\gamma_m = 1/m$)
Initialize: $m \leftarrow 0$; $Z_k \leftarrow 0$ for all $k \in B$; $BW_k = N_{\text{path}} \cdot b_{max}$; $b_k(0) = \chi_{k,0}$
repeat
  $m \leftarrow m + 1$
  for all Service Provider $k \in B$ **do simultaneously**
    check $\widetilde{U}_{\text{SP},k,m}$ using Eq. (5.9);
    if $\widetilde{U}_{\text{SP},k,m} > 0$ **then**
      measure marginal utility $w_{k,m} = \bigtriangledown_k U_{\text{SP},k,m}$;
      update score: $Z_k(m+1)$ using Eq. (5.10);
      request bandwidth $b_k(m+1)$ using Eq. (5.11);
    end if
  end for
until final iteration is reached.

5.2 Game Models

The dynamic decision-making mechanism between the stakeholders consists of two games. The first game is the Vickrey-Dutch auction played among the service providers to allocate fronthaul paths that reach RRHs. The second game is played between the users and service providers as a leader and follower game. The game models are explained in this section, and the sequence diagram of the games that includes both InP auction and user association is given in Figure 5.4. As depicted in this figure, all users send their initial network association information to the InP before the auction starts, so that the InP records the total user number and the list of users to transmit average user utility information. The auction begins when InP sends the available fronhtaul paths in the auction and the price to acquire these paths to service providers. Service providers calculate their bids by using Algorithm 2, and InP allocates the paths to service providers for the accepted bids. The service providers send their payments for the paths allocated to them at the end of the auction. The second phase of the game begins after InP calculates the average user utility value for the new path allocation distribution, and sends this information to all users. Users make a new association decision based on Algorithm 1, and send their association decision to service providers. At the end of the game iteration, InP and service providers calculate their revenue, and the users calculate their utility value after their association decision.

5.2.1 Vickrey-Dutch Auction

An auction that determines the price paid by a player based on its opponents' bids is considered as a Vickrey auction, also known as a second-price auction [239]. An iterative auction is defined as a sequential price adjustment procedure that takes

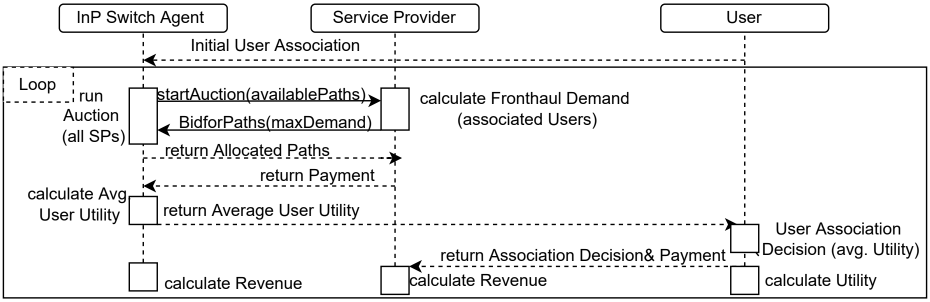


Figure 5.4: Sequence diagram of the interlinked game with Vickrey-Dutch auction between InP and SP and the Stackelberg game between user and SP

bids from buyers in each iteration, whereas a descending auction, also known as Dutch auction, starts with a high price at the first iteration and the price drops at each auction until the item is leased [240]. A Vickrey-Dutch auction is a modified version of this auction, where the player with the highest sealed-bid wins the auction; however, the player pays the amount of the second highest bid [239].

The VCG mechanism is used in problems in which the maximization of the total sum of all players' valuations is the main objective function [241]. The dependency on opponent players is achieved by adding the cost of the presence of the player to other players to the payments, making the bidding of the true valuation in every iteration an equilibrium strategy for all players [242]. The overall maximization property of VCG auctions is used by auctioneers that aim to optimize the use of all the items in the auction, such as a resource manager that aims to maximize the use of all the available spectrum resources in an area with licensed shared access in [243], or a spectrum reuse mechanism under the existence of co-channel interference in [244].

The objective function of the VCG mechanism is formulated in Eq. (5.12) [245], where $\chi \in F$ represents a feasible allocation, and F represents the set of all feasible allocations. A feasible allocation assigns items $I = \{1, \ldots, N\}$ to buyer set $B = \{1, \ldots, k\}$. $v_k(\chi_k)$ represents the item valuation of buyer k in allocation χ.

$$\chi* = \arg\max_{\chi \in F} \sum_{k \in B} v_k(\chi_k) \tag{5.12}$$

Set B_{-k} defines the set of buyers other than buyer k, and l represents an element in B_{-k}. Using these definitions, buyer k's VCG payment C_k is defined for a given efficient allocation $\chi*$ as:

$$C_k = \max_{\chi \in F} \sum_{l \in B_{-k}} v_l(\chi_l) - \sum_{l \in B_{-k}} v_l(\chi_l^*) \tag{5.13}$$

Given this VCG payment, the VCG payoff of buyer k is equal to $v_k(\chi_k^*) - C_k$. As seen from Eq. (5.13), buyer k's reported valuation cannot affect the seller's VCG payment calculation C_k. The buyer can therefore maximize its payoff only by maximizing its valuation function v_k. As each rational player bids their true maximum valuation for the items in the auction to obtain their VCG payoffs, it can be concluded that a VCG auction encourages truthful bidding.

Buyer k's bid in the auction is expressed in terms of their demand D_k. The set of all bundles of items is denoted by Ω, and for every bundle of items $S \subseteq \Omega$, buyer k has a valuation $v_k(S)$. With the assumption that $v_k(S) \leq v_k(T) \forall k \in B, \forall S, T \in \Omega$, with $S \subseteq T$, the demand set of buyer k for price vector $p \in \mathbb{R}^{|B|x|\Omega|}$ is:

$$D_k(p) = \{S \in \Omega : v_k(S) - p_k(S) \geq v_k(T) - p_k(T) \forall T \in \Omega\} \tag{5.14}$$

InP auctioning game in this study is modelled as an Vickrey-Dutch auction, in which fronthaul paths connected to the RRH are leased by the service providers. In the descending auction, each game round is represented by t. The number of paths to be allocated, the service providers registered as buyers, and the price charged in the first round are known before the auction begins. The price demanded by the InP is the highest in the first round, and the price descends at each round until the auction is terminated. The descending behavior of the auction is explicit to service providers.

Using the game theoretic model definition in Section 2.3, service providers constitute the *group* in the auctioning game. Services register to the InP in order to obtain a number of fronthaul paths that reach the RRH; therefore, there exists a definite number of buyers in the game, and the set of buyers can be modified as $B = \{1, \ldots, N_{\text{SP}}\}$. The items that are leased in the auction are the set of fronthaul paths, therefore the set of items is denoted by $I = \{1, \ldots, N_{\text{path}}\}$. As the bid of one player in the group effects the outcome of other players, it can be concluded that there is an *interaction* between this group of players. Service providers also bid in a *rational* and *strategic* way, as they try to optimize their utility by targeting a balance between not making an excessive payment and the risk of not obtaining any paths to serve the users in the defined area [101].

The Vickrey-Dutch auction is designed with multiple homogeneous items, non-increasing marginal values, and truthful bidding to obtain a VCG outcome [240]. In this auction, *homogeneous item* describes that all items in the auction are identical in an auction with multiple items. With homogeneous items, the valuation of the sets with equal number of elements are the same in this auction. For this reason, the number of the elements a is used to define the valuation of the buyers $v_k(a)$ for all sets with a elements. To ensure convergent bidding behavior by the buyers in the auction, the buyers have non-increasing marginal values for the items. The buyers have non-increasing marginal values if the following requirement is satisfied: $v_k(a) - v_k(a-1) \geq v_k(a+1) - v_k(a)$.

At each auction game round t, service providers send their maximal demand for the price set by the InP for a single path in that round, called a marginal price and represented with q^t. Service provider payments are determined after reaching the competitive equilibrium of the auction, therefore the payment of the service provider does not have to be equal to q^t. The demand of service provider k for a items in round t is given with Eq. (5.15):

$$D_k(q^t) = \begin{cases} 0 & \text{if } v_k(1) - v_k(0) < q^t \\ \max_{1 \leq a \leq N_{\text{path}}\}} \quad \text{s.t.} \quad v_k(a) - v_k(a-1) \geq q^t & \text{otherwise} \end{cases} \tag{5.15}$$

For the demand set definition given in Eq. (5.14), and with non-increasing marginal valuations, the maximum demand of all service providers satisfies the condition in Eq. (5.16) for all rounds after $t > 0$. This condition ensures that none of the service providers decrease their demand from round t to round $t+1$ with the decreasing marginal price q^{t+1}:

$$D_k(q^{t+1}) \geq D_k(q^t) \tag{5.16}$$

A provisional allocation χ_t is the allocation that generates the maximum revenue over all possible allocations in round t [240]. The paths are provisionally allocated to the service providers if the total maximum demand is less than the available paths, which constitute the supply set. After provisionally allocating the paths to the demanding service providers, the game continues with the next round until reaching the game round t', in which the demand of all service providers exceed the total number of paths N_{path} in the auction. To determine the number of paths that can be allocated to service provider k in this case, the path allocation in the previous round is kept, and the additional paths are allocated at random such that the maximum demand of any service provider is not exceeded [87]. If there is a tie in the bids of the service providers in the auction, then the tie is broken in favour of satisfying as many service providers as possible with the provisional allocation. If the maximum number of satisfied buyers do not change, then the tie is broken at random among the service providers demanding the item in the same game round.

Residual demand without service provider k is calculated by Eq. (5.17) for χ_t for all auction rounds $t \geq t'$:

$$R_{-k}(q^t) = \min(\chi_{t,k}, \sum_{j \neq k} [D_j(q^t) - \chi_{t,j}]) \tag{5.17}$$

The minimum value of the calculation that indicates how many path demands of other service providers remain unfulfilled at game round t, and the paths allocated to k with the provisional allocation $\chi_{t,k}$, gives the residual demand $R_{-k}(q^t)$ value. This value is used to calculate the payment of the service provider k. The game ends when the residual demand $R_{-k}(q^t)$ is equal to the number of paths allocated to the service provider k, denoted as N^k_{path}, for all $k \in B = \{1, \ldots, N_{\text{SP}}\}$. If every service provider bids truthfully, then this auction achieves the VCG outcome in service provider payments [240]. The VCG payment C_k of the service provider k is given in Eq. (5.18).

$$C_k^{VCG} = \sum_{t \geq t'} [q^t \cdot (R_{-k}(q^t) - R_{-k}(q^{t-1}))] \tag{5.18}$$

The main economy of the auction is denoted with $E(B)$. The collection of buyer sets is $\Phi = \{B, B_{-k}\}_{k \in B}$, and every $E(B_{-k})$ defines a marginal economy. The revenue of InP in Eq. (5.6) can be reformulated for price vector p and allocation χ as:

$$U_{\text{InP}} = \sum_{k \in \Phi} p_k(\chi_k) \tag{5.19}$$

The supply set of InP for price vector p is:

$$L(p) = \{\chi_k \in F(\Phi) : \sum_{k \in \Phi} p_k(\chi_k) \geq \sum_{k \in \Phi} p_k(y_k \; \forall y \in F(\Phi)\} \tag{5.20}$$

A price vector p and an allocation χ form a competitive equilibrium if $\chi_k \in D_k(p)$ for every k in B and $\chi \in L(p)$. Price vector p is the universal competitive equilibrium (UCE) of economy if it is the competitive equilibrium (CE) of $E(M)$ for every $M \in \Phi$. The VCG outcome is achieved if the auction terminates at UCE prices.

