National Technical University of Athens

School of Electrical and
Computer Engineering

Network Management and
Optimal Design Laboratory

Distributed decision making frameworks for resource allocation in cyber-physical systems

Dissertation submitted for the degree of Doctor of Philosophy

of

Giorgos Mitsis

Athens
September 28, 2021

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Advisory Committee: Symeon Papavassiliou
Ioanna Roussaki
Panayiotis Tsanakas

Approved by the seven-member committee on 28th September 2021.

....	....	....
S. Papavassiliou	I. Roussaki	P. Tsanakas
Professor NTUA	Asst. Professor NTUA	Professor NTUA
....	....	....
T. Varvarigou	E.E. Tsiropoulou	G. Matsopoulos
Professor NTUA	Asst. Professor UNM	Professor NTUA
	....	
	D. Askounis	
	Professor NTUA	

Athens, September 2021

....

Γιώργος Π. Μήτσης
Διδάκτωρ Ηλεκτρολόγος Μηχανικός και Μηχανικός Υπολογιστών Ε.Μ.Π.

Abstract

Towards realizing the fifth generation (5G) of wireless networks, the Internet of Things (IoT), and the Tactile Internet, intelligent communications and computing is key part of the technological stack. The next generation of wireless networks are expected to be characterized by limited availability of resources, thus, in this dissertation, we tackle the problem of efficient allocation of several types of communications and computing resources, while achieving high quality of service and experience for the devices or the users. Considering the interdependence of the devices while trying to access and share common resources as well as their increasing intelligence which enables them to make choices on supporting self-beneficial properties, it seems natural to adopt more user-centric approaches leading to decentralized solutions. In this PhD dissertation, we considered designing decision making frameworks where devices take advantage of the network's capabilities in order to reduce their resource consumption and more effectively perform their assigned tasks.

First, the prolongation of battery life of mobile machine-to-machine (M2M) devices is considered, in order to guarantee and sustain the operation of the IoT system for a longer period of time, while taking into account the management of information of the same nature in a more efficient way, by focusing on the use of social properties and characteristics of the devices. For that reason, a joint interest, physical and energy-aware cluster formation mechanism is proposed so that devices are effectively grouped and a high energy clusterhead can be assigned for each cluster. The clusterhead is then responsible to provide to the rest of the devices enough power to send their data via wireless energy transfer (WET), collect all the information from the devices on its cluster and forward the information to the eNB for further processing.

Then, a setting of Multi-access Edge Computing (MEC) is discussed, where servers offer computing resources at the edge of the network to mobile end-users. A multi user - multi MEC server environment is considered where users are willing to offload some of their computational tasks and the MEC servers are setting a price in order to process them. The user is able to chose the server to offload the data to, as well as determine the portion of the task that will be offloaded, while the server will set the price it will charge for each task. In order to achieve the best server selection, a reinforcement learning framework based on stochastic learning automata is adopted, while the amount of data offloading is determined via a non-cooperative game among users, and the optimal announced prices are determined via an optimization problem. The information exchange between the users and the MEC servers until the final offloading decision, is handled and realized by a Software Defined Network (SDN) controller.

In the rest of the dissertation, we introduced the concept of users' behavioural characteristics in order to capture and reflect the fact that users do not act as neutral maximizers but instead exhibit risk-aware behaviour. A MEC setting is considered as well, where multiple user devices are willing to offload their tasks to a MEC server responsible for handling them. Under this setting, the MEC server is considered as a Fragile Common Pool Resource (CPR), meaning that the more the server is used, the higher the probability of failure to execute its assigned tasks, resulting in losses for the users. The problem is modeled as a non-cooperative game between the users, where each user should choose the portion of the tasks to be offloaded to the server by selecting the amount of data to send. Towards capturing the users' behavioral characteristics in the data offloading decision-making process, we adopt the principles of Prospect Theory in order to model the users' decisions under risk and uncertainty of outcome. Additionally, a usage based pricing policy is considered to balance the usage of the MEC server by the users, since the additional cost prohibits users to over-exploit the servers' resources and thus reduces the Probability of Failure (PoF) of the server.

Finally, we extended the aforementioned concept on a multi-user multi-server environment where the additional problems of users' server selection and MEC servers' price selection arise. In order to more holistically address the users' decision-making process, we considered the server selection and the amount of offloading data selection as a joint optimization problem, allowing users to choose the combination that maximizes their perceived utility. In order to tackle the MEC servers' price selection problem we proposed two different approaches, a game-theoretic approach and a reinforcement learning one, considering different information availability scenarios on the system. The overall framework is modeled as a Stackelberg game where the servers are considered leaders, making their pricing decisions based on one of the proposed approaches, and the users are considered followers, making their data offloading decisions based on the prospect theoretic principles.

Keywords: Resource allocation, Distributed decision-making, Internet of Things (IoT), Machine-to-Machine (M2M) communication, Clustering, Power Management, Multi-access edge computing, Game Theory, Prospect Theory, Data offloading, Common Pool of Resources, Risk awareness, Reinforcement Learning, Multi-armed Bandit.

Περίληψη

Στην προσπάθεια υλοποίησης της πέμπτης γενιάς (5G) ασυρμάτων δικτύων, του Διαδικτύου των Πραγμάτων (Internet of Things) και του Απτού Διαδικτύου (Tactile Internet), η ανάπτυξη έξυπνων μεθόδων επικοινωνίας και υπολογισμού είναι κομβικής σημασίας. Η επόμενη γενιά ασύρματων δικτύων θα χαρακτηρίζεται από περιορισμένη διαθεσιμότητα πόρων, και έτσι στην παρούσα διατριβή προσπαθούμε να αντιμετωπίσουμε το πρόβλημα της αποτελεσματικής διάθεσης αυτών των υπολογιστικών και επικοινωνιακών πόρων, επιτυγχάνοντας παράλληλα υψηλή ποιότητα υπηρεσιών και εμπειρίας για τις συσκευές και τους χρήστες. Λαμβάνοντας υπόψιν την αλληλεξάρτηση των συσκευών, καθώς έχουν πρόσβαση και μοιράζονται κοινούς πόρους, αλλά και λόγω της αυξανόμενης νοημοσύνης που διαθέτουν, η οποία τους επιτρέπει να κάνουν οι ίδιες επιλογές με στόχο το προσωπικό τους όφελος, φαίνεται φυσική η υιοθέτηση μιας πιο ατομοκεντρικής προσέγγισης, η οποία οδηγεί σε πιο αποκεντρωμένες λύσεις. Στην παρούσα διδακτορική διατριβή εξετάσαμε τη δημιουργία πλαισίων λήψης αποφάσεων, όπου οι συσκευές εκμεταλλεύονται τις δυνατότητες του δικτύου προκειμένου να μειώσουν την κατανάλωση πόρων τους και να εκτελέσουν αποτελεσματικότερα τις εργασίες τους.

Αρχικά, εξετάσαμε την επέκταση της διάρκειας ζωής της μπαταρίας κινητών συσκευών σε περιβάλλοντα επικοινωνίας μηχανή με μηχανή, προκειμένου να διασφαλιστεί η λειτουργία του συστήματος Διαδικτύου των Πραγμάτων (IoT) για μεγαλύτερο χρονικό διάστημα, λαμβάνοντας υπόψη τη διαχείριση πληροφοριών παρόμοιου περιεχομένου και εστιάζοντας στη χρήση κοινωνικών ιδιοτήτων και χαρακτηριστικών των συσκευών. Για το λόγο αυτό, προτείναμε έναν μηχανισμό συσταδοποίησης που λαμβάνει υπόψη τόσο την φυσική απόσταση και την ενεργειακή διαθεσιμότητα, όσο και το περιεχόμενο των δεδομένων που διαθέτουν, έτσι ώστε να πετύχουμε αποδοτική ομαδοποίηση των συσκευών, καθώς και να ορίσουμε έναν υψηλής ενεργειακής διαθεσιμότητας εκπρόσωπο για κάθε ομάδα. Ο εκπρόσωπος αυτός είναι υπεύθυνος για να παρέχει στις υπόλοιπες συσκευές αρκετή ισχύ για την αποστολή των δεδομένων τους μέσω ασύρματης μεταφοράς ενέργειας (Wireless Energy Transfer), τη συλλογή όλων των πληροφοριών από τις συσκευές της ομάδας του και την προώθησή τους στον σταθμό βάσης για περαιτέρω επεξεργασία.

Στη συνέχεια επικυρωθήκαμε στα περιβάλλοντα Υπολογισμού στα Άκρα Πολλαπλής Πρόσβασης (Multi-access Edge Computing), όπου οι διακομιστές προσφέρουν υπολογιστικούς πόρους στους τελικούς κινητούς χρήστες. Μελετήθηκε ένα σενάριο πολλαπλών χρηστών και πολλαπλών διακομιστών στο οποίο οι χρήστες επιθυμούν να αποφορτίσουν μέρος των υπολογιστικών τους εργασιών και οι διακομιστές ορίζουν μια τιμή για την παροχή της υπηρεσίας τους. Ο χρήστης είναι σε θέση να επιλέξει τον διακομιστή στον οποίο θα στείλει τα δεδομένα του, καθώς και τον όγκο των δεδομένων που θα στείλει, ενώ ο διακομιστής θα

επιλέξει την τιμή που θα χρεώσει για κάθε εργασία. Για να πετύχουμε την βέλτιστη επιλογή διακομιστή, υιοθετούμε ένα πλαίσιο ενισχυτικής μάθησης βασισμένο στα στοχαστικά αυτόματα, ενώ ο όγκος των δεδομένων καθορίζεται μέσω ενός μη-συνεργατικού παιγνίου μεταξύ των χρηστών, και η βέλτιστη τιμολόγηση καθορίζεται μέσω ενός προβλήματος βελτιστοποίησης. Η ανταλλαγή πληροφοριών μεταξύ χρηστών και διακομιστών διευκολύνεται από έναν ελεγκτή Δικτύωσης Καθορισμένης από Λογισμικό (Software Defined Networking).

Στην υπόλοιπη διατριβή, εισάγαμε την έννοια των συμπεριφορικών χαρακτηριστικών των χρηστών, προκειμένου να αποτυπώσουμε το γεγονός ότι οι χρήστες δε λειτουργούν ως ουδέτεροι μεγιστοποιητές, αλλά αντίθετα επιδεικνύουν πιο περίπλοκη συμπεριφορά σε συνθήκες αβεβαιότητας. Μελετάμε ένα περιβάλλον Υπολογισμού στα Άκρα Πολλαπλής Πρόσβασης με πολλούς χρήστες και έναν διακομιστή, ο οποίος θεωρείται ως εύθραυστη πηγή κοινόχρηστων πόρων, και έτσι με βάση τη χρήση του ορίζεται και η πιθανότητα αποτυχίας εκτέλεσης των εργασιών που έχει αναλάβει, με αντίστοιχες απώλειες για τους χρήστες. Το πρόβλημα διαμορφώνεται ως ένα μη-συνεργατικό παίγνιο μεταξύ των χρηστών, με το οποίο οι χρήστες επιλέγουν τον όγκο δεδομένων που θα αποφορτώσουν στον διακομιστή. Προκειμένου να μοντελοποιηθούν αυτά τα συμπεριφορικά χαρακτηριστικά, υιοθετήσαμε τις αρχές της Θεωρίας Προοπτικής και επιλέχθηκε μια πολιτική τιμολόγησης που βασίζεται στη χρήση του διακομιστή από τους χρήστες, με σκοπό να αποτρέπεται η αλόγιστη χρήση του και να μειωθεί η πιθανότητα αποτυχίας του.

Τέλος επεκτείναμε την παραπάνω ιδέα σε ένα περιβάλλον πολλαπλών χρηστών και πολλαπλών διακομιστών, όπου εμφανίζονται δυο επιπλέον προβλήματα, το πρόβλημα της επιλογής διακομιστή από τους χρήστες και την επιλογή τιμών από τους διακομιστές. Προκειμένου να αντιμετωπιστεί πιο ολιστικά το πρόβλημα, ορίσαμε την επιλογή διακομιστή και την επιλογή όγκου εκφόρτωσης ως ένα κοινό πρόβλημα βελτιστοποίησης, επιτρέποντας στους χρήστες να επιλέξουν τον συνδυασμό που μεγιστοποιεί την αντιλαμβανόμενη ωφελιμότητά τους. Για να αντιμετωπιστεί το πρόβλημα της επιλογής τιμολόγησης των υπηρεσιών, προτείναμε δύο διαφορετικές προσεγγίσεις, μια βασισμένη στη Θεωρία Παιγνίων, και μια στην ενισχυτική μάθηση, ανάλογα με τη διαθεσιμότητα πληροφορίας στο σύστημα. Το συνολικό πρόβλημα διαμορφώθηκε ως ένα παίγνιο Stackelberg όπου οι διακομιστές έχουν τον ρόλο του ηγέτη, παίρνοντας αποφάσεις για την τιμολόγηση, και οι χρήστες θεωρούνται ως ακόλουθοι, λαμβάνοντας τις αποφάσεις εκφόρτωσης των δεδομένων τους με βάση τη Θεωρία Προοπτικής.

Λέξεις Κλειδιά: Κατανομή πόρων, Κατανεμημένα συστήματα απόφασης, Διαδίκτυο των Πραγμάτων, Επικοινωνία Μηχανής με Μηχανή, Συσταδοποίηση, διαχείριση ισχύος, Υπολογισμός στα άκρα, Θεωρία Παιγνίων, Θεωρία Προοπτικής, Εκφόρτωση Δεδομένων, Πηγές Κοινόχρηστων Πόρων, Τραγωδία των Κοινών Αγαθών, Επίγνωση Ρίσκου, Ενισχυτική Μάθηση, Πρόβλημα Πολλαπλών Κουλοχέρηδων

Contents

Preface

Acknowledgements

Even though the PhD is a journey that requires a lot of personal effort and dedication, it would have been impossible without the help and support of some very important people to whom I would like to express my sincere gratitude.

First and foremost, I would like to express my appreciation to my supervisor, Prof. Symeon Papavassiliou, who helped me immensely in the realization of my dissertation. With his scientific expertise he was able to effectively guide me, and his on point observations allowed me to overcome several roadblocks and obstacles. He gave me the opportunity to work in several different research areas, giving me the space to focus on my interests and obtain skills I deemed important. He was strict when needed and relaxed when not, rendering my journey to an enjoyable and anxious free experience. It has been an honor to have worked under his supervision and to have received his support.

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A very special thanks to my parents, Pantelis and Sofia, who never stopped supporting me, and who were always proud of my accomplishments (sometimes even more than myself), and to my sisters Anna and Anastasia, who kept reminding me how lucky I've been and what a great life

I've been living.

Finally, the last word goes to my friends who were always beside me, supportive in my every step and who were always more than willing to keep my mind off of work. Together we travelled, laughed, drank and talked, sharing our different views and agreeing on disagreeing, and even though their explicit support on my PhD was minimal, their implicit help was immense. I am sincerely grateful for my time with them and I am sure that my life would not have been the same without them.

Structure

The thesis is structured as follows.

In Chapter 1 we make a general introduction on the topics that concern our thesis, set the specific environment we consider and which motivated our work, and exhibit the contributions that we made.

In Chapter 2, some basic mathematical background that is deemed necessary to understand the methods used in our approaches to tackle the proposed problems are introduced. Additional information are provided in the main part of the thesis whenever required.

The following chapters are the main chapters of the thesis. Each chapter presents a specific problem that we consider important and we tackled in this thesis. First the general setting specific to the problem and the related work on the topic is provided, then our proposed framework is discussed by presenting the system model and the mathematical formulation of the problem and of our solution, and finally a thorough evaluation of the proposed framework is presented.

In particular, in Chapter 3 we introduce and discuss a joint interest, physical and energy-aware communication and cluster formation mechanism whose role is to manage the energy consumption of an IoT system in a more efficient way. The power needed for the operation of the cluster is provided by a more energy capable device via wireless energy transfer (WET) approach.

In Chapter 4 a Multi-access Edge Computing setting is discussed where servers offer computing resources at the edge of the network to less potent end-users. The users are incentivized to offload their tasks to the servers instead of locally executing them in order to achieve better Quality of Experience, while the servers compete price-wise until an equilibrium is reached.

In Chapter 5 we consider a similar Multi-access Edge Computing setting where a UAV assisted MEC server exists, but users are exhibiting risk-aware behavior. In this work, users do not act as neutral maximizers of their expected utility function, but instead they exhibit risk seeking and loss averse behavior. In order to capture and reflect their preferences, we incorporate the principles of Prospect Theory in their decision making process.

In Chapter 6 we extend the previous risk-aware framework to a multi-server environment where the additional problems of the users' server selection and the MEC servers' price selection arise. In order to more holistically address the users' decision-making process, the amount of offloading data and the server selection processes are handled as a single optimization problem, while the price selection problem is tackled either through a game theoretic approach or through a reinforcement learning approach.

Finally in Chapter 7 we present the conclusions to which we arrived based on our observations from our aforementioned research endeavors, as well as some propositions for future extensions of our work and future directions of the related research.

The thesis ends with Appendices containing some of the proofs of the theorems expressed throughout our thesis, that - due to their length - would otherwise break the flow of the main text. Whenever this is the case, the keen reader is referred to the relevant appendix.

Chapter 1

Introduction

The Internet has gone through several phases from its inception to the present, from a peer to peer network and mobile Internet, to Internet of Things (IoT) and the Tactile Internet (Fig. 1.1). During every transition phase, multiple new problems arise, demanding innovative solutions and different architectural decisions [1, 2].

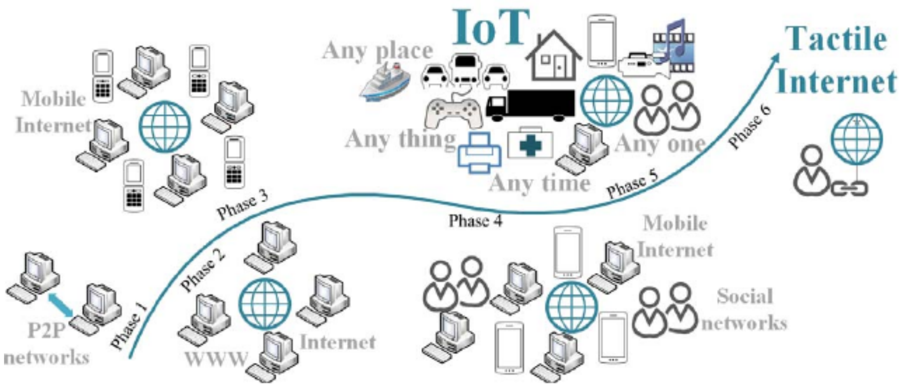


Figure 1.1: History of the Internet; *image credit: Porambage et al.* [1]

The IoT phase allows a heterogeneous and massive collection of devices to access and communicate through the Internet. According to Ericsson Mobility Report in 2018 [3], the worldwide mobile subscriptions will reach 8.9 billion, mobile broadband subscriptions will exceed 8.4 billion and there will be 6.2 billion unique mobile subscribers by 2024. The total mobile data traffic is expected to increase by five times, while cellular IoT connections are expected to reach 4.1 billion, with 27% annual growth rate. According to CISCO's prediction [4], the monthly global mobile data traffic will be 49 exabytes by 2021, and the annual mobile data traffic will exceed half a zettabyte. Other statistics anticipate as many as 101 billion connected IoT devices and a global economic impact of more than $12 trillion by 2025 [5] stressing its large economic impact. The future phase of Tactile Internet is expected to focus on advanced and more complex use cases of human-to-machine and machine-to-machine interaction where even more reliability, ultra low latency times, extremely high availability and more security are required.

The idea behind IoT is to connect anything, anyone, anytime and anyplace, and the fifth generation (5G) technology standard is trying to address the arising issues. Specifically, 5G enabled networks are expected to feature high bandwidth (e.g., 10Gbps), very low latency (e.g., 1ms), and low operational costs, improving the Quality of Service (QoS) and Quality of Experience (QoE) of users. The above requirements stress the need for major rethinking of the design and operation of wireless and fixed access networks.

By leveraging on the Radio Access Networks (RANs), with antenna improvements, the use of higher frequencies, the separation of user plane from the control plane and a general rearchitecture of the networks, there will be huge improvements on latency and bandwidth utilization [6]. Due to the emerging use cases on 5G enabled IoT and the difference in needs of each such use case, 5G is expected to provide enhanced mobile broadband, greater reliability, lower latency communications, and allow massive machine type communications as seen in Fig. 1.2.

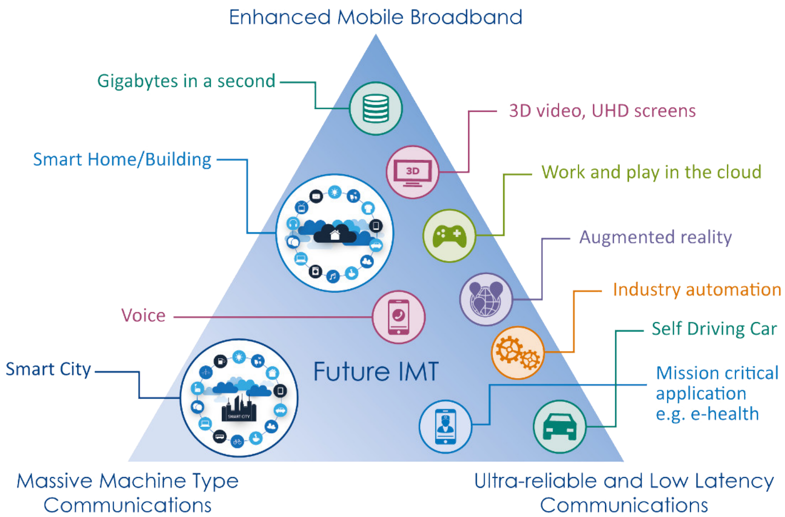


Figure 1.2: 5G technology standard requirements; *image credit: ETSI*

Apart from the need for faster and more reliable communication, there is also great need for energy efficiency and better power management on the IoT devices. Due to their small size and mobility, devices require low energy consumption and long battery life while being able to perform difficult computational tasks and retaining wide coverage of connectivity. The above requirements cannot be achieved with the existing technologies such as Low energy Bluetooth (BLE), WiFi, Zigbee and 2G/3G/4G. For that reason, multiple new technologies have been developed, such as LPWA, NB-IoT, longrange (LoRa), SigFox, Long Term Evolution category M1 (LTE-M), etc. [7].

New protocols, architectures, and algorithms are being developed in order to achieve better bandwidth exploitation and better spectrum efficiency. On the communication side, the traditional

Orthogonal Multiple Access (OMA) scheme, where only one user can be active on a particular resource in order to avoid interference [8], is replaced by Non-Orthogonal Multiple Access (NOMA), where more than one user transmits on a specific resource by assigning each one of them to different power levels [9], as seen in Fig. 1.3.

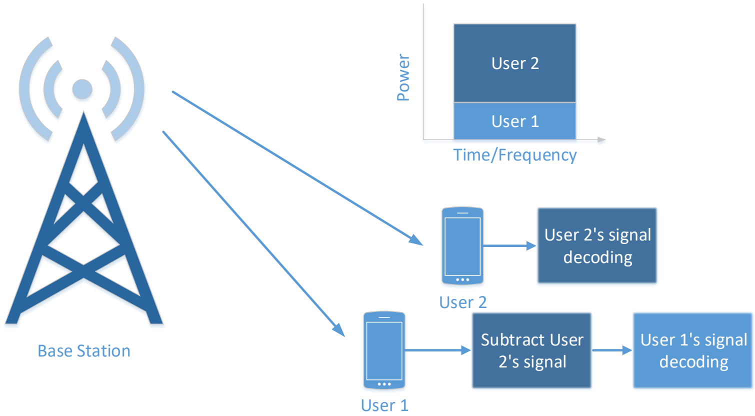


Figure 1.3: NOMA in Downlink

Another interesting technology that has gained traction in IoT environments is Wireless Powered Communication (WPC) that has emerged as a promising alternative to the conventional battery-powered operation and the energy harvesting technique based on natural energy sources such as solar or wind. In this scenario, the devices, whether battery-free or not, can benefit from adopting the WPC technique, due to the fact that they can harvest and store energy in a stable manner from the Radio Frequency (RF) signals during a so called Wireless Energy Transfer (WET) phase. Then, the saved energy can be used to transmit their information signals to a proxy device or evolved NB (eNB) during the Wireless Information Transmission (WIT) phase [10].

On the networking side, various technologies have been proposed to make networking more flexible, scalable and effective. Software Defined Networking (SDN) [11] wants to decouple the control plane from the data plane, thus enabling usage of virtualization for controlling the flow of data while low cost switches are responsible just for the actual exchange of the data. This provides a better fit in situations where there is an ever-changing network of users, devices, services and resources (such as data centers or IoT environments). The traditional hardware-based networks impose great complexity and effort, resulting in time consuming and difficult to scale infrastructures.

Complementary to SDN, Network Function Virtualization (NFV) is proposed to replace dedicated hardware, that provides specific network services, with virtualized software [12]. In that sense, software running on virtual machines can replace services such as routers, firewalls, encryption, load balancers and DNS. The need for proprietary and specific hardware for each different network service becomes obsolete and there is only need for inexpensive switches, storage and servers to run the virtual machines. NFV gives network administrators the capability to manage the network from a centralized point and add network functions at will. Virtualized network functions are thus under the control of a hypervisor, which is the role that SDN can fulfil in such a scenario.

As for the need to augment the capabilities of low energy and less computationally effective devices, one of the most prominent candidates proposed was Mobile Edge Computing which was introduced by the European Telecommunications Standards Institute (ETSI) Industry Specification Group (ISG) [13]. The idea was to have the same capabilities as the cloud but at the edge of the network, in order to take advantage of the proximity and exploit higher processing and storage capabilities. From 2017, the ETSI Industry group renamed it to Multi-Access Edge Computing, while keeping the already established MEC acronym, since the benefits from the proposed technology were not restricted to mobile networks but extended to Wi-Fi and fixed access technologies as well.

Cloud computing allows the outsourcing of processing and storage functionalities to other more powerful devices, so that the device does not have to handle the computation and management of the data itself. However, cloud computing suffers from a few disadvantages. Its centralized nature means there is a single point of failure and there can be reachability and latency issues. What's more, lots of IoT applications would favor a more distributed system to promote location awareness, easier scalability, lower latency and mobility management (e.g., factories or agricultural IoT automations). Additionally, the massive volume on devices in the IoT environment could result in large traffic on telecommunication networks due to the bandwidth usage needed.

The 'raison d'être' of MEC is thus to minimize network congestion and improve resource optimization, user experience and overall performance of the network, helping the individual devices achieve their assigned tasks. According to the ETSI, MEC allows the deployment of versatile and uninterrupted services on IoT applications and it creates new possibilities to services and content providers.

The combination of MEC and IoT provides mutual advantages. The IoT environment gives MEC a vast amount and a wider variety of devices as a playground for more sophisticated services, while MEC gives the ability to smaller IoT devices to perform complex jobs, by providing computational capabilities through computation offloading, and to communicate more freely and more energy efficiently, by acting as gateway to the rest of the Internet. According to Teleb et al. [14], the combination of MEC and IoT would lead to lower traffic passing through the infrastructure, would allow faster speeds and lower latency for applications due to proximity, and allow faster scaling of network services.

There are numerous scenarios of combined IoT and MEC applications including smart home and smart cities, healthcare, autonomous vehicles, augmented reality and virtual reality applications, retail, wearable IoT, IoT in mechanized agriculture, smart energy and industrial Internet of Things [1]. The major technical aspects of MEC enabled IoT are:

Scalability. IoT environments consist of billions of devices interconnected in a huge network of cyber-physical systems and thus scalability is of utter importance for efficiency and reliability.

Communication. Since all the aforementioned devices need to communicate, and since offloading data to a MEC server is a common task for using its computational resources, effective usage of bandwidth and spectrum is necessary.

Computation Offloading and Resource Allocation. In order to empower low powered and resource constrained IoT devices with augmented capabilities, a core component of the new architecture includes the decision making process of devices to partially or fully offload their computational tasks to a third party, and the management of the resources by the latter.

Mobility management. Since devices are no longer considered static but instead are moving inside the service provider's coverage area, a way to seamlessly handle that movement and avoid latency or reliability problems is needed in order to maintain a high Quality of Experience (QoE).

Security. Due to the amount of devices and the novel emerging architectures and communication protocols, new possible security attacks and exploits are emerging as well, that need to be mitigated.

Privacy. Many of the proposed applications (e.g. healthcare, industry etc.) have multiple rules and regulations as to the privacy of the data exchanged, while personal data protection and confidentiality of communication also dictate for stronger privacy standardization. Due to the above and since in the arising settings there is more than one data handler devices, the necessity for extended care on privacy issues is undeniable.

Trust management. Many services such as autonomous vehicles or remote surgeries need more than security and privacy, but reliability, efficiency and precision as well. That's why a wider sense of trustworthiness is to be reached in the new frameworks proposed.

Our thesis will mainly focus on the areas of communications and computation offloading and resource allocation tasks, while extending to some of the rest of the aspects as well.

To tackle the above problems, various approaches have been considered. Due to the need for more efficient and less energy consuming communication, the settings are often modeled as optimization problems, where an offline and centralized minimization or maximization algorithm is considered (linear programming, geometric programming). Often, more than one feature is being optimized (jointly optimizing energy consumption, execution time, pricing etc.), and numerous different parameters are taken into account (transmission time, transmission power, spectrum utilization, device reputation etc.) [15].

Another way to handle optimization problems in a more decentralized manner is by making use of Game Theory [16]. In this setting, the problem is formulated as a non-cooperative (or cooperative depending on the use case) game, and each user is considered as a greedy individual that independently wants to maximize his perceived utility. This approach does not necessarily lead to the best possible outcome but instead reaches a stable outcome known as Nash Equilibrium, where each user is satisfied with his own decisions and does not want to unilaterally change them. Adding an extra layer of complexity, and considering behavioral characteristics on devices in order to exhibit more realistic decision-making under risk, Prospect Theory is used. Prospect Theory is a commonly used tool in economics and social sciences, but which is not yet widely researched in the topic of IoT and 5G.

Due to the large variety of problems, lots of different mathematical techniques are explored, specifically tweaked for the peculiarities of each specific scenario. In order to create consistent clusters and make communications more efficient, algorithms such as k-means and hierarchical clustering are considered in the literature, while when there is need for task scheduling on a common resource (e.g. when talking on the same channel), dynamic programming seems more appropriate. The nature of the networks also allows the usage of network specific algorithms taken from complex network theory, where centralities (e.g. closeness centrality, betweenness centrality etc.) could be exploited to find important devices within a network, and graph theory algorithms (e.g. BFS, Dijkstra etc.) to handle the exchange of information.

Finally, due to the ever-changing environment and the necessity to periodically adapt to the new resulting setting, as well as to handle scenarios with incomplete information, techniques such as machine learning and reinforcement learning are considered. The complexity of the networks and the vast amount of data that need to be processed, make conventional algorithms unusable in some settings and thus new probabilistic or approximation algorithms are needed.

1.1 Motivation

Based on the above discussion, the necessity for solutions to the arising problems in the emerging IoT environments and the urgency for innovative research are evident. Technology has evolved in such a way that we now have multiple tools which enable us to come up with nifty solutions that were not feasible in the -not so distant- past. In our thesis, we wanted to take this opportunity and propose solutions in some modern and interesting problems by taking into account the following subjects:

User centric networks. In the IoT environments, devices are considered smart and their decision-making plays a big role in the performance of the network. For that reason, throughout our work, we consider users to be the core of the network, where their strategies and their interactions heavily affect the system which needs to dynamically adapt to their various needs.

Quality of Experience and Satisfaction of users. As already mentioned, in the Multi-access Edge Computing paradigm, user devices are willing to offload their corresponding tasks to a more potent server and thus a decision-making framework that takes advantage of the infrastructure of the network is needed. Generating value for the users and maintaining a high Quality of Service (QoS) provided by the servers is of utter importance and both those features are treated as core features in our proposed frameworks.

Behavioral characteristics of devices. In the majority of the literature, the user devices are considered as neutral utility maximizers, ignoring decision-making under probabilistic outcomes and risky environments. Taking into account behaviour influenced by risk and uncertainty leads to more realistic decision-making strategies and thus would allow for better real-life applicable frameworks.

Distributed decision making. The heterogeneity on the behavior and the subjectivity on the perception of the Quality of Experience by the users, as well as the need for flexible and scalable solutions, highlight the importance of a more distributed decision-making approach. The existence of omnipotent central entities that orchestrate the entire procedure is unrealistic in various modern scenarios and approaches where devices act on self interest lead to more interesting and viable solutions.

Holistic frameworks. With the introduction of the next generation networks and the drastic change in the volume of connected devices and exchanged information, major rework needs to be done in the whole process of data exchange and optimizing on a single component of older solutions is inefficient. Throughout our thesis we tried to propose cohesive procedures, where both users and servers jointly participate in the decision-making process exploiting various mechanisms and thus following a more holistic approach where various interconnected components are utilized to handle the use case scenarios.

Incomplete information. It is common in literature for all information to be considered accessible by the participants of the network - especially in cases where a central decision-making entity is considered - where knowledge of the perception, the decisions and the achieved rewards of the rest of the individuals is available. Since this is not always feasible, we wanted to explore situations where individuals have limited or incomplete information and are restricted to the information of their own decisions and to the observation of the environment.

1.2 Our Contributions

In our thesis we tried to tackle some of the aforementioned problems that arise in the emerging 5G architectures by proposing realistic solutions to several use case scenarios. Our main focus lied on the decision-making process of the participants, where individual devices and servers need to make their choices in a distributed manner, regarding the allocation and exploitation of the resources inside their environment. The primary contributions of our thesis can be summarized as follows:

1. **A joint interest, physical and energy-aware clustering formation mechanism for efficient M2M device communication:** In order to remove unnecessary communications and to minimize the energy consumption of the devices, we propose a clustering formation mechanism that takes into consideration the distance between devices, their power and the relevance of the information they are willing to share. The majority of the literature does not take into consideration the relevance of information which in IoT environments could be of major importance in order to minimize information exchanges.

2. **Usage of WPC technique to enable communication of less energy potent devices:** Since not all devices in the IoT environment have abundance of electric power (battery-free sensors, devices in remote locations etc.), and because energy harvesting techniques that

opportunistically harvest renewable energy such as solar or wind power are not consistent, we believe the Wireless Powered Communication (WPC) technique can be of vital importance for the communication in several scenarios. In our thesis we propose a selection mechanism for the device that will power the rest of the cluster based on its proximity and its power capabilities.

3. **Optimization on power efficient transmission:** In the Wireless Information Transmission (WIT) phase, the devices are responsible to exchange their information within the network. Due to the high number of devices that simultaneously want to transmit, there exists strong interference and noise in their communication channel. To solve this problem, we propose the appointment of a representative device for each cluster who is responsible of collecting the information of the rest of the devices and communicating them to the rest of the network as needed. The mechanism proposed, modeled as a non-cooperative game, aims at lowering the transmission power, avoiding high interference and achieving a high Quality of Experience (QoE) for the devices.

4. **Optimization on data offloading in a MEC environment:** In a MEC environment where the operator of the MEC server is different from the end-user, both sides want to maximize their perceived welfare with conflicting interests. For that reason we tackled the problem as a two-layer optimization problem, where in the first layer the users compete in a non-cooperative game in order to maximize their personal well-being by offloading part or all of their computing tasks, while in the second layer the MEC servers, given the offloaded data, try to maximize their achieved profits.

5. **Selection of MEC server in a multi-server competitive computing market using stochastic learning automata:** Since in a multi-server market, end-users do not have prior information on the quality of the server with whom they are about to interact, we propose a reinforcement learning mechanism based on stochastic automata that takes into account previous actions and reactions of the MEC environment, pricing and possible discount offerings, congestion problems and market penetration. By assigning a reputation score to each server, users probabilistically select the one with whom they want to associate.

6. **Risk-aware decision-making process:** Since MEC servers are not as potent as the cloud, we model their available resources as Common Pool Resources (CPR) and associate a probability of failure to their operations based on the usage. That incorporates risk for the users associated to the MEC server and in order to realistically model their decision-making process one needs to be aware of the users' risk-based behavior. In our work we proposed the usage of the principles of Prospect Theory, a behavioral economic theory that models users' decisions under uncertainty.

7. **Multi-leader multi-follower Stackelberg game:** In order to jointly solve the offloading problem and price selection, we formulated a Stackelberg game among the MEC servers

(leaders) and the users (followers) to determine the MEC servers' optimal computing service pricing policies and the users' optimal data offloading strategies. The users' data offloading decision-making is formulated as a non-cooperative subgame among them and an equilibrium point is determined while the servers' price selection is formulated as a separate non-cooperative subgame with its own equilibrium. The overall Stackelberg game converges to an equilibrium as well.

8. **Price selection in a multi-server competitive computing market using reinforcement learning:** In order to handle the exploration-exploitation tradeoff dilemma in a setting where MEC servers do not a priori know the price that leads to the most profitable outcome, we proposed the modeling of the problem as a Multi-Armed Bandit problem. The benefits of the proposed solution lie in the fact that no complex calculations nor specific knowledge of the actions of the rest of the actors are needed and the decisions are made based on simple observations from the environment.

9. **Evaluation of proposed frameworks with numerical results through simulations:** In order to test the effectiveness and the efficiency of our proposed frameworks, as well as to test the influence that each parameter has on the corresponding model, we performed thorough evaluation via realistic use case simulations.

Chapter 2

Background

2.1 Game Theory

Game Theory is the study of mathematical models of strategic interaction among rational decision-makers [17]. Modern game theory began with the work of John von Neumann, who together with Oscar Morgenstern published his Games and Economic Behavior [18], thus founding not only game theory but also utility theory and microeconomics. The theory was further enriched by John Nash who developed a criterion for mutual consistency of players' strategies known as the Nash equilibrium, applicable to a wider variety of games than the criterion proposed by von Neumann and Morgenstern [19]. Nash proved that every finite n-player, non-zero-sum (not just two-player zero-sum) non-cooperative game has what is now known as a Nash equilibrium in mixed strategies. There are lots of applications of Game Theory in many sciences, including economics [20], computer science, security [21], sociology and biology [22].

In Game Theory, a *game* is considered as the interaction between different parties with their own interests. The parties participating in the game are the *players* and each one of them has a set of choices called *strategies* on how to play or behave. The combined behavior of the players results in *payoffs* for each player which represent their satisfaction level. The function that gives the value of the payoff is the *payoff function* or *utility function*.

In formal notation we define a game G as

$$G = (N, \{A_i\}, \{U_i\}) \tag{2.1}$$

where N is the set of players, A_i is the strategy set of each player i and U_i is the utility/payoff function of each player.

The *Nash Equilibrium* is a solution concept of a game involving two or more players, where no player has anything to gain by changing only his own strategy, meaning he cannot achieve a higher payoff by changing his strategy while the other players keep theirs unchanged. The solution state can be either *pure*, meaning only one strategy is selected at all times, or *mixed*, meaning that multiple strategies are considered based on a probability distribution.

The *best-response* is the strategy which produces the most favorable immediate outcome for the current player, meaning the strategy that maximizes his payoff, taking other players' strategies as given. The Nash Equilibrium can be thus be expressed as the set of strategies such that each player is playing a best-response to the other players' strategies.

A commonly used example to explain the concept of a game and its equilibrium strategy is the *Prisoner's Dilemma* game. The game consists of two prisoners that are arrested for a crime. The police has insufficient evidence for a conviction and having separated both prisoners, an officer offers them the same deal: if one testifies for the prosecution against the other and the other remains silent, the betrayer goes free and the accomplice receives the full 10 year sentence. If both choose to stay silent, the police can sentence both prisoners only 6 months for a minor charge. If both choose to betray the other, the will each receive 5 years of sentence. Each prisoner must choose whether to betray the other or stay silent without knowing what choice the other prisoner will make.

The game can be visualized with a *payoff matrix* as shown in Table 2.1, where the first number on the cell corresponds to the payoff of the first prisoner on the specified state and the second number the payoff of the second prisoner. It should be noted that the higher the payoff, the more value the player gains and thus a full 10 year sentence results in a payoff $p = 0$, a 5 year sentence results in a payoff $p = 1$, a 6 months sentence results in a payoff $p = 3$ and leaving without any charges results in a payoff $p = 5$.

Table 2.1: Prisoner's Dilemma

Player B / **Player A**	**Silent**	**Betray**
Silent	$3, 3$	$0, 5$
Betray	$5, 0$	$1, 1$

From the table we can see that the most favorable outcome for both players would be to both stay silent since the payoff for both would be 3. But based on the above definitions, this is not a Nash Equilibrium since if both remain silent, then one player would want to deviate from this strategy and betray in order to achieve a payoff of 5. The pure Nash Equilibrium state of the game is thus that both betray each other and get a payoff of 1, since in that case, if the other player chooses to change his strategy and remain silent he can only worsen his position and achieve payoff 0. The state $(1, 1)$ is the set of strategies such that each player is playing a best-response to the other player strategies. The above example states that the Nash Equilibrium is not always the optimal solution for the players, even though it is the only stable state.

Another example game is the *Matching Penny* game. In this game we have two players that can choose either heads or tails on a coin toss. Player A wins a dollar from player B if their choices match and looses a dollar to player B if they don't. The game can be visualized as shown in Table 2.2.

Table 2.2: Matching Penny

Player A \ Player B	Heads	Tails
Heads	$1, -1$	$-1, 1$
Tails	$-1, 1$	$1, -1$

In this game there is no pure Nash Equilibrium since playing consistently one strategy by a player, would allow the other player to choose the strategy that maximizes his payoff at the first player's expense. The game has a unique mixed Nash Equilibrium that requires each player to choose each action with probability one-half. One feature of a mixed strategy equilibrium is that given the strategies chosen by the other player, each player is indifferent among all the actions that he or she selects with positive probability. Hence, here, given that player B chooses each action with one-half, player A is indifferent among choosing Heads, choosing Tails and randomizing in any way between the two. Same goes vice versa and thus both players should choose their actions with probability one-half to stay on the Nash Equilibrium.

The different types of games can be roughly categorized in the following classes in order to give an idea of the main features which can distinguish games [23].

- *Static and Dynamic games:* In static games the players have certain knowledge (information assumptions, behavior assumptions) which doesn't change, while dynamic games assume that players can extract some information from past moves, observations and chosen strategies and take them into account to adjust current and future actions.
- *Non-Stochastic and Stochastic games:* In stochastic games, a state in the game evolves over time and according to a certain stochastic rule, as opposed to non-stochastic games.
- *Non-Cooperative and Cooperative games:* In Cooperative games, players can form alliances in order to achieve their goals and compete against other players or coalitions, while in Non-Cooperative games each player acts egoistically. In Non-Cooperative games, the individual goals and strategies can be distinguished, whereas in Cooperative games this is not always possible.
- *Complete information and Incomplete information games:* In games with Complete information, it is assumed that the data of the game is common knowledge, meaning that every player knows the data of the game, that the other players know the data of the game, that every player knows that every player knows the data of the game and so on. In games with Incomplete information (Bayesian games) players have only partial information about the game.
- *Perfect information and Imperfect information games:* In Perfect information games, all the players know the history of the game perfectly, while in Imperfect information games, players miss information on what each player chose on previous steps of the game.
- *Zero-sum and Non Zero-sum games:* Zero-sum games are those where the sum of utilities is zero (or a constant). The idea is that if someone wins something, someone else necessarily

has to lose.

More explanations on game theory concepts will be provided when necessary in the main sections of the thesis.

2.2 Prospect Theory

Prospect theory was introduced by Daniel Kahneman and Amos Tversky in 1979 [24] (awarding Kahneman the Nobel price in 2002), as a more descriptive alternative to the *Expected Utility Theory* that dominated the analysis of decision making under risk. In Expected Utility Theory, users are considered as neutral utility maximizers ignoring decision making under probabilistic outcomes, whereas Prospect Theory takes into account behaviour influenced by risk, matching a more real-life decision-making scenario.

