

Distributed optimization of electric vehicles recharge in an urban environment

Julian Garbiso

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Fulfillment of the requirement of the following degrees:
Diplôme d'Ingénieur Télécom Bretagne
Research Master in Computer Science
(DNM - Master Recherche en Informatique)



Internship Report

Distributed optimization of electric vehicles recharge in an urban environment

Author:
Julian Garbiso

Supervisor:
Claude Chaudet
INFRES Department,
Telecom ParisTech



Abstract

The era of sustainable development has brought Electric Vehicles (EVs) to the spotlight. Since recharging an electric vehicle can take up to ten or more times the power consumption of a household, an increasing EV penetration in the market poses a challenge for the electricity companies. Using the Internet of Things (IoT) approach, we propose a model where electric vehicles communicate with the electrical grid infrastructure in order to determine the charging station where they should go to. We have consequently built a simulator, mixing both a microscopic traffic simulation and a complete network simulation including radio propagation analysis. In this work we run several simulations over a test map, taking service and network-level metrics, comparing four basic charging station assignment strategies. Our final analysis draws relevant conclusions concerning the fundamental aspects to take into account for developing a distributed system that optimizes the charging station assignation based on real-time network analysis and taking into account the grid's capacity.

Résumé

L'ère du développement durable a mis en lumière les véhicules électriques (VEs). Étant donné qu'un véhicule électrique peut consommer jusqu'à dix fois la puissance consommé par un foyer, voire plus, un taux de pénétration des VEs en hausse pose un défi pour les compagnies d'électricité. En nous appuyant sur l'approche de l'Internet des Objets (IdO), nous proposons un modèle où les véhicules électriques communiquent avec l'infrastructure de la grille électrique afin de déterminer la station de charge où il faudrait aller. Nous avons en conséquence construit un simulateur, en combinant à la fois une simulation microscopique de trafic et une simulation détaillé du réseau incluant l'analyse de la propagation radio. Dans ce travail nous avons fait tourner plusieurs simulations sur une carte de test, en prenant des métriques de niveau service et réseau, et en comparant quatre stratégies basiques d'attribution de station de charge. Notre analyse final montre des conclusions pertinentes concernant les aspects fondamentaux à prendre en compte pour développer un système réparti qu'optimise l'attribution des stations de charge en s'appuyant sur l'analyse en temps réel du réseau et en prenant en compte la capacité de la grille électrique.

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1 Internship presentation

1.1 Context

This internship takes place between March 18th, 2013 and September 20th, 2013 in the French *Grande École* Télécom ParisTech, in the Computer Science and Computer Networks (INFRES) Department, in the context of the SEIDO joint laboratory between Telecom ParisTech and EDF R&D, using the facilities of the LINCS.

1.1.1 Télécom ParisTech

Télécom ParisTech, formerly *École Nationale Supérieure des Télécommunications* (ENST), is a French state engineering school located in the city of Paris, specialized in the domain of Information Technology and Telecommunications. It was founded in 1878.

This engineering school is part of the *Institut Mines-Télécom* and is one of the founding members of *ParisTech*, a consortium that reunites twelve French *Grandes Écoles* considered as the best in their respective fields.

The INFRES (*Informatique et Réseaux*, French for Computer Science and Networks) department covers the fields corresponding to the study of infrastructure, systems and digital networks, focusing on mathematical modeling (stochastic models, extended information theory, cryptography, discrete mathematics), the communication functions (network architectures and communication protocols) for all kinds of future networks, and the embedded or distributed architectures for systems, and services in their programming aspect.

The department's research activity is situated in the context of telecommunication convergence, computer science and audiovisuals, in the general frame of the rise of the information society, of knowledge, communication and computing.

1.1.2 SEIDO Laboratory

EDF R&D and Telecom ParisTech have created a joint research laboratory, named SEIDO, concerning Internet of Things and Security for the electrical systems.

The strategic challenge is to prepare and facilitate the deployment of energy management services, based on the interaction of the equipment and thus contributing to ensure the coherence, efficacy and safety of the system

as a whole.

On one hand, the laboratory should propose solutions oriented to the commercialization of new offers, integrating, for instance, the potential of the Smart Homes and intelligent buildings. In this context, the client becomes an actor of his own consumption: in order to respond to the energetic and climatic challenges installed in society, the consumer will be incited to take an active role in energy management. The convergence towards great standards (IP) and the Internet of Things (IoT) concepts play a key role, making the automation of jointly decided policies (between the client and the provider) possible. A remarkable trend in the IoT area is the use of Wireless Sensor Networks (WSN) that make real-time analysis and control of the environment possible. In a wider view, the concept of Smart Cities integrates electric vehicles in the equation, acting in a way similar to WSNs, in the so-called Vehicular Ad-hoc Networks (VANETs). This is a matter of great interest for EDF, since one of the main challenges concerning the electrical grid's sustainability is the ability to control the way that electric vehicles recharge their batteries, since they represent a very significant load in the grid. The aim in this sense is to contribute to the technical-economical-ecological optimization of the electrical system, by arbitrating its usage, mainly via pricing incitement, and ahead in the future, the means of energy production and storage.

On the other hand, the SEIDO Lab is expected to provide solutions in the aspects of energy production and electrical network, by integration the IoT potential in order to improve the performance of the exploitation process and reduce costs.

1.1.3 The LINCS

The LINCS (Laboratory of Information, Networking and Communication Sciences), created in October 2010, is a joint laboratory reuniting the *Institut Mines-Télécom*, *INRIA*, *UPMC*, *Alcatel-Lucent* and *SystemX* in a shared facility, with the aim of creating a research *ecosystem* generating synergy between fundamental and experimental approaches.

The LINCS also aims to establish synergies between the academia and industrial partners, in order to bridge scientific results and innovation capacity, as well as reaching, in the mid-term, impact and visibility in the scientific community.

1.2 Mission

The increasing penetration rate of electric vehicles in urban environments will create the need to administrate the load these vehicles are going to add to the electrical grid. The internship objective was to define and evaluate a distributed system that is able to direct drivers to an available charging station.

The work consisted in:

- Modeling the scenario, the electrical aspect of the system (vehicle's characteristics, charging process, standards, charging stations) and the network (wireless access technology, network architecture).
- Proposing simple decision algorithms to suggest charging stations to the drivers, aiming at minimizing diverse criteria such as the supplementary distance required to go to the chosen charging station, the waiting time, or the probability of battery depletion.
- Evaluating the system performance using a network and a transportation simulators. Evaluation criteria include network metrics such as the communication delay, as well as service-level metrics such as the depletion probability.

2 Introduction

An efficient electrical grid has to take into account the variable power needs in different areas. It is practically impossible to stock all of the energy produced in order to use it when it is needed, and thus it is fundamental to balance production and consumption in a continuous manner, at all instants. This prevents local grid instability and avoids peaks and damage that might occur.

Through the years, the common usage of electricity has changed, and today we have more electronic devices than never before. The electrical grid infrastructure has also evolved, and the level of control in the network is nowadays at the scale of small zones of the size of a neighborhood, controlled by command points. In the case of an incident, the problem can be detected at the level of this small area and act in consequence, isolating the problem in that specific zone. However, for local problems involving a single household, it is up to the client to notify the problem, since there was no possible way to control up to the level of a single counter. Until now.

The communication standards convergence process, and the rise of the Internet of Things where many devices are now able to connect and trans-

mit control information in real time has opened the possibility of taking a big leap forward in the effectiveness, performance, control and innovation in the electrical grid. The Smart Grids use information and communication technologies to gather energy consumption information from every actor connected to the grid, even up to the level of singular electronic devices, and act in consequence.

In this context, millions of electric vehicles are expected to get to the streets in the years to come. They will add a new significant load to the grid, and their recharges will be mobile and *a priori* unpredictable. The infrastructure cost to support the new consumption peaks that the EVs would represent if not regulated would be extremely high. This is why we want to take the other option we have: making the grid more efficient. Making it smarter.

In this work, we have decided to take advantage of the new possibilities offered by the development of specialized standards for wireless access in vehicular environments, and design and evaluate a system where the electric vehicles communicate with the fixed network infrastructure in order to know the optimal charging station they should go to. We propose four basic assignment criteria, and using the simulator we have built, integrating traffic and network simulation, and adding the electric vehicle logic, the simulation of the charging process, and the charging stations, we evaluate a series of metrics and we present our conclusions of the existing compromises between the different network and service-level metrics in order to conceive a smart, multi-criteria optimization algorithm that would run in a distributed system, also interacting with the electrical grid. The design of that distributed system will take place in the PhD thesis following this Research Master's Degree.

The work done in this internship is introduced as follows: In section 3 we introduce the relevant aspects of the EVs that we need to know in order to build an accurate, realistic model. Once these concepts have been introduced, we can present in Section 4 a brief selection of related works in this particular problem. In Section 5 we introduce the wireless access technology that we have chosen to use in our model, and that we have used in our simulations. Once we have all the necessary theory to build our model, we expose, in Section 6 the way our simulator was built, and the projects that we have used as a basis for the simulator development. Finally, in Section 7 we present the complete, detailed model and the simulation results with the corresponding analysis, and the final conclusions in Section 8.

3 The electric vehicle

The center of attention in our model is the electric vehicle, and so we need to clearly define the subject of our study. Generally speaking, this kind of vehicles is not new. Let us remark that the first electric cars were manufactured between the late 19th century and the early years of the 20th century. Since then, the maximum range that electric vehicles can reach has been the major concern. Today we call it *range anxiety*. Electric cars enjoyed some popularity until the need of a hand crank to start fuel powered engines was eliminated with the introduction of electric starters. Some companies tried in a second electric car wave in the 1970s to reintroduce this option to the market, but they did not succeed, sales never really took off.

Since the early 2000s, the strengthened interest for sustainable development, greenhouse gases reduction in particular, and also the rising economical interest of finding a decent alternative to petrol, has brought this sector of the industry to the spotlight again. The efforts are now put in improving the three variables that are judged responsible for the stagnation of electric cars through history:

- Battery capacity and reliability, directly related to range anxiety
- Charging rate, and its counterpart, the time it takes to recharge the EV's battery, often seen as too long
- Charging station network density, which also influences in range anxiety, and becomes the "chicken and the egg" problem of electric vehicles: for a network of charging stations to develop, in order to make it economically viable, a considerable number of EVs is needed in the streets, but for these EVs to be sold, a charging station network is needed.

