Reconfigurable Intelligent Surface assisted Computation Offloading for autonomous systems in Mobile Edge Computing

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THESIS ACCEPTANCE CERTIFICATE

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Osama Saleem

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Dedicated to my beloved parents

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Abstract

Mobile Edge Computing (MEC) is a new paradigm that utilizes edge infrastructure to bring computation power closer to end-users. This reduces latency and improves performance. With the advancement of self-driving technology, real time traffic monitoring, and on-board entertainment services, vehicular networks have made significant progress. Roadside units (RSUs), or roadside edge servers, are used by MEC and strategically placed along highways to bring computing resources and services closer to the vehicle. Through optimized performance, vehicular services can meet the high standards of computation and precision necessary for efficient and reliable performance. However, a problem arises when the vehicle and roadside unit (RSU) are outside the line of sight (LOS) communication range of each other. Reconfigurable intelligent surfaces (RIS) have become a potential solution to solve this problem. These intelligently reflect the signal towards the receiver in mm Wave and THz communication when there is a blockage between the transmitter and receiver. In this thesis, we propose an RIS-assisted latency-aware computational offloading strategy for autonomous systems in a mobile edge computing environment. This strategy enables an autonomous vehicle to offload its task to an RSU even when the LOS view between the autonomous vehicle and RSU is blocked. We place an RIS at the center of this environment to enable line-of-sight communication between the vehicle and RIS, and between the RIS and RSU. Our simulations show that our proposed approach works well in a dynamic environment where the conditions are constantly changing, in terms of received signal strength and time delay. We also compared our results to the existing schemes, and our approach showed 10 dBm increase in receive power at RSU. The proposed solution achieved 5-7 seconds reduction in MES execution delay compared to local execution delay. The simulation results demonstrated a clear correlation between RTT and the number of states in the system.

Keywords – Reconfigurable Intelligent Surfaces, Mobile Edge Computing, Computation Offloading, Autonomous Systems

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Chapter 1

Introduction

In this chapter, the need of the solution proposed in this thesis is discussed. The problem statement to be solved by this thesis, the objectives of this thesis, and the organization of this thesis are also discussed in this chapter.

1.1 Overview

Cloud computing has emerged as a major force in the computing industry in recent years. It offers a number of benefits over traditional on-premises computing, including scalability, flexibility, cost savings, and improved security. Cloud computing is being used by businesses of all sizes, from small startups to large enterprises [1]. It offers computation for a variety of autonomous network applications, including collision avoidance, safety, blind crossing, dynamic route planning, and real-time traffic situation monitoring [2]. To further minimize the time delay and the transmission cost of the computation offloading, cloud-based mobile edge computing (MEC) offloading frameworks are recommended in autonomous vehicular networks [3]. They reduce the computational load on autonomous vehicles and save time. In vehicle-to-infrastructure (V2I) communication, the vehicles can transmit their computational assignments to the roadside units (RSUs), which are edge servers positioned at the side of the road and are used to carry out these costly computing activities. MEC's performance advantage over traditional mobile cloud computing (MCC) in terms of time delay, however, increases when compared to MCC [4] due to the MEC servers' close proximity to end users and vehicles.

Providing processing services to ensure minimum delay and high reliability is a key goal in vehicle networks. However, choosing a suitable task offloading and computation technique is the key challenge. Vehicles have a hard time making a choice, especially in areas where RSU communication ranges overlap. The task division technique can be used to lessen the service delay [5]. Task division technique is that in which a task is divided into smaller parts to be processed by multiple roadside units (RSUs).

Moreover, due to the vehicle's rapid speed and the edge servers' limited connection range, there is an in-service risk session [6]. The rationale is because service interruptions are brought on by the vehicle's quick location changes and potential for being out of communication range with the relevant RSU [7]. In [8], [9], and [10], the issue of choosing how to offload computing tasks in vehicular networks is discussed. Dynamic service placement and migration have been looked at in [11] to maintain service continuity employing MCC systems. As autonomous vehicles migrate across various geological areas, the task can be moved to another cloud server. As a result, by the end of the task execution, the vehicle may collaborate with a different cloud server [12] for the delivery of task.

Recent technology breakthroughs such as augmented reality (AR), virtual reality (VR), and 8K video conferencing/streaming require exceptionally high data rates that can be accommodated in wireless network utilizing millimeter wave (mmWave) or Terahertz (THz) communication [13]. Line of sight (LOS) linkages between the transmitter and receiver i.e., Vehicle and RSU, are necessary for such high frequency communication, although they may not always be available, especially in the case of densely populated areas with significant obstructions. To address this problem, Reconfigurable Intelligent Surfaces (RIS) have lately become a technology that can address the obstruction issue in such contexts by reflecting light [14]. RIS is made up of periodic patterns of reflecting components that offer fine control over the EM wave that is impinging, enabling functions like guiding the wave in a certain direction or its complete absorption to stop an unapproved user. The better attractive approach for implementing RIS is meta-surfaces since their subwavelength size allows for greater control of the incoming wave [15]. In [16], the authors focus on the scheme for coding meta surfaces to mathematically express meta-surface directivity and use it to calculate RIS transmit antenna gain. A meta-surface is a large array of small, inexpensive, and passive artificial "meta-atoms" integrated into an RIS which can be used to intelligently change the direction of reflection towards any desired users by adjusting a series of phase shifters [17].

Reconfigurable intelligent surfaces (RISs) can be used to provide an indirect line-of-sight (LoS) wireless communication link for vehicles traveling in areas where LoS to a roadside unit (RSU) is blocked by large buildings. This is known as a dark zone [18]. In these situations, the RSU can maximize the quality of service (QoS) for passing vehicles by jointly optimizing the RSU resource scheduling and the RIS element coefficients (passive beamforming). A few works have addressed the RIS phase-shift configuration in vehicular networks. However, these works have only considered the case where the RIS elements can have continuous element tuning. In practice, the RIS elements can only have a limited number of values due to limited hardware [19], [20]. There is a wealth of literature available on systems which utilize Mobile Edge Computing and Reconfigurable Intelligent Surfaces for vehicular networks. Some of this literature is discussed in Chapter 2 of the "Literature Review".

1.2 Problem Statement

When it comes to vehicular networks, there is a need to provide high quality processing services to guarantee low delay and high reliability. This is necessary because vehicular networks need to perform many applications which require near-real-time processing such as self-driving. Reducing time delay includes high speed processing as well as high quality and fast communication. All of this becomes even more necessary for autonomous systems. Moreover, vehicles can suffer from the problem of unavailability of direct Line-of-sight connection from the Road side unit. This will result in increased time delay and poor quality of communication. The problems addressed in this thesis are to find a viable solution for autonomous vehicles to provide them low latency communication even when there is no direct Line-of-sight connection, which is solved using Reconfigurable Intelligent Surfaces.

1.3 Objectives

The primary goal of this thesis is to propose a latency aware framework for computation offloading of autonomous systems in Mobile Edge Computing where autonomous vehicle and Roadside Unit (RSU) are in the non-Line of sight communication range of each other i.e., there is a blockage between them. The main contributions are as follows:

- A collaborative computing approach among Roadside Units (RSUs) for vehicular networks in the presence of RIS, which operates through Mobile Edge Computing (MEC) is introduced.
- Based on the optimal offloading policy, the proposed scheme enables parallel execution between two RSUs, that further optimizes the total service delay.
- As the vehicles send tasks which need to be processed, therefore the time delay for result delivery is also considered to improve service reliability and reduce the failure

of service sessions due to the high mobility of the vehicles so that the results get delivered back to the vehicle successfully.

1.4 Thesis Organization

The thesis is organized as follows: Chapter 2 details the literature review and related works. Chapter 3 explains about the system model of the proposed solution, it also explains all the formulae formulated for the proposed solution. Chapter 4 formulates the proposed solution. The simulation results are shown and discussed in Chapter 5. Finally, Chapter 6 concludes the thesis which is based on the results of simulations.

Chapter 2

Literature Review

In this chapter, different research papers are discussed on how they solved the problems they discovered and what methods they used in their system models. Firstly, the literature related to computational offloading is discussed. Then the literature related to Reconfigurable Intelligent Surfaces (RIS) is explored. Lastly, the literature exploring the multiple domains of integration of computation offloading in RIS for mobile edge computing is discussed.

2.1 Computation Offloading

Mobile Edge Computing (MEC) frameworks have been proposed in vehicular networks to reduce the time delay. They not only save time but also reduce the computational burden on vehicles. Road side units (RSUs) are manifestation of MEC, which are servers located at the edge of a road and vehicles can offload their tasks very quickly. A lot of research is done on RSUs in vehicular networks. In [21], the authors solve the resource allocation problem in MEC servers. They used a multi-agent deep deterministic policy gradient (MADDPG)-based method to solve the problem. The authors in [22] enabled the MEC server to independently make online scheduling based on the derived allocation probability in vehicular network. Their algorithm transforms the objective function into an augmented Lagrangian and achieves the optimal solution iteratively using the Alternating Direction Method of Multipliers (ADMM). To address the challenge of computation offloading in a heterogeneous vehicular network, deep deterministic policy gradient (DDPG) is utilized as the learning method in [23]. In [24], the authors proposed a resource management scheme for vehicular networks assisted by multi-access edge computing (MEC) and unmanned aerial vehicles (UAVs). The authors designed a deep deterministic policy gradient (DDPG)-based solution, where the optimization problem is transformed and trained offline to obtain optimal vehicle association and resource allocation decisions. The problem of service migration in a MEC-enabled vehicular network is explored in [25]. The problem is modeled as a multi-agent Markov decision process (MMDP) and solved using deep Q learning (DQL) algorithm.

The problem of offloading decision and resource allocation in SDN-assisted MEC-based vehicular networks is addressed in [26]. The paper formulates the problem as a load distribution problem and aims to find an optimal strategy that minimizes the system overhead while considering task heterogeneity and resource diversity. In [27], the authors propose a unique vehicular Mobile Edge Cloud (MEC) architecture where vehicular communication packets are routed through the MEC network, accommodating vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication with high scalability and low packet delay. A multi-armed bandit learning algorithm called Utility-table based Learning for workload balancing among MEC servers in [28]. In this paper, a utility table is established to determine the optimal solution by online learning of real-time workload distribution, which is updated based on the feedback signal of task assignment. In [29], the authors propose a federated offloading scheme for vehicular networks with mobile edge computing (MEC) to minimize latency. It considers vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communication for offloading computation tasks. A distributed algorithm is proposed in this paper to obtain an optimal routing for offloading the V2V part of the task, utilizing the available resources in neighboring vehicles. In [30], the paper presents a computation model for single vehicle computation offloading in MEC-enabled vehicular networks. It considers a unidirectional road with successive small cells, each consisting of a RSU and a collocated MEC server. The paper proposes a dynamic offloading scheduling scheme for MEC-enabled vehicular networks.

