

# Approaches to the Design and Implementation of Roadside Units in Vehicular Networks

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# Abstract

The traffic safety and efficiency applications made possible by vehicular communications have the potential to improve the lives of millions of people who, every day, use automobiles as their primary means of transportation. To be well connected and fully functional, these networks of cars require a minimum number of active nodes, which often may not happen due to a lack of radio-equipped vehicles on the road. These same networks can also be overwhelmed with traffic and signaling in the presence of too many cars, requiring careful coordination between all nodes to ensure proper operation.

One way to overcome both these problems is to supplement vehicle-to-vehicle (V2V) communications with vehicle-to-infrastructure (V2I) systems by deploying Roadside Units (RSUs) along the road to support the network of moving cars. RSUs are infrastructure nodes that can supplement sparse networks in low-density scenarios, and help coordinate and move data in denser networks. RSUs have an associated cost, however, and so their numbers need to be minimized while still maintaining a significant improvement to the vehicular network.

The work presented in this thesis quantifies the benefits of Roadside Unit deployments and proposes innovative approaches that can reduce and even eliminate the need for RSUs altogether. The first part of the thesis focuses on highway networks: first, an analytical model is developed to analyze communication delay in scenarios with sparse bi-directional traffic, considering both disconnected and connected RSUs. Then, a study on connectivity and message dissemination in these networks reveals how significant benefits of RSUs are only achieved when the deployed RSUs are interconnected. Extensive simulation work paired with sets of experimental measurements validate both model and study.

Supplementing the work on sparse highway networks, an infrastructure-less

approach is then proposed, consisting of two methods to improve communication delays in these scenarios: decelerate disconnected vehicles as they receive safety messages, and boost the same vehicles' radio transmit power, to shorten the time to restore connectivity. Both techniques are modeled analytically, and data from a simulation study validate the models and show significant improvements in the connectivity of sparse highway networks with this infrastructure-less approach.

The second part of the thesis sets its sights on urban vehicular networks. High costs associated with RSUs prevent their deployment at scale, and therefore finding alternative solutions to this longstanding problem is very important. A novel, low-cost self-organizing network approach to leveraging parked cars as RSUs in urban areas is proposed here, enabling parked cars to create coverage maps based on received signal strength and to decide whether to become RSUs from that knowledge. Initial simulation work reveals significant benefits to emergency message broadcasting delay in sparse scenarios and shows the ability of the self-organizing approach in providing robust and widespread coverage to dense urban areas, using only a small fraction of the cars parked in a city.

The parking behaviors of individual drivers are then studied, by analyzing and gathering statistics on travel survey data from various metropolitan areas. Daily and hourly analytical models of parking events are provided, along with important derivations. The statistical data show that parking events can be classified into two major groups based on the time a car spends parked, and that these patterns vary substantially throughout the day while being markedly similar across different cities.

The last part of the thesis focuses on self-organization for parked car RSUs. Novel mechanisms for self-organization are introduced that are innovative in their ability to keep the network of parked cars under continuous optimization, in their multi-criteria decision process, and in their control of each car's battery usage, rotating roadside unit roles between vehicles as required. The first comprehensive study of the performance of such approaches is presented, via realistic modeling of mobility, parking, and communication, thorough simulations, and an experimental verification of concepts that are key to self-organization. This analysis leads to strong evidence that parked cars can serve as an alternative to fixed roadside units, and organize to form networks to support smarter transportation and mobility.

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## Chapter 1

# Introduction

*“I do not think that the wireless waves I have  
discovered will have any practical application.”*

— H. R. Hertz

Wireless communications between automobiles have the potential to substantially improve the safety, the efficiency, and the comfort of millions of people who use this mode of transportation every day. A Vehicular Ad Hoc Network (VANET) enables a number of applications, both in the realm of what is already possible with a computer network (e.g., Internet access, content delivery, or even games), and in novel and highly relevant areas to drivers, such as advance collision warnings, efficient travel routes, or road hazard notifications.

To enable Dedicated Short Range Communications (DSRC) between vehicles, the basis for vehicular networks, IEEE introduced a new communication standard known as the 802.11p Wireless Access in Vehicular Environments (WAVE) [1, 2]. This standard adapts the popular 802.11 wireless technologies to work with the high mobility and harsh fading that characterize the vehicular environment, by increasing the robustness of car-to-car communications and increasing the opportunities for nodes to transmit data. It provides a multi-channel DSRC solution for multiple application types, with differentiated channels for network control, network services, safety applications, and long range data transmission.

Such vehicular ad hoc networks require a minimum number of nodes (cars) for the network to be well connected and functional. However, in sparse vehicular

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networks, the communication between vehicles is subject to very high transmission delays, which poses a significant problem for safety messages that should reach nearby vehicles as quickly as possible when an accident occurs, or for when road safety information needs to be disseminated. On these sparse networks, delays can often exceed hundreds of seconds [3].

One way to overcome this problem is to supplement vehicle-to-vehicle (V2V) communications with vehicle-to-infrastructure (V2I) support [4], by deploying infrastructure nodes known as Roadside Units (RSUs) along the road, in addition to the DSRC units within the vehicles which are generically known as On-Board Units (OBUs). Acting as message relays and data delivery points, Roadside Units can make a significant improvement to the usefulness and reliability of a vehicular network. Figure 1.1 shows examples of both testbed and commercial RSU hardware.

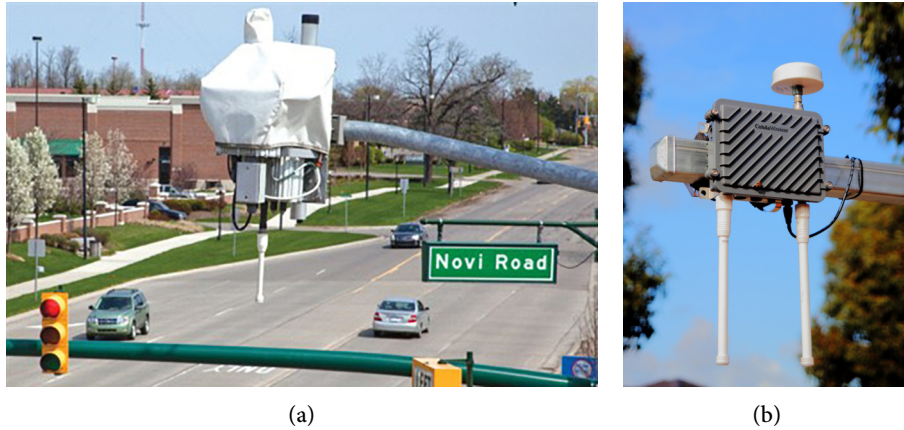


Figure 1.1: Examples of real-world roadside units. (a) One of 52 roadside units belonging to the US-DOT's Michigan Test Bed in Oakland County, Michigan [5]. (b) Roadside unit hardware manufactured by Cohda Wireless [6].

The first part of this thesis focuses on the benefits that deployments of Roadside Units can bring to a *sparse highway network*. In these sparse networks, the intermittent connectivity due to low node count and high node mobility can cause substantial delays in the broadcast of important safety messages. These issues can be mitigated by deploying RSUs along the road in either a standalone manner (*disconnected RSUs*) or linked together through a network backbone (*connected RSUs*). Although the

presence of these units may significantly improve communication performance, a careful study of the associated improvement needs to be conducted, since the cost of deploying and supporting RSUs in vehicular environments can be very high. A sample of RSU installation costs can be seen in table 1.1 [7].

TABLE 1.1  
ROADSIDE UNIT INSTALLATION COSTS

Hardware	\$3 000	Radio Survey per site	\$ 1 000
Incidentals	\$1 030	Map Generation	\$ 1 000
Comm. Connection Equipment	\$1 125	Planning	\$ 550
Power Connection Equipment	\$ 325	Design	\$ 1 600
Additional Installation Equipment	\$2 000	System Integration & License	\$ 1 500
Total Cost for Installation Labor	\$2 475	Traffic Control	\$ 1 000
Construction Inspection	\$1 075	<b>Total</b>	<b>\$17 680</b>

Existing studies on the physical distribution of RSUs to optimize communications fail to consider bi-directional traffic (where cars in one direction can relay messages to the cars in the opposite direction), or to give a clear comparison between using connected and disconnected RSUs in quantitative terms. Moreover, no studies are complemented with real-life testbed results. The work presented in this thesis aims to fill these gaps. We offer a comprehensive look at the impact of RSUs on the quality of the communications in highway scenarios, considering bi-directional traffic, and provide a detailed study based on analysis, simulations, and an experimental testbed, revealing the tradeoff between network packet delay and the number of RSUs deployed.

Our work shows that deployments of RSUs on highways provide little or no improvement in the end-to-end delay in safety message dissemination if the RSUs are disconnected from each other. Conversely, we observe that interconnected RSUs can reduce the re-healing time or the end-to-end delay by orders of magnitude. We believe that these findings bring a new perspective on how the RSU deployment issue should be handled.

The second part of this thesis is centered on vehicular networks that operate in *urban areas*, and in the use of *cars as Roadside Units* as an alternative to the costly RSU installations. A nationwide deployment of RSUs as supporting infrastructure

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for vehicular networks was anticipated to have happened by 2008 [8]. However, this forecast did not come to fruition due to difficulties in justifying the benefits of RSUs, lack of cooperation between the public and private sectors, but most importantly, a lack of funding for infrastructure whose widespread deployment is estimated to cost billions of dollars. A 2012 industry survey by Michigan’s Department of Transportation (DoT) and the Center for Automotive Research reiterated that “*one of the biggest challenges respondents see to the broad adoption of connected vehicle technology is funding for roadside infrastructure.*” [9].

These difficulties explain why one is unlikely to see substantial deployments of RSUs in the near future, and motivate the need for a credible, low-cost alternative to fixed infrastructure that can operate both independently and in conjunction with existing RSUs. In urban areas, one way to avoid the prohibitive expense of fixed RSUs is to use the vehicles themselves as RSUs and, in this thesis, we propose the use of parked cars as full-fledged RSU replacements, introducing a self-organizing network approach to allow them to form vehicular support networks. We tackle the specific problems of selecting which parked cars should become part of the network, how to measure each car’s utility to be able to make informed decisions, what algorithmic steps vehicles should follow when they park, and how to deal with possible disruptions in connectivity when parked cars leave. Simulation data from a unique platform built with real-life data show that parked cars bring tangible benefits in initial deployment stages, where insufficient numbers of DSRC-enabled vehicles cause the network to become sparse; in denser networks, we see how a support network that provides excellent coverage is possible using only a small fraction of the cars that park in a city.

The third part of this thesis takes a more in-depth look at the potential for parked car self-organization. We present a new approach that advances existing techniques in several ways: a new set of mechanisms optimize networks of parked cars beyond their initial grouping, which leads to a more efficient selection of cars to act as RSUs; a multi-criteria decision making process acts directly on key metrics of signal strength, coverage saturation, and network coverage, allowing for a precise control of the resulting support network; and car battery usage is factored into the decision process, with RSU roles being rotated among parked cars, ensuring a controlled use of each vehicle’s battery resources. We shed light on the number of parked cars that need to

be recruited to provide urban coverage in various scenarios, and analyze the quality and strength of the resulting networks in detail. We then bring in realistic models of the distribution of parking events and their respective duration, and validate the proposed mechanisms against them. Our analysis shows that this new approach makes use of fewer cars to reach identical levels of signal strength and coverage, and is more effective at stabilizing the resulting network. With this work, we provide strong confirmation that self-organizing approaches are suitable for the creation of vehicular support networks from parked cars.

## **1.1 Organization of the Dissertation**

This dissertation is organized as follows. Chapter 2 is focused on the deployment of Roadside Units in sparse highway vehicular networks. We develop analytical models that characterize message transmission delay in these scenarios, run simulations that validate the models and reveal the benefits that RSUs can bring, and show data from an empirical study to confirm our predictions. In chapter 3, we present an infrastructure-less approach to improve the transmission of important safety messages in highway networks, together with an analytical model, a simulation study, and a discussion on the viability of the proposed methods.

Chapter 4 shifts our focus towards urban areas. We introduce a new approach to allow the cars that are parked in a city to undertake the responsibilities of RSUs, and provide a set of self-organizing processes to choose which cars should be tasked with network support. We show the benefits that this approach can bring in sparse-density scenarios, and how a widespread network can be established in dense scenarios. In chapter 5, we analyze travel surveys from three US cities to reveal a number of parking trends and patterns, and provide hourly and daily models of these parking behaviors.

Chapter 6 develops a new approach to parked car self-organization based on neighborhood optimization and multi-criteria decision making. We present an extensive and thorough study of this approach, its advantages, and its performance under realistic parking behaviors. Finally, we show data from a pair of experimental studies that verify core assumptions of self-organization processes, and we touch on a few security considerations as well. Concluding remarks, a list of contributions, and directions for future research are presented in chapter 7.





## Chapter 2

# Roadside Units in Sparse Highway Vehicular Networks

In a sparse vehicular network, the intermittent connectivity due to low node count and high node mobility can cause substantial delays in the broadcast of important safety messages. Roadside Units may be used to strengthen network connectivity and to provide fast message dissemination; however, these infrastructure nodes have an associated cost, and so the number of RSUs needs to be minimized while still providing a significant improvement in communications. In this chapter, we study the benefits of deploying RSUs to improve communications in highway scenarios. We develop an analytical model to analyze communication delay in scenarios with bi-directional traffic, considering both connected and disconnected RSUs, and validate our model via simulations and experimental measurements with 802.11p equipment. Contrary to conventional wisdom, our results show that significant benefits of RSUs concerning connectivity and message dissemination are only achieved when the deployed RSUs are interconnected. Conversely, deploying a large number of disconnected RSUs will lead to little or no benefit in message dissemination delay [10, 11].

### 2.1 Introduction

The communication between vehicles in sparse vehicular ad hoc networks can be characterized by very high transmission delays, which adversely affect the quality of the communications. These delays pose a significant problem for safety messages,

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which should reach nearby vehicles as quickly as possible when an accident occurs, or when vehicle and road safety information needs to be disseminated.

The packet delivery delay experienced in end-to-end communication scenarios between disconnected vehicles has been modeled and analyzed in previous works (see, for example, [3]). This delivery delay is known as the re-healing time. It was shown that this time can be larger than 100 seconds in multi-hop disconnected communication scenarios, which is detrimental for vehicular communications.

Such results and findings provide motivation for the deployment of Roadside Units to improve communication between vehicles on a highway. These infrastructure nodes are fixed *base stations* deployed along the road with the goal of increasing the overall coverage of a vehicular network. They can be equipped with better hardware than the units used in the vehicles, and can have fewer power and cost constraints. When used as fixed points for communication on highways, they are expected to enhance the network's performance and improve the propagation delay of messages between the several disconnected vehicles. A network of RSUs can also connect to a backbone, enabling access to other Wide Area Networks (WANs) or to the Internet. Although the presence of these units may significantly improve communication performance, a careful study of the associated improvement needs to be conducted, since the cost of deploying and supporting RSUs in vehicular environments can be very high.

The existing studies on RSUs are mostly focused on vehicle to infrastructure (V2I) communications, for dissemination of information or Internet access [12–31]. Unfortunately, most of these studies only consider unidirectional traffic or assume that the RSUs are connected to a backbone. Such studies therefore provide little insight into the quality of communications when one deploys stand-alone RSUs.

In this chapter we present a comprehensive study of the impact of RSUs on the quality of the communications in highway scenarios, considering bi-directional traffic, where cars in one direction can relay traffic to the cars in the opposite direction. We present a detailed study based on analysis, simulations, and an experimental testbed, which provides insight into the tradeoff between network packet delay and the number of RSUs deployed.

To this end, we develop mathematical models to determine the average delay of a packet between a disconnected source-destination pair in the presence of RSUs

as relays or broadcasters of information. The models cover both the single-gap (the disconnection between adjacent clusters) and multi-gap communication scenarios. We study both the scenarios of disconnected RSUs, where RSUs are deployed without a physical connection between them, and interconnected RSUs, where RSUs are connected through fiber or wireless links.

Our analytical results are verified via extensive Monte Carlo simulations and further validated with empirical measurements, with real scenarios on the road, where cars and RSUs communicate through our own implementation of DSRC technology [32]. The results validate the accuracy of the proposed models, and highlight the disparity between deployment of disconnected and interconnected RSUs. For single-gap communications with *disconnected* RSU support, the transmission delay can be reduced by 15 % to 30 %; for traversing multiple gaps, a reduction of at most 25 % in end-to-end delay is possible. With *connected* RSUs the decrease in delay can be of several orders of magnitude, depending on the desired Region of Interest (RoI). These results are critical for the deployment of RSUs on highways: on the one hand, they show that the improvement by disconnected RSUs (where they are used as broadcasters of information) is quite modest even if the density of RSUs is very large; on the other hand, they show that connected RSUs (acting as relays of information) are the better choice for providing high-quality communications and better connectivity in vehicular highway scenarios. Through this key result, we provide major insights into how this interconnected RSU scenario can be implemented on highways.

## 2.2 Vehicle and Network Traffic Model

### 2.2.1 Parameters of Sparse Vehicular Networks

An ad-hoc network operating on a highway with vehicles as network nodes can be fully characterized by a discrete set of parameters. Research in [3] presents an empirical study of traffic characteristics on the Interstate 80 highway in California, for various times of day, based on the analysis of extensive sets and traces of real freeway data, independently collected by the Berkeley Highway Laboratory (BHL) [33].

This study has shown that late-night traffic tends to be low-volume and high-speed. When a vehicular network is formed, the low density of vehicles under such

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conditions leads to network sparsity — i.e., a network that is prone to disconnected gaps between its nodes. This research is focused on methods to overcome such disconnection, and therefore, late-night and low-volume traffic is the scenario that is most relevant to this work.

The inter-vehicle spacing of this type of traffic is shown, in [3], to follow the well-known exponential distribution, which in turn allows one to derive various characteristics of the vehicular network that these vehicles create. The exponential distribution has been known to provide a reasonable representation of inter-vehicle spacing for low-density traffic [34].

It can therefore be seen that the critical parameters for such a network are: the vehicle traffic density  $\lambda_t$ , in vehicles entering one lane of the highway per unit of time; the vehicles' speed  $v$ , which, from empirical observation of late-night traffic, is seen to have a relatively low deviation from the mean, and can therefore be treated as a deterministic value; the number of vehicles per unit of distance,  $\lambda_s = \lambda_t/v$ ; and on the network side, the expected radio range  $R$  of each vehicle's DSRC radio. In this work, vehicles can travel in either the east-bound or the west-bound direction (see figure 2.1).

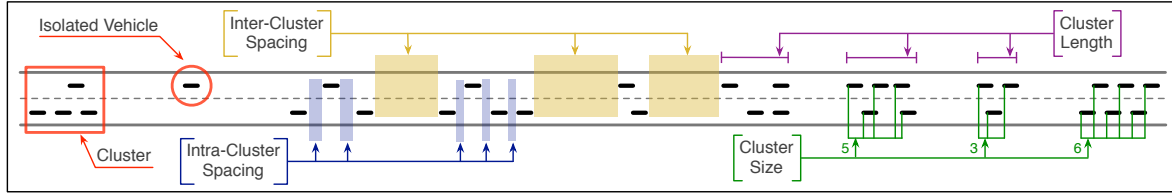


Figure 2.1: A standard highway scenario depicting several characteristics of a sparse vehicular network.

From the exponential distribution of inter-cluster spacing, and the concept of a vehicle cluster (a group of vehicles traveling in the same direction, where each vehicle is in the radio range of at least one other vehicle), a series of equations that describe core characteristics of the sparse vehicular network can be derived. We now list the ones that are critical to our analysis. Figure 2.1 illustrates some of these characteristics, and for further details on this base traffic model and how each core characteristic is derived, please refer to [3].

The probability of being the last vehicle in a cluster is given by

$$P_d = e^{-\lambda_s R} . \quad (2.1)$$

The Probability Distribution Function (PDF) of the spacing between cars in the same cluster,  $S_{intra}$ , as well as its expected value  $E[S_{intra}]$ , are given by

$$f_{S_{intra}}(s_{intra}) = \frac{\lambda_s e^{-\lambda_s s_{intra}}}{1 - e^{-\lambda_s R}}, \quad (2.2)$$

$$E[S_{intra}] = \frac{1}{\lambda_s} - \frac{R e^{-\lambda_s R}}{1 - e^{-\lambda_s R}}. \quad (2.3)$$

Similarly, the distribution and expectation of the spacing between clusters (i.e., the gaps),  $S_{inter}$ , is given by

$$f_{S_{inter}}(s_{inter}) = \lambda_s e^{-\lambda_s (s_{inter} - R)}, \quad (2.4)$$

$$E[S_{inter}] = R + \frac{1}{\lambda_s}. \quad (2.5)$$

The Probability Mass Function (PMF) of cluster size,  $C_N$ , in number of vehicles, is

$$f_{C_N}(c_n) = P_d (1 - P_d)^{c_n - 1}, \quad (2.6)$$

and the mean cluster size is given by

$$E[C_N] = \frac{1}{P_d}. \quad (2.7)$$

The vehicle cluster length distribution  $f_{C_L}(c_l)$ , in meters, involves a more complex derivation. We provide a numerical calculation of this PDF in Appendix A. The expected cluster length is given by

$$E[C_L] = \left( \frac{1}{P_d} - 1 \right) \left( \frac{1}{\lambda_s} - \frac{R e^{-\lambda_s R}}{1 - e^{-\lambda_s R}} \right). \quad (2.8)$$

With the deployment of fixed infrastructure units in the vehicular network, two new parameters are introduced: the distance  $C_I$ , in meters, between each RSU and the next, and the radio range  $R_I$  of these units, also in meters. Being specialized equipment, we observe that an RSU's physical hardware can be improved over the one deployed in vehicles, to enable increased transmission power and/or antenna gain, which in turn would result in an improved communication range.

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### 2.2.2 Analytical Modeling of Sparse Vehicular Networks

The transmission scenario that will be under consideration for the remainder of the chapter is the transmission of a message from a source vehicle, denoted as  $Src$ , to a destination vehicle,  $Dst$ , in a two-lane, bidirectional road. To better characterize each lane's traffic, the vehicle density is denoted as  $\lambda_e$  and  $\lambda_w$ , and the vehicle's speed as  $v_e$  and  $v_w$ , depending on whether we refer to east-bound or west-bound traffic.

$Src$  and  $Dst$  in our scenario must necessarily be members of two separate clusters, with any number of intermediate clusters in between — their exact number depends on the distance between  $Src$  and  $Dst$  and on network and traffic parameters. Therefore, there is at least one communication gap between  $Src$  and  $Dst$  that cannot be overcome without the aid of a third entity.

This entity is an opposite-lane vehicle, denoted as  $Z$ , that receives the message from  $Src$ , stores it, and delivers it to  $Dst$  once it communicates with  $Dst$ . This mechanism is called *Store-Carry-Forward* transmission, and the time for the message to be transmitted across a region of disconnection is designated the *Re-Healing Time*.

For a message transmission requiring one or more gaps to be traversed, the need for 're-healing' happens when the last car in a cluster (tail) has received a message and is unable to relay the message to the head of the following cluster. Using the last vehicle as a point of reference, which we consider to be the  $Src$  vehicle from now on, two main scenarios can be identified:

- The best-case scenario, which occurs when the  $Src$  vehicle is in the range of an opposite-lane vehicle capable of receiving and relaying the message (see figure 2.2a);
- The worst-case scenario, which occurs when there is no opposite-lane vehicle in range of  $Src$ , and thus  $Src$  must wait for one such vehicle to relay the message (see figure 2.2b).

These scenarios are fundamental for the understanding of how messages propagate in sparse vehicular networks, and are an important tool for understanding the contribution of infrastructure deployments. We now briefly describe the two scenarios.

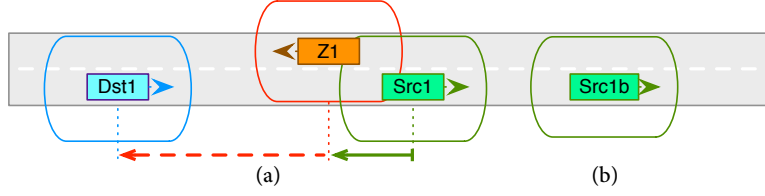


Figure 2.2: Examples of (a) a best-case scenario; (b) a worst-case scenario.

### Best-Case Scenario

In a best-case scenario, depicted in figure 2.2a, the source vehicle  $Src1$  is directly connected to vehicle  $Z$  in the opposite lane at the time it receives a message for  $Dst1$ . This scenario then considers two possibilities:

- No vehicles in  $Z$ 's cluster are in range of  $Dst1$ , in which case the lead vehicle of  $Z$ 's cluster must wait until it moves into range of  $Dst1$ ; this scenario occurs with probability  $p_{10}$  and its re-healing time is denoted as  $E[T_{r_{10}}]$ .
- Vehicle  $Z$  or a vehicle in its cluster might be directly connected to  $Dst1$ , in which case the re-healing time is instantaneous; this scenario occurs with probability  $(1 - p_{10})$ , and its re-healing time is denoted as  $E[T_{r_{11}}]$ .

Given these two events, it can be shown that the mean re-healing time in a best-case scenario is given by

$$\begin{aligned}
 E[T_{r_1}] &= E[T_{r_{10}}]p_{10} + E[T_{r_{11}}](1 - p_{10}) \\
 &= \left\{ (1 - P_d) \frac{1}{v_e + v_w} \left\{ \frac{1}{\lambda_e} - \frac{1}{2} E[S_{intra}] E[C_N | C_N \leq k] \right\} \right. \\
 &\quad \left. + P_d \frac{1}{v_e + v_w} (R + E[S_{inter}] - R) \right\} p_{10} . \tag{2.9}
 \end{aligned}$$

### Worst-Case Scenario

In a worst-case scenario, as depicted in figure 2.2b, the disconnected vehicle  $Src1b$  does not have any opposite-lane vehicle in its range. Therefore, for the message to be carried across the gap, it must now wait for an opposite-lane vehicle to move into its range, and then for that vehicle to carry the message to  $Dst1$ . Two delay components

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are discernible: the temporal delay from *Src* to *Z* (denoted as  $E[T_{r_{20}}]$ ), and then from *Z* to *Dst* (denoted as  $E[T_{r_{21}}]$ ).

The mean re-healing time in a worst-case scenario can be shown to be

$$\begin{aligned} E[T_{r_2}] &= E[T_{r_{20}}] + E[T_{r_{21}}] \\ &= p_{20}^1 \frac{E[C_L]}{v_e + v_w} + (1 - p_{20}^1) \frac{1}{2\lambda_w(v_e + v_w)} + \frac{E[S_{inter}]}{v_e + v_w}, \end{aligned} \quad (2.10)$$

where  $p_{20}^1 = P[C_L < E[S'_{inter}] - 2R]$ , is the probability that *Src* is in a small cluster. Details on the distinction between small and large clusters and on how this result is reached are outlined in [3].

### Mean Per-Gap Re-healing Time

The worst-case scenario occurs with probability  $P'_d = e^{-2R\lambda_w}$ , the probability of having no opposite-lane vehicles in a range of  $2R$ , which follows from the exponential distribution of vehicle spacing. It also follows that the best-case scenario occurs with probability  $1 - P'_d$ , and thus the mean re-healing time per gap is given by

$$E[T_r] = (1 - P'_d)E[T_{r_1}] + P'_dE[T_{r_2}]. \quad (2.11)$$

### Multi-Gap Delay

Often, a safety message will need to overcome many gaps before it reaches its destination or is delivered to all vehicles in a predetermined area of interest. As a result of the memoryless property of the exponential distribution [35], all gaps in the road are statistically independent, and can be analyzed individually.

In order to determine the mean re-healing time required for a message to be delivered to a given point in the road, one must first determine how many gaps exist between the source and the destination vehicles. Given the distance  $d$  between both vehicles, computing the mean number of gaps,  $G_C$ , from the cluster length and intercluster spacing, is straightforward:

$$G_C(d) = \frac{d}{E[C_L] + E[S_{inter}]} . \quad (2.12)$$

The mean re-healing time involving multiple gaps can be determined by multiplying the gap count,  $G_C$ , by the per-gap re-healing time,  $E[T_r]$ .



## 2.3 Communication Model for Infrastructure-Supported Networks

This section presents the analytical models to characterize vehicular networks with disconnected and connected RSU deployments. Together with the simulation data and the empirical studies, these constitute the core research that is presented in this chapter. One can envision several specific scenarios where RSUs can provide significant benefits to communications:

- RSUs as communication relays;
- RSUs as broadcasters of information (one-time or repeated information);
- RSUs as infrastructure communication points to and from a WAN (e.g., Internet).

When one considers the benefit of having RSUs assist communications in sparsely connected networks, the most critical scenario is the first one, where we envision deployments of RSUs to enable relaying of information when there is severe disconnection between vehicles. Therefore, this work specifically addresses this scenario, where we consider that vehicles flow in both directions and that RSUs, if present, are helping to relay information between disconnected sources and destinations.

### 2.3.1 Disconnected RSU Scenarios

The most straightforward scenario is a pure deployment of RSUs along the road, regularly spaced at a fixed distance, with no backbone to interconnect the RSUs. Our first model characterizes re-healing time on a highway where RSUs are deployed in a stand-alone or disconnected manner.

Working with the analytical framework described in section 2.2.2, we determine which communication scenarios can benefit from the presence of RSUs. Best-case and worst-case scenarios are evaluated independently, as each lead to a different set of benefits.

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### Best-Case Scenario - RSU Reduces Spatial Distance

In a best-case scenario (shown earlier in figure 2.2a) where the source vehicle *Src* is directly connected to a vehicle *Z* in the opposite lane to carry its message, improvements are seen when an RSU is positioned in a way where it can forward the message from *Z* to the destination *Dst*, effectively acting as a bridge between the two vehicles. To obtain the average reduction in the distance that *Z* needs to travel, we first note that, if the RSUs are placed at fixed intervals of  $C_I$  meters, then the probability of finding an RSU at an exact point in space is a uniformly distributed random variable in  $[0, C_I)$ :

$$f_{RSU}(r) = \begin{cases} 1/C_I, & 0 \leq r < C_I; \\ 0, & \text{otherwise.} \end{cases} \quad (2.13)$$

We now refer to figure 2.3. By taking as reference the point in time where the vehicles *Dst* and *Z* close in and reach a distance of  $2R_I$  to one another, we see a range of positions where an RSU can be found that would allow for the RSU to act as a relay between the two vehicles. In this scenario, if no RSUs were present, the two vehicles would have to close in to a distance of  $R$  to be able to communicate, i.e., they would have to travel a distance of  $2R_I - R$ .

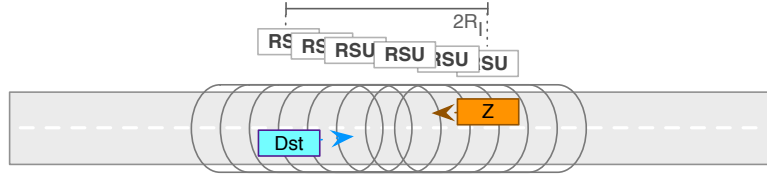


Figure 2.3: Favorable positions where disconnected RSUs can reduce the spatial distance between *Src* and *Z*.

The range of favorable RSU positions is between:

- The RSU being right on top of either vehicle *Dst* or *Z*. This is the least favorable scenario, and results in no improvement in delay.
- The RSU being in front of vehicle *Dst* by  $R_I$ . This is the most favorable scenario, where the travel distance reduction is highest (by  $2R_I - R$  meters) and vehicles can communicate immediately.

From this last point, we observe that the reduction in travel distance increases linearly from  $x = 0$  to  $R_I$  and decreases linearly from  $R_I$  to  $2R_I$ , with  $x$  as the distance from the RSU to  $Dst$ . The travel distance reduction,  $G(x)$ , is given by

$$G(x) = \begin{cases} \left(2 - \frac{R}{R_I}\right)x, & 0 \leq x < R_I; \\ -\left(2 - \frac{R}{R_I}\right)x + 2(2R_I - R), & R_I \leq x < 2R_I. \end{cases} \quad (2.14)$$

**Lemma 1.** *The mean reduction in travel distance achieved by the presence of an RSU in a favorable position to relay messages is given by*

$$E[L_I^1] = \int_0^{2R_I} G(x) f_{RSU}(x) dx = \frac{(2R_I - R)(R_I^2 + R^2)}{2R_I C_I}. \quad (2.15)$$

*Proof of Lemma 1.* Follows from equations (2.13) and (2.14). The range of favorable RSU locations is  $[0, R_I]$ , the probability of having an RSU in such a location is given by  $f_{RSU}$ , and each point in this range represents a reduction in travel length given by  $G(x)$ . ■

In a multi-gap scenario, an improvement is only seen if a vehicle in the new cluster has a new opposite-lane vehicle in range to act as a relay. Refer to figure 2.3: if vehicle  $Dst$  cannot immediately forward the message to a new opposite-lane vehicle, then it will have to use vehicle  $Z$  again as the new relay (which would then be the closest opposite-lane vehicle), thus nullifying possible gains.

**Lemma 2.** *The probability of a cluster of cars having at least one opposite-lane vehicle in range is given by*

$$\begin{aligned} P_{dC} &= 1 - \Pr[\text{no opposite-lane vehicles in a range of } C_L] \\ &= 1 - e^{-\lambda_w \cdot E[C_L]}. \end{aligned} \quad (2.16)$$

*Proof of Lemma 2.* Due to the exponential characteristic of traffic in both lanes, the probability of having no vehicles in a given range  $L$  will be given by  $e^{-\lambda L}$  (follows from zero realizations in a homogenous Poisson Point Process of rate  $\lambda$ ). The desired probability is the complement of having zero vehicles in the range of interest, which corresponds to the length of a cluster. Refer to Appendix A for the definition of  $E[C_L]$ . ■

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**Lemma 3.** *The mean reduction in travel distance achieved by a regularly spaced deployment of disconnected RSUs is given by*

$$\begin{aligned} E[L_I] &= E[L_I^1] \cdot P_{dc} \\ &= \frac{(2R_I - R)(R_I^2 + R^2)}{2R_I C_I} \left(1 - e^{-\lambda_w \cdot E[C_L]}\right). \end{aligned} \quad (2.17)$$

*Proof of Lemma 3.* Follows from lemmas 1 and 2. ■

The new best-case re-healing time,  $E[T'_{r_1}]$ , is the result of subtracting  $E[L_I]$  (from lemma 3) from the distance components in equation (2.9):

$$\begin{aligned} E[T'_{r_1}] &= \left\{ \frac{(1 - P_d)}{v_e + v_w} \left( \frac{1}{\lambda_e} - \frac{1}{2} E[S_{intra}] E[C_N | C_N \leq k] \right. \right. \\ &\quad \left. \left. - E[L_I] \right) + \frac{P_d}{v_e + v_w} (E[S_{inter}] - E[L_I]) \right\} p_{10}. \end{aligned} \quad (2.18)$$

### Worst-Case Scenario - RSU as Message Relay

In a worst-case scenario, the source vehicle is not connected to any vehicle capable of forwarding its message, and must wait for one to come into range.

With the presence of RSUs, a new scenario where an RSU acts as a relay becomes possible. This is shown in figure 2.4. This occurs when the delay to forward a message through an opposite-lane vehicle is larger than the delay for the source to get a message to an RSU, plus the delay for the destination to reach that RSU.

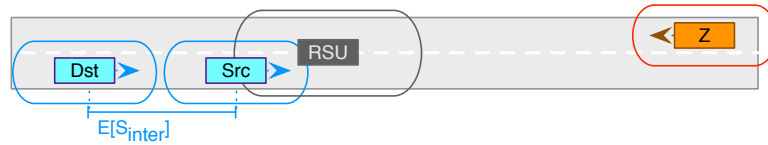


Figure 2.4: A scenario where a disconnected RSU can store and forward a message from *Src* to *Dst* faster than *Z* would.