We have to clarify an abuse of notation that we are going to use: when we talk about *electric vehicles* (EVs) we will refer to present-day electric cars. The reader must keep in mind that, strictly speaking, the term electric vehicle includes all types of transportation, such as trains, for instance, which are out of the scope of this report.

In the last years, we have witnessed the evolution of the above mentioned critical factors in the new EVs in the market. From the regular 10 kWh batteries that we used to see in urban electric cars a decade ago, we have jumped to around 25 kWh for most mid-range models. The latest high-end releases go far beyond that. For instance, the Tesla Model S has

an 85-kWh battery, which gives this car a driving range of 426 km (according to EPA), making it the electric car with the greatest range available in the market.

On the other hand, charging techniques have also evolved. From the first slow AC recharging standards, that allowed to charge an average battery in 6 to 12 hours, the latest fast DC charging stations can often recharge a regular battery in less than half an hour.

3.1 Charging modes: AC vs. DC

When analyzing the charging process of EVs, the first difference we need to know is the one between AC and DC charging modes. There are "*low-AC*" and "*high-AC*" modes in most standards. For the former, recharging a battery from *State of Charge* (SOC, te quotient between the amount of battery left and the total battery capacity) zero usually takes 8 to 10 hours, it has low charging rates around 2-3 kW, and is intended for overnight charging at home. For the latter, the full recharge may take from 4 to 6 hours, charging rates are around 8 kW, and it is intended for charging while at work or in a parking lot.

Fast DC charging, on the other hand, usually allows the user to recharge a battery in much less than an hour (between 15 to 30 minutes for mid-range vehicles), offering charging rates around 50 kW.

The reader may ask why DC charging alternatives are that much faster. The difference relies in the fact that batteries need to be charged in Controlled Current / Controlled Voltage (CC/CV) DC. When we use an AC supply, the connection goes through the electric vehicle's on-board charger. A rectifier converts AC in DC, and then it passes to the Power Control Unit (PCU) that in function of the control information it receives from the Battery Monitoring System (BMS), supplies a Variable DC that passes through the protection circuits and then goes to the battery (See Figure 1). For reasons of temperature control and costs, the amount of power that can pass through the rectifier and the on-board charger is limited.

In Fast DC charging modes, the current conversion takes place in the charging station, which provides CC/CV DC directly to the battery, previously passing through the protection circuits. The BMS information is sent via the CAN protocol to the charging station off-board equipment (See Figure 2). This way, the conversion can take place in a less constrained way in the charging station. However, this increases the cost of the charging infrastructure.

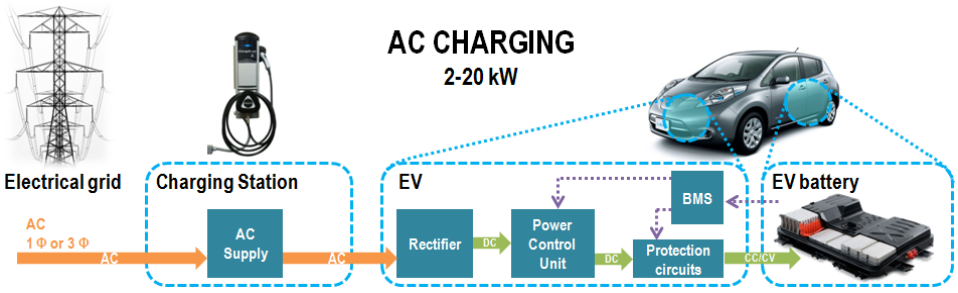


Figure 1: Schema of the AC charging process of an electric vehicle.

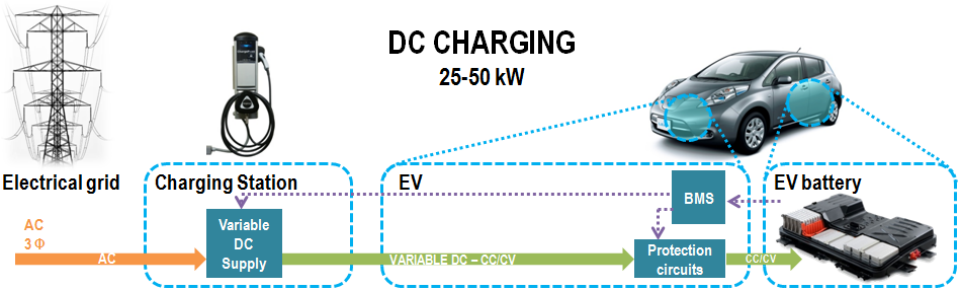


Figure 2: Schema of the DC charging process of an electric vehicle.

3.2 Standards, regulations and predictive analysis

In order to have a realistic model of the system, we were interested in many aspects coming from many different fields, and the EV charging process is one of them. Thus, I have dedicated a part of my bibliographic study for the analysis of present-day standards, data sheets and performance studies, since we needed to know specific characteristics of these vehicles, such as battery capacities, charging time or charging efficiency.

The IEC 62196 international standard for plugs, socket outlets, connectors and charging modes for EVs is becoming a convergence point for the present day standards, like the North American SAE J1772 or the European VDE-AR-E 2623-2-2. Part 1 (IEC 62196-1, 2nd edition released October 2011) establishes general requirements and describes charging modes. Part 2 (IEC 62196-2, 1st edition released October 2011) describes dimensional compatibility between plugs, establishing three accepted types. In terms of charging modes; these standards have already specified different modes of low and fast AC charging, while DC charging standardization is currently work in progress. The latter option provides an ultra fast service, achieving

a complete recharge from zero in minutes rather than hours.

For instance, the SAE J1772 revision ratified on January 2010 establishes two levels of AC charging, and one level of DC charging (under development, three AC levels and three DC levels are expected for future versions) [4]. The two AC charging levels require charging times between 6 and 12 hours in order to achieve full recharge (compared to less than 15 minutes in DC mode), and thus we are considering that these modes are going to be used under different scenarios (at home or while parked). This is why we make the hypothesis that every urban charging station will only offer DC charging modes. Anyway, we will certainly take into account the load that the EVs charging in AC modes put into the grid.

The IEC Technical Subcommittee 23H is working in the third part of the standard, IEC 62196-3, that will define the requirements and modes for DC charging. The expected release date is April 2014. Until then, we will base our model in a widespread DC charging system, the japanese CHAdeMO (by TEPCO), which is not standardized.

According to the EURELECTRIC Position Paper of March 2012 on EV charging infrastructure [7], the currently installed DC infrastructure in France is consists effectively of 30 installed and 100 commissioned (in 2012) CHAdeMO DC connectors, which have a maximum power level of 50 kW. For our first model, we will assume that all charging stations provide only this mode. The recharge and depletion processes can be supposed to be linear [5] [10]. The efficiency of the charging for AC modes is expected to be between 0.85 and 0.9 [6] [14], because of the lower output voltage (between 120V and 250V). In fast DC charging, particularly in the case of CHAdeMO, we have a higher voltage (500V in most of the available chargers in the market) and in consequence, an efficiency quite above 0.9 [1] [14] (see Figure 3). This makes efficiency a minor concern in the modeling process.

3.3 Charging stations: business models, charging time, and location

One of the biggest challenges of the EV problem is that we cannot be certain about which service model will succeed in the market, since there are plenty of alternatives to recharge an electric vehicle, as well as there are many possible business models and possible consequent structures for the market.

One one hand, we have the different offers that can be divided according to charging time. It is not the same to propose the client low AC recharge than a fast DC one, since the former can take up to 8 hours, while the latter

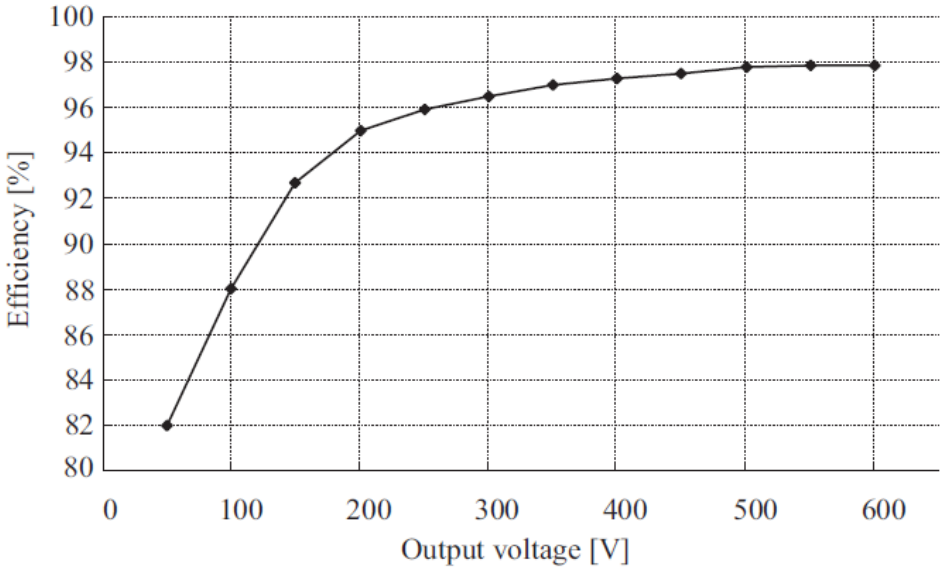


Figure 3: Efficiency in function of output voltage in a particular implementation of a DC fast charger. Source: [1]

would complete in minutes. The user experience is completely different in both cases, and also concerning the station's physical area, the potential economic benefit per square meter is different, as well as the cost of the infrastructure, since Fast DC charging equipment is more expensive.

On the other hand, several business models can be explored. An interesting example is the offer of the American electric vehicle manufacturer company Tesla for the customers that have bought their top-range Model S. These customers will have free for-life recharges in a network of the so-called Tesla Superchargers, that obtain their energy from solar panels and charge vehicles at 90 kW (twice as fast as CHAdeMO). Furthermore, another alternative consists in swapping batteries. Tesla has developed a swapping device that can change the Model S' battery in 90 seconds, twice as fast as filling a fuel tank. Those are just two examples, there is not only Tesla in this business, and we may have not seen all the possible business opportunities and models in this field yet. The construction of an adaptable, generic scenario is a fundamental task that we will have to accomplish in the future.