A descending auction example is given in Table 5.1 to explain the demand, allocation, residual demand and the payments of service providers in a setting, in which seven homogeneous fronthaul paths (N_{path}) are to be leased. The marginal price q^t is decreased at each auction round t. None of the service providers make a demand in the first iteration of the auction; therefore no paths are allocated to any service providers. In the second auction round, maximal demand D_{SP3} is equal to one, and there is no demand from other competitors. This iteration ends with a provisional allocation $\chi_3 = 1$ for SP_3, as the total supply is bigger than the total demand ($\sum_k D_k(q^t) < N_{\text{path}}$). However, no payment is made by the service provider at this iteration as no opponent bid is received for this item yet. The auction continues with these provisional allocations until auction round $t = 5$, as the maximum demand does not exceed the total supply.

At $t = 6$, the maximum demand of service providers exceed the supply of paths $N_{\text{path}} = 7$, as the maximal demand distribution is $[3, 3, 6]$. Pricing mechanism starts after this auction round as the CE of the main economy is reached, and residual demands are calculated to find the payments that realize the VCG outcome from the CE of the main economy. The provisional allocations made before this round are priced with the marginal price $q^6 = 5$, and the final item that is demanded by all service providers is randomly allocated to SP_2, in order to break the tie. The final allocation is random as all demands with the current price maximizes the InP revenue, and the number of satisfied buyers is already maximized as all service providers are allocated at least one path. At $t = 7$, the residual demand calculation shows that the termination condition, which is equal to $R_{-k}(q^t) = \chi_{t,k}$ for all k, is reached. The payment of the final path allocated to SP_2 is priced with the marginal price $q^7 = 4$, and the game is terminated.

Table 5.1: Vickrey-Dutch clinching auction example

Iteration	Price	Demand			Clinched Paths			Residual Demand			Payment		
t	q^t	D_{SP1}	D_{SP2}	D_{SP3}	χ_1	χ_2	χ_3	R_{-1}	R_{-2}	R_{-3}	C_1	C_2	C_3
1	10	0	0	0	0	0	0	0	0	0	0	0	0
2	9	0	0	1	0	0	1	0	0	0	0	0	0
3	8	0	0	1	0	0	1	0	0	0	0	0	0
4	7	1	0	3	1	0	3	0	0	0	0	0	0
5	6	1	1	4	1	1	4	0	0	0	0	0	0
6	5	3	3	6	1	2	4	1	2	3	5	10	15
7	4	4	4	6	1	2	4	1	2	4	5	10	19

5.2.2 Stackelberg Game between Users and Service Providers

Once the network slice resources are allocated to all service providers, the interaction among users and service providers starts. Inspired by [124], the multi-stakeholder resource allocation decision problem is defined as a two-stage Stackelberg game among service providers and users. The interaction among users and service providers is modeled as a hierarchical game, in which service providers act as leaders and users act as followers. Both service providers and users are self-interested agents that aim to maximize their own utility; therefore they play non-cooperative games.

In the first phase of the game, service providers compete with each other to allocate fronthaul paths by using the exponential reinforcement learning algorithm to anticipate the user behavior, as explained in the Vickrey-Dutch auction section. In this way, service providers request a number of paths to cover their forecast bandwidth demand from the InP. Service provider is the leader of the Stackelberg competition taking the first decision by leasing paths. As followers of the game, users remain connected to their previous service provider until the end of this path allocation.

The leader game ends after the path allocation, and average utility value of users is calculated and transmitted to all users by the InP. Users begin playing their game by observing the new average utility value, which is a result of the path allocation bids of service providers, and they compare their current utility to the average utility of all users. If their current utility is lower than the average, they obtain average user utility values of different service providers, and switch randomly to a service provider that has a higher average user utility than its current utility. If there are more than one service provider with higher average user utility, then the a probabilistic switch occurs, and the probabilities are calculated by using the difference between the average user utility of the service provider and the current user utility. The price of the service providers remains constant while the game between the users is being played.

In this Stackelberg game, users are dependent on the InP information; therefore the decision-making algorithm of users is not uncoupled. The user requires information about other user's utilities to imitate the users with higher utilities and choose its service provider. After converging to an equilibrium state in the users' game, service providers predict user behavior for the next step by calculating their marginal utilities and request new bandwidth at the next iteration.

For the follower game, users constitute the *group* with a definite number of players. The service provider selection of one user affects the outcome of other users, as user bandwidth b_n for user n decreases with the increasing number of users connected to the same provider k, denoted by n_k, there exists an *interaction* between this group of players. Users make decisions in a *rational* and *strategic* way, as they try to optimize their utility by trying to select a service provider with a higher utility by using the average utility comparison displayed in Algorithm 1. Hence, it can be concluded that the follower game is in line with the game theoretic model definition in Section 2.3.

The Stackelberg equilibrium (SE) is a Nash Equilibrium in which the players cannot have better outcomes by switching to a different strategy [246]. Stackelberg equilibrium can be solved with backward induction method, meaning that first solving the optimal outcome for the follower and then computing the optimal choice of the leader in a backward way provides the desired solution. Applying this method and starting with the follower game, it can be stated that user side equilibrium is reached when the utility of all users are equal, i.e., $U_{\text{user},n} = U_{\text{user},n'}$, for all $n, n' \in S$ [124]. This user side equilibrium distribution is indicated with $n*$. Given $n*$, a profile is the Stackelberg equilibrium for service providers when $U_{\text{SP},k}(b*, n*) \geq U_{\text{SP},k}(b, n*)$ for all $k \in B$, where $b \in \Psi$ is any bandwidth vector that contains bandwidth requests of each service provider, Ψ is the set of all bandwidth vectors, and $b* \in \Psi$ indicates the bandwidth vector that satisfies the equilibrium condition $b* = \arg\max U_{\text{SP},k}(b_k, b*_{-k}, n*)$. It should be noted that this is the theoretical equilibrium condition calculated by the service providers, which is not achievable when all users have random locations that affect their data rates, hence they obtain unique user utility values for their locations. However, service providers make their bids by aiming at this equilibrium condition.

5.2.3 Trial and Error Learning for Users

A network game for resource allocation optimization is likely to involve huge numbers of network users that can neither observe the network structure nor other users' actions. For this reason, it is reasonable to assume that many network situations occur in which users look for a satisfying QoS without having additional information about the network state, such as the average user utility value provided by the InP to users, as displayed in Figure 5.4. Modeling this user environment as a game requires users to choose their strategies despite the lack of information. As a consequence, probabilistic switch in Algorithm 1 that displays replicator dynamics behavior on the user side is replaced with trial and error learning given in

Algorithm 3 for distributed and completely uncoupled decision making. As stated in [247], trial and error learning rule is a completely uncoupled and distributed learning rule, as it does not need additional information about other players or the environment.

In trial and error learning user game $\mathcal{G}_{te}$, a state variable called *mood* (md_n) determines how a user responds to recent payoff history, based on the player's current expectations. *Content* (c), *Discontent* (x), *Watchful* (c^-) , and *Hopeful* (c^+) are the four moods defined for the users. The state of the user at iteration i is defined as $s_{n,i} = (md_{n,i}, k'_{n,i}, u'_{n,i})$, meaning that the state depends on the mood $md_{n,i}$ of the user n, its benchmark action $k'_{n,i}$, where k is a service provider in set $B = \{1, ..., N_{SP}\}$, and its benchmark utility $u'_{n,i}$, which is the maximum utility value observed by the user when it has been connected to service provider SP_k. These variables are compared with the received utility $U_{\text{user},n}$ and action SP_k at each iteration to decide for the mood at next iteration. The main structure of the user trial and error learning algorithm is given in Algorithm 3. The state updates for a user in *Content* mood is explained in Algorithm 4, *Watchful* and *Hopeful* moods are explained in Algorithm 5, and *Discontent* mood is explained in Algorithm 6.

Algorithm 3 Trial & Error Learning for all users

Initialize: $i \leftarrow 0,\ k'_{n,0} \leftarrow k_{n,0},\ u'_{n,0} \leftarrow U_{n,0};$
repeat
    $i \leftarrow i + 1$
    for all User $n \in H$ **do simultaneously**
        calculate $U_{n,i}$ using Eq. 5.7;
        compare $U_{n,i}$ with $u'_{n,i}$
        if $md_{n,i}$ is c **then**
            Update $s_{n,i+1} = (md_{n,i+1}, k'_{n,i+1}, u'_{n,i+1})$ using Algorithm 4
        end if
        if $md_{n,i}$ is c^- or c^+ **then**
            Update $s_{n,i+1} = (md_{n,i+1}, k'_{n,i+1}, u'_{n,i+1})$ using Algorithm 5
        end if
        if $md_{n,i}$ is x **then**
            Update $s_{n,i+1} = (md_{n,i+1}, k'_{n,i+1}, u'_{n,i+1})$ using Algorithm 6
        end if
    end for
until termination criterion is reached in $\mathcal{G}_{te}$.

If a player's utility value drops by another player's change of action for two iterations, the player becomes *Discontent* and randomly chooses another service provider from set B, and updates its benchmark action and utility according to the result of this new action. The active search leads the players toward higher payoffs and higher benchmark utilities until an equilibrium is reached or someone's

Algorithm 4 Trial & Error Learning for user n in *Content* mood

if $md_{n,i}$ is c **then**
  if experiment is done with probability ε **then**
    randomly choose a service provider $SP_{\text{user},i} \in B_{-k'_{n,i}}$
    if $U_{n,i} > u'_{n,i}$ & experiment is accepted with probability $\varepsilon^{K(\Delta u)}$ **then**
      $md_{n,i+1} = c,\ k'_{n,i+1} = SP_{\text{user},i},\ u'_{n,i+1} = U_{n,i}$
    else
      $md_{n,i+1} = c,\ k'_{n,i+1} = k'_{n,i},\ u'_{n,i+1} = u'_{n,i}$
    end if
  else
    if $U_{n,i} > u'_{n,i}$ **then**
      $md_{n,i+1} = c^{+},\ k'_{n,i+1} = k'_{n,i},\ u'_{n,i+1} = u'_{n,i}$
    end if
    if $U_{n,i} = u'_{n,i}$ **then**
      $md_{n,i+1} = c,\ k'_{n,i+1} = k'_{n,i},\ u'_{n,i+1} = u'_{n,i}$
    end if
    if $U_{n,i} < u'_{n,i}$ **then**
      $md_{n,i+1} = c^{-},\ k'_{n,i+1} = k'_{n,i},\ u'_{n,i+1} = u'_{n,i}$
    end if
  end if
end if

Algorithm 5 Trial & Error Learning for user n in *Watchful* and *Hopeful* moods

if $md_{n,i}$ is c^{-} **then**
  if $U_{n,i} > u'_{n,i}$ **then**
    $md_{n,i+1} = c^{+},\ k'_{n,i+1} = k'_{n,i},\ u'_{n,i+1} = u'_{n,i}$
  end if
  if $U_{n,i} = u'_{n,i}$ **then**
    $md_{n,i+1} = c,\ k'_{n,i+1} = k'_{n,i},\ u'_{n,i+1} = u'_{n,i}$
  end if
  if $U_{n,i} < u'_{n,i}$ **then**
    $md_{n,i+1} = x,\ k'_{n,i+1} = k'_{n,i},\ u'_{n,i+1} = u'_{n,i}$
  end if
end if
if $md_{n,i}$ is c^{+} **then**
  if $U_{n,i} \geq u'_{n,i}$ **then**
    $md_{n,i+1} = c,\ k'_{n,i+1} = SP_{\text{user},i},\ u'_{n,i+1} = U_{n,i}$
  else
    $md_{n,i+1} = c^{-},\ k'_{n,i+1} = k'_{n,i},\ u'_{n,i+1} = u'_{n,i}$
  end if
end if