**Lemma 4.** *The probability of having an RSU act as a message relay between two disconnected clusters (in a shorter time than an opposite-lane vehicle) is given by*

$$p_{2A} = e^{\lambda_w (R - K)}, \quad (2.19)$$

where  $K = 2[(E[S_{inter}] - R_I + C_I/2)(v_e + v_w) - (E[S_{inter}] - R)]/v_e$ .

*Proof of Lemma 4.* We begin by determining an expression for the probability of having the RSU as the main relay. This event occurs when the time it takes for *Src* to find a vehicle *Z*, and then for *Z* to reach *Dst*, is larger than the time it would take for *Src* to reach an RSU, and for *Dst* to come into range of that RSU:

$$P \left[ \frac{S_{inter} - R + S'_{inter}/2}{v_e + v_w} > \frac{S_{inter} - R_I + C_I/2}{v_e} \right], \quad (2.20)$$

where  $S'_{inter}$  is the inter-cluster spacing for vehicles in the opposite-lane. Rearranging the inequality as a function of  $S'_{inter}$ , we obtain a probability in the form of  $P[S'_{inter} > K]$ , with  $K = 2[(E[S_{inter}] - R_I + C_I/2)(v_e + v_w) - (E[S_{inter}] - R)]/v_e$ .

The probability  $p_{2A}$  can now be determined via the inverse Cumulative Distribution Function (CDF) of  $S'_{inter}$ :

$$\begin{aligned} p_{2A} &= 1 - P[S'_{inter} \leq K] \\ &= 1 - \int_R^K \lambda_w e^{-\lambda_w(S'_{inter}-R)} dS'_{inter} \\ &= e^{\lambda_w(R-K)}. \end{aligned} \quad (2.21)$$

■

**Lemma 5.** *The average re-healing time when an RSU is acting as the main relay is given by*

$$E[T_{r_{2A}}] = \left( \frac{C_I - 2R_I}{2} + R + \frac{1}{\lambda_e} \right) \frac{1}{v_e}. \quad (2.22)$$

*Proof of Lemma 5.* The re-healing time for the scenario addressed in Lemma 4 is given by the average distance from *Src* to the RSU, plus the distance from *Src* to *Dst*, which corresponds to the inter-cluster spacing in the lane of interest. Since a vehicle can be, at most,  $C_I - 2R_I$  meters away from an RSU, the average distance to an RSU is  $(C_I - 2R_I)/2$ , and

$$E[T_{r_{2A}}] = \left( \frac{C_I - 2R_I}{2} + E[S_{inter}] \right) \frac{1}{v_e}. \quad (2.23)$$

With equation (2.5), lemma 5 follows. ■

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### Worst-Case Scenario - RSU Reduces Spatial Distance

If the scenario described in section 2.3.1 does not occur, the standard worst-case scenario applies. Re-healing time is the sum of two components: *Src* must wait until an opposite-lane vehicle *Z* comes into range, and *Z* must carry this message to *Dst*. For the worst-case scenario, we observe that an RSU brings no advantage to the temporal delay between *Src* and *Z*. Even if the message from *Src* were to reach *Z* with the help of an RSU, *Z*'s time to deliver the message to *Dst* would not change.

The benefit of an infrastructure unit, in this scenario, comes as a reduction in the distance that *Z* needs to travel to reach *Dst* — this reduction is the same as the one shown in lemma 3.

**Lemma 6.** *In a worst-case scenario with RSU support, the re-healing time from *Z* to *Dst* is given by*

$$E[T_{r_{21}}] = \left( R + \frac{1}{\lambda_e} - E[L_I] \right) \frac{1}{v_e + v_w} . \quad (2.24)$$

*Proof of Lemma 6.* Follows from lemma 3 and equation (2.10). ■

Due to the inclusion of the new scenario as described in section 2.3.1, the worst-case total re-healing time is now simply

$$E[T'_{r_2}] = E[T_{r_{2A}}]p_{2A} + E[T_{r_{2B}}](1 - p_{2A}) , \quad (2.25)$$

where  $E[T_{r_{2B}}]$  is the previous worst-case re-healing time, from equation (2.10), after replacing  $E[T_{r_{21}}]$  with lemma 6.

With the best-case and worst-case scenarios appropriately extended for the presence of RSUs, we reach the global per-gap re-healing time equation, which is stated by the following theorem.

**Theorem 1.** *The re-healing time for a network with disconnected RSU support is given by*

$$\begin{aligned} E[T'_r] &= (1 - P'_d)E[T'_{r_1}] + P'_dE[T'_{r_2}] \\ &= (1 - e^{-\lambda_w 2R}) \left\{ \frac{(1 - P'_d)}{v_e + v_w} \left[ \frac{1}{\lambda_e} - \frac{1}{2}E[S_{intra}] \right] \right. \\ &\quad \times E[C_N | C_N \leq k] - E[L_I] \Bigg] + \frac{P'_d}{v_e + v_w} (E[S_{inter}] - E[L_I]) \Bigg\} \end{aligned}$$

$$\begin{aligned}
 & \times p_{10} + e^{-\lambda_w 2R} \left\{ e^{\lambda_w (R-K)} \left( \frac{C_I - 2R_I}{2} + R + \frac{1}{\lambda_e} \right) \frac{1}{v_e} \right. \\
 & + (1 - e^{\lambda_w (R-K)}) \left[ p_{20}^1 \frac{E[C_L]}{v_e + v_w} + (1 - p_{20}^1) \frac{1}{2\lambda_w (v_e + v_w)} \right. \\
 & \left. \left. + \left( R + \frac{1}{\lambda_e} - E[L_I] \right) \frac{1}{v_e + v_w} \right] \right\}. \tag{2.26}
 \end{aligned}$$

*Proof of Theorem 1.* Follows from equations (2.11), (2.18), (2.25), and lemmas 1-6. ■

To conclude the analysis on disconnected RSUs, we recall section 2.2.2 to note that the multi-gap re-healing time with disconnected RSUs can be computed by following the same rationale as before. The introduction of RSUs on the road does not change the number or the length of the clusters, so the average number of gaps in a given span remains the same.

### 2.3.2 Interconnected RSU Scenarios

In a highway where roadside units are deployed and interconnected, the network of RSUs is capable of quickly forwarding traffic over large distances by relaying traffic through its interconnected backbone. To characterize message propagation delay in this scenario, we break away from the previous models and take a more pragmatic approach where the message will be preferentially relayed through the connected network of RSUs. This approach is reasonable given the fact that we are primarily interested in characterizing re-healing time for messages that need to traverse multiple disconnected clusters over medium to high spans of road, and thus relying on the interconnected RSUs will almost always be the preferred method.

**Definition 1.** *In an interconnected RSU scenario, if the source and destination vehicles are spaced sufficiently far away (more than the RSU spacing), messages are primarily relayed through RSUs. Therefore, a vehicle is considered disconnected if it is not in range of an RSU. With interconnected RSUs, re-healing time is the average time a disconnected vehicle waits until it can contact an RSU, either by itself (single-hop) or through other vehicles in its cluster (multi-hop).*

The total re-healing time is both the average delay for the *Src* vehicle to reach an RSU and the average delay for the *Dst* vehicle to also reach an RSU. These events

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are indistinguishable, as the goal of both vehicles is to establish contact with an RSU. Two main cases can be identified:

- **Isolated vehicle:** if the vehicle is isolated, its re-healing time is the time for the vehicle to contact an RSU.
- **Clustered vehicle:** if the vehicle is part of a cluster, its re-healing time is the shortest time for any vehicle in the cluster to reach an RSU — intra-cluster communication can relay the message to the RSU as necessary.

We now derive analytical models that characterize the re-healing time in each of these cases.

### Isolated Vehicles

For an isolated vehicle, we identify the following three metrics: probability that an isolated vehicle is disconnected from an RSU,  $Pr[V_d]$ ; average delay for a disconnected vehicle to reach an RSU's radio range,  $E[T_{rv}|V_d]$ ; and probability that a vehicle is isolated,  $Pr[C_N = 1]$  (i.e., the vehicle is not part of a cluster). This scenario is depicted in figure 2.5.

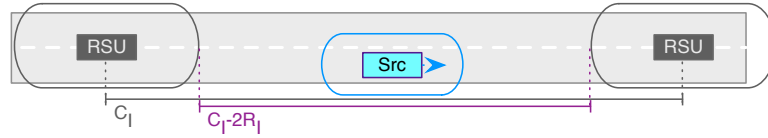


Figure 2.5: Example scenario of an isolated vehicle.

The probability that an isolated vehicle is disconnected from an RSU at the time of transmission or reception of a message is obtained in a straightforward manner from the density of RSUs and their radio range. For an RSU separation distance of  $C_I$ , and an RSU radio range of  $R_I$ , the proportion of road not covered by the RSUs' radio ranges equals the probability that, at any given point in time, a vehicle is disconnected from its nearby RSUs:

$$Pr[V_d] = \frac{C_I - 2R_I}{C_I} = 1 - \frac{2R_I}{C_I}. \quad (2.27)$$

If the vehicle is disconnected, then it must be located in the span of road between two consecutive RSUs' radio ranges, i.e., in figure 2.5 it must be located in the area



with a length of  $C_I - 2R_I$ . Statistically, it is safe to assume that, on average, the vehicle will be located in the center of this region; therefore, the average re-healing time is given by the time required to traverse half the length of the region with no RSU coverage:

$$E[T_{rv}|V_d] = \frac{C_I - 2R_I}{2} \frac{1}{v_e}. \quad (2.28)$$

**Lemma 7.** *In a highway with connected RSUs, the average re-healing time of an isolated vehicle is given by*

$$\begin{aligned} E[T_{rv}] &= E[T_{rv}|V_d]Pr[V_d] + E[T_{rv}|\neg V_d]Pr[\neg V_d] \\ &= \frac{C_I - 2R_I}{2v_e} \left(1 - \frac{2R_I}{C_I}\right). \end{aligned} \quad (2.29)$$

*Proof of Lemma 7.* Follows from equations (2.27) and (2.28); the re-healing time associated with event  $\neg V_d$  is zero, as the vehicle is connected. ■

### Clustered Vehicles

In a cluster of vehicles, it is sufficient to have a single vehicle in the cluster in range of an RSU for all vehicles in the cluster to be able to communicate with the RSU. This requires vehicle-to-vehicle multi-hop communications in the cluster. The following definition is based on this observation.

**Definition 2.** *In a highway where RSUs are deployed uniformly at a fixed distance of  $C_I$ , and where each RSU has a radio range  $R_I$ , if the length of a cluster of vehicles is equal to or larger than  $C_I - 2R_I$ , then at least one vehicle in that cluster will always be directly connected to an RSU, and therefore all vehicles in the cluster are considered ‘connected’.*

For clustered vehicles, we observe that the following must occur for the re-healing time to **not** be zero:

- As per definition 2, the length of the cluster the vehicle belongs to must be less than  $C_I - 2R_I$ . This event’s probability is  $P[C_L < C_I - 2R_I]$ .
- If the cluster’s length satisfies the above condition, it may still happen that one or more of the vehicles in the cluster are in range of an RSU in the time period

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where communication is requested. We denote the probability that this event does **not** occur by  $Pr[C_d]$  (*cluster disconnected*).

**Lemma 8.** *The probability that the length of a cluster is less than  $C_I - 2R_I$  is given by*

$$P[C_L < C_I - 2R_I] = 1 - \frac{e^{-\frac{C_I - 2R_I}{\mu}}}{kR + e^{-\frac{R}{\mu}}} . \quad (2.30)$$

*Proof of Lemma 8.* See Appendix A, where regression variables  $k$  and  $\mu$  are also defined. ■

**Lemma 9.** *The expected length of a cluster, conditioned on  $C_L < C_I - 2R_I$ , is given by*

$$E[C_L | C_L < C_I - 2R_I] = \frac{e^{\frac{R+C_I}{\mu}} kR^2 + 2e^{\frac{C_I}{\mu}} (R + \mu) - 2e^{\frac{R+2R_I}{\mu}} (\mu + C_I - 2R_I)}{2 \left( e^{\frac{C_I}{\mu}} - e^{\frac{R+2R_I}{\mu}} + e^{\frac{R+C_I}{\mu}} kR \right)} . \quad (2.31)$$

*Proof of Lemma 9.* See Appendix A. ■

Consider the scenario in figure 2.6. For the cluster to be disconnected, the edge vehicles of the cluster must be in the region  $[R_I, C_I - R_I]$ . Therefore, by taking the center of the cluster as reference, it follows that the cluster's center must be in a region of length  $(C_I - 2R_I) - E[C_L | C_L < C_I - 2R_I]$ , otherwise one of the edge vehicles will be in range of an RSU. The cluster's center can be located anywhere in  $[0, C_I)$ . Therefore, the probability of a cluster being disconnected from the RSU network,  $P[C_d]$ , is given by

$$Pr[C_d] = \frac{(C_I - 2R_I) - E[C_L | C_L < C_I - 2R_I]}{C_I} . \quad (2.32)$$

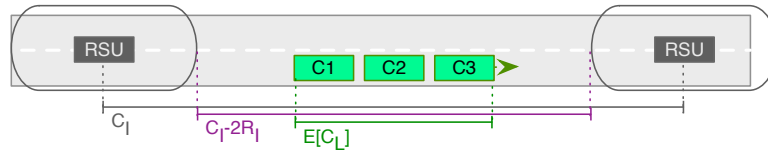


Figure 2.6: Example scenario of clustered vehicles.

Let us consider figure 2.6 again. Statistically speaking, it is correct to assume that the center of the cluster is in the middle of region  $[0, C_I]$ . Thus, the shortest re-healing time is the time for the frontmost vehicle in the cluster to reach the next RSU's radio range, which corresponds to a travel distance of  $(C_I - 2R_I - E[C_L|C_L < C_I - 2R_I])/2$ . The mean re-healing time for any vehicle in a cluster which is both disconnected and smaller than  $C_I - 2R_I$  is given by

$$E[T_{rc}|C_d \cap C_L < C_I - 2R_I] = \frac{(C_I - 2R_I) - E[C_L|C_L < C_I - 2R_I]}{2v}. \quad (2.33)$$

**Lemma 10.** *The average re-healing time of a vehicle in a disconnected cluster is given by*

$$\begin{aligned} E[T_{rc}] &= E[T_{rc}|C_d \cap C_L < C_I - 2R_I]Pr[C_d]Pr[C_L < C_I - 2R_I] \\ &= \frac{(C_I - 2R_I - E[C_L|C_L < C_I - 2R_I])^2}{2v_e C_I} \left( 1 - \frac{e^{-\frac{C_I - 2R_I}{\mu}}}{kR + e^{-\frac{R}{\mu}}} \right). \end{aligned} \quad (2.34)$$

*Proof of Lemma 10.* Follows from lemmas 8 and 9, equations (2.32) and (2.33), and the fact that the specific events  $\neg C_d$  and  $C_L \geq C_I - 2R_I$  correspond to a re-healing time of zero. ■

### Global Re-Healing Time Model

The final model for per-gap re-healing time, stated by the following theorem, is the consolidation of isolated vehicle and clustered vehicle scenarios.

**Theorem 2.** *The per-gap re-healing time for a network with interconnected RSU support is given by*

$$\begin{aligned} E[T_r] &= E[T_{rv}]Pr[C_N = 1] + E[T_{rc}]Pr[C_N > 1] \\ &= \frac{C_I - 2R_I}{2v} \left( 1 - \frac{2R_I}{C_I} \right) e^{-\lambda_s R} \\ &\quad + \frac{(C_I - 2R_I - E[C_L|C_L < C_I - 2R_I])^2}{2v C_I} \\ &\quad \times \left( 1 - \frac{e^{-\frac{C_I - 2R_I}{\mu}}}{kR + e^{-\frac{R}{\mu}}} \right) (1 - e^{-\lambda_s R}). \end{aligned} \quad (2.35)$$

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*Proof of Theorem 2.* Follows from lemmas 7 and 10, and the Cluster Size PMF in equation (2.6). ■

### 2.4 Evaluation of Infrastructure-Supported Networks

In this section we present the results obtained with the analytical model proposed in section 2.3, and with a Monte-Carlo simulation platform which is used for verifying the analytical model.

#### 2.4.1 Monte-Carlo Simulation Model

Our custom-designed simulator, written in C++, replicates a straight two-lane highway, with traffic flowing in both directions. Vehicles are generated at the beginning of each road at time intervals obtained from an exponential random number generator. Vehicles move at a constant speed, and there is no overtaking.

The transmission range of each vehicle and RSU can be controlled, and is set to 250 m unless otherwise stated. Radios are assumed to have perfect and instant communication, with no packet error when within the radio range, and no communication outside it. We also assume that, once a node receives a message, it immediately rebroadcasts it to every node in its vicinity. In section 2.5, we prove the validity of these assumptions for sparse networks with data from an experimental 802.11p testbed.

For each simulation, the setup is as follows: the simulator first runs for an arbitrarily long time, sufficient to fill the road in both lanes. Then, source and destination vehicles are picked in order to match the criteria of that particular simulation, e.g., if the goal is to transmit a packet between two vehicles which are 10 km apart, the simulator attempts to locate the pair of vehicles on the road that better matches that goal. Once this process is completed, the source vehicle generates and broadcasts a single message. After the message is received by the destination vehicle, metrics are recorded and the simulation setup is discarded.

### 2.4.2 Validation of Inner Model Characteristics

#### Disconnected RSUs

The two main components of re-healing time in disconnected RSUs are the best-case and the worst-case re-healing time. For this analysis, we set up a 10 km road with RSUs deployed at 1 km intervals, and once both lanes were filled with traffic, a vehicle in the eastbound lane was randomly selected to broadcast a message. The simulator then measured the time for the message to reach the next cluster in the eastbound lane, and reported whether we were in the presence of a best-case or a worst-case scenario.

Figure 2.7a shows the analytical and simulation results for the two main components of the disconnected RSU model, for vehicle densities ranging from 213 veh/h to 745 veh/h (the same density is used in both directions). Figure 2.7b shows the results of a simulation where *Src* and *Dsc* are 10 km apart, with disconnected RSUs deployed every 1 km, and is therefore a setup where both best case and worst case scenarios can occur randomly.

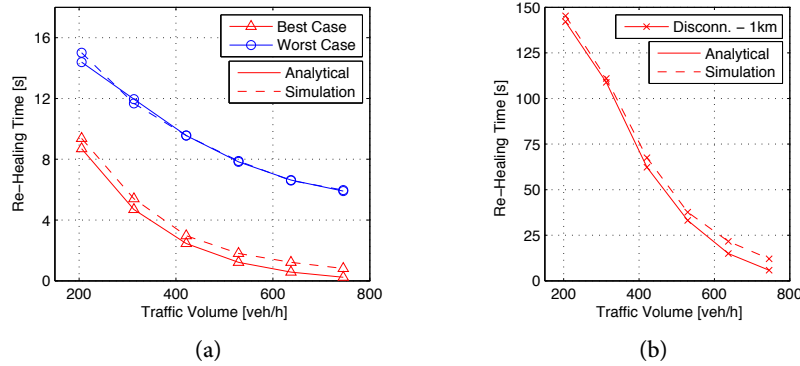


Figure 2.7: Comparisons between analytical and simulation results with disconnected RSUs. (a) Best-case and worst-case re-healing time with disconnected RSUs at 1 km intervals. (b) Total re-healing time for vehicles spaced 10 km apart, with disconnected RSUs.

We observe a very good match between the predictions of our analytical model and the output of the simulations. Results show that, as the traffic density increases, the re-healing time of both best- and worst-case scenarios decreases, as expected. As

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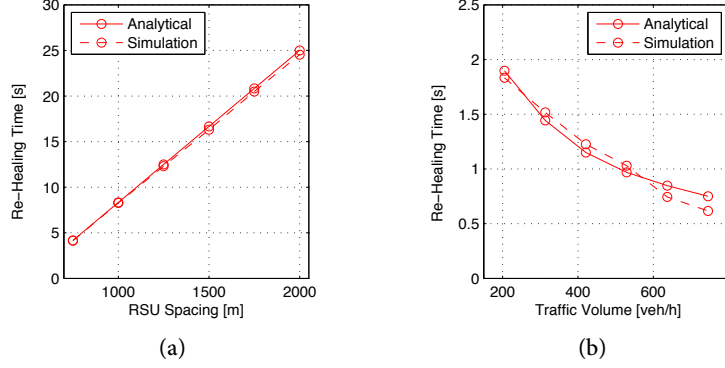


Figure 2.8: Comparisons between analytical and simulation results with connected RSUs. (a) Re-healing time for an isolated vehicle with connected RSUs. (b) Re-healing time for a clustered vehicle with connected RSUs.

a network grows sparser, so do the re-healing times; furthermore, the likelihood of being in the presence of a worst-case scenario also increases, which carries a higher penalty in re-healing time.

### Interconnected RSUs

As explained in section 2.3.2, our approach for scenarios with interconnected RSUs considers that the RSUs are the primary entities relaying messages. We consider two main cases: the case where a vehicle is isolated, and the case where it is part of a cluster.

A simulation is set up with a 10 km road, where RSUs are deployed at regular intervals and interconnected. We consider that, when an RSU receives a message, the message immediately becomes available at all other RSUs, which begin rebroadcasting that message. Figure 2.8a shows the re-healing time for *isolated vehicles*. The vehicle density has no effect on the re-healing time, as the scenario is conditioned to isolated vehicles — therefore, we plot this delay against the RSU density, for densities between 0.5 RSU/km to 1.25 RSU/km. Observe that there is an excellent match between the simulation results and the results of our analysis. Re-healing time is seen increasing linearly with the increase in distance between RSUs, which is an expected result given the fact that vehicles travel at a fixed speed.

The second scenario with connected RSUs considers that the target vehicle is part of a cluster. The length of the cluster the vehicle is part of depends directly on the vehicle density, higher densities leading to larger clusters.

Figure 2.8b plots the average re-healing time of vehicles that are part of clusters, for a fixed RSU spacing of 1 km. Again, we observe a very good match between simulation results and our analytical models. Comparing with the 1000 m data point in figure 2.8a, which corresponds to  $\sim 9$  s, one can conclude that being part of a cluster considerably improves the vehicle's time to connect to an infrastructure.

The excellent match between models and simulation results in figures 2.7a, 2.7b, 2.8a, and 2.8b, for both special cases and global end-to-end delays, upholds the validity of our analytical models and the conviction that all relevant possibilities for interactions with RSUs have been considered.

### 2.4.3 Single-Gap Communication Delay

We consider a road where RSUs are deployed in intervals of 1000 m and 750 m, and, conservatively, have the same radio range as vehicles. Vehicle speeds were set to 30 m/s (both lanes), and radio ranges to 250 m. Figure 2.9 shows a comparison of all three scenarios, for densities that go from 200 veh/h to 700 veh/h. Since it has been shown that the analytical models are in line with the simulation results, plots in this section feature data from the models only.

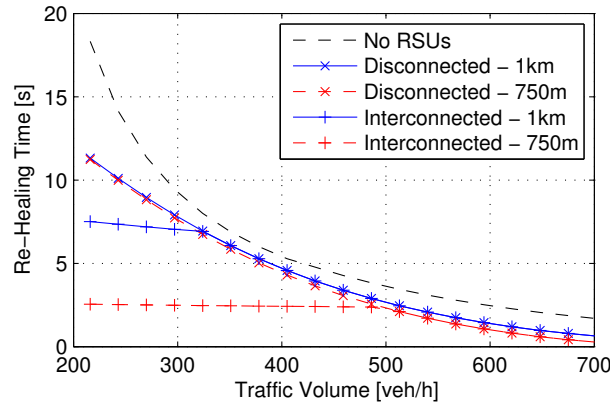


Figure 2.9: Single-gap re-healing time, to transmit over short distances.

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It can be observed that a deployment of isolated RSUs can yield a reduction of 1 s to 5 s in the network's mean re-healing time. This advantage becomes smaller for denser networks, as disconnection becomes less of an issue. A deployment of *connected RSUs* shows substantial improvement for very sparse networks, for densities under  $\sim 325$  veh/h for  $C_I = 1000$  m, and  $\sim 475$  veh/h for  $C_I = 750$  m. Due to the way the scenario for connected RSUs was designed, note that, for a transmission over a single hop and given sufficient vehicle density in both lanes, opposite-lane vehicles may be able to deliver a message in shorter time than if going through connected RSUs. This is evident from figure 2.9, for higher densities.

For a single-hop transmission, we observe that the best re-healing time in a road with connected RSUs is the shortest time between the opposite-lane store-carry-forward approach, and the delivery-through-infrastructure approach. This is particularly true for safety messages, where an ideal vehicular network must try to broadcast the message through any possible means. The re-healing metric will then be the shortest time for that message to be delivered.

### 2.4.4 End-To-End Communication Delay

In a multi-gap scenario, we study the delay involved in sending a message over a large segment of road (up to 30 km), which is essentially an accumulation of multiple re-healing delays, based on the number of clusters between source and destination, and on the inter-cluster spacing.

In the no-RSU and disconnected RSU models, store-carry-forward is the primary mechanism of transmission. For these scenarios, we fix the vehicle density in both directions and determine the mean number of clusters to be traversed. Then, the total delay is the sum of all re-healing times required to get a message from each cluster to the next. For connected RSUs, we determine the number of RSUs the message must travel to reach the destination, and add a conservative 50 ms delay per (RSU) hop to the re-healing time.

Figure 2.10 plots accumulated re-healing times for all three scenarios as a function of the length of road to transmit a message across, in a network where  $\lambda$  is fixed to a value indicative of a sparse network ( $\lambda = 425$  veh/h). All other parameters are the same as in the single-gap scenario above.

This is a scenario where a deployment of RSUs is capable of yielding significant



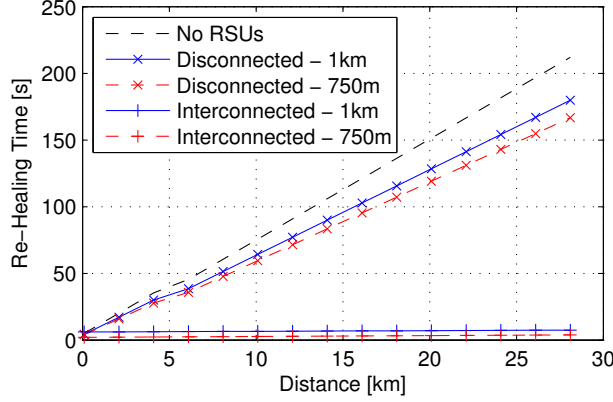


Figure 2.10: Multi-gap end-to-end delay, to transmit over large distances.

gains. The presence of disconnected RSUs steadily reduces the multi-gap accumulated delay by  $\sim 20\%$ , with higher gains possible for closer-spaced RSUs. The gains, however, are not what one would hope for. In this particular scenario, when RSUs are deployed 1 km apart with a 250 m range, 50 % of the road becomes covered by the RSUs alone, yet the re-healing time gains are modest at best.

Interconnected RSUs, on the other hand, show significant gains. A deployment of *interconnected* RSUs can thus be viewed as the only way to carry messages across long lengths of road with delays not exceeding 5 seconds. The results depicted in figure 2.10 are the key finding of this study: *the deployment of RSUs can only bring significant improvements if they are connected*. In other words, deploying a high number of *disconnected* RSUs will *not* lead to significant benefits.

#### 2.4.5 Effects of Cluster Spacing and Radio Range

Two parameters determine the benefits that RSUs can bring to a network: their expected radio range,  $R_I$ , and the distance they are deployed from each other,  $C_I$ . Figure 2.11a shows what delays can be expected in disconnected RSU setups, for different combinations of  $C_I$  and  $R_I$ , on a highway where vehicles *Src* and *Dst* are selected so that they are approximately 10 km away. Each pair of RSU spacing and radio range values has been chosen so that the length of road between two RSUs that is not serviced is at least 250 m, thus ensuring that the RSUs remain disconnected.

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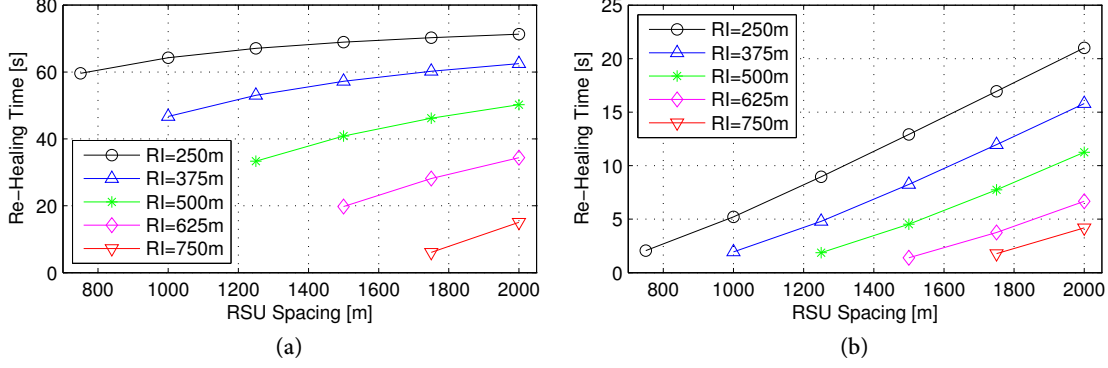


Figure 2.11: Impact of RSU spacing ( $C_I$ ) and RSU radio range ( $R_I$ ). (a) Disconnected RSU scenarios. (b) Interconnected RSU scenarios.

Results show that placing RSUs closer together in these scenarios yields only modest gains. For each 250 m reduction in  $C_I$ , the re-healing time improves by 2 s to 8 s. The effect of the RSU's radio range is significantly larger — each 125 m boost in the radio range can yield 10 s to 20 s less re-healing time, which is quite significant.

Next we analyze interconnected RSUs in more detail. Figure 2.11b plots the mean re-healing times achievable with different combinations of RSU radio range  $R_I$  and RSU spacing  $C_I$ . The results correspond to a highway setup where vehicles *Src* and *Dst* are selected to be approximately 10 km away. Again, a conservative 50 ms delay per RSU hop is added to the re-healing time.

Figure 2.11b is of great importance for the planning and design of highway RSU deployments. The impact of the RSU's radio range is very clear. As an example, for a threshold of 5 seconds, by increasing the RSU's radio range from 250 m to 500 m one can space the RSUs an extra 500 m apart while still observing the same expected re-healing time. In a 300 km road span, again as an example, improving the RSU's radio equipment to achieve the 500 m range would allow one to deploy 100 fewer RSUs in that particular road segment, a significant cost saving.

For interconnected RSU scenarios, the distance between RSUs is of much greater importance than for disconnected RSU scenarios, where more gains can be achieved by boosting the RSU's radio range.

### 2.4.6 Re-Healing Time Probability Distribution

To conclude this evaluation of infrastructure-supported networks, we present an analysis of the probability distribution of re-healing time, for two instances of disconnected and connected RSU scenarios. The goal of this analysis is to investigate the pattern of delay spread in representative scenarios, and to determine the spread around the statistical mean.

In order to obtain probability distribution functions (PDF) of the re-healing time in each scenario, we gathered data from the comprehensive sets of simulations that were performed previously to ensure the validity of the analytical models, and obtained the desired PDFs from this data. First, we analyze the re-healing time for a scenario with **disconnected** RSUs, spaced 1 km apart, where the time for a safety message to reach a vehicle 10 km away from the source of the message is measured. We considered five different traffic densities (all of them corresponding to sparse vehicular networks with very low densities), to ensure variety, and the default 250 m radio range. The results are shown in figure 2.12a.

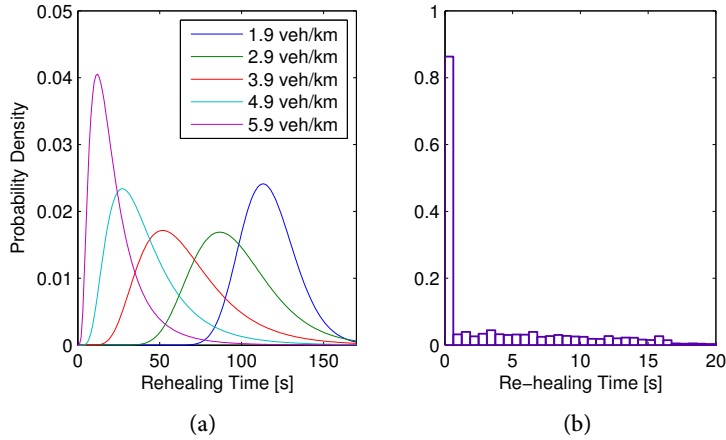


Figure 2.12: Re-healing time probability distributions. (a) Probability Distribution Functions for a 10 km re-healing time, with a deployment of disconnected RSUs placed 1 km apart. (b) Histogram of a 10 km re-healing time, with a deployment of connected RSUs placed 1 km apart. 5000 samples.

For this scenario, we attempted to distribution-fit the data to various known distributions and look for the closest match. We successfully fitted data from all

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traffic densities to the Log-Normal Distribution, with D-statistics of less than 4 % (a goodness-of-fit measure from the Kolmogorov-Smirnov test). This indicates that the re-healing time in disconnected RSU scenarios follows the log-normal distribution, and does so with a high degree of confidence.

One can also see, in figure 2.12a, that the spread of the delay around the mean is relatively small, if one takes into account how dynamic the evaluated scenarios can be. This provides further confidence that the results reported in this work are reliable as the plus or minus one standard deviation will be small.

For scenarios with **connected RSUs**, we found that the delay distributions feature unspecific patterns, and fitting the data to any known probability distributions with a reasonable degree of confidence was not possible. Figure 2.12b shows the histogram of simulation data for the 10 km re-healing time in a scenario with connected RSUs deployed at 1 km distances, and a traffic volume of 420 veh/h.

In connected RSU scenarios, when both source and destination vehicles are in range of an RSU, a safety message can be propagated instantly, thus explaining the large peak at the origin of the chart in figure 2.12b. The remaining data points exhibit very low probability of occurrence. Deployments of connected RSUs show such a vast improvement over disconnected RSUs, that any small observable delay spread is of little consequence for the purpose of broadcasting safety messages.

These results clearly show that in both regimes studied in this work (connected RSUs and disconnected RSUs) the spread around the statistical mean value is not significant.

## 2.5 Experimental Verification

To further strengthen the validity of the proposed models for RSU-aided vehicular communication, we designed and implemented a physical testbed for experimental verification of VANET technologies in Aveiro, Portugal. Our testbed comprises five hardware units, each consisting of a modern Single Board Computer (SBC) fitted with an IEEE 802.11p radio enhanced to operate in the regulated 5.9 GHz ITS band [32].

### 2.5.1 Testbed Hardware and Software

- **Board:** PCEngines Alix3D3, with a 500 MHz AMD Geode LX800 CPU at its core (32-bit x86 architecture) [36].
- **Radio:** Unex DCMA-86P2 5.86-5.92 GHz miniPCI radio for IEEE 802.11p applications (Atheros AR5414A-B2B chipset) [37].
- **Antenna:** L-Com 5.1-5.9 GHz 5 dBi omnidirectional antenna.
- **Operating System:** Linux Debian *Squeeze*, kernel version 2.6.32-5-486.
- **Driver:** Modified ath5k based on version *compat-wireless-2010-11-01*.

At the time of this writing, the publicly-available drivers for Atheros chipsets supported neither the 802.11p standard nor any hardware operating at 5.9 GHz. For this reason, we have modified the ‘ath5k’ driver that is freely available for Atheros-based chipsets, implemented the set of 802.11p standards, and modified the Central Regulatory Domain Agent (CRDA) and the software’s regulatory database to allow operation in the 5.9 GHz band.

