Location Aware Task Offloading Framework for Edge Computing Empowered by Reconfigurable Intelligent Surfaces

Md Sahabul Hossain

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Location Aware Task Offloading Framework for Edge Computing Empowered by Reconfigurable Intelligent Surfaces

by

Md Sahabul Hossain

B.Sc. in Electrical and Electronic Engineering, Islamic University of Technology, Bangladesh, 2015

THESIS

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To my loving parents, Md Amzad Hossain and Rashida Parvin, my dear wife, Mariam Islam, and my little brother, Riadus Salehin, for their boundless love and support, who motivated and guided me in this arduous journey.
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Abstract

In this thesis, an energy efficient task offloading mechanism in a multi-access edge computing (MEC) environment is introduced, based on the principles of Contract Theory. The technology of Reconfigurable Intelligent Surfaces (RIS) is adopted and serves as the enabler for the energy efficient task offloading, from the perspective of location-awareness and improved communication environment. Initially a novel positioning, navigation, and timing solution is designed, based on the RIS technology and an artificial intelligent method that selects a set of RISs to perform the multilateration technique and determine the Internet of Things (IoT) nodes’ positions in an efficient and accurate manner is introduced. Being aware of the nodes’ positions, a maximization problem of the nodes’ sum received signal strength at the MEC server where the nodes offload their computing tasks is formulated and solved, determining each RIS element’s optimal phase shifts. Capitalizing on these enhancements, a contract-theoretic task offloading mechanism is devised enabling the MEC server to
incentivize the IoT nodes to offload their tasks to it for further processing in an energy efficient manner, while accounting for the improved nodes’ communications and computing characteristics. The performance evaluation of the proposed framework is obtained via modeling and simulation under different operation scenarios.
Part of this work has been published in:

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Chapter 1

Introduction

In the forthcoming 6G networks, the number of Internet of Things (IoT) devices and their generated data will experience phenomenal growth, calling for a green communication solution and high-performance low-latency computing services. Towards supporting the computing needs of the next generation IoT devices, the Multi-Access Edge Computing (MEC) technology has emerged as a promising paradigm [2], providing computing resources at the edge of a wireless network by incorporating MEC servers at the next generation Node Bs (gNBs) [3]. The IoT devices can partially or fully offload their computing tasks to the edge servers in order to further process them while considering their latency and energy constraints [4]. This way they manage to increase their computing capabilities and services they may support, by migrating computation to more resourceful devices, located nearby, such as edge nodes, fog nodes, base stations, or access points. At the same time, the recent introduction of Reconfigurable Intelligent Surfaces (RIS) technology, provides the vehicle for realizing energy-efficient communication in next-generation wireless networks [5, 6]. The RISs are constructed based on engineered meta-materials and they appropriately reflect the multi-path propagated signal via creating a constructive beam, thus, enabling the software-based control of the signals’ electromagnetic properties [7]. Hence, by
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optimally controlling the phase shifts of the RIS elements, the overall received signal strength can be improved, resulting in superior energy efficiency \cite{8,9}. Last, but not least, in order to exploit the advantages of the aforementioned emerging technologies at their full potential, in supporting various applications with different communications and computing requirements, accurate and cost-efficient positioning, navigation, and timing services are required \cite{10}.

In this thesis, we design a RIS-enabled location-aware task offloading mechanism in edge computing environments. In particular, we initially introduce a RIS-based positioning, navigation, and timing solution enabling the IoT devices to accurately determine their position in a real-time manner under scenarios of Global Positioning System (GPS) denial \cite{11}. Based on the IoT devices’ accurate positioning, we design a contract-theoretic task offloading mechanism to support the IoT devices’ green computing. Throughout this process we determine the RIS elements’ optimal phase shifts to realize the energy efficient communication and computing in the system.

1.1 Related Work & Motivation

RISs are an emerging hardware technology and a dominant candidate among the transceiver approaches to support green communications in next-generation wireless networks \cite{12}. Recently, great attention has been cast on RISs in task offloading purposes. In \cite{13}, the authors have formulated a RIS-assisted bandwidth allocation problem in poorly wireless-covered areas while minimizing the overall system delay. A semi-definite relaxation (SDR) method was used to tackle this task offloading problem. Their results show greatly increased performance and network delay over other baselines. The authors in \cite{14}, on the other hand, considered both the delay and the service fee charged by the edge servers to the end-users in a RIS-assisted mobile edge computing network (MEC). They jointly minimized the delay and the
cost for the end-users while maximizing the edge servers’ profit. A Stackelberg game approach was used to find the optimal parameters. To tackle poor wireless coverage, authors in [15] proposed a joint UAV and RIS-assisted framework formulating a max–min computation capacity problem while using a concave–convex procedure (CCCP)-based algorithm to solve it. They have considered both active and passive beamforming, time slot slicing, UAV’s trajectory, etc, in their problem formulation. Results have shown superior performance in terms of computation capacity compared to cases where only UAV and only RIS were used. Apart from being computation-intensive and delay-sensitive, industrial IoT applications also need increased focus on security. A deep reinforcement learning (DRL) based approach was introduced in [16] to maximize system’s weighted sum secrecy computation efficiency by considering phase shift of RISs, power control, computation capacity, and time slot allocation. In [17], a deep reinforcement learning-based algorithm was again used to minimize network latency and maximize communication data rate in a mobile edge computing system. RISs were used to increase spectral efficiency and reduce interference by intelligently modifying the propagation environment using DRL. Compared to others, the authors in [18] took a slightly different approach. They studied the performance of active RISs in a MEC system. They proposed an alternating block coordinate descent (BCD) and successive convex approximation (SCA) method to minimize the maximum latency in the system. Active RISs were found to provide better performance than their passive counterparts. Authors in [19] have introduced a latency minimization, task offload data rate maximization problem by optimizing the uplink bandwidth allocation between the local computing node and a RIS-assisted MEC server. The problem is formulated as a quadratically constrained quadratic programming which is solved by a semi-definite relaxation method. A few use cases of RISs in MEC systems and task offloading were discussed in [20] along with their challenges, possible solutions and future research opportunities. According to the authors, the application of RISs in this particular field are: reducing task processing
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delay, improving task completion rate, secure task/data offloading, and improving energy efficiency. Some challenges and therefore, research opportunities include RISs reflection coefficient design, joint computation and communication optimization, deployment of RISs in a MEC system, etc.

Several recent research works have focused on the communications field studying the use of RISs to improve the system’s energy-efficient communication [21]. The problem of power control has been studied for several decades in the literature [22,23], mainly considering a non-controllable wireless communications medium [24,25]. Several pricing mechanisms have been introduced to improve the energy efficiency of the wireless communications systems [26–29]. However, the adoption of RIS technology can substantially improve the wireless system’s energy-efficient operation. In [30], the ground-to-air RIS-assisted links are optimized by appropriately controlling the RIS elements’ phase shifts in order to maximize the coverage and reliability of the considered Unmanned Aerial Vehicles (UAVs) communications system. Towards jointly optimizing the beamforming construction at the RIS elements, a fractional programming approach is introduced in [31]. The authors optimize the beamforming to maximize the uplink sum rate of all the users, and they examine the problem under perfect and imperfect channel state information. A similar approach is proposed in [32] focusing on maximizing the users’ downlink sum rate while considering a multiple-input single-output communication system. Moreover, focusing on the downlink communication, a joint optimization of the transmit power allocation and the RIS elements’ phase shifts to maximize the overall system’s energy efficiency is introduced in [33].

The research on the RISs’ benefits in terms of improving the system’s energy efficiency has been extended by jointly examining the computing and communication characteristics of the system. The problem of minimizing the users’ sum energy consumption is studied in [34] by jointly optimizing the users’ transmission power and
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time, decoding order, amount of data offloaded to a single MEC server, and the RIS elements’ phase shifts. Similarly, in [35, 36], the authors maximize the total amount of processed data by a MEC server, by further optimizing the received beamforming vectors by the MEC server and the users’ energy partition among the local data processing on their devices and offloading data to the MEC server. Towards improving the overall MEC system’s computing capability, the wireless powered technology is adopted in [37]. The authors introduce a scheduling mechanism by jointly optimizing the users’ task offloading decisions, the RIS elements’ phase shifts, and the users’ energy harvesting time. A method to increase task computing energy efficiency is introduced in [38] with the usage of RISs. The authors here have used a combinatorial optimization problem by jointly optimizing the transmit powers and computational capacity of users and base stations, task offloading rate of users, and passive beamforming matrix at the RISs. In [39], a joint task offloading and resource allocation problem is formulated as a multi-agent Markov game where a non-orthogonal multiple access (NOMA) and simultaneously transmitting and reflecting reconfigurable intelligent surfaces (STAR-RIS) assisted MEC system is studied. A multi-agent deep reinforcement learning (MADRL) based algorithm is used to minimize the system’s energy consumption. A RIS assisted energy efficiency maximization method is investigated in [40] where the authors consider a wireless power transfer (WPT) based energy harvesting and MEC network. Semi-definite relaxation is used to solve RISs’ phase shift optimization problem while a closed form solution for resource allocation is derived to minimize the energy consumption. Results show a 150% increase in energy efficiency compared to the case where no RIS is used. A STAR-RIS assisted MEC system is also studied in [41] where the main goal is to minimize the total energy consumed by all the users. The authors consider several important parameters including the transmission and reflection time and coefficients of the STAR-RIS to form a nonconvex optimization problem, decompose it to two subproblems and then solve them using alternating optimization method. In [42], the authors lever-
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aged the passive beamforming gain provided by RISs to design an energy efficient task offloading strategy in a OFDM-NOMA enabled MEC network. Again, a highly nonconvex optimization problem is formulated which is then solved by an alternating optimization method among others. The authors in [43] demonstrated that a UAV integrated with RISs can be an efficient alternative to massive antenna systems in terms of computing latency and energy consumption. A block-coordinate descent method is used to decouple the complex optimization problem into more manageable subproblems and subsequently solved. In [44], authors introduced a frequency dependant RIS assisted MEC environment to enable low energy consuming computation offloading while ensuring reliability. A state of the art Lorentzian model is used to formulate the optimization problem taking power, frequency and computation resource allocation constraints into consideration. A dynamic algorithm to optimize power, data rate, CPU usage and RIS phase shift is introduced in [45] to enable low latency, high energy efficient task offloading in a MEC system. The authors considered uncertainty involved in task arrival and in radio channel characteristics while maintaining end-to-end delay constraints.

