TOWARDS PROVISIONING VEHICLE-BASED INFORMATION SERVICES

by

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the degree of Doctor of Philosophy

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Dedication

To Dad, Mom, Hesham, and Mohamed.

...with love and gratitude.
Abstract

Smart vehicles are considered key enablers for intelligent transport systems. They are equipped with components to enable services for vehicle occupants, other vehicles on roads, and third parties. In-vehicle sensors, diversified communication modules, and an on-board unit with high computing and storage capabilities enable the smart vehicle to work as a mobile resource of diverse scopes of services.

With the high benefits the public sensing paradigm brought to the application domain, there is interest nowadays to widen the scope of applications by engaging more resources in the sensing loop. Although smartphones have been the main players in this domain, their use suffers from limitations due to the scarcity of their on-board resources and their unpredictable mobility patterns. Concurrently, the plethora of on-board resources in smart vehicles along with their ubiquitous mobility are pushing towards utilizing them for providing remarkable public sensing services.

In this thesis, we unveil the different resources a smart vehicle can provide on roads or at parking lots highlighting diversified information services that can come into action through utilizing such resources. Motivated by the high rise of the public sensing paradigm, we propose a vehicular public sensing platform that aims at exploiting the sensing, storage, processing and relaying resources of smart vehicles for provisioning ubiquitous, sensing-based information services. As parts of the proposed
platform, we present a collection of solutions to handle some challenges facing such use of vehicles for public sensing. Our proposed solutions involve a framework to handle reputation-aware recruitment and selection of smart vehicles for achieving desired coverage of an area of interest within a budget limit. In addition, the presented solutions involve a data delivery scheme that considers on-road caching and forwarding assistance in accessing the sensing-based vehicular resources targeting improving the incurred access cost and delay. Extensive performance evaluation is conducted showing the improvements achieved by the proposed solutions in their targeted objectives compared to other popular systems and schemes.
Co-Authorship

Books


Journal Articles


Conference Publications


**Technical Reports**


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Statement of Originality

I hereby certify that all of the work described within this thesis is the original work of the author. Any ideas and/or techniques from the work of others are fully acknowledged in accordance with the standard referencing practices.

Sherin Abdelhamid

November, 2014
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<table>
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<tr>
<th>Acronym</th>
<th>Description</th>
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<tbody>
<tr>
<td>ADAS</td>
<td>Advanced Driver Assistance Services</td>
</tr>
<tr>
<td>AoI</td>
<td>Area of Interest</td>
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<td>AP</td>
<td>Access Point</td>
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<td>AQI</td>
<td>Amortized Quality Index</td>
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<td>AVC</td>
<td>Autonomous Vehicular Cloud</td>
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<td>BMCP</td>
<td>Budgeted Maximum Coverage Problem</td>
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<td>CADD</td>
<td>Caching-Assisted Data Delivery</td>
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<td>CALM</td>
<td>Communication Access for Land Mobiles</td>
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<td>CAN</td>
<td>Controller Area Network</td>
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<tr>
<td>CoT</td>
<td>Confidence of sticking to Trajectory</td>
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<tr>
<td>DB-VDG</td>
<td>Delay-Bounded Vehicular Data Gathering</td>
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<td>DSRC</td>
<td>Dedicated Short Range Communication</td>
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<tr>
<td>ECU</td>
<td>Electronic Control Unit</td>
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<td>EPS</td>
<td>Electric Power Steering</td>
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<td>FR</td>
<td>Freshness</td>
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<tr>
<td>GPS</td>
<td>Global Positioning System</td>
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<tr>
<td>HetNet</td>
<td>Heterogeneous Network</td>
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<tr>
<td>HVAC</td>
<td>Heating, Ventilation and Air Conditioning</td>
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<td>Acronym</td>
<td>Description</td>
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<tr>
<td>I2V</td>
<td>Infrastructure-to-Vehicle</td>
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<td>ILP</td>
<td>Integer Linear Programming</td>
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<tr>
<td>IoT</td>
<td>Internet of Things</td>
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<td>ITS</td>
<td>Intelligent Transport System</td>
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<tr>
<td>LED</td>
<td>Light Emitting Diode</td>
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<tr>
<td>LRU</td>
<td>Least Recently Used</td>
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<td>OBU</td>
<td>On-Board Unit</td>
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<td>P²</td>
<td>Pothole Patrol</td>
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<td>P2P</td>
<td>Peer-to-Peer</td>
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<tr>
<td>PC</td>
<td>Personal Computer</td>
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<tr>
<td>PoA</td>
<td>Point of Attachment</td>
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<tr>
<td>QoE</td>
<td>Quality of Experience</td>
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<td>QoI</td>
<td>Quality of Information</td>
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<td>QoS</td>
<td>Quality of Service</td>
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<td>QR</td>
<td>Quality of Resources</td>
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<td>RAR</td>
<td>Roadside-Aided Routing</td>
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<td>RBMC</td>
<td>Reputation-aware Budgeted Maximum Coverage</td>
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<td>RBMC-MC</td>
<td>Reputation-aware Budgeted Maximum Coverage - Minimum Cost</td>
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<td>RBMC-MO</td>
<td>Reputation-aware Budgeted Maximum Coverage - Minimum Overlapping</td>
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<td>RCS</td>
<td>Road Caching Spot</td>
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<td>RL</td>
<td>Relevance</td>
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<td>RSU</td>
<td>Road Side Unit</td>
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<td>RTR</td>
<td>Reputation-aware, Trajectory-based Recruitment</td>
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<tr>
<td>Abbreviation</td>
<td>Description</td>
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<tr>
<td>SADV</td>
<td>Static-node assisted Adaptive</td>
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<td>SCP</td>
<td>Set Cover Problem</td>
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<td>SP</td>
<td>Service Provider</td>
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<td>TI</td>
<td>Trustworthiness Index</td>
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<td>TL</td>
<td>Trust Level</td>
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<tr>
<td>TM</td>
<td>Timeliness</td>
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<tr>
<td>TTL</td>
<td>Time-to-Live</td>
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<tr>
<td>V2I</td>
<td>Infrastructure-to-Vehicle</td>
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<tr>
<td>V2V</td>
<td>Vehicle-to-Vehicle</td>
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<td>V2VR</td>
<td>Vehicle-to-Vehicle Relay</td>
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<td>V2X</td>
<td>Vehicle-to-Any</td>
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<td>V3</td>
<td>Vehicle-to-Vehicle live Video</td>
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<td>VaaR</td>
<td>Vehicle as a Resource</td>
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<td>VANET</td>
<td>Vehicular Ad-hoc Network</td>
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<td>VLC</td>
<td>Visible Light Communication</td>
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<tr>
<td>VLP</td>
<td>Visible Light Positioning</td>
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<tr>
<td>VoD</td>
<td>Video-on-Demand</td>
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<td>VPS</td>
<td>Vehicular Public Sensing</td>
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<tr>
<td>WAVE</td>
<td>Wireless Access for Vehicular Environment</td>
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<tr>
<td>WP</td>
<td>Willingness to Participate</td>
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Chapter 1

Introduction

According to the World Health Organization’s global status report on road safety in 2013 [1], nearly 1.24 million people die every year in road crashes while an additional 20-50 millions are injured or disabled. Road traffic crashes are the eighth leading cause of death globally, and the leading cause of death for young people aged 15-29. Motivated by the high need to reduce on-road fatalities and improve the driving experience, the Vehicular Ad-hoc Network (VANET) paradigm has emerged to connect vehicles on roads. In a VANET, vehicles communicate with one another and with Road Side Units (RSUs) for relaying and sharing messages and information that support many application domains of the Intelligent Transport Systems (ITSs) such as safety applications (e.g., broadcasting safety warnings), traffic management applications (e.g., real-time traffic status), road condition monitoring applications (e.g., detecting potholes), infotainment applications (e.g., Internet access), advanced driver assistance services (ADAS) (e.g., automatic toll collection, remote diagnostics), to name a few [2][3][4][5][6].

A number of standards have been introduced for VANET wireless communication [7][8][9] with the most dominant being the Wireless Access for Vehicular Environment
(WAVE) standard. WAVE is an amendment of the IEEE 802.11 standard for WLAN and it is standardized to be known as IEEE 802.11p [10].

Generally speaking, vehicles communicate in a multi-hop fashion for sharing information. Four communication patterns are available for VANET communications to support the different types of services: 1) beaoning; 1-hop broadcasting for position and velocity information, 2) geocasting; sending information to a group of nodes in an area of interest, 3) unicasting; sending information to a specific destination, and 4) information dissemination; flooding the surrounding area with information [11]. Figure 1.1 illustrates these communication patterns.

The connected vehicles forming a VANET are known as “smart vehicles”. A typical smart vehicle is equipped with a wireless communication module, as mentioned earlier, and an abundant number of sensors that monitor the interior and exterior surroundings and provide assistance/alerts to the driver via an on-board unit (OBU) [3]. A vehicular OBU is also known as an in-vehicle PC and can be as powerful as some personal computers in terms of its storage and computational capabilities [12].

Figure 1.1: VANET communication patterns: (a) Beaconing, (b) Geocasting, (c) Unicasting, and (d) Information dissemination.
As well, a main piece of equipment in a smart vehicle is the navigational and positioning system whose output is a major part of most of the supported applications.

In parallel, with the ubiquitous availability of smartphones, a data collection and service provisioning paradigm has emerged in the past few years to utilize such mobile resources. With the availability of an array of embedded sensors (e.g., GPS, accelerometers, gyroscopes, cameras, and microphones) along with different interfaces of communication, smartphones have been utilized as providers of sensory data that can be the foundation of different applications. Such a paradigm is known as “public sensing” as it utilizes public owned devices and assistance for providing sensory services [13][14][15][16].

Examples of applications utilizing smartphone-based sensory data include the series provided by the MetroSense project [14] that range from monitoring users’ status and activities and posting them on social media, to tracking a mobile event (e.g., a lost child).

Public sensing can take one of two forms: participatory or opportunistic. In participatory sensing, a participant is engaged in the process by either controlling what is to be sensed and when, or by being responsible for performing the sensing task him/herself (e.g., taking camera shots or recording videos). In opportunistic sensing, a sensing task is handled and performed without any intervention from the device owner. Sensing is done in the background operation of the device based on scheduled times or detected events that need to be reported without having to involve the device owner in the process [14].

Although utilizing smartphones for public sensing has shown reasonable success, there are still challenges hindering the ubiquitous use of such applications and the
development of more powerful ones. The work presented in this thesis couples the VANET and public sensing paradigms for the target of providing information services that utilize the potential and benefits of the two vital scopes and mitigate the limitations of the use of smartphones in such services.

In the remainder of this chapter, we define our research statement in Section 1.1 followed by the motivations for the work in Section 1.2. We state the contributions of the work in Section 1.3 and elaborate on the thesis outline in Section 1.4.

1.1 Research Statement

With the abundance of the aforementioned on-board resources in smart vehicles engaged with the vehicular ubiquity and mobility, such vehicles can be considered major candidates for providing information services that can go beyond the array of services provided by other mobile devices such as smartphones. A smart vehicle on-road or at a parking lot can work as a mobile resource of sensing, storage, processing, cloud, relaying, infotainment, and localization. Considering the public sensing domain, the wide variety of in-vehicle sensors makes a smart vehicle a major enabler for many sensing applications and a significant resource of sensory data that are hard to be all acquired from a single sensory system.

We believe that by engaging smart vehicles for providing ubiquitous sensing-based services, a plethora of information services and applications will be unleashed to provide benefits not only for drivers and vehicle occupants, but for all people anytime anywhere.

The primary objectives of this thesis are: 1) unveiling the different resources smart vehicles can provide, 2) introducing a platform that utilizes public vehicular resources
of sensing, storage, processing, and relaying for provisioning ubiquitous, sensing-based information services, and 3) proposing a set of solutions targeting practical challenges that face such use of vehicles for public sensing.

1.2 Motivations

The work presented in this thesis is motivated by the hype of public sensing and the abundance of the hard-to-neglect vehicular resources. Currently, sensors in smartphones are extensively used to support public sensing applications. Although there is a wide scope of services made feasible with such engagement of smartphones [14], the use of these devices has challenges, in particular dealing with the relative scarcity of available resources and their unpredictable mobility patterns. Concurrently, the plethora of on-board resources in smart vehicles is pushing towards utilizing them as mobile providers for ubiquitous services. The abundance of various sensors along with other on-board vehicular resources, such as processing, storage and communication, make smart vehicles major enablers for many sensing applications and solutions mitigating the aforementioned challenges of smartphones. Furthermore, the mobility of vehicles can be utilized to widen coverage scope and, in turn, the range of applications that can be supported by engaging vehicles in the sensing loop.

Although utilizing vehicles as data contributors in public sensing brings many advantages, it comes with challenges that need to be handled. In urban environments, there can be many potential participants in an area of interest (AoI), especially in a congested area or well-travelled road segment. Such redundant availability brings a recruitment challenge. These participants cannot all be recruited for a sensing task as the recruited participants should be given incentives as a reward for the service they
provide and to encourage them to participate in the future. Since monetary incentives are the most encouraging ones, the service provider (SP) interested in collecting the data and who is responsible for paying such rewards would like to minimize the number of recruited participants and the amount paid for each sensing task to handle limited budgets and maximize profit, while providing an acceptable level of service to the end user. In addition, in the selection process, an SP faces the challenge of having diversity of participant’s behaviour and capabilities of participating vehicles resulting in different reputation for each candidate participant. Hence, effective recruitment schemes are needed to ensure the selection of the right number of participants achieving a required level of coverage for an AoI in a cost effective manner while considering the participants’ reputation and the budget cap dedicated for the sensing task.

Another major challenge is concerned with the communication between the SP moderating the task assignment and data collection, and the participants gathering the data. Such a communication brings a data delivery challenge that needs to be dealt with carefully through effective schemes for ensuring delivery of sensing requests and sensed data to the intended recipients and within the time bounds. The cost involved in the data collection process should also be taken into consideration with the target of minimizing it for achieving cost-effective data delivery and collection.

1.3 Thesis Contributions

The contributions of this thesis are as follows:

1. Vehicle as a Resource: We introduce the concept of Vehicle as a Resource (VaaR) to unveil the various resources smart vehicles can provide while being on-roads or parked. With the abundant capabilities of smart vehicles, we delineate
how they can be used as resources of sensing, data storage, computing, relaying, infotainment, and localization. We elaborate on how these resources can be utilized and shed light on some potential applications that can be supported by each resource. We also discuss some practical challenges that face the wide adoption of VaaR highlighting some open issues along with suggested solutions.

2. **Vehicular Public Sensing Platform**: We propose a Vehicular Public Sensing (VPS) platform that targets utilizing the sensing, storage, data relaying, and communication capabilities of smart vehicles for provisioning information services. We delineate the architecture of the platform, the different components forming it, and the interaction between these components in different environmental setups. VPS encapsulates all the following contributions as parts of its underlying components.

3. **Reputation-aware, Trajectory-based Recruitment (RTR) Framework**: We propose the RTR framework to handle the recruitment component of the VPS platform in urban environments where a variety of candidate participants are available for a sensing task. RTR targets selecting the minimum number of participants that achieve a required level of coverage for an AoI with the consideration of participants’ reputation and budget constraints. We propose a reputation assessment scheme, a pricing model, and a participant selection scheme as underlying modules of the RTR framework. The selection problem is formulated as an integer linear programming (ILP) optimization problem with different recruitment objectives. Greedy heuristic solutions are proposed as well to handle the real-time requirements of the selection process. The basic selection
problem and greedy solutions are adapted to handle some practical considerations. Performance evaluation is conducted to compare the ILP formulations and their corresponding heuristic solutions along with extensive evaluation of the different heuristics in terms of many performance metrics.

4. **Caching-Assisted Access for Vehicular Resources**: As a solution for the data delivery challenge, we propose a caching-assisted data delivery (CADD) scheme targeting minimizing both the delay and cost in accessing vehicular sensing resources for data collection. For the operation of CADD, we introduce a lightweight caching unit to work both as an on-road caching and forwarding assistant. CADD utilizes these caching units along with vehicles on roads for handling the data collection and delivery processes in a heading-aware manner. As a part of CADD, we propose a centrality-based caching mechanism that utilizes real-time information for selecting the caching units while considering popularity in cache replacement. Performance evaluation is conducted through both simulations to compare CADD to a scheme with no caching assistance, and a mathematical assessment comparing CADD to a scheme adopting connected RSUs. As well, we propose a mathematical model to compute the estimated delay from a requesting gateway to any AoI in a road topology.

### 1.4 Thesis Outline

The remainder of this thesis is outlined as follows. We proceed by introducing the VaaR concept in Chapter 2 along with the different instances of VaaR showing the different resources and their potential applications followed by a discussion of challenges facing the adoption of VaaR. We discuss the VPS platform in Chapter 3 delineating its
different components and the interactions among them along with some practical considerations guiding these interactions. Chapter 4 describes our RTR framework along with the details of the three underlying modules; the reputation assessment scheme, pricing model, and selection scheme including the ILP formulations and greedy heuristics proposed for handling the selection problem. The performance evaluation results comparing the ILP and heuristic solutions are presented in this chapter as well along with the results of extensive evaluation of the different greedy heuristics handling different recruitment objectives and practical considerations. Our proposed CADD scheme that targets providing on-road assistance for vehicle-based data collection and delivery is presented in Chapter 5 along with the schematic of the caching unit proposed to support its operation. This chapter includes the detailed operation of all the entities involved in the scheme along with the scheme’s underlying centrality-based and popularity-aware caching mechanism, followed by performance evaluation of the scheme using both simulation and mathematical assessment. Finally, we conclude our work in Chapter 6 along with presenting some future directions.
Chapter 2

Vehicle as a Resource

2.1 Introduction

With high demand for reducing the number of vehicular fatalities and enhancing ITS applications and services, many newly-manufactured vehicles will be equipped with components that will classify them as ‘smart vehicles’. Such components include sensors and actuators with intra-vehicle communication, and electronic control units (ECUs) for processing and operation control. Vehicles will be equipped with a wireless communication module for supporting three types of communication: 1) between vehicles, known as vehicle-to-vehicle (V2V) communication, 2) between vehicles and infrastructure (V2I and I2V), or 3) between vehicles and any neighboring object (V2X). In addition, an OBU will be integrated in each vehicle for interaction with drivers, displaying warnings, issuing alerts, offering automotive services/infotainment, and managing the communication with a vehicle’s surroundings. Powerful OBUs can be considered in-vehicle PCs that can handle computing tasks supported by abundant storage capabilities. Although currently partially available in some luxury models, the availability of such components will be expanded to most vehicles in the near
future. Pivotal components are shown in Figure 2.1.

With these components, a vehicle can be considered a mobile resource for many services such as sensing, data relaying and storage, computing, cloud, infotainment, and localization. We introduce the concept of **Vehicle as a Resource (VaaR)**, which focuses on such vehicular potential. The VaaR vision is stimulated by the ubiquity of vehicles (with predictable mobility patterns) and the vehicular resources that are readily available. The abundance of such on-board resources distinguishes the use of a vehicle as a resource from other mobile resource providers, viz. smartphones, which suffer from limited resources and lack of trajectory prediction. We anticipate that a vehicle will be a mobile provider for diversified resources currently unimagined and will be a key enabler for the revolution of the Internet of Things (IoT) [17][18]. Vehicles on a road or at a parking lot with idle resources and capabilities can cooperatively form a powerful resource for services that can benefit a wide scope of service domains.

Another enabler of VaaR is the availability of a multiplicity of wireless communication technologies for communication between a vehicle and its surroundings. One
such technology specifically introduced for vehicular use is the Wireless Access for Vehicular Environment (WAVE) technology [10] which is based on the IEEE 802.11p standard and Dedicated Short Range Communication (DSRC). Another is the Communication Access for Land Mobiles (CALM) standard [19]. CALM will support an integrated communication unit that provides many air interfaces that include 2G/3G cellular, infrared, millimeter-wave, mobile wireless broadband (HC-SDMA, 802.16e [WIMAX/WiBro] and 802.20), satellite, and DSRC. In addition, some Zigbee communication modules and systems are designed to support vehicular communication [20][21]. As well, Visible Light Communication (VLC) is now gaining high interest, and some systems have been proposed for the vehicular environment [22][23]. Having such technologies available in a vehicle will provide flexible communication with its surroundings regardless of the type of air interface available.

In this chapter, we delineate the diversified resources a vehicle can provide as instances of VaaR and elaborate on how these resources can be tapped into and pooled for performing certain tasks or providing certain services. In addition, for each resource, we highlight some potential applications/services that become feasible with the aid of using a vehicle as a provider for this resource. We also discuss some prominent challenges that face the wide adoption of VaaR.

The remainder of this chapter is organized as follows. In Section 2.2, we introduce the VaaR concept and present the different resources a vehicle can provide in discussing the various instances of VaaR. An Illustrative scenario that shows the benefit and applicability of VaaR is discussed in Section 2.3. In Section 2.4, we discuss some challenges that may face the widespread use of VaaR and can be considered open points for research. Section 2.5 concludes the chapter.
2.2 Vehicle as a Resource (VaaR)

2.2.1 VaaR-Sensing

According to the automotive sensors market growth in North America, the average number of sensors per vehicle has reached 70 in 2013 [24] - 100 in some luxury vehicles. A vehicle can then be considered a significant resource of sensory data. We categorize sensors according to their application domain: 1) Safety, 2) Diagnostics, 3) Convenience, and 4) Environment Monitoring, as shown in Figure 2.2. Safety sensors are the most crucial being targeted at decreasing accidents and driving fatalities. They are considered the basis of many safety-enhancing applications/systems such as the forward collision warning, backup crash warning, blind spot detection, antilock brake, and traction control systems. Diagnostics sensors provide on-board detection of component malfunction to avoid further breakdowns or damage. Examples include chemical sensors used for checking fluids quality and pressure sensors used for monitoring tire pressure. In addition to on-board services, the system can include a reporting capability to support remote diagnostics. Convenience sensors support comfort and convenience applications for drivers and passengers. Most of these sensors are deployed inside the vehicle compartment to provide direct services for its occupants (e.g., a temperature sensor that measures in-cabin temperature and

![Figure 2.2: Categories of in-vehicle sensors.](image-url)
adjusts the HVAC system settings accordingly), while others are deployed for providing driving assistance (e.g., a torque sensor measures the steering wheel torque and provides feedback to the electric power steering (EPS) system that reduces driving effort and provides steering assist). Finally, environment monitoring sensors provide alerts/warnings about road hazards or reports about traffic, road and weather conditions.

Having a variety of sensors along with communication capabilities shapes the concept of VaaR-Sensing. Many applications and platforms have been proposed to make use of vehicles as sensing resources, mainly for environment monitoring as their measured data can be of benefit beyond a vehicle’s compartment. In these applications, vehicles sense/monitor the surrounding environment and store the sensed data for further relaying—either without processing or after processing to search for data of interest. Such data can be reported to third parties through the Internet or V2X (Vehicle-to-Any) communications. These third parties can be data centers that can offer the data for public/commercial services, or can be other mobile users/drivers. Such sensing services can expedite the adoption of public sensing in its participatory and opportunistic forms [14].

An example of a vehicular sensing platform is the MobEyes platform [25] which utilizes vehicles as mobile sensors to monitor surroundings, recognize objects, store data, and advertise this data for potential sharing.

Unlike the MobEyes platform which depends on V2V communication for its operation, CarTel [26] is Internet-based. In CarTel, vehicles collect sensor data, process it locally, and send the processed data to database servers through the Internet for further analysis and publishing. CarTel is considered a delay-tolerant platform as it
depends on opportunistic connectivity for data delivery. More examples of internet-based platforms are discussed in [27].