Given the fact that slow charging modes are intended for overnight recharges at home or while a person is at work, and adding that fast DC charging modes represent a much more significant load to the grid, and that there are still very few related works in this area that involve fast DC charging stations in their models, whereas real-time regulation of the overnight

recharging process is a well-studied subject, we have chosen to focus on a model where, at least for the first stages that are covered in this report, all charging stations are considered fast DC charging stations. Future work should include the analysis of different charging station business models.

Many options are to be considered for the possible position of charging stations. The easiest way is to obtain information about current deployment plans from the electric company. If such plans do not yet exist, a possible option is to start by considering present day filling stations as a starting base. However, the deployment of filling stations and EV charging stations are quite different problems in terms of space constraints, required infrastructure and service time. These differences may lead to solutions that could certainly be dissimilar.

An interesting option proposed in [10] is to use *genetic programming* in order to heuristically find optimal solutions. The algorithm is provided a set of random feasible solutions (deployment maps), and for each of them a fitness value is computed (for instance, average trip time). Then, the list is sorted following this value. The worst part is discarded, and the remaining solutions are combined pairwise and added to the solution pool, repeating the process for a specified number of generations. Finally, the solution with the best fitness value is chosen. However, the metric used to compare two possible locations is not specified. We will see in Section 7 that the results that we can obtain with the simulator we have built can add the missing piece in this puzzle, offering a very interesting alternative to determine optimal charging station positions.

4 Related work

As we have previously stated, whereas the demand-response regulation of the overnight charging process is a well-studied research topic, the study of the optimization of the charging station assignment in the context of an Internet of Things approach to build Smart Grid solutions does not count as many precedents.

Among the few examples we can find, we have the work of Gharbaoui et al. in [8], where the authors do a comparative analysis through simulation of the impact of the penetration of 3G/4G and common IEEE 802.11 (WiFi) as communication devices for EVs, comparing only in terms of average waiting time. In this work, we use the IEEE 802.11p amendment of the standard, optimized for vehicular network communications, and we make a deeper analysis taking into account many different metrics, as well as a

comparison of further assignment strategies, adding also a detailed model of the electrical characteristics of the vehicles, and we settle the basis needed to take into account the electrical grid's load, analyzing the possible ways to incorporate this logic in a smart multi-criteria optimization algorithm that will take advantage of network analysis, intending to develop this optimization in a distributed system in further work.

Besides our specific subject, and in order to give an example of an interesting vision to take into account for the charging process regulation once the vehicle is connected to the grid (remember that this is not the problem we deal with, i.e. the assignation of the charging station prior to the vehicle's arrival) is a work by Huachun et al. [9] in which the authors propose two charging strategies for EVs: centralized and decentralized. Both of these strategies aim to optimize the charging schedules and charging rates.

In the decentralized strategy, the vehicle charging controller is in charge of all the optimization strategy. The algorithm it uses decides in function of the *state of charge*, the *price variation*, and the *grid stability*.

- **Charging immediately:** random charging time, makes load shaping impossible.
- **Timed charging:** the user defines a specific time to start charging
- **Price-based charging:** pricing is needed, the authors don't specify if it is received via network or not.
- **Charging response to DSM (Demand Side Management):** the system detects grid stress and acts consequently.
- **Battery-response charging:** according to the information sent by the Battery Management System (BMS)
- **V1G:** Charging process guided by grid commands

The authors give a flow chart establishing priorities between these charging methods, and this flow chart becomes in essence the strategy.

In future work, when the real-time interaction with the electrical grid will be gradually be deepened, works in this areas will get further analysis.

5 Wireless Access Technologies

In order to allow the vehicles to communicate with themselves (V2V) and with the infrastructure (V2I), we need a wireless access network. We have

chosen to model our network by using the WAVE (Wireless Acess for Vehicular Environments) standard.

5.1 WAVE : IEEE 802.11p and IEEE 1609

WAVE (*Wireless Access for Vehicular Environments*) is an amendment to the IEEE 802.11 standard for Intelligent Transportation Systems. We call WAVE the duo formed by the IEEE 802.11p amendment itself for physical and MAC layers, and the IEEE 1609 standard, for the upper layers: IEEE 1609.2 for communication security, IEEE 1609.3 for connection setup and management, and 1609.4 on top of IEEE 802.11p, providing abstraction of the physical parameters [11], [13]. WAVE disposes of seven 10 MHz physical channels, divided into six Service CHannels (SCH) and one Control CHannel (CCH).

IEEE 802.11p provides critical improvements in the physical and data link layers since at the high node mobility speeds that vehicles imply, the network needs instantaneous data exchanges. The MAC (*Media Access Control*) operations performed in classic IEEE 802.11 are considerably time consuming due to the BSS mechanism. A Basic Service Set (BSS) is a group of nodes connected under IEEE 802.11 to the same Acess Point (AP). Regular IEEE 802.11's mechanism requires channel scanning for finding beacons, and multiple handshakes. WAVE addresses this problem by incorporating the *WAVE mode*, allowing a station to exchange data frames by using the wildcard BSSID[1] without belonging to any BSS [11].

5.2 The WAVE protocol stack

WAVE offers the applications to communicate both via IPv6 or Wave Short Message Protocol (WSMP). IPv6 is a very interesting option for developing Intelligent Transport Systems (ITS) applications for convergence reasons. However, while WSMP is part of the IEEE 1609 family, and thus its implementation for WAVE is covered in detail, the considerations for implementing IPv6 over WAVE lack specificity and there are still many problems to solve. This is why we have developed our application running over WSMP, in order to simplify testing.

5.3 Energy consumption

In order to implement our system, we need the vehicles to have a communication device working at 5.9 GHz DSRC/WAVE frequencies. The authors of [10] give the example of a DCMA-86P2 card, manufactured by Unex.

[1] A Basic Service Set ID composed by all 1s

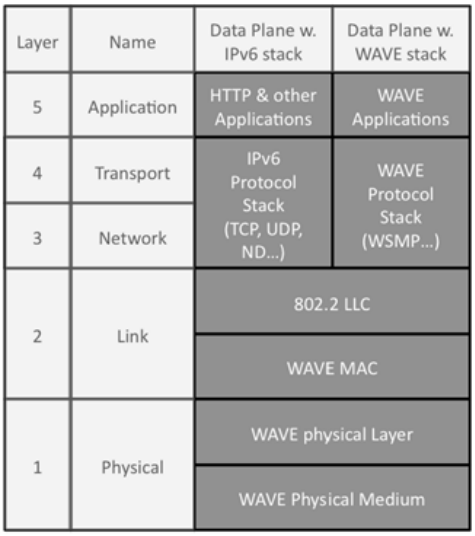


Figure 4: WAVE dual protocol stack, showing both WSMP and IPv6. Source: [2]

The company uses this card as the basis of two devices: the Unex OBE-101, which implements IEEE 802.11p and IEEE 1609 standards (US version), and the Unex OBE-102, compliant with IEEE 802.11p and ETSI TC ITS standards (EU version). According to the card's data sheet [16], assuming that in order to have the largest possible communication range we will always use maximum power for our radio interface (transmitting at an average power of 24 dBm, 6 Mbps), the card will consume 4.62 W when transmitting, and 0.86W when receiving data. Making the hypothesis that the card will be active 20% of the time for both transmission and reception, we get an average energy consumption of 0.0011 kWh per hour for our network connection. As it could obviously be expected, the energy consumption of the network card is negligible with respect to the vehicle's energy demands.

6 Construction of the simulator

One of the biggest accomplishments in these months of work was to build a simulator that integrates all the elements of our interest: electric vehicles, charging stations, Road Side Units, radio propagation, network simulation, and traffic simulation. This tool has been built in a way that will make it easily scalable, so that further detailed real-time interaction with the smart grid becomes a simple step forward to implement.

For constructing this, we have coupled a traffic simulator (SUMO) and a network simulator (OMNeT++) helping us with the Veins framework.

6.1 Microscopic traffic simulation : SUMO

SUMO [3] is an open source (licensed under the GPL) microscopic road traffic simulation package developed by the Institute of Transportation Systems at the German Aerospace Center. It is able to import road network maps from many platforms and convert them to its own format. The microscopic simulation concept means that each vehicle is simulated separately, individually, with their own identifier, departure time and route. The simulation is done in time steps in the order of 100 ms, where each vehicle gets its position updated. It takes into account complex following models, traffic light systems, accidents, etc.

It has a vast tool suite, and it is possible to control de simulation via a TCP socket by using the API called TraCI. We have used TraCI extensively in order to command our electric vehicles in the simulation.

6.2 Network simulation : OMNeT++ and IEEE 802.11p

OMNeT++ [17] is a modular component-based network simulation framework for building network simulators, including both wired and wireless technologies. The domain-specific functionality for a certain technology is usually provided by other model frameworks making part of independent projects. In our case, we have incorporated MiXiM's implementation of the IEEE 802.11p standard for vehicular networks. OMNeT++ provides an IDE based on Eclipse, a graphic runtime environment, as well as statistic tools. In order to develop a network, nodes have to be defined in a special NED format, similar to C++ but specific to OMNeT++. The rest of the coding is done in C++.

6.3 Veins: synchronizing SUMO and OMNeT++

Veins is an open source framework that constitutes the basis of a vehicular network simulation: it synchronizes SUMO and OMNeT++ in a way that every vehicle in SUMO is synchronized as a wireless node in OMNeT++. The network simulator's time steps are several orders of magnitude shorter than the traffic simulation because of the extreme rapidity of wireless network communications. It provides a set of classes with a big "Scenario Manager" (class TraCIScenarioManager) and the basic representation of a vehicle in the TraCIMobility class. It implements the C++ for the most part of the TraCI API.

6.4 Construction of an EV communication network simulation

Once the traffic and the network simulators were coupled, we extended the vehicular simulation, adding the battery logic (capacities, consumption, depletion), we added new OMNeT++ modules in order to create and simulate the Road Side Units, we did the same for charging stations and added the charging process logic, we configured the IEEE 802.11p wireless communication parameters, we modified and extended the Veins' implementation of the TraCI API in order to modify some specific behaviors for avoiding errors, or for implementing some specific options that we needed, we created a basic WAVE application that runs in both vehicles and RSUs and configured the behavior of their simulated network cards, we coded the implementation of the basic assignment strategies, we implemented the waiting queues, analyzed the radio propagation aspect, incorporated the SUMO map in OMNeT's graphic environment for clear visualization of the simulation, and performed a long debugging task (see Section 6.5).