Most of the studies mentioned above formulated the performance optimization problem in terms of power, bandwidth, CPU allocation, beamforming, channel selection, etc. [46]. But there is another crucial factor that can directly affect the energy efficiency, latency, data rate and the overall performance of a MEC system [47]: the locations of different end points. Previous studies show that a location-aware system can achieve better utilities by allowing the end points to consider how close they are to each other and thus, giving them more freedom of choice for optimization. In [48], a cloud server selection problem is proposed where the users can offload their tasks to either a central server or an edge server. With the goal of reducing latency, the authors show that a location-aware policy provides better performance compared to the resource-based and latency-based policies. A similar approach is taken in [49] considering a 2-tier cloud computing platform. Here, the user can offload tasks to a
Chapter 1. Introduction

local or a remote cloud server but can also decide to use their own CPU for computation. An efficient location-aware algorithm is introduced and shown to achieve better performance than other heuristics. The authors in [50] demonstrate that knowing the location of the users and the edge servers in a MEC environment is very critical and additional processing delay can be introduced if the locations are not known or considered. They propose a deep reinforcement learning based location-aware task offloading algorithm and show that this algorithm enhances the system’s performance compared to the algorithms where the location isn’t considered. Delay minimization in a vehicular edge computing network (VEC) was investigated in [51]. This study demonstrates that the location of a vehicle is a crucial parameter which can impact the task processing delays. So, taking the location into account in the optimization problem can provide a better solution. In [52], a location-sensitive UAV assisted MEC system is analyzed where the primary objective is to reduce the energy cost of the hovering UAVs. A nonlinear task allocation scheme is formulated with the energy constraint of the MEC nodes and the random movement of the users being taken into account. Simulations show that the proposed location-aware approach can indeed provide highly energy efficient MEC service. In [53], the authors explored a combination of MEC and wireless mesh network (WMN) which can offer better privacy, security, storage capacity than the traditional networks. They proposed a location-aware task offloading algorithm which considers the location of mesh clients (MCs) for optimization and provides improved network performance than other methods. Similarly, the authors in [54] proposed a area-based offloading policy in a MEC enabled WMN. With the assistance of ns-3 simulator, this study proves that the area and thus the location of a MC is imperative to the system’s performance. A mobility-aware reinforcement learning based solution was introduced in [55] where the authors formulated the task offloading problem as a Markov Decision Process (MDP). The novel RL algorithm takes the mobility of the mobile equipments (MEs) into account and is demonstrated to provide better revenue to the MEs.
Chapter 1. Introduction

However, all the aforementioned approaches make the fundamental assumption that the users, and in general the IoT nodes, know their exact position while deciding their optimal task offloading strategy and their corresponding transmission power. This assumption is often quite unrealistic and optimistic, as the Global Navigation Satellite System (GNSS)-based Positioning, Navigation, and Timing (PNT) services suffer from limited availability in indoor environments [56], instability due to satellite signals interference, jamming, and spoofing [57]. In [58], the authors presented that GPS outage or denial can result in hundreds of meters of inaccuracy and developing techniques and hardware that can provide alternative PNT services is really important. GPS lock can occur in confined spaces or lost in the presence of high rise buildings or mountains. A survey paper [59] details jamming attacks and anti-jamming technologies in wireless networks including the GPS system. Five types of jamming attack against the GPS system are described in this study. Adaptive antenna array and other types of reconfigurable strategies are mentioned to work well against the GPS jamming attacks. In [60], the authors developed a UAV assisted spoofing algorithm which is robust against detection. This study shows how effective it is to design and launch a GPS spoofing attack. Similarly, in [61], a pseudolite-based alternative PNT is proposed which can, in addition to providing navigational services to the desired receivers, can deny the same to the unwanted or targeted receivers. This technique can be adopted by malicious parties to deny PNT services to legit users. Researchers in [62] argued that the frequent occurrences of GPS or GNSS radio frequency interference (RFI) events is motivating location-sensitive systems to adopt alternative PNT solutions. They also claimed that a performance equivalent to the same level as the GNSS/GPS is not required when the APNT is used as a backup. In [63], the authors described different types of GPS spoofing attacks and strategies that can be used to counter or mitigate these types of attacks.

Towards alleviating the burden of GPS denial, several ground-based PNT solutions have been introduced, such as the pseudolites and Locata systems [64], the
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distance measuring equipment networks [65], and the passive wide area multilateration technology [66]. The common characteristic of these PNT solutions is the utilization of at least four signals stemming from the ground base stations and the multilateration method to determine the target’s (IoT nodes) position. The RIS technology has been recently used as a promising alternative to determine the gNBs’ position, taking into account that the aforementioned ground-based solutions suffer from high infrastructure cost and limited coverage [67]. In [68] the potential of RISs as an APNT service is discussed in detail and a survey of RIS assisted positioning and localization is presented. RISs are argued to be both energy efficient and cost efficient (in terms of production and deployment). They are also compatible with the existing communication and localization systems. In [69], a RIS assisted localization framework is investigated and the results show that the proposed RIS assisted approach is able to reduce the positioning error bound by two orders of magnitude and the orientation error bound by one order of magnitude. They also show that the localization accuracy heavily depends on the topology of the network so properly selecting the RISs is very critical. The authors in [70] and [71] leveraged RISs as an alternative PNT solution resulting in improved availability and accuracy of PNT services. They proposed a RL based scheme to intelligently select the proper sets of RISs which reduces positioning and timing errors while a iterative least square algorithm uses measurements from the RISs to calculate the targets’ positions. A similar approach was adopted in [72] but here the authors, in addition to the RL and ILS algorithms, also deployed a satisfaction game to strategically choose the number of RISs to consider for calculating the positions. Simulations show that the proposed method achieves higher positioning accuracy than other selection methods. In [73], a RIS assisted APNT scheme is introduced in an indoor navigation scenario. Indoor navigation, as discussed earlier, suffers from GPS/GNSS outage more than other systems. So, it is very crucial to develop APNT solutions for indoor environment.

It is evident from the recent studies that RISs can be leveraged to improve the
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overall performance of a MEC system by reducing latency and improving energy efficiency. And this can be achieved by utilizing their inherent ability to control the radio propagation environment in terms of both communication and localization. Knowing their position in advance can help the IoT nodes or the users make intelligent decisions like deciding on their optimal task offloading to a MEC server. Although taking communication and computing characteristics into account is common, very little work has been done in developing models to incentivize the nodes to offload their tasks to the MEC servers for further processing, while accounting for their location characteristics. In [74], the authors proposed a novel contract theory-based incentive mechanism for cooperative task-offloading in a VEC network. Compared to the linear price incentive baseline, the suggested approach achieves higher computation resource usage, lower energy consumption per computing resource utilization, and lower energy consumption per job performed. The authors in [75] combined contract theory with computational intelligence to create a two-stage resource sharing and task offloading strategy. They introduced an effective incentive mechanism that makes use of contract theory to incentivize servers to share their leftover computational resources. In [76], the authors explored a task offloading and resource sharing problem in a VEC network where the vehicles and the road side units cooperate with each other. A contract theoretic incentivization scheme was developed to motivate the participants in sharing information and promote cooperation. The authors argued in [77] that the highly uncertain nature of heterogeneous networks and the delays involved can deter the network participants from utilizing task offloading features. To address this issue, they proposed a two-stage contract theoretic incentive mechanism to motivate the consumers to offload their tasks. Similar approaches were taken in [78] and [79] by considering the network entities’ willingness to participate in task offloading and resource sharing. The proposed schemes are able to efficiently provide incentives to the participants and motivate them to take part in cloud computing systems.
Chapter 1. Introduction

1.2 Contributions & Outline

In this thesis, a location-aware task offloading mechanism is introduced based on the principles of Contract Theory and utilizing the RIS technology. Initially, a novel PNT solution is proposed based on the RIS technology and an artificial intelligent method to select a set of RISs to perform the multilateration technique and determine the IoT nodes’ positions in an accurate manner. Given the IoT nodes’ positions, a maximization problem of the nodes’ sum received signal strength at a MEC server, when the nodes offload their computing tasks to it, is formulated and solved via determining each RIS elements’ optimal phase shifts, thus, introducing an energy efficient data transmission process. Towards further improving the system’s energy efficiency, a contract-theoretic task offloading mechanism is introduced enabling the MEC server to incentivize the IoT nodes to offload their computing tasks to it for further processing in an energy efficient manner, while accounting for the nodes’ communications and computing characteristics. The main contributions of this research work are summarized below.