Algorithm 6 Trial & Error Learning for user n in *Discontent* mood

if $md_{n,i}$ is x **then**
  randomly choose a service provider $SP_{\text{user},i} \in B$
  if experiment is accepted with probability $\varepsilon^{J(u)}$ **then**
    $md_{n,i+1} = c,\ k'_{n,i+1} = SP_{\text{user},i},\ u'_{n,i+1} = U_{n,i}$
  else
    $md_{n,i+1} = x,\ k'_{n,i+1} = k'_{n,i},\ u'_{n,i+1} = u'_{n,i}$
  end if
end if

aspirations are disappointed before an equilibrium is reached. Even when the users are in the *Content* mood, they have the option to experiment with different actions in their action set with an experiment probability $\varepsilon = e^{-\beta_{exp}}$, where $\varepsilon \in (0,1)$ and $\beta_{exp} > 0$. Users remain in the experimented service provider only if their utility value increases when compared to the benchmark utility. The key element that distinguishes the trial and error learning approach in [248] is the probabilistic acceptance of experiments in the content state with probability: $\varepsilon^{K(\Delta u)}$, where $\Delta u = U_{n,i} - u'_{n,i} > 0$ and $0 < K(\Delta u) < 1/2$. Accepting the outcome of a random search in the *Discontent* state with a probability that is increasing in its realized level of utility with probability $\varepsilon^{J(U_{n,i})}$, where $0 < J(U_{n,i}) < 1/2n$, and n is the number of users playing the game. The log-linear format of these acceptance functions are presented below, in which the coefficients $\varphi_1, \varphi_2, \gamma_1, \gamma_2$ are chosen so that $J(U_{n,i})$ and $K(\Delta u)$ are decreasing functions and also positive for all $U_{n,i}$ and Δu:

$$J(U_{n,i}) = -\varphi_1 \cdot U_{n,i} + \varphi_2, \varphi_1 > 0 \tag{5.21}$$

$$K(\Delta u) = -\gamma_1 \cdot \Delta u + \gamma_2, \gamma_1 > 0 \tag{5.22}$$

In a game where the users make decisions based on trial and error learning, interdependency condition has to be satisfied for the game to reach an equilibrium or near-equilibrium state. Interdependency is defined as any subset of players can cause a payoff change for some player not in the subset, given any current choice of actions [248]. Interdependence holds in this Stackelberg game as the total fronthaul bandwidth in the paths allocated to a service provider is distributed among the users connected to this service provider. Thus, one user's service provider selection affects other users' utility values.

When all players in a game use trial and error learning, the play comes close to pure Nash equilibrium a high proportion of the time, provided that the game has such an equilibrium and the experimentation probability is sufficiently small [247]. Over the long run, states that are not stochastically stable will be observed infrequently compared to the states that are stable, provided that the probability of mistakes is small. The convergence of the trial and error algorithm must be understood regarding the time players remain at a given action profile [111]. Con-

Table 5.2: Simulation parameters

User	$\alpha_1 = 2$, $\alpha_2 = 1$, $\alpha_3 = 1$
SP	$\beta_1 = 1$, $\beta_2 = 2$, $p_{\text{user}} = 1$
Path	$b_{\max} = 100\,\text{MHz}$, $d_{\text{user}} = 5\,\text{ms}$
Rate	$LF = 0.5$, $OF = 0.2$

vergence rate also remains an open question due to the computational complexity of the inherent Markov Chain [249].

5.3 Results and Discussion

To evaluate the proposed resource allocation and auction mechanisms, the game is played with one InP and three service providers. As shown in Figure 5.4, the overall game consists of the auctioning game and service provider association decision of the users. The overall game has 10 iterations, denoted with i. The overall game terminates when $i = 10$. At each game iteration, the auctioning game is played for ten rounds, and each auction round is denoted with t. During the auction, the price descends one unit price from ten to one at each round t. The Stackelberg game between service proivders and users is played once at each iteration i; therefore the exponential reinforcement learning iteration m in Algorithm 2 is equal to i. Each fronthaul path to RRH has a maximum bandwidth of 100 MHz. The transmitter power P_{tx} is set to 30 dBm [223], and overhead and loss factors OF and LF are used in the SINR to rate conversion [224]; Table 5.2 lists the simulation parameters.

In Section 5.3.2 and Section 5.3.3, Shapiro-Wilk normality test [250], Levene equality of variances test [251], and Student T-test analysis [252] are used to explain the results obtained in simulations. Before presenting these results, the basic definitions of the two statistical procedures are provided here. Shapiro-Wilk test is used to check the normal distribution claim of a dataset. The null hypothesis $H0$ claims the data is from a normal distribution, and the alternate hypothesis $H1$ claims that the data is not from a normal distribution. If the p-value is above the significance threshold (0.05 in this study), then the null hypothesis is either true there is insufficient evidence to disprove it. If the p-value is below the significance threshold, then the normal distribution claim for the dataset is rejected. Levene test [251] null hypothesis $H0$ claims that population variances are equal, and the alternate hypothesis $H1$ claims that the variances are not equal. For p-values above the significance threshold of 0.05, the equal variances hypothesis is true or there is insufficient evidence to disprove it. As for the Student T-test method, the null hypothesis $H0$ claims that there is no significant difference between the sample means [252]. If a p-value is less than 0.05, then the null hypothesis is

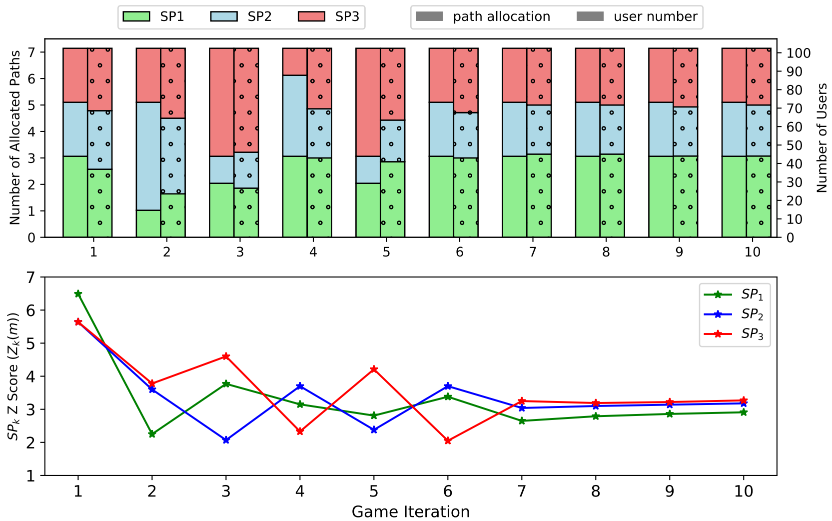


Figure 5.5: Service provider path allocation, user number, and marginal utility values

rejected and it can be concluded that a significant difference exists between the mean values of the compared samples.

5.3.1 Auctioning Game Analysis with 3 Service Providers

In order to observe the convergence behavior of the game in a path distribution that cannot be allocated equally by all SPs, the game is played with 100 users and 7 fronthaul paths. It is assumed that the users do not disconnect or hand over to other RRHs during the auction. The price and delay values for the users are kept constant. As for the weighting parameters, α_1 in Eq. (5.7) is given a higher value to be able to observe the impact of the data rate on the switching behavior of users. Similarly, β_2 in Eq. (5.8) is higher than β_1 for SPs to avoid high payments from SPs to the InP. Figure 5.5 displays the distribution of the paths allocated to each SP, users connected (n_k) to each SP, and the recursive score (Z_k) values of SPs at each game iteration. Figure 5.6 shows the data rate distribution of all users and the total number of users changing their SP association at each game iteration. The SPs have an initial user association distribution of $[34, 33, 33]$. One extra user increases the recursive score of SP_1 when compared to SP_2 and SP_3, as shown in Figure 5.5. As an expected outcome, SP_1 bids more for the paths and gets 3 paths at the end of the first iteration, with overall path allocation distributed as $[3, 2, 2]$. The user distribution at the end of the first iteration is recorded as $[36, 31, 33]$. As seen from the first iteration in Figure 5.5, there is a negative difference between the proportion of allocated paths and the number of users of SP_1, resulting in a

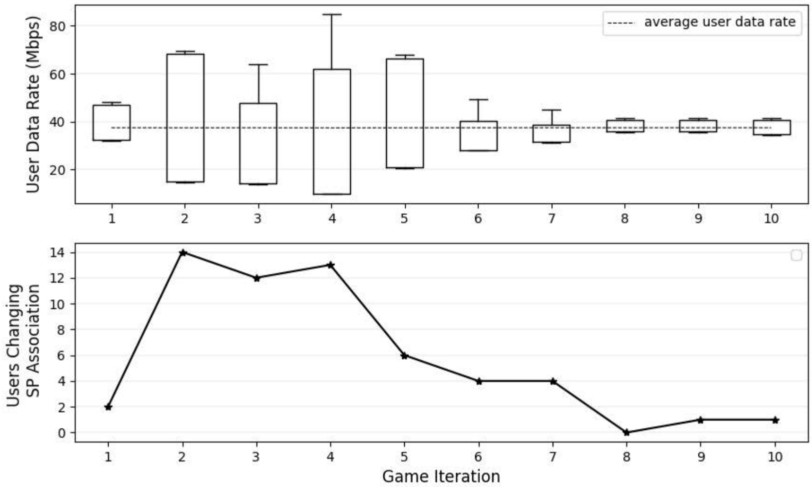
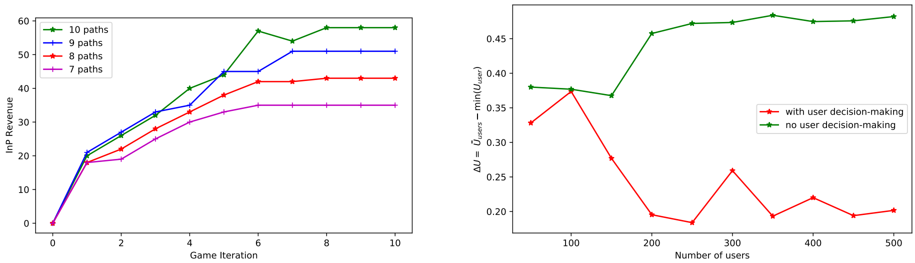


Figure 5.6: User data rate distribution and total number of users changing their SP association at each iteration

higher negative difference in the recursive score of SP_1 between iteration $i = 1$ and $i = 2$, as score is calculated for the $n*$ profile of the Stackelberg game. The difference between the $n*$ profile and the actual user distribution is due to the fact that switching the association is a probabilistic function; therefore a user might remain connected to the same SP despite having a lower utility than the average utility.

