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YOUR BOAT
LESS

WIRE CHARGE YOUR BOAT LESS

Spatial-temporal challenges for optimization of future wireless power transfer charging stations for electric vessels in Amsterdam.

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"All models are wrong. Some models are useful."

- George E.P. Box

Abstract

In recent years an effort to tackle pollution and achieve sustainability has been made throughout the world. In terms of energy and mobility, this has resulted in low or emission-free mobility implementation. Electric mobility in an urban area requires a well thought development plan, especially when considering the charging infrastructure required for it. In cities such as Amsterdam, electric mobility also involves boats.

To select a suitable location for charging infrastructure for boats in Amsterdam, this study proposes a paired approach: A Spatio-Temporal analysis combined with a Multiple Criteria Decision Analysis. Moreover, different charging technologies, such as Wireless power Transfer are reviewed.

Based on real life vessel location data, this study implements spatio-temporal analysis for location selection for new charging stations in Amsterdam Centrum, taking its unique characteristics into consideration. This study provides insights on route and flows, density of vessels, speeds, characterization of vessels. The results are followed by a spatial multicriteria decision analysis. By means of GIS tools, specific locations for charging infrastructure are calculated.

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List of figures and tables

List of Terms and Acronyms

AHP Analytic Hierarchy Process

CDR Call Detail Records

EV Electric Vehicle

EMF Electromagnetic Field

GIS Geographic Information System

GPS Global Positioning System

IC Inductive Coupling

kW Kilowatt

Kwh Kilowatt-Hour

MCDM Multi-Criteria Decision Making

MCLP Maximum covering location problem

MM Mathematical Modeling

MOORA Multi-objective optimization by ratio analysis

MSW Municipal Solid Waste

MRC Magnetic Resonance Coupling

RF Radio Frequency

SCLP Set Covering Location Problem

V2G Vehicle-to-grid

WPT Wireless Power Transfer

Introduction
01

Introduction

Context

Many cities around the world are facing multiple challenges of different nature; technical, environmental, social, or economical. These challenges are seldom isolated but are rather intertwined with each other.

The transition towards more sustainable technologies in mobility is inevitable, and today we can see steps have been taken towards a greener vehicle which take electricity instead of fossil fuels. Going electric, although promising, also has its disadvantages since it creates a new electric demand which had never been thought. These energetic transition creates opportunities for development. If mobility in a city wants to become electric, what must be taken care of today so that the city can be ready for tomorrow? This calls for an environmental solution which accepts technical, social and economic challenges.

In the case of Amsterdam, the Netherlands, the city aims for a better usage of its canal networks. Mobility solutions by waterways are an attractive part of the city logistics, services, or leisure. If implemented correctly, it can be part of the zero emission strategy and contribute to a healthier more accessible and attractive city.

As of 2022, this city has already taken the first steps towards improving air quality for its citizens. This means that all forms of transport will be emission free within 10 years, including transportation by water. (Gemeente Amsterdam, 2021b)

The Sailing Program (Nota Varen, 2018) contains policies to have a smart use of the waterways? including passengers pleasure boating and other type of waterborne transport. Together with other programs, such as the Clean Air Action Plan, the municipality is working towards a sustainable and emission free mobility in city, aiming to reduce CO_2 emissions by 55% by 2030 (Gemeente Amsterdam, 2020b). Waterways then play a very big role, as mobility in the city of Amsterdam entails more than just land mobility: it means also mobility by water.

According to a study conducted by the municipality at the end of 2018, 76% of smaller passenger vessels are already emission free, however more than 70% of larger vessels still operated with Diesel engines (Gemeente Amsterdam, 2020b). These numbers were obtained out of a 450 vessels survey, However the municipality acknowledges the presence of almost 12,000 pleasure vessels in Amsterdam with less than 5% of them emission free (Grachtenmonitor, 2021), in addition to 20 tugboats also diesel fueled.

Amsterdam has set the goal of having a mission for sailing in 2025 at least in the city center, to be expanded to larger areas by 2030. To achieve this sustainability goals by 2025, sustainability measures for vessels have to be established such as installation of charging infrastructure and moorings in public water, support marinas in installing charge infrastructure, and informative website for pleasure vessels as well as one for city logistics and the transport of goods on water.

The development of electric vessels requires the use of new technologies, and in some cases, the current vessels cannot be easily converted into electric vessels due to lack of on board space for the batteries.

The city is however not yet prepared for this transition. One of the problems current ship owners face is the lack of sufficient charging points for their electric vessels. The city of Amsterdam installed 10 charging stations mainly of use for pleasure crafts. spread out over its districts. In 2022 five of these stations were ready to use in the city center, with each station big enough for two vessels at the same time. 10 stations are insufficient to cover the electricity need of boating over the Amsterdam canals. The city of Amsterdam is aware of this and is looking for innovative sustainable solutions to cover the demand, for example a pilot with charging points at house boats in collaboration with private companies, one of these charging points is in the Houthavens.

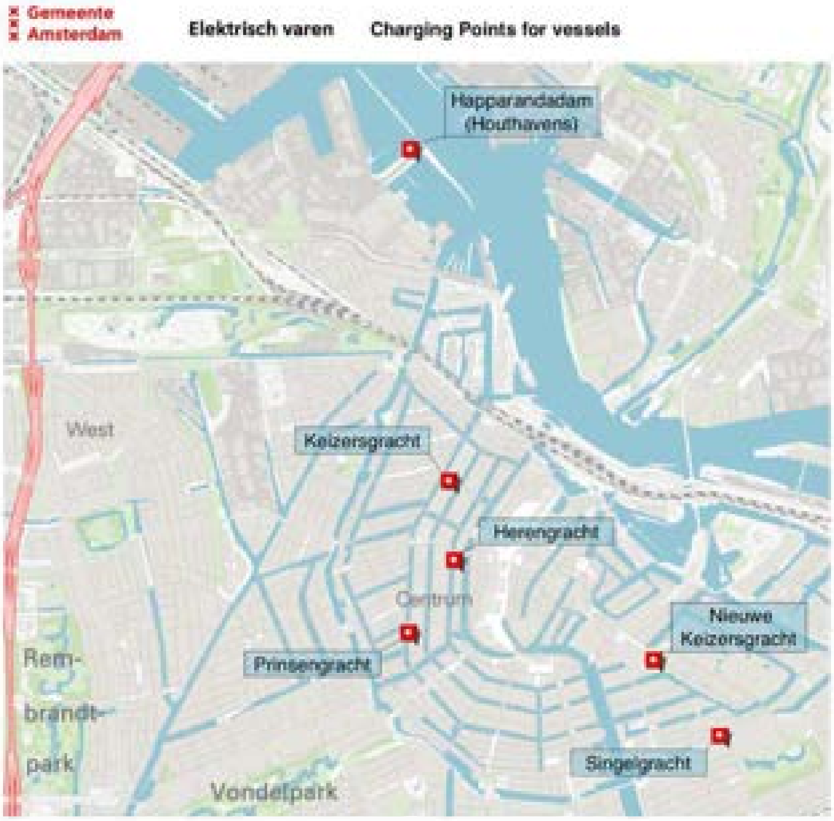

Figure 1 Charging points in Amsterdam Centrum and Houthavens

An initial plan for the location of charging points in the Houthavens was drafted in consultation with the area managers, The even distribution of charging locations and the ease of access to them were regarded as the most important criteria. A setup with even distribution of charging locations was thought to tackle the energy challenge. However, in order to deploy charging facilities for boats in the city of Amsterdam, a certain amount of space is required. The second criterion for this plan – ease of access- meant limiting charging facilities to the locations that had enough space for vessels to dock, space for charging equipment at the quay and from where vessels vould be easily boarded. Available space in the city and on the quays turned out to be an important player when imagining charging locations for vessels.

Amsterdam's ambition to become an emission-free sailing city by 2030 is a huge challenge. It requires a comprehensive plan, which should include the development of new technologies and the exploration of new ways of supplying energy to vessels, and the development and deployment of charging stations. According to the Municipality, Passenger and pleasure vessels amount up to 7% of nitrogen emissions and 4% of particulate emissions (Clean Air Action Plan, 2019).

In face of the energy transition, the deployment of charging stations for vessels must initially answer two questions: Where? How many?

These questions entail much more than a location and a number. Whether limited by the amount of vessels, the available space in the waterways and at the quays, the presence of power near the shore, several aspects come into play.

Existent Research and Knowledge Gap

There is currently little research done to link charging technologies with charging stations location optimization for electric vehicles. In many cases, the focus of these approaches lies solely on the spatial distribution of charging stations given a demand. In some other cases, the aim is to maximize user accesibility considering round-trip data. Many others try to optimize the location of charging stations by finding the shortest path from one point to another. A few have investigated battery depletion along a vehicle's path. Lastly, some have found suitable locations for charging station by analizing several parameters in what is called a multi criteria decision analysis.

(Schüßler et al., 2017) optimized the spatial distribution of charging stations with the demand given as a constant. You & Hsieh (2014) created a mixed-integer programming model to maximize the number of people that could access a charging station considering round-trip itineraries. A different solution, proposed by Cavadas et al. (2015), takes into account single journeys with long stops, allowing only for slow charging solutions. Other methods look into implementing new charging stations following Dijkstra's algorithm, as is done in the research by Niklaus (2017), and hence view the solution as a shortest path problem. Feng et al. (2019) followed a probabilistic approach for the deployment of electric vehicle charging stations, considering congestion at the stations. Fang et al. (2015) created a bi-level mathematical program coupled with a genetic-algorithm-based procedure to optimize the location of charging facilities. Iravani (2022) uses a GIS approach paired with a MCDM to optimize the location of EV charging stations. For the study, several parameters were used such as number of cars owned in high income areas, number of households not owning a car, walkability level and total number of trips. In (Frade et al., 2011) the location optimizing for EV charging stations was based on the estimation of the refuelling demand using a model for maximal covering. The demand was extracted from static census historic data. Other authors have simulated driver's behavior within a road network (Hess et al., 2012). In (Vazifeh et al., 2019) cellphone data record of 1 million people in Boston, call device records (CDR), were used. While GPS data shows accurate results, CDR has proven to work in urban settings (Calabrese et al., 2011). In many cases, the modeling via CDR loses accuracy due to incorrect assumptions, such as considering people movement equal to people in cars movement (Vazifeh et al., 2019), or may be incorrectly geographically aggregated due to the way the grid of the study area was built.

As can be seen, different models and approaches have been explored in the past, each of them with different goals in mind.

In an effort to support emission free sailing over the Amsterdam canals, this work aims to find locations for new charging stations in Amsterdam Centrum.

Objective and Research Scope

Although cities are constantly looking for ways in which to improve energy production whilst reducing energy consumption, the current work aims at finding locations for new charging stations for boats in Amsterdam Centrum canals. Moreover, this work will open a discussion on the possibilities of different charging methods such as wireless power transfer.

In the process of finding these new locations for charging stations for boats, this research will

- Identify how the vessels utilizing the Amsterdam's canals move spatially and temporally throughout a typical day.
- Investigate the feasibility of the locations of charging points and the installation, according to existent research and policies in order to meet the emissions goal by 2030.
- Discuss on the different charging methods

Research Questions

The following research questions set the compass for the current work and will in turn be answered:

1. How can real vessel mobility patterns help find locations for new electric vessel charging stations in Amsterdam Centrum considering spatial-temporal challenges?

Real vessel mobility patterns are used to find new locations for electric vessel charging stations in Amsterdam Centrum by taking into account spatial-temporal challenges.

Through a data-driven approach combined with GIS analysis the mobility patterns of vessels, such as the frequency of trips made, the most popular routes taken, and the amount of time vessels are usually docking or the amount of time vessels spend at specific locations, it is possible to identify areas of high capacity and areas of peak activity. The feasibility of results are supported by taking into account spatial-temporal challenges, such as seasonal shifts in vessel mobility, morphological and physical restrictions (e.g., bridge closures).

Several sub-research questions are formed to successfully answer the question stated above.

1.a What are the charging methods available for electric city vessel charging?

In the pursuit of a cleaner Amsterdam, in the near future all boats will be electric. However there are many ways in which energy can be delivered to the boat. Each method may have its advantages or disadvantages and it is important to understand their applications and limitations.

1.b How to classify vessel typologies in the context of Amsterdam's waterways?

Vessels in Amsterdam follow different uses and needs. As such, they can be classified in a number of ways. This can be by vessel type (e.g. sailboats, motorboats, barges, etc.), size (e.g. small, medium, large, etc.), purpose (e.g. passenger boats, commercial cargo vessels, etc.), or fuel type (e.g. diesel, electric, hybrid). Additionally, vessels can also be grouped by the type of route they typically follow, such as short-haul, long-haul, or tourist routes. This classification is important to understand the impacts, challenges and opportunities when developing a model optimal locations of vessel charging stations.

1.c What are the spatial considerations and limitations for implementing charging stations in Amsterdam?

Spatial considerations and limitations for implementing charging stations in Amsterdam include identifying viable locations in the city, locating potential charging stations near potential vessel routes, understanding physical constraints and restrictions such as bridge closures, available space in the quays, trees, parking spaces, historical heritage; And ensuring access to electrical power. It is important to note that special considerations are taken into account when discussing the possibilities of WPT. The challenge consists namely of integrating charging stations into an already existing network of vessels in Amsterdam without the disturbance of it.

1.d What methods are currently applied for spatio temporal analysis for movement data ?

This is important for understanding the behavior of moving boats in Amsterdam, -for example the speed and trajectory of a boat over time - as it can help to identify important patterns and correlations. The analysis requires the use of different techniques to examine data that is collected over both time and space.

1.e What techniques can be applied for location selection of electric charging stations for boats?

There are several techniques towards finding the location for new electric charging stations for electrical vehicles. In some cases this may involve using geographic information systems (GIS) to analyze the data and create a map-based visualization of the potential sites. In other cases, the selection of new locations may be achieved by analyzing current trajectory patterns, examining infrastructure, or considering environmental factors such as weather.

Thesis Outline

The present work conducts a literature review in Chapter 2 on electric vessels, charging technologies and location optimization models. Afterwards, in Chapter 3 the chosen methodology and framework are explained. This is then applied to the case study discussed in Chapter 4, followed by the results in Chapter 5 after which a 6th chapter serves to conclude the thesis. A final chapter allows for further discussion on results, insights and limitations.

Literature Review 02

Literature Review

Electric Vessels

An electric vessel is any type of boat or ship that is primarily powered by electric motors. They can be classified according to their type of propulsion, size and purpose. For example, there are electric pleasure vessels, commercial vessels, passenger ferries, tugboats, amongst others. Electric vessels may have on board or detachable batteries. There are advantages and disadvantages to both on-board and detachable vessel batteries. On-board batteries are usually more convenient, since they are already built into the boat, and made to match the size and weight requirements of the boat. However, they can be hard to access and service, and their capacity may be limited. Detachable batteries are more flexible, since they can be taken off the boat to be serviced or replaced, however, they can be heavy and may not fit all boats due to shape and size.

The City of Amsterdam setup a website to help people make an informed decision when retrofitting or buying an electric vessel. It is important to note that, while all vessels in Amsterdam will be electric by 2030, electric vessels have both advantages and disadvantages (Elektrisch Varen, 2021). As stated by the City of Amsterdam's knowledge website, some of the advantages are:

- No local emissions
- No sound . An electric motor runs almost silently.
- No vibrations from the engine, leading to higher comfort
- Lower maintenance and higher efficiency

While its current disadvantages are:

- Charging takes longer than refueling
- Travel distance on a single charge is smaller
- Dependency on charging stations
- Lifespan of a battery

Electric Charging Technologies

When charging a boat electricity is used near water. This poses several life risks. In recent times however, wireless charging technology has shown promising results.(Alam et al., 2022)

Charging Infrastructure and Connection Types

Charging infrastructure refers to the equipment needed to support the charging of electric vehicles (in land or water). This includes power outlets, charging stations, and cables that connect the charger to the vehicle's battery. Common connection types include AC Level 1, 2 chargers, and level 3 DC Fast Chargers, and wireless chargers.

AC Level 1 (standard wall outlet) and level 2 chargers use alternating current to charge the vehicle's battery and are typically the slowest type of chargers. Level 2 chargers range from 3 to 20kW (Charge Hub, 2023b). Level 3 DC Fast Chargers use direct current to provide a quicker charge. Wireless chargers are a form of wireless power transfer (WPT).

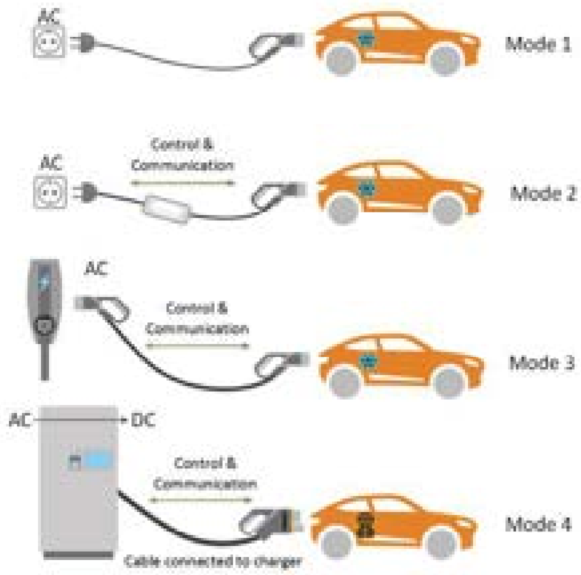

Figure 2 Charging infrastructure Modes, taken from TU Delft OpenCourseWare 2.3.2 Lecture Notes: AC and DC Charging

For wired connections, there are currently 4 modes used. Mode 1 and 2 belong to AC Level 1 chargers, with a slight difference; In mode 2 the cable is equipped with an In-Cable Control and Protection Device (TU Delft, 2022)

Mode 3 is the most widely used. It has a dedicated electrical socket for EV charging and englobe Level 1 or Level 2 charging. In this case, the charging station is responsible for the control, communication and protection of the charging process.

Finally, mode 4 corresponds to level 3 DC Fast Chargers. The AC/DC converted is located in the charging station and, again, the charging station is responsible for the control, communication and protection of the charging process.

Plug Types

There are different plug types for charging. The most common plug types are the J1772, Type 2 (Mennekes), Chademo, Tesla, and CCS. The J1772 plug is used by most electric vehicle models in the US and many other countries. The Type 2 (Mennekes) plugs are commonly used in Europe, while the Chademo plug is designed for DC Fast Charging. The Tesla plug is used exclusively by Tesla vehicles.

In the Amsterdam Centrum area the vast majority correspond to Mennekes plugs, according to data from Plugshare[1], OpenchargeMap[2] and the Municipality of Amsterdam[3]

Charging Power

The amount of charging power needed for an electric vehicle depends on the size of its battery and the vehicle's charging system. Generally, plug-in electric vehicles require between 3.3 kW and 22 kW of charging power (United States Environmental Protection Agency, 2023), while DC Fast Chargers may require up to 150 kW or more (Charge Hub, 2023a).

In water however, bigger systems have been installed for electric ferries, with MW chargers, where the time to charge is even smaller (Chen et al., 2020). The battery size and the charging system will determine the optimal amount of power needed for a particular electric vehicle. In the following chapters a special calculation for vessels in Amsterdam will be made.

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1 https://www.plugshare.com/

2 https://openchargemap.org/site

3 https://data.amsterdam.nl/data/vsd/oplaadpunten/

Charging Times

As can now be clearly seen, the charging time for an electric vehicle is a function of the type of charger used, the charging power required, and the size of the vehicle's battery. Generally, AC Level 2 chargers provide the slowest charging times while DC Fast Chargers provide the quickest charging times. Although many scientific articles state that fast charging starts at 30 min (Schüßler et al., 2017), it has been known for some EV to have charging times can range from as little as 20 minutes with a DC Fast Charger (TechRadar, 2021)

Wireless Power Transfer

Wireless power transfer (WPT) is a technology that enables the transmission of electrical power from a power source to an electrical load without the use of any wires or cables (Foote & Onar, 2017). It has been around since the late 19th century, when Nikola Tesla demonstrated the transmission of electrical power through the air using a Tesla coil, that was powered by a 300kW signal with a frequency of 150kHz (Detka & Górecki, 2022) This allowed for a wireless transmission of up to 3km. (Okoyeigbo et al., 2021).

Technologies in batteries keep improving, having each year more energy density capabilities than the last. However, in a utopian world, there would be no need for batteries, as energy would be found wirelessly. Needless to say, being able to wirelessly charge a vehicle while moving, i.e. while a canal passenger vessel cruises through the Amsterdam canals, can prove beneficial as the vessel will need smaller batteries. In 2013 the Korea Advanced Institute of Science and Technology (KAIST) developed the Online Electric Vehicle (OLEV). The OLEV could be charged while being stationary and while moving, resulting in a one-third reduction in the battery compared with that of a regular electric vehicle (Patil et al., 2018)

Classification of Wireless Power Transfer

Wireless Power Transfer can be easily divided into radiative and non-radiative power transfer. This also corresponds to the distance of the transmission, with radiative technologies reaching much farther (Popovic, 2017). The following figure shows this WPT classification.

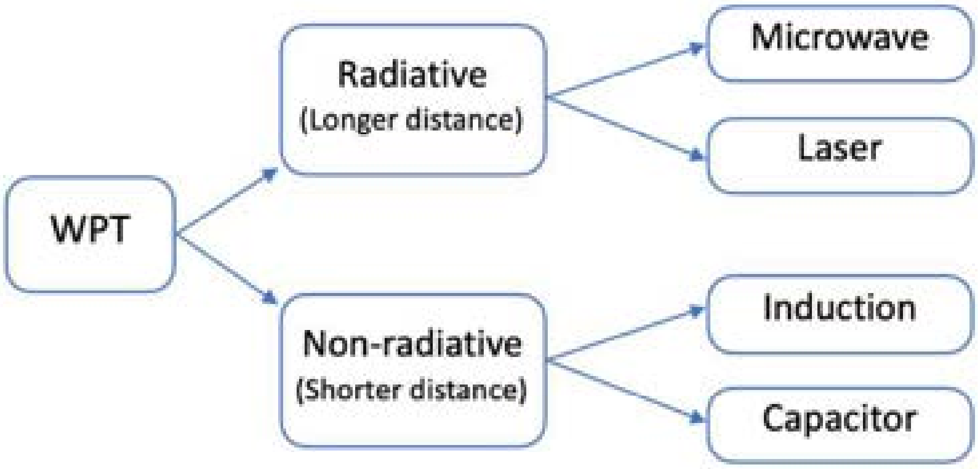

Figure 3 Wireless Power Transfer per distance classification

Non-Radiative Power Transfer

The most commonly used is inductive coupling, which is the transfer of energy from a primary source to a secondary source with the help of an electromagnetic field. This wireless technology can provide charge to vessels at a very short distance, and it requires for both plates (emitting plate and receiving plate) to stay parallel to each other and with very little movement. While this is indeed a wireless technology, it does not allow for mobility and it cannot provide charge to vessels in medium ranges, for example a couple of meters. Inductive coupling follows the same principle that smartphones use nowadays when wirelessly charging.

Potentially this technology, the municipality of Amsterdam will be adding new electric ferries to its fleet of 15 boats, beginning in 2024 (IAmExpat, 2022). By 2030, it is projected that 13.500 travelers will be using the ferry services each hour.

These electric ferries charge via contact plates that come in contact with the boat when it docks. A trial with a pilot electric ferry was conducted in 2017 and electric ferries have been put into operation in IJburg, the Houthavens and NDSM area.

The municipality has also conducted research on other inductive charging devices in order to charge vessels using an electromagnetic field. These systems do not require direct contact -although they are restricted to a close distance- with the vessel and instead, use a receiving unit that is added to electric boats, which receives energy from the dock. These docks are being explored as a possible solution for Amsterdam's charging infrastructure ambitions. When it comes to ferries, charging occurs every time the ferry docks. It means that charging must be done fast, as the vessel will spend little time at the dock. Inductive wireless charging allows a vessel to start charging at the moment the ferry docks because cables have not to be connected (Wartsila, 2023).

The principle for inductive wireless charging Wartsila[4] has is as follows

1) Current in inductive sending coil creates a controlled magnetic field
2) Magnetic field from sending coil creates a current in the receiving coil
3) High frequency current flowing in the inductive coil is converted to DC Power
4) Energy is stored in the ship batteries

There are many different ways in which inductive charging can be achieved. The main restriction is a lack of mobility and the distance in which this technology is useful. It would appear that it is wireless in the sense that it has no wire, however it does not allow for freedom, losing its advantage over a wired connection.

In the inductive connections can be also achieved underwater, such as the subsea USB, and under water connector the transfers of electrical power between the male and female connector separated by millimeters (BlueLogic, 2022).

Magnetic Resonance Coupling (MRC) is a form of wireless power transfer. It makes use of a magnetic field generated by an oscillating electrical current to send power over a short distance without the need for a physical connection. MRC is most commonly used in applications where a power source needs to be connected to a device without compromising the device's waterproofing. It has also been used in medical devices and implantable pacemakers. A good example of a Magnetic Resonance Coupling is the wireless charging of an electric toothbrush. The base of the toothbrush with an inductive coil creates an oscillating magnetic field. When the toothbrush is placed onto the base,

[4] https://www.wartsila.com/

this magnetic field couples with the second inductive coil inside the toothbrush, creating an electric current that is used to charge the battery of the toothbrush.