1. A multi-IoT nodes single-MEC server integrated communications and computing environment enabled by multiple RISs is considered. A novel ground-based PNT solution is introduced to accurately determine the IoT nodes’ position. Specifically, a reinforcement learning framework is proposed to enable each IoT node to select three RISs from the available ones in its environment for facilitating the realization of the PNT service, while the multilateration technique is adopted to determine the nodes’ position in a distributed manner.

2. Each RIS’s elements’ phase shifts are optimized in order to maximize the nodes’ sum received signal strength during the nodes task offloading process. This approach can result in decreasing the nodes’ uplink transmission power, thus, improving the system’s energy efficient operation.
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3. A novel contract-theoretic task offloading mechanism is introduced accounting for the nodes’ communications and computing characteristics. The latter ones define each node’s type, which is of continuous nature and the node’s effort in terms of offloading its computing tasks to the MEC server in an energy efficient manner. The MEC server offers personalized rewards to the nodes in order to incentivize their energy efficient operation. The realistic scenario of incomplete information of the nodes’ types from the MEC server’s perspective is studied.

The remainder of this thesis is organized as follows. Section 2 presents the system model and an overview of the proposed framework. Section 3 introduces the RIS-enabled PNT solution, while Section 4 determines the RIS elements’ optimal phase shifts to support the system’s energy efficient operation. Section 5 designs and analyzes the proposed contract-theoretic task offloading mechanism, while Section 6 presents a detailed performance evaluation of the overall proposed framework. Finally, Section 7 concludes the thesis.
Chapter 2

System Model & Framework

Overview

2.1 RIS-enabled Integrated Communications & Computing

We consider a multi-IoT nodes single-MEC server integrated communications and computing environment consisting of multiple RISs supporting both the PNT services and the energy efficient task offloading process. An overview of the considered environment is presented in Fig. 2.1. The set of nodes is denoted as $N = \{1, \ldots, n, \ldots, |N|\}$, and the set of RISs is $\mathcal{R} = \{\mathcal{R}_1, \ldots, \mathcal{R}_r, \ldots, \mathcal{R}_{|\mathcal{R}|}\}$. The MEC server is attached to the gNB [80]. Each node has unknown coordinates $\mathbf{r}_n = (x_n, y_n, z_n)$ and its corresponding distance from the MEC server is $d_{n,gNB}$ [m]. Each node has a computing task $A_n = (B_n, C_n, \phi_n)$ that needs to process, where $B_n$ [bits] denotes the total task’s bits, $\phi_n$ [CPU Cycles/bits] represents the computing task’s intensity, and $C_n = \phi_n \cdot B_n$ [CPU Cycles] is the number of CPU Cycles in order for the computing task $A_n$ to be executed. Each IoT node can fully
Chapter 2. System Model & Framework Overview

offload its computing task to the MEC server for further processing in order to save its battery from locally executing its task. For the purposes of offloading, the node needs to wirelessly transmit its data with uplink transmission power $P_n$ [Watts].

The key notation used in the paper is summarized in Tables 2.1 and 2.2.

**Table 2.1: Summary of Key Notations**

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N = {1, \ldots, n, \ldots,</td>
<td>N</td>
</tr>
<tr>
<td>$\mathcal{R} = {R_1, \ldots, R_r, \ldots,</td>
<td>\mathcal{R}</td>
</tr>
<tr>
<td>$\mathbf{r}_n = (x_n, y_n, z_n)$</td>
<td>Node’s coordinates</td>
</tr>
<tr>
<td>$d_{n,gNB}$ [m]</td>
<td>Node’s distance from the MEC server</td>
</tr>
<tr>
<td>$A_n$</td>
<td>Node’s computing task</td>
</tr>
<tr>
<td>$B_n$ [bits]</td>
<td>Node’s task’s bits</td>
</tr>
<tr>
<td>$\phi_n$ [CPU Cycles/bits]</td>
<td>Node’s task’s computing intensity</td>
</tr>
<tr>
<td>$C_n$ [CPU Cycles]</td>
<td>Node’s task’s number of CPU Cycles</td>
</tr>
<tr>
<td>$P_n$ [Watts]</td>
<td>Node’s uplink transmission power</td>
</tr>
<tr>
<td>$p_{\text{LoS}}$</td>
<td>Probability of LoS communication</td>
</tr>
<tr>
<td>$\mathbf{r}<em>{gNB} = (x</em>{gNB}, y_{gNB}, z_{gNB})$</td>
<td>gNB/MEC server’s coordinates</td>
</tr>
<tr>
<td>$\alpha, \beta \in \mathbb{R}^+$</td>
<td>Positive constants depending on the communication environment</td>
</tr>
<tr>
<td>$f_c$ [Hz]</td>
<td>Carrier frequency</td>
</tr>
<tr>
<td>$\theta$ [rad]</td>
<td>Elevation angle</td>
</tr>
<tr>
<td>$P_{\text{LoS}}, P_{\text{NLoS}}$</td>
<td>Path loss in the LoS and NLoS communication scenarios</td>
</tr>
<tr>
<td>$\eta_{\text{LoS}}, \eta_{\text{NLoS}}$ [dB]</td>
<td>Excessive path loss exponents in the LoS and NLoS communication scenarios</td>
</tr>
<tr>
<td>$c$ [m/s]</td>
<td>Speed of light</td>
</tr>
<tr>
<td>$\gamma \in \mathbb{R}$</td>
<td>Path loss exponent depending on the communication environment</td>
</tr>
<tr>
<td>$\mathcal{E} = {1, \ldots,</td>
<td>\mathcal{E}</td>
</tr>
<tr>
<td>$\omega_e \in [0, 2\pi)$</td>
<td>Element’s phase shift</td>
</tr>
<tr>
<td>$\Omega_r = \text{diag}(e^{j\omega_1}, \ldots, e^{j</td>
<td>\mathcal{E}</td>
</tr>
<tr>
<td>$g_{n,gNB}$</td>
<td>Channel gain of the direct communication link between the IoT node $n$ and the gNB/MEC server</td>
</tr>
<tr>
<td>$\tilde{g}$</td>
<td>Random variable</td>
</tr>
<tr>
<td>$g_{n,r}$</td>
<td>Channel gain of the link between the IoT node $n$ and each RIS $r$</td>
</tr>
<tr>
<td>$\zeta$</td>
<td>Path loss among the node $n$ and the RIS $\mathcal{R}_r$ at the reference point of 1m</td>
</tr>
<tr>
<td>$d_{n,r}$ [m]</td>
<td>Distance among the node $n$ and the RIS $r$</td>
</tr>
<tr>
<td>$\lambda$ [m]</td>
<td>Carrier signal’s wavelength</td>
</tr>
<tr>
<td>$\delta$</td>
<td>Antenna separation</td>
</tr>
<tr>
<td>$\phi_{n,r}$</td>
<td>Cosine of the arrival angle of the node’s $n$ transmitted signal at the RIS $r$</td>
</tr>
<tr>
<td>$g_{r,gNB}$</td>
<td>Channel gain of the link between each RIS $\mathcal{R}_r$ and the gNB/MEC server</td>
</tr>
</tbody>
</table>

During the nodes’ task offloading, the nodes can have both Line of Sight (LoS) communication with the MEC server and non-LoS (NLoS) communication due to
the signals reflections on the RISs. The probability of LoS communication is:

$$P_{r}^{LoS}(z_{gNB}, d_{n,gNB}) = \frac{1}{1 + \alpha e^{-\beta(\theta - \alpha)}}, \quad (2.1)$$

where $r_{gNB} = (x_{gNB}, y_{gNB}, z_{gNB})$ are the gNB/MEC server’s coordinates, $\alpha, \beta \in \mathbb{R}^{+}$ are positive constants depending on the communication environment, e.g., urban, rural, and the carrier frequency $f_{c}[Hz]$ and $\theta = \frac{180}{\pi} \sin^{-1}(\frac{z_{gNB}}{d_{n,gNB}})[rad]$ denotes the elevation angle between the node and the gNB/MEC server. The corresponding path loss in the LoS (Eq. 2.2) and NLoS (Eq. 2.3) communication scenarios are derived as follows:

$$P_{LoS}(d_{n,gNB}) = \eta_{LoS}(\frac{4\pi f_{c}d_{n,gNB}}{c})^{\gamma}, \quad (2.2)$$

$$P_{NLoS}(d_{n,gNB}) = \eta_{NLoS}(\frac{4\pi f_{c}d_{n,gNB}}{c})^{\gamma}, \quad (2.3)$$

where $\eta_{LoS}, \eta_{NLoS}[dB]$ denote the excessive path loss exponents, with $\eta_{NLoS} > \eta_{LoS} > 1$, $c[m/s]$ is the speed of light, and $\gamma \in \mathbb{R}^{+}$ captures the path loss exponent
depending on the communication environment. Based on Eq. 2.1-2.3, the overall expected path loss is derived as follows:

\[ \mathcal{P}(z_{gNB}, d_{n,gNB}) = P_{r,LoS} \mathcal{P}_{LoS} + (1 - P_{r,LoS}) \mathcal{P}_{NLoS} \]  

(2.4)

Each RIS consists of a uniform linear array with \( E = \{1, \ldots, e, \ldots, |E|\} \) reflecting elements and \( \omega_e \in [0, 2\pi) \) denotes each element’s phase shift of the reflection. Also, we consider that the amplitude of the reflection coefficient is 1 and the RIS is placed at a height \( z_r[m] \). For each RIS \( r \), the corresponding diagonal reflection matrix is \( \Omega_r = diag(e^{j\omega_1}, \ldots, e^{j|E|\omega}) \) and the first RIS element acts as the reference point for the rest of the calculations. Also, we consider that all the deployed RISs in the examined system have the same structure.