Currently, there is high focus on utilizing in-vehicle sensors for providing road condition monitoring services. Many techniques have been proposed from using accelerometers to the use of cameras for capturing photos and videos that are further analyzed to extract road features. For example, Yamada et al. [28] proposed a system for the detection of wet road conditions based on images captured by cameras on the rear view mirror of a vehicle. Their proposed system employs image analysis for extracting features related to water and snow on the road. Water is recognized on the road based on polarization properties from images while snow is recognized through texture analysis. Another example is the system proposed by Gailius et al. in [29] that detects ice on a road by analyzing tire-to-road friction ultrasonic noise. The system comprises a transducer installed to the front right wheel behind the front bumper to record acoustic vibrations. The Pothole Patrol ($P^2$) system [30] is an example that aims at monitoring road surfaces to detect potholes. It consists of three-axis acceleration sensors and a global positioning system (GPS) to assess vibrations caused by potholes and report the specific locations of these potholes. $P^2$ is one of the earliest systems targeting road condition monitoring and with the various benefits these systems have, many other platforms are proposed for this regard. CarMote [31] is a more recent example that supports a variety of techniques to extract road features.

2.2.2 VaaR-Data Storage and Computing

Data-storage and computing are tightly coupled as both services are offered through the on-board computers in smart vehicles. Advanced in-vehicle computers are currently available, some almost as powerful as personal computers, such as those in
with dual core processors up to 2.8GHz and storage capabilities in Gigabytes. Due to advances in data storage technologies, it is anticipated that in-vehicle storage capacity will reach multiples of Terabytes in the future, enabling the vehicle to act as a mobile data server.

With such powerful computing resources, it is foreseen that computing tasks would be offloaded to vehicles. Vehicles on a road or a parking lot can be considered a distributed system that can potentially manage computing tasks more efficiently and cost-effectively than a centralized computing center.

Many platforms are proposed to utilize vehicles as a resource for data storage for further diffusion or retrieval of the data by other agents. Vehicle-generated data or data obtained from neighboring vehicles can be stored until the vehicle reaches a dedicated data collector or kept in the vehicle until retrieved as a reply to queries sent by data-seeking vehicles/agents. This communication paradigm is considered a case of delay/disruption-tolerant networks [32][33].

The MobEyes platform mentioned earlier is an example of both VaaR-Sensing and VaaR-Data storage. Each vehicle keeps the sensed data in local storage, and advertises its stored data via metadata. While moving, other vehicles harvest the metadata and send queries to obtain data of interest. Another example is the FleaNet platform [34] that utilizes vehicles as information traders. In FleaNet, vehicles are used to resolve queries generated by other vehicles. While moving, vehicles receive queries and data advertisements from other vehicles and/or information generated by roadside advertisement stations (Adstations), and store this data/information locally. When vehicles receive queries, they try to resolve them by consulting their own local storage to provide a possible match.
Currently there is an emerging vision of utilizing smart vehicles for cloud services. With sensing, computing, and storage resources, and abundant power supply and communication modules, a vehicle can work as a powerful cloud. As with conventional clouds, the owner of a vehicle can rent out vehicular resources on demand when these resources are not in use.

Olariu et al. [35] introduced the term ‘autonomous vehicular clouds’ (AVCs), arguing that in-vehicle resources may be underutilized by traditional vehicular applications as motivation to ‘taking vehicular networks to the clouds’ [36]. They remark that the benefit of on-board resources will be maximized if resources of multiple vehicles are combined.

VaaR-Cloud has been proposed as a mobile experimental laboratory in areas with limited facilities that hinder the use of a remote service. Another scenario utilizes idle parked vehicles in a parking lot of a company as a distributed computing asset. Tasks can be offloaded to vehicles during the workday in lieu of building or renting an outsource infrastructure. Vehicle owners can be compensated so both the company and employees can benefit. Similar arguments can be applied to vehicles parked at an airport. Resources are ample and travelers’ vehicles may be left unutilized for days, resulting in computing resources that, if managed properly, could turn an airport parking lot into a data center. Travelers can share their travel plans with the airport, which can then schedule and manage the resources. Parked vehicles that are part of the vehicular cloud would be plugged into a standard power supply and can be provided with an Ethernet connection.

Vehicular clouds can have advantages over fixed clouds in applications such as the
mobile experimental laboratory. Another advantage of vehicular clouds is their autonomous formation. Neighboring vehicles can autonomously form a cloud to provide instantaneous services (e.g., collecting traffic information at congested intersections for traffic light management). A detailed comparative study of vehicular and conventional clouds is presented in [37].

2.2.3 VaaR-Data Relaying

A network of communicating vehicles forms an on-road VANET which is a subcategory of wireless multi-hop networks in which a source depends on intermediate nodes to relay messages to a destination. In this communication paradigm, vehicles can be considered a resource for relaying data to other nodes out of the communication range of the source node. A vehicle can be used not only for relaying data to other neighboring vehicles but also to/from RSUs.

As an example of VaaR-Data Relaying, Delay-Bounded Vehicular Data Gathering (DB-VDG) [38] is a solution that supports geographical data gathering services and depends heavily on vehicles as data relays. In DB-VDG, queries can be sent to retrieve information from areas of interest and replies can be routed back from vehicles in these areas. Both queries and replies are delivered via intermediate vehicles that act as relays. DB-VDG can also be considered an example of VaaR-Sensing as the gathered data is acquired from the in-vehicle sensors.

Vehicles can be good candidates for commercial advertisements that utilize vehicular mobility to disseminate the ads through relays. These commercial advertisements can be pushed to a vehicle either through the Internet or by Adstations. Examples include store special offers or restaurants menus.
VaaR-Data Relaying can also be a technique for extending network coverage as presented in [39]. The authors propose a vehicle-to-vehicle relay (V2VR) scheme to extend a road side access point (AP) service range and allow drive-thru vehicles to have an extended coverage range. In this scheme, when a vehicle approaches an AP, it selects a vehicle ahead to work as a relay of the AP traffic and allow early access to the AP services. When a vehicle is about to leave the direct AP coverage range, it selects another vehicle behind to work as a relay for the AP traffic and extend the access time while maintaining high throughput.

In addition to relaying data to/from other vehicles and RSUs, vehicles can act as data mules and mobile sinks in wireless sensor networks to assist in their operations [40] [41]. VaaR-Data Relaying can as well play a pivotal role in cases of emergency or natural disasters where infrastructure may be broken down. In these cases, vehicles can help deliver critical data to crisis/disaster-management authorities, collect environmental data, and inform emergency vehicles about optimal routes.

2.2.4 VaaR-Infotainment

Infotainment refers to the combination of information with entertainment. With the on-board communication capabilities supporting communication with surrounding mobile agents (e.g., other vehicles, cellular phones, or communication-enabled handheld devices), and providing possibility for always-on Internet access, a vehicle can be a great source of infotainment.

A vehicle can provide its occupants and other vehicles with information obtained
from its own sensors, other vehicles, RSUs, direct access to the Internet, or Ad-
stations. This information may include traffic and environmental conditions, navi-
gational and safety information, parking availability, or commercial advertisements. Many of the vehicular platforms mentioned earlier can be considered examples of VaaR-Infotainment when the utilization of the other vehicular resources is ultimately for the sake of providing information.

Some of the vehicular infotainment services are solely Internet-dependent (e.g., web surfing, email access, video downloads and online gaming), and others are supported by inter-vehicle communications (e.g., exchanging information and files between vehicles) \[42\]. Examples of proposed systems under the second category include CarTorrent \[43\], a BitTorrent-style protocol for content sharing through inter-vehicle communication. Limited availability and access ranges of on-road APs for content download pushed proposing CarTorrent as a means of file assembly by cooperative peer-to-peer (P2P) file sharing. In CarTorrent, each AP divides a file into pieces. While passing, a vehicle can download as many pieces as possible through direct access to the AP and the missed pieces can be pulled from neighboring vehicles after losing access to the AP. Unlike CarTorrent, some other systems depend on sharing content that is generated and consumed entirely by vehicles. An example of this category is the Vehicle-to-Vehicle live Video (V3) streaming architecture \[44\] that allows vehicles to stream videos generated at certain areas of interest. V3 consists of video triggering and video transmission sub-systems where the triggering sub-system is responsible for sending video triggering requests to the area of interest and the transmission sub-system is responsible for sending video packets back to the request originator. V3 can be considered a good example of VaaR-Relaying as well. More
detailed examples of these infotainment services can be found in [45].

Currently, researchers are focusing on proposing applications and solutions that widen the scope of on-board infotainment. An example of those recent applications is the introduction of Video-on-Demand (VoD) to the vehicle compartment. In the QoE-driven User-centric VoD (QUVoD) [46], the authors present a video streaming solution that focuses on improving the user’s Quality of Experience (QoE) and is enhanced by both 4G P2P and V2V communication layers.

As most of the infotainment applications are real-time, such applications face challenges caused mainly by the highly dynamic vehicular topologies. These challenges must be dealt with to support the required QoS levels. The work in [47] presents some of these challenges along with proposed solutions and some issues that still need consideration.

2.2.5 VaaR-Localization

Vehicles can be considered potential resources for locating objects. Through their sensing and communication capabilities, they can recognize and locate objects, and send this information. For instance, MobEyes can be used to enable vehicles to recognize the license plate numbers, store them, and broadcast representative metadata. Other mobile agents (e.g., police patrol cars) can retrieve the recognized plate numbers to locate and track lost or stolen vehicles.

Vehicles can be used to locate neighboring vehicles for the sake of estimating the distance to these vehicles or informing them about their positions for accuracy purposes, etc. An example of this positioning ability is the ‘Visible Light Positioning (VLP)’ technique [48] that utilizes the visible light communication as an inter-vehicle
communication technology and introduces a scheme for positioning neighboring vehicles using such a technology.

Vehicles, as well, can use self-localization techniques to determine their own position complementing and/or refining GPS information.

2.3 VaaR in Action

In this part, we discuss a scenario illustrating some of the various resources a vehicle can provide on the move. The main scenario depicted in Figure 2.3 shows an emergency scenario caused by an accident on the road.

Vehicles G and H had a head-on collision. Due to that collision, traffic has stopped moving in the vicinity of the collision. Vehicle D is a truck carrying goods that need to be delivered on time for shipping. The driver of the truck needs to know how severe the situation is. He sends a request using his vehicle’s OBU asking for information about the collision from the neighbors of the involved vehicles. He receives a reply from vehicle A that it can provide live video streaming of the situation. He agrees and starts getting live video streaming from node A. Vehicles A and D are out of communication range of each other. Therefore, they depend on vehicles B and C to work as data relays for their shared content. In this scenario, vehicle A can be considered an example of VaaR-Infotainment, while vehicles B and C can be considered examples of VaaR-Data Relaying.

As a consequence of the collision, vehicle H had a malfunction in its GPS. The driver of vehicle H needs to know its location to call for help. He can depend on the resources of vehicle A to locate his vehicle. In this case, vehicle A can be considered an example of VaaR-Localization as well.
2.3. VAAR IN ACTION

As a direct neighbor of vehicle G, vehicle F has recorded the collision using its on-board camera. It decides to store the recorded video for further reporting. Therefore, vehicle F can be considered an example of VaaR-Data Storage.

Finally, on the other side of the road, vehicle E has detected falling rocks using its in-vehicle sensors. It reports this hazard using its communication module to the municipality to take proper action to avoid accidents. This is considered an example of VaaR-Sensing.

Figure 2.3: An illustrative scenario showing the viability of VaaR. Vehicles G and H had an accident and vehicles F, A, B, and C work as resource providers while being in the vicinity of the emergency situation. Vehicle E as well works as a resource after detecting falling rocks on its way.
2.4 Challenges and Open Issues

Although VaaR brings a wide scope of benefits to various applications, many challenges face its wide penetration and adoption. In this part, we highlight some of the prominent challenges and open issues. A summary of the challenges and some potential solutions can be found in Table 2.1.

Privacy, quality, and redundancy pose major challenges in collecting data from and offloading tasks to vehicular resources

The open access and resources sharing that VaaR promises bring privacy to the forefront. Since a vehicle’s resources may be accessible to many users to share, data privacy should be guaranteed for all users sharing these same resources. Privacy should be maintained for vehicles’ owners as well. This issue can be handled by virtualization and scheduling techniques for coordinating access to shared resources. Other techniques can be used for protecting data and controlling its access to its owner only. Examples of such techniques include the use of personal data vaults, which are individually controlled data repositories [49]. Privacy is needed as well to hide the identity of participants when they prefer to remain anonymous. Pseudonymity can be considered a solution that can help in hiding the actual identities for the sake of reducing the possibility of linking between the sent data and participants [50].

The quality of information (QoI) retrieved from vehicles is also a concern. Data/information retrieved needs to be verified and validated before making decisions and/or publishing to the public. As well, quality reports about cooperating vehicles and corresponding reputation scores should be maintained for future reference. Depending on the criticality of the supported services, such reputation scores can
be computed based on either short or long-term participation history. Tasks can be offloaded to those participants with reputation scores higher than a certain threshold to guarantee a certain level of QoI. Feedback can be given to participants about the quality of their reported data and their perceived reputation levels.

While having a plethora of vehicles on the road increases the pool of resources, it may lead to having large amounts of redundant data reported resulting in waste of both communication and computation resources. Such redundancy can be eliminated by adopting data aggregation and fusion techniques [51]. Vehicular clusters and chains can be formed on the road while electing a leader node to take care of the intra-cluster/chain data aggregation [52][53]. It is noteworthy that the success of data aggregation depends on the type of road (e.g., highway, in-city urban road, rural road) since it determines the speed of vehicles; hence, the ability to select the cluster/chain leader node. As well, redundancy of the reported data can be avoided by applying proper selection and recruitment techniques that ensure selecting participants with minimal overlapping.

- The intermittent/dynamic availability of resources hinders extended usage

Vehicles’ mobility is considered as a plus that allows vehicles to cover wider areas compared to their static counterparts. However, while pooling resources from a vehicle, the vehicle may leave the area of interest or connectivity before reporting/relaying the desired data, or finishing the task in hand. Dynamic availability of resources may also be temporal stemming, for instance, from the high need for resources during the rush hours and their idleness during late nights. Effective resource management techniques
are needed for proper task assignment and retrieval. A vehicle’s cyber-physical existence should be taken into consideration in pooling/tapping into vehicular resources. This is influenced by the type and speed of roads which, in turn, affect how long a vehicle would be present. Prediction techniques can help in anticipating the spatiotemporal availability span; hence, taking more informed allocation decisions. Task sharing and handover can also be potential solutions of the partial availability.

- Incentives are needed to encourage owners to offer their vehicular resources

The VaaR concept cannot thrive without active user participation especially if users (vehicle owners) lose their willingness to participate and share resources. Some form of incentive and direct service/reward must be provided in return. Some of the incentive mechanisms proposed for P2P file sharing [54][55] can be applied for incentivizing vehicular users especially for those applications that have major commonalities with the P2P paradigm. In general, incentives can be of three types: 1) willingness to serve the public, 2) getting service in return, or 3) getting monetary returns. It has been shown that incentives with monetary values are the most effective. Monetary incentives can be in the form of pecuniary returns, vouchers, or passes. Another incentive for the owners of parked vehicles can be offering them free parking, while their idle resources are being accessed. The value of such incentives can be determined by the data collecting/task distributing party through the use of pricing models that can consider the level of participation and QoI, or through reverse auction techniques that are currently getting popular in the rewarding models [56][57][58].
– **Recruitment mechanisms should be deployed for efficient selection of participants**

In urban environments, offloading tasks to vehicles to utilize their resources is challenging in terms of participant selection as there can be many potential participants in an area of interest that may reach a hundred of vehicles in a congested area. These participants cannot all be recruited for a task as this would result in a higher cost in terms of participants rewards. Selecting the right number of potential participants in a cost-effective manner, while providing an acceptable level of service, is called for through efficient recruitment mechanisms. Such mechanisms must also consider the QoI challenge mentioned earlier. For load balancing and robustness purposes, these mechanisms should also ensure that not always the same vehicles are chosen. Although the recruitment schemes proposed for utilizing the resources of smartphones cannot be directly applied to vehicles due to the different design considerations, a study of potential adaptation of such schemes is worthwhile.

– **Cost-effective and delay-bounded delivery of task requests and data should be ensured**

One of the major challenges that face VaaR adoption is the delivery of the task requests and the corresponding generated data when on-board Internet connectivity is not available or restricted against vehicular use. In such cases, data delivery and message exchange should be handled through VANET communication involving other vehicles on roads and assisting infrastructure (if there is any) using V2V, V2I, and I2V multi-hop communication. Although there is a bunch of VANET routing and data delivery schemes proposed in the literature [59][60][61], an extensive comparative study of the prominent schemes is needed to reach a conclusion about the
best mechanisms that should be adopted for data delivery considering the different application types and their delay and QoS delivery requirements. In addition, new data delivery schemes need to be proposed taking into account the cost incurred in accessing the vehicular resources and the round-trip delay.

- **How to power up the resources of parked vehicles for tasking is a technical challenge**

Parked vehicles considered for resource utilization should be plugged into a power supply. However, it is not logical to keep their PCs on all the time waiting for potential tasking. Solutions are needed to power these PCs only when required. These solutions can be categorized into ‘on-demand’ and ‘pre-scheduled’ techniques. An on-demand approach in [62] requires ECUs and the in-vehicle PC to be connected through the Controller Area Network (CAN) bus [63] working as the main intra-vehicle communication bus. One of the features of CAN-connected nodes is that they can operate in a sleep mode such that while a vehicle is stopped, these nodes consume a minimum amount of battery. The CAN-connected in-vehicle PC of a parked vehicle can be remotely powered up on-demand. Experiments are needed though to test the feasibility of the wakeup/probing techniques. Other techniques that fit under the second category include deploying scheduling mechanisms to schedule the power up times a priori and sending this schedule whenever vehicles are on. Such techniques may also include assistance from mobility prediction mechanisms to anticipate a vehicle’s daily parking times.

- **Consolidation of different resources is expected and interoperability should be guaranteed**
2.5. SUMMARY

It is expected that vehicles as resources of services will be integrated with other resource providers. For example, VaaR-Sensing may be merged with other sensing resources like smartphones and sensor networks with each paradigm being assigned a part of a sensing task based on its availability and capabilities. Such consolidation of resources entails the development of communication, synchronization, and resource management techniques that ensure syntactic and semantic interoperability and seamless handover among the different paradigms. Sensor fusion techniques can be considered to handle the collaborative-sensing example mentioned above. Generally speaking, information fusion/integration techniques should be considered to handle merging information from different sources. Work proposed for the operation of the heterogeneous networks (HetNets) is promising [64].

2.5 Summary

With its diversified on-board resources, a smart vehicle can be considered a mobile service provider that can assist in a wide scope of applications and domains. In this chapter, we introduced the concept of Vehicle as a Resource (VaaR) to unveil the potential of a smart vehicle on the road or in a parking lot. We showed that a vehicle can be a resource for sensing, data storage, computing, cloud, data relaying, infotainment and a means for locating other objects. As well, we presented a demonstrating scenario, challenges, and open issues related to the adoption of VaaR. With the presented VaaR vision, we anticipate that a smart vehicle will get the information services and the intelligent transportation systems to an era of service revolution.
### 2.5. SUMMARY

<table>
<thead>
<tr>
<th>Challenge</th>
<th>Potential Solutions</th>
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<tbody>
<tr>
<td>Privacy</td>
<td>- Applying virtualization and scheduling techniques.</td>
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<td>- Use of personal data vaults.</td>
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<td></td>
<td>- Hiding identities through pseudonymity.</td>
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<tr>
<td>Data quality</td>
<td>- Adopting verification and analysis techniques to build quality reports and history.</td>
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<td></td>
<td>- Computing reputation scores to be considered in selection refinement.</td>
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<td></td>
<td>- Giving feedback to participants about their data quality.</td>
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<td>Redundancy</td>
<td>- Can be eliminated by adopting data aggregation and fusion techniques while forming vehicular clusters and chains with representative nodes.</td>
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<td>- Can be avoided with proper participant selection.</td>
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<td>Dynamic availability of resources</td>
<td>- Adopting effective resource management techniques for proper task assignment and retrieval.</td>
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<td>- Adopting prediction techniques to anticipate the availability spatiotemporal span.</td>
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<td>- Considering task sharing and handover techniques.</td>
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<td>Incentives for offering resources</td>
<td>- Adopting P2P incentive mechanisms.</td>
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<td>- Offering vehicles’ owners some rewards in return.</td>
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<td></td>
<td>- Focus on the encouraging monetary incentives and their corresponding pricing models.</td>
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<tr>
<td>Participant selection</td>
<td>- Proposing efficient recruitment mechanisms that consider the rewards, budget, and data quality.</td>
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<td></td>
<td>- Studying the feasibility of adapting the smartphone recruitment schemes.</td>
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<tr>
<td>Data delivery</td>
<td>- Extensively studying the proposed VANET routing and data delivery schemes and building practical conclusions.</td>
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<td>- Proposing new vehicular data delivery schemes that take into account the access cost and delay.</td>
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<td>Powering up parked vehicles PCs</td>
<td>- Utilizing features of the CAN bus connecting the intra-vehicular resources.</td>
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<td></td>
<td>- Use of scheduling and mobility prediction mechanisms.</td>
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<tr>
<td>Consolidation of different resource providers</td>
<td>- Considering data fusion and information integration techniques to merge data/information from different sources.</td>
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<td>- Considering on-going research in the area of ‘integration of heterogeneous networks.’</td>
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Chapter 3

On the Provisioning of Vehicle-Based Public Sensing Services

3.1 Introduction

With the high benefits the public sensing paradigm brought to the service and application domain, there is interest nowadays to widen the scope of applications by engaging more resources in the sensing loop. Although smartphones have been the main players in this domain [13][16][15], their use suffers from limitations due to the scarcity of their on-board resources and their unpredictable mobility patterns. Concurrently, smart vehicles with their abundant resources are offering promising sensing solutions. With the wide variety of in-vehicle sensors, high processing and storage capabilities, and diversified communication modules, smart vehicles are becoming major enablers for remarkable public sensing-based applications. The abundant on-board resources of smart vehicles highlighted in Chapter 2 along with their ubiquity and mobility allow them to mitigate the challenges of the use of smartphones and to bring a wider array of applications into action.

We categorize the applications that can be provided by vehicular sensing into: 1)
3.1. INTRODUCTION

Instant sensing and 2) on-move sensing applications. Smartphones typically provide instant sensing. With the high sensing capabilities of vehicles, the scope of such applications can be widened. An example of an instant sensing application is reporting weather conditions such as temperature and ambient barometric pressure. The second category is made feasible by utilizing the movement of vehicles and generating sensing data on the go. Examples include monitoring road and traffic conditions, reporting how crowded it is near points of interest, and providing estimates of parking availability. These supported applications can benefit a wide scope of service providers and consumers that include municipalities, governmental authorities, news and weather centers, end users, and other vehicles.

The general architecture of public sensing consists of three main elements as shown in Figure 3.1. These elements are the data contributors/participants, the service provider, and the data consumers/end users. The process involves three main stages as depicted in Figure 3.1: 1) the service provider asks data contributors to perform sensing tasks, 2) after collecting the required data, the data contributors send it to the service provider, 3) the service provider, after performing required data analytics, presents meaningful information to the data consumers as part of a subscribed service. Data consumers/end users may also initiate the process asking for specific information.

We propose a Vehicular Public Sensing (VPS) platform that aims at utilizing vehicular resources of sensing, storage, processing, and relaying for provisioning information services under the umbrella of public sensing.

In this chapter, under Section 3.2, we discuss the general architecture of the VPS platform, the functions of its underlying components, and the interactions among
3.2. THE VEHICULAR PUBLIC SENSING PLATFORM - ARCHITECTURE, COMPONENTS, AND INTERACTIONS

Towards provisioning sensing-based vehicular information services, our VPS platform targets providing an inclusive architecture that handles the full vehicular public sensing operation starting from the participant selection and task assignment till having the collected data ready for publishing/use.

Since the VPS platform works on utilizing the resources of smart vehicles, it shares some of the aforementioned challenges facing the VaaR adoption. Among the general challenges of VaaR, we focus through the VPS platform on solving:

- The challenges of participant selection, incentive assignment, redundant and dynamic availability, and QoI diversity through an underlying ‘recruitment’ component.
- The data delivery challenge through underlying ‘communication’ and ‘sensing’

Figure 3.1: The architecture of public sensing.
3.2. THE VEHICULAR PUBLIC SENSING PLATFORM - ARCHITECTURE, COMPONENTS, AND INTERACTIONS

and reporting’ components.