An example of inductive coupling is the wireless charging of a smartphone. A transmitter station with an inductive coil creates an oscillating magnetic field when an electric current is passed through it. When a receiver coil on the phone is placed close to the transmitter station the magnetic field couples with it, creating an electric current to charge the battery of the phone.

The main difference between inductive coupling and magnetic resonance coupling is the distance that the power can travel. Inductive coupling works over short distances, usually less than a foot, while magnetic resonance coupling can transfer power over larger distances up to a few meters. Kurs et al. (2007) demonstrated the transmission of 60 watts over a distance of 2 meters. In this case however, the efficiency was around 40%. Nevertheless, this offers an advantage over inductive coupling, as inductive coupling requires that the two inductive coils be precisely aligned, while magnetic resonance coupling requires no alignment of the coils.

Radiative Power Transfer

Laser beaming is a form of wireless power transfer that uses focused laser beams to transfer electricity from a transmitter to a receiver. It is primarily used for sending power to devices that are far away or in hard-to-reach places, such as remote sensors or space-based telecoms. This form of wireless power transfer is extremely efficient, and can pass power over very long distances without significant energy loss.

The main drawback of laser beaming as a form of wireless power transfer is that it requires a very high degree of accuracy. Laser beams must be precisely aligned between the transmitter and the receiver, otherwise power will not be transferred. Furthermore, the receiver must be able to capture the laser beam, otherwise power will be lost. This becomes an issue when dealing with harsh atmospheric conditions, as rain or clouds can block the transmission (Zheng et al., 2019). Additionally, laser beaming is not suitable for transferring power to multiple receivers.

Lasers use a concentrated beam of light energy which falls within the visible and near-infrared spectrum of the electromagnetic radiation spectrum. Lasers are a type of Electromagnetic Radiation (EMR). The differences are in the way the energy is transmitted. While EMR can contain a wide range of wavelengths, laser light has a single wavelength, in the visible or near-infrared range.

Electromagnetic Radiation, is a form of wireless power transfer that uses radio waves to send energy from a transmitting station to a receiver. While EM Radiation is not as efficient as laser beaming (sometimes not exceeding 10% efficiency (Wang et al., 2022)) it is highly versatile, and can transfer power to multiple receivers simultaneously. This makes it ideal for powering remote devices, such as cell towers and other telecoms, or for powering devices that move around, like on a solar powered vehicle.

Beam Forming Microwave is a form of wireless power transfer that uses microwaves to send energy. The microwaves are sent out in a beam, this is to say that the signals are combined into a pattern that is more directional (Microwaves101, 2023), and are steered to a receiver using either antennas or mirrors. This form of wireless power transfer is usually used for recharging robots, drones, and other autonomous devices. Beam Forming Microwave is more efficient than EM Radiation, but it is limited in the amount of power that can be transferred due to the narrow beam of the microwaves.

There are several parties around the world developing new technologies for wireless power transfer. Based in New Zealand, EMROD develops and manufactures products that use electromagnetic radiation for power transfer, communications, and sensing. They specialize in designing custom wireless power systems and wireless sensing systems for a variety of applications, such as in robotics, industrial automation, and energy management. According to EMROD, their approach is safe as it uses beams in the ISM (Industrial, Scientific, and Medical) band with frequencies commonly used in WiFi (2.4GHz, 5GHz), Bluetooth 92.4 GHz), and RfID (125 kHz – 5.85Ghz) (EMROD, 2023).

The ISM (Industrial, Scientific, and Medical) band is a part of the radio spectrum that is reserved for non-commercial and low power uses (ITU, 2019). Microwaves in this band are used for data transmission, wireless power transfer, and a variety of other applications.These wireless technologies use radio waves, typically within a few hundred feet, and are safe to use without causing interference with other wireless systems, according to the International Telecommunication Union (ITU).

Table x shows a quick qualitative comparison of some of the available technologies and illustratively allows for a quick valorization of their characteristics.

	Power	Efficiency	Distance	Multicast	Mobility
Inductive Coupling	Very High	Very High	Very Short	No	No
Magnetic Resonant Coupling	High	High	Short	Yes	Difficult
Last Beaming	High	High	Long	No	Difficult
EM Radiation	Low	Low	Long	Yes	Yes
Beam Forming Microwave	High	High	Long	Yes	Yes

Table 1 Comparison of radiative WTP (EMROD,2020)

WPT Safety and Health

It is clear now that WPT has an immense potential for many human activities, transportation included. Safety and health concerns arise when using radiative WPT solutions. The challenge with WPT is to provide enough power with adequate efficiency without jeopardizing human health and safety (Spectrum IEEE, 2006). In other words, it is safe to use wireless power transfer technology when designed properly, either via radiative or non radiative technologies. However, certain criteria and regulations for RF exposure limits must be met. In practical matters, this means that the electromagnetic frequency employed may restrict the amount of power that can be safely transmitted. In all cases, safety concerns increase as the power rises and large fields are transmitted (Adewuyi, 2022).

There are many standards for WPT, the Qi, Alliance for Wireless Power (A4WP), SAE, and International Electrotechnical Commission (IEC).

The Qi[5] standard is popularly known, as it is mostly used for inductive charging of applications such as smartphones.

SAE International[6] specializes in automotive engineering. It is best known for its J1772 standard for electric vehicle charging connectors mentioned earlier.

[5] https://www.wirelesspowerconsortium.com/

[6] https://www.sae.org/

IEC[7] (International Electrotechnical Commission) standards are international standards for electrical, electronic, and related technologies. These standards are created and maintained by the IEC and are used to ensure safety and consistency of the electrical and electronic products and services in the world. IEC standards are recognized internationally and are used in many countries around the world, including in Europe, North America, and Asia.

In Europe, wireless power transfer standards are regulated by the European Committee for Electrotechnical Standardization[8] (CENELEC). This committee was created in 1973 to develop common standards for the electrical, electronic, and related industries in Europe.

In order to facilitate a consensus-finding process between European and international standards, in 1996 CENELEC and IEC signed "agreement on common planning of new work and parallel voting", later in 2016 they reconfirmed their cooperation and signed a new agreement. CENELEC recognized that "close to 80% of CENELEC standards are identical to or based on IEC publications" (CENELEC, 2022).

The IEEE's[9] International Committee on Electromagnetic safety also creates guidelines regarding EMF and exposure to humans. Besides the organizations mentioned earlier, the International Communication Union[10] (ITU) creates recommendations for electromagnetic field safety. Lastly, the World Health Organization[11] also holds guidelines and recommendations on exposure to electromagnetic fields.

In WPT, electromagnetic radiation can be ionizing and non-ionizing. Ionizing radiation has the ability to directly alter the atomic structure of the body by ionizing atoms, e.g. X-rays, Gamma-rays. Non-ionizing radiation is more common and can be found in the electromagnetic waves used for communication and power (e.g., kilohertz to gigahertz). This type of radiation is generally safe, as long as its intensity is under the prescribed limits in order to avoid interference with other systems (AirFuel Alliance, 2021). Non-ionizing radiation normally does not cause any immediate effects in the body, however, humans may perceive this radiation through heat. SAR (specific absorption rate) is the measure of power absorbed in tissue per weight of the tissue (Kshetrimayum, 2008).

[7] https://www.iec.ch/publications/international-standards

[8] https://www.cencenelec.eu/

[9] https://ieeexplore.ieee.org/Xplore/home.jsp

[10] https://www.itu.int/en/Pages/default.aspx

[11] https://www.who.int/health-topics/electromagnetic-fields#tab=tab_1

Currently, the IEEE C95.1-2019/Cor 2-2020[12] standard is the up-to-date regulation and covers frequencies from from 0 Hz to 300 GHz.

One way to keep electromagnetic waves within the safety range is to make sure that the Dosimetric Reference Limit (DRL) is not surpassed(IEEE SA, 2020).

In other words, the dosimetric reference limit refers to the level of radiation that is permissible for a person to be exposed to without any adverse effects on their health.

WPT Technology for City Vessels

Developments using magnetic resonant wireless power transmission systems for smaller vehicles such as bikes (Zhao et al., 2020) , larger electric vehicles (Cai et al., 2018) and ships (Lu et al., 2022) and inductive coupling (Wartsila, 2023) are already in place around the world.

Radiative technologies are also in being used for mid and long range power transmission such as EMROD's microwave beaming that uses frequencies commonly used in WiFi, Bluetooth, and RfID (EMROD, 2022). Parallel to EMROD, the US Naval Research Laboratory (NRL) successfully demonstrated a 1km transfer of 1.6kW (Executive Government USA, 2022) under the project Safe and COntinuous Power bEaming – Microwave (SCOPE-M). In this setup, the power density was within safety limits set by international standards bodies, meaning the WPT demonstration was safe for birds, animals, and people (U.S. Naval Research Laboratory, 2022).

As stated before, WPT technologies shows promising results and has already been applied in land and in water, however an even larger step to the future is taken if charging can be done while moving. An interesting concept to embrace is the dynamic wireless power transfer (DWPT), which allows for mobility during the transfer of power and can be used for EV (Adewuyi, 2022). DWPT has already been tested for trams and electric buses in urban areas (Beeton D, 2014).

As previously mentioned, the cost of batteries represent a high percentage of an EV and one way to improve the cost and performance of an EV is to match the needs of the EV to the size of the battery(Beeton D, 2014). If a vehicle can continue it travel pattern without stopping to charge (dynamic) or stopping fewer times (semi-dynamic)

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[12] https://ieeexplore.ieee.org/document/9238523

the battery of said vehicle will be smaller. WPT opens a window towards reducing battery sizes on board EVs.

Examples of dynamic charging are the commercially available dynamic charging transportation system OLEV (Jeong et al., 2015) in Korea or the Qualcomm[13] wireless electric vehicle (WEVC) that was able to charge an EV dynamically while moving at 100 km/h with 20 kW (Qualcomm, 2017).

Geoffrey A. Landis (2005) designed a smart WPT method via microwave beaming with a possibility of emitters setup in arrays. This method could locate the device being charged and its position was analyzed in order to select which of the emitters should be used. Moreover, obstacle detectors were set inlace so that if there was to be any obstruction, the microwave array emitter would reduced the output until the obstruction was no longer there.

The solutions for WPT that can be applied for boats in Amsterdam vary widely according to the technology that one wishes to use, the scalability of it and the amount of energy that one wishes to transfer.

In line with Amsterdam's goals to lower carbon emissions an achieve zero emissions by 2030, WPT is an appropriate green solution that eliminates the need for a physical cable connection between the ship and shore power and is seen as the future of power supply for ships (Lu et al., 2022). However the distance of transmission plays a huge role in WPT.

WPT Implementation and Limitations

As previously mentioned, one main aspect for radiative charging technologies to be considered is human safety. The following serves as a short recap:

1. Inductive Coupling: This technology uses electromagnetic fields to transfer power between two coils. Fort eh case at hand, inductive charging pads can be placed on the docking platforms, piers or on the quaywalls, and the counterpart – receivers – should then be installed on the boats. However, we have now learnt

[13] https://www.qualcomm.com/products/application/automotive

that inductive coupling requires close proximity between the charging pad and the receiver, usually within a few centimeters. Moreover, it requires for both paths to remain "coupled" which is difficult to achieve with boats in motion.

2. Magnetic Resonance: Magnetic resonance enables power transfer over slightly larger distances compared to inductive coupling. It uses resonant coils that allow power transfer between loosely coupled coils. In contrast with inductive coupling, magnetic resonance offers greater flexibility in positioning, alignment, and distance. Power transfer can be achiecved within a few meters, and the distance may still be limited for moving boats.

3. Laser Beaming: Laser-based WPT technology is not suitable for boats in Amsterdam due to its limitations, namely because it requires a a direct line of sight and because the energy density is usually harmful for humans. Some of the safety concerns are: Direct Eye Exposure (Laser beams can be hazardous if they come into direct contact with the eyes. Even low-power lasers can cause eye damage, including retinal injury or blindness.), Laser Beam Divergence (Laser beams can diverge and spread out over longer distances, potentially increasing the area of exposure.), environmental factors (Laser beams are sensitive to environmental conditions such as fog, rain, or other atmospheric particles, increasing the risk of unintended exposure to humans)

1. Microwaves: WPT using microwaves, can transfer power wirelessly over longer distances. Beamforming microwave technology can focus the power transmission in a specific direction. However, there are safety concerns, namely exposure to microwaves,since the microwaves can penetrate the body and cause heating effects, which can lead to tissue damage or burns. Moreover, microwaves can spread and propagate beyond the intended charging area, potentially exposing nearby people. Finally, microwaves can interfere with electronic devices and wireless communication systems.

When it comes to the safe parameters for humans regarding Wireless Power Transfer (WPT) technologies, two primary organizations provide guidelines for human exposure to electromagnetic fields: The International Commission on Non-Ionizing Radiation Protection (ICNIRP) and the Institute of Electrical and Electronics Engineers (IEEE). Here are some key points regarding safe parameters for humans:

1. Specific Absorption Rate (SAR): SAR is a measure of the rate at which energy is absorbed by the human body when exposed to electromagnetic fields.

2. Frequency and Power Density: Different frequency ranges and power densities may have different safety limits. For example, exposure to higher-frequency microwaves, such as those used in Wi-Fi or Bluetooth devices, typically has lower safety limits compared to lower-frequency electromagnetic fields.

3. Distance and Shielding: The intensity of electromagnetic fields decreases with distance from the source. Maintaining a safe distance from the WPT source or implementing proper shielding can help minimize human exposure. This is a challenge in the Waters of Amsterdam, where people are in close contact with the water.

Regarding the energy density requirements, there is no specific rule of thumb since it varies depending on the specific requirements and design of the boat. However, a general approach to estimate the energy density for charging a boat using WPT is as follows:

1. Determine the Battery Capacity: Typically measured in kilowatt-hours (kWh), represents the total amount of energy the battery can store. (For comparison, a Tesla EV has a 100kwh battery) (TechRadar,2021)

2. Determine the Charging Time: Typically measured in hours (h). This could depend on various factors, such as the available charging infrastructure, the boat's usage pattern, and the urgency of recharging.

3. Calculate the Required Power: Divide the battery capacity (in kWh) by the charging time (in hours) to calculate the required power.

For example, let's assume the boat has a battery capacity of 100 kWh, and the desired time to charge is 30 minutes. The required power would be 100 kWh / 0.5 h = 200 kW. This "back-of-the-envelope" calculation does not take into account efficiencies, energy losses and battery rate of charge ranges.

If we recall form previous chapters generally, plug-in electric vehicles require between 3.3 kW and 22 kW of charging power (United States Environmental Protection Agency, 2023), while DC Fast Chargers may require up to 150 kW or more (Charge Hub, 2023a). At the same time, dynamic charging transportation system OLEV (Jeong et al., 2015) in Korea or the Qualcomm[14] wireless electric vehicle (WEVC) that was able to charge an EV dynamically while moving at 100 km/h with 20 kW (Qualcomm, 2017).

[14] https://www.qualcomm.com/products/application/automotive

Hence, there is a wide variety of possibilities that relate energy density and placement, following a simple concept: a high density at point A may be equivalent to many lower density points B,C,D,E along a route.

It's important to note that this calculation represents the average power needed during the charging process and does not consider the efficiency of the WPT system. Currently WPT systems in the market for induction and resonant coupling have a lower efficiency than a wired connection, for the most cases not exceeding 80% efficiency. The actual energy density required might then be higher due to conversion losses. Efficiency considerations are crucial in determining the suitable power and energy transfer rates for WPT.

Research around the world is being carried out to improve the rate of transfer while maintaining hsafety standards for WPT. For many applications, namely IoT, the frequencies such as WiFi, Bluetooth, and RFID is sufficient. However this is generally low if the aim is to charge a boat, since these frequencies are usually aimed at different purposes:

WiFi (2.4GHz, 5GHz): WiFi frequencies, such as 2.4GHz and 5GHz, are commonly used for wireless communication and data transfer

Bluetooth (2.4GHz): Bluetooth operates in the 2.4GHz frequency range and is primarily used for short-range wireless communication between devices.

RFID (125 kHz – 5.85GHz): Radio Frequency Identification (RFID) technology operates at various frequencies, including 125 kHz to 5.85 GHz. RFID is commonly used for identification, tracking, and inventory control rather than power transfer. The energy density achievable through RFID frequencies is typically minimal and not suitable for efficient power transfer.

In summary, while it is possible to transfer power using WiFi, Bluetooth, and RFID frequencies, the energy density achievable through these frequencies for WPT purposes is generally low compared to dedicated WPT technologies optimized for power transfer. There are however some examples of companies testing these frequencies for WPT.

At a IEEE Powercon 2020 (EMROD. (2020), about Long-Range Wireless Power Transmission, EMROD stated that the power density achieved by their system is typically around 1-10 kilowatts per square meter. (On average, the power density of sunlight at the Earth's surface is approximately 1000 watts per square meter (W/m²) under clear, sunny conditions. This value is often referred to as the solar constant.), with an end-to-end efficiency of around 50-60%.

In summary, considering the specific context of Amsterdam's electric boats, a combination of inductive coupling and magnetic resonance technologies might be more suitable:

1. Inductive coupling can be utilized in docking areas or marinas where boats can be stationary for longer durations. This technology could be integrated into the existing EV infrastructure, using charging pads and receivers specifically designed for boats.

2. Magnetic resonance can be deployed in areas where boats are in motion, such as along busy canals or designated waterways. Charging stations using magnetic resonance technology can be strategically placed to allow for efficient power transfer at moderate distances.

Distance plays a crucial role in WPT implementation. While magnetic resonance can offer charging at slightly longer distances than inductive coupling, the optimal distance is still limited. Therefore, charging stations should be strategically located along the waterways to ensure convenient access for boats and minimize route pattern deviation.

Vessels in Amsterdam : Categories

Besides the known tens of thousands registered boats cruising the canals of Amsterdam, in 2018 the Municipality estimated 300 illegal passenger boats within the Amsterdam canals, out of which 80 of them were thought to operate commercially (Nota Varen, 2018).

Currently boats are monitored and classified. The classification of boats in Amsterdam can be quite diverse. Boats can be classified according to their use (Goods transportation, leisure, passenger boats, navy), by their size (width and length), by their power system (fossil fueled or electric), by their structure (covered, uncovered).

Varen in Amsterdam (2013) established a classification based on boat sizes

Manned Large: Manned large enclosed vessels: > 14 x 3.75m and <=20 x 4.25m

Manned Enclosed: Manned enclosed vessels: < 14 x 3.75 metres

Manned Open: Manned open vessels: < 10 x 3.15 metres

Unmanned: Unmanned vessels: < 5.50 x 2.00 metres

This classification is still used in many documents, however years later the Municipality created a new segmentation for boats (2019):

1) Large: More than 50 seats
2) Medium and Small: Maximum 50 seats
3) Unmanned: Maximum 5.50x2.00m

This however did not fully represent the cultural-historically valuable background, as part of UNESCO World Heritage. Fo this reason a later classification including historical and iconic boats was set in place (Gemeente Amsterdam, 2019):

1) Large
2) Medium and Small
3) Unmanned
4) Historic and Iconic Large
5) Historic and Iconic Medium and Small

Internationally, an Automatic Identification System (AIS) is used. The AIS is a classification system developed by the International Maritime Organization (IMO) to identify and categorize the different types of vessels (IMO, 2023). This system is based on the size, type, and purpose of the vessels, and is commonly used for traffic monitoring, search and rescue operations. As this is a much thorough way to classify vessels, this thesis will take AIS Classification as reference and divide boats by size:

Unmanned: <5.50m

Small: >5.50m and <14m

Medium: >14m and <20m

Large: >20m

With three major groups:

Cargo, e.g. Cargo-ship, Container, Tanker

Passenger, e.g., Ferry, Pleasure Crafts, Tourism

Other, e.g., Law Enforcement, Maintenance vessels, Tugboats

For the current work, the classification to be used corresponds to AIS that allows for classification by both type and size. This classification will be helpful when characterizing vessel behavior in the canals of Amsterdam Centrum.

Spatial considerations and limitations for charging stations

One of the limiting factors for facilitating transport on water in the Amsterdam canals is naturally the availability of space. The Municipality has classified the canal according the available passage width, length and depth, in short: the canal capacity.

The capacity of a canal in the current work refers then to the maximum number of boats that can navigate through it within a given time period, ensuring efficient and safe traffic flow. This information is important as it allows for analysis and decision making regarding infrastructure improvements, maintenance, and operational strategies for optimal boat transit.

[redacted]

[redacted]

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- [redacted]

- [redacted]

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[redacted]

[redacted]

Besides these important aspects, there are other spatial limitations such as bridges. This will be expored in future chapters. Morover, there are specific rules and guidelines in place regarding the installation of infrastructure along the canals or waterfront areas. This however falls beyond the scope of the current work.

Models for Mobility Services and Facilities

In recent years, many different models to optimize facilities for mobility services have been tested. In (Baum et al., 2019) a theoretical MM approach for location optimization considering battery constraints was carried out, computing several user profiles into a shortest path problem.

Bian et al.(2019) proposes a Mixed Integer Linear Programming (MILP) model based on GIS to place charging station in cities and maximize the return of investments. In this model traffic flow and land-use classifications served as input for the city of Västerås, Sweden.

Similarly, Cai et al., (2014) uses travel patterns from almost 12,000 taxis in Beijing to represent population travel patterns. This research helped deepen the understanding of charging demand for electrified private fleet. Moreover, since real data was used, it was possible to discover the real power demand throughout the day. This in turn allowed for a more accurate approximation of charging stations siting.

Blad (2021) proposes a methodology for assessing the feasibility of regional infrastructure, in this case not EV charging stations, but mobility hubs, taking into account perspectives from different stakeholders: Operators, users and government. In this, a MCDM approach was followed, using Analytic Hierarchy Process (AHP). While the method is limited to assessing the potential of regional mobility hubs, it is applicable for other cases. In some cases one of the aims is to minimize driver's discomfort and as such, try to alter their behavior as little as possible.

Bouguerra et al. (2019) tackle this issue by employing Integer Linear Programs based on weighted set covering models with two interesting constraints: They addressed the a real case study (Tunis City, Tunisia) where charging stations could be located in already existent parking and gas stations. Other efforts to match charging stations with travelers demand have been made by using Dijkstra's shorts path algorithm in combination with a dynamic area modeling, that limits Dijkstra's nodes (Cai et al., 2020).

Cavadas et al., (2015) propose a model to determine the location of charging stations, with a given value for the demand. The demand is calculated by analyzing the time that a vehicle would charge during a day at a specific location. This approach takes into account single journeys with long stops, allowing for slow charging solutions.

In 2015 (Chen et al.) investigate the optimal location for charging stations using a MILP method. Several constraints were used in the model, such as investment cost, transportation cost, convenience, users demand, stations capacity and coverage of the whole area. To solve for this multi-objective optimization a genetic algorithm is used. This approach has many benefits and needs special attention in order to remove redundancy or bias. Moreover, a factor is sometimes used (as was in this case) to limit the model in the freedom to "build" charging stations. While it is true that limits must be set in place, it suggests for the creation of additional design constraints that would serve to build a more robust model.

Conrow et al., (2018) analyze the optimal distribution of shared bike stations in the city of Phoenix, United Stated by means of a GIS spatial optimization covering model. A series of scenarios are created according to investment levels, that would in turn determine the amount and location of the shared vehicles. In this study, the coverage is calculated with Euclidean distance and then it was not limited to the street network.

Cui et al. (2022) analyze the current usage of charging stations in Beijing and developed a MIP model to improve the distribution of charging station taking as input the charging frequency of taxis in Beijing. The result of the model allows to categorize stations according to their usage and provided insights for future layout optimization. Deza et al., (2022) also aim at attaining balance in the network given estimates of traffic flow. Through a similar MIP approach, this research was later tested using trip data from Ontario, Canada. In this research the time given to park or charge the vehicle was given as an average of 10 min.

Guler et al, (2018) suggest a GIS approach paired with MCDM analysis to locate EV charging stations in Istanbul, Turkey. In this study criteria such as population density, land value, road infrastructure, park areas, green areas, income rates, and shopping malls amongst others, were considered. The result showed a heat map of suitable locations, ranging from unsuitable to highly suitable locations. Two years later, a couple of studies to determine the optimal location of facilities were carried out.

In (2020a) Guler et al. present an analysis to site bicycle lanes and bicycle stations. In this research fuzzy functions were set in place to assess criteria accurately. Moreover, the weights of criteria were obtained though Analytic Hierarchy Process (AHP), the Fuzzy AHP (FAHP), and Best Worst Method (BWM). By combining and these methods, a sounder decision could be made. Finally the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method was used to rank the locations. A parallel study was performed to find location suitability for EV fast charging stations (Guler & Yomralioglu, 2020b).

In (Fazio et al., 2021) a spatial approach with a MCDM results in the optimal location for bicycle stations using a 100 by 100 square grid. In this study the different criteria were normalized and indexed so that they could then be ready to be evaluated. A focus on bike oriented development served as a compass for the decision making.