Use of deep reinforcement learning in vehicular networks is explored in [31]. The paper proposes a novel resource allocation algorithm based on deep reinforcement learning to allocate computation and transmission resources in MEC-enabled vehicular networks. The algorithm proposed in the paper improves the long-term average task success ratio and transmit power performance. In [32], the authors formulate the constrained optimization problem of offloading decisions as a game based on game theory. The paper considers the mutual interference of tasks in the same channel and proposes a TM algorithm and a COMO algorithm to address this issue. In [33], Joint Optimization of Wireless and Computation Allocation (JOWCA) algorithm is proposed to minimize global delay in MEC-enabled vehicular networks. The optimization problem is formulated as minimizing global delay in the vehicular network. It is decomposed into two sub-problems: V2X matching and MEC computation capability optimization. In [34], the authors formulate the offloading decision and resource allocation problem as a mixed integer nonlinear programming (MINLP) problem and decomposes it into two subproblems: offloading decision subproblem and resource allocation subproblem. It proposes a coalition game-based algorithm to solve the subcarrier assignment problem and a convex optimization method to solve the power allocation problem. Finally, the offloading decision is obtained by solving a linear program (LP) problem. In [35], the authors address the problem of energy optimization in massive multiple-input-multiple-output (MIMO) unmanned aerial vehicle (UAV)-aided mobile edge computing (MEC)-enabled vehicular networks. They propose a novel architecture that utilizes UAVs as ARSUs (aerial road side units) or relays and employs line-of-sight (LoS) massive MIMO technology.

In [36], the authors propose a novel framework that combines Deep Neural Network (DNN) and Particle Swarm Optimization (PSO) to address the joint offloading decision and resource allocation problem in Multi-access Edge Computing (MEC)-based vehicular networks. PSO accelerates the training of DNN by providing high-quality labeled data, while DNN performs real-time decision-making based on simple algebraic calculations. In [37], the authors propose a user association policy for a UAV-aided time-varying vehicular network with Multi-access edge computing (MEC) servers. The authors derive achievable video chunks and link reliability based on the vehicle mobility model and content caching model, and formulate the user association problem as a utility optimization problem. They propose an improved Dijkstra algorithm to solve the NP-hard problem of user association, which is transformed into a shortest path selection problem. In [38], the authors discuss the time consumption and off-loading cost of various transmission modes in the proposed framework. They designed a task-file transmission strategy with predictive V2V relay and proposes an optimal predictive combination-mode off-loading scheme. The results demonstrated a significant reduction in off-loading cost. In [39], the authors propose a Mobile Edge Computing (MEC)-based cooperative Collision Avoidance (MECAV) system for vehicular networks. The system utilizes a Collision Avoidance (CAV) service allocated in the MEC infrastructure, which processes data received from vehicles and transmits relevant information within each vehicle's collision risk area. The problem of resource allocation in the context of Internet of Vehicles (IoV) services is explored in [40]. The authors design a resource allocation algorithm based on deep reinforcement learning (DRL) to adapt to the changeable MEC environment and process high-dimensional data.

2.2 Reconfigurable Intelligent Surfaces (RIS)

Reconfigurable intelligent surfaces (RISs) are a new type of technology that can be used to improve the performance of wireless networks. They work by reflecting electromagnetic waves in a way that can be controlled. This allows them to be used to enhance the signal strength, coverage, and reliability of wireless networks. A good amount of research is being done on RISs. In [41], the paper provides a comprehensive overview of the state-of-the-art on RISs, including their operating principles, performance evaluation, beamforming design, resource management, applications of machine learning, and integration with other emerging technologies. It also identifies major issues and research opportunities associated with the integration of RISs and other technologies for next-generation networks. In [42], the paper provides a tutorial overview of reconfigurable intelligent surfaces (RIS) for wireless communications, explaining their working principles and different candidate implementations using metasurfaces and reflectarrays. It discusses suitable channel models and the feasibility of obtaining accurate channel estimates for RIS implementations. This paper also highlights the challenges and potential opportunities associated with RIS optimization compared to traditional MIMO arrays. RISs are aimed at intentionally and deterministically controlling the propagation environment to boost signal quality at the receiver. They are nearly passive and ideally do not require a dedicated energy source. This distinguishes RISs from other systems, such as smart mirrors, which are more focused on reflecting signals [43]. In [44], the authors investigate the adoption of Reconfigurable Intelligent Surfaces (RIS) for downlink multi-user communication from a multiantenna base station. They proposed energy-efficient designs for transmit power allocation and phase shifts of the surface reflecting elements, leading to non-convex design optimization problems. The paper demonstrates that properly designing the phase shifts applied by the RIS leads to higher energy efficiency than traditional amplify-and-forward relays. In [45], the authors discuss the potential applications of reconfigurable intelligent surfaces (RISs) in wireless networks operating at high-frequency bands, such as millimeter wave and sub-millimeter wave frequencies. They compared the similarities and differences between RISs and relays, highlighting the spectral efficiency gains of RISs when their size is sufficiently large compared to the wavelength of the radio waves.

In [46], the authors provide an overview of the applications of RISs in wireless networks, present an electromagnetic-based communication-theoretic framework for analyzing and optimizing metamaterial-based RISs, discuss the current state of research, and highlight the need to reconcile Shannon's theory of communication with Green's and Maxwell's theories of electromagnetism for modeling and deploying RIS-empowered smart radio environments (SREs). In [47], the authors aim to validate the potential gains of reconfigurable intelligent surfaces (RISs) in realistic communication environments. RISs can modify the wireless channel and provide physical layer security in wireless networks. The authors present a low-power and portable proof-of-concept RIS prototype and evaluates its performance in real-world scenarios. In [48], the authors focus on three fundamental physical-layer challenges for incorporating RISs into wireless networks: channel state information acquisition, passive information transfer, and low-complexity robust system design. They summarize the state-of-the-art solutions and explores potential research directions. Additionally, the paper discusses other promising research directions of RISs, including edge intelligence and physical-layer security. In [49], the authors discuss optimization techniques for phase shifts in RIS-assisted wireless communications, including joint optimization for point-to-point communication systems and hybrid beamforming for multi-user MIMO systems. In [50], the authors propose a deep learning method for efficient online configuration of Reconfigurable Intelligent Surfaces (RISs) in indoor communication environments. They used a database of coordinate fingerprints and a Deep Neural Network (DNN) to map the measured position information of a user to the optimal phase configurations of the RIS, maximizing the received signal strength at the intended location.

The authors of [51] discuss the limitations of using the independent and identically distributed (i.i.d.) Rayleigh fading channel model in the context of reconfigurable intelligent surfaces (RIS) with rectangular geometry. They propose an alternative physically feasible Rayleigh fading model that can be used as a baseline for evaluating RIS-aided communications. To maximize energy efficiency, [52] focuses on resource allocation in a wireless communication network with distributed reconfigurable intelligent surfaces (RISs). It proposes two iterative algorithms for the single-user and multi-user cases, which optimize transmit beamforming and RIS control to achieve higher energy efficiency. In [53], the authors present a general hardware model for simultaneous transmitting and reflecting reconfigurable intelligent surfaces (STAR-RISs) and propose channel models for both near-field and far-field scenarios. This paper analyzes and compares the diversity gain of STAR-RISs with conventional RISs. In [54], the paper discusses the placement of RIS in an indoor environment and its impact on the Path Estimation Bias (PEB). It shows that placing RIS on the wall facing the RIS can provide better coverage and that using multiple RISs can provide uniform coverage in the deployment region. In [55], the authors propose an RIS-enhanced multiple-input single-output system with reflection pattern modulation (RPM) to achieve passive beamforming and information transfer simultaneously. The active and passive beamforming is jointly optimized to maximize the average received signal power, considering the communication outage probability. Their proposed scheme outperforms the conventional RIS-assisted system without information transfer in terms of achievable rate.

The challenge of overhead in reconfigurable intelligent surfaces (RIS) used in wireless networks is addressed in [56]. It proposes an overhead-aware resource allocation framework that optimizes the system rate and energy efficiency by considering the phase shifts of the RIS, transmit and receive filters, power and bandwidth used for communication and feedback phases. In [57], the authors highlight the potential of RISs for enhancing positioning and orientation estimation in next-generation cellular networks. They mention that RISs have not yet received much attention in wireless localization, despite their promise for various 6G applications such as augmented reality and self-driving cars. The authors propose a localization scheme that utilizes infrastructures envisioned for next-generation communication systems. In [58], the paper explores the use of Reconfigurable Intelligent Surfaces (RISs) for radar surveillance in Non-Line Of Sight (N-LOS) scenarios. It describes the geometry of the scene, the required operative modes, and the role played by the RIS in N-LOS radar surveillance. Nonterrestrial communications, including unmanned aerial vehicles (UAVs), high-altitude platforms (HAPs), and satellites, have emerged as a key enabler for seamless connectivity in upcoming generation networks. Reconfigurable intelligent surfaces (RIS) are expected to be a cost-efficient solution to address practical implementation limitations, such as power consumption, blockage, and dynamic propagation environment. RIS can bypass blockages, create multiple line-of-sight links, and provide controllable communication channels [59]. In [60], the authors demonstrate through numerical results how approximate global designs can be achieved using locally passive RISs with zero electrical resistance, even for large angles of reflection and at high power efficiency.

2.3 RIS assisted Computation Offloading

The attractive benefits of Reconfigurable Intelligent Surfaces (RIS) have led to numerous investigations in recent years, particularly in relation to the performance improvements brought on by programmable wireless settings in MEC-enabled vehicular networks. In [61], the authors have utilized multiple reconfigurable intelligent surfaces (RIS) between a source and destination to create a line-of-sight (LOS) connectivity. However, problems like signal strength and time delay overhead cannot be evaded. In [62], the authors proposed a system for RIS-aided vehicular networks that considers two scenarios for channel estimation. In the first scenario, the channels are assumed to be fixed within a coherence time, which is the time it takes for the channel to change significantly. In the second scenario, the small-scale fading is neglected, which is the variation of the channel due to factors such as the movement of vehicles. This is possible because the positions of vehicles can be known in advance. In [63], the authors analyzed the outage probability in vehicular networks that use reconfigurable intelligent surfaces (RISs). They derived an expression for the outage probability, which is the probability that the signal strength between a vehicle and an RIS is too low to be decoded. The analysis showed that RISs can reduce the outage probability for vehicles in their vicinity. The analysis also showed that higher density roads increase the outage probability. This is because passing vehicles can block the communication links between the RIS and the vehicles. In [64], the paper focuses on optimizing the local computing frequencies and transmission power of IoT devices, time-slot assignment, and phase beamforming of the RIS to achieve max-min computation efficiency under secure computation rate requirements. An iterative algorithm is developed to solve the formulated nonconvex problem, utilizing the Dinkelbach-type method and block coordinate descent technique. In [65], the authors investigate the use of RIS (Reconfigurable Intelligent Surface) and NOMA (Non-Orthogonal Multiple Access) in a UAV-MEC (Unmanned Aerial Vehicle-Mobile Edge Computing) network. They explored the use of a deep Q-network algorithm to minimize energy consumption in a UAV-NOMA-RIS system. The algorithm helped to optimize the RIS strategy in the network.

In [66], the authors propose the use of UAV-enabled aerial RIS (ARIS) technology in MEC networks to address the drawbacks of terrestrial MEC networks. By mounting the edge server on a UAV, the mobility, flexibility, and maneuverability of network components are improved, leading to an energy-efficient design that prolongs the UAV's service time. The results of the paper show that the ARIS-assisted MEC network offers four main benefits: improved MEC performance, reduced energy consumption, guaranteed latency, and high spectral and energy efficiencies. The concept of reconfigurable intelligent surfaces (RIS) into edge computing also supports low-latency applications [67]. RIS can enhance the quality of wireless communication by intelligently altering the radio propagation environment. It establishes a distributed computing environment by deploying computation and storage resources in proximity to end users. In [68], the authors explore the use of RIS-aided simultaneous wireless information and power transfer (SWIPT) systems under QoS constraints.