The bids for the auction in iteration $i = 2$ is based on the SP recursive score values in Figure 5.5. The scores indicate that SP_2 and SP_3 start demanding fronthaul paths at higher prices than SP_1. As a result, overall path allocation in iteration $i = 2$ ends as $[1, 4, 2]$. If there is a tie in the bids of the SPs in the auction, the additional paths are distributed at random such that the maximum demand of any SPs is not exceeded [87]. In the given example, the ties are randomly broken in favor of SP_2. The user distribution at the end of $i = 2$ is $[23, 40, 37]$. SP_2 has a lower number of users than the $n*$ profile of this iteration, which is theoretically close to [14, 57, 29]. whereas SP_1 and SP_3 have higher recursive scores. Consequently, iteration $i = 3$ ends with [2,1,4] path allocation. The SP that has more allocated paths also cannot reach the expected utility by reaching the $n*$ profile in the user distribution in $i = 4$ and $i = 5$. As seen from Figure 5.6, the data rate provided to users after the first round expands to a large interval due to the changes in SP path allocation. For instance, the data rate difference between the user that obtains the best data rate and the worst data rate is higher



(a) InP revenue for different number of fronthaul paths as auction items with 3 service providers and 100 users.

(b) The difference between average user utility and least well-off user utility for switching and no switching scenarios.

Figure 5.7: InP and user behavior in 3SP Game

than 70 Mbps at game iteration $i = 4$. It can also be observed that the number of users changing their association is higher than most of the other game iterations, as more than 12 users change their association in each round between $i = 2$ and $i = 4$. While not reaching their expected utility values, SPs demand paths by increasing the price of their bids, which can be observed in the increase in the InP revenue for 7 paths in Figure 5.7a. InP revenue at each round is a direct result of the increase in SPs payments.

The auction ends with a $[3, 2, 2]$ distribution for seven paths after game iteration $i = 6$, and the SP path demands converge to this distribution in the following rounds, as seen in Figure 5.5. The user distribution at the end of the last iteration is [43, 27, 30], which is close to the $n*$ profile for the identical users. The total number of users switching decays after $i = 6$, and the data rate difference between least well-off and the best performing user is minimized, with all users concentrated around the mean data rate value of 37.5 Mbps, as the game converges to an equilibrium. Figure 5.6 demonstrates that the convergence behavior of users differs from the classical idea of convergence at the equilibrium due to the probabilistic switching function of users. However, a distance minimization to a particular $n*$ profile is achieved in the user distribution, as the number of users switching after the SP path allocation convergence is sufficiently small. Hence, it can be concluded that Vickrey-Dutch auction with VCG outcomes and Stackelberg game solved with exponential reinforcement learning provide a profit – social welfare trade-off for non-cooperative SPs in sharing fronthaul resources.

Finally, the InP revenue with different number of paths in auction and the user utility of the least well-off user with increasing number of users are discussed. InP revenue in Figure 5.7a is evaluated for cases from seven to ten paths with 100 users. The markers indicate the revenue obtained in that iteration. InP revenue increases with the increasing number of paths, with SP provider bids reaching an equilibrium point after eight iterations in all cases. Figure 5.7b shows the difference ΔU between the average utility of all users and the least well-off user utility for a range

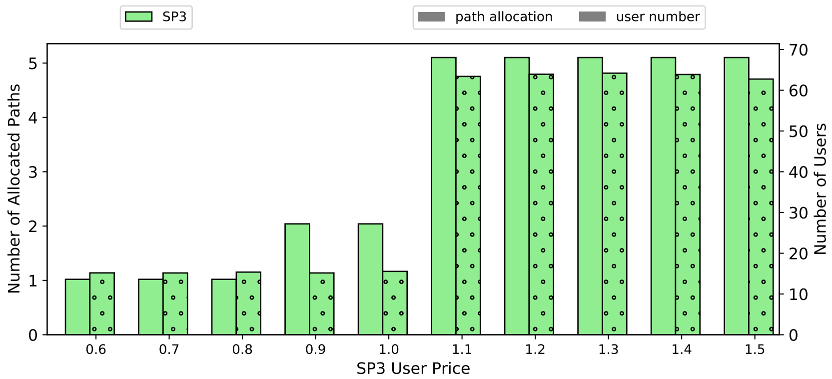


Figure 5.8: Number of allocated paths and average number of users for SP3 when user price ranges from 0.6 to 1.5

of users between 50 and 500. The utility values with user decision-making and no decision-making are compared, and it is shown that the utility of the least well-off user improves with simple decision-making with increasing number of users. Thus, the InP also increases social welfare by sharing average user utility value with the users.

5.3.2 User Price Parameter Adjustment

As it can be seen from Eq. (5.7) and Eq. (5.8), user price (p_{user}) impacts both user utility U_{user} and service provider utility U_{SP}, and is also used to calculate the marginal utility value in Algorithm 2. This marginal utility value is used the calculate the service provider's valuation of a fronthaul path and its bid in the auction. To analyze the impact of user price on service providers in the auctioning game, the average user number and fronthaul paths allocated to the service provider in 50 experiments are presented in Figure 5.8. The average service provider payoffs are displayed with the changing user price in Figure 5.9. It should be mentioned that the condition for randomly allocating paths to break ties is changed with a rule that assigns path to the service provider with more paths for these experiments. This obviously is not a social-welfare maximizing outcome, but it does not contradict with the maximum InP revenue generating allocation condition, and it gives the opportunity to observe the service provider behavior that is only subject to the randomness caused by the switching probability of users.

The results are obtained in a setting with 3 service providers, 7 fronthaul paths, and 100 users. The parameters in Table 5.2 are used except for the p_{user} parameter of SP_3, which ranges from 0.6 to 1.5. p_{user} parameter of SP_1 and SP_2 are kept constant as 1. For p_{user} values below 0.6, SP_3 cannot obtain any fronthaul paths in the auction as its path valuation is too low when compared to SP_1 and SP_2. And for values p_{user} values above 1.5, SP_2 cannot obtain a fronthaul path in the auction

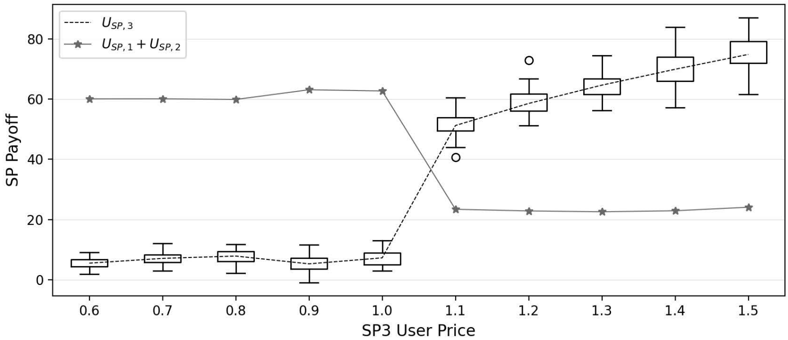


Figure 5.9: SP payoffs when SP3 user price ranges from 0.6 to 1.5

and the users are divided between two service providers. In order to measure the user number and payoff values in a setting with three service providers, p_{user} range is kept between 0.6 to 1.5. The auction is iterated for a single round with different p_{user} to obtain the results. As in Section 5.3.1, the SPs have an initial user association distribution of $[34, 33, 33]$.

Figure 5.8 demonstrates the number of allocated paths and the average number of users for SP_3. When the p_{user} value of SP_3 increases from 0.6 to 1.5 with a step size of 0.1, the auction ends with 3 different path distributions. For p_{user} values between 0.6 and 0.8 of SP_3, SP_3 obtains 1 fronthaul path, as its valuation is lower than other SPs. This behavior is expected as the expected revenue of SP_3 is lower than its competitors when its p_{user} value is low. For p_{user} values between 0.9 and 1.0 of SP_3, a $[3, 2, 2]$ distribution is obtained for seven paths. For SP_3, p_{user} values above 1.1, SP_3 path valuation is higher than its competitors as it expects a higher revenue from the connected users, hence it obtains 5 fronthaul paths at the end of the auction.

For the obtained results, the action set of a service provider consists of changing the user price at a level that does not change the SP path allocation, and to a level that changes the SP path allocation. To analyze the outcomes of these service provider actions separately, five actions of the service provider are selected for comparison, and Student T-test [252] results are calculated for 50 experiments with 95% confidence interval to evaluate the significance of the change in the average user numbers in Figure 5.8, and average payoff results in Figure 5.9. Before using Student T-test, normal distribution condition is tested for each user price. Shapiro-Wilk [250] normal distribution test results of average payoff results are given in Table 5.3 for all user prices, showing that the probability of a normal distribution is high in W values and the p-value is above the significance threshold of 0.05. Thus, the normal distribution hypothesis is true or there is insufficient evidence to disprove it. The W value and p-value results of Shapiro-Wilk test is

Table 5.3: Shapiro Wilk test results for SP3 average payoff values per user price

$UserPrice$	0.6	0.7	0.8	0.9	1.0	1.1	1.2	1.3	1.4	1.5
W	0.970	0.957	0.969	0.973	0.965	0.976	0.958	0.955	0.974	0.974
$p-value$	0.237	0.067	0.229	0.313	0.143	0.423	0.081	0.058	0.334	0.328

Table 5.4: Levene Test results for SP3 average payoff and average user number values

	Test 1		Test 2		Test 3		Test 4		Test 5	
	Payoff	Users	Payoff	Users	Payoff	Users	Payoff	Users	Payoff	Users
W	2.474	0.209	1.301	0.140	3.274	0.561	3.773	0.569	0.856	1.695
$p-value$	0.119	0.649	0.257	0.709	0.995	0.456	0.055	0.452	0.357	0.196

the same for average user number values of SP_3.

The Student T-test results for 1 allocated path (Test 1), the change from 1 to 2 allocated paths (Test 2), 2 allocated paths (Test 3), the change from 2 to 5 allocated paths (Test 4), and 5 allocated paths (Test 5) are evaluated. Before obtaining T-test results, the equality of variances condition of these pairwise comparisons are evaluated with Levene test [251]. The results are displayed in Table 5.4, and p-values are above the significance threshold of 0.05 for all pairwise tests. Thus, the equal variances hypothesis is true or there is insufficient evidence to disprove it.

As mentioned above, paired student T-test is used to evaluate the differences in user prices set by SP_3. If a p-value is less than 0.05, then a significant difference exists between the mean values of the compared samples. The results obtained for the 5 tests are as follows:

- Test 1: For 1 allocated path results, the difference in the average SP_3 user numbers between 0.6 and 0.8 p_{user} is not significant $(t = 0.339, p = 0.736)$; however, there is a significant gain in the average payoff U_{SP3} $(t = 5.65, p = 0.000)$, as SP_3 increases its revenue without changing its payment to InP, as displayed in Figure 5.9.

- Test 2: The average payoff drops when SP_3 allocates a second path with $p_{\text{user}} = 0.9$. To display this, a paired t-test is done to compare $p_{\text{user}} = 0.8$ and $p_{\text{user}} = 0.9$ scenarios. There is a significant average payoff drop when switching from $p_{\text{user}} = 0.8$ to $p_{\text{user}} = 0.9$ $(t = -5.018, p = 0.000)$. As the difference between mean number of users in two cases are not significant $(t = -0.365, p = 0.716)$, the drop in the average payoff is due to the increase in the InP payment with the second path. This result shows that increasing the user price and path valuation for bidding does not linearly increase the SP payoff.

- Test 3: The result obtained in Test 2 indicates that SP_3 needs to increase its payoff when it obtains 2 fronthaul paths instead of 1. Comparing the means of 2 fronthaul path cases with $p_{\text{user}} = 0.9$ and $p_{\text{user}} = 1.0$ shows that SP_3 can increase its average payoff ($t = 3.406, p = 0.001$) for a similar average number of users ($t = 0.645, p = 0.522$) by increasing p_{user} value to 1.0.