The work done in (He et al., 2016) presents a comparison between different location optimization models, namely p-median model (where the goal is to minimize the demand-weighted distance between the demand point and a charging station), maximal covering location model (whose aim is to maximise the level of demand, given a distance an a number of facilities), set covering model (where the objective is to minimize the number of facilities with all the demand covered within a given distance. In this model the level of demand is not considered. Each demand point has the same relevance as the other).

In 2004, (Nicholas et al.) investigated the siting and networks of Hydrogen stations for the city of Sacramento, United States, through a GIS based approach. The study area was divided in zones (Traffic Analysis Zone), and many factors came into play such as gasoline network, traffic flows and driving estimates within the Traffic Analysis Zones. A handfull of behavioral assumptions were made in order to run a "normal "scenario. These assumptions could however be changed to fit any given scenario. The result was a map with the number and location of hydrogen stations as well as the routes drivers would take towards them.

The methods towards determining the population demands vary widely, from stakeholder interviews or physical networks infrastructure constraints and assumptions, to mathematical modeling. In some cases the demands are obtained given the route of the vehicle. This becomes even more interesting when the model considers the vehicle to have range limitations, namely when the fuel runs out, i.e. gasoline, hydrogen, battery usable capacity. In 2005 (Kuby & Lim, 2005) conceptualized a model where vehicles needed to refuel multiple times refueling locations were set along the path of the vehicle.

Huang & Kockelman (2019) use a MM namely a genetic algorithm, traffic assignment algorithm and a station choice algortithm to determine charging station locations for the city of Boston, United Stated. In this case, fast charging stations were placed on a congested network, were the model solves for charging locations with an equilibrium traffic assignment.

Iravani (2022) optimizes the location of EV charging stations with a GIS approach parked with a MCDM. Several parameters were taken into account such as number of residents, number of jobs, number of cars owned in high income areas, number of households not owning a car, number of Students, walkability level and total number of trips. Using a hexagonal grid with a radius of 2km, the model proposes a Set Covering Location Problem followed by a Maximum Covering Location Problem. The result shows a map with the location of the highest ranked EV Charger Stations.

In (Jia et al., 2019) an interesting approach to tackle location optimization was used: Cellular Signaling Data (CSD). With this data, the trajectory of people were reconstructed. The model created clusters for the charging demand location and identified optimized the siting for the charging stations for the city of Tianjin, China. Three different clustering mechanisms were used and compared. The resulting map showed the charging station layouts for all three cases.

Kabak et al. (2018) present a GIS based approach coupled with AHP and MOORA methods for bike station site selection in the city of Karsiyaka, Turkey. The result was a suitability map that was then ranked by means of the MOORA method.

In Bangkok, charging station siting for taxis was optimized using the Google Maps Distance Matrix API and data for a single day (Keawthong et al., 2022). This tool coupled with a thought-of algorithm allowed for time analysis and placed the vehicles on the road infrastructure. Battery ranges, work shifts for taxis and charging times were given values. The model was then run for three different dates and results were compared between them validating the accuracy of the model.

Ni et al., (2020) implement a so called Immune Algorithm for the location of charging stations for the municipality of Shenzhen, China based on trajectory data of 2,000 taxis, considering the charging would be done after the end of a trip and when the SoC demanded for the vehicle to be charged again. Immune Algorithms are optimization algorithms imitating the immune system (Ge & Mao, 2002) maintaining diversity of a group towards finding an optimal solution. Where a genetic algorithm is a type of optimization algorithm that uses the principles of natural selection and genetics to search for an optimal solution to a problem. It mimics the process of evolution and uses techniques such as mutation, crossover, and selection in order to find the most optimal solution. On the other hand, an immune algorithm is a type of AI-based optimization algorithm that uses the principles of artificial immune systems to search for an optimal solution to a problem.

Philipsen et al., (2016) present a study defined by user criteria by means of questionnaires. The goal is to understand which criteria are most important when siting charging stations, and both EV users as well as non-users were involved in the study. In this research they demonstrate that dual use, reliability, and accessibility are important aspects when locating charging stations

Vanilla et al., (2023) investigate the implementation of slow type 2 charging station in commercial and industrial zones in Delhi, India. An assumption of 7-8 working hours allows for slow charging (5-6 hours) to occur. The result is a map with a 2 km by 2 km or 3 km by 3 km grid with charging location layout.

(Vazifeh et al., 2019) tackle the location of charging stations in the city of Boston, United States by using CDR to recreate a path taken by people. These paths are assumed to be paths taken by EV. This research uses a grid square cells and calculates the amount of trips in the cells. The model then follows a greedy algorithm paired with a genetic algorithm. The result is a map with a charging station layout.

Yan et al., (2020) conceptualize a charging behavior by analyzing stations, hours and days in a 3D tensor[15] and a network expansion algorithm to find an optimal solution. The result is a map showing the redundant, optimal and overflowed stations for Wuhan central region.

Zhang et al., (2017) look into charging stations for ships based on a three-step backup coverage model (Hogan & Revelle, 1986). The first step concerns a feasibility analysis of candidate sites. The second step considers the charging demands of the ships, while the last step focuses on the costs of construction and service capacity.

(Zhang & Iman, 2018) suggest a MCDA paired with a GIS method to locate the potential of charging stations in the city of Wasatch Front, United States. This method uses several factors which are indexed and scored. By using a square grid of 0.5 miles per cell, the result is a heat map with low, moderate or high suitability for charging stations.

(Zhang et al., 2020) demonstrate the optimization of MSW for the city of Amsterdam by implementing a GIS-based closest facility algorithm. A series of constraints gathered from the city's context are given as input, such as population, number of homes, existent trash bins. The result is a map showing the optimal location for trash bins in the city's center.

[15] A tensor is a mathematical object that is used to describe and express relationships between objects. A 3D tensor is a specific type of tensor that has 3 dimensions.

Spatial temporal analysis for movement data

Analysis in space and time can be achieved in many ways. The some of the known methods are the following:

1. Trajectory Analysis: Trajectory analysis focuses on individual movement trajectories and their characteristics. It involves analyzing the spatial and temporal patterns of movement, such as speed, direction, acceleration, and turning angles.(Graser, 2020) Techniques such as interpolation, segmentation or clustering, help identify meaningful in movement trajectories.

2. Point Pattern Analysis: Point pattern analysis deals with the spatial distribution of discrete events or locations over time. It involves examining the intensity, clustering, and dispersion of events or locations at different spatial and temporal scales (Gimond, 2023). Methods like density estimation or nearest neighbor analysis are commonly used in this type of analyses.

3. Spatial Network Analysis: Spatial network analysis focuses on movement data that follows a network structure, such as road networks or transportation networks. It usually involves analyzing properties of the network. Network-based methods may involve shortest path analysis, least-cost routes, route allocation.(de Smith et al. 2009)

4. Space-Time Cube Analysis: Space-time cube analysis involves representing movement data in a three-dimensional cube, with spatial dimensions on two axes and time on the third axis (O'Sullivan, 2014). It allows for the visualization and exploration of spatiotemporal patterns in the data. Techniques like hotspot analysis, space-time clustering, and change detection can be applied to analyze patterns within the space-time cube.

5. Geostatistical Analysis: Geostatistical analysis combines spatial and temporal data with statistical methods to model and analyze movement patterns. It may be used to predict values at unobserved locations.

As can be seen, spatial temporal analysis can be tackled in many ways. The current work aims at using real vessel mobility data to analyze the movement patterns and suggest locations for new electric charging stations. From the preceding list it seems the first two options would be suitable to fulfill the task at hand.

(Graser, 2018) focuses on trajectory data models and point-based data models. Several trajectory analysis tasks are conducted, including computing trajectory duration and length, applying temporal and spatial filters, extracting positions at specific times, and visualizing trajectories in desktop GIS. The research also explores the potential and limitations of contextual trajectories and moving area object trajectories. The results demonstrate that functions for moving point object trajectories are efficient and simplify query complexity, thus reducing computational time.

(UBER, 2020) uses a methodology to calculate travel times, routes and speed along the routes by segmenting the roads and aggregating speeds of vehicles according to GPS data. For this, GPS locations of different vehicles over time and map data showing the network of the roads is needed. The data used is recorded every 2 seconds and includes latitude, longitude, speed, course and timestamp.

(Wang et al., 2021) propose a method to evaluate the trajectory data by vector space modelling and matrix decomposition. A charging station optimised for cost minimisation is also proposed.

(Tavares et al., 2008) demonstrate the use of GIS 3D route modelling software for optimising waste collection and transportation vehicle routing networks. It accounts for the effects of road inclination and vehicle weight to minimize fuel consumption.

(Lei et al., 2022) examine the charging behaviour of a city-wide electric taxi (ET) fleet in Shenzhen, China. Combining the trajectory and charging infrastructure data, the authors show infrastructure utilization, temporal and spatial charging dynamics, and individual driver's charging preferences.

(Li et al., 2022) propose a spatio-temporal modelling approach for optimal charging station planning. For this, the temporal and spatial distribution of EV trips is analysed in an open-source taxi trajectory dataset. This allows for analysis of interaction between traffic and electrical attributes of the EVs.

Finally, research team led by Dr. Anita Graser created MovingPandas. MovingPandas is a Python library that simplifies work with spatiotemporal movement data. It is built on top of GeoPandas, and extends its functionality to handle trajectories and time-sensitive spatial data, it is highly compatible with GIS processing software. According to its website, MovingPandas[16] "provides trajectory data structures and functions for movement data exploration and analysis".

Summary

This chapter showed different technologies used to charge electric vehicles and the possibilities available for wireless charging for boats. Finally, a comprehensive literature review showed the methods that have been used for spatio temporal pattern analysis given movement data as well as for the location optimization of charging stations for EVs.

In reality, there is no universal way to consider one model better than another regarding facility location optimization, as it largely depends on the way the effectiveness of the facility location is measured (Jia et al., 2007). That being said, when studying an area within a city, models that analyze flows have had more stable results than others (Upchurch & Kuby, 2010).

Table xserves as a summary for some of the previous work by other authors.

Table 2 Summary of methods and approache. MM: mathematical modeling, GIS: geographic information system, MCDM: multi-criteria decision making

Reference	Goal	Method			Case Study
		GIS	MCDM	MM	
(Bouguerra et al., 2019)	Determine optimal location for EV charging stations constrained to parking lots and gas stations			x	Tunis, Tunisia
(Baum et al., 2019)	Minimize energy consumption of a battery by finding the optimal path between two locations.			x	Rundown Model
(Bian et al., 2018)	Maximize return of investments identifying optimal locations for EV charging stations	x		x	Västerås, Sweden

[16] https://movingpandas.org

Reference	Goal	Method			Case Study
		GIS	MCDM	MM	
(Blad, 2021)	Create a heat map with highest potential locations for mobility hubs from stakeholders' point of view	x	x		Rotterdam, The Netherlands
(Cai et al., 2014)	Maximize overall travel electrification using real travel pattern data	x		x	Beijing, China
(Cai et al., 2020)	Smart charging guidance strategy using Dijkstras algorithm			x	Rundown Model
(Cavadas et al., 2015)	Location of charging stations taking into account successive activities of the travelers			x	Coimbra, Portugal
(Chen et al., 2015)	Optimal Location of Electric Vehicle Charging Stations Using Genetic Algorithm			x	Rundown Model
(Conrow et al., 2018)	Maximize bicycle network coverage, and user demand coverage to enhance station accessibility and gain spatial and social equity	x		x	Phoenix, United States
(Cui et al., 2022)	Assess and balance charging demand based on charging frequency			x	Beijing, China
(Graser, 2018)	Locate Benefits and limitations of contextual trajectories and moving area object trajectories using trajectory analysis from point data.	X			Rundown Model
(Guler et al., 2018)	Optimal Location of Electric Vehicle Charging Stations Using GIS, considering economic, environmental and social aspects	x	x		Istanbul, Turkey
(Fazio et al., 2021)	Selecting locations for cycle stations through a spatial approach	x	x		Catania, Italy
(He et al., 2016)	Incorporate local constraints of supply and demand on EV charging stations with facility location models to compare optimal solutions from three different location models.			x	Beijing, China
(Huang & Kockelman, 2019)	Location optimization under congested-travel and congested-station under elastic demand and BEV scenarios			x	Boston, United States

Reference	Goal	Method			Case Study
		GIS	MCDM	MM	
(Iravani, 2022)	Minimize driver discomfort while considering the potential demand and aiming for a equitable siting of charging stations	x	x		Dubai, UAE
(Jia et al., 2019)	Cellular Signaling Records as a way to recreate real world travel patterns and hourly demand.	x		x	Tianjin, China
(Kabak et al., 2018)	Site suitability analysis for bike stations, considering existent stations, transportation network and urban facilities	x	x		Karsiyaka, Turkey
(Keawthong et al., 2022)	Location selection of charging stations using Taxis GPS trajectory data, estimating travel times and charging demands.	x			Bangkok, Thailand
(Kuby & Lim, 2005)	A flow capturing model to locate charging points along the shortest paths of vehicles			x	Rundown Model
(Lei et al., 2022)	Examine the temporal and spatial charging dynamics of a city-wide electric taxi (ET) fleet combining trajectory and charging infrastructure data, ,			x	Shenzhen, China
(Li et al., 2022)	Spatio-temporal modelling approach for optimal charging station planning using open-source taxi trajectory dataset.				Xi'an, China
(Ni et al., 2020)	Optimization of Charging Stations for taxis based on real trajectory data, with SoC and other behavioral constraints	x		x	Shenzhen, China
(Nicholas et al., 2004)	Locate Hydrogen Stations within a given network and one-way driving route from point A to a station	x			Sacramento, United States
(Tavares et al., 2008)	Optimize waste collection and transportation vehicle routing networks.	X			Praia, Cape Verde
(Vansola et al., 2023)	Locate slow charging stations with 5-6 hour charging time, considering OD data in Delhi	x			Delhi, India

Reference	Goal	Method			Case Study
		GIS	MCDM	MM	
(Wang et al., 2021)	Charging station optimization for cost minimisation evaluating the trajectory data	x		x	Hangzhou, Chiina
(Yang et al., 2020)	Eliminate redundant charging stations and identify congestion areas	x		x	Wuhan, China
(Zhang et al., 2017)	Location for ship charging stations around an island integrating a feasibility analysis		x	x	Yanqi Lake, China
(Zhang & Iman, 2018)	Create a hotspot map with suitability areas for charging stations by analyzing 27 different factors	x	x		Utah, United States
(Zhang et al., 2020)	Improve waste collection by implementing location selection for floating dumpsters.	x	x		Amsterdam, The Netherlands

Methodology

03

Methodology

To answer the research question "How can real vessel mobility patterns help find locations for new electric vessel charging stations in Amsterdam Centrum considering spatial-temporal challenges?" a series of supporting research questions (RQs) are investigated. For some, literature review was conducted to understand the vessels and vessel typologies, charging methods available and spatio-temporal analysis methods commonly used. Some of these RQ's have been answered in the Literature review chapter. With the information obtained a spatio-temporal trajectory analysis is implemented for the Amsterdam Centrum case study.

Table 3 Methodology and RQ

	Research Question	Method
Main RQ	How can real vessel mobility patterns help find locations for new electric vessel charging stations in Amsterdam Centrum considering spatial-temporal challenges?	RQ 1.a-1.e Case Study: Amsterdam Centrum – Analysis & Results
RQ 1 a	What are the charging methods available for electric city vessel charging?	Literature Review
RQ 1 b	How to classify vessel typologies in the context of Amsterdam's waterways?	Literature Review
RQ 1 c	What are the spatial considerations and limitations for implementing charging stations in Amsterdam?	Literature Review
RQ 1 d	What methods are currently applied for spatio temporal analysis for movement data ?	Literature Review
RQ 1 e	What techniques can be applied for location selection of electric charging stations for boats?	Literature Review Case Study: Amsterdam Centrum

From the previous chapter it is evident that the integration of several methods towards performing spatio-temporal analysis is not only useful, but recommended. While the main RQ at hand suggests a trajectory analysis, using available tools such as MovingPandas, for the location planning of charging stations, a later integration of MCDA is beneficial for this work.

While previous work has been done in Amsterdam to select locations for charging stations, some have considered spatial characteristics of the city but none have considered the vessel trajectories. As such, this research aims to develop an analysis for location siting of new charging stations in Amsterdam Centrum, taking its unique characteristics into consideration paired with real life vessel trajectories analysis.

For this work, The geographic scope of this research will be limited to Amsterdam Centrum, as it will be the first area impacted in the energy transition towards electric vessels in the Amsterdam canals.

As a brief reminder, it is worht to know that the path towards sustainable boating in the Netherlands is not something new. Years ago, in 1998, the Rondvaart Delft company had one vessel outfitted with diesel-electric propulsion (Inland Waterways International, 2020a).

By fall of 2013, the city of Amsterdam set out the Zero Emission program. This meant that all private and smaller cruise vessels would be electric by 2020 and larger vessels would also be emission free by 2025 (Gemeente Amsterdam, 2022).

In 2016 a study by TNO (Pim van Mensch, 2016) concluded that "...an electric fleet is technically possible, but much still needs to be developed and tested to build a reasonably optimal powertrain and infrastructure. In addition to the technical challenges, significant financial investments are also required."

In 2017, the City of Amsterdam banned 2-stroke engines on private vessels and pushed all commercial vessels in the city (530 canal vessels at that time) to reach "zero emission" status by 2020 (Inland Waterways International, 2020b) . At the same time, the city offered subsidies on the license fees, where the vessels to be electric (Gemeente Amsterdam, 2020).

In 2020, the GVB announced that five electric ferries were being built in the shipyards (Corvus Energy, 2020).

Overview of the method

The method to be applied to the Amsterdam Centum Case Study is a trinity:

1) Vessel trajectories for pattern analysis (spatio-temporal analysis).
2) Multi-Criteria Decision Analysis considering spatial constraints.
3) Location allocation analysis.

The vessel trajectory analysis will provide insights on route and flows, density of vessels, speeds at specific locations, stops, characterization of vessels and time spent at different locations. This research will focus on passenger vessels. The spatio-temporal analysis will transform the datapoints into paths or trajectories. Moreover, vessel stops duration will be measured. Parallel to this, the energy demand will be obtained. With this information the method will assume the vessels to be electric and to sail their paths on loop until the battery reached a DoD (Depth of Discharge) of 80%, as this is a known value that helps extend battery life (Pim van Mensch, 2016).However, is the stop duration is sufficient to charge the vessel, this will be a chosen location. This step will provide a series of "demand locations" that can be further analysed and adjusted in the MCDA step.

These results will be aggregated to a spatial MCDA that will serve as a filter where finally by means of GIS software a location selection technique will provide the siting for the new charging stations in Amsterdam Centrum.

This MCDMA allows the combination of different criteria relevant to the selection of sties for charging infrastructure. These different criteria will follow policy documents and previous research done by the Municipality: As such, the spatial analysis will consider the availability of space at quays, shore power, street lighting, bridges and existing EV charging stations near the water.

The location allocation analysis is posible using GIS software. Based on the results from the spatial constraints given in the previous steps, the location solver tool in QGIS allows to show the new sites for the charging stations. The tools available in GIS software, such as Network Analysis Toolbox[17], Networks[18], or WhiteBox[19] tools, allow to solve for maximum coverage given a series of time or distance parameters. For the purpose of

[17] https://root676.github.io
[18] https://plugins.qgis.org/plugins/networks/
[19] https://www.whiteboxgeo.com

this research, the numbers of vessels to consider in the analysis directly impacts the computational time. Therefore it is wise to considera simplification of the data points in order to accelerate the analysis and result the computational stress. This however may impact the veracity of the results. A way must be found to alter the original data as little as possible. Keeping in mind the spatial restricctions discussed earlier, one objective to find the location for new charging stations for boats is the integraton with existing facilities in Amsterdam Centrum. This means inevitably a restriction for the location allocation tool in GIS. Finally for each chosen location, a service area is determined.

Workflow of the method

In table XX a brief overview of the different steps for the discussed method is shown. This required the input from some of the already answered RQ. Specific data is needed to successfully carry out this research.

Table 4 Workflow of the method

Step 1	Data Preprocessing	
1.1	Determine spatial criteria	Select relevant spatial criteria that could potentially influence vessels or charging infrastructure in Amsterdam
1.2	Ensure data access	Ensure that access to datasets is present
Step 2	Unit characterization	Creation of a relevant unit to analyze. In this particular case, the characterization of Vessels, as the study will focus on vessels.
Step 3	Constraints and Boundaries	
3.1	Establish rules for each criterion	Establish the logical boundaries and behaviour for each criterion.
3.2	Use boundaries and constraints from policy document and previous research	Establish the logical boundaries and behaviour for each criterion.
Step 4	Spatio-Temporal Analysis	

4.1	Location point analysis	Transform location data into movement data
4.2	Unit segmentation	Classify vessels in different segments to analyze and gain insights
4.3	Trajectory aggregation	Create trajectories from point data, aggregate and simplify when possible
4.4	Trip segmentation	Create segments of the trajectories where orphan datapoints or irregulatiries occur
4.5	Stops detection	Locate spots where vessels stop, by means of time deltas or location restriction
4.6	Speed analysis	Analyse the speed of vesels along a particular trajectory to discuss possible WPT
Step 5	Charging Demand Analysis	
5.1	DoD and path	Compute energy demand point from loop trajectory, consumption rate and DoD
5.2	Stop interval duration	Compute energy demand point stop location with enough time delta
Step 6	MCDA	
6.1	Integrate results from step 5	Use the given demand points with the ready criteria from step 3
6.2	Calculate criteria in the grid	Arrange criteria within the grid
6.3	Set weight mechanism	Parwise weighting, MCDA with specified weights per criterion
6.4	Proximity Analysis	MCDA raster proximity analysis
Step 7	Location allocation	
7.1	Suitability decision	Analyze the obtained results. Compare results of step 5 and step 6. Decide and give insights for future planning

Data Acquisition

In order to conduct an analysis with sufficient data availability, a broad database was created which only selected criteria meeting the standards. Most of the data used come from public sources. In a few cases the data was directly requested and obtained free to use as-is for the purpose of academic research.

Data Availability

The available data is handled through a GIS software, which allows to pile multiple layers of different types of information and visualize it into a single map (Lepuschitz, 2015). In this way an extensive analysis can be done to understand patterns and relationships. The figure 5 (National Geographic Society, 2014) gives an example of various data sources being piled into a multi-layered georeferenced dataset. The table XXX shows the data used in this research as well as the source.

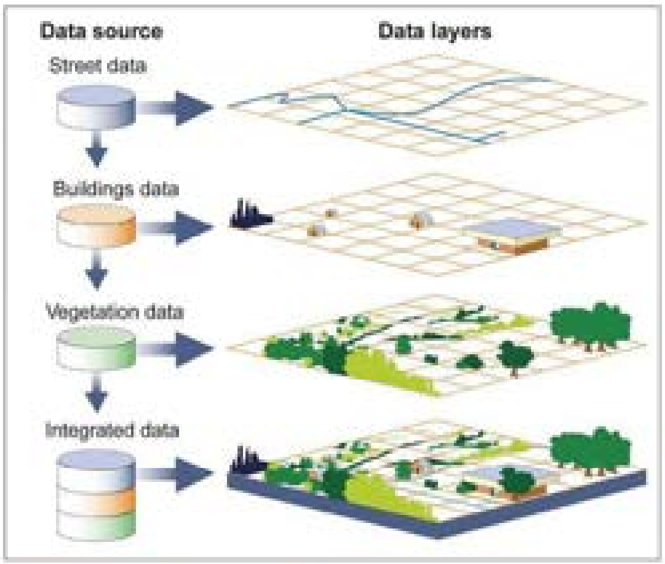

Figure 5GIS Data Handling

Table 5 Data acquisition for the research

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[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]
		[redacted]	[redacted]

	Description	Source	Data Custodian
Air Quality	Information on air quality with three measures parameters	Google Environmental Insights Explorer	Healthy Urban Living Data and Knowledge Hub (DKH GSL)
OSM POI	Points of interest such as churches, schools, parks, gas stations, bus stops, EV Charging stations	OpenStreetMap Query	OpenStreetMap
OSM Street and Canal Network	Street and canal network	OpenStreetMap	OpenStreetMap
Land Use	Land use zoning, according to the Municipality of Amsterdam	data.amsterdam.nlhttp://data.amsterdam.nl/	Gemeente Amsterdam
Buildings	Building ins the area, including usage type type of building	data.amsterdam.nlhttp://data.amsterdam.nl/	Gemeente Amsterdam
Bridges and quaywalls	Specific information on status of bridges and bank structures in Amsterdam Centrum	Programma Bruggen en Kademuren	Gemeente Amsterdam
Administrative zones	Polygons with information aggregated at zip code level	data.amsterdam.nlhttp://data.amsterdam.nl/	Gemeente Amsterdam
City Infrastructure	Point location of parking, street lamps, traffic signals, posts, waste bins	OpenStreetMap Query	OpenStreetMap
Waste bins	Point location of waste bins	data.amsterdam.nlhttp://data.amsterdam.nl/	Gemeente Amsterdam
Noise Level	Information on noise level in the city center	data.amsterdam.nlhttp://data.amsterdam.nl/	Gemeente Amsterdam
Vessel Speed Limit	Speed limits on the canals of Amsterdam Centrum	Waternet	Waternet
[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]

Step 1 Data Handling and Preprocessing

Often, charging infrastructure is implemented even when the number of EVs is low, with the hope of generating more interest in electric mobility(Straka & Buzna, 2019) . In the case of Amsterdam Centrum, it is known that all vessels will become electric. For this reason, this research will work using real world GIS vessel data taken from Marine Traffic,

In order to decide the length of data collection, a series of snapshots were taken in representative years. This means the exclusion of periods where the COVID pandemic was highly active. At the same time, these snapshots of data allow to see where the highest possible numbers of vessels occurred. The highest number would be most beneficial for this research, as it would mean that at any given moment a maximum number of vessels could be found in the Amsteram Centum Canals.