There are five main phenomena addressed by the proposed model that the standard model violates [25]:

- *Framing effects*: While a rational choice theory assumes that different formulations of the same choice problem would result in the same choices, there is evidence suggesting that individuals have different preferences when the way that the choices are presented varies (e.g. in terms of gains or losses).
- *Nonlinear preferences*: The standard model assumes the utility of a risky prospect is linear in outcome probabilities, while there is evidence that this is not a case.
- *Source dependence*: The source of the event (and not just the degree of uncertainty) also affects the choices of the individual (e.g. people are more willing to bet on an event in their area of expertise).
- *Risk seeking*: The standard model assumes a risk averse behaviour under uncertainty. This is not the always the case as in some settings people tend to adopt risk seeking behaviours. More specifically a) people tend to overvalue small probabilities of wining large prices over the expected value of that prospect and b) people tend to disfavor a sure loss over a substantial probability of a larger loss.
- *Loss aversion*: Individuals tend to be loss averse, meaning that under risk and uncertainty, they are more concerned about loses than gains. This asymmetry is not captured by the standard model.

The model that we will be using throughout our thesis corresponds to the model used by Hota et al. [26]. It tries to address the above phenomena in such a way that it is easier to formulate the model in a mathematical way.

The features of the model that match the proposed model by Kahneman and Tversky are:

- *Reference dependence*: In order to capture the difference in behaviour in case of gains or losses, a reference point is considered based on which which gains and losses are measured.
- *Loss aversion*: Gains and losses of equal magnitude are treated differently in the proposed model since participants exhibit greater dissatisfaction in a loss compared to a gain of the

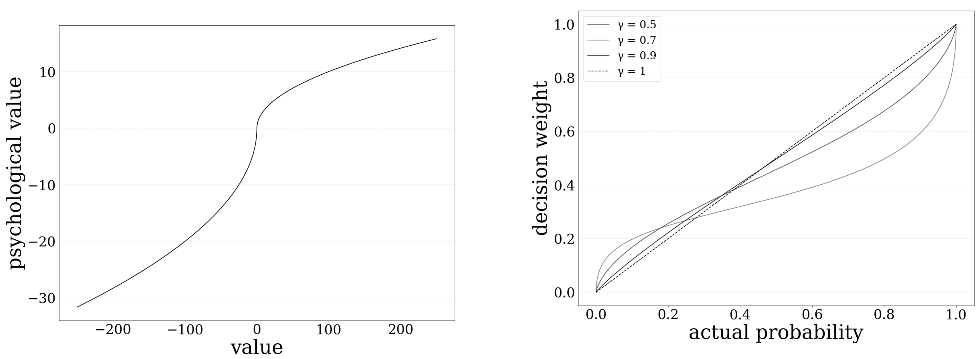
same amount.

- *Diminishing sensitivity*: The perceived utility function should be a concave function for positive outcomes and a convex one for negative outcomes, meaning that the participants exhibit risk averse behavior in gains and risk seeking behavior in losses.
- *Probability weighting*: Probabilities are not treated equally across all the probability spectrum and participants tend to overestimate low probabilities and underestimate high probabilities.

In order to formalized the above features in a mathematical form, concerning the perceived utility function of the participants, we define the following equation:

$$u(z) = \begin{cases} (z - z_0)^\alpha, \text{ when } z \geq z_0 \\ -k(z_0 - z)^\beta, \text{ otherwise} \end{cases} \tag{2.2}$$

where z_0 is the *reference point* from where the losses and gains are defined, $\alpha \in (0, 1]$ and $\beta \in (0, 1]$ are *sensitivity parameters* and $k \in [0, \infty)$ is the *index of loss aversion*. An indicative representation of the function $u(z)$ can be seen in Fig.2.1a.



(a) Value function. Sensitivity is different to losses and gains, in respect to a reference point.

(b) Decision weighting function. The weighting is concave for low probabilities and convex for high probabilities.

Figure 2.1: Prospect Theory functions

From eq. 2.2 we can see that the higher the value of α (respectively β), the greater the sensitivity towards gains (respectively losses) of higher magnitude compared to those of smaller magnitude, while the larger the value of k, the greater the degree of loss aversion. What's more, considering $\alpha = \beta$ for simplicity, when $k > 1$, the individual weights losses more than gains, exhibiting a *loss averse* behaviour, while when $0 \leq k \leq 1$, the individual weights gains more than losses, exhibiting a *gain seeking* behaviour. If $\alpha = \beta = k = 1$, the players are simply risk neutral, rendering the prospect theoretic model a generalization over the original expected utility maximizer model.

Concerning the inconsistency in probability weighting, where individuals overestimate lower probabilities and underestimate higher probabilities, Tversky and Kahneman in [25] proposed the computation of decision weights by weighting cumulative probabilities. More specifically, the function proposed denotes the weight of the probability p of gaining at least (respectively at most) a certain amount greater (respectively less) than the reference point:

$$w(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}} \tag{2.3}$$

where $\gamma \in (0, 1)$ is the only parameter used to encompass the function with a concave region on lower probabilities and a convex region in higher probabilities as seen in Fig.2.1b. It can also be noted that the smaller the γ the steepest the curves and thus the larger the difference between the decision weight and the actual probability of the event.

Another interesting function with similar characteristics to the one proposed by Tversky and Kahneman was proposed by Prelec in [27] and is defined as follows:

$$w(p) = e^{-(-\ln(p))^\gamma} \tag{2.4}$$

where $\gamma \in (0, 1)$ denotes the distortion parameter and has similar behaviour as in Fig.2.1b.

More explanations on prospect theory concepts will also be provided in our thesis whenever needed.

Chapter 3

Interest-aware Energy Collection & Resource Management in Machine to Machine Communication

3.1 General Setting

As mentioned in chapter 1, wireless communication systems and networks have grown explosively in recent years and Machine to Machine (M2M)-driven IoT differs fundamentally from the classic internet that focused on human to human communications. M2M features orders of magnitude more nodes, most of which are extremely low-powered or self-powered devices.

Among the key concerns related to the IoT applications is the prolongation of the M2M devices' battery life, towards guaranteeing the operation of the IoT system for a longer time period [28]. In the vast majority of the IoT applications, the energy efficient communication and the stable energy supply to them have become among the primary objectives in resource allocation. The latter becomes even more critical due to the growing proliferation of M2M devices, which are often deployed in areas where frequent human access or battery replacement is not always feasible [29].

In this chapter, we consider low powered IoT devices that are performing certain tasks and wish to share their information to the rest of the network. In order to avoid congestion on the network, the devices choose to send their information to another intermediate device, responsible of transmitting it to the rest of the network. Since devices are smart and their information have a particular context, we believe that taking into account the type of the content is of utter importance in order to make communications and transmission more efficient. The selection of the intermediate device is not a trivial task since devices may have different proximities and different interest in each type of data. The communication phase poses some non-trivial challenges as well since low powered devices need to seek energy efficient methods to communicate while maintaining a high Quality of Service (QoS). In the rest of the chapter we will walk through the way we attempted to tackle some of the aforementioned challenges.

3.2 Related Work

Aiming at improving the energy efficient communication among the M2M devices, and in parallel overcoming the wireless access congestion problem, the joint clustering of devices and resource management arises as a promising solution. Various M2M device clustering methods have been proposed in the recent literature based on different criteria, such as M2M devices' achievable signal to interference plus noise ratio [30], transmission delay [31], etc. The induced hierarchy for management and control via the clustering methods provide an immediate and intuitive benefit [32–34]. Furthermore, the concept of data priority has been adopted towards devising energy efficient and congestion mitigated clustering algorithms thus improving the energy efficient transmission of the M2M devices for the IoT applications. The authors in [35] proposed a data-centric clustering algorithm of the M2M devices in a resource constrained M2M network by prioritizing the quality of the overall data transmitted by the individual devices. Following the concept of data priority, a healthcare IoT application was studied in [36], where the criterion of health-based priority of the transmitted data was utilized towards performing M2M devices' clustering. In [37] the problem of energy-efficient clustering was studied by jointly considering cluster formation, transmission scheduling and power control while the problem of energy efficient transmissions of M2M devices has been studied in [38] considering an existing clustering in the M2M network. More specifically, the authors allowed the cluster-head to coordinate the congestion within the existing cluster via assigning weights to the M2M devices based on various criteria, such as data priority, energy availability, and M2M devices' mobility. In [39], a primitive joint interest, energy and physical-aware framework for coalitions' formation among the wireless IoT devices and an energy-efficient resource allocation in M2M communication networks was introduced. Finally, in [40], a coalition formation method among devices is proposed, where the operation mode correlation between multipurpose devices expressing social metrics is considered in addition to the devices spacial proximity and their energy availability.

In parallel of devising clustering algorithms to improve the energy efficiency, the stable energy supply to the M2M devices is of great importance to prolong their battery life, as well as the operational life of the overall IoT network. Towards this direction, the Wireless Powered Communication (WPC) technique has emerged as a promising alternative to the conventional battery-powered operation or the energy harvesting technique based on natural energy sources such as solar or wind. The M2M devices participating in an IoT application, whether battery-free or not, can benefit by adopting the WPC technique, due to the fact that they can harvest and store energy in a stable manner from the Radio Frequency (RF) signals via dedicated neighbour devices, during the wireless energy transfer (WET) phase. Then, the saved energy can be further exploited via adopting energy efficient transmission techniques and transmit their information signals to the cluster-head or evolved NB (eNB) during the wireless information transmission (WIT) phase [10]. Several research works have been proposed in the literature dealing with the energy utilization efficiency via adopting the wireless powered communication technique and devising intelligent resource management frameworks. In [41], a joint time allocation and power control framework was proposed towards maximizing network's energy efficiency under different conditions, such as the initial battery energy of each mobile device and the minimum system throughput constraints. The maximization problem of the uplink sum-rate network's performance was studied in [42], while adopting the WPC technique and via jointly determining the optimal energy and time resource allocation for the multiple mobile devices. This work has been extended in [43] considering additional constraints, such as infinite or finite capacity energy storage. Furthermore, the problem of joint subcarrier scheduling and power allocation via jointly adopting the orthogonal frequency division multiplexing (OFDM) and WPC techniques has been studied in [44] towards maximizing system's sum-rate. Finally, in [45], an efficient energy management in WPC is proposed in order to ensure a high Quality of Experience for the users of the network.

Game Theory has been widely used in various settings in order to determine the optimal resource management in a distributed way. In [46], the problem of joint users' uplink transmission power and rate allocation in NOMA wireless networks is studied and formulated as a non-cooperative game, while in [47], a dual transmission interface is introduced in 5G networks, where the users can simultaneously exploit the OFDMA and NOMA technique and a user-centric distributed power control problem is formulated. In [48] the efficient Resource Block allocation to the users and the transmission power allocation in a network with cellular users and machine to machine users is handled via a bilateral symmetric interaction game and in [49] the simultaneous allocation of users' uplink transmission power and rate in multi-service two-tier open-access femtocell networks is treated. The problem of efficient distributed power control via convex pricing of users' transmission power in the uplink of CDMA wireless networks supporting multiple services is addressed in [50] with a Multiservice Uplink Power Control game, and the problem of joint users' uplink transmission power and data rate allocation in multi-service two-tier femtocell networks is tackled in [51] as a two-variable optimization problem and formulated as a non-cooperative game, while in [52], the problem of uplink power allocation in a 5G environment is formulated as a contract between each BS and its corresponding users following the principles of Contract Theory.

3.3 Proposed Framework

3.3.1 System Model

We consider the uplink of an LTE/LTE-Advanced Machine-to-Machine (M2M) communication type network consisting of an evolved NB (eNB) and multiple LTE based M2M devices (e.g., actuators, sensors). Within the IoT era and its corresponding smart applications, the majority of M2M communications traffic is in the uplink direction, due to the periodic transmission of sensing and measurement data to a central controller for further exploitation. The set of energy-collecting M2M devices is denoted by M, where $M = \{1, \dots, m, \dots, |M|\}$. Sensors are typically used to collect data as per their functionality and forward them to the central application controller through the eNB. Considering sensors' data collection, two types of communication are possible: (a) eNB-M2M communication, i.e., each device communicates through the eNB and (b) direct M2M communication, i.e., direct communication among energy-collecting M2M devices. In our work, owing to its energy-efficiency superiority [29], we focus on direct M2M communication, while proposing an interest and energy-aware cluster formation mechanism. The data from the M2M devices are collected to a selected cluster-head, which further forwards the aggregated and processed information to the eNB. M2M devices are organized in $|C|$ clusters, where $C = \{1, \ldots, c, \ldots, |C|\}$ denotes the corresponding set of clusters. The idea of clustering M2M devices based on sophisticated criteria stems from the need of manageability and scalability of the extremely crowded M2M networks. Through the proposed cluster formation we will discuss in section 3.3.2) and energy-collection and resource allocation mechanisms we will discuss in section 3.3.3), each M2M device is associated with a cluster-head for communication to and from the eNB. The cluster-head is appropriately selected among the set of M2M devices, i.e. $ch_c \in M$, where $c \in C$, and is in charge of more functionalities and responsibilities compared to the rest of M2M devices, e.g., perform traffic aggregation or data compression before relay. Each M2M device m belongs exclusively to a cluster c with cluster-head ch_c. The number of the devices belonging to the cluster c with cluster-head ch_c is denoted by $|M_c|$, while their corresponding set is $M_c = \{1, \ldots, |M_c|\}$.

3.3.2 Interest and Energy Aware Clustering

In this section, we describe an admission control policy based on Chinese Restaurant Process (CRP) in order to create clusters among numerous M2M devices. Suppose that we have a collection of entities − in our case the M2M devices − and we want to cluster them into groups. In Chinese Restaurant metaphor, each group corresponds to a table and each entity to a customer entering the Chinese Restaurant. The Chinese Restaurant is assumed to have countably infinitely many tables, labeled $1, 2, \ldots$. In our case, the tables correspond to the clusters. The customers walk in and sit down at some table. The customers are assumed to prefer sitting at popular tables, however there is always a non-zero probability that a new customer will sit at a currently unoccupied table. The tables are chosen according to the following random process: (a) the first customer always chooses the first table and (b) the m^{th} customer chooses an occupied table with probability $\frac{c}{m-1+\alpha}$ (where c is the number of customers already sitting at that table) and the first unoccupied table with probability $\frac{\alpha}{m-1+\alpha}$, where a is called the "concentration parameter" of the CRP, indicating the willingness of each customer to stay alone and create a new cluster.

In the following analysis, the concept of CRP is adopted towards clustering M2M devices into groups. However, in order to make the clustering results more practical, we will extend CRP towards considering several M2M related factors, including interest of M2M devices to communicate with each other, physical proximity, as well as their energy availability.

Cluster Formation

The CRP approach can correlate interest similarity and physical proximity among M2M devices to group them into clusters. The proposed Interest and Physical-aware CRP (IP-CRP) approach will exploit the interest based and distance based graphs to form the clusters in an intelligent manner. Moreover, the energy availability of the M2M devices will be further exploited to select the cluster-head ch_c of each cluster $c, c \in C$, as it will be explained in the next subsection.

Based on the system model introduced in section 3.3.1, we define the interest based graph $G^I = \{\nu, \epsilon^I\}$ and the physical based graph $G^P = \{\nu, \epsilon^P\}$, where the set of M2M devices ν represents the vertex set and the edges $\epsilon^I = \{\epsilon^I_{m,m'}, \forall m, m' \in \nu\}$ and $\epsilon^P = \{\epsilon^P_{m,m'}, \forall m, m' \in \nu\}$ represent the edges set. The edges on the first set $\epsilon^I_{m,m'} = p(m,m'), p(m,m') \in [0,1]$ denote the level of interest for communication among m and m', while the edges on the second one denote the normalized (as explained later) distance weights $\epsilon^P_{m,m'} = d(m,m')$, $d(m,m') \in [0,1]$. The probability of M2M device m to select device m' as its partner to form a cluster can be calculated as follows:

$$P(m,m') = \begin{cases} \frac{f(\mathrm{IDD}(m,m'))}{\sum\limits_{m \neq m'} f(\mathrm{IDD}(m,m'))+\alpha}, & \text{if } m \neq m' \\ \frac{\alpha}{\sum\limits_{m \neq m'} f(\mathrm{IDD}(m,m'))+\alpha}, & \text{if } m = m' \end{cases} \tag{3.1}$$

where α is the parameter of IP-CRP showing the willingness of each M2M device to stay alone and create a new cluster, as explained before. The function $f(\mathrm{IDD}(m,m'))$ is the interest and distance based function defined as:

$$f(\mathrm{IDD}(m,m')) = w_1 \frac{1}{\mathrm{ID}(m,m')} + w_2 \mathrm{D}(m,m') \tag{3.2}$$

where w_1 and w_2 are weights showing the importance of interest and distance factor in M2M devices' decision influence for clustering, respectively. It is noted that $w_1 + w_2 = 1$. Furthermore, the factor $\mathrm{IDD}(m,m')$ shows the M2M devices' decision relation with respect to both individual influential factors, i.e., the interest distance $\mathrm{ID}(m,m')$ and the physical proximity $\mathrm{D}(m,m')$. The interest distance $\mathrm{ID}(m,m')$ between the M2M devices is formulated in order to evaluate the effect of their mutual interest to communicate and exchange information. Thus, we calculate the interest distance based on the level of interest $p(m,m')$ as:

$$\mathrm{ID}(m,m') = -\log_2(p(m,m')) \tag{3.3}$$

where as explained before $p(m,m') \in [0,1]$ is the level of interest between M2M devices m and m'. Note that larger value of $p(m,m')$ concludes to smaller $\mathrm{ID}(m,m')$, which is interpreted as follows: the shorter the interest distance between two M2M devices is, the larger the probability of willingness to communicate with each other, thus larger is their intention to belong to the same cluster. The above formulation stems from the observation that the M2M devices have different interests to interact with each other in order to achieve a common goal. For example, in a smart home application there are included several M2M devices, e.g. smart thermostats, connected lights, smart fridge sensors, smart door lock sensors, etc. The smart thermostats and the sensors measuring the temperature have greater interest to communicate with each other, form a coalition and transmit their data to the coalition-head, which further transmits all the collected data to the eNB for further exploitation and decision making. The same holds true for the set of sensors participating in the smart lighting system or smart fridge application and so on and so forth.

In addition, the physical proximity or physical distance function $\mathrm{D}(m, m')$ is defined as:

$$\mathrm{D}(m, m') = -\log_2(d(m, m')) \tag{3.4}$$

where $d(m, m')$ is the normalized (with reference to the maximum distance) physical distance among M2M devices m and m' such that $d(m, m') \in [0, 1]$.

Based on eq. 3.1, we can calculate the probabilities of M2M device m to select other devices in order to form a cluster. Thus, M2M device m determines the probability of joining cluster c with the set of M2M devices M_c as follows:

$$P_c(m) = \sum_{m' \in M_c} \frac{f(\mathrm{IDD}(m, m'))}{\sum\limits_{m \neq m'} f(\mathrm{IDD}(m, m')) + \alpha} \tag{3.5}$$

Following this methodology both the physical and interest distance among the M2M devices are jointly taken into consideration for the cluster formation mechanism. It is noted that by jointly considering the interest and physical distance to form the clusters, our proposed IP-CRP methodology can boost the benefits from both the interest-based and physical-based information of the M2M devices. Specifically, in the proposed IP-CRP scheme, M2M devices belonging to the same cluster have high interest to exchange information while they are in relevantly close physical proximity, thus the system performance can be enhanced in terms of both decreased energy-consumption and increased system throughput by involving IP-CRP M2M devices clustering.

Clusterhead selection

Given the cluster formation as presented in the previous section, the next step is to appropriately select the cluster-head among the members of each cluster. The cluster-head is selected based on the following factors: (a) interest ties among M2M devices, (b) physical proximity and (c) energy availability. Recalling the aforementioned interest based graph G^I and physical based graph G^P, we introduce the interest and physical-based graph $G^{IP} = \{\nu, \epsilon^{IP}\}$, where $\nu = M_c$ denotes the set of M2M devices belonging to the same cluster c and ϵ^{IP} denotes the edge among the two M2M devices. The weight of each edge is a composite distance that consists of the interest distance and the physical distance of the potentially connected M2M devices and is defined as follows:

$$w(m, m') = w_I \frac{\mathrm{ID}(m, m')}{\mathrm{ID}_0} + w_D \frac{\mathrm{D}_0}{\mathrm{D}(m, m')} \tag{3.6}$$

where w_I, w_D are the corresponding weights for different indexes, i.e., interest and distance, respectively. The parameters ID_0 and D_0 are assumed to be the maximum values of the corresponding indexes of M2M devices belonging to the same cluster.

Towards selecting the cluster-head ch_c of cluster c, we propose the concept of closeness centrality considering the factors of interest and physical distance (CC-IP). Given the graph G^{IP}, the metric CC-IP(m) for each M2M device m is formulated as follows:

$$\text{CC-IP}(m) = \sum_{\substack{m \in M_c \\ m \neq m'}} \left[\frac{sp(m, m')}{|M_c| - 1} \right]^{-1} \tag{3.7}$$

where $sp(m, m')$ is the overall cost/weight of the shortest path between M2M devices m and m'. The final score of each device, which is the one that defines which one M2M device we choose as a cluster-head is calculated as follows.

$$\text{score}(m) = w_{\text{CC}} \text{CC-IP}(m) + w_E \frac{E_0}{E(m)} \tag{3.8}$$

where E_0 is the maximum value of the available energy values of the devices and w_{CC} and w_E are the weights of closeness centrality and energy availability, respectively. The M2M device with the largest value of score(m) is selected as the cluster-head ch_c of the cluster c, $c \in C$,

$$ch_c = \arg\max_{m \in M_c} \{\text{score}(m)\} \tag{3.9}$$

Based on equation 3.8, we observe that the cluster-head ch_c has a balance between having increased available energy, being closest to the rest of the M2M devices organized in the same cluster c and its neighbour devices having high interest to communicate with it.

3.3.3 Energy Collection & Resource Management

As already mentioned, energy-efficient uplink transmission power and long-lasting system lifetime are among the major concerns of various IoT applications adopting M2M communication. In this section, we formulate the process of energy collection of M2M devices, as well as the problem of resource management, which is solved in a distributed manner. The “harvest and then transmit” protocol is considered, adopting the WPC technique, where the M2M devices in each cluster harvest energy from the broadcasted RF signals by the cluster-head (downlink communication) during the wireless energy transfer (WET) phase and then transmit their information signals (uplink communication) during the wireless information transmission (WIT) phase. The proposed energy collection and resource management approach aims at determining the optimal transmission power of each M2M device towards fulfilling its QoS prerequisites and maximizing its perceived satisfaction from its operation within the M2M network, as well as at ensuring the optimal charging transmission power of each cluster-head in order to guarantee the smooth operation of the overall system.

The thermal noise components and the M2M devices’ control signals can be regarded together as an Additive White Gaussian Noise (AWGN) process, with constant power spectral density I_0. Therefore, the overall sensed interference by an M2M device $m \in M$ can be formulated as follows:

$$I_m = \sum_{m \neq m'} G_{m,m'} P_{m'} + I_0 \tag{3.10}$$

where $m' \in M$, $P_{m'}$ is the transmission power of the M2M device m' and $G_{m,m'}$ is the channel gain from the transmitter m' to the receiver m. We assume that each M2M device is aware of its location (i.e., its coordinates) and the eNB can send via a broadcast message the locations and the uplink transmission powers of all connected M2M devices. From this information, each M2M device can calculate in a distributed manner its sensed interference, as described in equation 3.10. The corresponding received signal-to-interference-plus-noise-ratio (SINR) γ_m of M2M device m at its corresponding cluster-head ch_c belonging to cluster c, $c \in C$ is given by [53]:

$$\gamma_m = \frac{G_{m,ch_c} P_m}{I_{ch}} \tag{3.11}$$

where I_{ch} is the sensed interference of the cluster-head as defined in equation 3.10.

Furthermore, each M2M device m adopts a utility function towards expressing its QoS prerequisites, which are differentiated per type of IoT application that the M2M device participates. The adopted utility function is a continuous, $C^{(n)}$ differentiable function with respect to M2M device's transmission power P_m and is given as follows:

$$U_m(P_m, P_{-m}) = \frac{W \cdot f_m(\gamma_m)}{P_m} \tag{3.12}$$

where W is the system's bandwidth and $f_m(\gamma_m)$ is M2M device's efficiency function representing the successful transmission probability of M2M device m belonging to cluster c to its cluster-head ch_c. The efficiency function $f_m(\gamma_m)$ is a continuous, differentiable and increasing function of γ_m and has a sigmoidal shape such that there exists γ_m^{target} below which $f_m(\gamma_m)$ is convex and above which $f_m(\gamma_m)$ is concave. For presentation purposes and without loss of generality, we adopt $f_m(\gamma_m) = (1 - e^{-\lambda \gamma_m})^{\mu}$, where λ, μ are real valued parameters controlling the slope of the sigmoidal-like function. It is noted that for different IoT application, different γ_m^{target} are requested by the M2M devices. These differentiated M2M devices' QoS prerequisites can be captured by the adopted efficiency function via the control parameters λ and μ.

The cluster-head ch_c, as it was determined in the previous section (based on equation 3.8), has better energy availability compared to the rest of the M2M devices in the same cluster c. We consider that the latter collect energy from the cluster-head ch_c for time τ_1, while they transmit their data for time τ_2 and $\tau_1 + \tau_2 = t$, where t is the duration of each timeslot. Let us assume that the timeslot is split as $\tau_1 = \tau \cdot t$ and $\tau_2 = (1 - \tau) \cdot t$, where τ is the control parameter of energy collection. The received energy of M2M device m belonging to cluster c by the cluster-head ch_c is

$$E_m^{\text{rec}} = n \tau_1 P_{ch_c} G_{ch_c,m} \tag{3.13}$$

where $n \in (0, 1]$ is the energy conversion efficiency factor, depending on the type of the receivers. The average uplink transmission power of the m^{th} M2M device during τ_2 is:

$$P_m = \frac{E_m^{\text{rec}}}{\tau_2} = \frac{n\tau_1 P_{ch_c} G_{ch_c,m}}{\tau_2} = \frac{n\tau P_{ch_c} G_{ch_c,m}}{1-\tau} \tag{3.14}$$

The goal of each M2M device is to maximize its utility, as it has been introduced in equation 3.12, via selecting an appropriate strategy of the uplink transmission power. Therefore, for each M2M device the following distributed utility maximization problem is formulated:

$$\begin{aligned} &\max_{P_m \in A_m} U_m(P_m, \boldsymbol{P_{-m}}) \\ &\text{s.t. } 0 < P_m \leq P_m^{max} \end{aligned} \tag{3.15}$$

where $A_m = (0, P_m^{\max}]$ is the strategy space of the m^{th} M2M device, $P_m^{\max}$ is its maximum available power and $\boldsymbol{P_{-m}}$ is the uplink transmission power vector of all the M2M devices except for the m^{th} device.

The above presented distributed utility maximization problem is confronted as a non-cooperative game $G = (M, \{A_m\}, \{U_m\})$. The solution of the non-cooperative game G should determine the optimal equilibrium for the system, concluded by the individual decisions of each M2M device, given the decisions made by the rest of the devices. A Nash equilibrium point of the game $G = (M, \{A_m\}, \{U_m\})$ is a vector of M2M devices' uplink transmission powers $\boldsymbol{P^*} = [P_1^*, \ldots, P_m^*, \ldots, P_{|M|}^*]^T \in A$, where $A = A_1 \times \cdots \times A_m \times \cdots \times A_{|M|}$ and T denotes the transpose operation of a vector. The Nash equilibrium point of the game G can be defined as follows:

Definition 1. *A power vector $\boldsymbol{P^*} = [P_1^*, \ldots, P_m^*, \ldots, P_{|M|}^*]^T$ in the strategy set $A = A_1 \times \cdots \times A_m \times \cdots \times A_{|M|}$ is a Nash equilibrium of the game $G = (M, \{A_m\}, \{U_m\})$ if for every M2M device m the following condition holds true:*

$$U_m(P_m^*, \boldsymbol{P_{-m}}) \geq U_m(P_m, \boldsymbol{P_{-m}}) \ , \forall P_m \in A_m$$

Towards showing the existence of the Nash equilibrium point, we study the properties of M2M device's utility function.

Theorem 1. *The non-cooperative power control game $G = (M, \{A_m\}, \{U_m\})$ has a unique Nash equilibrium point $\boldsymbol{P^*} = [P_1^*, \ldots, P_m^*, \ldots, P_{|M|}^*]^T$, where*

$$P_m^* = \min\left\{\frac{\gamma_m^* I_m}{W G_{m,ch_c}}, P_m^{max}\right\} \ , \forall m, m \in M, \tag{3.16}$$

where γ_m^* is the unique positive solution of the equation $\frac{\partial f_m(\gamma_m)}{\partial \gamma_m}\gamma_m - f_m(\gamma_m) = 0$

Proof of Theorem 1. The proof of the above theorem can be concluded following similar steps as in [32, 54]. □

The interpretation of the Nash equilibrium point, as determined by equation 3.16, is that no M2M device has the incentive to change its strategy, due to the fact that it cannot unilaterally

Table 3.1: Table of parameter notation

Parameter	Description
M, C	Set of M2M devices, clusters
$\|M\|, \|C\|$	Number of M2M devices, clusters
ch_c	Cluster-head of cluster c
$M_c, \|M_c\|$	Set and number of M2M devices belonging to cluster c
$p(m, m')$	Communication interest among m, m' devices
$d(m, m')$	Physical distance among m, m' devices
$\mathrm{ID}(m, m')$	Interest distance function among m, m' devices
$\mathrm{D}(m, m')$	Physical distance function among m, m' devices
$\mathrm{ID}_0, \mathrm{D}_0$	Maximum values of ID(.), D(.)
γ_m	Signal-to-interference-plus-noise-ratio
W	System's bandwidth
$f_m(.)$	Efficiency function
P_m	M2M device's transmission power
$G_{m,m'}$	Channel gain from the transmitter m' to the receiver m

improve its personal utility by making any change to its own strategy, given the strategies of the rest of the M2M devices. Moreover, it is concluded that the existence of the Nash equilibrium point guarantees a stable outcome of the non-cooperative game $G = (M, \{A_m\}, \{U_m\})$.

Given the optimal uplink transmission power of each M2M device m as determined in equation 3.16, we determine the optimal charging transmission power P_{ch_c} of the cluster-head ch_c to its M2M devices belonging to the same cluster c, as follows:

$$P^*_{ch_c} = \min\left\{\max_{m \in M_c}\left\{\min\left\{\frac{\gamma^*_m I_m}{W G_{m,ch_c}}, P_m^{max}\right\}\right\}, P^{\max}_{ch_c}\right\} \tag{3.17}$$

It should be noted that in case that a user during the WIT phase does not exhaust all of the energy harvested during the corresponding WET phase of the timeslot under consideration, he could store any excessive energy in a rechargeable built-in battery, in order to be available for use in future transmissions or for performing other processing tasks. In our work, however we do not consider this feature and assume that if some energy is not fully exploited in current timeslot it is not accounted for transmissions in future timeslots, but could be used for performing other functions if desired. The consideration of this feature in turn would influence the value of the maximum available uplink transmission power of M2M device m, as the stored energy should be properly reflected in the calculation.

3.4 Framework Evaluation

In this section, we provide some numerical results evaluating the operational features and performance of the proposed clustering methodology and resource management framework adopting the WPC technique in M2M communication networks. Initially, we focus on the operation performance achievements of the proposed framework, in terms of power consumption during the wireless energy transfer (WET) and information transmission (WIT) phase. The above detailed study is performed via considering different implementation scenarios, in terms of devices' interest and physical ties among them, as well as topologies and network sizes. Then, we provide a comparative evaluation of the proposed approach against other conventional approaches that are merely based on either interest or distance, with respect to the achievements in devices' power savings.

Initially we consider an M2M network consisting of $|M| = 50$ M2M devices randomly distributed in a square coverage area $500m \times 500m$ and an eNB residing outside of the square. Parameter α of the clustering methodology, which shows the willingness of each M2M device to stay alone and create a new cluster, is assumed to be $\alpha = 2$. The weights w_1 and w_2 showing the importance of interest and distance factor in M2M devices' decision influence for clustering are $w_1 = 0.5$ and $w_2 = 0.5$. The weights w_1 and w_2 for the different indices, i.e., interest and distance, considered in the overall weight of each edge ϵ^{IP} are $w_I = 0.5$ and $w_D = 0.5$ while the weights w_{CC} and w_E showing the importance of the closeness centrality and energy availability, respectively, in order to select the cluster-head are $w_{CC} = 0.5$ and $w_E = 0.5$ The thermal background noise is $I_0 = 5 \cdot 10^{-15}$, the system bandwidth is $W = 10^6$ Hz, the energy conversion efficiency factor is $n = 0.6$ and the timeslot's control parameter is $\tau = 0.4$, while the timeslot duration is $t = 0.5$ msec.

Towards providing realistic and representative results, we examine three different simulation scenarios as follows:

- Random scenario: The level of interest between two devices distributed in the examined topology i.e., $p(m, m')$, is randomly assigned.
- Best-case scenario: The devices which are close to each other have high interest to communicate, as well as the devices which are far from each other have small communication interest among them.
- Worst-case scenario: The devices which are close to each other have small communication interest, while the devices that are placed far from each other have high communication interest.

Based on the aforementioned examined scenarios, we examine a wide range of possible real-life communication scenarios and IoT applications.

First, we study the power consumption of the devices during the WIT phase, i.e., information transmission from the devices of each cluster to their corresponding cluster-head and from the cluster-head to the eNB. Fig. 3.1 represents the total cumulative consumed power as a function of the time in the examined M2M network in order for the M2M devices to report their information to their corresponding cluster-head and the cluster-head to the eNB, under the examined scenarios, i.e., random, best-case and worst-case scenario. The results reveal that the best-case scenario achieves improved power savings, due to the fact that the M2M devices with high communication interest reside close to each other, thus their communication channel conditions are improved, and therefore their necessary power consumption during the WIT phase is low. On the other

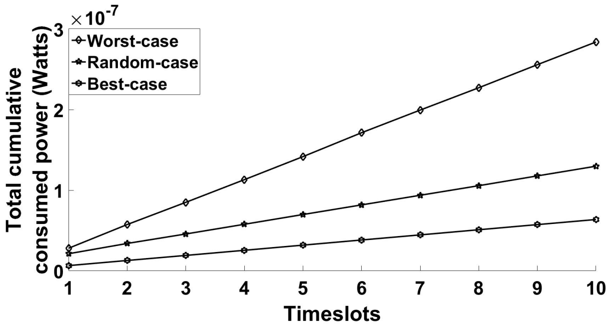


Figure 3.1: Total cumulative consumed power during the WIT phase as function of time (slots).

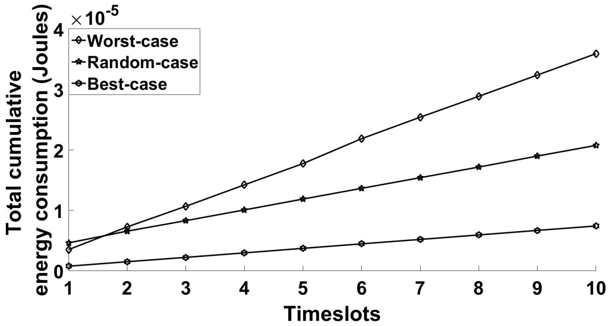


Figure 3.2: Total cumulative energy consumption during the WIT and WET phase as function of time (slots).

hand, considering the worst-case scenario, the exact opposite behavior with respect to the power consumption is observed. More specifically, the M2M devices spend a lot of power to communicate with each other, due to the fact that the devices which have high interest of communication reside far from each other, thus they experience deteriorated channel conditions. An average state of the wireless IoT environment with respect to the power consumption for information transmission is observed in the random scenario. Specifically, in the random scenario, the M2M devices with high communication interest reside in an average distance among each other, thus their corresponding total power consumption lies in between the best and the worst-case scenario.

Fig. 3.2 illustrates the total cumulative energy consumption of all the devices (i.e. $|M| = 50$) in the examined M2M network, during both the WET and WIT phases, as the time evolves, i.e., for 10 consecutive timeslots. Specifically, the presented total energy consumption consists of the following components: (a) the consumed energy of the devices to send their information to the cluster-head (WIT phase) and (b) the charging consumed energy of the cluster-head to charge the M2M devices residing in each cluster (WET phase). It is noted that based on the conditions of forming the clusters, i.e, best, worst and random case scenario, the corresponding overall consumed energy is influenced. More specifically, the results reveal that in the case where the M2M devices in the same cluster lie far from each other, i.e., worst-case scenario, the cluster-head consumes

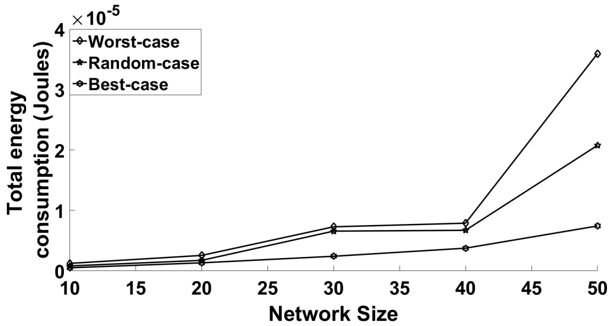


Figure 3.3: Total energy consumption as a function of network size.

increased energy in order to charge them, due to the devices' deteriorated channel conditions, while the exact opposite holds true for the best-case scenario, where the M2M devices reside closer to their corresponding cluster-head. In the random case scenario, the M2M devices have an average distance from their corresponding cluster-head, thus the corresponding overall consumed energy lies in between the worst and the best-case scenario.

Fig. 3.3 presents the overall energy consumption, as presented in Fig. 3.2, at the 10^{th} timeslot, as a function of the network size, i.e., for topologies ranging from 10 to 50 M2M devices. The illustrated results show the scalability behavior of our proposed framework as the number of devices in the M2M network increases. Also, the overall consumed energy for the three examined scenarios follow the same trend, as discussed in Fig. 3.1 and Fig. 3.2. It should be highlighted that the low values of the total energy consumption, i.e., order of magnitude of μJ for a medium density IoT network and the total energy consumption's slow increase with respect to the number of devices, support the scalability of the proposed interest-aware energy collection and resource management framework in M2M communications.

Below we perform a comparative study towards illustrating the benefits in power savings of jointly considering the interest and physical ties among the M2M devices during the cluster formation process. More specifically, we compare the following three different methodologies for clustering formation.

- IP-approach. The proposed clustering formation process as it has been proposed in this work, where the weight of each edge in the M2M devices' graph considers both the interest and the physical ties among the devices.
- I-approach. The clustering methodology considers only the interest ties among the M2M devices in order to create the clusters.
- P-approach. The clusters are created via considering only the physical ties among the M2M devices.

Towards comparing the above presented scenarios in a fair manner, we propose two indicative normalized Interest-based Aggregation Factors (IAF) for each cluster, as follows:

$$\mathrm{IAF}_1 = |M_c| - \sum_{\substack{m \in M_c \\ m \neq ch_c}} p(m, ch_c) \tag{3.18}$$

and

$$\mathrm{IAF}_2 = \left\{ |M_c|(|M_c| - 1) - \sum_{\substack{m,m' \in M_c \\ m \neq m'}} p(m, m') \right\}^{1/2} \tag{3.19}$$

The physical meaning of the IAF_1 and IAF_2 is explained below. The IAF_1 quantifies the interest of the M2M devices belonging to the same cluster to communicate with their corresponding cluster-head. Specifically, the second term of the IAF_1 represents the cumulative communication interest of the $|M_c|$ devices in cluster c with their corresponding cluster-head ch_c. The maximum value of $\sum_{\substack{m \in M_c \\ m \neq ch_c}} p(m, ch_c)$ is $|M_c|$. Thus, a small IAF_1 value corresponds to the successful cluster-head selection within the cluster, due to the fact that the $|M_c|$ devices belonging to cluster c have high communication interest with their cluster-head ch_c. Following the same philosophy, the IAF_2 quantifies the homogeneity of all the M2M devices in the same cluster, by taking into account in a pair-wise manner the corresponding interests between all pairs of the devices of the cluster, i.e., $\sum_{\substack{m,m' \in M_c \\ m \neq m'}} p(m, m')$. A small IAF_2 value shows that the cluster is homogeneous, i.e., the M2M devices have high interest to communicate with each other. As a result, when the devices create clusters based only on their physical proximity, P-approach, they do not have high interest to communicate with each other and with the cluster-head, thus their overall interest expressed is low and therefore the corresponding aggregation factors obtain high values. The opposite observations hold true for the I-approach. The aforementioned drawbacks are faced via considering both physical and interest ties among the devices towards creating the clusters communities, i.e., IP-approach. Implicitly both these factors express different degrees of aggregation that can be achieved at the cluster-head − due to the commonalities and homogeneity that the devices of a cluster present − which in turn can be translated to the transmission of reduced information from the cluster-head to the eNB. As a consequence, and in order to quantify the importance of the clustering approaches as expressed through these factors, in the following we examine the total cumulative transmission power during the WIT phase considering the potential aggregation that can be achieved due to the efficient clustering.

Specifically, in Fig. 3.4 and Fig. 3.5, we present the combined outcome of the total cumulative transmission power during the WIT phase, considering the IAF_1 and IAF_2, respectively, as time evolves (indicatively for 10 consecutive time slots), considering the three examined approaches, i.e., IP, P and I-approach, for an M2M network consisting of $|M| = 40$ devices, following the random scenario described above. The comparison of the three different clustering approaches reveals the pure benefits in power savings, while considering jointly the interest and physical ties among the M2M devices in order to form the clusters. It is noted that especially in the P-approach the M2M

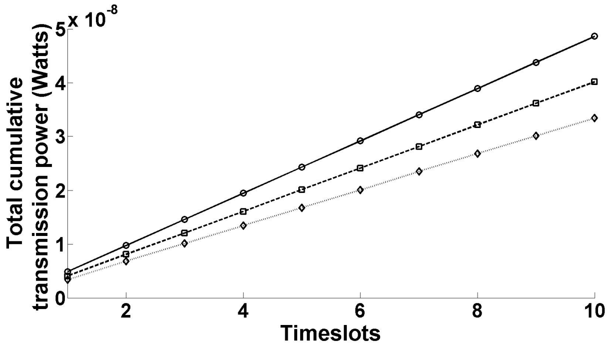


Figure 3.4: Total cumulative transmission power during the WIT considering IAF_1 as function of time (slots).

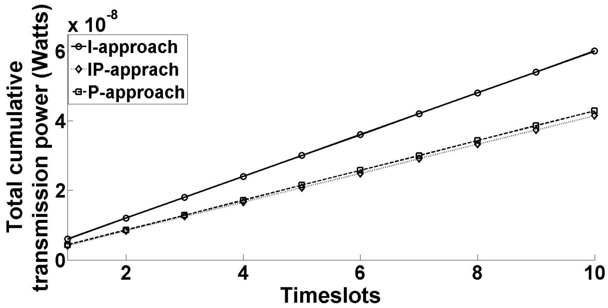


Figure 3.5: Total cumulative transmission power during the WIT considering IAF_2 as function of time (slots).

devices will create clusters based on their physical proximity and their good channel conditions without however having high interest to communicate with each other (i.e., large values of IAF_1 and IAF_2). The main drawback of the P-approach is that the cluster-head will mainly act as a relay reporting to the eNB the collected information from the M2M devices in the same cluster for further exploitation. Therefore, in the P-approach the cluster-head has to perform multiple transmission and consume high power in order to report the collected data to the eNB. On the other hand, the main drawback of the I-approach is that the M2M devices belonging to the same cluster may present large distances among them, thus they consume increased transmission power to send their data to the cluster-head. The cluster-head needs fewer transmissions to send the processed data to the eNB (i.e., small values for IAF_1 and IAF_2) due to the fact that the M2M devices have high communication interest. Finally, the combined benefits of simultaneously considering the physical and interest ties among the M2M devices is achieved by the IP-approach, which results in decreased total cumulative power consumption, as shown in Fig. 3.4 and Fig. 3.5. Finally, Fig. 3.6 and Fig. 3.7 presents the power consumption during the WIT phase at the 10^{th} timeslot of the evolving system operation, as a function of the network size, i.e., for topologies ranging from

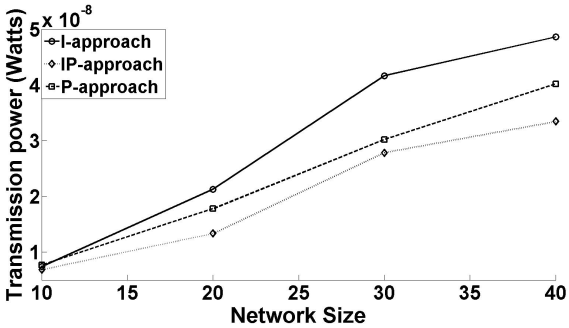


Figure 3.6: Transmission power during the WIT considering IAF_1 as function of network size.