In addition to the above mentioned components, the VPS platform includes a ‘data analytics’ component needed as a final stage in the public sensing process to analyze the collected data and get it ready for use.

In the following, we delve into the functions of each component, its adaptation according to practical considerations, and its interaction with the other components in the platform.

3.2.1 The Recruitment Component

This component is mainly responsible for selecting a set of participants among all the possible candidates in a way that satisfies the application and cost requirements. A main input to the recruitment component is the recruitment policy which is used to define different requirements related to the task of interest and participant selection. These requirements include all thresholds related to the sensing attributes and the corresponding pecuniary issues. They also include all restrictions on the selected participants such as excluding participants who have not participated before, or confining the selection to participants owning a specific vehicle make/brand.

A vital element of any recruitment policy is the incentive given for participants as a reward for the service they provided and to encourage them to keep engaged for future participation. An overview about the participation incentives and their different types is presented in Section 2.4. Among these types, it has been shown that the incentives based on monetary values are the most encouraging ones. Regardless of how that monetary value is represented, the SP paying such rewards for participants
is in need of minimizing such paid rewards especially with having a budget cap controlling the recruitment process.

We remark that the average traffic density of an environment directs how participant recruitment can be handled. In that regard and based on the density factor, we distinguish between recruitment in urban and rural environments as follows.

a) Urban Environments
One of the major challenges that face an SP during the recruitment process in urban environments is the wide availability of candidate participants in an AoI. Due to the aforementioned incentive perspective, those available participants cannot all be recruited for a sensing task as they all will have to be paid for their participation. Therefore, in such environments, an SP has to select a sufficient number of participants that can provide a required level of coverage for the intended AoI. In this selection process, the SP should consider first the availability of participants to limit the selection to those that are spatiotemporally available in the AoI. In addition, with the diversity of participant’s behavior and the quality of vehicular resources and reported data, a recruiting SP has to consider participants' reputation in the selection process to maximize the benefit and QoI out of the recruited participants. Since in practical scenarios a sensing task would have a budget cap that controls the amount of rewards paid for the recruited participants, the recruitment process has to take this budget constraint into account.

Directed by these recruitment requirements, we propose our reputation-aware, trajectory-based recruitment (RTR) framework to handle such requirements. This proposed framework and its underlying modules are detailed in Chapter 4.
b) Rural Environments
Due to the scarcity of candidate participants in rural environments, there is no need to use a participant selection scheme for recruitment. In rural environments, we use what we call the ‘naive’ solution where an SP tasks whoever participants are available in the AoI during the determined sensing period.

3.2.2 The Communication Component
The main function of the communication component is linking SPs and participants. It handles sending sensing requests/tasks by SPs to participants and sending the sensed data back. It is also responsible for delivering the availability indicators (e.g., trajectories) of vehicles sent by potential participants to the dedicated SP for recruitment purposes as discussed in the next chapter.

The operation of the communication component differs based on the availability of broadband connectivity.

a) Broadband-Connected Environments
In environments with ubiquitous availability of broadband communication infrastructure, we adopt the Internet to be the dominant communication backbone supporting real-time communication between SPs and participants.

b) Broadband-Restricted Environments
It may happen that the SP moderating the sensing and data collection process cannot use the Internet for communication with participants to avoid the cost of accessing broadband networks. Such restrictions of the use of broadband connectivity are encountered also in rural environments where it is not feasible to depend on the Internet
for connectivity because of the lack/difficulty of using a broadband infrastructure.

Therefore, for the aforementioned practical setups to be supported by our proposed platform, we propose the caching-assisted data delivery (CADD) scheme to handle the delivery of both interest and data reply packets between the SPs and participants. CADD depends mainly on V2V, V2I, and I2V multi-hop communication to handle packet exchange and delivery. To minimize the round-trip communication delay and the cost of accessing vehicular resources for each sensing request, CADD employs an on-road caching concept to introduce cache hits of previously collected data. Details of the CADD scheme and the functionalities of the involved entities are presented in Chapter 5.

Figure 3.2 shows examples of the operation of the communication component in different environments where vehicle $S$ needs to send a packet to a service provider $P$. In Figure 3.2(a), the environment is broadband-connected, therefore $S$ manages to communicate directly with $P$ to deliver the packet using the backbone network. In the broadband-restricted environment shown in Figure 3.2(b), $S$ has to deliver the packet using V2V and V2I multi-hop communication to an on-road data collector $D$. Examples of data collectors are mentioned later in the reporting module. The data can be kept at $D$ for later retrieval by $P$, or $D$ can be supported with a limited Internet access to report the collected data periodically to $P$.

3.2.3 The Sensing and Reporting Component

After getting an assigned sensing task through the communication component, it is the responsibility of the sensing and reporting component at the selected vehicle to perform this task and report data back to the SP.
1) The Sensing Module

After getting tasked, a vehicle starts sensing the phenomenon and generating data periodically as long as it is in the area of interest defined in the sensing request or till the required sensing period expires, whichever comes first.

After generating the required sensing data, the sensing module passes this data to the reporting module.

2) The Reporting Module

The role of the reporting module is getting data out of the participating vehicle through the communication component to be delivered to the SP. A vehicle should report the collected data based on a reporting period, and one of the main functions of the reporting component is determining that period.

The reporting period is controlled by two parameters; the data type (data criticality) and the communication paradigm.

Figure 3.2: Communication in broadband-connected vs. broadband-restricted environments.
- **Data type**

  - Delay-critical data should be reported once sensed using the available broadband connectivity (reporting rate = sensing rate).

  - Delay-tolerant data gives some sort of flexibility in its reporting rate. For example, such data can be stored and aggregated to be reported at a later time depending on the connectivity paradigm (reporting rate < sensing rate).

- **Connectivity paradigm**

  - If the collected data has to be reported using an on-board broadband connectivity and this data is delay-critical, it should be reported once sensed as mentioned above. If the data is delay-tolerant and has to be sent also using broadband connectivity, aggregated data can be reported at the end of the sensing task.

  - If data has to be delivered to an on-road data collector (e.g., a wireless RSU or sink at an intersection), data can be stored and carried until the participating vehicles come in contact with the dedicated data collector. If the data-carrying vehicle will not encounter the data collector on its trajectory, the vehicle can utilize the data-relaying capabilities of other vehicles on the road to send the data to the collector using multi-hop V2V communication.

  - In cases where data is to be delivered through opportunistic connectivity, aggregated data should be stored and carried until the carrying vehicle reaches a connectivity opportunity.
3.2.4 The Data Analytics Component

The role of the data analytics component is to receive reported data and apply necessary data aggregation, filtering, or analytical functionalities. In addition, based on assessing the quality level of retrieved data and its matching with the corresponding task, the component builds a reputation score for each participant. Such reputation scores can be used as inputs for the recruitment component to guide the selection process. The data aggregation and filtering parts of this component are out of the scope of our work. The reputation assessment part for building the participants’ reputation scores is handled through our proposed RTR framework and discussed in Chapter 4 as a main module of the framework.

Based on the above discussion of the different components forming our VPS platform, we summarize the core architecture of the platform showing these underlying components and the interaction among them in Figure 3.3.
3.3 Summary

Motivated by the high rise of public sensing and the abundant resources of smart vehicles, we proposed the vehicular public sensing (VPS) platform that utilizes such vehicular resources for the purpose of provisioning vehicle-based public sensing services. The platform consists of four main components that handle the sensing and data collection process starting from participant selection until having the collected data ready for use. Our platform aims at solving the challenges of quality of information, redundancy, dynamic availability of resources, incentives, and participant selection through an underlying recruitment component. As well, the proposed platform addresses the data delivery challenge through underlying communication and sensing and reporting components. In addition, the platform takes into consideration the final analytical stage needed by the public sensing process through a data analytics component. We discussed how the different components can be adapted to handle different practical setups (e.g., environmental densities and available connectivity), and how they interact with one another. Under its components, the platform encapsulates the work presented in the next chapters.
Chapter 4

Reputation-Aware, Trajectory-Based Recruitment of Smart Vehicles for Public Sensing

4.1 Introduction

Although utilizing vehicles as data contributors in public sensing brings many advantages, it also comes with challenges. There can be many potential participants in an area of interest, especially in a congested area or well-travelled road segment. These participants cannot all be recruited for a sensing task as the recruited participants should be given incentives as a reward for the service they provide, and to encourage them to participate in the future. Hence, effective recruitment schemes are needed to ensure the selection of the right number of “trusted” participants achieving a required level of coverage for an area of interest in a cost effective manner. Based on the above perspective directing recruitment of participants, the main objective of this chapter is to introduce a recruitment framework that handles the aforementioned recruitment requirements.

In our recruitment framework, the pool of potential participants is first determined by their spatial and temporal availability to achieve a desired coverage for the area
of interest during a given time period. In contrast to some models that consider only instantaneous availability to achieve instantaneous coverage, we consider on-move coverage to support the wide scope of on-move monitoring applications mentioned earlier in Section 3.1. With on-move coverage, the number of participants to achieve a desired coverage can be small compared to those achieving coverage without considering mobility of participants. For example, in covering a road to build an estimate of parking availability, we may find that just a few vehicles taking camera shots on the go can provide complete coverage of the road. As a main part of the on-board vehicular resources, the navigation system is a vital component that provides information to support many of the vehicular applications. Our recruitment framework is designed to utilize input from such systems represented in vehicle trajectories as indicators of the on-move availability of those vehicles.

In practice and with the diversity of participant’s behaviour and capabilities of participating vehicles, depending solely on availability for recruitment would not be adequate to differentiate among the variety of potential participants. The reputation of participants must be considered along with availability. The recruitment process would then aim to maximize the benefit out of the chosen participants by selecting those who are more likely to contribute with high quality data. Furthermore, since in real scenarios SPs will have a budget cap that the total recruitment cost cannot exceed, introducing a budget constraint while selecting the participants is called for. Consequently, in this chapter, we present a reputation-aware, trajectory-based recruitment (RTR) framework that accommodates the consideration of participant’s reputation and the budget constraint while building on the availability of participants.
The proposed RTR framework consists of three main modules: 1) a reputation assessment scheme, 2) a pricing model, and 3) a selection scheme used for choosing the participating vehicles achieving a required level of coverage in a reputation-aware manner with cost consideration. The outputs of the first two modules are fed as inputs to the third module.

The selection problem is formulated first as an integer linear programming (ILP) optimization problem for two different recruitment objectives. The first objective considers maximizing the available coverage while minimizing the overlapping among the chosen segments to avoid data redundancy problems. The second objective targets maximizing the available coverage, while minimizing the total recruitment cost. The purpose of the optimization formulation is to present performance benchmarks for each recruitment objective giving some performance bounds on these schemes. Greedy heuristic solutions are also presented targeting the objectives of the optimization formulation. Such heuristic solutions are needed to cope with practical real-time selection requirements. The performance of the proposed optimization and greedy solutions are compared. In addition, extensive evaluation is conducted to show the quality of the collected sensing data and the performance of the selection scheme under some practical cases.

The remainder of this chapter is organized as follows. In Section 4.2, we discuss some related work in the areas of recruitment for public sensing and reputation assessment. The proposed RTR framework is introduced in Section 4.3 with the focus in this section on its selection part including the ILP formulations and the greedy heuristics. In Section 4.4, we present the proposed reputation assessment scheme and pricing model as parts of the proposed RTR framework. In Section 4.5, we discuss
4.2. RELATED WORK

the performance of the proposed greedy heuristics comparing them to the benchmark performance results of the ILP formulations. Finally, we conclude the chapter in Section 4.6.

4.2 Related Work

4.2.1 Recruitment for Public Sensing

Many platforms are proposed for utilizing the sensory resources of smart vehicles. Examples of such platforms are presented in Section 2.2.1. Although those platforms are good examples of using vehicles as mobile sensors, they neglect consideration of a recruitment scheme that chooses which vehicles are going to participate in the sensing task. Most of them depend on specific pilot vehicles for evaluation purposes. For use in practical situations, these platforms are in need of some sort of recruitment scheme for selecting participants.

In the area of participant recruitment for public sensing, a few models are available in the literature. These models focus mainly on recruiting smartphones to utilize their on-board sensors. In [65], the authors propose a recruitment framework that considers a participant’s availability and participation habits for selection. To maximize the coverage of the area of interest within a limited budget, the authors use the greedy solution of the budgeted maximum coverage problem [66]. Their recruitment framework differs from the proposed framework in that it does not consider on-move availability as it is limited to smartphone use. In addition, it does not consider availability and reputation simultaneously; it supports selection by any of the metrics independently based on user choice. Some other models are proposed for recruitment purposes that do not pay attention to the reputation of participants. A mechanism
that considers the location and budget constraints is proposed in [67]. This mecha-
nism depends on the Reverse Auction pricing model [68] in which the participants bid
for their data, in contrast to the pricing model used in [65] where the participants’
costs are identical. With a different perspective, the authors in [69] propose a mobile
phone-based collaborative sensing scheme that aims at forming a sensing schedule
with the target of minimizing energy consumption of the participating phones. As a
second target, the authors consider fairness as well in designing their sensing schedule.

Although these schemes can be effective at selecting smartphones, they are not ef-
fficient for the recruitment of vehicles because they only consider instantaneous sensing
and coverage which is not suitable for the wide scope of on-move sensing applications
supported by vehicular mobility.

Instead of depending on an efficient recruitment scheme for participant selection,
some other public sensing platforms depend on relatively simplistic schemes for col-
lecting data. Random selection of data contributors is one of these schemes. Another
scheme, which we refer to as the ‘naive’ scheme, is one in which the SP simply asks
all the contributors in the area of interest to generate and send data. Although these
two schemes are simple, they have drawbacks that hinder their use. The ‘random’
selection scheme is less likely to provide coverage of the area of interest and also more
likely to result in collected data which may have undue redundancy, compared to
a more targeted recruitment scheme. Although it is the easiest to implement, the
‘naive’ scheme has potentially serious disadvantages. First, by getting data from all
participants in an area of interest, the cost of such data to the SP may be unnecessar-
ily and prohibitively high. Second, with many participants in an area of interest, the
data retrieved will have high levels of correlation and redundancy. Such unnecessary
4.2. RELATED WORK

Collection of redundant data is considered a waste for both the SP’s budget and the communication bandwidth.

With these limitations of the available sensing platforms and recruitment models, we are in need of efficient recruitment frameworks that ensure the required coverage of the area of interest with both reputation and budget considerations, and in a way that utilizes vehicular mobility efficiently to support the on-move sensing applications. These are the main features of our recruitment framework presented in this chapter.

4.2.2 Reputation Assessment

In the area of reputation/trust assessment, we classify the assessment schemes into two main categories; redundancy-dependent and redundancy-independent. In the former category, the SP/truster responsible for computing a reputation score for each participant depends on correlated readings reported from other participants who are asked to do the same task. The outlier detection technique [70] is commonly used under this category. To compute a reputation score/trust level of a reporter, outlier detection measures the distance of the reported data value to a common value (e.g., average of the correlated data) such that the shorter the distance is, the higher the reputation/trust of this reporter is. The system presented in [71] is an example that uses outlier detection for building a reputation system for smartphone-based sensing applications.

In the second category, redundancy-independent, the truster does not require redundant data to assess the reputation of a certain participant. The truster depends on assessment metrics that either take the performance history of the trustee into
Consideration or depend on some current features associated with the trustee’s device/data, or both. The aforementioned recruitment framework presented in [65] is an example of a system within this category. Since in our framework we target recruiting participants in a cost-effective manner, we do not consider redundant coverage, unless required, as discussed later. Therefore, we adopt the redundancy-independent category in our reputation assessment scheme.

4.3 The Reputation-Aware, Trajectory-Based Recruitment Framework

As a main component of a smart vehicle, the navigation system plays a pivotal role in most of the vehicular applications and services. In addition to providing navigational information to the driver, the output of the navigation system is utilized by a multiplicity of applications including safety, infotainment, and diagnostics. We remark that with the assistance of this system, the trajectories of vehicles can be easily acquired and utilized as a precise indicator of vehicles’ availability. As mentioned earlier, we consider the participants’ spatiotemporal availability as a main criterion for recruiting participants and achieving a required coverage. By noting that vehicles’ trajectories overlap with sensing parameters (the sensing area and duration) defined in the sensing request, we can tighten our solution space to those that are spatiotemporally available in the area of interest. In addition, as trajectories represent on-move availability, they are suited for handling recruitment for the wide scope of on-move sensing applications.

Members of the data collection process (drivers registered with the service) will need to enter their destination before starting their trip. This way, the service application can calculate the trajectory and have it stored and ready to be accessed by
the SP when needed. To request a sensing task, an SP sends sensing requests to the participants. The sensing request defines the sensing task, the area of interest, and the time span of the task. The in-vehicle service application then sends relevant trajectory information (i.e., overlapping parts with the sensing task) to the SP to start the selection process. Figure 4.1 shows an example of a trajectory segment solution space existing in the targeted area of an event.

With the diversity of driver behaviour and vehicle capabilities, considering reputation of participants and their reported data is an important criterion that will aid in distinguishing among participants and picking those that ensure an adequate level of quality. As in practice an SP responsible for the recruitment process will have a budget cap that cannot be exceeded, it is necessary to include a budget constraint in the selection process. Bearing in mind this perspective, we present the reputation-aware, trajectory-based recruitment (RTR) framework that considers both the spatiotemporal availability and reputation of participants while accommodating budget constraints in recruiting vehicles for public sensing services. The RTR framework consists of three main modules: 1) a reputation assessment scheme used for computing a reputation score for each candidate participant, 2) a dynamic pricing model for computing a recruitment cost for each participant based on his/her reputation score.

Figure 4.1: An example showing trajectory segments of vehicles in an event area.
and the distance traversed, and 3) a selection scheme for choosing the participants
to be recruited to achieve a required level of coverage for the area of interest in a
reputation-aware manner with cost consideration. The outputs of the first two mod-
ules; the participants’ reputation scores and recruitment costs, are inputted into the
selection scheme along with the vehicles’ trajectories to start the selection process.
In this section, we focus on the selection part of the framework. The reputation as-
seessment scheme and the pricing model are detailed in the next section.

For the selection part, we first present an ILP formulation for the selection prob-
lem as a benchmark for the sake of providing the upper bounds of the recruitment
solutions. Second, we present greedy heuristic solutions that follow the objectives
of the optimization formulation. Such heuristic solutions are needed to handle real-
time services that the optimizer fails to handle. In addition, we generalize the basic
solution of the selection problem to handle practical situations, including departing
vehicles and varying redundancy requirements.

Later in this section, we elaborate on two data acquisition models that are sup-
ported by the proposed RTR framework.

4.3.1 System Model and Problem Formulation

We consider an area of interest $A$ with a trajectory segment set $S$ of $S$ segments are
spatiotemporally available in this area. An arbitrary segment is denoted by $i \in S$.
Each segment $i \in S$ is associated with a reputation score $r_i$ and a recruitment cost
$c_i$ computed using the reputation scheme and the pricing model, respectively, as
discussed in the next section. A budget cap $B$ and a reputation threshold $R_{Th}$ will
be determined by the SP interested in the recruitment process.
4.3. THE REPUTATION-AWARE, TRAJECTORY-BASED RECRUITMENT FRAMEWORK

Based on the information available and the main recruitment target, we can define our recruitment problem as follows.

**Inputs**

\[ A : \text{Area of interest} \]
\[ S : \text{Set of trajectory segments} \]
\[ B : \text{Budget cap} \]
\[ R_{Th} : \text{Reputation threshold} \]

**Output**

\[ S' \subseteq S : \text{Covering Set of Segments} \]

**Problem Definition** - Find a segment set \( S' \subseteq S \) that achieves coverage to the area \( A \), such that the coverage function \( F(S', y \in A) = 1 \) for the maximum number of points \( y \in A \), satisfying a recruitment objective while considering the reputation and budget constraints, \( r_i \geq R_{Th} \forall i \in S' \) and \( \sum_{i \in S'} c_i \leq B \), respectively. \( F(S', y) \) is defined as

\[
F(S', y) = \begin{cases} 
1 & \text{if } y \text{ is covered by } S' \\
0 & \text{if } y \text{ is not covered by } S'
\end{cases}
\]

It is worth mentioning that although Figure 4.1 shows a straight road, our model is not restricted to this road topology. The proposed model is generic and can support a multiplicity of roads based on the fact that curved/non-straight roads can be
4.3. THE REPUTATION-AWARE, TRAJECTORY-BASED RECRUITMENT FRAMEWORK

treated as a series of straight roads.

Two different recruitment objectives are considered in our framework that reflect practical recruitment requirements. The first objective targets minimizing overlapping among the chosen segments while achieving the maximum available coverage to avoid problems resulting from data redundancy. In addition to being a waste of money, having large volumes of data redundancy unnecessarily wastes the bandwidth and overloads the transmission networks. In some other practical considerations, SPs may favor getting the covering solution with the minimum cost regardless of the level of data redundancy incurred in that solution. Therefore, we present another recruitment objective that targets minimizing the total recruitment cost while achieving the maximum available coverage. Note that the solution with the minimum overlapping among segments may not correspond with the minimum cost one. The example shown in Figure 4.2 demonstrates such a case.

Figure 4.2: An example showing that the solution with the minimum overlapping may not be the one with the minimum cost. The solution with minimum overlapping consists of segments $s_3, s_2, s_5$ with a total recruitment cost $= 18.5$ while the solution with minimum cost consists of segments $s_1, s_2, s_4$ with a total recruitment cost $= 14.5$. 
4.3.2 ILP Formulation

The recruitment problem handled by the framework is formulated as an ILP optimization problem for the two different recruitment objectives defined above. As each of the main objectives involves two sub-objectives, the recruitment problem can be considered a multi-stage optimization problem. The first stage of the optimization formulation targets the sub-objective of maximizing the available coverage. After attaining the maximum available coverage through the first stage, the role of the second optimization stage is refining the solution with the maximum coverage according to a second sub-objective targeting either minimizing the overlapping among the chosen segments or minimizing the total recruitment cost, according to the main recruitment objective chosen by the SP.

For the sake of implementation, we divide the area of interest into a set of adjacent road sectors $\mathcal{T}$ of $T$ sectors. An arbitrary road sector is denoted by $k \in \mathcal{T}$. Before discussing each stage, we introduce the following optimization variables:

- $x_i$: Binary decision variable set to 1 if segment $i$ is chosen and 0 otherwise
- $\vec{x}$: $\vec{x} = \{x_i \in \{0, 1\} : i \in S\}$
- $M$: Matrix of size $T \times S$ representing the mapping of the $S$ segments to the $T$ sectors
- $t_k$: Number of selected trajectory segments covering sector $k$
- $\vec{t}$: $\vec{t} = \{t_k : k \in \mathcal{T}\}$ and is computed as $\vec{t} = M \vec{x}$.
- $t_k'$: Binary variable set to 1 if sector $k$ is covered and 0 otherwise and is computed as $\min(t_k, 1)$
- $l_i$: Length of trajectory segment $i$
To illustrate how the mapping matrix $M$ is formed and $\vec{t}$ is computed, Figure 4.3 shows an example of the computation $\vec{t} = M\vec{x}$ to the minimum cost solution of the use case in Figure 4.2. Note that the rows of $M$ represent the sectors and the columns represent the segments.

As the first optimization stage targeting the maximum coverage is common to the two main recruitment objectives, we present its ILP formulation below then we present the second stage of the two main objectives separately afterwards.

