



MSc thesis in Geomatics for the Built Environment

An advanced prospecting method for assessing the quantity of underground metal cables in urban mines

Matthijs Bon
2017

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AN ADVANCED PROSPECTING METHOD FOR ASSESSING THE
QUANTITY OF UNDERGROUND METAL CABLES URBAN MINES

A thesis submitted to the Delft University of Technology in partial fulfillment of the
requirements for the degree of

Master of Science in Geomatics for the Built Environment

by

Matthijs Bon

November 2017

ABSTRACT

One way to stimulate a more circular economy, is to explore opportunities for urban mining. This thesis explores a new method to assess the quantity of underground electricity cables which could one day become available for urban mining. This research answers the question: "To what extent can topological networks be used to localize and quantify underground metal cables in order to assess the quantity of an underground urban mine?" Three case study areas in Amsterdam have been selected to exemplify the method.

The Dutch National Road Network has been used as a topological skeleton to approximate the electrical network. Three different methods were used to connect buildings and transformers to this network. The 'Connect to Closest Point' method, connects every point to the closest point on the street network. The 'Connect to Closest Junction Vertex' method connects every point to the closest junction vertex of the street network, which is divided into segments with maximum length of 75 meters. The 'Iteratively Connect to the Closest Junction Vertex' method iteratively connects every point to the closest junction vertex, within a threshold, until all nodes are connected to the street network.

By evaluating the edge betweenness [[Girvan and Newman, 2002](#)] for every edge in the topological networks, cable current and thickness could be determined and the urban mine was quantified in terms of electrical cables. The 'Connect to Closest Junction Vertex' method showed to be most accurate, with up to 88% accuracy in Geuzenveld. Although this method is suitable for finding a minimum quantity of an underground urban mine, locational accuracy is too low to pinpoint the exact location of underground cables.

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CONTENTS

1	INTRODUCTION	3
1.1	Social relevance	3
1.2	Scientific Relevance	4
1.3	Problem statement	5
1.4	Relation to MSc Geomatics Programme	6
2	THEORETICAL BACKGROUND	7
2.1	Underground urban mining	7
2.1.1	Motivation for Underground Urban Mining	8
2.1.2	Methods for Underground Urban Mining	9
2.1.3	Conclusions	10
2.2	Electrical Network Design	10
2.2.1	Dutch electricity networks	11
2.2.2	Network layout design	14
2.2.3	Conclusion	15
2.3	Validation	16
2.4	Storing Methods	16
3	RESEARCH APPROACH AND METHODS	19
3.1	Research question	19
3.1.1	Scope of research	19
3.2	Methodology	20
3.3	Tools and code	25
4	DATA ACQUISITION AND ASSESSMENT	27
4.1	Data for validation	27
4.2	Data for quantification	29
4.2.1	Data pre-processing	30
5	GENERATING A TOPOLOGICAL NETWORK	35
5.1	Connecting to topological network	36
6	NETWORK ANALYSIS	41
6.1	Shortest paths	42
6.2	Calculating edge betweenness	42
6.3	Quantification	44
7	VALIDATION	47
7.1	Validation of location	47
7.2	Validation of quantity	48
7.3	Discussion	49
8	DATA MANAGEMENT	53
8.1	Spatial databases	53
8.2	Data storage	55
9	FUTURE RESEARCH AND CONCLUSIONS	57
9.1	Conclusions	57
9.1.1	Sub-questions	58

9.2	Discussion	60
9.2.1	Review of datasets	60
9.2.2	Critical review of used methods	60
9.3	Future Research and Recommendations	62
9.4	Reflection	63

ACRONYMS

ac	Alternating Current	10
ams	Amsterdam Institute for Advanced Metropolitan Solutions	4
bag	Basisregistratie Adressen en Gebouwen (Building and Address Database)	22
bgt	Basisregistratie Grootchalige Topografie (Large Scale Topographic Database)	29
dc	Direct Current	10
gis	Geographical Information System	6
gplk	Gepantserd Papier Lood Kabel (Paper Insulated Lead Covered Cable)	12
gpr	Ground Penetrating Radar	5
klic	Kabels en Leidingen Informatie Centrum	4
mfa	Material Flow Analysis	4
nwb	Nationaal WegenBestand (National Road Network)	6
pilc	Paper Insulated, Lead Covered	12
puma	Prospecting the Urban Mine of Amsterdam	4
sql	Structured Query Language	53
uum	Underground Urban Mining	6
vbo	Verblijfsobject(en) (Stay Object(s))	31
wfs	Web Feature Service	29
wkt	Well-Known Text	37
xlpe	Cross-Linked PolyEthylene	12

LIST OF FINAL DATASETS

	BAG
Purpose	Building polygons
Source	Esri NL content from ArcGISOnline
Actuality	January 2017
Coverage	Netherlands
Geometry type	Vector: File Geodatabase:Polygons
CRS	EPSG:28992
Rights	ESRI Terms of Use
	NWB
Purpose	Geometric skeleton for network analysis
Source	Esri NL content from ArcGISOnline
Actuality	June 2017
Coverage	Netherlands
Geometry type	Vector: File Geodatabase:Polylines
CRS	EPSG:28992
Rights	ESRI Terms of Use
	Electrical network
Purpose	Validation
Source	Alliander
Actuality	May 2017
Coverage	Netherlands
Geometry type	Vector: Shapefile:Polylines
CRS	EPSG:28992
Rights	Data can be used for this research only. All data remains property of Alliander.

1

INTRODUCTION

If we keep up the current resource usage and waste production, the Earth will not be the planet she is today. Fossil fuels and other resources are depleting rapidly and more and more waste is produced every year. Our economy is based on a linear process in which we *take* resources from the Earth, *make* a product out of it and *dispose* of the product once the product has reached its end-of-life [Webster and Johnson, 2009]. A shift towards a circular economy in which waste is *reduced*, products are *reused* and *recycled* into new products or materials (3R principle) is necessary.

A step towards such a circular economy is the Waste Management Directive 2008/98/EC [EC, 2008], published by the European Committee, which sets concrete goals to improve the efficiency in waste management in the European Union. The directive aims at decreasing packaging and landfill waste and promotes the reuse of municipal waste. In September 2016, the Dutch government released a note that by the year 2050, the Dutch economy will have made the transition towards a circular economy [Rijksoverheid, 2016].

On a more local level, the municipality of Amsterdam is progressively stimulating local circular economies. Some districts in Amsterdam built in the 1950's or earlier, contain valuable resources that might become (partly) available for reuse or recycling when these building have to be demolished or redeveloped. But before one is able to efficiently extract resources from the urban environment, so called 'Urban Mining', prospecting of such an urban mine is necessary.

1.1 SOCIAL RELEVANCE

Underground urban infrastructure can be seen as an Urban Mine [Zhu, 2014; Brunner and Rechberger, 2004], a reserve that contains high amounts of valuable resources, hidden within the urban landscape. Urban mining is the process of extraction of resources from the urban environment for reuse or recycling Brunner and Rechberger [2004]. A problem that arises with urban mines is the lack of quantitative and qualitative data of the recyclable resources. Additionally, it is often unclear what exactly happens during the construction and demolition processes [Scheuer et al., 2003] and data is therefore very hard to obtain.

Furthermore, urban infrastructures such as (waste) water distribution systems, power supply grids, gas pipes and telecommunication cables, which were once part of the above-ground urban landscape are now buried underground [Kaika and Swyngedouw, 2000]. Such urban infrastructures can lose their function once an area is redeveloped. More often than not, underground infrastructures are not recovered by network operators or waste

management companies due to high costs. This results in underground waste accumulating over time, resulting in high amounts of wasted underground resources. These wasted resources have been termed hibernating stocks [Bergbäck and Lohm, 1997], due to their inoperable nature.

Wallsten et al. [2013] conducted a study on prospecting urban mines in Sweden and found that these resources can be spatially located by performing Material Flow Analysis (MFA), investigating the history of infrastructural systems and using current geographical data. The highest quantity of recyclable metal was found to be Iron, followed by copper. Given the increasing price for copper, prospecting the underground urban mine in terms of copper in electrical cables would be very useful. This research was conducted in Sweden, but it shows how many recyclable underground resources could be available. This might also be the case for the Netherlands, especially given the fact that the Netherlands is a very densely populated country, containing maybe even more recyclable copper per square kilometre.

In the Netherlands, management of the underground infrastructures is monitored by the Dutch Cadastre. On a national level, the Kabels en Leidingen Informatie Centrum (KLIC) requires every network operator to register their underground infrastructure. This results in a vast database with the underground infrastructure of the Netherlands. Every excavation work is registered to prevent damages to the infrastructure. On a more local level, some municipalities have additional information on underground infrastructure and require network operators to register their cables also with the municipality. However, contact with the municipality of Amsterdam revealed that they have a high demand for a dataset on underground (electricity) cables, since they have not implemented such a database.

1.2 SCIENTIFIC RELEVANCE

As [van der Voet and Huele, 2016, p. 4] already put it: *“the urban mine will have to be prospected as to viability and value. Only then will we be able to include urban mines in our planning for the future materials supply of societies.”* In most cases, being able to prospect depends on data availability. In the Netherlands, almost all data is available, but when this is not the case, data collection is necessary. Jeong and Abraham [2004] developed a decision support tool to be able to determine which techniques are most appropriate for data collection in a certain case study area, but the result always remains a combination of techniques that will be utilized. Furthermore, most existing techniques for underground localization rely on someone to be at a physical location to determine the location of electrical cables and thus the quantity. In the literature there are so far no methods for assessing the location of cables with high accuracy and therefore the quantity without going out into the field. It seems a method is needed for assessing the quantity of an urban mine from other input data, that will result in a location and quantity of underground infrastructure on a more detailed scale.

In Amsterdam, the Prospecting the Urban Mine of Amsterdam (PUMA) project, conducted by Leiden University, Waag Society and the Amsterdam Institute for Advanced Metropolitan Solutions (AMS) [van der Voet and Huele, 2016], focussed on prospecting the above-ground urban mine of Amsterdam, but

omitted the *underground* urban mine. A ground truth check was performed by Metabolic [Blok and Roemers, 2016] to determine whether the predicted quantity of the urban mine was realistic.

Although underground localization techniques, such as electromagnetic line locators, Ground Penetrating Radar (GPR) and metal detectors exist, they are often expensive or labour-intensive, since they rely on different technologies that can only detect a specific set of materials. Furthermore, automated methods for assessing the quantity of urban mines do not exist yet. An automated method that uses (geographical) data as input could limit costs to a minimum.

1.3 PROBLEM STATEMENT

An automated localization technique could make use of the principle of network analysis. In network analysis, a topological network consists of vertices and edges. Objects can be seen as vertices and the relations between objects are modelled as edges. In such a way, the underground infrastructure can be modelled from a design perspective. If all electrical connections (e.g. to buildings) are considered as vertices and the cables connecting them as edges, with a weight equal to the distance between vertices, it is possible to model the location and quantity of a electrical network as the minimum length of cables needed to connect all vertices and therefore assess the (minimum) metal cable quantity of the underground urban mine.

When it is unclear if a certain area contains underground infrastructure, underground localization techniques are used to localize the underground cables. There are numerous techniques available to do this, but not one technique is capable of localization of all underground infrastructure, since they rely on different technologies that can only detect a specific set of materials. Additionally, most of these techniques require technicians to be at the physical location of the expected underground infrastructure. A method that would be able to estimate or measure the quantity of an underground urban mine directly, without having to go to a location, is desired.

In the Netherlands, such localization techniques are used rarely, since most of the underground infrastructure is already localized when they are registered. However, this might not be the case in other countries and to be able to assess the quantity of urban mines, knowing the location of underground infrastructure is essential. Building on the PUMA project at the AMS and the demand from the Amsterdam municipality for data on underground infrastructure, there is a need for a method to automatically assess the resource quantity of underground urban mines. By approximating the location of cables using a topological skeleton, it is possible to provide an estimation of the minimum amount of cables, where they are located and how much metal they contain.

1.4 RELATION TO MSC GEOMATICS PROGRAMME

In this research, the Geomatics courses on Python, Geographical Information System (GIS), Databases and Datasets and Quality (GEO3001, GEO1002, GEO1006, GEO1008) proved very useful. Topics of network analysis and the implementation in Python, as well as topology and data management are all part of this thesis and the knowledge that was acquired during these course was put into practise.

This research shows the possibilities for network analysis on a sustainable topic such as Underground Urban Mining (UUM). This resulted in a methodology that showed to what extent the underground urban mine of Amsterdam could be quantified using the Nationaal WegenBestand (National Road Network) (NWB) as a topological skeleton. In relation to the Datasets and Quality course, this methodology showed how different datasets yield different and sometimes inaccurate results. The iterative process of experimenting with different datasets, in order to find the most appropriate combination of datasets was an extensive part of the methodology. The final datasets and methods resulted in a better result on quantitative level, but a high locational accuracy could not be achieved.

2 | THEORETICAL BACKGROUND

This study focusses on estimating the location and quantity of an electricity network with the use of network analysis to determine the minimum amount of underground metal cables that might one day become available for urban mining. Therefore, this research is situated between the topics of UUM and electrical network design. Graph theory is often used as a method to optimize electrical networks and is therefore an essential part of the theoretical background. The resulting grey area in Figure 2.1 represents the area of research for this thesis. It is important to understand Underground Urban Mining methods, as well as knowing where cables are laid in the ground and how to determine the quantity of these cables to be able to make correct assumptions for the used methods. Additionally, topic of storing embedded graphs and validation techniques will be discussed in this chapter.

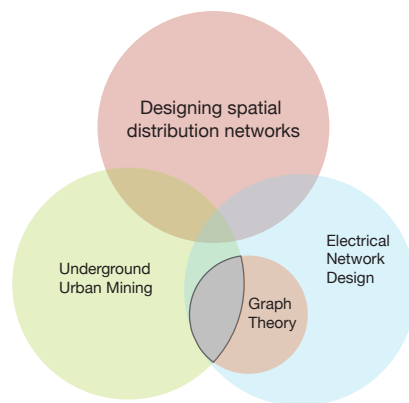


Figure 2.1: Situation of this research in existing literature.

2.1 UNDERGROUND URBAN MINING

Traditional waste management is a rather linear process of extraction, production, use and disposal. In a circular economy, the process shifts towards a cycle, in which products are recycled and reused. Currently, only 6% of the global processed materials is being recycled and contributes to a circular economy. Among the limitations to achieve a more circular economy is the fact that a very large part of the material stock is accumulated as in-use stock [Haas et al., 2015]. Urban mining research focusses on overcoming this barrier. This section discusses the body of literature on Urban Mining and in particular UUM, aimed at the urban mining of underground resources, such as infrastructure.