The authors have discussed the limitations of existing technologies (11p and C-V2X), in meeting the QoS requirements for advanced vehicular applications and high-data-rate transmission. In [69], the paper focuses on the optimization of task scheduling in Intelligent Reflecting Surface (IRS)-aided Multi-access Edge Computing (MEC)-served vehicular networks. The authors have considered factors such as vehicle mobility patterns, transmission conditions, and task sizes to improve the allocation of limited processors and IRS resources. Various research contributions that leverage artificial intelligence (AI) techniques to address the challenges of RIS-assisted networks such as AI-based channel estimation, phase-shift optimization, and resource allocation have been explored in [70]. The authors have focused on the challenges of reconfigurable intelligent surfaces (RISs) in terms of channel state information (CSI) acquisition and passive beamforming optimization.

The problem of resource allocation in IRS-aided vehicular networks, specifically in high-density urban areas where signal propagation is affected by buildings and infrastructure has been addressed in [71]. The authors have proposed an intersection-based IRS-aided vehicular network model and formulates the resource allocation problem as a mathematical model. It considers the mutual interference and blocking effects of buildings and aims to optimize the IRS resource allocation to accelerate the average offloading rate. In [72], the authors have discussed the deployment of IRS in high-speed mobile vehicles to aid passengers in communicating with roadside base stations, mitigating fast channel fading caused by the Doppler effect. In [73], the authors have explored an optimization approach to minimize weighted total energy consumption (WTEC) while considering transmit power constraints, timeslot scheduling, and task allocation. They have proposed a novel computation offloading framework for Internet of Vehicles (IoV) networks, utilizing a dual-RIS configuration and an unmanned aerial vehicle (UAV) as an aerial road side unit (ARSU) and relay. In [74], the paper addresses the problem of energy minimization in an IRS-assisted and wireless-powered mobile edge computing (MEC) system for vehicular networks. The problem is decomposed into two subproblems: downlink energy transfer and uplink data offloading phases. The uplink phase is efficiently optimized using the conventional semi-definite relaxation (SDR) method, while the downlink phase is solved through alternating optimization between users' offloading decisions and joint active and passive beamforming strategies. In [75], the paper addresses the problem of resource allocation and task offloading in an internet of vehicles (IoV) network with multi-access edge computing (MEC) servers and reconfigurable intelligent surfaces (RISs). The authors introduce a multi-agent deep reinforcement learning (MA-DRL) algorithm for optimizing task offloading decisions.

In [76], the paper aims to solve the problem of maximizing the energy efficiency of reconfigurable intelligent surface (RIS)-assisted unmanned aerial vehicle (UAV)-enabled mobile edge computing (MEC) systems. The paper proposes an iterative algorithm with a double-loop structure to jointly optimize the bit allocation, phase shift, and UAV trajectory. The algorithm is based on Dinkelbach's method and the block coordinate descent (BCD) technique. To solve the problem of poor quality of service (QoS) on task latency in a complicated environment where unmanned aerial vehicles (UAVs) are frequently blocked by ground obstacles, leading to blocked UAV-ground terminal (GT) links. The authors in [77] proposed a joint optimization approach that considers UAV trajectory, task offloading, cache, and phase-shift design of reconfigurable intelligent surfaces (RIS) to maximize the energy efficiency of RIS-assisted UAVs. The authors utilize the successive convex approximation (SCA) method to solve the non-convex joint optimization problem. In [78], the authors proposed a Digital Twin-Driven Vehicular Task Offloading and IRS Configuration Framework (DTVIF) to efficiently monitor, learn, and manage the Internet of Vehicles (IoV) by employing Mobile Edge Computing (MEC) and Intelligent Reflective Surface (IRS) technologies. In [79], the authors discuss the use of Intelligent Reflecting Surfaces (IRS) in 6G-driven vehicle tracking in smart cities. The paper provides formulas and equations to solve the wave equation in different scenarios, such as a curved tunnel and a straight-line tunnel, to calculate the received power at the mobile device.

Chapter 3

Problem Formulation and Proposed Solution

In this chapter, the topics under consideration include system model, how it is designed, how it works, and the mathematical formulation of the problem. Furthermore, the proposed solution and the methods used in the solution; the constraints utilized in the solution are also discussed.

3.1 System Model

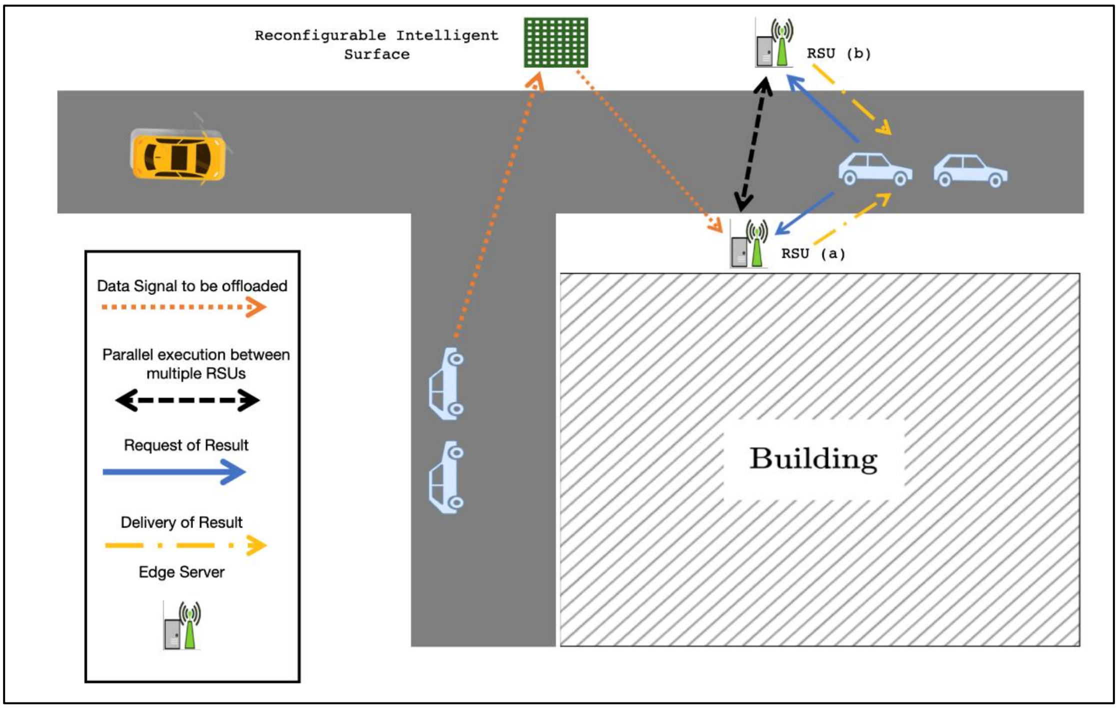


Fig.1. System Model

Think of a group of autonomous vehicles $V = \{V_1, V_2, V_3, \ldots, V_n\}$ where any vehicle V_a, $a \in V$ wishes to hand over a task to a roadside unit (RSU). Each RSU acts as a MEC server for autonomous vehicles and connects to nearby RSUs through wireless networks to exchange information. Since there is a blockage between the vehicle and RSU, the Line of sight (LOS) view between them is blocked, and RIS is placed in the center that enables Line of sight communication between both to preserve the signal strength at the RSU. A vehicle interacts with a roadside unit (RSU) at time x from a specific distance. Since both are in the non-LOS region to each other, this interaction will pass through RIS. Meta-surfaces of RIS are coded such that to obtain directivity of RIS antenna to maximize the RIS antenna gain, which in turn maximizes the data rate and reduces the time delay. During this interaction, the vehicle communicates data about its trajectory and a certain scale of computing. $Z(x)$ refers as the computing task's size. In exchange, the RSU allocates an ID to the computing task that the vehicle has offloaded and provides both the ID and the task ID to the vehicle. It is presumed that each vehicle's interaction must be completed before the next iteration. A binary vector $\pi_a(x)$ at time x represents each vehicle's offloading choice, where a represents RSU_a. If $\pi_a(x)$ = 1, the computation tasks of the vehicle are offloaded to RSU_a at time x. If $\pi_a(x)$ = 0, the computation tasks are not offloaded to RSU_a at time x. For the computing task created at time x, "a" is the receiver RSU. Another RSU_b exists that might execute a portion of the computing task in tandem and send the finished results back to the vehicle.

3.2 Scenario

A scenario is depicted in Fig. 1 where a vehicle assigns its computational task to RSU_a at time x. To minimize the time delay, another RSU's cooperation is required to accomplish a part of the task through parallel computing. The task is intelligently separated into two sub-components by RSU_a. After that, RSU_a retains a portion of the task while sending the remainder to another RSU in the vehicle's trajectory, RSU_b. These two RSUs process their respective tasks in parallel. When each component of task is completed, RSU_a forwards its result to RSU_b for combination. The output of the entire task will be accessible at RSU_b, quoted as the supporter RSU for computational tasks created at time x. A supporter RSU is one that either processes the computational task's component in parallel with RSU_a or processes the entire computational task individually.

3.3 Problem Formulation

Mathematical formulae used in the system model are explained below: The path-loss between a transmitter and receiver at a distance "*d*" [80] can be calculated as follows:

$$P(d) = 40(1 - 4 \times 10^3 h) \log_{10} d - 18\log_{10} h + 21\log_{10} f + 80, \tag{1}$$

where h is the height of receiver antenna, d is the distance between transmitter and receiver and f is the carrier frequency. Directivity of IRS [13] can be computed using:

$$D(\theta, \phi) = \frac{4\pi U(\theta,\phi)}{\int_0^{2\pi}\int_0^{\pi} U(\theta,\phi)\sin\theta \, d\theta \, d\phi}, \tag{2}$$

where $U(\theta, \phi)$ is a transmitter's radiation output in the direction indicated by θ and ϕ.