**The first stage of optimization targeting the maximum coverage**

Maximize $\frac{\sum_{k=1}^{T} t'_k}{T}$  \hspace{1cm} (4.1)

subject to

\begin{align*}
C1 : & \quad r_i x_i \geq R_{Th} x_i \quad \forall \; i \in S \\
C2 : & \quad \sum_{i=1}^{S} c_i x_i \leq B \\
C3 : & \quad \vec{t} - M\vec{x} = \vec{0} \\
C4 : & \quad t'_k \leq 1 \quad \forall \; k \in T \\
C5 : & \quad t'_k \leq t_k \quad \forall \; k \in T
\end{align*}

Eq. 4.1 is the objective function maximizing the ratio of the covered sectors. C1 and C2 are the reputation and budget constraints, respectively. C3 ensures that the vector $\vec{t}$ holds the number of selected segments covering each road sector $k$ through a multiplication of the vector $\vec{x}$ and matrix $M$ as defined earlier. C4 and C5 map the
4.3. THE REPUTATION-AWARE, TRAJECTORY-BASED RECRUITMENT FRAMEWORK

Figure 4.3: An example illustrating the computation $\vec{t} = M \vec{x}$. The values relate to the minimum cost solution obtained in the use case of Fig. 4.2.

value of $t_k$ into a binary value stored in $t'_k$ for each sector $k$, and they represent the equation $t'_k = \min(t_k, 1)$.

The coverage ratio of the solution obtained in this stage represents the maximum coverage, $V_{\max}$, that can be achieved by the set of available trajectory segments (vehicles).

A) Maximum Coverage with Minimum Overlapping

As the solution of the first stage may involve overlapping among the chosen segments for the sake of maximizing coverage, we consider a second optimization stage with a targeted objective of minimizing segments’ overlapping, while achieving the maximum coverage bound obtained from the first stage. The formulation of this stage is presented below.

The second stage of optimization targeting the minimum overlapping

\[
\text{Minimize} \sum_{i=1}^{S} l_i x_i
\]
subject to

\[ C1, C2, C3, C4, C5 \]

\[ C6 : \quad \frac{\sum_{k=1}^{T} t_k'}{T} \geq V_{\text{max}} \]

Eq. 4.2 is the objective function minimizing the overlapping among the chosen segments through minimizing the sum of the chosen segments’ length. C6 ensures that the solution obtained guarantees the maximum coverage ratio obtained from the first stage.

B) Maximum Coverage with Minimum Cost

The first optimization stage may find many solutions achieving the maximum coverage but each with a different recruitment cost. To handle recruitment with the minimum cost desire, we consider a second optimization stage targeting minimizing the total recruitment cost while achieving the maximum coverage bound obtained from the first stage. The formulation of this stage is presented below.

\textbf{The second stage of optimization targeting the minimum cost}

Minimize \[ \sum_{i=1}^{S} c_{i}x_{i} \] \hspace{1cm} (4.3)

subject to

\[ C1, C3, C4, C5 \]

\[ C7 : \quad \frac{\sum_{k=1}^{T} t_k'}{T} \geq V_{\text{des}} \]
where \( V_{\text{des}} \) is the desired coverage ratio determined by the SP with its upper bound being the possible maximum coverage ratio, \( V_{\text{max}} \), obtained from the first stage.

Eq. 4.3 is the objective function minimizing the total recruitment cost. C7 ensures that the solution obtained guarantees the desired coverage ratio.

It is worth mentioning that the selection problem formulated above is NP-hard. In the following, we propose greedy heuristic solutions to approximate the solutions obtained through the optimization formulation. Such heuristic solutions are needed to handle the practical use of the recruitment framework handling the selection process for services with real-time requirements.

### 4.3.3 The Proposed Greedy Heuristic Solutions

By representing the area of interest and the overlapping parts of participants’ trajectories with the area of interest as intervals, we argue that our problem can be solved with variations to the set cover problem (SCP) [72] altering it to an interval cover one.

One of the variations of the SCP that considers a budget cap in the selection process is known as the budgeted maximum coverage problem (BMCP) [66]. Although the BMCP shares the budget consideration with our targeted problem, it ignores the reputation-awareness part. In addition, the objective of the BMCP does not match with any of our recruitment objectives. Therefore, the solution for the BMCP cannot be applied to our work. In the following, we discuss our basic reputation-aware budgeted maximum coverage (RBMC) solution and its different versions that handle our recruitment objectives.
A) The reputation-aware budgeted maximum coverage (RBMC) greedy solution

In the basic SCP, the input is a set of elements $E = \{E_1, E_2, ..., E_m\}$ and a collection of subsets $H = \{H_1, H_2, ..., H_n\}$ s.t. $\bigcup_i H_i = E$. The goal in the problem is to find a solution that covers the set $E$ with the minimum number of subsets from $H$. The greedy approximation solution proposed for solving the SCP works through iterations to find the subset that covers the maximum number of uncovered elements in each iteration until all the elements in the set $E$ are covered.

In our proposed RBMC solution, we alter the SCP to consider covering an interval instead of a set of elements and generalize it to accommodate the reputation and budget constraints. The solution maps the collection of subsets to the collection of trajectory segments and the domain of elements to the area of interest to be covered. The basic RBMC targets maximizing the coverage which corresponds to the first stage of the optimization formulation. Two variations to the RBMC that handle the main recruitment objectives are discussed later in this section.

Algorithm 1 shows our basic RBMC solution. Let $S$ be the set of trajectory segments, $G \subseteq S$ be the collection of segments forming the selected covering set, and $W_i$ be the length of the interval (area) covered by segment $i$ but not covered by any segment in $G$. The algorithm consists of two main procedures. The procedure $REPUTATION\_FILTER(S)$ is a pre-processing step that aims at filtering out the segments with a reputation score $r_i$ below the threshold $R_{Th}$ and storing those satisfying the reputation constraint in $U$ to apply the selection process on. The procedure $GREEDY\_BUDGETED\_COVERAGE(U)$ aims at selecting the collection of segments $G$ that maximizes $W_i$ without exceeding the given budget cap $B$. The output set $G$.
Algorithm 1: The Reputation-Aware Budgeted Maximum Coverage (RBMC) Solution

REPUTATION_FILTER(S)
Begin
$U \leftarrow \emptyset$
for all $S_i \in S$
do
if $r_i \geq R_{Th}$ then
$U \leftarrow U \cup S_i$
return $U$
End

GREEDY_BUDGETED_COVERAGE(U)
Begin
$G \leftarrow \emptyset$ and $C \leftarrow 0$
while $U \neq \emptyset$ do
select $S_i \in U$ that maximizes $W_i$
if $C + c_i \leq B$ then
$G \leftarrow G \cup S_i$
$C \leftarrow C + c_i$
$U \leftarrow U \setminus S_i$
update $W_j$ for each $S_j \in U$
for all $S_j \in U$ do
if $W_j = 0$ then
$U \leftarrow U \setminus S_j$
return $G$
End

holds the minimum number of segments achieving the maximum available coverage with satisfying both the budget and reputation constraints.

B) The greedy solutions for the reputation-aware budgeted coverage with multi-objectives

In this part, we discuss our proposed reputation-aware budgeted maximum coverage with minimum overlapping (RBMC-MO) and the reputation-aware budgeted maximum coverage with minimum cost (RBMC-MC) greedy solutions corresponding to the main recruitment objectives handled by our recruitment framework.

Algorithm 2 shows the common approach followed in our RBMC-MO and RBMC-MC solutions. After the pre-processing REPUTATION_FILTER(S) procedure, the procedure GREEDY_BUDGETED_MULTIOBJ(U) is used to handle the selection process. It works similar to the GREEDY_BUDGETED_COVERAGE(U) procedure.
in Algorithm 1 aiming at selecting the collection of segments $\mathcal{G}$ that maximizes $W_i$ without exceeding $B$, with an added condition that handles the case when there are more than one trajectory having the same coverage weight $W_i$. In this case, the procedure selects the one with the minimum $z_i$. In RBMC-MO, $z_i$ is equal to $o_i$ that represents the length of the part of trajectory $i$ overlapping with the selected trajectories so far in $\mathcal{G}$, while in RBMC-MC, $z_i$ is equal to $c_i$ which represents the recruitment cost of trajectory $i$. The output is the covering set $\mathcal{G}$. A final post-processing step is included in the algorithm to improve the output towards the recruitment objectives. In this step, defined in the $\textit{POST\_PROCESSING}(\mathcal{G}, \mathcal{U}')$ procedure, the algorithm works on reducing the redundant coverage in the covering set through replacing each selected trajectory in $\mathcal{G}$ with another trajectory, from the reputation-filtered set $\mathcal{U}'$.

**Algorithm 2 : The Reputation-Aware Budgeted Coverage with Multi-Objectives**

```
U ← REPUTATION\_FILTER(S)       //as in Algorithm 1
GREEDY\_BUDGETED\_MULTIOBJ(U)
Begin
G ← $\phi$, C ← 0, and U' ← U
while U $\neq$ $\phi$ do
  select $S_i ∈ U$ that maximizes $W_i$
  if there are many candidates with the same maximum $W_i$ then
    select $S_i ∈ U$ that maximizes $W_i$ and minimizes $z_i$
  if $C + c_i ≤ B$ then
    G ← G $∪$ $S_i$
    C ← C $+$ $c_i$
    U ← U $\setminus$ $S_i$
    update $W_j$ for each $S_j ∈ U$
    for all $S_j ∈ U$ do
      if $W_j = 0$ then
        U ← U $\setminus$ $S_j$
  G ← POST\_PROCESSING(G, U')
return G
End

POST\_PROCESSING(G, U')
Begin
for all $S_k ∈ G$ do
  if there is a segment $S_i ∈ U'$ with the same unique coverage of $S_k$ and $\text{length}(S_i) < \text{length}(S_k)$ then
    replace $S_k$ with $S_i$
    update the unique coverage of all $S_k ∈ G$
return G
End
```
that has the same unique coverage and shorter length than the replaced one, if there is any.

We highlight that the time complexity of Algorithms 1 and 2 is $O(N^2)$ with $N = |S| = S$.

### 4.3.4 Practical Considerations

Our main recruitment problem assumes complete confidence in vehicle trajectory information and equal importance of road parts. In practical scenarios, such an ideal case is not guaranteed. In the following, we discuss two generalized cases of the basic problem. These generalized cases reflect practical situations the SP would face during the recruitment process. These are: i) having a probability that a vehicle will not stick to the trajectory it announced, and ii) having events that require redundancy at some parts of an area of interest.

**Case I: RTR with Probability of Leaving**

In realistic scenarios, it is not guaranteed that a vehicle will stick to its announced trajectory. We consider a generalized case of the basic selection problem that assigns different probabilities of sticking to the announced trajectory.

For each vehicle, we calculate a degree of confidence $D_i$ (such that $0 \leq D_i \leq 1$) based on the participation history of this vehicle assuming that it was involved in earlier tasks. $D_i$ is computed as the average of traversed portions of the segments in the past interactions. For first-time participants, $D_i$ will be set to 1. Based on the calculated degree of confidence, a probability of sticking to the announced segment...
of trajectory $i$, $p(i, y), \forall y \in i$, is defined as follows

$$p(i, y) = \begin{cases} 
1 & \text{if } y \leq D_i \\
0 & \text{if } y > D_i 
\end{cases}$$  \hspace{1cm} (4.4)$$

where $y$ is normalized to be in $[0, 1]$ to ease mapping to $D_i$ values.

Having $p(i, y)$ equal to 1 means that the vehicle will cover this segment and having it equal to 0 means that this part is not covered by this vehicle. Hence, we can define a vehicle’s coverage function to be

$$f(i, y) = p(i, y) \ \forall y \in i$$ \hspace{1cm} (4.5)

for the vehicle corresponding to trajectory $i$.

Recall that, as defined earlier, the solution coverage function $F(S', y)$ should be equal to 1 for the maximum number of points $y \in A$. To compensate for having a part of a vehicle’s trajectory with a probability of being not traversed by the vehicle (not covered), this part should be covered by another vehicle with probability 1. Therefore, we can define the solution covering function of a point $y \in A$ to be the summation of all the vehicles’ coverage functions of $y$ as follows

$$F(S', y) = \sum_{i \in S' \text{ where } i \text{ includes } y} f(i, y)$$ \hspace{1cm} (4.6)$$

such that $F(S', y)$ should be at least 1 to ensure coverage of $y$, as long as there are candidate coverage trajectories satisfying both the reputation and budget constraints.

To handle this case, the use of the proposed greedy algorithms can be adjusted as
i. For each trajectory, calculate $p(i, y)$ based on the computed $D_i$.

ii. Map the announced segment of trajectory to a projected one based on $p(i, y)$.

iii. Apply the greedy algorithms on the projected segments to achieve coverage.

The example in Figure 4.4 shows the first two steps of the operation above. We highlight that with considering probabilities of leaving, more segments/vehicles are needed to ensure coverage compared to the case with full confidence of sticking to the trajectory.

It may happen that, when considering the probability of leaving, coverage of a certain area may be intermittent if there are no vehicles satisfying the constraints to compensate the part of the segment with a probability of coverage less than 1. To handle this case, two different approaches can be deployed based on the criticality of the service as follows.

![Figure 4.4: An example of RTR with probability of leaving. In part (a), each segment is mapped to a probability distribution based on its corresponding $D_i$. Part (b) shows the projected segments.](image)
If the service is *delay-critical*, coverage should be achieved in the exact duration of the event, otherwise, data generated and reported will be obsolete. In this case, the greedy algorithms can be used to provide the maximum coverage possible at that time. If the service is *delay-tolerant*, the greedy algorithms can be adjusted such that if a solution with the required coverage cannot be achieved, the algorithms will report a failure and they can be re-run at a later time. Re-running the algorithm should be accompanied with a maximum threshold of re-runs based on the delay-tolerance of the service.

Intermittent coverage may also happen when an SP cannot find a sufficient number of vehicles that achieve continuous coverage for the area of interest in the case of monitoring of an environment that is not dense enough, or when the penetration rate of the service and its corresponding application are not high enough in certain areas. These two cases can be handled in the same way discussed above.

**Case II: RTR with Redundancy Requirements**

The basic problem assumes that only one vehicle is needed to monitor an area. In practical situations, the SP may require readings from multiple vehicles monitoring the same area to achieve a certain level of reliability. We adapt the basic case to give an SP the ability to determine the level of redundancy needed by determining the degree of importance for different parts of the area of interest. For example, as shown in Figure 4.5, in the case of a severe accident, an SP may ask for different degrees of importance relative to the location of the accident with the highest degree at the exact location of the accident, and lower degrees farther from the accident location.

In order to handle this case, we define the degree of importance stated by the SP
4.3. THE REPUTATION-AWARE, TRAJECTORY-BASED RECRUITMENT FRAMEWORK

Figure 4.5: An example of RTR with redundancy requirements. The area of interest is divided into 5 main parts each with a certain degree of importance based on its proximity to the event.

for each part of the area of interest to be $I_{rp}$, where $\bigcup_{1}^{m} rp = A$, and $m$ is the number of parts the area of interest is divided into. $I_{rp}$ will be translated to the number of vehicles needed to monitor a part $rp$ in the area. In a certain part with a certain degree $I_{rp} = g$, we assign each vehicle/segment in this part a coverage degree $CD_i$ such that

$$CD_i = \frac{1}{I_{rp}} = \frac{1}{g} \forall i \text{ in part } rp \quad (4.7)$$

To relate to the notations used in the previous and basic cases, we can define a vehicle’s coverage function $f(i, y)$ to be equal to its coverage degree as follows

$$f(i, y) = CD_i \forall y \in \text{segment } i \quad (4.8)$$

As aforementioned, the solution coverage function of a point $y$ is defined to be the summation of all the vehicles’ coverage functions of $y$ as defined in Eq. 4.6. As mentioned previously, to ensure coverage of a point $y$, $F(S', y)$ should be at least 1. This implies that to achieve coverage for a point $y$ in a part of the area with an importance degree $g$, $g$ vehicles (each with $CD_i = 1/g$) are needed to make the value
of $F(S', y)$ equal to 1.

The basic greedy algorithm targeting maximizing coverage (RBMC) and the algorithm targeting maximizing coverage with minimum cost (RBMC-MC) can be adjusted to handle this case. Each part can be divided into sectors and the algorithms can be adjusted to ensure that each sector in a part with $I_{rp} = g$ has $g$ vehicles covering it through selecting more segments using the same selection procedures until satisfying each sector’s redundancy requirement, as long as the budget constraint allows for it. The algorithm targeting maximizing coverage with minimum overlap (RBMC-MO) contradicts with this redundancy objective so they cannot be combined.

We remark that the case with redundancy and probability of vehicles leaving is a straightforward extension.

### 4.3.5 Data Acquisition Models

When collecting data, smart vehicles can follow different models for data acquisition. We consider two models: solicited and unsolicited. These two models differ in when data is generated.

**A) The Solicited Model**

In this model, data acquisition is done on-demand upon a request from an SP. While on the go, vehicles receive requests for sensing tasks. Based on the availability of resources at that moment, the application installed on the on-board unit of the vehicle can decide if the vehicle is ready to participate or not (i.e., accepting the sensing request or declining it). This type of handling sensing tasks without intervention from the driver or any of the vehicle’s occupants falls under the “opportunistic”
In addition to handling service requests initiated by an SP, this model can also handle requests initiated by a data consumer through an SP.

**B) The Unsolicited Model**

In this model, vehicles sense their surroundings, collect data, and store it without being tasked. When an SP needs some information about an area of interest, the provider can check which vehicles have data stored about that area. After selecting the data holders, the SP informs them to send the stored data. This model can involve some sort of advertisements by vehicles about the data they carry. Such advertisements can be handled by metadata that describes the actual data and lists some of its features (e.g., when and where they are generated).

The unsolicited model is only suitable for the delay-tolerant services that allow storing data and reporting it at a later time. An example of such services is using vehicles for monitoring road conditions.

It is worth mentioning that the proposed RTR framework supports these two data acquisition models. In the solicited model, the trajectories considered for recruitment are those that vehicles are supposed to follow and can be retrieved from the navigation software. For the unsolicited model, the trajectories are those that vehicles have already traversed and stored sensed data.

**4.4 Reputation Assessment and Access Pricing**

In this section, we present our reputation assessment scheme and pricing model that are responsible for computing a reputation score and a recruitment cost for each
participating vehicle, respectively. These parameters are used by the selection module as discussed in the previous section.

4.4.1 Reputation Assessment

In assessing the reputation of a participant, the data acquisition model controls the metrics used for assessment and computing a reputation score. In the following, we delineate how the reputation score can be computed for each participant according to the data acquisition model to be used.

A) Reputation Assessment in the Solicited Model

Since in the solicited model data will be collected after the participant gets tasked, the computed reputation score will help in anticipating the behavior of the participant and the quality of the reported data. The score will be used in the selection process as the expected reputation of the participant.

1) Computing the Reputation Score

We adopt the Beta reputation system [74] for computing a reputation score, $r$, for each candidate participant. The Beta system is used in reputation and trust management systems for computing reputation/trust scores for a set of trustees by a centralized truster interacting with them. Details of the Beta system is discussed in Appendix A. In our reputation assessment scheme, we consider the truster to be the SP responsible for the recruitment process and the trustees to be the candidate participants.

As detailed in Appendix A, the use of the Beta system for computing a reputation score for a participant involves computing two variables $x$ and $y$ representing the
number of past successful interactions and unsuccessful interactions with this participant, respectively. The system’s main parameters $\alpha$ and $\beta$ are computed based on the $x$ and $y$ values according to Eq. A.2. Then, the reputation score is computed as the expectation of the Beta distribution of the computed $\alpha$ and $\beta$, as in Eq. A.3.

In the aforementioned approach, statistical values are used for computing $x$ and $y$. Another approach that is discussed as well in Appendix A and can be used for such a computation involves considering the assessment of a participant after an interaction with the SP with $x$ representing the degree of satisfaction of the SP and $y$ representing the degree of dissatisfaction. To consider the first approach in our scheme, we have to classify past interactions with a participant into successful and unsuccessful ones. This can be handled through setting a performance threshold for deciding on the success of an interaction. This approach is binary and does not give a precise distinction of degree of success. Therefore, we opt to consider the second approach in our scheme. Instead of providing the $x$ and $y$ assessment values separately, we adopt the alternative detailed in Appendix A for providing the per-interaction assessment as a single value $v$ in the [0,1] range. Then, the $x$ and $y$ values can be computed according to Eq. A.4. Providing the per-interaction assessment as a single value is more appealing to the practical models.

The following summarizes the basic procedure followed by our reputation scheme under the solicited model. After an interaction with a participant $i$, the SP computes a per-interaction assessment, as discussed later, and plugs the assessment value $v_i$ into Eq. A.4 for computing the $x_i$ and $y_i$ parameters with considering the weight $w$ to be 1. These parameters are used for computing $\alpha_i$ and $\beta_i$ according to Eq. A.2. An expectation of the score, $E(p)_i$, can be computed according to Eq. A.3. Then,
the expected score is used as the participant’s reputation score after normalizing it to be in the [0,1] range as shown in Eq. 4.9.

\[ r'_i = [E(p)]_{\text{norm}} = \frac{E(p)_i - \min(E(p))}{\max(E(p)) - \min(E(p))} \]  

(4.9)

In the aforementioned basic operation, only the last interaction with a participant is used for computing the reputation score. Ignoring the historical information (i.e., the past contributions) may be misleading if the participant has an uncommon performance in the latest interaction. In our scheme, we consider the last \( n \) interactions with a participant for computing his/her reputation score. If the SP has encountered more than \( n \) interactions with that participant, a sliding window of length \( n \) will be considered when the score has to be updated after an interaction with that participant. For each interaction, the assessment value \( v \) is computed followed by the computation of the corresponding \( x \) and \( y \) parameters. The aggregated \( x \) and \( y \) values of the \( n \) interactions are computed as in Eq. A.5. Then, the \( x_{ag} \) and \( y_{ag} \) are used for computing \( \alpha_{ag} \) and \( \beta_{ag} \) according to Eq. A.2 which are used for computing \( E(p)_{ag} \) as in Eq. A.3. The final reputation score to be considered in the recruitment process is computed as follows for participant \( i \)

\[ \text{reputation score}(r_i) = [E(p)_{ag}]_{\text{norm}} \]  

(4.10)

where \([E(p)_{ag}]_{\text{norm}}\) is \( E(p)_{ag} \) of participant \( i \) normalized to the [0,1] range using Eq. 4.9.
2) Per-interaction Assessment

A participant’s reputation score in the solicited model is computed based on per-interaction assessments as previously discussed. In this part, we discuss how the per-interaction assessment is handled and define the different metrics that are used for computing the assessment value \((v)\).

The per-contribution assessment value is computed based on three main metrics: 

a) Participation Commitment, b) Quality of Information (QoI), and c) Trust Level.

The first two main metrics involve underlying sub-metrics as delineated below and shown in Figure 4.6.

a. Participation Commitment:

For assessing the commitment of a participant, two metrics can be considered as follows.

- The confidence of sticking to the announced trajectory (CoT): It may happen that a participant does not stick to the trajectory announced to the SP either intentionally or because of an unexpected sudden detour. For a contribution \(j\) by

![Figure 4.6: The reputation metrics used in the solicited model.](image-url)
participant $i$, this metric can be assessed as a binary variable as shown below:

$$CoT_i^j = \begin{cases} 
1 & \text{if } i \text{ traversed the whole announced trajectory} \\
0 & \text{if } i \text{ did not stick to the whole announced trajectory}
\end{cases}$$

(4.11)

- The willingness to participate (WP): We represent a participant’s willingness as the number of times that participant has participated in an evaluation period, $e_{prd}$, ending with that last interaction (e.g., $e_{prd}$ can be a 1 month period). This number is then normalized to be in the $[0,1]$ range taking into consideration the values achieved by the other candidate participants. Let the date of an interaction $j$ to be $Dt_j$, the value of the willingness metric of participant $i$ performing $j$ can be computed as

$$WP_i^j = \left[ \frac{\text{no. of participations}_i^{Dt_j - e_{prd}}}{\text{normalization}} \right]$$

(4.12)

The values of these two metrics are combined using a weighted additive utility function to compute the participation commitment, $P$, of a participant $i$ after a contribution $j$, as follows

$$P_i^j = w_1^P \times CoT_i^j + w_2^P \times WP_i^j$$

(4.13)

where $w_l^P$ is the weight of each metric such that $\sum_{l=1}^{2} w_l^P = 1$.

b. Quality of Information (QoI)

We consider three metrics that can give a valuation of the quality of the reported information by a participant performing an interaction.