- Test 4: When $p_{\text{user}} = 1.1$, SP_3 has the highest path valuation; therefore it becomes the highest bidder in the auction and obtains 5 fronthaul paths. T-test is applied to compare the means of $p_{\text{user}} = 0.9$ with 2 fronthaul paths and $p_{\text{user}} = 1.1$ with 5 fronthaul paths. The significant increase in the user number ($t = 70.389, p = 0.000$) and the SP payoff ($t = 79.442, p = 0.000$) are also demonstrated in Figures 5.8 and 5.9. In Figure 5.9, it can be observed that SP_3 payoff is higher than the sum of the payoffs of SP_1 and SP_2 for $p_{\text{user}} = 1.1$.

- Test 5: After becoming the highest bandwidth supplier to the users with 5 fronthaul paths, SP_3 can further increase its average payoff by increasing p_{user} value from 1.1 to 1.3 ($t = 14.932, p = 0.000$), as shown in Figure 5.9. The change in the user number during this change is not significant ($t = 1.123, p = 0.267$), meaning that the user utility values remain above the average user utility despite the increase in the user price in this scenario.

Before closing this section, it should be stated that different game outcomes can be achieved by adjusting the system parameters. For instance, if the population size is different or the QoS of the service provided is affected less from lower data rates, this outcome can be changed by adjusting α_1 and α_3 weights in Eq. (5.7), or by changing the InP payments of service providers.

5.3.3 Trial and Error Learning vs. Average User Utility Comparison

The user distribution and user utility results of Algorithm 1, which displays replicator dynamics behavior on the user side, and Algorithm 3, which produces uncoupled decision making outcomes, are compared in this section. Algorithm 1 represents a guided search example with average user utility information provided to users by the InP, whereas Algorithm 3 displays a blind search algorithm with no external network information provided to users. The experiments are done with static fronthaul paths values, meaning that the service providers do not bid in the auction or change the user price during these game iterations. In order to only observe the impact of these two user side algorithms on the game, parameters such as the user distance to the RRH d_{3D}, and the simulation parameters in Table 5.2 are kept constant, apart from the total number of users. The total number of users is increased to 105 from 100, so that the user side equilibrium profile $n*$ is calculated as [45, 30, 30] with [3,2,2] static path allocation, in which $U_{\text{user},n} = U_{\text{user},m}$, for all $m, n \in S$.

Table 5.5: Trial and Error Learning parameters

Discontent mood acceptance probability (5.21)	$\varepsilon^{J(U)}$	$\varphi_1 = 0.0002$, $\varphi_2 = 0.0047$
Content mood acceptance probability (5.22)	$\varepsilon^{K(\Delta u)}$	$\gamma_1 = 0.2$, $\gamma_2 = 0.5$
Experiment probability	$\varepsilon = e^{-\beta_{exp}}$	$\varepsilon = 0.0018$, $\beta_{exp} = 4$

Table 5.6: Shapiro Wilk test results for SP1 average user number with Trial and Error Learning ($\beta_{exp} = 4$)

Iteration	1	2	3	4	5	6	7	8	9	10
W	1.000	1.000	0.970	0.969	0.965	0.966	0.957	0.959	0.983	0.980
$p - value$	1.000	1.000	0.238	0.208	0.149	0.152	0.069	0.083	0.678	0.535

Adjusting Experimentation Probabilities for Trial and Error Learning

The notion of convergence in trial and error algorithm is different than the classical understanding; therefore, a sufficiently small experiment probability should be adjusted before starting the game, in order to stay near the equilibrium state for a high proportion of the time. The experiment probability is defined as $\varepsilon = e^{-\beta_{exp}}$ and is kept the same for all users. Trial and learning algorithm parameters used in these simulations are shown in Table 5.5. It should be noted that *Hopeful* and *Watchful* moods are transition states, and users only experiment in *Content* and *Discontent* states. 10 iterations are run in each game to observe the behavior in both transitory and experimenting states. The restrictions for the experiment probability parameters are given in [248] as follows:

- Functions $J(U)$ and $K(\Delta u)$ are strictly decreasing linear functions.
- Functions $J(U)$ and $K(\Delta u)$ satsify $0 < K(\Delta u) < 1/2$ and $0 < J(U) < 1/2n$ conditions, with n being the number of users playing the game. The conditions imply that the acceptance probabilities are quite large relative to the probability of conducting an experiment.

Table 5.7: Shapiro Wilk test results for SP2 average user number with Trial and Error Learning ($\beta_{exp} = 4$)

Iteration	1	2	3	4	5	6	7	8	9	10
W	1.000	1.000	0.951	0.958	0.974	0.970	0.957	0.969	0.960	0.979
$p - value$	1.000	1.000	0.070	0.101	0.329	0.239	0.066	0.221	0.090	0.531

Table 5.8: Shapiro Wilk test results for SP3 average user number with Trial and Error Learning ($\beta_{exp} = 4$)

Iteration	1	2	3	4	5	6	7	8	9	10
W	1.000	1.000	0.954	0.967	0.971	0.979	0.981	0.953	0.974	0.977
$p-value$	1.000	1.000	0.052	0.170	0.250	0.527	0.581	0.054	0.343	0.445

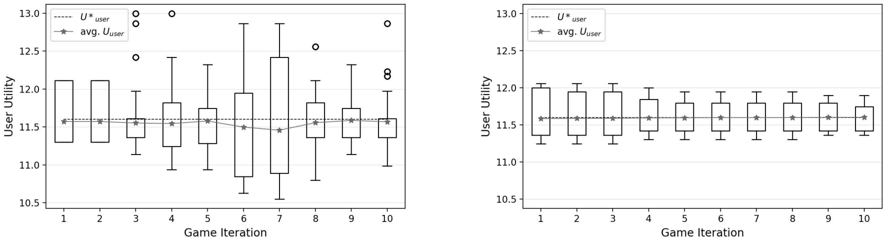
In order to determine these parameters, simulations are done with different probability values, and Shapiro-Wilk results of the simulations are compared to decide for the parameter values. The target of these simulations is to obtain a parameter set for the experiment probabilities that gives a normal distribution for average user number values of each service provider at every iteration. The simulations are run 50 times to calculate the Shapiro-Wilk results in Table 5.6, Table 5.7, and Table 5.8. As it can be seen from these tables, with an experimentation probability $\varepsilon = 0.0018$ and $\beta_{exp} = 4$, the probability of a normal distribution is high in W values and the p-value is above the significance threshold of 0.05. For lower values of β_{exp}, the high number of experiments keep p-value lower than 0.05.

User Utility Comparison

In this section, the performance of uncoupled trial and error learning algorithm and average user utility comparison algorithm are evaluated in terms of user utility. The service providers start the game with an equal user distribution of [35,35,35], whereas the fronthaul paths are distributed unequally as [3,2,2] among service providers. The users are identical and it is assumed that all users obtain the same data rate from the bandwidth allocated to them.

Trial and error learning is completely uncoupled and the users only aim to maximize their own utility, without any considerations for the social welfare maximization or any extra information about the state of the population at any iteration. On the other hand, switching based on average user utility comparison takes population dynamics into account and it only allows users that have lower utilities to change their service provider association to reach the theoretical equilibrium condition, prioritizing the social welfare of all users in the game. The results given in Figure 5.10 display these characteristics of the two algorithms. The dashed lines in the figures show the theoretical utility value for $U_{\text{user},n} = U_{\text{user},m}$, for all m, n. The guided search with average utility comparison converges to this theoretical utility value, whereas blind search with trial and error learning does not display such a convergence behavior and many outliers can be spotted in the utility values during the experiments.

For the users with trial and error learning algorithm, user utility values during the first round with the equal user distribution are recorded as the benchmark utility value $\overline{u}_i$. The users change their mood only based on this benchmark utility and they do not receive the average user utility value from the InP at any iteration



(a) User utility per game iteration with Trial Error Learning based service provider switching

(b) User utility per game iteration with average user utility based service provider switching

Figure 5.10: User utility comparison between blind search and guided search algorithms

of the game. The benchmark utility is updated by transiting first to the *Hopeful* and then to the *Content* stage, if the user gets a u_i above $\overline{u}_i$ for two consecutive rounds. As it can be observed from Figure 5.10a, in the first two iterations of the game, there is no utility change for the users, as all users are in *Content* mood in the first iteration. The users are allowed to change their association when they are in *Content* mood, and they remain connected to the new service provider if the utility value they obtained is higher than their benchmark utility. However, the experimentation probability ε is extremely low to impact the overall outcome in a state in which all users are *Content.* The users can only switch to *Hopeful* or *Watchful* transitory states in the second iteration. The users do not switch their service provider if they are in one of these two transitory states. After these two iterations, the utility difference between the peak user and the least well-off user can get over 16% of the average value in some iterations. This ratio is 7% for the average utility comparison algorithm, which is obtained in the first two iterations. It can also be observed that the number of oscillations in trial and error learning algorithm is higher than the average user utility comparison case.

In this experiment, the users connected to SP_2 and SP_3 are below the average user utility in the first round, thus they have the incentive to switch their service provider and increase their utility with the average user utility comparison algorithm to show replicator dynamics behavior. As seen from Figure 5.10b, ΔU between the average utility of all users and the least well-off user utility decreases as the game iterates. As a result, a convergence behavior can be observed in the user utilities in Figure 5.10b, and the amount of time that it takes the users to reach a near equilibrium condition is lower than the trial and error learning case, in which the user learning is completely uncoupled. Hence, it can be stated that by providing average user utility information to users, InP increases the convergence speed of the game, given that the users display replicator dynamics behavior. Based on the replicator dynamics behavior premise, it can also be concluded that the users end in a more social welfare providing result with the guided search in comparison with the blind search observed in the trial and error learning case.

(a) The difference between peak user and theoretical user utility for trial and error learning and average utility comparison

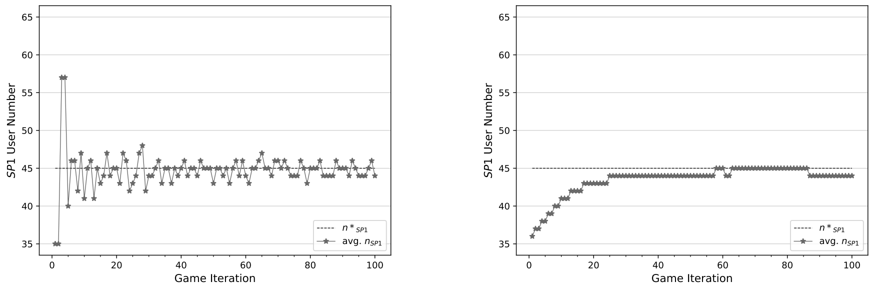
(b) The difference between theoretical user utility and least well-off user utility for trial and error learning and average utility comparison

Figure 5.11: Peak user and least well off user utility values with Trial and Error Learning and Average Utility Comparison algorithms

Figure 5.11 demonstrates the difference ΔU between both the peak user and least well-off user utility and the theoretical user utility at each game iteration. As it can be seen from Figure 5.11a, a user can reach higher peak utilities than the utility at the initial game state with trial and error learning algorithm, either by allowing users to take random searches during the game or by the frequent association changes of the *Discontent* users. The graph; however, also shows that this peak utility values do not show a stable character. In average user utility comparison, the users do not have the initiative to search for better outcomes if their utility is above the average. In addition to this, more users switch to the service provider that delivers higher user utility at each iteration, thus dropping the peak achievable user utility value as the game iterates. On the contrary, the least well-off user gets a better utility value in a social welfare providing manner; however this is not the case with trial and error learning, as seen from Figure 5.11b.