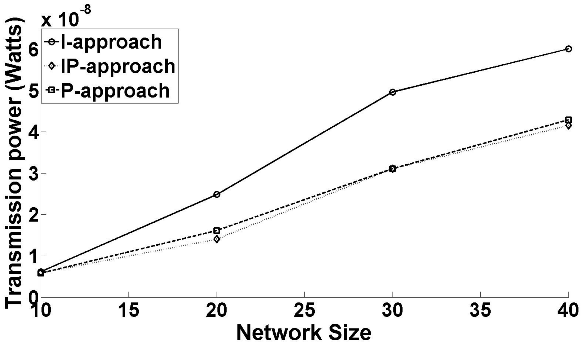


Figure 3.7: Transmission power during the WIT considering IAF_2 as function of network size).

10 to 40 M2M devices, where similar observation can be concluded.

3.5 Summary

In this chapter, we introduced the concept of joint consideration of interest, physical and energy related properties in the clustering and resource management processes in M2M communication networks supporting various IoT applications. Initially, a joint interest, physical and energy-aware cluster formation mechanism was proposed based on the low-complexity Chinese Restaurant Process in order to create clusters among the M2M devices and select the cluster-head, while WPC technique was adopted, where the cluster-heads that are characterized by improved energy-availability as a result of their election process, where responsible of charging the M2M devices belonging to their cluster during the WET phase. Each M2M device was associated with a generic utility function representing its Quality of Service prerequisites. A holistic utility-based transmission power allocation approach was introduced, formulating the power control problem as a distributed non-cooperative game among the devices. The existence and uniqueness of a Nash equilibrium point was proven, determining devices' transmission powers during the WIT phase. Based on the equilibrium transmission powers of the M2M devices, the necessary and sufficient charging transmission powers of the cluster-heads where determined.

In order to evaluate the operational efficiency and efficacy of the proposed framework we performed a modeling and simulation under various topologies and scenarios that illustrate and reveal its benefits. It should be noted that the proposed approach facilitates the creation of a more flexible and general framework, where the control intelligence and the decision-making process lie at the M2M device, thus enabling the realization of mobile node's self-optimization and self-adaptation functionalities. Therefore, the proposed framework can be applied in realistic IoT applications, towards enabling and supporting the battery-life extension of the M2M devices via realizing an efficient clustering methodology among them and adopting the WPC technique. Furthermore, the proposed approach could be easily adopted in the emerging multi-purpose sensor devices, where communication and clustering among the various devices is determined based on proximity, the type of extended data, and the interest or the objective of each device.

Chapter 4

Intelligent Dynamic Data Offloading in Multi-access Edge Computing

4.1 General Setting

Apart from the Machine-to-Machine driven communication explored in the previous chapter, another candidate technology to empower small and powerless devices in the IoT environment is the aforementioned Multi-access Edge Computing solution. The existence of a powerful server at the edge of the network that offers his computing resources in close vicinity to the mobile end-users could potentially allow sensors or other computationally and energy restricted devices to perform complex tasks that otherwise could be impossible.

In this setting, end-users are able to offload their computation tasks to the MEC servers, which can further process the subscribers' offloaded tasks. The main benefits of the MEC technology, as already discussed in chapter 1 are: its potential to reduce the latency, provide location-awareness, improve the performance of the mobile applications, reduce the energy consumption of the mobile devices by alleviating the burden of executing their computing tasks locally, and provide accurate computing outcomes in a time-wise manner. However, the adoption of the MEC technology in the overall networking architecture has created the need of devising control mechanisms to route the mobile end-users' offloading tasks to the MEC servers, while accounting for network's congestion, MEC servers computation capabilities and end-users Quality of Service (QoS) prerequisites. Towards this direction, we consider the exploitation of the Software Defined Networking (SDN) technology, complementary to the MEC, to allow the design of dynamic, manageable, adaptable, and cost-effective networks. Via the SDN, the MEC environment can substantially benefit, as the decision making, with respect to end-users' selection of the specific MEC server to perform their data offloading, the routing of the end-users' offloading traffic and the guarantee of the end-users' QoS constraints, can be performed in the control plane, which is implemented within the SDN controller, in a dynamic manner.

In the proposed framework, we considered a setting of multiple mobile devices that need to execute their assigned tasks and multiple MEC servers that are willing to handle the tasks at a specified price. Through our approach, we managed to tackle the problems of selecting the appropriate server that each user will offload his tasks to, the volume of the task that the user will offload and the price that the server is willing to set.

4.2 Related Work

The problem of data offloading from the end-users to the MEC servers for further computing has been extensively studied in the recent literature, while examining both the computation and the communication limitations [55]. In [56], a minimization problem of the long-term average weighted total devices' and MEC server's power consumption is formulated and solved in a multi-user MEC environment, concluding to a joint radio and computing resource management scheme, where both the optimal users' transmission power to offload their data and the corresponding computing power to process them are determined. In [57], a femto-based MEC environment is introduced and the authors exploit the trade-off between the end-users' energy consumption and latency towards minimizing the end-users' affordable latency while executing an application. A centralized optimization problem is introduced in [58] targeting at the minimization of the weighted sum end-users' energy consumption, while accounting for the end-users' computation latency constraints. The authors consider that the end-users adopt the orthogonal frequency division multiple access technique to offload their data to the MEC servers and they capture the end-users' workload offloading priorities in the problem formulation and solution, while a similar approach is also followed in [59]. In [60], the authors propose a joint resource allocation scheme of the computation and communication resources of the MEC system aiming to minimize the end-users' energy consumption and the latency of the applications' execution at the MEC servers. Moreover, in [61], the authors focus on the energy efficient operation of the MEC system and they propose a dynamic data offloading and resource allocation scheme to minimize the computation application completion time and the end-users' energy consumption. A holistic framework of minimizing the total cost of energy, computation, and delay for the end-users is introduced in [62].

Game Theory has also been adopted to deal with the data offloading problem in the MEC environment, while providing the enhanced flexibility to the end-users to make autonomous data offloading decisions in a distributed manner [63]. In [64], a data offloading decision-making game is formulated among the end-users, who choose the amount of data that will be offloaded to a single MEC server, as well as the part of the computation task that will be executed locally at their devices. A similar problem is addressed in [65], while a multiple MEC servers environment is considered and the end-users have to additionally select to which MEC server they will offload part of their data. The problem of activating the MEC servers based on the end-users computing demands is addressed in [66], where the MEC servers' activation problem is formulated as a minority game and a distributed reinforcement learning algorithm is executed by each MEC server in order to determine if it will be active or not. The concept of applying usage-based pricing policies to the end-users while they exploit the MEC servers' computing capabilities is introduced in [67, 68] towards providing incentives to the end-users to consume the MEC servers' computing services in a fair manner. An other interesting game theoretic concept has recently emerged, the Satisfaction Equilibrium, where players are willing to satisfy instead of maximize their Quality of Experience, leading to interesting results [69, 70].

Recently, the capabilities of the SDN have been exploited by the MEC environment to efficiently and effectively deal with the data offloading problem, the activation of the MEC servers, the routing of the end-users offloading data, and the announcement of pricing mechanisms to control the smooth operation of the MEC system [71]. The problem of selecting a computing mode (i.e., local, MEC, or cloud computing) for each end-users' computation task is studied in [72], where the SDN controller executes the Computing Mode Selection algorithm and announces the corresponding routing policies to the end-users. The benefits of the combined use of SDN and MEC within the Internet of Things (IoT) systems are discussed in detail in the surveys [1] and [73]. In [74], a smart e-health IoT service is introduced, which is based on SDN-powered MEC within a vehicular ad-hoc network architecture to detect heart attacks in a real-time manner. In [75], the authors focus on virtual reality and vehicular IoT applications and they propose an SDN-based MEC framework to provide the necessary data-plane flexibility, programmability, and reduced latency. Furthermore, in [76], the adoption of SDN and MEC is presented to overcome the barriers of network densification of IoT cloud integration within a smart home environment.

4.3 Proposed Framework

4.3.1 System Model

Our proposed SDN-powered MEC architecture consisting of multiple MEC servers $s \in S$ where $S = [1, ..., s, ...|S|]$ and multiple end-users $u \in U$ where $U = [1, ..., u, ...|U|]$ is presented in Fig. 4.1. Each MEC server s communicates with the SDN controller towards setting the price $p_s^{(t)}$ [\$/bits] of its computing services per time slot t. The whole operation of the examined system is divided in time slots, where $T = [1, ...t, ..., |T|]$ denotes their corresponding set. At each time slot the SDN controller determines the MEC server selection by the end-users (section 4.3.2), as well as the optimal price $p_s^{(t)}$ for each MEC server and the optimal data offloading $b_{u,s}^{(t)}$ [bits] of each end-user u to the selected server s (section 4.3.3). Each end-user u, receives the required information by the SDN controller to offload its data $b_{u,s}^{(t)}$ to the selected server s. Each end-user u has a maximum amount of data $I_u^{(t)}$ that should be processed to perform a computing task, and part of them are offloaded to the MEC server, i.e., $b_{u,s}^{(t)} \in A_u^{(t)} = [0, I_u^{(t)}]$, while the rest of the data are processed locally.

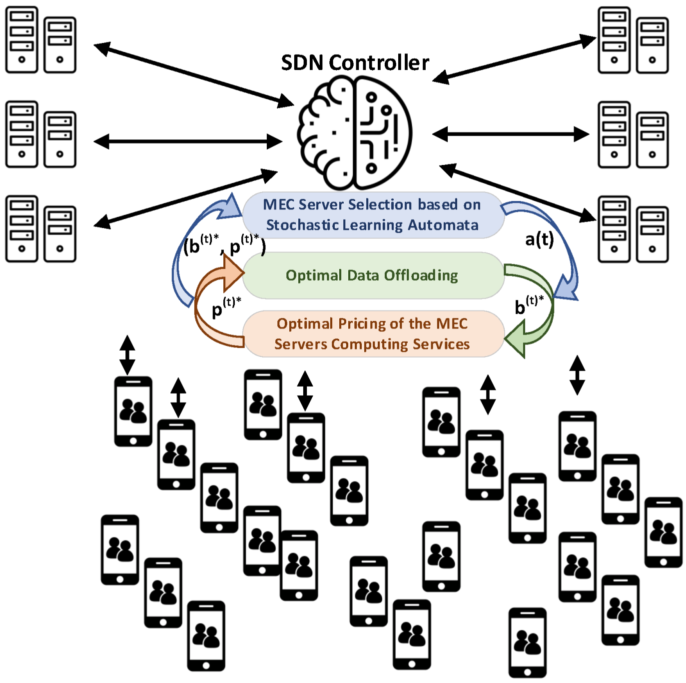


Figure 4.1: SDN-powered MEC architecture

End-User Utility Function

At the beginning of each time slot, each end-user u sends to the SDN controller its total computing demands $I_u^{(t)}$ that are needed to execute a computing task, while the SDN controller determines the optimal amount of offloaded data $b_{u,s}^{(t)}$ for end-user u at the MEC server s, as it will be explained in detail in section 4.3.3. Given that the MEC servers have bounded and limited computing capabilities, the data offloading strategies of the rest of the end-users, i.e., $\mathbf{b_{-u}^{(t)}}$, contribute to the configuration of the prices announced by the MEC servers and influence the data offloading $b_{u,s}^{(t)}$ of end-user u. Thus, towards formulating the user's u perceived satisfaction, the end-user's relative data offloading is defined as $r_u^{(t)} = \frac{b_{u,s}^{(t)}}{B_{-u}^{(t)}}$, where $B_{-u}^{(t)} = \sum_{s\in S}\sum_{u'\in U, u'\neq u} b_{u',s}^{(t)}$ expresses the total data offloading of the rest of the end-users $u' \in U - \{u\}$. The end-user's actual perceived satisfaction $s_u^{(t)}$ at time slot t is increasing with respect to its relative data offloading $b_{u,s}^{(t)}$, as part of the requested computing task is offloaded to the MEC server and does not consume the end-user's local computing resources. Also, after the end-user offloads its total data $I_u^{(t)}$ to the MEC server, its perceived satisfaction is saturated as the end-user cannot benefit more by the MEC server's computing services as presented in Fig. 4.2. Thus, without loss of generality and for presentation purposes only, in this work we adopt a logarithmic function with respect to the end-user's offloaded data $b_{u,s}^{(t)}$ to capture end-user's actual perceived satisfaction, as follows.

$$s_u^{(t)}(b_{u,s}^{(t)}, \mathbf{b_{-u}^{(t)}}) = \alpha_u log(1 + \beta_u r_u^{(t)}) \tag{4.1}$$

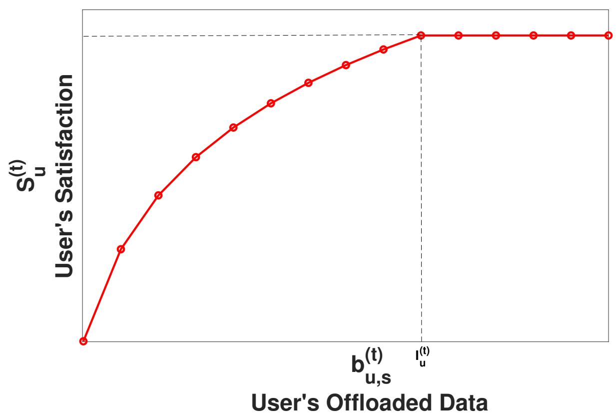


Figure 4.2: End-user's actual perceived satisfaction by data offloading

where $\mathbf{b_{-u}^{(t)}}$ is the vector of all end-users data offloading excluding end-user u, and the $\alpha_u, \beta_u \in \mathbb{R}^+$ parameters determine the slope of the logarithmic function in a personalized manner for end-user u, thus, expressing how easily or not an end-user u becomes satisfied by offloading its data to the MEC server.

Additionally, each end-user is charged for using the MEC server's computing services in a fair manner accordingly to its relative data offloading. This policy enables even the low-budget end-users to exploit the MEC servers' capabilities at some degree, by prohibiting the high-budget ones to dominate the system. Thus, the cost function of end-user's u offloaded data is formulated as follows.

$$c_u^{(t)}(b_{u,s}^{(t)}, \mathbf{b_{-u}^{(t)}}) = d_u^{(t)} p_s^{(t)} r_u^{(t)} \tag{4.2}$$

where $d_u^{(t)} \in \mathbb{R}^+$ expresses end-user's u spending dynamics in order to use the MEC server's computing services. Specifically, a smaller value of $d_u^{(t)}$ reflects end-user's u dynamic behavior to spend more money in order to buy computing support from the MEC servers. The price announced by the MEC server s is denoted as $p_s^{(t)}$ [\$/bits].

Following the above analysis, end-user's u utility function captures both its actual perceived satisfaction $s_u^{(t)}$ and its corresponding cost $c_u^{(t)}$ in order to enjoy the MEC server's computing services. The end-user's u utility function is defined as follows.

$$U_u^{(t)}(b_{u,s}^{(t)}, \mathbf{b_{-u}^{(t)}}, \mathbf{p^{(t)}}) = s_u^{(t)}(b_{u,s}^{(t)}, \mathbf{b_{-u}^{(t)}}) - c_u^{(t)}(b_{u,s}^{(t)}, \mathbf{b_{-u}^{(t)}}) = \alpha_u log(1 + \beta_u r_u^{(t)}) - d_u^{(t)} p_s^{(t)} r_u^{(t)} \tag{4.3}$$

where $\mathbf{p^{(t)}} = [p_1^{(t)}, ..., p_s^{(t)}, ..., p_{|S|}^{(t)}]$ denotes the vector of the prices announced by all the MEC servers.

Multi-access Edge Computing Server Characteristics & Profit

Each MEC server s supports a total computing demand of the end-users per time slot equal to $\sum_{u\in U} b_{u,s}^{(t)}$ from all the end-users that selected the specific MEC server to offload their data. Also, towards providing incentives to the end-users to select a specific MEC server to be served from, the latter provides some discounts $f_s^{(t)}$ expressed as a percentage of the original announced price of its computing services. Furthermore, the MEC server has an actual cost $c_s^{(t)}$ [$/bits] in order to process the amount of data that it receives. Please be also reminded that the MEC server charges the end-users with a price $p_s^{(t)}$ [$/bits] for the computing services that it offers.

Additionally, a MEC server increases its positive reputation towards the end-users if it is characterized by a good penetration within the end-users' computing demands. Specifically, the penetration of a MEC server s is defined as the total amount of data that the server s processed over the total amount of data that are processed within the SDN-powered MEC system for a total time period T, i.e., $\frac{\sum_{t\in\{1,\ldots,T\}}\sum_{u\in U} b_{u,s}^{(t)}}{\sum_{s\in S}\sum_{t\in\{1,\ldots,T\}}\sum_{u\in U} b_{u,s}^{(t)}}$. Also, we assume that each MEC server s can handle a total amount of data B_s^{Max}. Thus, an indicative parameter showing the congestion of the MEC server per time slot in terms of processing the end-users' offloaded data is expressed as the ratio of the total amount of data $\sum_{u\in U} b_{u,s}^{(t)}$ that the MEC server processes in time slot t over its total computing capability of data B_s^{Max}, i.e., $CONG_s = \frac{\sum_{u\in U} b_{u,s}^{(t)}}{B_s^{Max}}$.

Following the above analysis and combining all the aforementioned factors and parameters that characterize the MEC server s, its reputation score within the SDN-powered MEC environment is defined as follows.

$$R_s^{(t)} = w_1 \frac{\frac{\sum_{k\neq s}[(1-f_k^{(t)})]p_k^{(t)}}{K}}{(1-f_s^{(t)})p_s^{(t)}} + w_2 \frac{1}{(1+CONG_s)^3} + w_3 \frac{\sum_{t\in\{1,\ldots,T\}}\sum_{u\in U} b_{u,s}^{(t)}}{\sum_{s\in S}\sum_{t\in\{1,\ldots,T\}}\sum_{u\in U} b_{u,s}^{(t)}} \tag{4.4}$$

In Eq. 4.4, the first term expresses the relative pricing of a MEC server s in terms of offering its computing services to the end-users, the second term expresses the level of MEC server's congestion towards serving the end-users, while the third term expresses its penetration in serving end-users' computing demands. The weights w_1, w_2, w_3 are configurable parameters that express the relative weight of each term within our study, and it should hold true that $w_1 + w_2 + w_3 = 1$.

The revenue of each MEC server s from processing a total amount of end-users' offloaded data $\sum_{u\in U} b_{u,s}^{(t)}$ depends on the announced price $p_s^{(t)}$ and the corresponding discount $f_s^{(t)}$ that the MEC server provides, and is given as follows.

$$REV_s^{(t)}(\mathbf{b^{(t)}}, \mathbf{p^{(t)}}) = (1-f_s^{(t)})p_s^{(t)} \sum_{u\in U} b_{u,s}^{(t)} \tag{4.5}$$

where $\mathbf{b^{(t)}}$ is the data offloading vector of all the end-users and $\mathbf{p^{(t)}}$ denotes the announced prices by all the MEC servers in the system.

On the other hand, the MEC server's total monetary cost to perform the processing of the offloaded data, is given as follows.

$$C_s^{(t)}(\mathbf{b^{(t)}}) = c_s^{(t)} \sum_{u \in U} b_{u,s}^{(t)} \tag{4.6}$$

where $c_s^{(t)}$ is the MEC server's s computing cost per unit of data. Thus, the MEC server's profit is concluded by subtracting its cost from its revenue and is given as follows.

$$P_s^{(t)}(\mathbf{b^{(t)}}, \mathbf{p^{(t)}}) = REV_s^{(t)}(\mathbf{b^{(t)}}, \mathbf{p^{(t)}}) - C_s^{(t)}(\mathbf{b^{(t)}}) = (1 - f_s^{(t)})p_s^{(t)} \sum_{u \in U} b_{u,s}^{(t)} - c_s^{(t)} \sum_{u \in U} b_{u,s}^{(t)} \tag{4.7}$$

4.3.2 MEC as a Learning System

At the SDN controller's side, the end-users are represented and considered as stochastic learning automata that sense the environment and make future decisions based on their past experience. At each time slot t, the end-user can select to be served by a MEC server s, thus, the set of end-users' actions at time slot t is $a(t) = \{a_1, ..., a_s, ..., a_S\}$. The SDN controller has the information of the end-users' offloaded data $\mathbf{b^{(t)}}$ and the prices $\mathbf{p^{(t)}}$ that the MEC servers announce regarding offering their computing services. The SDN controller can determine the reputation score $R_s^{(t)}$ for each MEC server, which can be normalized towards defining the reward probability as follows.

$$rew_s^{(t)} = \frac{R_s^{(t)}}{\sum_{s \in S} R_s^{(t)}} \tag{4.8}$$

The reward probability $rew_s^{(t)}, 0 \leq rew_s^{(t)} \leq 1$ represents the potential reward that an end-user may experience by choosing to offload its data to the MEC server s. Following the theory of the stochastic learning automata, the action probability vector of an end-user u is $\mathbf{Pr_u^{(t)}} = [Pr_{u,1}^{(t)}, ..., Pr_{u,s}^{(t)}, ..., Pr_{u,S}^{(t)}]$, where $Pr_{u,s}^{(t)}$ is defined as the probability of the end-user u to select the MEC server s to offload its data. Based on the theory of stochastic learning automata, the rule of updating the end-users' action probabilities at the SDN controller is defined as follows [77, 78].

$$Pr_{u,s}^{(t+1)} = Pr_{u,s}^{(t)} - b \cdot rew_s^{(t)} \cdot Pr_{u,s}^{(t)}, \quad s^{(t+1)} \neq s^{(t)} \tag{4.9a}$$

$$Pr_{u,s}^{(t+1)} = Pr_{u,s}^{(t)} + b \cdot rew_s^{(t)} \cdot (1 - Pr_{u,s}^{(t)}), \quad s^{(t+1)} = s^{(t)} \tag{4.9b}$$

where $0 < b < 1$ denotes the learning parameter expressing how fast the end-users explore the available options of the MEC servers towards offloading their data. Eq. 4.9a represents the probability of end-user u selecting a different MEC server to offload its data in the next time slot $t + 1$ compared to end-user's choice in the current time slot t, while Eq. 4.9b expresses the probability of end-user u to keep being served by the same MEC server. It is noted that initially, the end-users' action probabilities are initialized as $Pr_{u,s}^{(t=0)} = \frac{1}{S}$. The MEC servers selection learning process executed at the SDN controller is presented in the Data Offloading and MEC Server Selection (DO-MECS) algorithm in the next section.

4.3.3 Autonomous Data Offloading & Price Setting

Problem Formulation

Following the above described reinforcement learning technique of the stochastic learning automata, each end-user has concluded to the selection of a MEC server to offload its data. Then, the goal of each MEC server is to maximize its profit by processing the end-users' data, while the goal of each end-user is to maximize its perceived satisfaction, as expressed by its utility function, by offloading the optimal amount of data to the selected MEC server. Thus, a two-layer optimization problem is formulated, as follows.

$$\mathbf{b^{(t)*}} = argmax_{b_{u,s}^{(t)}} U_u^{(t)}(b_{u,s}^{(t)}, \mathbf{b_{-u}^{(t)}}, \mathbf{p^{(t)}}) \tag{4.10a}$$

$$\mathbf{p^{(t)*}} = argmax_{\mathbf{p^{(t)}}} P_s^{(t)}(\mathbf{b^{(t)}}, \mathbf{p^{(t)}}) \tag{4.10b}$$

As it is observed by Eq. 4.10a and Eq. 4.10b, the MEC servers optimal price $\mathbf{p^{(t)*}}$ and the end-users optimal data offloading $\mathbf{b^{(t)*}}$ are interdependent, thus, the joint optimization problem is formulated as a two-layer optimization framework. Initially, the end-users determine their optimal data offloading $\mathbf{b^{(t)*}}$ via confronting the optimization problem of their personal utility functions as a non-cooperative game among them. Then, at the second layer, the MEC servers determine their optimal announced prices $\mathbf{p^{(t)*}}$ given the data offloading of the end-users, via solving an optimization problem. The formulation and solution of the optimization problem is performed at the SDN controller, where its advanced computing capabilities enable the fast decision-making. In the following two subsections, we will analyze in detail each layer of the optimization problem.

Optimal Data Offloading

Initially, the optimal data offloading $b_{u,s}^{(t)*}$ of each end-user u that has chosen to offload its data to the MEC server s at the time slot t is determined. A non-cooperative game $G = (U, \{A_u^{(t)}\}, \{U_u^{(t)}\})$ is formulated among the end-users who compete with each other towards determining their optimal data offloading. The game G consists of three components: (a) the set of end-users (i.e., players) $U = [1, ..., u, ..., |U|]$, (b) the strategy space $A_u^{(t)} = [0, I_u^{(t)}]$, where $b_{u,s}^{(t)} \in A_u^{(t)}$, and (c) the end-user's utility function $U_u^{(t)}$. Each end-user wants to maximize its personal utility function, while considering the physical limitations, as follows.

$$max_{b_{u,s}^{(t)}} U_u^{(t)}(b_{u,s}^{(t)}, \mathbf{b_{-u}^{(t)}}, \mathbf{p^{(t)}}) \tag{4.11a}$$

$$s.t. \quad 0 \leq b_{u,s}^{(t)} \leq I_u^{(t)} \tag{4.11b}$$

The concept of Nash Equilibrium is adopted towards determining a stable operation point for the system. At the Nash Equilibrium point, any of the end-users has no incentive to change its amount of data offloading, as no end-user can improve its utility by unilaterally changing its data offloading strategy.

Definition 2. *A data offloading vector* $\mathbf{b_u^{(t)*}} = [b_{1,s}^{(t)*}, ..., b_{u,s}^{(t)*}, ..., b_{|U|,s}^{(t)*}], s \in S$ *is the Nash Equilibrium point of the game* $G = (U, \{A_u^{(t)}\}, \{U_u^{(t)}\})$*, if for every end-user* u *it holds true that* $U_u^{(t)}(b_{u,s}^{(t)*}, \mathbf{b_{-u}^{(t)*}}) \geq U_u^{(t)}(b_{u,s}^{(t)}, \mathbf{b_{-u}^{(t)*}}), \forall b_{u,s}^{(t)} \in A_u^{(t)}$.

In the following analysis, our goal is to show the existence and uniqueness of a Nash Equilibrium for the data offloading game. The necessary and sufficient conditions are: (i) the strategy space $A_u^{(t)}, \forall u \in U$ should be non-empty, convex and compact subset of an Euclidean space $\mathbb{R}^U$ and (ii) the utility function $U_u^{(t)}(b_{u,s}^{(t)}, \mathbf{b_{-u}^{(t)}}, \mathbf{p^{(t)}})$ is continuous in $\mathbf{b_u^{(t)}}$ and quasi-concave in $b_{u,s}^{(t)}$.

Theorem 2. *The Nash Equilibrium point of the game* $G = (U, \{A_u^{(t)}\}, \{U_u^{(t)}\})$ *exists and the end-user's best response data offloading strategy is given as follows.*

$$BR_u(\mathbf{b_{-u}^{(t)*}}) = b_{u,s}^{(t)*} = \frac{B_{-u}^{(t)}}{\beta_u}[\frac{\alpha_u \beta_u}{d_u^{(t)} p_s^{(t)}} - 1] \tag{4.12}$$

where $0 \leq b_{u,s}^{(t)*} \leq I_u^{(t)}$.

Proof. See appendix A.1. □

Theorem 2 proves the existence of the Nash Equilibrium point of the game G and determines the best response strategy for each end-user u. In the following theorem, the uniqueness of the Nash Equilibrium point of the game G is examined.

Theorem 3. *The Nash Equilibrium point* $b_{u,s}^{(t)*}, \forall u \in U, s \in S$ *of the game* G *is unique.*

Proof. Towards proving the uniqueness of the Nash Equilibrium point $b_{u,s}^{(t)*} = BR_u(\mathbf{b_{-u}^{(t)*}})$, for cases 1 and 2 of the proof of theorem 2, the Nash Equilibrium point is trivially unique, while for case 3 we should show that the best response strategy $BR_u(\mathbf{b_{-u}^{(t)*}})$ is a standard function. The properties of a standard function are the following [79]:

- Positivity $\mathbf{f}(\mathbf{x}) > \mathbf{0}$;
- Monotonicity: if $\mathbf{x} \geq \mathbf{x'}$, then $\mathbf{f}(\mathbf{x}) \geq \mathbf{f}(\mathbf{x'})$;
- Scalability: for all $a > 1$, $a \cdot \mathbf{f}(\mathbf{x}) \geq \mathbf{f}(\mathbf{a} \cdot \mathbf{x})$.

If a fixed point exists in a standard function, then it is unique. Using Eq. 4.12, the above properties of the standard function can be easily shown for the end-user's best response function $BR_u(\mathbf{b_{-u}^{(t)*}})$. Thus, the Nash Equilibrium point of the game G is unique. □

In conclusion, it is noted that the optimal data offloading of each end-user is given by Eq. 4.12.

Optimal Pricing of the MEC Servers Computing Services

In this subsection, the optimal pricing of the MEC server's computing services is determined towards maximizing the MEC servers' profit given the offloaded data of the end-users. Combining Eq. 4.7, Eq. 4.10b and Eq. 4.12, the corresponding optimal pricing problem of the MEC servers can be written as follows.

$$\mathbf{p^{(t)*}} = argmax_{\mathbf{p^{(t)}}} P_s^{(t)}(\mathbf{b^{(t)}}, \mathbf{p^{(t)}}) = (1-f_s^{(t)})p_s^{(t)} \sum_{u \in U} [\frac{B_{-u}^{(t)}}{\beta_u}[\frac{\alpha_u \beta_u}{d_u^{(t)} p_s^{(t)}} - 1]] - c_s^{(t)} \sum_{u \in U} [\frac{B_{-u}^{(t)}}{\beta_u}[\frac{\alpha_u \beta_u}{d_u^{(t)} p_s^{(t)}} - 1]] \tag{4.13}$$

Based on Eq. 4.13, it is observed that the optimal pricing problem of the MEC servers' computing services is a function only of their prices $p_s^{(t)}$.

Theorem 4. *The optimal pricing announced by each MEC server for its computing services given the end-users offloaded data and towards maximizing its own profit is given as follows:*

$$p_s^{(t)*} = [\frac{\alpha_u \beta_u c_s^{(t)} \sum_{u \in U} \frac{B_{-u}^{(t)}}{d_u^{(t)}}}{(1 - f_s^{(t)}) \sum_{u \in U} B_{-u}^{(t)}}]^{1/2} \tag{4.14}$$

Proof. See appendix A.2. □

Data Offloading and MEC Server Selection (DO-MECS) Algorithm

In order to solve the aforementioned joint problem, an iterative and low-complexity algorithm is introduced towards realizing the Data Offloading and MEC Server Selection (DO-MECS algorithm). The DO-MECS algorithm consists of two main components. At the first component, the MEC server selection by the end-users is executed following the theory of the stochastic learning automata, as presented in section 4.3.2. Then, at the second component of the DO-MECS algorithm, the end-users' optimal data offloading and the MEC servers' optimal pricing is determined, as presented in section 4.3.3. It is noted that the first part of the DO-MECS algorithm runs at the beginning of each time slot, while the second part of the algorithm runs for multiple iterations within each time slot. The pseudocode of the proposed algorithm is presented in Algorithm 1.

Algorithm 1 DO-MECS Algorithm

Step 1: ***Initialization*** $\rightarrow$ At the first time slot $t = 0$, set the initial MEC server selection probability vector as $\mathbf{Pr_u(t = 0)}$, where $Pr_{u,s}(t = 0) = \frac{1}{S}, \forall u \in U, s \in S$.
Step 2: ***MEC Server Selection*** $\rightarrow$ At the beginning of each time slot ($t > 0$), each end-user chooses a MEC server to offload its data based on its action probability vector $\mathbf{Pr_u(t)}$. If $Pr_{u,s}(t) \geq 0.999$ for all the MEC servers s, then stop. Otherwise, set $i = 0$, where i denotes the iteration of the second part of the algorithm.
Step 3: ***Optimal Data Offloading*** $\rightarrow$ Each end-user has been associated with a MEC server and all the MEC servers announce their prices. Each end-user determines its optimal data offloading based on Eq. 4.12.
Step 4: ***Optimal Pricing*** $\rightarrow$ Given the end-users' offloading data, each MEC server determines the optimal pricing of its computing services based on Eq. 4.14.
Step 5: ***Convergence*** $\rightarrow$ If $|b_{u,s}^{(t)*}|_{i+1} - b_{u,s}^{(t)*}|_i| \leq \epsilon_1$ and $|p_s^{(t)*}|_{i+1} - p_s^{(t)*}|_i| \leq \epsilon_2, \forall s \in S, u \in U$, where ϵ_1, ϵ_2 (small positive constants) are the convergence control parameters, then stop. Otherwise, go to Step 3.
Step 6: ***Update*** $\rightarrow$ Update the end-users' action probabilities based on Eq. 4.9a and Eq. 4.9b and return to Step 2.

4.4 Framework Evaluation

In this section, we provide some numerical results illustrating the operation, features and benefits of the proposed DO-MECS framework. In section 4.4.1, we focus on the pure operational characteristics of our framework, while in section 4.4.2 a comparative evaluation of our approach against alternative methodologies is provided. The algorithm and simulations were implemented in Python (with NumPy), and executed on a Intel Core i5-4300U laptop with CPU @ 1.90GHz x 4 and 8Gb RAM. Unless otherwise explicitly indicated, a detailed Monte Carlo analysis has been executed for all the presented numerical results considering averages over 1000 executions.

4.4.1 Operation of the DO-MECS Framework

Towards illustrating the successful operation of the DO-MECS framework, we performed detailed simulations considering two main cases regarding the end-users that reside within the MEC environment: a) homogeneous end-users, and b) heterogeneous end-users, with reference to their sensitivity on the pricing imposed by the MEC servers (i.e., end-user dynamics $d_u^{(t)}$ in Eq. 4.2). In our simulations, we consider $S = 5$ MEC servers and $U = 100$ end-users, while for demonstration purposes the weights w_1, w_2, w_3 in Eq. 4.4 have been considered of same importance, and each one equal to 1/3.

We consider a business perspective with respect to the MEC servers, in the sense that they present different characteristics with respect to parameters such as cost, discount factor, etc.. The parameters that characterize the different MEC servers are presented in Table 4.1. Regarding the communication part of the network operation, each MEC server assumes to receive data from the users via its own wireless channel (e.g., subcarrier). Thus, each user senses the interference only from the users that are offloading to the same MEC server. It is noted however that in this work,

Table 4.1: MEC servers' characteristics

Server	**cost** c	**discount** f_s
server 1	0.12	0.05
server 2	0.14	0.04
server 3	0.20	0.02
server 4	0.17	0.03
server 5	0.13	0.05

the transmission power control problem is not treated, and is assumed that users transmit with fixed power.

Homogeneous End-users

Initially, with respect to the scenario of homogeneous end-users, we present in a comprehensive manner indicative numerical results regarding the pure operation of the DO-MECS algorithm, in order to gain some insight about the key operational characteristics and contributions of the various components of our framework. We have considered a simplistic demonstration scenario where each users' maximum amount of data is the same $I_u^{(t)} = 1000$ Bytes, which however does not harm the validity of the observations but instead verifies the operational characteristics of our proposed approach. We do not consider or differentiate them based on the nature of the executed tasks or on parameters related to the computing or data intensity. It is also stressed that the focus of this work and of the corresponding evaluation results is on the decision making process of the data offloading (i.e. server selection and part of data to be offloaded), and not on the actual offloading or the computation processing itself.

Specifically, Fig. 4.3 presents the relative pricing of each MEC server, i.e., $\frac{\frac{\sum_{k \neq s}[(1-f_k^{(t)})]p_k^{(t)}}{K}}{(1-f_s^{(t)})p_s^{(t)}}$, as it is determined at the end of each time slot with respect to the time slots that the DO-MECS algorithm needs to converge. It is observed that in all cases convergence is obtained in less than 3000 time slots, while for practical purposes less than 2000 time slots are sufficient, corresponding to actual running time of less than 14 seconds for learning rate $b = 0.2$. Note that significantly lower convergence times can be achieved if higher learning rates are considered, as demonstrated later in section 4.4.2. It also clarified that the times measured and reported here, refer to the convergence of the overall DO-MECS algorithm in our simulation (i.e. decision making process), where the users conclude to a stable selection of MEC servers in order to offload their data to be further processed.

As it is presented in Fig. 4.3 and Fig. 4.4, the greater the relative pricing for each MEC server, the more attractive it becomes for the end-users. Server 1 clearly accumulates the majority of the end-users since from Table 4.1 we notice that Server 1 has both the smallest cost and offers the highest discount compared to the other MEC servers. The same trend and reasoning follows for the rest of the servers. Please note here that due to the homogeneity of the considered population

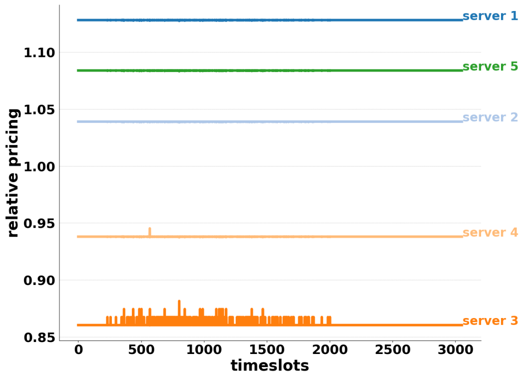


Figure 4.3: Relative pricing of MEC servers vs time slots

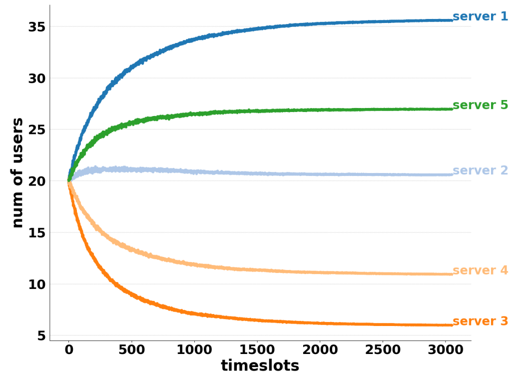


Figure 4.4: Number of end-users per MEC server vs time slots

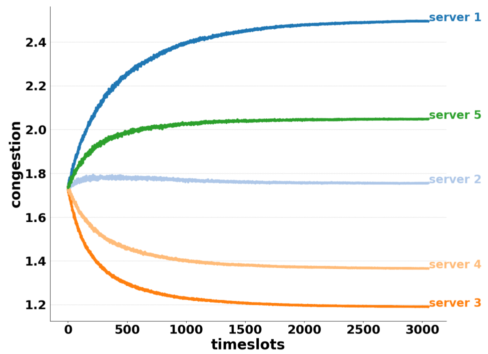


Figure 4.5: MEC servers' congestion vs time slot

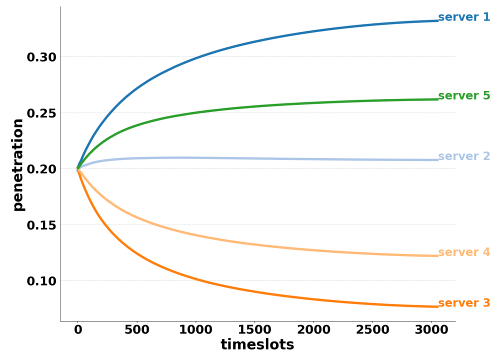


Figure 4.6: MEC servers' penetration vs time slots

each end-user offloads the same amount of data (in this experiment offloads its total data, i.e., $I_u^{(t)} = 1000$ Bytes), to the corresponding selected MEC server, as determined by the MEC Server Selection process (Step 2 of DO-MECS Algorithm) based on the theory of the stochastic learning automata (section 4.3.2). In the following section, a different scenario with heterogeneous end-users is considered and demonstrated, where the end-users decide to offload different amounts of data, based on the overall system dynamics.

As expected, the congestion on each MEC server, i.e., $(1 + CONG_s)^3$, follows the same trend as the number of end-users selecting each MEC server. The latter observation is expected, as the more end-users select to offload their data to a MEC server, the more congested that MEC server becomes (Fig. 4.5) and a greater penetration, i.e., $\frac{\sum_{t\in\{1,\dots,T\}}\sum_{u\in U} b_{u,s}^{(t)}}{\sum_{s\in S}\sum_{t\in\{1,\dots,T\}}\sum_{u\in U} b_{u,s}^{(t)}}$, is achieved by that server. In particular, the MEC servers' penetration in serving the end-users computing demands

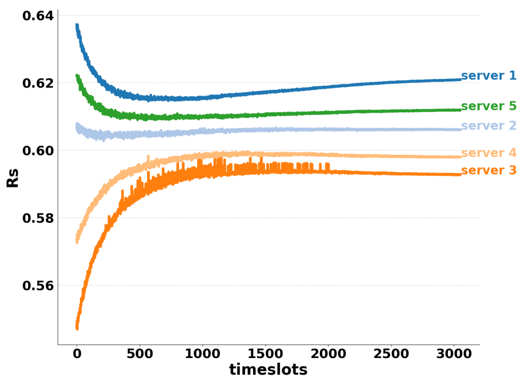


Figure 4.7: MEC server's reputation score vs time slots

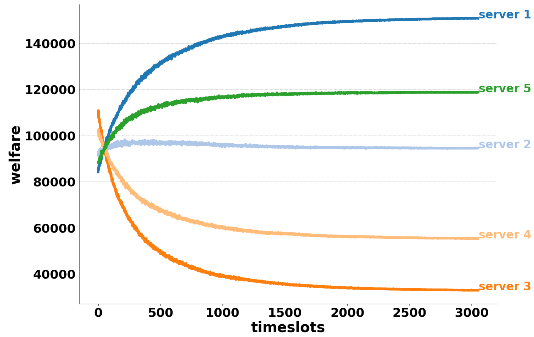


Figure 4.8: MEC server's profit vs time slots

is presented in Fig. 4.6.

Furthermore, from Eq. 4.4, we observe that the reputation score R_s depends on the relative pricing, the congestion and the penetration of the MEC servers. The R_s essentially controls the probability based on which each end-user will select a server to offload its data. In Fig. 4.7, the results illustrate that the proposed DO-MECS framework tries to boost "weaker" servers in order to allow them to gain some traction on the market. Additionally, Fig. 4.8 presents the profit $P_s^{(t)}(\mathbf{b^{(t)}}, \mathbf{p^{(t)}})$ that each MEC server receives based on its price announcement and the end-users' data offloading. The results reveal that Server 1 achieves the highest profit due to the combined effect of having the lowest cost (Table 4.1) and attracting a large number of end-users, despite the fact that it presents the lowest price as shown in Fig. 4.3. The same trend is followed from the rest of the servers, which indicates that the announced price by the MEC server is not the only dominant factor in shaping the server's profit, but also the number of end-users that select to be served by a server is a key parameter in determining the server's overall profit.