For the mobile units, we installed hardware in a range of common mid-size vehicles, deploying the units on the rooftops of the vehicles. For the fixed RSUs, we installed battery-powered hardware in tripods that were then deployed on the side of highways, at the same height as mobile units. To connect RSUs for the interconnected RSU tests, we used 802.11g hardware operating in the 2.4 GHz ISM band.

### 2.5.2 Case Scenarios and Setup

To evaluate the validity of our models, a number of experimental measurements were carried out to evaluate the performance of RSU-supported sparse highway networks. These include the verification of real-life radio range of 802.11p radios, multi-hop communication delay, and backbone interconnection of RSUs.

All tests were performed in a low-traffic, 2 km straight road at the edge of the city of Aveiro, Portugal. For safety reasons and to comply with local road regulations, the drivers maintained the mobile units at a fixed 50 km/h speed, and therefore all the analytical data points to which our experimental data are matched with are derived for a speed of 13.89 m/s. Regarding the radio’s transmission range, after calibration all

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our radios exhibited 0 % packet loss at 240 m range, which then decayed to having no communication at distances of 260-270 m, which matches well with our theoretical 250 m radio range. For this behavior, the transmission power measured at the radio's output was 4 dBm.

To begin, we verified the assumption that multi-hop communication has sufficiently low delay to be considered negligible. The first scenario, depicted in figure 2.13a, places four vehicles in a row, each at a 250 m radio range to match the maximum radio range that we assume throughout this work, and attempts a 3-hop communication. This test revealed delays of 0.49 ms, 5.51 ms and 15.58 ms for 1-hop, 2-hop and 3-hop links, respectively, which are at least two orders of magnitude lower than the re-healing times given in this work, and can therefore be safely ignored.

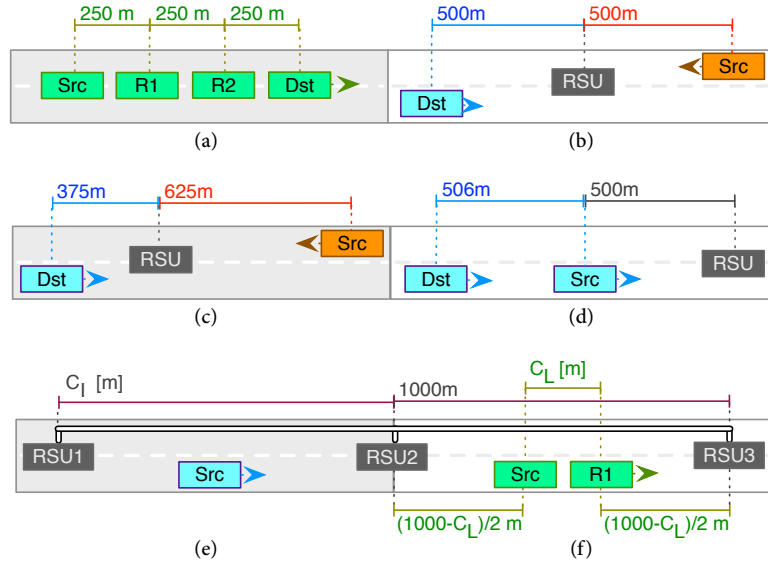


Figure 2.13: Experimental setups. (a) Multi-hop communication setup. (b), (c), (d) Disconnected RSU setups, D1, D2 and D3 scenarios, respectively. (e), (f) Connected RSU setups, isolated vehicle and clustered vehicle scenarios, respectively.

The exhaustive evaluation of disconnected RSU scenarios is a complex and cumbersome process, due to the number of possible sub-scenarios that the model deals with. For disconnected RSUs, three sample scenarios were designed to represent the main communication systems, and are depicted in figures 2.13b, 2.13c and 2.13d.

- **Scenario D1:** in this scenario, a *Src* and a *Dst* vehicle are positioned at equal relative distance to an RSU; in such a setup, the RSU should provide maximum benefit and reduce the distance the vehicles must travel for a message to be delivered to *Dst*.
- **Scenario D2:** similar to *Scenario D1*, but in this case we position the RSU in a location where it is at the edge of providing no benefit to the communication. The expectation is for the transmission to proceed as if no RSU was present.
- **Scenario D3:** in this scenario, both *Src* and *Dst* travel east-bound in the same lane, but are disconnected. An RSU is placed away from both vehicles, and is expected to receive *Src*'s message, hold it, and deliver it to *Dst*.

For scenarios where *connected RSUs* are deployed, the experimental setup is easier to automate, and so we verified the analytical and simulation results previously given in figures 2.8a (isolated vehicle) and 2.8b (clustered vehicle) directly, now with a speed of 13.89 m/s as reference. Figures 2.13e and 2.13f show the two setups. In both cases, the backbone between the two RSUs was established with 802.11g radios operating in the 2.4 GHz ISM band.

For isolated vehicles (Figure 2.13e), a single car, *Src*, was designed to generate a new message as soon as it reached the middle of two RSUs, and measured the delay for that message to reach the opposite-end RSU1 (which requires backbone relaying of the message from RSU2). The tests were then repeated for different separation distances between the RSUs.

For clustered vehicles (Figure 2.13f), the setup is similar but in this case, instead of a single car, one has a cluster formed by three vehicles. The tail of the cluster generates a message as soon as the cluster is in the middle of two RSUs which are 1 km apart, and the time for that message to reach RSU2 is measured. The tests were then repeated for different cluster lengths, according to the mean cluster lengths expected for a road with vehicle densities ranging from 95 veh/h to 345 veh/h.

### 2.5.3 Experimental Results

Figure 2.14a plots the analytical delay predictions and experimental results for scenarios D1, D2 and D3. The results show, for the three test scenarios under consideration,

## 2. ROADSIDE UNITS IN SPARSE HIGHWAY NETWORKS

that the basic communication in disconnected RSU-supported networks can be expected to operate as per the assumptions upon which our analytical models are built, and that analytical results closely match the experimental data.

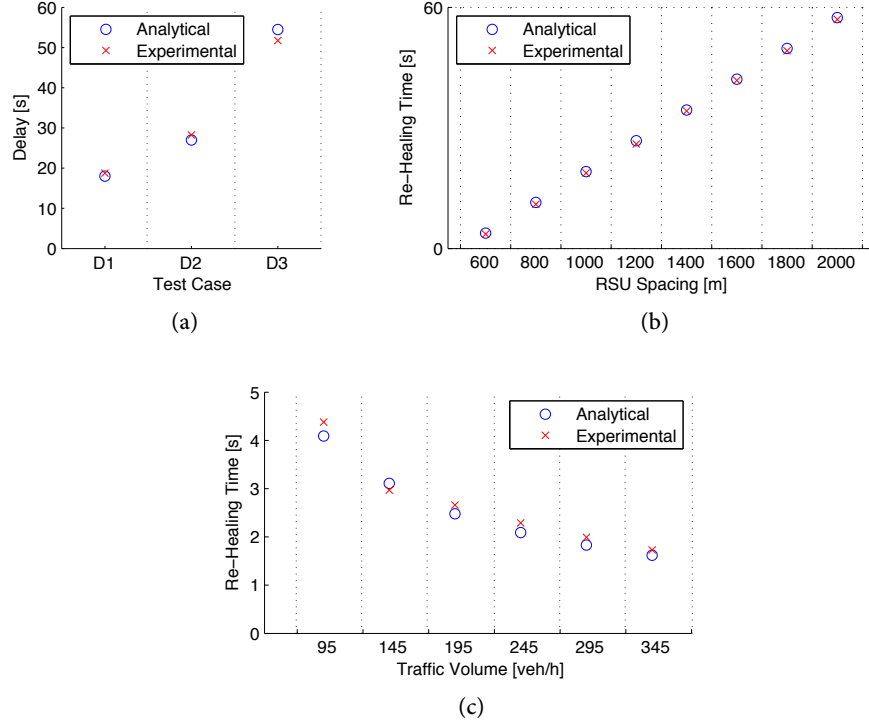


Figure 2.14: Experimental results. (a) Test scenarios D1, D2, and D3, with disconnected RSUs. (b) An isolated vehicle with interconnected RSUs. (c) A clustered vehicle with interconnected RSUs.

The experimental results for the scenarios with interconnected RSUs, for isolated and cluster vehicles respectively, can be seen in figures 2.14b and 2.14c. Once again, the experimental results closely follow our analytical model's predictions, both for isolated and clustered vehicles, and both for various RSU spacings and various traffic densities, further strengthening the validity of these models.

These are very important empirical results as they show how close the analytical models follow the reality of vehicular communications. The close match between our analytical models and experimental results with real-life 802.11p equipment are a key result.



## 2.6 Discussion

Our results show that RSUs are indeed able to significantly decrease the re-healing time in vehicular networks. However, for scenarios with low vehicle density, a significant improvement can only be achieved with a strong deployment of RSUs, but the underlying costs of such a large deployment scenario may be prohibitive.

How to interconnect the RSUs in real life is an important practical issue. Many highways now carry a fiber optic backbone to which RSUs can ideally be attached to, or are covered by broadband cellular wireless access, though the latter has a much lower bandwidth when compared to the fiber optic backbone. Regardless, these solutions require leasing the existing infrastructure to a third party, which would incur additional costs.

New wireless technologies may also be viable for establishing point-to-point links between RSUs. In particular, upcoming technologies such as WiMAX and LTE have been shown capable of establishing point-to-point links over tens of kilometers (whereas we expect RSUs to be deployed at much closer distances) while providing more throughput than the theoretical maximum of 802.11p [38, 39].

An important observation of this work is that disconnected RSUs, when deployed with standard equipment, provide modest improvements to the network's re-healing time, whereas the interconnection of RSUs results in tremendous improvement, as shown in figure 2.10.

Regarding possible application scenarios, our analytical models can be used to show how an infrastructure-assisted vehicular network can be designed in order to support protocols with specific delay requirements. For example, to prepare a deployment to support a routing protocol such as AODV (which requires a maximum per-gap delay of 2 s) when  $\lambda = 425$  veh/h, one would need to deploy disconnected RSUs every 295 m, or connected RSUs every 740 m.

Finally, highway entries and exits should be taken into account in any comprehensive analysis. The main consequence of such structures is a change in vehicle density. By splitting the highway into shorter segments of road, at entries and exits, each segment can be analyzed independently, computing each mean re-healing time, and aggregating the results.

### 2.7 Related Work

The dynamics of two-way highway traffic and VANET capacity have been studied in previous works such as [3, 12–14], with detailed analysis on the network performance and information storage capability of the VANET. The physical distribution of RSUs to optimize communication is an important design consideration for real-life scenarios, and studies exist on the placement of RSUs for Internet access [15, 16], RSU deployment at popular junctions [17], and determination of critical network points [18–20]. All these works are based on urban areas. Network connectivity in V2I has also been an important research area [21–23], where the tradeoffs between RSU density/placement and overall VANET connectivity can be determined.

Information dissemination and Internet access are the subject of many works [16, 24–26], all of which use a V2I approach, relegating V2V communications between vehicles to a secondary role. Others study the RSU network’s ability to deliver messages over large distances [27, 28], but consider uni-directional traffic and disconnected infrastructure only.

Of more relevance to this work are studies [29] and [30], which also approach the relation between infrastructure density and network delay performance. The former, [29], considers both two-way traffic and the same store-carry-forward method for infrastructure-less communication, but with a different viewpoint for the concept of re-healing: the authors consider that re-healing is achieved once the message is relayed to an RSU or to a vehicle in the region of interest. The latter, [30], studies vehicle-to-RSU packet delivery delay and RSU separation distance, and obtains a maximum delay violation bound. The study does not, however, consider packet retransmission via opposite-lane vehicles, which is an important method for message forwarding in highways.

It is important to mention that among these studies, very few address bidirectional communication, and none of them gives a clear comparison between using connected and disconnected RSUs in quantitative terms. Moreover, none of the aforementioned studies is complemented with real-life testbed results. The work here reported aims to bridge these gaps.

## 2.8 Summary

With the work presented in this chapter we have shown that, contrary to conventional wisdom, deployments of RSUs on highways provide little or no improvement in the re-healing time or the end-to-end delay in safety message dissemination if the RSUs are disconnected from each other. Conversely, interconnected RSUs can reduce the re-healing time or the end-to-end delay by orders of magnitude. In countries where broadband wired or wireless communications capability exists along major highways, this does not pose any serious problems. When such capability does not exist, however, the results of this study have shown that for significant improvements the RSUs must be connected. The analysis, the simulations, and the experiments conducted all endorse the validity of these observations and conclusions. We believe that these findings bring a new perspective on how the RSU deployment issue should be handled.



## Chapter 3

# Infrastructure-less Approaches for Highway Networks

Deployments of Roadside Units are an effective solution for mitigating network disconnection caused by the lack of DSRC-enabled vehicles in sparse highway vehicular networks. However, due to the costs associated with the deployment and maintenance of these infrastructure units, the majority of highways are unlikely to see RSU support in the near future. To improve the timely broadcast of important safety messages, methods that do not rely on the presence of infrastructure must be considered. In this chapter, we introduce two methods for improving communication delays in infrastructure-less highway scenarios: a first method where a disconnected vehicle decelerates when it receives a safety message, and a second method where a disconnected vehicle boosts the transmission power of its radio, to achieve faster connectivity with following vehicles. Our results show significant improvements in the connectivity of sparse vehicular networks when one applies these methods [40].

### 3.1 Introduction

Low traffic density in a vehicular highway network, during certain hours of the day, impacts the network's ability to react to emergencies by alerting drivers and diverting traffic. High re-healing times, caused by frequent node disconnection, push the delays associated with the propagation of safety messages to tens and hundreds of seconds. Chapter 2 showed how a deployment of connected RSUs could substan-

### 3. INFRASTRUCTURE-LESS APPROACHES FOR HIGHWAY NETWORKS

tially improve sparse highway networks, while one of disconnected RSUs, although cheaper, would yield very modest gains. However, the cost of such infrastructure deployments is often prohibitive, and it is unlikely that all but a small portion of the world's highways will see RSU installations in the near future.

One approach to improving re-healing time in infrastructure-less roads is to have vehicles acting as self-organizing RSUs, *i.e.*, having vehicles perform the functionality of deployed RSUs. In this chapter, we show that vehicles in a sparse network, under the right conditions, can act as mobile RSUs, thus obviating the need for the deployment of infrastructure. The vehicles' mobility, lack of backbone access, and a general need to not impact each driver's freedom of movement must be carefully considered to see if one can apply the aforementioned approach and develop vehicular networks with a reduced number of RSUs. With these concerns in mind, we research two techniques that we believe are socially and technologically viable. They are:

- Deceleration of vehicles in the accident lane, to hasten approach by rear disconnected vehicles, which is feasible if the deceleration is not abrupt and if the vehicle can move to an emergency lane.
- Power control (by the means of range boosting) at the head and tail vehicles of each cluster, increasing the vehicles' transmission range in case of a disconnection, which is feasible as long as the transmission power is kept under the IEEE 802.11p maximum of 44.8 dBm EIRP (Effective Isotropic Radiated Power).

To this end, we first outline an analytical model for the one-way traffic scenarios based on the characteristic exponential distribution of vehicles on highways. Then, we perform comprehensive Monte Carlo simulations of highway traffic where an accident has occurred, with the deceleration and range boosting techniques applied. We study the re-healing time of an emergency message, which is the time it takes for a message originating at the accident to reach other disconnected vehicles approaching the accident location, for both one-way traffic and two-way traffic scenarios.

The impact on re-healing time caused by the deceleration and the range boosting techniques is first evaluated separately, for different levels of deceleration and range boosting, and then jointly, with both techniques applied simultaneously. The results

show that the effectiveness of these techniques is very different, and is heavily affected by traffic density and by the presence or absence of opposite-lane traffic.

## 3.2 Analytical Models and Simulation Platform

In this section we outline the key steps of an analytical framework that characterizes the expected re-healing time in a single-lane scenario. This section presents the analytical models for studying the effects of braking and range boosting, which we then use in section 3.3 to validate our simulation results.

The density of sparse traffic in highway scenarios has been shown to follow an exponential distribution [3]. The framework is designed with the assumption that vehicles travel at fixed speeds — this is an approximation for sparse highway traffic that previous research has found to be realistic and to not cause meaningful loss of statistical significance [3].

Given a fixed radio transmission range  $R$ , in meters, and a road traffic density  $\lambda$ , in vehicles per meter, we define clusters as *groups of vehicles that can communicate with one another through a single- or multi-hop path*. For the purpose of studying the effects of tail vehicle range boosting, a second range variable,  $R_b$ , is introduced. When range boosting is applied,  $R_b$  is increased to the desired range for the tail vehicle; otherwise,  $R_b = R$ . It is assumed that the network can identify which vehicle in a cluster is the tail vehicle, which is trivial through GPS positioning, but also possible through existing network protocols [41].

When the tail vehicle in a cluster begins decelerating, it will connect with the lead vehicle from the following cluster when the vehicles reach a distance of  $R_b$ . With the frame of reference centered on the tail vehicle, the preceding vehicle has a zero relative speed (as it travels at the same speed as the braking vehicle), and will be accelerating towards the tail vehicle as that vehicle decelerates. The distance that must be traveled by that vehicle before communication is established is given by  $s_{inter} - R_b$ , where  $s_{inter}$  represents the distance between clusters (inter-cluster spacing, see [3]).

We assume that the deceleration of a vehicle is constant up to the point where the vehicle stops. From the point of view of the decelerating vehicle  $\underline{A}$ , the next vehicle's speed is initially zero (it follows  $\underline{A}$  at the same speed); then, as  $\underline{A}$  decelerates, the

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next vehicle's speed towards it increases linearly; and when  $\underline{A}$  reaches a full stop, the next vehicle will be approaching  $\underline{A}$  at its full, constant speed.

Consider a vehicle's braking acceleration to be  $a_b$ , each vehicle's top speed  $v$ , and an arbitrary distance  $X$  between two disconnected vehicles ( $X > R_b$ ). Using elementary equations of motion, one can determine the time for the vehicles to connect as the forward vehicle begins to decelerate:

$$\text{delay} = \begin{cases} \sqrt{2(X - R_b)a_b^{-1}}, & X - R_b < \frac{v^2}{2a_b} ; \\ \frac{v}{a_b} + (X - R_b - \frac{v^2}{2a_b})\frac{1}{v}, & X - R_b \geq \frac{v^2}{2a_b} . \end{cases} \quad (3.1a)$$

$$(3.1b)$$

One can now calculate the expected delay,  $E[Tr_A]$ , when the vehicles are exponentially distributed and their inter-cluster distance is  $S_{inter}$ . From the delay equation above, one can first obtain the probability  $P_A$  for  $X - R_b < \frac{v^2}{2a_b}$ , and then the delays  $E[Tr_A^1]$  from equation (3.1a) and  $E[Tr_A^2]$  from equation (3.1b).

The probability  $P_A$  that the vehicles will connect before the braking vehicle arrives at a full stop is given by

$$P_A = P\left[S_{inter} - R_b < \frac{v^2}{2a_b}\right] = e^{\lambda\left(R - \frac{v^2 + 2a_b R_b}{2a_b}\right)}. \quad (3.2)$$

The expected inter-cluster spacing that will lead to the vehicles connecting before full stop is given by

$$\begin{aligned} E[S_{inter}|S_{inter} < \kappa] &= \int_R^\kappa s_{inter} \cdot \frac{f_{S_{inter}}(s_{inter})}{F_{S_{inter}}(\kappa)} ds_{inter} \\ &= \frac{\kappa - R}{e^{\lambda(R - \kappa)} - 1} + \frac{1}{\lambda} + \kappa, \end{aligned} \quad (3.3)$$

where  $\kappa = v^2/2a_b + R_b$ . The delay, from equations (3.1a) and (3.3), will be:

$$E[Tr_A^1] = \sqrt{2E[S_{inter}|S_{inter} < \kappa] a_b^{-1}}. \quad (3.4)$$

If the vehicles only connect after the braking vehicle comes to a full stop, both the time when the vehicle is decelerating and the time when the vehicle is stopped must be considered. This case occurs when inter-cluster spacing  $S_{inter}$  is greater than  $v^2/2a_b + R_b$ :

$$\begin{aligned} E[S_{inter}|S_{inter} \geq \kappa] &= \int_\kappa^\infty s_{inter} \frac{f_{S_{inter}}(s_{inter})}{1 - F_{S_{inter}}(\kappa)} ds_{inter} \\ &= \kappa + \frac{1}{\lambda}. \end{aligned} \quad (3.5)$$



The resulting delay, from equations (3.1b) and (3.5), will be:

$$E[Tr_A^2] = \frac{v}{a_b} + \left( E[S_{inter}|S_{inter} \geq \kappa] - \frac{v^2}{2a_b} \right) \cdot \frac{1}{v} . \quad (3.6)$$

Combining the two cases from (3.4) and (3.6), and their associated probabilities from (3.2), one can obtain the expected re-healing time  $E[Tr_A]$ :

$$E[Tr_A] = P_A \cdot E[Tr_A^1] + (1 - P_A) \cdot E[Tr_A^2] . \quad (3.7)$$

This re-healing time,  $E[Tr_A]$ , is the delay from one cluster to the next. In order to determine the time to reach a vehicle that is  $d$  meters away from the source (such as the 10 km re-healing time, which is our reference metric in section 3.3), one must first determine how many gaps exist between the source and the destination vehicles. Given the distance  $d$  between both vehicles, computing the mean number of gaps ( $G_C$ ) from the cluster length ( $C_L$ ) and intercluster spacing ( $S_{inter}$ ) is straightforward:

$$G_C(d) = \frac{d}{E[C_L] + E[S_{inter}]} . \quad (3.8)$$

The cluster length and intercluster spacing distributions can also be derived from the exponential distribution of vehicles in a straightforward way [3]. The mean re-healing time involving multiple gaps can be determined by multiplying the Gap Count,  $G_C$ , with the per-gap re-healing time,  $E[Tr_A]$ .

The methodology presented here for one-way traffic can be applied similarly to a statistical two-lane model, such as the one in [3], to obtain a model suitable for analysis of two-way traffic.

### 3.3 Effects of Deceleration and Power Control

In this section we present the results of our simulation platform and analytical models, and show how deceleration and range boosting can improve re-healing time in sparse vehicular networks. We consider both scenarios where two-way traffic exists (typical with highways) and where only one-way traffic is present.

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#### 3.3.1 Monte Carlo Simulation Model

Our network simulations are built on top of NS3 [42], and implement a two-lane highway where traffic can flow in one or two directions. The vehicle generation routine inserts vehicles at the start of the lane following the exponential distribution, with definable density. An accident can be generated, blocking the road and causing vehicles in the same lane of the accident to form a dense queue behind it.

As was explained in section 3.2, vehicles move at a constant speed, and there is no overtaking. Each vehicle is equipped with a radio device, and for two-way traffic scenarios, the vehicles in the lane opposite to the accident are capable of performing *Store-Carry-Forward*, where a vehicle can hold an emergency message until it is in reach of another vehicle. Upon receiving an emergency message, vehicles are instructed to broadcast it to all neighbors. The transmission range of vehicles is set to 250 m, and can be dynamically controlled for the range boosting scenarios.

Each simulation begins by allowing time for the road to fill with vehicles. Then, the accident is triggered at the specified location, broadcasting a message, and the time for that message to reach another vehicle that is 10 km away from the accident is registered. For statistical significance, each data point is averaged over a minimum of 100 repetitions, and 95 % confidence intervals are generated to ensure that sufficient repetitions are performed.

Our reference performance metric for emergency message broadcasts is a 10 km re-healing time: the time it takes for an emergency message to reach a vehicle that is 10 km away from the point of origin, in the lane of interest. The re-healing time is the most crucial metric in emergency broadcast, as the goal is to reach vehicles approaching the emergency site so drivers can quickly be made aware of the emergency. From a traffic optimization perspective, informed drivers may also divert to alternate routes, either by their own choice or by recommendation by the vehicle's GPS unit. The distance of 10 km is chosen so as to ensure that there is a reasonable number of disconnected clusters between source and destination, when vehicle density is low.

The following sections will present primarily simulation results. When available, data from the analytical model presented in section 3.2 are overlaid with the simulation data for the purpose of validating our approach.

### 3.3.2 Decelerating vs. Proactive Queuing

We begin by evaluating the re-healing time in a network where tail vehicles decelerate, versus a similar network where vehicles just queue behind the source of the emergency message (e.g.: an accident). We consider vehicle densities that go from  $\sim 200$  veh/h to  $\sim 650$  veh/h, which represent low- and medium-density scenarios [3]. The vehicle's top speed is set to 30 m/s, and if deceleration occurs, vehicles do so at a deceleration level of  $5 \text{ m s}^{-2}$ .

Figure 3.1 shows the total re-healing time required to propagate an emergency message to a destination that is 10 km away from the event that caused the message. For 1-way traffic with deceleration, the data from the analytical model ('An.') is also plotted, for comparison.

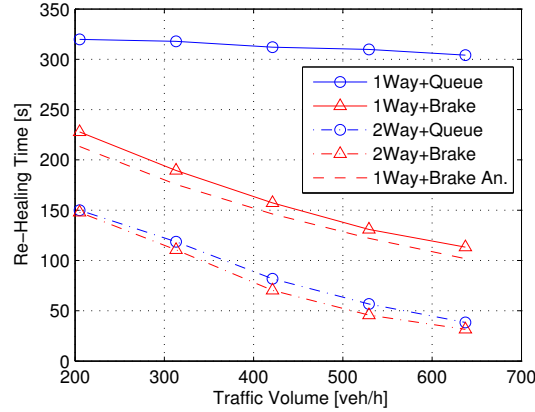


Figure 3.1: Re-healing time comparison between queuing behind an accident and proactive deceleration.

It can be seen that proactive deceleration is only effective for scenarios with one-way traffic, where the re-healing time can improve between 30 % to 60 % (depending on traffic volume) versus the queueing scenario. The data also show a very good agreement between the simulation data and the analytical model predictions for one-way traffic with deceleration.

This result seems to indicate that deceleration is very inefficient in scenarios with two-way traffic, where the forwarding of emergency messages through opposite-lane vehicles can be much faster. One can see minimal improvements in re-healing

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time when using both delivery methods (decelerating in the lane of interest plus forwarding with opposite-lane vehicles), but the impact of requiring tail vehicles to decelerate might not be justified for such a modest gain.

#### 3.3.3 Effects of Proactive Deceleration

We now study the relation between proactive deceleration and re-healing time. In a real-life scenario deceleration is unlikely to be a controllable variable, as each driver will brake the vehicle differently, but nevertheless deceleration can be estimated based on road conditions and driving patterns.

Figure 3.2 shows what kind of gains can be had given an expected deceleration. For the 1-way traffic scenario, re-healing time can improve up to 28 %, while for the 2-way traffic scenario, the effects of deceleration are negligible. Again, there is a good match between simulation results and data from the analytical model.

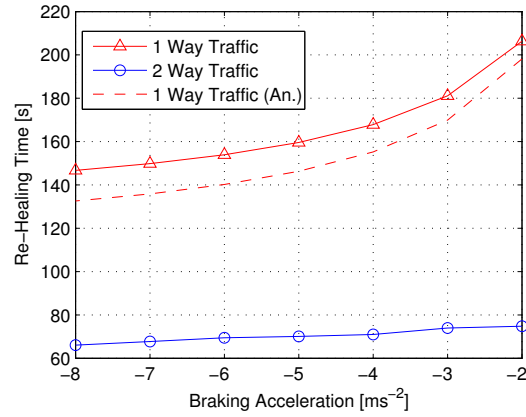


Figure 3.2: Re-healing time as a function of deceleration strength.

#### 3.3.4 Effects of Range Boosting

To evaluate the effects of an increase in transmission power by the last vehicle in the cluster, we ran sets of simulations where that vehicle's radio range is instantly increased as it receives an emergency message broadcast, while also decelerating at a  $5 \text{ m s}^{-2}$  level. We evaluate the 10 km re-healing time with radio ranges boosted from 50 m to 200 m, from a base range of 250 m. We have also ensured, through

simulations with 802.11p radio models, that these range boosts are possible without exceeding the maximum transmission power of 48.8 dBm EIRP that is defined in the 802.11p standard.

In figure 3.3, we see that power control at the tail nodes can yield gains for both the one-way and two-way traffic scenarios. With only one lane of traffic, the delay can be reduced by as much as 53 %, while for the two-way scenario, delay can go down by as much as 78 %, from 70 s to just 15 s to reach a span of 10 km. Data from the analytical model ('An.') are a near-perfect match to the simulation results.

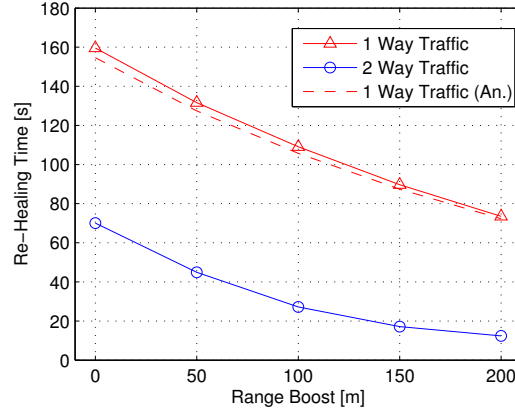


Figure 3.3: Effects of tail vehicle range boosting on the network's re-healing time.

### 3.3.5 Same-Lane and Opposite-Lane Traffic Density

An emergency message travels in a single direction in the lane of interest, and in a 2-way traffic scenario, it can be carried by opposite-lane vehicles. We study the effects of varying traffic density in a single lane, to determine if a lack of vehicles in the opposite lane can be more detrimental than a lack of vehicles in the lane of interest, or vice-versa.

The results of a set of simulations where traffic is fixed in one lane and varied in the other can be seen in figure 3.4, where the east-bound lane is where the message originates and the deceleration occurs, while the west-bound lane is the opposite lane. The data show that traffic density is equally important both in the main lane (where deceleration occurs) and in the opposite lane where vehicles carry the emergency

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message across. For higher traffic densities, the density of cars in the main lane is more important than in the opposite lane, and an increase in it (i.e., fixing density in the west-bound lane) yields better results than an increase in opposite-lane traffic.

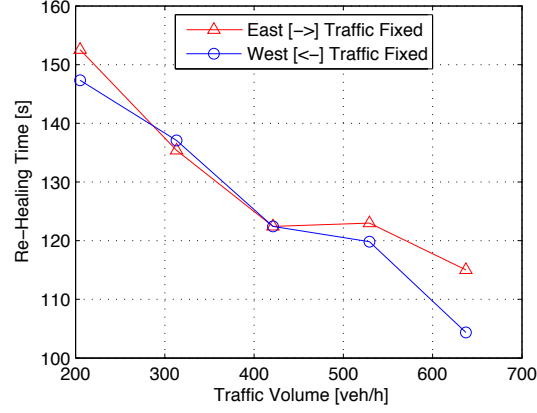


Figure 3.4: Re-healing time in a two-way scenario with different densities of traffic per lane.

#### 3.3.6 Deceleration & Power Control

The final set of results shows the combined effects of deceleration and power control in the re-healing time of the vehicular network. Figures 3.5 and 3.6 plot the re-healing time analysis for one-way and two-way traffic, respectively, for selected pairs of edge vehicle radio power boost and deceleration. The range boost levels of 0 m, 100 m and 200 m, and the deceleration levels of  $3 \text{ m s}^{-2}$ ,  $4 \text{ m s}^{-2}$  and  $5 \text{ m s}^{-2}$  are considered, for traffic densities ranging from 200 veh/h to 650 veh/h.

##### 1-Way Traffic

With only one-way traffic on the road, figure 3.5 shows that both deceleration and power control have an impact on the re-healing time — however, decelerating yields comparatively small improvements against a radio power boost.

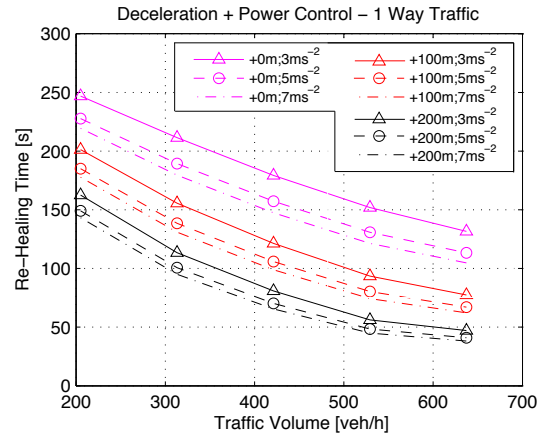


Figure 3.5: Re-healing time as a function of deceleration and tail vehicle power control, with one-way traffic only.

## 2-Way Traffic

When two-way traffic exists on the road, the data in figure 3.6 confirm that decelerating vehicles in the lane of interest bring negligible improvements to the network's re-healing time, which we hypothesized earlier from the data in figure 3.1.

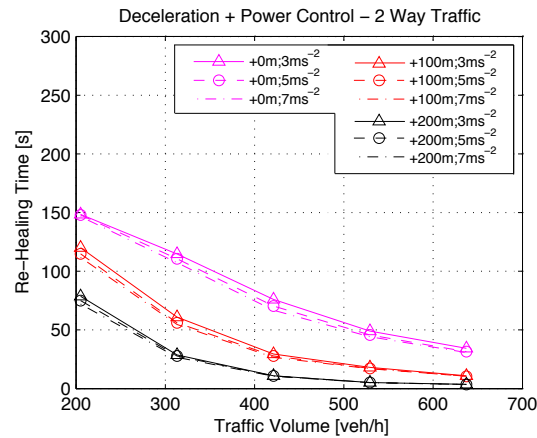


Figure 3.6: Re-healing time as a function of deceleration and tail vehicle power control, with two-way traffic.

This confirms that opposite-lane forwarding of emergency messages is substantially more efficient than deceleration in the lane of interest. Furthermore, one can

### 3. INFRASTRUCTURE-LESS APPROACHES FOR HIGHWAY NETWORKS

see that power control at tail vehicles is crucial for a quicker message broadcast, and boosting the radio range by 100 m and 200 m can cut the total re-healing time down by 50 % to 75 %.

## 3.4 Discussion

Providing connectivity in sparse vehicular ad hoc networks remains a major challenge in the design and operation of vehicular networks, especially in disseminating safety messages in a timely manner. While conventional wisdom suggests that roadside units might be able to mitigate this problem, the past decade has proven that this is a costly proposition that might be hard to implement on a large scale. These realities motivate our quest for finding alternative solutions that rely on the members of a vehicular ad hoc network as opposed to deploying additional hardware.

### 3.4.1 Social Impact of Proposed Measures

One issue that merits discussion is the social acceptability of the proposed techniques, in particular the one where vehicles reduce or halt their movement while on the highway. While there is no doubt that such a request is an inconvenience to the drivers, one must also note that: *i*) it is only asked of for the transmission of important safety messages, which can be likened to the way drivers now give way to emergency vehicles; *ii*) it only applies in low-density scenarios — network connectivity is not an issue with large numbers of vehicles; and *iii*) the deceleration only impacts a limited number of vehicles, therefore reducing the number of drivers affected.

### 3.4.2 Technical Approach

In this work, we have opted to evaluate a more straightforward method for power control. In dense networks, power control schemes must try to not be disruptive, by progressively increasing transmitted power in a staircase fashion, while monitoring the power levels of surrounding nodes. In sparse networks, however, the lack of nodes is the main concern, and cluster tail nodes are by definition disconnected from the rear nodes. We therefore believe that a more aggressive boosting of power levels might be more appropriate. In particular, in sparse networks for safety mes-



sage broadcasting, it is our opinion that the urgency of the messages surpasses the concerns of mitigating interference. Safety messages are, by design, small, and infrequent broadcasting of small packets at high power levels should not be detrimental to the overall performance of the network.