Service Provider User Number Comparison

In order to understand the impact of the oscillation observed in user association on the stability of the trial and error learning game, the pure equilibrium condition is relaxed with staying near equilibrium with a minimized user distribution distance. The user distribution distance shows how close the user distribution number is to the equilibrium state. Distance 1 is equal to the 0.05 distance from the equilibrium state, meaning that the service provider in the worst condition gets 95 percent of the users that it would get in an equilibrium condition. Similarly, Distance 2 indicates a distance of 0.10 and Distance 3 indicates a distance of 0.15 from the equilibrium condition. Figure 5.12 shows $SP1$ user number distribution with the two algorithms per game iteration, and Figure 5.13 and Figure 5.14 display the fraction of time in which $SP1$ user number is in pure equilibrium and near equilibrium conditions. The users connected to $SP2$ and $SP3$ have the incentive



(a) SP1 user number distribution with Trial and Error Learning

(b) SP1 user number distribution with Average Utility Comparison

Figure 5.12: SP1 user number distribution per game iteration

to switch to $SP1$, as the fronthaul paths are unequally distributed between the service providers as [3,2,2], but the game starts with an equal user distribution of [35,35,35] The results in this section are obtained from 50 experiments that run for 100 game iterations. The impact of the initial phase, short-term learning, and long-term learning periods are evaluated separately.

Figure 5.12 shows the separate convergence characteristics of the two algorithms. The dashed line at $n = 45$ represents the theoretical equilibrium value $n*$ in the two figures. Figure 5.12a demonstrates that the system is not stable in reaching the pure equilibrium or near equilibrium conditions without multiple iterations with the trial and error learning algorithm, and a sudden jump is observed in the number of users connected at iteration $i = 3$ and $i = 4$. As explained in the user utility results section, all users are in *Content* mood after the first iteration, and they record their current utility value as their benchmark utility value. This benchmark utility value is the same for all users, and the utility change due to the fronthaul path difference is only recorded at the end of the first iteration. After recording this utility change, the users can only reach *Discontent* mood at the second iteration; therefore they start to experiment and change their service provider association action at $i = 3$. The shift from the group of $SP1$ users to *Discontent* state leads to a significant decrease in the user number of $SP1$ at iteration $i = 5$, and the user number starts to reach near equilibrium conditions with blind search after this iteration. As it can be observed from Figure 5.12b and Figure 5.14, the gradual increase in the user number is also not sufficient to reach near equilibrium conditions. The users are only able to reach Distance 3 equilibrium in 6% of the experiments at $i = 5$ with average utility comparison algorithm.

As it can be seen from Figure 5.13 and Figure 5.14, after reaching iteration $i = 5$, the average time spent in near equilibrium state increases in both cases. The user number results of the two algorithms between $i = 5$ and $i = 15$ can be compared as follows:

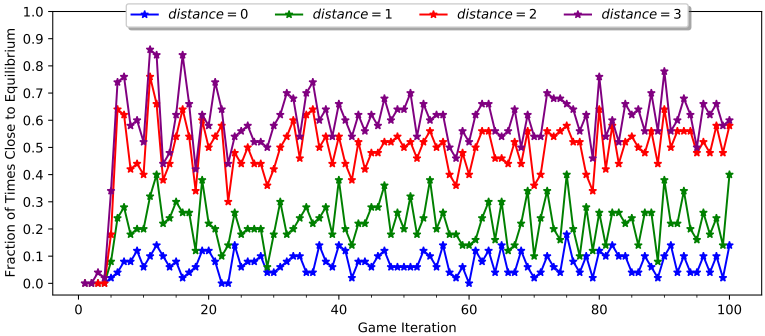


Figure 5.13: Fraction of times SP1 user number is close to equilibrium with Trial and Error Learning

- Distance 3 equilibrium is reached in 68% of the cases with average utility comparison algorithm. With trial and error learning, Distance 3 equilibrium is observed in 64% of the experiments, with the results fluctuating between 44% to 86% at different iterations.

- Distance 2 equilibrium is reached in 46% of the cases with average utility comparison algorithm. With trial and error learning, Distance 2 equilibrium is observed in 53% of the experiments, with the results fluctuating between 38% to 76% at different iterations.

- Distance 1 equilibrium is reached in 11% of the cases with average utility comparison algorithm. With trial and error learning, Distance 1 equilibrium is observed in 26% of the experiments, with the results fluctuating between 18% to 40% at different iterations.

- Distance 0 equilibrium is reached in 2% of the cases with average utility comparison algorithm. With trial and error learning, Distance 0 equilibrium is observed in 9% of the experiments, with the results fluctuating between 4% to 14% at different iterations.

Distance 3, Distance 2, and Distance 1 near equilibrium results can be obtained for a similar proportion of times with trial and error learning and average utility comparison for short iteration periods after the sudden jump behavior in the first iterations is surpassed. For both learning algorithms, pure equilibrium (Distance 0) condition is hard to reach with short-term learning. This similarity in the proportion of times in reaching the near equilibrium states; however, does not indicate a similar convergence characteristic, as shown in Figure 5.12. There is a sharp increase in the user number towards the theoretical equilibrium in average

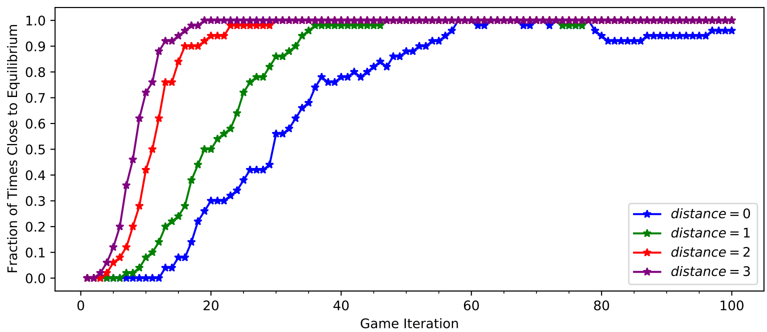


Figure 5.14: Fraction of times SP1 user number is close to equilibrium with Average Utility Comparison

utility comparison, whereas trial and error learning shows an oscillating behavior around the equilibrium value.

As it can be clearly observed from Figure 5.13 and Figure 5.14, guided search with average utility comparison is superior to blind search with trial and error learning in longer term, and guided search converges both to near equilibrium and theoretical equilibrium cases after a given iteration period. Average comparison algorithm also shows a stable character without almost no oscillations after reaching the equilibrium. As seen in Figure 5.14, this algorithm reaches a Distance 3 equilibrium in all cases after $i = 18$, whereas trial and error learning can reach Distance 3 equilibrium only in 60% of the total cases after $i = 18$, with the result oscillating between 44% to 78% at different iterations. Average utility comparison reaches Distance 2 equilibrium in all cases after $i = 29$ and Distance 1 in 98% of the cases after $i = 35$. On the other hand, trial and error learning algorithm can only reach Distance 2 in 50% of the cases after $i = 29$ with a range between 34% to 64%, and Distance 1 equilibrium can be observed in 23% of the cases after $i = 35$ with a fluctuation between 8% and 40% at different iterations. The user number for $SP1$ reaches the theoretical equilibrium ($n*$) value in 96% of the experiments after $i = 50$ with the use of the average utility comparison algorithm; however, this value is only 8% with trial and error learning algorithm after $i = 50$. The characteristics of the curves clearly show that average utility comparison can converge to stable near equilibrium and pure equilibrium conditions after long iteration periods; however, this is not the case for trial and error learning algorithm.

Before closing this section, a remark must be made again at this point that the algorithms are not direct alternatives to each other, but they rather represent different search conditions for users depending on the network information available to them. As seen in the results, coupled learning with external information and replicator dynamics leads to a more stable network behavior. However, and service providers may refuse InPs to share the average utility information with the users as part of their contracts. Blind search algorithms such as trial and error learning can still be applied as a distributed learning method to reach near equilibrium conditions in such cases, as the algorithm is not dependent on any external information.

5.4 Summary

The converged optical and dense mmWave radio network structure envisioned for 5G and beyond-5G networks is expected to increase the dynamicity in the environment, with the increasing number of nodes both at the user and the service side. In order to respond to this evolution, this chapter studies the following research question:

Can a balanced profit—social welfare trade-off be achieved in converged optical and mmWave radio networks infrastructure sharing scenario with distributed decision-making?

To provide an answer to this question, an iterative descending Vickrey-Dutch auction is designed for resource allocation among different service providers demanding optical resources for their network slices. The auction is used to lease identical fronthaul paths that reach the same RRH, with the aim of obtaining VCG outcomes for a social-welfare maximizing outcome among self-interested agents. The VCG mechanism is used to maximize the total sum of all service providers' valuations for the fronthaul paths. The results show that a balanced profit—social welfare trade-off can be achieved with distributed decision-making. These results can be exploited during a pre-deployment phase in which different fronthaul topology options can be simulated to reach a desired market solution by choosing the optimal profit-making topology.

During this auction, service providers bid in a rational and strategic way with reinforcement learning, while trying to optimize their utility. The learning algorithm relies on marginal utilities that can be calculated with locally available information. Service providers and network users play a Stackelberg game, in which service providers compete with each other to maximize their revenue. In addition, adjusting user price can be used as a service provider strategy to maximize revenue. The price strategy also impacts the bidding strategy of the service provider as the expected marginal utility of the service provider increases with increasing user prices.

In the auction with VCG outcomes, InP aims to provide a social-welfare maximizing outcome by sharing average user utility values with all the users in the RRH coverage area, helping the users to make decisions as the followers of the Stackelberg game. Based on this average utility value, users change their service provider association with a simple utility comparison algorithm, and maximize their utility by dynamically switching between the service providers. The results of this replicator dynamics based guided search decision making algorithm is compared to a completely decoupled trial and error learning algorithm. It is shown that blind search with trial and error learning algorithm leads to many oscillations in the results even after long iterations, and there is a clear superiority in terms of reaching equilibrium conditions with the average utility comparison algorithm. In addition, a pure equilibrium condition cannot be reached in an overwhelming proportion of the cases with trial and error learning algorithm. However, relaxing the pure equilibrium condition with staying near equilibrium with a minimized distance shows that near equilibrium conditions can also be reached with simple trial and error learning algorithm, and comparable results can be obtained between the two algorithms in short-term learning periods with less number of iterations, after the destabilized period in the first iterations is surpassed.

The framework provided in this study can be extended to other stakeholders of the network for distributed decision-making. For example, the infrastructure provider might be regarded as an intelligent agent that implements global policies for the network. The global policy of the network operator can be maximizing the number of satisfied users, achieving fairness by distributing the resources as equal as possible, reserving some physical resources to be resilient against network failures, or a mix of strategies, depending on the use case. As adjusting each QoS parameter for each network user creates a scalability issue, the network operator can learn over the key factors such as the utility values of the services in aggregate forms and determine its policy accordingly with meta-learning. Furthermore, within the interlinked game explained in this paper, a feedback loop between the service provider and the user can change the reputation value of a service provider in real-time.