Zhu [2014], discusses the concept of Urban Mining, reusing and recycling resources which are dispersed among urban infrastructure, buildings, consumer products and waste. These resources could be reclaimed if the exact location data is available. Based on [Brunner and Rechberger, 2004], urban mining is defined in this thesis as the process of extraction of resources from the urban environment for reuse or recycling. For UUM this is limited to the extraction of underground resources, such as infrastructure cables and pipes. There are a multitude of terms used in the literature for such disused underground resources, e.g.: [Bergbäck and Lohm, 1997] discusses the concept of 'hibernating stock', resources that were once part of the in-use stock but have been disconnected but are not yet disposed of. Other underground infrastructure papers use the word 'urks', an abbreviation of the Swedish word "urkopplad", which means disconnected [Wallsten and Krook, 2016].

2.1.1 Motivation for Underground Urban Mining

The challenge of UUM is to prospect the underground urban mine to increase certainty about the availability of underground resources. As with raw extraction of materials in natural mines, economic feasibility is an important motive for UUM. Krook et al. [2015] defined four factors that influence the (economic) feasibility of cable extraction:

1. Extraction technology, the technology with which the cable is extracted;
2. Geographical location, the urban environment, e.g. city center;
3. Recovery type, indicating if the cable is recovered in an joint operation or just for that particular cable extraction;
4. Surface material, the material on top of the cable, e.g. cobblestone, asphalt.

They found that the highest costs of recovery comes from excavation, which depends mostly on the location and replacement of the surface material. These problems can be overcome with the use of new technologies such as Kabel-X, but that particular technology has the limitation that it is only possible for plastic insulated cables. However, plastic insulated cables are the new standard, thus it might be an application in the (near) future. Access to a technology such as Kabel-X, which uses a machine that pulls the core of a cable out and replaces it with a new core, could make underground mining more appealing and economically feasible.

Furthermore, Krook et al. [2011] conducted a study in Sweden and found that cables often end up in hibernation because cables cannot be replaced at once, since end-users would then be disconnected. The economic conditions to extract a cable are influenced by the material price (copper or aluminium) and the fee for the processing of the material. The revenue of the sold copper should outweigh the costs for processing (and transportation). Unfortunately, the copper content is often too low, which means it is not very likely that single cable extraction can be executed with economic benefits [Krook et al., 2011].

2.1.2 Methods for Underground Urban Mining

Since Urban Mining is a term from the MFA field, numerous studies conducting urban mining research use a form of MFA to assess an underground urban mine (see Wallsten [2015]; van der Voet and Huele [2016]). Other studies have included GIS in their research, but even though there have been a multitude of studies combining MFA research and GIS data (Tanikawa and Hashimoto [2009]; Wallsten et al. [2013]; Zhu [2014]), these studies still involve aggregated data and have a low level of detail. Another study in Sweden achieved a higher level of detail by using actual (geographical) data of cable networks to find the out-of-use cables and perform GIS operations to estimate the copper and aluminium content of the cables on a street scale [Wallsten et al., 2015].

Although these studies are very informative and provide interesting insights in the field of UUM, there are always some uncertainties in these studies. For example, Wallsten et al. [2013] make use of GIS data, but unfortunately data is not always available. Similar problems occur for digitized maps, a big dependency in this study. Not only does the digitization process bring various uncertainties and inaccuracies, sometimes these historic maps are unavailable or incomplete, let alone out of date. Even when a higher level of detail is used, as described in Wallsten et al. [2015], where each cable is individually assessed, the study still relies on available data. Their study also showed that with combined maintenance and recovery, there are possibilities for economical benefits and with the use of more advanced extraction techniques such as Kabel-X, the benefits could be even higher. Additionally, they recommend that additional ground truth checks using underground localization techniques could provide extra certainty.

The study by Wallsten et al. [2013] highlights the opportunities for combined recovery and maintenance of underground infrastructure, which limits the costs of recovery to a minimum. Additionally, they point out that the underground network is greatly influenced by the urban environment, such as buildings. But they also emphasize that their study cannot be generalized for other cities, since cities are often too unique. Nevertheless, there are similarities between the Swedish city Norrköping and Amsterdam, e.g. the DC-system for trams, which is present in the both cities. Such similarities can help to build political recognition to do a similar study in another city.

Wallsten and Krook [2016] carried out a study to investigate how and where political decision makers should intervene to stimulate recovery from underground infrastructure. From multiple interviews with respondents, they could classify five interpretations of urks. Each different interpretation has different aspects and problems that should be resolved to stimulate resource recovery. Such a classification of urks can help build political recognition and stimulate resource recovery. One particular interesting interpretation of urks is that of a mineral resource deposit. Usually the costs of recovery are much higher than the revenue from recycling, which makes it uninteresting to recover. However, in the case of redevelopment of an area, recovery of urks might be feasible, because that site is excavated anyway, e.g. for sanitation purposes, which lowers the overall costs [Wallsten and Krook, 2016].

Furthermore, in both Swedish and Dutch law, anything that the owner can-

not or does not want to use anymore is regarded as waste and should therefore be disposed of. Although there are differences in opinion whether this should be the case for urks, this could be one of the reasons why urks are often said to be a reserve or spare part, just to avoid the responsibility of disposing it [Wallsten and Krook, 2016].

2.1.3 Conclusions

When investigating underground urban mines, one of the biggest issues is data on the urban mine. Ideally, network operators have a well-maintained database on all the cables in a their service area. However, sometimes the cables that are not in use anymore have just been removed from the database, but not from the soil. In better situations, network operators can update the cable by saying it is out of use, but unfortunately this is not always what happens in reality. In many studies, there is a big dependence on data, but what if that data is sparse or unavailable?

From the small body of literature on UUM that is available, it can be stated that the field of research is still developing and prospecting an underground urban mine is necessary to increase certainty regarding available resources. Special attention should be paid to situations in which data is limited or not available.

2.2 ELECTRICAL NETWORK DESIGN

In UUM, all materials used in the urban environment are considered to be resources that could once become available for recovery. Even the parts of an underground infrastructure network that are currently in use, could once become obsolete, for example if technology advances and electricity is generated locally or if data can be transferred wireless. Another motive for extracting all resources from the urban environment, is raw material shortage, such as during war periods [Klinglmair and Fellner, 2010]. In these situations, it might be necessary to extract copper from electrical networks for military use (ammunition). Estimating the amount of copper in electrical networks requires knowledge of the electrical network.

There are two types of electricity networks: Direct Current (DC) and Alternating Current (AC) networks. Hammerstrom [2007] discuss the (dis)advantages of both systems and provides a model to compare the two systems. One particular reason why AC currently predominates the distribution networks, is its ability to easily transform high voltages to lower voltages and vice versa. This is possible since a higher voltage allows a lower current through a cable, while maintaining the same power output. In DC networks, this is currently not yet as efficiently possible as with AC networks. Due to the simple transformation of AC power into lower voltages, the distribution network has an inherent hierarchical nature.

This hierarchical structure consists in the Netherlands of approximately three levels: High Voltage (HV), Medium Voltage (MV) and Low Voltage (LV). In this research only distribution networks in neighbourhoods and districts are considered, therefore HV networks are not discussed in this thesis. In the Netherlands, the Dutch Power organization promotes innovative so-

lutions to present-day challenges to cope with an increasing demand for energy as well as the need to decrease emissions and contribute to a circular economy [Dutch Power, 2017].

2.2.1 Dutch electricity networks

As a work of reference to describe the electrical network in the Netherlands, Phase To Phase, a company specialized in informatics for network company operators, has written a book in cooperation with network operator Alliander, that summarizes current knowledge and use cases for the Dutch electricity networks [Van Oirsouw and Cobben, 2011]. Particularly interesting for this research are the topics on Medium and Low Voltage networks and the design of appropriate cables. The majority of information in this subsection is acquired from that book.

History

Due to governmental pressure, the many electricity companies that existed before 1985 in the Netherlands, have been merged into four main electricity companies, each providing one or more provinces with electricity. There is one national network operator responsible for the upkeep of the power network of 110 kV and higher, which is also called the connecting and transport network. The other, regional network operators are responsible for regional (25 - 50 kV) and local distribution of electricity. The latter is subdivided in MV networks of 20 - 10 kV and LV networks of 400 V.

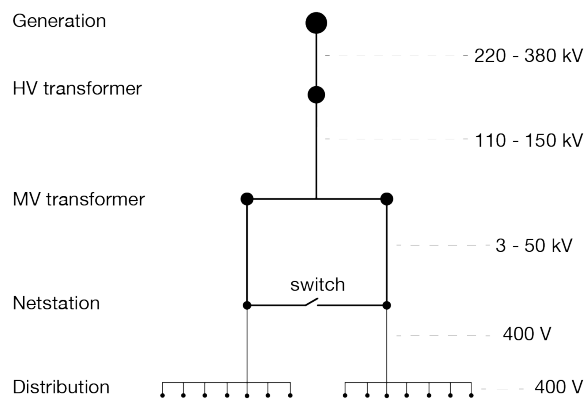


Figure 2.2: Hierarchy in electricity networks

Hierarchy

An abstraction of the hierarchical nature of the electrical system is depicted in Figure 2.2. To connect the hierarchical levels, transformers can scale down the voltage that is needed in the network. At the lowest level, so-called 'net-stations' provide consumers with electricity in a distribution network. In such a distribution network, the network follows a tree-like structure, so

that every netstation supplies electricity to an amount of households. Usually, the amount of households connected to a netstation is between 50 and 250, while there can be 250 - 500 netstations connected to a MV/LV transformer. This illustrates that the LV distribution network largely determines the density of the total network.

Because of the hierarchical nature of the electricity grid, there are standard cables connecting the different levels. Although there are a multitude of different types of cables, the MV cables are usually constructed with three veins from either copper or aluminium. The arrangement and thickness of the cable conductor section is determined by the function of the cable, where transport cables are often three single vein cables while distribution cables are usually cables with three veins.

Cable design & composition

Distribution cables in MV networks contain conductors with a cross-section area between 16 and 240 mm², whereas transport cables contain conductors of 240 up to 630 mm². In LV networks there is a distinction between connecting cables, connecting buildings to the network, and main cables. Connecting cables consist of three conductor veins between 6 and 16 mm², main cables are similar to MV distribution cables.

Of all LV cables in the Netherlands, approximately 40% use a copper conductor and Gepantserd Papier Lood Kabel (Paper Insulated Lead Covered Cable (GPLK) insulation, the other 60% use an newer Cross-Linked PolyEthylene (XLPE) insulation. Assuming that XLPE insulated cables are 50/50 divided between copper and Aluminium, 70% of all cables consist of copper conductors, while 30% consist of aluminium conductors. However, cables with an aluminium conductors also contain a copper shielding and occasionally an auxiliary copper wire between 2.5 and 6 mm². There are mainly two specific implemented cables in the Netherlands: GPLK or sometimes called Paper Insulated, Lead Covered (PILC) cable and XLPE cables.

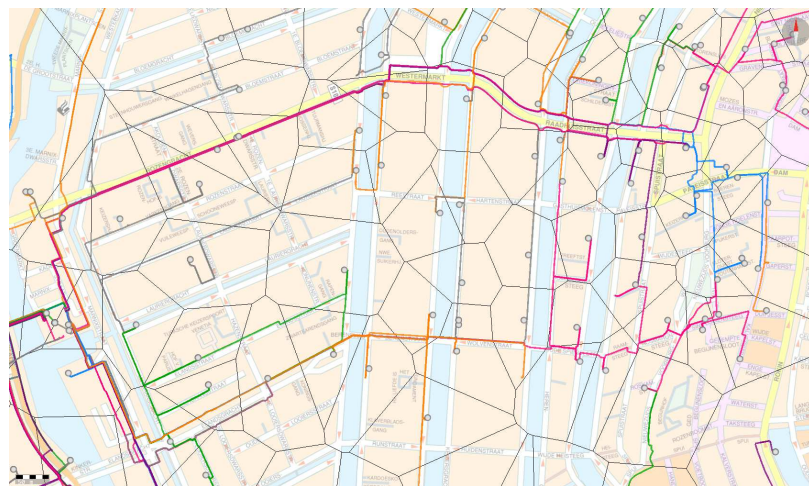


Figure 2.3: Geographical spread of netstations and service areas [Van Oirsouw and Cobben, 2011].

Design aspects

When designing an electricity network, the main design factor is the power

exchange in a certain geographic service area. This power exchange happens mostly on the LV distribution networks. The amount and capacity of netstations that are required in a LV network is driven by the number of connected households in a particular service area, shown as a voronoi diagram in Figure 2.3.

Within a distribution network, the maximum amount of connected households depends on the current flowing through a cable. Figure 2.4 shows the maximum current through different types of cable, copper or aluminium. The current supposed to be flowing through any cable can be calculated using Ohm's Law and the Strand-Axelsson formula, taking into account the stochastic behaviour of household power demand [Axelsson and Strand, 1975]. For a single household, the maximum power demand can be calculated using:

$$P_{max,1} = k_1 \cdot E + k_2 \cdot \sqrt{E} \quad (2.1)$$

and for multiple households:

$$P_{max,n} = n \cdot k_1 \cdot E + 3 \cdot k_2 \cdot \sqrt{\frac{n \cdot E}{3}} \quad (2.2)$$

Where:

$P_{max,1}$ = Maximum power demand for one household

$P_{max,n}$ = Maximum power demand for n households

E = Yearly energy demand for one household.

n = number of households

Factors k_1 and k_2 are coefficients derived from experiments, specific to a type of household. These factors are derived from the application Gaia¹, a product by Phase2Phase². The 3 is used to indicate a single phase (230 V) connection to the household, so that load can be distributed over 3 phases. With P_{max} it is possible using Ohm's Law, to find the maximum current through a cable:

$$I = \frac{P_{max}}{230} \cdot m \quad (2.3)$$

The factor m is used to indicate a margin that is used to oversize cables to be on the safe side. From interviews with Alliander it was found that cables are using approximately 70% of their capacity, therefore this research uses a margin of 100/70. Figure 2.4 matches a resulting current I to a cable type, which can be used in the final quantification.

Simultaneity

Another factor that is important here, is the simultaneity. This factor decreases by a larger amount of connected households, indicating that not all power exchange happens at the same moment. The Strand-Axelsson formula takes this simultaneity into account in the calculation of power consumption.