Transmitter gain of IRS antenna [13] can be computed using:

$$G_t = \varepsilon D \tag{3}$$

where ε is the efficiency and D is the directivity of IRS antenna. The data rate can be computed using:

$$R = B\log_2(1 + \frac{P_T G_t G_r 10^{-P(d)/10}}{\delta_2}), \tag{4}$$

where B is the bandwidth, P_T is the transmit power of transmitter antenna, $P(d)$ is the Path Loss at a distance d, δ_2 is the gaussian noise in the channel, G_t is the transmitter antenna gain and G_r is the receiver antenna gain. Orthogonal frequency division multiple-access (OFDMA) is the system paradigm utilized for network implementation. In this model, subcarriers are used to separate the bandwidths allocated for a vehicle and an RSU to transfer the task that was offloaded at time x, denoted by $c_M \in C_M = [1, 2, ..., M]$ and $c_D \in C_D = [1, 2, ..., D]$, respectively. OFDMA is commonly used in modelling system models, as demonstrated by related works [80], and [81]. This thesis also considers OFDMA for comparison. A fixed channel condition for the duration of task offloading is assumed. Since the task to be offloaded goes from vehicle to RSU through RIS, the transmission time for offloading a computation task at time x to RSU_a is:

$$T_a(x) = \frac{Z(x)}{R_a} + \frac{Z(x)}{R_b}, \tag{5}$$

where R_a is the data rate from Vehicle to RIS, and R_b is the data rate from RIS to RSU_a. The forwarding time for a portion of task at time x to RSU_b is:

$$T_b(x) = \frac{\zeta_a(x) \times Z'(x)}{R_{(a,b)}}, \tag{6}$$

where $\zeta_a(x)$ is a binary vector that has a value of "1" if RSU_b takes help in the execution of some portion of task and it has a value of "0" if RSU_b does not take help in the execution and whole task is executed at RSU_a. $R_{(a,b)}$ is the data rate reserved from RSU_a to RSU_b. The time for execution of a task on RSU_a at time x is:

$$T_c(x) = \frac{V[Z(x) \times n]}{W}, \tag{7}$$

Similarly, the time for execution of a task on RSU_b at time x is:

$$T_d(x) = \frac{V[\zeta_a(x) \times Z'(x) \times n]}{W}, \tag{8}$$

where, V is the number of computation cycles needed to execute one bit measured in bits per second and W is the computing capabilities of MEC server available at RSU and $Z'(x)$ in the amount of task that needs to be executed at RSU_b and n is the CPU cores available at RSU_b for execution of subtask. The receiving delay for the delivery of results might be regarded as minimal, since the output data is typically smaller than the input data [80], [81]. The reception delay can be computed as:

$$T_r(x) = \frac{\alpha \times Z(x)}{R_v}, \tag{9}$$

where α is the value used to estimate the size of result regarding the size of the computational task and R_v is the data rate reserved for delivery RSU to vehicle. Delivery RSU can be any one of both RSU_a and RSU_b. The complete list of notations used in this thesis is shown in Table I.

Notation	Description
$\boldsymbol{P}$	Path Loss
$\boldsymbol{D}$	Directivity of RIS antenna
$\boldsymbol{B}$	Bandwidth
$\boldsymbol{P_T}$	Transmit Power
$\boldsymbol{\delta_2}$	Gaussian Noise
$\boldsymbol{Z}$	Task at RSU_a
$\boldsymbol{Z'}$	Task at RSU_b
$\boldsymbol{V}$	CPU clock cycle per byte
$\boldsymbol{W}$	Computing Capability of an RSU
$\boldsymbol{\zeta}$	Binary vector representing if RSU_b takes part in execution or not
$\boldsymbol{T_a}$	Transmission to RSU_a delay
$\boldsymbol{T_b}$	Forwarding from RSU_a to RSU_b delay
$\boldsymbol{T_c}$	RSU_a execution delay
$\boldsymbol{T_d}$	RSU_b execution delay
$\boldsymbol{T_r}$	Reception delay
$\boldsymbol{T_k}$	Round Trip Time (RTT)
$\boldsymbol{\omega^\circ}$	SNR threshold for V2I and I2I communication
$\boldsymbol{\omega^r}$	SNR threshold for result delivery

Table I – Notations

3.4 Proposed Solution

For any task offloaded by a vehicle, there can be a specific number of policies, which is depend on the division of the task into two components, e.g., a 3MB task can be divided into 4 possible combinations, i.e., (3, 0), (2, 1), (1, 2), and (0, 3). The first number in each bracket shows the size of a subtask that needs to be executed at RSU_a and the second number shows the size of subtask that needs to be executed at RSU_b. These combinations can also be called offloading policies. Out of these four policies, RSU_a intelligently selects that policy whose combination will give the least time delay. A computational task is offloaded to RSU_a only if its signal-to-noise ratio is positive. Since, in this system model the computational task offloaded by vehicle to RSU goes through RIS, SNR is considered to be SNR from vehicle to RIS added to the SNR from RIS to RSU_a. Similarly, SNR must also be positive at the time of delivery of result from RSU to vehicle. If the SNR threshold is not met, the task will be discarded, and it will not be given to RSU at the time of transmission and to Vehicle at the time of delivery. The main goal is to reduce the round-trip time (RTT) and enhance the received signal strength at the RSU. Therefore, the RTT for offloading the computational task to RSU can be obtained as:

$$T_k(x) = T_a(x) + T_r(x) + \max\{T_c(x), T_b(x) + T_d(x)\}, \tag{10}$$

where $T_a(x)$ is the transmission delay of task from vehicle to RSU_a, $T_r(x)$ is the reception delay of result from RSU to vehicle, $T_c(x)$ is the execution delay at RSU_a, $T_b(x)$ is the forwarding delay to RSU_b, and $T_d(x)$ is the execution delay at RSU_b at time x. When it comes to offloading policy, there are three possible scenarios for each task:

- When computing the total computational task, if receiver RSU_a is responsible for it while supporter RSU_b is not, $\zeta_a(x)$ will be "0". This causes both $T_b(x)$ and $T_d(x)$ to be zero as well. Therefore, $T_c(x)$ will be selected by the maximum function.
- When supporter RSU_b is responsible for computing the total computational task, receiver RSU_a does not perform any computation in this scenario. Thus, $T_c(x)$ will be zero, and the max function will select $T_b(x) + T_d(x)$ as the optimal decision.
- When both receiver RSU_a and supporter RSU_a are involved in a computational task, both will execute a subtask of an entire task. In such scenario, the maximum function will select the greater value between $T_c(x)$ and $T_b(x) + T_d(x)$, since both RSUs are computing in parallel.

3.5 Optimization Constraints

Some constraints are designed for the optimization problem that should be considered when calculating the total service delay.

3.5.1 Time threshold for total service delay

A threshold is set for the maximum time delay that a computational task can take to be processed. If a task takes longer than the threshold, it is discarded. The threshold is set to 15 minutes, which is a flexible value that can be adjusted as needed. This means that the total service delay for a task should be between 0 and 15 minutes.

3.5.2 SNR threshold for RIS to RSU_a

A computational task will be accepted by RSU_a when it satisfies a signal-to-noise ratio (SNR) threshold, ω°. Therefore,

$$\pi_a(x) = \begin{cases} 1, & if \quad \frac{P_T\, 10^{-P(d_a)/10}}{\delta_2} \geq \omega^{\circ} \\ 0, & Otherwise \end{cases}, \tag{11}$$

where d_a is the distance between RIS and RSU_a.

3.5.3 SNR threshold for I2I

A computational task or sub-component of the task can be forwarded from RSU_a to RSU_b only when it satisfies an SNR threshold, ω°. Therefore,

$$\zeta_a(x) = \begin{cases} 1, & if \quad \frac{P_T\, 10^{-P(d_{a,b})/10}}{\delta_2} \geq \omega^{\circ} \\ 0, & Otherwise \end{cases}, \tag{12}$$

where $d_{a,b}$ is the distance between RSU_a and RSU_b.

Moreover, at the end of service session, if a vehicle gets out of the range of RSU_b, then the vehicle will not be able to receive the results. Which will cause the service session to fail. The SNR threshold for result delivery is denoted by ω^r. A binary variable is kept which tells if the service session has failed or not, and is denoted by *r(x)*. If *r(x)* = 1, then it means that the service session has failed. If *r(x)* = 0, it means that the service session is not failed. Hence,

$$r(x) = \begin{cases} 1, & if \quad \frac{P_T\, 10^{-P(d_v(x+T_k))/10}}{\delta_2} \leq \omega^{r} \\ 0, & Otherwise \end{cases}, \tag{13}$$

where $d_v(x + T_k)$ is the distance between the deliver RSU and vehicle. This is the distance which is taken when the offloaded task has been computed and the results are received at the deliver RSU. This is why the round-trip time at epoch x is added.

Chapter 4

Simulation Results

Simulation results were obtained using three algorithms in comparison with the proposed scheme. These algorithms include the Closest Server method, the Continuous Server relocation method, and the random method [7]. In the closest server method, a task is transmitted to RSU_a by vehicle without considering the division of tasks or the support of RSU_b. The entire task is processed at the RSU_a, which is then responsible for delivering the task to the vehicle. In the continuous server relocation method, a task is transmitted to RSU_a by a vehicle, but the entire task is shifted to supporter RSU_b as the vehicle approaches it. The whole task is then executed at the RSU_b, which functions as a supporter RSU and hands over the task to the vehicle. As part of the Random method, a vehicle sends a task to RSU_a in two components. One component is retained at RSU_a, while the other is sent to supporter RSU_b both the sub components are executed in parallel, combined together after execution and delivered back to the vehicle. This process is done randomly.

Parameter	Value
Height of IRS antenna	10 m
Height of RSU antenna	5 m
$\boldsymbol{f}$	25 GHz
$\boldsymbol{B}$	24 MBps
$\boldsymbol{P_T}$	20 dBm
$\boldsymbol{\theta}$	45
$\boldsymbol{\Phi}$	90
$\boldsymbol{\varepsilon}$	0.9
$\boldsymbol{\delta}$	158 dBm
Distance between vehicle and RIS	30 m
Distance between RIS and $\boldsymbol{RSU_a}$	10 m
Distance between $\boldsymbol{RSU_a}$ **and** $\boldsymbol{RSU_b}$	10 m
Distance between delivery RSU and vehicle	15 m
Size for the RIS	5λ x 5λ
Size for each unit cell	$\frac{\lambda}{3}$
Reflecting elements in RIS	15 x 15
$\boldsymbol{N_s}$	4

Table II – Simulation Parameters

4.1 MES execution delay vs Local execution delay

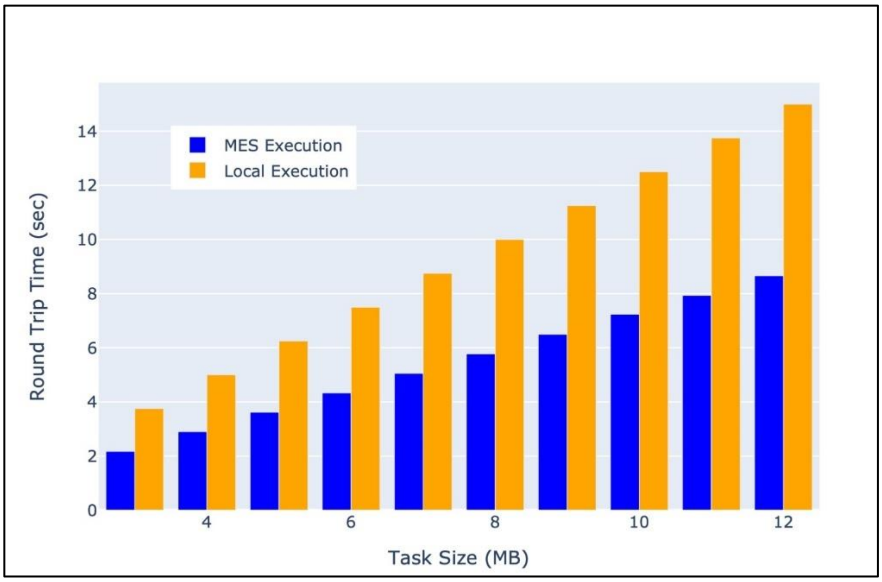


Fig. 2. MES execution delay vs Local execution delay

Fig. 2 shows the round-trip time of a complete task when it is offloaded to the server and when it is executed locally. Note that for every size of task, offloading is a better option compared to executing it locally. The height of IRS antenna, height of RSU antenna, f, B and P_T are considered as 10m, 5m, 25GHz, 24MBps and 20dBm [81] respectively. θ, ϕ and ε are taken as 45, 90 and 0.9 respectively. The values for δ, distance between vehicle and RIS, distance between RIS and RSU_a, distance between RSU_a and RSU_b and distance between delivery RSU and vehicle are taken as − 158dBm, 30m, 10m, 10m and 15m respectively. The complete list of simulation parameters is shown in Table II. In RIS, the angle of reflection of the incoming electromagnetic wave is determined by elevation angle (θ_r) and angle of azimuth (ϕ_r). In scenario specified as reference, there is 5λ x 5λ size for the RIS and $\frac{\lambda}{3}$ size for each unit cell, given the wavelength (λ). It is also assumed that there are 15 x 15 reflecting elements in RIS, and each reflecting element can attain four different states (N_s = 4).