CHAPTER 6

Conclusions and Future Outlook

6.1 Summary and Conclusions

This dissertation aims to present a framework that enables efficient and fair resource management decisions with multiple stakeholders for converged optical and mmWave radio network architectures; therefore it is centered around the main topics of game theory-based distributed learning, autonomic network management, and enabling concepts of softwarized beyond-5G and 6G networks. The main research objective is to create a multi-stakeholder environment, in which players dynamically adjust their strategies in response to changing information and the game model to maximize their utilities. Players of this environment extend from network operators or infrastructure providers (InPs) with the objective of overcoming their business challenges to make profit and ensure that the overall network serves efficiently to the maximum number of users at the same time, network components that aim to adapt to changing demand from users, service providers (SPs) that target keeping their service quality within the defined thresholds to obtain the maximum revenue from their clients, and end-users that utilize network resources to make use of the ever-increasing range of network applications.

The first part of the dissertation covers the state-of-the-art analysis to understand autonomic network management principles for beyond 5G networks, and discusses how game theoretic machine learning techniques can be utilized in order to organize converged optical and mmWave radio network architectures. Furthermore, a literature review is presented to provide an overview on the existing resource optimization algorithms for converged optical and mmWave radio networks, categorized under the main optimization targets of throughput maximization, delay minimization, energy-efficiency, and virtual resource allocation. The second part involves the mathematical evaluation of the joint radio access network (RAN) optimization for limited resources with a bankruptcy game and a dynamic fronthaul path allocation auctioning game that defines the interactions between the network stakeholders that have different targets with cooperative and non-cooperative games.

As communication networks expand towards connecting everything with everything, the growth trend predictions show the expected increase in connected devices, number of mobile subscribers, and overall mobile data traffic. Higher throughput requirements of novel services drive toward crowded wireless bands, as resource expansion with mmWave spectrum bands and dense deployments provide a feasible solution to reach the throughout targets of the next generation mobile networks despite the challenging propagation characteristics. As a result of these advancements, it can be foreseen that beyond-5G and 6G use cases, and key performance indicators (KPIs) set to realize these use cases require a remarkable increase in the demand for network resources from multiple network stakeholders. The cooperation of these stakeholders and their involvement in decision-making are required to overcome the challenges of these use cases.

End-to-end management of these networks needs to deal with operations and maintenance (O&M) goals, service targets, user demands, application KPIs, and dynamic topology changes in the network simultaneously, bringing autonomous network management (ANM) concept into the equation. ANM paradigm is required for translating high level objectives into low-level technical parameters without any human involvement, and then monitoring the network status to reconfigure the available resources. The massive expansion of network also leads to an autonomous resource management composition that should enable distributed decision-making to extract knowledge from locally available information over network stakeholder interaction. All these expected changes and the use cases require a management infrastructure that is able to collect different types of data, store and aggregate this data for processing and analysis with cloud integration, and extract knowledge from the collected data with machine learning applications at every possible network segment.

The evolution of autonomic network management towards beyond-5G/6G networks is explained as a basis for highlighting the paradigm changes from hardware-centric to software-centric management with novel technologies such as self-organizing networks (SON), software-defined networking (SDN), network function virtualization (NFV), and network slicing. The influence of these technologies on the ANM concept is also discussed, as an ANM framework should be able to handle the flexibility offered by virtualization technologies. The beyond-5G/6G challenge in network management is to design an ANM mechanism that learns the behavior of different network domains and enables coordination between those domains.

An ANM Framework [J1] based on cognitive control loops is presented as a platform that translates high layer policies to the network domains. Through this framework, a hierarchy is formed over the mobile network domains, hence objective functions are distributed from global to local domain within the network. Each network domain is controlled by a separate control loop that makes use of the observations from the monitoring stage in the analysis & decision-making stage. These two stages are supported by a learning stage that performs artificial intelligence and machine learning (AI/ML) techniques as an additional stage for knowledge generation and anticipatory decision-making in the control loop structure of beyond-5G/6G networks. Given the complex relationships between the stakeholders and the dynamics of applications, network services, and network operators, conflicts in stakeholders' objectives are likely to exist in distributed network management. In consequence, a game theory-based approach that defines multi-party decision making with both common and conflicting interests is also a part of this ANM concept. Network vs. network, external stakeholder vs. network games in the literature are presented to describe how network policy making mechanisms can be created in a distributed way, including the examples of novel network management games with network slicing and virtualization concepts.

After discussing the evolution of autonomic network management towards beyond-5G and 6G networks, the functional components of autonomic management, and stakeholder involvement in decision-making, resource management optimization algorithms for converged dense radio and optical mmWave architectures are presented. Converged optical and mmWave radio networks seek to deliver the appropriate Quality of Experience (QoE) to the population of network users by increasing the available bandwidth resources with the utilization of mmWave spectrum. Firstly, the architectural changes resulting from mmWave technical requirements to make best use of mmWave radio and transport capacity boost such as dense radio deployments, multiple-input and multiple-output (MIMO), and spectrum sharing are presented. In light of these technological developments, the use of mmWaves introduces new challenges and new learning techniques to be integrated into the resource allocation problem. The complexity increases as the multi-dimensional resources of dense networks not only include frequency, time, power, space, and multi-user diversity, but also involve energy, computation and storage resources, making knowledge extraction with AI/ML solutions a key topic in the next-generation communication systems.

To identify the benefits and the barriers of the existing resource management algorithms for converged optical and mmWave wireless networks, a survey is conducted of works published in the literature that cover the identified optimization requirements. The key concepts and the key network state parameters used to evaluate the performance of AI-based network optimization algorithms are identified. The solution methods are categorized under the main objectives of throughput maximization, delay minimization, energy-efficiency and virtual resource allocation.

A discussion from an ANM perspective, specific to each of these optimization topics, is also provided as part of the survey. The discussion shows that the existing resource allocation solutions are not decomposed into clear functional components, but instead designed as solutions to specifically modelled problems. To bring the novel network stakeholders into resource allocation decision-making, creating common abstractions and information exchange interfaces between the stakeholders is required. The discussion also reveals that the collected measurements are considered only in the operations and management phases; however measurements also play an important role during the cost-effective planning and pre-deployment phases, especially for deploying energy-efficient solutions.

Higher throughput requirements of beyond-5G and 6G applications are one of the main drivers of dense deployments, and these deployments create resource allocation problems that can be solved with game theoretic models. The throughput scales with the available bandwidth in mmWave fronthaul for dense deployments; however, the problem of dynamic bandwidth allocation remains in situations where the user demand exceeds the provided fronthaul capacity. As the transport network always aims to allocate the entire fronthaul resource capacity, a bankruptcy game is created and the outcomes of the division rules are observed under different network conditions. The results show that the grand coalition formed with the cooperative solution called recursive completion provides the highest Jain's fairness index values and user satisfaction by managing to keep all user data rates above the defined service thresholds. Contrary to the pre-defined division rules, this method also opens the way for distributed decision-making solutions as it gives each RRH the option to join the coalition or refuse it based on the payoff it obtains.

As the focus shifts towards service creation in networks with networks slicing and virtualization technologies, network infrastructure ownership has to consider the trade-off between profit generation and social-welfare in resource allocation decisions in order to provide the outcomes that meet the demands of users. By taking these developments into consideration, interlinked games are designed to distribute resource allocation decisions among the the InP, service providers, and network users in a network infrastructure sharing scenario. An InP auctioning game is modelled as an iterative descending auction, in which virtualized fronthaul paths are leased by the service providers for their network slices. The auction is designed for a space division multiplexing-enabled mmWave centralized radio access network (C-RAN) network architecture, where many RRHs are connected with a centralized baseband unit (BBU) pool. The auction aims to provide welfare by ensuring Vickrey-Clarke-Groves (VCG) outcomes that maximize the total sum of all service providers valuations for a set of identical fronthaul paths.

Service providers make their bidding decisions by anticipating the user demands with an exponential reinforcement learning algorithm to maximize their revenue. In this way, additional resources can dynamically be added to the slices of service providers based on their users' demands. Service providers act selfishly to individually maximize a utility function, hence they do not cooperate and do not exchange information among each other. The auction is linked with a two-stage Stackelberg game, in which service providers act as leaders and users act as followers. The users observe other users' decisions by receiving the average user utility value, and they imitate these decisions by probabilistically switching between the service providers if it is expected to improve their own utility. The user side equilibrium is reached when the utility of all users are equal. The results show that Vickrey-Dutch auction and Stackelberg game provide a profit – social welfare trade-off for the InP with VCG outcomes and by sharing average user utility value with the users, and service providers have the option to maximize their revenue by adapting their bidding strategy and by setting the user prices. It can also be observed that auction results and user behavior is dependent on the actions of other SPs in the auction.

Finally, the performance of trial and error learning is compared with the average utility comparison algorithm to observe the effects of uncoupled and coupled learning mechanisms on the user side. After adjusting the experimentation probabilities of the trial and error learning algorithm, it can be observed that an uncoupled learning mechanism can also be used for users by relaxing the pure equilibrium condition while staying near equilibrium with a minimized distance given that user learns over the history for a given amount of initial iterations; however, the number of oscillations in trial and error learning algorithm is higher than the average user utility comparison case.

6.2 Future Outlook

With the guidance of autonomic network management principles and learning and resource optimization objectives set for beyond-5G and 6G converged mmWave radio and optical network architectures, this dissertation presents distributed game-theory based learning algorithms to optimize resource allocation in these architectures. The interactions among the network stakeholders are defined by cooperative and competitive models depending on their relation. Infrastructure providers and network stakeholders can benefit strongly from having this discussion during the planning phase, as integration of management framework after implementation would be costly and effort consuming. Nevertheless, challenges still remain to fully realize an autonomic network management perspective in converged mmWave radio and optical networks. Before concluding this dissertation, the ongoing work with visionary and innovative ideas and future research directions are briefly highlighted.

6.2.1 Flexible Functional Splits

In this dissertation, the traditional RRH -BBU split concept is used to model the interactions between radio and optical network segments. However, as mentioned in Chapter 3, fiber-wireless integration is expected to become more flexible and radio and optical network interaction is likely to increase in beyond-5G networks with dynamic functional splits. For this reason, enabling network segment interaction and flexible decision making for functional splits should be considered as part of ANM for next generation networks, either in the pre-deployment phase for fixed functional splits or on-the-fly if both the distributed unit (DU) and the radio unit (RU) share the same set of baseband functions, allowing dynamic changes in functional splits.

The fifth generation new radio (5G NR) architecture introduces several split options between the centralized unit(CU), DU, and RU in the RAN [253], with each split having different data rate and delay requirements from the fronthaul segment. For the network functionalities that can be framed as VNF, this fact directly links VNF placement and transport network bandwidth allocation, creating a joint physical and virtual resource optimization problem. These decisions directly impact the external network stakeholders in the form of users and service providers, as each decision changes the topology of the network and the available resources at different network segments from active antenna ports to fronthaul paths.

On the network operator scale, flexible functional splits allow for applying multiple objective functions as a strategy in increasing the overall QoE of users, resource utilization, or energy-efficiency by considering dynamic splitting based on user traffic load, central processing unit (CPU) utilization on the cloud infrastructures supporting RAN units at different levels, fronthaul bandwidth and delay adjustment, and the network slicing requests of service providers. Objective functions can be distributed among RAN network components to organize functional split control decisions.