Legislation

Although the electricity system is very complicated, there is little legislation on where underground cables should be placed. NEN 7171-1, [Nederlands Normalisatie Instituut, 2009] provides legislation on the depth of cables and

¹ <https://phasetophase.nl/vision-lv-network-design.html>

² <https://phasetophase.nl/>

	Cu	Al	I (A)		Cu	Al	I (A)
GPLK 3-ad.	10	16	63	XLPE 3-ad.	-	95	215
	16	25	85		-	150	280
	25	35	110		-	240	360
	35	50	130	XLPE 1-ad.	95	-	335
	50	70	160			240	355
	70	95	190		drie	400	450
	-	120	205		hoek	630	575
	95	150	240		plat	630	645
	120	185	275				
	150	240	320				
	185	-	350				
	240	-	410				
	300	400	450				

Figure 2.4: Cable cross section area (in mm²) per cable type [van der Eerden, 2017].

distance between other cables, but no exact location in the public space. However, it does provide an ideal profile of a street and its subsurface infrastructure, but since the public space is very irregular, such an ideal profile can not always be followed.

The COB (Centre for Building Underground) published a book aimed to provide insights in the underground infrastructure in the Netherlands [Taselaar, 2009]. Although it does not provide extra rules or legislation, it is a good practical overview of guidelines as well as an overview of the current underground infrastructure. There is a special emphasis on the information supply such as KLIC and its importance for accurate and efficient asset management.

2.2.2 Network layout design

[Van Der Sluis, 2001, p. xi] describes the electrical power system as “one of the most complex systems ever built and managed by engineers”. Given that the electricity must be supplied through cables, the layout design of the network of cables and transformers is inherently also complex. Even though the system is complex, there are often many different alternatives for installing a LV network, since the costs for excavation are often the largest expenses [Willis, 2004]. This has also been concluded in studies by Wallsten et al. [2013, 2015]; Krook et al. [2011, 2015]. This results in fluctuating network layouts, while costs stay roughly the same. This subsection will elaborate on the automatic generation of various layout designs and optimization of such methods, for LV networks.

Layout design methods

Table 24.1 in Chapter 24 of [Willis, 2004] provides an overview of various decision support tools that can assist network planners in finding an optimal design layout for feeder networks. Feeder networks are similar to the MV networks in the Netherlands, and supply neighbourhoods with electricity

that can be further distributed through LV distribution. As [Willis, 2004] acknowledges, the idea of optimization is simple, while its mathematics are often very complex. Most of these algorithms use a form of graph network analysis to find solutions to layout planning problems.

In [Adams and Laughton, 1974], a linear programming method is proposed to optimally plan a LV network. Using an algorithm including graph network analysis, an optimal solution was found for a housing layout, taking into account power loads as well as costs. However, the proposed layout is optimal in network space, but the spatial location of the houses is not taken into account. This could result in sub-optimal solutions when put into practice. Although this solution might be sub-optimal, it shows that there are interesting ways to use graph networks to approximate the reality of the complex electrical networks. Likewise, power network optimization studies such as Parada et al. [2004]; Adams and Laughton [1974]; Míguez et al. [2002]; Oliveira et al. [1995]; Ramirez-Rosado and Bernal-Agustin [1998] also make use of graph network analysis to arrive at optimal network layouts. Unfortunately, neither of the methods in these studies are applied in practice. Therefore, starting from reality and arguing backwards to derive a location is not possible.

Approximate reality

As the examples given above show, graph network analysis can be used as a methods for planning the layout of a network. In a similar manner, one could try to estimate the location of metal cables from such a design perspective. Since most metal cables are used for electricity and data transmission, finding the metal cables can be translated to a design process for finding an optimal power network design. If one could estimate the location of electricity cables and if it is known how many end-users are connected to that cable, the thickness of that cable could be calculated using the Strand-Axelsson formula and Figure 2.4.

Such an estimation of a electrical network can be given by using an Steiner Minimal Tree approach. A Steiner Minimal Tree is a graph G in which the total length of the edges is minimized [Kou et al., 1981]. Unlike a Minimum Spanning Tree, a Steiner tree can add extra nodes to the graph in order to optimize, i.e. minimize, the final result. Using this graph and public space as an constraint, it might be possible to derive minimum quantity of metal cables available for recycling.

Other than Steiner Trees, methods like Medial Axis Transformations [Lee, 1982], Straight Skeletons or Segmented Voronoi can also approximate the location of cables in the public space.

2.2.3 Conclusion

Many different aspects influence the design, operation and maintenance of the electrical network. From an urban mining perspective, it is essential to understand how the system is built, what its hierarchical nature means and what possible design problems could arise, since they all influence the cable quantity and location. Currently, no method exists to estimate location and quantity with graph network analysis. By approximating the electrical

network with a topological skeleton, the urban mine could be quantified. However, a topological skeleton would decrease locational accuracy.

2.3 VALIDATION

The predicted model of the electrical network should be validated in order to assess the meaning of this research. Validation of both the location and quantity is needed, but it is important to note that if the location is validated to be correct to a certain degree, the quantity will probably also be closer to the quantity in reality, since the quantity depends on the location of the cables.

Thacker et al. [2004] explains the concept of validation and verification as the process in which one is able to quantify the confidence that the predicted model represents reality. They also mention the use of an accuracy requirement, a requirement that indicates when a model is a good enough representation of reality to fit its intended use. For example, in the case of localization of cables it could be that the accuracy requirement is: *the predicted cables should be within one meter with 95% confidence*. This confidence can be given by finding the standard deviation between the predicted cable and the real cable, assuming the data is normally distributed.

The location of the cable can also be validated by determining the percentage of predicted cables within a certain distance of the real cable. By using different sizes for the buffer, it is possible to talk about the validity of the location in terms of: *50% of the predicted cables are within one meter of the real cable*.

The quantification validation is, unlike the location, more a process of comparing the predicted quantitative values with the real quantity, determining their differences and examining the cause of differences, possible by looking at possible errors in the data.

2.4 STORING METHODS

The final results of the predicted cables and total mass should be stored in such a way, that reuse and visualization is possible. When storing spatial data, there are a number of factors that should be taken into consideration, including topology and indexing. [van Oosterom, 2017c] discusses Spatial Access Methods such as clustering and indexing, to increase performance of queries. By using a spatial index in a database that contains spatial data, performance can be increased, since the search for the specific object is shortened. This could be very useful if the results from this research turn out to be very large in size, or if the methodology is scaled up to the level of one or more cities.

Modelling a topological structure is essential for large databases with many adjacent objects. When a certain dataset contains many polygons with overlapping boundaries, the topology should be extracted from the geometry. With the topology, the boundary of a polygon is only stored once and

overlapping polygons use the same boundary. Furthermore, [van Oosterom \[2017a\]](#) explains that topology is essential if spatial queries are needed. In this research, it would be interesting to visualize the paths from every transformer to a building. Such a query could be facilitated by using a topological data structure.

3

RESEARCH APPROACH AND METHODS

3.1 RESEARCH QUESTION

This thesis is guided by the following research question:

To what extent can topological networks be used for localization of underground metal cables in order to assess the quantity of an underground urban mine?

The objective of this research is to provide one comprehensible method that can assess the quantity of an underground urban mine in terms of metal cables. The following sub questions for this research are relevant:

1. What data on underground infrastructure is already available?
2. Is graph theory fit to approximate an electrical network from a design perspective?
3. What input data and methods are necessary for creating a topological network?
4. How can the resulting location and quantities be validated?
5. What is the most efficient way to store the resulting data?

The question numbers correspond to parts of the methodology flowchart in Figure 3.1.

3.1.1 Scope of research

This thesis aims at locating cables in underground infrastructure, specifically focussing on electrical cables in the LV networks. Cables that are studied, are cables in the underground public space and cables from buildings to the network. Since electricity cables usually consist of copper or aluminium veins, those are the materials that will be considered. However, since it is nearly impossible or very improbable to automatically estimate whether a cable consists of copper or aluminium veins, a ratio is used to indicate the total metal content. Additionally, only cables for residential use are considered, because industrial cable can require a higher voltage or current and will therefore be more irregularly connected to the network.

This thesis will not focus on the *quality* of the cables, since this would require to actually examine the metal cables and thus digging up the cables. The economic aspects, i.e. the feasibility of the actual process of recovering the cables, will not be evaluated. However, the economic motives that indicate which conditions are necessary to facilitate underground urban mining have been discussed in Chapter 2. Since the PUMA project [van der Voet and Huele, 2016] already covered the above-ground urban mine, cables located in buildings will not be considered. Furthermore, cables supplying train

and tram tracks with power are not considered, since these cables use DC electricity and their thickness is calculated differently.

3.2 METHODOLOGY

Figure 3.1 shows the structure of this thesis and how each of the research sub questions was answered. Each phase, shown in a grey area in the figure, is explained in more detail in this section.

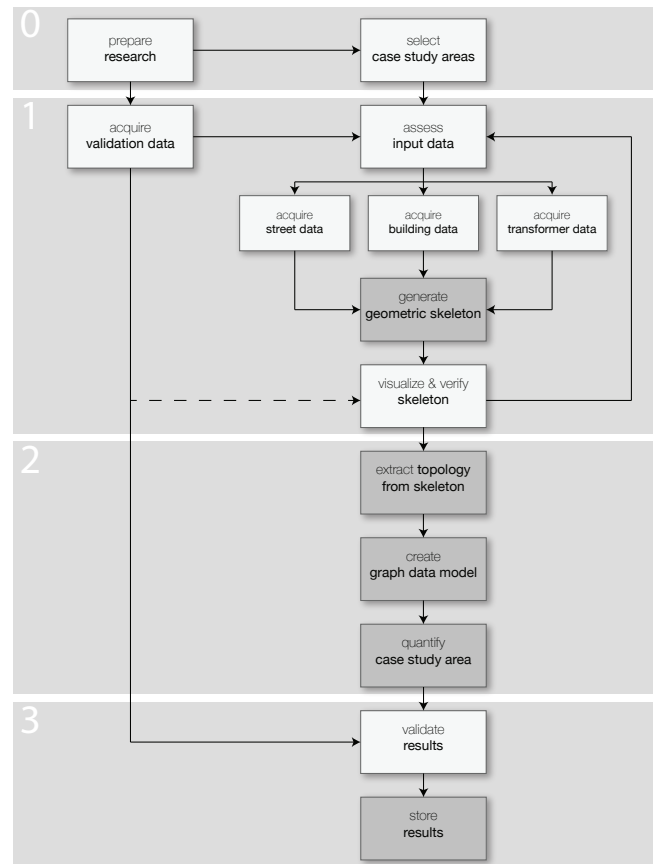


Figure 3.1: Methodology.

Phase 0: Preparation

The preparation specified what the research problem at hand was, as well as the goals and research questions that were answered. With the research problem, several case study areas could be identified, on which the chosen methodology could be carried out as an example. The case study areas for this research were chosen based on two criteria: First, the case study area is located within the Amsterdam Metropolitan Area, to fit the objectives of the AMS. Second, the buildings are built in the 1950's or 1960's, since these buildings might soon become available for redevelopment or demolishing.

The main research question provided a guideline to identify appropriate literature. This research's literature study covered the topics of underground urban mining, electrical network design and graph theory.

Phase 1: Data Assessment & Selection

Two data assessments have been carried out in this research. First, an assessment was necessary to verify if and where validation data was available. Validation data, with information on the actual location and quantity of underground metal cables, was essential to determine to what extent the used method was appropriate to locate and quantify underground urban mines and to verify if a dataset yielded proper results. This assessment consisted of interviews with municipalities and network operators, as well as an online search for open data. Four parties have been contacted for validation data: 1) the municipality of Amsterdam; 2) the municipality of Rotterdam, 3) the Dutch cadastre and; 4) network operator Alliander.

The second assessment was necessary to find different datasets that could be used as input to create a topological skeleton. Three types of input data were needed: 1) street geometries, 2) building polygons and 3) transformer house locations. In an iterative process, multiple datasets have been experimented with, until the most appropriate combination of datasets had been found. In the iterative process to find the final datasets, first each dataset was cleaned and filtered. Second, all building points were added to the building polygons, Third, a topological skeleton was estimated from the input data. And fourth, the results were visualized and verified. Finally, if the results were not satisfactory, a new dataset was chosen and the process repeated. This process is also depicted in Figure 3.2.

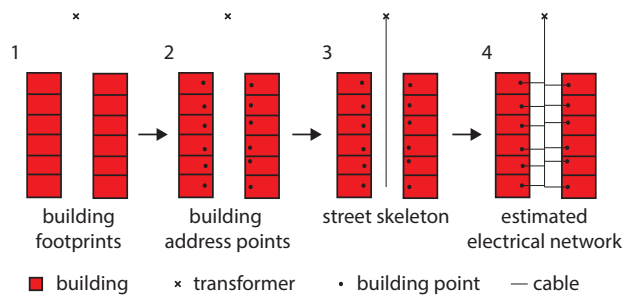


Figure 3.2: Approach to construct geometric skeleton

In order to clean the data, the data was first clipped to the case study areas. Secondly, only buildings with residential function were kept. Finally, attributes that were redundant for this research were removed for faster processing. The final data was transformed into classes for optimal handling.

In the iterative process of generation of a geometric skeleton, verification of the location and determining the fitness for use of the used dataset, each dataset was subjected to two operations to build a geometric skeleton, finally resulting in a cable connecting buildings and transformers. The two operations consist of 1) the selection of the closest street for any building and 2) the creation of the geometry representing the cable between the closest transformer and the building. The generation of this geometry is dependent on the type of input geometry that was used, e.g. for a building represented by lines, the street façade can be offset to generate a cable.

The location of this cable and its geometry was then visualised on a map

that also displays water and buildings. In the iterative process of generating a geometric skeleton, spatial challenges occurred that increased the complexity of the methodology. Three cases were defined indicating the degree of accuracy. Cases where a cable was placed correctly between street and building, with some margin, were defined as *workable* cases. *Solvable* cases involved cables that are not always placed correctly between street and building, and require extra data or operations to correct this. *Unsolvable* cases are the cables that are not at all located between building and street and involved cables with one or more intersections with other buildings or water.