In Nota Varen Deel 1 (2018) a measurement for boat movements in Amsterdam canals concluded that summer weekend days are the most crowded period within a year, ranging from 60 to about 200 boat movements per hour at the busiest locations

Figure 6 Average passages of vessels at different intersections

Knowing which time of the year is busiest was crucial. However, in some cases, the collection of vessel position data proved to be expensive. Finally, a dataset from MarineTraffic gathered by the MIT Senseable City Lab Team for a summer day in 2017 was selected. The dataset collected hold a total of 167344 different features for vessel positions.

Case Study 04

Amsterdam Centrum Case Study

Region Selection: Amsterdam Centrum

Electrification of the Amsterdam vessel fleet will help reduce CO_2, but it brings a multilayered challenge to the table, specially when deciding the specifications for the electric vessels and those of the charging infrastructure (Pim van Mensch, 2016). As previously stated, the City of Amsterdam has placed 10 charging stations for pleasure vessels in various areas of the city. These charging stations are located in the East, South and Center districts and 5 of them are now available for use. Each charging station has a capacity for two vessels at the same time (Gemeente Amsterdam, 2021a). These stations are not enough for the increasing demand.

[redacted]

Figure 7Amsterdam Centrum (Pink)

Because the vessels sail through the water and not in land, the analysis will only focus on the canals of Amsterdam Centrum. For this, a data extraction from OpenStreetMap was performed to obtain only the Canals in Amsterdam Centrum, as depicted in Figure 8. After this, we can see all the vessel points on the map, coinciding with the canals.

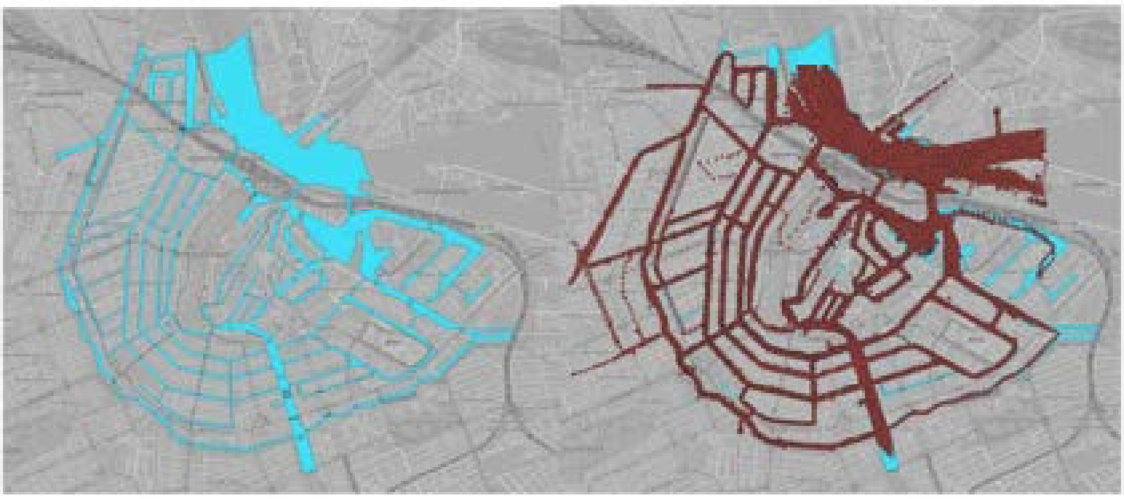

Figure 8 Canal Network of Amsterdam Centrum (Blue) and vessel track points (dark red)

GeoGrid Coverage

Many location allocation methods tackle the optimization problem on a geographical grid (Vazifeh et al., 2019), in many cases the grid is partitioned into non-overlapping square cells. This of course can lead to many errors, specially when conducting an analysis on proximity and distances. Kistenfeger (2022) thought of a solution by "chopping" off the edges of grid cells where they would normally intersect if overlapped. A more accurate shape would be that of the circle. However, if a grid is made with non-overlapping circles, there will inevitable be empty spaces.

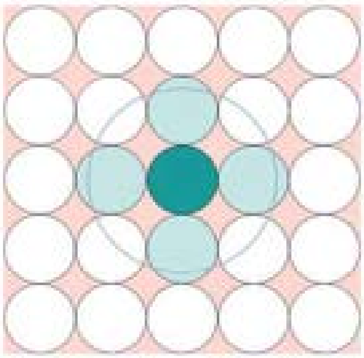

Figure 9 Circle grid with empty spaces (light red)

Since the current work will deal with dynamic data, it is vital to have a virtual sieve that will maintain its behavior though the extent of the map : Hexagon cells.

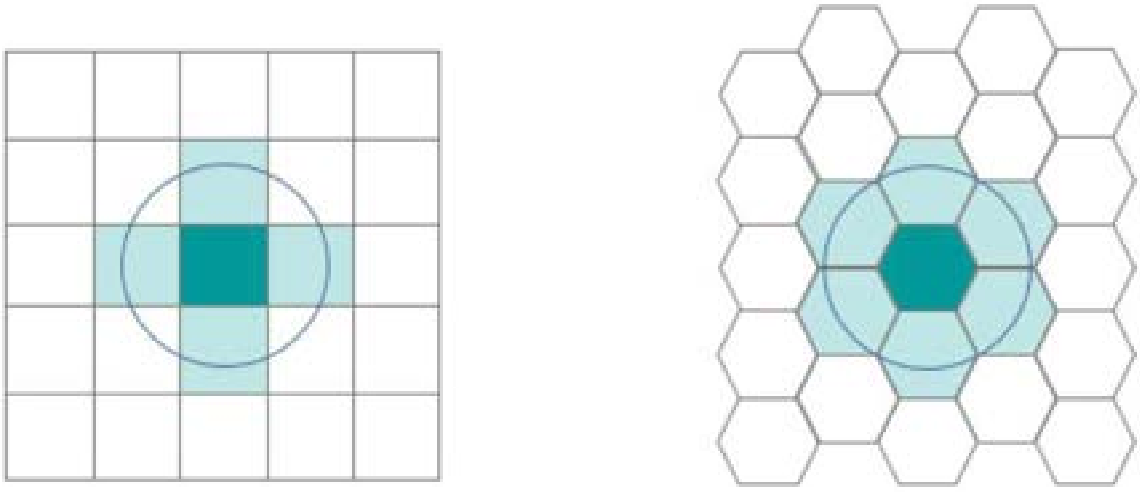

Figure 10 Comparison of square and hexagon cells.

The square grid is the most widely used shape in GIS analysis (ArcGIS PRO, 2022), however hexagons are better suited as they reduce sampling bias due to their lower perimeter-to-area ratio, which is more similar to a circle than a square. This circularity allows hexagons to better represent curves in pattern data more accurately than square grids can. Additionally, hexagons make it easier to find neighbors as the centroid of each neighbor is equidistant – unlike with a square grid, where the distance between centroids is not the same in all directions.(Birch et al., 2007) This means that there is less chance of important features being missed or overlooked.

Before any grid can be made, all layers and datasets have to share the same Coordinates Reference System. For the current work, CRS a 50m hexagon grid was created. While a smaller grid – such as 20m- would be more accurate, the computational time proved to be counterproductive.

While a grid can cover the extent of the canvas, in this work we are only interested in the areas where the vessels are located. The grid originally was set over Amsterdam Centrum, a next step to remove the grid polygons whithout vessel points was carried out. For this, features from the grid were extracted when intersecting data from the vessel tracking dataset. This is depicted in Figure 23.

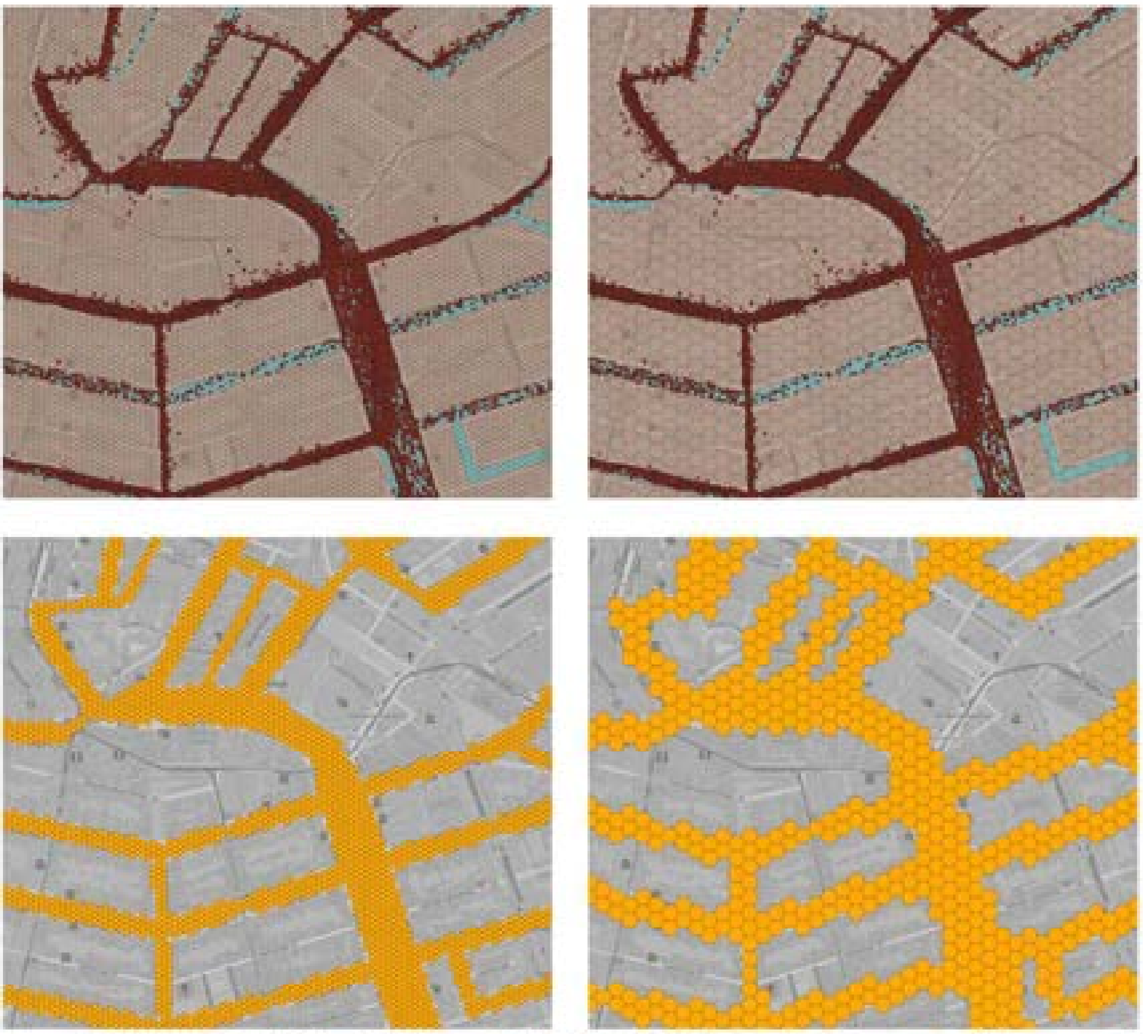

Figure 11 Hexagonal grid 20 by 20 (Left) and 50 by 50 (Right) for Amsterdam Centrum, and the extracted grid covering only the canals.

Step 2 Unit characterization: Amsterdam Fleet

Previously it was established that the vessel characterization followed the AIS Classification as reference and divide boats by size:

Unmanned: <5.50m

Small: >5.50m and <14m

Medium: >14m and <20m

Large: >20m

With three major groups:

Cargo, e.g. Cargo-ship, Container, Tanker

Passenger, e.g., Ferry, Pleasure Crafts, Tourism

Other, e.g., Law Enforcement, Maintenance vessels, Tugboats

Vessel Segments

After the preprocessing of the data obtained from Marine Traffic, the dataset for the Amsterdam Centrum fleet has 513 different vessels, with their characterization as follows:

[redacted]

[redacted]	[redacted]	[redacted]
		[redacted]
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[redacted]	[redacted]	[redacted]
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[redacted]	[redacted]	[redacted]

This work will solely focus on passenger vessels.

Table 7 shows the classification of the vessels present in the processed dataset, according to the agreed characterization of vessels in Amsterdam Centrum. The distribution of these vessels by category is shown in Figure 12.

Table 7 CLassification of vessels in dataset

	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
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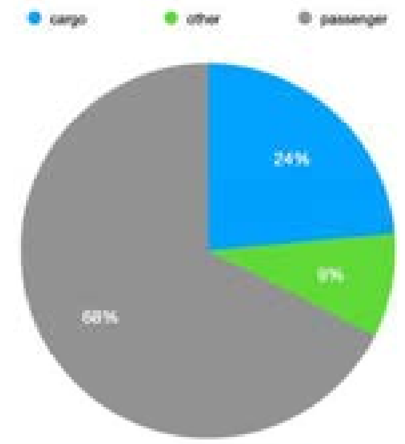

Figure 12 Vessel distribution (%) by category

The vessels found in the dataset and present in Amsterdam Centrum canals are common to the naked eye, however we must pay special attention to the "ferry" boats. Amsterdam has a series of Ferry boats that serve as a bridge between Amsterdam Centrum and Amsterdam Noord, however the AIS definition for ferry boat is much broader. As a way of clarification, the next figures show examples of the different vessel subtypes.

Figure 13 Ferry (small) MMSI 244615958 and Ferry (Medium) MMSI 244615912 found in the dataset

Figure 13 Ferry (Large) MMSI 244750688 and Ferry (Large) MMSI 211479640 found in the dataset.

Figure 14 Tug (small) MMSI 244615787 and Cargo (Medium) MMSI 244850894 found in dataset

Figure 15 Cruise (Large) MMSI 269027481 and General (Small) MMSI 244810807 found in the dataset

Figure 17 Cargo (Large) MMSI 244820369 and Container (Large) MMSI 244660307 found in dataset

Figure 16 General (Medium) MMSI 2442609496 and General (Large) MMSI 2442609497 found in the dataset

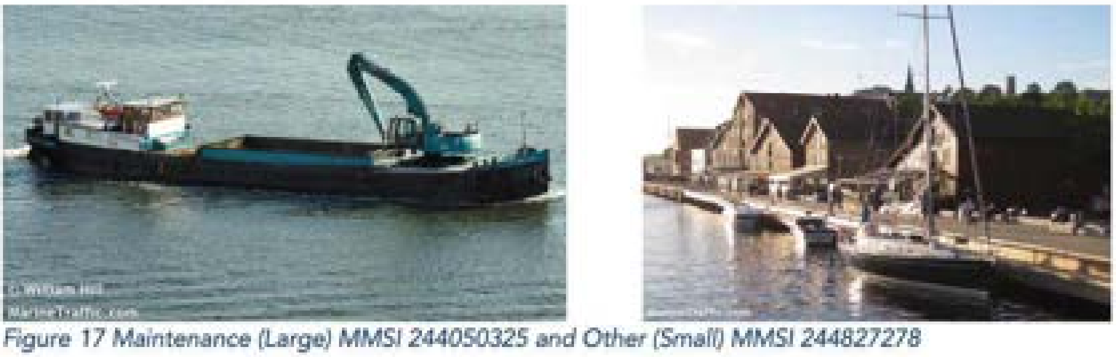

Figure 17 Maintenance (Large) MMSI 244050325 and Other (Small) MMSI 244827278

Figure 18 Law Enforcement (Small) MMSI 244810216 and Law Enforcement (Large) MMSI 244690186 found in dataset


Figure 19 Pleasure Craft (Small) MMSI 244730681 and Pleasure Craft (Mediuum) MMSI 244860885 found in dataset

Figure 20 Pleasure Craft (Large) MMSI 2440209072 and Tanker (Large) MMSI 2440892845 found in dataset


Figure 21 Tourism (Small) MMSI 244780811 and Tourism (Medium) 244535627 found in dataset

As can be seen, the subtype classification is not easy to follow to the naked eye, fortunately the category (Passenger, cargo and Other) is much easier to follow, as is the classification by size (small, medium, large).

Step 3 Constraints and Boundaries: Spatial Characteristics and Urban Morphology

Every city is unique. As such, Amsterdam has very specific spatial characteristics. For example, things like the size of the area, the landscape, the way the buildings are laid out, amongst others. Urban morphology is the study of urban forms and of the agents and processes responsible for their transformation over time (Vitor Oliveria, 2020). The spatial analysis using GIS software offers the possibility to understand Amsterdam's urban morphology and identify limitations and possibilities. Objects such as trees, trash bins or existent charging stations play a role in the available space of the city as well as in the city dynamics. City structures such as bridges also play an important role, since the heights of the quay walls increase as they approach bridges(Zhang et al., 2020), in many cases it renders these locations useless or physically difficult for alternate purposes.

Spatial characteristics play a big role to decide which geo-locations along the Amsterdams canal network are suitable for charging stations as well as to identify most used routes with the purpose of predicting needs of energy of the different vessels that traverse Amsterdam canals.

As mentioned earlier, for the current research availability of space at quays, shore power, street lighting, bridges and existing EV charging stations near the water are the spatial parameters to be considered.

The temporal part of the thesis will be focused in modeling the movement of vessels in the canals of Amsterdam with the aim to find the routes, speed and frequency of vessels crossings in order to best predict the needs of charging stations along the route and locations where these should be provided.

[redacted]

Available space in quays and Bridges

An important aspect to determine is a charging station can be built is the physical availability of space. Even then, in some cases there might be enough space in the quay, but the canal may be too crowded for vessels to dock. According to previous studies conducted by the Municipality, it is important to analyze certain aspects such as the space on the water (length of the berth), space on the land (available are on the quay), physical obstacles (bridges, bollards, trees, waste bins), availability of time (charging, docking, loading and unloading).

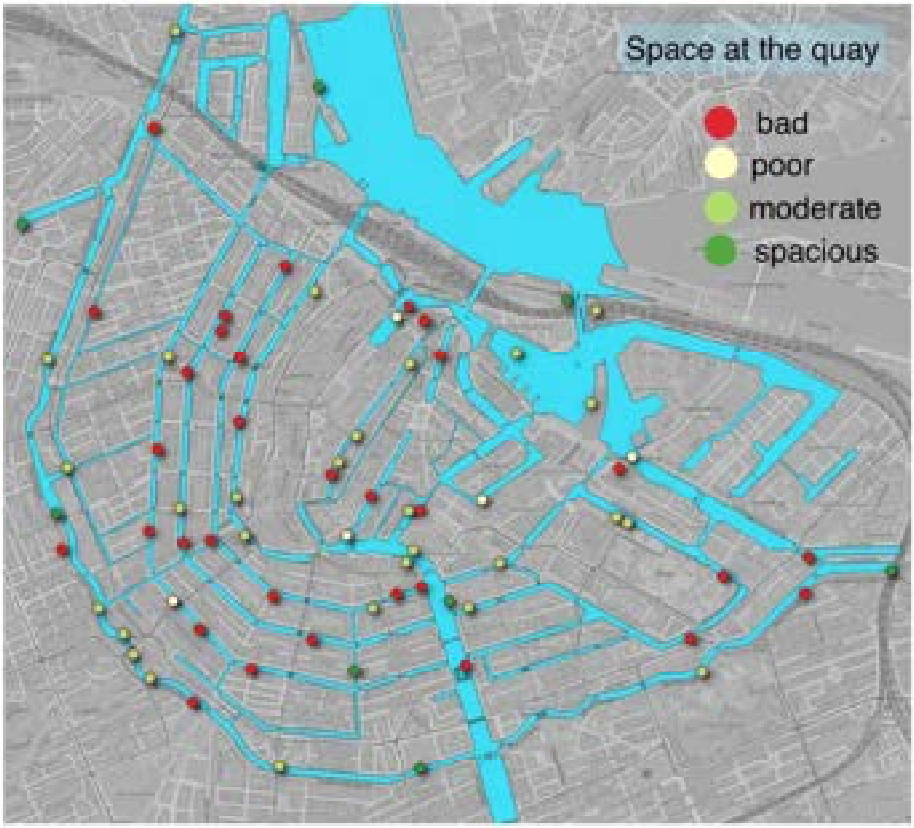

Figure 23 Available space at quay

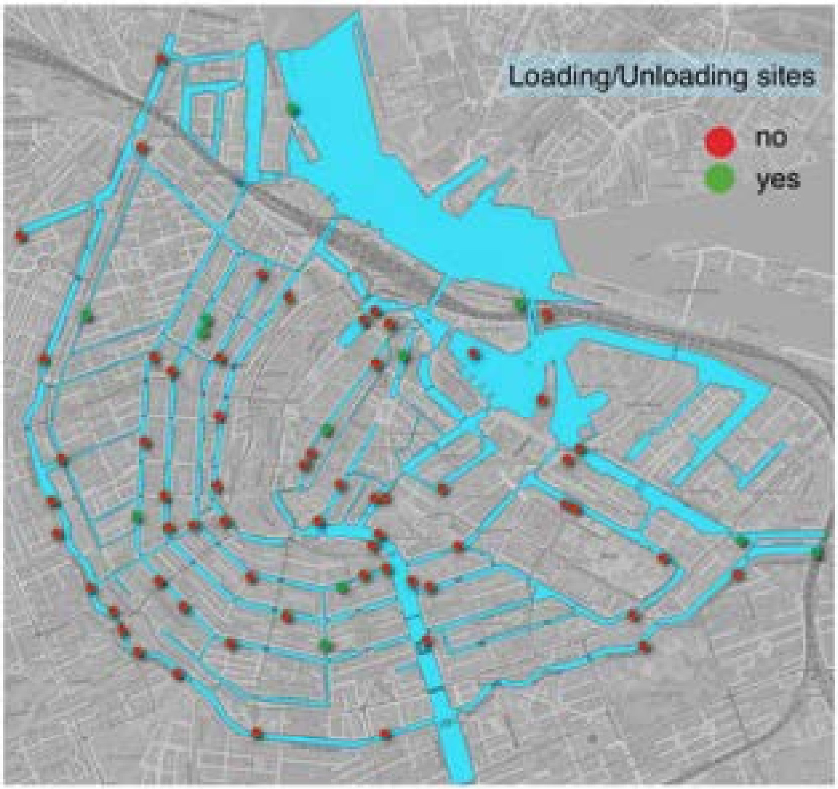

Figure 24 Loading and unloading sites

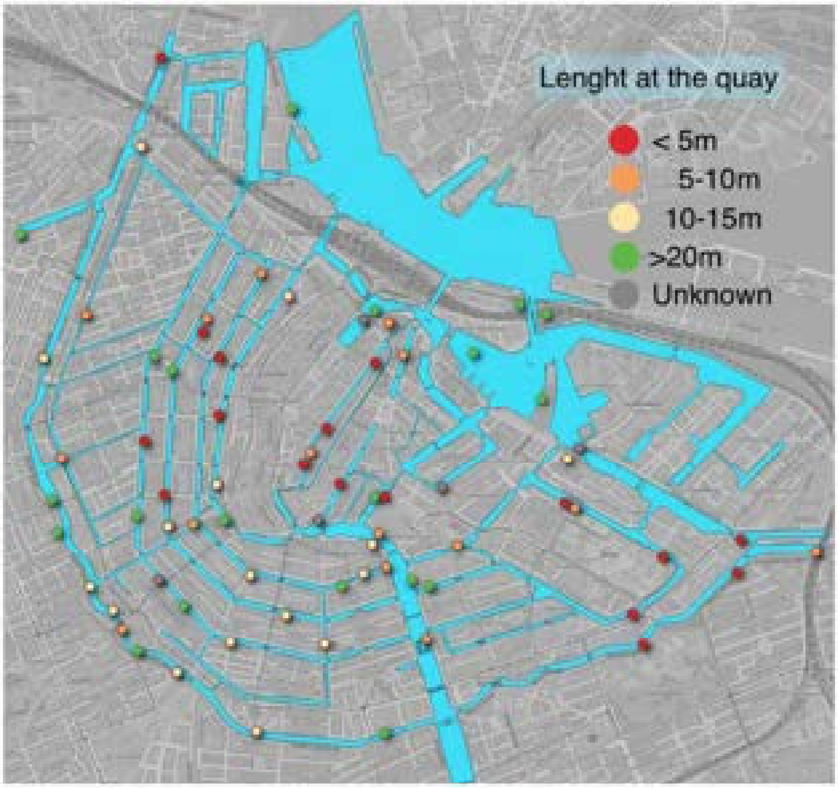

Figure 25 Length at the quay

Moreover, a buffer zone from the bridges is considered, circa 20m, since in most cases the canal walls typically increase as they approach bridges(Zhang et al., 2020) and would render it useless for the task at hand.