- Timeliness (TM): Timeliness represents how promptly a participant sends the required information after getting assigned a sensing tasks. The timeliness value is
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the highest when the reply is promptly sent after the task assignment. Let the reply time be \((T_r)\), the task assignment time be \((T_a)\), and the task duration be \((t_{dr})\). The timeliness value is at its maximum when the difference between \(T_r\) and \(T_a\) \((dif_t)\) is almost 0 and it decreases exponentially as that time difference increases. We use the inverse Gompertz function, shown in Figure 4.7, to evaluate timeliness as its shape is compatible with the timeliness evolution discussed above. The lower asymptote of the general inverse Gompertz function is 0 and the function approaches it in infinity. In our case, we need the function to reach 0 when \(dif_t\) exceeds \(t_{dr}\) as that means the reported information is useless. In short, we can measure the timeliness value of the information reported by participant \(i\) in interaction \(j\) using the inverse Gompertz function if \(dif_t\) does not exceed \(t_{dr}\), and assign it 0 otherwise. This is summarized in Eq. 4.14.

\[
TM_i^j(dif_t) = \begin{cases} 
    ae^{b(e(dif_t))} & \text{if } dif_t \leq t_{dr} \\
    0 & \text{otherwise}
\end{cases}
\quad (4.14)
\]

The parameter \(a\) of the inverse Gompertz function represents the higher asymptote which is equal to 1 in our case since the maximum of the Timeliness value is

![Figure 4.7: An example of an inverse Gompertz function with \(a = c = 1\) and \(b = 2 \times 10^{-4}\) for \(t_{dr} = 10\).](image)
1. The parameters $b$ and $c$ represent the displacement on the x-axis and the decay rate, respectively. We need the function to be as close to 0 as possible at $diff = t_{dr}$. This fact directs the assignment of the parameters $b$ and $c$. By assigning $c$ the value 1, the value of $b$ that lets $TM^j_i(diff)$ close to 0 (let it be 0.01) at $diff = t_{dr}$ can be computed as follows

$$b = \frac{-\ln(0.01)}{e^{t_{dr}}}$$

(4.15)

It is worth noting that the ability of adjusting the shape of the function through parameters can help in handling the delay requirements of the different applications to be supported by the framework. The nature of the application and its delay requirements control the assignment of the task duration value which, in turn, controls the assignment of the parameter $b$ and the computation of the timeliness metric.

- **Relevance (RL)**: Relevance of the reported information to the sensing task can be spatial, temporal, or both. The spatial relevance ($S_{RL}$) measures the portion of the reported information that spatially fits in the area of interest declared in the sensing task. Per a participation report, it can be computed as the length of the covered area overlapping with the area of interest ($l_{overlap}$) to the total length of the covered area ($l_{total}$). This computation is shown in Eq. 4.16 for information reported by participant $i$ in interaction $j$. The temporal relevance ($T_{RL}$) measures the portion of the reported information that timely fits in the task interval ($t_{inter}$). Considering the start and end times of the reported information, it can be computed as the length of the reporting duration overlapping with $t_{inter}$ ($r_{dr_{overlap}}$) to the total length of the reporting duration ($r_{dr_{total}}$). We show this computation in Eq. 4.17 for information reported by participant $i$ in interaction $j$. For computing the spatiotemporal relevance, which is the value that represents our RL metric, we
multiply the $S_{RL}$ and $T_{RL}$ values, as shown in Eq. 4.18.

\[
S_{RL_i}^j = \frac{l_{overlap_i}^j}{l_{total_i}^j}
\]  

(4.16)

\[
T_{RL_i}^j = \frac{r_{dr_overlap_i}^j}{r_{dr_total_i}^j}
\]  

(4.17)

\[
RL_i^j = S_{RL_i}^j \times T_{RL_i}^j
\]  

(4.18)

- **Quality of Resources (QR)**: For assessing this metric, a hashtable can be created with a record for each brand model and a corresponding weight based on its features and manufacturing year.

The values of these three metrics are also combined using a utility function as shown in Eq. 4.19 to compute the QoI, $Q$, reported from a participant $i$ after a contribution $j$, per

\[
Q_i^j = w_1^{QS} \times TM_i^j + w_2^{QS} \times RL_i^j + w_3^{QS} \times QR_i^j \quad \text{where} \quad \sum_{l=1}^3 w_l^{QS} = 1
\]  

(4.19)

c. **Trust Level**

The trust level (TL) main metric measures how much a candidate participant is reliable and can be trusted to perform a task. Some participants may behave deceitfully seeking to maximize their own gains. Other malicious participants may provide incorrect data with the purpose of degrading/misleading the service to be provided. This metric is used to detect and disqualify such malicious/untrustworthy participants. Many techniques can be used to measure the TL value of a participant after an interaction. These techniques vary based on the nature of the task that participant has performed and is being assessed after, and the type of sensors used. For example, if
the task involved using the on-board camera for capturing on-road images or videos, the viability and correctness of these images/videos provided by the participant can be evaluated using feature matching algorithms that depend on image processing to measure the degree of feature matching between past images of the road/object defined in the sensing task and the images/videos of this road/object captured by the participant. This degree of matching is an indicator of the participant’s reliability and can be used as his/her TL. Other sensing tasks may involve reporting raw sensing data such as traffic volume and pollution levels. In such cases, the reported value can be compared to the range of expected values computed based on the average of past values. The degree of closeness to the expected range can represent the TL of the reporter. Regardless of the used evaluation technique, the computed TL value should be normalized to the $[0,1]$ range before plugging it into Eq. 4.20 of our assessment scheme.

Finally, the per-interaction assessment, $v$, of a participant $i$ after a contribution $j$ is computed by combining the participation commitment ($P^j_i$), the QoI ($Q^j_i$), and the trust level ($TL^j_i$) using the following additive utility function

$$v^j_i = w_{v1} \times P^j_i + w_{v2} \times Q^j_i + w_{v3} \times TL^j_i$$

where $\sum_{l=1}^{3} w_{vl} = 1$ (4.20)

B) Reputation Assessment in the Unsolicited Model

Computing reputation scores in the unsolicited model primarily depends on the advertised metadata that gives an insight to the quality of the to-be-retrieved data.

1) Computing the Reputation Score

Two main metrics can be used for assessing the reputation in the unsolicited model:
a) Quality of Information (QoI) and b) Trust Level (TL). The QoI metric involves underlying sub-metrics as shown in Figure 4.8. The participation commitment metric considered in the solicited model is not needed here since the participant has already sensed the data and there is no probability of not committing to a sensing request.

The assessment needed for computing a reputation score for a participant involves two parts: pre-interaction and post-interaction. Since the data to be collected has been already measured, the evaluation of the QoI main metric and its sub-metrics is handled using a pre-interaction assessment before selecting the participants based on the features of the data they advertised holding and the features of the data holding vehicles themselves.

The post-interaction assessment is done by the SP pro-actively after each interaction with a participant to compute his/her TL. These post-interaction assessments are utilized for computing an expected TL value for a participant to be combined with the computed value of the QoI metric corresponding to the data advertised by that participant, resulting in a reputation score to be considered in the selection of the data advertised by that participant. The aggregation of the past TL post-interaction assessments for computing the expected TL value is handled using the Beta system.

![Figure 4.8: The reputation metrics used in the unsolicited model.](image-url)
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using the same steps detailed in the system use in the solicited model.

After computing the expected TL value of participant $i$ ($TL_i$) and the QoI of the data advertised by that participant ($Q_i$), the SP combines these two values using an additive utility function to compute the reputation score of that participant ($r_i$) to be considered in the selection process. This computation is shown below.

$$r_i = w_{r1}^* \times Q_i + w_{r2}^* \times TL_i \quad \text{where} \sum_{l=1}^{2} w_{rl}^* = 1$$ (4.21)

In the following we detail how the pre-interaction and post-interaction assessments are handled.

2) Pre-interaction Assessment

This assessment is used for computing the QoI value of the data advertised by a participant right before considering him/her in the selection process. The two metrics we use for computing the QoI value are the freshness of the advertised data and the holding vehicle’s quality of resources.

- **Freshness (FR)**: The freshness metric is needed since the target is to collect measured and stored information. Let the information acquisition time be $T_q$ and the time of information collection by the SP be $T_c$. Freshness evaluates how recent this measured information is such that the minimal the difference between $T_c$ and $T_q$ ($diff$) is, the higher the freshness value is. The freshness value reduces as $diff$ increases.

We also use the inverse Gompertz function to represent the freshness evolution and evaluate its value. The information to be considered is bounded by a time window with length ($w_{len}$) such that if $diff$ exceeds $w_{len}$, the information is useless and its freshness value is assigned 0. Eq. 4.22 summarizes how the freshness value of the
4.4. REPUTATION ASSESSMENT AND ACCESS PRICING

information hold by participant $i$ is computed.

$$FR_i(dif_f) = \begin{cases} \ \ae^{-be^{(dif_f)}} & \text{if } dif_f \leq \text{w_len} \\ \ 0 & \text{otherwise} \end{cases}$$  \hspace{1cm} (4.22)

with having $a = c = 1$ and $b$ computed as in Eq. 4.15 replacing $t_{.dr}$ with $w_{.len}$.

- The Quality of Resources (QR) can be computed as discussed under the solicited model.

The values of these two metrics are combined using a utility function as shown in Eq. 4.23 to compute the QoI ($Q_i$) of the data advertised by participant $i$.

$$Q_i = w_1^{QU} \times FR_i + w_2^{QU} \times QR_i \quad \text{where } \sum_{i=1}^{2} w_i^{QU} = 1$$  \hspace{1cm} (4.23)

3) Post-interaction Assessment

This assessment is used for computing a TL value of a participant after an interaction. The TL metric is used for the same purposes aforementioned under its use in the solicited model; yet, different techniques of measuring the TL value of a participant can be used. Since the unsolicited model involves advertisements of the carried data through metadata, a matching evaluation can be used that involves comparing the advertisement metadata ($adv.meta$) received by the SP and corresponding metadata extracted from the received data ($rec.meta$). A similarity function $f_{sm}(adv.meta, rec.meta) \rightarrow s$ can be used for such a comparison resulting in a similarity score $s$, in the $[0,1]$ range, representing the matching between $adv.meta$ and $rec.meta$. The similarity score $s$ is an indicator of the reporter reliability and
can be used as his/her TL as summarized in Eq. 4.24 for participant $i$ after an interaction $j$. Many similarity functions are proposed in the literature for data matching in semantic web and data management applications, with the simple string matching being the basic form [75].

$$TL_i^j = s = f_{sm}(adv_{meta}, rec_{meta})$$

The $TL_i^j$ is mapped to the $v_i^j$ value to be plugged into Eq. A.4 of the Beta system to initiate its operation targeting computing the expected $TL_i$ value.

### 4.4.2 Pricing Model

Taking reputation into consideration along with participant availability, a dynamic pricing model can be adopted with participant rewards based on their computed reputation score. Reward/price assigned to each participant is proportional to distance traversed (a measure of availability) as well. We compute a participant price $pr_i$ which, in turn, is the cost $c_i$ incurred by the SP for recruiting participant $i$, as follows

$$c_i = C_{init} + (C_m \ast d_i \ast r_i)$$

where $C_{init}$ is a constant initial reward paid to incentivize participants, $C_m$ is a constant cost per meter determined by the SP, $d_i$ and $r_i$ are the covering distance (in meters) and reputation score of participant $i$, respectively, for $1 \leq i \leq N$, where $N$ is the number of potential participants.

For flexibility of implementation, the rewards and costs are represented as a number of tokens that can be mapped to any form of incentives by the SP.
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It is worth mentioning that the operation of the recruitment framework is generic and is not restricted to the use of the presented assessment scheme and pricing model.

4.5 Performance Evaluation

In this section, we present numerical results of the proposed RTR selection scheme comparing both the ILP optimization and greedy heuristic solutions with the two main recruitment objectives: 1) maximum coverage with minimum overlapping (which we refer to as MinOverlap in the ILP and RBMC-MO in the heuristics) and 2) maximum coverage with minimum cost (which we refer to as MinCost in the ILP and RBMC-MC in the heuristics). The results of the ILP optimization represent upper bounds of the budgeted reputation-aware recruitment that can be achieved. In addition, to show the gain achieved through the multi-objective recruitment, we compare the solutions to a solution targeting only the maximum coverage (which we refer to as MaxCov in the ILP and RBMC in the heuristics). The solutions are compared in terms of the ratio of the achieved coverage, the fraction of the overlapped coverage to the total length of the obtained covering set, and the total recruitment cost. Also, we study the effect of changing the reputation threshold $R_{Th}$ while keeping the density of vehicles fixed through comparing the three heuristic solutions.

In addition to the aforementioned evaluation metrics, we consider two more metrics that show the quality of the sensed data collected by the selected participants. The first metric is the amortized quality index (AQI) indicating the overall quality of sensing averaged over the selected group of participating vehicles. The AQI is computed as the average QoI, $\text{avg}(Q_i)$, of the selected participants. The second metric is the trustworthiness index (TI) that indicates the level of trust in the viability and
4.5. PERFORMANCE EVALUATION

The correctness of the collected data over the selected vehicles. The TI metric is computed as the average of $[QR_i \times TL_i]$ of the selected participants.

We also assess the coverage achieved by the RTR selection scheme with probability of vehicles leaving their announced trajectories through evaluating the RBMC solution considering this probability with different ranges of the degree of confidence $D_i$.

All the shown results represent the average results of running the algorithms for 1000 rounds per comparison.

4.5.1 Implementation Setup

We use Gurobi 5.6.3 [76] to solve the ILP optimization formulation with Matlab as a simulation environment. The greedy heuristic algorithms are implemented in C++. We simulate an area of interest of 5kms divided into 100 road sectors, each is 50 meters long. The vehicular trajectories are randomly generated within that area of interest. $C_{\text{init}}$ is set to 1, $C_m$ is set to 0.01, and $R_{Th}$ is set to 0.5.

We consider the reputation assessment under the solicited model since the assessment under the unsolicited one is much simpler. Our reputation assessment scheme is applied to compute a reputation score $r_i \forall i \in S$. For each participant $i$, the $CoT_i$ metric is assigned the value 1 as we do not assume a probability of leaving in the basic comparisons. The $WP_i$, $TM_i$, $RL_i$, and $TL_i$ values are randomly generated in the $[0,1]$ range. The QoR hashtable has 10 records each associated with a value in the $[0.5,1]$ range. The values of the participation commitment ($P_i$) and QoI ($Q_i$) metrics are then computed based on Eqs. 4.13 & 4.19, respectively. The per-interaction assessment value ($v_i$) is computed based on Eq. 4.20. Equal weights are given to the
underlying metrics in each utility function. The final reputation score \( r_i \) is computed using the Beta reputation system as discussed in part 4.4.1-A. We consider only one interaction in computing the reputation score \( n = 1 \) for simplicity since considering more past interactions will not affect the overall performance comparison. We apply our pricing model to compute \( c_i \) according to Eq. 4.25 \( \forall i \in S \).

4.5.2 Numerical Results and Analysis

For the comparison between the ILP and heuristic solutions, we first compare them in terms of the first three metrics with a budget cap that allows for achieving full coverage to the area of interest (\( B \) is set to 100). Figure 4.9 shows the results of this comparison for various densities of vehicles (number of vehicles per area of interest). In terms of the ratio of achieved coverage, Figure 4.9(a) shows that all the solutions achieve the same coverage ratio as they all work on achieving the maximum coverage that can be provided by the set of available trajectories without restrictions on the number of chosen trajectories since the budget cap allows for that. With increasing the vehicle density, the proposed solutions succeed in achieving better coverage since the opportunity that more sectors have vehicles passing by increases. Comparing the solutions in terms of the fraction of overlapping, as expected, the RBMC-MO solution gives the best results among the three heuristic solutions as shown in Figure 4.9(b) with a reasonable difference compared to the bound of the ILP MinOverlap. The RBMC-MC solution improves on the basic RBMC one since while it is trying to minimize the cost, it may avoid segments with long overlapping as opposed to the RBMC that does not consider either the cost or overlapping. The same reasoning applies to the comparison between MinCost and MaxCov. In Figure 4.9(c), the solutions are
4.5. PERFORMANCE EVALUATION

(a) Ratio of coverage with varying densities.

(b) Fraction of overlapping with varying densities.

(c) Total recruitment cost with varying densities.

Figure 4.9: Performance results with $B = 100$ and full coverage can be achieved.
4.5. PERFORMANCE EVALUATION

compared in terms of the total recruitment cost with the RBMC-MC solution achieving the best performance compared to the other two heuristic solutions and with a slight increase to the lower bound achieved by the ILP MinCost. RBMC-MO works better than RBMC and MinOverlap works better than MaxCov in terms of the cost because minimizing overlapping may implicitly lead to reducing the cost.

Second, we perform the same comparison but with a strict budget cap that only allows for achieving partial coverage (B is set to 30). Results are shown in Figure 4.10. In terms of the achieved coverage ratio, Figure 4.10(a) shows that the RBMC-MC solution succeeds in achieving higher coverage than the RBMC-MO and the basic RBMC. The reason is that while RBMC-MC selects a trajectory/vehicle, it tries to minimize the recruitment cost so it manages to recruit more vehicles; hence, achieving higher coverage using the same limited budget cap. The three ILP solutions achieve the same coverage ratio as the ILP formulation computes the maximum available coverage in the first stage which is common in the three solutions. In the second stage of the MinOverlap and MinCost solutions, it picks the best trajectory set achieving this maximum coverage in terms of the recruitment objective. The optimal coverage achieved by the ILP solutions is slightly higher than the best coverage achieved by the heuristic solutions through RBMC-MC. Among the three heuristic solutions, RBMC-MO is the best in terms of the fraction of the overlapped coverage as shown in Figure 4.10(b). The effect of having budget limits can be seen in the lower improvements achieved while increasing the number of trajectories compared to the improvements shown in Figure 4.9(b). This can be obvious comparing the performance in the vehicular densities of 300, 400, and 500. The reason is that even with increasing the selection options by increasing the number of vehicles, many of these options cannot
4.5. PERFORMANCE EVALUATION

(a) Ratio of coverage with varying densities.

(b) Fraction of overlapping with varying densities.

(c) Total recruitment cost with varying densities.

Figure 4.10: Performance results with $B = 30$ and only partial coverage can be achieved.
be considered due to the limited budget that restricts the selection process. The higher coverage achieved by the MinOverlap and MaxCost solutions explains why they are encountering higher fractions of overlapping compared to their RBMC-MO and RBMC counterparts. In terms of recruitment cost, we can see in Figure 4.10(c) that all the solutions incur almost the same total recruitment cost as they all try to achieve their objectives within the budget limits so their total recruitment cost will always be close to the budget cap.

We study the effect of changing the reputation threshold $R_{Th}$ on the total recruitment cost while keeping the density of vehicles fixed (200 vehicles per the 5km area). We compare the performance of the three heuristic solutions with different values of $R_{Th}$. As expected, Figure 4.11 shows that with increasing $R_{Th}$, the total recruitment cost increases and the three solutions converge because they all get restricted to very limited options which are the vehicles with $r_i$ above the threshold.

Figure 4.12 shows the results related to the AQI metric. In Figure 4.12(a), we show the effect of increasing the reputation threshold on both the ratio of coverage and the AQI considering the RBMC algorithm with different densities (100, 300, 500

![Figure 4.11: Total recruitment cost with varying reputation thresholds.](image)
vehicles per the area of interest). We can see that with increasing the reputation threshold, the ratio of coverage decreases due to the decrease in the number of candidate participants, while the AQI increases resulting in a tradeoff. As expected, in RBMC, changing the vehicular density has no effect on the AQI value. On the contrary, we can see in Figure 4.12(b) that in the RBMC-MC algorithm, the AQI value decreases with increasing the vehicular density while maintaining the same reputation threshold. The reason is that the RBMC-MC algorithm works on minimizing

(a) The tradeoff between the AQI and coverage with varying reputation thresholds.

(b) The tradeoff between the AQI and coverage in RBMC-MC with varying densities.

Figure 4.12: The tradeoff between the AQI and ratio of coverage.
4.5. PERFORMANCE EVALUATION

cost. Increasing the vehicular density results in the selection of less expensive options which are linked to participants having lower reputation resulting in lower AQI. Apparently, with increasing the density, the ratio of coverage increases resulting in a tradeoff between the AQI and coverage in this case as well. Figure 4.12(b) shows these results for different reputation thresholds (0.3, 0.5, and 0.7). We highlight that the change in the vehicular density does not affect the AQI achieved through the RBMC and RBMC-MO algorithms since having more selection options for these algorithms does not affect the average of the selected participants’ reputation if the reputation threshold is kept the same.

The results involving the TI metric are shown in Figure 4.13. The same discussion related to the AQI metric applies to the TI metric. Figure 4.13(a) shows that there is a tradeoff between the ratio of achieved coverage and the TI value of the covering set with changing the reputation threshold. Figure 4.13(b) shows that the same tradeoff is maintained under the RBMC-MC algorithm while changing the vehicular density.

Finally, we assess the coverage achieved by the RTR selection with probability of vehicles leaving their announced trajectories. In Figure 4.14, we present the assessment results obtained with four ranges of $D_t$ considering different densities of vehicles available in the area of interest. The results show that, in a dense environment (400-500 vehicles in the 5km area), even with low values of $D_t$ (high probabilities of a vehicle not sticking to its trajectory), our scheme achieves a high coverage ratio based on the fact that the scheme includes sufficient vehicles in the covering set to compensate for probabilities of leaving which enhances the reliability of our framework. In a sparse environment (100 vehicular densities), the achieved coverage ratio is lower because of the non-sufficient availability of covering vehicles. We remark
4.6. SUMMARY

(a) The tradeoff between the TI and coverage with varying reputation thresholds.

(b) The tradeoff between the TI and coverage in RBMC-MC with varying densities.

Figure 4.13: The tradeoff between the TI and ratio of coverage.

that both RBMC-MO and RBMC-MC with probability of leaving, and RBMC with redundancy and probability of leaving are straightforward extensions.

4.6 Summary

In this chapter, we proposed the reputation-aware, trajectory-based RTR framework for recruiting vehicles for public sensing services. The framework utilizes the spatiotemporal availability of participants and their reputation to select a set of vehicles
that achieves coverage of an area of interest with a budget cap. We proposed a reputation assessment scheme and a pricing model as parts of the framework that are used to feed the third proposed module, the selection scheme, with a reputation score and a recruitment cost of each candidate participant to start the selection process. We formulated the selection problem as an ILP optimization problem for two different recruitment objectives: maximizing coverage with minimum overlapping and maximizing coverage with minimum cost. We presented greedy heuristic solutions that handle the aforementioned recruitment objectives for real-time services. The RTR framework generalizes the basic selection case to some practical cases that an SP faces during the recruitment process such as probability of a vehicle not sticking to its announced trajectory and having redundancy requirements at certain parts of an area of interest. The performance evaluation results showed that the proposed greedy heuristics achieve results close to the optimal benchmarks and succeeds in efficiently handling cases with high probabilities of vehicles not sticking to their trajectories.
Chapter 5

Caching-Assisted Access for Vehicular Resources

5.1 Introduction

Utilizing vehicular resources for providing sensing-based services is very promising in terms of the wide scope of applications that can be provided. Such access for vehicular sensing resources faces two major concerns. The resource owners need to get rewarded each time their resources are accessed which brings forward an access cost challenge. Also, when data is needed from a specific area of interest, a sensing request needs to be forwarded towards that area which imposes an access delay challenge. In this chapter, we present a solution that handles the aforementioned access concerns through applying caching on the delivery path of the service data (i.e., caching the collected sensing data needed for providing the service).

Our argument is that caching of collected data somewhere on the road helps in resolving later interests in similar data without having to access vehicular resources again. In addition, bringing the data of interest closer to the requesters through
5.1. INTRODUCTION

Caching aids in reducing the access delay. In this chapter, we propose a caching-assisted data delivery (CADD) scheme that depends on utilizing caching spots deployed on the road for assisting in collecting vehicular data and providing vehicle-based information services.