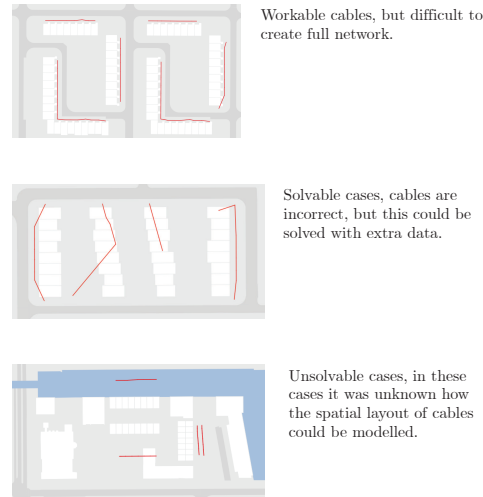


Figure 3.3: Three defined cases in previous methods

Table 3.1 shows an overview of the datasets that have been experimented with, in chronological order. These datasets were selected based on three criteria: **1)** the dataset contains geometry of streets, buildings or transformers, **2)** the dataset is complete and uniform for all case study areas, and **3)** it is possible to determine the closest street for every building.

Table 3.1: Used datasets in chronological order.

Subject	Source	Use
Buildings	Plot boundaries	Offset street side façade for cable
Streets	BGT	Polygons without names
Buildings	BAG	Building polygons with address and building point
Streets	BGT	Street polygons without street names
Buildings	BAG	Building polygons with address and building point
Streets	BGT + NWB	Join BGT (no street names) with NWB (with names)
Buildings	BAG	Building polygons with address and building point
Topology	NWB	Use topology of NWB to approximate location

For the final methodology, the Basisregistratie Adressen en Gebouwen (Building and Address Database) (BAG) and NWB were combined with the transformer datasets from Alliander as the final data. This combination of datasets has the advantage over previously tried methods of having a more or less

complete geometric network that can be translated to a topological network with trivial methods. Although the use of the **NWB** does decrease accuracy of the location of cables, since it simplifies cables as the centreline of the roads, but it does increase the overall accuracy of the quantification, resulting in a closer to optimal solution. All other methods and datasets yielded incomplete networks or only parts of a network, meaning decent network analysis could not be carried out.

Phase 2: Methods and Analysis

The **NWB** is a geometric model which is topologically consistent. But before the network is transformed into a graph data model, the **NWB** lines had to be connected to the buildings, in order to find shortest paths from buildings to transformers. This process included three different methods of connecting, each of the three methods with its own characteristics, affecting the cable length, as well as the performance and complexity of the network.

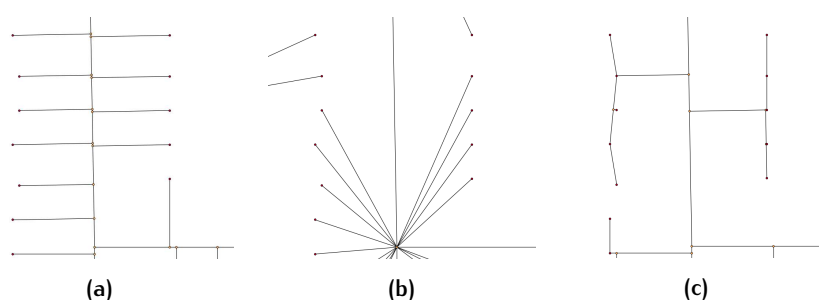


Figure 3.4: Three different connecting methods (a) Connect to Closest Point (b) Connect to Closest Junction Vertex (c) Iteratively Connect to the Closest Junction Vertex.

These three methods are processed individually, yielding slightly different results in terms of topology, number of vertices and edges and edge length. (1) The first method, 'Connect to Closest Point', connects every point to the closest point on the street network. (2) The second method, 'Connect to Closest Junction Vertex' connects every point to the closest junction vertex of the street network, which is divided into segments with maximum length of 75 meters. (3) The third method, 'Iteratively Connect to the Closest Junction Vertex' iteratively connects every point to the closest junction vertex, within a threshold, until all nodes are connected to the street network. Figure 3.4 shows the three different methods for connecting points to a network that have been used and compared in this thesis.

Constructing a topological model from this network was done using a library in QGIS that simplifies the network into edges and vertices, where each edge represents the relationship between its start and endpoint. The indices of vertices are added to the attributes of the shapefile of the **NWB**, where each edge has a start and end attribute, referring to the start and endpoint. Subsequently, this shapefile is read in the NetworkX library for Python to create a graph data model, consisting of an adjacency list. The process is visualised in Figure 3.5 and Table 3.2.

With a topological network in place, the total amount of metal content in the electricity network can be found by **1)** finding the amount of buildings connected to one transformer and **2)** determining the betweenness for each

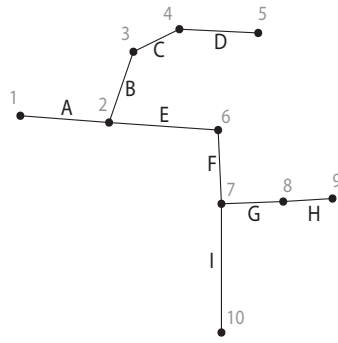


Figure 3.5: Lines and points to vertices and edges in a topological network.

<i>edge</i>	<i>start</i>	<i>end</i>
A	1	2
B	2	3
C	3	4
D	4	5
E	2	6
F	6	7
G	7	8
H	8	9
I	7	10

Table 3.2: Relations between edges and vertices as visualized in Figure 3.5.

edge (cable), to be able to 3) evaluate the thickness and therefore the quantity using statistical methods.

1. Finding the closest transformer for all buildings

For every building, it was found which transformer was closest in the network. The path from each building to the closest transformer represents the cable providing the building with electricity. This path was then used to determine the total cable use for every cable. To ensure the paths were the actual shortest paths, a plugin for QGIS was written to visualise these paths.

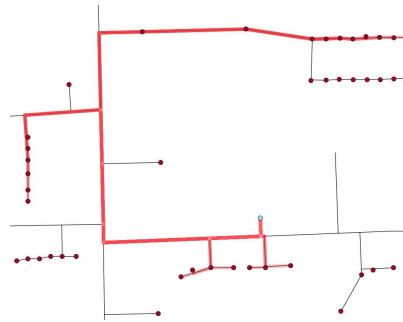


Figure 3.6: Shortest paths from a selection of buildings to the closest transformer.

2. Determining edge betweenness

With the shortest path from every building to a transformer, it was possible to determine the edge betweenness [Girvan and Newman, 2002], e.g. the number of households that use the same (part of a) cable. Taking into account the number of households was very important, since one building can contain several households and each household uses a set amount of power. The cable use was evaluated by finding the number of times an edge (part of a cable) appeared in the path from every building to a transformer.

3. Evaluating thickness & quantity

With the cable use, the thickness could be approximated, resulting in a cable cross-section area. By multiplying the area with the material density and length, the total mass per cable was calculated. The sum of the masses for all cables resulted in a total mass, quantifying the underground urban mine.

Phase 3: Finalization

The final phase of this methodology included validation and storing of the results. The first two steps to determine to what extent this methodology answers the research question, is to validate the location and the quantity. Location was validated by comparing the results with the validation data acquired in Phase 1, while the mass was validated by comparing the quantification of the validation data with the quantification of the generated data. It is important to note here that validation of the location was an important way in this research to verify if the used method could be used in the network analysis.

When a final result had been achieved, the data had to be stored. For three relatively small case study areas in Amsterdam, shapefiles suffice in terms of performance in both Python and QGIS. However, if this methodology were to be scaled up to the level of one or more cities, a spatial database is needed to cope with the vast amounts of data.

Two steps were taken to determine the manner of storage: First, literature study was conducted to find appropriate ways of storing both location and quantity. Second, the data was stored in such a way that visualization afterwards was possible. To achieve this, an approach has been found that stores the full calculation of the quantity in an attribute, to be able to extract extra information as well, instead of only a number.

3.3 TOOLS AND CODE

The source code for this project was programmed in Python and additional libraries, with the help of QGIS. For visualizing shortest paths in QGIS, a plugin was built. All code and scripts are available on Github: <https://github.com/MatthijsBon/undergroundLocalization> and <https://github.com/MatthijsBon/PathVisualizer>

4

DATA ACQUISITION AND ASSESSMENT

The first step in assessing to what extent quantification of underground urban mines in terms of metal cables is possible, it is essential to know which data to use. Input data for every case study area is necessary to exemplify the methodology. Validation data is essential to determine the degree of accuracy with which the used methodology approximates reality. This chapter elaborates on the results of acquisition of validation data at different parties as well as an assessment of the available sources that can be used as input data.

Two municipalities, the Dutch cadastre, and network operator Alliander have been contacted to request data for validation. Moreover, if there is no data available, it is useful to know whether there is a demand for such data.

Case Study Areas

To exemplify the methods in this research, three case study areas in the region of Amsterdam have been selected. These three areas have an average building age of 60-70 years in common, meaning the buildings and their surroundings might soon become available for redevelopment or demolition and thus provide opportunities for urban mining. The three case study areas that have been selected are:

1. Slotervaart
2. Geuzenveld
3. Indische Buurt

Figure 4.1 shows the case study areas in the context of Amsterdam. These three neighbourhoods were built around 1950 and consist of mostly residential buildings. Other building functions, such as offices, retail and industrial use are filtered out, resulting in 2438, 2085 and 1140 buildings for Slotervaart, Geuzenveld and Indische Buurt respectively. Only residential buildings are kept, since other functions might use different cable connections, possibly to the MV network, which cannot be generalised. The difference in size and building layout could potentially influence the results and are therefore variable among the different case study areas.

4.1 DATA FOR VALIDATION

Four parties have been contacted to determine the availability of data on underground metal cables: 1) the municipality of Amsterdam; 2) the municipality of Rotterdam; 3) the Dutch cadastre and; 4) network operator Alliander. The municipality of Amsterdam replied quickly, but does not possess datasets on underground infrastructure. Unlike Amsterdam, the

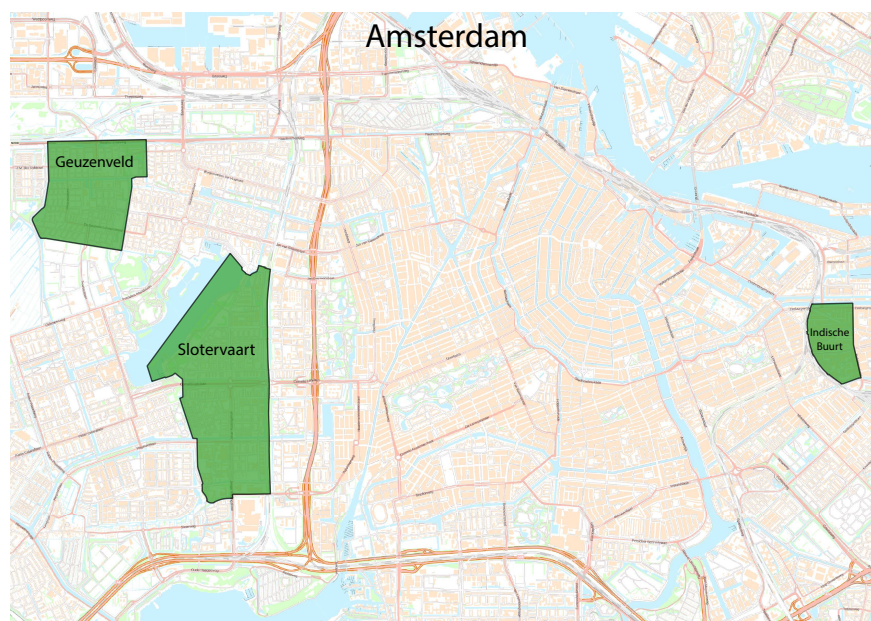


Figure 4.1: Case study areas in the context of Amsterdam

municipality of Rotterdam does keep their own database on underground infrastructure. But since this research is focussed on the region of Amsterdam, data from Rotterdam is kept as backup only. The Dutch cadastre has data on underground infrastructure available for sale. Finally, Alliander does not share their (sensitive) data as open data, but they provided datasets for validation, as well as point data on transformers.

At the municipality of Amsterdam, the data lab is in possession of various datasets with geo-information¹, such as traffic, bicycle routes and more. Unfortunately, there is no data available on underground infrastructure. However, they are very interested in such a dataset, since that would contribute to the ambition of being a progressive municipality and the national goal to have a full circular economy in the Netherlands by 2050. However, for this thesis they could not provide a dataset to validate the methodology.

The Dutch cadastre obligates every network operator to submit their data to the cadastre for their **KLIC** database. This database is consulted whenever a KLIC alert is made. With every (mechanical) excavation in The Netherlands such an alert is needed, to make sure no underground infrastructure is damaged. Such a KLIC alert could provide the validation data necessary for this research, however, such an alert is quite expensive and only covers up to 500 square meter.

Although Alliander does not make their data available to the public, they did provide datasets for the specific case study areas for validation purposes as well as locations of transformers in the LV networks. Additionally, they provided a table to use that maps currents through a cable (I_{nom}) to a certain cable type and cross-section area. This table is used in Chapter 6.

¹ <https://data.amsterdam.nl/>

4.2 DATA FOR QUANTIFICATION

Before starting with programming, it is necessary to determine what data is available, publicly online or at other locations, to use as input data. Since this thesis was an iterative process, a multitude of sources have been used. Table 4.1 shows an overview of the reviewed datasets and its purposes and results. The next sections will elaborate further on each dataset and especially on the final dataset.

Table 4.1: Used datasets and working status

Source	Subject	Geometry	Status
BAG	Buildings	Polygon	Working, improvements possible
Cadastre	Plots	MultiLineString	Insufficient
BGT	Buildings	Polygon	Insufficient
	Streets	MultiPolygon	Working, improvements needed
	Water	MultiPolygon	Working
NWB	Streets	MultiLineString	Working
Alliander	Transformers	Point	Working

Buildings

Three different sources were tried as dataset for buildings, the BAG, the Basisregistratie Grootchalige Topografie (Large Scale Topographic Database) (BGT) and the Dutch cadastral building plots. Both BAG and BGT should be actual and up-to-date and therefore contain the same information. However, the BAG buildings were easily downloadable from the ESRI ArcGis Online website, whereas the BGT only provided partial downloads in Web Feature Service (WFS) format, up to 1000 features. The BAG contains both building polygons as well as address points and information on the use, such as function and number of households.

The third source for buildings was the Dutch cadastral building plots. While polygons are a logic choice for a building, it might be useful to know the boundary of the area around it as well, given that private property cannot be used for public cables. By offsetting the property boundary closest to the street, a line could be created, representing the skeleton of the cable. However, these property boundaries are represented using polylines and are topologically inconsistent or incorrect, with overlapping lines and odd segmentations. Offsetting the boundaries resulted in very irregular cables, making this method not sufficient enough to use (Figure 4.2).