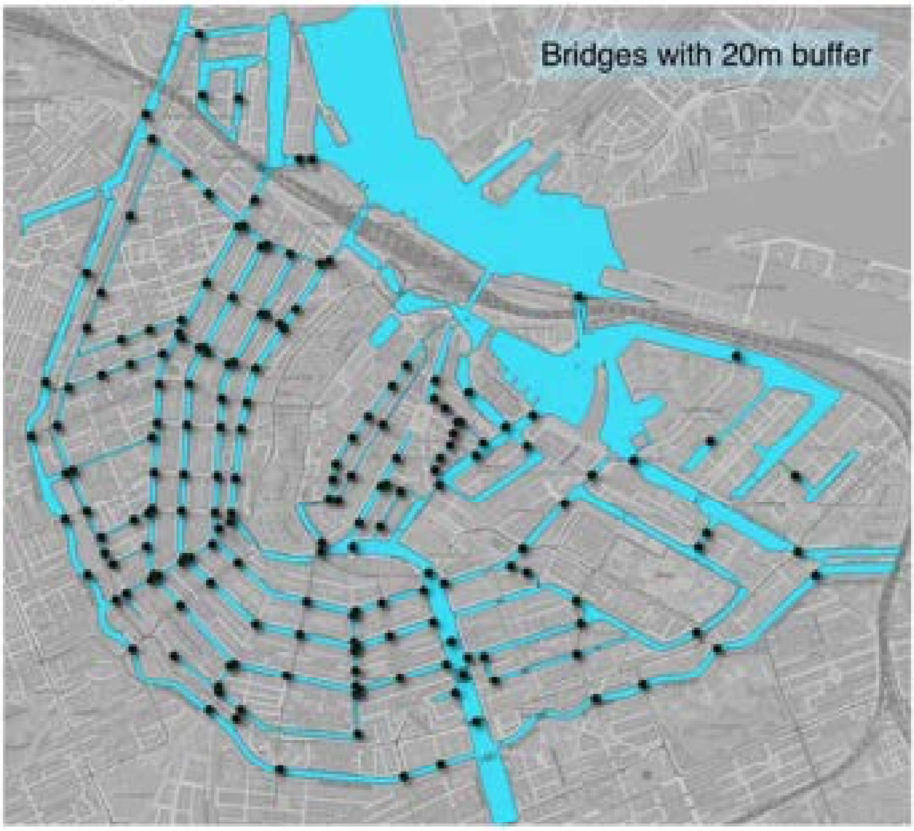

Figure 26 Bridges with 20m buffer

Canal Transit Profiles

In the city center (Amsterdam Centrum) the Municipality has classified the canal according the available passage width, length and depth for all shipping (Transport Over Water, 2020) . As can be seen in the following figure, most of the canals in the center of the city fall within the profile B classification.

Figure 27 Sailing profiles

While the canals allow for a dynamic interaction between the vessels, the Municipality found out that there are some canal segments and intersections that are too crowded, specially during afternoon hours (Gemeente Amsterdam, 2020a).This helped understand to what extent the capacity of a canal segment is reached, and where and when the good transportation can take place in the city. This study was conducted through vessel counts. However, the number of counts performed at some locations is limited and require more extensive data (Transport Over Water, 2020) . Speed in Amsterdam Centrum canals is regulated, the speed limits are shown in Figure 30.

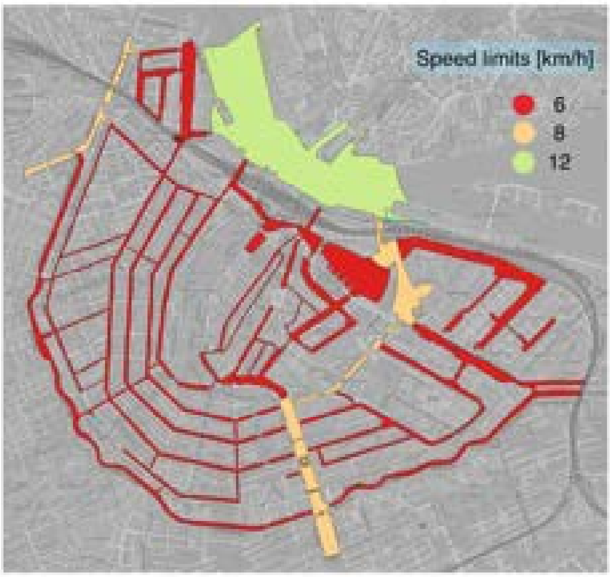

Figure 28 Speed limits in Amsterdam Centrum

It is important to understand what kind of vessels are sailing in those areas. We can already see where the different vessel categories sail. (Figure 31)

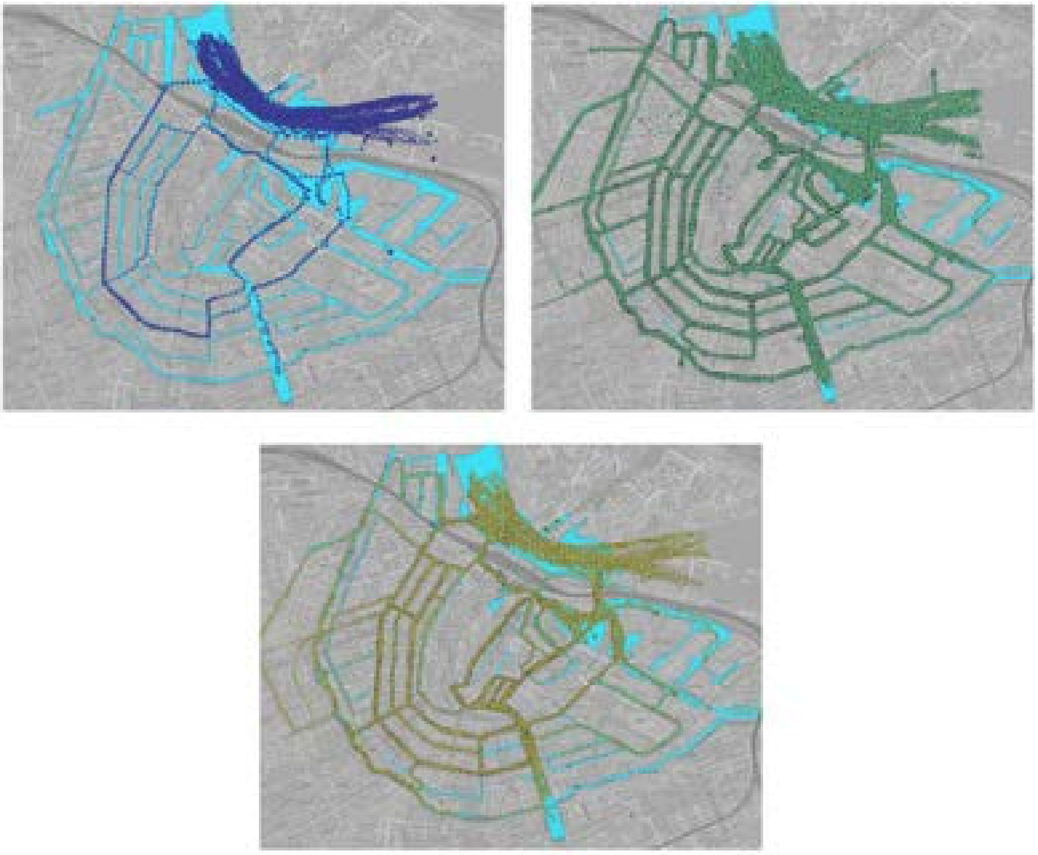

Figure 30 Vessel track points per category. Cargo (blue) Passenger (green) Other (yellow)

By creating density maps we can see the locations where many different vessels - different MMSI- sail through as well as the locations where vessels stay for longer periods of time – A cluster of data points from the same MMSI at a specific location -.

This is done by counting the number of data points within the hexagon grid and adding a weight field to MMSI feature. In this way, The count generated is the sum of the weight field for each point contained by the polygon. Since the location records update at constant intervals, this would mean that a vessel stayed longer at that location.i.e. Density by duration of stay. This can be corroborated later while performing speed analysis.

Figure 32 Vessel geographic density by duration of stay per grid cell

Similarly, by choosing a class field instead of a weight field, the data points are classified based on the selected attribute – In this case MMSI -. If the data points share the same attribute and are within the same polygon or cell (a hexagon), only one of them is counted. Choosing class field for the analysis positively results in the count of different classes that are found within a cell. This shows the locations where different vessels sail the most through, or the vessel density by unique count.

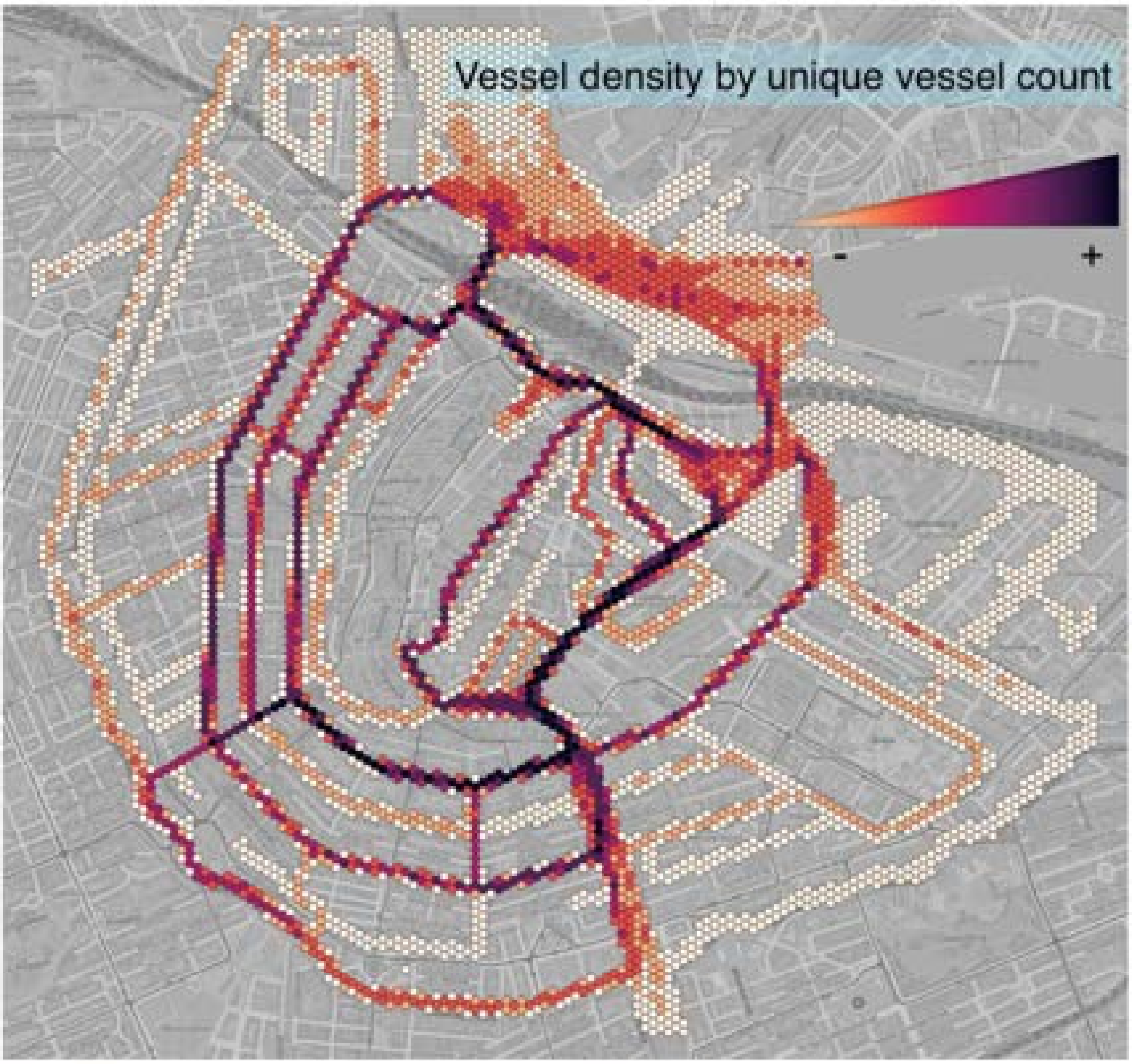

Figure 33 Vessel density by unique vessel count in grid cells

While both maps appear similar to the naked eye, it is already possible to gather some insights, for example the fact that vessels seem to spend more time (or go slower) in the inner rings of Amsterdam and along the touristic attractions. On the second map there is a slightly more even distribution, which means that there are other vessels using the rest of the canals. This can suggest a divergence between the routes that tourist vessels follow and the routes that the rest of the vessels follow. As expected, Cruise vessels stay outside of the Amsterdam Centrum canals. Ferries, as previously discussed, do not only the GVB vessels travelling between Centrum and Noord, although the analysis shows that they account for the most travels within that subtype. Figure 34 shows several position heatmaps comparing the different vessel subtypes.

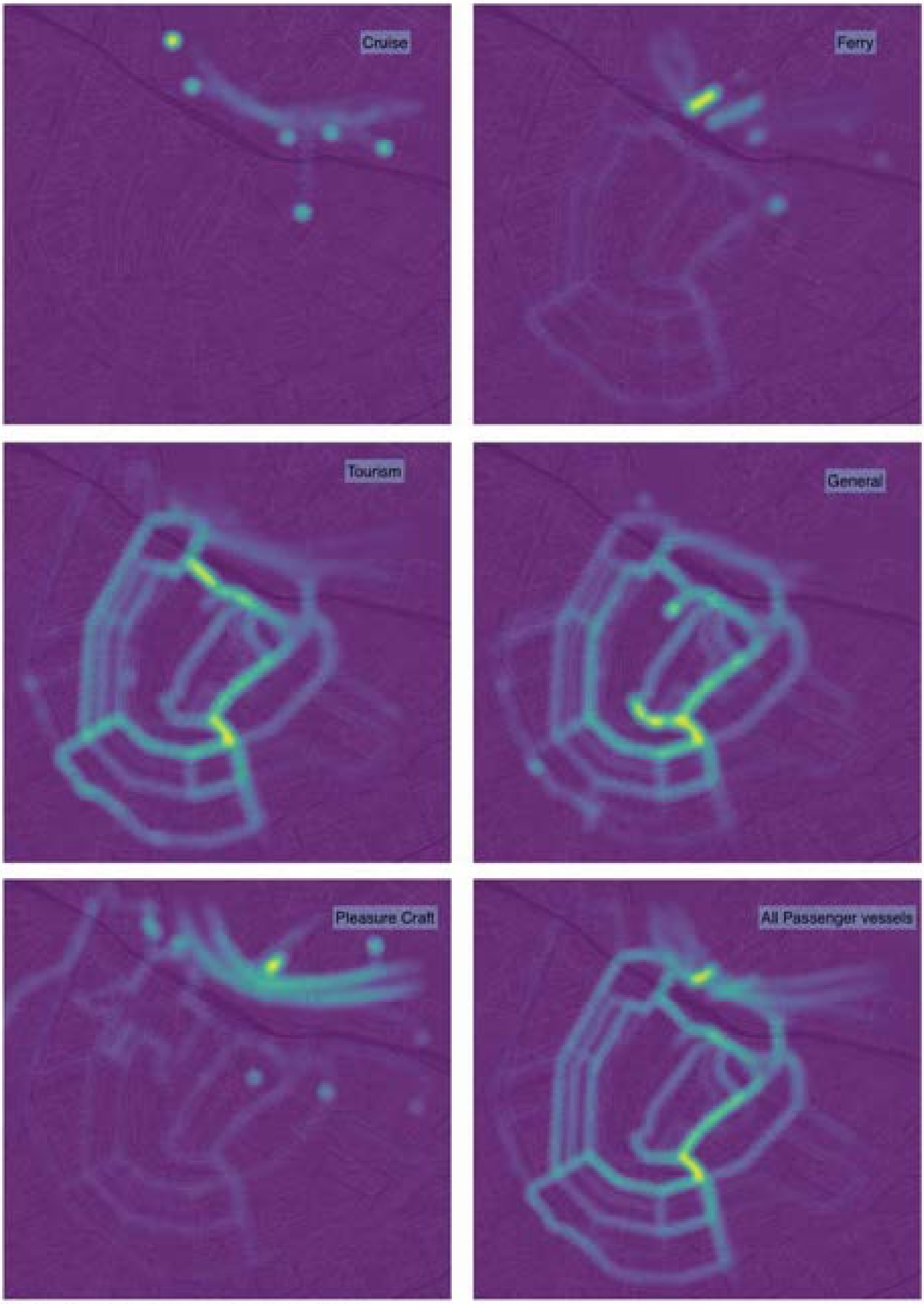

Figure 31 Heatmaps for each vessel subtype

Electricity at the quay

Today, the city of Amsterdam is not equipped to charge vessels even at points where there is shore power, as the power required for charging vessels can often higher than what is supplied by the current shore power. The existing shore power point in Amsterdam Centrum are mostly used for "hotel functions" of vessels. (Heating, cooling, appliances). A research done by TNO (Pim van Mensch, 2016)discovered that vessels in the Amsterdam Centrum canals will require batteries between approximately 100 to 350 kWh, depending whether the charging routines involved charging overnight or charging between trips. As previously mentioned, an EV such as a Tesla model S has a battery capacity of 100kWh. This means that even when a suitable location for a charging station is found, the capacity for successfully charging the vessel will be severely degraded. This is no news, as the city is adamantly investing in solutions for electric vessel charging. One possibility however is the exploitation of existing vehicle charging stations.

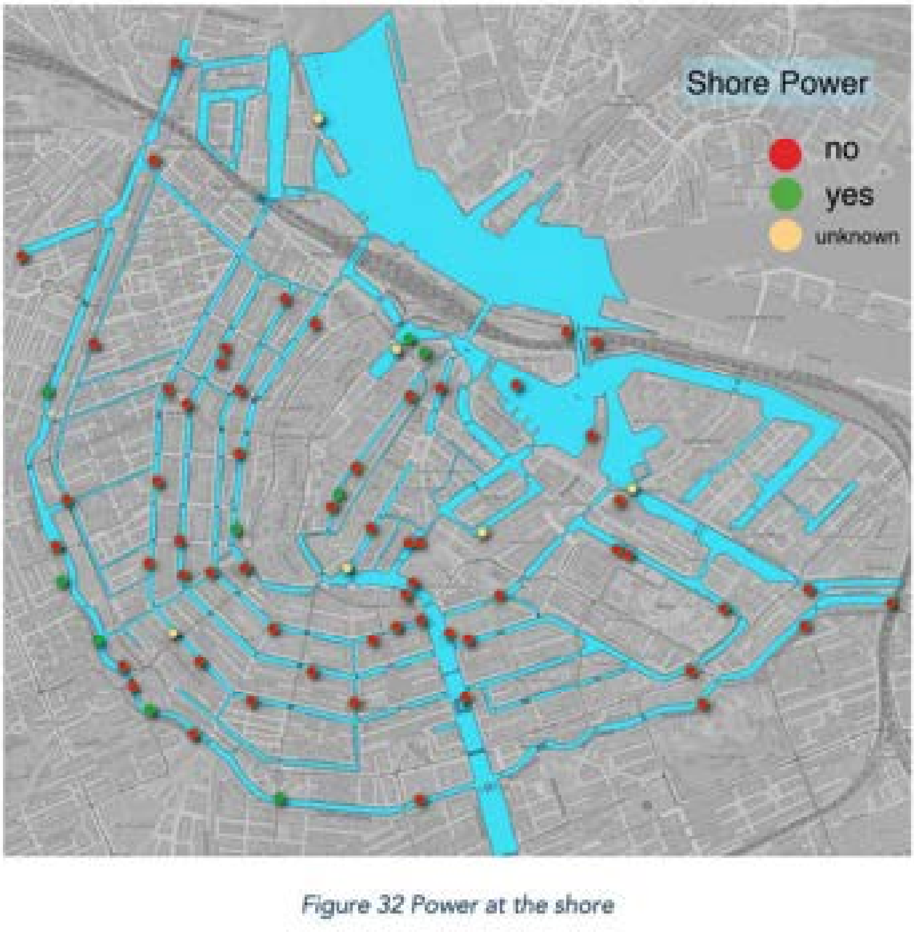

Figure 32 Power at the shore

Existent EV charging stations

Amsterdam Centrum, being the historical city center of Amsterdam, has a limited number of EV charging stations due to its dense and old infrastructure. The available data taken from the Municipality of Amsterdam holds 338 datapoints and allowed to see which charging station are close to the canals. Most of the the existing charging stations have a capacity of 11kW.

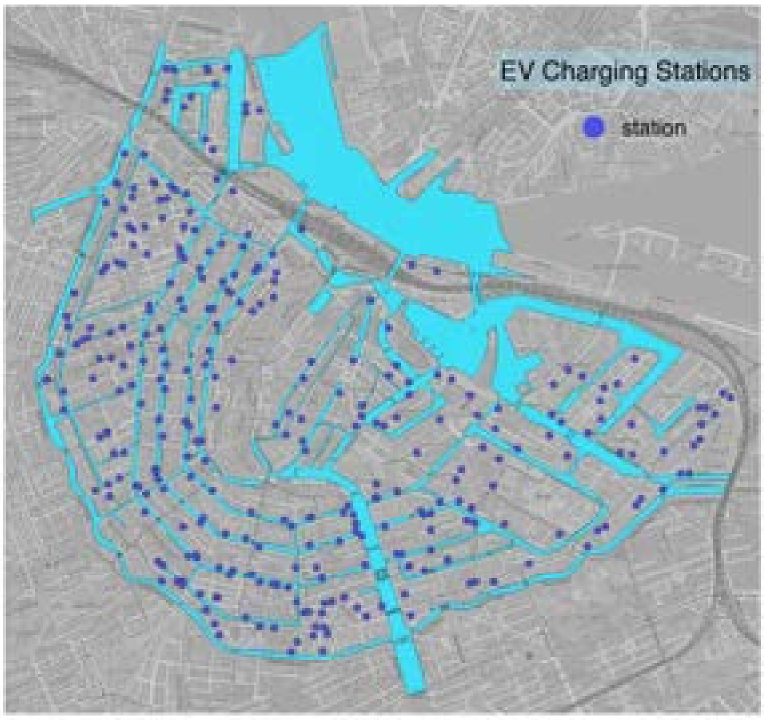

Figure 33 Existing EV charging stations

It seems reasonable to take advantage of existing charging installations for EV's to be used for boats. This is only possible in place where the existing station is close to the water, as such, The stations located near the water were extracted from the layer and used for this research. This led to a reduction of 196 stations. After this, a buffer overlay analysis was performed to remove stations within a bridge zone. This left a total of 139 stations shown in Figure 38.

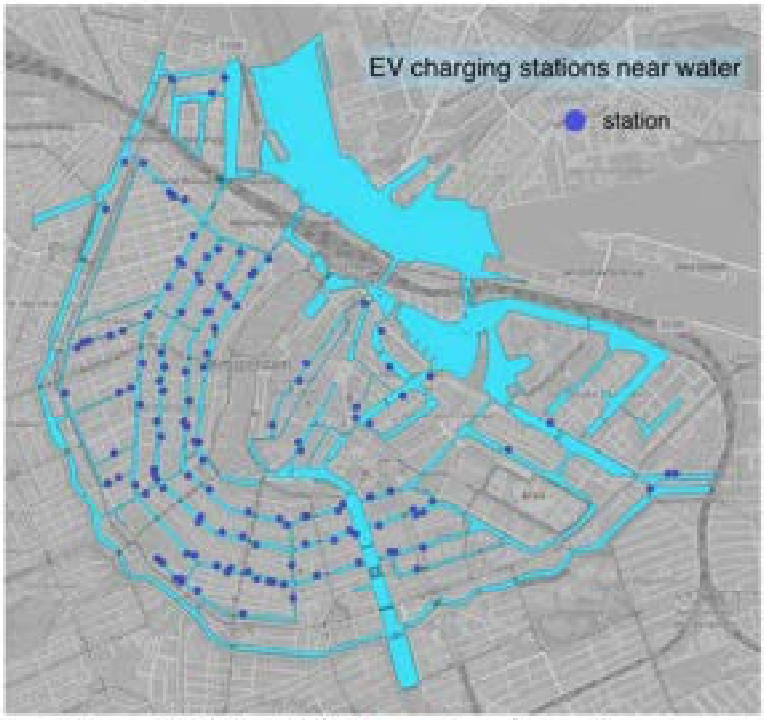

Figure 34 Existing EV charging stations close to the water

Demand Estimation

As previously stated, this research will focus on passenger vessels. There are many ways to estimate the energy demand of the vessels. For the case of Amsterdam Centrum there are serious studies that have accurately done so. In 2016, a study by TNO (Pim van Mensch, 2016) determined the total energy requirement for the Amsterdam canal cruise fleet, (in this report, passenger vessels) as 9000 MWh/y. At the time this fleet consisted of approximately 310 ships. In this study ferry boats that link Centrum and Noord are perhaps not considered. The dataset used in this study shows similar values for the passenger vessels, with a total of 347 vessels, including ferry boats and other larger vessels (larger than 29m). Larger vessels will be taken into account for visual exploration, but will not be considered in the final analysis. As a quick note, the ferries that travel from Centrum to Noord are smaller than 29m in length.