Heterogeneous End-users

In this section, we consider the scenario of heterogeneous end-users, i.e., the end-users demonstrate different spending dynamics (i.e., $d_u^{(t)}$) and therefore potentially may offload different parts of their total data $I_u^{(t)}$ to the selected MEC server. Specifically, in Fig. 4.9, we present the convergence of the amount of offloaded data for 10 indicative end-users from the overall available set in the simulated scenario. The results indicate that as the end-users have different spending dynamics, the announced price by each MEC server has different impact on each end-user in terms of determining its amount of offloaded data. Due to the differentiation of the end-users' spending dynamics, the MEC servers are motivated to adjust their announced prices in order to better adapt to the volume of the end-users' offloaded data. The aforementioned behaviour is captured in Fig. 4.10, where it is

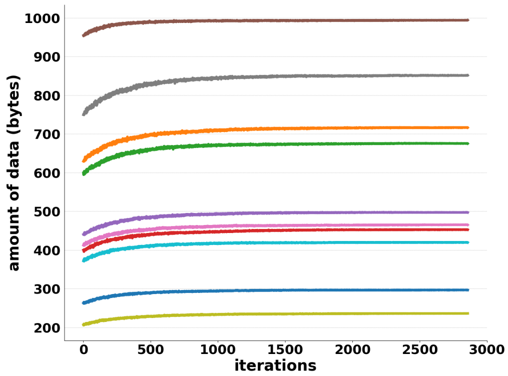


Figure 4.9: End-users' amount of offloaded data vs time slots

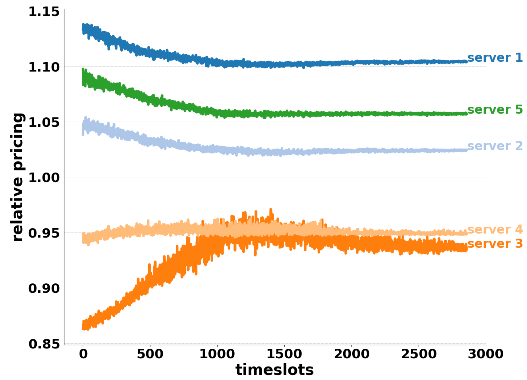


Figure 4.10: Relative pricing of MEC servers vs time slots

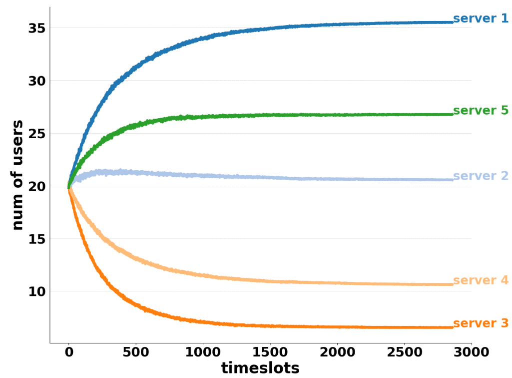


Figure 4.11: Number of end-users per MEC server vs time slots

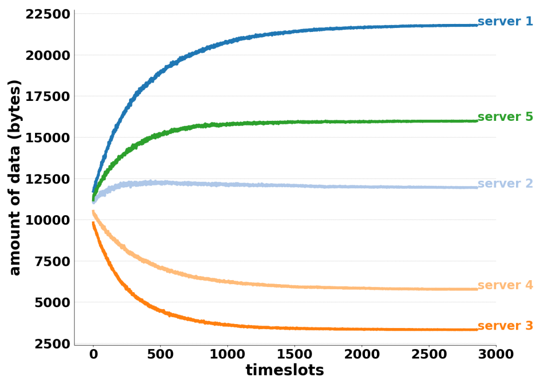


Figure 4.12: Offloaded data to each MEC server vs time slots

observed that the "weaker" servers are willing to drop their price in order to increase their stability and penetration on the market, while the stronger ones increase their price to avoid congestion. Moreover, in Fig. 4.11 and Fig. 4.12, the total number of end-users per MEC server and the corresponding amount of offloaded data per MEC server are presented, respectively.

4.4.2 Comparative Evaluation

In this section, we present some comparative results of the performance of our proposed framework against some alternative strategies, in order to reveal its benefits and advantages. Initially, we present the impact of the learning rate parameter of the stochastic learning automata as presented in section 4.3.2 in the operation of the DO-MECS framework, and then we evaluate the benefits and drawbacks of different data offloading mechanisms.

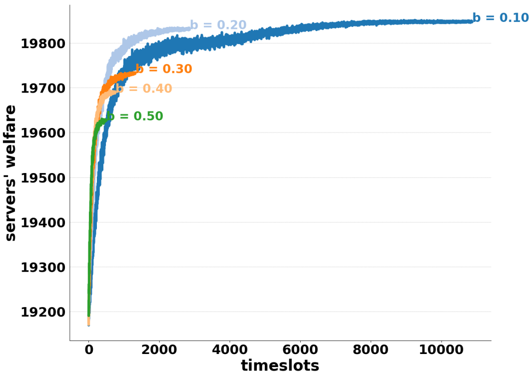


Figure 4.13: Average MEC servers' profit vs time slots for different learning rates

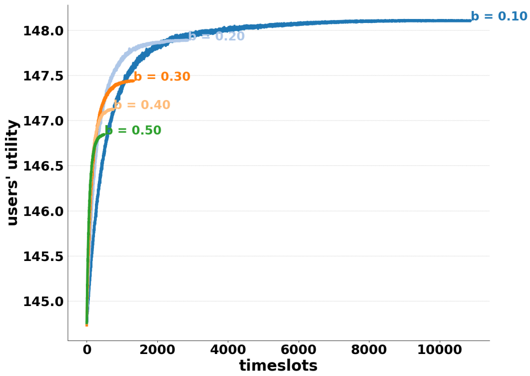


Figure 4.14: Average end-users' utility vs time slots for different learning rates

Different learning rates

As we can see from Eq. 4.6 and 4.7, the learning rate parameter b is an important factor regarding the convergence of the DO-MECS framework to the optimal stable state. Greater values of the learning rate would lead to faster convergence, however smaller ones allow the end-users to better exploit the available options and ultimately conclude to better states. In order to demonstrate the above tradeoff, a comparative evaluation between different values of the learning rate are performed. Table 4.2 shows the average execution time of our DO-MECS framework until convergence is achieved, while Fig. 4.13 and Fig. 4.14 present the average MEC server's profit and the average end-user's utility for different learning rates, respectively. Indeed, it is observed that small values of the learning rate parameter b conclude to slow convergence of the DO-MECS algorithm, however, they allow the MEC servers and the end-users to achieve higher average profit and higher average utility, respectively. Based on Fig. 4.13 and Fig. 4.14, we can see that the difference on the convergence state (i.e., average MEC servers' profit and average end-users' utility) between learning rates $b = 0.1$ and $b = 0.2$ is negligible, while the difference in the convergence time is significant. This is also evident from the execution times presented in Table 4.2, where for $b = 0.2$ the DO-MECS algorithm converges five times faster than in the case where $b = 0.1$, while by using a higher value for b (i.e. $b = 0.5$) we can achieve convergence times lower by an order of magnitude. Thus, a learning rate of $b = 0.2$ presents a good balance between optimality and efficiency. The convergence time of the DO-MECS algorithm can be further improved by adopting one of the following strategies or a combination of them: (a) increase the learning rate b, (b) initiate the algorithm from an "educated" point of MEC servers' selection by the users, i.e., instead each user randomly selecting a MEC server at the first step of DO-MECS algorithm, it can use previous knowledge that will be available in a realistic environment after the initial interaction of the users with the MEC servers, and (c) simplify the functions used at the expense of precision.

Table 4.2: Execution time for different learning rate values.

learning rate	**Execution Time (sec)**	Number of timeslots
$b = 0.1$	147.2s	11053
$b = 0.2$	27.5s	2959
$b = 0.3$	11.6s	1357
$b = 0.4$	6.4s	773
$b = 0.5$	4.2s	504

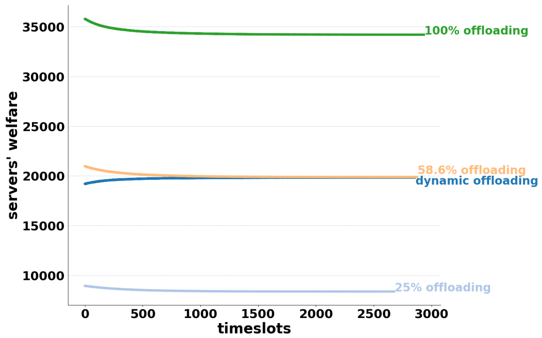


Figure 4.15: Average MEC servers' profit vs time slots for different offloading mechanisms

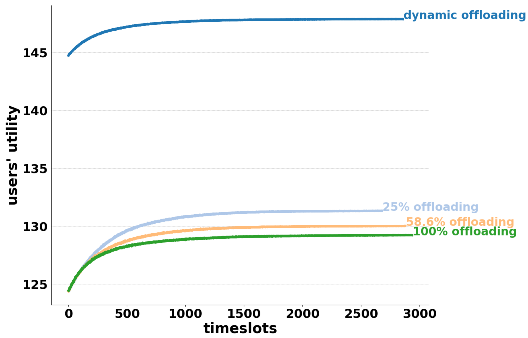


Figure 4.16: Average end-users' utility vs time slots for different offloading mechanisms

Different offloading mechanisms

Towards evaluating the significance of the game theoretic data offloading mechanism proposed by our DO-MECS framework, a comparison between our mechanism and a computationally simplistic mechanism where each end-user offloads a fixed portion (i.e., percentage) of its data was performed, while for fairness purposes the rest of our proposed framework (i.e., server selection and optimal pricing mechanisms) was kept intact in all strategies. Specifically, with respect to the alternative data offloading mechanism three different variations were examined, where the end-users send 25%, 58.6% and 100% of their total data $I_u^{(t)}$, respectively, to the selected MEC servers. It should be noted here that the alternative with fixed portion (i.e., percentage) of 58.6% data offloading of user's maximum amount of data was selected because it corresponds to the same exactly average end-user data offloading, as the one produced by our proposed framework in the considered experiment.

The corresponding comparative results are depicted in Fig. 4.15 and Fig. 4.16, where the average MEC servers' profit and the average end-users' utility, respectively, as a function of the time for the different offloading mechanisms are obtained. In particular, it is evident that as expected the more data the end-users offload to the MEC servers, the higher profit the MEC servers experience. However this happens at the cost of very low average utility experienced by the end-users, as clearly demonstrated from the curves corresponding to the 100% offloading alternative. Moreover, it is observed that by allowing the end-users to send a constant amount of data without enabling them to dynamically adapt their offloading amount of data based on the system's conditions, as proposed by our framework, always results to significantly lower average end-users' utility. As a result, the proposed DO-MECS framework offers incentives to the end-users to participate in the non-cooperative data offloading game in order to dynamically and autonomously determine the optimal amount of data, while the MEC servers experience the best levels of profit that they can achieve based on the decisions of their customers, i.e., the end-users.

4.5 Summary

In this chapter, the joint problem of MEC server selection by the end-users, along with their optimal data offloading and the optimal price setting by the MEC servers was studied in a multiple MEC servers and multiple end-users environment. The flexibility and programmability offered by the SDN technology, enables the realistic implementation of the proposed framework. In particular, the MEC server selection part of the framework was based on a reinforcement learning technique adopting the theory of the stochastic learning automata. The end-users optimal data offloading and the MEC servers' optimal pricing of their computing services was formulated as a two-layer optimization problem. At the first layer, a non-cooperative game among the end-users of each server was formulated towards maximizing the perceived satisfaction of each end-user, as expressed by an appropriately formulated utility function. The existence and uniqueness of the game's Nash Equilibrium point was proven, thus concluding to the end-users' optimal data offloading strategy. At the second layer of the proposed framework, an optimization problem of each MEC server's profit was formulated and the corresponding optimal price of its computing services is determined.

A low-complexity Data Offloading and MEC Server Selection (DO-MECS) algorithm was introduced to realize the overall framework. The operation and performance of the proposed framework was extensively evaluated through modeling and simulation, while the presented detailed numerical results demonstrate its performance and benefits in the examined setting.

Chapter 5

Risk-aware Data Offloading in UAV-Assisted Multi-access Edge Computing

5.1 General Setting

The ways to effectively make use of Multi-access Edge Computing vary, depending on the setting and the underlying infrastructure. More recently, Unmanned Aerial Vehicle (UAV)-assisted Multi-access Edge Computing (MEC) systems have emerged as a flexible and dynamic computing environment, providing task offloading service to the users. Combined with the MEC concept, Unmanned Aerial Vehicles (UAVs), equipped with communication and computing facilities, could become a core component of next generation networks due to their salient attributes, such as hovering ability, flexibility and effortless deployment, maneuverability, mobility, low cost, strong line-of-sight (LoS) connection links, adjustable usage, and adaptive altitude. The MEC servers are embedded in the UAVs that fly in closer proximity to the users compared to the conventional MEC servers typically residing at the Macro Base Stations (MBSs) or at the Access Points (APs). Thus, the UAV-mounted MEC servers more efficiently support the end users applications' data offloading and processing at the flying edge servers, by creating a flexible and dynamic computing environment paradigm [80].

In order for such a paradigm to be viable, the operator of a UAV-mounted MEC server once again should enjoy some form of profit by offering its computing capabilities to the end users. To deal with this issue, we proposed a usage-based pricing policy for allowing the exploitation of the servers' computing resources which implicitly introduced a more social behavior to the users with respect to competing for the UAV-mounted MEC servers' computation resources. In order to properly model the users' risk-aware behavior within the overall data offloading decision-making process, the principles of Prospect Theory were adopted, while the exploitation of the available computation resources was considered based on the theory of Common Pool Resources and the theory of the Tragedy of the Commons [81]. Initially, the user's prospect-theoretic utility function was formulated by quantifying the user's risk seeking and loss averse behavior, while taking into account the pricing mechanism. The users' risk-aware data offloading problem was thus formulated as a distributed maximization problem of each user's expected prospect-theoretic utility function and addressed as a non-cooperative game among the users, enabling them to make their own decisions concerning their perceived Quality of Experience. In order to prove the existence of a Pure Nash Equilibrium (PNE) for the resulting game, the theory of submodular games was utilized and an iterative and distributed algorithm which converges to the PNE was proposed, following the learning rule of the best response dynamics.

In particular, we assumed that the users have two available options for executing their tasks, namely the local computation and the remote computation, the latter achieved through data offloading. The local computation resources of the user's device acts as safe resources, since the users do not compete with each other for consuming those resources. On the other hand, the computation resources of the UAV-mounted MEC server were treated as a Common Pool of Resources (CPR), as they are non-excludable, i.e., all the users have the right to exploit them, while they are rivalrous and subtractable, i.e., their exploitation by one user reduces the ability to be exploited by another user. In principle, the UAV-mounted MEC server resources have the potential to provide significantly higher satisfaction to the user (compared to the lower satisfaction that could be obtained through the limited user local computation resources), if properly utilized and allocated. However, if the users selfishly offload their data to the UAV-mounted MEC server, then the computing capabilities of the latter will be overexploited resulting in suboptimal outcomes for the entire set of users, possibly leading to the complete "failure" of the CPR UAV-mounted MEC server. The failure of the CPR UAV-mounted MEC server refers to its inability to concurrently handle the large amount of offloaded data and corresponding computation tasks by the users, due to its limited computation capability.

5.2 Related Work

Several studies have been made on UAV-mounted MEC servers and various solutions have been proposed to the arising problems. [82] discusses the benefits introduced by the UAV-mounted MEC servers with respect to caching and computing, in a hybrid architecture consisting of UAV-mounted and ground MEC servers. In [83] a cloud-based UAV-assisted system is introduced and its stability with respect to the sensors big data offloading rate is studied while in [84, 85] the usage of a UAV-assisted public safety network is investigated. In [86] a fleet of UAV-mounted MEC servers is considered and the optimization problem of increasing the UAVs fleet lifetime, while decreasing the overall computation time of the users' offloaded tasks, is formulated and solved. In particular, the authors exploit neighboring UAV clusters with sufficient computing resources to offload the users' computation tasks. In [87] the power investment of users in a UAV assisted communication environment with both normal and malicious users is considered, while in [88] the bandwidth usage of a UAV-based communication is studied.

In [89] a joint optimization problem to optimize the users' data offloading to the UAV-mounted

MEC servers, the UAVs' trajectory, and the data allocation during transmission to the different UAVs is formulated. An end-to-end solution is introduced in [90], where the authors jointly optimize the users' data offloading to the UAV-mounted MEC servers (i.e., uplink) and the output processed data returned to the users (i.e., downlink), while considering the computation tasks' latency constraints. [91] focuses on the UAV-mounted MEC servers' energy constraints to jointly optimize the users' data offloading by considering orthogonal and non-orthogonal communication multiple access techniques, and the UAVs' trajectory. Furthermore, [92, 93] consider a wireless powered communication environment, where the UAVs except from acting as UAV-mounted MEC servers providing computing services to the end-users, they also provide energy to them. Accordingly, the users can exploit the harvested energy to perform local computing and/or transmit their data to the UAV-mounted MEC servers.

Research has also been performed concerning the loss averse and risk seeking behavior in terms of exploiting the system's available resources, especially in resource-constrained environments. In order to capture this risk-aware behavior, Prospect Theory has been adopted in various environments and application domains. In [94] the problem of spectrum usage by virtual wireless operators is studied, where users can sense for unused spectrum in a licensed band or lease spectrum from a spectrum owner while in [77, 95] the unlicensed band is treated as a Common Pool Resource and the concept of pricing users' power investment is investigated. In [96] a device-to-device (D2D) communication is considered as a promising alternative to cellular mode of communications where D2D devices receive strong interference opportunistically accessing the same spectrum, resulting in uncertainty of the resulting QoS. By allowing users to engineer the protocols in wireless communications, [97] allows users to adjust their transmission probabilities over a random access channel in order to successfully transmit, leading to energy and delay costs, and in [98] the utility function of each user is considered time-varying depending on the previously observed user experience and a dynamic reference point on the utility function and a dynamic value function are proposed. Interesting problems on antijamming [99], autoscaling in cloud computing [100] and network slicing [101] have also been tackled with the help of Prospect Theory. Finally the principals of Prospect Theory have been combined with blockchain and in [102] and similar prospect-theoretic approaches have been successfully applied in other environments as well such as power grids [103, 104], network security [105, 106] and more.

5.3 Proposed Framework

5.3.1 System Model

A UAV-assisted multi-access edge computing system is considered, consisting of a set of mobile users $\mathcal{N} = \{1, \dots, n, \dots, N\}$ and a UAV-mounted MEC server. Each user n has a computation task J_n that needs to execute. Each task is accordingly defined as $J_n = (b_n, d_n)$, where b_n [bits] is the user's n size of the input data needed for the computation task and d_n [CPU-cycles] is the number of CPU cycles required in order to accomplish the computation task. The UAV-mounted MEC

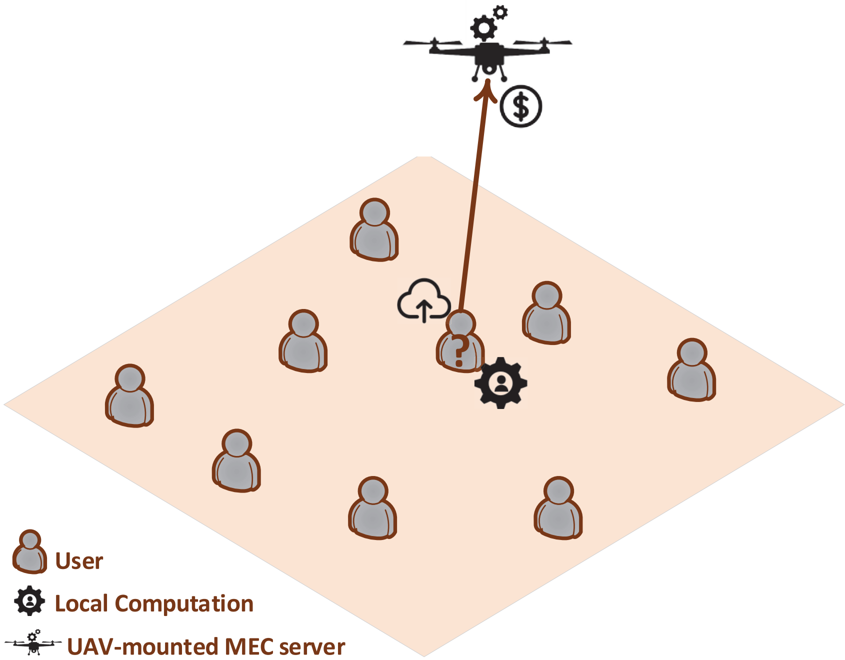


Figure 5.1: UAV-assisted multi-access edge computing system.

server is available to the users to offload and process their data remotely instead of processing them locally on their device and consuming their own local resources. Each user decides to offload b_n^{MEC} [bits] data to the UAV-mounted MEC server, while the rest $(b_n - b_n^{MEC})$ [bits] data are processed locally on the user's device. An indicative topology of the considered UAV-assisted MEC system is presented in Fig.5.1. In this work we mainly focus on the modeling and provisioning of the computing resources, rather than on the user to UAV wireless communication aspects. The UAV flexibility and adaptability capabilities can ensure strong communication channels and links with the users.

For each user n, the time $\hat{t}_n$ [sec] to process the whole amount of data b_n locally is defined as:

$$\hat{t}_n = \frac{d_n}{f_n} \tag{5.1}$$

where f_n [CPU-cycles/s] is the computation capability of each user's n device. Apart from the processing time needed, each computation task has some energy requirements as well. The energy $\hat{e}_n$ [J] needed to process the whole amount of data b_n locally for each user n is defined as:

$$\hat{e}_n = \gamma_n d_n \tag{5.2}$$

where γ_n [J/CPU-cycle] is the coefficient denoting the consumed energy per CPU cycle locally at each user's n device.

We assume that the UAV-mounted MEC server applies a fair usage-based pricing policy to the users, while charging them proportionally to their offloaded data and to their demand of consuming computation resources, as they are indicated by the nature of their computation task. Thus, the cost imposed by the UAV-mounted MEC server to the user n in order to process the user's offloaded data b_n^{MEC} is defined as:

$$c_n(b_n^{MEC}) = cd_n \frac{b_n^{MEC}}{b_n} \tag{5.3}$$

where c [1/CPU-cycles] represents a constant pricing factor imposed by the UAV-mounted MEC server to every user. Intuitively, the cost imposed to each user is proportional to the percentage of the number of CPU cycles d_n of the user's computation task that is actually offloaded, i.e., the greater the part of the computation task offloaded to the UAV-mounted MEC server is, the greater is the cost that the user experiences by the UAV-mounted MEC server to process remotely its data. It is noted that, without loss of generality, the cost $c_n(b_n^{MEC})$ imposed by the UAV-mounted MEC server to the user n in order to process the offloaded data of the latter is assumed to be a unitless metric in this research work, and can represent any type of usage-based cost or monetary cost in a realistic implementation.

Based on the above proposed model, we can therefore formulate the problem of determining the optimal b_n^{MEC*} that each user should offload considering each user's risk-aware behavioral characteristics and the pricing imposed by the UAV-mounted MEC server.

5.3.2 Users' Prospect-Theoretic Utility

In the dynamic computation environment considered in this research work, consisting of the UAV-mounted MEC server's and the users' local computing capabilities, the users exhibit a risk-aware behavior in terms of deciding where to process the data of their computation tasks. Therefore, the users do not act as risk-neutral utility maximizers following the conventional Expected Utility Theory (EUT) [107], but instead they rather exhibit a loss averse or gain seeking behavior when utilizing the UAV-mounted MEC server's computation resources. To capture the exploitation and usage characteristics and principles of the available computation resources in the considered UAV-assisted MEC system, we adopt the theory of the Tragedy of the Commons [81]. Specifically, the UAV-mounted MEC server's computation resources are considered as a Common Pool of Resources (CPR), as all the users have access to them and can offload their data to the UAV-mounted MEC server in order to be processed. If the users overexploit the computation resources of the UAV-mounted MEC server, the latter will fail to serve their computation demands and none of the users will be satisfied. On the other hand, the user's device's local computation resources are considered as safe resources, as each user exclusively exploits them for its own benefit. It is noted that the safe resources provide a guaranteed satisfaction to the user; however, the user can potentially experience lower satisfaction compared to exploiting the CPR, as the user has to spend its own resources, e.g., energy to process locally its data.

Towards capturing the users' loss averse and gain seeking behavior in terms of exploiting the CPR and safe computation resources, the principles of Prospect Theory are adopted [24]. As we saw in section 2.2, Prospect Theory is a behavioral economic theory that quantifies individuals' behavioral patterns, which demonstrate systematic deviations from the Expected Utility Theory. Under the prospect-theoretic model, the users experience greater dissatisfaction from a potential outcome of losses compared to their satisfaction from gains of the same amount. In addition, the level of the users' satisfaction and dissatisfaction is evaluated with respect to a reference point, which is considered as the ground truth of the examined system. Following the principles of Prospect Theory, the user's prospect-theoretic utility is defined as [24]:

$$P_n(U_n) = \begin{cases} (U_n - U_{n,0})^{\alpha_n}, & \text{if } U_n \geq U_{n,0} \\ -k_n(U_{n,0} - U_n)^{\beta_n}, & \text{otherwise} \end{cases} \tag{5.4}$$

where $U_{n,0} = \frac{1}{\hat{t}_n \hat{e}_n} b_n$ denotes the reference point expressing the user's n perceived satisfaction by processing all of its data locally at its device, which is the safe choice in terms of receiving a guaranteed satisfaction. Similarly, U_n denotes the user's actual perceived satisfaction from offloading part of its data to the UAV-mounted MEC server, and is given by Eq.5.5 below.

The parameters α_n, β_n where $\alpha_n, \beta_n \in (0, 1]$ express the sensitivity of users to the gains and losses of their actual perceived satisfaction U_n, respectively. In particular, the user's risk averse behavior in gains and risk seeking behavior in losses is captured by small values of the parameter $\alpha_n \in (0, 1]$. Similarly, a small value of the parameter $\beta_n \in (0, 1]$ captures a higher decrease in the user's prospect-theoretic utility, when its actual perceived satisfaction is close to the reference point. It is noted that the values of the parameters α_n, β_n can be determined and quantified based on statistical analysis of existing open datasets stemming from qualitative results of users' behavioral models (e.g. [108]). Furthermore, the loss aversion parameter $k_n \in (0, \infty)$ quantifies the impact of losses compared to the gains in user's prospect-theoretic utility. Specifically, for $k_n > 1$, the user weighs the losses more than the gains, while the exact opposite holds true for $0 \leq k_n \leq 1$. For simplicity and without loss of generality, in this work, we assume $\alpha_n = \beta_n$.

Specifically, the user's actual perceived satisfaction from offloading part of its data (denoted by b_n^{MEC}) to the UAV-mounted MEC server is denoted as $U_n(b_n^{MEC})$ and is formally defined as follows:

$$U_n(\mathbf{b^{MEC}}) = \begin{cases} \frac{1}{\hat{t}_n \hat{e}_n} b_n, & \text{if } b_n^{MEC} = 0 \\ \frac{1}{\hat{t}_n \hat{e}_n}(b_n - b_n^{MEC}) + b_n^{MEC} RoR(d_\tau) - c_n(b_n^{MEC}), & \text{if } b_n^{MEC} \neq 0 \text{ \& MEC survives} \\ \frac{1}{\hat{t}_n \hat{e}_n}(b_n - b_n^{MEC}) - c_n(b_n^{MEC}), & \text{if } b_n^{\mathrm{MEC}} \neq 0 \text{ \& MEC fails} \end{cases} \tag{5.5}$$

The first branch of Eq.5.5 expresses the user's actual perceived satisfaction from processing all of its data locally to its mobile device. The second branch of Eq.5.5 captures the user's actual perceived satisfaction by processing part of its data locally (first term) and part of them to the UAV-mounted MEC server (second term), while experiencing the corresponding usage-based cost (third term) for exploiting the UAV-mounted MEC server's computation resources in the case that the MEC server can process all the users' requests. The third branch of Eq.5.5 represents the user's utility in the case that the MEC server fails to process the users' data due to its overexploitation. The user's actual perceived satisfaction from processing part of its data to the UAV-mounted MEC server depends on the server's rate of return function $RoR(d_\tau)$, where $d_\tau(\mathbf{b^{MEC}})$, $\mathbf{b^{MEC}} = (b_1^{MEC}, \ldots, b_N^{MEC})$ is a normalized increasing function with respect to the users' total demand of computation resources by the UAV-mounted MEC server. The vector $\mathbf{b^{MEC}} = (b_1^{MEC}, \ldots, b_N^{MEC})$ denotes the data offloading strategies of all the users in the examined system to the UAV-mounted MEC server. For demonstration purposes and without loss of generality, the users' total demand function $d_\tau(\mathbf{b^{MEC}}) \in [0, 1]$ of computation resources by the UAV-mounted MEC server is defined as follows:

$$d_\tau(\mathbf{b^{MEC}}) = -1 + \frac{2}{1 + e^{-\theta \sum_{n=1}^{N} d_n \frac{b_n^{MEC}}{b_n}}} \tag{5.6}$$

where $\theta > 0$ is a positive constant calibrating the sigmoidal curve of Eq.5.6 based on the computing capabilities of the UAV-mounted MEC server. The users' total computation demand function $d_\tau(\mathbf{b^{MEC}})$ is a continuous and strictly increasing function with respect to the users' total amount of offloaded data. Eq.5.6 is a representative example of the users' total computation demand function, while any other function that follows the above described properties can be adopted for the following analysis without loss of generality. In a nutshell, the UAV-mounted MEC server's rate of return function $RoR(d_\tau)$ provides positive experience, i.e., $RoR(d_\tau) > 0$, if the server has sufficient computation resources to serve the users' total computation demand $d_\tau(\mathbf{b^{MEC}})$. The UAV-mounted MEC server's rate of return function $RoR(d_\tau)$ is a continuous, monotonically decreasing, and concave function with respect to the users' total demand of computation resources, since the server's computation resources assigned to each user and correspondingly the users' perceived actual satisfaction decrease for increasing values of the users' total computation demand. For demonstration purposes, in this work, we adopt an indicative rate of return function that respects all aforementioned properties and is defined as follows [109]:

$$RoR(d_\tau) = 2 - e^{d_\tau - 1} \tag{5.7}$$

Following the above discussion and focusing on the user's prospect-theoretic utility function, it is noted that the first branch of Eq.5.4 expresses the user's n risk-aware satisfaction in the case that the UAV-mounted MEC server survives and can support the users' total computation demand. In that case, each user targets at the maximization of its gains, while, in the opposite case, i.e., the second branch of Eq.5.4, the user targets at the minimization of its losses, as the UAV-mounted

MEC server has failed due to overexploitation.

If the UAV-mounted MEC-server survives, then the user's actual utility is determined by the second branch of Eq.5.5, given that the user offloaded part of its data to the MEC server. Thus, in combination with the first branch of Eq.5.4, the user's prospect-theoretic utility is given as follows:

$$\begin{aligned} P_n^{surv.}(U_n) &= (U_n - U_{n,0})^{\alpha_n} \\ &= (b_n^{MEC})^{\alpha_n}[(2 - e^{d_\tau - 1}) - \frac{1}{\hat{t}_n \hat{e}_n} - c\frac{d_n}{b_n}]^{\alpha_n} \end{aligned} \tag{5.8}$$

If the opposite holds true, that is, the UAV-mounted MEC server's computation resources are overexploited by the users and the server fails to serve them, then by combining the second branch of Eq.5.4 and the third branch of Eq.5.5, the user's prospect-theoretic utility can be written as follows:

$$\begin{aligned} P_n^{fail}(U_n) &= -k_n(U_{n,0} - U_n)^{\alpha_n} \\ &= -k_n(b_n^{MEC})^{\alpha_n}(\frac{1}{\hat{t}_n \hat{e}_n} + c\frac{d_n}{b_n})^{\alpha_n} \end{aligned} \tag{5.9}$$

Furthermore, the probability of failure of the UAV-mounted MEC server, which is the server's probability to fail serving the users' total computation demand d_τ (Eq.5.6), is denoted by $Pr(d_\tau)$. The UAV-mounted MEC server's probability of failure function $Pr(d_\tau), 0 \leq Pr(d_\tau) \leq 1$ is assumed to be continuous, strictly increasing, convex, and twice differentiable function with respect to the users' total computation demand d_τ. In the following, we adopt the square function to present the UAV-mounted MEC server's probability of failure, as shown below:

$$Pr(d_\tau) = d_\tau^2 \tag{5.10}$$

It is noted that the rest of the analysis still holds true for any probability of failure function that is characterized by the properties described above and the selection of the square function for the probability of failure is mainly made for presentation purposes. Accordingly, the UAV-mounted MEC server's probability to survive and process the users' total amount of offloaded data is $(1 - Pr(d_\tau))$. Moreover, due to the nature of the user's total computation demand (Eq.5.6), the UAV-mounted MEC server's probability of failure (Eq.5.10) is convex on low to medium users' computation demand and concave on high demand, while it asymptotically converges to one, as shown in Fig.5.2.

Combining Eq. 5.8-5.10, the user's expected prospect-theoretic utility by offloading b_n^{MEC} data to the UAV-mounted MEC server is defined as follows, jointly capturing the uncertainty of the UAV-mounted MEC server's computation resources, the pricing of the UAV-mounted MEC server, as well as the user's risk-aware characteristics in its data offloading decision:

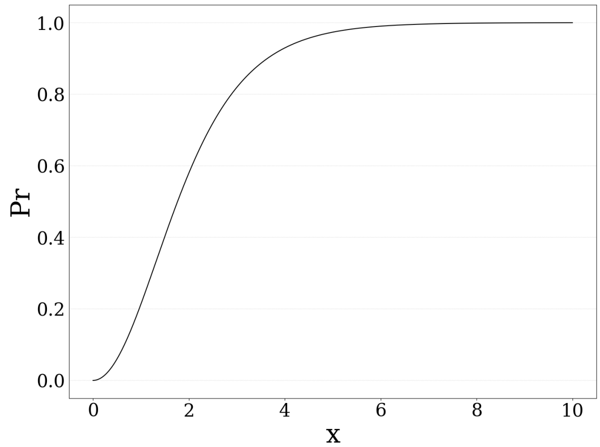


Figure 5.2: Probability of failure vs x when $Pr(x) = (-1 + \frac{2}{1+e^{-x}})^2$

$$\mathbb{E}(U_n) = P_n^{surv.}(U_n)(1 - Pr(d_\tau)) + P_n^{fail}(U_n)Pr(d_\tau). \tag{5.11}$$

5.3.3 Risk-Aware Data Offloading

In this section, the distributed risk-aware data offloading problem in UAV-assisted multi-access edge computing systems is formulated by adopting the principles of non-cooperative game theory and solved based on the theory of S-modular games.

Each user aims at maximizing its expected prospect-theoretic utility function (Eq.5.11) by distributedly and autonomously deciding its optimal data offloading strategy b_n^{MEC*} to the UAV-mounted MEC server, while considering the imposed pricing policy and its personal risk-aware characteristics. Accordingly, the users' risk-aware data offloading problem is formulated as a distributed optimization problem as follows:

$$\begin{gathered}\max_{b_n^{MEC} \in [0, b_n]} \mathbb{E}(U_n(b_n^{MEC}, \mathbf{b_{-n}^{MEC}})) \\ \text{s.t. } 0 \leq b_n^{MEC} \leq b_n\end{gathered} \tag{5.12}$$

where $\mathbf{b_{-n}^{MEC}}$ denotes the amount of the offloaded data by the rest of the users except for user n.

The distributed optimization problem of users' data offloading can be formulated as a non-cooperative game among the users $G = [\mathcal{N}, A_n, \mathbb{E}(U_n(b_n^{MEC}, \mathbf{b_{-n}^{MEC}}))]$, where $\mathcal{N}$ is the set of users, $A_n = [0, b_n]$ is the user's n data offloading strategy space, and $\mathbb{E}(U_n(b_n^{MEC}, \mathbf{b_{-n}^{MEC}}))$ denotes the user's n expected prospect-theoretic utility function, as defined in the previous section. The solution of the non-cooperative game G should determine each user's optimal data offloading strategy b_n^{MEC*} in order to maximize its expected prospect-theoretic utility. Towards analytically seeking the solution of the risk-aware data offloading problem (Eq.5.12) we seek to find the Pure Nash Equilibrium (PNE) of the game G.

Definition 3. (Pure Nash Equilibrium Point): A data offloading vector $\mathbf{b_n^{MEC*}} = (b_1^{MEC*}, \ldots, b_N^{MEC*})$ in the strategy space $b_n^{MEC*} \in A_n = [0, b_n]$ is a Pure Nash Equilibrium point if for every user n the following condition holds true:

$$\mathbb{E}(U_n(b_n^{MEC*}, \mathbf{b_{-n}^{MEC*}})) \geq \mathbb{E}(U_n(b_n^{MEC}, \mathbf{b_{-n}^{MEC*}})) \tag{5.13}$$

for all $b_n^{MEC} \in A_n$.

The physical interpretation of the above definition is that, at the Pure Nash Equilibrium point, no user has the incentive to unilaterally change its data offloading strategy to the UAV-mounted MEC server given the data offloading strategies of the rest of the users, as its achieved expected prospect-theoretic utility cannot be improved.

In order to prove the existence of at least one PNE of the non-cooperative game G as a solution of the maximization problem of Eq.5.12, the theory of submodular games is adopted [110]. The submodular games are characterized by strategic substitutes, i.e., when a user offloads more data to the UAV-mounted MEC server, the rest of the users tend to avoid following similar behavior, as the UAV-mounted MEC server's computation resources can become overexploited and none of the users be satisfied. The submodular games are of great interest and practical importance as an optimization tool, due to the fact that they guarantee the existence of at least one PNE, while learning and adjustment tools (such as the best response dynamics) can be used in order to determine such a point.

Definition 4. (Submodular Games): The non-cooperative game $G = [\mathcal{N}, A_n, \mathbb{E}(U_n)]$ is submodular, if, for all the users, the following conditions hold true [16, 111]:

1. A_n is a compact subset of an Euclidean space.
2. $\mathbb{E}(U_n(b_n^{MEC}, \mathbf{b_{-n}^{MEC}}))$ is smooth, submodular in b_n^{MEC}, and has non-increasing differences in $(b_n^{MEC}, \mathbf{b_{-n}^{MEC}})$, i.e., $\frac{\partial^2 \mathbf{E}_n(\vec{b}^{MEC})}{\partial b_j^{MEC} \partial b_n^{MEC}} \leq 0$.

Theorem 5. *The non-cooperative game $G = [\mathcal{N}, A_n, \mathbb{E}(U_n(b_n^{MEC}, \mathbf{b_{-n}^{MEC}}))]$ is submodular for all $d_\tau \in (0, \mu)$, where $\mu \in (0, 1)$, and $c < \frac{b_n}{d_n}(1 - \frac{1}{\hat{t}_n \hat{e}_n})$, and has at least one Pure Nash Equilibrium point.*

Proof. See appendix A.3. □

5.3.4 Distributed Data Offloading Algorithm

Towards enabling the users to determine their optimal data offloading strategy b_n^{MEC*} in a distributed manner, the Best Response Dynamics (BRD) approach is adopted. The best response

Algorithm 2 Risk-aware data offloading algorithm

Input: N, c, b_n, d_n, f_n, γ_n, $\forall n \in \mathcal{N}$
Output: $\mathbf{b^{MEC*}}$
for $n \in N$ **do**
  $b_n^{\mathrm{MEC}} \leftarrow$ user selects an arbitrary value
end for
$t = 0$
while not converged **do**
  $t++$
  for $n \in N$ **do**
    $b_n^{\mathrm{MEC}} \leftarrow \arg\max \mathbb{E}_n(b_n^{\mathrm{MEC}}, \mathbf{b}_{-\mathbf{n}}^{\mathrm{MEC}})$
  end for
  if $\mathbf{b_t^{MEC*}}{==}\mathbf{b_{t-1}^{MEC*}}$ **then**
    converged
  end if
end while
return $\mathbf{b_t^{MEC*}}$

strategy of each user subject to the selected data offloading strategies of the rest of the users is formally determined as follows:

$$BR(b_n^{MEC}, \mathbf{b_{-n}^{MEC}}) = b_n^{MEC*} = \underset{b_n^{MEC} \in [0, b_n]}{\arg\max} \; \mathbb{E}(U_n(b_n^{MEC}, \mathbf{b_{-n}^{MEC}})). \tag{5.14}$$

Given that we have already proven that the non-cooperative game $G = [\mathcal{N}, A_n, \mathbb{E}(U_n)]$ belongs to the class of submodular games as stated above, and therefore possesses at least one PNE point, it also readily follows that the iterated best-response dynamics always converges to a Pure Nash Equilibrium point [112, 113].

Subsequently, capitalizing on the above argumentation, a distributed iterative and low-complexity algorithm is introduced in order to determine the users' optimal data offloading strategies to the UAV-mounted MEC server and is presented in Algorithm 2. The proposed algorithm follows the philosophy and principles of the best response dynamics learning mechanism, and, at each iteration, each user aims at maximizing its expected prospect-theoretic utility given the data offloading strategies of the rest of the users. The complexity of the risk-aware data offloading algorithm is $O(N * Ite * A)$, where Ite is the total number of iterations in order for the algorithm to converge to the PNE, and A is the complexity of solving Eq.5.14. Detailed numerical results regarding the operation performance and scalability of our approach and algorithm, in terms of iterations, are presented in the following section as well.

5.4 Framework Evaluation

In this section, we provide a series of numerical results, obtained via modeling and simulation, evaluating the performance and the inherent attributes of the proposed risk-aware data offloading

Table 5.1: Values for simulation parameters

Param.	Value	Description
b_n	$10^7 \pm 10^6$ [bytes]	User's n computation task's input data
d_n	$8 * 10^9 \pm 10^9$ [CPU cycles]	CPU cycles required to accomplish user's n computation task
f_n	$6 * 10^9 \pm 10^9$ [CPU cycles/sec]	User's n device's computational capability
γ_n	$4 * 10^{-9} \pm 10^{-9}$ [J/CPU cycles]	Coefficient of the locally consumed energy per CPU cycle
a_n	0.2	User's n sensitivity on gains and losses
k_n	1.2	User's n loss aversion parameter
c_n	$0.5 * \frac{b_n}{d_n}(1 - \frac{1}{\hat{t}_n \hat{e}_n})$ [1/CPU cycles]	Pricing factor (satisfies condition of Theorem 5)
θ	$2 * 10^{-11}$	Parameter denoting the processing capability of the server

framework.

Initially, in section 5.4.1 the pure operational characteristics of the proposed framework are presented, while in section 5.4.2 the impact of the introduced usage-based pricing scheme is quantified and studied. Moreover, a scalability analysis of the proposed framework is performed in section 5.4.3, while the impact of the prospect-theoretic parameters reflecting the user behavioral pattern in terms of loss aversion and sensitivity, on the overall system performance is evaluated in section 5.4.4. The performed simulations were executed on an Intel Core i5-4300U CPU @ 1.90 GHz x 4 with 8 GB RAM. The main parameters used in our simulation, along with their typical values, are presented in Table 5.1. In the rest of the analysis, and in particular in sections 5.4.1 and 5.4.2, we have considered $N = 25$ users, and sensitivity parameter's k_n and loss aversion parameter's α_n values as indicated in Table 5.1. However, in sections 5.4.3 and 5.4.4, a wider range of the number of users and the loss aversion and sensitivity parameters are considered.