Based on Eq. 2.4, we can determine the channel gain \( g_{n,gNB} \) of the direct communication link between the IoT node \( n \) and the gNB/MEC server as follows:

\[ g_{n,gNB} = \sqrt{\frac{1}{\mathcal{P}(z_{gNB}, d_{n,gNB})}} \cdot \tilde{g}, \]  

(2.5)

where \( \tilde{g} \sim \mathcal{CN}(0, 1) \) is a random variable following the complex Gaussian distribution with \( m_{\tilde{g}} = 0 \) and \( \sigma^2_{\tilde{g}} = 1 \) and it captures the transmitted signal’s scattering.

Focusing on the link between the IoT node and each RIS \( r \), the channel gain coefficient is derived as follows:

\[ g_{n,r} = \sqrt{\frac{1}{\mathcal{P}_{n,r}}} [1, e^{-j\frac{2\pi}{\lambda}[\delta \phi - \phi_n, r], \ldots, e^{-j\frac{2\pi}{\lambda}(|E|-1)\delta \phi_n, r}]T, \]  

(2.6)

where \( g_{n,r} \in \mathbb{C}^{|E| \times 1} \), \( \mathcal{P}_{n,r} = \zeta(d_{n,r})' \), \( \zeta \) is the path loss among the node \( n \) and the RIS \( R_r \) at the reference point of 1m, \( d_{n,r} \) is the distance among the node \( n \) and the RIS \( r \), \( \lambda[m] \) is the carrier signal’s wavelength, \( \delta \) is the antenna separation, and \( \phi_n, r \)
represents the cosine of the arrival angle of the node’s transmitted signal at the RIS $r$.

Focusing on the communication between each RIS $R_r$ and the gNB/MEC server, the channel gain $g_{r,gNB} \in \mathbb{C}^{|E| \times 1}$ is:

$$g_{r,gNB} = \sqrt{\frac{1}{\mathcal{P}_{r,gNB}} \left( \sqrt{\frac{\kappa}{1 + \kappa}} g_{r,gNB}^{\text{LoS}} + \sqrt{\frac{1}{1 + \kappa}} g_{r,gNB}^{\text{NLoS}} \right)},$$

(2.7)

where $\mathcal{P}_{r,gNB} = \mathcal{P}(z_{gNB} - z_r, d_{r,gNB})$ denotes the path loss of the link, $\kappa$ represents the Rician factor and $g_{r,gNB}^{\text{LoS}} = [1, e^{-j\frac{2\pi}{\lambda} \delta \phi_{r,gNB}}, \ldots, e^{-j\frac{2\pi}{\lambda} (|E| - 1) \delta \phi_{r,gNB}}]^T$ and $g_{r,gNB}^{\text{NLoS}} \sim \mathcal{CN}(0,1)$ capture the LoS and the NLoS components, respectively, with $\phi_{r,gNB}$ representing the cosine of the signals departure angle.

Combining all the above, we can derive the total channel gain as follows:

$$G_n = |g_{n,gNB} + \sum_{\forall r \in R} g_{r,gNB}^H \Omega_r g_{n,r}|^2.$$

(2.8)

Without loss of generality, we consider $G_1 \leq \cdots \leq G_n \leq \cdots \leq G_{|N|}$. The non-orthogonal multiple access (NOMA) technique is adopted to facilitate the IoT node to offload its computing task’s data to the MEC server, while ensuring high bandwidth utilization efficiency. Also, the Successive Interference Cancellation (SIC) technique is applied at the receiver to further mitigate the interference sensed by each node [81]. Thus, each node’s achieved data rate is:

$$R_n = W \log_2 \left( 1 + \frac{G_n P_n}{\sum_{n' = 1}^{n-1} G_{n'} P_{n'} + I_0} \right)[\text{bps}],$$

(2.9)

where $W[H\text{z}]$ is the system’s bandwidth, and $I_0$ is power of the Additive White Gaussian Noise (AWGN).
Chapter 2. System Model & Framework Overview

Figure 2.1: Overview of the RIS-enabled integrated communications and computing environment

2.2 Location-aware Task Offloading Framework

In the following, we provide an overall overview of the proposed location-aware task offloading framework, by presenting each component, while also highlighting their interactions and the information and control flow among the different components. The first two main components serve as the enablers for the energy efficient task offloading, from the perspective of location-awareness and improved communication environment. Those two components provide input to the third one in order to perform the sophisticated decision-making of the energy efficient task offloading process.

Initially, an artificial intelligent method is introduced based on a reinforcement learning (RL) model and the RIS technology, to enable each IoT node to accurately determine its position. It is noted that at least four signals are needed in order to accurately predict a node’s position. Specifically, each node selects a set of three RISs based on a low-complexity RL model. Then, based on the signal stemming from the gNB and the reflected signals on the three selected RISs, each node determines its position in a distributed manner following a Least Square Algorithm [82]. Thus,
Chapter 2. System Model & Framework Overview

each node can also determine its distance from the gNB/MEC server. Second, the optimal phase shifts of each RIS’s elements are determined aiming at maximizing the total received signal strength from the nodes, thus partially controlling the radio propagation conditions. This approach enables the nodes to ultimately decrease their uplink transmission power, thus, contributing to the energy efficient transmission of the node’s data to the MEC server for further processing. Third, a contract-theoretic task offloading framework is developed enabling the MEC server to provide personalized rewards to the nodes in order to offload their data to it, instead of consuming their limited energy for processing them locally on their devices. The MEC server learns the nodes’ communications and computing characteristics, while interacting with them, in order to provide optimal rewards following the principles of Contract Theory. The optimal effort of the nodes, consisting of their optimal uplink transmission power, and their offloaded data to the MEC server, is also determined. In the following sections, a detailed analysis of the components’ operation is provided.
Chapter 3

RIS-enabled PNT Services

In this section, we introduce a novel PNT solution to enable each node to distribu-
edly and accurately determine its position. Four signals are needed to perform the
multilateration and determine the node’s position. One signal stems from the gNB’s
periodic transmissions, while the rest of the three signals can be derived by the re-
lected signals at three strategically selected RISs by the IoT node. An indicator that
quantifies the node’s accurate position calculation is the Geometric Dilution of Preci-
sion (GDOP). The GDOP indicates the success of the RISs’ geometric constellation
to accurately determine the node’s position, while a low GDOP value concludes to
better accuracy. Based on the existing literature, the lowest reported GDOP value
is 1.5811, as derived by the GNSS with four satellites [83].

The set of possible RIs strategies is denoted as $S = \{s_1, \ldots, s_s, \ldots, s_{|S|}\}$, where
$s_s = \{R_i, R_j, R_r\}, i \neq j \neq r, R_i, R_j, R_r \in R$. Each node can select a RIs
strategy (i.e., triplet of RIs), which will result to a corresponding $GDOP(s_s)$. Thus,
we define the reward that the node experiences by selecting a strategy, as:
$f(s_s) = \frac{1.5811}{GDOP(s_s)}$. An RL model is introduced based on the gradient ascent al-
gorithms to enable each node to autonomously select a strategy of three RISs to
Chapter 3. RIS-enabled PNT Services

determine its position. Specifically, the IoT nodes act as learning automata and they probabilistically learn to either select the same strategy (Eq. 3.1a) or a different one (Eq. 3.1b) based on the received reward.