This study suggested that sailing requires 15 kW on average (Small vessels have an average consumption of approximately 8.2 kWh per hour, while Medium and large vessels require over 18.5 kWh). With batteries ranging from 100kWh to 350kWh, and a charging capacity from 22kW to 100kW. To reduce computational time, an average for the three vessel sizes is made to match battery sizes with vessels, according with this information.

Step 4 Vessel trajectories spatio-temporal analysis

This work uses data from MarineTraffic obtained via MIT Senseable City Lab. The analysis covers vessel traffic on the 12th of August 2017 in Amsterdam Centrum. For this analysis several packages are used, including MovingPandas.

Thi analysis was done using a Jupyter notebook through Anaconda Navigator. Some steps may seem repetitive or obvious, however ther are needed in order to split the computing time into several smaller tasks. The following lines are comments for the written code.

The Jupyter notebook goes as follows:

1. Trajectory data prepping
2. Loading data and adding geospatial information
3. Exploring vessel distributions
4. Obtaining vessel trajectories
5. Visualization and further analysis of vessel trajectories

MovingPandas credits. Graser, A. (2019)[20].

The first step for the vessel analysis is to convert the data frame to a GeoDataFrame that can be python-read. After all Python dependencies and packages are loaded, it is time to load the data. The data was originally obtained as a CSV file. This has however no Geolocation. Thus we first used QGIS to read the csv file and export as a GeoPackage file to be read in the jupyter notebook.

There is a column recording the speed of the vessels. In some cases we see there are some values where speed is zero '0'. We will clean the data by taking those values out of the analysis. Perhaps its useful to see how many zero values there are. We will show them in histograms, Figure 39.

[20] MovingPandas: Efficient Structures for Movement Data in Python. GI_Forum – Journal of Geographic Information Science 2019, 1-2019, 54-68. doi:10.1553/giscience2019_01_s54.

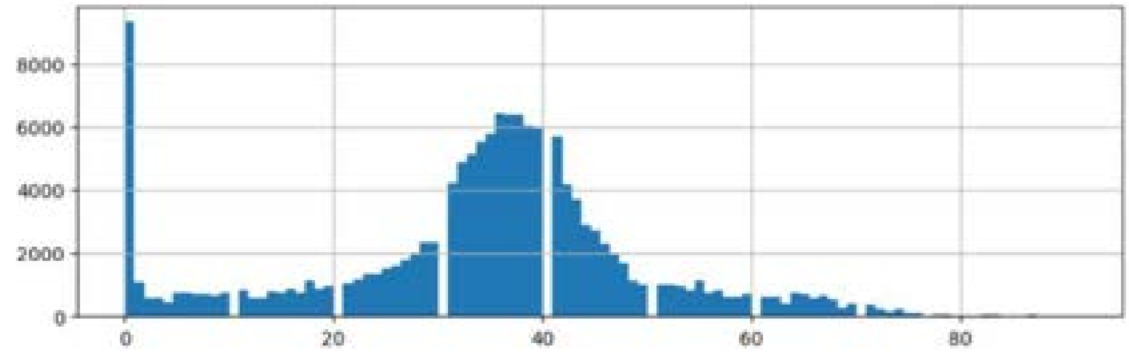

Figure 35 Histogram of vessel speed, including zero values

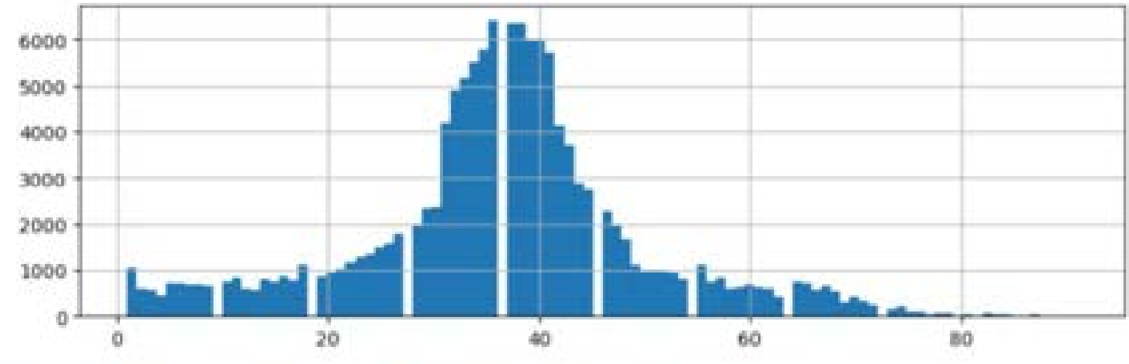

Figure 36 Histogram of vessel speeds, excluding zero values

After filtering out the zero ´0´values, we now see that the original size with 167343 data points was reduced to 154751 data points.

Before proceeding to create trajectories from the given coordinates for each of the vessels, taking the MMSI as a unique ID, let's see which types of boats are in our data.

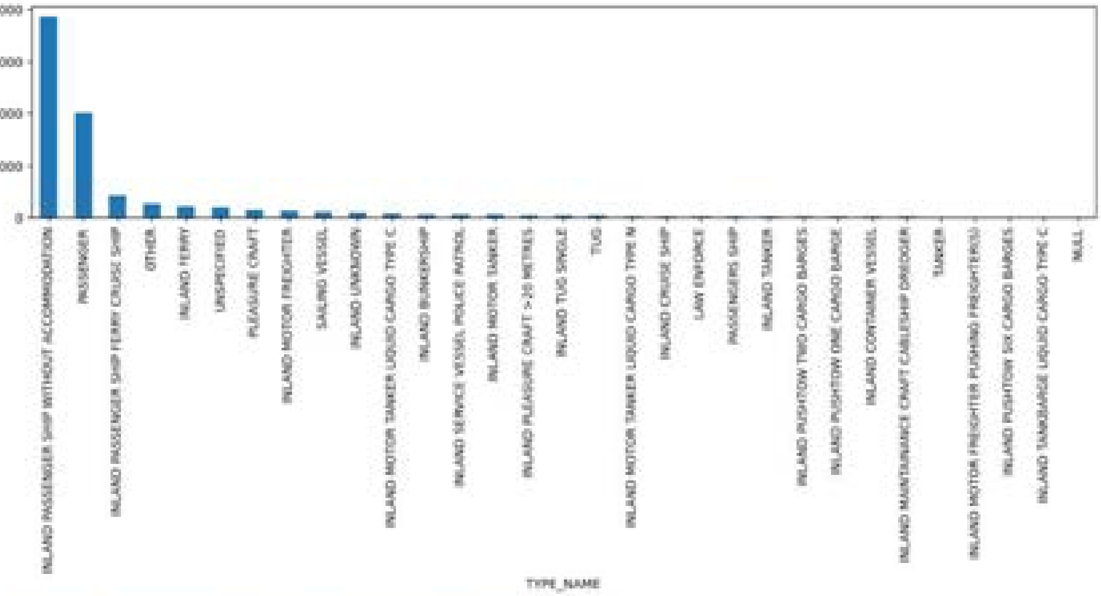

Figure 37 Bar chart for all vessel types in the dataset

This can be confusing, are there are many names for vessel types. We will categorize them and cluster them, using the vessel category defined in earlier chapters.

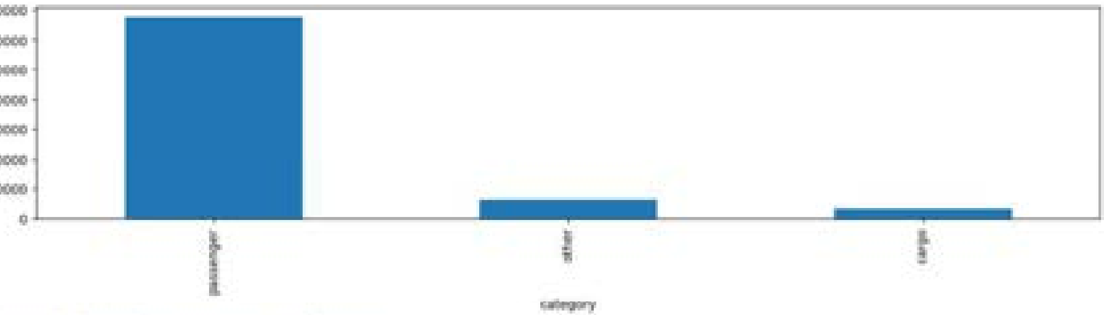

Figure 38 Vessel categories in dataset

It is reasonable to take passenger boats as a boat category to study.
We can further look into their subtype, and the overall vessel geographic distribution.

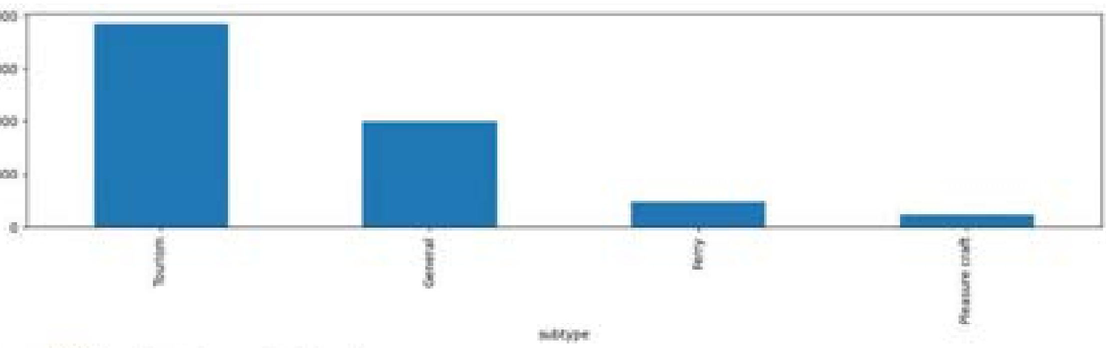

Figure 39 Vessel subtypes in dataset

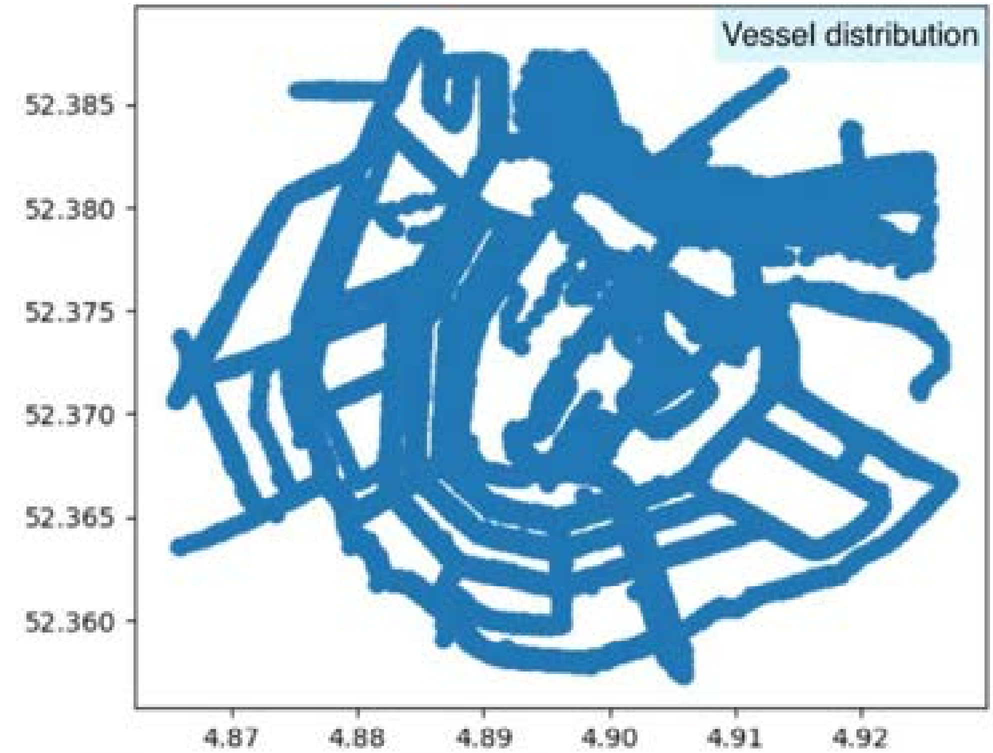

Figure 40 Vessel geographic distribution (datapoints)

For the passenger vessels, we can quickly see how many data points exist for each vessel size. We know from previous chapters that for passenger vessels the dataset holds 96 Large, 87 Medium and 163 small. These unique values aggregated per MMSI differ from the number of datapoints in the dataset, that hold 35811 Large, 57914 Medium and 52669 Small. This means that although there are almost double the amount of small vessels than medium vessels in the dataset, medium vessels have more records in the dataset.

Table 8 Vessels in dataset by size

Size	MMSI (Unique)	Datapoints (sum)	Ratio (Points per vessel)	MMSI %	Datapoints %
Large	96	35811	373	27,75	24,46
Medium	87	57914	666	25,14	39,56
Small	163	52669	323	47,11	35,98

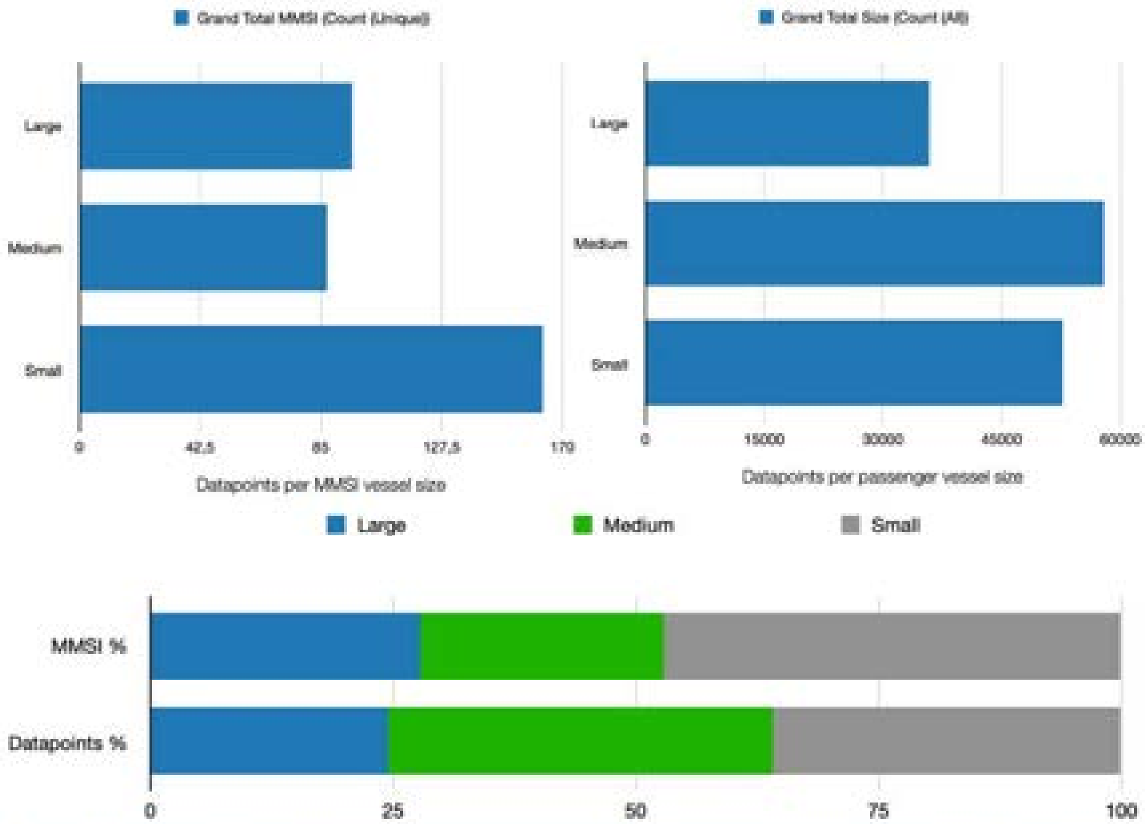

Figure 41 Number of unique passenger vessels per size in percentage (MMSI) and number of average data point per passenger vessel size in percentage (Datapoints)

Visualizing Trajectories

From all these datapoints we can create trajectories. A minimum of 100 meters is chosen for a trajectory. This means that all trajectories under 100m will not be considered. This results in 448 different trajectories. The trajectory collection is shown in Figure 46.

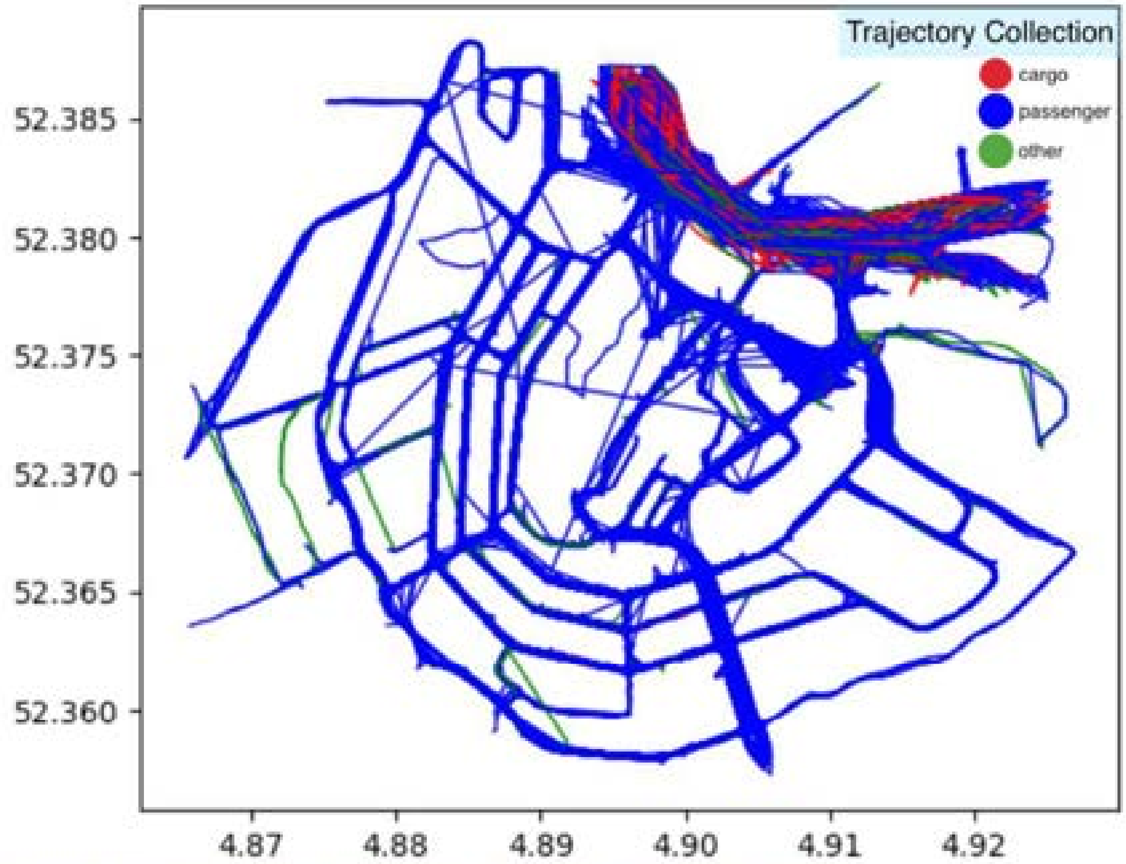

Figure 42 Vessel trajectory generation from datapoints. (Trajectory collection)

As can be seen, the canals in Amsterdam Centrum are mostly transited by passenger boats. With the other categories only using the Ij but not going into the city. This work focuses on the passenger boats. It is worth noting that the straight lines that seem to cross Amsterdam Centrum regardless of the canals mean that a particular vessel was out of the observation area and re-entered de observation area at a given moment, or that there was no data between several observation moments. Thus, the algorithm links these two points.

A generalization method for the trajectories is used taking into consideration time for one case an position and standard deviation – the case of Douglas-Peucker – for the other. The tolerance in the Time Generalizer provided is the miminum time that has to expire between consecutive points, and everything in below said time is removed. In the case of the Douglas Peucker Generalizer, the tolerance corresponds to the maximum deviation allowed between consecutive points of the data. This being said, if the value is too big, it will eventually simply connect a line from de beginning to the end. In both cases, the generalization is done to remove irrelevant points and finally to simplify the analysis and reduce computational time. Figure 47 shows the generalization comparison of both methods. Using the time generalizer (left) seems more adequate for the current work.

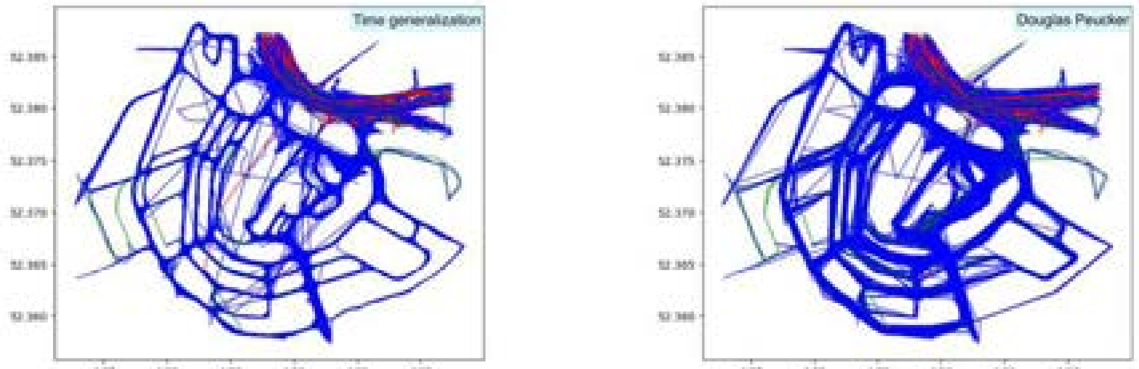

Figure 43 Generalization methods for trajectory simplification

It is important to remove the vessels that do not fall within the passenger category. Parallel to this, the straight lines linking two "orphan" datapoints must also be cleared. Figure 48 shows the passenger vessel trajectories on a basemap, prior to orphan links' removal.

Figure 44 Trajectory collection on basemap

With these trajectories per vessel, we can compute the total distance travelled for each vessel, which is a necessary piece of information to obtain the location where the vessels will need to charge batteries.

Identifying trips

Earlier the 'zero' values were removed. This inveitably created several segments of trips that we have not yet analyzed. However, we can split each of this segments and define them as trips. In this step 1352 individual trips were obtained. The result is Shown in Figure 49.