### 3.5 Related Work

Research on the performance of vehicular networks in areas of low vehicle density has been relatively sparse, with most works focusing on well-connected scenarios. The broadcast of emergency messages, and techniques to decrease the time that these messages take to reach their intended destinations, is an important design consideration for any safety-oriented vehicular network.

Interference and packet collisions in vehicular networks can lead to failures in the reception of safety-critical messages. The work in [43] proposes a distributed power control scheme to limit the load of periodic messages on the network and secure bandwidth for emergency broadcasts. In [44], a distributed MAC scheme with strict priority requirements for emergency messages is proposed as an alternative to previous statistical-based priority MAC schemes, reducing the node-to-node propagation delay. In [45], a cross-layer approach is proposed to address the same reliability issue, with a relay selection mechanism that jointly integrates geographical location, vehicle speed and physical layer data in the decision process. A broadcast control mechanism specifically tailored for emergency warning packets is also shown in [46], where the criteria for rebroadcasting safety messages is dynamically adapted to the number of neighbors of each vehicle. In the framework of emergency message dissemination, [47] suggests segmenting the vehicles in range of the message source, delegating the forwarding duty to a single vehicle and thereby reducing broadcast delay.

Most of these studies are focused on the performance of the broadcast medium and the reliability of safety messages. This work's focus, however, is on the delay for an emergency message to be broadcast across a segment of road to vehicles that are not in the immediate vicinity of the accident, and on techniques that can be used to reduce that delay without introducing additional infrastructure on the road.

## 3.6 Summary

We have evaluated two different techniques to minimize the broadcast time of safety messages on infrastructure-less highways, during low-traffic periods (or during the initial deployment phase of the DSRC technology) where the network becomes sparse and disconnected. We developed mathematical models and a simulation platform to analyze the communication improvements when employing tail vehicle deceleration, and tail vehicle power control. The metric of choice was the re-healing time, which is the time it takes for a safety message to be broadcast across a given span of road.

It has been shown that the technique of reducing the speed of vehicles (i.e., deceleration) in order to quickly close gaps in sparse networks can yield good improvements, but only if the road in question has one-way traffic exclusively. When one has two-way traffic, our study shows that deceleration is not as effective, as message forwarding by opposite-lane vehicles is substantially more efficient. This is true even when the density of opposite-lane vehicles is low. Conversely, the application of power control and radio range boosting techniques to cluster edge vehicles can lead to significant gains in the re-healing time of safety messages, both in the cases of one-way and two-way traffic. In light of these results, a suitable approach would be to enforce both deceleration and power control in sparse one-way highway vehicular networks, and restricting networks of two-way traffic to power control alone.

## Chapter 4

# Leveraging Parked Cars as Urban Roadside Units

A comprehensive implementation of the envisioned traffic safety and efficiency applications of the IEEE 802.11p and WAVE standards assumes the premise of the use of DSRC technology both as On-Board Units (OBUs) and as Roadside Units (RSUs). The high cost associated with RSUs, however, has so far prevented massive deployment of RSUs. Finding alternative solutions to this longstanding problem is therefore very important. In this chapter, we propose a self-organizing network approach to using parked cars in urban areas as RSUs. This self-organizing network approach enables parked cars to create coverage maps based on received signal strength and make important decisions, such as if and when a parked car should serve as an RSU. Our results show the feasibility and cost-effectiveness of the proposed approach, which can provide excellent coverage using only a small fraction of the cars parked in a city [48, 49].

### 4.1 Introduction

Vehicular networks require a minimum number of cars to be well connected and functional, which can fail to happen due to either low numbers of vehicles on the road or insufficient radio-equipped vehicles. Studies show that in urban areas of low vehicle density, important safety broadcasts can take more than 100 seconds to reach all nearby cars [50]. On the other hand, dense networks with too many vehicles

#### 4. PARKED CARS AS URBAN ROADSIDE UNITS

can be overwhelmed with traffic and signaling [2], requiring careful coordination between the nodes to ensure proper operation. One way to overcome both these problems is to supplement vehicle-to-vehicle (V2V) communications with vehicle-to-infrastructure (V2I) support systems, that is, to deploy infrastructure nodes known as Roadside Units along the road, in addition to the On-Board Units within the vehicles [1]. These units can supplement a sparse network in a low-density scenario, and help coordinate and move data in dense scenarios.

The U.S. Department of Transportation (DoT) anticipated a nationwide deployment of supporting infrastructure of RSUs for vehicular networks to have happened by 2008 [8] — however, this forecast did not come to fruition due to difficulties in justifying the benefits of RSUs, lack of cooperation between the public and private sectors, but most importantly, a lack of funding for infrastructure whose widespread deployment is estimated to cost billions of dollars. A 2012 industry survey by Michigan’s DoT and the Center for Automotive Research reiterated that “*one of the biggest challenges respondents see to the broad adoption of connected vehicle technology is funding for roadside infrastructure.*” [9] and, in 2014, a nationwide study sponsored by the U.S. DoT reported average costs of \$17 680 per deployed Roadside Unit [7], for both hardware and installation. These prohibitive costs explain why one is unlikely to see substantial deployments of RSUs in the near future, despite their importance to vehicular networks.

One way to avoid the prohibitive expense of RSU deployment is to use the vehicles themselves as RSUs [51], and in urban areas the idea of leveraging parked cars to assist a vehicular network has been suggested [52], although only for specific use cases (e.g., overcoming corner obstructions, or increasing node density in sparse areas). The objective of this work is to propose a credible, low-cost alternative to a Roadside Unit deployment that can operate both independently and in conjunction with existing RSUs.

To this end, we introduce a *self-organizing network approach* that allows parked cars to function as RSUs forming a vehicular support network. We tackle the specific problems of selecting which parked cars should become part of the network, how to measure each car’s utility to be able to make informed decisions, what algorithmic steps vehicles should follow when they park, and how to deal with possible disruptions in connectivity when parked cars leave.

Simulation data from a unique platform with real-life data validate our proposed approach and its methods. The results show that an on-line, greedy decision process based on self-generated coverage maps and limited communication between vehicles can achieve an average coverage that is 93 % to 97 % as good as an optimum solution. The proposed algorithms can also optimize the number of parked cars that are designated as RSUs, selecting on average only 12 % more cars than an optimum process. A second set of data shows, additionally, that parked cars bring tangible benefits in initial deployment stages, where insufficient numbers of DSRC-enabled vehicles cause the network to become sparse. In these scenarios, using small numbers of parked cars to act as RSUs can reduce the time for emergency messages to be broadcast by 40 % to 50 %. Through these key results, we verify that parked cars can indeed serve both as RSUs and as an extension to vehicular infrastructure deployments, and can self-organize to do so with no significant overhead to the existing networks of moving cars. Combined, the two analyses in this work encompass both low-, medium- and high-density scenarios, and their corresponding challenges.

## 4.2 Advantages of Parked Cars as RSUs

While the first suggestions for the use of cars as Roadside Units aimed at recruiting the moving vehicles for this purpose [51], in urban areas parked cars present themselves as equally compelling candidates. For one, parked cars share many of the benefits of fixed RSUs, of which one of the most significant is that *they do not move*.

As cars move, buildings and other obstructions enter and leave the line of sight between them, causing detrimental fading and shadowing effects on the communication channel. Eventually, the nodes move too far apart from each other, and the channel disappears. A parked car in an urban area has a fixed, known position for extended periods of time and consequently, a more stable communication channel with nearby cars and RSUs is possible. Their fixed location is also beneficial to applications that rely on *geocasting* (the broadcasting of messages to specific geographic areas), making it simpler to route such messages to their intended location. Furthermore, in areas of low vehicle density, the activation of parked cars can supplement the network by increasing the number of available nodes and, consequently, strengthening connectivity.

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We introduce three methods of operation for parked cars to become a part of the vehicular network — they are depicted in figure 4.1. When no fixed RSUs exist in the urban area, parked cars can form a **mesh network** with each other (see figure 4.1a), each parked car connecting to its neighboring parked cars. This mesh network can support the moving vehicles by offering to relay and broadcast messages, with the benefit of having a stable node structure and stable links between nodes (moving cars do not enjoy this benefit).

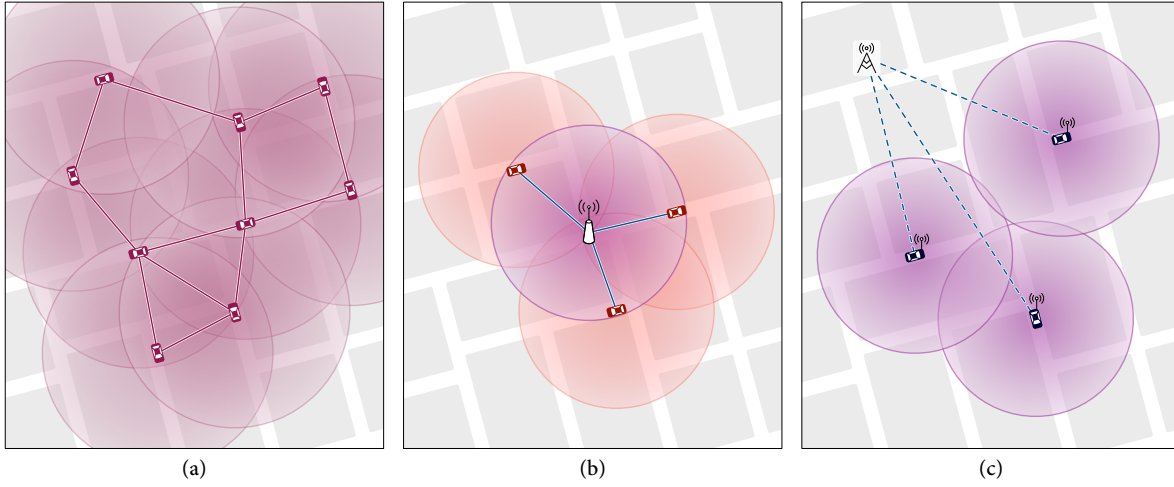


Figure 4.1: Modes of operation for parked cars acting as RSUs. (a) Parked cars form a mesh network with point-to-point links to other parked cars in range, using 802.11p. (b) Parked cars extend the range of a fixed 802.11p RSU, acting as relays to it. (c) Parked cars with access to an uplink establish themselves as standalone RSUs (depicted: using a cellular network as an uplink).

When a limited deployment of fixed RSUs is already present, parked cars in the vicinity of an RSU can act as **relays** to it (see figure 4.1b), extending the reach of the fixed unit. In this mode, the value of a deployed RSU can be increased by enlarging its coverage area. Parked cars acting as relays advertise their ability to forward messages to an RSU, so moving vehicles use them as such. Around these relays, other parked cars can continue to form the previously-described mesh network, further amplifying the coverage of the original RSU via relays of relays.

Lastly, a parked car with the access to a backbone uplink can leverage that link to establish itself as a **standalone RSU** (see figure 4.1c). In this mode, a parked car can communicate with other existing RSUs and uplink-enabled cars via the Inter-

net, allowing it to send messages to distant locations in adequate time. Increasing numbers of vehicles now come equipped with Internet connectivity (using 3G or LTE/LTE-A cellular technologies), and there is the possibility for the car's electronics to be allowed the use of this link for selected purposes (e.g., safety messages).

In urban areas that have seen limited deployments of fixed infrastructure, cars that are parked can be used to fill in the gaps, providing coverage in areas not serviced by existing RSUs, directing messages to the RSUs as necessary. Parked cars can, therefore, serve both as the main solution to providing support to a mobile vehicular network and as a complementary solution to the existing infrastructure.

The remainder of this chapter will focus on the crucial issue of deciding which parked cars should become a part of this vehicular support network.

### 4.3 A Self-Organizing Network Approach to Creating RSUs

This section describes a self-organizing approach for constructing a vehicular support network from parked cars. Together with the simulation data on sparse networks and the performance analysis on dense networks, these constitute the main research presented in this chapter.

At the core of this self-organizing approach lies a single decision: when a vehicle parks, should it become an RSU, or should it enter a sleep mode? The decision depends on what the support network aims to accomplish. When a parked car takes a Roadside Unit role, this has non-negligible costs both to the battery of that vehicle, as it must then power the DSRC electronics, and to the vehicular network, as active nodes will broadcast their presence and answer requests from other cars, causing overhead. So, for dense areas, the primary goal should be to maximize the reach of this support network, while minimizing the number of active RSUs.

With this objective in mind, we introduce an *on-line, greedy* algorithm that allows each car to decide whether to become an RSU or not. The process is necessarily on-line since the network is in constant evolution, as cars park and leave; our approach is also greedy, in the sense that we attempt to make a locally optimum decision whenever a vehicle is parked, aiming to approach a global optimum solution.

With full knowledge of each parked car at every location, one can evaluate all possible combinations of turning cars on and off, and reach a global optimum

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solution. Evidently this is not feasible, as not only would it quickly amount to millions of computations, it would also need to repeat itself whenever a car parked. With this work, we aim for an approach that requires *minimal communication between nodes*.

##### 4.3.1 Self-Observed Coverage Maps

To be able to optimize the number of parked cars that become active and take the role of RSUs, we require a new metric that can represent each vehicle's value to the network. The primary goal of this RSU network is to be able to reach as many locations in the city as possible — therefore, we are interested in knowing the *signal coverage* of each parked car, i.e., which areas it can reach, and how well it can do so.

Cars, however, can park in numerous distinct locations. Using propagation models, one could estimate the coverage map of each particular car, but doing so would also require the local roadmap, as well as knowing the shapes and structures of nearby buildings (to determine obstructions). Such a process would still fail to account for undocumented obstacles such as trees, trucks, billboards, etc.

With this work, we introduce a system whereby parked cars listen to beacons being broadcast by other nearby cars on the road and use those beacons to build maps of their coverage. By doing so, parked cars learn about which areas in their vicinity they can send and receive messages from. These beacons, which include position, speed, and bearing, are standardized and known as Cooperative Awareness Messages (CAMs), and are broadcast at rates no lower than 1 Hz [53]. When the signal strength of incoming beacons is made available from the lower protocol layers, parked cars can take advantage of this valuable information to track how strong coverage is at each location, building a distribution of the signal power of incoming messages and using it to estimate the quality of coverage.

In figure 4.2, we illustrate the process of learning a coverage map, while also demonstrating coverage tracking in the shape of cells. In this work, we divide the urban area into a logical 2D cell map that is common to all cars. This approach stems from the need to have coverage maps that are easily representable, storable and shareable, and that can track coverage in irregular street maps with adequate precision. To ensure that all vehicles share the same grid division, we opt to align cell boundaries to GPS coordinates, a universal reference for all GPS-enabled cars.

Under this cellular division, a self-observed coverage map can be represented



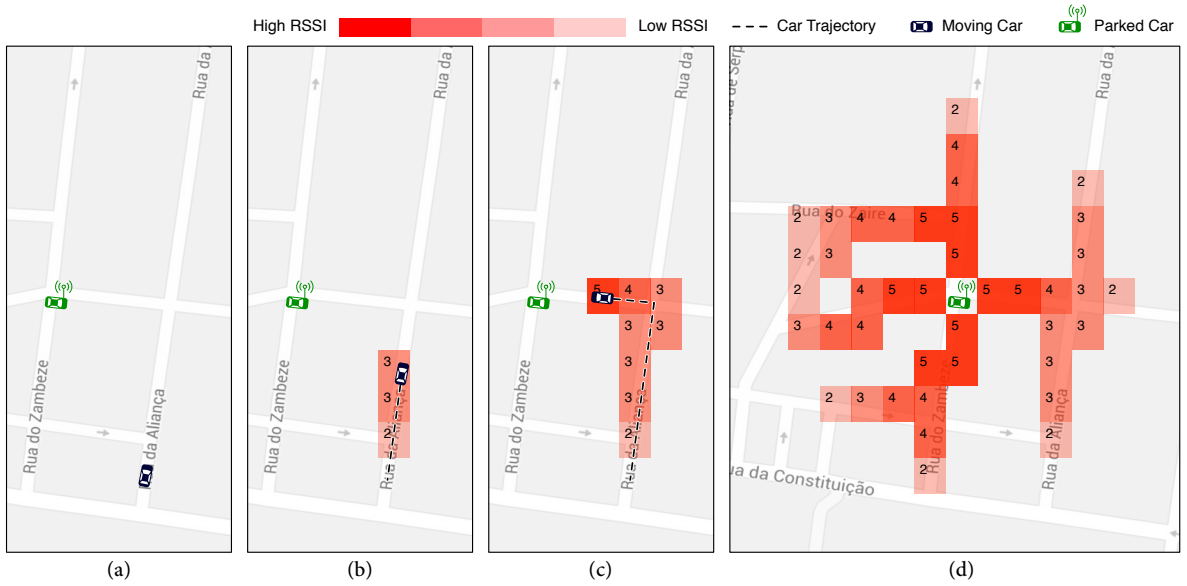


Figure 4.2: In this example, (a), (b), and (c) show how a parked car (the green car in the figure) observes parts of its coverage map by listening to beacons from a nearby moving vehicle. As a vehicle moves nearer, our parked car overhears its beacons and corresponding signal strength, tagging the cells in its local map. The complete, self-observed coverage map is seen in (d).

as a matrix containing signal strength values, with 5 meaning *excellent signal* and 0 meaning *no coverage*. In this work, we align cell boundaries to the nearest GPS second (a standard WGS84 coordinate point multiplied by 3600, rounded down<sup>1</sup>), which results in a cell that is approximately 30 m wide. Figure 4.3 illustrates this division by showing a grid map with cells delimited by the nearest GPS second. A coverage map for a vehicle with a maximum radio range of 150 m will be  $11 \times 11$  cells large (with the vehicle positioned at the center cell); 3 bits per cell can represent the 6 levels of coverage, which makes a map  $\sim 46$  bytes in size. To center the map, the latitude and longitude of the vehicle (2 bytes each) is sent along with the data matrix. In this matrix form, coverage maps can be shared between vehicles through the WAVE Short Message Protocol (WSMP), a part of the WAVE standard [54].

<sup>1</sup>E.g., the decimal WGS84 coordinate 43.917500 000 000 00 can be expressed as 158 103 s, or N43°55'3.00" (hours (°), minutes (′), seconds (″)).

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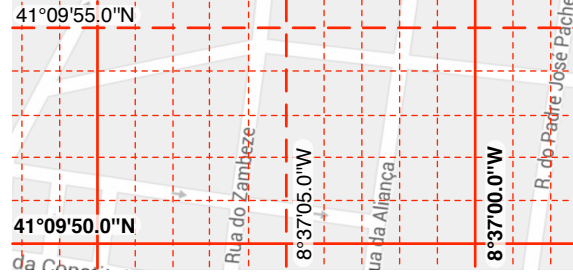


Figure 4.3: A section of the city of Porto overlaid with a grid aligned to one GPS second.

##### 4.3.2 Procedures for Newly Parked Cars

Each newly parked car must follow a logical set of actions to allow it to decide whether it should become an RSU. A newly parked car begins by listening for beacons being broadcast by other vehicles in its vicinity, which can be seen in figure 4.4. During this process, the vehicle builds its coverage map, as described in the last section. We provide reference values for the duration of this step later on, in section 4.4.3.

Once the step of building a map of coverage is complete, the vehicle requests the coverage maps of neighboring active RSUs, using WAVE Short Messages (WSMs). The decision process only requires maps from fixed RSUs and active parked cars. An alternative to this step is to instruct RSUs to broadcast their coverage maps periodically, so newly parked cars can simply receive them while listening for beacons.

The outcome of this algorithm ultimately decides whether the parked car should become an RSU or switch to a power-saving (sleep) mode. The decision made by each car depends on its observed coverage and the maps it receives from other RSUs in its 1-hop neighborhood. We opt to keep the decision down to each vehicle, while relying only on information from the car's 1-hop neighbor nodes, to minimize the associated network overhead. We describe this decision process in more detail in the next section.

The process that newly parked cars must follow is straightforward. However, it is possible for a car's coverage map to change after the decision step, which can occur if no vehicles passed through a nearby road during the listening step. Coverage can also worsen if an obstruction appears near a parked car, e.g. if a large truck decides to park next to it. To account for this possibility, when a car detects that its coverage map has changed significantly, it reevaluates its decision, by following the steps in

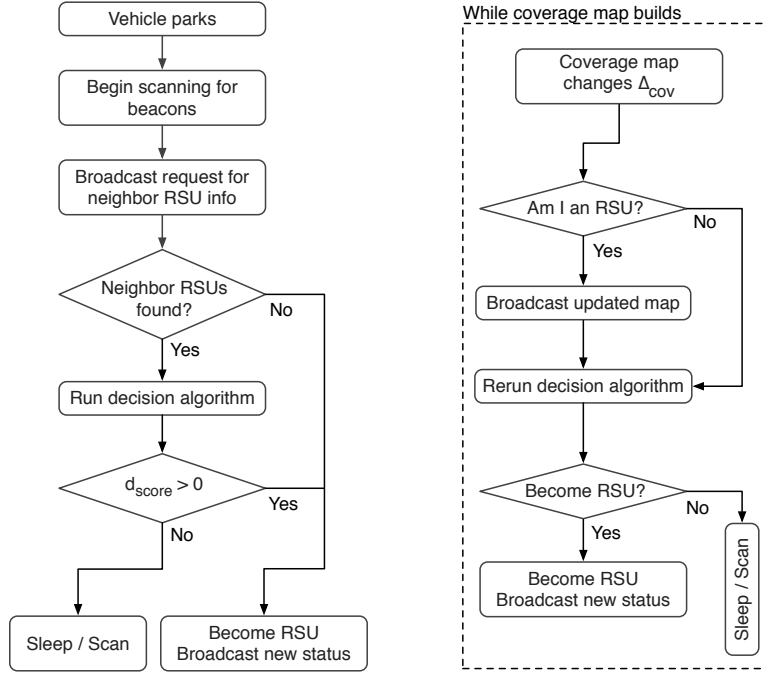


Figure 4.4: Left: flowchart of actions taken by a newly parked car in order to decide whether to become an RSU. Right: a parked car may see a substantial update to its coverage map, triggering a new decision process.

figure 4.4. A delta value,  $\Delta_{cov}$ , tracks how many cells have changed since the last decision, and crossing a pre-specified threshold triggers a new decision step.

### 4.3.3 Making a Decision

At the core of the decision process lies the *decision score* ( $d_{score}$ ), a measure of each car's added value to the network. As mentioned in the previous section, each car must make a decision when it parks, once it has inferred its coverage map and received the maps from nearby RSUs (which can be other active parked cars, as well). With these data in hand, the now-parked vehicle estimates what will happen to the network should it decide to become an RSU at the location where it parked. In essence, it measures its net benefit against its perceived detriment.

The coverage matrixes from neighboring RSUs are combined to obtain two maps of the local area: a first map with the best signal coverage available at every cell, and

#### 4. PARKED CARS AS URBAN ROADSIDE UNITS

a second map with the number of RSUs that serve each cell. When the decision process is triggered, the new parked car overlays its coverage map with these local area maps. For each cell in this map, the parked car will see one of the following occur:

- **Establishing new coverage.** If the new parked car is covering a cell that no other RSU in its vicinity can reach, then becoming an RSU will provide new coverage to the network. This action is a major benefit.
- **Improving existing coverage.** If the newly parked car can cover an existing cell at a signal level better than any other nearby RSU, then becoming an RSU will improve the strength of the existing coverage provided by the RSUs. This action also benefits the network.
- **Adding redundant coverage.** A parked car that adds coverage to an already-covered cell, but does so at a signal strength level equal to or lower than what is already provided by other RSUs, is adding unnecessary weight to the network. We refer to this as *saturating* the network.

Each of these three effects is then quantified, and a weighted sum of each results in the decision score. In this work,  $d_{score}$  is given by

$$d_{score} = \kappa \cdot d_{new} + \lambda \cdot d_{boost} - \mu \cdot d_{sat} , \quad (4.1)$$

where  $d_{new}$ ,  $d_{boost}$  and  $d_{sat}$  are metrics for *new coverage*, *improved coverage*, and *excess coverage*, respectively. The coefficients  $\kappa$ ,  $\lambda$  and  $\mu$  weight each component of the decision score, adjusting the balance between improvement and degradation to the network. Later on, in section 4.4.3, we will provide reference values for these coefficients.

We now formalize each of these metrics and how they are calculated. All notation is summarized in table 4.1. A newly parked vehicle on its decision step has its own observed coverage map,  $[scm_o]$ , whose elements  $scm_{ij}$  represent geographic cells. At this point, the vehicle also holds a collection of its neighbors' coverage maps,  $\mathcal{N} = \{scm_1, scm_2, \dots, scm_n\}$ . Coverage matrixes are square matrixes of order  $n$  (but not symmetric, i.e.,  $scm_{m1} \neq scm_{1n}$ ) where  $n$  is always odd, so that a single cell exists at the center of the matrix that corresponds to the vehicle's location.

TABLE 4.1  
ALGORITHM NOTATION REFERENCE

Definition	Notation
Matrix indices (row, col.)	$i, j$
Geographic indices (lat., lon.)	$x, y$
Self-observed coverage map	$[\text{SCM}] = (\text{scm}_{ij})$
Center coordinates of an SCM	$x_{\text{center}}, y_{\text{center}}$
Deciding vehicle's own SCM	$\text{SCM}_o$
Collection of neighbor SCMs	$\mathcal{N} = \{\text{SCM}_1, \text{SCM}_2, \dots, \text{SCM}_n\}$
Local map of coverage	$[\text{LMC}] = (\text{lmc}_{ij})$
Local map of saturation	$[\text{LMS}] = (\text{lms}_{ij})$

In this work, we use the subscripts  $(i, j)$  to refer to matrix rows and columns, and the subscripts  $(x, y)$  to refer to geographic coordinates. Coverage matrixes are always accompanied by the coordinates  $(x_{\text{center}}, y_{\text{center}})$  of the center cell located at  $\text{scm}_{\lfloor n/2 \rfloor \lfloor n/2 \rfloor}$ , which allows any element to be mapped to a latitude/longitude pair — when  $(x, y)$  is used, the mapping is implied, since it is straightforward.

We begin by constructing two cell maps of the local neighborhood: a local map of signal coverage  $\text{LMC} = (\text{lmc}_{ij}) \in \{0, 1, \dots, 5\}$  and a local map of coverage saturation  $\text{LMS} = (\text{lms}_{ij}) \in \mathbb{N}_o$ . These maps give a picture of the existing RSU support network:  $\text{LMC}$  tracks the best coverage being provided at each cell, and  $\text{LMS}$  counts the number of RSUs covering that cell at the same time. Algorithm 1 shows how these local maps are built.

Local maps span from the lowest to the highest latitudes/longitudes seen in all SCMs, i.e., they are as large as the total geographic area covered by the underlying self-observed coverage maps.

With the  $\text{LMC}$  and the  $\text{LMS}$ , the metrics in equation (4.1) can now be calculated as described in algorithm 2 below.  $\mathbf{d}_{\text{new}}$  sums the strength of new coverage: e.g., a new cell covered with signal 4 will add 4 to  $\mathbf{d}_{\text{new}}$ . This way, the decision process can distinguish between new coverage that can be stronger or weaker.  $\mathbf{d}_{\text{boost}}$  measures the improvements to already-covered cells, summing the delta between the existing and new signal levels.  $\mathbf{d}_{\text{sat}}$  tracks redundant coverage (network saturation): for every cell that the new vehicle covers, sum the number of neighbors that already service it.

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**Algorithm 1:** BuildLocalMaps

---

**Data:**  $\mathcal{N} = \{SCM_1, SCM_2, \dots, SCM_n\}$   
**Result:** Local maps LMC, LMS  
1  $\triangleright$   $lmc_{xy}$  and  $lms_{xy}$  are initialized to 0  
2 **foreach**  $SCM_n \in \mathcal{N}$  **do**  
3     **foreach**  $scm_{n[xy]} \in SCM_n$  **do**  
4         **if**  $scm_{n[xy]} > lmc_{xy}$  **then**  $lmc_{xy} \leftarrow scm_{n[xy]}$   
5         **if**  $scm_{n[xy]} > 0$  **then**  $lms_{xy} \leftarrow lms_{xy} + 1$   
6     **end**  
7 **end**

---

For example, if a given cell that the car can reach is already serviced by 5 RSUs, add 5 to  $d_{sat}$ . This additive increase process helps keep a balanced number of RSUs that serve each cell.

Figure 4.5 shows two contrasting examples of the self-organizing decision process, in a simplified environment with no obstructions. The first, in figures 4.5a and 4.5b, shows a new car parking in an advantageous location and evaluating its decision score. The algorithms reveal that, of the 93 cells in the car's coverage map, 86 will add new coverage to the network while 7 will bring no improvement to the existing coverage. This car will, therefore, have a positive  $d_{score}$  and become an RSU. With two RSUs now active, figures 4.5c and 4.5d give a second example where another vehicle parks in between the RSUs. This new vehicle sees, from its decision algorithms, that it can add coverage to 10 new cells, and improve existing coverage to 25 cells — however, it will also be adding to network saturation to 58 cells, and may therefore have a negative  $d_{score}$ , and enter a sleep state.

The decision process builds from coverage matrixes that reflect the real-life status of the RSU support network and returns a Yes/No decision on each newly parked car. With the procedure for gathering coverage maps, the algorithms for newly parked cars, and the decision score equation, the self-organizing approach is fully functional.

**Algorithm 2: ScoreMetrics**


---

**Data:**  $SCM_o$ ,  $LMC$ ,  $LMS$

**Result:** A tuple of score metrics ( $d_{new}$ ,  $d_{boost}$ ,  $d_{sat}$ )

```

1  $d_{new} \leftarrow d_{boost} \leftarrow d_{sat} \leftarrow 0$ 
2 foreach  $scm_{xy} \in SCM_o$  do
3   if  $scm_{xy} > 0$  then
4     if  $lmc_{xy} = 0$  then
5        $d_{new} \leftarrow d_{new} + scm_{xy}$ 
6     else if  $lmc_{xy} < scm_{xy}$  then
7        $d_{boost} \leftarrow d_{boost} + (scm_{xy} - lmc_{xy})$ 
8     end
9      $d_{sat} \leftarrow d_{sat} + lms_{xy}$ 
10  end
11 end

```

---

**4.3.4 Substituting Displaced Cars**

We now outline an optional mechanism to preserve the structure of the support network whenever an RSU is displaced. When a parked car that is taking a Roadside Unit role becomes mobile again, we refer to this situation as the RSU having been *displaced*. Because decisions only occur when cars park, the service that was being provided by that RSU is not reestablished until a new car parks in the area.

One optimization to the self-organizing approach is to allow inactive parked cars to wake up periodically and listen to the 802.11p Control Channel (CCH), so they can react to changes in the network or respond to requests to come back on-line. We begin by showing how this periodic wake-up can be achieved, and then propose a limited communication system for inactive vehicles to elect a replacement to a displaced RSU.

**Periodic Wake-Up**

A periodic wake-up allows inactive parked cars to be recalled in case of need. For a replacement protocol to be able to act upon all viable candidates, the wake-up events

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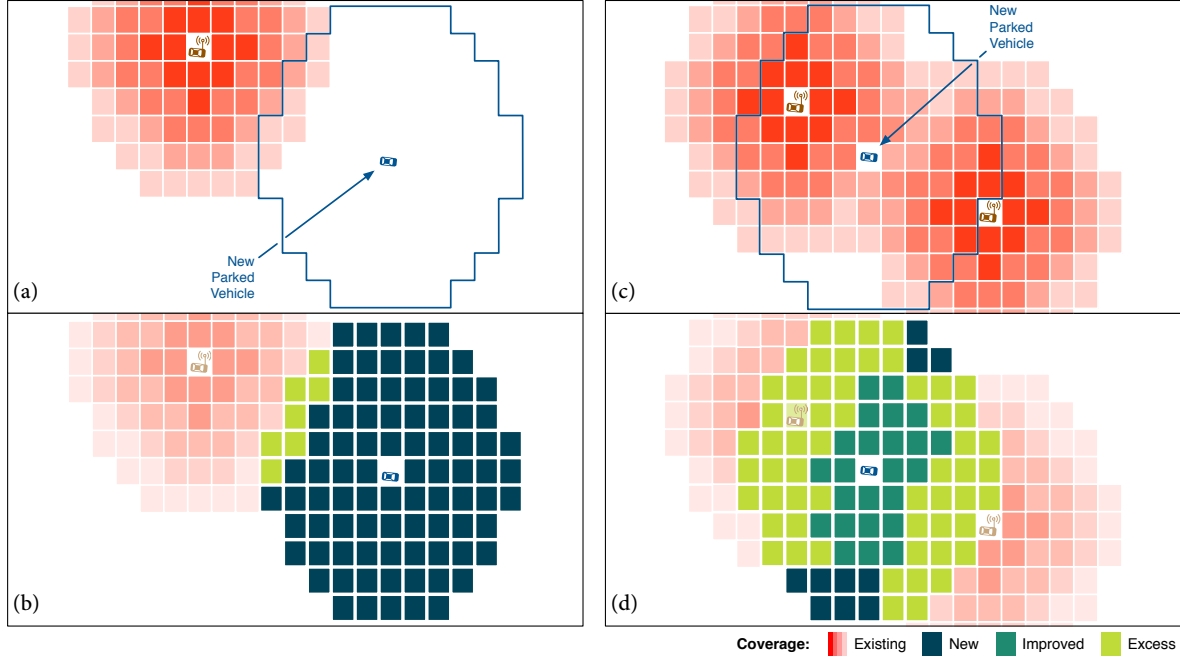


Figure 4.5: Two contrasting examples of the self-organizing decision process. (a) A new vehicle parks in an advantageous location, in the vicinity of a single existing RSU. (b) The decision algorithms show that it can cover a substantial new area, and so the car establishes itself as a second RSU. (c) Later on, another vehicle parks in between the two existing RSUs. (d) The algorithms now show that this car would be a net loss to the network, adding more redundant cells than new and improved cells. This vehicle does not become an RSU. These examples are simplified and shown for illustration purposes only.

must be synchronized, which can be achieved with ease through 802.11p's mandatory time synchronization.

Through Time Advertisement messages and GPS timecode data, all On-Board Units (OBUs) of a vehicular network are synchronized to UTC (Universal Time Coordinated). We can then implement modular arithmetics based on the local time  $t_{\text{OBU}}$  to ensure all OBUs wake up in parallel. A modulo operation triggers a wake-up when the remainder of  $(t_{\text{OBU}} \bmod N)$  is zero: e.g., with  $t_{\text{OBU}}$  in seconds and  $N = 15$ , the OBUs will wake 4 times a minute. On each wake-up, the OBU must listen for a single CCH interval (50 ms), so with a 15-second interval inactive cars only have to have their OBUs active 0.3 % of the time, with a corresponding energy savings. There is therefore a tradeoff between the reaction time of inactive parked cars and the energy required to allow inactive cars to be contacted.



### Electing a Replacement

An inactive parked car detects a displaced RSU when it fails to hear a beacon coming from said RSU during its periodic wake-up interval. Beacons in 802.11p do not benefit from guaranteed delivery, so a car should only react once it fails to hear multiple beacons in a row. Figure 4.6 illustrates the election process, which works by quickly eliminating as many candidates as possible with no communication between them. This silent elimination ensures that a network in an area with hundreds of inactive cars (e.g. in a parking lot) is not flooded with messages every time an RSU is displaced.

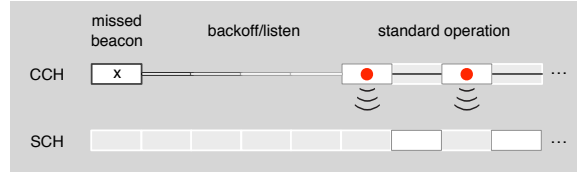


Figure 4.6: The proposed election process, occurring on every inactive car that detects the loss of an RSU. This process occurs exclusively in IEEE 1609.3's Continuous Channel Access, where the radios remain on the Control Channel (CCH), and do not switch to the Service Channels (SCH). Slots correspond to CCH Intervals, standardized as 50 ms.