\[
P(s^{i+1}_s) = P(s^i_s) + \mu_1 f(s^i_s)(1 - P(s^i_s)) - \mu_2(1 - f(s^i_s))P(s^i_s), \text{ if } s^{i+1}_s = s^i_s \quad (3.1a)
\]

\[
P(s^{i+1}_s) = P(s^i_s) - \mu_1 f(s^i_s)P(s^i_s) + \mu_2(1 - f(s^i_s))\left(\frac{1}{|S| - 1} - P(s^i_s)\right), \text{ if } s^{i+1}_s \neq s^i_s \quad (3.1b)
\]

where \(i\) denotes the iteration of the RL algorithm, and \(\mu_1, \mu_2 \in [0, 1]\) are the learning parameters. For large values of \(\mu_1\), the node performs extensive exploration of its available strategies, thus, the RL algorithm converges slowly. In our approach, we consider \(\mu_2 = 0\), implementing the Linear Reward-Inaction (LRI) algorithm, and enabling the target to probabilistically select the strategy with the highest reward, without performing an exhaustive exploration. After convergence of the RL algorithm is achieved, i.e., when the probability of choosing one strategy is close to one, the node has determined its RISs selection. The node’s position is determined following the Least Square Algorithm (LSA) [82]. Specifically, each node can measure the four pseudoranges based on the four received signals from the gNB and the three selected RISs, as follows:

\[
r_{gNB,t} = |r_t - r_{gNB}| - \Delta t \cdot c \quad (3.2)
\]

\[
r_{gNB,R_i,t} = 1_{gNB,R_i}(r_{R_i} - r_{gNB}) + 1_{R_i}(r_t - r_{R_i}) - \Delta t \cdot c \quad (3.3)
\]

\[
r_{gNB,R_j,t} = 1_{gNB,R_j}(r_{R_j} - r_{gNB}) + 1_{R_j}(r_t - r_{R_j}) - \Delta t \cdot c \quad (3.4)
\]

\[
r_{gNB,R_r,t} = 1_{gNB,R_r}(r_{R_r} - r_{gNB}) + 1_{R_r}(r_t - r_{R_r}) - \Delta t \cdot c \quad (3.5)
\]
where $\Delta t$ denotes the gNB’s and the node’s time clock offsets. We set Eq. 3.2 - 3.5 equal to zero and we derive the corresponding functions $h_1 - h_4$, where the four unknown variables are $x_n, y_n, z_n$ and $\Delta t$. We solve the algebraic system and determine the values $\mathbf{t}_{n}^{(i^{'})=1} = (x_n^{(i^{'})=1}, y_n^{(i^{'})=1}, z_n^{(i^{'})=1})$ and $\Delta t^{(i^{'})=1}$, where $i'$ denotes the iteration of the Least Square Algorithm. Then, we determine the Jacobian (Eq. 3.6) and Residual (Eq. 3.7) matrices, by setting $\zeta^{(ite')} = (x_n^{(i^{'})=1}, y_n^{(i^{'})=1}, z_n^{(i^{'})=1}, \Delta (\Delta t))$.

$$J^{(ite')} = \begin{bmatrix}
\frac{\partial h_1}{\partial x_n}(\zeta^{(i^{'})}) & \frac{\partial h_1}{\partial y_n}(\zeta^{(i^{'})}) & \frac{\partial h_1}{\partial z_n}(\zeta^{(i^{'})}) & \frac{\partial h_1}{\partial \Delta t}(\zeta^{(i^{'})}) \\
\frac{\partial h_2}{\partial x_n}(\zeta^{(i^{'})}) & \frac{\partial h_2}{\partial y_n}(\zeta^{(i^{'})}) & \frac{\partial h_2}{\partial z_n}(\zeta^{(i^{'})}) & \frac{\partial h_2}{\partial \Delta t}(\zeta^{(i^{'})}) \\
\frac{\partial h_3}{\partial x_n}(\zeta^{(i^{'})}) & \frac{\partial h_3}{\partial y_n}(\zeta^{(i^{'})}) & \frac{\partial h_3}{\partial z_n}(\zeta^{(i^{'})}) & \frac{\partial h_3}{\partial \Delta t}(\zeta^{(i^{'})}) \\
\frac{\partial h_4}{\partial x_n}(\zeta^{(i^{'})}) & \frac{\partial h_4}{\partial y_n}(\zeta^{(i^{'})}) & \frac{\partial h_4}{\partial z_n}(\zeta^{(i^{'})}) & \frac{\partial h_4}{\partial \Delta t}(\zeta^{(i^{'})})
\end{bmatrix} \quad (3.6)$$

$$\mathbf{R}_{es}^{(i^{'})} = \begin{bmatrix}
h_1(\zeta^{(i^{'})}) \\
h_2(\zeta^{(i^{'})}) \\
h_3(\zeta^{(i^{'})}) \\
h_4(\zeta^{(i^{'})})
\end{bmatrix} \quad (3.7)$$

The nodes’ position and the clock’s offset are determined by solving the least square problem, as $(\Delta x_n, \Delta y_n, \Delta z_n, \Delta (\Delta t)) = (J^{(i^{'})T} \cdot J^{(i^{'})})^{-1} \cdot J^{(i^{'})T} \cdot \mathbf{R}_{es}^{(i^{'})}$ and a new estimate is determined as $\zeta^{(i^{'})+1} = (x_n^{(i^{'})} + \Delta x_n, y_n^{(i^{'})} + \Delta y_n, z_n^{(i^{'})} + \Delta z_n, \Delta t^{(i^{'})} + \Delta (\Delta t))$. The LSA is repeated iteratively until the point-wise difference of the estimates between two consecutive iterations are sufficiently small. Based on the final estimate of $\zeta^{(i^{'})}$, the GDOP value is estimated as $GDOP = (J^{(i^{'})T} \cdot J^{(i^{'})})^{-1}$ and provided as input to the RL algorithm to enable the nodes’ RISs selection.
Chapter 4

RIS Elements’ Phase Shifts Optimization

In this section, we study the optimization of the RISs’ phase shifts towards maximizing the overall signal strength received by the nodes to the gNB, while the signals being reflected at each RIS. We denote as $\omega_r = [\omega_1, \ldots, \omega_e, \ldots, \omega_{|E|}]$ the phase shifts vector of each RIS $r$. Thus, the corresponding optimization problem for the nodes signals reflected at each RIS is formulated as follows:

$$\max_{\{\omega_r\}_{r \in R}} \sum_{n=1}^{|N|} |g_{n,gNB} + \sum_{r \in R} g_{r,gNB}^H \Omega_n |^2$$

s.t. $0 \leq \omega_e < 2\pi, \forall e \in \mathcal{E}$

Towards addressing the optimization problem (4.1a) - (4.1b), we set: $v_e = e^{j\omega_e}, \forall e \in \mathcal{E}$ and we have the corresponding vector $v_r = [v_1, \ldots, v_e, \ldots, v_{|E|}] \in \mathbb{C}^{|E| \times 1}$. By setting $g_{n,r}^H = g_{r,gNB}^H \cdot \text{diag}(g_{n,r}) \in \mathbb{C}^{|E| \times 1}$, we can rewrite the optimization problem (Eq. 4.1a) - (4.1b), as follows.
Chapter 4. RIS Elements’ Phase Shifts Optimization

\[
\max_{\{\mathbf{v}_r\}_{r \in \mathcal{R}}} \sum_{n=1}^{\left|\mathcal{N}\right|} \left| g_{n,gNB} + \sum_{\forall r \in \mathcal{R}} \hat{\mathbf{g}}^H_{n,r} \mathbf{v}_r \right|^2 \quad (4.2a)
\]

s.t. \(|v_e| = 1, \forall e \in \mathcal{E}\) \quad (4.2b)

It is easily observed that the optimization problem (Eq. 4.2a) - (4.2b) is non-concave, as both the objective function (Eq. 4.2a) is non-concave with respect to \(\mathbf{v}_r\), and the constraint (Eq. 4.2b) defines a non-convex set. Therefore in the following analysis, we introduce a low-complexity heuristic approach to determine \(\mathbf{v}_r\) and correspondingly the RISs’ phase shifts \(\omega_r\), \(\forall r \in \mathcal{R}\).

Initially, we observe that in a multi-nodes scenario, the optimal phase shifts of the RISs elements are in general different for each transmitting node. Thus, we need to design a method to determine the optimal phase shifts that will simultaneously improve the channel gain of all the nodes. Initially, we consider the simple scenario of one node residing in the system. In this case, the direct signal to the gNB should be perfectly aligned with the reflected signals at each RIS’s elements. Thus, we can derive the optimal phase shifts \(\omega_r^*\) for each RIS as follows:

\[
\angle g_{1,gNB} = -\angle \hat{\mathbf{g}}_{1,r} + \angle \mathbf{v}_r \Leftrightarrow \angle \mathbf{v}_r = \angle g_{1,gNB} + \angle \hat{\mathbf{g}}_{1,r}.
\]

Generalizing the above outcome to a multi-nodes scenario, and denoting \(\mathbf{v}_r^{(n)} = [v_1^{(n)}, \ldots, v_e^{(n)}, \ldots, v_{|\mathcal{E}|}^{(n)}] \in \mathbb{C}^{|\mathcal{E}| \times 1}\) for each node, we conclude to the following optimal outcome for each node \(n\) that its signal is reflected to a RIS \(r\): \(\mathbf{v}_r^{(n)} = e^{j\angle g_{n,gNB}} e^{j\angle \hat{\mathbf{g}}_{n,r}}, \forall n \in \mathcal{N}\). We observe that the optimal phase shifts for each node are different. Therefore, in order to holistically accommodate all the nodes’ signals transmission characteristics, we introduce a weighted summation of their individual \(\mathbf{v}_r^{(n)}\) values, as follows:

\[
\mathbf{v} = \sum_{n=1}^{\left|\mathcal{N}\right|} w_n \mathbf{v}_r^{(n)}, \text{ with } \sum_{n=1}^{\left|\mathcal{N}\right|} w_n = 1.
\]