5.4.1 Pure Operation of the Framework

Fig.5.3 presents the amount of offloaded data by each user to the UAV-mounted MEC server, as well as the average amount of offloaded data as a function of the risk-aware data offloading algorithm's iterations. The results reveal that the introduced best response dynamics-based algorithm converges to the PNE quite fast and in small iterations (less than 10 iterations are required for all users). Moreover, Figs.5.4 and 5.5 illustrate each user's expected prospect-theoretic utility and the corresponding usage-based pricing imposed by the UAV-mounted MEC server as a function of the algorithm's iterations. The corresponding results reveal that initially the users tend to offload a great portion of their data to the MEC server, as observed in Fig.5.3, and therefore their expected prospect-theoretic utility increases (Fig.5.4). Specifically, at the first iteration of the algorithm, the users present an aggressive behavior in terms of offloading a large amount of data to the UAV-mounted MEC server (Fig.5.3) towards enjoying a high expected utility (Fig.5.4). However, at the same time, this behavior is expected to lead to the increase of the probability of failure of

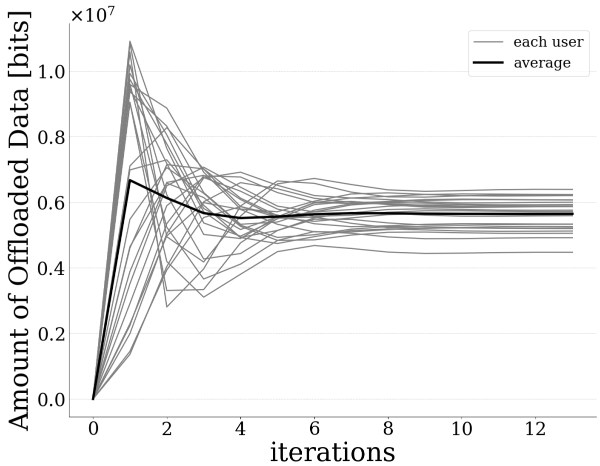


Figure 5.3: Amount of data offloaded by each user vs. iterations.

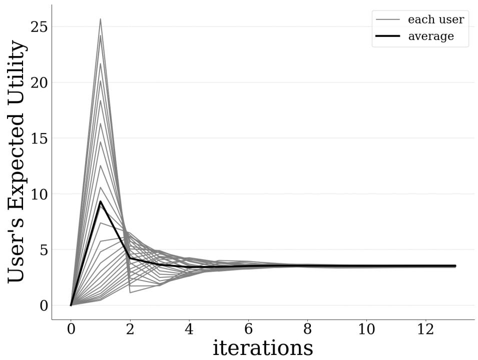


Figure 5.4: Expected utility of each user vs. iterations.

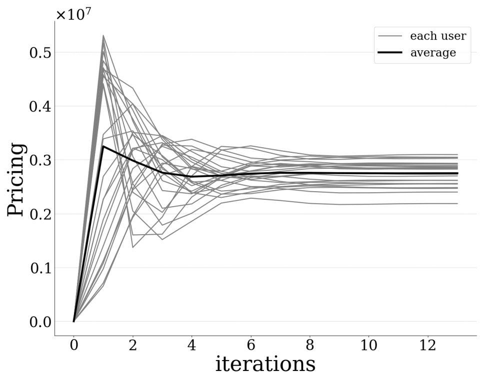


Figure 5.5: Pricing imposed by the server on each user vs. iterations.

the UAV-mounted MEC server (as it is confirmed below in Fig.5.7), and accordingly to the users having to pay a high price. This is demonstrated in Fig.5.5, where, due to the fact that the users exploit more the computing capabilities of the MEC server, the latter imposes on them a higher usage-based pricing. Consequently, in combination with the impact of probability of failure and rate of return, as the iterations evolve, the users decrease the amount of data that they offload to the MEC server (Fig.5.3) following the learning mechanism of the best response dynamics, in order to converge to the PNE.

Fig.5.6 depicts the users' average expected prospect-theoretic utility and the users' average experienced usage-based pricing for exploiting the UAV-mounted MEC server's computing capabilities, as a function of the algorithm's iterations. In addition, Fig.5.7 presents the UAV-mounted

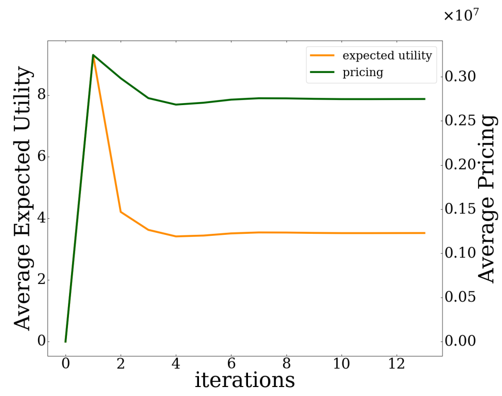


Figure 5.6: Average users' expected utility and average users' pricing vs. iterations.

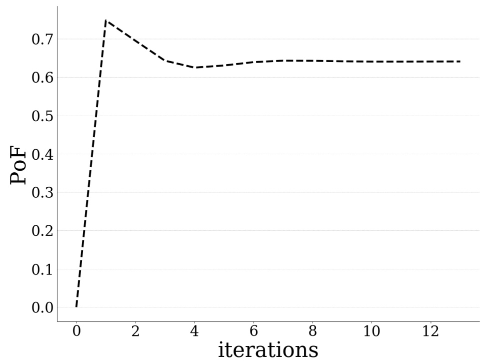


Figure 5.7: Probability of failure of MEC server vs. iterations.

MEC server's probability of failure as a function of the algorithm's iterations. The above described trend in users' data offloading strategies is observed from the system's point of view. Specifically, all the users tend initially to aggressively offload a large amount of data to the MEC server in order to achieve a greater utility (Fig.5.6). However, the probability of failure of the UAV-mounted MEC server increases due to the over-exploitation of its computing capabilities (Fig.5.7) which in combination to the high price that the users have to pay (Fig.5.6) leads to a balance on their greedy and selfish data offloading behavior.

5.4.2 Impact of Pricing

In this section, we study the impact of the usage-based pricing imposed by the UAV-mounted MEC server on the users' data offloading strategies, as well as on the overall operation of the system. Specifically, Fig.5.8 presents the probability of failure of the MEC server as a function of the pricing factor c (Eq.5.3). Moreover, the users' average expected utility, the users' average amount of offloaded data, and the pricing imposed by the MEC server are presented in Fig.5.9, as a function of the pricing factor c as well. The results reveal that, as the pricing policy becomes stricter (i.e., increasing values of the pricing factor), the usage-based pricing experienced by the users increases (Fig.5.9) and the exploitation of the MEC server's computing capabilities becomes cost inefficient after some point (with respect to the total offloaded data). Consequently, the users tend to offload a smaller amount of data to the MEC server (Fig.5.9), and the MEC server becomes less congested in terms of processing the users' computation tasks, and its probability of failure decreases (Fig.5.8).

Based on the results presented in Fig.5.9, it is observed that the users' average expected utility is concave with respect to the pricing factor. Specifically, small values of the pricing factor correspond to less-strict pricing policies; thus, the users over-exploit the MEC server's computing capabilities (i.e., high values of MEC server's probability of failure and low rate of return from the servers

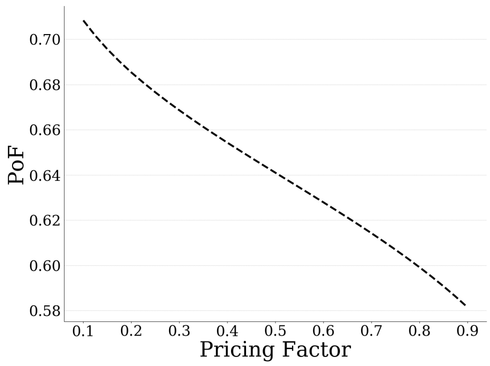


Figure 5.8: Probability of failure of MEC server vs. the pricing factor.

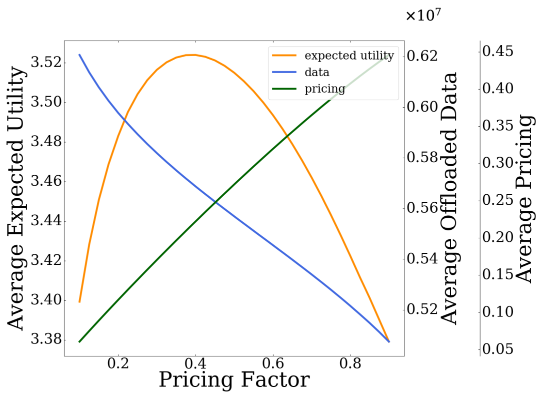


Figure 5.9: Average expected utility, offloaded data, and pricing vs. the pricing factor.

are observed), resulting in low values of expected utility. On the other hand, high values of the pricing factor result in discouraging the users to exploit the UAV-mounted MEC server's computing capabilities, thus concluding again to low levels of users' average expected utility. Therefore, a balanced pricing policy is required to keep the quality of experience of the users at high levels.

5.4.3 Scalability Evaluation

In this section, a scalability evaluation of the proposed risk-aware data offloading framework is provided considering an increasing number of users in the system. Table 5.2 presents the iterations and the overall corresponding simulation time of the proposed algorithm in order to converge to the PNE point. Given the distributed nature of the best response dynamics approach, we observe that its simulation time scales quite well for increasing number of users, achieving a close to real-time implementation in realistic scenarios. Respectively, the users' average expected utility, the users' average amount of offloaded data, and the imposed pricing by the UAV-mounted MEC server are presented in Fig.5.10, as a function of the number of users. The scalability evaluation is complemented by the results presented in Fig.5.11 that depict the convergence of the users' average amount of offloaded data as a function of the required number of iterations, for different numbers of users. In particular, we observe that, as the number of users in the system increases, they tend to offload a lower average amount of data to the MEC server (Figs.5.10 and 5.11), as the latter becomes over-congested. Thus, they experience both lower pricing (Fig.5.10) and lower expected utility (Fig.5.10), as they drive themselves in processing more data locally on their local devices and accordingly consume their own resources, i.e., battery. It is also observed that the user's experienced pricing $c_n(b_n^{MEC})$ and the user's offloaded data b_n^{MEC} (Fig.5.10) has the same trend, due to their one-to-one relationship stemming from Eq.5.3, while the corresponding curves also appear to be overlapping. However, it should be noted here that the actual values for the two curves are different, since there are two different right vertical axes in Fig.5.10 (each one reflecting

Table 5.2: Algorithm's simulation time per user for a different number of users

N	Iterations	Time Per User [sec]
1	3	0.0036
2	3	0.0042
5	3	0.0049
10	6	0.0095
25	14	0.0122
50	31	0.0282
75	54	0.0640
100	83	0.0979

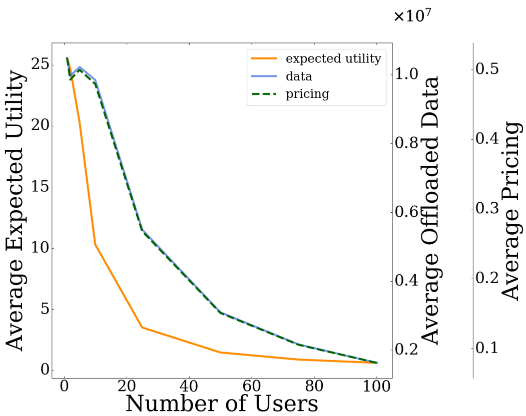


Figure 5.10: Users' average expected utility, users' average offloaded data and pricing at the PNE vs. number of users on the system.

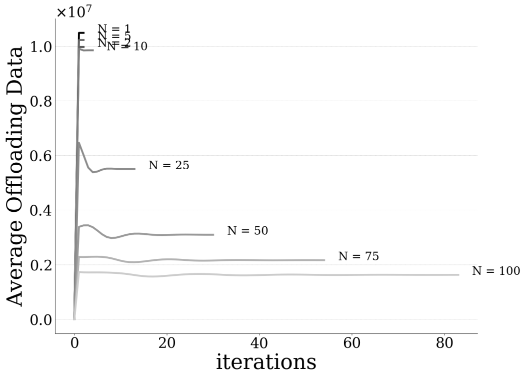


Figure 5.11: Users' average data offloading vs. iterations for different numbers of users.

the values of each curve respectively).

5.4.4 Impact of Prospect-Theoretic Parameters and User Competition

In the following, the impact of the prospect-theoretic parameters, reflecting the user behavioral pattern in terms of loss aversion and sensitivity, on the overall system performance is evaluated.

Specifically, in Figs.5.12 and 5.13, initially we present the average user offloaded data and corresponding probability of failure, as functions of the sensitivity parameter α_n and the loss aversion index k_n, respectively. As can be seen from Fig.5.12, by increasing the sensitivity parameter α_n, the users tend to offload more data to the MEC server since they opt to value more the larger gains, compared to those of smaller magnitude. The increased volume of data offloaded results in an increase in the corresponding probability of failure of the server as well. In Fig.5.13, on the other hand, we can see that, as the loss aversion index k_n increases, less data are offloaded to the server, since higher value signifies more loss aversion for the users, resulting in smaller probability

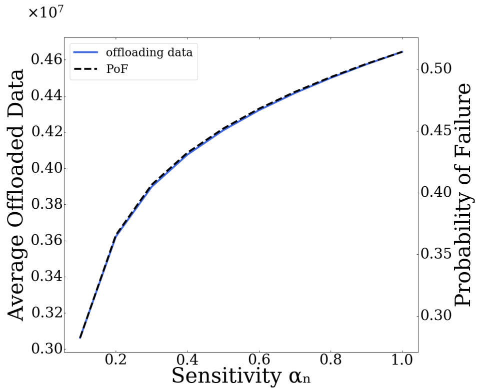


Figure 5.12: Average offloading data and PoF vs. sensitivity parameter α_n.

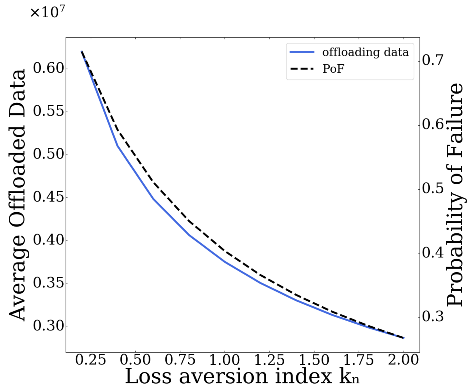


Figure 5.13: Average offloading data and PoF vs. loss aversion index k_n.

of failure of the server.

In order to further study the effect of competition of users for the CPR (i.e., UAV-mounted MEC server), we use the Fragility under Competition (FuC) metric [26]. This metric is expressed as the ratio between the probability of failure of the MEC server when N users are competing for the MEC server's resources at the equilibrium state, versus the probability of failure of the MEC server when there is only one user offloading data. Formally, the Fragility under Competition is defined as: $FuC = \frac{Pr(\mathbf{b_N^{MEC^*}})}{Pr(\mathbf{b_1^{MEC^*}})}$, where $b_N^{MEC^*}$ denotes the equilibrium point when N users are present and $b_1^{MEC^*}$ denotes the corresponding equilibrium point if only one user was present, with the same risk preferences as the group of N users.

In Figs.5.14 and 5.15, we present the FuC metric as a function of the number of users in the system, for different values of the sensitivity parameter α_n and the loss aversion index k_n, respectively. In both figures, we observe that, as the number of users increases, the FuC increases as well, since more users are competing for the CPR and consequently more data are offloaded to the server, until it eventually plateaus. Concerning the effect that the prospect-theoretic parameters have on the FuC metric, in Fig.5.14, we can see that the higher the value of the sensitivity parameter α_n, the higher the FuC as well. This is justified by the fact that, the higher the values of α_n, the greater the sensitivity of the users towards gains and losses of higher magnitude compared to those of smaller magnitude (Fig.5.12). As a result, users tend to offload more data to the MEC server and the server is more prone to failure, and accordingly an increase in FuC is expected. With respect now to the loss aversion index k_n, we can see in Fig.5.15 that, as k_n increases, the FuC decreases. This is due to the fact that, as k_n increases, users become more loss averse and thus they tend to offload less data to the MEC server in order to avoid potential failure as already shown in Fig.5.13. The less data are offloaded to the server, the less the probability that the server will fail, thus resulting in lower FuC. It is clarified that the overall observed increasing trend of the FuC w.r.t. the increasing number of users in these figures is well aligned with the fact that the

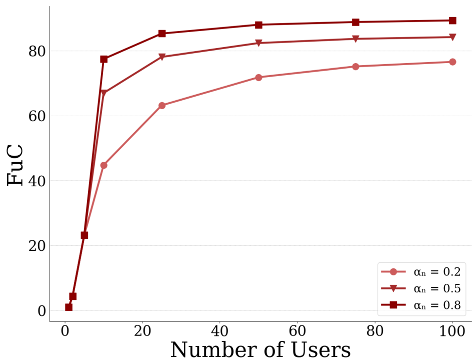


Figure 5.14: Fragility under Competition vs. number of users for different sensitivity parameters α_n.

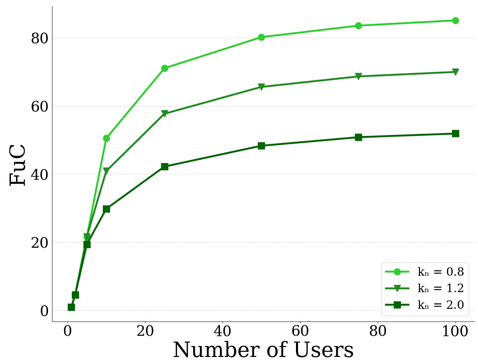


Figure 5.15: Fragility under Competition vs. number of users for different loss aversion indices k_n.

failure probability is an increasing function of the total offloaded data of all users. However, the actual slope of the corresponding curves mainly depends on the used values for α_n and k_n for the generation of these curves, which are selected here only for demonstration purposes, and are not correlated with each other in any way.

5.5 Summary

In this chapter, a resource-based pricing and user risk-aware data offloading framework was proposed for UAV-assisted multi-access edge computing systems. In particular, a usage-based pricing mechanism was utilized regarding the exploitation of the MEC server's computing capabilities by the users, and was properly incorporated within the principles and modeling of Prospect Theory, which was used to capture the users' risk-aware behavior in the overall data offloading decision-making. On the other hand, the UAV-assisted MEC server's resources were modeled based on the theory of Common Pool Resources and the theory of the Tragedy of the Commons.

Initially, the user's prospect-theoretic utility function was formulated by quantifying the user's risk seeking and loss aversion behavior, while taking into account the pricing mechanism. Accordingly, the users' pricing and risk-aware data offloading problem was formulated as a distributed maximization problem of each user's expected prospect-theoretic utility function and addressed as a non-cooperative game among the users. The existence of a Pure Nash Equilibrium for the formulated non-cooperative game was proven based on the theory of submodular games. An iterative and distributed algorithm was introduced that converges to the PNE, following the learning rule of the best response dynamics. Detailed numerical results were presented highlighting the operation feature and scalability properties of the proposed framework, the dependency of the framework on the different variables of the introduced model, while at the same time providing useful insights about the benefits of adopting the usage-based pricing scheme.

Even though the proposed framework mainly treats the problem from a computing resources perspective, it is interesting to note that it could easily be adapted and extended to treat other aspects as well, such as the wireless communication aspects between the UAV and users, depending on the environment assumed. This could be done either implicitly through the cost factors and functions considered when using the server resources, or explicitly by modeling the transmission characteristics (e.g., delay, rate, energy) involved in the offloading process. Additionally, more complex functions could be used to more realistically model the aforementioned concepts, as long as they follow the aforementioned established principles.

Chapter 6

Pricing & Risk-aware Data Offloading in Multi-server Multi-access Edge Computing

6.1 General Setting

In the previous chapter we tackled the problem of computational task offloading to a Multi-access Edge Computing server, where users exhibit risk-aware behavior on their decision-making process, while treating the MEC server as a Common Pool Resource. In order to formulate the problem under the aforementioned considerations, we applied the principles of Prospect Theory and the Tragedy of the Commons theory to our framework design. While the results where promising, we focused on the user's side decision-making process, with the existence of a single MEC server to offload to, and a fixed pricing mechanism for the service provided.

In this chapter we will extend the existing framework in order to address this issue, by introducing multiple servers in the environments and studying the impact of the users behavioral characteristics and the MEC servers pricing policies on determining the optimal users data offloading strategies, by simultaneously maximizing the users' perceived service satisfaction and the MEC servers' profit. More specifically users are modeled as risk-aware maximizers willing to achieve the best perceived Quality of Experience by jointly selecting the server and the amount of data that they wish to offload to, given the servers' pricing for the service. On the other hand, the servers are responsible of selecting the pricing policy that they will impose for their service to the users, given the choices of the users. In order to avoid omnipotent and omniknowing centralized entities, we modeled the problem as a Stackelberg game, where servers act as leader and users act as followers. The behavioral and economic modeling is once again performed based on the principles of Prospect Theory and Network Economics, while the users' and MEC servers' distributed decision-making is facilitated by game-theoretic and reinforcement learning-based approaches.

6.2 Related Work

Significant research efforts have been devoted to the investigation of the problem of multi-user and multi-server data offloading in MEC environments, under various settings. In [114], the authors introduced a multi-variable centralized minimization problem of the users' energy cost and experienced latency by jointly determining the optimal users' data offloading strategies, users' scheduling, and resource allocation. In [115], the authors focused their study on small cell networks, where each small cell's access point is equipped with a MEC server. In particular, the authors determined the users' optimal data offloading strategies in a distributed manner via a game-theoretic approach based on the theory of potential games, while also addressing the minimization problem of the users' energy consumption and service delay. The data offloading problem in vehicular networks was studied in [116], where the MEC servers reside at the road side units. A combination of convex optimization and a game-theoretic approach was introduced to optimize the system wide profit of both the vehicles and the network operator via determining the optimal communication channel allocation, data offloading, and task scheduling at the MEC servers. A similar approach was introduced in [117] enabling the patients' medical nodes to offload data to MEC servers. The authors considered the patients' nodes' medical criticality, age of information, and energy constraints to determine their optimal data offloading strategies and communication channel allocation, based on a non-cooperative game-theoretic approach. The incorporation of both communication and computational capabilities of the system, utilizing principles of prospect theory, has been studied in single MEC environments [118] and multi MEC environments [119, 120].

Apart from the game-theoretic approaches, reinforcement learning-based techniques have also been devised in the literature to address the data offloading problem. In [121, 122] principles of machine learning and reinforcement learning have been applied in MEC environments to enhance the reputation of the system and the Quality of Experience of the users. In [123], a budged-limited multi-armed bandit problem was formulated in order to enable the users to select the MEC server that minimizes their latency and energy consumption, as well as the corresponding amount of offloaded data. A similar problem formulation was introduced in [124] with application on vehicular networks. Specifically, the authors consider the vehicles' mobility, the MEC servers' heterogeneous computation resources, and the vehicles diverse computation demand in the designed multi-armed bandit learning algorithm. Moreover, an ϵ-greedy non-stationary multi-armed bandit-based scheme for online data offloading was introduced in [125] targeting at the minimization of the users' energy consumption and latency, and the MEC servers' computation resource usage optimization.

On the other hand, rather limited research effort has been devoted to the problem of optimal computing service pricing from the MEC servers' side. In [67], several types of pricing policies, such as multi-dimensional pricing, penalty pricing, and discount pricing, have been proposed to study the different number of virtual machines that a cloudlet can accommodate. Aiming at minimizing the users' cost, while jointly maximizing the edge cloud's profit, a two-side game is introduced in [126] and [127] to determine the optimal MEC servers' price and the users' data offloading strategies. In [128], a static pricing-based approach is proposed to guide the users' cooperation with the MEC servers to conclude to a stable operational point. A dynamic pricing mechanism is introduced in [129] to minimize the overall MEC system's cost, while guaranteeing the satisfaction of the users' Quality of Service (QoS) constraints.

It should be noted that all the aforementioned research works consider the users as rational decision-makers aiming at maximizing their perceived utility, while interacting with the MEC servers. However as already mentioned in Chapter 5, in a realistic edge computing environment this is not always the case as the users typically demonstrate a risk-aware decision-making behavior, where the risk primarily stems from the scarcity due to the potential over-exploitation of the computation resources available to the MEC servers. Related work on the use of Prospect Theory whose principles are often exploited to tackle the decision-making under uncertainty can be found in section 5.2.

6.3 Proposed Framework

6.3.1 Multi-Access Edge Computing

Behavior and Price-aware Modeling

We consider a multi-user multi-server multi-access edge computing environment, consisting of a set of users $N = \{1, \dots, n, \dots, |N|\}$ and a set of MEC servers $S = \{1, \dots, s, \dots, |S|\}$. Each user requests a service that is characterized by a computation task $J_n = (b_n, i_n)$, where b_n [bits] denotes the input bits that need to be processed and i_n [CPU Cycles] the computation demand of the user's service, expressing the number of necessary CPU Cycles to process the b_n bits. Each user can select one server to offload $b_{n,s}^{MEC}$ [bits] amount of data, while the rest of the data, i.e., $b_n - b_{n,s}^{MEC}$, are processed locally on the user's device. The user's device computation capability is denoted as f_n [CPU Cycles/sec] and the consumed energy per CPU Cycle to locally process the user's data is γ_n [J/CPU Cycles]. The total processing time for each user's computation task, if it is fully processed locally, is $t_n = \frac{i_n}{f_n}$ [sec] and the corresponding consumed energy is $e_n = \gamma_n i_n$ [J]. Each MEC server charges p_s [$/bit] monetary units per bit of processed data to perform the computing.

The computing capabilities of the MEC servers are assumed to be shared among the users, thus, they are treated as a Common Pool of Resources (CPR). Given that the CPR is excludable, rivalrous, and can be commonly accessible to all users, the phenomenon of the Tragedy of the Commons may arise [81]. Thus, the MEC servers may fail to serve the users due to potential over-exploitation, and no user will enjoy the computing capabilities of the server that failed. The users may experience risks in their decision-making process, i.e., to which server to offload part of their data, which may stem from either the complete failure or the depletion of the computing resources, caused by the potential (over)exploitation of the CPR, i.e., fragility of the shared resources. Thus, each user reacts in a personalized risk-aware manner based on its perception of the MEC servers' computing resources' usage. It is highlighted that in emerging complex MEC systems, due to the fact that different MEC servers may be owned by different service providers, the solution of a centralized entity performing admission control and task scheduling would not be realistic, or even feasible is several cases.

Based on the general principles of Prospect Theory, the users present different behavior (i.e., utility values), expressed as satisfaction or dissatisfaction, based on the gains or losses they experience from a service. Specifically, based on the loss aversion property, the users experience greater dissatisfaction in the case of losses compared to the perceived satisfaction from gains of the same magnitude. The aforementioned gains and losses are determined with respect to a predefined reference point $U_{n,0}$, which in our case is defined as $U_{n,0} = \frac{b_n}{t_n e_n}$. The latter captures the user's perceived utility if it processed the whole amount of its data locally on its own device.

The user's prospect-theoretic utility by offloading $b_{n,s}^{MEC}$ data to a MEC server follows the same principles as in 5.3 and, as before, it is defined formally as follows:

$$P_{n,s}(U_{n,s}) = \begin{cases} (U_{n,s} - U_{n,0})^{\alpha_n}, & \text{if } U_{n,s} \geq U_{n,0} \\ -k_n(U_{n,0} - U_{n,s})^{\beta_n}, & \text{otherwise} \end{cases} \tag{6.1}$$

where $\alpha_n, \beta_n \in [0,1]$, and $k_n \in R^+$. The risk-aware parameters α_n, β_n reflect the users' risk-averse behavior in gains, and risk-seeking behavior in losses, respectively. Also, the loss aversion parameter k_n captures the way that the user weighs the losses and gains. Specifically, the user weighs the gains more than ($k_n < 1$) or equal to ($k_n = 1$) the losses, while the opposite holds true if $k_n > 1$. In the following analysis, without loss of generality, we consider that the users' risk-aware parameters are equal, i.e., $\alpha_n = \beta_n, \forall n \in N$.

The user's actual utility function $U_{n,s}(b_{n,s}^{MEC})$ captures the user's actual satisfaction from: either a) processing all its data locally on its device (first branch of Eq. 6.2 or b) offloading part of its data to a MEC server while the latter one survives (second branch of Eq. 6.2), or c) offloading part of its data to a MEC server while the latter one fails (third branch of Eq. 6.2). The user's actual utility function is defined as follows:

$$U_{n,s}(\mathbf{b}_s^{MEC}) = \begin{cases} \dfrac{b_n}{t_n e_n}, & \text{if } b_{n,s}^{MEC} = 0 \\ \frac{b_n - b_{n,s}^{MEC}}{t_n e_n} + b_{n,s}^{MEC} R(D_s) - c_s(b_{n,s}^{MEC}), & \text{if } b_{n,s}^{MEC} \neq 0 \\ & \text{\& } s \text{ survives} \\ \dfrac{b_n - b_{n,s}^{MEC}}{t_n e_n} - c_s(b_{n,s}^{MEC}), & \text{if } b_{n,s}^{MEC} \neq 0 \\ & \text{\& } s \text{ fails} \end{cases} \tag{6.2}$$

where $\mathbf{b}_s^{MEC}$ denotes the data offloading vector of all the users, and $c_s(b_{n,s}^{MEC})$ denotes the user's cost by processing its data to the MEC server s. The latter is obtained based on the announced price p_s [$] by the MEC server s and the corresponding normalized amount of its offloaded data. Therefore, the user's cost are formally defined as follows:

$$c_s(b_{n,s}^{MEC}) = p_s i_n \frac{b_{n,s}^{MEC}}{b_n} \tag{6.3}$$

The physical meaning of Eq. 6.3 is that, as expected, a user experiences a higher cost from the MEC server either due to a high computing service price or if it requests a large amount of data to be processed or if the data are characterized by high computation demand to be processed at the MEC server. Furthermore, the second branch of Eq. 6.2 is formulated based on the satisfaction that a user experiences from offloading part of its data to the MEC server (first term), while considering the cost that is charged with to process its data at the server (third term) and the rate of return $R(D_s)$ that it experiences by having its data $b_{n,s}^{MEC}$ processed at the edge (second term). The rate of return implicitly reflects the value that the user gains from to the remote execution of its task. In particular, the rate of return function $R(D_s)$ is assumed to be continuous and monotonically decreasing with respect to the users' normalized effective demand D_s from the server (formally defined below). Thus, if the users' normalized effective demand D_s is high, meaning that the MEC server's computing capabilities are over-exploited, the satisfaction that the users experience by processing their data to the server is decreased due to an increased data processing delay. For demonstration purposes, in the following analysis, the MEC servers' rate of return function is formulated once again as follows:

$$R(D_s) = 2 - e^{D_s - 1}. \tag{6.4}$$

The users' normalized effective demand D_s from the MEC server s is a sigmoidal function that maps the users' actual computing demand $d_s = \sum_{n=1}^{|N|} i_n \frac{b_{n,s}^{MEC}}{b_n}$ from the MEC server s to the interval $[0, 1]$ and is a continuous and strictly increasing function with respect to d_s, defined as follows:

$$D_s(d_s) = -1 + \frac{2}{1 + e^{-\theta_s d_s}}. \tag{6.5}$$

where parameter $\theta_s > 0$ is a positive constant which is used to calibrate the sigmoidal curve to appropriately capture the MEC servers' computing capabilities. Given the CPR nature of the MEC server's computing capability, due to the joint exploitation from multiple users that offload their data to the same server, the latter one is characterized by a probability of failure $Pr_s(D_s)$ depending on the users' normalized effective demand D_s. The MEC server's probability of failure is a continuous and strictly increasing function with respect to the users' demand D_s and can be indicatively defined as $Pr_s(D_s) = D_s^2$.

Based on the previous analysis and discussion, and for simplicity in the presentation, let us denote as $U_{n,s}^{surv.}$ and $U_{n,s}^{fail}$ the second and third branch of Eq. 6.2, respectively. Then the user's prospect-theoretic utility function, as expressed in Eq. 6.1, can be rewritten as follows,

$$P_{n,s}(b_{n,s}^{MEC}, \mathbf{b}_{-n,s}^{MEC}) = \begin{cases} P_{n,s}^{surv.} = (U_{n,s}^{surv.} - \frac{b_n}{t_n e_n})^{\alpha_n}, & \text{if } U_{n,s}^{surv.} \geq U_{n,0} \\ P_{n,s}^{fail} = -k_n(\frac{b_n}{t_n e_n} - U_{n,s}^{fail})^{\alpha_n}, & \text{otherwise} \end{cases} \tag{6.6}$$

where $\mathbf{b}_{-n,s}^{MEC}$ denotes the data offloading vector of all the users except for user n to the MEC server

s.

One of the key principles and findings of Prospect Theory, states that the users tend to overestimate the likelihood of events with low probability of failure and underweight outcomes with high probability of failure, i.e., $\pi(Pr_s) > Pr_s$ for small Pr_s values and $\pi(Pr_s) < Pr_s$ for large Pr_s values. This latter observation of how humans behave under risk-aware decision-making processes is defined as the probability weighting phenomenon. The prospect-theoretic probability weighting function $\pi(Pr_s)$ of outcomes with different likelihood to occur, following the proposed function in [27], is defined as follows:

$$\pi(Pr_s) = e^{-(-\ln(Pr))^{\gamma}} \tag{6.7}$$

where $\gamma \in (0, 1)$ denotes the psychological distortion parameter.

Considering the aforementioned probabilities, the user's expected prospect-theoretic utility function from offloading part of its data to a selected MEC server is defined below.

$$\mathbb{E}(P_{n,s}(b_{n,s}^{MEC}, \mathbf{b}_{-n,s}^{MEC})) = P_{n,s}^{surv.}(1 - \pi(Pr_s)) + P_{n,s}^{fail}\pi(Pr_s) \tag{6.8}$$

Focusing on the MEC servers' side, each MEC server announces the price p_s for serving the user's computing requests, while bearing an operational cost κ_s [\$] to process the data and support its operation. Each MEC server's reward from participating in the MEC environment is defined as

$$\mathcal{R}(p_s) = B_s(p_s - \kappa_s) \tag{6.9}$$

where $B_s = \sum_{n=1}^{|N|} b_{n,s}^{MEC}$ is the total amount of offloaded data to the MEC server s.

Focusing on the network economics-based operation of a MEC server, we make the following observations. A MEC server naturally tends to increase its announced price p_s if: a) its operational cost is high, b) it processes a large amount of data, reaching its maximum capacity B^{MAX} [bits] in terms of data that can simultaneously process, and c) the rest of the MEC servers increase their price $\mathbf{p}_{-s} = [p_1, \dots, p_{s-1}, p_{s+1}, \dots, p_{|S|}]$, in order to remain competitive in the edge computing market. Based on these observations, we define the MEC server's payoff function that captures the aforementioned aspects, as follows.

$$W(p_s) = -(p_s - \frac{B_s}{B^{MAX}}\kappa_s \frac{\sum_{\forall j \neq s} p_j}{p_s})^2 \tag{6.10}$$

An overview of the operation of the proposed risk and price-aware multi-user multi-server multi-access edge computing system is presented in Fig.6.1. We formulate its operation as a multi-leader multi-follower Stackelberg game, where the users act as followers, determining their optimal amount of offloaded data, and the MEC servers behave as leaders, announcing their optimal price to provide their computing services to the users.

Initially, the MEC servers select the prices to impose to the users (e.g. randomly) without any knowledge on the amount of data that each user is willing to offload. Given the MEC servers' prices,

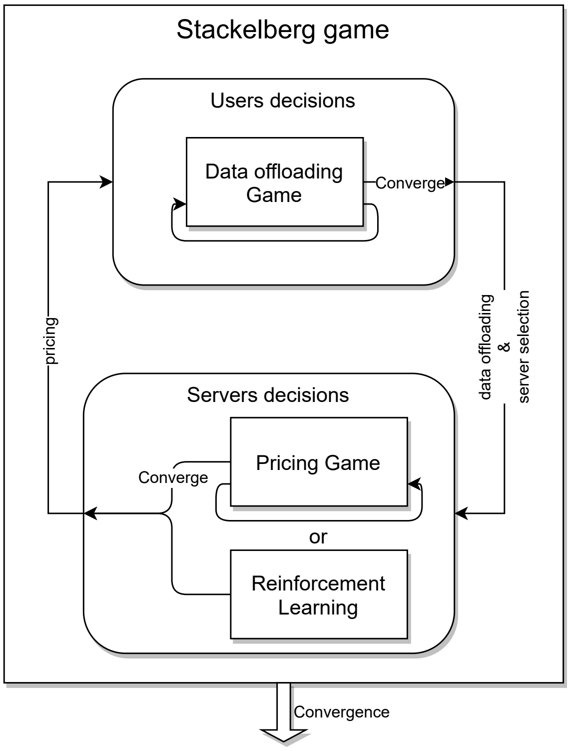


Figure 6.1: Overview of the proposed framework

the users participate in a non-cooperative game among them, in order to determine the server with whom they want to associate with, as well as the optimal amount of offloaded data. This is done based on the criterion of each user maximizing its perceived expected prospect-theoretic utility function, as defined in 6.8. The latter outcome in turn acts as input to the MEC servers, who determine the optimal announced prices to offer their computing services to the users. It is noted that the optimal prices of the MEC server are determined with two different alternatives based on the information availability among the MEC servers, as well as the methodological learning philosophy adopted to conclude to the optimal solutions. Specifically, a semi-autonomous game-theoretic model and a fully-autonomous reinforcement learning-based model are introduced and their drawbacks and benefits are discussed and demonstrated in a comparative manner. The interaction among the users and MEC servers is repeated iteratively until the overall system converges to a Stackelberg equilibrium, where the users' data offloading strategies and the MEC servers' prices have converged to the optimal values.

6.3.2 Optimal Data Offloading

In this section, the problem of determining the MEC servers' selection by the users and the optimal data offloading strategies is formulated as a distributed optimization problem. Each user aims at selecting the MEC server that will eventually maximize the user's expected prospect-theoretic utility, while in parallel determining the optimal data offloading strategy. The corresponding optimization problem is formulated as follows:

$$\begin{aligned} &\max_{\forall s \in S}\{\max_{b_{n,s}^{MEC}} \mathbb{E}(P_{n,s}(b_{n,s}^{MEC}, \mathbf{b}_{-n,s}^{MEC}))\}, \\ &\text{s.t. } 0 \leq b_{n,s}^{MEC} \leq b_n \end{aligned} \tag{6.11}$$

Thus, a user selects the MEC server that maximizes the maximum potential expected prospect-theoretic utility. Towards determining the latter value, the nested optimization problem should be addressed as follows:

$$\max_{b_{n,s}^{MEC} \in [0, b_n]} \mathbb{E}(P_{n,s}(b_{n,s}^{MEC}, \mathbf{b}_{-n,s}^{MEC})). \tag{6.12}$$

The optimization problem in Eq. 6.12 can be addressed as a non-cooperative game among the users, who compete among each other about the MEC server's computing resources in the same way as in chapter 5. The non-cooperative game is defined as $G = [N, \{\mathcal{B}_n\}_{\forall n \in N}, \{\mathbb{E}(P_{n,s})_{\forall n \in N}\}]$, where N is the set of users, $\mathcal{B}_n = [0, b_n]$ is each user's strategy set, and $\mathbb{E}(P_{n,s})$ is the user's expected prospect-theoretic utility function. Our goal is to determine a Nash Equilibrium (NE) point, where the users have converged to their optimal data offloading strategies.

Towards determining the existence of a Nash Equilibrium of the non-cooperative game G, we show that the game is submodular.

Theorem 6. *The non-cooperative game $G = [N, \{\mathcal{B}_n\}_{\forall n \in N}, \{\mathbb{E}(P_{n,s})_{\forall n \in N}\}]$ is submodular and has at least one Nash Equilibrium point.*

Proof. The proof can be concluded following similar reasoning and steps as A.3 after replacing the probability function Pr_s with the weighted probability function $\pi(Pr_s)$ from Eq.6.7. □

Based on Theorem 6, the existence of at least one Nash Equilibrium point is shown. Thus, each user can determine its optimal amount of offloaded data $b_{n,s}^{MEC*}$ to a MEC server s and select the MEC server s that maximizes its maximum expected prospect-theoretic utility, as expressed in Eq. 6.11. The Nash Equilibrium point can be practically determined by following a Best Response Dynamics algorithm as in section 5.3.4.

6.3.3 Computing Service Pricing

In the following section our goal is to determine the optimal announced prices by the MEC servers given the users' optimal data offloading strategies $b_{n,s}^{MEC*}, \forall n \in N, s \in S$. It should be noted that these prices are utilized by the process described in section 6.3.2 to determine the users' optimal data offloading, in an overall iterative manner. As defined in Eq. 6.10, each MEC server aims at maximizing its payoff, and therefore, the optimization problem can be defined accordingly as follows.

$$\max_{\{p_s\}_{\forall s \in S}} W(p_s) = -(p_s - \frac{B_s}{B^{MAX}} \kappa_s \frac{\sum_{\forall j \neq s} p_j}{p_s})^2 \tag{6.13}$$

The above optimization problem can be treated and solved in principle based on standard convex optimization techniques, given that the payoff function $W(p_s)$ is concave with respect to the price p_s. However, such an approach would not be realistic in a real-life implementation, as a centralized entity should perform the optimization and inform the MEC servers about their optimal prices. Several reasons however would render such an approach either infeasible or prohibitive in practice. Indicatively we refer to the fact that MEC servers may be owned by different providers, the centralized entity making the decisions is a single point of failure, while significant signaling overhead would be imposed to the MEC servers to interact with the centralized entity. Thus, the need of devising an autonomous decision-making approach for the MEC servers arises. In the following subsections, we particularly focus on this problem and present two strategies to determine each MEC server's optimal announced price: a semi-autonomous game-theoretic approach which has the objective of directly treating the problem in Eq. 6.13, and a fully-autonomous alternative approach of concluding to the optimal price, based on reinforcement learning.

Game-Theoretic Approach

The optimization problem in Eq. 6.13 can be formulated as a non-cooperative game $\mathbb{G} = [S, \{P_s\}_{\forall s \in S}, \{W(p_s)\}_{\forall s \in S}]$ among the servers, where $P_s = [p_{min}, p_{max}]$ denotes their strategy set and $W(p_s)$ their payoff function. Towards showing the existence and uniqueness of a Nash Equilibrium point, and accordingly determining their optimal prices $p_s^*, \forall s \in S$, we follow the theory of n-person concave games, where $n = |S|$.

Lemma 1 (Existence and Uniqueness of Nash Equilibrium)**.** *A non-cooperative game $\mathbb{G} = [S, \{P_s\}_{\forall s \in S}, \{W(p_s)\}_{\forall s \in S}]$ is an n-person concave game and admits a unique Nash Equilibrium point, if the following conditions hold true [130]:*

1. *the strategy sets $P_1, \dots, P_{|S|}$ are non-empty, compact, convex subsets of finite dimensional Euclidean spaces,*
2. *all payoff functions $W(p_1), \dots, W(p_{|S|})$ are continuous on $P = P_1 \times \cdots \times P_{|S|}$, and*
3. *every payoff function is concave with respect to p_s, if all other strategies are held fixed.*

Theorem 7. *The non-cooperative game $\mathbb{G} = [S, \{P_s\}_{\forall s \in S}, \{W(p_s)\}_{\forall s \in S}]$ is an n-person concave game and its unique Nash Equilibrium point is:*

$$p_s^* = \sqrt{\frac{B_s}{B^{MAX}} \kappa_s \sum_{\forall j \neq s} p_j} \tag{6.14}$$

Proof. By definition, the strategy sets $P_1, \dots, P_{|S|}$ are non-empty, compact and convex, and the payoff function $W(p_s)$ of each server is continuous on p_s. Also, it holds true that

$$\frac{\partial^2 W(p_s)}{\partial p_s^2} = -2 - 6\frac{(\frac{B_s}{B^{MAX}}\sum_{\forall j \neq s} p_j)^2}{p_s^4} < 0, \tag{6.15}$$

thus, the payoff function of each MEC server is concave with respect to p_s. Therefore, the non-cooperative game $\mathbb{G}$ is an n-person concave game and admits a unique Nash Equilibrium point:

$$\frac{\partial W(p_s)}{\partial p_s} = 0 \Rightarrow p_s^* = \sqrt{\frac{B_s}{B^{MAX}}\kappa_s \sum_{\forall j \neq s} p_j} \tag{6.16}$$

□

The Nash Equilibrium point in Eq. 6.14 can be determined by implementing a Best Response Dynamics algorithm. Based on Eq. 6.14, it is observed that each MEC server needs to be aware of the summation of the prices of all the rest of the MEC servers existing in the examined edge computing environment. In practice, the overall summation of the MEC servers' prices can be broadcasted by a market regulatory entity, which monitors the proper operation of the computing market, to all the MEC servers/edge computing providers. However, the final decision of the optimal announced price is performed by each MEC server in a distributed manner. Thus, the proposed game-theoretic approach to determine the MEC servers' optimal prices is characterized as semi-autonomous. Towards realizing a fully-autonomous decision-making approach for the MEC servers' optimal announced prices, a reinforcement learning model is proposed.