To this end, we propose an initial backoff period inversely related to each car's decision score, as described earlier in section 4.3.3. Each car detecting a displaced RSU computes its  $d_{\text{score}}$  setting aside the coverage map of the displaced RSU. Its backoff time  $t_{\text{backoff}}$  is given by

$$t_{\text{backoff}} = \left\lceil \left( 1 - \frac{d_{\text{score}}}{d_{\text{score}_{\text{max}}}} \right) \times N_{\text{backoff slots}} \right\rceil \times t_{\text{CCH}} , \quad (4.2)$$

where  $d_{\text{score}_{\text{max}}}$  is the largest value a decision score can take (which is found empirically),  $N_{\text{backoff slots}}$  specifies how many intervals the backoff process is allowed to last for, and  $t_{\text{CCH}}$  is the duration of a CCH Interval, 50 ms. In this calculation, the car's decision score is used as a ratio to the number of backoff intervals. Larger (better) decision scores will then lead to shorter wait times. As the backoff timer on the best candidate expires, it begins to broadcast new RSU beacons, advertising itself as the winner of the process and instructing other candidates to return to sleep.

The number of backoff slots determines the balance between how quickly a

#### 4. PARKED CARS AS URBAN ROADSIDE UNITS

replacement RSU is found and how many candidates are excluded by the process. When multiple listeners are assigned the same expiration timer, contention at the Medium Access layer ensures that only one will broadcast a beacon first, but at this point, the choice is random.  $N_{\text{backoffslots}}$  should therefore be sufficiently large to eliminate most candidates based on their decision scores (e.g., 40 backoff slots can exclude 97.5 % of all candidates in 2 seconds).

### 4.4 Performance Analysis

Here, we present a study of the benefits that parked cars can bring to sparse urban areas and an analysis of the performance of the self-organizing approach shown in section 4.3. To do so, we run simulations on a platform that integrates real road topologies, realistic vehicle mobility, real maps of obstructions, and empirical signal measurements with 802.11p hardware, all of which are gathered from and applied to the city of Porto, Portugal. The platform, which was custom-developed for this work, is described next.

#### 4.4.1 An Urban Simulation Platform Using Real Data

The urban environment introduces a number of challenges to a vehicular network. The movement of cars is dependent on factors such as the time of day, the type of road the car is on, and the activity of intersection traffic lights; the propagation of radio waves is affected by obstructing buildings of varied sizes and composition, signal reflection and diffraction on multiple surfaces, and even by other cars themselves blocking the communication path; moreover, constant node mobility causes these conditions to change at a rapid pace.

To better characterize the complexities of urban areas, we set out to design simulation scenarios that are highly realistic, so that the resulting data are reliable and indicative of what can happen in a real-life scenario. With this goal in mind, we developed a platform with the following features:

- Realistic vehicle mobility and traffic light patterns, obtained with the well-known open-source vehicle simulator SUMO [55].

- Real urban street layouts generated from publicly-available city maps that include lane numbers, speed limits and traffic lights [56].
- An accurate, vectorial model of urban obstructions, made available by the Porto City Council. With this obstruction data, in the form of a *shapefile*, we created a Geographic Information System (GIS) [57] to determine Line-Of-Sight status between any two vehicles.
- Realistic modeling of core wireless network metrics such as Bandwidth and Packet Loss, as a function of node distance and Line-Of-Sight status, derived from empirical measurements gathered with actual 802.11p-equipped vehicles circulating in Porto as well [32].

In our simulations, the signal strength between two cars is modeled with the results presented in [32]. The data from this study are used to assign levels of coverage quality while a parked vehicle is building its coverage map, through the process described earlier in section 4.3.1, and the final signal quality for each cell is determined by averaging the signal of all received beacons. These classification criteria are shown in table 4.2. In a real-life scenario, coverage strength can be determined with received signal strength measurements from the DSRC radios.

TABLE 4.2  
QUALITY MEASURE CRITERIA FOR COVERAGE MAPS

Quality		5	4	3	2
Distance	LOS	70 m	115 m	135 m	155 m
	NLOS	58 m	65 m	105 m	130 m

#### 4.4.2 Improving Broadcast Delay in Sparse Networks

In the initial stage of a vehicular network deployment, insufficient numbers of vehicles with DSRC equipment will cause the network to become sparse. A sparse network is one where some of its nodes are too far apart from their neighbors for communication to occur, leading to network disconnection. In an urban area, this causes virtual clusters of cars to form, where cars in a cluster can talk to one another,

#### 4. PARKED CARS AS URBAN ROADSIDE UNITS

but are unable to send messages to other neighboring clusters. This sparse network problem has been well studied on highway vehicular networks [3] and, in these environments, connected Roadside Unit deployments bring substantial benefits, as was shown in chapter 2. While this issue is prevalent in scenarios of low market penetration, it can also occur in periods of low traffic, even with full market penetration of DSRC hardware.

Here, we study a scenario where the urban area sees a low density of DSRC-enabled vehicles, which in turn also results in small numbers of parked cars that can join the network as RSUs. Our goal is to determine whether the approaches introduced in this chapter bring tangible benefits in these sparse scenarios. For the problem at hand, we simulate an accident that occurs at a random point in the city, automatically triggering the dispatch of an emergency message. In real life, these messages have a dual purpose: to reach any nearby emergency vehicles, hospitals or police stations, and to quickly inform other drivers of the accident, so they can anticipate danger, expect congestion, and take alternative routes. The latter may also aid in the former, by reducing traffic in the vicinity of a crash, which helps emergency services en route.

This scenario serves as a tool to study the overall performance of a message broadcast in an urban vehicular network, and is not exclusive to safety applications. Our metric of interest is then the *message reachability*: the rate at which the message spreads to nearby vehicles, and how quickly everyone in the immediate neighborhood is informed. To broadcast the message, we select UV-CAST, a well-known urban broadcasting protocol designed specifically for vehicular networks [50]. When the need to disseminate a message occurs, UV-CAST comes into play by locating the edge nodes of the cluster the message is coming from, with a gift-wrapping algorithm. These edge nodes are then designated as the ideal message broadcasters and continue to rebroadcast the message as they meet new vehicles on the road. Figure 4.7a shows an example of the algorithm at work.

In this analysis, we adapt UV-CAST to support multiple message origins, by making use of the support network of parked cars. An example of this multi-origin system is seen in figure 4.7b — here, active parked cars in the area assist the rebroadcasting of messages to other parts of the network. At locations where other active parked cars exist, UV-CAST’s algorithms are executed again, and new sets of broad-

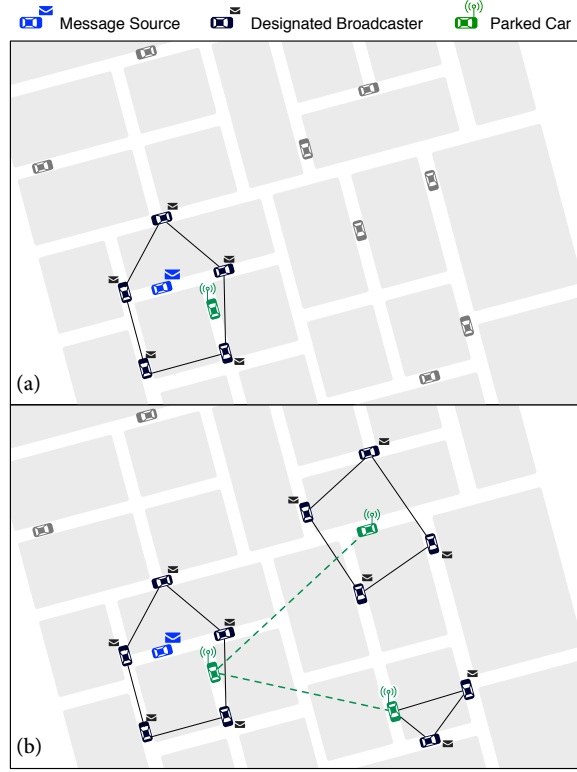


Figure 4.7: UV-CAST selecting forwarders for a message broadcast with (a) no RSUs; (b) 3 parked cars active in standalone mode.

casters are selected, effectively increasing the numbers of vehicles that redistribute our emergency message, as well as their geographical dispersion.

For simulation purposes, we set up a  $1 \text{ km}^2$  area in the city of Porto, as described earlier in section 4.4.1, featuring a diverse mix of road structures, speed limits, and functional traffic lights. We predefine a ratio of 1 parked car acting as an RSU for every 10 cars on the road (a 1:10 ratio) and analyze three densities of vehicles:  $20 \text{ veh/km}^2$ ,  $40 \text{ veh/km}^2$  and  $80 \text{ veh/km}^2$ . The first two densities match low-density and early-morning scenarios, while the third is a medium-density scenario where network sparsity is expected to be less problematic. Parked cars are placed randomly in the area, and the 1:10 ratio between parked cars and moving cars is chosen to be conservative — often, close to 80 % of all cars in a given area are parked. The reduced number of parked cars that are able to operate as RSUs in standalone mode is intentionally

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chosen to emulate environments where uplink availability is scarce.

Figure 4.8 shows the evolution of an emergency message's *reachability* for the three densities under consideration. Here, reachability denotes the number of nodes that have received the message — e.g., for the 40-vehicle scenario, the maximum reachability is 40. We compare six scenarios, three with and three without parked car support, and average the results over 50 repetitions each. The data show improvements of 47 %, 45 % and 41 % in the time required for full reachability, for the 20-, 40- and 80-vehicle densities respectively. These are substantial gains that effectively cut an emergency message's broadcast delay in half in these sparse scenarios.

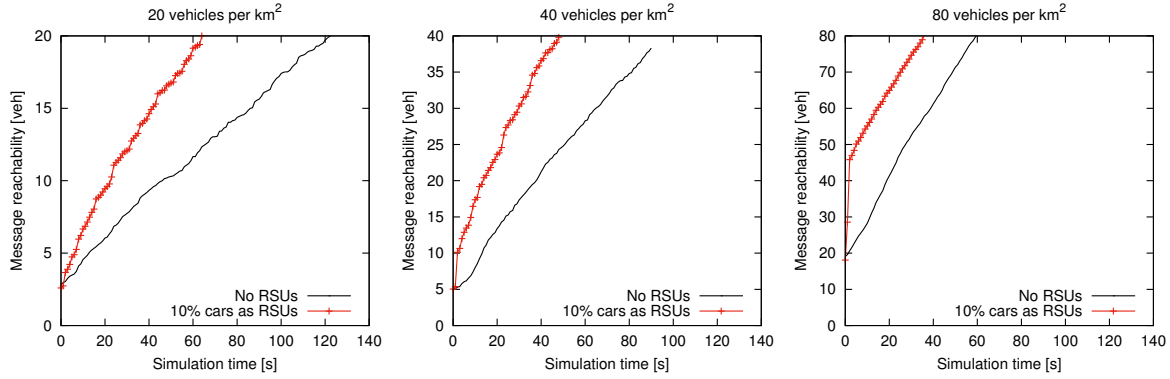


Figure 4.8: Multi-origin UV-CAST message reachability over time, with 10 % of the cars on the road parked and active as standalone RSUs.

The improvements diminish, proportionately, as the number of cars on the road increases, which is an expected result given that higher vehicle density translates to improved network connectivity (less sparseness). For example, in the medium-density scenario (80 cars), because the network is less sparse, the emergency message immediately reaches ~60 % of all cars with the first broadcast — a consequence of the improved connectivity is to have fewer and larger clusters, and so a higher proportion of vehicles will be in the same cluster as the broadcast source. Seeing smaller gains in well-populated networks does not, however, mean that RSUs are not needed when the network is not sparse — in higher-density scenarios, the benefits of RSUs will come in the form of controlled broadcasting (e.g., preventing *broadcast storms*) and improved network efficiency, among others.

The simulation results shown in figure 4.8 indicate that even a small number of

parked cars randomly-distributed throughout an urban area can bring substantial improvements to the broadcast of important emergency messages, which is one of the most important applications of a vehicular network.

#### 4.4.3 Performance of Self-Organization Mechanisms

We now turn our attention to the performance of our self-organizing approach. To do so, we run a series of simulations in a 1 km<sup>2</sup> region in the city of Porto using the simulation platform detailed earlier, and analyze the behavior of the algorithms and mechanisms that were shown in section 4.3.

##### Time to Build Coverage Maps

The coverage maps that the vehicles build are a fundamental part of the proposed approach, but due to the randomness inherent in a vehicular network, a parked car may not have a reliable way to know if it has overheard enough beacons to form a reliable coverage matrix. A simulator is an ideal tool to analyze this observation step, as it can determine the complete map of a specific car beforehand, and track its evolution. We run a series of simulations where cars are parked at random locations in the city, introduce traffic at three different densities, and track the evolution of each car's coverage map. Figure 4.9 plots the maps' percentage of completeness as a function of time.

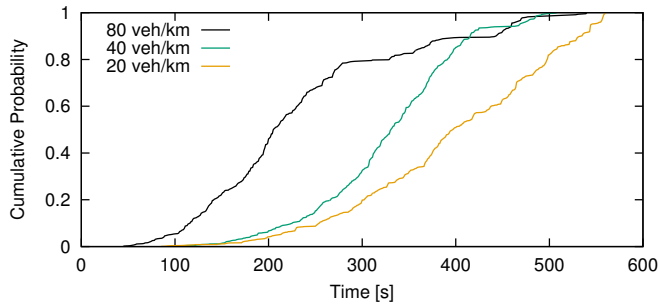


Figure 4.9: Probability that a car's self-coverage map has been completely observed, as a function of elapsed time, in low- and medium-density scenarios.

The data confirm the intuition that with more moving cars a reliable map will take less time to build. For 80 % of the map to be statistically complete, in these

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low-density scenarios, the newly parked car must receive beacons for 498 s, 392 s and 330 s, for the 20-, 40- and 80-vehicle densities, respectively. A conservative approach for a real-life scenario is then to instruct cars to build coverage maps for 500 s to 600 s (i.e., for about 10 minutes) after they park, to ensure a sufficiently complete map. A decision may be executed earlier, particularly if large numbers of beacons are received from multiple directions (suggesting a dense network) — in the worst case, the car will temporarily take an unnecessary RSU role, and once more coverage is learned, the decision process is retaken. In higher-density scenarios, our tests show that coverage maps are typically built in 30 s to 60 s.

##### Decision Algorithm vs. an Optimal Solution

Given the cell map division proposed in section 4.3.1, our core metrics for a support network of parked cars are: the mean signal level available to each cell (network coverage); the average number of RSUs covering each cell (network saturation); and a count of how many parked cars take on the RSU role. In dense networks where considerable numbers of parked cars exist, the selection of which cars should take on Roadside Unit roles becomes the primary concern. The optimal solution to a given set of parked cars can be determined by evaluating each possible combination of active and inactive vehicles, with complete knowledge of the candidates and their coverage maps. Here,  $2^{\#cars}$  scenarios are possible, easily exceeding millions of computations, which makes optimal decisions infeasible in real-life.

We design a simulation scenario of high vehicle density where 24 cars are instructed to park randomly in a small 0.18 km<sup>2</sup> section of the map. This constraint forces the cars to park on nearby streets, so that their coverage overlaps and a decision is made on which cars to keep active. For comparison purposes, we first determine the optimal solution by bruteforcing the  $2^{24}$  possible combinations (approx. 16.7 million runs), and we also calculate the effects of simply activating all available parked cars. The results are shown in table 4.3. Predictably, the activation of all available vehicles leads to the best coverage, but also causes each cell to see an average of 8 RSUs, which is inefficient and may be problematic. The optimal solution provides roughly the same level of signal coverage, now with only 1.6 RSUs seen at each cell, and just 5 out of the 24 cars left active. These results show that, given perfect decisions, 19 of these 24 parked cars are not needed and can enter an energy-efficient sleep state.



TABLE 4.3  
REFERENCE OPTIMAL METRICS AND PARAMETER SET METRICS

Scenario	Signal Coverage	Coverage Saturation	RSU Count
All RSUs active	4.13	8.28	24
Optimal selection	4.06	1.63	5
Set1 ( $\mu = 0.1$ )	3.93	2.42	7.2
Set2 ( $\lambda = 8.0$ )	3.76	2.02	5.6

Next, we analyze our self-organizing approach, with sharing of coverage maps and decisions taken at each node, to determine whether it can approach the outcome of an optimal solution. To do so, we vary the weights of each component in the decision criteria  $d_{\text{score}}$ , rerun the simulation scenario, and plot the resulting signal strength, coverage saturation and RSU count metrics. In figure 4.10, each of the coefficients  $\kappa$ ,  $\lambda$  and  $\mu$  is adjusted individually from 0.1 to 10.0, causing a corresponding decrease/increase in the weight that the  $d_{\text{new}}$ ,  $d_{\text{boost}}$  and  $d_{\text{sat}}$  metrics have in the final decision score of each parked car. The resulting city-wide metrics are shown. Figure 4.11 then plots these same metrics for two preselected parameter sets: *Set1* is geared towards better coverage, and *Set2* aims for fewer active RSUs.

The data in figures 4.10 and 4.11 show that a decision process optimized towards improved coverage can reach a global signal strength of 3.93, which is only 3 % worse than the Optimal selection. This particular scenario occurs by setting  $\mu = 0.1$  (the  $d_{\text{sat}}$  coefficient). However, the result is also that 7.2 parked cars remain active, which is 2.2 cars more than the optimal solution. A second set of coefficients can be selected to reduce the number of active cars to a minimum: with  $\lambda = 8$ , the resulting signal strength is of 3.76 (7 % worse than Optimal), and only 5.6 parked cars remain active.

The data presented in this section show that our decision process can obtain near-optimal results without the need for an extensive knowledge of a network's RSUs, and that it can also be directed towards specific goals, such as better signal strength or fewer active parked cars. Extrapolating the results to a 1 km<sup>2</sup> area, we observe that about 28 to 30 parked cars per km<sup>2</sup> may be sufficient to form an extensive vehicular support network. This number is an order of magnitude smaller than the typical

#### 4. PARKED CARS AS URBAN ROADSIDE UNITS

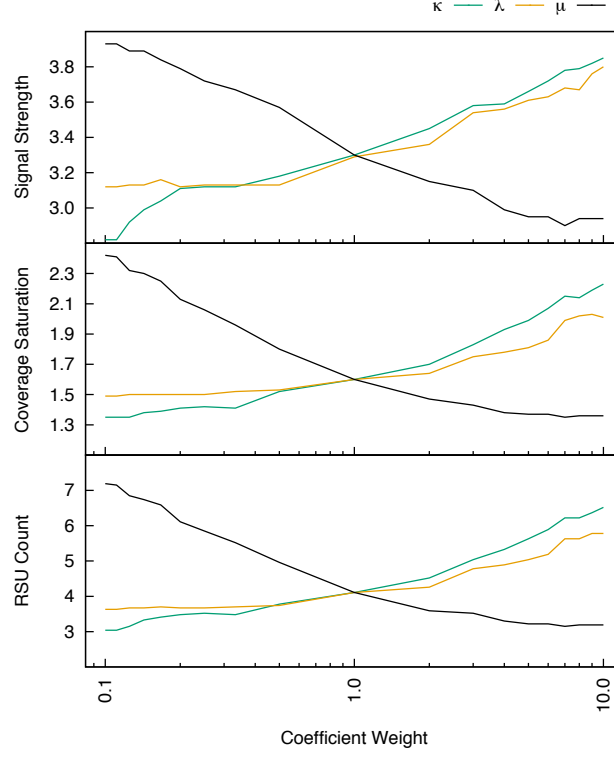


Figure 4.10: Effect of varying the coefficients  $\kappa$ ,  $\lambda$  and  $\mu$  (and the corresponding components of the decision score,  $d_{\text{new}}$ ,  $d_{\text{boost}}$  and  $d_{\text{sat}}$ ) on signal strength, coverage saturation, and number of active RSUs. A single coefficient is varied at a time, while the others remain fixed at 1.0.

density of parked cars in a city. And while our study so far has been heuristic in its nature, varying coefficients and analyzing the corresponding outcomes, chapter 6 will introduce a scoring mechanism that acts directly on the metrics of signal strength, coverage saturation, total area covered, and energy usage, allowing for principled ways to tailor the decision process to fit a specific goal.

### 4.5 Discussion

Leveraging parked vehicles as roadside units is a relatively new and unexplored concept, and the mechanisms and algorithms we present in this work should be considered as initial explorations of this idea. This work is the first to approach the

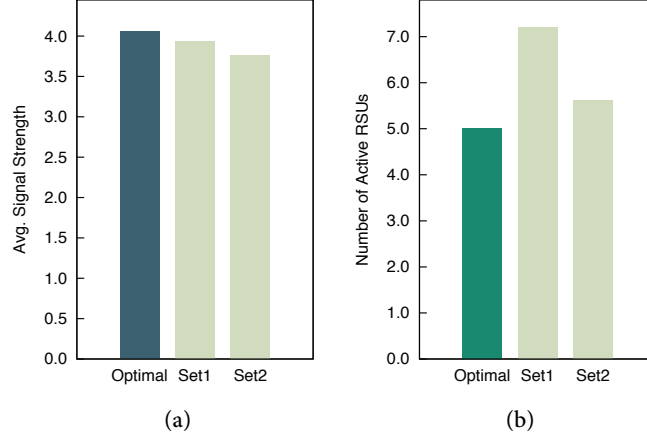


Figure 4.11: City-wide metrics for two coefficient sets with different optimization goals, versus an optimal selection. (a) Average strength of coverage. (b) Number of parked cars activated. *Set1* attempts to maximize the quality of service coverage, while *Set2* is aimed at reducing the number of active parked cars.

problem of assigning RSU roles to a large pool of candidates, while optimizing the network in a self-organized way, thereby showing the viability of the concept in an urban environment. Our results show that a self-organizing approach with limited information can indeed approach a globally optimal coverage solution, indicating that parked cars are able to form a vehicular support network without the need for centralized control and decisions. The following are some of the open problems and possible areas of improvement.

In this work, we restricted exchanges of coverage maps to a conservative 1-hop neighborhood. Relaxing this limitation may yield more efficient algorithms (e.g., issuing a map request to the 2-hop neighborhood, or geocasting that same request), at the expense of incurring a higher overhead on the network.

The second part of our study analyzed how the network establishes itself in areas where no network existed before. This initial setup represents a transient state in the support network. In urban areas where parked vehicles exist at every hour of the day, once the initial RSUs are established a steady state is reached, and the replacement mechanism provided in section 4.3.4 takes over. The proposed mechanism aims to be overhead-efficient, and preserve the initially-established structure by picking the

#### 4. PARKED CARS AS URBAN ROADSIDE UNITS

replacement that is most similar to the departing vehicle. Here, steady state coverage may be improved by picking the replacement car that optimizes the network at the local neighborhood instead. This, however, may require large numbers of inactive parked vehicles to communicate so an informed decision can be performed.

The use of the car's battery is also a concern to the self-organizing approach. In chapter 6, we will show empirical data indicating that an OBU that operates for the average parking duration of a car will drain under 5 % of the car's available battery capacity (see section 6.4.1 on page 126). Other factors such as aging batteries, prolonged parking events or the presence of other power-hungry electronics may require this power draw to be reduced even further, however. With the mechanism shown in section 4.3.4, that allows inactive cars to react to displaced RSUs and automatically select a replacement, an active parked car can intentionally disable itself after a pre-specified amount of time (e.g., after 1 hour, the power draw will be under 1 %) and be automatically compensated for by neighboring cars. More advanced mechanisms can elect replacements beforehand and execute a soft handoff. We introduce one such method in chapter 6.

Finally, this work uses a cellular division of the urban area to be able to represent coverage maps as 2D arrays of signal strength, and proposes that such divisions be geographically aligned to GPS seconds. The precision (or lack thereof) of car GPS signals may be of concern for this type of approach. Small GPS inaccuracies can cause beacons sent at the edge of a cell to be erroneously assigned to a nearby cell and, should that be found to be an issue in real-life scenarios, the system may opt to discard beacons sent near these boundaries, or to filter beacons with high Dilution of Precision (a measure of GPS signal quality). An empirical study of the process through which cell-based coverage maps are built is given, later on, in chapter 6 (see section 6.4.2 on page 128).

### 4.6 Related Work

The concept of using cars as Roadside Units began to gain traction as it became apparent that the cost of these units would pose a significant barrier to their deployment. Leveraging moving cars as temporary RSUs in urban areas, by requesting that they make brief stops to aid in emergency message broadcasts, was shown to bring

a measurable improvement to such goals [51]. The work in chapter 3 showed how similar concepts, when applied to highway vehicular networks, were able to reduce broadcast delay when opposite-lane traffic was insufficient to relay packets

The specific idea of *parked cars* as members of the vehicular network is first introduced in [52]. This work suggested activating parked cars to increase the number of nodes in a sparse network, improving its connectivity. It reported a 3.3x improvement in node density when 10 % of available parked cars became active. These results follow from tenuous assumptions of stable 250 m radio ranges in the urban area, which empirical data have shown to be improbable [32].

The interesting work in [58] suggests using parked cars as a means to overcome the signal degradation that occurs when buildings block the line of sight between two vehicles. By activating parked cars at key intersection points, other cars can use the parked car at the intersection as an unobstructed message relay. With this approach, cars were shown to be able to receive nearby emergency messages up to 17 s faster. A follow-up to this work [59] also demonstrated how parked cars can be used to aid existing RSUs in content downloading. By caching content from fixed RSUs, bandwidth demands on the main RSU for distributing content could be alleviated. These works presented data obtained under the assumption of 200 m radio ranges, irrespective of obstructions.

The existing body of work on parked cars has revealed the interesting possibilities that can be brought by leveraging parked cars as RSUs, albeit in specific, limited scopes. While these works describe some interesting use cases for parked cars in urban vehicular networks, they do not address the fundamental question of how these entities should be selected, managed, and replaced using a self-organizing network approach, nor whether they can assume more flexible support roles in the network, instead of being relegated to these specific uses. Our work aims to show that using a self-organizing network approach, parked cars can serve as a low-cost and very efficient alternative to deploying RSUs in urban areas.

## 4.7 Summary

We have showed that using a self-organizing network approach, the large numbers of parked vehicles in urban areas can be leveraged to serve as RSUs and provide

#### 4. PARKED CARS AS URBAN ROADSIDE UNITS

support to the networks of moving vehicles. These networks of parked cars can serve as low-cost, efficient alternatives to expensive deployments of fixed Roadside Units. To function as RSUs, they require only the means to keep DSRC electronics powered while vehicles are parked. Our proposed self-organizing network approach introduced novel ways for cars to determine their ability to act as RSUs and to decide whether to become RSUs from that knowledge. Our analysis showed how a support network that provides excellent coverage is possible using only a small fraction of the cars that park in a city.

## Chapter 5

# Statistics of Cars Parking in Urban Areas

The ability to model and predict the behavior of cars that park in an urban area is essential to the development of vehicular networks that leverage these parked cars. In this chapter we analyze the mobility patterns of people living in US cities who use cars as their primary means of transportation. We process and analyze survey data from the metropolitan areas of Atlanta, Chicago, and Knoxville, to extract statistics on the parking behaviors of individual cars. We then provide daily and hourly numerical models of parking events, along with useful derivations of the main parking statistics. The data we present conclusively show that parking events are classified into two major, clearly identifiable groups according to the time cars spend parked; that these patterns vary substantially throughout the day; and finally, that these trends are very similar across different cities [60].

### 5.1 Introduction

Regional travel surveys have been commissioned by city transportation committees from as early as 1965 [61]. These surveys consist of randomly-sampled person-to-person interviews that inquire about a person's travels on a specific date, collecting departure and arrival times, locations, and means of transportation, among others. Earlier surveys consisted of in-person interviews — nowadays, Computer-Assisted Telephone Interviews (CATI) are standard. Studies that make use of these travel surveys are often tailored towards the development of urban parking spaces and parking lots [62], and so data are aggregated in metrics such as *parking spot occupa-*

## 5. STATISTICS OF CARS PARKING IN URBAN AREAS

*tion* throughout the day. While this gives us a broad picture of how parking spaces are used, it does not let us infer the parking behaviors of each individual car.

In this chapter, using data from recent travel surveys, we draw statistics on how single cars park in urban areas. These statistics are of particular use to vehicular urban network research. Recent studies have brought forth the idea of leveraging parked cars as active nodes in an urban network, increasing network connectivity [52], relaying messages across intersections [63], and acting as supporting Roadside Units (as seen in chapter 4). So while the potential for parked cars in these networks seems clear, a number of pitfalls need to be addressed as well — for example, the electronics that enable the network must run limited by the power available from the car’s battery, and cars can vacate their spots and become mobile at any time.

With this work, we provide a probabilistic view of how individual cars park, allowing for informed decisions to be made concerning these cars. Specifically, we analyze how total time parked is distributed, how parking behaviors evolve throughout the day, and how these trends differ from one city to another. We then show how parking time can be accurately modeled through a dual Gamma stochastic process, to characterize distinct short-term and long-term parking behaviors, and provide derivations for estimating parking duration and remaining parking time of individual cars.

### 5.2 Applications in Vehicular Networks

Our research has shown that parked cars can be leveraged to improve urban vehicular networks, simply by activating the radios in these otherwise unused entities (refer to section 4.6 on page 82). A support network that consists of parked cars will necessarily require some degree of self-organization, as cars park and depart often and unpredictably. When selecting a parked car for a specific role in the network, with the models presented in this chapter one is able to prioritize cars that are statistically more likely to stay parked for longer, so the chosen car can fulfill its role for longer as well.

Another concern with this approach is that power consumption of the radio electronics must be kept in check, in order not to risk draining the car’s battery (whose primary purpose is to kick-start a stopped engine). In this context, a system



to rotate the supporting roles in the vehicular network among nearby parked cars can be implemented. Using the models in this work, an algorithm can rotate roles among cars based on how long each car is likely to remain parked, and how much of its battery is left.

In general, we believe that most systems that leverage parked cars will benefit from taking the statistics presented in this chapter into consideration.

### 5.3 Travel Survey Data Sources

Performing a metropolitan travel survey demands a substantial amount of work and logistics, along with adequate funding to employ interviewers and collect data on a household-by-household basis. Figure 5.1 shows the number of surveys performed in the USA, from 1965 to date. The 1990s and 2000s saw a significant growth in the number of surveys performed per year, which has since then declined.

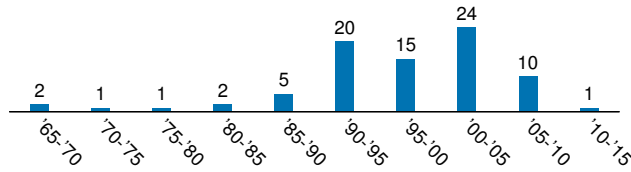


Figure 5.1: Histogram of travel surveys conducted by metropolitan areas, states and localities of the United States over the past 50 years.

In this work, we analyze data from three specific surveys: Atlanta 2011 [64], Knoxville 2008 [65], and Chicago 2007 [66]. In order to draw statistics that reflect modern parking trends, we specifically select surveys that are no older than 10 years, from medium- and large-sized urban areas. At the time of this writing, these were the surveys we were able to locate that fit the criteria. As our goal is to analyze the individual parking behavior of vehicles in a city, we process these survey data, and exclude samples in which the mode of transportation does not cause a parking event. Traveling on foot, by bicycle or by collective public transportation (bus, train, subway) are some examples of samples that were excluded. Table 5.1 lists the surveys, the number of samples contained in each survey, the percentage of these samples where the person traveled by car, and the population size in each metropolitan area.

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TABLE 5.1  
CHARACTERISTICS OF TRAVEL SURVEY DATA

Survey	Number of samples	Car-only samples	% Car samples	Metro. pop.
Atlanta 2011	119 478	81 863	68 %	5.5 m
Knoxville 2008	15 313	11 535	75 %	0.9 m
Chicago 2007	159 856	103 964	65 %	9.5 m

### 5.4 Statistics of Urban Parking

#### 5.4.1 24-Hour Model of Parking Events

We begin by analyzing the complete 24-hour dataset in each survey, as a whole, and deriving important characteristics from these data. For improved presentation, we apply kernel density estimators to the survey data, using Normal distributions as the kernel function  $K(\cdot)$ , its bandwidth calculated through the normal distribution approximation [67]. Figure 5.2 shows how the duration of parking events in a single day is distributed, for each survey's urban area.

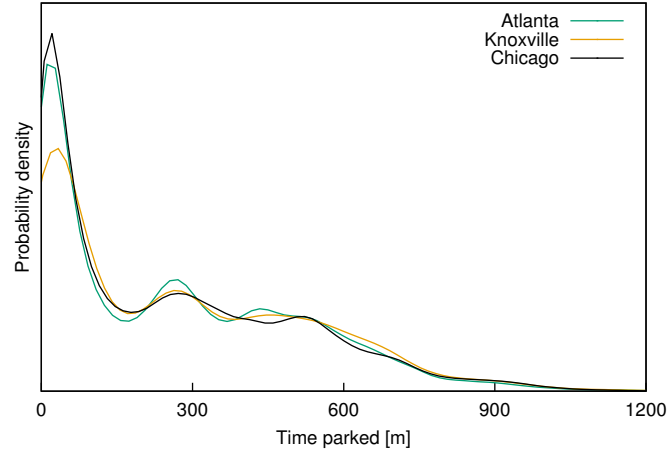


Figure 5.2: Probability density functions of total time parked, in minutes, for each of the three survey sets.

Important observations can be drawn from figure 5.2, the first one being that the main characteristics of parking duration are remarkably similar among all three cities. A second observation is that a large mass of cars park for 3 hours or less (the first peak from 0 to 180 minutes), which are then followed by a series of smaller overlapping peaks that represent longer-term parking.

Using the 180-minute mark as a classifier, we now analyze the short-term and long-term parking event groups. Figure 5.3 plots the distribution of the times of day at which vehicles first park, for the two groups, in the city of Chicago. The data show that short-term and long-term parking events are also very distinct in terms of the time at which the car is parked. Short-term parking (in red) is mostly consistent throughout the daytime, while long-term parking (in blue) peaks substantially between 6 and 9 A.M., with a second smaller peak occurring again around 1 P.M.

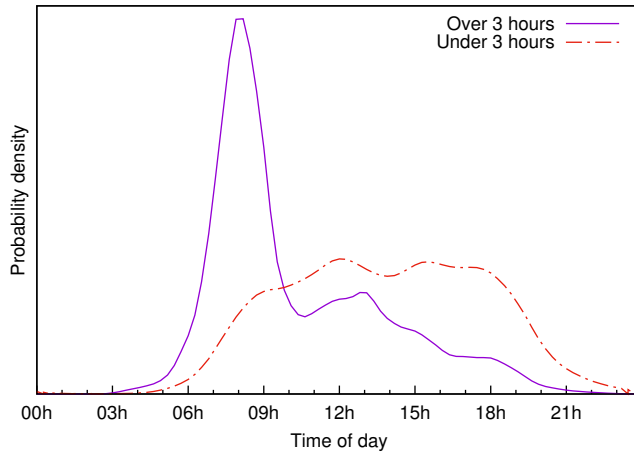


Figure 5.3: Time of day at which vehicles park, for short-term (under 3 hours) and long-term (over 3 hours) parking.

The probability distribution of the time cars spend parked, in figure 5.2, is useful to vehicular research, and this 24-hour aggregate of events can be fitted to known probability distribution functions. We fitted the survey data in the Chicago dataset, the largest of our three chosen surveys in terms of sample size, to various well-known distributions and applied the Kolmogorov-Smirnov test (which quantifies the distance between two distributions) to judge the best fit.