4.2 RTT vs Number of States

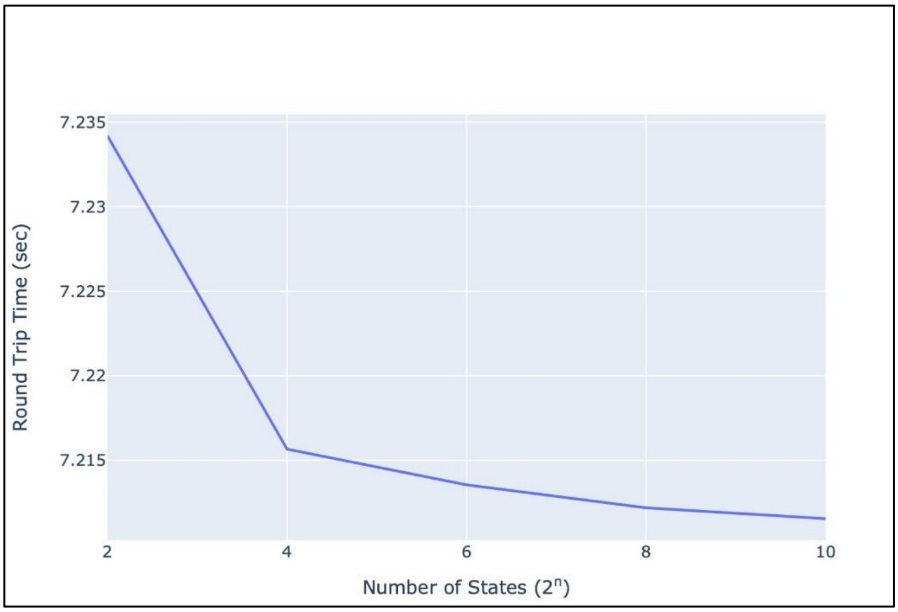


Fig. 3. RTT vs Number of States

Fig. 3 shows the relationship between round-trip time (RTT) and Number of states (2^n) of RIS. To see the effect on the round-trip time, the number of states of RIS is increased gradually. It can be seen from Fig. 3 that by increasing the number of states of RIS, the round-trip time decreases. This is because when the number of states of RIS increase, it causes the transmitter gain to increase. Because of that the data rate of communication increases and hence finally the round-trip time decreases.

Therefore, to provide real-time services the number of states of RIS need to be appropriate. Because fast communication is also dependent on the number of states.

4.3 RTT vs Size of RIS

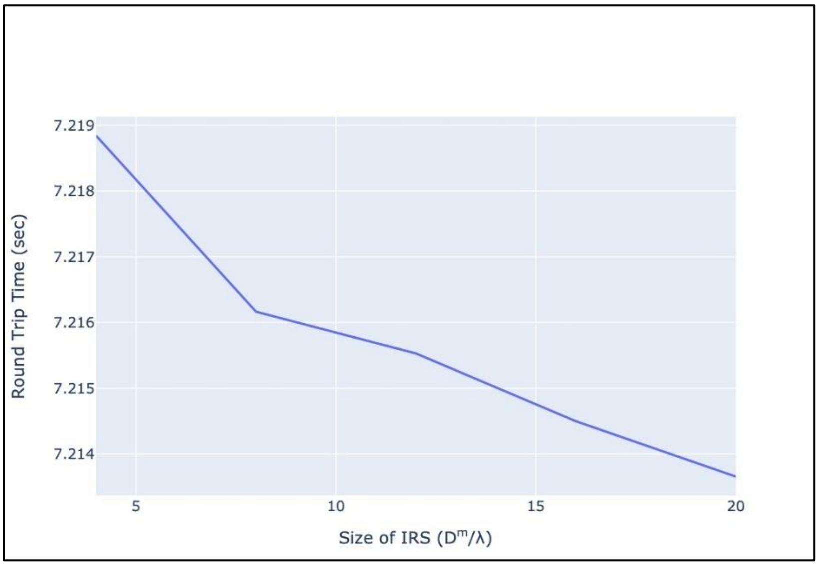


Fig. 4. RTT vs Size of RIS

Fig. 4 shows the relationship between round-trip time (RTT) and the Size of RIS ($\frac{D^m}{\lambda}$). It can be seen that by increasing the size of RIS, the transmitter gain increases, which increases the data rate of communication and hence the round-trip time decreases. Hence, appropriate size of RIS needs to be selected so that reliable services for vehicular networks can be provided.

4.4 RTT vs Size of Unit Cell

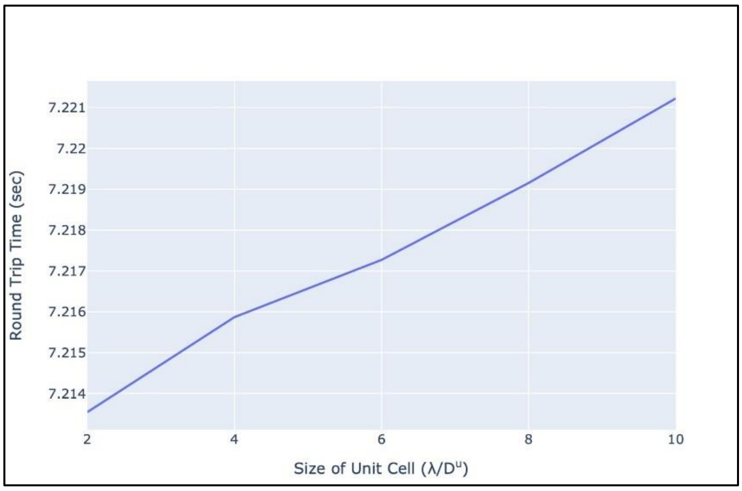


Fig. 5. RTT vs Size of Unit Cell

Fig. 5 shows the relationship between round-trip time (RTT) and varying the size of Unit Cell ($\frac{\lambda}{D}$). It can be seen that as the Size of Unit Cell increases, transmitter gain decreases, because of which, the data rate decreases and the RTT increases. This is because when the size of unit cell of RIS increases, the number of 'meta-atoms' of RIS also increases. Which means that the incoming signal will be stronger and of high quality after being redirected.

4.5 RTT vs Distance from Vehicle to RIS

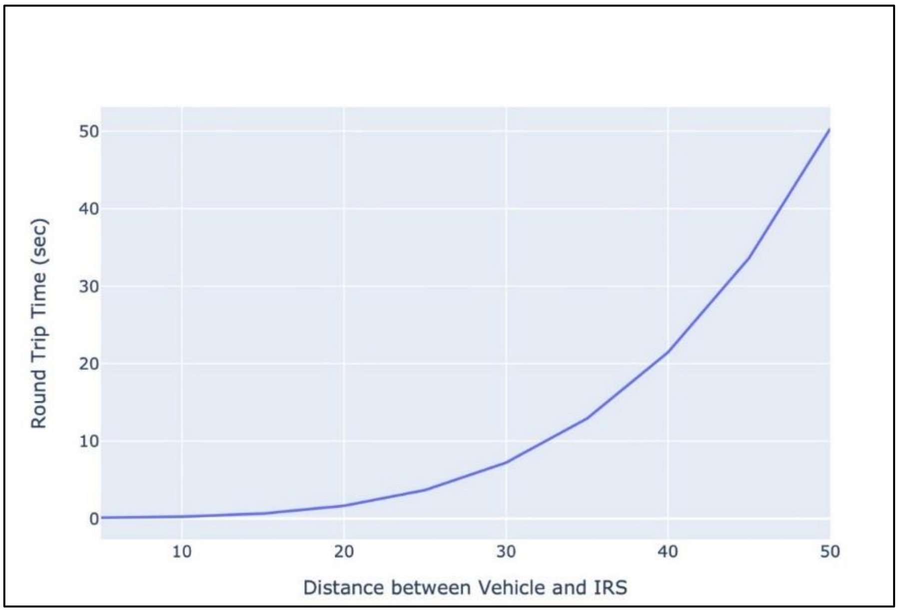
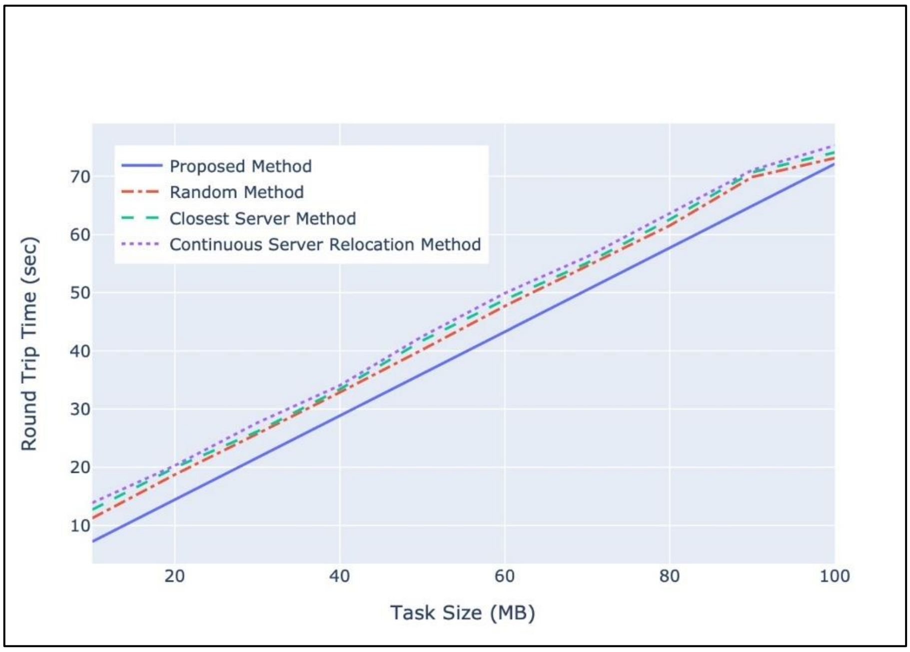


Fig. 6. RTT vs Distance from Vehicle to RIS

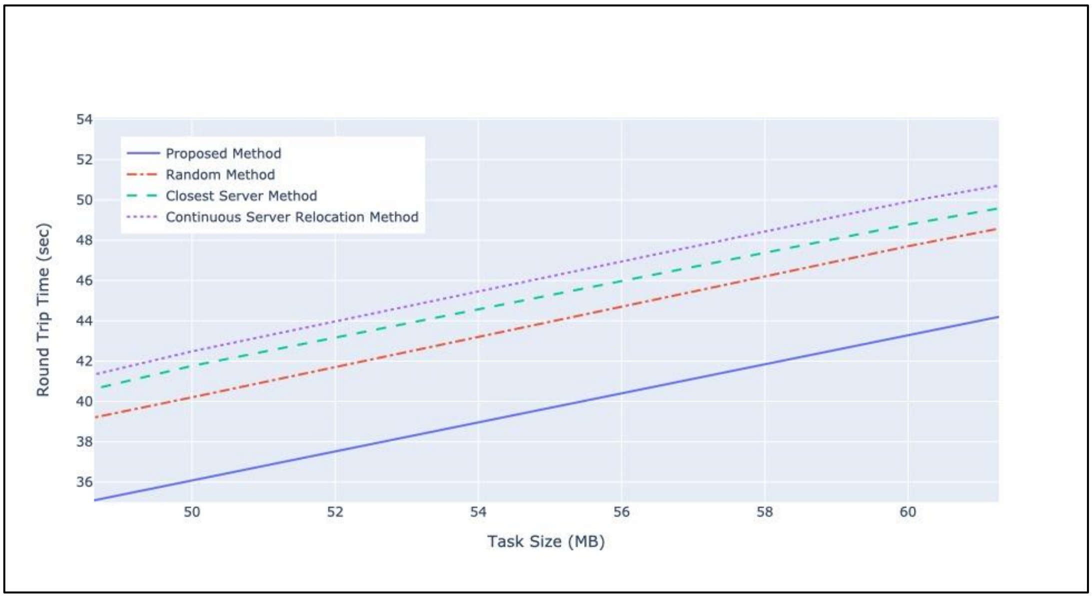
Fig. 6 shows the round-trip time (RTT) as the distance between the vehicle that wants to transmit its task and RIS increases. It can be seen that as the distance between the vehicle and RIS increases, the round-trip time also increases. This is because if the distance if vehicle from RIS is large, then the signal-to-noise ratio from vehicle to RIS will be of low quality. Because of this, the data from the vehicle will take longer to reach RIS and then RSU and so it will take longer time to process the task from the vehicle.