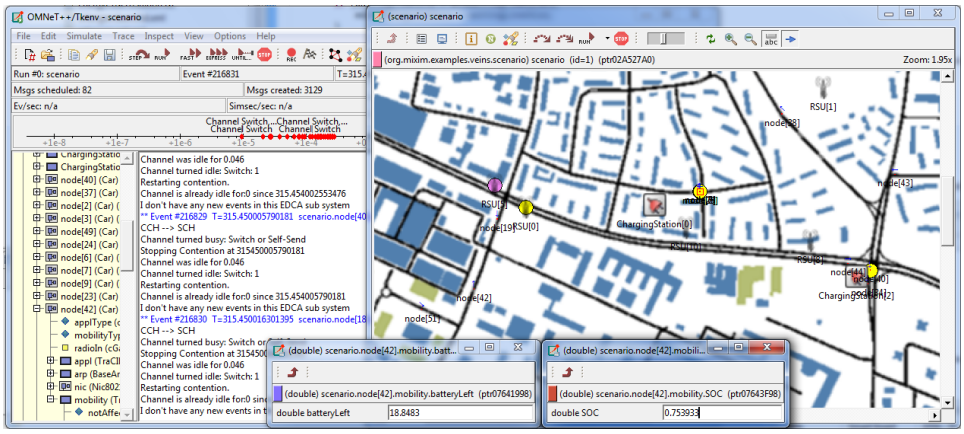


Figure 5: The aspect of the simulator's graphic interface, showing some nodes (EVs), RSUs and Charging Stations in the map.

6.5 Difficulties encountered

Integrating two different, complex open-source simulators is not trivial. The first extra difficulty is the fact that you need to learn the structure of these simulators, learn how to use them, study their functions and APIs, and even a new "language" like the way to code OMNeT's NED files, which looks similar to C++. The fact of not knowing in the beginning if the simulators had all the functions we needed for implementing our simulation without modifying OMNeT's or SUMO's source code made it hard to estimate the time that building our simulator would take. The period of learning how to use

these simulators, however, was no longer than expected.

The unexpected aspect that took more time than predicted was getting familiar with Veins. The problem is that Veins, an academic project, had not enough documentation, and was constituted of a big set of C++ classes of which the interaction and control chain may be hard to deduce on your own. The way these classes were integrated (with several mutual includes, which is a troublesome thing when programming in C++) made it hard to scale the framework with new classes and entities. At the moment of writing this report, some concurrency conflicts were observed sometimes with these classes, causing an unstable behavior. We will need to analyze the rest of Veins' structure in order to determine the origin of these conflicts.

Some stability problems were observed in SUMO, with some vehicles in invalid positions or states. We had to add extra code sometimes in order to detect and correct this kind of errors, and there are other rare SUMO stability problems that may seldom happen that we still need to solve.

7 Simulation model and results

7.1 Model summary

7.1.1 Terrain

The simulation is run in the Erlangen map, which is the default example in Veins. It is actually a specific area of the city of Erlangen, Germany. The model of the terrain was directly imported in SUMO from OpenStreetMap, a collaborative project consisting of a free editable map of the Earth (in OpenStreetMap, data are crowd-sourced from a wide variety of devices and free sources, and inspired in Wikipedia's success, it is nowadays a recognized competitor of proprietary map data). We have added four *Charging Station* (CS) points in the map, and eleven *Road Side Units* (RSUs), as shown in Figure 6. The number of available sockets in each charging station can variate, and we will analyze the impact of such modifications in the simulation.

It would have been interesting to analyze the effect of changing the number of charging points, fixed at four for these tests, but the slightly hasty release of the simulator due to time constraints, in order to be able to run all the necessary simulations for this report, caused the charging station addition process to be unstable. However, in terms of the metrics that we wanted to evaluate, we can estimate *a priori* that changing the number of charging stations would have only affected the supplementary distance and the total number of fully depleted batteries.

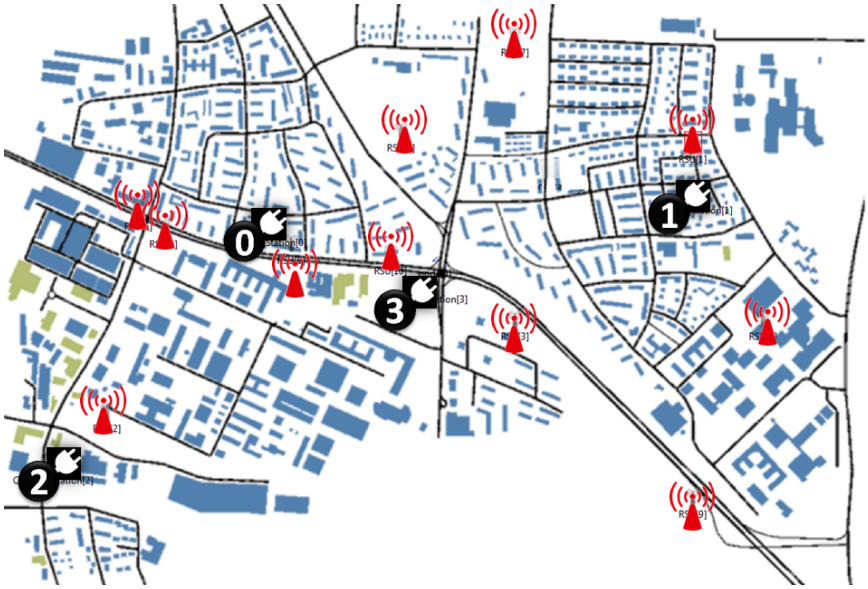


Figure 6: The Erlangen map, with four charging points and ten RSUs added

7.1.2 Electric Vehicles

We have decided to take a popular medium-range electric vehicle as a reference for our simulations. We take the *Nissan Leaf* 2011 model, featuring a 24 kWh battery. As a first hypothesis, we will assume that the battery depletion process is linear. This approach is commonly used in related research work such as [5] and [10]. Following that hypothesis, we can estimate the Nissan Leaf's battery consumption per km by dividing its battery capacity by its maximum range, for which there are several performance tests. However, the published results vary considerably. We have decided to keep the value published in [12], thus estimating consumption at 0.211 kWh per km. This EV is compatible with the *CHAdeMO* fast DC charging technology, so it is possible to charge it at rates up to 44 kW.

It is easy to extend our simulator and incorporate different vehicle models, with a completely different set of characteristics. For the purpose of this work, we have considered that this model was already satisfying.

Since there are no statistics regarding the initial *State Of Charge* (SOC) of the EVs at the beginning of their daily trips yet, we have decided to make a first model, assigning each EV an initial SOC based on a cropped normal distribution of mean 0.5 and standard deviation 0.2, and recharge request

Vehicle model	Nissan Leaf (2011)
Battery capacity	24 kWh
Battery consumption	0.211 kWh per km
CHAdeMO compatible	Yes
Depletion type	Linear
Initial SOC	Normal distribution ($\mu = 0.5, \sigma^2 = 0.2$)
Threshold SOC	Uniform distribution [0.05,0.4]

Table 1: Characteristics of the simulated electric vehicles

threshold (the SOC at which the vehicles will start sending requests to the system) following an uniform distribution between 0.05 and 0.4. In Figure 7 we see how many EVs fall in each possible range of initial State Of Charge, and we compare those numbers with how many vehicles in that range will start sending requests to the system from the moment they are placed in the simulation (the case where Initial SOC < Threshold SOC). Those cases are around 20%.

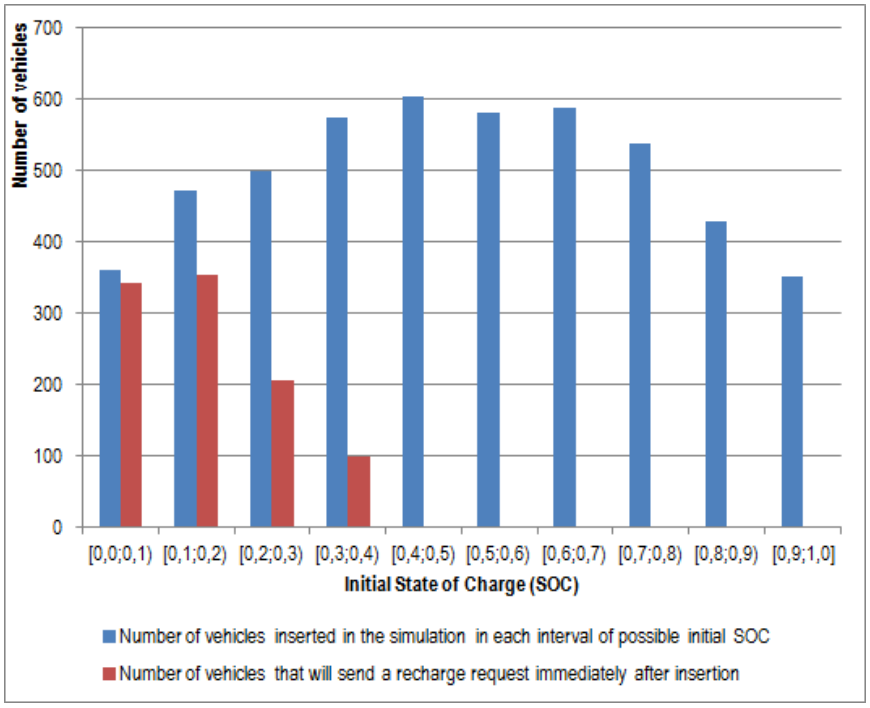


Figure 7: Simulation of the creation of 5000 EVs with the chosen distributions for their Initial SOC and Threshold SOC

7.1.3 Vehicle traces

The Erlangen map is a demo scenario with no associated vehicular traces. There are projects where the vehicular traffic in a certain zone is registered along with the map, in order to use realistic vehicular traces. This is particularly useful when we intend to analyze traffic related problems that depend on real behavior and habits. This has the downside that if we want to keep those traces realistic, we are not able to modify the number of vehicles in order to test the system's response. In our case, we have decided that it was more important to evaluate this latter aspect.