Therefore, the optimization problem (Eq. 4.2a) - (4.2b) can be rewritten as follows:

\[
\max_{\mathbf{w}} \sum_{n=1}^{\left|\mathcal{N}\right|} \left| g_{n,gNB} + \mathbf{g}^H_{r,n,gNB} \Omega g_{n,r} \right|^2 \quad (4.3a)
\]
Chapter 4. RIS Elements’ Phase Shifts Optimization

\[ 0 \leq w_n \leq 1, \forall n \in N \quad (4.3b) \]

\[ \sum_{n=1}^{\lfloor N \rfloor} w_n = 1. \quad (4.3c) \]

where \( \Omega_r = \text{diag}(e^{j\varphi}) \) and \( w = [w_1, \ldots, w_n, \ldots, w|N|] \). The optimization problem (Eq. 4.3a) - (4.3c) consists of a non-negative linear objective function and constraints, thus, it can be solved based on standard optimization tools, and the optimal weights \( w^* \) can be determined. Thus, we can determine the optimal optimal RISs elements’ phase shifts \( \varphi^*_r, \forall r \in \mathcal{R} \).
Chapter 5

Contract-theoretic Energy Efficient Data Offloading

In this section, we introduce a novel contract-theoretic task offloading mechanism to enable the IoT nodes to process their computing tasks in an energy efficient manner. Following the principles of Contract Theory, the MEC server offers personalized rewards to the nodes, in order for the latter ones to offload their computing task’s data to the MEC server in an energy efficient manner. Each node is characterized by its personal communications and computing characteristics. Based on this observation, we define the IoT node’s $n$ type, as $t_n = \frac{G_n}{d_{n,gNB}} \cdot \frac{B_n}{\phi_n}$. The physical meaning of the node’s type reflects the potential of the node to offload a large amount of data to the MEC server in an energy efficient manner, i.e., with low transmission power levels. A large value of the node’s type represents a node that is close to MEC server, is characterized by improved channel gain, and can offload a large amount of non-computationally intensive data. For presentation purposes, we map the node’s type in the interval $t_n \in [0, 1]$.

The nodes’ types are private information and the MEC server estimates them...
Chapter 5. *Contract-theoretic Energy Efficient Data Offloading*

probabilistically (incomplete information) via a probability density function (PDF) \( f(t) \), with cumulative distribution function \( F(t) \). The MEC server’s PDF can be derived and dynamically adapted based on the MEC server’s interactions with the nodes. In contrast, in a benchmarking scenario, the MEC server deterministically knows the nodes’ types. Considering the energy efficient operation of the system, each node should offload its data with low transmission power not only to save its own energy, but also to avoid increasing the interference. Also, each node should be incentivized to offload its computing task’s data to avoid processing them locally and consuming its device’s energy. Thus, we define the effort \( q(t_n) \) that each node can contribute to the energy efficient operation of the system as \( \frac{B_n}{P_n} \), and by making the mapping \([0, \frac{B_n}{P_n}] \to [0, 1], \forall n \in N\), we have \( q(t_n) \in [0, 1] \). It is noted that the node’s effort \( q(t_n) \) is a strictly increasing function of its type, as a node with improved communications and favorable computing characteristics (e.g., low computationally intensive data) can contribute more to the system’s energy efficient operation.

The MEC server aims to incentivize the IoT nodes to operate in an energy efficient manner by providing personalized rewards accounting for their communications and computing characteristics. The personalized rewards are defined as \( r(t_n) = t_n \cdot q(t_n) \), and depend on the node’s type and its corresponding provided effort \( q(t_n) \) to the energy efficient operation of the system. It is noted that in a real-life implementation the rewards can be mapped to correspondingly proportional computing capacity that the MEC server allocates to the nodes in order to remotely process their computing tasks’ data. Therefore, each node’s utility from offloading and processing its data at the MEC server is derived as follows.

\[
U_n(t_n, q(t_n), r(t_n)) = t_n e(r(t_n)) - c \cdot q(t_n) \tag{5.1}
\]

where \( c \in \mathbb{R}^+ \) denotes the nodes’ cost to provide their effort \( q(t_n) \) and \( e(r(t_n)) \) denotes the nodes’ evaluation function in terms of assessing the received rewards.
from the MEC server. The evaluation function is concave and strictly increasing with respect to the reward capturing the increasing satisfaction of the nodes from receiving a higher reward. Thus, the node’s utility reflects the node’s overall satisfaction accounting for its invested effort and the received rewards.

Focusing on the MEC server’s benefits, (and respectively, the benefits of the service provider), the MEC server’s utility can be structured as follows.

\[
U_{MEC}(t) = \int_0^1 f(t)[q(t) - cr(t)]dt
\]

(5.2)

where \( c \in \mathbb{R}^+ \) denotes the MEC server’s cost to provide the rewards and:

\[ t = \{t_n\}_{n \in N} \]

The physical meaning of the MEC server’s utility is its (unitless) profit/benefit from incentivizing the nodes to operate in an energy efficient manner. The MEC server probabilistically estimates the nodes’ types based on the PDF \( f(t) \), thus, the nodes’ indices are omitted in Eq. 5.2.

Towards determining the nodes’ optimal effort and rewards, the principles of Contract Theory are adopted [84]. The MEC server provides a personalized contract \( \{r(t_n), q(t_n)\} \) to each node, considering each node’s invested effort \( q(t_n) \). The provided contract should respect the conditions of Individual Rationality (IR) and Incentive Compatibility (IC) in order to be feasible and accepted by each node.

Definition 1. Each IoT node’s utility should be non-negative, i.e.,

\[ U_n(t_n, q^*(t_n), r^*(t_n)) \geq 0 \]

for the optimal contract \( \{r^*(t_n), q^*(t_n)\} \) under the Individual Rationality condition.

Definition 2. An optimal contract \( \{r^*(t_n), q^*(t_n)\} \) is Incentive Compatible, if each node achieves the highest utility as compared to any other contract designed for another node of different type \( t' \), i.e.,

\[ te(r^*(t)) - cq^*(t) \geq te(r^*(t')) - cq^*(t') \]
Chapter 5. Contract-theoretic Energy Efficient Data Offloading

The MEC server aims at maximizing its achieved utility while guaranteeing the nodes appropriate incentivization via the IR and IC conditions. Thus, the corresponding optimization problem in order to determine the optimal contracts among the MEC server and the IoT nodes is formulated as follows.

\[
\begin{align*}
\max_{\{r(t), q(t)\}_{t \in [0, 1]}} & \int_{0}^{1} f(t)[q(t) - cr(t)]dt \\
\text{s.t.} & \ t(c(r(t)) - c \cdot q(t)) \geq 0, \forall t \in [0, 1] \quad \text{(IR)} \\
& \ t(c(r^*(t)) - cq^*(t)) \geq t(c(r^*(t')) - cq^*(t')), \forall t \neq t' \quad \text{(IC)}
\end{align*}
\] (5.3a)

The optimization problem (Eq. 5.3a) – (5.3c) is non-convex due to the form of the objective function and its constraints. Towards addressing this problem, we reduce its constraints.

**Theorem 1 (Reduction of IR Constraints).** The IR constraints can be reduced to \( t_{\min}c(r(t_{\min})) - c \cdot q(t_{\min}) = 0 \), with \( t_{\min} \to 0^+ \), if the IC constraints hold true.

**Proof.** If the IC constraints hold true, we have \( t(c(r(t)) - c \cdot q(t)) \geq t(c(r(t_{\min})) - c q(t_{\min})) \geq t_{\min}c(r(t_{\min})) - c q(t_{\min}) \), given that \( t \geq t_{\min} \) and \( c(\cdot) \) is a strictly increasing function with respect to \( t \). Also, it holds true that \( t_{\min}c(r(t_{\min})) - c q(t_{\min}) = 0 \), given that the MEC server will provide just the sufficient and necessary rewards, to the IoT nodes in order to contribute to the system’s energy efficient operation. \( \square \)

Based on Theorem 1, the IR constraints are reduced. In the following theorem, we further reduce the IC constraints.