Some data delivery schemes that utilize assistance from road-side entities are available in the literature. These schemes depend on utilizing powerful RSUs for forwarding assistance without caching consideration. These RSUs can be adjusted and utilized for supporting the proposed caching concept; however, the cost of ubiquitous deployment will be high since the off-the-shelf RSU models available are not inexpensive. As a solution, we propose the use of a simple, light-weight device that can complement RSUs when ubiquitous RSU deployments are not feasible. Having only the components needed for forwarding and caching assistance, our proposed road caching spot (RCS) is lower-priced than an RSU.

As a default caching mechanism in caching-assisted schemes, ubiquitous caching is used for caching every packet everywhere. Apparently, this mechanism is not efficient and other caching mechanisms are proposed to solve its inefficiency [77]. One approach gaining popularity is the centrality-based caching approach [78] which aims at finding a subset of caching nodes that are the most central nodes in the network and directing caching to these nodes as these are the spots that are more likely to get many interests passing by and hence, more cache hits. Unfortunately, most of the caching mechanisms utilizing this approach use static computations for the centrality values as they target networks with static topologies such as the Internet backbone. As a vehicular network is dynamic in nature, such mechanisms cannot fit in our scheme. Therefore, we propose a dynamic centrality-based caching mechanism as part of the
proposed CADD scheme. Another feature of the proposed mechanism is considering data popularity in cache replacement, favoring data types with more interests from end users. As well, in cache replacement, the proposed mechanism works on giving the to-be-replaced data chunk another caching opportunity instead of dropping it as commonly followed by other caching mechanisms.

In addition to being caching-assisted, the proposed data delivery scheme is heading-aware in the sense that vehicles carrying packets to be forward check at intersections whether they are heading towards the packet destination or not. If a vehicle finds that it is heading away from the destination and it has no potential neighboring vehicle to forward the carried packet to, it seeks forwarding assistance from the neighboring RCS by offloading the packet to that RCS giving it a better delivery chance. Taking vehicles’ headings into consideration improves the data delivery ratio and lowers the delivery delay through saving the carried packets from going away from their destinations.

We evaluate the performance of the proposed CADD scheme using the NS-3 simulator and compare it to the popular store-carry-forward (SCF) mechanism with no road-side assistance. In addition, we mathematically compare CADD to a scheme with inter-connected RSUs. As well, we present an assessment mathematical model to compute the estimated delay to reach an AoI from a considered gateway providing a means for assessing the scheme performance in a considered region.

To the best of our knowledge, CADD is the first data delivery scheme that considers caching-assistance from road-side entities to support location-based vehicular information services.

The remainder of this chapter is organized as follows. In Section 5.2, we discuss
some related work on roadside-assisted data delivery for VANETs, vehicular data gathering schemes, and data caching. We present the proposed CADD scheme in Section 5.3 including the caching mechanism. In Section 5.4, we present the performance evaluation of the scheme and the assessment results. We highlight some practical considerations related to the operation of the proposed scheme in Section 5.5. Finally, we conclude the chapter in Section 5.6.

5.2 Related Work

5.2.1 Roadside-assisted Data Delivery for VANETs

Among the various VANET data delivery schemes available in the literature [59][60][61], some are proposed with roadside-assistance to enhance the forwarding performance. All these schemes utilize assistance from RSUs deployed at intersections. Some of these schemes depend mainly on multi-hop V2V, V2I, and I2V communication for forwarding [79] [80], and others assume that RSUs are inter-connected through the Internet and utilize that for delay-critical forwarding [81] [82].

One of the early schemes proposed under the former category is the Roadside-Aided Routing (RAR) scheme [79]. RAR partitions the geographical area of interest into closed sectors formed by RSUs at the borders of each sector. A routing protocol is involved to manage exchanging packets among vehicles in different sectors through RSUs. One of the drawbacks of RAR is that it requires deployment of a large number of RSUs to form sectors, which in a practical sense, is not feasible. In addition, RAR requires the use of an affiliation protocol associating vehicles to sectors which increases its complexity. Another example is the Static-node assisted Adaptive (SADV)
routing protocol [80] that utilizes RSUs at intersections for reducing the delivery delay. In SADV, a data packet can be stored at an RSU until a forwarding vehicle is encountered on the best delivery path for expedited forwarding. By obligating packet transmissions to be only through the best delivery path, SADV improves the data delivery performance. However, in deciding on the best path, SADV depends mainly on the vehicular density ignoring vehicle’s headings which may lead to directing packets away from their destinations.

An example of the latter category is the Infrastructure-Assisted Geo-Routing scheme [81] that utilizes inter-connectivity of RSUs for improved end-to-end performance through reducing the number of hops and, hence, the delivery delay. Another example is the Infrastructure-Assisted Routing scheme proposed in [82] that follows the same concept proposed in [81] with the focus being on the RSUs buffer allocation and management challenges.

Although the aforementioned schemes succeed in achieving performance improvements, they build on an assumption of having a ubiquitous RSU deployment. As mentioned earlier, existing RSU models are expensive and, therefore, do not readily support such ubiquitous deployments. In addition, the assistance sought from RSUs in these schemes is only for forwarding purposes without caching considerations. Besides, these schemes do not take vehicles’ headings into account, which leads to eventual packet dropping and long delays. Our proposed CADD scheme tackles these limitations through the introduction of the lower-priced RCS and using it for both caching and forwarding assistance in a heading-aware manner.
5.2. RELATED WORK

5.2.2 Vehicle-based Data Gathering

Some platforms and schemes are proposed in the literature to utilize the resources of vehicles for gathering on-road data on-demand and handling interest and reply dissemination. The Vehicular Information Transport Protocol (VITP) [83] is proposed for the retrieval of vehicular information over VANETs through directing queries to areas of interest and retrieving resolved replies with both query and reply dissemination being handled by intermediate vehicles via multi-hop communication. VITP is only responsible for specifying the syntax and semantics of messages carrying location-dependent queries and replies between the nodes of a VANET. It works independently of the underlying VANET transmission and routing protocols.

Unlike VITP, the Delay-Bounded Vehicular Data Gathering (DB-VDG) solution [38] supports geographical vehicle-based data gathering services with taking into consideration the routing of query and reply messages. DB-VDG depends on vehicles as mobile sensors and data relays, and on a fixed base station to create queries and collect replies back. Based on a delay-bound, vehicles in DB-VDG decide on either forwarding the packets immediately or carrying them while moving aiming at reducing the communication overhead and aggregating data from multiple sources.

Although the aforementioned solutions share with the proposed CADD scheme its basic target of accessing the vehicular sensing resources, they include very simplistic data gathering mechanisms that do not take the access cost into consideration.

5.2.3 Data Caching

Different data caching mechanisms have been proposed in the literature to handle, for instance, the web caching [84] and information-centric network (ICN) caching
5.2. RELATED WORK

[77] components. Examples of such mechanisms include the ubiquitous, probabilistic, and centrality-based caching. Among the aforementioned mechanisms, centrality-based caching has proven to be highly efficient in terms of cache hits with reasonable storage requirements [78]. Unfortunately, the centrality-based caching mechanisms proposed in the literature are designed for use in networks with static topologies, mainly the Internet. For example, the betweenness centrality-based caching mechanism [78] computes a node’s centrality value as the number of times that node lies in the set of shortest paths between all pairs of nodes in the network, with the argument that if a node lies in many delivery paths, it is more likely to experience a cache hit. Apparently, this approach cannot be applied directly to a dynamic network such as a VANET. Therefore, there is a need for a mechanism that utilizes this centrality-based concept with support for highly dynamic networks.

In the area of caching in VANETs, a few schemes are proposed in the literature that utilize the caching concept considering the mobile vehicles themselves to be the caching entities. In [85], the authors extend the location-aware VITP protocol [83] to enable in-vehicle caching. The caching-enabled VITP allows the intermediate nodes to cache the replies on their way to the requesting nodes. While propagating the queries to the areas of interest, the VITP-enabled nodes check their local cache for the possibility of cache hits. If a matching replica is not found locally, the query is forwarded to a neighboring vehicle. The authors use the Time-to-Live (TTL) value of the messages as the metric for cache replacement and management. A message is removed from the cache once its TTL reaches a pre-defined value. Another example is the CRoWN framework [86] that brings the content-centric networking (CCN) concept [87] to the vehicular environment implemented on top of the IEEE 802.11p
standard. In CRoWN, communications are driven by the contents instead of host addresses while exploiting in-network caching and replication to achieve fast content retrieval. Although these schemes have achieved performance improvements compared to their counterparts that do not consider caching, with the very dynamic nature of VANETs, caching replicas on mobile nodes that can be reached fortuitously limits the opportunities of cache hits. In addition, with the large-scale nature of VANETs, finding a vehicle with a replica of interest requires querying a huge number of vehicles. Thus, a solution that utilizes static nodes for on-road caching is much more desirable to increase the opportunities of cache hits and minimize the interest dissemination overhead.

5.3 Caching-Assisted Data Delivery (CADD)

One of the main goals of the proposed CADD scheme is to minimize the cost of accessing the vehicular resources through deploying road caching spots, one at each intersection, that can cache previously asked-for data for satisfying later interests. The second goal is to reduce the roundtrip delay of the interest-reply cycle through utilizing the caching concept for bringing data closer to requesters and introducing cache hits on the interest dissemination path. In order to achieve these goals, the CADD scheme depends on the caching and forwarding capabilities of the deployed RCSs and vehicles on the road that work as carriers of both interests and replies.

As the caching concept is a main part of our proposed scheme, we introduce the RCS that works as our caching and delivery-assistant to be deployed at each intersection. An RCS has only the components necessary for forwarding and caching therefore it is less expensive than the regular RSU models on the market. Details about the
RCS structure and deployment are presented in Section 5.5.1.

Since our CADD scheme aims at providing vehicle-assisted information services to remote end users, a connection needs to be established between those end users and the vehicular network in order to be able to inject the service requests and get the data replies. As part of our system, we deploy gateway entities to work as the points of attachment (PoA) of end users to the vehicular network. A single gateway will be deployed at each area of a city/deployment region which will be divided into main non-overlapping areas. An end user interested in a service communicates with a gateway through the Internet. Each end user, in the subscription stage, selects which gateway will be his/her PoA based on the user’s preference and the area he/she will be interested in getting services from more often.

In addition to the caching-assisted feature of the proposed CADD scheme, another main feature is being heading-aware considering vehicles’ headings in packet forwarding for the goals of improving the data delivery ratio and reducing delay.

In the next subsections, we discuss the general operation of CADD through illustrating scenarios that show the benefit of on-road caching and the heading-awareness feature, then we describe the detailed operations of the three main entities involved in the scheme; a vehicle on the road, an RCS at an intersection, and a gateway.

5.3.1 CADD General Operation

The service acquisition process starts with an end user sending a request to the designated gateway which formulates a corresponding interest, then injects it into the vehicular network. The interest is disseminated in the network through vehicles and RCSs towards the AoI defined in the interest packet. While passing by RCSs in its
5.3. CACHING-ASSISTED DATA DELIVERY (CADD)

path, the interest is checked at each passed-by RCS for a cached match (a cache hit). Unless a cache hit happens, the interest is forwarded towards the AoI using heading-aware geographical forwarding as detailed later in this section.

Once the interest reaches a vehicle in the AoI, this vehicle generates a data reply packet resolving the interest parameters. On the way back to the requesting gateway, the reply is cached at the RCS with the maximum centrality among all the RCSs in the interest-followed path. Details about the proposed centrality-based caching mechanism are discussed in subsection 5.3.3-E. With caching the collected data on the reply delivery path, the scheme brings chances for cache hits to be encountered by subsequent interests in the same data.

The scenario illustrated in Figure 5.1 shows the benefits of caching-assistance in reducing access to the vehicular resources, implying reducing the service access cost, and minimizing the data retrieval delay. In Figure 5.1(a), requester $K$ needs information about an event in the area of interest $A$. Since he has registered to gateway $G_2$, his request goes to it through the Internet. $G_2$ generates a corresponding interest, $I_k$, and sends it to the closest neighboring vehicle. The carrying vehicles follow the CADD heading-aware forwarding procedure detailed later to get the interest towards $A$ resulting in the forwarding path shown in Figure 5.1(a). During the forwarding process, the RCSs that are passed by the interest packet check the availability of a matching reply in their caches. In addition, they store information in the interest header about the maximum central and second maximum central RCSs to be used for the caching purposes. In the case shown, no match has been encountered so the interest went to $A$.

In Figure 5.1(b), $I_k$ is received by a vehicle $S$ in $A$. $S$ generates a reply packet,
5.3. CACHING-ASSISTED DATA DELIVERY (CADD)

Figure 5.1: An illustrating scenario showing the benefit of caching on the service data delivery path. Requester K needs information about an event in area A. He sends a request to $G_2$ that generates an interest following the path shown in part (a). A reply is generated by vehicle $S$ in A and sent back to $G_2$ following the path shown in part (b) with a replica cached at RCS$_{11}$. A moment later, requester J asks for similar data from A. His interest meets the cached replica at RCS$_{11}$ resulting in the shortened interest and reply paths shown in part (c).
5.3. CACHING-ASSISTED DATA DELIVERY (CADD)

$P_k$, with corresponding data matching the parameters of $I_k$, and caching-related fields matching those carried in $I_k$. $S$ follows the CADD forwarding procedure to send $P_k$ back to $G_2$ resulting in the path shown in Figure 5.1(b). At each intersection, the carrying vehicle of $P_k$ checks if the neighboring RCS is the one with the maximum centrality stored in the packet header. In the illustrated scenario, it happened that $RCS_{11}$ was the maximum central node on the interest path and, therefore, it is where a replica of $P_k$ is cached on the way back. Note that an RCS at an intersection $i$ is abbreviated as $R_i$ in the figure for simplicity.

A moment later, a requester $J$, registered with gateway $G_1$, gets interested in information similar to that requested by requester $K$. $G_1$ generates a corresponding interest $I_j$ and sends it towards $A$ through the vehicular network. As $I_j$ is checked at the passed-by RCSs for a matching reply, it happens that it hits the replica of $P_k$ cached in $RCS_{11}$. Since $P_k$ matches the parameters of $I_j$, a replica of it is forwarded to $G_1$. In this case, $I_j$ is kept from going all the way towards $A$ minimizing the roundtrip access delay. Since the reply sent to $J$ was a replica of a previously-generated data packet, no access for vehicular sensing resources was required saving the cost that would have been incurred if caching was not considered. The interest and reply paths of this case are shown in Figure 5.1(c).

While propagating the interest and reply packets, the data carrying vehicles keep checking their headings at any approached intersection. If it happens that a vehicle does not find a neighboring vehicle as a potential forwarder, it keeps carrying the packet if it finds that it is going towards the packet’s destination, otherwise, it leaves the packet at the neighboring RCS to give it a chance for a better forwarding opportunity towards its destination which means a higher delivery probability for that
packet. The benefit of this heading-awareness feature is better understood by way of a scenario as illustrated in Figure 5.2, and explained in the following paragraphs, where a source vehicle $S$ needs to deliver data to destination $G$, with $S$’s route as shown in the dashed arrow.

In a pure vehicular data delivery mechanism with no road-side forwarding assistance, a vehicle continues to carry the data if it does not find a potential next-hop forwarder even if the vehicle is heading away from the destination’s direction following the traditional SCF delivery mechanism. This might lead to eventual packet dropping because packets are being moved far from the destination with such direction-neglectful delivery mechanism. The scenario depicted in Figure 5.2(a) illustrates this case. As shown, the source $S$ does not find a possible forwarder and has to keep carrying the packet. At intersection 5, it moves farther from the destination while carrying the packet which will lead to eventual dropping.

In the proposed CADD scheme however and as shown in Figure 5.2(b), when $S$ reaches $RCS_5$ finding that it has no neighbors in the vicinity to which it can forward the packet, since it is not heading towards $G$, it decides to forward the data to $RCS_5$. As can be seen in Figure 5.2(c), $RCS_5$ keeps checking for encountered neighboring vehicles approaching the intersection. In this case, it finds vehicle $M$ and forwards the packet to it. $M$, upon reaching intersection 8, finds that it has no neighboring vehicles. Before it decides to forward the data to $RCS_8$, it checks first if it is heading towards the destination. Since it is heading towards $G$, as depicted by its route shown in Figure 5.2(c), it decides to keep the data further getting it delivered to its designated destination eventually.
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Figure 5.2: CADD heading-awareness illustrative scenario. Source vehicle $S$ is carrying a packet to be delivered to destination $G$, and its path is as shown in the dashed lines. The vehicles with the distinct color are the packet carrying ones. In (a), there is no vehicle/RCS to relay data to, so $S$ continues to carry the packet getting it away from the destination. Parts (b) and (c) show the potential improvement offered by CADD by utilizing RCSs. In (b), $S$ forwards the packet to $RCS_5$ after realizing it is going away from $G$. In (c), $RCS_5$ forwards the packet to vehicle $M$ after encountering it on a segment leading to $G$. $M$ eventually succeeds in delivering the packet to $G$. 
All vehicles and RCSs exchange periodic beacon packets carrying their IDs, positions, and velocities (for vehicles) to announce their presence. Such beacons are used for neighbor discovery needed by the geographical forwarding procedure.

5.3.2 CADD at a Vehicle on the Road

In CADD, vehicles work as the main carriers for both interest and reply packets. We detail the forwarding logic followed by a vehicle in Algorithm 3 for both forwarding an interest (lines 10-25) and forwarding a reply (lines 28-52). On a road, a vehicle can be in one of two modes: a segment mode or an intersection mode. In the segment mode, a vehicle is moving on a road segment and not close to any intersections while in the intersection mode, a vehicle is approaching an intersection and hence, has the opportunity of getting RCS assistance. We discuss the detailed forwarding logic below.

A) Interest Forwarding

When a vehicle gets an interest packet which is not expired yet, it checks if it is in the defined AoI. If so, it generates a reply packet, sets the corresponding caching values in the header which it retrieves from the interest header, and triggers the reply forwarding procedure (lines 12-14). Otherwise, the vehicle checks its current mode of operation to start forwarding the interest. If it is in the segment mode (lines 18-22), it anchors the packet towards the next RCS ($RCS_{next}$) through the use of greedy forwarding. It checks its neighboring vehicles to find the one closest to $RCS_{next}$ and if this potential forwarder is closer to $RCS_{next}$ than the vehicle itself, it forwards the packet to it, otherwise, it keeps holding the packet until a better forwarder is encountered or it approaches $RCS_{next}$. 
When a vehicle gets a beacon from an approached RCS, it activates the intersection mode of forwarding (lines 16 & 17). The carrying vehicle sends the interest to

\textbf{Algorithm 3} : CADD at a Vehicle

\begin{verbatim}
1: Input:
2: Forwarding vehicle \( V \)
3: Interest packet \( i \)
4: Reply packet \( p \)
5: Gateway \( Q \)
6: Set of neighboring road segments \( S \) sent from a neighboring RCS along with their densities
7: Neighborhood list \( N \)
8: 
9: forward_interest(\( i \))
10: Begin
11: if \( i \) is not expired then
12: if \( V \) is in the area of interest defined in \( i \) then
13: generate a reply packet \( p \) and set its \( RCS_{max} \) and \( RCS_{2max} \) fields as carried in \( i \)
14: forward_reply(\( p \))
15: else
16: if Intersection_Mode = true then
17: send \( i \) to \( RCS_{cur} \)
18: else //In the segment mode
19: if \( N \) is empty then
20: keep holding \( i \)
21: else
22: send \( i \) to the neighbor closest to \( RCS_{next} \) if it is closer than \( V \)
23: else
24: drop \( i \) // \( i \) is expired
25: End
26:
27: forward_reply(\( p \))
28: Begin
29: if \( V \) is a neighbor to \( Q \) then
30: send \( p \) to \( Q \)
31: else
32: if Intersection_Mode = true then
33: prioritize \( S \) according to the density and direction priority
34: for all \( s_i \in \) the prioritized segment set do
35: if list of neighboring vehicles on \( s_i \) is not empty then
36: send \( p \) to the farthest vehicle on \( s_i \)
37: break
38: if \( p \) is not relayed then
39: if \( V \) is heading towards \( Q \) then
40: keep holding \( p \)
41: else
42: send \( p \) to \( RCS_{cur} \) with the forwarding flag ON
43: if \( RCS_{cur} = RCS_{max} \) then
44: send a replica of \( p \) to \( RCS_{cur} \) with the caching flag ON
45: else if \( V \) is heading away from \( RCS_{max} \) then
46: send a replica of \( p \) to \( RCS_{max} \) using the same procedure
47: else //In the segment mode
48: if \( N \) is empty then
49: keep holding \( p \)
50: else
51: send \( p \) to the neighbor closest to \( RCS_{next} \) if it is closer than \( V \)
52: End
\end{verbatim}
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$RCS_{cur}$ which checks the possibility for a cache hit, if it has a matching reply in its cache, or continues the forwarding process towards the AoI, otherwise.

B) Reply Forwarding

The reply forwarding procedure gets called when a vehicle generates a reply packet itself (if it gets an interest while it is in the corresponding AoI), or receives a generated one to be forwarded. If the vehicle is in the *segment mode*, it forwards the packet towards $RCS_{next}$ the same way defined above in the interest forwarding (lines 47-51). If in the *intersection mode*, it goes through many check points as follows.

(a) **The vehicle checks if it has a candidate neighbor for forwarding the packet.** The beacon packet sent from $RCS_{cur}$ carries the RCS’s real-time assessment of the densities of its linked road segments. A segment density assessed by an RCS is defined as the number of beacons heard by that RCS from vehicles on that road segment during an assessment period ($asmt_{prd}$):

$$density(s_i) = \text{no. of received beacons}_{s_i}|_{t+asmt_{prd}}$$

(5.1)

where $t$ is the start time of the current period. The vehicle uses the received densities for prioritizing the neighboring segments through computing a weighted priority for each segment as follows

$$weighted\_priority(s_i) = \alpha \times density(s_i) + \beta \times direction\_priority(s_i)$$

(5.2)

where $direction\_priority(s_i)$ is the priority of road segment $i$ in terms of its direction towards the packet destination. The parameters $\alpha$ and $\beta$ are tunable weights with $\alpha + \beta = 1$. The vehicle uses the prioritized segment list for finding
its next-hop forwarder. It checks the availability of neighboring vehicles on the segments in a prioritized order and if it finds any, it stops looping on the segments and selects the next forwarder on the segment with availability in a greedy fashion (lines 33-37).

(b) If not (a), the vehicle checks if it is going towards the packet destination. If it is, it keeps carrying the packet till it finds a better forwarder (38-40). Otherwise, it sets a designated forwarding flag in the packet to ON then sends it to $RCS_{\text{cur}}$ to give it a better forwarding opportunity (lines 41 & 42).

(c) The vehicle checks if $RCS_{\text{cur}}$ is the RCS with maximum centrality ($RCS_{\text{max}}$) stored in the header for caching. If so, the vehicle generates a replica of the reply packet, marks its caching flag as ON, and sends it to $RCS_{\text{cur}}$ to be cached (lines 43 & 44).

(d) If not (c), the vehicle checks if it is going far from $RCS_{\text{max}}$ so that the packet may not pass by the caching RCS on its way. If this is the case, the carrying vehicle generates a replica of the packet, sets its destination to $RCS_{\text{max}}$, and forwards it towards $RCS_{\text{max}}$ using the same forwarding procedure (lines 45 & 46). The idea behind this is to maintain the caching opportunity for that packet regardless of the path followed by the original packet itself.

5.3.3 CADD at an Intersection RCS

RCSs are used mainly for caching replicas of the reply packets with the aim of resolving later relevant interests so that there will not be a need to access vehicular resources every time an interest is injected into the vehicular network. They are also used for
forwarding assistance in cases when the packet-carrying vehicles are heading away from the destination. The logic followed by an RCS for both caching and forwarding is detailed in Algorithm 4 and discussed in the following.

**A) Receiving an Interest**

When an RCS receives an interest packet from a vehicle, if this interest is not expired yet, it checks its cache for a matching replica. If it finds a match, it sends a reply back to the requesting gateway (lines 11 & 12), otherwise, it forwards the interest towards the AoI using the forwarding procedure discussed later in this section (line 18).