We have used a tool included in the SUMO suite: a Python script called *randomTrips.py*, in order to generate random vehicular traces. The script chooses random origin and destination edges in the map. It is possible to use a uniform or weighed distribution. We have decided to leave the default uniform option, since there was not a particular interest of setting weights. This program then creates a .trip XML file that can be used with *DUAROUTER*, another program of the SUMO suite that builds the route files (one of the simulator's input files) connecting those edges. It also warns the user if there is no connection between an origin and prevents that trip from becoming an invalid route.

RandomTrips will evenly distribute the generated routes between a starting and an ending time that have to be specified. The number of vehicles that will circulate in the map is determined by those starting and ending times, and an extra parameter that determines the time in seconds that separates each departure. For this map, we have created different route files, corresponding to a total number of vehicles between 200 and 2000 evenly distributed in the total simulated time of four hours.

7.1.4 Charging Stations

Since it is a small map, we have placed four charging stations in the locations shown in Figure 6. Since the highway that traverses the map acts as a crucial connection point, we have decided to place two charging stations at the sides and the other two near the zones with higher building density. No other criterion has been followed.

The charging stations will offer a certain number of Fast DC charging sockets, at a charging rate of 45 kW. We will make the number of available places vary for our four stations (see Table 2).

Total	C. Station 0	C. Station 1	C. Station 2	C. Station 3
12 pl.	3 places	3 places	3 places	3 places
24 pl.	8 places	3 places	5 places	8 places
33 pl.	12 places	3 places	6 places	12 places

Table 2: The three different configuration for the total number of places in each charging station

IEEE 802.11p Network Card Configuration	
Carrier frequency	5.890 GHz
Channel bandwidth	10 MHz
Maximum transmission power	20 mW
Bitrate	18 Mbps
Sensitivity	-89 dBm

Table 3: Parameters used for all the EV network cards

7.1.5 Wireless Access Network and Radio Propagation

EVs and RSUs communicate by using a basic WAVE application. The EVs are equipped with IEEE 802.11p network cards of which the parameters can be observed in Table 3.

We use the simple free space path loss model where the signal attenuation in free space, L (in dB), is calculated in function of the wavelength λ, distance d and path loss exponent α as follows [15]:

$$L_{freespace}[dB] = 10log\left(\frac{16\pi^2}{\lambda^2}d^{\alpha}\right)$$

For the obstacle shadowing caused by the buildings (which are also included in the Erlangen map), we have also used the method suggested by the authors of the Veins framework [15], who extend the regular path loss calculation by adding the following term:

$$L_{obs}[dB] = \beta n + \gamma d_m$$

This term is applied for the obstacles in the line of sight, and represents the additional attenuation that the signal suffers when it intersects n times the building's border and traverses d_m meters inside it. The two factors, $\beta[dB/wall]$ and $\gamma[dB/m]$ have been obtained by the authors of [15] by calibrating them by contrasting with experimental results obtained with real vehicles equipped with IEEE 802.11p antennas.

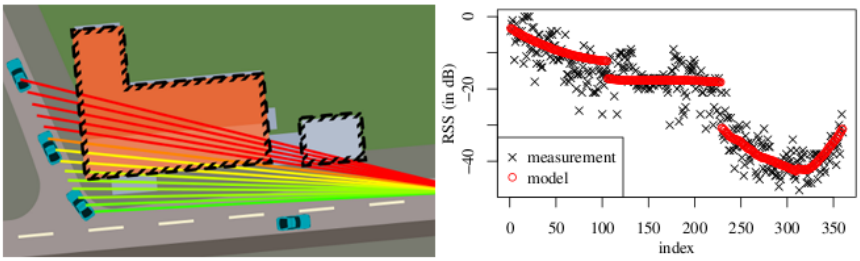


Figure 8: Evolution of the received signal strength: results obtained with the chosen path loss and obstacle shadowing models compared to experimental measurements. Source: [15]

7.1.6 WAVE Application

For these simulations, the WAVE application that the vehicles and RSUs use to communicate is quite simple: all the Road Side Units belong to a single multicast group (they have the same address), while each vehicle has its own address.

Vehicle logic:

- If the battery level is below the threshold value, propagate a message addressed to the RSU multicast group, containing the vehicle's current position.
- If no response is received after 1 s, repeat the message.
- If a message from an RSU is received, and it is addressed to this vehicle, telling the address of a suggested charging station, store the current destination[2], and set route to the received address. Ignore all following messages of the same kind[3].

RSU logic:

- If a message from a vehicle is received, execute the assignment algorithm (see Section 7.1.7) to determine the corresponding charging station. Send a message addressed to the corresponding vehicle containing the charging station's address.

[2]This is an implementation issue. We store the original destination so that the vehicle object (in programming terms) remembers where it has to go once the recharge is done.

[3]For the moment, we consider that all the RSUs dispose of the same data and so their responses will be the same.

As it can clearly be seen, there is no need for an acknowledgment procedure. Duplicate requests are not detected by the infrastructure, since there is no reservation procedure. Rather than an assignment, the message the infrastructure sends to the vehicle could be considered as a *suggestion*. That is why, for instance, in the case of an asymmetric communication where the messages sent by the vehicle are detected by a Road Side Unit, but the reciprocal is not true, the vehicle could send 100 requests in 100 seconds, and each time the system would simply run the chosen algorithm (for instance, determining the nearest station) and send the answer to the vehicle.

Of course, such a simple system is not very useful in real situations, but it is enough to test the four basic strategies that we wanted to analyze in our simulations. The next step will involve the creation of a smart optimization algorithm possibly coupled with a reservation system that would undoubtedly need a more sophisticated WAVE application.

7.1.7 Assignment strategies

We will compare four basic strategies to assign a charging station to a vehicle:

- **Nearest charging station (abbreviated *Nearest*):** The station that is closer to the vehicle's position included in the request will be assigned.
- **Station with the most free places (abbreviated *Most Free Places*):** The station with the most free places is assigned. If there are two or more stations that have the same amount of free places (and this number is the maximum), the previous strategy applies.
- **Smallest Waiting Line:** The station with the minimum amount of vehicles waiting until a place becomes available is assigned. If two or more stations fulfill this criterion (including the case where there are no waiting lines in any station), the previous strategy applies.
- **Random:** Any charging station can be assigned, with uniform probability.

We will explore these basic alternatives (some of which are commonly used as an example in related work) and their results in order to identify their effect in our metrics and settle the basis for a multi-criteria optimization strategy. In future work, the optimization should be resolved in a distributed manner, locally, also taking into account the available power in the grid.

For this first simulations, we have not divided our relatively small map in regions, local areas, or station clusters, and we have not considered any constraints in the electric power supply.

7.1.8 Metrics

We are now going to analyze the evolution of the following metrics, in function of the chosen assignment strategy, the number of vehicles in the system, and the number of available places in the charging stations:

- **Supplementary distance:** The difference between the origin-to-destination distance calculated in the beginning and the total distance that the vehicle has actually covered by the time it reaches destination after going to a charging station. In other words, it is a measurement of the detour taken to go to the charging station. Please note that this metric is only measured for vehicles that complete the whole process of sending a request, going to a charging station, and then arrive to destination.
- **Energy required to reach the charging station:** It is the energy in kWh consumed from the vehicle's battery from the moment it sends its first request until it arrives in a charging station.
- **Communication delay:** It is the time elapsed between the moment when the first request is sent, until a response is received. Remember that there is no coverage warranty and that it is possible that none of the RSUs is at reach at a certain moment.
- **Number of occupied places per Charging Station:** It is the result of taking the average number of occupied places in each charging station, and calculating the average.
- **Waiting queue size:** Similar to the previous item, but analyzing the number of cars that are waiting in each station for a place to become available.
- **Waiting time:** It is the average waiting time of all vehicles that go to a charging station (that includes those who found an available place at their arrival and did not have to wait).
- **Number of fully depleted batteries:** The number of vehicles of which the battery level reaches zero before arriving at a charging station.

7.2 Detailed results

7.2.1 Supplementary distance

In Figure 9 we see, for the scenario with 24 total places in the charging stations, the average supplementary distance, expressed in percentage of the original distance, in function of the total number of vehicles in the simulation, compared for the four different assignment criteria.

It must be remarked that it is normal that the percentages are high since it is a small area, with very short trips, and few charging stations. Those percentages would be lower if there were more charging stations, but the aspect of the curves would remain similar. Expressing the supplementary distance in absolute values (in m or km) would also be of little interest.

It can easily be seen that the random assignment is, as it could be expected, the worst case since it is the only criterion that does not take proximity into account (both "Most Free Places" and "Smallest Waiting Line" do, as a secondary step). Of course, the nearest station strategy being the theoretical optimum for this metric, it outperforms any other possibility in this category.

We have observed that most metric evaluation tend to show two different scenarios, one when there are few vehicles and thus waiting lines are extremely rare, and another one when an apparent equilibrium point is passed, and waiting lines and waiting times grow very fast in function of the number of vehicles. In this case, we can observe this phenomenon for the *Most Free Places* and *Smallest Waiting Line* strategies. By definition, when there are no waiting lines, they behave exactly the same. At this point, both strategies seem to be a good compromise between the best and the worst case. However, once that the service capacity is exceeded by an increasing number of vehicles, they behave completely differently.

Finding a free place becomes rare, and so, according to the formulation of the Most Free Places strategy, when all charging stations are full, the number of free places is the same for all of them (zero), and so when this happens, Most Free Places becomes Nearest. The curves never become the same since even if after a certain point these strategies behave equally, at least at the beggining of the simulation they behave differently, and each point of these curves represents the average values in the whole four simulated hours.

On the other hand, when waiting lines become important, Smallest Waiting Line will privilege the optimization of the waiting time, completely ig-

noring and sacrificing proximity, and thus becoming, for this analysis, very similar to Random.

The analysis of the variation of the available places in the charging stations is uninteresting.