**Theorem 2 (Reduction of IC Constraints).** The IC constraints can be reduced to the following two constraints (i) \( r'(t) \geq 0 \) (monotonicity), (ii) \( t \cdot r'(t) \cdot c'(r(t)) = c q'(t) \) (local incentive compatibility), if the Spence-Mirrlees condition \[84\] \( \frac{\partial}{\partial t} \left[ -\frac{\partial u}{\partial r} \cdot \frac{\partial u}{\partial q} \right] > 0 \) holds true for each node’s utility.
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Proof. Based on Eq. 5.1, we have \( \frac{\partial U_n}{\partial q} = -c < 0 \), as \( c \in \mathbb{R}^+ \) and \( \frac{\partial U_n}{\partial r} = t \frac{\partial e(r(t))}{\partial r} > 0 \), as \( e(r(t)) \) is a strictly increasing function with respect to \( r(t) \) and \( t \in [0,1] \). Thus, we have \( \frac{\partial^2 U_n}{\partial r \partial t} = \frac{\partial e(r(t))}{\partial r} + t \frac{\partial^2 e(r(t))}{\partial r^2} \left[ q(t) + t \frac{\partial q(t)}{\partial r} \right] > 0 \), given that \( e(r(t)), \ r(t), \) and \( q(t) \) are strictly increasing functions with respect to \( t \), and \( e(r(t)) \) is a concave function with respect to \( t \). Therefore, the Spence - Mirrlees condition holds true. Then, we check the necessity and sufficiency of the monotonicity and Local Incentive Compatibility (LIC) constraints. First, we show that the latter two conditions hold true, if the IC constraints hold true. Given that the IC constraints hold true, we have \( te(r(t)) - cq(t) \geq te(r(t')) - cq(t') \Leftrightarrow U_n(t,q(t),r(t)) \geq U_n(t,q(t),r(t')), \forall t \neq t' \). This means that the value \( U_n(t,q(t),r(t)) \) is the optimal one for the node of type \( t \), thus, the following hold true: \( \frac{\partial U_n(t,r(t'),q(t'))}{\partial t'} = 0 \) and \( \frac{\partial^2 U_n(t,r(t'),q(t'))}{\partial t'^2} \mid _{t'=t} \leq 0 \). Based on \( \frac{\partial U_n(t,r(t'),q(t'))}{\partial t'} \mid _{t'=t} = 0 \), we have \( tr'(t')e'(r(t')) = cq'(t') \), thus, the local incentive compatibility condition holds true for \( t' = t \). Based on \( \frac{\partial^2 U_n(t,r(t'),q(t'))}{\partial t'^2} \mid _{t'=t} \leq 0 \) we have \( tr''(t')e'(r(t')) + t(r'(t'))^2e''(r(t')) \leq cq''(t') \) and by differentiating the equation \( \frac{\partial U_n(t,r(t'),q(t'))}{\partial t'} \mid _{t'=t} = 0 \) with respect to \( t \), we have \( cq''(t') = r'(t')e'(r(t')) + tr''(t')e'(r(t')) + t(r'(t'))^2e''(r(t')) \). Therefore, we have \( r'(t')e'(r(t')) \geq 0 \), and we know that \( e'(r(t')) > 0 \) given that \( e(\cdot) \) is a strictly increasing function. Therefore, we conclude that \( r'(t') \geq 0 \) for \( t' = t \), showing that the monotonicity condition holds true. By following the reduction at absurdity approach, we show that the IC constraints hold true, if the monotonicity and the LIC constraints hold true. Assuming that the IC constraints are not valid, we have: \( te(r(t)) - cq(t) < te(r(t')) - cq(t') \Leftrightarrow \int_t^{t'} [tr'(x)e'(r(x)) - cq'(x)]dx > 0 \). We integrate the LIC condition, and we have: \( \int_t^{t'} [tr'(x)e'(r(x)) - cq'(x)]dx = 0 \). From the monotonicity condition, we have \( t' < x < t \) \( r'(x) \geq 0 \Leftrightarrow tr'(x) < x r'(x) \Leftrightarrow r'(x)e'(r(x)) < x r'(x)e'(r(x)) \Leftrightarrow tr'(x)e'(r(x)) - cq'(x) \Leftrightarrow x r'(x)e'(r(x)) - cq'(x) \Leftrightarrow \int_t^{t'} [tr'(x)e'(r(x)) - cq'(x)]dx < 0 \). Thus, there is a contradiction, and, the IC constraints hold true. \( \square \)
Based on Theorems 1 and 2, the optimization problem (Eq.5.3a) - (5.3c) can be rewritten as follows:

\[
\max_{\{r(t), q(t)\}} \int_{0}^{1} f(t)[q(t) - cr(t)]dt \quad (5.4a)
\]

\[
s.t. \quad t_{min}e(r(t_{min})) - cq(t_{min}) = 0, t_L \to 0^+ \quad (5.4b)
\]

\[
r'(t) \geq 0 \quad (5.4c)
\]

\[
tr'(t)e'(r(t)) = cq'(t), \forall t \in [0, 1] \quad (5.4d)
\]

Following the approach introduced by Mirrlees [84], we initially solve the above optimization problem considering only the constraints (5.4b) and (5.4d), and subsequently we check if the derived solution satisfies the monotonicity constraint (5.4c). Towards this direction, we define the function:

\[
W(t) = te(r(t)) - cq(t) = \max_{t'}\{te(r(t')) - cq(t')\} \quad (5.5)
\]

and we have \(\frac{\partial W(t)}{\partial t}|_{t=t'} = e(r(t))\). Then, we integrate the latter expression and we get

\[
W(t) = \int_{t_{min}}^{t} e(r(x))dx + W(t_{min}), t_{min} \to 0^+. \quad \text{It is noted that for } t_{min} \to 0^+, \text{the IR constraint for the IoT node with the lowest type is binding. Therefore, we get} \quad W(t_{min}) = 0 \text{ and } W(t) = \int_{t_{min}}^{t} e(r(x))dx. \quad \text{Thus, we have } q(t) = \frac{1}{\xi}te(r(t)) - \frac{1}{\xi}W(t) \text{ and the MEC server's utility (Eq. 5.2) is rewritten as follows: } U_{MEC}(t) = \int_{0}^{1} f(t)[\frac{1}{\xi}te(r(t)) - \frac{1}{\xi}W(t) - c\Lambda(t)]dt = \int_{0}^{1} f(t)[\frac{1}{\xi}te(r(t)) - \frac{1}{\xi}\int_{0}^{1} e(r(x))dx - c\Lambda(t)]dt = \int_{0}^{1} f(t)[\frac{1}{\xi}te(r(t)) - c\Lambda(t)]dt - \frac{1}{\xi}\int_{0}^{1} e(r(x))dx f(t)dt. \quad \text{The latter integral can be analyzed as follows: } \int_{0}^{1} e(r(x))dx f(t)dt = \int_{0}^{1} \Lambda(t)f(t)dt, \quad \text{with } \Lambda(t) = \int_{0}^{1} e(r(x))dx. \quad \text{We can further analyze the integral as: } \int_{0}^{1} \Lambda(t)f(t)dt = [\Lambda(t)F(t)]_{0}-\int_{0}^{1} \Lambda'(t)F(t)dt = \Lambda(1)F(1) - \Lambda(0)F(0) - \int_{0}^{1} \Lambda'(t)F(t)dt = \Lambda(1) - \int_{0}^{1} \Lambda'(t)F(t)dt = \int_{0}^{1} e(r(t))dt - \int_{0}^{1} e(r(t))F(t)dt = \int_{0}^{1} e(r(t))[1 - F(t)]dt, \quad \text{and rewrite the MEC server's utility, as: } U_{MEC}(t) = \int_{0}^{1} f(t)[\frac{1}{\xi}te(r(t)) - c\Lambda(t)] - \frac{1}{\xi}e(r(t))[1 - F(t)]dt. \quad \text{Thus, we can rewrite the optimization problem (Eq.5.4a) - (5.4d) as follows.}
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\[
\max_{r(t), t \in [0, 1]} \left[ \frac{1}{\epsilon} \ell(r(t)) - c r(t) - \frac{\ell(r(t))[1 - F(t)]}{\epsilon f(t)} \right] f(t) \tag{5.6a}
\]

\[\text{s.t.} \quad t_{\min} \ell(r(t_{\min})) - c q(t_{\min}) = 0, t_{\min} \to 0^+ \tag{5.6b}\]

\[r'(t) \geq 0 \tag{5.6c}\]

\[t r'(t) e'(r(t)) = c q'(t), \forall t \in [0, 1] \tag{5.6d}\]

In order to solve the above optimization problem, we take the first order condition of Eq. 5.6a and we have: \(\ell'(r(t)) \frac{1}{\epsilon} [t - \frac{1 - F(t)}{f(t)}] = c\), based on which the optimal reward \(r^*(t)\) can be derived. The optimal reward \(r^*(t)\) should also satisfy the monotonicity constraint. In order for the latter statement to hold true, the hazard rate \(H(t) = \frac{f(t)}{1 - F(t)}\) should be an increasing function with respect to the model type \(t\). Indeed, we can easily observe that if the hazard rate \(H(t)\) is an increasing function with respect to \(t\), then the constraint (5.6c) holds true. By setting \(g(t) = t - \frac{1 - F(t)}{f(t)}\) we have \(\frac{1}{\epsilon} g(t) \ell'(r(t)) = c \Rightarrow r'(t) = -\frac{g'(t) \ell'(r(t))}{cg(t) \ell''(r(t))} \geq 0\), as \(g(t) > 0, g'(t) = 1 + \frac{H'(t)}{H^2(t)} > 0, \ell'(r(t)) > 0\) and \(\ell''(r(t)) < 0\).