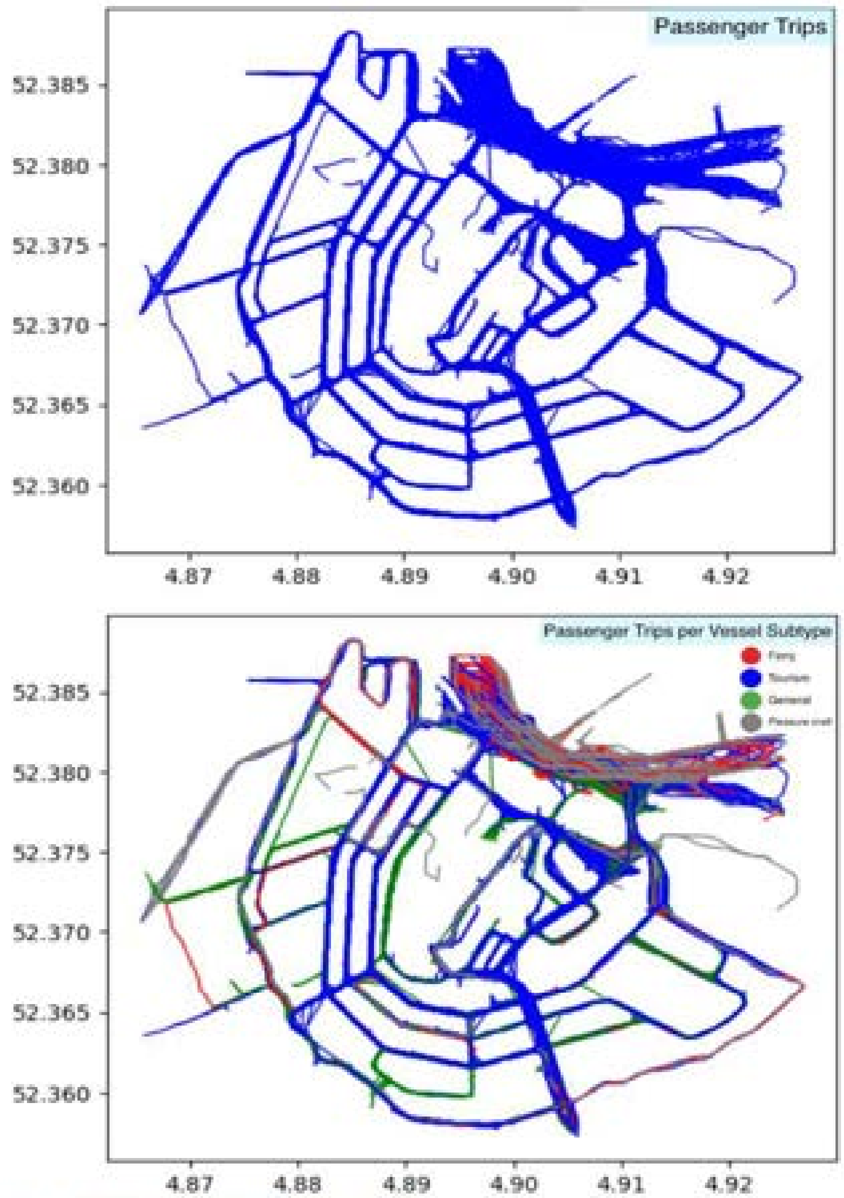

Figure 45 Creation of passenger trips

With this information we can now see the trips for each vessel size. (Figure 50)

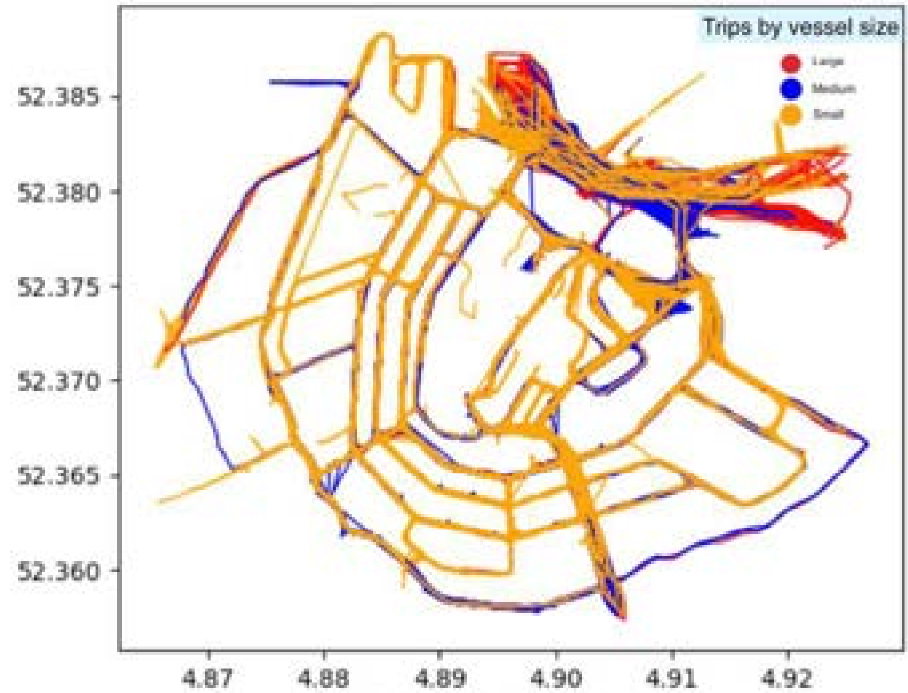

Figure 46 Trips by vessel size

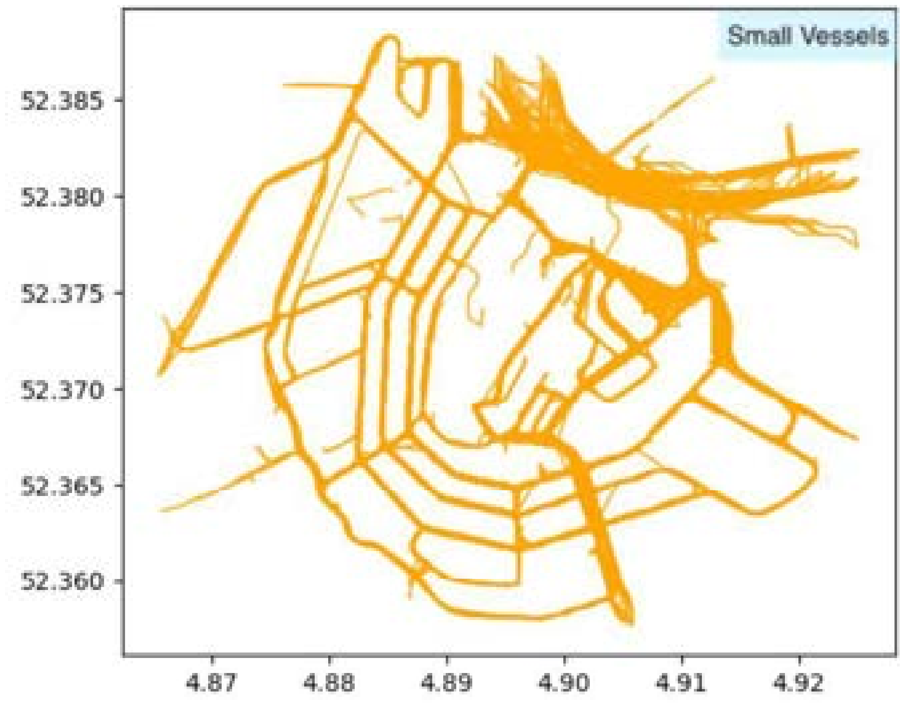

Figure 47 Small vessel trips

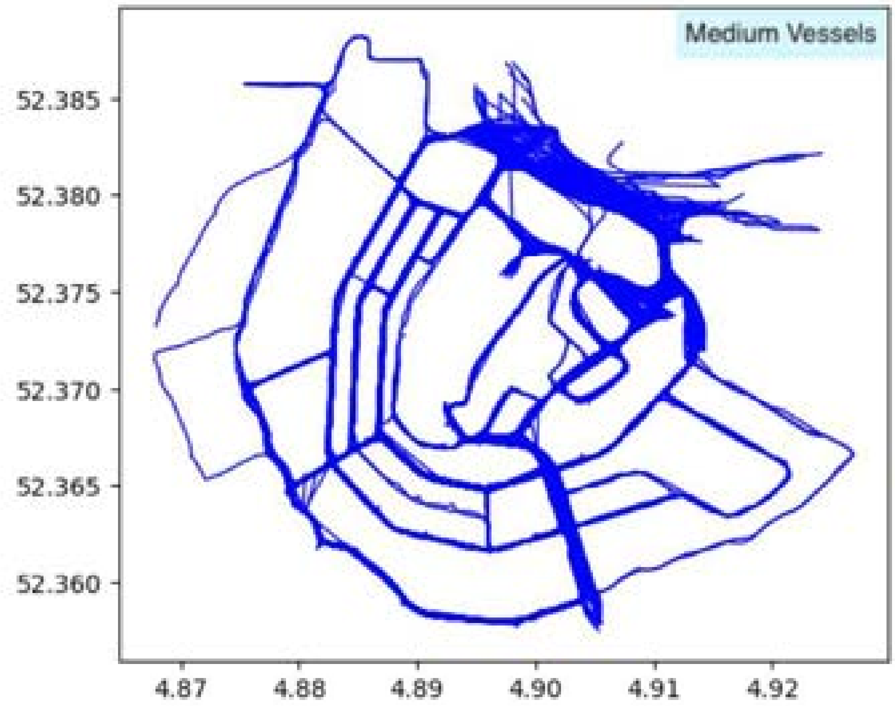

Figure 48 Medium vessel trips

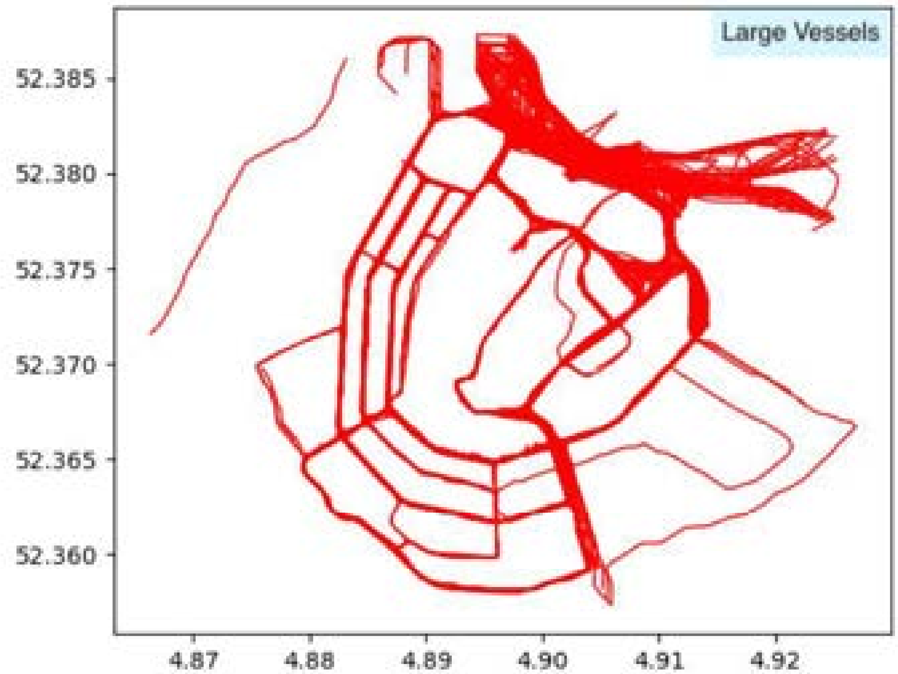

Figure 49 Large vessel trips

Step 5 Charging Demand Analysis

Charging demand points by sailing time

Now that the trips and trajectories are classified, and earlier, the battery per vessel size was decided. With this information it is possible to estimate the approximate maximum sailing time per vessel on average. The spatio-temporal analysis provides the trajectories that the different vessels follow. By computing these trajectories with the indicated timestamp, a maximum distance can be obtained given a defined kWh per hour consumption. Effectively, the algorithm will assume the vessels to repeat their routes until the battery has reach a Depth of Discharge of 80%. [redacted]

[redacted]

[redacted]

[redacted]

To repeatedly divide one field by another until the result is smaller than a specific value (in this case Ltraj, QGIS with a recursive approach is used. However, it's important to note that the field calculator in QGIS does not support recursive calculations directly. To achieve this, the QGIS Python Console is used instead.
The result is a distance value. This distance must be overlapped with the trajectory of each vessel and finally the point where at the end of this distance needs to be extracted. This is the point that will define the geographic charging demand point at DoD 80%, earlier shown as "C". This is done by extracting specific vertices along a linestring, or

trajectory. The values for each vessel will differ, as the trajectories and average consumption are not the same throughout the Amsterdam passenger fleet. These demand points can be seen in Figure 54.

[redacted]

Since the dataset contains vessels that were "passing through" outside of Amsterdam Centrum canals, the algorithm is unable to understand it is not the "full trajectory". As it provides a recursive approach, it assumed that within that small area, the vessels went back and forth, and while this is true for the Amsterdam ferries, is it not so for some others, as is shown in Figure 55.

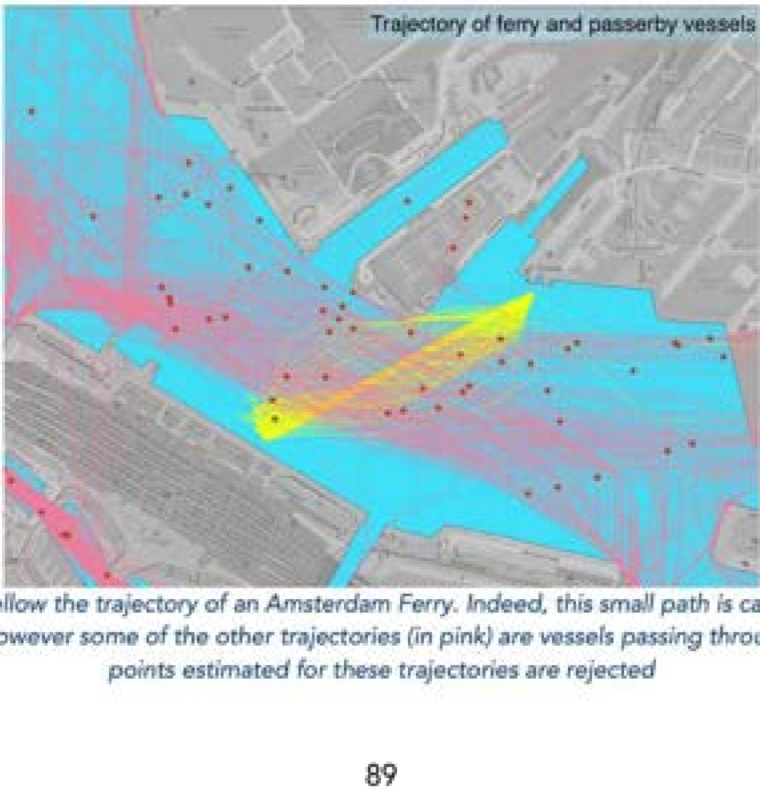

Figure 51 In yellow the trajectory of an Amsterdam Ferry. Indeed, this small path is carried out many times in a day, however some of the other trajectories (in pink) are vessels passing through. The demand points estimated for these trajectories are rejected

Since many of these demand points are close together, a clustering step follows. Using QGIS clustering can be done using DBSCAN method or the K-means method. DBSCAN method finds clusters based on vector point densities(Carleton University, 2021); it groups together data points that are close to each other and separates points that are far away. On the other hand, K-means is a centroid-based clustering algorithm, and partitions the data into "K" clusters, where K is a given number. It does not take density into account. The amount of charging stations can vary, since power output and number of charging stations can be decided through policy agreements.
The Municipality aims to have 22 charging locations in the near future to be later expanded to 44 places throughout the city(Gemeente Amsterdam, 2021). There is no publicly available document stating how many of these charging stations are considered for Amsterdam Centrum. In this work, different scenarios are analyzed, considering 5, 10 and 20 charging points. This work helps policymakers in the decision-making process, as the number of stations can be adjusted according to specific needs. The clusters created are shown in Figure 56.

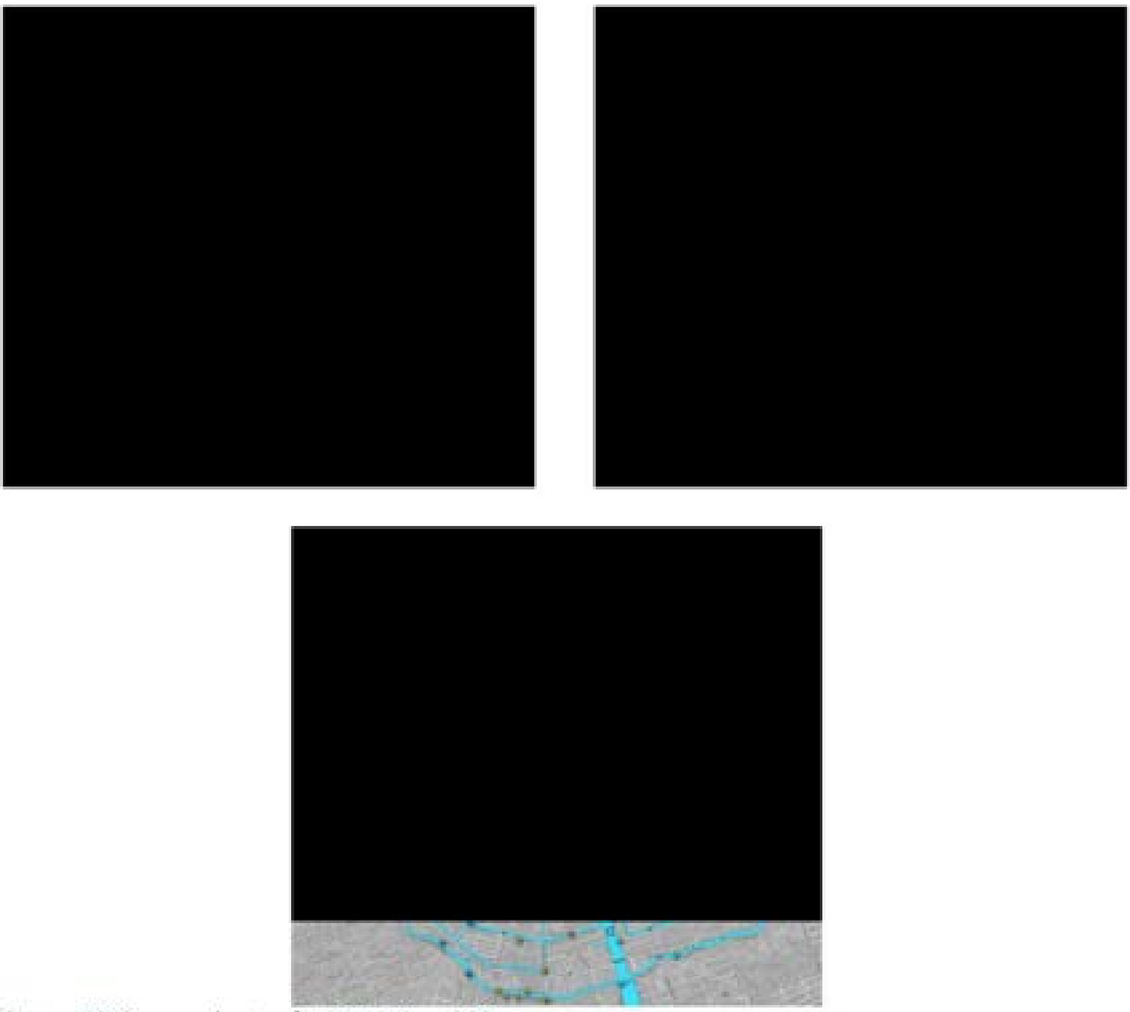

Figure 52 K-mean clusters for K=5, 10 and 20

The centroid for these clusters must be snapped to the waterways layer, since a charging point in the middle of a building is useless for the boats. Shown in Figure 57

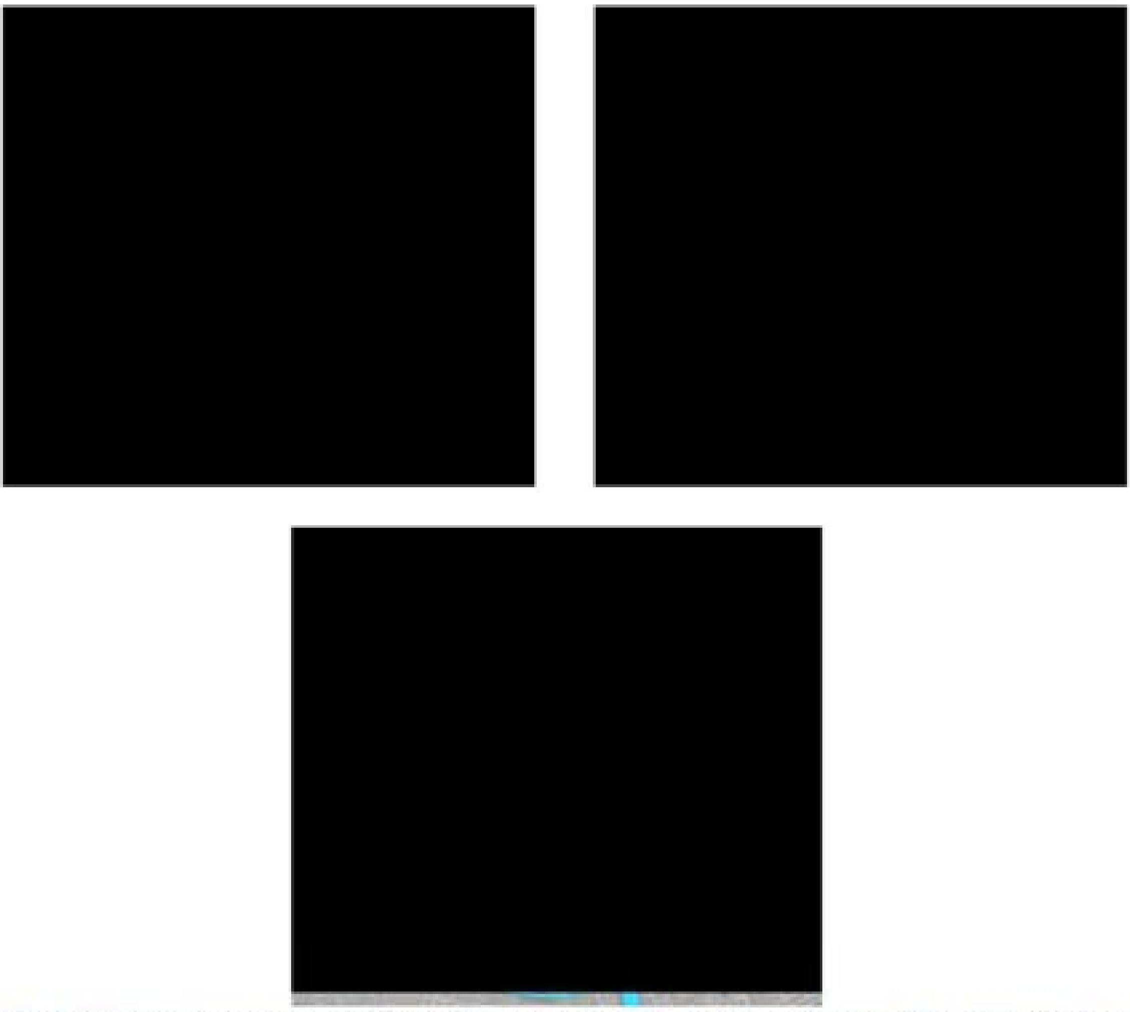

Figure 53 Demand points centroid from clusters with K=5, 10, 20. Centroids snapped to waterways layer

Charging demand points by stop duration

The trips are obtained by means of observation gaps. This means that the algorithm deletes the datapoints between consecutive points if the elapsed time is higher than the value input into the algorithm. For example, we chose an observation gap of 5 minutes, the algorithm will remove all consecutive datapoints that have a longer period between them, thus creating segments, or trips. Because vessels need to recharge, we can also find the moments where the vessels stopped. The study (Pim van Mensch, 2016) conducted a scenario analysis with boats charging overnight or charging between trips. A limited timeframe of 15 minutes was given for the "charging between trips" scenario, and concluded that with a specific battery setup, 15 minutes of quick charge would allow for 1 hour of sailing. This is in most cases, enough for a trip. When analyzing real vessel movement, it is hard to detect the exact place where a vessel reached a speed of zero. (Figure 58)

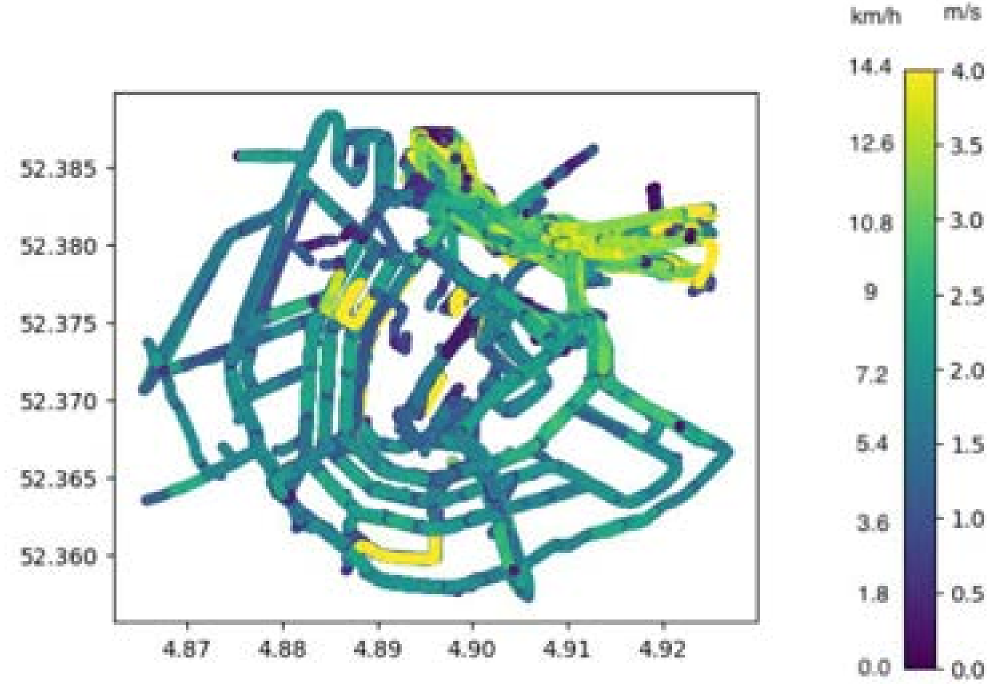

Figure 54 Calculated speed of vessels from trips

In the current work, using MovingPandas package, a stop is detected if the location points of the vessel stay within a given area for a specific amount of time. In slow speed canals, a shorter timeframe will possibly result in many "stop points". For the current work, demand points will be determined considering stops of 0.5h and 1h.

The rate of charge that a boat can have with different stop times can be seen in Figure 59, that shows the charging speed "C" vs the battery size in kWh and the charging power in KW. The unit for "C" is [1/h]. This means for example that a Li-ion battery of 150 kWh will need approximately 1,5 hours to charge with a charging power of 100kW or approximately 4 hours with a charging power of 44kW.