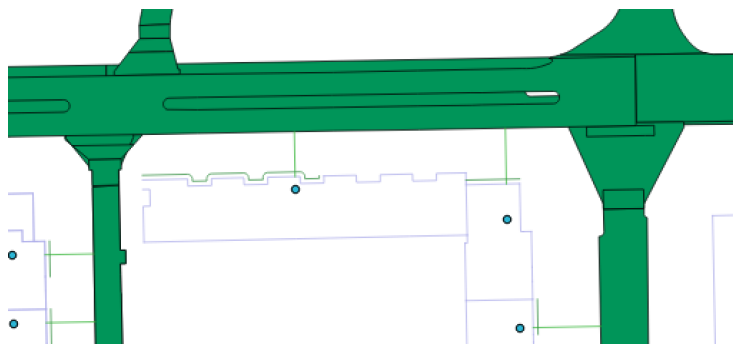


Figure 4.2: Example of offsetting of property boundaries.

Streets

Two sources were experimented with for the street data. First, the BGT polygons were used. This method seemed to work and yield sufficient results, although there were some improvements needed that could further increase the performance. First of all, the street polygons are a planar partition of multiple types of roads. This meant that one street could be made up of multiple polygons, which caused problem in finding closest streets and adding street names to the polygons.

The **NWB** represents all the road in the Netherlands as lines. Since these lines do contain street names, a spatial join of the **NWB** with the BGT streets could have improved the BGT streets. However, due to subdivisions of BGT streets and slightly mismatching geometry (Figure 4.3), this did not increase the performance, and was therefore disregarded. But the **NWB** alone did provide a good topological network. This topological network was less accurate than manual generation of a topological skeleton in terms of location, but more accurate in terms of quantity.

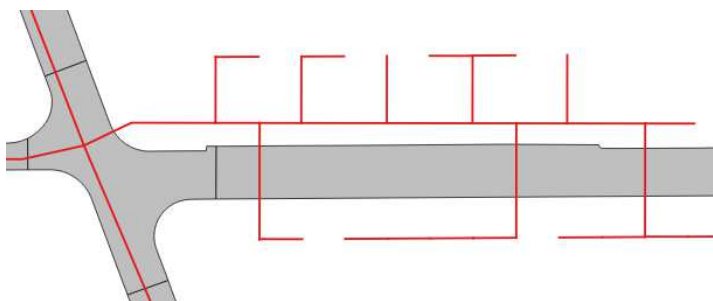


Figure 4.3: Example of a geometry mismatch between **NWB** (red lines) and BGT streets (grey polygons).

Transformers

Alliander provided point data of the transformers in the LV network. These transformers transform 10kV electricity to 400V electricity. Each transformer can serve up to approximately 500 households within a 500 meter radius. Dutch electricity regulations allow a maximum voltage drop of only a few percent. Since the voltage drop is linked to the cable length, the maximum length of a cable in LV networks is approximately 500 meters.

Other

Other used datasets include the BGT water polygons as well as the BGT 'kast' points. These points represent transformer boxes that divide electricity, internet or telecom cables directly to the houses. In other parts of the Netherlands, these points contain useful attributes, indicating the specific type of box. However, since the BGT is not fully finished, the lack of attribute information of points in the region of Amsterdam did not allow for distinction of different types of boxes.

4.2.1 Data pre-processing

After selecting the final dataset, the **NWB** and **BAG** for topological network and buildings respectively, the second step of the methodology is to clean and filter the datasets to make them ready for use. The **NWB** is a relatively

clean and ready-to-go dataset, but the BAG contains all the buildings, addresses and Verblijfsobject(en) (Stay Object(s)) (VBO) in the Netherlands in three separate sources. Figure 4.4 shows the relation between the three different shapefiles before transformation, filtering and cleaning.

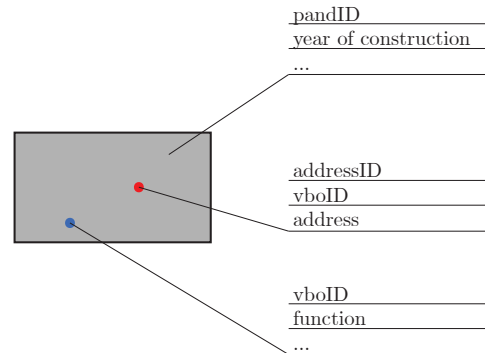


Figure 4.4: Relation between stay objects (VBO, blue), address points (red) and buildings (pand, grey).

The transformation workflow is visualized in Figure 4.5. This transformation was needed in order to correctly attach building functions and addresses from point data to the buildings. First, all data is clipped to the case study areas and stay objects are filtered on residential function.

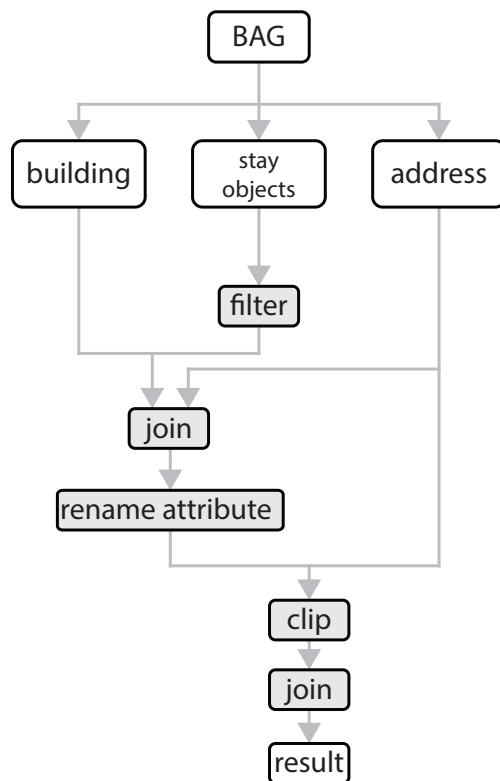


Figure 4.5: Workflow to transform the BAG data.

Second, the buildings are joined with the stay objects with the use of a relational table that comes with the **BAG**. Every building has one or more related stay object, with accompanying attributes such as function, and main address ID. In case of a multitude of stay objects, the main address ID is found for every stay object and the address with the highest occurrence is joined with the building. This way, a building is joined with a residential stay object and the joined address is most likely the street that connects that building. The attribute 'matched records' from the join shows the total number of residential stay objects in that building, which is renamed to 'stayobjects'.

Finally, the addresses are clipped to the remaining buildings. The result, after removal of unnecessary attributes, is a shapefile containing building polygons with the number of stay objects, which represents the number of households. In previous iterations of the methodology, more attributes were kept, which were needed in order to group buildings. This was not necessary anymore when using the **NWB**, since that dataset already contained the topological network.

The next step of pre-processing, is to find the appropriate building point for each building polygon. This building point is an essential part of the algorithm, since its location affects the closest street and the length of the connection cable. When looking at the **BAG**, it was noted that often, the address points would lie close to the entrance of a building, when verified in Google Maps. This would seem logical, since that is where the distribution board is usually located. With this assumption in mind, it would make sense to choose the address points within a building that is closest to the boundary of the polygon. That way, if there would be more address points within a building, the one most likely to be the distribution board would be chosen. Using the distribution board as a building point also made sense from an urban mining perspective, since that is the location in a building where the building is connected to the power network, thus being an accurate position for the cable connection point.

It is possible for more than one address point to exist in the same building, e.g. 24 A or B, or even multiple numbers in cases of large apartment buildings. In such cases it is often hard to determine which point exactly is closest to the distribution board. Since Dutch law requires a distribution board to be within one meter range of the entrance, it was chosen to find the closest point to the boundary of the polygon and use that as the building point. Although there is no way in the **BAG** to extract entrances, this method would often find the point of, or close to, the distribution board, although some exceptions may occur.

One could argue that for a building point, the centroid of a building could be used. However, this has two flaws. First, some 'U' or 'O'-shaped buildings would have a centroid outside the polygon of the building. Second, in many single family houses, there is only one building point and it is often placed near the entrance, indicating that it might be put there on purpose. In that case, using the centroid would decrease the accuracy when connecting the building to the network. Figure 4.6 shows the situation before and after the transformation.

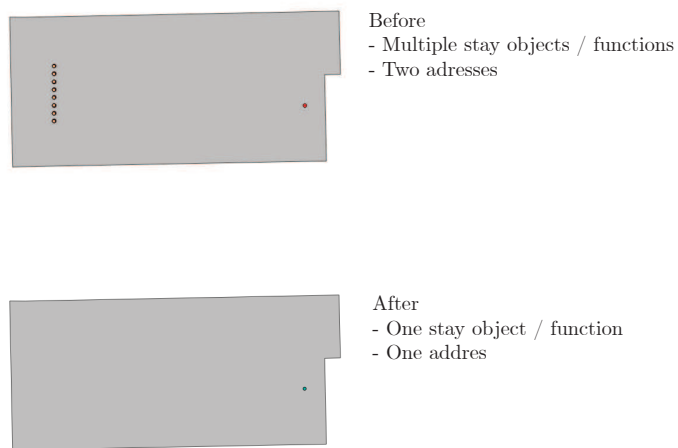
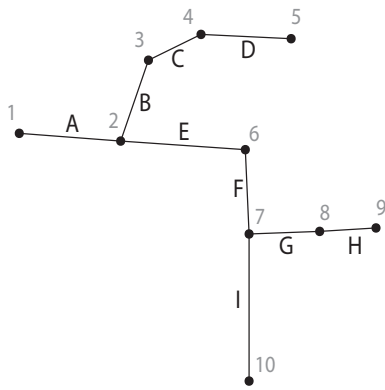


Figure 4.6: A building before and after transformation.

The building point, with an attribute indicating the number of households, is then exported to a new shapefile and ready to be connected to the **NWB** network. The next chapter elaborates further on the connection of the transformers and buildings to the network of the **NWB**.

5 | GENERATING A TOPOLOGICAL NETWORK

The pre-processed data can be used to generate three topological networks, one for each method. A topological network is a representation of vertices and edges where the relations between vertices are most important. By assigning an identifier to a point and using lines as the relation between point A and B, a structure can be created like in Table 5.1. This can be done for every single part of the network, resulting in a topological network that can be translated into a graph data model. Figure 5.1 shows an example of a set of lines and points and how that data can be transformed into a topological network.



<i>edge</i>	<i>start</i>	<i>end</i>
A	1	2
B	2	3
C	3	4
D	4	5
E	2	6
F	6	7
G	7	8
H	8	9
I	7	10

Figure 5.1: Lines and points to vertices and edges in a topological network.

Table 5.1: Relations between edges and vertices as visualised in Figure 5.1.

As mentioned in the previous chapter, before the final dataset was chosen to be the *NWB*, a topological network had to be created from scratch. The workflow that was followed is shown in Figure 5.2, and shows the steps to get from building and street data to a topological skeleton that can be transformed into a topological network similarly as the final method. First, buildings are grouped together to ensure optimal feature handling in Python scripts, as well as improve the accuracy with which the closest street is found. Then, the closest street is found, from which a cable point can be created. This cable point represents the junction where the connection cable to the building would be attached. Subsequently, all cable points can be combined to represent one cable. Finally, all cables connected together form the topological skeleton to be used in network analysis.

Unfortunately, combining cable points into a cable and then connecting multiple cables to create a topological skeleton did not yield results sufficient enough to approximate reality in terms of quantity as well as location.

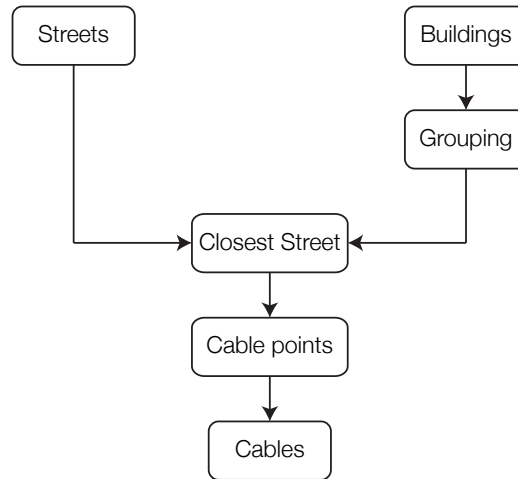


Figure 5.2: Previous workflow from buildings and streets to topological skeleton.

5.1 CONNECTING TO TOPOLOGICAL NETWORK

The **NWB** is already topologically ready to be transformed into a topological network, but the buildings and transformers still have to be connected to this network. There are different ways to connect buildings to a network and each method affects the cable length, as well as the performance and complexity of the network. **1)** The first method, *'Connect to Closest Point'*, connects every point to the closest point on the street network. **2)** The second method, *'Connect to Closest Junction Vertex'* connects every point to the closest junction vertex of the street network, which is divided into segments with maximum length of 75 meters. **3)** The third method, *'Iteratively Connect to the Closest Junction Vertex'* iteratively connects every point to the closest junction vertex, within a threshold, until all nodes are connected to the street network. This GRASS GIS algorithm creates extra vertices if necessary, similar to a Steiner Tree, to minimize total edge length. Figure 5.3 shows the three different methods for connecting points to a network that have been used and compared in this thesis. Henceforth the names for the three methods will be shortened in tables by *'Closest Point'*, *'Closest Junction'* and *'Iterative Closest Junction'*.

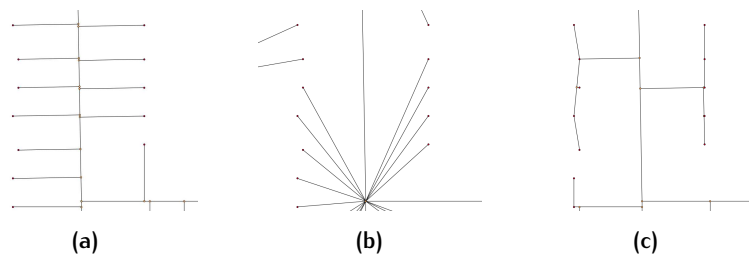


Figure 5.3: Different connecting methods. (a) *'Connect to Closest Point'* (b) *'Connect to Closest Junction Vertex'* (c) *'Iteratively Connect to the Closest Junction Vertex'*.