The Nakagami probability distribution, a distribution related to the Gamma

## 5. STATISTICS OF CARS PARKING IN URBAN AREAS

distribution (that often models waiting times between events), exhibited the best fit to the data shown in figure 5.2. Table 5.2 shows the Nakagami parameters of shape ( $m$ ) and spread ( $\Omega$ ) resulting from the fit, and the upper and lower bounds of the Kolmogorov-Smirnov test. The error between the empirical survey data and the fitted probability distribution does not exceed 6 %.

Having a single mathematical model capable of describing the time vehicles will spend parked can be useful — however, we will now show how parking behaviors vary throughout the day, which will suggest the need for more complex models.

TABLE 5.2  
FITTING PARAMETERS AND KOLMOGOROV-SMIRNOV TEST RESULTS

	Parameters		K-S Test	
	$m$	$\Omega$	$D^+$	$D^-$
Nakagami Distribution	0.282 598	125 292	5.48 %	5.97 %

### 5.4.2 Hour-by-Hour Analysis

We know, intuitively, that parking trends vary significantly throughout the day, matching people's daily routines. We saw already, in figure 5.3, that most long-term parking happens in the early hours of the morning, which coincides with the hours at which most day jobs begin. In this section, we show these trends in finer detail.

Figure 5.4a shows probability density functions of the total time vehicles stay parked, in an hour-by-hour basis: for example, the top figure pertains to the vehicles that parked between 4:00 and 4:59. Once again, this analysis is repeated for the three chosen surveys. Data begin at 4 A.M., as there were insufficient data points in earlier hours for us to be able to perform meaningful statistical analyses.

These detailed plots let us draw important conclusions. First, we can see that the split between short-term and long-term parking is only meaningful until 10 A.M. Past that hour, long-term parking events almost cease to exist. Second, the peak duration of long-term parking events grows shorter each passing hour: at 4 A.M., long-term parking averages 10 hours of parking time, but four hours later, at 8 A.M., the density peaks at 7.5 hours. The data show very clearly that the earlier a vehicle

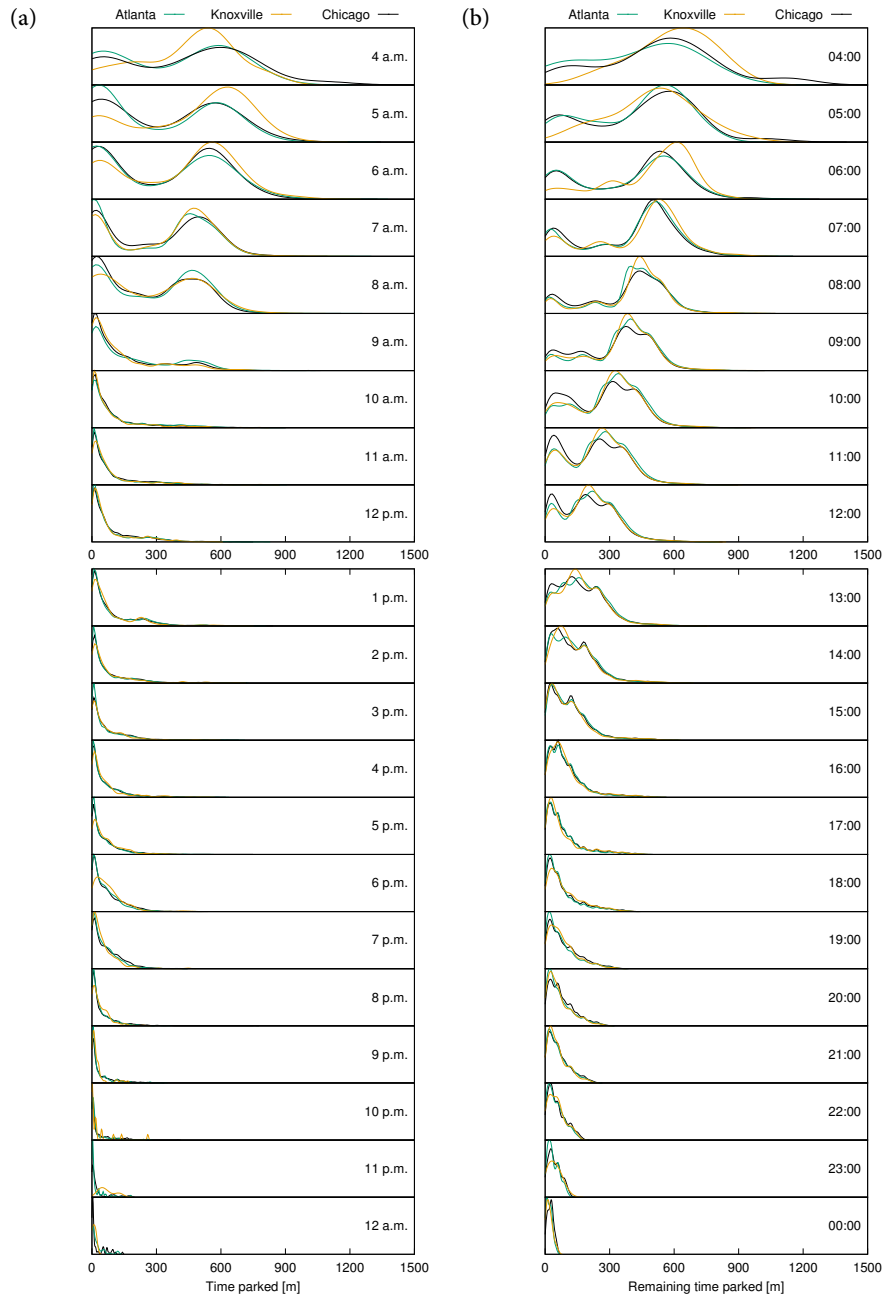


Figure 5.4: (a) Probability distribution of total time parked, grouped by the time of day at which parking occurred. (b) Distribution of remaining time until parking ends, from global snapshots at the start of each hour.

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is parked, the longer it will stay parked for. And figure 5.4a again shows that major parking trends are consistent across different cities, though the Knoxville survey data (the smallest of the three) may be sufficiently distinct from Chicago and Atlanta to warrant further research into smaller-sized urban areas.

For the purposes of vehicular research, knowing these distributions and the hour at which a car parked allows one to estimate that vehicle's parking duration, and how likely it is that it will park for a short or a long period. And when one cannot ascertain the time of parking, important information can still be obtained.

Figure 5.4b shows the distribution of time that a parked vehicle has left in that state (until it becomes mobile again), at specific hours of the day. These data are obtained by taking a snapshot of all parked cars at the beginning of the hour, and determining how long each vehicle will remain parked for. This way, knowing only the current time of day, one can scan a car or a group of cars and make an informed estimate of when these cars will be leaving their parking spots. The probability density functions are similar to the ones in figure 5.4a, with important differences. The average remaining parked time on each vehicle is higher, which means that, from a random sample of cars that are parked, one is more likely to find cars parking for a longer time. This effect propagates throughout the day: at 1 P.M., while most new cars are parking for an hour or less, the ones already parked will remain in that state for up to 5 hours.

### 5.4.3 Mathematical Model of Parking Behavior

We now attempt to obtain a mathematical model for a car's parking behavior, from the data that were just presented. From the hourly data in figure 5.4a, and by splitting the data points at the first observable trough in the distribution, we were able to heuristically determine that both short-term and long-term parking can be accurately modeled with a dual Gamma probability distribution. This also tells us that our initial analysis of the whole data set — which, absent this classification, appeared to be best fit by a Nakagami distribution — can be improved upon.

From figure 5.4a we observe that the distribution of short-term parking mimics an exponential distribution (with the distinction that very short parking events (e.g. under 1 minute) are empirically rare), which is itself a special case of the Gamma distribution. Long-term parking events resemble a normally-distributed random

variable, and in fact a Gaussian model will reasonably fit the data — however, such a distribution is defined in  $\mathbb{R}$ , which does not apply here as parking events cannot have a negative duration. A Gamma distribution, defined in  $\mathbb{R}^+$ , models long-term behavior equally well, and the resulting dual model is substantially more tractable as we no longer need to be concerned with negative tails in the normal distribution.

From our data, a car's parking behavior can then be described by a stochastic process  $X$ , indexed by discrete time  $t$ , where each  $X_t$  is a continuous random variable representing the time the vehicle will spend parked, when it parks at hour  $t$ . The individual random variables follow a mixture distribution of the aforementioned Gamma models. The first-order density of  $X$  is given by

$$\begin{aligned} f(\mathbf{x}, \mathbf{t}) &= D_{1,t} \times \frac{1}{\Gamma(\kappa_{s,t})\theta_{s,t}^{\kappa_{s,t}}} x^{\kappa_{s,t}-1} e^{-\frac{x}{\theta_{s,t}}} \\ &+ D_{2,t} \times \frac{1}{\Gamma(\kappa_{l,t})\theta_{l,t}^{\kappa_{l,t}}} x^{\kappa_{l,t}-1} e^{-\frac{x}{\theta_{l,t}}} \\ \mathbf{x} &> 0, \quad \mathbf{t} = \{0, 1, 2, \dots, 23\}, \end{aligned} \quad (5.1)$$

where  $\kappa_s$  and  $\theta_s$  are the shape and scale parameters of the Gamma distribution that models short-term parking, and  $\kappa_l$  and  $\theta_l$  are their equivalents, but for the distribution that models long-term events. Coefficients  $D_1$  and  $D_2$  weight each distribution, as a valid density function must always integrate to one (and therefore,  $D_1 + D_2 = 1$ ). The  $t$  subscript indicates that the variable is specific to time  $t$ .

The first-order distribution  $F_X(x)$  of the stochastic process  $X_t$  is then given by

$$\begin{aligned} F(\mathbf{x}, \mathbf{t}) &= D_{1,t} \frac{\gamma\left(\kappa_{s,t}, \frac{x}{\theta_{s,t}}\right)}{\Gamma(\kappa_{s,t})} + D_{2,t} \frac{\gamma\left(\kappa_{l,t}, \frac{x}{\theta_{l,t}}\right)}{\Gamma(\kappa_{l,t})} \\ \mathbf{x} &> 0, \quad \mathbf{t} = \{0, 1, 2, \dots, 23\}, \end{aligned} \quad (5.2)$$

where  $\Gamma(\cdot)$  and  $\gamma(\cdot)$  are the upper and lower incomplete Gamma functions, respectively. Knowing the hour  $t$  at which a car parked, the expected time that the car will be parked for can be shown to be:

$$\begin{aligned} E[X_t, \mathbf{t} = t] &= \int_0^\infty x f(x, \mathbf{t} = t) dx \\ &= D_{1,t} \kappa_{s,t} \theta_{s,t} + D_{2,t} \kappa_{l,t} \theta_{l,t}, \end{aligned} \quad (5.3)$$

where  $\kappa\theta$  is, by definition, the expected value of the Gamma distribution.

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An equally important derivation is the probability that a car still has  $n$  more hours left parked — useful if, e.g., one knows that a car has been parked for  $t$  hours, and wishes to know the probability that it will stay parked for at least  $n$  more hours. Let  $t_a$  be the time the car has been parked for, and  $t_p = t_a + n$  the parked time we wish to know the probability of. This conditional probability will be given by

$$P[X_t > t_p | X_t > t_a] = \frac{1 - F_X(t_p)}{1 - F_X(t_a)}, \quad t_a < t_p$$

$$= \frac{D_1 \gamma\left(\kappa_s, \frac{t_p}{\theta_s}\right) \Gamma(\kappa_l) + D_2 \gamma\left(\kappa_l, \frac{t_p}{\theta_l}\right) \Gamma(\kappa_s) - \Gamma(\kappa_l) \Gamma(\kappa_s)}{D_1 \gamma\left(\kappa_s, \frac{t_a}{\theta_s}\right) \Gamma(\kappa_l) + D_2 \gamma\left(\kappa_l, \frac{t_a}{\theta_l}\right) \Gamma(\kappa_s) - \Gamma(\kappa_l) \Gamma(\kappa_s)}, \quad (5.4)$$

where  $\{\kappa_s, \theta_s, \kappa_l, \theta_l, D_1, D_2\}$  are specific to the time  $t$  when the vehicle in question parked.

### Data Fitting

We fit the hourly survey data points shown in figure 5.4a to the probabilistic model of equation (5.1), through an Expectation-Maximization (EM) routine. Due to the considerable number of parameters ( $\kappa_s, \theta_s, \kappa_l, \theta_l, D_1, D_2$ ), we opted to augment the EM process with an iterative fitting routine, drawing from concepts of evolutionary computation. As all three surveys show similar parking trends, we fitted only the data in the Chicago 2007 set, the largest of the three.

The fitting routine works by mutating one variable on each iteration, and then determining the log-likelihood of the resulting model, to evaluate its *goodness of fit* to the survey data. If a particular mutation improves the goodness of fit, it is kept — if not, it is discarded. As the routine iterates, it converges towards a set of variables that is a better fit to the data. We applied this process to every hourly subset of data, and drew the values of all variables once fitness stabilized. The raw fitting results can be found at the end of this chapter, in table 5.3.

From the results of the fitting process, figure 5.5 shows the main characteristics of the short-term and long-term Gamma-distributed parking behaviors, and their evolution over time. Figure 5.5a plots the mean parking time which, as could be observed earlier in figure 5.4a, grows shorter throughout the day. The variance of parking time also grows tighter throughout the day, with brief increases at 9 A.M. and around 6 P.M.



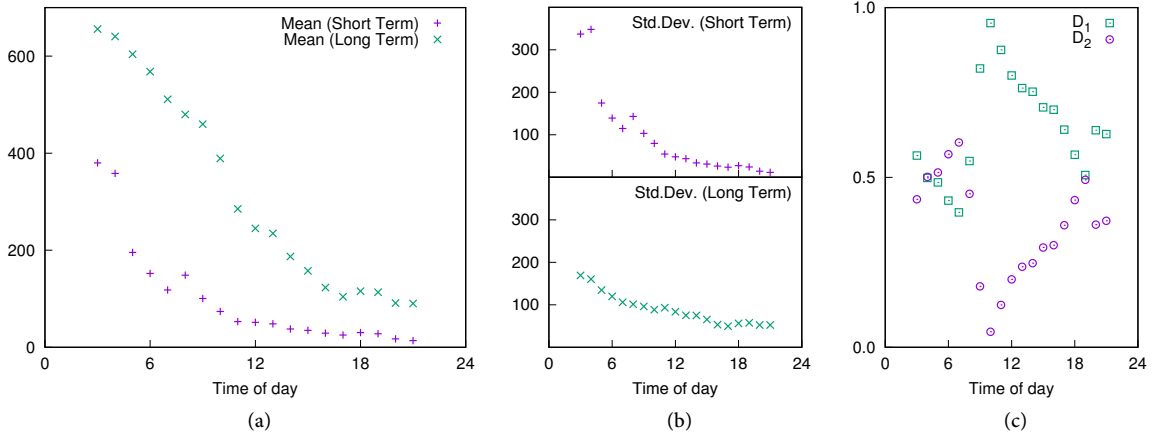


Figure 5.5: Main characteristics of the short-term and long-term Gamma-distributed parking behaviors, and their evolution over time. (a) Expected value of each distribution, in minutes. (b) Standard deviation of each distribution. (c) Distribution weight coefficients.

### Validation

To validate the hourly model that resulted from the fitting process, we applied the Kolmogorov-Smirnov test to each hourly snapshot of data. Figure 5.6 shows the  $\{D^-, D^+\}$  range of the K-S test for both the general (daily) and the hourly models. We can see that the hourly model fits the data with errors not exceeding 10 %, and stays under 5 % error in many of the hourly slices. In comparison, the general (daily) model will undershoot and overshoot on most of the partitioned data.

## 5.5 Summary

In this chapter, we studied vehicular parking trends in medium-sized urban areas. By analyzing recent travel surveys from the cities of Atlanta, Chicago, and Knoxville, we provided a probabilistic view of how individual cars park. We have shown how parking events naturally separate into two major groups of short-term and long-term parking, and conducted an hour-by-hour analysis of the data, revealing how trends evolve throughout the day. Modeling each event group separately, we determined that short-term parking resembles an exponential distribution, while long-term parking is predominantly gaussian in its nature. Drawing from these observations,

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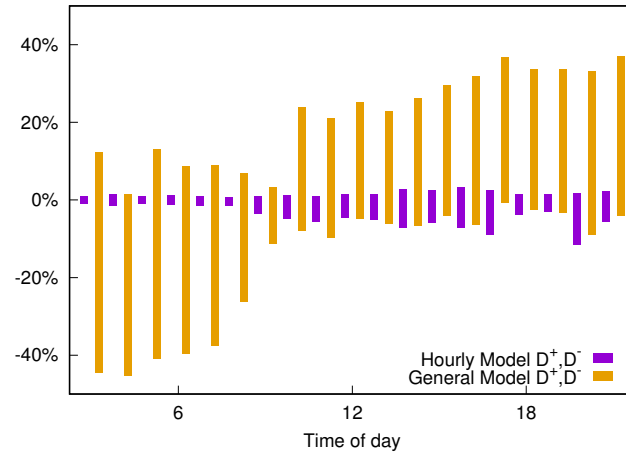


Figure 5.6: Kolmogorov-Smirnov test results for the data against the general and hourly models.

we developed a numerical model that accurately reflects vehicles' parking behavior in an urban area, along with important derivations that are of particular relevance to vehicular network research that intends to leverage parked cars.

TABLE 5.3  
FITTING COEFFICIENTS FOR THE STOCHASTIC HOURLY MODEL

Hour	$D_1$	$D_2$	$\kappa_s$	$\theta_s$	$\kappa_l$	$\theta_l$
3	0.5642	0.4358	1.272	298.7	15.00	43.73
4	0.4984	0.5016	1.059	338.4	15.95	40.14
5	0.4854	0.5146	1.252	156.1	20.09	30.06
6	0.4317	0.5683	1.195	127.5	22.50	25.24
7	0.3972	0.6028	1.057	111.6	23.27	21.96
8	0.5482	0.4518	1.079	137.8	22.36	21.46
9	0.8206	0.1794	0.9479	106.0	22.90	20.08
10	0.9543	0.0457	0.8640	85.58	19.39	20.07
11	0.8755	0.1245	0.9315	56.75	9.388	30.38
12	0.8000	0.2000	1.153	44.69	8.545	28.69
13	0.7631	0.2369	1.224	39.52	9.682	24.23
14	0.7523	0.2477	1.233	30.55	6.246	29.97
15	0.7061	0.2939	1.252	27.84	5.831	27.02
16	0.6995	0.3005	1.224	23.82	5.335	23.06
17	0.6407	0.3593	1.129	22.34	4.384	23.73
18	0.5669	0.4331	1.229	24.59	4.244	27.27
19	0.5071	0.4929	1.309	21.23	3.849	29.47
20	0.6390	0.3611	1.451	11.93	3.031	30.10
21	0.6277	0.3723	1.454	9.482	2.966	30.41



## Chapter 6

# Improving Parked Car Self-Organization

Vehicles that park in urban areas can be leveraged to take on the roles of fixed Roadside Units, positioning themselves as an effective alternative to costly deployments of vehicular network infrastructure. Chapter 4 showed how parked cars equipped with DSRC technology were able to self-organize and create a vehicular support network in an urban area, replacing or augmenting existing RSUs. In this chapter, we introduce novel mechanisms for parked vehicles to self-organize and form efficient vehicular support networks that provide widespread coverage to a city. These mechanisms are innovative in their ability to keep the network of parked cars under continuous optimization, in their multi-criteria decision process that can focus on specific network performance metrics, and in their control of each car's battery usage, rotating roadside unit roles between vehicles as required. We also present the first comprehensive study of the performance of such an approach, via realistic modeling of mobility, parking, and communication, thorough simulations, and an experimental verification of concepts that are key to self-organization. Our analysis brings strong evidence that parked cars can serve as an alternative to fixed roadside units, and organize to form networks that can support smarter transportation and mobility [68].

### 6.1 Introduction

As the world population continues to shift from rural to urban areas, smarter transportation becomes an increasingly necessary part of urban development. With

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urbanization comes a greater need for mobility, both in the form of personal vehicles and of public transportation, and consequently a demand for better transit and parking information. A greater awareness of available transportation resources is therefore a key element of a Smart City.

The advent of vehicular networking, through the IEEE 802.11p and WAVE standards, allows individual vehicles to communicate and report their activity, which enables the direct monitoring of transportation resources. Traffic density and road congestion can be measured in real-time [69–71], parking space availability estimated from cars that arrive and depart [72, 73], and the location of buses and other public transport can be tracked directly and efficiently [74]. The envisioned traffic efficiency applications assume one such infrastructure deployment in the form of Roadside Units (RSUs), but the prohibitive costs associated with RSU hardware, installation, and maintenance have severely limited their adoption [7, 9]. Vehicles that park in urban areas can be leveraged to take on the roles of fixed roadside units, positioning themselves as an effective alternative to costly deployments of network infrastructure. Our initial research on this area, presented in chapter 4, has shown that parked cars equipped with 802.11p technology are able to self-organize and create a vehicular support network in an urban area, replacing or augmenting existing roadside units.

This work introduces a new approach for parked car self-organization. This approach advances existing techniques in several ways: the proposed mechanisms optimize networks of parked cars beyond their initial grouping, which leads to a more efficient selection of cars to act as RSUs; a multi-criteria decision making process acts directly on key metrics of signal strength, coverage saturation, and coverage area, allowing for a precise control of the resulting support network; and car battery usage is factored into the decision process, with RSU roles being rotated among parked cars, ensuring a controlled use of each vehicle's battery resources.

The work presented in this chapter also includes the first comprehensive evaluation of the concept of leveraging parked cars as effective roadside unit replacements. Exhaustive simulation studies analyze how parked cars can organize to form new networks, and how those networks behave in their steady-state. We shed light on the number of parked cars that need to be recruited to provide adequate urban coverage in various scenarios, and analyze the quality and strength of the resulting networks in detail. Upper and lower bounds are established for the balance between better

coverage strength and fewer roadside units, providing a unique frame of reference to judge the performance of self-organizing approaches, and various iterations on the design of the newly introduced decision processes are all seen to operate near the optimal bounds. We bring in the detailed, realistic models of the distribution of parking events and their respective duration from the work in chapter 5, and validate the proposed mechanisms against them. Our analysis shows that this new approach makes use of fewer RSUs to reach the same levels of signal strength and coverage as the earlier proposals, and is more effective at stabilizing the parked car network.

Finally, this work presents the first empirical study of the process through which vehicles learn their own coverage map by overhearing beacons from other moving cars, an essential element to the self-organization process, and prove its validity. With this, we provide strong confirmation that self-organizing approaches are suitable for the creation of vehicular support networks from parked cars, and provide both an efficient set of new decision algorithms to do so and a comprehensive simulation platform to evaluate their performance on.

## 6.2 A New Self-Organizing Approach

To form a network, parked cars must work towards self-organization while meeting a number of goals: providing widespread coverage to the urban area; selecting, from large pools of parked vehicles, which should take on RSU roles; and managing the battery power drain on those cars. These goals are reached through collaboration and informed decisions between the cars themselves.

Our approach is designed to work in any scenario where a widespread deployment of **fixed infrastructure RSUs** (**fRSUs**) is not available. This may mean that fRSUs exist in limited numbers, or that no fRSUs have been deployed at all. In cities where no fRSUs exist, **parked car RSUs** (**pcRSUs**) can self-organize to create a mesh network and provide coverage and support to the urban area (see figure 6.1). When a limited deployment of fRSUs is in place, pcRSUs can also coexist by acting as relay nodes to those fRSUs, extending their coverage area.

In chapter 4, we introduced a number of novel concepts that facilitate this self-organization between cars. Specifically, we proposed a cellular division of the urban area, aligning cell boundaries to GPS coordinates (with a 1 GPS second interval).

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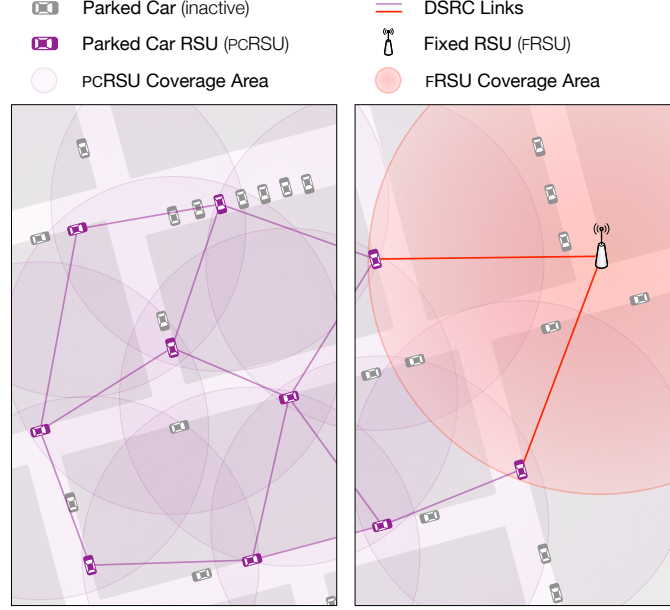


Figure 6.1: Example of an efficient RSU role assignment to parked cars, enabling the formation of a stable and widespread mesh network using only a fraction of the available vehicles. When present, fixed RSUs can also have their coverage area extended by parked car RSUs.

With this cell division as a common reference, parked cars can then be instructed to listen to Cooperative Awareness Messages (CAMs) from neighboring vehicles, and to build their own coverage maps from these beaconing messages, marking cells where beacons were received from with the signal strength of those messages. The exchange of coverage maps between cars allows decision processes to know the utility of each car to the network, and optimize using that information.

The mechanisms presented in the following section make use of these core concepts. We advance existing work by introducing a completely new approach for the decision process, one where newly parked cars are given the authority to make decisions for their neighbors, assigning and revoking RSU roles to other neighbor pCRSUs to optimize the local network. Additionally, we formulate the decision problem as a Multiple-Criteria Decision-Making (MCDM) problem that explicitly evaluates key metrics of the resulting network of parked cars, and factors battery usage data from active pCRSUs into each decision.



### 6.2.1 Local Decision Maker

As a new vehicle parks, it first constructs its own coverage map by listening to beacons being sent from moving cars, and gathers the coverage maps of its neighboring  $\text{pRSUs}$  and  $\text{pcRSUs}$ . Then, it creates a list of candidate roadside unit entities in its 1-hop neighborhood, consisting of itself and other active parked cars. From this pool, the decision maker lists the possible combinations obtained from assigning or revoking  $\text{RSU}$  roles to the entities in the pool, and assigns a score to each combination. We name a combination of active/inactive entities a *Coverage Solution*, and designate it by  $S_k$  (where  $k$  is the index of the coverage solution).

Once all coverage solutions are ranked, the one with the highest score is applied to the network. Figure 6.2 illustrates this decision process. To do this, the newly parked car, acting as a authoritative decision maker, sends specially crafted messages reassigning  $\text{RSU}$  roles in its vicinity. Through this approach, the network of  $\text{pcRSUs}$  sees a local optimization every time a new vehicle parks.

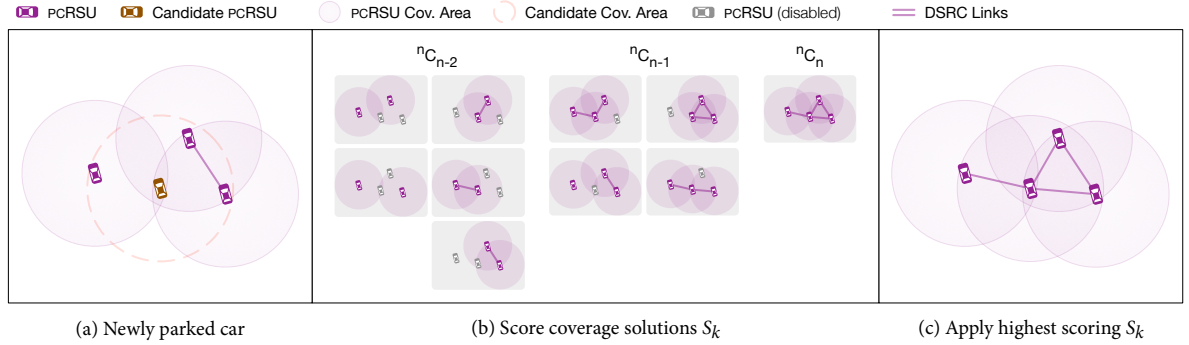


Figure 6.2: Enumerating and scoring coverage solutions. (a) A newly parked car learns its coverage map and queries its neighbor parked car  $\text{RSUs}$  for their maps. (b) Coverage solutions are enumerated and scored according to the various criteria. (c) The best coverage solution is communicated to the neighborhood, and becomes active.

### 6.2.2 Ranking Coverage Solutions

A self-organizing approach for parked cars has a number of core goals: the network of cars should aim to provide widespread coverage to the urban area in all of its locations, whenever possible, and to supply that coverage with strong signal, so that moving nodes can connect to the  $\text{pcRSU}$  network reliably and with high data rates.

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It must also aim to minimize the number of parked cars that take on RSU roles, and the time those vehicles spend active as pcRSUs, drawing power from their respective batteries.

Because the network is intended to be self-organized, there is an implicit assumption that a central controller is not available, and so decisions must be taken by the parked vehicles themselves, communicating only between them as needed. Poor decisions may lead to either (a) more parked cars being assigned RSU roles than necessary, creating a more crowded network and wasting battery energy, or (b) a pcRSU network that is suboptimal in signal strength, coverage area, or both.

To score a coverage solution, we resort to dimensionless analysis: a Weighted Product Model (WPM) [75], where the utility of each solution is determined by multiplying a series of attributes, each of which is raised to the power of a coefficient that represents its weight to the solution's score. This approach eliminates any units of measure, which is ideal to our multi-dimensional decision-making problem. The score of a coverage solution  $\mathcal{S}_k$  is, then, a product of attributes  $a_{j,k}$ , each weighted by a coefficient  $w_j$ :

$$\text{score}(\mathcal{S}_k) = \prod_{j=1}^n (a_{j,k})^{w_j} . \quad (6.1)$$

Our scoring function integrates the following four attributes:

- **Signal Strength** ( $a_{\text{sig}}, w_{\text{sig}}$ ): An average of the best signal strength available at each cell. It is the main attribute that pushes towards a city-wide network with strong coverage.
- **Coverage Saturation** ( $a_{\text{sat}}, w_{\text{sat}}$ ): The counterweight to signal strength, coverage saturation represents the number of RSUs that provide coverage to a cell. Higher average signal strength in the city demands a larger number of RSUs and, therefore, higher coverage saturation.
- **Coverage Area** ( $a_{\text{cov}}, w_{\text{cov}}$ ): The span of the coverage being provided by the RSU network. A strong signal strength does not imply widespread coverage, as it only considers cells where coverage is provided. This attribute can favor solutions with wider coverage.
- **Energy Usage** ( $a_{\text{bat}}, w_{\text{bat}}$ ): A measure of how much energy active pcRSUs in a coverage solution have expended, and how close they are to a maximum

threshold. This attribute pushes towards coverage solutions that remove aging pCRSUs from the network, keeping the battery utilization of active parked cars under control.

Each of these attributes is calculated on the expected outcome of a coverage solution, i.e., on the RSU network that would theoretically result if the coverage solution were applied, assigning and revoking RSU roles.

### 6.2.3 Constraining the Search Space

For a decision maker to score all coverage solutions that may be possible in its neighborhood, it needs to search a space of  $2^N$  possible combinations, with  $N$  being the number of neighbors plus the decision maker itself. For denser networks of pCRSUs, the number of coverage solutions in the search space can become too unwieldy and computationally expensive.

We adopt a more restrained approach, by restricting the search space to coverage solutions that do not revoke more than two RSU roles in the decision maker's neighborhood. Because the self-organized pCRSU network is grown incrementally as each new car parks, pCRSUs seen by a decision maker are the result of earlier, equally-optimized decisions, so coverage solutions that revoke higher numbers of roles are unlikely to lead to high decision scores, and it is therefore safe to exclude them from the search space.

Under these constraints, valid coverage solutions will belong to one of three possible categories. Examples of this selection can be seen in figure 6.2.

1. **No entities are disabled:** the candidate parked car becomes a pCRSU, and all neighboring pCRSUs remain active. A single such solution exists ( ${}^nC_n = 1$ ), which we denote as  $S_o$ . It increases the number of RSUs in the city by one.
2. **One entity is disabled:** either the newly parked car or a neighboring pCRSU. A total of  ${}^nC_{n-1}$  such solutions exist, and they do not change the number of RSUs in the city. The solution that only disables the newly parked car is a 'no-action' solution, leaving the network unchanged. We denote this specific case as  $S_{NA}$ .

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3. **Two entities are disabled:** the parked car takes on an RSU role and replaces two existing pCRSUs; or, both the parked car and a neighbor pCRSU are disabled. A total of  $n C_{n-2}$  such solutions exist, and they decrease the number of RSUs in the city by one.

With this search space restriction we reduce the time complexity of evaluating coverage solutions from  $\mathcal{O}(2^n)$  (exponential time) to  $\mathcal{O}(n^2)$  (quadratic time), a significant improvement. As an example, a decision maker with 8 neighbors will now need to evaluate only 37 solutions of the 256 that were possible.

### 6.2.4 Attribute Models

We now show how to quantify each of the four attributes that are part of the scoring function. Our aim here has been to keep these models as straightforward as possible, so that our subsequent analysis can show, with clarity, what each attribute contributes towards the resulting network of parked cars. An algorithm to calculate all attributes and produce a final decision score is shown afterwards, in section 6.2.5.

#### Signal Strength

Our signal strength attribute is the average signal strength that is expected of a given coverage solution. From the received coverage maps and the vehicle's coverage map, the signal strength of each cell in the resulting solution is taken and averaged.

In this work we use a 1-5 classification that corresponds linearly to a Received Signal Strength Indicator (RSSI). Because the decision algorithm is dimensionless, RSSI may also be used directly. Other metrics such as signal power (e.g., in dBm) or network bandwidth (e.g., in Mbit/s), should be equally practicable, but are not evaluated here. For accuracy, only the cells that the decision maker can cover should be considered, since the vehicle acting as decision maker does not have a complete view of the network beyond these cells.

#### Coverage Saturation

The coverage saturation attribute reflects the overlap in coverage between active roadside units. For a given cell in a coverage solution, its saturation value equals

the number of RSUs that can cover the cell (i.e., the number of RSUs that a vehicle located on the cell will see). This metric reflects the number of RSUs in the area, and also their arrangement: a poor RSU role assignment where  $\text{pcRSUs}$  are stacked too close sees more cells with higher saturation (more overlap between the  $\text{pcRSUs}$ ' coverages), while a more efficient distribution gives a more widespread coverage and more cells with lower saturation.

Saturation is also a measure of redundancy in the RSU network, which may be desirable from an availability standpoint: when cells are covered by more than a single RSU (saturation greater than 2), if a car with the RSU role is removed from the network, continued access to the network can be ensured by other RSUs.

As with the signal strength attribute, our saturation attribute is the average of the coverage saturation seen at each cell of a coverage solution. Average saturation can range from 1 to  $\infty$ , but in practice, an efficient algorithm will keep mean saturation in a range of 1.44 to  $\sim 5$  (see sections 6.3.1 and 6.3.4).

### Coverage Area

The signal strength and coverage saturation attributes, on their own, do not ensure a widespread coverage by the network of parked cars, which is also a desired trait for this network. Consider that, once a base network is established, new coverage will be available primarily at the fringes of the covered area, where the signal is weaker, therefore pushing average signal strength down and penalizing coverage solutions that expand the network's reach. To make sure that local decisions push towards widespread coverage, we include an attribute that quantifies the area of service provided by each coverage solution.