Reinforcement Learning Approach

The proposed reinforcement learning-based model aims to generate the highest profit for the servers without requiring any knowledge on how their choice affects the amount of data offloaded to them or the pricing of the other servers; the decisions are achieved by simply observing the effects that each server's actions have on its own profit. Towards achieving this goal, we model the decision-making problem as a Multi-Armed Bandit problem, where the MEC servers have to make a selection from a set of actions [131]. In the Multi-Armed Bandit problem, each action provides a random reward from a probability distribution specific to the action and the MEC server selects the action that generates the highest reward. During this process, a balance should be kept among exploiting the actions that have already been found to perform well and exploring new actions in order to gather more information on the expected reward of the rest of the actions. It should be noted that in our case, the reward does not derive from a probability distribution but rather from a complex decision making process from the users and the rest of the servers.

Initially, we discretize the pricing strategy space $P_s = [p_{min}, p_{max}]$ in distinct actions within a range of a minimum and a maximum price thus having a set A of M actions $A = \{a_1, \dots, a_m, \dots, a_M\}$ where $a_m \in [p_{min}, p_{max}]$. Each server can choose at each timeslot a pricing action from the action set A based on which the users play their data offloading game. Thus, at the end of the timeslot the servers observe the reward that they gain (Eq. 6.9) and can decide on the pricing action of the next timeslot.

In order to solve the Multi-armed Bandit problem, we adopt the Upper Confidence Bound algorithm (UCB1) [132] that has been proven to have a bounded cumulative regret. The cumulative regret is the metric measuring the efficiency of the algorithm and corresponds to the difference between the cumulative reward of the proposed action and that of the best possible action (which is unknown to the MEC server beforehand). Apart from the regret guarantees, the proposed algorithm allows us to fine-tune the range of the confidence interval and favor exploration, increasing the probability of choosing less explored actions or exploitation, increasing the probability of selecting a well performing action, according to each individual use case

The main idea of the Upper Confidence Bound algorithm is that the MEC server keeps a record of the average reward that it obtains, via selecting each action, as well as a confidence interval based on the total number of times the action was selected. Then, instead of choosing the action with the best average reward, it chooses the action with the best upper bound of the interval, meaning that it chooses the action with the best potential. Specifically, the MEC server chooses the action that maximizes the following score:

$$score_{a_m} = \bar{x}_{a_m} + \sqrt{\frac{2\ln(n_{a_m})}{t}} \tag{6.17}$$

where a_m is the action, $\bar{x}_{a_m}$ is the average reward experienced by the MEC server for the action a_m, n_{a_m} is the number of times that the action a_m has been chosen and t is the total number of iterations of the algorithm.

6.4 Framework Evaluation

In this section, the performance evaluation of the proposed optimization and decision-making framework is realized via modeling and simulation. Initially in section 6.4.1, we demonstrate the pure operation performance of the proposed framework, considering the semi-autonomous game-theoretic model to determine the MEC servers' optimal prices. Subsequently, in section 6.4.2, the evaluation is extended to demonstrate the operation and tradeoffs of the adoption of a fully-autonomous decision-making approach in determining the MEC servers' prices. Finally, section 6.4.3 presents a detailed comparative evaluation of the proposed framework against baseline alternatives to demonstrate its operational superiority and efficiency.

The default system and users' parameters utilized in the following performance evaluation, unless otherwise explicitly stated, are as follows. The total number of users and servers in the examined multi-access edge computing environment is set to $|N| = 50$ and $|S| = 4$, respectively. The users' amount of input bits b_n, the computation demand of the users' applications i_n, the computation capability of the users' devices f_n, and the users' local consumed energy per CPU Cycle follow uniform distributions with mean 10^7 bits, $8 * 10^9$ CPU Cycles, $6 * 10^9$ CPU Cycles/sec, and $4 * 10^{-9}$ Joule/CPU Cycles, respectively. Furthermore, for demonstration only purposes, the MEC servers' operational cost is $\kappa = [1, 3, 5, 3] * 10^{-3}$ \$/bit, while the users' behavioral characteristics

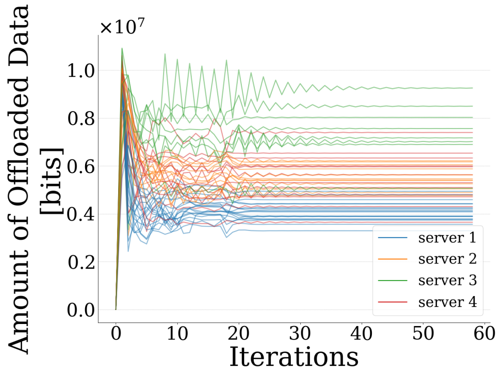


Figure 6.2: Data offloaded by each user to each server

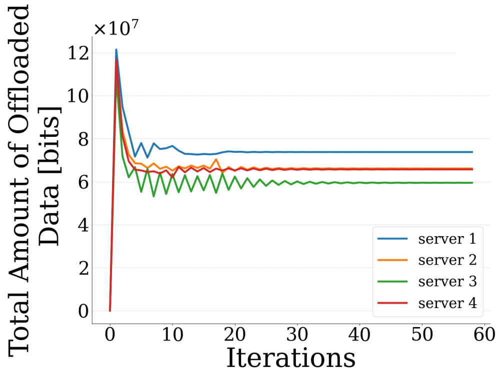


Figure 6.3: Total amount of offloaded data per server

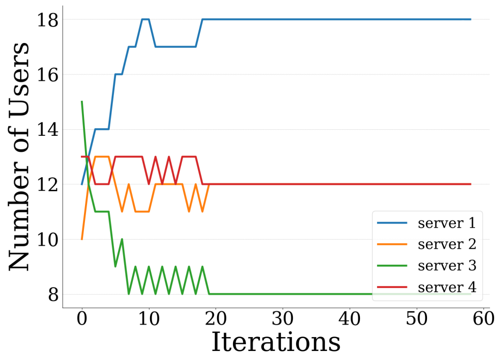


Figure 6.4: Number of users associated with each server

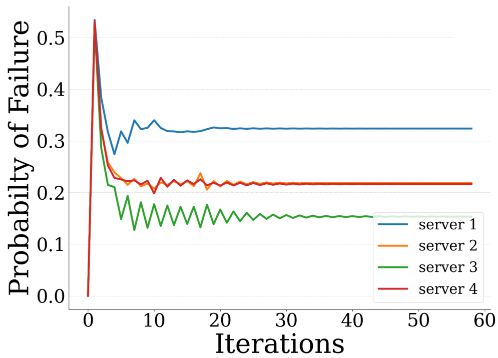


Figure 6.5: Probability of Failure of each server

are captured by the risk-aware parameter $a_n = 0.2$, the loss aversion parameter $k_n = 1.2$, and the distortion parameter $\gamma = 0.6$. All simulations were performed on an Intel Core i5-4300U CPU @ 1.90GHz $\times$ 4 with 8GB RAM.

6.4.1 Semi-autonomous Game-theoretic Decision-making Model

Several performance metrics were captured in order to present the pure operation and performance of the proposed framework, considering the semi-autonomous game-theoretic decision-making of the MEC servers' optimal prices. Initially, we present the evolution of several system parameters of interest as a function of the required iterations for convergence to a stable solution, including both the decision-making parameters under consideration here, namely the average user offloaded data and the MEC server prices. In particular, Figs.6.2-6.7 present each user's amount of offloaded data, the total amount of offloaded data per server, the total number of users associated with each

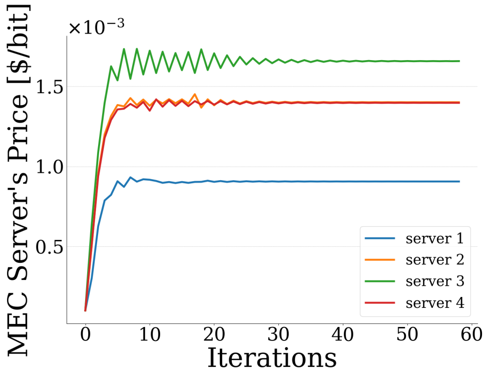


Figure 6.6: Optimal announced price by each server

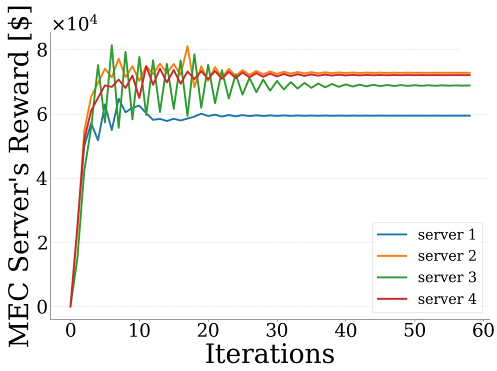


Figure 6.7: Reward experienced by each server

server, the servers' probability of failure, the optimal announced prices, and the servers' reward (Eq. 6.9), respectively, as a function of the Stackelberg game's iterations.

Based on the above figures, we note that the overall proposed behavior and price-aware edge computing framework converges quite fast to the Stackelberg equilibrium, i.e., users' optimal data offloading strategies (Fig.6.2) and MEC servers' optimal prices (Fig.6.6), as for practical purposes less than 40 iterations are needed (corresponding approximately to less than 5 seconds in simulation time). It is observed that the MEC servers with lower operational cost ($\kappa_1 < \kappa_2 = \kappa_4 < \kappa_3$), announce a lower price (Fig.6.6), thus attracting a larger number of users (Fig.6.4) which in turn offload an overall larger amount of data (Fig.6.3). However, this strategic decision-making by some of the MEC servers results in a higher probability of failure (Fig.6.5), showing that these servers struggle to process the users' offloaded data. Also, those MEC servers which are characterized by low operational cost and decide to announce a low price in order to attract a large portion of the users' computing demand, result in experiencing low reward (Fig.6.7), as expressed in Eq. 6.9. On the other hand, it is observed that the servers, which have intermediate operational cost and announce a conservative price, enjoy a greater reward, even if they process a comparatively intermediate amount of data (Fig.6.3).

6.4.2 Fully-Autonomous Reinforcement Learning Decision-making Model

In this section, we extend our previous analysis and evaluation considering that the MEC servers decide their optimal prices without the need of explicitly receiving any external information or a meticulously crafted payoff function such as Eq.6.10. Instead they perform exploration and exploitation based on the reinforcement learning model presented in section 6.3.3, towards determining the optimal prices. Based on the insight we gained from the results obtained in section 6.4.2, for implementation and demonstration purposes, we bound the MEC servers' strategy space

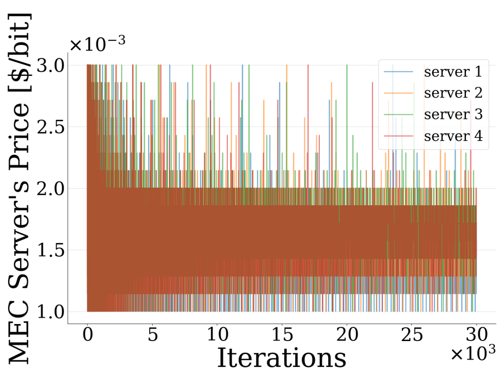


Figure 6.8: Pricing set by each server

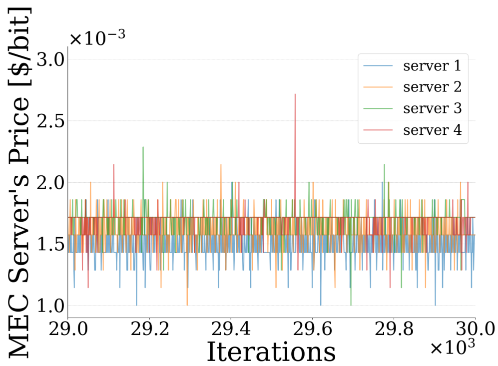


Figure 6.9: Pricing set by each server at the last 1000 iterations

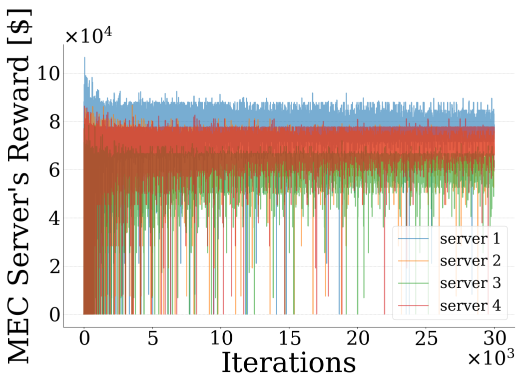


Figure 6.10: Profit gained by each server

as $P_s = [10^{-3}, 3 * 10^{-3}]$ and we equally quantize it in 15 possible actions. Please note that in the following for better understanding and comprehending the operation and achieved system performance by the proposed reinforcement learning model, the results are discussed, wherever possible, in comparison with the corresponding ones achieved by the semi-autonomous game-theoretic model.

Specifically, in Fig.6.8 we present the MEC servers' optimal announced prices for the overall execution period of the reinforcement learning algorithm as a function of the corresponding iterations, while in Fig.6.10 the corresponding MEC servers' reward is also presented. To gain some more insight about the algorithm operation and convergence, in Fig.6.9 the evolution of the MEC servers' optimal prices during the last 1000 iterations is highlighted. The results demonstrate that initially the MEC servers explore several prices to be announced to the users (Fig.6.8) as shown by the high price variations in consecutive iterations, but as the reinforcement learning algorithm thoroughly explores the potential pricing strategies, it finally concludes and converges towards an optimal announced price with very limited exploration (Fig.6.9).

Also, it is observed that the fully-autonomous decision-making model follows the same trend regarding the MEC servers' announced prices, i.e., $p_1 < p_2 = p_4 < p_3$ (Fig.6.9), as the semi-autonomous game-theoretic model (Fig.6.6). However, the servers with lower operational cost learn better the characteristics of the edge computing environment, and better account for the total amount of processed data (Fig.6.3), thus, they announce a higher price (i.e., p_1) in the fully-autonomous reinforcement learning decision-making model (Fig.6.9) vs. the corresponding prices obtained in the semi-autonomous game-theoretic model (Fig.6.6). Thus, the MEC servers with lower operational cost eventually achieve to enjoy a higher reward (Fig.6.10) in contrast to the results obtained by the semi-autonomous game-theoretic decision-making model.

The above obtained results conclude to the following fundamental and interesting observations regarding the fully-autonomous reinforcement learning (RL) and the semi-autonomous game-theoretic (GT) decision-making models. Both of them result in similar benefits regarding the users' computing requests' satisfaction, their corresponding achieved utility, and their optimal data offloading strategies. On the other hand, the RL-based model supports better the free market competition among the MEC servers, which autonomously learn and decide the optimal announced prices, without the need for the involvement of a (centralized) market regulatory entity. In this case, the MEC servers operate in a myopic and selfish manner resulting in higher achieved rewards, even for the servers that announce lower prices. On the other hand, the GT-based decision-making model concludes faster to the users' optimal data offloading strategies and the MEC servers' optimal announced prices, compared to the RL-based model.

6.4.3 Comparative Evaluation

Subsequently, we present a detailed comparative evaluation of the proposed framework - under the two operational alternatives and models - against four different benchmarking scenarios, with respect to determining the optimal MEC server's prices. In particular, we compare the proposed fully-autonomous reinforcement learning (RL) model and the semi-autonomous game-theoretic (GT) one, against the following strategies: i) RL-AVG, where the MEC servers constantly announce the average prices that the RL model has learned over $30,000$ iterations, ii) MAX, iii) MIN, and iv) RANDOM, where the MEC servers always announce a maximum, minimum, and random price to the users, respectively.

Figs.6.11 and 6.12 demonstrate the cumulative MEC servers' rewards (Eq.6.9) over the iterations of the reinforcement learning model, over two different scenarios corresponding to 100 and 30000 iterations, respectively. The results reveal that the MAX scenario, as expected, constantly presents the worst rewards for the MEC servers, as their computing services become extremely expensive for the users, and the latter ones prefer to locally process their data on their devices. On the other hand, the RL-AVG scenario constantly achieves the best rewards for the MEC servers, as they always announce the educated optimal prices that the RL-model has observed. The MIN and RANDOM scenarios on the other hand, present worse results than the GT and the RL models, in

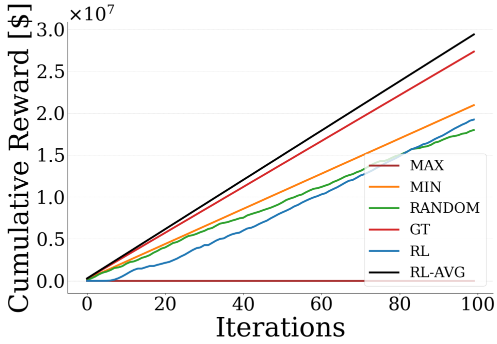


Figure 6.11: Cumulative rewards of servers for the first 100 iterations

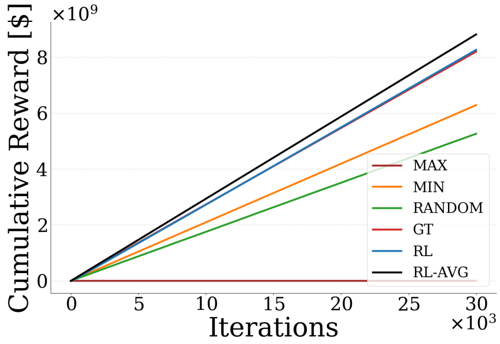


Figure 6.12: Cumulative rewards of servers for the first 30000 iterations

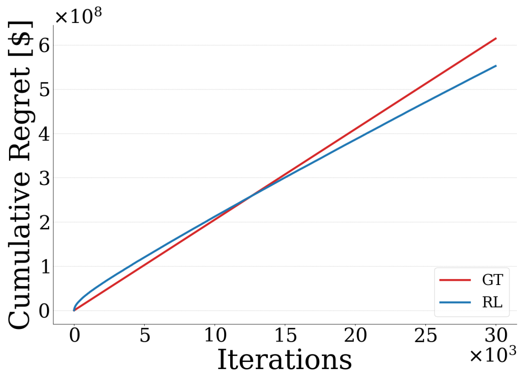


Figure 6.13: Cumulative regret of servers for the first 30000 iterations

particular after the point that the latter one has performed sufficient exploration of the available pricing strategies (Fig.6.12). Thus, even if the MEC servers set a low price to attract more users (MIN scenario), this decision results in worse rewards compared to the optimal decision-making performed by the GT and RL scenarios, due to the combined effect of the low price and the phenomenon of the Tragedy of the Commons which results in the over-exploitation of the MEC servers' computing resources.

Placing our emphasis on the GT and RL scenarios, we observe that the GT model achieves fast a stable optimal outcome (Figs.6.11 and 6.12), while the RL model progressively explores the MEC servers' strategy space and eventually results in similar, and even slightly better rewards for the MEC servers. Moreover, Fig.6.13 comes as a verification to the above argument and observation, since even though initially the RL leads to greater regret for the servers compared to the GT approach, after approximately $12,000$ iterations this trends reverses and the RL approach leads

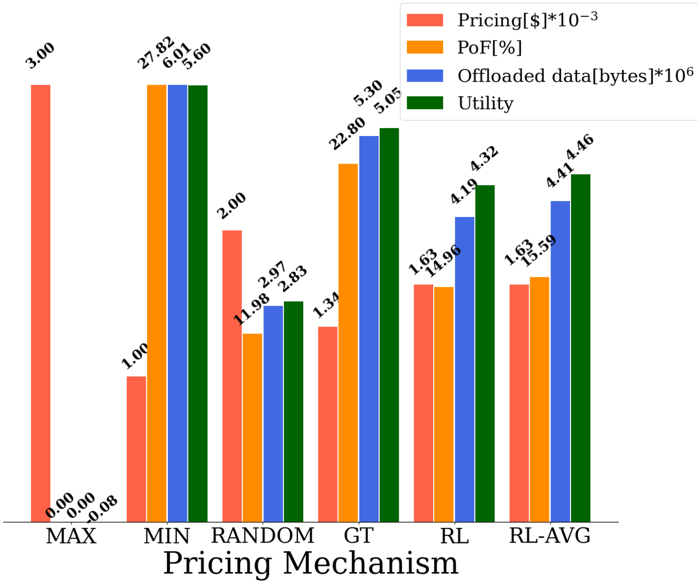


Figure 6.14: System Performance for various pricing mechanisms

to lower and diminishing regret, thus becoming more favorable in the long run. Please recall that the regret as it has been defined in section 6.3.3, represents the difference between the cumulative profit that the servers would have obtained if they had been playing the best pricing strategy from the beginning (which in practice is unknown and is only theoretical) - here is the RL-AVG strategy - and the cumulative profit that the servers actually receive until iteration i under the corresponding strategy. The latter observation is well aligned with the findings in section 6.4.2, where it was concluded that the RL model benefits more the MEC servers, presenting superior rewards when compared to the GT model, while guaranteeing similar performance for the users, as we will see below.

Finally, in Fig.6.14 we present a comprehensive evaluation of various system performance metrics for all the different considered alternative strategies, in order to better validate the relative efficiency and effectiveness of our proposed approaches in a more holistic manner. Specifically, we observe that both GT and the RL approaches outperform all the alternative baseline methods in balancing the rewards for both users and servers. For instance, selecting the RANDOM approach may result in lower probability of failure for the servers as less data are offloaded to them, however relatively poor performance is observed with respect to the rest of the metrics, noting that both users' utility and offloading data (Fig.6.14) and servers' profit (Fig.6.12) remain low. On the other hand, by setting a constant pricing equal to the minimum one (i.e., MIN), users offload more data to the servers thus achieving greater utility, however this happens at the cost of reduced reward for the servers (Fig.6.12). On the opposite side, setting a constant pricing equal to the maximum price (i.e., MAX) forces users to keep all their data for local execution, thus resulting in almost zero probability of failure, but extremely low reward for the users.

Turning our attention to the GT approach, from the results in Fig.6.14 we notice that it presents a final solution more beneficial for the users, since the corresponding game converges to a stable outcome with lower average price than its counterpart of the RL approach. This in turn allows the offloading of a greater amount of data to the servers, and consequently results in higher perceived expected utility by the users. On the other hand, the RL approach presents a behavior that favours the servers perspective. That is, though the higher concluding price leads to lower offloaded data and expected utility, it still allows for higher profit for the servers (Fig.6.13). It should also be noted that the RL approach, as expected, closely follows the performance of the constant price of the average Reinforcement Learning pricing, which strengthens our case and arguments regarding obtaining low regret values for the respective servers' choices.

6.5 Summary

In this chapter, we proposed a behavior and price-aware multi-user multi-server multi-access edge computing operation framework, conceptualized and realized based on the principles of Prospect Theory, Game Theory, and Reinforcement Learning.

The users' behavior on the one hand, and the potential servers' computing resource usage and over-exploitation on the other, are captured via appropriately designed prospect-theoretic utility functions and the theory of the Tragedy of the Commons respectively, while the interactions among the users and the MEC servers are captured via a Stackelberg game. Towards determining the Stackelberg Equilibrium, a non-cooperative game among the users is introduced to determine their optimal data offloading strategies to the MEC servers. Complementary to this, a game-theoretic and a reinforcement learning model are proposed, in order to enable the MEC servers to determine their optimal announced prices in a semi and fully-autonomous manner, respectively.

Based on our observations it should be noted that both proposed price selection approaches have their own benefits and deficiencies and the selection between them should be done based on the availability of information on the system, the underlying infrastructure and the goal of the system designer.

Chapter 7

Conclusions & Future Work

7.1 Conclusions

As we already established within our work, the massive increase in the number of connected devices and the emerging 5G and IoT environments bring major changes to the existing communication models and infrastructures, and multiple new and demanding problems arise. The need for more efficient, faster and more reliable communication is evident in order to handle the increasing traffic, as well as to be able to realize the use cases envisioned. In our PhD, we studied the underlying cyber-physical networks and more specifically two promising potential network architectures, the Machine to Machine (M2M) architecture and the Multi-access Edge Computing (MEC) architecture.

In the M2M architecture, the devices, instead of connecting to a central eNB, can establish a connection between them and exchange data and information, avoiding the need of transferring their data trough the rest of the network. By locally handling the information exchange, the data can be collected or aggregated to few devices responsible of processing them or passing them to a more appropriate network component, minimizing - among other benefits as we saw in Chapter 3 - the energy usage and the bandwidth utilization.

On the other hand, in the MEC architecture, powerful but not omnipotent servers reside at the edge of the network, so that devices can utilize their resources and perform computationally intensive tasks that would otherwise be costly or even impossible to perform locally. Similar benefits are offered by the Cloud architecture but its centralized nature as well as its physical distance from the devices fails to handle the increased traffic and the 5G requirements of reliability, scalability and latency.

Towards the envisioned 6G and Tactile Internet, and their focus on more advanced use cases of human-to-machine and machine-to-machine interactions, even more reliable, fast, always available and secure communication is expected. Our proposed frameworks could help towards paving the way to meet such requirements.

During our dissertation, we investigated the existing literature and were able to locate the unexplored territories. The field has been excessively studied, but the wide range and variety of existing problems remains a very fertile ground for research. By locating those gaps, we tried to propose holistic frameworks under which the operation of the networks could be rendered more efficient, as well as practical algorithms that effectively converge to the problem's solution. Due to the need for near to real time solutions, we tried to focus on low complexity and practically feasible formulations.

In our work we mainly tackled the problem of decision-making concerning the allocation and the considerate exploitation of the networks resources. More specifically, we focused on the power availability, the computational capability, the pricing and the maximization of the system's performance and the Quality of Experience of the participating devices. In order to successfully accomplish these tasks, we made use of a wide variety of mathematical concepts, and principles of the theory of social networks, clustering, Game theory, Common Pool Resources, Tragedy of the Commons, Prospect Theory and Reinforcement Learning were applied to formulate our proposed solutions.

Throughout our thesis, resource allocation problems were modeled as non-cooperative games, where the participating devices act as individuals trying to allocate the underlying resources in order to maximize their perceived satisfaction. The stability of the outcome of those games, based on the Nash Equilibrium point solution concept, has been confirmed through concrete mathematical proofs. Mathematical tools such as submodular games, quasi-concave games etc. where utilized.

The conclusions to which we arrived throughout the realization of this dissertation are the following:

- **Distributed decision making is of utter importance due to privacy, security, reliability and scalability concerns.**

  The majority of the existing literature handles the optimization in a centralized manner, where an omnipotent component is responsible of distributing the resources to the network's participants. We argue that distributed approaches are more appropriate in some situations and can lead to increased performance of the network, while assuring higher privacy and security standards. The existence of different servers, owned by different providers, handling the MEC traffic, dictate the distributed nature of the infrastructure. Allowing a centralized entity to handle the decision making could potentially harm individual servers' well being or have their operation exploited by some malevolent participants. Centralized entities could also lead to single point of failure, as well as reachability and latency issues. Additionally, sensitive information (such as in medical or industrial use cases) could be prohibitive for such an approach since the transfer and central collection of those information could pose serious security and privacy risks. The existence of a central entity imposes an additional signaling overhead for the exchange of information while the centralized computation needed for the decision-making process can render the entity a bottleneck for the whole framework's operation. By handling the decision-making process on the devices in a distributed manner, the whole process can be parallelized and thus avoid some of the centralized approaches pitfalls. Finally, due to the amount of devices and the power that omnipotent entities could have in such scenarios, there is always the possibility (e.g. when the central entity is operated by a separate for profit organization) of exploiting that power and imposing self benefiting goals, a possibility that is avoidable through a distributed approach.

- **Game Theory can be a very successful tool to enable decentralized decision making.**

  Having established the benefits of distributed decision-making approaches, in our works we extensively applied Game Theory principles in our proposed frameworks. Modeling the optimization problems as a game where every participant selfishly tries to maximize his perceived Quality of Experience, empowers the devices and a central decision-making entity is rendered obsolete. The underlying problem via appropriate modeling becomes a maximization problem over a well defined function. Additionally, Game Theory offers the tools for concrete mathematical formulations and provides interesting solution concepts leading to stable game outcomes. The Nash Equilibrium point is a common but effective way of measuring the effectiveness and stability of a proposed framework. It should be noted though that the Nash Equilibrium may not always be the socially optimum outcome and it could be in the hand of the framework designer to design the game in such a way that it achieves a satisfactory goal.

- **The M2M communication paradigm can lead to a decreased overall energy consumption for the system.**

  By allowing the direct communication between devices, power can be managed more efficiently resulting in lower power requirements and extended battery life. In M2M networks, the distance between the communicating devices is generally short and the information on the system could require less hops to reach its final destination. Additionally, the underlying setting enables us to perform interesting power management operations such as autonomous game-theoretic solutions. By adding the information's context in the M2M communication paradigm, machines can be more effectively paired and exchange less information either by selectively transferring the information necessary, or by aggregating similar types of information and forwarding the reduced aggregated outcome (e.g. sensors' average metrics). Techniques such as clustering and complex network analysis can be performed in M2M networks leading to extended battery life and to faster and more reliable network operation.

- **Inserting interest based elements on the M2M communication allows for better communication (e.g. aggregating results) and less data transfer (e.g. selective forwarding) through the network.**

  The majority of M2M communication traffic is in the uplink direction where sensing and other measurement data are transferred to more potent servers for further exploitation. The goal is to send the same type of data to a central application controller through an eNB. By incorporating the information about the type of information exchanged in the M2M communication, devices can make use of the relevance of the data and transfer aggregated and processed information to the rest of the network. Bandwidth and spectrum utilization could be greatly reduced and distributed computations and parallelization of several tasks could be achieved. Combining the above relevance with physical elements such as distance or power availability can lead to a balance between power consumption and effective communication, as per the introduced metrics IAF1 and IAF2 in Chapter 3.

- **Clustering the devices and assigning an appropriate clusterhead leads to less power consumption and more efficient data transfer.**

  Organizing the participating devices in clusters, possibly hierarchical, brings devices conceptually closer, enhancing the M2M communication's efficiency. By indicating the neighbouring devices and associating each device with a cluster-head responsible with more functionalities such as traffic aggregation and data compression, local networks can be created, better utilizing bandwidth and spectrum, leading to less resource consumption and reducing the work of outside network devices (e.g. data transfer, server computation). The cluster-head could also be responsible of powering the associated devices and ensuring the operation of the network.

- **The Chinese restaurant process reformulation can be used to incorporate the interest aware elements in the clustering phase though favoring the creation of a single large cluster.**

  The mathematical model used to describe the Chinese restaurant process is generic enough to allow the incorporation of the concept of similarity in the cluster formation process. The definition of the probability that each customer sits on an existing table, can be reformulated to exploit information about the interests or physical proximity of devices and thus allow the design of a more specialized clustering mechanism. The fact though that in the CPR the aforementioned probability is proportional to the size of the cluster, leads generally to the formation of a large cluster (parameter α in section 3.3.2 is small) or a large number of single device clusters (parameter α is high).

- **The WPC technique can help power low energy devices efficiently and enable complex real life IoT use cases.**

  Wireless Powered Communication is a promising technique that could potentially enable various use case scenarios of IoT networks, such as as sensors in remote areas or disaster recovery, since the distribution of low powered tiny sensors and the extension of battery life of bigger ones is possible. Additionally, conventional energy harvesting techniques such as solar or wind power are not consistent and greatly depend on the environmental conditions, and thus WPC can provide stable power supply to the devices. In our work we applied power management techniques in order to pinpoint the optimal transmission power necessary in the

M2M network and thus transfer only the necessary amount of energy during the Wireless Energy Transfer phase.

- **Multi-access Edge Computing can be very effective in enabling low powered devices to execute high computation tasks.**

  In the Multi-access Edge Computing paradigm, a relatively potent server resides at the edge of the network and end-user devices can exploit its resources in order to execute some of their personal tasks. Since the server is more powerful than themselves, the task can be performed faster and with lower energy consumption. The deployment of tiny and low battery life devices becomes possible, benefiting several potential use cases such as UAVs, sensor networks and augmented reality applications on low end devices. As concluded through our works, data offloading frameworks can be applied, and the exploitation of the available resources can be achieved with great efficiency, enabling its application in real life situations. By carefully modeling the components of the framework, the designer is able to set its goals and lead the choices of the players in its favor (e.g. targeting time efficiency, energy efficiency, communication overhead etc.).

- **SDN controllers can be used as a support mechanic for distributed solutions.**

  As already mentioned, Software Defined Networking's vision is the decoupling of the control and the data plane, enabling the virtual control of the flow of the data. This allows the dynamic design, manageability, adaptability and cost-effectiveness of networks. In our work we argue that SDN controllers can act as a support mechanism to a decentralized framework, enhancing its capabilities by adding centralized operations when needed. SDN can facilitate the exchange of information necessary for the decision-making process, minimizing the information flow within the network and obscuring private information from the rest of the devices. In particular cases, when there are no privacy or scalability issues, SDN controllers could also be responsible for the decision-making itself. Additional operations, such as aggregation of data or reinforcement learning mechanisms (Chapter 4) are made possible by disburdening the end-users from some of the computationally intensive components of decision-making.

- **The usage of pricing in the MEC paradigm, where servers provide their service for a price, can be fundamental to the design of a successful MEC offloading framework.**

  In some Multi-access Edge Computing use cases, end-user devices and MEC servers are operated by different entities and thus an incentive for MEC servers to participate in the game is necessary. A reward in the form of an intangible award or monetary compensation would lure MEC operators in offering their resources to the system. Applying a price policy has a dual effect as it both gives the incentive needed but also discourages users from overexploiting the available resources. The game designer can make use of the imposed policy and render the resource exploitation less or more attractive, depending on the scenario, tackling the Tragedy of the Commons phenomenon. Throughout our works we concluded that the imposition of a price, together with the reduced Return on Investment that an overloaded server provides to the end-users, leads to a lower and more stable Probability of Failure and greater Quality of Experience for the users.

- **A balanced pricing can lead to better rewards for both users and servers of a MEC environment.**

  The way the above pricing policy is imposed is of major importance in the seamless operation of the proposed framework. Conceptually, lower pricing may seem beneficial to users since their observed cost for the service provided is lower, but leads to increased usage, lower return from servers and higher probability of failure. In turn, this leads to lower actual user satisfaction, as well as lower benefits for the servers, which gain a lower reward for their service and become more susceptible to failures. Contrarily, higher prices may seem beneficial for the servers since they gain higher rewards when utilized, but lead to loss of incentive for users to take advantage of the provided service and to prefer the local execution of their tasks. Network resources remain idle and unused, unable to be effectively exploited, and the servers fail to benefit from the promised rewards. Through our simulations, the effect of the imposed price on the behavior of users and the measured welfare of the servers was consistent, leading to the conclusion that a balanced pricing leads to a better satisfaction for both users and servers.

- **The design of the utility function of the game-theoretic model is of utter importance in the success of a proposed framework in order to ensure satisfactory Quality of Experience for its participants.**

  The utility function is a core component in every game-theoretic model since its maximization marks the solution of the game. In order to successfully reach the goals concerning the networks performance and efficiency, the game designer should take into account several parameters when designing the underlining utility function. During our dissertation, we studied the impact of many of such parameters in the design process such as pricing, discount, congestion, market penetration, power consumption, physical distance, interest distance and task execution satisfaction. The effect of those parameters on the behavior of the individual devices was measured and presented via corresponding simulations. It should be noted that in all of our works we tried to propose frameworks in a way where any utility function with specified characteristics could be utilized, depending on the underlying tasks and the system's goals, rendering the proposed methods more widely applicable.

- **Prospect Theory principles can be effectively applied to capture decision-making under uncertainty in wireless network scenarios.**

Realistic decision-making is an inherently behavioral process and the conditional availability of network's resources demands a more complex and involved modeling than the classical game-theoretic models. Prospect Theory proposed by Kahneman and Tversky has been widely adopted and is commonly used to describe and explain the behavior of individuals, but its application in practical scenarios such as in decision-making frameworks is still limited. In our work we managed to incorporated its principles in our framework design in the Multi-access Edge Computing paradigm with relative success, and thus generalize on the classical game-theoretic designs. The players in our frameworks do not act as neutral maximizers but rather, by taking into account the uncertainty of the servers ability to process the tasks and the reduced gains in case of overexploitation, deviate from the expected classical game-theoretic decisions, exhibit more realistic behavior and make their selections by maximizing their perceived prospect-theoretic Quality of Experience.

- **Reinforcement Learning is another powerful tool that enables the decision-making in situations where perfect information on the system is impossible.**

  In most centralized solutions of optimization problems, the central entity is expected to have perfect information on the network in order to successfully perform the resource allocation to the participants. In distributed systems this is not always possible due to scalability and privacy concerns, but also due to communication restrictions. Using such information (e.g. actions or perceived satisfaction of other participants) can be beneficial and should be considered when available, but methods with minimal information should be investigated as well. Reinforcement Learning techniques can successfully fulfill this role since they allow decision-making simply based on user's previous actions and the observation of its effects on himself or the environment, possibly ignoring the effect on other users or more precise network information. Additionally, as seen in Chapter 6, by applying reinforcement learning techniques, it is possible to avoid using complex mathematical models (e.g. carefully crafted game-theoretic utility functions) and allow the end-users to select the best strategy based on the actual perceived reward.

- **Reinforcement Learning techniques could lead to better results than meticulously crafted game-theoretic functions in the long run.**

  Even though Reinforcement Learning could require less predefined knowledge, this is not at the expense of efficiency and effectiveness. Given that the algorithm essentially tries to find the solution in the strategy space without us telling it exactly *how* but instead only *what* we want to achieve, it generally needs some time to explore the available solutions and a balance between exploration of new strategies and exploitation of promising ones should be achieved. In our work in Chapter 6 we concluded that Reinforcement Learning, given enough time, has the potential to achieve comparable and even greater rewards for the users following the corresponding strategy, leading to lower regret than the proposed game-theoretic approach. Other techniques in more complex use cases could also propose probabilistic strategies, where the actions chosen derive from a probabilistic distribution, in order to maximize the expected rewards received.

- **The Upper Confidence Bound algorithm can be used to solve a non stochastic Multi-armed Bandit problem with satisfactory success.**

  In the original Multi-armed Bandit problem, each action provides a random reward from a fixed but unknown probability distribution and the player needs to select the one that generates the highest reward, while in the Adversarial Bandit problem, all assumptions on distribution are dropped and when a player chooses an action, another player simultaneously chooses its payoff structure. In Chapter 6 we defined a problem that does not assume a probability distribution, but the players don't act as adversaries and thus an optimistic algorithm could lead to a faster convergence. Our simulations indicated that in such a scenario, the Upper Confidence Bound algorithm, designed to solve the stochastic Multi-armed Bandit problem, can be successfully used and a sufficient regret can be achieved by following the proposed selection strategy.

- **For real-life application of the frameworks, the model may be complex but low-complexity algorithms are needed.**

  Real-life applications on the IoT environment generally require real time computations and decision-making since the latency is of crucial importance to the Quality of Experience of the participants. Additionally, for scalability reasons, a high-complexity centralized algorithm could rapidly become a bottleneck for the network and thus efficient algorithms are needed. Game-theoretic and reinforcement learning algorithms tend to fit the above description since they can distribute the process, allowing each individual to perform the corresponding calculations themselves. Throughout our thesis, we proposed relatively complex models that capture the participants' behavior in a realistic manner, but require low-complexity computations to actually convergence to the optimum outcome.

7.2 Future Work

Despite all the interest and work on 5G and IoT environments, there are still a lot of research topics open for exploration before every arising problem is sufficiently resolved. Even though we tried to tackle some of them in our dissertation, we have pinpointed many topics that are yet to be studied and could act as a starting point for future research.

One interesting work would be the examination of the framing effects - a prospect theoretic property as mentioned in section 2.2 - in the decision-making process. Depending on the way a choice is formulated, even if the result is the same (e.g. 25% lower price vs. 25% discount), the players' decision would vary and more importantly, based on prospect theory, could be predicted. Incorporating such a mechanism in our proposed prospect-theoretic decision-making framework could result in a more holistic and more realistic approach.

Another way to enhance the applicability of our framework would be the introduction of communication components in the design of the underlying functions. Since our current research focuses on treating the overall key problem of data offloading in various cloud computing and MEC computing environments, the overall process could be affected by the wireless communication aspects between the participants (e.g. UAVs, urban environments etc.). In our work we mainly treated the problem from a computing resources perspective but our proposed frameworks could be easily adapted and extended to treat the communication aspect as well, by modeling the transmission characteristics, such as the potential interference, the achievable transmission rate and the power involved in the offloading process.

More application specific attributes could be incorporated as well in the design of the framework depending on the scenario. The use cases of Multi-access Edge Computing vary, each one requiring a different set of attributes to consider. UAV mounted MECs, a very promising use case since UAVs can stay closer to the end-users, more easily maintain line of sight and serve remote locations, may consider mobility, path finding and flying time efficiency and constraints, while spectrum management should take into account the access technique (e.g. OMA or NOMA) and the devices channel gain. Our proposed frameworks could easily be extended to handle the above use cases as well.

A combination of the various types of computing environments, such as Multi-access Edge Computing and Cloud components, could also be worth exploring. The cloud may have greater latency and higher communication cost than the MEC servers but is generally more powerful and could potentially handle tasks that a MEC server would struggle. Additionally, since the MEC server is considered a fragile common pool resource, the cloud could potentially alleviate some of the burden in case of overexploitation. Combining the two has the potential to achieve even greater satisfaction and Quality of Experience for the network's components.

Part of our current and future work targets at extending the proposed framework via considering the edge computing market dynamics among the users and the MEC servers following a more holistic labor economics based approach. In particular, our goal is to devise appropriate incentive mechanisms at the MEC servers to attract more users towards improving their profit. A dynamic pricing mechanism where the actual price depends on the capabilities of the user in order to favor less powerful devices, may promote fair usage of the network resources and provide greater control to the game designer over the proposed framework.

In cases where pricing is unnecessary (e.g. agricultural IoT or industrial IoT where the MEC servers and the IoT devices are operated by the same entity), new ways to balance the exploitation of the available resources and avoid the Tragedy of the Commons should be explored, such as cost functions based on usage to promote fair usage, or based on type of operation so that easier tasks have higher cost and devices have less incentive to offload their task. In those cases, the framework's goal could be the maximization of the systems' overall performance instead of the Quality of Experience of individual devices that was tackled in our dissertation.

In another scenario, end-users could potentially contribute some of their resources to the common pool, increasing the computing power available to the rest of the network. An incentive, monetary or not, could be considered, so that users have a reason to make their resources available for consumption. The common pool could also be considered as a Fragile Common Pool Resource (CPR) and thus follow the same principles described in Chapter 5, but with adjustable volume depending on the load offered by each user. This could allow lower failure probability for the network, better perceived utility by the users and the usage of idling computing power. Heterogeneous resource types (e.g. fast or power efficient computational resources) could be considered as well.

The above leads to another interesting research idea considering the handling of incomplete information, since individuals don't always have full knowledge of the state of the game they are playing. In the previous setting where users share their resources to the common pool, the resource availability is uncertain at different times, but there are also a lot of potential use cases where network security and information privacy is important (e.g. aerospace, healthcare, defence etc.), leading to less information availability. To address such issues, reinforcement learning algorithms seem like a promising candidate worth considering.

Another example where incomplete information is apparent would be use cases where users can't know how much data other users are willing to or actually offload to the servers. In our proposed frameworks, an SDN or a direct communication between devices allowed for such information diffusion but there are cases where end-users can only observe the reactions of the MEC servers and their own perceived utility from the offloading procedure. In this cases as well, mechanisms such as reinforcement learning could potentially allow the prediction of other users' decisions and thus overcome the problem of incomplete information. The above idea could be extended to the price selection framework component, where pricing from the MEC server is dynamic and thus prediction of the imposed price by the rest of the servers is also worth considering.

By applying reinforcement learning techniques on both user and server side for data offloading and price selection respectively, we could potentially come up with a fully autonomous model, where no complex underlying functions are needed. All the information available to the system could stem from the observation of the environment and the personal satisfaction of each participant, and users and servers could autonomously converge to the optimal strategy while possibly adapting to environmental changes.