In addition to the traditional mobile network objective functions like link adaptation, handover optimization, etc., network virtualization decisions are an integral part of flexible functional splits with VNF placement decisions on DU/CU, and the abstraction of data monitoring for higher layers with edge computing. Frequency of switching between the split options and the cost of splitting are novel parameters to be considered by an autonomic control loop in making split decisions. In light of all these aspects, it can be concluded that flexible functional splits provide a network vs. network inter-domain interaction and cooperation case for game theory-based learning between the radio and transport segments, with functional split options defined as possible actions of a strategy set.

6.2.2 Extending Network Virtualization to End Users

In Chapter 5, the importance of using a learning algorithm that reflects the characteristics of end users is discussed. A learning algorithm that reflects user group behavior can be considered as a meaningful alternative for massive IoT scenarios with many simple and complex end devices that serve inside the same system; whereas end users of a communication network might be more likely to seek their own best utility without considering the group benefit. As the definition of end users extends from humans to IoT devices, robots, drones, vehicles and smart factory machines, obtaining the contextual knowledge of end users becomes a critical factor for resource allocation optimization.

There exists a modeling concept called the digital twin [10] that creates the digital representations of the entities in both physical and virtual domains. This concept is considered as a promising method to extend network virtualization towards end-users [254]. The use of ontologies in digital twins for describing the critical contextual knowledge of end users such as frequently visited location, use case and the type of operation in which network resources are utilized can all become important parameters in creating the utility functions of the users. Monitoring contextual data over digital twins, and training network data analytics functions with this data links the concept with multi-access edge computing (MEC) solutions that are able to identify the data storage and processing requirements of the local network and adapt themselves according to the locally collected data.

Extending virtualization to end users involves both simple and complex devices and human actors. Regarding ML components that generate knowledge over human actors' data, engineers and researchers cannot overlook the privacy and security related issues during the acquisition, storage, and transfer of this data when developing these ML-based solutions. Applying *"privacy and security by design"* at each data-related operation in network management designs should therefore be considered as a critical future research direction. A network management system should carefully develop secure methods to manage the acquisition of the data, and consider human privacy toward the ethical usage and storage of data. Human actors must have the right to decide how and to what extent their collected data will be used and shared by the ML algorithms and cyber-physical systems.

6.2.3 Towards Fully Automated 6G Network Management

In this dissertation, the characteristics of beyond-5G mmWave networks are identified to emphasize the need for the proposed ANM framework that defines the type of data to be collected for monitoring, and the possible actions of the stakeholders that take part in the decision-making mechanism. The resource allocation solution methods in converged mmWave radio and optical networks are analyzed to reveal the key concepts and the key network state parameters. With a user-centric approach, the effectiveness of the simple strategic algorithm implementations to optimize resource allocation by modeling user behavior on a simulation environment are presented. Finally, interlinked games that include an auction designed by InP and a Stackelberg game show that dynamic revenue gains can be obtained with network resource virtualization by achieving a social-welfare – profit trade-off, even in presence of utility maximizing algorithms of self-interested external network stakeholders.

ANM is a concept that cannot be disregarded from 6G network management, and converged optical and radio networks can greatly benefit from the integration of the provided AI-ML solutions to concrete data analytics frameworks provided by ITU-T, 3GPP and other regulatory bodies. 3GPP Release 16 includes enablers for network automation architecture for 5G to enable the use of network data analytics function (NWDAF) with clear functional components and to support network automation. For each network function, input & output parameters, and network data analytics procedures to be provided to network functions are defined with an analytics ID. Using this network control infrastructure for network slicing, VNF placement and other control decisions defines a new era in network management and will be the next step towards realizing all the ambitious 6G applications.

As new deployment spaces spread across the world with private networks of organizations and the industry, novel use cases ranging from rapidly deployable edge networks for emergency services to electricity grid control and energy systems optimization, beyond-5G and 6G networks extend the scope of network management with multiple actors and decision makers. Furthermore, the underlying technologies such as deploying wireless bands in THz frequencies and analog/hybrid beamforming solutions to realize Tbps transport bring new properties and requirements into the network management picture. ANM creates opportunities to resolve conflicting goals between various stakeholders such as the private network and infrastructure owners, network users, application developers, and the regulatory bodies in governmental and global scale. It can also provide a concrete framework to base the future research on overcoming the challenges in improving the KPIs, maintaining QoE/QoS, and optimization of distributed network management processes. Thus, future research on ANM frameworks has the potential to drive novel solutions and enable a higher degree of adaptation and interoperability among all the above mentioned applications and technologies.

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List of Acronyms

5G NR	Fifth generation new radio
5GCM	Fifth generation channel model
ACM	Association for Computing Machinery
AI	Artificial intelligence
ANM	Autonomic network management
ANN	Artificial neural network
AP	Access point
APM	Adjusted proportional method
ARoF	Analog radio-over-fiber
BBU	Baseband unit
BSS	Business support system
CE	Competitive equilibrium
CEA	Constrained equal awards
CEL	Constrained equal losses
CG	Contested garment
CO	Central office
CPU	Central processing unit
C-RAN	Centralized radio access network
CU	Centralized unit
DAF	Data analytics function
DBA	Dynamic bandwidth allocation
DU	Distributed unit
EI	Expectation index
eMBB	Enhanced mobile broadband
FiWi	Fiber-wireless

gNB	Next Generation Node Base Station
IaaS	Infrastructure as a service
ICN	Information-centric networking
IEEE	Institute of Electrical and Electronics Engineers
IET	Institution of Engineering and Technology
InP	Infrastructure provider
IoT	Internet of Things
KPI	Key performance indicator
LF	Loss factor
LOS	Line-of-sight
LTE	Long term evolution
M**2**M	Machine-to-machine
MANO	Management and orchestration
MDAF	Management data analytics function
MDPI	Multidisciplinary Digital Publishing Institute
MEC	Multi-access edge computing
MIMO	Multiple-input and multiple-output
ML	Machine learning
MLB	Mobility load balancing
mMTC	Massive machine type communication
mmWave	Millimeter wave
MOS	Mean opinion score
MRO	Mobility robustness optimization
NFV	Network function virtualization
NFVI	Network function virtualization infrastructure
NFVO	Network function virtualization orchestrator
NMA	Network management application
NP-**hard**	Non-deterministic polynomial time hard
NSA	Non-Standalone
NSSF	Network slice selection function
NWDAF	Network data analytics function
O&M	Operations and maintenance
OF	Overhead factor
OLT	Optical line terminal
ONU	Optical network unit
OSA	Optical Society
OSS	Operation support system
PD	Proportional division

PON	Passive optical networks
QoE	Quality of experience
QoS	Quality of service
RAN	Radio access network
RC	Recursive completion
RF	Radio frequency
RoF	Radio-over-fiber
RRH	Remote radio head
RSS	Received signal strength
RU	Radio unit
RWP	Random waypoint model
SDM	Space division multiplexing
SDN	Software-defined networking
SE	Stackelberg equilibrium
SINR	Signal-to-interference-plus-noise ratio
SLA	Service layer agreement
SNR	Signal-to-noise ratio
SON	Self-organizing networks
SP	Service provider
UCE	Universal competitive equilibrium
UDN	Ultra-dense networks
UMi	Urban micro
URLLC	Ultra reliable low latency communications
V2X	Vehicle-to-everything
VCG	Vickrey-Clarke-Groves
VIM	Virtualized infrastructure manager
VNE	Virtual Network Embedding
VNF	Virtual network function
WDM	Wavelength division multiplexing

List of Publications

Journal articles

[J1] M. A. Khan, S. Peters, D. Şahinel, F. D. Pozo-Pardo, and X.-T. Dang, "Understanding autonomic network management: A look into the past, a solution for the future," *Computer Communications*, vol. 122, pp. 93–117, 2018. DOI: `10.1016/j.comcom.2018.01.014`.

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[J3] D. Şahinel, S. Rommel, and I. T. Monroy, "Resource management in converged optical and millimeter wave radio networks: A review," *Applied Sciences*, vol. 12, no. 1, 2022. DOI: `10.3390/app12010221`.

Conference contributions

[C1] D. Şahinel, C. Akpolat, O. C. Görür, and F. Sivrikaya, "Integration of human actors in IoT and CPS landscape," in *2019 IEEE 5th World Forum on Internet of Things (WF-IoT)*, 2019, pp. 485–490. DOI: `10.1109/WF-IoT.2019.8767276`.

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Other scientific publications

[O1] D. Şahinel, C. Akpolat, O. C. Görür, F. Sivrikaya, and S. Albayrak, "Human modeling and interaction in cyber-physical systems: A reference framework," *Journal of Manufacturing Systems*, vol. 59, pp. 367–385, 2021. DOI: 10.1016/j.jmsy.2021.03.002.

[O2] C. Akpolat, D. Şahinel, F. Sivrikaya, G. Lehmann, and S. Albayrak, "CHARIOT: An IoT middleware for the integration of heterogeneous entities in a smart urban factory," in *FedCSIS Position Papers*, 2017, pp. 135–142. DOI: 10.15439/2017F527.

[O3] Y. Luo, P. N. Tran, D. Şahinel, and A. Timm-Giel, "Handover prediction for wireless networks in office environments using hidden markov model," in *2013 IFIP Wireless Days (WD)*, 2013, pp. 1–7. DOI: 10.1109/WD.2013.6686448.

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It consoles me to think that my grandparents Sevinç and Muzaffer Sebükcebe are watching me now from heaven with pride today. It was also my wish to make my grandparents Necla and Erdoğan Şahinel, and the whole Şahinel family proud by adding our surname to the university libraries in Germany and the Netherlands with this dissertation. I hope the future generations of Şahinels will carry the flag much forward than my humble scientific contribution.

This dissertation is dedicated to my mother Melek Gül Şahinel and my father Semih Şahinel. Their contributions to this dissertation and my PhD journey are second to none of the names mentioned here. I would like to express my gratitude to them for supporting me from my first day as a primary school student in Ankara until my last day as a PhD student in Eindhoven with the same passion. This work is nothing but an outcome of their never ending trust in me. Their love is my greatest treasure in life and I love them back with all my heart as well.

Curriculum Vitae

Doruk Şahinel was born on 03-05-1989 in Eskişehir, Turkey. He received his BSc degree in Electrical and Electronics Engineering from Middle East Technical University, Turkey and his MSc degree in Information and Commmunications Systems from Hamburg University of Technology, Germany, in 2010 and 2013, respectively. In 2010, he was awarded a joint scholarship from German Academic Exchange Service (DAAD) and Turkish Education Foundation (TEV) for his Master's Study in Germany.

In 2014, he joined German-Turkish Advanced Research Center (GT-ARC) in Berlin, Germany and worked in several computer networks research projects. Some of the highlights of his tasks was the deploying a wireless mesh network for smart city services in An Intelligent Framework for Service Discovery and Composition (ISCO) project, the implementation of the Human-CPS interface and communication layer of an IoT middleware in A Scalable Holistic Middleware Approach for Internet of Things (CHARIOT) project, leading to several scientific publications and conference contributions.

In 2018, he started a PhD project within DAI Labor at Technische Universität Berlin (TUB), Germany. His work was transferred to Terahertz Systems group in Eindhoven University of Technology (TU/e) as part of a dual doctorate agremeent signed in 2020 between TUB and TU/e, which are also partners in 5G for Cooperative and Connected Automated Mobility on X-border Corridors (5G-Mobix) EU H2020 project. His research has been carried out as part of 5G-Mobix project, and the results obtained in the PhD project are presented in this dissertation. His main areas of research include mobility management, resource management in 5G networks and game theory-based algorithms.