To compute this attribute, the algorithm begins by counting the number of covered cells in the  $\mathcal{S}_0$  coverage solution, which we defined earlier as the solution that disables no  $\text{pcRSUs}$  and, therefore, has the widest possible coverage area (since all other coverage solutions involve disabling at least one entity). The coverage attribute  $a_{\text{cov}}$  is then defined as the ratio between a solution's number of covered cells and the

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widest possible coverage in that decision step (belonging to  $\mathcal{S}_0$ ):

$$\begin{aligned} \text{cvg}(\mathcal{S}_n) &:= \text{'number of cells with service in } \mathcal{S}_n \text{'}, \\ a_{\text{cov}}(\mathcal{S}_n) &= \frac{\text{cvg}(\mathcal{S}_n)}{\text{cvg}(\mathcal{S}_0)}. \end{aligned} \quad (6.2)$$

Unlike  $a_{\text{sig}}$  and  $a_{\text{sat}}$ , the coverage area attribute must include all cells covered by the decision maker and its neighboring RSUs. This ensures that new coverage at the edges of the existing network is correctly scored.

### Battery Usage

To compute the battery usage attribute  $a_{\text{bat}}$ , the car acting as the decision maker must first query its neighbor pCRSUs for an indicator of their energy expenditure. This request can be sent together with the request for coverage maps that the decision process requires. Vehicles can have different battery capacities, which are in turn affected by the age of the battery, so this indicator is best calculated individually by each vehicle, and not by the decision maker.

In this work we use a straightforward model where each vehicle has predefined standard ( $\tau_m$ ) and maximum ( $\tau_M$ ) times of activity. The indicator decreases linearly once  $\tau_m$  is exceeded, and the parked car relinquishes its RSU role forcefully at  $\tau_M$ :

$$\begin{aligned} \tau_{n,i} &:= \text{'active time of entity } \xi_{n,i} \text{'}, \\ \text{bat}(\xi_{n,i}) &= \begin{cases} 1, & \tau_{n,i} < \tau_m; \\ 1 - \frac{\tau_{n,i} - \tau_m}{\tau_M - \tau_m}, & \text{otherwise.} \end{cases} \end{aligned} \quad (6.3)$$

This design keeps battery concerns invisible to the decision process, at first, and then allows for RSU roles to be reassigned by decision makers before a hard limit on a vehicle's battery resources is reached. The resulting battery attribute of a coverage solution is the averaging of all the neighboring roadside units' battery indicators:

$$\begin{aligned} \xi_n &:= \text{'set of entities in solution } \mathcal{S}_n \text{'}, \\ |\xi_n| &:= \text{cardinality of } \xi_n, \\ \xi_{n,i} &:= \text{'active entity } i \text{ in solution } \mathcal{S}_n \text{'}, \\ a_{\text{bat}}(\mathcal{S}_n) &= \frac{\sum_{i \in \xi_n} \text{bat}(\xi_{n,i})}{|\xi_n|}. \end{aligned} \quad (6.4)$$

Coverage solutions that are able to revoke longer-standing RSU roles without affecting the network (e.g., by handing over an older RSU role to a new vehicle in a similar location) will see higher decision scores. We analyze this attribute in detail in section 6.3.3.

### 6.2.5 Scoring Algorithms

Pseudocode to score a coverage solution via the Weighted Product Model shown in section 6.2.2 is given here, with algorithms 3 and 4. The first, *CountCoveredCells*, counts the number of cells covered by a given coverage solution or coverage map. It is used to measure the size of a coverage solution ( $\text{cov}_{\mathcal{S}_k}$ ), the size of the best possible coverage in a decision step (in  $\mathcal{S}_o$ ,  $\text{cov}_{\mathcal{S}_o}$ , used in  $a_{\text{cov}}$ ), and to average mean signal strength and mean coverage saturation values. The second, *ScoreCoverageSolution*, computes the attributes  $a_{j,k}$  and weighs them according to their respective weights  $w_j$ , producing the final scoring metric, score ( $\mathcal{S}_k$ ). These algorithms make use of the decision maker's coverage map ( $\text{scm}_o$ ), and the coverage maps from its 1-hop and 2-hop neighborhood ( $\mathcal{N}_1, \mathcal{N}_2$ ). New notation is summarized in table 6.1, supplementing the notation provided earlier in table 4.1 (on page 67).

TABLE 6.1  
ALGORITHM NOTATION SUPPLEMENT

Definition	Notation
2-hop neighbor SCMs	$\mathcal{N}_2 = \{\text{scm}_1, \text{scm}_2, \dots\}$
Coverage solution	$\mathcal{S}_k$
Number of covered cells in $\mathcal{S}_k$	$\text{cov}_{\mathcal{S}_k}$
pCRSU SCMs in $\mathcal{S}_k$	$[\text{scm}_{\mathcal{S}_k}] = \{\text{scm}_1^k, \text{scm}_2^k, \dots\}$
pCRSU battery indicators in $\mathcal{S}_k$	$[\text{bat}_{\mathcal{S}_k}] = (\text{bat}_n^k)$

## 6.3 Evaluation of Self-Organized Networks of Parked Cars

We now analyze the performance of the decision process shown in section 6.2. To do so, we run simulations on a 1 km<sup>2</sup> area in the city of Porto, on a custom-designed platform that simulates realistic vehicle mobility [55], and features real obstruction

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### Algorithm 3: CountCoveredCells

---

**Data:**  $[SCM_{S_k}], \mathcal{N}_2$   
**Result:**  $cov_{S_k}$ : the number of covered cells in  $S_k$

```

1  $\triangleright lm_{xy}$  (in an empty LM) are initialized to 0
2  $cov_{S_0} \leftarrow 0$ 
3 foreach  $SCM_n \in \{SCM_{S_k}, \mathcal{N}_2\}$  do
4   foreach  $scm_n[xy] \in SCM_n$  do
5     if  $scm_n[xy] > 0$  then  $lm_{xy} \leftarrow 1$ 
6   end
7 end
8 foreach  $lm_{xy} \in LM$  do
9   if  $lm_{xy} == 1$  then  $cov_{S_k} = cov_{S_k} + 1$ 
10 end
```

---

masks [57], road topologies [56], and a communication model that follows empirical signal measurements taken in Porto [32]. The custom platform and all of its associated data have been made available in [76], as part of this research.

We begin this study by evaluating separate attributes of the decision process in controlled scenarios, to see how each attribute contributes to the resulting pCRSU network. Then, we create randomized pCRSU networks and determine best and worst bounds for the self-organized processes, and see how our decision algorithms fare against these bounds. We then look into the decisions' sensitivity to the number of cars on the road and the OBU radio range, their behavior under realistic parking trends, and conclude with a comparison between self-organizing approaches. A summary of the simulations' parameters is shown in table 6.2.

### 6.3.1 Balancing Coverage Saturation

Signal strength and coverage saturation are the two core attributes of our decision process, as they balance one another: stronger mean signal can be reached by assigning new RSU roles in underserved areas, which in turn increases the coverage saturation in the network. We begin our study by looking at a decision process with the  $a_{sig}$  and  $a_{sat}$  attributes alone. We ran sets of 2-hour simulations where the  $1 \text{ km}^2$



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**Algorithm 4:** ScoreCoverageSolution

---

**Data:**  $\text{SCM}_0, [\text{SCM}_{\mathcal{S}_k}], [\text{BAT}_{\mathcal{S}_k}], \mathcal{N}_2, \text{COV}_{\mathcal{S}_0}, w_{\text{sig}}, w_{\text{sat}}, w_{\text{cov}}, w_{\text{bat}}$   
**Result:**  $\text{score}(\mathcal{S}_k)$

- 1  $\triangleright \text{lmc}_{xy}$  (in an LMC) and  $\text{lms}_{xy}$  (in an LMS) are initialized to 0
- 2  $a_{\text{sig}} \leftarrow a_{\text{sat}} \leftarrow a_{\text{cov}} \leftarrow a_{\text{bat}} \leftarrow 0$
- 3 *// create signal and saturation maps*
- 4 **foreach**  $\text{SCM}_n \{ \text{SCM}_{\mathcal{S}_k}, \mathcal{N}_2 \}$  **do**
- 5     **foreach**  $\text{scm}_{n[xy]} \in \text{SCM}_n$  **do**
- 6         **if**  $\text{scm}_{n[xy]} > \text{lmc}_{xy}$  **then**  $\text{lmc}_{xy} \leftarrow \text{scm}_{n[xy]}$
- 7         **if**  $\text{scm}_{n[xy]} > 0$  **then**  $\text{lms}_{xy} \leftarrow \text{lms}_{xy} + 1$
- 8     **end**
- 9 **end**
- 10 *// average signal strength to get  $a_{\text{sig}}$*
- 11 **foreach**  $\text{lmc}_{xy} \in \text{LMC}$  **do**
- 12     **if**  $\text{lmc}_{xy} > 0$  **and**  $\text{scm}_{xy} \in \text{SCM}_0 > 0$  **then**  $a_{\text{sig}} \leftarrow a_{\text{sig}} + \text{lmc}_{xy}$
- 13 **end**
- 14  $a_{\text{sig}} \leftarrow a_{\text{sig}} / \text{COV}_{\text{SCM}_0}$
- 15 *// average coverage saturation to get  $a_{\text{sat}}$*
- 16 **foreach**  $\text{lms}_{xy} \in \text{LMS}$  **do**
- 17     **if**  $\text{lms}_{xy} > 0$  **and**  $\text{scm}_{xy} \in \text{SCM}_0 > 0$  **then**  $a_{\text{sat}} \leftarrow a_{\text{sat}} + \text{lms}_{xy}$
- 18 **end**
- 19  $a_{\text{sat}} \leftarrow a_{\text{sat}} / \text{COV}_{\text{SCM}_0}$
- 20 *// compute  $a_{\text{cov}}$*
- 21  $a_{\text{cov}} \leftarrow \text{COV}_{\mathcal{S}_k} / \text{COV}_{\mathcal{S}_0}$
- 22 *// compute  $a_{\text{bat}}$*
- 23 **foreach**  $\text{bat}_n^k \in \text{BAT}_{\mathcal{S}_k}$  **do**
- 24      $a_{\text{bat}} \leftarrow a_{\text{bat}} + \text{bat}_n^k$
- 25 **end**
- 26  $a_{\text{bat}} \leftarrow a_{\text{bat}} / |\mathcal{S}_k|$
- 27 *// produce a decision score*
- 28  $\text{score}(\mathcal{S}_k) \leftarrow a_{\text{sig}}^{w_{\text{sig}}} \cdot a_{\text{sat}}^{w_{\text{sat}}} \cdot a_{\text{cov}}^{w_{\text{cov}}} \cdot a_{\text{bat}}^{w_{\text{bat}}}$

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TABLE 6.2  
SIMULATION PARAMETERS

GENERAL PARAMETERS			
Urban area size	1 km <sup>2</sup>	Cell division	1'' (WGS84)
Vehicle density	55 veh/km <sup>2</sup>	Cell size	~23 m × 31 m
Max. radio range	~155 m	Total cells	1400 (1 km <sup>2</sup> )
Simulation time	2 h	Road cells	650 (0.47 km <sup>2</sup> )
SIMULATION SPECIFIC			
6.3.1 Saturation	$w_{\text{sat}} = 0.05 \dots 0.40$		
6.3.2 Coverage	$w_{\text{cov}} = 0.00 \dots 1.00$		
6.3.3 Battery	$w_{\text{bat}} = 0.00 \dots 1.50$		
6.3.5 Density	vehicles = 20 .. 55		
6.3.6 Radio Range	$\text{range}_{\text{coeff.}} = 1.00x \dots 2.00x$		

urban area saw an average of 55 moving vehicles in circulation, entering the city at a rate of 0.5 veh/s. The weight of the signal strength,  $w_{\text{sig}}$ , remained constant at 1.0, while the weight of the saturation attribute,  $w_{\text{sat}}$ , was adjusted.

The evolution of the number of active pCRSUs and the percentage of the city covered by those pCRSUs is plotted in figure 6.3, with samples taken in 1-second intervals. Beginning with a network devoid of RSUs, the transient state of the network lasted for approximately 1060 s (~17 min) from the moment the first vehicle parked until the city's coverage area stabilized. Both figures show that the network of parked cars enters a steady state, and these decision mechanisms keep the network stable in terms of pCRSUs and coverage. The same behavior was seen in the mean signal strength and mean coverage saturation (not shown).

We present a steady state analysis of the network in table 6.3, as the weight  $w_{\text{sat}}$  that controls the coverage saturation attribute is increased. Both attributes behave as expected: higher weights on  $w_{\text{sat}}$  push towards fewer active pCRSUs and, consequently, a lower mean signal strength (as the signal strength attribute,  $a_{\text{sig}}$ , is de-prioritized in favor of  $a_{\text{sat}}$ ). The metrics' standard deviations become tighter depending on which attribute is leading the decision process, which is desirable.

We continued to push  $w_{\text{sat}}$  beyond 0.4, but no meaningful changes were observed in the network. The best (lowest) coverage saturation that was observed was 1.4 RSUs

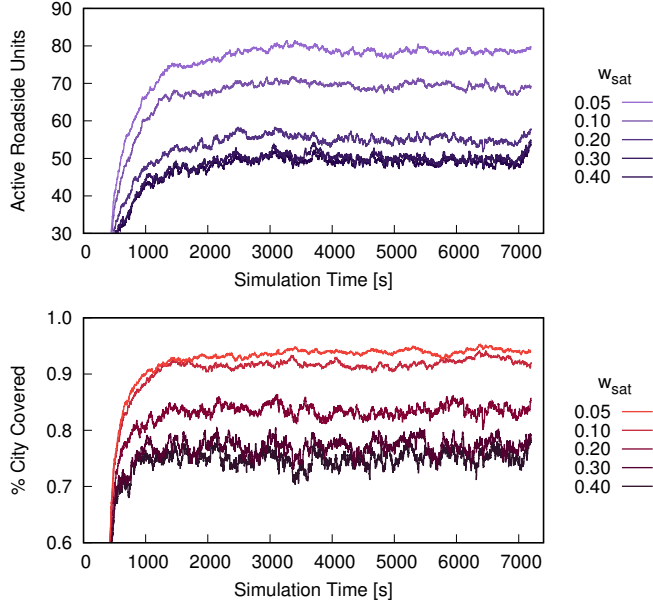


Figure 6.3: Parked cars with active RSU roles (top) and percentage of the urban area where parked car RSU service is made available (bottom), through the course of 2-hour simulations, as the weight controlling the coverage saturation attribute is varied. Data sampled in 1-second intervals.

per cell. This self-organized process is unable to push for lower saturation levels (ideally, towards the minimum of 1.0, a single RSU per cell), for the understandable reason that it requires communication between  $p_c$ RSUs in order to function. For a pair of  $p_c$ RSUs to communicate with one another, their coverages must necessarily overlap — therefore, coverage saturation in that overlap must exceed 1.0.

Increasing  $w_{sat}$  pushes the saturation of the network down, decreasing the number of  $p_c$ RSUs while also increasing efficiency in terms of urban area covered per  $p_c$ RSU. The 1 km<sup>2</sup> urban area in Porto where we run our simulations has 650 usable cells (i.e., where vehicles can move through), which corresponds to a 468 000 m<sup>2</sup> (0.47 km<sup>2</sup>) area that the parked cars can provide coverage to. At the lowest  $w_{sat}$ , the average area covered per  $p_c$ RSU was 5600 m<sup>2</sup>, while at the highest  $w_{sat}$ , each  $p_c$ RSU was able to cover 7200 m<sup>2</sup>, a 28 % increase. We observed a strong inverse correlation between coverage saturation and urban area covered per  $p_c$ RSU (at a linear correlation coefficient of  $-0.995$ ).

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TABLE 6.3  
NETWORK STEADY STATE VARYING A SATURATION ATTRIBUTE

$w_{\text{sat}}$	Signal Distribution				City Cov.	Signal Str.	Cov. Sat.	Active RSUs
	2	3	4	5				
0.05					94 %	4.51 $\pm 0.86$	2.62 $\pm 1.11$	79
0.10					92 %	4.38 $\pm 0.93$	2.21 $\pm 0.95$	69
0.20					83 %	4.05 $\pm 1.07$	1.64 $\pm 0.72$	55
0.30					77 %	3.90 $\pm 1.12$	1.48 $\pm 0.65$	50
0.40					75 %	3.86 $\pm 1.13$	1.45 $\pm 0.63$	49

$w_{\text{sig}} = 1.0$

### 6.3.2 Expanding Network Coverage

The previous analysis showed that restricting the number of  $\text{pcRSUs}$  in the city causes the undesired side effect of reducing the citywide coverage that the  $\text{pcRSU}$  network is able to provide. While this is expected (coverage and RSU count are inherently linked), a scoring algorithm must be able to optimize the network towards providing a more widespread coverage, as well. We now see how the inclusion of a coverage attribute into the decision process helps achieve this goal.

We repeated the 2-hour simulation sets, fixing  $w_{\text{sat}} = 0.2$  to serve as a baseline from the previous analysis, while increasing the weight  $w_{\text{cov}}$  of the coverage attribute. Figure 6.4 shows how the percentage of the city that is covered evolves throughout the simulation, for the different attribute weights. The data show that the coverage attribute pushes the  $\text{pcRSU}$  network's total coverage to high levels, and improves the stability of that coverage. The duration of the transient state does not appear to change through different attribute sets, as well.

We provide an analysis of the network's steady state in table 6.4. The data show that higher  $w_{\text{cov}}$  values lead to a more widespread coverage of the network with fewer  $\text{pcRSUs}$  than in our initial analysis. To push towards better coverage, the decision process does recruit additional  $\text{pcRSUs}$ , increasing both signal strength and coverage

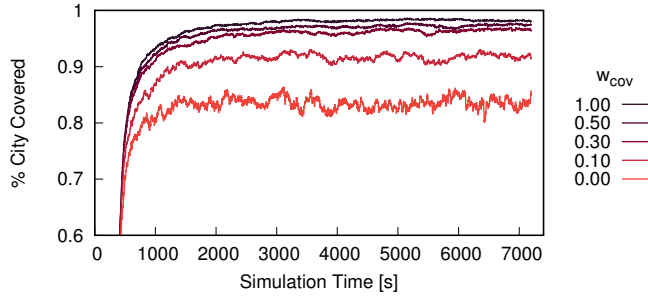


Figure 6.4: Percentage of the urban area covered by the self-organized RSU network, through the course of 2-hour simulations, as the weight controlling the coverage attribute is varied. Data sampled in 1-second intervals.

saturation as a result. However, it does so at a more optimal distribution of pCRSUs (more area covered per pCRSU) than before. To illustrate this fact, table 6.5 compares two parameter sets that recruit similar numbers of pCRSUs and achieve similar mean signal strength in the city, the first set with  $a_{\text{sig}}$  and  $a_{\text{sat}}$  attributes only, and the second with the  $a_{\text{cov}}$  attribute included in the scoring algorithm. This comparison shows that the inclusion of  $a_{\text{cov}}$  increased citywide coverage by 5 % and reduced coverage saturation by 8 %, at no increase to the number of active pCRSUs or cost to the mean signal strength that is being provided.

TABLE 6.4  
NETWORK STEADY STATE VARYING A COVERAGE ATTRIBUTE

$w_{\text{cov}}$	Signal Distribution	City Cov.	Signal Str.	Cov. Sat.	Active RSUs
	2 3 4 5				
0.00		83 %	4.05 $\pm 1.07$	1.64 $\pm 0.73$	55
0.10		92 %	4.18 $\pm 1.00$	1.77 $\pm 0.77$	60
0.30		96 %	4.30 $\pm 0.94$	1.94 $\pm 0.82$	65
0.50		97 %	4.36 $\pm 0.90$	2.03 $\pm 0.84$	68
1.00		98 %	4.43 $\pm 0.87$	2.19 $\pm 0.85$	72

$$w_{\text{sig}} = 1.0, w_{\text{sat}} = 0.2$$

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TABLE 6.5  
PARAMETER SET COMPARISON IN STEADY STATE

$w_{\text{sat}}$ $w_{\text{cov}}$	Signal Distribution	City Cov.	Signal Str.	Cov Sat.	Active RSUs
	<div> <div>2</div> <div>3</div> <div>4</div> <div>5</div> </div>				
0.10 0.00		92 %	4.38 $\pm 0.93$	2.21 $\pm 0.95$	69
0.20 0.50		97 %	4.36 $\pm 0.90$	2.03 $\pm 0.84$	68

$w_{\text{sig}} = 1.0$

A look into the topologies of the parked car networks reveals that this approach is able to create well-connected mesh networks, with most pCRSUs forming a stable link with two or more RSU neighbors. Link quality between pCRSUs ranges between 4.5 Mbit/s to 6 Mbit/s ( $\sim 42\%$  of links) and 12 Mbit/s to 27 Mbit/s ( $\sim 39\%$  of links), which is suitable for low-bandwidth applications (e.g., monitoring vehicular traffic, collecting data from urban sensors, or tracking the location of public transportation). This reflects the optimization goals of the proposed algorithms, which are targeted towards wide coverage at a reduced number of pCRSUs. For bandwidth-intensive content delivery applications, the inclusion of a link quality attribute in the decision algorithm is a straightforward solution to push the resulting network towards a tighter mesh, enabling higher-throughput links.

With this analysis, we showed that a coverage attribute improves the self-organization of the parked cars, ensuring not only a higher citywide coverage but also a better distribution of RSU roles, with lower coverage saturation and higher area covered per pCRSU.

### 6.3.3 Managing Battery Utilization

The fourth and final attribute of our decision scoring algorithm concerns the time a parked car spends with its DSRC electronics activated, performing RSU roles, and drawing power from the car's battery. A vehicle's battery, when its engine is off, is a finite resource that must be managed correctly. Not only must the car's energy budget be shared with electrical systems that are active when the car parks (e.g., alarm systems, and keyless entry systems), but failing to do so has the serious

consequence of leaving the driver stranded, should the battery be too drained for engine re-ignition.

By including the battery utilization of active pCRSUs in the scoring algorithm, we aim to drive the decision makers towards coverage solutions that replace aging pCRSUs with newly parked cars, while at the same time attempting to preserve the existing structure of the pCRSU network.





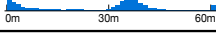
To study the efficacy of this attribute, we begin by setting a hard threshold of 1 hour on the maximum time a parked vehicle can hold RSU roles for. Active parked cars that exceed this threshold are forcefully removed from the pCRSU network. We then set the  $\tau$  parameters in equation (6.3) to begin penalizing pCRSUs once their active time exceeds 30 minutes ( $\tau_m = 1800$ ,  $\tau_M = 3600$ ). With this configuration, pCRSU battery life does not factor into the decision process until 30 minutes of activity have elapsed, allowing for decisions to focus exclusively on the quality of the network as long while the parked cars' activity times are within expected values. Empirical data provided in section 6.4.1 will show that an OBU operating for ~6.5 h consumes approximately 4.2 % of a typical car battery. We opt for a more conservative limit in this evaluation: 30 minutes to 1 hour with an active OBU would result in a battery usage of 0.32 % to 0.64 %.

The figures in table 6.6 show the distribution of the lifetime of RSU roles in the network during 8-hour simulations, together with the network's metrics after the transient state, as we increase the weight  $w_{\text{bat}}$  of the battery attribute. When  $a_{\text{bat}}$  is not in play ( $w_{\text{bat}} = 0.0$ ), we see most pCRSUs being disabled at our designated 1-hour threshold. A noticeable number of RSU roles are also revoked shortly after they are assigned, which can be attributed to the initial set of roles being rotated out as newly parked cars in more optimal locations become available. As  $w_{\text{bat}}$  is increased, the pCRSUs that were hitting the 1-hour threshold begin to be replaced instead by decisions from decision makers in the city, with higher weights leading to earlier role revocation, pushing the lifetime of pCRSUs closer to  $\tau_m$ .

The steady-state analysis of various city metrics in table 6.6 indicates that a well-designed attribute can rotate RSU roles efficiently, with a negligible impact to the existing self-organized pCRSU network. Mean signal strength, coverage saturation, coverage area, and number of active pCRSUs all deviated less than 3 % as  $w_{\text{bat}}$  was increased, relative to the baseline where the battery attribute was not included. This

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TABLE 6.6  
ROADSIDE UNIT LIFETIME ANALYSIS

$w_{\text{bat}}$	pcRSU Lifetime ■ density	City Cov.	Signal Str.	Cov. Sat.	RSU Count
0.00		95 %	4.24 $\pm 0.98$	2.09 $\pm 0.85$	68
0.30		96 %	4.29 $\pm 0.97$	2.13 $\pm 0.84$	70
0.50		96 %	4.28 $\pm 0.95$	2.12 $\pm 0.86$	70
1.00		95 %	4.27 $\pm 0.96$	2.10 $\pm 0.85$	69
1.50		95 %	4.26 $\pm 0.97$	2.10 $\pm 0.84$	69

Lifetime histograms span 3600 seconds.  $w_{\text{sig}} = 1.0$ ,  $w_{\text{sat}} = 0.2$ ,  $w_{\text{cov}} = 0.3$

important result shows the efficacy of our proposed algorithm in the management of a parked car's battery utilization as it takes on RSU tasks.

Finally, we note that a small percentage of RSU roles still exceed the 1-hour threshold and have to be forcefully revoked, even at the highest  $w_{\text{bat}}$  weights we evaluated. We hypothesize that these are pcRSUs in critical locations where not enough new parking events occur for a decision maker to be able to find an adequate replacement. Increasing the time allotted for an RSU role to be replaced ( $\tau_M - \tau_m$ ) may mitigate this behavior.

### 6.3.4 Decision Performance

An essential measure of the quality of a self-organized network of parked cars is its ratio of signal strength to coverage saturation. For a certain mean signal quality that is achieved in a given area, there is an optimal and a sub-optimal number and placement of pcRSUs that may lead to it. We study this ratio in our simulation setup by filling the network with parked vehicles, and assigning RSU roles to those vehicles in a random manner. For each random attribution of roles, we then measure the resulting signal strength and coverage saturation in the network. The data in figure 6.5 show 500 000 random assignments, on top of which we overlay the citywide metrics collected from the simulations in the previous sections.



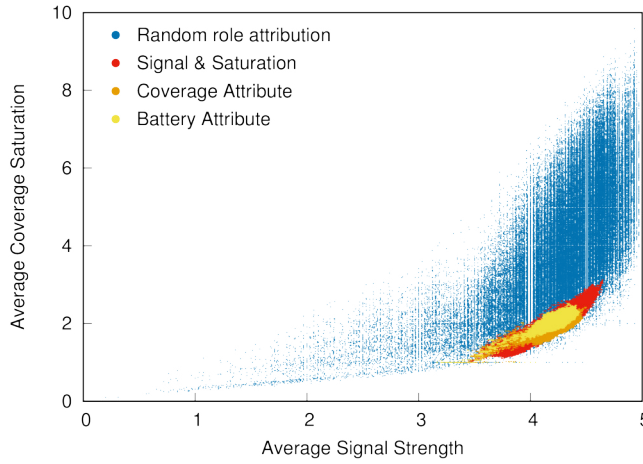


Figure 6.5: Signal strength and coverage saturation metrics sampled in 1-second intervals from the simulations in sections 6.3.1, 6.3.2 and 6.3.3.

Relatively clean upper and lower bounds can be observed from the sets of random attributions. These bounds are an important finding: for self-organized networks of cars, they reveal that the ratio between the number of recruited cars and the strength of the coverage being provided will be bounded. Here, the lower bound represents the most optimal placement of pCRSUs for each observation of signal strength, while the opposite is true for the upper bound. This gives us an important frame of reference to analyze the performance of any decision making process. The data show that an increasing effort is required to push the network to higher signal strengths. For example, improving mean signal from 2.0 to 4.0 is possible with, on average, one extra pCRSU, however the same effort is required to move the mean signal from 4.0 to 4.5, and more than double that effort will be needed to go from 4.5 to 4.9. This assumes an optimal assignment of RSU roles, which might not always be possible.

The overlaid data from the decision mechanisms demonstrate that these operate very close to the lower signal-to-saturation bound revealed by the random role assignment data, and quantified performance metrics against the bound can be seen in Figure 6.6. The scoring algorithm that included a coverage attribute, in section 6.3.2, operates closer to this lower bound than the initial 2-attribute algorithm, which matches our earlier observation that this attribute may lead to a more optimal

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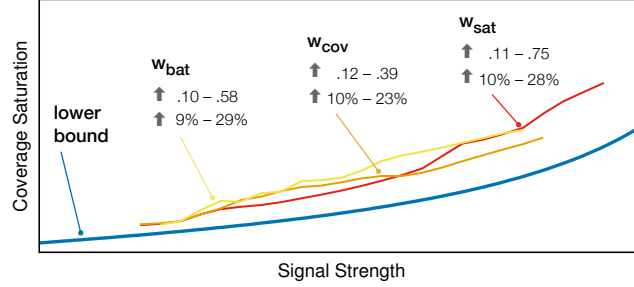


Figure 6.6: Coverage saturation averages for the data in figure 6.5, and corresponding increases over the optimal lower bound (higher is worse). For reference, the upper bound is 5.2 to 9.2 (495 % to 550 %) higher, which places the various configurations in the 95<sup>th</sup> percentile of possible RSU selections. The lower bound shown here is a curve-fit of the most optimal points in random role attribution.

distribution of RSU roles. The introduction of a  $\rho$ CRSU lifetime threshold and the inclusion of a battery attribute, in section 6.3.3, sees the data samples pushed away from this ideal lower bound to a small degree, which is an expected consequence from the forceful revocation of RSU roles from parked cars that have been active for some time. In all three cases, regardless, the decision algorithms place the resulting  $\rho$ CRSU network in a very optimal region.

These important results show that our decision mechanisms are operating near the best observed efficiency for a network comprised of parked cars, achieving various levels of signal strength at the smallest possible coverage saturation and, consequently, the lowest number of  $\rho$ CRSUs at their most optimal arrangement.

### 6.3.5 Sensitivity to Vehicle Density

The simulation studies presented so far saw an average number of 55 moving vehicles per  $\text{km}^2$  on the road, which matches a medium-low density scenario. We now analyze identical scenarios where we reduce the number of moving vehicles, to find out how the decision mechanisms respond to the lower vehicle density. This density affects primarily the time parked cars take to build their coverage maps and the frequency of parking events.

The evolution of the number of active  $\rho$ CRSUs, mean signal strength, mean coverage saturation, and total city coverage can be seen in figure 6.7. Four densities

of vehicles were considered: 55 veh/km<sup>2</sup>, 35 veh/km<sup>2</sup>, 25 veh/km<sup>2</sup> and 20 veh/km<sup>2</sup>, which range from medium- to low-density scenarios.

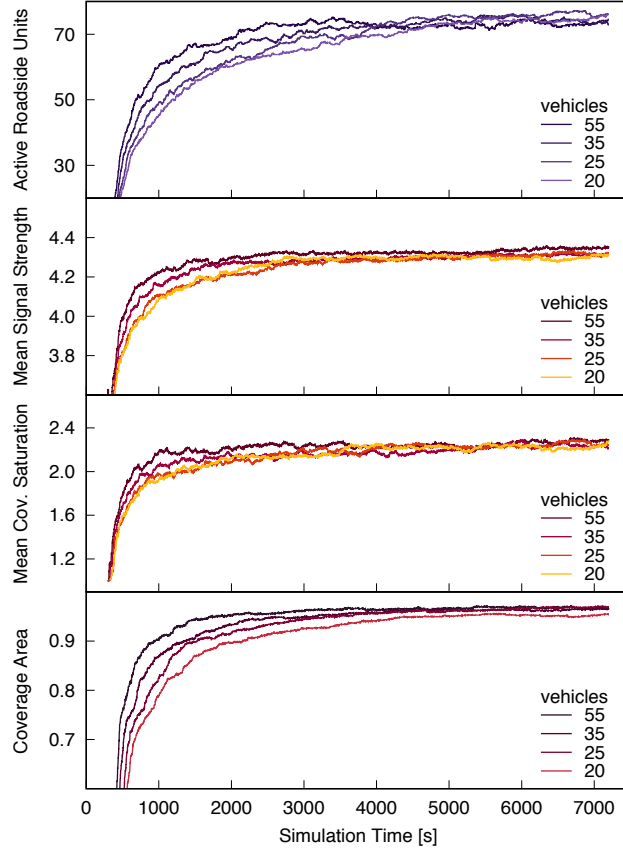


Figure 6.7: Evolution of various network metrics throughout 2-hour simulations, as the density of vehicles per km<sup>2</sup> is altered. Scoring algorithm weights set to  $w_{\text{sig}} = 1$ ,  $w_{\text{sat}} = 0.2$ ,  $w_{\text{cov}} = 0.3$ , and  $w_{\text{bat}} = 0$ . Data sampled in 1-second intervals.

The data in these figures show that only the duration of the network's transient state is affected by the decrease in the number of road vehicles, with all four metrics eventually converging to a similar steady state. This indicates that the decision mechanisms are robust and should operate equally well in the face of varying vehicle densities, as is expected from real life scenarios. A small 2 % decrease can be seen in the steady state citywide coverage, which could indicate that the lowest-density sce-

narios have insufficient new parking events for the algorithm to completely optimize the network.

### 6.3.6 Sensitivity to Wireless Radio Range

We now provide an analysis of the decision mechanisms' sensitivity to the radio range of the OBUs used in the vehicles. Figure 6.8 shows various network metrics in the network's steady state as a multiplier is applied to our propagation models, scaling the effective range of the vehicles' DSRC radios. The data indicate that the number of RSU roles assigned by the self-organizing mechanisms decreases nearly linearly with the corresponding increase in radio range: doubling the radio range halves the number of pCRSUs, from  $\sim 69$  to  $\sim 33$ . This is an interesting result due to the fact that the total area that a vehicle's radio can reach should increase quadratically with the radio range (area =  $\pi r^2$ ), assuming perfect conditions for propagation. In an urban environment, however, vehicles's signals are constrained by the road layout, in effect being tunneled by surrounding buildings. We hypothesize this to be the reason behind the near-linear relation that is observed.

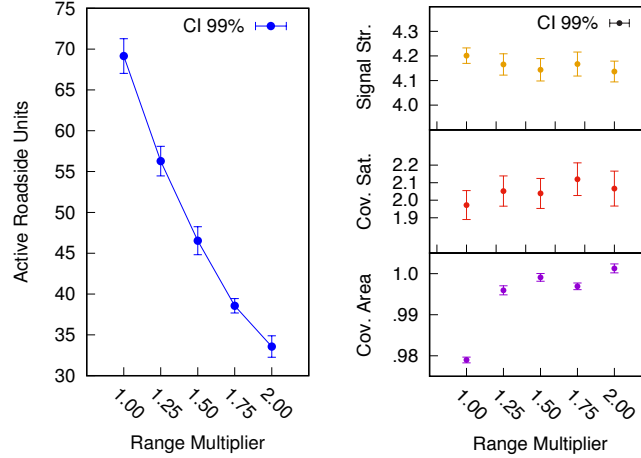


Figure 6.8: Steady state averages of various network metrics of 2-hour simulations, as a multiplier is applied to the radio range of vehicles and parked cars. Scoring algorithm weights set to  $w_{\text{sig}} = 1$ ,  $w_{\text{sat}} = 0.3$ ,  $w_{\text{cov}} = 0.5$ , and  $w_{\text{bat}} = 0$ . Confidence intervals stated in the 99 % level.

Besides the number of active pCRSUs, both signal strength and coverage saturation remain relatively constant, despite the change in radio range, indicating that the

algorithms are resilient to this network aspect. In terms of coverage area being provided, the range increase also grew this metric by 2 %, to a near-complete coverage level.

### 6.3.7 Realistic Parking Behavior

To see how the self-organizing mechanisms operate under realistic parking conditions, we integrated the realistic parking models presented in chapter 5, which include a distribution of vehicle arrivals (and subsequent parking) throughout the day, and a comprehensive hour-by-hour stochastic model of the time these same vehicles remain parked. The data from whole-day simulations performed with accurate parking models is presented in figure 6.9. Parking events at two densities (4000 and 2000 vehicles parked over 24 hours) are distributed throughout the day following the dual-Gamma stochastic model (see section 5.4.3 on page 92).