In Chapter 6 we proposed the usage of the UCB1 algorithm as a reinforcement learning technique for the price selection by the Multi-access Edge Computing servers. The UCB1 algorithm adopts an optimistic approach to solve the multi-armed bandit problem and was chosen due to the fact that users were designed to behave according to a well defined utility function. In some scenarios, this may no longer be the case since users may select their strategies in a more adversarial way and thus approaches based on adversarial bandits theory (e.g. exp3) or other type of reinforcement learning techniques (e.g. Q-learning) should be explored.

Introducing an auction perspective in the decision-making frameworks could also be of interest since auctions are inherently distributed and solve the joint problem of selling goods at the highest price and buying goods at the lowest price. Combining auctions with the fragility of Common

Pool Resources and the behavioural characteristics of Prospect Theory could allow for elegant and applicable solutions.

The consistent evaluation of the proposed frameworks is another worth exploring topic. A problem that we encountered in all of our works was the lack of universal metrics or common “playgrounds” that could be used to evaluate rivaling methods. In order to be able to make direct comparisons between frameworks, similar settings with specific characteristics should be provided and targets to be met should be set. Consistent simulations could both measure the framework’s efficiency more effectively and give more insight on the working components of each framework.

Another way to solve the above problem would be the actual experimentation on existing infrastructure. Predefined testbeds could be built in order to test the efficiency of the proposed methods as well as their applicability under realistic conditions. Different frameworks could be easily compared and the working prototypes could result in faster market adoption.

Finally, due to the generic nature of our proposed frameworks, it would be interesting to apply those methods in different contexts beyond wireless networking and telecommunications, such as transportation networks, smart grid networks and smart cities, where participants exhibit similar behavior and are responsible of maximizing the satisfaction gained from the consumed services. The formulated models used in our frameworks, incorporating human characteristics and behavior, could also allow the extension of our approaches to even more “humane” disciplines, such as computational sociology or biology.

Since network evolution is a never ending procedure, new and interesting problems will keep arising and more intelligent solutions will be needed. With 5G and IoT stressing the existing infrastructure and the coming of 6G and the Tactile Internet, where even more reliability, ultra low latency times, extremely high availability and more security required the field is research-wise more fruitful than ever.

Appendix A

Proofs

A.1 Proof of Theorem 2

Proof. The strategy space $A_u^{(t)} = [0, I_u^{(t)}]$ represents the amount of data that the end-user u can offload to a MEC server s, thus by definition it is non-empty, convex, and compact subset of the Euclidean space $\mathbb{R}^U$. Also, based on Eq. 4.3, the utility function $U_u^{(t)}(b_{u,s}^{(t)}, \mathbf{b_{-u}^{(t)}}, \mathbf{p^{(t)}})$ is continuous in $\mathbf{b_u^{(t)}}$. Furthermore, we determine the second order derivative of the utility function $U_u^{(t)}(b_{u,s}^{(t)}, \mathbf{b_{-u}^{(t)}})$ with respect to $b_{u,s}^{(t)}$, as follows.

$$\frac{\partial^2 U_u^{(t)}(b_{u,s}^{(t)})}{\partial b_{u,s}^{(t)2}} = -\frac{\alpha_u \beta_u^2}{B_{-u}^{(t)2}} \cdot \frac{1}{[\beta_u + \frac{\beta_u b_{u,s}^{(t)}}{B_{-u}^{(t)}}]^2} < 0$$

Given that $\frac{\partial^2 U_u^{(t)}(b_{u,s}^{(t)})}{\partial b_{u,s}^{(t)2}} < 0$, the $U_u^{(t)}(b_{u,s}^{(t)}, \mathbf{b_{-u}^{(t)}}, \mathbf{p^{(t)}})$ is concave in $b_{u,s}^{(t)}$, thus, it is also quasi-concave in $b_{u,s}^{(t)}$. Therefore, the Nash Equilibrium point of the game $G = (U, \{A_u^{(t)}\}, \{U_u^{(t)}\})$ exists.

Towards determining the best response strategy of each end-user, we calculate the critical points of the $U_u^{(t)}(b_{u,s}^{(t)}, \mathbf{b_{-u}^{(t)}}, \mathbf{p^{(t)}})$, as follows.

$$\frac{\partial U_u^{(t)}}{\partial b_{u,s}^{(t)}} = 0 \Leftrightarrow b_{u,s}^{(t)} = \frac{B_{-u}^{(t)}}{\beta_u}(\frac{\alpha_u \beta_u}{d_u^{(t)} p_s^{(t)}} - 1)$$

The data offloading of each end-user u should satisfy the physical limitations, i.e., $0 \leq b_{u,s}^{(t)} \leq I_u^{(t)}$, thus we have the following cases.

Case 1. *If $d_u^{(t)} p_s^{(t)} > \alpha_u \beta_u$ then the best response strategy is $b_{u,s}^{(t)*} < 0$. But since the physical limitation imposed states that $0 \leq b_{u,s}^{(t)}$ and our function is concave, then the best response should be $b_{u,s}^{(t)*} = 0$.*

Case 2. *If $d_u^{(t)} p_s^{(t)} < \frac{\alpha_u \beta_u}{I_u^{(t)} \frac{\beta_u}{B_{-u}^{(t)}} + 1}$ then the best response strategy is $b_{u,s}^{(t)*} > I_u^{(t)}$. But since the physical limitation imposed states that $b_{u,s}^{(t)} \leq I_u^{(t)}$ and our function is concave, then the best response should* *be* $b_{u,s}^{(t)*} = I_u^{(t)}$.

Case 3. *If* $\frac{\alpha_u \beta_u}{I_u^{(t)} \frac{\beta_u}{B_{-u}^{(t)}} + 1} \leq d_u^{(t)} p_s^{(t)} \leq \alpha_u \beta_u$ *then the best response strategy is* $0 \leq b_{u,s}^{(t)*} \leq I_u^{(t)}$ *which satisfies the physical limitation. In this case, the best response is given by the equation* $b_{u,s}^{(t)*} = \frac{B_{-u}^{(t)}}{\beta_u}(\frac{\alpha_u \beta_u}{d_u^{(t)} p_s^{(t)}} - 1)$.

□

A.2 Proof of Theorem 4

Proof. Towards determining the optimal pricing announced by each MEC server, we take the first order derivative with respect to $p_s^{(t)}$ and determine the critical points.

$$\frac{\partial P_s^{(t)}(\mathbf{b^{(t)}}, \mathbf{p^{(t)}})}{\partial p_s^{(t)}} = -\frac{1}{\beta_u}(1 - f_s^{(t)}) \sum_{u \in U} B_{-u}^{(t)} + \frac{c_s^{(t)} \alpha_u}{p_s^{(t)2}} \sum_{u \in U} \frac{B_{-u}^{(t)}}{d_u^{(t)}} = 0$$

Thus, the critical points are given by the following equation.

$$p_s^{(t)*} = [\frac{\alpha_u \beta_u c_s^{(t)} \sum_{u \in U} \frac{B_{-u}^{(t)}}{d_u^{(t)}}}{(1 - f_s^{(t)}) \sum_{u \in U} B_{-u}^{(t)}}]^{1/2}$$

By checking the second order derivative of $P_s^{(t)}(\mathbf{b^{(t)}}, \mathbf{p^{(t)}})$ with respect to $p_s^{(t)}$, we have:

$$\frac{\partial^2 P_s^{(t)}(\mathbf{b^{(t)}}, \mathbf{p^{(t)}})}{\partial p_s^{(t)2}} = -2c_s^{(t)} \frac{\alpha_u}{p_s^{(t)3}} \sum_{u \in U} \frac{B_{-u}^{(t)}}{d_u^{(t)}} < 0$$

Thus, $p_s^{(t)*}$ maximizes the MEC server's profit $P_s^{(t)}(\mathbf{b^{(t)}}, \mathbf{p^{(t)}})$. □

A.3 Proof of Theorem 5

Proof. The strategy space $A_n = [0, b_n]$ is a compact subset of a Euclidean space. The user's expected prospect theoretic utility function $\mathbb{E}(U_n(b_n^{MEC}, \mathbf{b_{-n}^{MEC}}))$, as defined in Eq.5.11, is smooth, as it has derivatives of all orders everywhere in its domain A_n. Towards showing that the user's expected prospect theoretic utility function is submodular in b_n and has non-increasing differences in $(b_n^{MEC}, \mathbf{b_{-n}^{MEC}})$, we examine the properties of the second order partial derivative of the user's expected prospect theoretic utility function, i.e., $\frac{\partial^2 \mathbf{E}_n(\vec{b}^{MEC})}{\partial b_j^{MEC} \partial b_n^{MEC}} \leq 0$.

We can rewrite Eq.5.11)using Eqs.5.8 and 5.9, as follows:

$$\begin{aligned}\mathbb{E}(U_n(b_n^{MEC}, \mathbf{b_{-n}^{MEC}})) =& (b_n^{MEC})^{\alpha_n} \{[(2 - e^{d_\tau - 1}) - \frac{1}{\hat{t}_n \hat{e}_n} - c\frac{d_n}{b_n}]^{\alpha_n} (1 - Pr(d_\tau)) - \\ & k_n(\frac{1}{\hat{t}_n \hat{e}_n} + c\frac{d_n}{b_n})^{\alpha_n} Pr(d_\tau)\}\end{aligned} \tag{A.1}$$

We define $\overline{RoR}(d_\tau) = [(2 - e^{d_\tau - 1}) - \frac{1}{\hat{t}_n \hat{e}_n} - c\frac{d_n}{b_n}]^{\alpha_n}$ as the user's specific rate of return, which should be positive in order for the user to have an incentive to offload part of its data to the UAV-mounted MEC server. From Eq.5.7, the UAV-mounted MEC server's rate of return function $RoR(d_\tau)$ is decreasing. Thus, the minimum value of $RoR(d_\tau)$, and correspondingly of the function $\overline{RoR}(d_\tau)$, is determined at $d_\tau = 1$. The physical notion of $d_\tau = 1$ is that all the users offload their total amount of data to the UAV-mounted MEC server for further processing. Following this observation, we can determine the boundaries of the constant pricing factor c that the UAV-mounted MEC server imposes on the users, in order for the latter to still have an incentive to offload part of their data to the MEC server without the imposed pricing to become a prohibitive factor. Therefore, the feasible boundaries of the constant pricing factor are determined as follows:

$$\overline{RoR}(d_\tau = 1) > 0 \Rightarrow c < \frac{b_n}{d_n}(1 - \frac{1}{\hat{t}_n \hat{e}_n}) \tag{A.2}$$

In addition, the following conditions hold true by performing the corresponding derivations: $\frac{\partial d_\tau}{\partial b_n^{MEC}} > 0$, $\frac{\partial d_\tau}{\partial b_j^{MEC}} > 0$, $\frac{\partial \overline{RoR}(d_\tau)}{\partial b_n^{MEC}} < 0$, $\frac{\partial \overline{RoR}(d_\tau)}{\partial b_j^{MEC}} < 0$, $\frac{\partial^2 \overline{RoR}(d_\tau)}{\partial b_j^{MEC} \partial b_n^{MEC}} < 0$, $\frac{\partial Pr(d_\tau)}{\partial b_n^{MEC}} > 0$, $\frac{\partial Pr(d_\tau)}{\partial b_j^{MEC}} > 0$, $\frac{\partial^2 Pr(d_\tau)}{\partial b_n^{MEC} \partial b_j^{MEC}} = 0$. For notational convenience, we set $A = k_n(\frac{1}{\hat{t}_n \hat{e}_n} + c\frac{d_n}{a_n})^{\alpha_n} > 0$, and we calculate the second order partial derivative of the user's expected prospect theoretic utility function, as follows:

$$\begin{aligned}
\frac{\partial^2 \mathbb{E}(U_n(b_n^{MEC}, \mathbf{b_{-n}^{MEC}}))}{\partial b_j^{MEC} \partial b_n^{MEC}} =& \alpha_n (b_n^{MEC})^{\alpha_n - 1}\{\frac{\partial \overline{RoR}(d_\tau)}{\partial b_j^{MEC}}[1 - Pr(d_\tau)] - \overline{RoR}(d_\tau)\frac{\partial Pr(d_\tau)}{\partial b_j^{MEC}} - \\
& A\frac{\partial Pr(d_\tau)}{\partial b_j^{MEC}}\} + (b_n^{MEC})^{\alpha_n}\{\frac{\partial^2 \overline{RoR}(d_\tau)}{\partial b_j^{MEC} \partial b_n^{MEC}}[1 - Pr(d_\tau)] - \\
& \frac{\partial \overline{RoR}(d_\tau)}{\partial b_n^{MEC}}\frac{\partial Pr(d_\tau)}{\partial b_j^{MEC}} - \frac{\partial \overline{RoR}(d_\tau)}{\partial b_j^{MEC}}\frac{\partial Pr(d_\tau)}{\partial b_n^{MEC}}\} \\
=& (b_n^{MEC})^{\alpha_n - 1}\{\alpha_n \frac{\partial \overline{RoR}(d_\tau)}{\partial b_j^{MEC}}[1 - Pr(d_\tau)] - \alpha_n \overline{RoR}(d_\tau)\frac{\partial Pr(d_\tau)}{\partial b_j^{MEC}} - \\
& A\alpha_n \frac{\partial Pr(d_\tau)}{\partial b_j^{MEC}} + b_n^{MEC}\frac{\partial^2 \overline{RoR}(d_\tau)}{\partial b_j^{MEC} \partial b_n^{MEC}}[1 - Pr(d_\tau)] - \\
& b_n^{MEC}\frac{\partial \overline{RoR}(d_\tau)}{\partial b_n^{MEC}}\frac{\partial Pr(d_\tau)}{\partial b_j^{MEC}} - b_n^{MEC}\frac{\partial \overline{RoR}(d_\tau)}{\partial b_j^{MEC}}\frac{\partial Pr(d_\tau)}{\partial b_n^{MEC}}\}
\end{aligned} \tag{A.3}$$

Let $\psi(d_\tau) = \frac{\partial \overline{RoR}(d_\tau)}{\partial b_j^{MEC}}[\alpha_n - \alpha_n Pr(d_\tau) - b_n^{MEC}\frac{\partial Pr(d_\tau)}{\partial b_n^{MEC}}] - b_n^{MEC}\frac{\partial \overline{RoR}(d_\tau)}{\partial b_n^{MEC}}\frac{\partial Pr(d_\tau)}{\partial b_j^{MEC}}$. We can rewrite Eq.A.3, as follows:

$$\frac{\partial^2 \mathbb{E}(U_n(b_n^{MEC}, \mathbf{b_{-n}^{MEC}}))}{\partial b_j^{MEC} \partial b_n^{MEC}} = (b_n^{MEC})^{\alpha_n - 1} \{ \psi(d_\tau) - \alpha_n \overline{RoR}(d_\tau) \frac{\partial Pr(d_\tau)}{\partial b_j^{MEC}} - A\alpha_n \frac{\partial Pr(d_\tau)}{\partial b_j^{MEC}} + b_n^{MEC} \frac{\partial^2 \overline{RoR}(d_\tau)}{\partial b_j^{MEC} \partial b_n^{MEC}} [1 - Pr(d_\tau)] \} \tag{A.4}$$

It is observed that the last three terms of Eq.A.4 are negative; thus, we study the properties of the function $\psi(d_\tau), \forall n \in \mathcal{N}$. For $d_\tau = 0$, we have $b_n^{MEC} = 0$. Thus, we calculate:

$$\psi(d_\tau = 0) = \frac{\partial \overline{RoR}(0)}{\partial b_j^{MEC}} \alpha_n < 0 \tag{A.5}$$

For $d_\tau \approx 1$, we have $b_n^{MEC} = b_n, \forall n \in \mathcal{N}$. Thus, we calculate:

$$\psi(d_\tau \approx 1) = -b_n [\frac{\partial \overline{RoR}(1)}{\partial b_j^{MEC}} \frac{\partial Pr(1)}{\partial b_n^{MEC}} + \frac{\partial \overline{RoR}(1)}{\partial b_n^{MEC}} \frac{\partial Pr(1)}{\partial b_j^{MEC}}] > 0 \tag{A.6}$$

Since $\psi(d_\tau)$ is continuous, using the Bolzano Theorem [133], we conclude that there exists at least one $\mu \in (0, 1)$ such that $\psi(d_\tau = \mu) = 0$. Given that $\psi(d_\tau = 0) < 0$ (Eq.A.5), then, if μ is the smallest possible value in $(0, 1)$ such that $\psi(d_\tau = \mu) = 0$, then $\psi(d_\tau) < 0, \forall d_\tau \in (0, \mu)$. Thus, we conclude that

$$\frac{\partial^2 \mathbb{E}(U_n(b_n^{MEC}, \mathbf{b_{-n}^{MEC}}))}{\partial b_j^{MEC} \partial b_n^{MEC}} < 0, \forall d_\tau \in (0, \mu), \mu \in (0, 1). \tag{A.7}$$

Thus, the non-cooperative game G is submodular $\forall d_\tau \in (0, \mu), \mu \in (0, 1)$ and $c < \frac{b_n}{d_n}(1 - \frac{1}{\hat{t}_n \hat{e}_n})$. Therefore, the non-cooperative game $G = [\mathcal{N}, A_n, \mathbb{E}(U_n(b_n^{MEC}, \mathbf{b_{-n}^{MEC}}))]$ has at least one Pure Nash Equilibrium point $\mathbf{b_n^{MEC*}} = (b_1^{MEC*}, \ldots, b_N^{MEC*})$ [134]. $\square$

Appendix B

Author's Publications

International Peer Reviewed Journals

- **Giorgos Mitsis**, Eirini Eleni Tsiropoulou, and Symeon Papavassiliou. Price and risk awareness for data offloading decision-making in edge computing systems. *IEEE Systems Journal*, 2021. (submitted)
- **Giorgos Mitsis**, Eirini Eleni Tsiropoulou, and Symeon Papavassiliou. Data offloading in uav-assisted multi-access edge computing systems: A resource-based pricing and user risk-awareness approach. *Sensors*, 20(8):2434, 2020
- **Giorgos Mitsis**, Pavlos Athanasios Apostolopoulos, Eirini Eleni Tsiropoulou, and Symeon Papavassiliou. Intelligent dynamic data offloading in a competitive mobile edge computing market. *Future Internet*, 11(5):118, 2019
- **Giorgos Mitsis**, Nikos Kalatzis, Ioanna Roussaki, and Symeon Papavassiliou. Trend discovery and social recommendation in support of documentary production. *International Journal on Advances in Software*, 12(1,2):103–124, 2019
- Eirini Eleni Tsiropoulou, **Giorgos Mitsis**, and Symeon Papavassiliou. Interest-aware energy collection & resource management in machine to machine communications. *Ad Hoc Networks*, 68:48–57, 2018

International Conferences

- **Giorgos Mitsis**, Nikos Kalatzis, Ioanna Roussaki, Eirini Eleni Tsiropoulou, Symeon Papavassiliou, and Simona Tonoli. Social media analytics in support of documentary production. IARIA Content, 2018

International Conference Posters

- **Giorgos Mitsis**, Nikos Kalatzis, Ioanna Roussaki, Eirini Eleni Tsiropoulou, Symeon Papavassiliou, and Simona Tonoli. Emerging ict tools in support of documentary production. In *14th European Conference on Visual Media Production*, 2017

Εκτεταμένη Περίληψη

Στην προσπάθεια υλοποίησης της πέμπτης γενιάς (5G) ασυρμάτων δικτύων, του Διαδικτύου των Πραγμάτων (Internet of Things) και του Απτού Διαδικτύου (Tactile Internet), η ανάπτυξη έξυπνων μεθόδων επικοινωνίας και επεξεργασίας δεδομένων είναι κομβικής σημασίας. Στα νέα δίκτυα που προκύπτουν ο αριθμός των συσκευών είναι τάξης μεγέθους μεγαλύτερος από τα υπάρχοντα δίκτυα, υπάρχει μεγάλη ετερογένεια μεταξύ των συσκευών και περιορισμένη διαθεσιμότητα πόρων (ενέργεια, εύρος ζώνης, επεξεργαστική ισχύς κλπ.). Επιπλέον, στις επόμενες γενιές (6G) αναμένονται περισσότερες περίπλοκες εφαρμογές αλληλεπίδρασης ανθρώπου-μηχανής και μηχανής με μηχανή, οι οποίες θα απαιτούν μεγαλύτερη αξιοπιστία, πολύ μικρούς χρόνους καθυστέρησης, μεγαλύτερη διαθεσιμότητα και ακόμα μεγαλύτερη ασφάλεια.

Η ιδέα πίσω από το Διαδίκτυο των Πραγμάτων είναι να συνδέονται όλα, όλοι, πάντα και παντού, και οι τεχνολογίες δικτύων πέμπτης γενιάς προσπαθούν να αντιμετωπίσουν τα προβλήματα που προκύπτουν. Πιο συγκεκριμένα, τα δίκτυα που χρησιμοποιούν τεχνολογίες 5G αναμένεται να έχουν μεγάλο εύρος ζώνης (πχ. 10Gps), χαμηλούς χρόνους καθυστέρησης (πχ. 1ms), και μικρό κόστος λειτουργίας, αυξάνοντας την Ποιότητα Υπηρεσιών (Quality of Service) και την Ποιότητα Εμπειρίας (Quality of Experience) των χρηστών.

Σχετικά με την αποδοτικότερη χρήση του εύρους ζώνης και την βελτίωση της ταχύτητας μετάδοσης, έχουν γίνει σημαντικά βήματα με την χρήση βελτιωμένων κεραιών, την χρήση υψηλότερων συχνοτήτων, τον διαχωρισμό του πεδίου μετάδοσης των πληροφοριών από το πεδίο ελέγχου καθώς και με την γενικότερη αλλαγή της αρχιτεκτονικής των δικτύων. Όσον αφορά την ενεργειακή απόδοση και την διαχείριση ισχύος, οι υπάρχουσες τεχνολογίες όπως χαμηλής ενέργειας Bluetooth, WiFi, Zigbee κλπ. δεν επαρκούν και γι' αυτό αναπτύσσονται νέες τεχνολογίες όπως οι LPWA, NB-IoT, LoRa, SigFox και LTE-M. Επιπλέον, νέα πρωτόκολλα όπως το NOMA αναπτύσσονται για την βελτιωμένη εκμετάλλευση του εύρους ζώνης και του φάσματος επικοινωνίας, ενώ για την τροφοδότηση των συσκευών, μια πολλά υποσχόμενη τεχνολογία έχει κάνει την εμφάνισή της, η WPC (Wireless Powered Communication), η οποία δίνει την δυνατότητα στις συσκευές να συλλέγουν και να αποθηκεύουν ενέργεια με πιο αξιόπιστο τρόπο μέσω ραδιοσυχνοτήτων - σε αντίθεση με τις πιο επισφαλείς ανανεώσιμες πηγές όπως η ηλιακή ενέργεια - την οποία στη συνέχεια μπορούν να χρησιμοποιήσουν για να μεταδώσουν τα δεδομένα τους.

Στο δικτυακό κομμάτι, τεχνολογίες όπως η Δικτύωση Καθορισμένη από Λογισμικό (Software Defined Networking - SDN) και η Εικονοποίηση Δικτυακών Λειτουργιών (Network Function Virtualization) παίζουν επίσης βασικό ρόλο στην επίτευξη των στόχων των δικτύων πέμπτης γενιάς. Με την τεχνολογία SDN, επιτυγχάνεται η αποσύνδεση του πεδίου ελέγχου από το πεδίο μετάδοση των πληροφοριών, επιτρέποντας την εικονοποίηση των λειτουργιών ελέγχου της ροής των δεδομένων από συσκευές γενικής χρήσης, ενώ η μετάδοση πραγματοποιείται από χαμηλού κόστους μεταγωγείς. Με αυτόν τον τρόπο δεν χρειάζονται πλέον ακριβοί και έξυπνοι μεταγωγείς, ενώ παράλληλα διευκολύνεται η επεκτασιμότητα και διαχείριση των δικτύων. Από την άλλη, η τεχνολογία NFV λειτουργεί συμπληρωματικά, αντικαθιστώντας ειδικής χρήσης συσκευές όπως δρομολογητές, εξισορροπιστές φορτίου, τείχη προστασίας, συσκευές κρυπτογράφησης κ.α. με εικονικούς εξομοιωτές και προγράμματα, με την τεχνολογία SDN σε αυτή την περίπτωση να λειτουργεί ως διαχειριστής των παραπάνω λειτουργιών.

Στο πλαίσιο όμως των νέων αυτών μορφών δικτύου, δημιουργείται επιπλέον η ανάγκη αύξησης των ικανοτήτων συσκευών χαμηλής ενέργειας και υπολογιστικής ισχύος, καθώς μέρος του δικτύου αποτελούν συσκευές μικρές σε μέγεθος, αισθητήρες και κινητές συσκευές που διαθέτουν περιορισμένους πόρους. Η τεχνολογία νέφους (Cloud) χρησιμοποιείται ήδη για την ανάθεση υπολογιστικών και αποθηκευτικών λειτουργιών σε πιο ισχυρές συσκευές, παρουσιάζει ωστόσο σημαντικά μειονεκτήματα. Η κεντρική φύση του νέφους σημαίνει μοναδικό σημείο αποτυχίας σε περίπτωση προβλήματος, αλλά και πιθανή ύπαρξη προβλημάτων προσβασιμότητας και καθυστέρησης. Επιπλέον, πολλές εφαρμογές του Διαδικτύου των Πραγμάτων μπορεί να ευνοούνται από την ύπαρξη ενός κατανεμημένου συστήματος που διαθέτει επίγνωση της τοποθεσίας, είναι πιο εύκολα επεκτάσιμο, έχει μικρότερη καθυστέρηση και είναι πιο εύκολα διαχειρίσιμο (όπως στις περιπτώσεις εργοστασίων ή αυτοματισμών σε γεωργικής φύσεως δίκτυα αισθητήρων). Τέλος, ο τεράστιος αριθμός των συσκευών μπορεί να δημιουργήσει προβλήματα στα δίκτυα τηλεπικοινωνιών λόγω του τεράστιου όγκου δεδομένων που μεταδίδονται και του περιορισμένου διαθέσιμου εύρους ζώνης του εξωτερικού διαδικτύου.

Για τους παραπάνω λόγους, έχει προταθεί η τεχνολογία Υπολογισμού στα Άκρα Πολλαπλής Πρόσβασης (Multi-access Edge Computing - MEC) με την οποία προτείνεται η τοποθέτηση ισχυρών, αλλά πεπερασμένων δυνατοτήτων, διακομιστών στα άκρα του δικτύου, που αναλαμβάνουν την διεκπεραίωση των εργασιών συσκευών με περιορισμένους πόρους. Με αυτόν τον τρόπο, ο συνδυασμός Υπολογισμού στα Άκρα Πολλαπλής Πρόσβασης και Διαδικτύου των Πραγμάτων έχει αμοιβαία οφέλη, καθώς τα περιβάλλοντα Διαδικτύου των Πραγμάτων παρέχουν μεγάλο αριθμό και μεγάλη ποικιλία συσκευών που μπορούν να χρησιμοποιηθούν για ενδιαφέρουσες και πολυσύνθετες υπηρεσίες, ενώ οι διακομιστές στα περιβάλλοντα Υπολογισμού στα Άκρα Πολλαπλής Πρόσβασης δίνουν την δυνατότητα στις συσκευές να πραγματοποιήσουν περίπλοκες εργασίες, παρέχοντας υπολογιστική ισχύ, και να επικοινωνούν πιο ελεύθερα και με καλύτερη ενεργειακή απόδοση, λειτουργώντας ως συσσωρευτές και ως πύλες για το υπόλοιπο διαδίκτυο.

Οι εφαρμογές του παραπάνω συνδυασμού είναι πολλές και περιλαμβάνουν έξυπνα σπίτια, έξυπνες πόλεις, εφαρμογές υγείας, αυτόνομα αυτοκίνητα, επαυξημένη πραγματικότητα, εικονική πραγματικότητα, λιανεμπόριο, φορητές συσκευές, εργοστάσια, έξυπνη ενέργεια και γεωργία. Η προσφορά τους βρίσκεται στην επεκτασιμότητα, την επικοινωνία, την εξυπηρέτηση υπολογισμού και την διαχείριση πόρων, την διαχείριση κινητικότητας των συσκευών, την ασφάλεια, την ιδιωτικότητα, την αξιοπιστία, την αποδοτικότητα και την ακρίβεια των υπηρεσιών. Στην παρούσα διατριβή επικεντρωθήκαμε στις περιοχές της επικοινωνίας, της διαχείρισης πόρων και της εκφόρτωσης υπολογισμού.

Για την επίλυση των προβλημάτων που προκύπτουν, η βιβλιογραφία ακολουθεί διάφορες προσεγγίσεις. Λόγω της ανάγκης για πιο αποτελεσματική και μικρότερης ενεργειακής κατανάλωσης επικοινωνία, συχνά τα προβλήματα μοντελοποιούνται ως προβλήματα βελτιστοποίησης, με κεντρικούς και offline αλγόριθμους να χρησιμοποιούνται για την μεγιστοποίηση ή ελαχιστοποίηση συναρτήσεων (γραμμικός προγραμματισμός, γεωμετρικός προγραμματισμός κ.α.). Συχνά μεγιστοποιούνται περισσότερες από μια μεταβλητές (πχ. χρόνος εκτέλεσης και ενέργεια μετάδοσης), και λαμβάνονται υπόψιν πληθώρα άλλων παραμέτρων (πχ. χρόνος μετάδοσης, χρήση φάσματος, φήμη συσκευής κ.α.).

Ένας άλλος τρόπος επίλυσης των προβλημάτων βελτιστοποίησης με πιο κατανεμημένο τρόπο βασίζεται στη χρήση της Θεωρίας Παιγνίων. Τα προβλήματα μοντελοποιούνται ως μη-συνεργατικά (ή σε ορισμένες περιπτώσεις συνεργατικά) παίγνια, και κάθε χρήστης προσπαθεί εγωιστικά να μεγιστοποιήσει την συνάρτηση ωφελιμότητάς του. Σημαντική έννοια σε αυτή την περίπτωση είναι η έννοια της ισορροπίας κατά Nash, η οποία αντιπροσωπεύει την κατάσταση στην οποία κανένας χρήστης δεν επωφελείται από το να αλλάξει μόνος του την στρατηγική που ακολουθεί. Προσθέτοντας ένα ακόμα επίπεδο πολυπλοκότητας, γίνεται χρήστη της Θεωρίας Προοπτικής, η οποία λαμβάνει υπόψιν συμπεριφορικά χαρακτηριστικά των χρηστών σε συνθήκες αβεβαιότητας αποτελέσματος κατά την διαδικασία λήψης αποφάσεων. Η Θεωρία Προοπτικής έχει χρησιμοποιηθεί ευρέως ως εργαλείο στις οικονομικές και κοινωνικές επιστήμες αλλά η χρήση της στο πεδίο του Διαδικτύου των Πραγμάτων και στα δίκτυα πέμπτης γενιάς γενικότερα δεν έχει ερευνηθεί σε βάθος.

Λόγω της πολυπλοκότητας των προβλημάτων που προκύπτουν, πολλές διαφορετικές μαθηματικές τεχνικές έχουν χρησιμοποιηθεί και τροποποιηθεί ώστε να αντιμετωπίσουν τις ιδιομορφίες κάθε σεναρίου. Έτσι στην βιβλιογραφία συναντάμε τεχνικές όπως τεχνικές συσταδοποίησης για την ομαδοποίηση των συσκευών, δυναμικό προγραμματισμό για την χρονοδρομολόγηση των εργασιών, μεθόδους εμπνευσμένες από την θεωρία πολύπλοκων δικτύων (ενδιαμεσική κεντρικότητα, ιδιοδιανύσματα κλπ.) για την εύρεση σημαντικών κόμβων και αλγορίθμους από την θεωρία γραφημάτων (BFS, Dijkstra κ.α.) για την αποτελεσματική ανταλλαγή πληροφοριών μεταξύ των κόμβων. Τέλος, λόγω της συνεχής αλλαγής του περιβάλλοντος και της ελλιπούς πληροφορίας εντός του συστήματος, τεχνικές όπως μηχανική μάθηση, ενισχυτική μάθηση και προσεγγιστικοί αλγόριθμοι φαίνεται να οδηγούν σε ενδιαφέρουσες λύσεις.

Με βάση τα παραπάνω, η αναγκαιότητα εύρεσης λύσεων στα προβλήματα που προκύπτουν στα προαναφερθέντα δίκτυα και το ερευνητικό ενδιαφέρον είναι εμφανή. Στην διατριβή μας επιλέξαμε να επικεντρωθούμε σε προβλήματα που αναφέρονται στα παρακάτω θέματα:

Ατομοκεντρικά δίκτυα. Στα περιβάλλοντα Διαδικτύου των Πραγμάτων, οι συσκευές θεωρούνται έξυπνες και η λήψη αποφάσεων παίζει σημαντικό ρόλο στην απόδοση του δικτύου. Για το λόγο αυτό, καθ'όλη τη διάρκεια της διατριβής μας, θεωρούμε τους χρήστες ως πυρηνα του δικτύου, όπου οι στρατηγικές τους και οι αλληλεπιδράσεις μεταξύ των χρηστών επηρεάζουν σε μεγάλο βαθμό το σύστημα, το οποίο καλείται να προσαρμοστεί δυναμικά στις διάφορες ανάγκες τους.

Ποιότητα Εμπειρίας και ικανοποίηση των χρηστών. Όπως προαναφέρθηκε, με βάση την τεχνολογία Υπολογισμού στα Άκρα Πολλαπλής Πρόσβασης, οι συσκευές των χρηστών είναι πρόθυμες να μεταφορτώσουν τις εργασίες τους σε έναν πιο ισχυρό διακομιστή, και συνεπώς ένα πλαίσιο λήψης αποφάσεων που εκμεταλλεύεται την υποδομή του δικτύου είναι απαραίτητο. Η δημιουργία επιπρόσθετης αξίας για τους χρήστες και η διατήρηση υψηλής Ποιότητας Υπηρεσιών που παρέχονται από τους διακομιστές είναι υψίστης σημασίας και αμφότερα αυτά τα χαρακτηριστικά αντιμετωπίζονται ως βασικά στοιχεία στα πλαίσια που προτείνουμε.

Συμπεριφορικά χαρακτηριστικά των συσκευών. Στο μεγαλύτερο κομμάτι της βιβλιογραφίας, οι συσκευές θεωρούνται ουδέτεροι μεγιστοποιητές της συνάρτησης ωφελιμότητας τους, αγνοώντας κατά την λήψη αποφάσεων την αβεβαιότητα των προοπτικών τους και το συμπεριλαμβανόμενο ρίσκο στο περιβάλλον. Η συνεκτίμηση της συμπεριφοράς που επηρεάζεται από το ρίσκο και την αβεβαιότητα οδηγεί σε πιο ρεαλιστικές στρατηγικές λήψης αποφάσεων και συνεπώς επιτρέπει την πιο επιτυχημένη εφαρμογή των προτεινόμενων πλαισίων σε πραγματικά σενάρια.

Κατανεμημένη λήψη αποφάσεων. Η ετερογένεια στη συμπεριφορά και η υποκειμενικότητα στην αντίληψη της Ποιότητας Εμπειρίας από τους χρήστες, καθώς και η ανάγκη για ευέλικτες και κλιμακούμενες λύσεις, υπογραμμίζουν την σημασία μιας πιο κατανεμημένης προσέγγισης στην λήψη αποφάσεων. Η ύπαρξη παντοδύναμων κεντρικών οντοτήτων που ενορχηστρώνουν ολόκληρη τη διαδικασία δεν είναι πλέον ρεαλιστική σε πολλά σύγχρονα σενάρια, και προσεγγίσεις όπου οι συσκευές δρουν με βάση το προσωπικό τους συμφέρον μπορεί να οδηγήσουν σε πιο ενδιαφέρουσες και βιώσιμες λύσεις.

Ολιστικά πλαίσια. Με την εισαγωγή των δικτύων επόμενης γενιάς και τη δραστική αλλαγή στον όγκο των συνδεδεμένων συσκευών και στις μεθόδους ανταλλαγής πληροφοριών, απαιτούνται σημαντικές αλλαγές σε ολόκληρη τη διαδικασία ανταλλαγής δεδομένων, και η βελτιστοποίηση σε ένα μόνο συστατικό παλιότερων λύσεων είναι αναποτελεσματική. Καθ'όλη τη διάρκεια της διατριβής, προσπαθήσαμε να προτείνουμε συνεκτικές διαδικασίες, όπου τόσο οι χρήστες όσο και οι διακομιστές συμμετέχουν από κοινού στη διαδικασία λήψης αποφάσεων, αξιοποιώντας διάφορους διασυνδεδεμένους μηχανισμούς και συνεπώς ακολουθώντας μια πιο ολιστική προσέγγιση για την συνολική αντιμετώπιση του εκάστοτε προβλήματος.

Ελλιπείς πληροφορίες. Συχνά στη βιβλιογραφία, το σύνολο των πληροφοριών του περιβάλλοντος θεωρείται προσβάσιμο από τους συμμετέχοντες - ειδικά στις περιπτώσεις κεντρικής λήψης αποφάσεων - και συνεπώς η γνώση για την αντίληψη, τις επιλογές και τις ανταμοιβές όλων των χρηστών καθώς και όλων των υπόλοιπον χαρακτηριστικών του δικτύου και του περιβαλλοντος είναι διαθέσιμη. Δεδομένου ότι αυτό δεν είναι πάντα εφικτό, μας ενδιέφερε η διερεύνηση των καταστάσεων στις οποίες τα άτομα έχουν περιορισμένες ή ελλιπείς πληροφορίες, και για την λήψη των αποφάσεών τους περιορίζονται στις πληροφορίες των δικών τους αποφάσεων και στην παρατήρηση του περιβάλλοντος στο οποίο βρίσκονται.

Στην παρούσα διατριβή προσπαθήσαμε να προτείνουμε λύσεις συνυφασμένες με τα παραπάνω πεδία και η συνεισφορά μας συνοψίζεται στα εξής:

- Προτείναμε έναν μηχανισμό συσταδοποίησης συσκευών που λαμβάνει συνδυαστικά υπόψιν τη συνάφεια των δεδομένων, την φυσική απόσταση των συσκευών και την ενεργειακή κατανάλωση, για την πιο αποτελεσματική επικοινωνία μεταξύ των συσκευών. Στην πλειοψηφία των εργασιών της βιβλιογραφίας δεν λαμβάνεται υπόψιν η συνάφεια των πληροφοριών η οποία στα περιβάλλοντα Διαδικτύου των Πραγμάτων μπορεί να παίξει καθοριστικό ρόλο στην ελαχιστοποίηση των περιττών ανταλλαγών πληροφορίας.
- Προτείναμε την χρήση της τεχνολογίας WPC για να καταστεί δυνατή η επικοινωνία σε συσκευές χαμηλής ενεργειακής διαθεσιμότητας. Δεδομένου ότι στο περιβάλλον του Διαδικτύου των Πραγμάτων δεν διαθέτουν όλες οι συσκευές αφθονία ηλεκτρικής ενέργειας (πχ. αισθητήρες χωρίς μπαταρία, συσκευές σε απομακρυσμένη τοποθεσία) και επειδή οι ευρέως χρησιμοποιούμενες τεχνικές συλλογής ενέργειας (πχ. ηλιακή, ανεμογεννήτριες) λειτουργούν ευκαιριακά και συνεπώς δεν μπορούν να εγγυηθούν σταθερή παροχή ενέργειας, πιστεύουμε ότι η τεχνολογία WPC μπορεί να είναι κομβικής σημασίας για την επικοινωνία των συσκευών σε κάποια σενάρια. Στην διατριβή μας προτείνουμε έναν μηχανισμό για την επιλογή της συσκευής που θα τροφοδοτεί με ενέργεια τις υπόλοιπες συσκευές, με βάση την εγγύτητα και τις ενεργειακές της δυνατότητες.
- Στοχεύσαμε στην βελτιστοποίηση της ενεργειακής απόδοσης των συσκευών για τη μετάδοση των δεδομένων. Κατά την φάση μετάδοσης των δεδομένων, οι συσκευές είναι υπεύθυνες για την ανταλλαγή των πληροφοριών εντός του δικτύου. Λόγω του μεγάλου αριθμού συσκευών που επιθυμούν να μεταδώσουν την ίδια χρονική στιγμή, υπάρχει ισχυρή παρεμβολή και θόρυβος στο κανάλι επικοινωνίας τους. Για την επίλυση αυτού του προβλήματος, προτείναμε τον ορισμό μια συσκευής ως αντιπρόσωπος για κάθε συστάδα, η οποία είναι υπεύθυνη για τη συλλογή των πληροφοριών από τις υπόλοιπες συσκευές και για την μετάδοσή τους στο υπόλοιπο δίκτυο. Ο προτεινόμενος μηχανισμός μοντελοποιήθηκε ως ένα μη-συνεργατικό παίγνιο, που στοχεύει στη μείωση της ισχύος μετάδοσης, στην αποφυγή υψηλών παρεμβολών και στην επίτευξη υψηλής Ποιότητας Εμπειρίας για τις συσκευές του δικτύου.
- Στοχεύσαμε στην βελτιστοποίηση της αποφόρτωσης δεδομένων στα περιβάλλοντα

Υπολογισμού στα Άκρα Πολλαπλής Πρόσβασης. Σε ένα τέτοιο περιβάλλον, όπου ο διαχειριστής του διακομιστή είναι διαφορετικός από τον τελικό χρήστη, αμφότερες οι δύο πλευρές επιθυμούν να μεγιστοποιήσουν την αντιλαμβανόμενη εμπειρία τους με αντικρουόμενα συμφέροντα. Ως εκ τούτου, αντιμετωπίσαμε το πρόβλημα ως ένα πρόβλημα βελτιστοποίησης δύο επιπέδων, όπου στο πρώτο επίπεδο οι χρήστες ανταγωνίζονται σε ένα μη-συνεργατικό παίγνιο προκειμένου να μεγιστοποιήσουν την προσωπική τους ευημερία, αποφορτίζοντας ένα μέρος ή το σύνολο των υπολογιστικών τους εργασιών, ενώ στο δεύτερο επίπεδο, οι διακομιστές, λαμβάνοντας υπόψιν τα δεδομένα που τους αποστέλλονται, επιχειρούν να μεγιστοποιήσουν το κέρδος που θα επωμιστούν.

- Μοντελοποιήσαμε ένα μηχανισμό επιλογής διακομιστή από τους χρήστες σε μια ανταγωνιστική αγορά πολλαπλών διακομιστών, βασισμένο στα στοχαστικά αυτόματα. Δεδομένου ότι σε μια αγορά πολλαπλών διακομιστών οι τελικοί χρήστες δεν διαθέτουν a priori πληροφορίες σχετικά με την ποιότητα του κάθε διακομιστή με τον οποίον πρόκειται να αλληλεπιδράσουν, προτείνουμε έναν ενισχυτικό μηχανισμό μάθησης βασισμένο στη θεωρία στοχαστικών αυτομάτων, ο οποίος λαμβάνει υπόψιν προηγούμενες ενέργειες των χρηστών, την τιμολόγηση και πιθανές εκπτώσεις, προβλήματα συμφόρησης και το μερίδιο του κάθε διακομιστή στην αγορά, προκειμένου να επιλέξουν οι χρήστες τον κατάλληλο διακομιστή. Αναθέτοντας μια βαθμολογία φήμης σε κάθε διακομιστή, οι χρήστες επιλέγουν πιθανοτικά αυτόν με τον οποίο επιθυμούν να συσχετιστούν.
- Ενσωματώσαμε συμπεριφορικά στοιχεία στην διαδικασία απόφασης. Οι διακομιστές στα περιβάλλοντα Υπολογισμού στα Άκρα Πολλαπλής Πρόσβασης, καθώς δεν είναι τόσο ισχυροί όσο στα περιβάλλοντα νέφους, μοντελοποιήθηκαν ως Κοινόχρηστες Πηγές Πόρων (Common Pool Resources), συσχετίζοντας την πιθανότητα αποτυχίας εκτέλεσης των λειτουργιών τους με την έκταση χρήσης τους. Αυτή η αβεβαιότητα στην λειτουργία τους παίζει σημαντικό ρόλο για την ρεαλιστική αναπαράσταση και μοντελοποίηση της συμπεριφοράς των χρηστών κατά την λήψη των αποφάσεών τους. Στην εργασία μας προτείναμε την χρήση της Θεωρίας Προοπτικής, μιας συμπεριφορικής οικονομικής θεωρίας που μοντελοποιεί τις αποφάσεις ατόμων σε συνθήκες αβεβαιότητας.
- Για την από κοινού επίλυση των προβλημάτων αποφόρτωσης δεδομένων από τους χρήστες και επιλογής τιμών από τους διακομιστές, διαμορφώσαμε ένα παίγνιο Stackelberg μεταξύ των διακομιστών (ηγέτες) και των χρηστών (ακόλουθοι), για να καθορίσουμε τη βέλτιστη τιμολόγηση των υπολογιστικών υπηρεσιών και τις βέλτιστες στρατηγικές εκφόρτωσης δεδομένων. Η διαδικασία λήψης απόφασης για την εκφόρτωση των δεδομένων των χρηστών διατυπώνεται ως ένα μη-συνεργατικό υποπαίγνιο μεταξύ των χρηστών, ενώ η επιλογή της τιμολόγησης ως ένα ξεχωριστό μη-συνεργατικό υποπαίγνιο μεταξύ των διακομιστών.