For the *'Connect to Closest Point'* and *'Iteratively Connect to the Closest*

Junction Vertex' method, the workflow was very similar. First, the **NWB** was connected with the buildings and transformers, using a GRASS algorithm for the 'Iteratively Connect to the Closest Junction Vertex' method and the QGIS plugin 'Networks' for the 'Connect to Closest Point' method. For the 'Connect to Closest Junction Vertex' method, the geometry of the connections were created in Python and exported to Well-Known Text (**WKT**) in order to be loaded into QGIS. These geometries were then merged with the **NWB**. Second, a graph was constructed, again using the 'Networks' plugin. For all methods, a spatial join of the network of points and the transformers and buildings made sure that each point in the network could be given a specific type, either 'road', 'building' or 'transformer'. Figure 5.4 shows the generic process of connecting buildings and transformers.

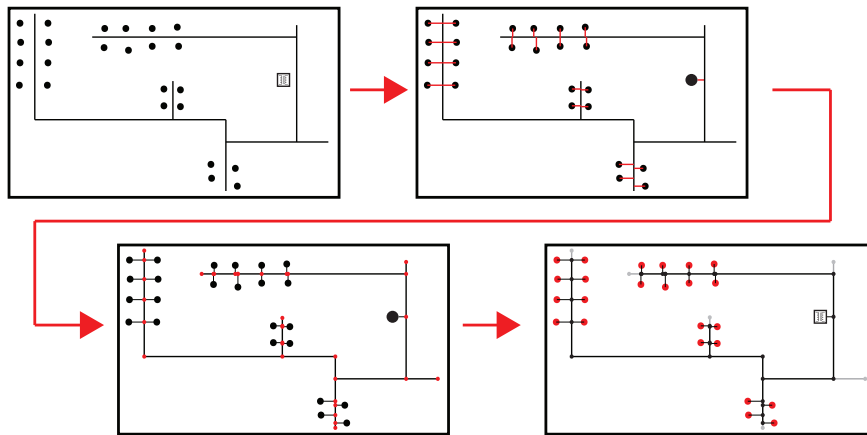


Figure 5.4: Steps to connect buildings and transformers to the **NWB**, resulting in a connected network with three types: road points, buildings and transformer.

The **NWB** only contains the road network lines. Therefore, each line that is added to the network in each of the three different methods, has to be correct, meaning a shortest path from one point to another should really be the shortest path. Even the smallest error in the process of connecting buildings and transformers can mean a partially disconnected network. Figure 5.5 shows why correct topology is important and what happens if the network is 'broken'.

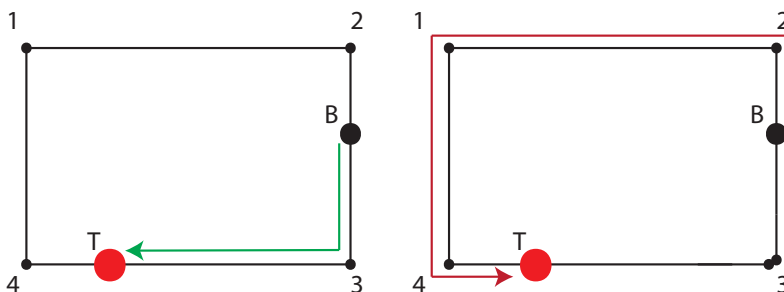


Figure 5.5: Correct path (green) and wrong path (red) due to points not snapped together at 3, from a building B to a transformer T.

On all three methods a series of transformations was performed, to decrease the change of such errors. The networks were cleaned of topological errors using GRASS. The first step was to break all lines at intersection points. Secondly, all endpoints were snapped together if the points were within a threshold of 0.1 meter. These two steps were particularly important in the 'Connect to Closest Junction Vertex' method, since the connections to the vertices were made in a Python script, not directly in QGIS, which caused minor differences because of rounding errors. Additionally, to ensure that the resulting network in each of the networks was correct, a small plug-in, that could quickly visualize one or more paths, was built for QGIS. By visualizing a path in the network, it was easy to see whether or not the chosen path was indeed the shortest path. This made it a useful tool for detecting errors.

When buildings and transformers have been connected to the network, the three different methods can be compared in terms of cable length and number of vertices. Table 5.2 shows an overview of the three methods and their statistics.

Table 5.2: Statistical comparison of the three connecting methods

<i>Closest Point</i>	<i>vertices</i>	<i>Total edge length (m)</i>	<i>Average edge length (m)</i>
Geuzenveld	4409	59165.47	12.79
Slotervaart	5278	81960.25	14.58
Indische buurt	2415	26016.75	10.43
<i>Closest Junction</i>	<i>vertices</i>	<i>Total edge length (m)</i>	<i>Average edge length (m)</i>
Geuzenveld	2774	72247.88	24.95
Slotervaart	3520	98393.17	26.62
Indische buurt	1455	34503	22.59
<i>Iterative Closest Junction</i>	<i>vertices</i>	<i>Total edge length (m)</i>	<i>Average edge length (m)</i>
Geuzenveld	3634	46936.02	10.25
Slotervaart	4410	69828.31	12.55
Indische buurt	2022	22268.04	8.95

The statistics show that the 'Connect to Closest Point' method is in general the average method, except for amount of vertices, which is approximately 1.2 times larger than the the 'Iteratively Connect to the Closest Junction Vertex' method and 1.5 times larger than the 'Connect to Closest Junction Vertex' method. More vertices increases complexity of the graph and therefore require more computing power, resulting in longer processing times. The 'Iteratively Connect to the Closest Junction Vertex' method does indeed minimize total and average edge length, while keeping the number of vertices lower than the 'Connect to Closest Point' method. The 'Connect to Closest Junction Vertex' method has the largest total edge length, but the lowest amount of vertices. This will increase performance, but might result in longer edges than in reality, therefore probably decreasing the resemblance with reality. Figure 5.6 shows the three different networks as the result of the three different connecting methods.

As the statistics of the three methods showed, the three resulting networks are all slightly different. In terms of topology, the 'Iteratively Connect to the Closest Junction Vertex' method and 'Connect to Closest Junction Vertex'

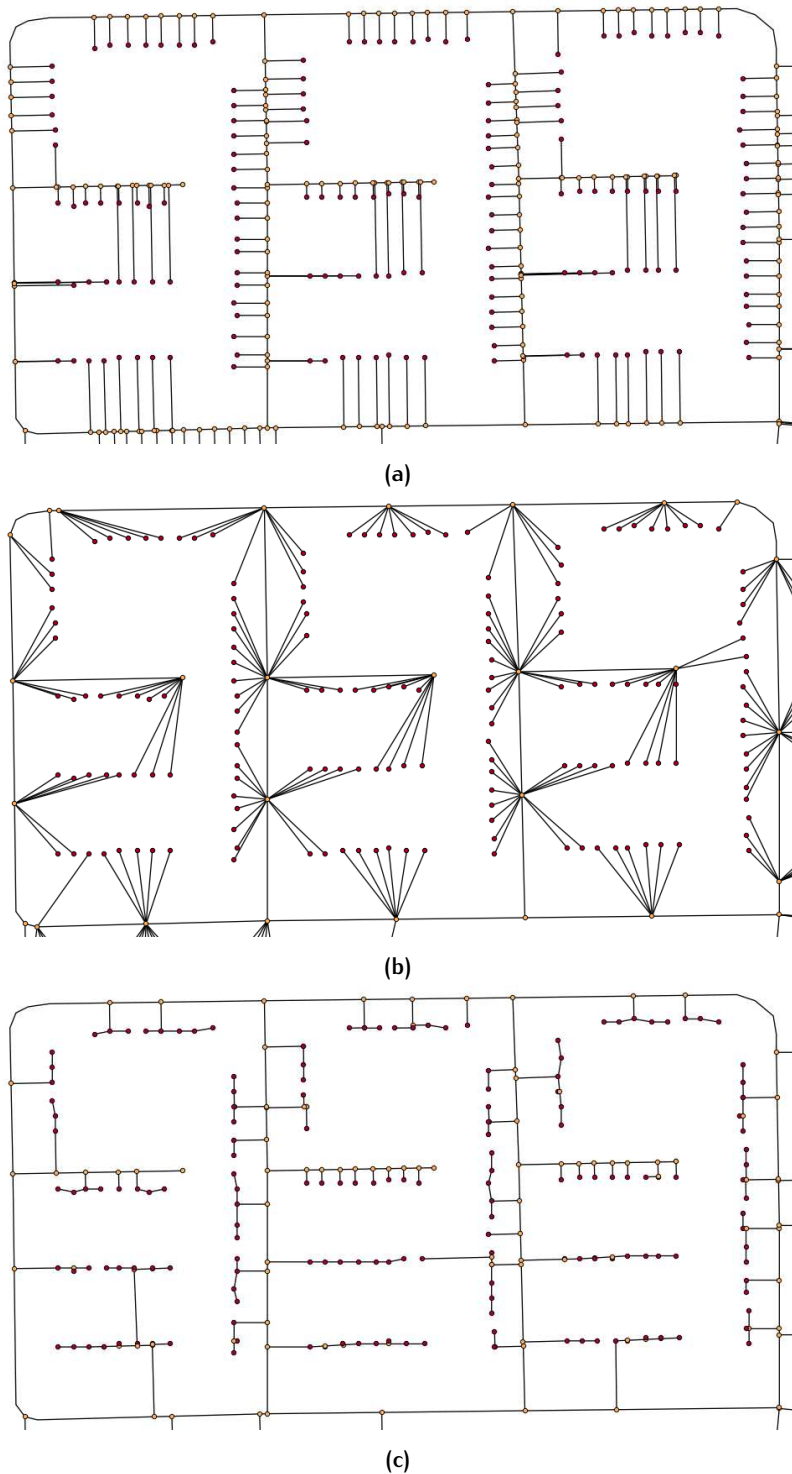


Figure 5.6: (a) Connect to Closest Point (b) Connect to Closest Junction Vertex (c) Iteratively Connect to the Closest Junction Vertex.

method look very similar, although the 'Iteratively Connect to the Closest Junction Vertex' method adds an extra vertex to connect multiple buildings to whereas the 'Connect to Closest Junction Vertex' method uses an existing vertex to connect buildings to. Looking at reality, the 'Connect to Closest Point' method seems to approximate reality more accurate than other meth-

ods. In reality, all buildings are individually connected to the main network, while the 'Iteratively Connect to the Closest Junction Vertex' method connects other buildings through one additional vertex.

The next chapter will focus on finding shortest paths from every building to the closest transformer and the quantification of the urban mine. This process is greatly affected by the number of vertices in the network. All three methods will be discussed and their final results will be compared and validated.

6 | NETWORK ANALYSIS

A graph data model consists of a matrix or list, indicating the adjacency of nodes. The topological network that has been created from the **NWB** and buildings and transformers can be translated in a graph data model. First, the **NWB** containing lines, buildings and transformers, is read and the information, for example "edge 1 connects vertex A to vertex B", is used as a guide to construct the graph data model from the points. This model can then be used to perform analysis, such as shortest paths.

There are four analysis computations that have to be conducted to analyse the location and quantity of the underground infrastructure. The first step in the analysis process, is to find shortest paths in the network, from every building to every transformer. The closest transformer will most likely be the supplier of electricity to that building, since it is optimal to minimize cable length. Second, each edge in the network will be assigned an attribute that stores the use of that particular edge. For example, consider the situation in Figure 6.1. Transformer *T* supplies a number of buildings with electricity. Vertices 2 and 4 are large 'junctions' that supply 50 and 100 households respectively. This means that the electricity assumed to be running through edge A would be half the size of the electricity running through edge C. Additionally, the electricity running through edge B would be the total sum of the electricity running through A and C.

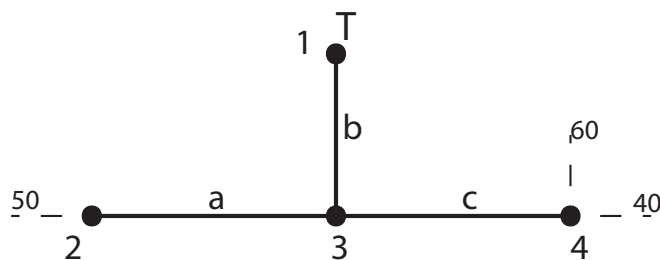


Figure 6.1: Example of amount of electricity assumed to be running through edges (cables).

The third step is calculating the maximum current through a cable. Since every building consists of one or more households and each household uses an amount of power, the load of every household can be computed. Using Ohm's Law ($P = V * I$), it is possible to compute the current through a LV cable if the power is known. Finally, the fourth step matches a current to a cable type which is the final requirement to calculate the amount of metal in a cable.

6.1 SHORTEST PATHS

Once the graph data model is in place, each building has to be connected to the closest transformer. In graph theory, two main types of shortest path problems can be identified: (1) Single source shortest path problems and (2) All pairs shortest path problems. Finding the shortest path from every building to every transformer (which is necessary to determine which is closest) seems like an all pairs shortest path problem. However, there is no need for shortest paths between buildings or between transformers. Therefore, the problem can be considered a multitude of single source shortest path problems. Single source shortest path problems are often solved with Dijkstra's Algorithm [Dijkstra, 1959].

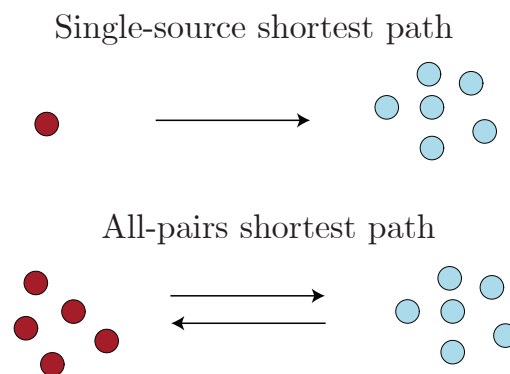


Figure 6.2: Difference between types of shortest paths.

The shortest path from any building to a transformer is found by iterating over all buildings within the graph and finding the shortest path to every transformer using Dijkstra's Algorithm. Then, the path to the transformer which is closest is saved as the 'supply path' for that particular building. All paths are stored and used in the next step in the analysis process.

Finding the shortest paths from every building to every transformer is a computationally expensive process and network of Slotervaart with more than 5000 vertices, this process can take up to one hour with the current methods. Chapter 8 discusses this challenge, particularly if the networks are scaled up to the size of cities or provinces.

6.2 CALCULATING EDGE BETWEENNESS

The path from every building to the closest transformer is used to determine how many times a certain edge is used. This is often referred to in graph theory as edge betweenness centrality. The edge betweenness centrality indicates how often an edge appears in shortest paths within a network [Girvan and Newman, 2002]. Every building consists of one or more households that requires a certain amount of electricity. Since the current through a cable affects the thickness of that cable, it is necessary to know how much current exactly is supposedly running through a cable. Or, from a design perspective, what is the maximum current running through a cable?