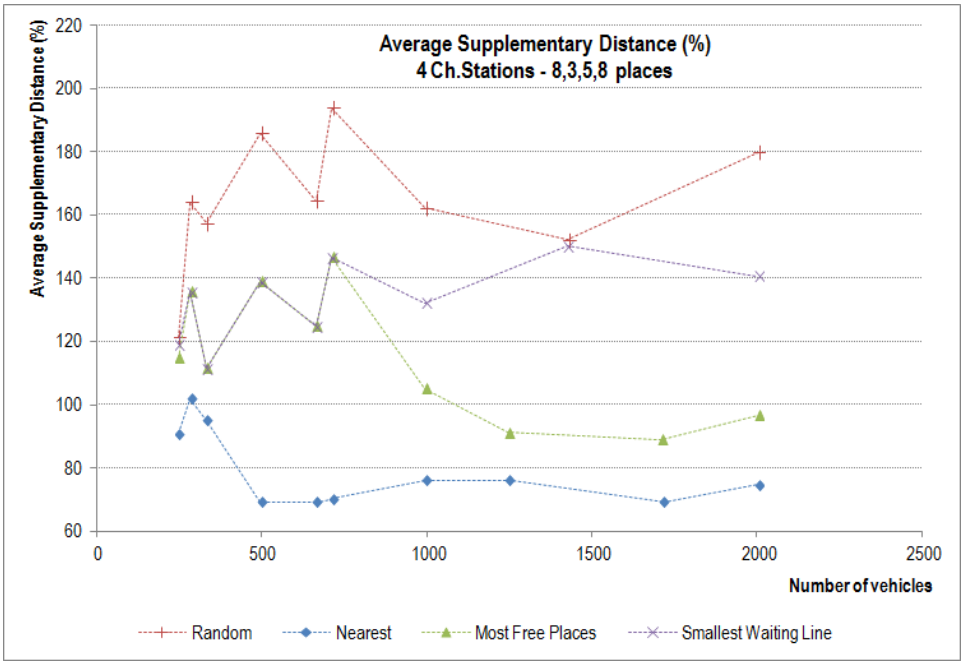


Figure 9: Average supplementary distance percentage in function of the number of vehicles in the simulation. Comparison between the four different criteria.

7.2.2 Energy required to reach the charging station

This metric becomes a direct echo of the previous one. In Figure 10 we will observe the same behavior, and we see that, for this scenario in particular, the amount of energy needed is between 0.2 and 0.35 kWh.

Even if under the current hypothesis (all vehicles have the same characteristics and there is a constant, exclusive linear relation between distance and battery consumption) this metric may seem trivial, the measurement is made in a way which is completely isolated from the distance and thus the simulator is prepared for analyzing more complex cases where 2D distance and battery consumption have a less exclusive link. For instance, we can consider that battery consumption changes in function of the speed and the acceleration, being in consequence traffic-sensitive. This measurement could then become really useful for more complex optimization strategies.

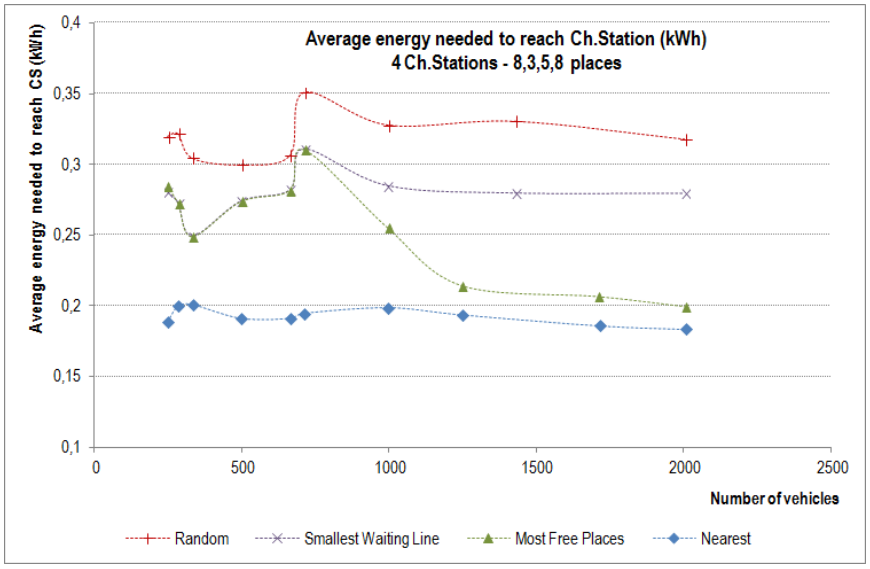


Figure 10: Average energy required to reach the charging station, counting from the moment of the first request. Comparison between the four different criteria.

7.2.3 Communication delay

This is an important metric to decide the best geographic distribution of our RSUs, with the convenient economic analysis: what is the maximum delay we could tolerate for a certain amount of expenditures in network deployment.

If we see Figure 11, we learn quickly that the assignment criteria has nothing to do with the communication delay. Almost the same for the total number of vehicles. It only depends of the density of our RSU network. For our current scenario, the average of this delay is around 20 seconds. Clearly, this analysis shows very little information about this problem. That is why in Figure 12 we see the individual communication delay for several vehicles in a single simulation. It should not be a surprise to see that while a considerable part of these vehicles experience a minimum communication delay of around 0.15s, the vehicles that start sending requests when they are very far from the coverage area experience delays of up to 120 s.

We are interested in this metric because in the case of high node density or in presence of interference, we might have missing messages in the wireless network, and also the communication delay is useful for comparing centralized and distributed approaches.

However, this is hard to simulate at this stage, since we need to have

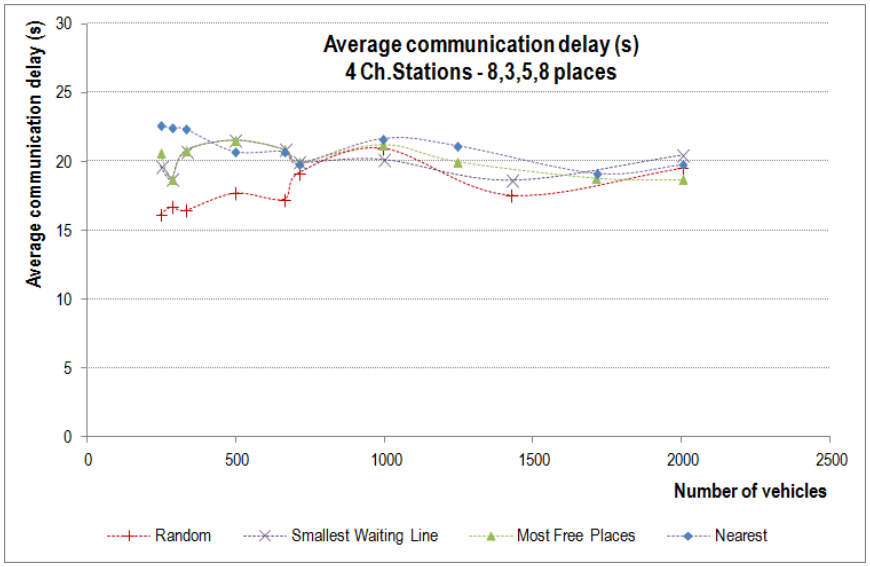


Figure 11: Average communication delay in function of the nomber of vehicles. Comparison between different assignment criteria.

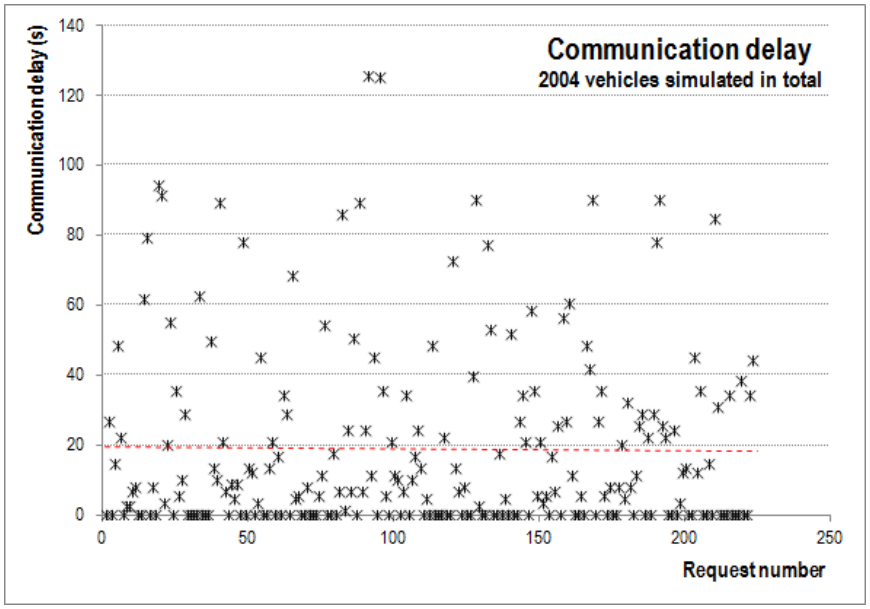


Figure 12: Communication delay for individual vehicles in a single simulation of 2004 vehicles.

a server model and augment the network traffic volume. In big scenarios, this will have an impact and we would be able to find the limits of a given system in part by studying the communication delay.

7.2.4 Number of occupied places per Charging Station

Figure 13 shows us, for the four analyzed criteria, the evolution of the average number of occupied places per charging station for the 24-place configuration. It is important to notice that, while each charging station has a different total number of places, this graphic takes the average for all of the charging stations' individual average measures taken during the four simulated hours. This is why the asymptote for the four curves is 6 (the number of places that each charging station would have if the places were distributed evenly).

We can see that the Random strategy seems to have noticeably inferior average values once the equilibrium point is passed. This is because the Random stategy does not take into account any kind of even distribution of the vehicles in order to take advantage of existing free places, and by doing so, vehicles start forming waiting lines much earlier (see Section 7.2.5). Remember that only the vehicles that are actually being charged (not waiting) are taken into account for this metric.