Before forwarding a received interest, an RCS checks its centrality value relevant to the interest type and area, as discussed later in this section, to determine if it is a candidate for the maximum central RCS ($RCS_{max}$) or the second maximum central RCS ($RCS_{2max}$) among the RCSs encountered on the interest-traversed path so far (lines 14-17). In the interest header, the ID and location of $RCS_{max}$ and $RCS_{2max}$ is recorded along the path and is updated by a passed-by RCS if it is a better candidate than any of the recorded ones.

**B) Receiving a Reply**

After receiving a reply packet by an RCS, it starts checking the forwarding and caching flags carried in the reply header. If the caching flag is $ON$, the RCS calls the caching procedure for handling both the storage and cache replacement (lines 27 & 28). If the forwarding flag is $ON$, the RCS inserts the packet into the forwarding queue to be forwarded as discussed below (lines 25 & 26).
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Algorithm 4: CADD at an RCS

1: Input:
2: Interest packet i
3: Reply packet p
4: Gateway Q
5: Set of neighboring road segments S
6: Neighborhood list N
7: interest_received(i)
8: Begin
9: if i is not expired then
10: if there is p matching i in Cache then
11: forward p to Q by calling forward_packet(p)
12: else
13: if centr_i(tp,a) of the RCS > centr of RCS_max then
14: update RCS_max, RCS_2max, and their stored locations
15: else if centr_i(tp,a) of the RCS > centr of RCS_2max then
16: update RCS_2max and its stored location
17: forward_packet(i)
18: else
19: drop i // i is expired
20: End
21: reply_received(p)
22: Begin
23: if the packet’s forwarding flag is set to ON then
24: forward_packet(p)
25: else if the packet’s caching flag is set to ON then
26: cache_reply(p)
27: End
28: forward_packet(k) // k can be a reply packet or an interest packet
29: Begin
30: prioritize S according to the density and direction priority
31: for all s_i ∈ the prioritized segment set do
32: if list of neighboring vehicles on s_i is not empty then
33: send p to the farthest vehicle on s_i
34: break
35: if a forwarder is not found then
36: keep holding k to be re-transmitted
37: End
38: cache_reply(p)
39: Begin
40: if Cache is not full then
41: store p in Cache
42: else //Cache is full, consider replacement
43: lowest_pop ← the packet with the lowest popularity in Cache
44: if p.pop < lowest_pop.pop then
45: forward p to p.RCS_2max
46: else
47: forward lowest_pop to lowest_pop.RCS_2max
48: store p in Cache
49: End
50: //The following two functions will be called periodically upon the firing of corresponding timers.
51: calculate_popularity() //as in Eq. 5.3
52: calculate_centrality() //as in Eq. 5.4
C) Forwarding a Packet

The packet forwarding procedure is called by an RCS when it has to forward either an interest or a reply packet. An RCS’s forwarding logic has similarities with the one used by a vehicle for forwarding a reply. When a packet needs to be forwarded, the carrying RCS uses Eq. 5.2 for computing a weighted priority for all of its linked segments based on the density and direction criteria as discussed earlier. Afterwards, the RCS searches for a neighboring vehicle on these road segments in the order of their weighted priorities (lines 33 & 34). If neighbors are found on a segment while searching, the RCS sends the packet to the farthest vehicle on that segment (lines 35 & 36). If no potential forwarder is encountered, the RCS keeps carrying the packet and marks it to be re-transmitted (lines 38 & 39).

D) Caching a Reply

When an RCS receives a reply packet to be cached, it checks the availability of a vacant spot in its cache; if there is any, it caches the packet right away (lines 44 & 45). If the RCS’s cache is full, it considers replacing a previously cached packet, (lines 46-52), as discussed below.

One of the main contributions of this chapter is the proposed cache replacement mechanism which, compared to other caching mechanisms that drop the replaced packet, gives this packet another caching chance to stay longer in the network and increase the chances for a cache hit. In contrast to many caching mechanisms that consider picking the to-be-replaced packet using the Least Recently Used (LRU) policy while ignoring the popularity of the different packets, our replacement mechanism considers this popularity criterion in picking the replacement candidate. Considering
popularity favors the packets with more interests from end users which enhances the QoS.

When a replacement needs to be considered, the RCS with the full cache picks the least popular packet among those stored in its cache (line 47). Details about popularity computation are discussed later in this part. When it happens that an RCS finds many packets with the same lowest popularity value, it picks the LRU one among those of equal popularity. Then, the RCS compares the popularity of the candidate packet ($lowest_p$) to the to-be-cached packet ($p$). The one with the higher popularity will be the caching winner and the other one will be given another caching chance. Each reply packet carries in its header information about the second maximum RCS ($RCS_{2max}$) encountered on the interest path and there is where the other caching chance will be targeted. The packet with the lower popularity between $lowest_p$ and $p$ will be offloaded to the $RCS_{2max}$ recorded in its header using the same forwarding procedure (lines 48-52). A packet is kept in an RCS’s cache till the packet expires or gets replaced.

E) Centrality Computation

Another main contribution in this chapter is our dynamic, decentralized mechanism for computing the centrality of the RCSs. These centrality values are used for caching purposes through directing a reply replica to the maximum central node encountered on the interest forwarding path. A replaced replica is directed to the second maximum central node encountered on its interest path, as discussed before.

The concept of centrality-based caching aims at directing caching to the nodes that are most central in the network as they are more likely to get many interests
passing by and hence, more cache hits. Unlike the static centrality-based caching mechanisms that compute the centrality value of a node based on its position in the static network topology, our proposed mechanism handles the computation in a dynamic way based on the number of interests received by a node such that the more interests a node has received, the more central it is in the network and the more likely it will get upcoming interests.

In CADD, all the potential interests are classified into main types (e.g., traffic conditions, road conditions, and crowd). Each RCS maintains an Interest Type.Area table that lists these pre-defined interest types each associated with the different pre-defined main areas of the whole region in (type, area) 2-tuples. The RCS computes its centrality for each tuple and uses it when it receives an interest of that tuple for checking its candidacy to be the $RCS_{max}$ or the $RCS_{2max}$ on that interest forwarding path.

As shown in Eq. 5.3, an RCS’s centrality of a specific tuple is computed as the number of interests of that type towards that area received during a pre-defined centrality period ($centr_{prd}$).

\[
centrality_i,(type,area) = \left| \text{no. of interest}_i,(type,area) \right|_{t+centr_{prd}}
\] (5.3)

F) Popularity Computation

Using a similar dynamic mechanism to the one used for computing the centrality, an RCS computes a popularity value for all of the different packets it carries in its cache as the popularity of its corresponding interest tuple. A tuple popularity is computed as the number of interests of that type towards that area received during a popularity
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period $pop_{prd}$, as shown below

$$popularity_{i,(type,area)} = \text{no. of interest}_{i,(type,area)}|_{t+pop_{prd}}$$ (5.4)

The RCS uses the computed popularity values for picking the caching replacement candidate as discussed before.

5.3.4 CADD at a Gateway

In CADD, a gateway is used as the PoA of the requesters to the vehicular network. Their main job in the scheme is injecting the service requests into the network and waiting for the replies, which is presented in Algorithm 5 through the $request_data$ procedure. When a gateway receives a service request through the Internet, it generates an interest packet with the corresponding parameters defined in the request including the interest type, AoI, and the expiry times of the interest and its requested reply. Before injecting the interest into the network, the gateway initializes the caching-related fields of the interest header; the centrality, IDs and locations of $RCS_{max}$ and $RCS_{2max}$. Then, it sends the generated interest to its closest neighbor of the vehicular network. A gateway keeps track of all the interests it sent until it gets matching replies or the interests expire. Once a gateway receives a reply matching

<table>
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<th>Algorithm 5 : CADD at a Gateway</th>
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<td>1: Input:</td>
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<tr>
<td>2: Neighborhood list $N$</td>
</tr>
<tr>
<td>3: $request_data()$</td>
</tr>
<tr>
<td>4: Begin</td>
</tr>
<tr>
<td>5: generate interest $i$ with the corresponding parameters</td>
</tr>
<tr>
<td>6: initialize the centrality-related caching fields of the header</td>
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<tr>
<td>7: send $i$ to the nearest neighbor in $N$</td>
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<tr>
<td>8: keep track of $i$ till either getting a reply or it expires</td>
</tr>
<tr>
<td>9: End</td>
</tr>
</tbody>
</table>
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with a stored interest, it sends this reply back to the requester through the Internet.

5.4 Performance Evaluation

In this section, we evaluate the performance of the CADD scheme in comparison to the non-assisted SCF scheme using simulation assessment. In addition, using mathematical assessment, we compare CADD to a scheme utilizing RSUs with interconnection. As well, we propose a mathematical model to compute the estimated delay from a considered gateway to any AoI in a road topology.

5.4.1 CADD and SCF

In this part, the performance of CADD is analyzed and compared to SCF (explained in subsection 5.3.1) in terms of: 1) the average round-trip access delay since an interest is sent until its reply is received, 2) the ratio of received replies through accessing vehicular resources to the total received replies, which is an indicator of the incurred access cost, and 3) the packet delivery ratio, highlighting the benefit of the heading-awareness feature.

A) Simulation Setup

Both CADD and SCF are implemented using the NS-3 network simulator [88]. Simulations were performed over different vehicle densities for a period of 2000 seconds each. We considered a grid simulation topography similar to the part of Kingston city shown in Figure 5.3 with one gateway deployed at each corner and a scale mapped to 1km × 1km area. The interest generation is uniformly distributed among the four gateways with the default injection rate equal to 1 per 20 seconds. In generating
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Figure 5.3: The part of Kingston city representing the simulation topography.

interests, 4 interest types and 4 targeted areas of interest are considered leading to
16 different interest tuples. The SUMO (Simulation of Urban MObility) vehicular
simulator [89] in conjunction with MOVE (MObility model generator for VEHicu-
lar networks) [90] are used to generate realistic mobility traces. The IEEE 802.11p
WAVE standard is used for communication in the vehicular network with the bea-
coning interval set to 0.5 second and the transmission range set to 150 meters.

In CADD, an RCS is added at each intersection. The centr_prd is set to 250
seconds and the pop_prd is assigned the whole simulation time (2000 sec). The α
and β weights for calculating segments’ priorities are set to 0.2 and 0.8, respectively,
giving a higher weight at each RCS to the segment whose direction brings a packet
closer to the destination. We consider two different cache sizes (the maximum num-
ber of cached packets at each RCS) to show the effect of the popularity-based cache
replacement. Cache sizes of 5 (CADD-5) and 20 (CADD-20) are considered. In
CADD-5, only the 5 most popular tuples are kept at an RCS_max while less popular
ones are offloaded to their corresponding $RCS_{2max}$, while in CADD-20, an RCS can accommodate a replica of each possible interest.

**B) Simulation Results and Analysis**

First, we compare CADD-5, CADD-20, and SCF in terms of the average round-trip delay over varying vehicular densities. As shown in Figure 5.4(a), CADD decreases the delay compared to SCF. This decrease is due to: a) the caching-assistance feature that brought the replies closer to the requesters saving the interests from having to go to their designated AoIs, and b) the heading-awareness feature that saved the interests and replies from going farther from their destinations. Comparing CADD-5 and CADD-20, we can notice a slight increase in the delay with reducing the cache size. Since our cache replacement mechanism gives a replaced packet another caching chance instead of dropping it, reducing the cache size has not greatly affected the delay as still there have been chances for cache hits for the replaced replicas.

We perform the same comparison considering the second main metric; the ratio of vehicular resource-accessed replies to the total received replies. The higher this ratio is, the higher the incurred access cost is. Since SCF does not involve any caching assistance, all the received replies are vehicle-generated so the ratio is always equal to 1, as shown in Figure 5.4(b). With caching assistance, CADD achieves significant reduction in this ratio. For the same reason discussed earlier, CADD-5 has a slight increase in the access cost compared to CADD-20.

We also consider a similar comparison in terms of the packet delivery ratio metric. As shown in Figure 5.4(c), CADD significantly improves the delivery ratio in its two versions, CADD-20 and CADD-5, compared to SCF. The main reason for
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(a) Average delay of CADD and SCF with varying densities.

(b) Ratio of access to vehicular resources of CADD and SCF with varying densities.

(c) Packet delivery ratio of CADD and SCF with varying densities.

Figure 5.4: Comparison of CADD and SCF with varying densities.
such improvement is the heading-awareness feature of CADD that saves packets from eventual dropping due to going away from their destinations.

Second, we compare CADD with its underlying centrality-based caching mechanism (referring to it as CADD-Centrality) to another version with random caching (referring to it as CADD-Random) to show the effect of the proposed caching mechanism. In terms of the average round-trip delay, Figure 5.5(a) shows that CADD-Centrality achieves lower delay than CADD-Random due to ensuring to have the

![Comparison of CADD with centrality-based caching vs. random caching with varying densities.](image)

(a) Average delay of CADD-Centrality and CADD-Random with varying densities.

![Ratio of access to vehicular resources of CADD-Centrality and CADD-Random with varying densities.](image)

(b) Ratio of access to vehicular resources of CADD-Centrality and CADD-Random with varying densities.

Figure 5.5: Comparison of CADD with centrality-based caching vs. random caching with varying densities.
cached replicas at the maximum central RCSs, which have higher probabilities for cache hits than randomly-chosen RCSs. For the same reason, we can see in Figure 5.5(b) that CADD-Centrality incurs lower cost (lower ratio of replies accessed through vehicular sensing resources, not through replicas) than CADD-Random. We considered CADD-20 in the above comparison, as well as the following.

Third, We compare CADD in its complete form (referring to it in this comparison as CADD-Caching) and SCF to another version of CADD with relaxing the caching feature (referring to it as CADD-NoCaching) to show the effect of the heading-awareness feature independently. In terms of the average round-trip delay, as expected, Figure 5.6(a) shows that CADD-NoCaching achieves a value between these achieved by CADD-Caching and SCF, respectively, highlighting the delay reduction achieved through taking vehicles’ headings into consideration. Figure 5.6(b) shows similar comparison in terms of the packet delivery ratio emphasizing significant improvements through CADD with and without caching compared to SCF due to the heading-awareness feature as well.

Finally, we study the effect of changing the interest generation period ($int_{prd}$) in CADD-20 and CADD-5, showing the results in Figures 5.7 and 5.8, respectively, for varying vehicular densities. We considered values 20 and 60 for $int_{prd}$ (generating an interest every 20 and 60 seconds, respectively). In terms of the average delay, Figures 5.7(a) and 5.8(a) show that with increasing $int_{prd}$, the delay increases. The reason being is that with such an increase in $int_{prd}$, some cached replicas expire before being asked for by later interests leading to reduced cache hits hence, longer delay. For the same reason, Figures 5.7(b) and 5.8(b) show that the ratio of access to vehicular resources also increases with increasing $int_{prd}$. We can also see from
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(a) Average delay of CADD with and without caching, and SCF over varying densities.

(b) Packet delivery ratio of CADD with and without caching, and SCF over varying densities.

Figure 5.6: Comparison of CADD with and without caching, and SCF over varying densities.

Figures 5.7 and 5.8 that the results of \textit{int/prd} 60 is quite the same in CADD-5 and CADD-20 for the same reason mentioned above: the reduced cache hits, diminishing the effect of the cache size.

5.4.2 CADD and Connected_RSUs

In this section, we present a mathematical model to compare CADD to a scheme utilizing RSUs with inter-connection (C_RSU). We consider an \( m \times n \) grid topology.
with an RSU deployed at each corner working as a gateway for both schemes. In C_RSU, the four RSUs can communicate with one another through the Internet such that they can move the interests and replies closer to their destinations through their backhaul connection. For CADD, an RCS is deployed at each intersection point of the grid.

In assessing the performance of CADD, we consider its best case (CADD_B) when a cache hit is encountered at the next intersection RCS, and its worst case (CADD_W)

(a) Average delay of CADD-20 with different interest generation periods over varying densities.

(b) Ratio of access to vehicular resources of CADD-20 with different interest generation periods over varying densities.

Figure 5.7: Comparison of CADD-20 with different interest generation periods over varying densities.
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(a) Average delay of CADD-5 with different interest generation periods over varying densities.

(b) Ratio of access to vehicular resources of CADD-5 with different interest generation periods over varying densities.

Figure 5.8: Comparison of CADD-5 with different interest generation periods over varying densities.

when no cache hits happen on the interest path so the interest has to be resolved by a vehicle at the AoI.

In our assessment scenario, we consider each segment on the grid as a possible AoI with one interest generated to it by an RSU/gateway. In an $m \times n$ grid, the number of segments ($NS$), which equals to the total number of generated interests ($NI$), is computed as: $NS = NI = 2mn - m - n$.

As a first assessment metric, we consider the total cost ($TCost$) incurred by each
scheme for getting a reply to each of the $NI$ interests. Assume the cost of getting a single reply through accessing vehicular resources is $c$. In both CADD,W and C,RSU each interest is resolved by a vehicle in the AoI, so their $TCost$ is equal to $NI \times c$. For CADD,B, as all interests are resolved through cache hits, its $TCost$ is equal to 0.

As a second metric, we compute the average delay ($ADelay$) of reaching all the segments from the requesting RSU. We assume that the propagation delay over a road segment is $\tau$ and is the same for all segments. Since in CADD,B a cache hit is encountered at the next intersection (one segment away), the delay of getting a reply targeting any segment is equal to $\tau$, except for the two segments directly linked to the requesting gateway where the delay is 0. Consequently, the $ADelay$ of CADD,B is computed as

$$ADelay(CADD,B) = (NI - 2) \times \tau/NI$$ (5.5)

For CADD,W, the delay of reaching an AoI/segment starting at point $(i,j)$ on the grid and the average delay can be computed as in Eqs. 5.6 and 5.7, respectively.

$$Delay(CADD,W)_{(i,j)} = (i + j) \tau$$ (5.6)

$$ADelay(CADD,W) = \frac{[2 \sum_{i=0}^{m-2} \sum_{j=0}^{n-2} (i + j) + \sum_{i=0}^{m-2} (i + n - 1) + \sum_{j=0}^{n-2} (j + m - 1)]\tau}{NI}$$ (5.7)

To reach an AoI starting at point $(i,j)$ in C,RSU, since the RSUs are connected, the delay is the minimum delay of reaching this segment from the four RSUs, as computed in Eq. 5.8. Eqs. 5.9 and 5.10 show the computation of the C,RSU average delay for all different cases of the $m$ and $n$ values.

$$Delay(C\_RSU)_{(i,j)} = min[(n-1-i+j),(i+j),(m-i+n-j-2),(m-1-i+j)] \times \tau$$ (5.8)
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\[ A_{\text{Delay}}(C_{\text{RSU}}) = \frac{\text{Total}_{\text{Delay}}(C_{\text{RSU}})}{NI} \quad (5.9) \]

\[
\text{Total}_{\text{Delay}}(C_{\text{RSU}}) =
\begin{cases} 
W \times \tau, & \text{if both } m \& n \text{ are odd} \\
[W + X + Z] \times \tau, & \text{if } m \text{ is even and } n \text{ is odd} \\
[W + Y + Z] \times \tau, & \text{if } m \text{ is odd and } n \text{ is even} \\
[W + X + Y + (Z \times 4)] \times \tau, & \text{if both } m \& n \text{ are even}
\end{cases}
\quad (5.10)
\]

where:
\[ W = \left( 8 \times \sum_{i=0}^{u-1} \sum_{j=0}^{v-1} (i + j) + 2 \times \left( \sum_{i=0}^{u-1} (i + v) + \sum_{j=0}^{v-1} (j + u) \right) \right), \]
\[ X = 4 \times \sum_{i=0}^{u-1} (i + v), \quad Y = 4 \times \sum_{j=0}^{v-1} (j + u), \]
\[ Z = u + v, \quad u = \lfloor \frac{m - 1}{2} \rfloor, \quad v = \lfloor \frac{n - 1}{2} \rfloor \]

Figure 5.9 shows the assessment results of the CADD_W, CADD_B, and C_RSU in terms of the average delay computed based on Eqs. 5.5, 5.7, and 5.9 with varying grid sizes and \( \tau \) equal to 10. The results show that in small areas (small grid sizes), the average delay of CADD_B is almost equal to that of C_RSU. In larger areas, the average delay of C_RSU is significantly higher than the delay of CADD_B and getting closer to that of CADD_W as many of the segments get farther from the corner RSUs.

5.4.3 CADD to a specific AoI

Here we consider the delay to reach a specific AoI by an interest packet initiated from a specific gateway. First, we consider this assessment under the assumptions of having a fixed traffic density for each road with non-uniform density distribution for the whole
set of segments (i.e., each segment has a fixed density which may differ from other segments’ densities), and having a fixed uniform popularity for all the interest tuples. Second, we consider the assessment under the fixed non-uniform density distribution assumption with fixed non-uniform popularity distribution for the interest tuples.

**A) Assessment Considerations**

We consider an $m \times n$ grid topology with a gateway deployed at each corner and an RCS deployed at each intersection point of the grid. The delay is estimated for an interest packet going from a gateway to the starting point of an AoI (road segment) on the grid. Note that the location points of the gateway, AoI reaching point, and the RCSs are mapped to points on the grid in terms of $m$ and $n$.

The density of road segments, popularity of interest tuples, and locations of RCSs on the grid are known and used as inputs to the assessment model. Based on this information, the full paths from the considered gateway ($G_y$ s.t. $y = 1, ..., no. of Gateways$) to each candidate AoI ($A_k$ s.t. $k = 1, ..., no. of AoIs$) are computed a priori based on the CADD forwarding procedure as a list of junction/intersection points. Therefore,
the set of RCSs on the full path from $G_y$ to $A_k$ is known and referred to as $S_{y\rightarrow k}$.

B) Assessment Model

**Case I: Fixed Non-uniform Density and Fixed Uniform Popularity**

First, based on the inputs mentioned above and the computed full path between the considered $G_y$ and $A_k$, we compute the locations of $RCS_{max}$ and $RCS_{2\text{max}}$ on that path. For each $RCS_l \in S_{y\rightarrow k}$, we compute a corresponding degree of centrality $DC_l$ that indicates the candidacy of that RCS to be the most central node. $RCS_{max}$ on a path represents the node with the highest number of interests passing by. In case there is more than one RCS encountering the same highest number of interests, $RCS_{max}$ is chosen to be the one closest to the gateways among those nodes with the maximum centrality. Based on this centrality notion, the $DC_l$ of $RCS_l$ is computed as below

$$DC_l = ADens_l \times \frac{1}{ADis2G_l}$$

(5.11)

where $ADens_l$ is the average density of $RCS_l$’s incoming road segments and $ADis2G_l$ is the average distance between $RCS_l$ and the gateways considering only those having $RCS_l$ between the gateway and AoI (i.e., the gateways that might have $RCS_l$ on the path to the considered AoI).

According to the computed degrees of centrality, we determine $RCS_{max} \in S_{y\rightarrow k}$ and $RCS_{2\text{max}} \in S_{y\rightarrow k}$ of the path from $G_y$ to $A_k$ as follows

$$RCS_{max} \leftarrow RCS_l \text{ with } max(DC_l)$$
Consider the probability of having a cached replica on the path to be $P_{\text{cache}} = P_{c,\text{max}} + P_{c,\text{2max}}$, where $P_{c,\text{max}}$ is the probability of having a cached replica at $RCS_{\text{max}}$ and $P_{c,\text{2max}}$ is the probability of having a cached replica at $RCS_{\text{2max}}$. Note that according to the scheme, a cached replica can only be found at either $RCS_{\text{max}}$ or $RCS_{\text{2max}}$, but not in both. Accordingly, the estimated distance to be traversed by an interest $r$ initiated through $G_y$ and directed towards $A_k$ can be computed as in Eq. 5.12.

$$EDist_{r,y\rightarrow k} = [P_{c,\text{max}} \times D_{\text{max}}] + [P_{c,\text{2max}} \times D_{\text{2max}}] + [(1 - P_{\text{cache}}) \times D_{A_k}]$$

(5.12)

where $D_{\text{max}}$, $D_{\text{2max}}$, and $D_{A_k}$ are the distances from $G_y$ to the determined $RCS_{\text{max}}$ and $RCS_{\text{2max}}$, and $A_k$, respectively. Note that the distances in the model are expressed in the number of road segments between a pair of points on an $m \times n$ grid.