In realistic scenarios, decision mechanisms face two new issues. The first is a possible shortage of newly parked cars, which constrains the assignment of RSU roles to vehicles that may not always be at locations optimal for a *pcRSU* network. The second concerns the vehicles's parking durations: evidently, cars parking for only a short time make for poor *pcRSUs*, and this parking duration is not known beforehand; but a more pernicious effect occurs when a car parking for a short time makes the decision to disable a nearby car that is parked for a longer time. Without knowledge of the time each vehicle will spend parked, or a means to recruit previously-disabled *pcRSUs*, this side effect is difficult to mitigate.

Despite these issues, the data in figure 6.9 show that, under realistic parking conditions, a self-organized network of parked cars is able to provide and maintain widespread coverage of the urban area throughout the day, at adequate levels of coverage strength, while assigning roles to only a fraction of the vehicles that park throughout the day. Practical applications for parked cars may benefit from attempting to predict the parking duration for each vehicle, prioritizing those more likely to remain parked in RSU role assignment. As an example, the models in section 5.4.3 indicate that long-term parking occurs primarily in the early morning hours, so vehicles that park in these hours may be more suitable candidates for RSU roles.

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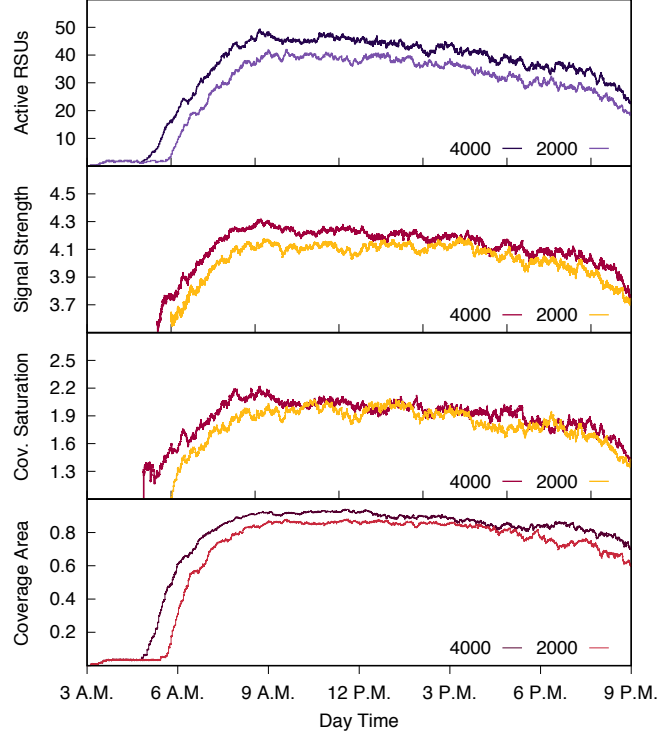




Figure 6.9: Evolution of various network metrics throughout whole-day simulations with realistic parking behavior. The first plot shows a simplified view of how parking events are distributed, with long-term and short-term parking behaviors split up. The remaining plots compare two densities of parking events: 4000 and 2000 vehicles parked (over 24 hours). Scoring algorithm weights set to  $w_{\text{sig}} = 1$ ,  $w_{\text{sat}} = 0.2$ ,  $w_{\text{cov}} = 0.3$ , and  $w_{\text{bat}} = 0$ .

### 6.3.8 Approach Comparison

We conclude our simulation work with a comparison between the self-organizing approaches presented in chapter 4 and this chapter. To recap, with the former approach newly parked cars make *individual decisions* on whether they should become `pcRSUs`. It is intended to be simple and minimally demanding on the network, requiring only 1-hop exchanges of neighbors' coverage maps. The latter approach, seen in this chapter, allows parking cars to act as local *decision makers*, reconfiguring their local neighborhood by reassigning RSU roles among neighbors in an effort to achieve the best possible network.

For this comparison, we identified two sets of parameters for the decision algorithms belonging to each approach that, when applied, resulted in two networks of parked cars that were able to provide similar levels ( $<1\%$  difference) of signal strength and coverage size. We then compared the remaining performance metrics to see which approach was most efficient. The steady state metrics of each of these networks can be seen in table 6.7, for sets of 2-hour simulations. The data show that the approach where cars act as *decision makers* is more efficient, assigning 13 fewer RSU roles in total, and in turn decreasing coverage saturation by 27 %. This

TABLE 6.7  
PERFORMANCE COMPARISON OF SELF-ORGANIZING APPROACHES

Approach	Signal Distribution				City	Signal	Cov.	Active
	2	3	4	5	Cov.	Str.	Sat.	RSUs
<i>individual decisions</i>					97 %	4.3 $\pm 1.0$	2.6 $\pm 1.0$	78
<i>decision makers</i>					96 %	4.3 $\pm 0.9$	1.9 $\pm 0.8$	65

$$\kappa = 1.0, \lambda = 1.0, \mu = 4, w_{\text{sig}} = 1.0, w_{\text{sat}} = 0.2, w_{\text{cov}} = 0.3$$

is expected, as it is the more powerful approach, and gathers maps from a wider (2-hop) neighborhood, gaining a better picture of the local RSU network.

We also compared the evolution of the number of active RSUs and coverage saturation, to see how each approach behaved over time. These metrics can be seen in figure 6.10. The data show that *individual decisions* cause monotonically increasing metrics, due to the fact that each parked car can only join the network or remain as-is. When cars act as *decision makers*, the metrics oscillate as RSUs are occasionally disabled if deemed beneficial by the decision algorithm. One can also see that the latter approach enters a steady state in a much shorter time, and is therefore the superior solution here as well.

## 6.4 Experimental Work

In this section we present the results of two empirical studies aimed at verifying base assumptions of self-organizing approaches for parked cars. With the first study,

## 6. IMPROVING PARKED CAR SELF-ORGANIZATION

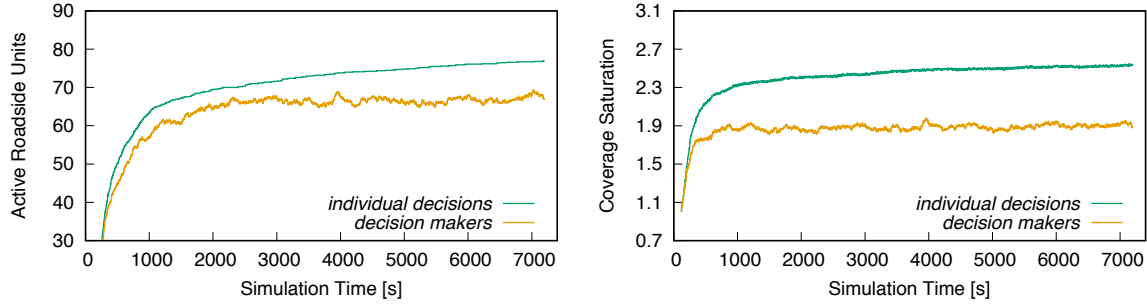


Figure 6.10: Parked cars with active RSU roles (left) and coverage saturation (right), through the course of 2-hour simulations, for both self-organizing approaches. Data sampled in 1-second intervals.

we analyze the power consumption of a DSRC On-Board Unit to determine what impact it may have on the battery of a parked vehicle. With the second study, we replicate the learning process a newly parked car goes through in order to determine its own coverage map, showing its viability.

### 6.4.1 Power Requirements of DSRC Equipment

The main requirement for a vehicle to work as a Roadside Unit is to be able to maintain power to the DSRC electronics. Ordinary passenger cars have two sources of energy: when the engine is running, an alternator generates electricity, powering the car's electronics and recharging its battery; when the engine is off, power is sourced from that same battery. DSRC electronics, when the car is parked and its engine is off, must be powered from the latter. The amount of energy that is drained should be controlled, as other applications (such as security systems and keyless entry systems) will also be draining the battery at the same time.

To understand the impact that DSRC hardware will have on the battery of a parked vehicle, we have performed a comprehensive study of the power consumption of the *NetRider*, an OBU/RSU prototype hardware unit developed by the company *Veniam* [77]. The *NetRider* devices consist of a Single-Board Computer with GPS and separate DSRC and WiFi radios. The units that were generously provided to us for this study are used at the core of the company's testbed deployments.

In a laboratory setting, we attached digital multimeters to a pair of *NetRiders* and measured the power draw of these equipments in the following activity states:



powering the base hardware; powering the unit's DSRC radio; powering the unit's WiFi radio; simulating a 100 % computational load on the processor; transmitting data on the DSRC interface at 100 % and 50 % duty cycles; and receiving data on the DSRC interface at 100 % and 50 % duty cycles. Power consumption measurements for each activity state were then taken for a duration of 30 seconds, at a rate of 10 measurements per second, and averaged. A complete set of activities and its respective power consumption can be seen in figure 6.11.

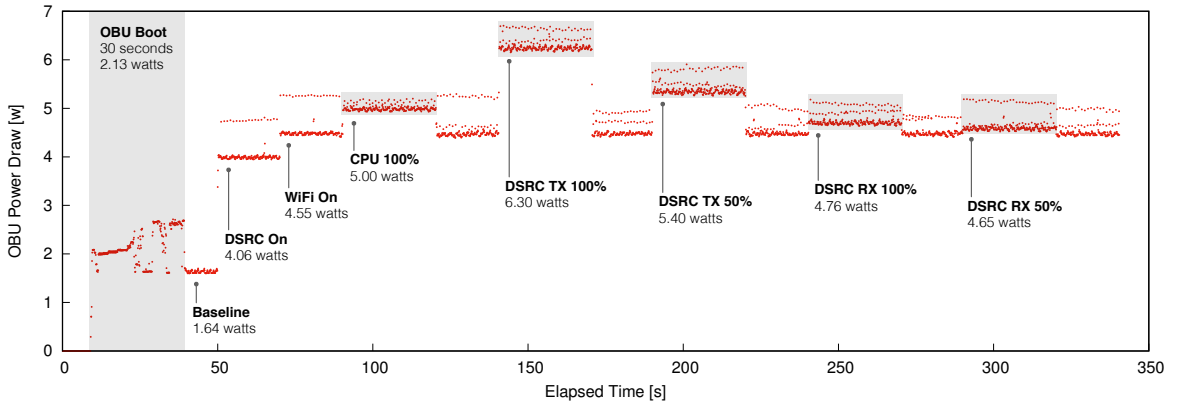


Figure 6.11: Instantaneous power demand by an on-board unit performing various tasks.

Table 6.8 reports the power that was required by each activity. From this data, we estimate the power consumption of a hypothetical RSU scenario where the DSRC channel is averaging 50 % utilization, the unit is transmitting and receiving similar amounts of data, and the mean CPU load nears 30 % (a number commonly seen in our testbeds), to be of approximately 4.62 W. We can now predict that, for the average 6.64 hours that a car spends parked every day [62], having an active DSRC unit will take a 4.2 % toll on a car's battery. This is calculated as follows: a standard 12-volt automotive battery on a passenger vehicle has a capacity of 60 Ah (ampere/hour), or 720 Wh (watt/hour). The energy consumed by an OBU over the ~ 6.64 hours the vehicle is parked is equal to  $E = P_{OBU} \times t_{parked} = 30.68 \text{ Wh}$ , and  $30.68/720 \approx 4.2 \%$ . Battery capacity degrades with age and usage, and car batteries reach End-Of-Life (EOL) when less than 50 % of the original capacity remains. At this EOL point, the battery toll would be of ~8.4 %, still less than one tenth of the total capacity.

We underline the fact that the hardware units we were able to obtain are proto-

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TABLE 6.8  
AVERAGE POWER DRAW OF MAJOR OBU SYSTEMS

OBU System	Power Draw
Base system	1.64 W
Powering DSRC radio	2.42 W
Powering WiFi radio	0.49 W
CPU under 100 % load	0.45 W
DSRC transmission at 100 % duty cycle	1.75 W
DSRC transmission at 50 % duty cycle	0.75 W
DSRC reception at 100 % duty cycle	0.21 W
DSRC reception at 50 % duty cycle	0.10 W

types meant for testbed deployments, and that production hardware is expected to draw under 3 W in operation, further decreasing battery use. Nevertheless, parked cars with RSU roles should limit their activity to safeguard excessive battery drain.

### 6.4.2 Inferring Coverage Maps from Received Beacons

A primary concern of any self-organizing approach that relies on a parked car's ability to determine its own coverage map so that informed decisions can be made, is the reliability of the process that creates the car's coverage map. Radio signals can vary greatly in an urban environment, due to the significant number of obstructions that cause the signal to fade. Wave reflections and corner diffraction also contribute to the received signal in an urban environment.

We performed an experimental study of the process of creating a coverage map by a parked vehicle. For this study, we parked a DSRC-enabled vehicle and instructed it to collect beacons being broadcast from neighboring vehicles. These beacons contain the GPS coordinates of the transmitting vehicles, and the parked car can determine the signal strength (RSSI) of each received beacon. We then drove other vehicles equipped with OBUs in the neighboring roads of the parked car.

This experiment was performed in the city of Aveiro, Portugal, in an urban area with a variety of small residences, low-rise apartments, and commercial buildings. Figure 6.12 shows an aerial view of the area in question.

From the beacon data points that were recorded by the parked car, the car then

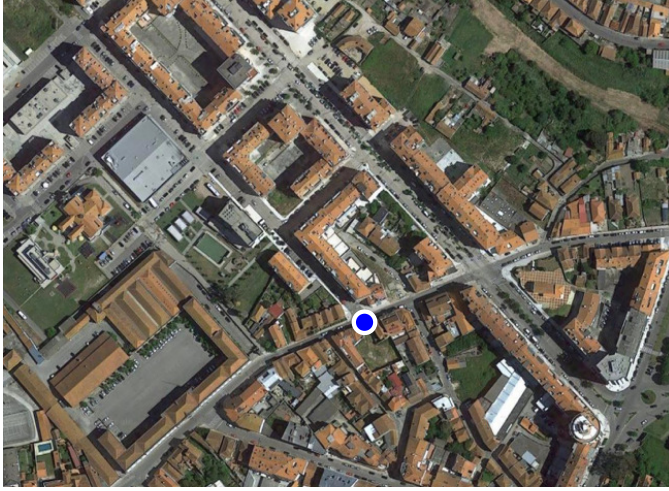


Figure 6.12: Aerial view of the urban area where data was collected. The blue centre dot shows where the observing car was parked.

grouped measurements by their geographic cell, and computed the average signal strength and standard deviation of the measurements belonging to each cell. The resulting coverage map and statistics are shown in figure 6.13, and complete RSSI histograms for each cell can be seen in figure 6.14, at the end of the chapter.

The data show that vehicle-to-vehicle signal strength in an urban vehicular network is well-behaved over short distances. This suggests that a self-organizing approach can depend on coverage maps that were learned by parked cars (by observing beacons), and that the signal strength values estimated for each cell will be representative of the strength of coverage that can be provided to that cell by the listening vehicle. On most cells, the spread of the signal strength around the mean is relatively small, particularly if one considers how dynamic the environment can be. Our OBUs report RSSI in a range of 1 to 50, and of the 75 cells from which beacons were received, 88 % of the cells showed a standard deviation under 5.0.

The nature of cell-based coverage maps does imply that a level of abstraction is applied to the city map and, consequently, there may be situations where a deep fade occurs within a cell, and the average received power from beacons fails to reflect the coverage quality on that cell. In these situations, a bimodal distribution can often be seen.

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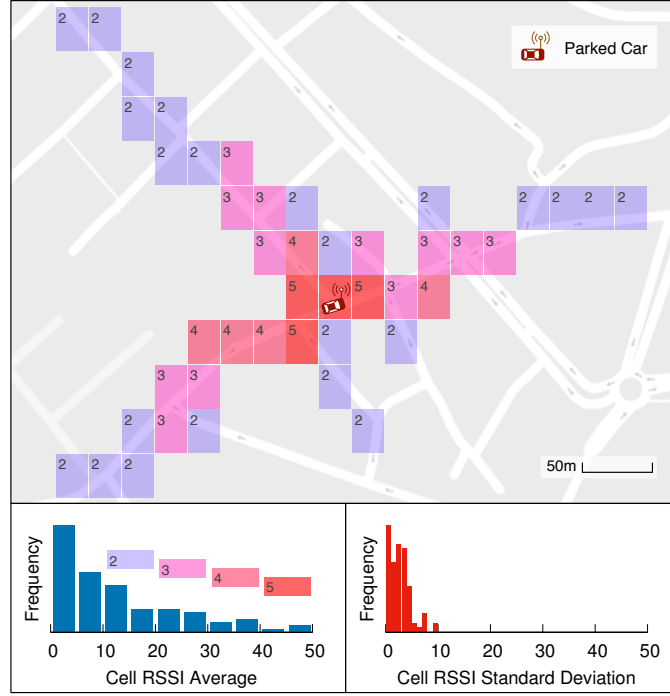


Figure 6.13: A real-life coverage map learned by a parked car equipped with DSRC radios, by listening to beacons transmitted from moving vehicles. Bottom-left: distribution of the average RSSI observed at each cell, and corresponding 0 to 5 signal strength classification. Bottom-right: distribution of RSSI variance at each cell.

### 6.5 Considerations on Vehicular Network Security

We now discuss some of the security considerations of our proposed self-organizing network approaches and suggest possible techniques to mitigate security issues. Vehicular networks, by themselves, inherit many of the problems that affect computer networks, wireless networks, highly mobile networks, and very dense and large-scale networks. The approaches presented in this work do not introduce new weaknesses to vehicular networks, which are already vulnerable to attacks of impersonation, bogus information, denial of service, or hardware tampering [78]. They may, however, exacerbate some of these problems within certain security models.

A rogue parked car bypassing the decision process may attempt to announce itself as an RSU, an attack of *impersonation*. It may then deliberately fail to trans-

mit important safety messages (*message suspension*), or, e.g., falsify an emergency warning to reroute traffic (*bogus information*). Rogue entities may also fake the type of messages that are used to revoke RSU roles, aiming to disable RSUs in a given area. One solution to both these issues is to collectively replay and verify decision processes before accepting their outcomes, by having the neighbors of a new parked car RSU and RSUs seeing their roles revoked repeat the decision algorithms themselves. At the cost of a higher network overhead, groups of vehicles can then defend against misbehaving nodes by identifying decision mismatches and banning the nodes from the network [79]. Alternatively, one may forego direct RSU revocation, inform neighboring RSUs of the new parked car RSU, and allow each active RSU to understand, by itself, whether it should remain in its role or not.

Rogue entities may attempt to win the decision process legitimately, and only then transmit bogus information — however, such problems are not limited to the self-organizing approach (moving vehicles with rogue OBUs can also falsify information), and thus require broader security models. Specific security solutions that depend on fixed RSUs being relatively tamper-proof are also not applicable to the self-organizing solution, since it moves the RSU roles to the vehicles where tamper-proofing is considerably more challenging [80]. Restricting the use of parked cars as message relays for existing fixed (and trusted) RSUs can still bring the benefits of wider and more robust city coverage, and overcome these issues.

## 6.6 Summary

A novel approach has been provided to enable parked cars to self-organize and form widespread vehicular support networks in the urban area, which can then be used to monitor vehicular traffic, public transportation, and available parking. Through newly introduced mechanisms and a multi-criteria decision process, the vehicular support network that is created can be continuously optimized through time, designed to target specific metrics of signal strength, coverage saturation, and coverage area, while rotating RSU roles between vehicles to manage battery utilization. An extensive simulation study, coupled with an experimental verification of key concepts, provides the first strong evaluation of a self-organizing approach for parked cars. It reveals, for the first time, how such a network forms and evolves, what quality of

## 6. IMPROVING PARKED CAR SELF-ORGANIZATION

coverage is possible and how it is distributed, what balance is achievable between recruited vehicles and network strength, and validates the proposed mechanisms against simulations that integrate realistic models of parking behavior. Also, the analysis shows a ~25 % improvement in the efficiency of RSU role assignment against the previous self-organizing approach, as well as increased stability of signal and coverage.

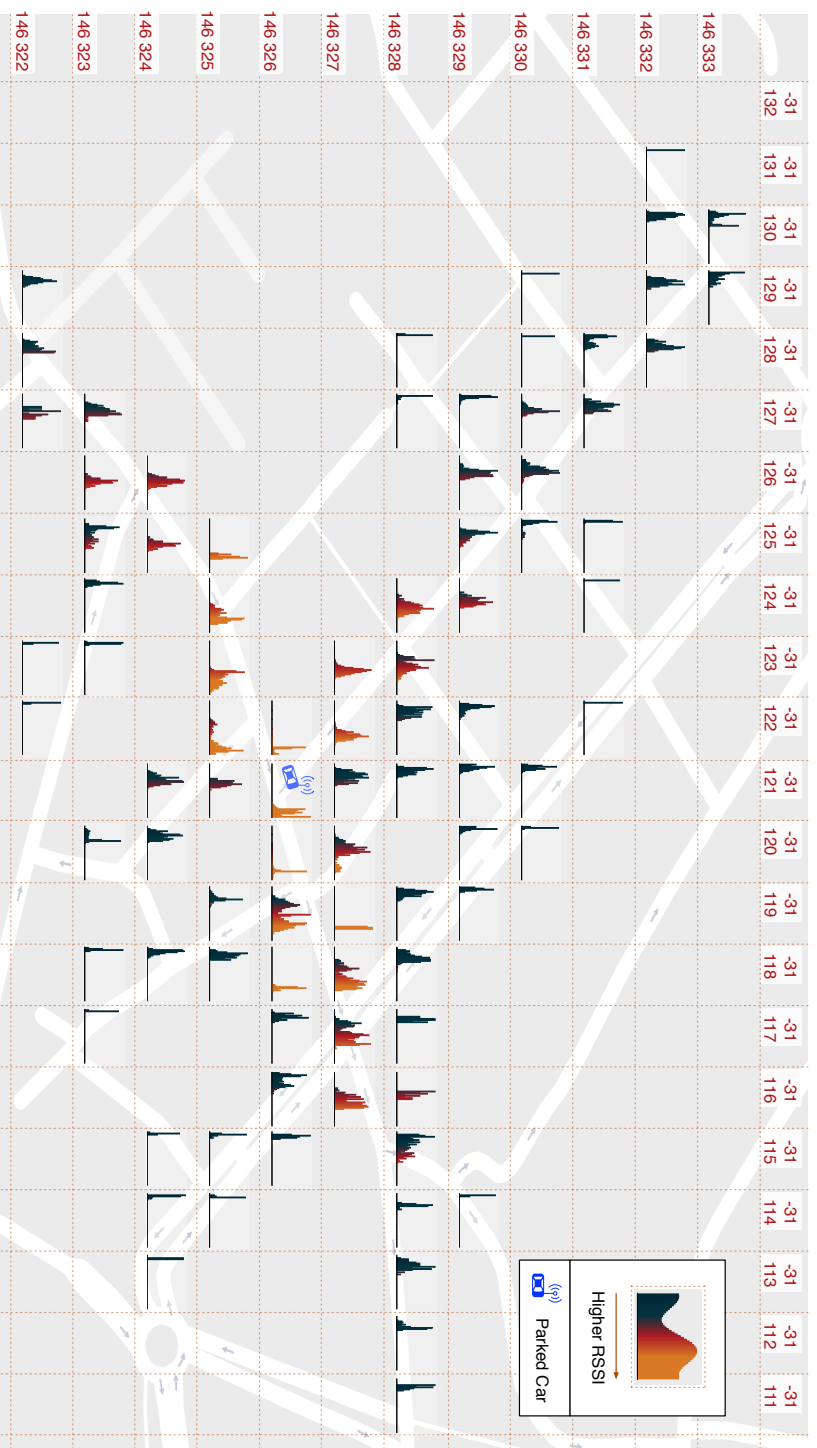


Figure 6.14: Histograms of signal strength measurements made by a parked car (in blue) of beacons received from other vehicles traveling through neighboring cells. Each histogram shows the distribution of the RSSI of all beacons overheard from the cell it is plotted in.





## Chapter 7

# Conclusion

The work in this thesis focuses on methods that improve the connectivity and the coordination of vehicular networks through the use of Roadside Units, improving the overall performance of the network in the face of node sparsity and challenging environments. By evaluating the benefits of deployments of Roadside Units, and presenting alternative methods for network support when these units are not available, we provide significant insight into optimizing the performance of these networks under most circumstances. We now review the main research contributions of this dissertation.

### 7.1 Contributions

On the topic of infrastructure support in highway vehicular networks, the main contributions of this dissertation are as follows:

- **An analytical framework for characterizing re-healing time in sparse highway networks with infrastructure support**, for two different types of RSU deployments (disconnected and interconnected), based on core traffic, network, and infrastructure deployment parameters. The closed-form analytical models accurately characterize all of the scenarios where RSUs can assist in the propagation of safety messages through a sparse network, and cut down the end-to-end delay. Using these models, an RSU deployment can be designed to match the specific requirements of a number of applications.

## 7. CONCLUSION

- **Showing the substantial difference in performance between disconnected and interconnected RSUs**, via the analytical models and Monte Carlo simulations. Comprehensive simulation sets validate all subcomponents of the analytical models and reveal that even dense deployments of disconnected RSUs bring only modest benefits to a sparse network, while connected RSUs can reduce re-healing time by more than an order of magnitude. In addition to this key result, we also provide valuable insights into the influence that the density of RSUs and their radio range have in re-healing time.
- **An experimental verification of the infrastructure support models for highways**, from a testbed with DSRC-enabled vehicles and RSUs, showing that the predictions of the models in this work are accurate and realistic. There is an excellent match between the measurement results and our analytical data.
- **An infrastructure-less approach to reducing re-healing time in highway networks**, with an aim to improve the dissemination of critical messages in sparse scenarios lacking deployments of RSU infrastructure. Two methods, proactive braking and range boosting, are analytically modeled and evaluated, showing the effectiveness of the first on roads with one-way traffic, and the benefits of the second when also in the presence of opposite-lane vehicles.

On the topic of urban vehicular networks, and the use of *cars as roadside units*, our contributions are as follows.

- **A low-cost solution to the problem of deploying RSUs for providing support to urban vehicular networks, by leveraging the parked cars in cities.** A self-organizing network approach to selecting RSUs from a large pool of parked cars is introduced, employing a novel way for vehicles to assess their value to the network by listening to beacons transmitted by other cars, and piecing together a map of their coverage. A division of the urban area in cells aligned to GPS coordinates is also proposed, allowing vehicles to efficiently share coverage maps and efficient decisions to be made based on those maps.
- **A simple on-line algorithm to maximize the coverage of the support network of parked cars**, while minimizing the number of cars that are required to be enabled. Using the coverage maps, this algorithm requires only brief

1-hop exchanges between RSUs. A detailed study is provided for the benefits of the proposed approach at the initial stages of implementation, where the small market penetration rate of DSRC-equipped vehicles will imply that only a few parked cars in a given area will be able to become RSUs.

- **A statistical analysis of the mobility patterns and parking trends in urban areas.** Travel survey data from the metropolitan areas of Atlanta, Chicago, and Knoxville are analyzed, and the time and duration of parking are extracted and modeled numerically as daily and hourly models. An analysis of these models reveals that parking events can be categorized into two broad groups according to the time the cars spend parked, and parking trends are shown to be remarkably similar across different cities.
- **An advanced approach for creating support networks of parked cars.** By giving newly parked cars the role of decision makers, and allowing them to reconfigure RSUs in their vicinity, a continued optimization of the support network is ensured. A multi-criteria decision-making solution is formulated for the problem of assigning RSU roles to available cars, and a system to limit the battery power draw on each car is developed, allowing RSU tasks to rotate between available vehicles as a part of each decision step.
- **An extensive evaluation of the performance of parked car self-organization.** This study reveals, for the first time, how networks of parked cars come together; the quality of the support network that is created; what the best balance between the number of recruited cars and the quality of the network is; the sensitivity to the frequency of parking events, and to the radio range of the vehicles' hardware; and the performance of the network under realistic parking behaviors modeled from empirical data.
- **Experimental studies verifying key assumptions of the proposed processes for self-organization.** A first study, analyzing the power consumption of On-Board Units in detail, shows that these have a small impact on the battery of a parked car. A second study, on the process through which cars learn their own map of coverage by overhearing message beacons, shows the small variance in received signal strength, and therefore its resilience.

## 7. CONCLUSION

### 7.2 Future Research

Directions for future research of relevance to the work shown in this dissertation are presented in this section. On the topic of Roadside Unit placement, and the benefits these units bring to both overly sparse and overly dense networks, the existing body of work is now considerably mature. Interesting work remains on how to best integrate these units into the existing network, and in the development of protocols that leverage the availability of supporting infrastructure.

On the theme of self-organizing vehicular networks, and the concept of using parked cars as urban RSUs, there is considerable room for further exploration. These are some of the items that warrant future study:

- **Experiment with further degrees of decision centralization.** In this dissertation, we explored decisions that affected either the local neighborhood of parked cars or a single car. With hybrid approaches, where the network of parked cars extends a small number of fixed RSUs, it may be of interest to defer the decisions on which cars should become RSUs to these permanent RSUs. Coverage maps, instead of being broadcast, may be collected at the central RSUs, and they can assign RSU roles with a broader knowledge of the urban area and the existing networks. Without fixed RSUs, the self-organizing approach can also elect a form of ‘super-coordinator’, a node that is responsible for decisions in a wider area (wider than its immediate neighborhood). These approaches may improve decision efficiency and the stability of the RSU support network.
- **Investigate methods for data permanence in the network of parked cars.** One shortcoming of the use of parked cars as RSUs is this network’s ability to store and hold data. Content distribution and collection of sensor data are two tasks often assigned to RSUs. However, parked cars are only temporary RSUs, and once a car loses its RSU role any data it is holding is lost. Two topics may be studied here: first, distribute copies of necessary data among neighbors, to add redundancy to the stored data and allow it to survive RSU disappearance. Second, develop a collective system for the storage of larger information blocks that would not fit on a single OBU by themselves, but can be split and distributed among multiple nodes.

- **Implement and evaluate a self-organizing approach in a large-scale testbed.** As a continuation to the experimental work presented in chapter 6, a larger-scale real-world evaluation with multiple parked cars may yield important insights. We have strived to perform accurate and realistic simulations, and have leveraged substantial empirical data for that purpose — nevertheless, we realize the limitations of simulation work, and suggest testing the decision algorithms and the interactions between vehicles and RSUs with a more extensive testbed.
- **Evaluate the proposed approaches in suburban and rural areas.** The simulation work in this dissertation replicated a central area of a major city, with a rich urban topology. It would be quite interesting to see how a self-organizing approach performs in areas of lower population density, and how it may be adapted to these new environments. To maintain the same degree of realism adopted by our work, four sets of empirical data are required for each area: a road map, a vector map of buildings and obstructions, signal measurements in the DSRC frequency band to derive a communication model, and a travel survey to extract realistic parking behaviors.
- **Extend the multi-criteria decision algorithms to adapt to increased traffic demands.** Areas of high node density may have greater demand for sending and receiving data through the RSU network, and the fundamental goal of widespread coverage may not be sufficient here. Measuring and integrating these requirements into the multi-criteria decision process would allow the self-organizing approach to recruit more RSUs in response to the increased demand. IEEE 802.11p standardizes six non-overlapping service channels, which allows the coexistence of multiple communication paths to source and sink data from these areas of increased demand.



## Appendix A

# Numerical Model of Cluster Length Distribution

To determine the distribution of cluster lengths, we ran 49 Monte-Carlo simulations with each run filling a highway with one million vehicles. These 49 simulations correspond to  $7 \times 7$  pairs of vehicle density and vehicle radio range, the two parameters that impact the distribution of the cluster length. The chosen ranges of values were: for vehicle density  $\lambda_s$ , from 0.0019 veh/m to 0.0079 veh/m, in 0.0010 intervals; for vehicle radio range  $R$ , from 50 m to 650 m, in increments of 100 m. From the simulation data, we observe the following characteristics of the distribution of cluster lengths:

- The distribution of cluster lengths comprises two separate, non-contiguous branches.
- The first branch closely resembles the uniform probability distribution, in the domain  $[0, R[$ .
- The second branch resembles the exponential probability distribution, in the domain  $[R, \infty[$ .

Through numerical interpolation, we were able to obtain the following PDF for

## A. CLUSTER LENGTH DISTRIBUTION

cluster length,  $C_L$ :

$$f_{C_L}(c_L) = \begin{cases} k(R, \lambda) \left( Rk(R, \lambda) + e^{-R/\mu(R, \lambda)} \right)^{-1}, & 0 < c_L < R; \\ \mu(R, \lambda)^{-1} \left( Rk(R, \lambda) + e^{-R/\mu(R, \lambda)} \right)^{-1} e^{-c_L/\mu(R, \lambda)}, & c_L \geq R. \end{cases} \quad (\text{A.1})$$

The term  $k(R, \lambda)$  characterizes the uniform branch of  $f_{C_L}(c_L)$ :

$$k(R, \lambda) = \alpha + \beta \cdot \lambda + \frac{\gamma}{R + \delta}, \quad (\text{A.2})$$

with:

$$\begin{aligned} \alpha &= 0.0003295, & \beta &= -0.2942, \\ \gamma &= 0.7212, & \delta &= -24.67. \end{aligned}$$

The  $R^2$  [81] of this fit equals 0.9817. The term  $\mu(R, \lambda)$  characterizes the exponential branch of  $f_{C_L}(c_L)$ :

$$\mu(R, \lambda) = \kappa + \omega \cdot e^{\theta \cdot R \cdot \lambda}, \quad (\text{A.3})$$

with:

$$\kappa = -161.1, \quad \omega = 199.8, \quad \theta = 0.9063.$$

The  $R^2$  of this fit equals 0.9905.

*Proof of Lemma 8.* The probability  $P[C_L < C_I - 2R_I]$  can be obtained through integration of equation (A.2) in the domain  $[0, C_I - 2R_I]$ . To limit complexity, we only consider the scenario where  $C_I - 2R_I$  is larger than  $R$ , an assumption that is valid for the scenarios we evaluate with the re-healing models.

$$\begin{aligned} P[C_L < C_I - 2R_I] &= \int_0^{C_I - 2R_I} f_{C_L}(x) dx \\ &= \int_0^R f_{C_L}(x) dx + \int_R^{C_I - 2R_I} f_{C_L}(x) dx \\ &= 1 - \frac{e^{-\frac{C_I - 2R_I}{\mu}}}{kR + e^{-\frac{R}{\mu}}}. \end{aligned} \quad (\text{A.4})$$

■



*Proof of Lemma 9.* The conditional expected length of a cluster  $E[C_L|C_L < C_I - 2R_I]$  can be computed in a straightforward manner from  $f_{C_L}$ :

$$\begin{aligned}
E[C_L|C_L < C_I - 2R_I] &= \\
&= \int_0^{C_I - 2R_I} c_L \frac{f_{C_L}(c_L)}{F_{C_L}(C_I - 2R_I)} dc_L \\
&= \frac{1}{F_{C_L}(C_I - 2R_I)} \left[ \int_0^R c_L f_{C_L}(c_L) dc_L + \int_R^{C_I - 2R_I} c_L f_{C_L}(c_L) dc_L \right] \\
&= \frac{e^{\frac{R+C_I}{\mu}} kR^2 + 2e^{\frac{C_I}{\mu}} (R + \mu) - 2e^{\frac{R+2R_I}{\mu}} (\mu + C_I - 2R_I)}{2 \left( e^{\frac{C_I}{\mu}} - e^{\frac{R+2R_I}{\mu}} + e^{\frac{R+C_I}{\mu}} kR \right)}. \tag{A.5}
\end{aligned}$$

■



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