First all routes are divided into edges, where each edge is a pair of subsequent vertices in the route. For example: the shortest path from vertex 20 to vertex 65 is given by: 20, 23, 34, 65. Now each pair of subsequent vertices is added to a list of edges, such that $edgelist = [(20, 23), (23, 34), (34, 65)]$. This process is repeated for every building, and stored in a dictionary keyed by building-id. Algorithm 6.1 shows the process that uses this list of edges to calculate the number of households for every edge.

Algorithm 6.1: WORKFLOW FOR CALCULATING EDGE BETWEENNESS

Input: List of edges $edgelist$
Output: D : Dictionary {edge: households}

```

1  $D =$  empty dictionary {}
2 for  $bldID, edges$  in  $edgelist$  do
3   for  $edge$  in  $edges$  do
4     if  $edge$  not in  $D$  then
5        $\_$  add ( $edge: bld.households$ ) to  $D$ 
6     else
7        $\_$  add  $bld.households$  to  $edge.value$ 
8 return  $D$ 

```

With the households attribute, the currents can now be calculated using Ohm's Law and the Strand-Axelsson formula, taking into account the stochastic behaviour of household power demand [Axelsson and Strand, 1975]. For a single household, the maximum power demand can be calculated using

$$P_{max,1} = k_1 \cdot E + k_2 \cdot \sqrt{E} \quad (6.1)$$

and for multiple households as

$$P_{max,n} = n \cdot k_1 \cdot E + 3 \cdot k_2 \cdot \sqrt{\frac{n \cdot E}{3}} \quad (6.2)$$

where:

$P_{max,1}$ = Maximum power demand for one household,
 $P_{max,n}$ = Maximum power demand for n households,
 E = Yearly energy demand for one household and
 n = number of households.

Factors k_1 and k_2 are coefficients derived from experiments, specific to a type of household. These factors are derived from the application Gaia, produced by Phase2Phase¹. The factor 3 is used to indicate a single phase connection to the household, so that load can be distributed over 3 phases. With P_{max} it is possible using Ohm's Law, to find the maximum current through a cable with

$$I = \frac{P_{max}}{230} \cdot m \quad (6.3)$$

The factor m is used to indicate a margin that is used to oversize cables to be on the safe side. From interviews with Alliander it was found that cables are using approximately 70% of their capacity, therefore this research uses a margin of 100/70. Figure 6.3 matches a resulting current I to a cable type, which is used in the final quantification.

¹ <https://phasetphase.nl/vision-lv-network-design.html>

	Cu	Al	I (A)		Cu	Al	I (A)
GPLK 3-ad.	10	16	63	XLPE 3-ad.	-	95	215
	16	25	85		-	150	280
	25	35	110		-	240	360
	35	50	130	XLPE 1-ad.	95	-	335
	50	70	160			240	355
	70	95	190		drie	400	450
	-	120	205		hoek	630	575
	95	150	240		plat	630	645
	120	185	275				
	150	240	320				
	185	-	350				
	240	-	410				
	300	400	450				

Figure 6.3: Cable cross section area (in mm²) per cable type [van der Eerden, 2017].

6.3 QUANTIFICATION

The quantification combines the cable type derived from Figure 6.3, the density of the material and the cable length from the length of the geometry of each edge in the network. To quantify the network, the thickness values have to be multiplied with the length and the density of the metal in order to calculate the amount of metal in the network. Table 6.1 shows the metal densities for copper and aluminium in gram per cubic centimetre.

Table 6.1: Densities for copper and aluminium.

Material	Density
copper	8.96 g/cm ³
aluminium	2.70 g/cm ³

The total mass is calculated by summing the weight of every edge using:

$$\sum_1^n M = \sum_1^n l_n \cdot A_n \cdot d_n \quad (6.4)$$

with:

M = Total mass (kg),

l_n = length of edge n (cm),

A_n = cross section area of edge n (cm²) and

d = density of the edge n material (g/cm³).

Since cables are made out of either copper or aluminium, there is still an uncertainty about the real quantity of metal in underground infrastructure. From literature [Van Oirsouw and Cobben, 2011], it was found that approximately 70% of cables are made out of copper, and 30% out of aluminium. This margin is applied, resulting in the final quantification of the underground urban mines of Geuzenveld, Slotervaart and Indische Buurt, shown in Table 6.2.

Table 6.2: Final results of quantification.

Geuzenveld	Iterative Closest Junction		Closest Point		Closest Junction	
Calculated cable length	36.078,6	(m)	49.824,8	(m)	60.685,6	(m)
	<i>Cu (kg)</i>	<i>Al (kg)</i>	<i>Cu (kg)</i>	<i>Al (kg)</i>	<i>Cu (kg)</i>	<i>Al (kg)</i>
Metal mass from algorithm	14.147,0	2.816,6	16.766,9	3.351,5	19.557,6	3.961,4
Indische Buurt						
Calculated cable length	19.082,2	(m)	23.377,7	(m)	30.253,0	(m)
	<i>Cu (kg)</i>	<i>Al (kg)</i>	<i>Cu (kg)</i>	<i>Al (kg)</i>	<i>Cu (kg)</i>	<i>Al (kg)</i>
Metal mass from algorithm	9.910,2	1.898,2	10.681,6	2.064,6	13.153,1	2.581,2
Slotervaart						
Calculated cable length	46.795,2	(m)	60.450,7	(m)	74.060,5	(m)
	<i>Cu (kg)</i>	<i>Al (kg)</i>	<i>Cu (kg)</i>	<i>Al (kg)</i>	<i>Cu (kg)</i>	<i>Al (kg)</i>
Metal mass from algorithm	15.625,1	3.074,5	18.061,8	3.568,6	21.386,7	4.219,8

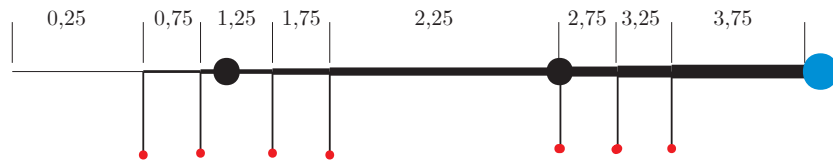
Although this table shows no baseline to compare the results to, comparing the three different methods and three different case study areas gives valuable insights. Because of the larger area, it is no surprise that Slotervaart has the longest cable length in all three methods. However, in terms of quantity, the difference is smaller. To better investigate these results, Table 6.3 shows the relative differences in mass between methods and case study areas.

Table 6.3: Comparison of results between case study areas and methods

		Geuzenveld			Indische Buurt			Slotervaart		
		Closest Junction	Closest Point	Iterative Closest Junction	Closest Junction	Closest Point	Iterative Closest Junction	Closest Junction	Closest Point	Iterative Closest Junction
Geuzenveld	Closest Junction	117%	138%		149%	183%	197%	91%	108%	125%
	Closest Point	86%		119%	127%	157%	169%	78%	93%	107%
	Iterative Closest Junction	72%	84%		108%	132%	143%	66%	78%	91%
Indische Buurt	Closest Junction	67%	78%	93%		123%	133%	62%	73%	84%
	Closest Point	55%	64%	76%	81%		108%	50%	59%	68%
	Iterative Closest Junction	51%	59%	70%	75%	93%		46%	55%	63%
Slotervaart	Closest Junction	109%	128%	151%	163%	200%	216%		118%	137%
	Closest Point	92%	108%	128%	137%	169%	182%	84%		116%
	Iterative Closest Junction	80%	93%	110%	119%	146%	158%	73%	87%	

This table shows the mass of the case study area and method on the left, divided by the case study area and method at the top. This reveals which method resulted in the highest quantity, per case study area, but also in comparison with the other case study areas.

In all case study areas, the 'Connect to Closest Junction Vertex' method achieved highest quantities, while the 'Iteratively Connect to the Closest Junction Vertex' method got the lowest quantity. When looking at the topological network and its resemblance to reality, this is a counter intuitive result, since the 'Connect to Closest Junction Vertex' method is not at all close to reality. However, the total cable length does increase by connecting to the closest vertex and by connecting to the closest vertex in the network the result is more cable length with more thickness. This is further explained in Figure 6.4.



- building (current = 0.5)

● transformer

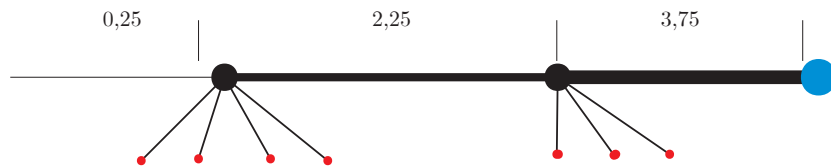


Figure 6.4: Difference in cable length and thickness between 'Connect to Closest Point' (top) and 'Connect to Closest Junction Vertex' (bottom) methods. Considering seven buildings with each a (fictional) current of 0.5, a segment of a network and a transformer, cable current and therefore thickness is higher with each added building.

In the 'Connect to Closest Point' method this results in shorter cables with each a lower current, whereas the 'Connect to Closest Junction Vertex' method yields longer cables with higher currents and therefore a higher metal quantity.

7 | VALIDATION

To determine whether the results presented in Chapter 6 are true, validation of the results is necessary. With the use of network data from network operator Alliander, the location and quantity of the created cables can be compared with the location of their cables.

In this chapter, validation is conducted in three steps. First, the location of the cables will be examined and compared with the location of the real cables. Second, the quantity of the cables will be compared to the quantity of cables according to the data from Alliander. In the final step, both results are discussed and the cause of differences and errors in the validation process are examined.

7.1 VALIDATION OF LOCATION

Using the **NWB** causes a systematic error regarding accuracy of the location, since the design of the methodology neglects the fact that cables are usually placed near a street, not in the center of the street, like the **NWB** is modelled. But to be able to generate a topological network that could be used to quantify the underground urban mine, accuracy had to be traded in for precision. Therefore, this section will elaborate only on the location of the cables and its impact on the quantification. Table 7.1 provides an overview of the computed and actual cable lengths.

Table 7.1: Overview of cable lengths (in meter) in the three case study areas

Geuzenveld	Computed length	Real length	%
Closest Junction	72.247,9	73.876,7	97,8%
Closest Point	59.165,5	73.876,7	80,1%
Iterative Closest Junction	46.936,0	73.876,7	63,5%
Indische buurt	Computed length	Real length	%
Closest Junction	34.503,0	58.028,2	59,5%
Closest Point	26.016,8	58.028,2	44,8%
Iterative Closest Junction	22.268,0	58.028,2	38,4%
Slotervaart	Computed length	Real length	%
Closest Junction	98.393,2	107.375,7	91,6%
Closest Point	81.960,3	107.375,7	76,3%
Iterative Closest Junction	69.828,3	107.375,7	65,0%

Looking at this information, the 'Connect to Closest Junction Vertex' method seems to closely resemble reality in terms of cable length. As the 'Connect to Closest Junction Vertex' method connects buildings to the closest vertex in

the network, with a maximum distance of 75 meter, this adds a lot of edge length to the network. Moreover, as explained in Figure 6.4, this method results in thicker segments of cables between vertices.

7.2 VALIDATION OF QUANTITY

While exact validation of the location does not provide new insights, the systematic error is clearly recognisable when the quantity is validated. The dataset from Alliander contains an attribute indicating the specific type of cable that was placed, which is exploited to calculate the thickness of the cable and the metal content. Multiplying the thickness for every individual cable by its length and the material density yields the final quantity per cable and a total quantity per case study area. Table 7.2 shows the computed metal content and the metal content from validation data in the three case study areas.

Table 7.2: Final results of quantification.

Geuzenveld	Iterative Closest Junction	Closest Point	Closest Junction
Calculated cable length	36.078,6 (m)	49.824,8 (m)	60.685,6 (m)
Real cable length	73.813,4 (m)	73.813,4 (m)	73.813,4 (m)
	<i>Cu (kg)</i>	<i>Al (kg)</i>	<i>Cu (kg)</i> <i>Al (kg)</i>
Metal mass from algorithm	14.147,0	2.816,6	16.766,9 3.351,5
Metal mass in reality	44.013,1	13.262,9	44.013,1 13.262,9
Adjusted metal mass	28.294,0	5.633,3	33.533,7 6.703,0
Indische Buurt			
Calculated cable length	19.082,2 (m)	23.377,7 (m)	30.253,0 (m)
Real cable length	57.792,4 (m)	57.792,4 (m)	57.792,4 (m)
	<i>Cu (kg)</i>	<i>Al (kg)</i>	<i>Cu (kg)</i> <i>Al (kg)</i>
Metal mass from algorithm	9.910,2	1.898,2	10.681,6 2.064,6
Metal mass in reality	44.449,7	13.394,4	44.449,7 13.394,4
Adjusted metal mass	19.820,3	3.796,4	21.363,3 4.129,1
Slotervaart			
Calculated cable length	46.795,2 (m)	60.450,7 (m)	74.060,5 (m)
Real cable length	107.282,4 (m)	107.282,4 (m)	107.282,4 (m)
	<i>Cu (kg)</i>	<i>Al (kg)</i>	<i>Cu (kg)</i> <i>Al (kg)</i>
Metal mass from algorithm	15.625,1	3.074,5	18.061,8 3.568,6
Metal mass in reality	84.255,3	25.389,4	84.255,3 25.389,4
Adjusted metal mass	31.250,2	6.149,0	36.123,6 7.137,3

The quantification in Table 7.2 clearly shows a difference between the calculated quantity and the quantity from validation data. First to notice is the large difference between the cable length from validation data and the calculated edge length, for the Indische Buurt this factor even goes up to three. This difference can be explained by visualizing the paths (in red) from buildings to transformers, as shown in Figure 7.1. The figure shows that although all buildings are connected to a transformer, not all edges in the network are utilised. This could be due to the fact that for this thesis, only residential buildings are used in the calculation. A longer total cable length does not necessarily mean a higher quantity, since the spatial distribution of buildings is also very important.

Furthermore, the **NWB** is a simplification of the electrical network, meaning that only one single edge is considered per street, while in reality there are



Figure 7.1: Visualisation of paths from buildings to each closest transformer.

at least two. By considering only a single edge, the quantification is always going to be less than reality. To compensate for this difference and to give a more accurate estimation of the metal content in an area, the quantification result is doubled. This results in the 'Adjusted metal mass' in Table 7.2.