- Χρησιμοποιήσαμε ενισχυτική μάθηση για την επιλογή τιμολόγησης σε ανταγωνιστικές αγορές με πολλούς διακομιστές. Προκειμένου να αντιμετωπιστεί το δίλημμα εξερεύνησης - εκμετάλλευσης σε ένα περιβάλλον όπου οι διακομιστές δεν γνωρίζουν εκ των προτέρων την τιμή που οδηγεί στο πιο κερδοφόρο αποτέλεσμα, προτείναμε την μοντελοποίηση του προβλήματος ως προβλημα Πολλαπλών Κουλοχέρηδων (Multi-armed Bandit). Τα οφέλη της συγκεκριμένης μοντελοποίησης έγκεινται στην αποφυγή περίπλοκων υπολογισμών και συναρτήσεων, αλλά και στην μειωμένη ανάγκη πληροφορίας σχετικά με τις ενέργειες των υπόλοιπων συσκευών. Οι αποφάσεις λαμβάνονται από κάθε χρήστη ξεχωριστά με βάση απλές παρατηρήσεις του περιβάλλοντος.
- Υλοποιήσαμε και αξιολογήσαμε τα προτεινόμενα πλαίσια μέσω προσομοιώσεων. Για να ελέγξουμε την αποτελεσματικότητα και την αποδοτικότητα των πλαισίων που προτείναμε, καθώς και για να ελέγξουμε την επιρροή κάθε παραμέτρου στο αντίστοιχο μοντέλο, πραγματοποιήσαμε προσομοιώσεις σε όσο το δυνατόν ρεαλιστικότερα σενάρια.

Πιο αναλυτικά, θα αναφερθούμε στις επιμέρους εργασίες που συνθέτουν την παρούσα διατριβή καθώς και στα προβλήματα που μελετήθηκαν και επιλύθηκαν.

Συλλογή ενέργειας και διαχείριση πόρων, λαμβάνοντας υπόψιν τα κοινά ενδιαφέροντα των συσκευών.

Σε αυτή την εργασία, θεωρήσαμε ένα περιβάλλον Διαδικτύου των Πραγμάτων με συσκευές χαμηλής ισχύος οι οποίες επιθυμούν να μεταδώσουν τις πληροφορίες που διαθέτουν στο υπόλοιπο δίκτυο μέσω της επικοινωνίας μηχανής με μηχανή (Machine to Machine). Στόχος μας είναι η χαμηλή ενεργειακή κατανάλωση για την επέκταση του χρόνου ζωής της μπαταρίας των συσκευών και την εξασφάλιση της απρόσκοπτης λειτουργίας του συστήματος για μεγαλύτερο χρονικό διάστημα. Το τελευταίο είναι εξαιρετικής σημασίας σε περιβάλλοντα στα οποία η ανθρώπινη πρόσβαση είναι δύσκολη ή η αλλαγή μπαταρίας δεν είναι εφικτή.

Για να αποφευχθεί η συμφόρηση στο δίκτυο αλλά και για να μειώσουμε την απόσταση επικοινωνίας, οι συσκευές επιλέγουν να στείλουν τα δεδομένα τους σε μια ενδιάμεση συσκευή, υπεύθυνη για την μεταβίβαση των δεδομένων στο υπόλοιπο δίκτυο. Δεδομένου ότι οι συσκευές είναι έξυπνες και οι πληροφορίες που διαθέτουν έχουν συγκεκριμένο περιεχόμενο (πχ. θερμοκρασία, πίεση κλπ.) πιστεύουμε ότι ο τύπος του περιεχομένου αποτελεί σημαντικό στοιχείο για την αποδοτικότερη επικοινωνία και μετάδοση. Η επιλογή της ενδιάμεσης συσκευής λοιπόν δεν είναι τετριμμένη διαδικασία καθώς οι συσκευές έχουν διαφορετική εγγύτητα και διαφορετικά ενδιαφέροντα ως προς τον τύπο δεδομένων. Επιπλέον, προκύπτουν μη τετριμμένα προβλήματα και κατά την φάση επικοινωνίας, καθώς οι χαμηλής ισχύος συσκευές χρειάζονται επαρκή ενέργεια για να μεταδώσουν τα δεδομένα τους, ενώ ταυτόχρονα οφείλουν να διατηρήσουν την Ποιότητα Υπηρεσίας υψηλά, παρά τον θόρυβο και τις παρεμβολές στο κανάλι μετάδοσης.

Στοχεύοντας στην επίλυση των παραπάνω προβλημάτων, αρχικά δημιουργήσαμε ομάδες συσκευών χρησιμοποιώντας την Διαδικασία Κινέζικου Εστιατορίου (Chinese Restaurant Process), κατά την οποία κάθε ομάδα αντιστοιχεί σε ένα τραπέζι και κάθε συσκευή σε έναν πελάτη. Οι πελάτες καλούνται να επιλέξουν το τραπέζι στο οποίο θα κάτσουν, επιλέγοντας με μη μηδενική πιθανότητα ανάμεσα σε ένα άδειο τραπέζι και στα ήδη κατειλημμένα. Στην περίπτωση τον συσκευών, η πιθανότητα επιλογής της ομάδας στην οποία θα ενταχθούν εξαρτάται τόσο από την φυσική τους απόσταση, όσο και από την φύση των δεδομένων που διαθέτουν.

Για να υπολογιστεί η παραπάνω πιθανότητα, δημιουργήσαμε δύο γράφους με κόμβους τις συσκευές του δικτύου, και βάρη των ακμών, στη μία περίπτωση την μεταξύ τους φυσική απόσταση, και στην δεύτερη την ομοιότητα των ενδιαφερόντων τους. Με αυτόν τον τρόπο, η επιθυμία δύο συσκευών να συσχετιστούν προκύπτει από το σταθμισμένο άθροισμα των αποστάσεων των κόμβων στους δύο γράφους μετά από κανονικοποίηση των βαρών. Η τελική πιθανότητα κάθε κόμβος να επιλέξει την κάθε ομάδα προκύπτει από το μέσο όρο του σκορ συσχέτισης με όλους τους υπόλοιπους κόμβους της ομάδας.

Αφού πραγματοποιηθεί ο διαχωρισμός των ομάδων, καλούμαστε να επιλέξουμε μια συσκευή από κάθε ομάδα η οποία θα λειτουργεί ως αντιπρόσωπος και θα είναι υπεύθυνη για συλλογή και προώθηση των δεδομένων στο υπόλοιπο δίκτυο, καθώς και για την αποστολή επαρκούς ενέργειας προς τις υπόλοιπες συσκευές της ομάδας της. Για το λόγο αυτόν, δημιουργήσαμε έναν γράφο του οποίου οι ακμές αποτελούν έναν συνδυασμό της φυσικής απόστασης και της ομοιότητας των ενδιαφερόντων τους, και χρησιμοποιήσαμε την έννοια της κεντρικότητα εγγύτητας για να καταλήξουμε στη συσκευή που είναι πιο "σημαντική" ως προς την απόστασή της από τις υπόλοιπες. Συνδυάζοντας αυτήν την τιμή με τα ενεργειακά αποθέματα κάθε συσκευής, οδηγηθήκαμε στην επιλογή της πιο υποσχόμενης συσκευής ως αντιπρόσωπο.

Καθώς ο επιλεγμένος αντιπρόσωπος είναι υπεύθυνος για την επάρκεια ενέργειας στην ομάδα του, μοντελοποιήσαμε μια διαδικασία συλλογής ενέργειας από τις συσκευές με βάση την τεχνική WPC (Wireless Powerd Communication) η οποία περιλαμβάνει ένα στάδιο μεταφοράς ενέργειας μέσω ραδιοσυχνοτήτων (Wireless Energy Transfer) και ένα στάδιο αποστολής δεδομένων (Wireless Information Transmission). Η προσέγγιση που προτείναμε για τον υπολογισμό της ενέργειας που απαιτείται από τις συσκευές έχει ως στόχο την μεγιστοποίηση της ικανοποίησης των συσκευών και την διασφάλιση της ομαλής λειτουργίας του συστήματος.

Για την επίτευξη των παραπάνω, μοντελοποιήσαμε τη διαδικασία επιλογής ισχύος μετάδοσης ως ένα μη-συνεργατικό παίγνιο μεταξύ των συσκευών, η συνάρτηση ωφελιμότητας των οποίων ορίστηκε με βάση το εύρος ζώνης του δικτύου, την ισχύ μετάδοσης και την πιθανότητα επιτυχημένης μετάδοσης. Οι συσκευές, συμμετέχοντας σε αυτό το παίγνιο και προσπαθώντας να μεγιστοποιήσουν την συνάρτηση ωφελιμότητάς τους, συγκλίνουν σε μια στρατηγική η οποία αποτελεί και την ισορροπία κατά Nash του παιγνίου. Αφού βρεθεί η ισχύς που απαιτείται για την μετάδοση, ο αντιπρόσωπος κάθε ομάδας στέλνει την ανάλογη ενέργεια στο στάδιο μεταφοράς ενέργειας και οι συσκευές είναι πλέον ικανές να μεταδώσουν τα δεδομένα τους. Στην περίπτωση που η ενέργεια που λαμβάνουν είναι μεγαλύτερη από την απαιτούμενη, οι συσκευές μπορούν να αποθηκεύσουν μέρος της ενέργειας αυξάνοντας το ενεργειακό τους απόθεμα για μελλοντική χρήση.

Δυναμική αποφόρτωση δεδομένων σε περιβάλλοντα Υπολογισμού στα Άκρα Πολλαπλής Πρόσβασης.

Στην επόμενη εργασία μας, επικεντρωθήκαμε σε περιβάλλοντα Υπολογισμού στα Άκρα Πολλαπλής Πρόσβασης (MEC), με την ύπαρξη ισχυρών διακομιστών στα άκρα του δικτύου, οι οποίοι προσφέρουν τις υπολογιστικές τους δυνατότητες σε πιο αδύναμες συσκευές - χρήστες. Εντάσσοντας στα περιβάλλοντα αυτά τεχνολογίες Δικτύωσης Καθορισμένη από Λογισμικό (SDN), η λήψη αποφάσεων εκ μέρους των χρηστών, η δρομολόγηση της κίνησης των δεδομένων καθώς και η διασφάλιση της Ποιότητας Υπηρεσίας μπορεί να πραγματοποιηθεί στο πεδίο ελέγχου από τον ελεγκτή SDN με δυναμικό τρόπο.

Το περιβάλλον που μας απασχόλησε αποτελείται από πολυάριθμες κινητές συσκευές οι οποίες είναι υπεύθυνες για την εκτέλεση ορισμένων εργασιών, και πολυάριθμους διακομιστές που είναι διατεθειμένοι να τις αναλάβουν έναντι κάποιας τιμής. Στόχος μας είναι η κάθε συσκευή να επιλέξει τόσο τον διακομιστή με τον οποίο θα συσχετιστεί όσο και το μέγεθος της εργασίας που θα του αποστείλει, ενώ παράλληλα ο κάθε διακομιστής να επιλέξει την τιμή την οποία θα θέσει για την υπηρεσία του. Κάθε συσκευή διαθέτει έναν ορισμένο όγκο δεδομένων που αντιστοιχούν στην εργασία του και επιλέγει το πλήθος των δεδομένων που θα στείλει στον διακομιστή, και αντίστοιχα το πλήθος που θα κρατήσει για τοπική επεξεργασία.

Αρχικά οι χρήστες επιλέγουν το διακομιστή με τον οποίο επιθυμούν να συσχετιστούν με βάση μια πιθανότητα, με μια διαδικασία που βασίζεται στην θεωρία των στοχαστικών αυτόματων (stochastic learning automata). Η πιθανότητα αυτή καθορίζεται σύμφωνα με την πρότερη εμπειρία των χρηστών κατά την διαδικασία επιλογής. Πιο συγκεκριμένα, ο ελεγκτής SDN διαθέτει μια βαθμολογία για κάθε διακομιστή, η οποία εκφράζει την φήμη που έχει ο διακομιστής με βάση τη συμπεριφορά του σε προηγούμενες χρονικές στιγμές. Η βαθμολογία αυτή εκφράζεται ως το σταθμισμένο άθροισμα της σχετικής τιμής που θέτει ο διακομιστής σε σχέση με τους υπόλοιπους (λαμβάνοντας υπόψιν και πιθανές εκπτώσεις που εφαρμόζει), της συμφόρησης του κατά τη χρήση του και του ποσοστού του μεριδίου αγοράς που έχει. Στη συνέχεια οι χρήστες, με βάση αυτήν τη βαθμολογία, και ανάλογα με το διακομιστή που επέλεξαν, ανανεώνουν την πιθανότητα με την οποία θα επιλέξουν τον κάθε διακομιστή στην επόμενη χρονική στιγμή.

Αφού πραγματοποιηθεί η επιλογή του διακομιστή, οι χρήστες συμμετέχουν σε ένα μη-συνεργατικό παίγνιο για τον υπολογισμό του όγκου των δεδομένων που θα του αποστείλουν. Ως συνάρτηση ωφελιμότητας του κάθε χρήστη ορίζεται η διαφορά της ικανοποίησης που λαμβάνει από την αποστολή των δεδομένων του και του κόστους που αντιλαμβάνεται για την λήψη αυτής της υπηρεσία από τους διακομιστές. Λόγω της ετερομορφίας των χρηστών, η ικανοποίηση που λαμβάνει ο καθένας είναι διαφορετική και μοντελοποιείται ως μια αύξουσα αλλά κοίλη συνάρτηση. Από την άλλη, το κόστος που αντιλαμβάνεται ο κάθε χρήστης ορίζεται ως το γινόμενο των δεδομένων που στέλνει επί την τιμή ανά bit που θέτουν οι διακομιστές σε κάθε χρονική στιγμή, πολλαπλασιασμένο με μια σταθερά, διαφορετική για κάθε χρήστη, που υποδηλώνει την αντίληψη κόστους που έχει ο καθένας τους. Με τη διαδικασία βέλτισης απόκρισης για τη μεγιστοποίηση της συνάρτησης ωφελιμότητάς τους, οι χρήστες οδηγούνται στο σημείο ισορροπίας κατά Nash του παιγνίου.

Τέλος, αφού ολοκληρωθεί η επιλογή του όγκου των δεδομένων που θα αποστείλουν οι χρήστες, ο κάθε διακομιστής επιλέγει εκ νέου την τιμή που θα θέσει για τις υπηρεσίες του, προσπαθώντας να μεγιστοποιήσει τη δική του συνάρτηση ωφελιμότητάς, η οποία ορίζεται ως το καθαρό κέρδος του, δηλαδή τη διαφορά ανάμεσα στον τζίρο που έχει και στο κόστος για την διεκπεραίωση των εργασιών. Ο τζίρος του κάθε διακομιστή ορίζεται ως το γινόμενο των δεδομένων που λαμβάνει και της τιμής που θέτει, αφαιρώντας την πιθανή έκπτωση που παρέχει, ενώ το κόστος ορίζεται ως το γινόμενο του αριθμού των δεδομένων και του κόστους ανά bit που έχει ο κάθε διακομιστής. Το πρόβλημα αυτό ορίζεται ως ένα πρόβλημα μεγιστοποίησης και ο αναλυτικός του υπολογισμός μπορεί να πραγματοποιηθεί στον ελεγκτή SDN του συστήματος.

Οι διαδικασίες επιλογής διακομιστή και επιλογής δεδομένων από τους χρήστες, και επιλογής τιμής από τους διακομιστές, επαναλαμβάνεται συνεχώς μέχρι ο κάθε χρήστης να επιλέγει τον διακομιστή που τον ενδιαφέρει με βεβαιότητα, και τόσο ο αριθμός δεδομένων όσο και οι τιμές των υπηρεσιών να συγκλίνουν στην τελική τους τιμή.

Αποφόρτωση δεδομένων σε περιβάλλοντα Υπολογισμού στα Άκρα Πολλαπλής Πρόσβασης υποβοηθούμενα από Συστήματα μη Επανδρωμένων Αεροσκαφών, σε συνθήκες ρίσκου και αβεβαιότητας.

Για την αποτελεσματική εφαρμογή της τεχνολογίας Υπολογισμού στα Άκρα Πολλαπλής Πρόσβασης έχουν προταθεί διάφορα σενάρια ανάλογα με την υποδομή του δικτύου. Στη συγκεκριμένη εργασία θεωρήσαμε ένα περιβάλλον με πολλούς χρήστες οι οποίοι επιθυμούν να αποφορτώσουν τα δεδομένα τους σε έναν διακομιστή πάνω σε ένα Σύστημα μη Επανδρωμένου Αεροσκάφους (ΣμηΕΑ). Η χρήση των ΣμηΕΑ έχει παρουσιάσει έντονο ενδιαφέρον καθώς καθιστούν τον διακομιστή πιο ευέλικτο, επιτρέποντάς του να πλησιάσει πιο κοντά στους χρήστες, βελτιώνοντας το κανάλι επικοινωνίας τόσο λόγω απόστασης όσο και ορατότητας, επιτρέπουν τη μετακίνησή του σε νέες θέσεις ανάλογα με τις ανάγκες του δικτύου και δίνοντάς του τη δυνατότητα να εξυπηρετήσει δυσπρόσιτες περιοχές, χαρακτηριστικά που δεν διαθέτει ένας διακομιστής εγκαταστημένος σε σταθμό βάσης.

Οι διακομιστές στα περιβάλλοντα Υπολογισμού στα Άκρα Πολλαπλής Πρόσβασης, πόσο μάλλον πάνω σε ΣμηΕΑ, παρότι ισχυροί, διαθέτουν πεπερασμένο αριθμό πόρων για την διεκπεραίωση εργασιών. Γι'αυτόν το λόγο χρησιμοποιήσαμε τη θεωρία Κοινόχρηστων Πόρων και τη θεωρία της Τραγωδίας των Κοινών Αγαθών για τη μαθηματική τους μοντελοποίηση. Έτσι, ο διακομιστής έχει μειωμένη αποδοτικότητα ανάλογα με την χρήση, και του αντιστοιχεί μια πιθανότητα, επίσης ανάλογα με την χρήση, για να αποτύχει ολοσχερώς να εκτελέσει τις εργασίες του. Η εγγενής αυτή πιθανότητα αποτυχίας των διακομιστών να ικανοποιήσουν τις ανάγκες των χρηστών, οδηγεί στην ανάγκη υιοθέτησης πιο σύνθετων θεωριών για την μοντελοποίηση της συμπεριφοράς των χρηστών υπό συνθήκες αβεβαιότητας. Στην εργασία μας επιλέξαμε τη Θεωρία Προοπτικής για την περιγραφή της συνάρτησης ωφελιμότητας των χρηστών, στόχος των οποίων είναι η εύρεση του πλήθους των δεδομένων που θέλουν να αποφορτώσουν στον διακομιστή που βρίσκεται πάνω στο ΣμηΕΑ και το αντίστοιχο πλήθος που επιθυμούν να κρατήσουν για τοπική επεξεργασία.

Σύμφωνα με τη Θεωρία Προοπτικής, οφείλουμε να ορίσουμε ένα σημείο αναφοράς με βάση το οποίο υπολογίζονται τα κέρδη και οι απώλειες του συστήματος, η ύπαρξή του οποίου είναι ιδιαίτερα σημαντική καθώς ίδια μεγέθη κερδών και απωλειών έχουν διαφορετική επίδραση στις επιλογές των ατόμων. Ως σημείο αναφοράς θεωρήσαμε την επένδυση στους ασφαλείς πόρους, δηλαδή την τοπική επεξεργασία όλων των δεδομένων. Η συνάρτηση ωφελιμότητας κάθε χρήστη για την αποφόρτωση των δεδομένων του εξαρτάται από το αν ο διακομιστής κατάφερε ή όχι να εκτελέσει τις εργασίες που ανέλαβε, και περιλαμβάνει την απόδοση της επένδυσης στον διακομιστή, την τιμή χρέωσης της υπηρεσίας από τον διακομιστή και την ικανοποίηση από την τοπική επεξεργασία των εναπομεινάντων δεδομένων. Η διαφορά ανάμεσα στην τιμή της ωφελιμότητας και το σημείο αναφοράς είναι αυτή που μας δίνει την αντιλαμβανόμενη ωφελιμότητα σύμφωνα με τη Θεωρία Προοπτικής.

Συνδυάζοντας την πιθανότητα αποτυχίας με την αντιλαμβανόμενη ωφελιμότητας που περιγράψαμε, το πρόβλημά μας μοντελοποιείται ως ένα μη-συνεργατικό παίγνιο και η λύση του προκύπτει από τη μεγιστοποίηση της αναμενόμενης αντιλαμβανόμενης ωφελιμότητας. Ως λύση επιλέγεται και πάλι το σημείο ισορροπίας κατά Nash του παιγνίου, στο οποίο μπορεί να φτάσει σταδιακά το σύστημα, ακολουθώντας την τεχνική της καλύτερης απόκρισης.

Το πλαίσιο λήψης αποφάσεων που προτείνεται στην συγκεκριμένη εργασία αναφέρεται κυρίως στο πρόβλημα από την οπτική της χρήσης υπολογιστικών πόρων. Ωστόσο αξίζει να σημειωθεί ότι μπορεί εύκολα να προσαρμοστεί και να επεκταθεί και προς άλλες κατευθύνσεις όπως την ασύρματη επικοινωνία, εντάσσοντας επιπλέον κάποια χαρακτηριστικά επικοινωνίας στον ορισμό των υποκείμενων εξισώσεων.

Αποφόρτωση δεδομένων και επιλογή χρέωσης σε περιβάλλοντα Υπολογισμού στα Άκρα Πολλαπλής Πρόσβασης με πολλαπλούς διακομιστές σε συνθήκες ρίσκου και αβεβαιότητας.

Στην τελευταία μας εργασία, μελετήσαμε ένα περιβάλλον Υπολογισμού στα Άκρα Πολλαπλής Πρόσβασης παρόμοιο με την προηγούμενη, στο οποίο όμως υπάρχουν πολλοί διακομιστές που ανταγωνίζονται για την παροχή της υπηρεσίας τους. Λόγω των πεπερασμένων πόρων των διακομιστών, για άλλη μια φορά χρησιμοποιούμε τις θεωρίες Κοινόχρηστων Πόρων και Τραγωδίας των Κοινών Αγαθών για τη μοντελοποίηση της απόδοσης των διακομιστών και τη Θεωρία Προοπτικής για τη μοντελοποίηση της συμπεριφοράς των χρηστών υπό συνθήκες αβεβαιότητας. Ωστόσο, στην προσπάθειά μας να επεκτείνουμε την ιδέα της αποφόρτωσης δεδομένων σε ένα περιβάλλον με πολλούς διακομιστές, καλούμαστε να λύσουμε δύο επιπλέον προβλήματα, το πρόβλημα της επιλογής διακομιστή από τους χρήστες, και το πρόβλημα της επιλογής τιμής χρέωσης από τους διακομιστές.

Για την από κοινού επίλυση των προβλημάτων, μοντελοποιήσαμε το πρόβλημά μας ως ένα παίγνιο Stackelberg, όπου οι διακομιστές ενεργούν ως ηγέτες (leaders) και οι χρήστες ως ακόλουθοι (followers). Το παίγνιο χωρίζεται σε δύο υποπαίγνια, όπου στο πρώτο οι διακομιστές συμμετέχουν για να αποφασίσουν την τιμή που θα θέσουν για την υπηρεσία τους, ενώ στο δεύτερο οι χρήστες συμμετέχουν για να αποφασίσουν τόσο σε ποιον διακομιστή θα στείλουν τα δεδομένα τους όσο και τον όγκο των δεδομένων που θα στείλουν.

Για την επίλυση του δεύτερου προβλήματος, χρησιμοποιήσαμε παρόμοια μεθοδολογία με την προηγούμενη εργασία, όπου οι χρήστες συμμετέχουν σε ένα μη-συνεργατικό παίγνιο, για τον υπολογισμού του όγκου των δεδομένων που τους συμφέρει να αποστείλουν, με τις συναρτήσεις ωφελιμότητας βασισμένες στη Θεωρία Προοπτικής να περιλαμβάνουν την ικανοποίηση από την τοπική εκτέλεση, την απόδοση του διακομιστή και το κόστος της υπηρεσίας. Επιπλέον στην συγκεκριμένη εργασία, μοντελοποιήσαμε και ενσωματώσαμε την διαστρεβλωμένη αντίληψη της πιθανότητας από τους παίκτες που πρεσβεύει η Θεωρία Προοπτικής. Οι χρήστες υπολογίζουν την τιμή της συνάρτησης ωφελιμότητας για κάθε έναν από τους διαθέσιμους διακομιστές και τελικά επιλέγουν αυτόν ο οποίος τους προσφέρει το μεγαλύτερο κέρδος. Με αυτόν τον τρόπο επιτυγχάνουμε να επιλύσουμε από κοινού το πρόβλημα της επιλογής διακομιστή και της εύρεσης του όγκου των δεδομένων που θα αποσταλούν σε αυτόν.

Για την εύρεση της βέλτιστης τιμολόγησης από τους διακομιστές, δοκιμάσαμε δύο διαφορετικές μεθόδους, ανάλογα με τη διαθέσιμη πληροφορίας στο δίκτυο καθώς και την απαιτούμενη γνώση για τη μοντελοποίηση των συναρτήσεων που χρησιμοποιούνται. Έτσι, προτείναμε μια μέθοδο βασισμένη στην Θεωρία Παιγνίων η οποία οδηγεί σε μια ημιαυτόματη προσέγγιση για την επίλυση του προβλήματος και μια μέθοδο βασισμένη στην ενισχυτική μάθηση (reinforcement learning) που στοχεύει σε μεγαλύτερη αυτονομία του συστήματος.

Σύμφωνα με τη μέθοδο που βασίζεται στην Θεωρία Παιγνίων, οι διακομιστές με την σειρά τους συμμετέχουν σε ένα μη-συνεργατικό παίγνιο για τον ορισμό της επιθυμητής τιμής, η οποία προκύπτει από το σημείο ισορροπίας κατά Nash του προβλήματος. Η συνάρτηση ωφελιμότητας των διακομιστών εξαρτάται από το κόστος που έχει ο ίδιος ο διακομιστής για την παροχή της υπηρεσίας του, από το ποσοστό των δεδομένων που λαμβάνει καθώς και από την τιμολόγηση που θέτουν οι υπόλοιποι διακομιστές. Συνεπώς απαιτείται ένας μηχανισμός μεταφοράς αυτών των δεδομένων καθώς και μια προσεκτικά διαμορφωμένη συνάρτηση ωφελιμότητας για την επιτυχημένη λειτουργία της μεθόδου.

Αντίθετα, με την μέθοδο που βασίζεται στην ενισχυτική μάθηση, οι πληροφορίες που απαιτούνται για την επιλογή της στρατηγικής τιμολόγησης είναι λιγότερες. Σε αυτή την περίπτωση, μοντελοποιήσαμε το πρόβλημα ως ένα πρόβλημα Πολλαπλών Κουλοχέρηδων (Multi-armed Bandit), όπου οι διακομιστές καλούνται να επιλέξουν την στρατηγική τιμολόγησης χωρίς να διαθέτουν κάποια γνώση εκ των προτέρων για την ποιότητα της κάθε λύσης. Στόχος τους είναι να βρουν μέσα στον χώρο καταστάσεων την τιμή η οποία θα τους επιστρέψει τα μεγαλύτερα κέρδη με μοναδική πληροφορία το κέρδος που αντιλαμβάνονται όταν επιλέγουν την συγκεκριμένη στρατηγική. Ως κέρδος ορίζουμε την διαφορά ανάμεσα στην τιμή που θέτουν επί τον αριθμό των δεδομένων που λαμβάνουν, μείον το κόστος ανά bit επί τον αριθμό των δεδομένων. Για να φτάσουν στην επιθυμητή λύση, επιλέξαμε τον αλγόριθμο UCB1, ο οποίος παρέχει μια ισορροπία ανάμεσα στην εξερεύνηση νέων λύσεων και στην εκμετάλλευση αποδεδειγμένα καλών λύσεων, ενώ ταυτόχρονα εξασφαλίζει μικρή απογοήτευση (regret) σε βάθος χρόνου για τους χρήστες που επιλέγουν την στρατηγική τους με βάση τον συγκεκριμένο αλγόριθμο.

Συγκρίνοντας αυτές τις δύο μεθόδους, καταλήξαμε στο ότι η μέθοδος που βασίζεται στην ενισχυτική μάθηση απαιτεί λιγότερες πληροφορίες αλλά περισσότερο χρόνο εκτέλεσης για να έχει ανταγωνιστικά αποτελέσματα καθώς απαιτούνται πολλές επιλογές από τους διακομιστές ώστε να εξερευνήσουν ενδελεχώς τον χώρο στρατηγικών. Ωστόσο, μετά από επαρκές χρονικό διάστημα, καταλήγει σε μεγαλύτερα κέρδη για τους διακομιστές. Αντίθετα, η μέθοδος που βασίζεται στην Θεωρία Παιγνίων απαιτεί πιο προσεκτικά διαμορφωμένες συναρτήσεις και περισσότερες πληροφορίες σχετικά με τις δράσεις των υπολοίπων παικτών και του περιβάλλοντος, αλλά φτάνει γρήγορα σε καλές λύσεις του προβλήματος.

Μέρος της έρευνάς μας, ήταν η απόδειξη της αποδοτικότητας των πλαισίων και των αλγορίθμων που προτείναμε και η επιβεβαίωση της αξίας των λύσεών μας στα προβλήματα που προκύπτουν στα περιβάλλοντα επικοινωνίας μηχανή με μηχανή και Υπολογισμού στα Άκρα Πολλαπλής Πρόσβασης.

Αρχικά αποδείξαμε την αξία των αποκεντρωμένων μεθόδων λήψης αποφάσεων, οι οποίες ισχυριζόμαστε ότι είναι υψίστης σημασίας, καθώς στα σύγχρονα δίκτυα δίνεται μεγάλη βάση στην ιδιωτικότητα, την ασφάλεια, την αξιοπιστία και την επεκτασιμότητα τους. Η χρήση κατανεμημένων τεχνικών συχνά ταιριάζει περισσότερο στη φύση των προβλημάτων, και μπορεί ταυτόχρονα να οδηγήσει και σε καλύτερες επιδόσεις για το δίκτυο, καθώς ευνοείται η παράλληλη επεξεργασία από κάθε συσκευή ξεχωριστά. Η ύπαρξη κεντρικών οντοτήτων που διαχειρίζονται τη λήψη αποφάσεων οδηγεί σε κινδύνους μοναδικού σημείου αποτυχίας, ενώ επίσης μπορούν να προκύψουν ζητήματα προσβασιμότητας και καθυστέρησης. Η ευαισθησία των δεδομένων, η επιπλέον διαδικασία αποστολής δεδομένων στην κεντρική οντότητα και η πιθανότητα κατάχρησης της από κακόβουλους χρήστες ή κερδοσκοπικές εταιρίες, λειτουργούν επίσης απαγορευτικά ως προς μια τέτοια προσέγγιση σε ορισμένα περιβάλλοντα.

Για να πετύχουμε την αποκεντρωμένη επεξεργασία και λήψη αποφάσεων, ελέγξαμε την εφαρμοσιμότητα της Θεωρίας Παιγνίων, μοντελοποιώντας το πρόβλημα ως πρόβλημα μεγιστοποίησης της ωφελιμότητας των συσκευών. Χάρη στην εκτεταμένη βιβλιογραφία πάνω στη Θεωρία Παιγνίων, μας δόθηκε η δυνατότητα να χρησιμοποιήσουμε ήδη υπάρχοντα εργαλεία και μαθηματικά μοντέλα, επεκτείνοντας την χρήση τους στο πλαίσιο που μας αφορά. Η έννοια της ισορροπίας κατά Nash είχε κομβική σημασία στο έργο μας καθώς αποτέλεσε ένα συνεπή τρόπο για τον έλεγχο της αποδοτικότητας και της ευστάθειας των προτεινόμενων πλαισίων. Επεκτείνοντας την παραπάνω ιδέα σε περιβάλλοντα λήψης αποφάσεων σε συνθήκες αβεβαιότητας, εφαρμόσαμε τη Θεωρία Προοπτικής και πετύχαμε την ενσωμάτωσή της σε σενάρια ασύρματης δικτύωσης, καθιστώντας πιο ρεαλιστική την συμπεριφορά των συσκευών και των χρηστών του δικτύου, μεγιστοποιώντας παράλληλα την αντιλαμβανόμενη Ποιότητα Εμπειρίας τους. Με την επιτυχημένη εφαρμογή της Θεωρίας Προοπτικής στα ασύρματα δίκτυα πέμπτης γενιάς θεωρούμε ότι ανοίγει ένα μεγάλο πεδίο έρευνας με σημαντικές εφαρμογές στον συγκεκριμένο τομέα.

Ενδιαφέρον παρουσίασε η αξία της πληροφορίας του περιεχομένου των δεδομένων που διαθέτουν οι συσκευές για την μείωση της ενεργειακής κατανάλωσης επικοινωνίας και την αποδοτικότητα στη μετάδοση πληροφοριών. Συμπεριλαμβάνοντας αυτήν την πληροφορία στη διαδικασία ομαδοποίησης των συσκευών, η χρήση του εύρους ζώνης και του φάσματος επικοινωνίας μπορεί να βελτιωθεί σημαντικά, και επιλέγοντας κατάλληλους αντιπροσώπους για κάθε ομάδα, μπορούμε να πετύχουμε σημαντικά μειωμένη ανάγκη για ενέργεια. Συνδυάζοντας τα παραπάνω με τεχνικές ασύρματης μετάδοσης ενέργειας, καταφέραμε να προτείνουμε ένα συνολικό πλαίσιο ώστε να καταστήσουμε εφικτές πολλές εφαρμογές στο Διαδίκτυο των Πραγμάτων οι οποίες δεν είναι δυνατές στα υπάρχοντα δίκτυα.

Σημαντικά αποτελέσματα παρατηρήθηκαν και σχετικά με την αξία της τιμολόγησης και την ανάγκη ισορροπίας μεταξύ συσκευών - χρηστών και διακομιστών στα περιβάλλοντα Υπολογισμού στα Άκρα Πολλαπλής Πρόσβασης. Παρόλο που διαισθητικά μικρότερη τιμολόγηση θα έπρεπε να οδηγεί σε βελτιωμένη εμπειρία για τους χρήστες, κάτι τέτοιο δεν συμβαίνει καθώς οδηγεί σε αυξημένη χρήση του διακομιστή, μικρότερη απόδοση προς τον χρήστη και μεγαλύτερη πιθανότητα αποτυχίας της διαδικασίας. Αυτό έχει σαν αποτέλεσμα, τόσο μικρότερη ικανοποίηση για τους χρήστες, όσο και μικρότερα κέρδη για τους διακομιστές. Από την άλλη, παρόλο που μεγαλύτερες τιμές θα περιμέναμε να δίνουν μεγαλύτερα κέρδη για τους διακομιστές, στην πράξη οδηγούν σε μείωση κινήτρου για τους χρήστες για να αποφορτίσουν τα δεδομένα τους, προτιμώντας τοπική εκτέλεση των εργασιών τους. Οι πόροι του δικτύου σε αυτή την περίπτωση μένουν ανεκμετάλλευτοι και δεν επιτυγχάνονται τα οφέλη που πρεσβεύει ο Υπολογισμός στα Άκρα Πολλαπλής Πρόσβασης.

Συνεπώς, μια μεθοδολογία εύρεση της βέλτιστης τιμολόγησης είναι κομβικής σημασίας για την απόδοση των παραπάνω δικτύων.

Μελετώντας την απόδοση των μεθοδολογιών μας, ενδιαφέρον παρουσίασαν λύσεις βασισμένες σε τεχνικές ενισχυτικής μάθησης καθώς είναι ικανές να δώσουν λύσεις σε προβλήματα στα οποία οι πληροφορίες σχετικά με την κατάσταση του δικτύου ή τις επιλογές των υπόλοιπων συμμετεχόντων σε αυτό είναι περιορισμένες. Συγκεκριμένα, παρατηρήσαμε ότι παρόλο που αρχικά οι τεχνικές αυτές παρουσιάζουν μειωμένη αποδοτικότητα στη φάση της εξερεύνησης του περιβάλλοντος, μετά από εύλογο χρονικό διάστημα μπορούν να καταλήξουν σε λύσεις καλύτερες απ' ότι τεχνικές της Θεωρίας Παιγνίων, παρόλο που οι τελευταίες προϋποθέτουν προσεκτικά κατασκευασμένες συναρτήσεις ωφελιμότητας και περισσότερες πληροφορίες για τις επιλογές των υπόλοιπων παιχτών. Μέσα από τις εργασίες μας, αποδείξαμε ότι η επιλογή στρατηγικής με βάση την ενισχυτική μάθηση, μπορεί να οδηγήσει σε συνολικά καλύτερη εμπειρία και μικρότερες αθροιστικά απώλειες για τους συμμετέχοντες.

Συνειδητοποιήσαμε ωστόσο ότι παρά το αυξημένο ενδιαφέρον για τα δίκτυα πέμπτης γενιάς και το Διαδίκτυο των Πραγμάτων από την επιστημονική κοινότητα, παραμένουν πολλά ανοιχτά και επείγοντα προβλήματα που αναζητούν επίλυση, και η διατριβή μας θα μπορούσε να λειτουργήσει ως έναυσμα για μελλοντική έρευνα ανοίγοντας νέα και ενδιαφέροντα ερευνητικά μέτωπα. Μεγάλο ρόλο στην επιτυχημένη εφαρμογή των πλαισίων που προτείνουμε διαδραματίζουν οι συναρτήσεις ωφελιμότητας και η εισαγωγή επιπλέον παραγόντων (πχ. κόστος επικοινωνίας, κίνηση συσκευών) για πιο ρεαλιστικά ή διαφορετικού τύπου σενάρια αφήνει μεγάλο περιθώριο διερεύνησης. Επιπλέον, ο συνδυασμός του περιβάλλοντος Υπολογισμού στα Άκρα Πολλαπλής Πρόσβασης και Υπολογιστικού Νέφους μπορεί να έχει σημαντική επίδραση στην Ποιότητα Εμπειρίας των χρηστών του δικτύου, καθώς δίνεται η δυνατότητα να επωφεληθούν και από τις δύο προσεγγίσεις, ελαχιστοποιώντας τα μειονεκτήματα των δύο μεθόδων, ενώ η δυνατότητα συνεισφοράς των υπολογιστικών πόρων των χρηστών στην κοινόχρηστη πηγή πόρων μπορεί να βελτιώσει την αποδοτικότητα, στοχεύοντας στην εκμετάλλευση όλων των διαθέσιμων πόρων στο σύνολο του δικτύου.

Στην εργασία μας η επιλογή χρήσης τιμολόγησης ήταν ιδιαίτερα σημαντική στα πλαίσια που προτείναμε καθώς αποτελούσε αντισταθμιστικό παράγοντα για την κατάχρηση των διαθέσιμων πόρων. Υπάρχουν ωστόσο πολλά περιβάλλοντα στα οποία δεν είναι δυνατή μια τέτοια προσέγγιση καθώς ο τύπος του δικτύου μπορεί να μην το επιτρέπει. Ενδιαφέρον λοιπόν παρουσιάζει η αναζήτηση νέων κινήτρων και η ενσωμάτωσή τους στα πλαίσια που προτείνουμε, έτσι ώστε να μπορεί να προαχθεί η δίκαιη χρήση των πόρων και να αποφευχθεί το φαινόμενο της Τραγωδίας των Κοινών Αγαθών και σε αυτά τα περιβάλλοντα. Επιπλέον, οι λοιπές αρχές της Θεωρίας Προοπτικής όπως η εξάρτηση από τον τρόπο που παρουσιάζονται οι επιλογές στον χρήστη ή από την πηγή που προέρχεται κάποιο συμβάν, θα μπορούσαν να ενταχθούν στον σχεδιασμό των πλαισίων λήψης αποφάσεων για την καθοδήγηση των επιλογών των χρηστών προς ευνοϊκότερα για το σύστημα σημεία ισορροπίας.

Τέλος, κατά τη διάρκεια της εκπόνησης της διατριβής παρατηρήσαμε μια έλλειψη στην ύπαρξη πλαισίων σύγκρισης για την αποτελεσματική και δίκαιη σύγκριση μεθοδολογιών στο πρόβλημα της εκφόρτωσης δεδομένων σε περιβάλλοντα Υπολογισμού στα Άκρα Πολλαπλής Πρόσβασης. Καθώς τα προβλήματα που ερευνώνται είναι πολύπλοκα, κάθε εργασία υιοθετεί ένα διαφορετικό σενάριο και η έγκυρη σύγκριση μεταξύ τους είναι δύσκολη. Θεωρούμε ότι η μελέτη και η δημιουργία ενός ενιαίου πλαισίου, καθώς και η εύρεση καθολικών μετρικών για την αξιολόγηση της αποδοτικότητας των μεθοδολογιών είναι καθοριστικής σημασίας για την προώθηση της έρευνας στον συγκεκριμένο τομέα, και σε συνδυασμό με την δημιουργία κατάλληλων δοκιμαστικών υποδομών μπορούμε να φτάσουμε ένα βήμα πιο κοντά στην υιοθέτηση των προτεινόμενων μεθοδολογιών σε πραγματικά δίκτυα.

Αξίζει να σημειωθεί ότι παρότι οι προσεγγίσεις που προτείνουμε περιορίζονται σε τηλεπικοινωνιακά και υπολογιστικά δίκτυα, οι εφαρμογές τους μπορούν να επεκταθούν και σε άλλα περιβάλλοντα. Συνεπώς, με κατάλληλες τροποποιήσεις, τα προτεινόμενα πλαίσια θα μπορούσαν να χρησιμοποιηθούν και σε δίκτυα μεταφορών, έξυπνες πόλεις και ευφυή δίκτυα ενέργειας, αλλά πιθανώς και σε πιο ανθρωπιστικά πεδία όπως κοινωνιολογία και βιολογία, σε προκύπτοντα προβλήματα αντίστοιχης φύσεως.

Λέξεις Κλειδιά: Κατανομή πόρων, Κατανεμημένα συστήματα απόφασης, Διαδίκτυο των Πραγμάτων, Επικοινωνία Μηχανής με Μηχανή, Συσταδοποίηση, διαχείριση ισχύος, Υπολογισμός στα άκρα, Θεωρία Παιγνίων, Θεωρία Προοπτικής, Εκφόρτωση Δεδομένων, Πηγές Κοινόχρηστων Πόρων, Τραγωδία των Κοινών Αγαθών, Επίγνωση Ρίσκου, Ενισχυτική Μάθηση, Πρόβλημα Πολλαπλών Κουλοχέρηδων

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