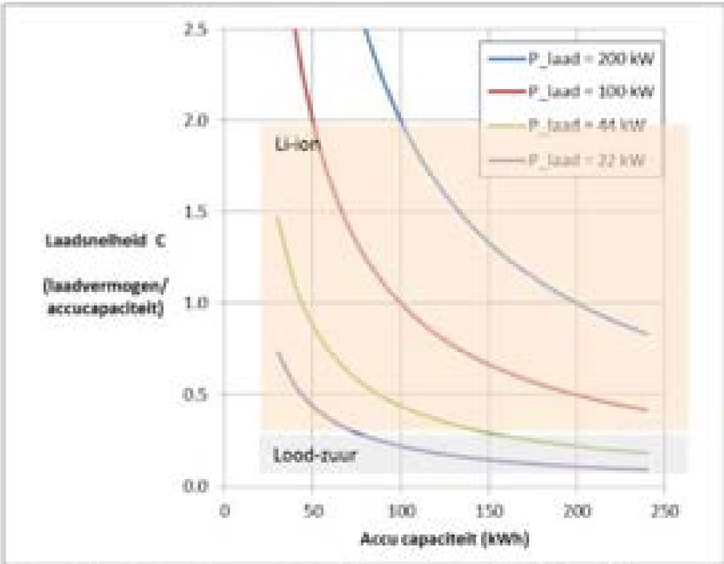

Figure 55 Calculation of the charging rate 'C' vs battery size in kWh for different charging capacities (TNO, 2016)

By setting a time limit and a maximum distance, Figure 60 shows the locations where the vessels remained for 30 minutes or 60 minutes within an area of a 100m in diameter.

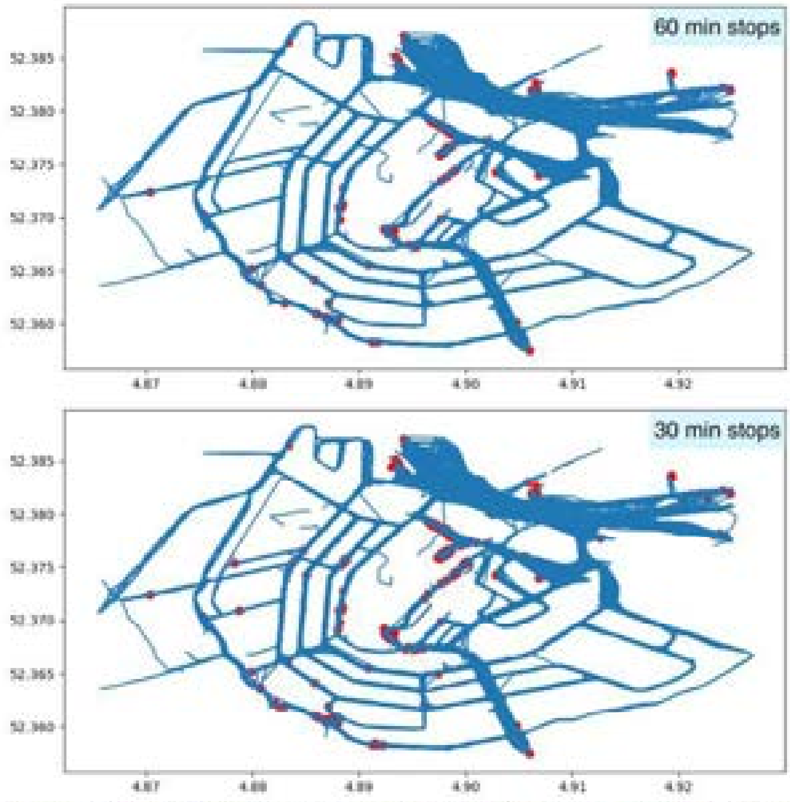

Figure 56 Points (red) where vessels stop for 30 or 60 minutes, witthin a 100m range

For this, a density clustering process takes place (Figure 61), followed finally by a centroid calculation snapped to the waterway layer that shows the demand locations, shown in Figure 62.

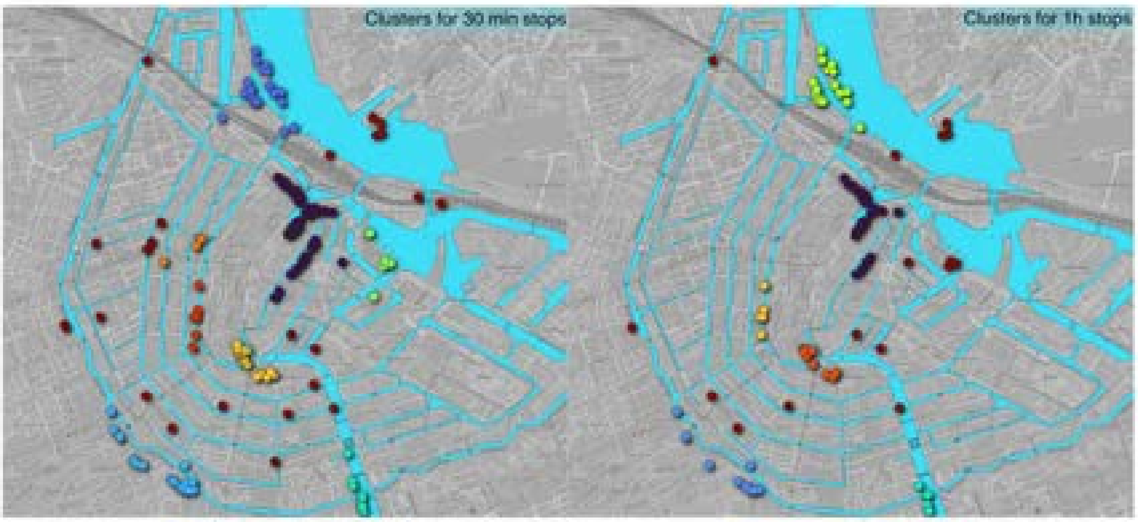

Figure 57 Density clustering process for vessel stop locations

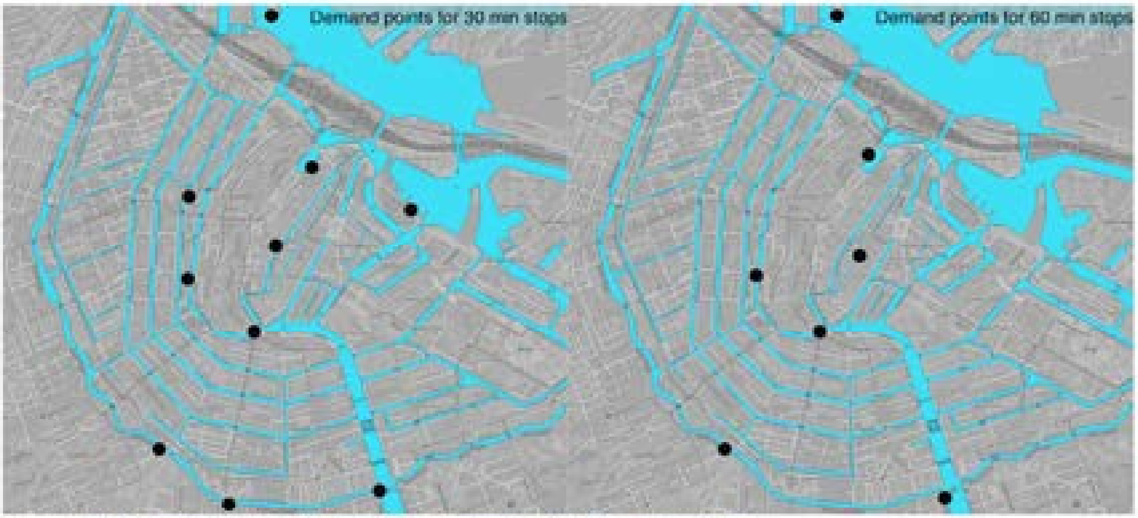

Figure 58 Demand points obtained from density clustering centroids

Results
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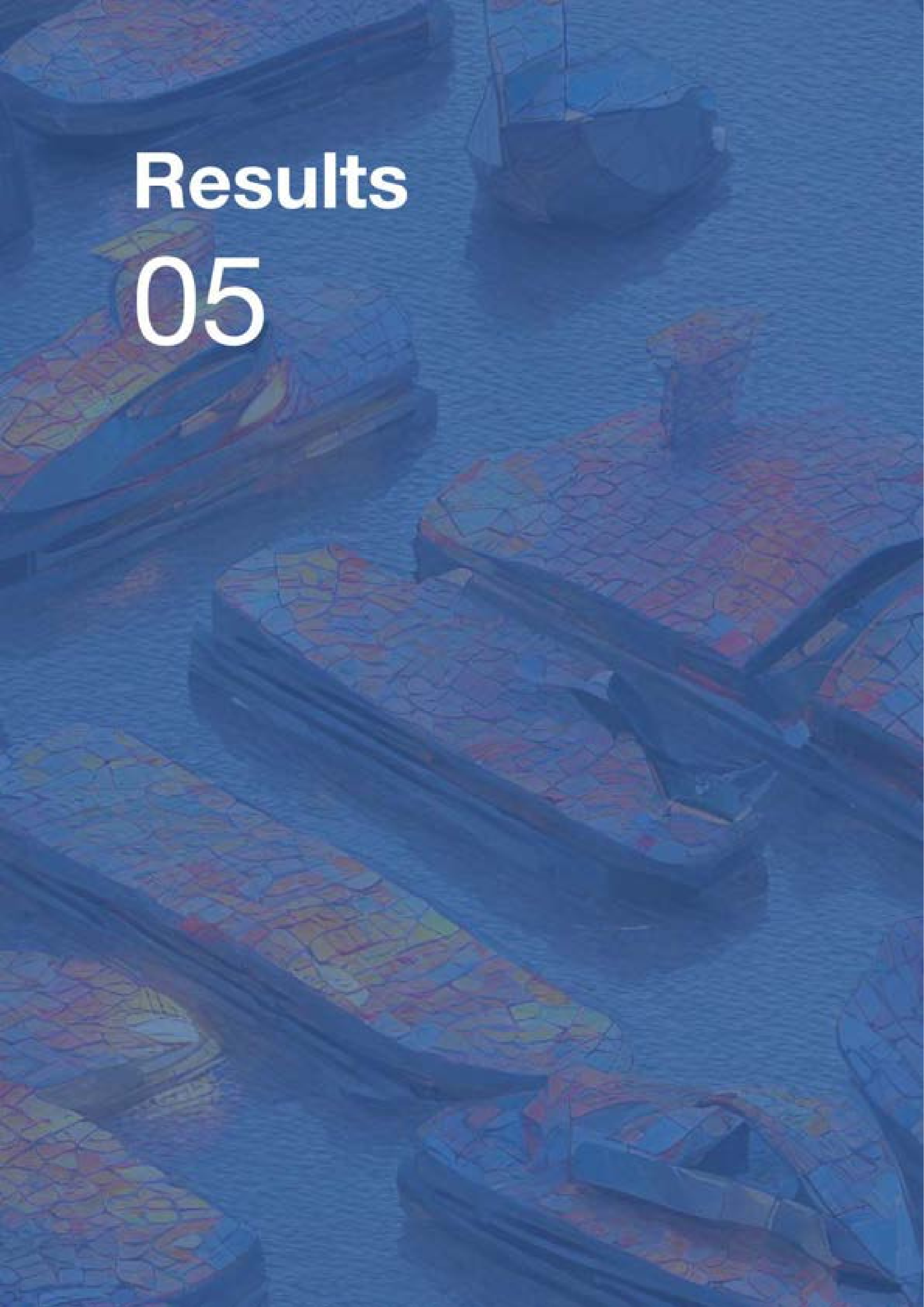

Step 6 Multi Criteria Decision Analysis

The spatial considerations described earlier are used for the MCDA. (Shore power, length of quay, EV charging stations near water, distance from bridges, space at quays and loading sites). While MCDA can be done as a simple overlay analysis on vector layers using geoprocessing tools like buffer, dissolve, difference, and intersection, the result will be binary (Ghandi Ujaval, 2020). However, by interpolating and rasterizing the vector layers, a ranking of suitability is obtained. Additionally, this gives the flexibility to combine multiple input layers and assign different weights to each criterion. Once the layers representing the spatial constraints are rasterized and weighted, a proximity analysis will provide the suitable areas within a certain distance from. Weighting of the raster layers is given in two steps. Initially, when rasterizing the layer, qualitative information is convertes to cuantitative information. While this is not a weighting per se, it already serves as a scoring value. Later weighting is done using an MCDA pairwise weighting method. This method compared the given criteria against each other to determine the relative importance, with a higher number as the the value most preferred. After this, the pairwise method creates a normalized matrix dividing each element by the geometric mean of its corresponding column (Figure 63).

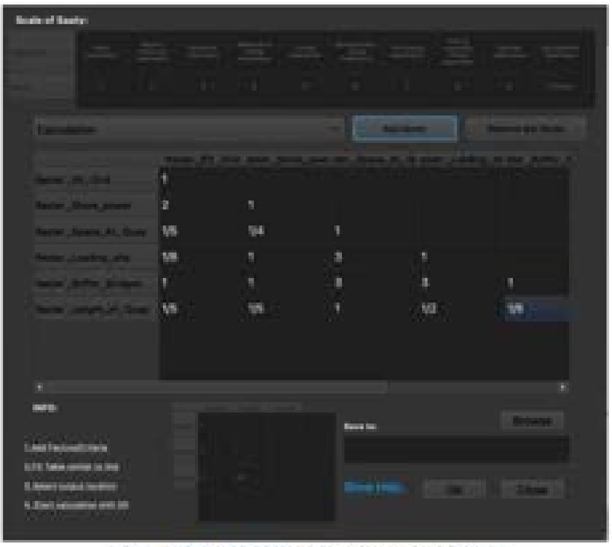

Figure 59 MCDA pairwise weighting

This allows for a structured simplification of priorities given several criteria. Once the weighting is obtained, the raster calculator tool allows performing algebraic operations between the different raster layers, to be analyzed as a single layer with multi criteria. Finally a proximity analysis will determine the suitable areas for charging stations in Amsterdam Centrum within a given distance from the input. Figure 64 shows the initial rasterization and clipping of the rasters within the Amsterdam Centrum's canals extent.

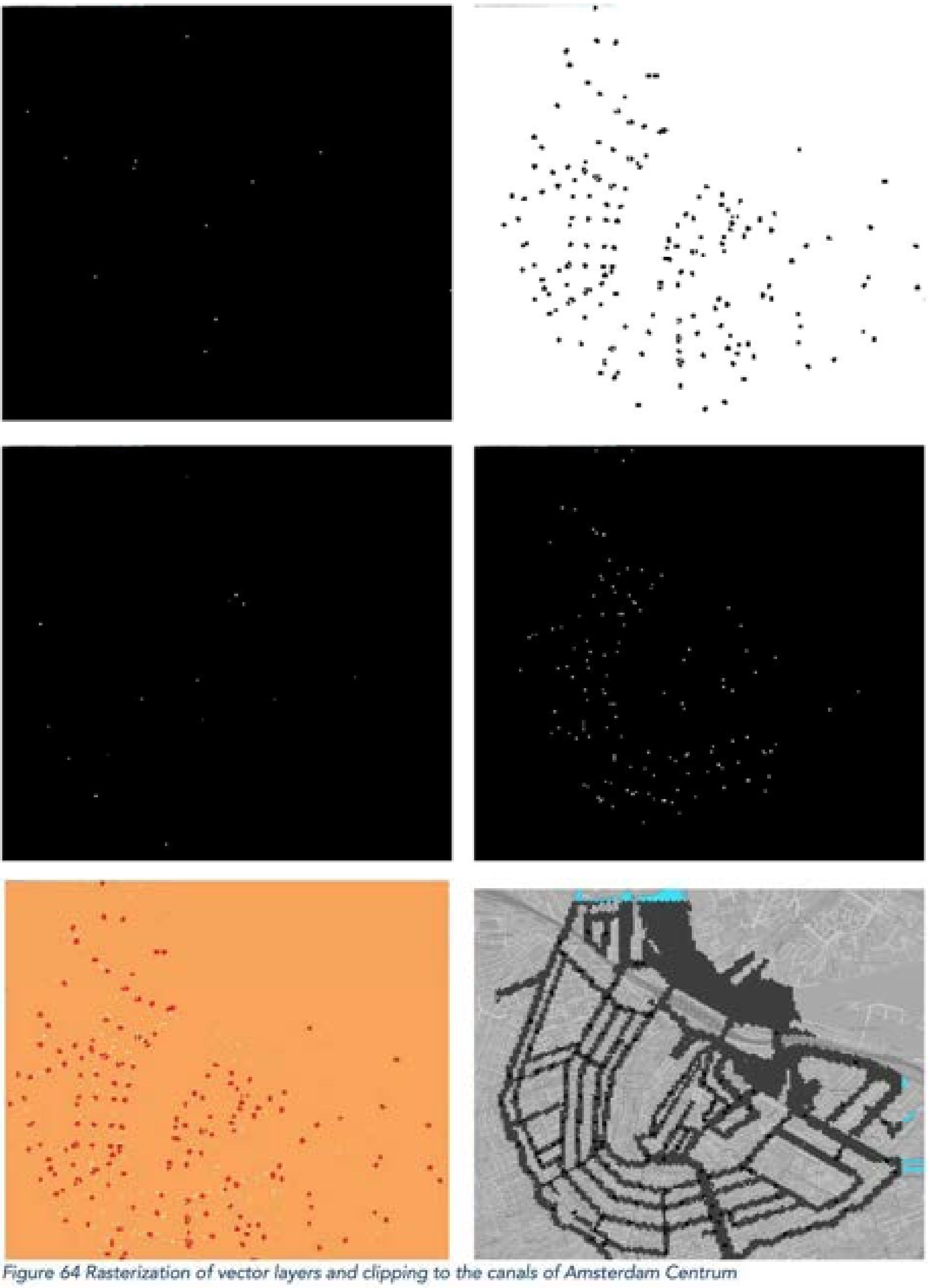

Figure 64 Rasterization of vector layers and clipping to the canals of Amsterdam Centrum

The proximity analysis on the rasterized layers keept a standardized distance used for stop location (100m). An example is shown for proximity of EV charging stations, Figure 65.

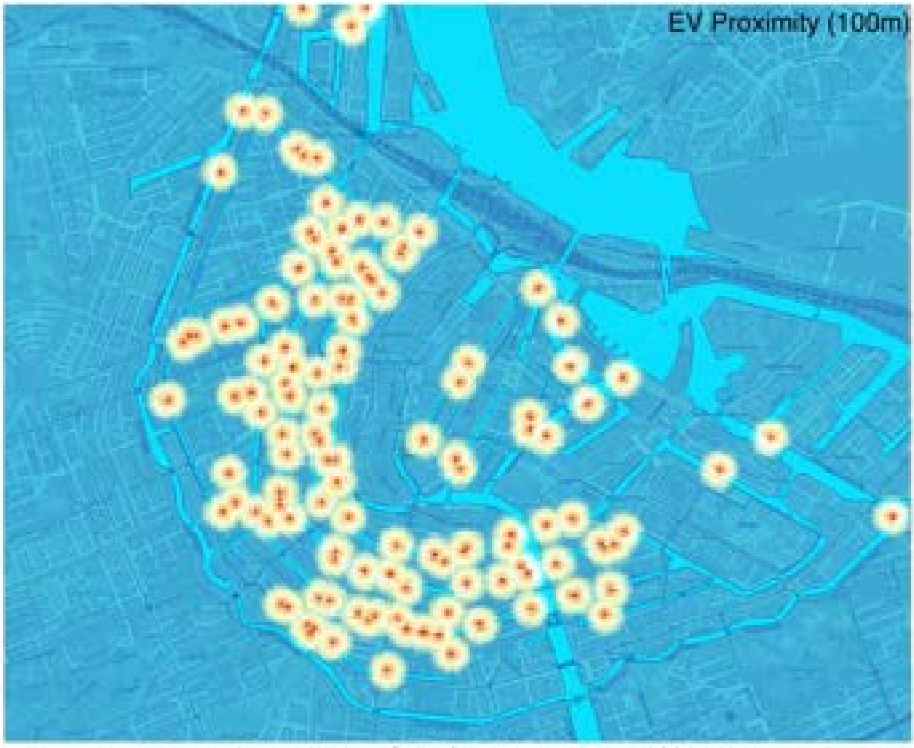

Figure 60 Proximity of EV charging stations within 100m

Using the proximity analysis, the weighted features are later aggregated into a single raster, where the most suitable locations can be seen. The raster then clipped to the waterways layer.

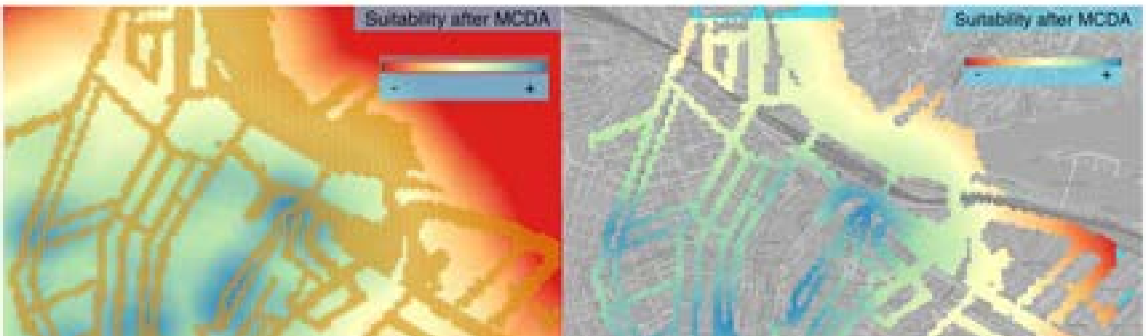

Figure 61 Suitability analysis, MCDA.

This suitability analysis took all the spatial constraints as input but did not consider yet the demand points obtained through the vessel stop method nor the DoD method. The raster result is very valuable as it gives a dissolved area for suitability and allows for a quick glance at the possibilities for future development. However, while the use of proximity functions and buffers allow to create a seamingless map, a specific grid vector analysis is also performed, where adjacent values remain unmodified by neighboring values (Figure 67).

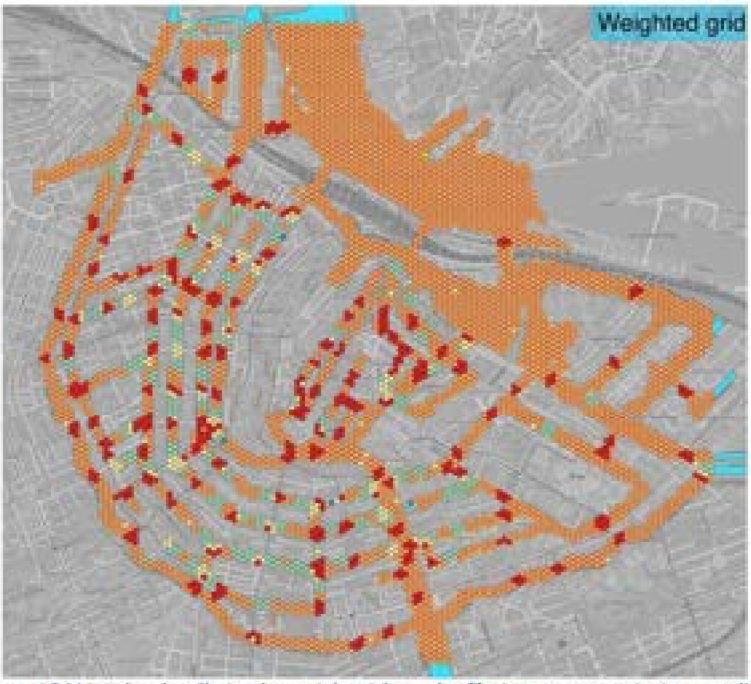

Figure 62 Weighed cells in the grid, with no buffering nor proximity modifiers

Step 7 Location Allocation

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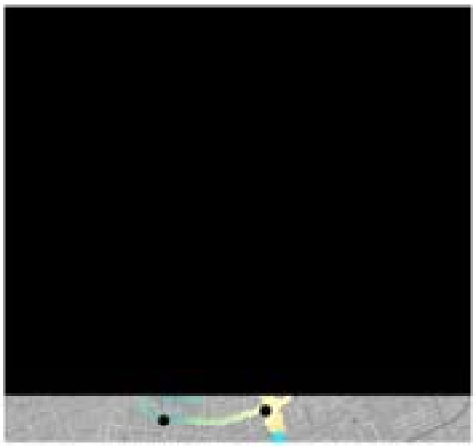

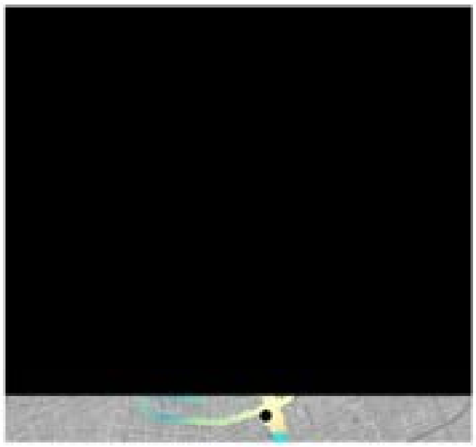

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