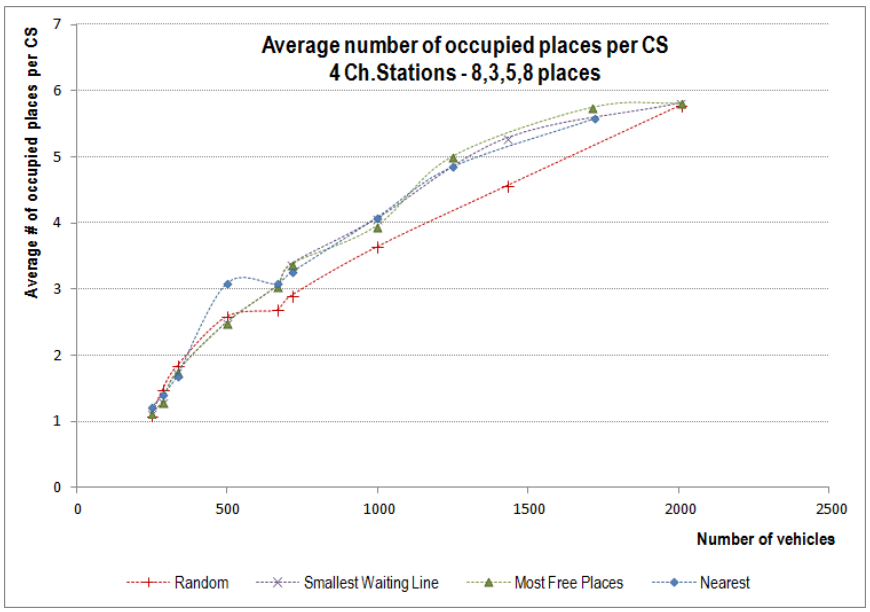


Figure 13: Average number of occupied places per charging station in function of the number of vehicles in the system for the four criteria analyzed.

The reader may ask why, then, the Nearest strategy does not perform as bad as the Random strategy, given the fact that it does not administrate free places either. The trick in this aspect is that we are one step ahead in this analysis, because the chosen distribution of the amount of free places

in each station is not random: both the 24-place and the 33-place configurations were dimensioned in function of the demand analyzed in the first simulation set that has been run (the 12-place configuration, with evenly distributed places). We can deduce, then, than if a correct dimensioning of the demand is done for a specific scenario, the Nearest strategy will perform as good as the other two "smart" strategies, while Random will always have a poorer performance.

The results that have been taken into account in order to do this dimensioning can be seen in Figure 14, where we can see the evolution of the average number of occupied places for each charging station in particular. This way, we see that there is a very important demand for the charging stations 0 and 3, which can be considered to be "central" stations. Charging station 1 only approaches full capacity for the highest amount of simulated vehicles and thus it does not need to be redimensioned. Charging station 2 is in between both situations, but since it approaches full capacity for a very high number of simulated vehicles, we can assume that only a very modest redimensioning should be done, if necessary.

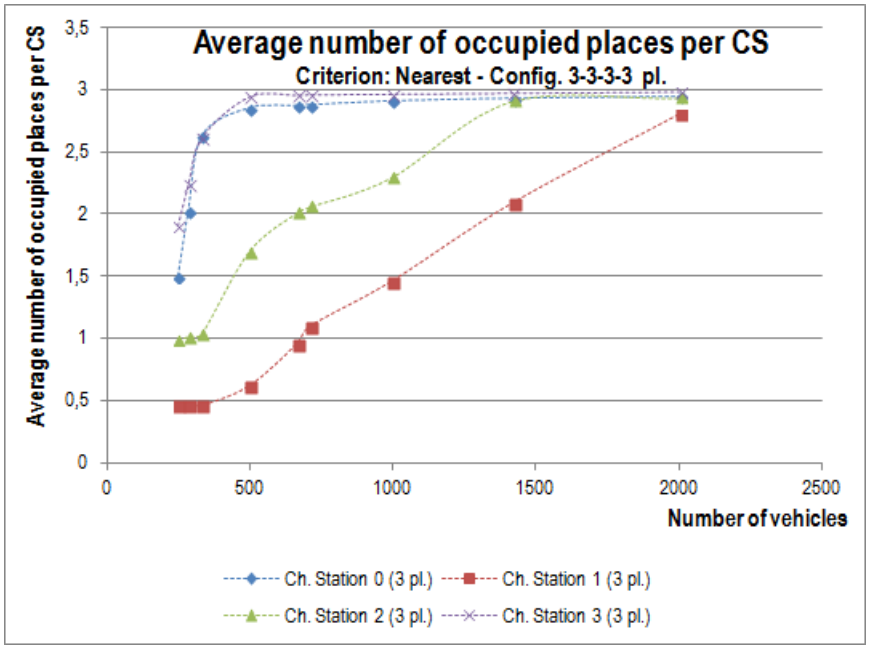


Figure 14: Individual average number of occupied places for each charging station in function of the number of vehicles in the system for the 12-place configuration.

We can now compare with Figure 15, that shows the case of the 33-place

configuration, seeing that now each charging station smoothly approaches full capacity.

We have shown an approximate, informal method for dimensioning the charging stations according to the demand. In further work, this method could be formalized in such a way that we would only need to have the realistic, measured vehicular traces in an area of our interest in order to be able to suggest possible dimensions for the charging stations in the points of our interest. Even further work would be an optimization problem to find the best n-subset in a set of possible charging station locations that takes the most profit of the available places.

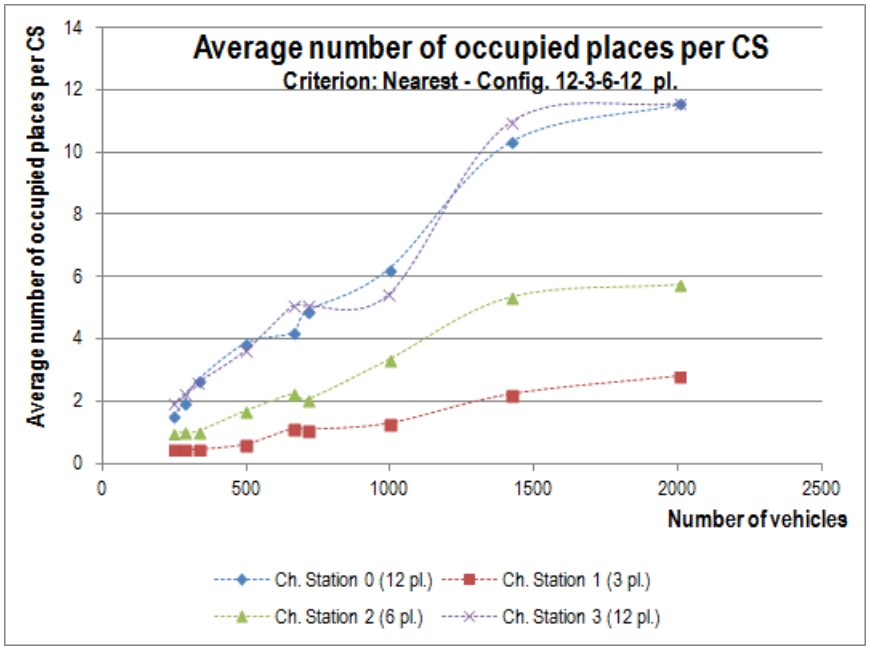


Figure 15: Individual average number of occupied places for each charging station in function of the number of vehicles in the system for the 33-place configuration.

7.2.5 Waiting queue size and waiting time

Figures 16 and 17 represent the evolution of the waiting queue size and waiting time in function of the number of vehicles for the four strategies, respectively. Together with the supplementary distance, these are probably the most important metrics from the user's point of view, since queues and long waiting times are undoubtedly an unpleasant experience for everyone.

One of the first things that becomes evident is the clear identification of the equilibrium point of the system, with the 24-place configuration. For up to approximately 700 vehicles, for any strategy, in this particular scenario there are seldom waiting lines, and waiting times. After this point, the size of the queues and the waiting times rise very fast, quickly reaching possibly unacceptable values. Please note that these are average values, and that means that when the average waiting time in the system is 10 minutes, there will be drivers that will have to wait much longer than that. Thus, in order to maximize user satisfaction, it will be fundamental to clearly identify this equilibrium.

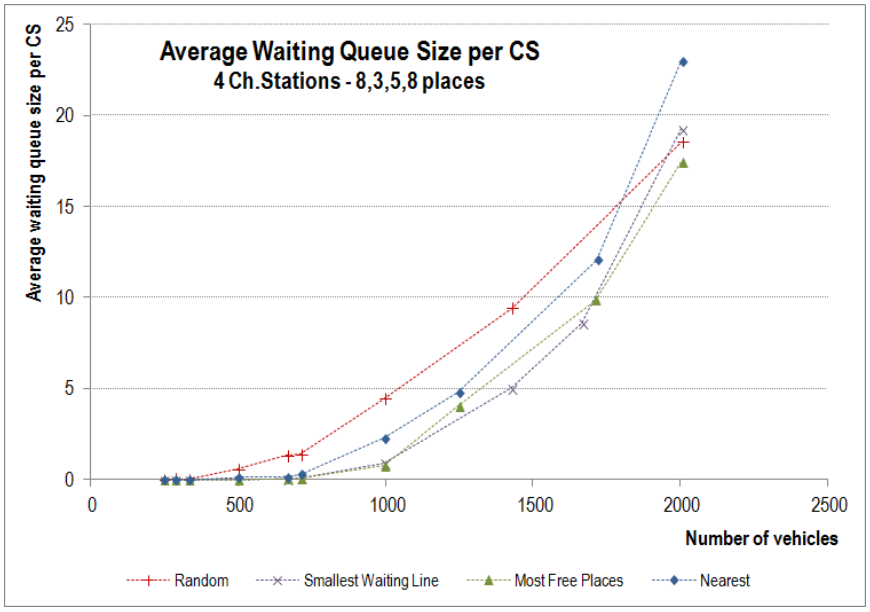


Figure 16: Evolution of the average waiting queue size per charging station for each one of the four stategies, in function of the number of vehicles.

As expected, the Random strategy is the first one to take off, much earlier than the others, in terms of both queue size and waiting time. However, we can observe that for an over-saturated system, the Nearest strategy reverses the tendency and becomes the worst case in both curves. We should think now, again, why would Nearest perform better than Random in this case. The only reason why Nearest has a performance similar to the two queue-aware ones is that there is an artificial equilibrium generated by the way the charging stations were dimensioned, in order to improve Nearest's performance. This is why we see, for the highest vehicular densities, a second equilibrium that breaks and shows that Nearest actually performs worse than random when there are zones of very high demand.