Concluding the analysis of determining the optimal contracts, we clarify that the hazard rate \(H(t)\) is increasing with respect to \(t\) for the majority of the well-known distributions, e.g., normal, exponential, uniform. In the worst case scenario that the optimal reward \(r^*(t)\) does not satisfy the monotonicity constraint, we can apply the “bunching and ironing” approach to identify the infeasible intervals \([a, b] \subseteq [0, 1]\) and derive the optimal reward as \(r^*(t) = \arg\max_{r(t), t \in [0, 1]} \int_a^b \frac{1}{\epsilon} t \ell(r(t)) - c r(t) - \frac{\ell(r(t))[1 - F(t)]}{\epsilon f(t)} f(t) dt, \forall t \in [a, b]\) [84].
Chapter 6

Numerical Evaluation

In this section, we provide a detailed numerical evaluation of the proposed location-aware task offloading framework via modeling and simulation. Initially, the pure performance and operation of the proposed framework, under both scenarios of complete and incomplete information availability, is demonstrated in Section 6.1. Second, the impact of the RIS technology on the energy efficient operation of the system is studied in Section 6.2. Subsequently, the impact of our proposed PNT solution in terms of accurately determining the nodes’ position and contributing to the system’s energy efficient operation, is enclosed in Section 6.3. Finally, in Section 6.4 a detailed comparative evaluation of the proposed approach against alternative contract-theoretic task offloading strategies is provided, in order to show the benefits and tradeoffs of the proposed framework. The experimentation setting adopted is initialized as follows, unless otherwise explicitly stated. We consider 10 RISs and 4 indicative IoT nodes. The gNB/MEC server’s coordinates are \( \mathbf{r}_{gNB} = (100, 100, 150) \) [m]. The IoT nodes’ computing tasks’ characteristics are \( B \in [40, 50] \) Mbits, and \( \phi \in [5, 10] \) [MCPU Cycles/bits] and both of them follow a uniform distribution. The channel gain modeling parameters are as follows: \( \alpha = 11.95, \beta = 0.14, n_{\text{LoS}} = 3\, \text{dB}, n_{\text{NLoS}} = 23\, \text{dB}, f_c = 2\, \text{GHz}, c = 3 \cdot 10^8 \text{m/s}, \gamma = 2, \zeta = 100, \gamma' = 2.8, \delta = \lambda/2, \)
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\( W = 5 \text{MHz}, \ I_0 = -174 \text{dBm/Hz} \). The simulation parameters for the contract-theoretic model are: \( c = 0.85 \), and \( c = [0.65, 0.75, 0.85] \). All the following presented results are derived based on a Monte Carlo analysis, averaged over 1,000 executions of each experiment.

6.1 Pure Operation & Performance

In this section, we demonstrate the pure operation and the inherent characteristics of the proposed task offloading framework. Fig. 6.1a-6.1e present the IoT nodes reward, effort, transmission power, the MEC server’s utility, and the system’s social welfare, as a function of the IoT nodes. It is noted that the nodes are sorted with increasing order of their type. Also, the scenarios of complete and incomplete information of the nodes’ types from the MEC server’s perspective are demonstrated for different costs \( c \) for the MEC server to provide rewards. The results reveal that under the complete information scenario, the MEC server can fully exploit the communications and computing characteristics of the IoT nodes, thus, incentivizing them to provide a higher effort (Fig. 6.1b) via transmitting at lower power levels (Fig. 6.1c) and ultimately receiving higher reward (Fig. 6.1a). Therefore the MEC server achieves a higher utility (Fig. 6.1d), as well as the social welfare of the system is improved (Fig. 6.1e) under the complete information scenario. Moreover, the results confirm that a node of a higher type provides a higher effort (Fig. 6.1b) to the energy efficient operation of the system by transmitting with lower power (Fig. 6.1c) (please recall that the effort has an inverse proportional relation to the power), and thus getting a higher reward (Fig. 6.1a) from the MEC server. Furthermore, we observe that as the cost of the MEC server becomes higher in terms of providing rewards, the corresponding amount of offered rewards is decreasing (Fig. 6.1a) both under the complete and incomplete information scenarios. Therefore, the nodes are less
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Figure 6.1: Pure operation and performance.
incentivized to provide their effort (Fig. 6.1b), resulting in transmitting with higher transmission power (Fig. 6.1c). The latter observation concludes to a lower outcome both for the MEC server’s utility and the system’s social welfare (Fig. 6.1e).

### 6.2 Impact of RIS Technology

In this section, we study the impact of the RIS technology on the energy efficient operation of the proposed framework and the corresponding examined edge computing system. Fig. 6.2a-6.2f present the IoT nodes’ reward, effort, transmission power, rate, Signal-to-Interference-plus-Noise-Ratio (SINR), energy efficiency, the MEC server’s utility and the social welfare for an increasing number of RIS elements (ranging from 500 to 1500) at each RIS, under the complete and incomplete information contract-theoretic scenarios. For comparison purposes we also study a topology that is not supported by the RIS technology (i.e., 0 RIS elements). Also, Fig. 6.3a-6.3b demonstrate the nodes’ types and channel gain as a function of the nodes’ ID, respectively, for increasing number of RIS elements. The results reveal that the RIS technology contributes to the substantial improvement of the IoT nodes’ channel conditions (Fig. 6.3b), which contribute to the construction of a more directed beam in order to offload their data to the MEC server. Therefore, given the improved channel gain for an increasing number of RISs’ elements, the nodes’ types also increase (Fig. 6.3a), resulting in investing higher effort (Fig. 6.2b) by offloading their data with lower transmission power (Fig. 6.2c), under both the complete and incomplete scenarios. This in turn results in receiving a higher reward by the MEC server (Fig. 6.2a). Furthermore, given the IoT nodes’ lower transmission power levels and improved channel conditions the nodes sense less interference resulting in higher data rate (Fig. 6.2g) and experienced SINR (Fig. 6.2h), and ultimately higher achieved energy efficiency (Fig. 6.2d). Finally, we observe that both the MEC server’s utility
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Figure 6.2: Impact of RIS technology on the system’s energy efficient operation (solid line: Incomplete information scenario, dotted line: Complete information scenario).
6.3 Impact of PNT Solution

In the following, we evaluate the impact of the RIS technology on the accuracy of the PNT solution and the resulting node’s position, which in turn affects the energy efficient operation of the system. Initially, in Fig. 6.4a, we present the Average Percentage Error (APE) of the nodes’ transmission power and the corresponding runtime of the Least Square Algorithm, when a different number of RISs are used to perform the nodes localization, e.g., 3, 5, 7, or 9 RISs (please note that 3 RISs is the minimum required number of RISs to perform localization). The results show that the APE of the nodes’ transmission power decreases as the signals from more RISs are used to perform the nodes’ localization, given that the nodes’ position can be more accurately determined. However, the latter benefit comes at the cost of longer
execution time of the Least Square Algorithm, which considers more pseudoranges in order to determine the nodes’ positions. Also, we study the performance of the reinforcement learning-based RISs selection by the nodes in order to determine their position. Specifically, Fig. 6.4b presents the APE of the nodes’ transmission power and the corresponding runtime of the nodes’ RL-based RISs’ selection for increasing values of the learning parameter $\mu_1$. It is noted that as the value of the learning parameter increases, the nodes explore less their RISs strategies in order to determine their position. Thus, a worse RISs choice (strategy) is performed resulting
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in a higher APE of the nodes’ transmission power. However, given the decreased level of performed exploration by the nodes, it is observed that the corresponding convergence time of the reinforcement learning algorithm decreases.

6.4 Comparative Evaluation

In this section, we provide a comparative analysis of our proposed framework against other contract-theoretic task offloading alternatives to identify its benefits and trade-offs. Five comparative scenarios are considered with respect to the definition of the IoT nodes’ types, i.e., considering only the node’s (i) distance $d_{n,gNB}$ from the MEC server, (ii) amount of task’s data $B_n$, (iii) computing task’s intensity $\phi_n$, (iv) channel gain $G_n$, and (v) all previous characteristics, as introduced in this research work. Fig. 6.5a - 6.5e present the IoT nodes’ reward, effort, transmission power, the MEC server’s utility, and the system’s social welfare as a function of the IoT nodes under all the aforementioned scenarios. The results reveal that the holistic consideration of the nodes’ communications and computing characteristics results in better outcomes in terms of incentivizing the nodes to provide a higher effort (Fig. 6.5b), thus, transmitting to the MEC server at lower power levels (Fig. 6.5c). Therefore, given their energy efficient operation, they receive a higher reward (Fig. 6.5a) from the MEC server, which correspondingly enjoys a higher utility (Fig. 6.5d), while also the system’s social welfare (Fig. 6.5e) improves given its overall energy efficient operation. In contrast, the rest of the comparative scenarios present worse performance given their myopic view regarding the IoT nodes’ characteristics. Specifically, it is worth noting that the IoT nodes’ channel gain characteristics become dominant in the system’s performance, as they impact the energy efficient transmission of the nodes’ data to the MEC server.
Figure 6.5: Comparative evaluation.
Chapter 7

Conclusions and Future Works

In this paper, a location-aware energy efficient task offloading mechanism in an edge computing environment is introduced, enabled by the technology of reconfigurable intelligent surfaces. Initially, a novel positioning, navigation, and timing solution supported by the RIS technology is designed to determine the IoT nodes’ positions. Then, the RISs’ elements optimal phase shifts are determined to optimize the IoT nodes’ channel conditions in a software-defined manner, thus facilitating an energy efficient operation by decreasing their transmission power levels. Finally, a contract-theoretic model is introduced to support the nodes’ energy efficient task offloading process accounting for their communications and computing characteristics. Part of our current and future work contains the extension of the proposed model in the end-to-end digital continuum, by jointly optimizing the energy efficient task offloading process to the edge, the fog, and the core cloud options, while accounting for both the communications and computing resource availability and uncertainties and exploiting advanced positioning, navigation, and timing solutions [85–88].
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