For example, the distance between a specific $G_y$ at point $(0,n-1)$ and an $A_k$ reachable through point $(m-1,2) = |m-1-0| + |2-(n-1)| = m-n+2$ segments.

The last term in Eq. 5.12 represents where the requested interest $r$ has not been previously requested, or was requested and reached its expiry time before initiating the current interest packet, as the worst case of CADD where the interest packet has to go all the way towards the AoI. The probability of a cache hit, $P_{\text{cache}} = P_{c,\text{max}} + P_{c,\text{2max}}$, can be computed as detailed below.

We consider the popularity of the interest tuples and the cache sizes of the RCSs for computing $P_{\text{cache}}$. Based on the full path set computed a priori from the gateways
to the AoIs, for each $RCS_l$, we compute the set of interest paths going through it, referring to it as $P_l$. Accordingly, with the assumption that all interest tuples have the same popularity, $P_{c,max,r}$ and $P_{c,2max,r}$ of an interest $r$ from $G_y$ to $A_k$ are computed as in Eqs. 5.13 and 5.14, respectively.

$$P_{c,max,r} = \frac{1}{|P_{RCS_{y\rightarrow k}}|} \times RCS_{c,Size} \quad (5.13)$$

$$P_{c,2max,r} = \frac{1}{|P_{RCS_{y\rightarrow k}}|} \times RCS_{c,Size} \times (1 - P_{c,max,r}) \quad (5.14)$$

where $RCS_{c,Size}$ is the cache size of an RCS. In cases where the values of $P_{c,max,r}$ and $P_{c,2max,r}$ are greater than 1 due to having $|P_{RCS_{y\rightarrow k}}|$ much smaller than $RCS_{c,Size}$, $P_{c,max,r}$ and $P_{c,2max,r}$ are assigned the probability upper bound 1.

The probabilities of caching obtained through Eqs. 5.13 and 5.14 are plugged into Eq. 5.12 to compute $EDist_{y\rightarrow k}$. Finally, following the general assumption considered in Section 5.4.2 of having the propagation delay over a road segment to be $\tau$, we can compute the estimated delay for an interest $r$ initiated through $G_y$ and targeting data about $A_k$ as shown in Eq. 5.15.

$$EDelay_{y\rightarrow k} = EDist_{y\rightarrow k} \times \tau \quad (5.15)$$

**Case II: Fixed Non-uniform Density and Fixed Non-uniform Popularity**

The same model and formulation discussed under Case I applies to this case as well except for the computation of $P_{c,max,r}$ and $P_{c,2max,r}$. Since non-uniform popularity is considered (i.e., each interest tuple may have a different popularity), we rank the
different interest paths in $P_1$ of each $RCS_i$ in ascending order according to the popularity of its corresponding interest tuple, s.t. the interest tuple with the highest popularity gets a rank of 1. Each interest path $i.p \in P_1$ is assigned a degree of popularity, $DP_{i.p}$, equivalent to its rank in $P_1$. $P_{c,\text{max}_r}$ and $P_{c,2\text{max}_r}$ of an interest $r$ from $G_y$ to $A_k$ following a path $i.p$ are computed as in Eqs. 5.16 and 5.17, respectively.

$$P_{c,\text{max}_r} = \begin{cases} 1, & \text{if } DP_{i.p}^{RCS_{\text{max}}_{y \rightarrow k}} \leq RCS_{c,\text{Size}} \\ 0, & \text{otherwise} \end{cases}$$  \hspace{1cm} (5.16)$$

$$P_{c,2\text{max}_r} = \begin{cases} 0, & \text{if } DP_{i.p}^{RCS_{2\text{max}}_{y \rightarrow k}} > RCS_{c,\text{Size}} \\ \text{or } P_{c,\text{max}_r} \text{ is equal to 1} \\ 1, & \text{otherwise} \end{cases}$$  \hspace{1cm} (5.17)$$

C) Numerical Results

Below are the results of computing the average estimated delay for reaching data about all the segments in the $m \times n$ grid topology, considering each segment on the grid as a possible AoI and one of the corner gateways to be the initiator of all the interests targeting the segments. To generalize and assess the model for different grid sizes, we adopt uniform traffic density with uniform interest popularity for all the segments in the grid.

Since having uniform density over the segments leads to having multiple potential paths between the gateway $G_y$ and an area of interest $A_k$, we adopt the following strategy to form a path from $G_y$ to $A_k$. Among the set of shortest paths from $G_y$ to $A_k$, we select the one giving priority in segment selection in a counterclockwise
fashion (e.g., considering the gateway in the top right, the selection strategy picks all the segments to the left until reaching the same grid column of \( A_k \), then moves down selecting all the segments on the way until reaching \( A_k \)). Due to the use of uniform density as well, the use of the \( ADens_t \) parameter in Eq. 5.11 is relaxed leading to considering only the average distance to gateways \( (ADis2G_t) \) in computing \( DC_t \) of \( RCS_t \).

For each AoI/road segment, we generate a random value to indicate if an interest to that AoI was requested before or not (i.e., there is a probability of a cache hit or not). If this generated value is greater than a pre-defined threshold \( (C_{Th}) \), it will be assumed that an interest \( r \) to that AoI will not meet a cached replica anywhere on the grid leading to having \( P_{cache_r} = P_{c_{max_r}} = P_{c_{2max_r}} = 0 \); hence, having the estimated delay converges to that of CADD_W for that AoI. If this value is less than or equal to \( C_{Th} \), the values of \( P_{c_{max_r}}, P_{c_{2max_r}}, \) and \( P_{cache_r} \) are computed according to the proposed model.

We compare this model, referring to it as CADD_E, to CADD_W and CADD_B defined in the previous part in terms of the average delay to reach all the segments in the grid for different grid sizes. Figure 5.10 shows the results of the comparison considering a cache size equals to 20, \( C_{Th} \) equals to 0.5, and \( \tau \) equals to 10. As expected, the delay of CADD_E lies between these of CADD_W and CADD_B. For larger grid sizes, the difference between CADD_W and CADD_E is more apparent as the distances between the gateway and some of the segments get longer, with a probability of not being traversed in CADD_E due to the potential cache hits.

We also assess the average delay computed by CADD_E with considering different cache sizes \( (RCS_c\_Size) \) over different grid sizes. The results in Figure 5.11 show
5.4. PERFORMANCE EVALUATION

Figure 5.10: Average delay of CADD\(_E\), CADD\(_W\), and CADD\(_B\) with varying grid sizes.

Figure 5.11: Average delay of CADD\(_E\) with different cache sizes over varying grid sizes.

that with increasing the cache size, the average delay decreases due to increasing the values of \(P_{c,\text{max}}\) and \(P_{c,2\text{max}}\) per an interest \(r\) which decreases the corresponding \(EDist_r\), according to Eq. 5.12.

Finally, we assess CADD\(_E\) with considering different values for \(C_{,Th}\) over different grid sizes. The results in Figure 5.12 show that with increasing \(C_{,Th}\) the delay decreases, as fewer segments would be assumed not having a cached replica leading to lower estimated distances to more segments.
5.5. PRACTICAL CONSIDERATIONS

In this section, we highlight the practical considerations related to the operation and implementation of the CADD scheme and the deployment of the required components.

5.5.1 The Road Caching Spot

Compared to the different RSU models that are on the market (e.g., the LOCOMATE devices that are used in the US pilot and test-field programs [91]), the proposed RCS is a more cost-effective solution for data delivery assistance as it only holds the components needed for the caching and multi-hop data delivery processes. The other RSU models include a variety of components that are not required for those processes such as the Ethernet, M2M, and GPS modules. Our proposed RCS is a simple, lightweight device that can be deployed on traffic lights or electric poles to complement RSUs for providing ubiquitous road-side assistance. It consists of an 802.11p radio for communication which comes with an embedded processor, a memory chip for caching, and a power port. Figure 5.13 shows the basic architecture of an RCS.

Figure 5.12: Average delay of CADD_E with different caching probability thresholds over varying grid sizes.
is worth noting that the RCS is not proposed to replace the RSU; it will be used to complement and assist the RSUs when/where their ubiquitous deployment is not feasible.

5.5.2 Communication Technologies

The IEEE 802.11p communication standard is suggested as the main communication technology between the RCSs and vehicles since each smart vehicle will be equipped by default with an 802.11p radio to support the ITS services. Our proposed RCS is equipped with an 802.11p radio as well to support such a communication. However, the scheme operation is not confined only to the 802.11p use; other inter-vehicle communication technologies can be utilized without affecting the scheme. For example, some Zigbee modules [20] [92] are introduced to the market to support communication among vehicles, and between vehicles and infrastructure. These modules can be easily attached to vehicles and road units. The VLC technology is currently gaining interest as a candidate for vehicular communication [22] [23]. A vehicle’s regular lights can be replaced with light emitting diodes (LEDs) as VLC transmitters and each vehicle can be equipped as well with a VLC receiver which can be either an image sensor or a photo diode. To support such type of communication, our basic RCS can be modified
to include a VLC transmitter and a receiver instead of the 802.11p radio.

It is worth mentioning that with the flexibility and ease of altering the communication interface of the RCSs, the penetration rate of the road-side assistance can be boosted through adjusting such interfaces to cope with whichever vehicular communication technology is available.

The gateways needed as the PoA to the vehicular network are equipped with two communication interfaces: 1) a broadband interface to be connected to the Internet for receiving and sending service requests and replies, respectively, and 2) a communication interface to communicate with the vehicular network supporting the same technology used by that vehicular network. A gateway can either have the same architecture as an RCS with an added capability for Internet-connectivity, or can be an RSU.

5.5.3 Backward Compatibility

Our scheme depends mainly on smart vehicles as carriers of interest and reply packets between RCSs and as the main resources of the sensing-based data; however, the entities involved in the scheme can be adjusted to support backward compatibility with regular/legacy vehicles having no on-board connectivity. Owners of legacy vehicles who are willing to participate in public sensing services supported by the proposed scheme can equip their vehicles with an 802.11p radio to be engaged in the forwarding loop. The owner of these vehicles can depend on the sensing resources of smartphones for potential tasks (e.g., depending on a smartphone camera for monitoring an event on the road). For the communication between the smartphone and the outside vehicular network (for getting sensing interests and replying with sensed...
data), a Bluetooth interface can be integrated with a standalone 802.11p radio for establishing an in-vehicle communication between the smartphone and the added communication module that is responsible for the out-of-vehicle communication.

We also highlight that the operation of the scheme does not require that all vehicles should be CADD-enabled. Regular communication-enabled vehicles can also be involved in the system for basic data relaying through their default data forwarding capabilities and V2V communication. The CADD-enabled vehicles support interoperability with such regular vehicles, as well as communication with on-road RSUs and RCSs, see Figure 5.14. Regular vehicles (referred to as RVs) can be involved in regular V2V, V2I, and I2V communications. CADD-enabled vehicles (referred as CVs) can support all the aforementioned types of communication in addition to communication with RCSs; denoted as V2R and R2V communications.

For the backward compatibility of road-side assistance, as mentioned earlier, the RCS is proposed to complement the RSU operation not to replace it. For an intersection with a deployed RSU, the scheme does not require an RCS to be deployed; only the storage capacity of the deployed RSU can be upgraded to support caching.

![Figure 5.14: Interoperability of CADD-enabled vehicles with regular vehicular networks.](image-url)
5.5. PRACTICAL CONSIDERATIONS

5.5.4 Distributed Storage and Processing

Currently, there is a great push towards the adoption of fog/edge computing [93][94] and cloudlets [95][96] aiming at providing local distributed computing as opposed to cloud central computing to handle the torrent of data being generated by the IoT [17][18]. Such trends move computing to a virtualized layer between the users and traditional cloud computing platforms bringing content closer to consumers of local interest. Following these hot trends, our scheme builds on distributed storage and processing through RCSs deployed in a distributed fashion. In our scheme, data of interest is cached and processed locally relaxing the need for central/cloud computing for the sake of an efficient use of the broadband bandwidth, and a fault-tolerant and load-balanced caching of the generated data avoiding directing the caching load to one central node.

5.5.5 Advantageous Delivery Features

The proposed scheme works on utilizing the current state of vehicular density efficiently for data delivery. In cases of congested areas, the scheme utilizes the dense availability of vehicles for faster multi-hopping even if the carrying vehicles are quasi-stationary, while in sparse environments, the scheme depends on moving vehicles and their heading for bringing packets closer to/from areas of interest. Therefore, the proposed scheme can successfully operate in both cases considering its adaptive delivery features.
5.6 Summary

In this chapter, we proposed the caching-assisted data delivery (CADD) scheme that enhances access to vehicular resources for vehicle-based public sensing services. Through applying caching on the data delivery path, CADD aims at reducing the cost and delay of accessing vehicular resources. CADD relies on the deployment of a light-weight road caching spot (RCS) at each intersection, and vehicles work as carriers of both interests and replies between the RCSs. As part of CADD, a novel centrality-based caching mechanism was proposed that handles the dynamic nature of vehicular networks and considers popularity in cache replacement. CADD considers vehicles’ headings to direct interests and replies towards their destinations. Simulation and mathematical-based performance evaluation showed that CADD achieves significant improvements in the access cost, delivery delay, and packet delivery ratio compared to other schemes that do not involve caching-assistance and do not take vehicles’ headings into consideration.
Chapter 6

Conclusions and Future Directions

Thanks to their abundant on-board capabilities, ubiquity, and mobility, smart vehicles can be considered major candidates for providing pervasive information services. With a plethora of sensing, storage, computing, and communication resources, smart vehicles can bring a wide scope of applications into action outstripping other candidate mobile devices such as smartphones. Public sensing is one of the scopes that can be greatly enhanced through utilizing smart vehicles and engaging them into the sensing loop.

Although utilizing smart vehicles for providing public sensing services is enormously promising, such utilization faces some practical challenges. In areas with ubiquitous availability of vehicles, an SP interested in getting data from an AoI faces the challenge of recruitment. Many candidate participants would be available for selection in the intended AoI and each may have different reputation according to past behaviors, reported data, and quality of on-board resources. To meet specific budget and quality requirements, an SP has to adopt a recruitment scheme to effectively select a set of participants achieving the targeted coverage of the AoI.
Moreover, in areas where broadband communication is restricted, communication of the sensing interest and reply packets should be handled through multi-hop communication using vehicles and any available road-side assistance. Such multi-hop communication brings a data delivery challenge that also entails consideration to ensure cost-effective and delay-bounded access to vehicular sensing resources.

6.1 Summary and Concluding Remarks

In Section 2, we unveiled the diversified resources a smart vehicle can provide through introducing the concept of Vehicle as a Resource (VaaR). We demonstrated that a smart vehicle on a road or at a parking lot can be considered a resource of sensing, storage, computing, data relaying, infotainment, and localization. We shed light on these different resources discussing some existing and proposed examples utilizing each resource. We also presented a potential scenario that shows VaaR in action and emphasizes benefits it can provide on roads. In addition, we presented different challenges that face the adoption of VaaR concluding some open issues and potential solutions for each challenge.

The main objective of this thesis is to provide a platform that utilizes smart vehicles for public sensing. In Chapter 3, we presented our Vehicular Public Sensing (VPS) platform that utilizes the abundant sensing, storage, processing, and communication capabilities of smart vehicles for providing ubiquitous public sensing services. The VPS platform encompasses different components that address the recruitment, communication, sensing, reporting, and data analytic functionalities of a typical public sensing process. Taking into account different environmental and practical setups,
the VPS platform provides potential adjustments and different options for the operation of each component. To handle different challenges facing some of its underlying components, the VPS platform encapsulates the work presented in Chapters 4 and 5.

In Chapter 4, we considered the aforementioned recruitment challenge through proposing the Reputation-aware, Trajectory-based Recruitment (RTR) framework. RTR targets the selection of a set of participating vehicles to perform a sensing task in a way that guarantees a required level of coverage of an intended AoI while considering budget and reputation constraints. RTR consists of three main modules: 1) a reputation assessment scheme, 2) a pricing model, and 3) a selection scheme that makes use of the outputs of the first two modules along with retrieved participants’ trajectories. We formulated the selection problem as an ILP optimization problem with two different recruitment objectives. We also proposed greedy heuristics handling the real-time requirements of these objectives. The selection problem was generalized to include practical considerations. We evaluated the performance of the proposed greedy heuristic solutions comparing them to their optimization counterparts and assessing the quality of the collected sensing data. The results showed that the greedy heuristics succeed in achieving results close to the optimal benchmarks, and in efficiently handling cases with high probabilities of vehicles not sticking to their trajectories. We conclude from the results that the recruitment objective of maximum coverage with minimum cost (MaxCov-MinCost) is better to be adopted compared to the other one handling maximum coverage with minimum overlapping (MaxCov-MinOverlap). The reasons are: a) in terms of the achieved coverage, MaxCov-MinCost achieves similar coverage to MaxCov-MinOverlap in cases where the available budget allows for achieving full coverage, while the former achieves better coverage where only partial coverage
can be achieved, b) although the main target of minimizing overlapping among the recruited participants is to avoid unnecessary cost, \textit{MaxCov-MinCost} achieves better results than \textit{MaxCov-MinOverlap} in terms of the total recruitment cost even with having larger overlapped coverage areas.

Chapter 5 addressed the previously-highlighted data delivery challenge. Through proposing the Caching-assisted Data Delivery (CADD) scheme, we presented a solution to the access cost and delay concerns facing accessing vehicular resources for sensing services. CADD utilizes caching of the collected sensing data on the road for the sake of satisfying later interests in the same data. We proposed the road caching spot (RCS) to be both a caching and forwarding assistant for CADD deployed at road intersections. Vehicles are used as carriers of the service interest and reply packets and the generators of the requested data. As part of CADD, we proposed a novel dynamic centrality-based caching mechanism that considers popularity in cache replacement. CADD also considers vehicles’ headings in data forwarding for preventing the carried packets from heading-away from their destinations. \textit{The simulation results conclude that considering caching-assistance and heading-awareness in data delivery achieves significant improvements in the access cost, delivery delay, and packet delivery ratio compared to the traditional SCF delivery mechanism that has no road-side assistance.} We presented mathematical assessment comparing CADD in its best and worst performances to a scheme with interconnected RSUs (C\_RSU). \textit{We conclude from the comparison that although utilizing RSUs with interconnectivity in small areas achieves results close to the best case of CADD in terms of the average delay, in larger areas the performance of C\_RSU gets closer to the worst performance of CADD. In terms of the recruitment cost, C\_RSU is always similar to the worst
of CADD giving advantages to the adoption of CADD compared to C\_RSU. We also proposed a mathematical model to compute the estimated delay from a considered gateway to any AoI in a road topology.

6.2 Future Directions

Several future directions and open issues stem from our work. We pointed out some general issues related to the utilization of the vehicular resources in Section 2.4. In the following, we highlight some more open directions closely related to the contributions of Chapters 4 and 5.

1. In our recruitment framework, we built the selection scheme on vehicles’ trajectories that can be acquired from the on-board navigation systems. Such trajectories are used as indicators of the spatiotemporal availability of candidate participants. Another direction for acquiring such availability is through applying mobility prediction mechanisms. However, the use of prediction should be confined only to non-critical applications to accommodate prediction errors.

2. We proposed an altered version of the set-cover problem to handle the greedy selection part of the RTR framework. The use of other schemes from computational geometry can be explored and compared to the proposed scheme and the ILP solutions.

3. One of the interesting aspects that can be investigated is the possibility of engaging vehicular clouds in the recruitment process. Instead of handling the reputation assessment and participant selection at the SP’s premise, these tasks
can be offloaded to vehicles utilizing their computational, storage, and communication capabilities.

4. One of the extensions to the proposed CADD scheme is to consider reputation in selecting the next forwarder/hop. This requires coupling the delivery scheme with a reputation assessment scheme that considers metrics related to the reliability of forwarding.

5. For a potential increase of the cache hits, a future extension to the proposed CADD scheme is to allow neighboring RCSs to periodically exchange metadata with one another carrying information about the interest tuples they are caching replies of. In such a way, when an RCS gets an interest that cannot be satisfied with a replica in its local cache, it may direct the interest to a neighboring RCS that carries a matching replica, instead of forwarding it towards the area of interest.

6. An interesting future direction can be about investigating how different SPs can share the reputation scores of participants to use the same reputation assessment for different services. Introducing unification methodologies that consider past behaviors of participants across different services is an open direction. Such methodologies should take into consideration the different requirements and assessment metrics of each service along with the criticality of services compared to one another through impact/importance merging weights.
Bibliography


Appendix A

The Beta Reputation System

The Beta reputation system [74] is based on the Beta probability density function, which is commonly used as a distribution for random variables that take continuous values in the interval [0,1]. The general formula of the beta distribution can be defined as a function indexed by the two parameters \( \alpha \) and \( \beta \), as shown below:

\[
f(p|\alpha, \beta) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} p^{\alpha-1}(1 - p)^{\beta-1}, \text{ where } 0 \leq p \leq 1, \alpha > 0, \beta > 0 \quad (A.1)
\]

The parameters \( \alpha \) and \( \beta \) control the shape of the beta density function when plotted where the horizontal axis represents the possible values of the random variable and the vertical axis represents probability that each of these values is the true value of the variable. Figure A.1 shows an example of a beta density function with \( \alpha = 8 \) and \( \beta = 2 \).

The following example can simplify the mapping of the beta distribution to the reputation systems [74]. Consider a process with two possible outcomes \( k, \bar{k} \). Let \( x \) represents the observed number of outcome \( k \) and \( y \) represents the observed number of outcome \( \bar{k} \). The probability density function of observing the outcome \( k \) in the
future can be expressed as a beta function of the past observations with $\alpha$ and $\beta$ computed as

$$\alpha = x + 1 \quad \text{and} \quad \beta = y + 1,$$

where $x \& y \geq 0$ \hspace{1cm} (A.2)

with the expectation value of observing $k$ in the future can be computed as the expectation of the beta distribution as shown below

$$E(p) = \frac{\alpha}{\alpha + \beta}$$ \hspace{1cm} (A.3)

Following the same computation modeled in the example above, the beta distribution has been widely used in trust/reputation models for computing a trust level or a reputation score for a trustee. Based on a trustee’s past interactions with a truster, a reputation of the trustee can be computed by directly mapping the $x$ and $y$ values to the number of past successful interactions and unsuccessful interactions, respectively. The expectation that the trustee would have a successful interaction in the future can be computed using Eq. A.3, which is used as the assessed trust/reputation score.
Instead of using statistical values for computing \( x \) and \( y \) as discussed above, another approach can be used as well for such a computation by considering the assessment of a trustee after an interaction with a truster with \( x \) representing the degree of satisfaction of the truster and \( y \) representing the degree of dissatisfaction. The purpose of providing the per-interaction assessment, \( q \), as an \((x, y)\) pair is to reflect the fact that a trustee’s performance can be partly satisfactory [74]. As an alternative to provide \( q \) as a pair, a normalization weight, \( w \), can be used as the sum of the \( x \) and \( y \) parameters to allow \( q \) to be provided as a single value \( v \) in the range \([0,1]\). Hereinafter, the \( x \) and \( y \) values can be computed as functions of \( w \) and \( v \) per

\[
x = w \frac{(1 + v)}{2} \quad \text{and} \quad y = w \frac{(1 - v)}{2}
\]

(A.4)

For computing the score, the above computation depends only on one interaction, which is usually the most recent one. Another approach can be used to involve historical information through considering the last \( n \) interactions with a participant for computing his/her reputation score. The aggregated \( x \) and \( y \) values of the \( n \) interactions can be computed as follows

\[
x_{ag} = \sum_{j=1}^{n} \lambda^{(n-j)} x_j \quad \text{and} \quad y_{ag} = \sum_{j=1}^{n} \lambda^{(n-j)} y_j
\]

(A.5)

where \( x_{ag} \) and \( y_{ag} \) are the aggregated \( x \) and \( y \) values, respectively. The parameter \( \lambda \) is an aging factor used to give lower weight to the old contributions than the recent ones such that \( 0 \leq \lambda \leq 1 \) [74].