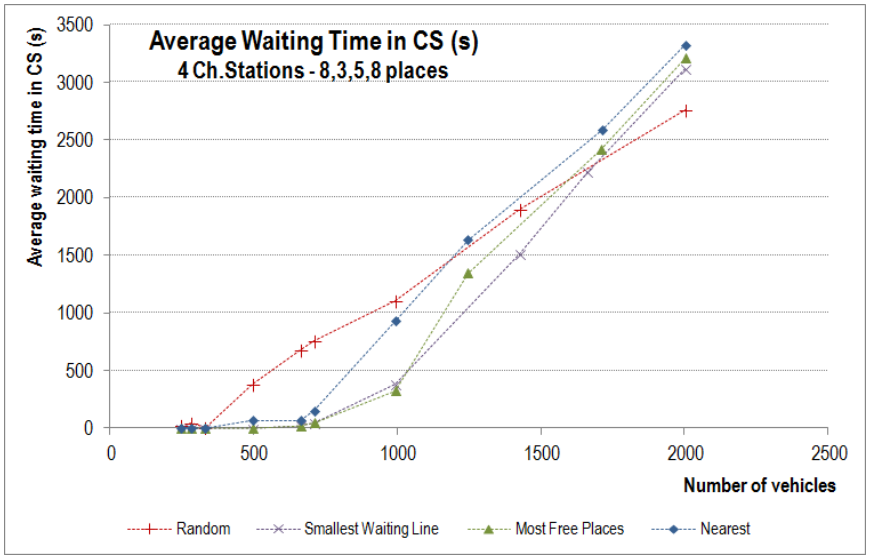


Figure 17: Evolution of the average waiting time of the electric vehicles for each one of the four stategies, in function of the number of vehicles.

Finally, in Figure 18 we analyze the evolution of the average waiting queue size in function of the total number of vehicles for the different dimensioning possibilities. As it could be expected, additional places will simply delay the transition between both regimes, but will not change the vertiginous rise of the curve.

7.2.6 Number of fully depleted batteries

The event where a vehicle's battery reaches zero before getting to the charging station is very rare. There are no occurrences registered when the Nearest strategy is used, and there are seldom singular cases with Most Free Places or Smallest Waiting Line. The worst case comes for Random, as we can see in Figure 19.

There is also a perhaps very hardly quantifiable influence of the number of RSUs, since it could be possible to have a case where a low RSU density implies for a particular vehicle that risks full depletion a very significant communication delay that might be the factor that seals the vehicles inability to reach the station.

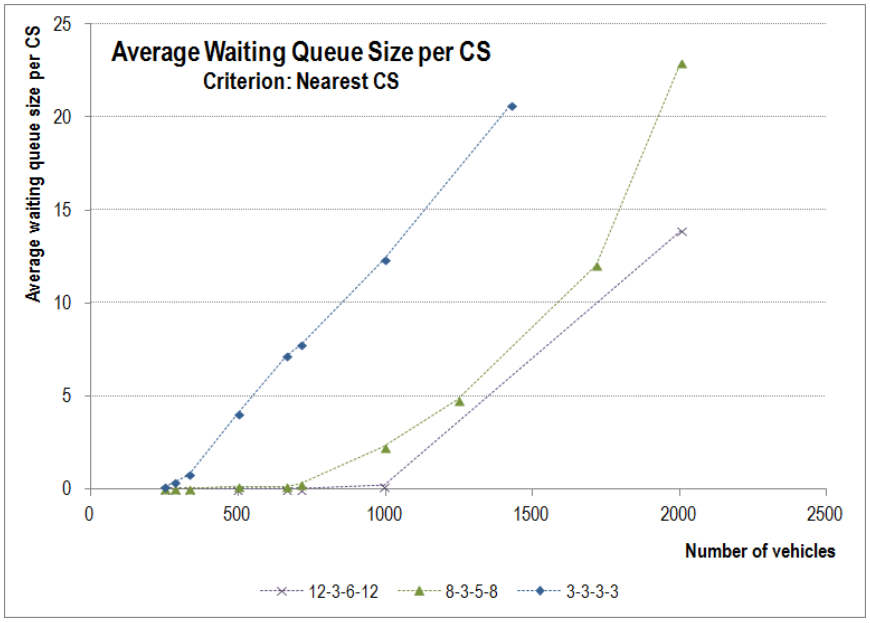


Figure 18: Evolution of the average waiting queue size per charging station for the different dimensioning possibilities, in function of the number of vehicles.

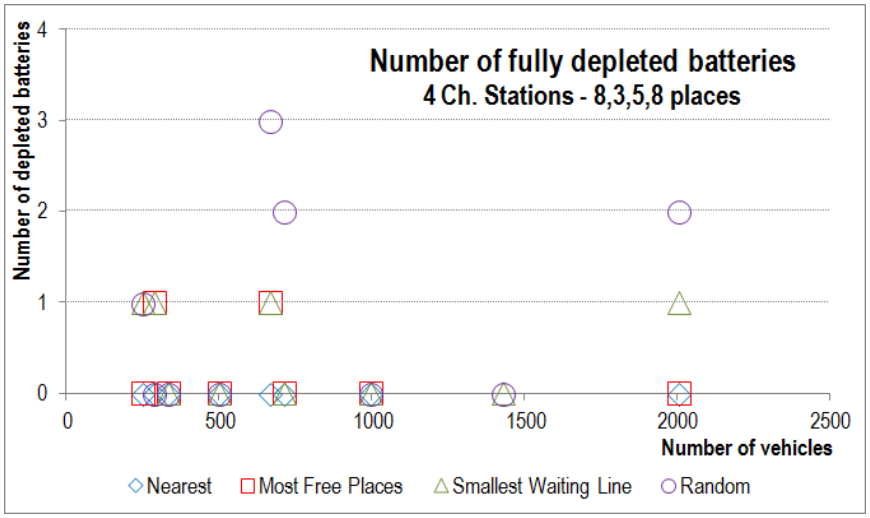


Figure 19: Number of fully depleted batteries in function of the total number of vehicles simulated for the four strategies.

8 Conclusions and future work

Over the last months, we have built a simulator that allows us to accurately represent an Intelligent Transport System (ITS) in which the electric

vehicles, charging stations and communication devices are modeled in a realistic manner, based on previously studied bibliography. We have coupled a microscopic traffic simulation, and an extremely detailed network simulation, including radio propagation analysis, and an in-depth reconstruction of every layer (from physical to application) of every communicating device in the system, configuring their characteristics following the specifications of the IEEE 802.11p standard, intended for vehicular environments. We have added the electric vehicle battery simulation, and the corresponding recharging process in the charging stations, as well as a network of Road Side Units (RSUs) for wireless access. We have then created a first basic ITS application that allows the vehicles to ask the system (via the RSUs) for the position of the charging station they should go to.

We have compared four basic criteria to choose the charging station to be assigned to each vehicle. The simulator we have built allowed us to evaluate several service and network-level metrics, as we have seen in Section 7. The analysis of these metrics for our basic assignment criteria allowed us to identify and quantify their benefits and shortcomings, and study their behavior in general. By doing so, we have settled the basis to develop a weighed multi-criteria optimization.

From the results we have seen, we remark the importance of doing a demand analysis prior to dimensioning the proposed recharging infrastructure, if not given. We can also see that given the normal amount of time required for recharging a battery, if in the environment under study the EV penetration level is high, a reservation system could be a very significant added value. We have also seen that for a certain installed capacity in the recharging infrastructure, there is an equilibrium point depending on the vehicular density, that becomes a turning point in every strategy's performance concerning the most part of the metrics involved. A smarter optimization algorithm should take advantage of the WAVE wireless network to deduce the approximate vehicular density in real time and perhaps modify the strategy to apply in consequence.

Concerning future work, the most immediate needs are including a simulation of the electrical grid's available power in different areas of the map, incorporating the associated metrics, and using bigger maps in order to pass to a distributed logic. The distributed protocol to implement will radically change the simple communication scheme presented here for testing purposes, and will be based on the diffusion of charging station capacity and vehicle charging intention information, regulating data freshness in order to keep the communication load reasonable.

Later on, this work will continue in a PhD thesis in which we will conceive

a generic scenario, making it easily adaptable to the technological evolution, and we will focus on developing solid optimization algorithms and specifying a distributed architecture. We will start the PhD by dealing with the following problems:

1. Identifying the system's limits not only in terms of traffic or EV and charging station density but also in terms of network load.
2. Incorporating the distributed aspect to the problem. Until now we have a centralized architecture in which all of the RSUs have the same information. What happens when we only dispose of local information? How do we take advantage of the vehicular network? How to manage data freshness, network load and, in the case of having a reservation system, how to correctly diffuse the associated information and do the assignments?
3. Approximating our problem to known models. For instance, the presented results for charging stations' availability is coherent with the exponential queuing theory. We could eventually use this model to help improving the system's predictions.
4. Discussing how to find a good compromise between the electrical operator's and the user's interests, in order to build a multi-criteria optimization algorithm.
5. Managing uncertainty, since there are plenty of factors that are difficult to predict, such as driver's behavior, penetration rate evolution estimation, charging station business models, etc.
6. Analyzing the interaction between the smart grid and the user in strategic and economical terms, such as variable pricing, bonus incentives, etc.

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Glossary

EV	Electric Vehicle
RSU	Road Side Unit, the wireless access points for vehicular networks
CS	Charging station
OBU	On-board unit, the wireless network equipment in the electric vehicles
WAVE	Wireless Access for Vehicular Environments, formed by the IEEE 802.11p amendment and the IEEE 1609 standard family
SUMO	Simulation of Urban MObility, a microscopic traffic simulator
TraCI	SUMO's Application Program Interface for remote control of the simulation via TCP connection
WSMP	WAVE Short Message Protocol, a network protocol specifically designed for carrying short messages over WAVE
WSM	WAVE Short Message, the kind of message used in WAVE's native protocol
SOC	State Of Charge, the quotient between the amount of battery left and the battery capacity of an electric vehicle
CHAdeMO	A commercial brand of Fast DC charging at 45 kW
DSRC	Dedicated Short-Range Communication. USA and Europe have reserved frequencies around 5.9 GHz for this type of communications. These frequencies are used by WAVE.
ITS	Intelligent Transport Systems
MAC	Media Access Control
BMS	Battery Management System