However, the selection for offloading a task based on the distance between vehicle and RIS may vary depending upon the speed of vehicle, urgency of task, and size of task.

4.6 Comparison of RTT with respect to Total task size



(a)



Zoomed version of (a)

Fig. 7. Comparison of RTT with respect to Total task size

Fig. 7 shows the comparison of round-trip time of the proposed method with the closest server method, the continuous server relocation method, and the random method. It can be seen from Fig. 7, that the round-trip time increases with respect to increase in the size of task. This increase in the round-trip time is because the execution time of a task on the server increases, as more time will be required for a bigger task.

As the complexity of task increases, the RTT also increases because its execution time on the server increases. However, no algorithm from closest server method, continuous server relocation method, and random method, achieves a lower round-trip time than the proposed method, which means that the proposed method reduces the total service delay to its minimum attainable level.

4.7 Comparison of Proposed scheme by varying the total number of Vehicles approaching RSU_a for offloading their task

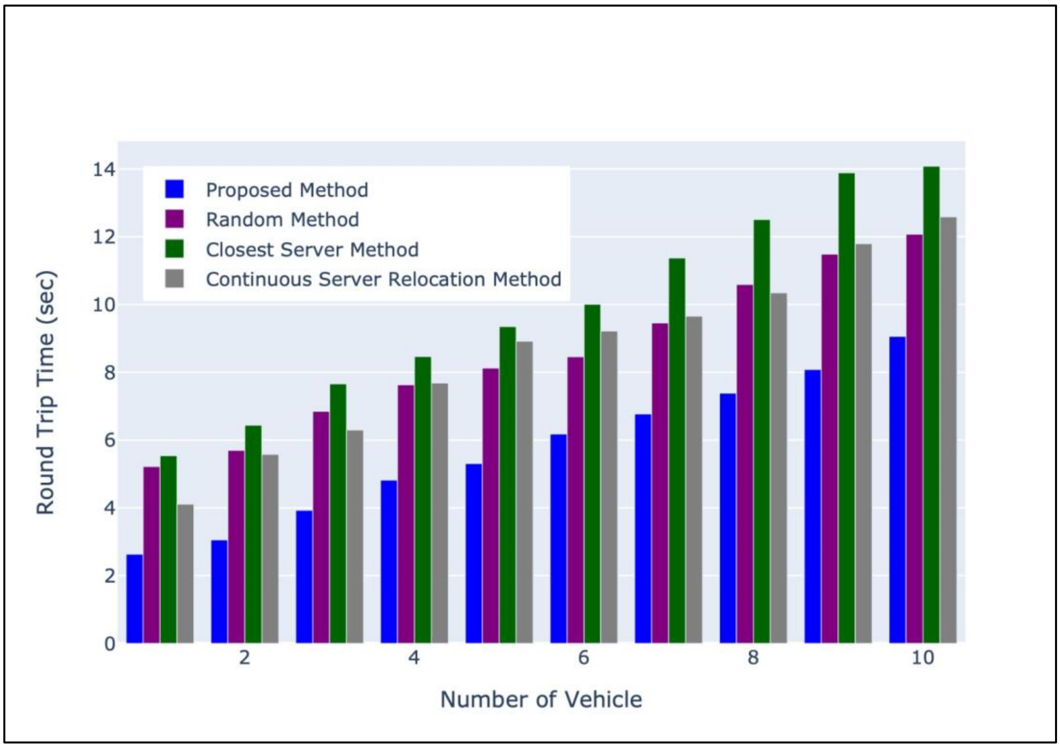


Fig. 8. Comparison of Proposed scheme by varying the total number of Vehicles approaching RSU_a for offloading their task

In Fig. 8, the relationship between round-trip time and the total vehicles requesting task processing by both the RSU_a and RSU_b is explored. In this simulation all the variables are kept constant, the only variable is the number of autonomous vehicles which varies from 1 to 10.

The values are taken in this way because only the relation between round-trip time and the number of vehicles that wish to have their tasks processed is explored. All the tasks are combined. Therefore, the overall amount of data that has to be processed is the sum of tasks from each vehicle. As the traffic on the RSU increases, the resources of the RSU are divided among the vehicles, resulting in a division of the parameter W in eq. 7 and eq. 8. This leads to an increase in the RTT for the combination of all tasks of every vehicle. It can be seen that the round-trip time of the random method fluctuates and at some points it is comparable to the round-trip time of the continuous server relocation method. However, the proposed method performs better than the benchmark policies and achieves the minimum round-trip time.

Chapter 5

Conclusion and Future Works

The complete thesis is concluded in this chapter using bullet points. The proposed solution, the methods used to get the results, as discussed in chapter 4, and the what those results show, are discussed in this chapter. Moreover, the future work to continue this thesis is also discussed.

5.1 Conclusion

This thesis proposes a solution to the challenge of reliable and efficient communication between an autonomous vehicle and a Roadside Unit (RSU) in real time environments.

- The challenge of reliable and efficient communication between an autonomous vehicle and a RSU is due to the fact that these vehicles are often moving and can be in obstructed environments. This can make it difficult for the vehicle to maintain a clear line of sight with the RSU, which can lead to communication problems.
- The RIS is a new technology that can be used to improve the reliability and efficiency of communication in these environments. The RIS is a surface that can be programmed to reflect radio waves in a specific way. This can be used to create a virtual line of sight between the vehicle and the RSU, even if they are obstructed.
- The RIS improves transmission reliability and reduces signal attenuation, ensuring seamless communication between the autonomous vehicle and RSU.
- The thesis also proposes a task distribution mechanism to reduce latency and improve system efficiency.
- This research opens up new possibilities for enhancing the reliability and performance of vehicular communication networks in the 25GHz frequency band.

5.2 Future Work

For the future work, research on different intelligent schemes can be conducted to integrate them with the proposed system model to further improve the efficiency and reliability of vehicular networks. Different AI models, such as Deep Learning, Reinforcement Learning, and also Federated Learning can be explored to see the improvement. By utilizing these approaches, the total service delay will minimize even further and a model can be developed that will work even in situations where there are more RISs and RSUs.

References

[1] A. Jaiswal, M. K. Rai, R. Saha and T. H. Kim, "Recent Developments in Cloud Computing Environment: Current Challenges and Future Prospects," 2019 3rd International Conference on Data Science and Business Analytics (ICDSBA), Istanbul, Turkey, 2019, pp. 409-414, doi: 10.1109/ICDSBA48748.2019.00089.

[2] N. Slamnik-Krijestorac, M. Peeters, S. Latre and J. M. Marquez-Barja, “Analyzing the impact of VIM systems over the MEC management and orchestration in vehicular communications,” in 29th International Conference on Computer Communications and Networks (ICCCN), Honolulu, HI, USA, 2020, pp. 1-6.

[3] S. Zhou, P. P. Netalkar, Y. Chang, Y. Xu and J. Chao, "The MEC-Based Architecture Design for Low-Latency and Fast Hand-Off Vehicular Networking," 2018 IEEE 88th Vehicular Technology Conference (VTC-Fall), Chicago, IL, USA, 2018, pp. 1-7, doi: 10.1109/VTCFall.2018.8690790.

[4] C. M. Huang and C. F. Lai, “The delay-constrained and network-situation-aware V2V2I VANET data offloading based on the multi-access edge computing (MEC) architecture,” in IEEE Open Journal of Vehicular Technology, vol. 1, pp. 331-347, 2020.

[5] O. Saleem, S. Munawar, S. Tu, Z. Ali, M. Waqas, and G. Abbas (2022, May). Intelligent Task Offloading for Smart Devices in Mobile Edge Computing. In 2022 International Wireless Communications and Mobile Computing (IWCMC) (pp. 312-317). IEEE.

[6] M. Waqas, Y. Niu, Y. Li, M. Ahmed, D. Jin, S. Chen, and Z. Han, “A Comprehensive Survey on Mobility Aware D2D Communications: Principles, Practice and Challenges,” in IEEE Communications Surveys and Tutorials, vol. 22, no. 3, pp. 1863-1886, thirdquarter 2020.

[7] M. Li, J. Gao, N. Zhang, L. Zhao and X. Shen, “Collaborative computing in vehicular networks: A deep reinforcement learning approach,” in IEEE International Conference on Communications (ICC), Dublin, Ireland, 2020, pp. 1-6.

[8] Y. He, N. Zhao, and H. Yin, “Integrated networking, caching, and computing for connected vehicles: A deep reinforcement learning approach,” in IEEE Transactions on Vehicular Technology, vol. 67, no. 1, pp. 44–55, Jan. 2018.

[9] Q. Qi, J. Wang, Z. Ma, H. Sun, Y. Cao, L. Zhang, and J. Liao, "Knowledge-driven service offloading decision for vehicular edge computing: A deep reinforcement learning approach," in IEEE Transactions on Vehicular Technology, vol. 68, no. 5, pp. 4192–4203, May 2019.

[10] X. Wang, Z. Ning, and L. Wang, "Offloading in internet of vehicles: A fog-enabled real-time traffic management system," in IEEE Transactions on Industrial Informatics, vol. 14, no. 10, pp. 4568–4578, Oct. 2018.

[11] T. Taleb, A. Ksentini, and P. A. Frangoudis, "Follow-me cloud: When cloud services follow mobile users," in IEEE Transactions on Cloud Computing vol. 7, no. 2, pp. 369–382, Apr. 2019.

[12] Y. Zhao, X. Liu, L. Tu, C. Tian and C. Qiao, "Dynamic Service Entity Placement for Latency Sensitive Applications in Transportation Systems," in IEEE Transactions on Mobile Computing, vol. 20, no. 2, pp. 460-472, 1 Feb. 2021.

[13] A. B. Asif, C. Liaskos, A. Pitsillides, H. K. Qureshi, and M. Lestas (2022, September). Optimal Path Selection in Cascaded Intelligent Reflecting Surfaces. In 2022 IEEE 96th Vehicular Technology Conference (VTC2022-Fall) (pp. 1-5). IEEE.

[14] E. Basar, M. D. Renzo, J. Rosny, M. Debbah, M.-S. Alouini, and R. Zhang, "Wireless communications through reconfigurable intelligent surfaces," in IEEE Access, vol. 7, pp. 116 753–116 773, 2019.

[15] C. You, B. Zheng and R. Zhang, "Wireless Communication via Double IRS: Channel Estimation and Passive Beamforming Designs," in IEEE Wireless Communications Letters, vol. 10, no. 2, pp. 431-435, Feb. 2021, doi: 10.1109/LWC.2020.3034388.

[16] H. Taghvaee et al., "Scalability Analysis of Programmable Metasurfaces for Beam Steering," in IEEE Access, vol. 8, pp. 105320-105334, 2020, doi: 10.1109/ACCESS.2020.3000424.

[17] E. Basar, "Reconfigurable intelligent surface-based index modulation: A new beyond MIMO paradigm for 6G," IEEE Trans. Commun., vol. 68, no. 5, pp. 3187–3196, May 2020.

[18] B. Di, H. Zhang, L. Song, Y. Li, Z. Han, and H. V. Poor, "Hybrid beamforming for reconfigurable intelligent surface based multi-user communications: Achievable rates with limited discrete phase shifts," IEEE J. Sel. Areas Commun., vol. 38, no. 8, pp. 1809–1822, 2020.

[19] H. Zhang, B. Di, L. Song, and Z. Han, “Reconfigurable intelligent surfaces assisted communications with limited phase shifts: How many phase shifts are enough?” IEEE Trans. Veh. Technol., vol. 69, no. 4, pp. 4498–4502, 2020.

[20] Q. Wu and R. Zhang, "Beamforming Optimization for Wireless Network Aided by Intelligent Reflecting Surface With Discrete Phase Shifts," in IEEE Transactions on Communications, vol. 68, no. 3, pp. 1838-1851, March 2020, doi: 10.1109/TCOMM.2019.2958916.

[21] H. Peng and X. Shen, "Multi-Agent Reinforcement Learning Based Resource Management in MEC- and UAV-Assisted Vehicular Networks," in IEEE Journal on Selected Areas in Communications, vol. 39, no. 1, pp. 131-141, Jan. 2021, doi: 10.1109/JSAC.2020.3036962.

[22] P. Dai, K. Hu, X. Wu, H. Xing, F. Teng and Z. Yu, "A Probabilistic Approach for Cooperative Computation Offloading in MEC-Assisted Vehicular Networks," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 2, pp. 899-911, Feb. 2022, doi: 10.1109/TITS.2020.3017172.

[23] H. Ke, J. Wang, L. Deng, Y. Ge and H. Wang, "Deep Reinforcement Learning-Based Adaptive Computation Offloading for MEC in Heterogeneous Vehicular Networks," in IEEE Transactions on Vehicular Technology, vol. 69, no. 7, pp. 7916-7929, July 2020, doi: 10.1109/TVT.2020.2993849.

[24] H. Peng and X. S. Shen, "DDPG-based Resource Management for MEC/UAV-Assisted Vehicular Networks," 2020 IEEE 92nd Vehicular Technology Conference (VTC2020-Fall), Victoria, BC, Canada, 2020, pp. 1-6, doi: 10.1109/VTC2020-Fall49728.2020.9348633.

[25] A. Abouaomar, Z. Mlika, A. Filali, S. Cherkaoui and A. Kobbane, "A Deep Reinforcement Learning Approach for Service Migration in MEC-enabled Vehicular Networks," 2021 IEEE 46th Conference on Local Computer Networks (LCN), Edmonton, AB, Canada, 2021, pp. 273-280, doi: 10.1109/LCN52139.2021.9524882.

[26] H. Zhang, Z. Wang and K. Liu, "V2X offloading and resource allocation in SDN-assisted MEC-based vehicular networks," in China Communications, vol. 17, no. 5, pp. 266-283, May 2020, doi: 10.23919/JCC.2020.05.020.

[27] S. Zhou, P. P. Netalkar, Y. Chang, Y. Xu and J. Chao, "The MEC-Based Architecture Design for Low-Latency and Fast Hand-Off Vehicular Networking," 2018 IEEE 88th Vehicular Technology Conference (VTC-Fall), Chicago, IL, USA, 2018, pp. 1-7, doi: 10.1109/VTCFall.2018.8690790.

[28] P. Dai et al., "Multi-Armed Bandit Learning for Computation-Intensive Services in MEC-Empowered Vehicular Networks," in IEEE Transactions on Vehicular Technology, vol. 69, no. 7, pp. 7821-7834, July 2020, doi: 10.1109/TVT.2020.2991641.

[29] H. Wang, X. Li, H. Ji and H. Zhang, "Federated Offloading Scheme to Minimize Latency in MEC-Enabled Vehicular Networks," 2018 IEEE Globecom Workshops (GC Wkshps), Abu Dhabi, United Arab Emirates, 2018, pp. 1-6, doi: 10.1109/GLOCOMW.2018.8644315.

[30] H. Wang, X. Li, H. Ji and H. Zhang, "Dynamic Offloading Scheduling Scheme for MEC-enabled Vehicular Networks," 2018 IEEE/CIC International Conference on Communications in China (ICCC Workshops), Beijing, China, 2018, pp. 206-210, doi: 10.1109/ICCChinaW.2018.8674508.

[31] G. Tan, H. Zhang and S. Zhou, "Resource Allocation in MEC-enabled Vehicular Networks: A Deep Reinforcement Learning Approach," IEEE INFOCOM 2020 - IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), Toronto, ON, Canada, 2020, pp. 406-411, doi: 10.1109/INFOCOMWKSHPS50562.2020.9162980.

[32] H. Wang, T. Lv, Z. Lin and J. Zeng, "Energy-Delay Minimization of Task Migration Based on Game Theory in MEC-Assisted Vehicular Networks," in IEEE Transactions on Vehicular Technology, vol. 71, no. 8, pp. 8175-8188, Aug. 2022, doi:10.1109/TVT.2022.3175238.

[33] M. Zhu, Y. Hou, X. Tao, T. Sui and L. Gao, "Joint Optimal Allocation of Wireless Resource and MEC Computation Capability in Vehicular Network," 2020 IEEE Wireless Communications and Networking Conference Workshops (WCNCW), Seoul, Korea (South), 2020, pp. 1-6, doi: 10.1109/WCNCW48565.2020.9124737.

[34] L. Zhang, Y. Sun, Y. Tang, H. Zeng and Y. Ruan, "Joint Offloading Decision and Resource Allocation in MEC-enabled Vehicular Networks," 2021 IEEE 93rd Vehicular Technology Conference (VTC2021-Spring), Helsinki, Finland, 2021, pp. 1-5, doi: 10.1109/VTC2021-Spring51267.2021.9448637.

[35] E. T. Michailidis, N. I. Miridakis, A. Michalas, E. Skondras, D. J. Vergados and D. D. Vergados, "Energy Optimization in Massive MIMO UAV-Aided MEC-Enabled Vehicular Networks," in IEEE Access, vol. 9, pp. 117388-117403, 2021, doi: 10.1109/ACCESS.2021.3106495.

[36] C. -H. Hsu, Y. Chiang, Y. Zhang and H. -Y. Wei, "Mobility-Aware QoS Promotion and Load Balancing in MEC-Based Vehicular Networks: A Deep Learning Approach," 2021 IEEE 93rd Vehicular Technology Conference (VTC2021-Spring), Helsinki, Finland, 2021, pp. 1-6, doi: 10.1109/VTC2021-Spring51267.2021.9448705.

[37] B. Hang, B. Zhang, L. Wang, J. Wang, Y. Ren and Z. Han, "A User Association Policy for UAV-aided Time-varying Vehicular Networks with MEC," 2020 IEEE Wireless Communications and Networking Conference (WCNC), Seoul, Korea (South), 2020, pp. 1-6, doi: 10.1109/WCNC45663.2020.9120610.

[38] K. Zhang, Y. Mao, S. Leng, Y. He and Y. ZHANG, "Mobile-Edge Computing for Vehicular Networks: A Promising Network Paradigm with Predictive Off-Loading," in IEEE Vehicular Technology Magazine, vol. 12, no. 2, pp. 36-44, June 2017, doi: 10.1109/MVT.2017.2668838.

[39] F. Vázquez-Gallego et al., "Demo: A Mobile Edge Computing-based Collision Avoidance System for Future Vehicular Networks," IEEE INFOCOM 2019 - IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), Paris, France, 2019, pp. 904-905, doi: 10.1109/INFCOMW.2019.8845107.

[40] G. Wang and F. Xu, "Regional Intelligent Resource Allocation in Mobile Edge Computing Based Vehicular Network," in IEEE Access, vol. 8, pp. 7173-7182, 2020, doi: 10.1109/ACCESS.2020.2964018.

[41] Y. Liu et al., "Reconfigurable Intelligent Surfaces: Principles and Opportunities," in IEEE Communications Surveys & Tutorials, vol. 23, no. 3, pp. 1546-1577, thirdquarter 2021, doi: 10.1109/COMST.2021.3077737.

[42] M. A. ElMossallamy, H. Zhang, L. Song, K. G. Seddik, Z. Han and G. Y. Li, "Reconfigurable Intelligent Surfaces for Wireless Communications: Principles, Challenges, and Opportunities," in IEEE Transactions on Cognitive Communications and Networking, vol. 6, no. 3, pp. 990-1002, Sept. 2020, doi: 10.1109/TCCN.2020.2992604.

[43] E. Basar, M. Di Renzo, J. De Rosny, M. Debbah, M. -S. Alouini and R. Zhang, "Wireless Communications Through Reconfigurable Intelligent Surfaces," in IEEE Access, vol. 7, pp. 116753-116773, 2019, doi: 10.1109/ACCESS.2019.2935192.

[44] C. Huang, A. Zappone, G. C. Alexandropoulos, M. Debbah and C. Yuen, "Reconfigurable Intelligent Surfaces for Energy Efficiency in Wireless Communication," in IEEE Transactions on Wireless Communications, vol. 18, no. 8, pp. 4157-4170, Aug. 2019, doi: 10.1109/TWC.2019.2922609.

[45] M. Di Renzo et al., "Reconfigurable Intelligent Surfaces vs. Relaying: Differences, Similarities, and Performance Comparison," in IEEE Open Journal of the Communications Society, vol. 1, pp. 798-807, 2020, doi: 10.1109/OJCOMS.2020.3002955.

[46] M. Di Renzo et al., "Smart Radio Environments Empowered by Reconfigurable Intelligent Surfaces: How It Works, State of Research, and The Road Ahead," in IEEE Journal on Selected Areas in Communications, vol. 38, no. 11, pp. 2450-2525, Nov. 2020, doi: 10.1109/JSAC.2020.3007211.

[47] G. C. Trichopoulos et al., "Design and Evaluation of Reconfigurable Intelligent Surfaces in Real-World Environment," in IEEE Open Journal of the Communications Society, vol. 3, pp. 462-474, 2022, doi: 10.1109/OJCOMS.2022.3158310.

[48] X. Yuan, Y. -J. A. Zhang, Y. Shi, W. Yan and H. Liu, "Reconfigurable-Intelligent-Surface Empowered Wireless Communications: Challenges and Opportunities," in IEEE Wireless Communications, vol. 28, no. 2, pp. 136-143, April 2021, doi: 10.1109/MWC.001.2000256.

[49] H. Zhang, B. Di, L. Song and Z. Han, "Reconfigurable Intelligent Surfaces Assisted Communications With Limited Phase Shifts: How Many Phase Shifts Are Enough?," in IEEE Transactions on Vehicular Technology, vol. 69, no. 4, pp. 4498-4502, April 2020, doi: 10.1109/TVT.2020.2973073.

[50] C. Huang, G. C. Alexandropoulos, C. Yuen and M. Debbah, "Indoor Signal Focusing with Deep Learning Designed Reconfigurable Intelligent Surfaces," 2019 IEEE 20th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), Cannes, France, 2019, pp. 1-5, doi: 10.1109/SPAWC.2019.8815412.

REFERENCES

[51] E. Björnson and L. Sanguinetti, "Rayleigh Fading Modeling and Channel Hardening for Reconfigurable Intelligent Surfaces," in IEEE Wireless Communications Letters, vol. 10, no. 4, pp. 830-834, April 2021, doi: 10.1109/LWC.2020.3046107.

[52] Z. Yang et al., "Energy-Efficient Wireless Communications With Distributed Reconfigurable Intelligent Surfaces," in IEEE Transactions on Wireless Communications, vol. 21, no. 1, pp. 665-679, Jan. 2022, doi: 10.1109/TWC.2021.3098632.

[53] J. Xu, Y. Liu, X. Mu and O. A. Dobre, "STAR-RISs: Simultaneous Transmitting and Reflecting Reconfigurable Intelligent Surfaces," in IEEE Communications Letters, vol. 25, no. 9, pp. 3134-3138, Sept. 2021, doi: 10.1109/LCOMM.2021.3082214.

[54] E. Björnson, H. Wymeersch, B. Matthiesen, P. Popovski, L. Sanguinetti and E. de Carvalho, "Reconfigurable Intelligent Surfaces: A signal processing perspective with wireless applications," in IEEE Signal Processing Magazine, vol. 39, no. 2, pp. 135-158, March 2022, doi: 10.1109/MSP.2021.3130549.

[55] S. Lin, B. Zheng, G. C. Alexandropoulos, M. Wen, M. D. Renzo and F. Chen, "Reconfigurable Intelligent Surfaces With Reflection Pattern Modulation: Beamforming Design and Performance Analysis," in IEEE Transactions on Wireless Communications, vol. 20, no. 2, pp. 741-754, Feb. 2021, doi: 10.1109/TWC.2020.3028198.

[56] A. Zappone, M. Di Renzo, F. Shams, X. Qian and M. Debbah, "Overhead-Aware Design of Reconfigurable Intelligent Surfaces in Smart Radio Environments," in IEEE Transactions on Wireless Communications, vol. 20, no. 1, pp. 126-141, Jan. 2021, doi: 10.1109/TWC.2020.3023578.

[57] A. Elzanaty, A. Guerra, F. Guidi and M. -S. Alouini, "Reconfigurable Intelligent Surfaces for Localization: Position and Orientation Error Bounds," in IEEE Transactions on Signal Processing, vol. 69, pp. 5386-5402, 2021, doi: 10.1109/TSP.2021.3101644.

[58] A. Aubry, A. De Maio and M. Rosamilia, "Reconfigurable Intelligent Surfaces for N-LOS Radar Surveillance," in IEEE Transactions on Vehicular Technology, vol. 70, no. 10, pp. 10735-10749, Oct. 2021, doi: 10.1109/TVT.2021.3102315.

[59] J. Ye, J. Qiao, A. Kammoun and M. -S. Alouini, "Nonterrestrial Communications Assisted by Reconfigurable Intelligent Surfaces," in Proceedings of the IEEE, vol. 110, no. 9, pp. 1423-1465, Sept. 2022, doi: 10.1109/JPROC.2022.3169690.

REFERENCES

[60] M. Di Renzo, F. H. Danufane and S. Tretyakov, "Communication Models for Reconfigurable Intelligent Surfaces: From Surface Electromagnetics to Wireless Networks Optimization," in Proceedings of the IEEE, vol. 110, no. 9, pp. 1164-1209, Sept. 2022, doi: 10.1109/JPROC.2022.3195536.

[61] V. K. Chapala and S. M. Zafaruddin, "Reconfigurable Intelligent Surface Empowered Multi-Hop Transmission over Generalized Fading," 2022 IEEE 95th Vehicular Technology Conference: (VTC2022-Spring), Helsinki, Finland, 2022, pp. 1-5, doi: 10.1109/VTC2022-Spring54318.2022.9860783.

[62] D. Dampahalage, K. B. Shashika Manosha, N. Rajatheva and M. Latva-aho, "Intelligent Reflecting Surface Aided Vehicular Communications," 2020 IEEE Globecom Workshops (GC Wkshps, Taipei, Taiwan, 2020, pp. 1-6, doi: 10.1109/GCWkshps50303.2020.9367569.

[63] J. Wang, W. Zhang, X. Bao, T. Song, and C. Pan, “Outage analysis for intelligent reflecting surface assisted vehicular communication networks,” arXiv preprint arXiv:2004.08063, 2020.

[64] S. Mao et al., "Reconfigurable Intelligent Surface-Assisted Secure Mobile Edge Computing Networks," in IEEE Transactions on Vehicular Technology, vol. 71, no. 6, pp. 6647-6660, June 2022, doi: 10.1109/TVT.2022.3162044.

[65] Y. Xu, T. Zhang, Y. Zou and Y. Liu, "Reconfigurable Intelligence Surface Aided UAV-MEC Systems With NOMA," in IEEE Communications Letters, vol. 26, no. 9, pp. 2121-2125, Sept. 2022, doi: 10.1109/LCOMM.2022.3183285.

[66] B. Shang, H. V. Poor and L. Liu, "Aerial Reconfigurable Intelligent Surfaces Meet Mobile Edge Computing," in IEEE Wireless Communications, vol. 29, no. 6, pp. 104-111, December 2022, doi: 10.1109/MWC.001.2200009.

[67] Y. Dai, Y. L. Guan, K. K. Leung and Y. Zhang, "Reconfigurable Intelligent Surface for Low-Latency Edge Computing in 6G," in IEEE Wireless Communications, vol. 28, no. 6, pp. 72-79, December 2021, doi: 10.1109/MWC.001.2100229.

[68] Y. Chen, Y. Wang, J. Zhang and M. D. Renzo, "QoS-Driven Spectrum Sharing for Reconfigurable Intelligent Surfaces (RISs) Aided Vehicular Networks," in IEEE Transactions on Wireless Communications, vol. 20, no. 9, pp. 5969-5985, Sept. 2021, doi: 10.1109/TWC.2021.3071332.

[69] Y. Zhu, B. Mao and N. Kato, "A Dynamic Task Scheduling Strategy for Multi-Access Edge Computing in IRS-Aided Vehicular Networks," in IEEE Transactions on Emerging Topics in

Computing, vol. 10, no. 4, pp. 1761-1771, 1 Oct.-Dec. 2022, doi: 10.1109/TETC.2022.3153494.

[70] Basharat S., Khan M., Iqbal M., et al.: Exploring reconfigurable intelligent surfaces for 6G: State-of-the-art and the road ahead. *IET Commun.* **16**(13), 1458–1474 (2022). doi: https://doi.org/10.1049/cmu2.12364

[71] Y. Zhu, B. Mao, Y. Kawamoto and N. Kato, "Intelligent Reflecting Surface-Aided Vehicular Networks Toward 6G: Vision, Proposal, and Future Directions," in IEEE Vehicular Technology Magazine, vol. 16, no. 4, pp. 48-56, Dec. 2021, doi: 10.1109/MVT.2021.3113890.

[72] Y. Zhu, B. Mao and N. Kato, "Intelligent Reflecting Surface in 6G Vehicular Communications: A Survey," in IEEE Open Journal of Vehicular Technology, vol. 3, pp. 266-277, 2022, doi: 10.1109/OJVT.2022.3177253.

[73] Michailidis, Emmanouel T., Nikolaos I. Miridakis, Angelos Michalas, Emmanouil Skondras, and Dimitrios J. Vergados. 2021. "Energy Optimization in Dual-RIS UAV-Aided MEC-Enabled Internet of Vehicles" *Sensors* 21, no. 13: 4392. https://doi.org/10.3390/s21134392

[74] Y. Tan, Y. Long, S. Zhao, S. Gong, D. T. Hoang and D. Niyato, "Energy Minimization for Wireless Powered Data Offloading in IRS-assisted MEC for Vehicular Networks," 2022 International Wireless Communications and Mobile Computing (IWCMC), Dubrovnik, Croatia, 2022, pp. 731-736, doi: 10.1109/IWCMC55113.2022.9824966.

[75] B. Hazarika, K. Singh, C. -P. Li and S. Biswas, "Multi-Agent DRL-Based Computation Offloading in Multiple RIS-Aided IoV Networks," MILCOM 2022 - 2022 IEEE Military Communications Conference (MILCOM), Rockville, MD, USA, 2022, pp. 1-6, doi: 10.1109/MILCOM55135.2022.10017765.

[76] X. Qin, W. Yu, Z. Song, T. Hou, Y. Hao and X. Sun, "Energy Efficiency Optimization for RIS-Assisted UAV-Enabled MEC Systems," 2022 IEEE Globecom Workshops (GC Wkshps), Rio de Janeiro, Brazil, 2022, pp. 1164-1169, doi: 10.1109/GCWkshps56602.2022.10008478.

[77] H. Mei, K. Yang, J. Shen and Q. Liu, "Joint Trajectory-Task-Cache Optimization With Phase-Shift Design of RIS-Assisted UAV for MEC," in IEEE Wireless Communications Letters, vol. 10, no. 7, pp. 1586-1590, July 2021, doi: 10.1109/LWC.2021.3074990.

REFERENCES

[78] X. Yuan, J. Chen, N. Zhang, J. Ni, F. R. Yu and V. C. M. Leung, "Digital Twin-Driven Vehicular Task Offloading and IRS Configuration in the Internet of Vehicles," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 12, pp. 24290-24304, Dec. 2022, doi: 10.1109/TITS.2022.3204585.

[79] A. Shakeel, A. Iqbal, A. Nauman, R. Hussain, X. Li and K. Rabie, "6G driven Vehicular Tracking in Smart Cities using Intelligent Reflecting Surfaces," 2023 IEEE 97th Vehicular Technology Conference (VTC2023-Spring), Florence, Italy, 2023, pp. 1-7, doi: 10.1109/VTC2023-Spring57618.2023.10199356.

[80] J. Chen, W. Xu, N. Cheng, H. Wu, S. Zhang, and X. Shen, “Reinforcement learning policy for adaptive edge caching in the heterogeneous vehicular network,” in IEEE Global Communication Conference, Dec. 2018, pp. 1–6.

[81] S. Munawar, Z. Ali, M. Waqas, S. Tu, S. A. Hassan, and G. Abbas (2022). “Cooperative Computational Offloading in Mobile Edge Computing for Vehicles: A Model-based DNN Approach”, IEEE Transactions on Vehicular Technology, 72(3), 3376-3391