With this adjusted quantity, the 'Connect to Closest Junction Vertex' method yields the highest quantity and is therefore closest to reality. This indicates that although the topology of the 'Connect to Closest Junction Vertex' method seems counter-intuitive to reality, it does provide a more realistic estimation of the metal mass in an area, as it outperforms other methods.

7.3 DISCUSSION

One explanation for the discrepancy between the adjusted quantity and quantity from validation is that cables in reality are largely oversized. To compensate for the over sizing of cables, a margin of $100/70$ is applied, but in reality over sizing might actually be more, not only to be on the safe side from a design perspective, but also from an economic perspective, since it is cheaper to anticipate growth and therefore a larger power consumption than to replace a cable that is already underground.

Another explanation could be that the topological model of the **NWB** is oversimplified. By using the **NWB** as topological skeleton, the underground electricity network is simplified. Figure 7.2 shows the cables from validation data and the **NWB** for a small area in Geuzenveld. Notice how the **NWB** is not completely geometrically accurate with the road in the streets in the background layer. It also shows cables on either side of the road, whereas the **NWB** is simplified using a single line.

Lastly, Figure 7.2 shows that there are multiple cables leading out from a transformer, while the quantification in this research only takes into account

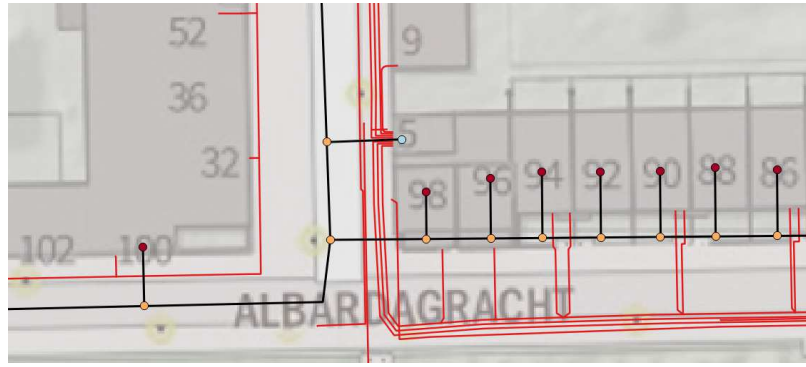


Figure 7.2: Visualisation of validation data (red lines), NWB (black lines), buildings (red points), transformers (blue points) and background layer.

one single three-phase cable per edge of the network. This simplification could decrease total quantity and therefore accuracy.

Table 7.3: Total quantity of copper and aluminium per case study area

Geuzenveld	Computed metal mass		Real metal mass		Accuracy	
	Cu (kg)	Al (kg)	Cu (kg)	Al (kg)	Cu	Al
Closest Junction	39.115,20	7.922,75	44.013,09	13.262,87	88,9%	59,7%
Closest Point	33.533,73	6.702,95	44.013,09	13.262,87	76,2%	50,5%
Iterative Closest Junction	28.294,03	5.633,29	44.013,09	13.262,87	64,3%	42,5%
Indische buurt	Cu (kg)	Al (kg)	Cu (kg)	Al (kg)	Cu	Al
Closest Junction	26.306,27	5.162,36	44.449,66	13.394,43	59,2%	38,5%
Closest Point	21.363,26	4.129,12	44.449,66	13.394,43	48,1%	30,8%
Iterative Closest Junction	19.820,31	3.796,40	44.449,66	13.394,43	44,6%	28,3%
Slotervaart	Cu (kg)	Al (kg)	Cu (kg)	Al (kg)	Cu	Al
Closest Junction	42.773,36	8.439,52	84.255,30	25.389,43	50,8%	33,2%
Closest Point	36.123,55	7.137,28	84.255,30	25.389,43	42,9%	28,1%
Iterative Closest Junction	31.250,22	6.149,05	84.255,30	25.389,43	37,1%	24,2%

Further investigation of the accuracy of the three methods in three case study areas is shown in Table 7.3. Highest accuracies are achieved in case study area Geuzenveld, with up to 88% and 59% accuracy for copper and aluminium respectively with the 'Connect to Closest Junction Vertex' method.



Figure 7.3: Spatial distributions for (a) Indische Buurt (b) Slotervaart (c) Geuzenveld.

Slotervaart performed less with every method, but this can be explained by

the much larger area and spatial distribution of buildings in that area. As pointed out before, more cable length does not necessarily mean a higher mass, since some cables segments might not be part of shortest paths between transformers and buildings. Furthermore, the spatial distribution of buildings in Slotervaart is much less dense than that of the Indische Buurt and although the spatial distribution is similar to that of Geuzenveld, Slotervaart has longer edges on average and is less densely populated than Geuzenveld.

8

DATA MANAGEMENT

Just as important as creating a topological network and performing analysis on it is the management of the data. Storing is important since it allows other users to examine the results as well as provide a basis from which further research or visualization can continue. If storing of spatial data is not properly thought through, access can be limited.

Currently, the size of the data processed and produced in this research is relatively small. Three case study areas and three methods with a total of almost 30.000 nodes and approximately 500 km of line data is still not comparable to the size of the data if the whole city of Amsterdam was processed, let alone multiple cities. The current datasets are stored in shapefiles and can easily be read in any GIS. However, if the research is scaled up to the city of Amsterdam, the network for one single method becomes too vast to handle in shapefiles. This chapter shows why a spatial database could overcome this barrier and what such a database would look like.

8.1 SPATIAL DATABASES

In a spatial database such as PostGIS, an extension to the PostgreSQL database, geographic objects can be stored and spatial queries can be run in Structured Query Language (SQL). By using a spatial database for this research, the user can:

- Store buildings, transformers and the NWB as spatial objects.
- Index the database with spatial indices to increase performance.
- Access relational queries specifically designed for spatial objects (distance, topological relations, etc.)
- Use spatial operations (length/area, intersection matrices, buffers, etc.)

Using a relational database without the spatial possibilities as mentioned above, limits performance, since normal indices are optimized for spatial data. Normally, indices use some kind of linear search, such as sorting, to quickly find the object to be found. However, spatial objects are not so easily linearly sorted. Spatial indices use the location to index an object, such as a quadtree or other space filling curves. Such a spatial index usually divides the database space into smaller partitions. Figure 8.1 shows a quadtree for indexing spatial objects.

The subdivision of space is necessary and very useful in many stages of this research, especially if research covers a whole city. By using Python and shapefiles to connect the buildings and transformers to the network, the process would be very slow for a city. However, by subdividing the data into smaller 'tiles', one does not have to search the full dataset for the

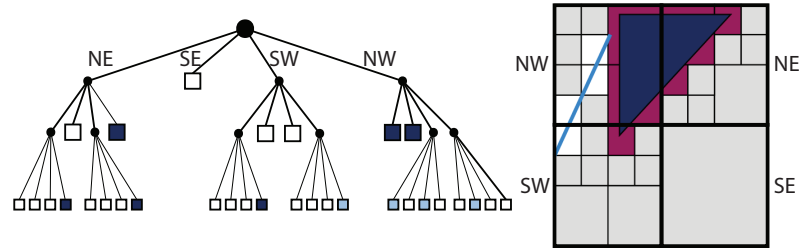


Figure 8.1: Quadtree for two spatial objects.

Connect to Closest Junction Vertex or edge, but only the closest within the bounds of the particular tile. This decreases the search area and increases performance. This also applies to finding shortest paths from buildings to transformers. Figure 8.2 shows how subdividing the data into tiles could increase the performance in finding the closest transformer.

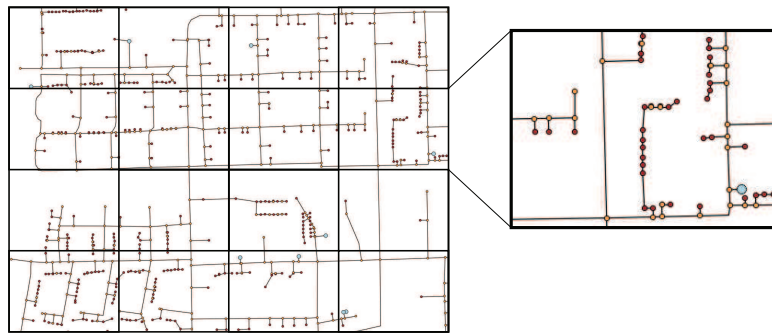


Figure 8.2: Decreased search area when using subdivided data.

Finding shortest paths in a spatial database such as the PostGIS extension for PostgreSQL, can be done by using the pgrouting extension. With this extension it is possible to find single source shortest paths, for example Dijkstra's algorithm, as well as multiple source shortest paths, such as the Floyd-Warshall algorithm. This way, all nodes with type building (red) can be selected and the shortest path to all nodes with type transformer (blue) can be found. By making use of a spatial index such as an quadtree, only part of the data has to be searched.

While indexing increases performance by knowing where to find the data at hand, clustering methods make sure that similar data values are stored close to each other. This means that spatial objects close to each other in space, can be stored close to each other on disk. By doing so, access times can be decreased and queries can be optimized. Clustering methods often use so-called space filling curves as in Figure 8.3 to store geometries close to each other.

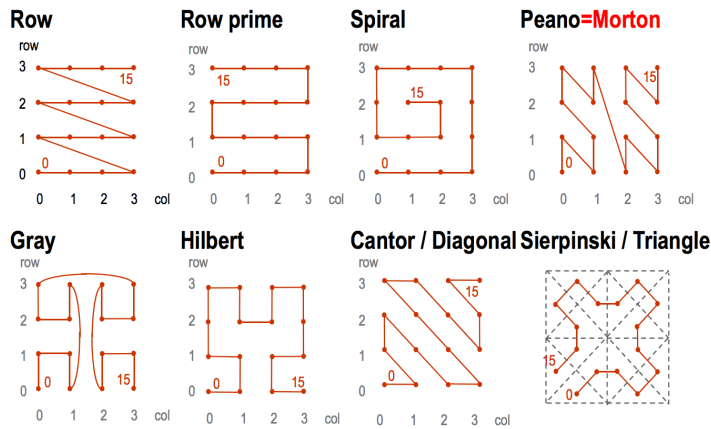


Figure 8.3: Different space filling curves [van Oosterom, 2017b].

8.2 DATA STORAGE

A spatial database is not only useful when accessing and processing data, but even more so for storing results and to provide a easy access method for other purposes, such as visualization. When all processing is done in PostGIS, the final result can be a table containing the quantification, as well as the topological network. The topological network is made up of a table with all edges, the relation between nodes, and the nodes themselves. Table 8.1 shows the table of edges in the network. Each edge has a start and end value, that refers to a node in the nodes table.

Table 8.1: Resulting table of edges with the quantification result and the edges as spatial objects.

id	start	end	length	cableStr	geometry
1	1	3	27,8	4x150-Cu-PILC	LINestring(...)
2	2	3	37,7	4x50-Al-PILC	LINestring(...)
3	3	4	42,0	4x95-Cu-XLPE	LINestring(...)
4	3	5	47,0	4x120-Al-XLPE	LINestring(...)

The quantity of a cable can be directly attached as an attribute of every cable, but for reasons such as visualization it would be interesting to have as much information on a cable as possible, such as cable type and length. This information can be stored in the database together with every edge. The two necessary attributes to visualize the thickness are: the cable length and the cable type, which consists of: **1)** material, **2)** cross section area, **3)** number of veins, and; **4)** insulation type. These four main parts that the cable type consists of can be stored in a similar way as the validation data from Alliander is stored.

By using a string with the specification of the type, values for each of these four attributes can be easily retrieved by splitting the string at the delimiters 'x' or '-'. Important to note here is the fact that it is currently unknown whether a cable contains aluminium or copper veins. This can be solved by adding a second string attribute containing the specification of the cable for the other metal. The metal ratio of copper and aluminium of 70 / 30%

can be taken into account when the total quantity is calculated. Similarly, the current methodology only takes into account PILC insulated cables, but other types can be added. The type specification string could be represented as follows:

$$AxB - C - D$$

With:

A Number of veins

B Cross section area in mm²

C Material

D Insulation type (PILC or XLPE)

Example:

$$4x150 - Cu - PILC$$

9

FUTURE RESEARCH AND CONCLUSIONS

This thesis explored the possibilities of increasing certainty about the location and quantity of the underground urban mine with the use of topological networks. From the literature on UUM and electrical networks, it has become clear that a more precise and accurate method is needed to fill the gap of information about the location and quantity of underground urban mines.

Although increasing certainty ultimately results in knowing the total mass of the underground urban mine, a minimum quantity could be very useful as well. In this research, a multitude of datasets have been used to generate a topological skeleton in order to perform network analysis. Ultimately, the NWB was chosen to provide the topological network from which a quantification could be carried out. This chapter will further elaborate on the answers to the research questions, as well as critically review the used methods and provide recommendations for future research.

9.1 CONCLUSIONS

This thesis aimed to answer the main research question:

To what extent can topological networks be used for localization of underground metal cables in order to assess the quantity of an underground urban mine?

In Chapter 5, it was shown how the NWB was used to provide the topological skeleton that can facilitate network analysis. Important to note is the fact that by using the NWB, location accuracy is traded in for precision. Although manual generation of topological skeletons could yield networks with higher accuracy, a full topological network could not be constructed, therefore limiting the overall value of such a method. But by using the NWB, it is possible to generate a topological skeleton and quantify that network, providing a minimum bound of the metal quantity. By using the NWB and the BAG as input data, this method can be transferred to any other city in the Netherlands quite easily. However, transformer point data is essential for this method and should be obtained from a network operator or other source.

Quantification of the underground urban mine was carried out, starting with the topological network from the NWB and adding buildings and transformers, using three different connecting methods. In terms of metal content, the quantification matched to reality for up to 88% in Geuzenveld for the 'Connect to Closest Junction Vertex' method. As the method is an estimation of the quantity in reality, an approximation with up to 88% accuracy is very good. Furthermore, any amount lower than the actual quantity would be

valuable, as long as the quantification does not overshoot the real quantity. If recovery might be feasible based on a minimum quantity, it probably will be feasible if there is more metal to be recovered.

Looking at the three different methods that were used in this methodology to quantify the underground urban mines, it becomes clear that the 'Connect to Closest Junction Vertex' method did yield the highest quantity in all three case study areas. Since none of the methods resulted in an overshoot of quantity, all methods performed well enough to estimate a minimum quantity, with the 'Connect to Closest Junction Vertex' method being the most accurate.

To exemplify the possible income gains if the underground electrical cables in the underground urban mine of Geuzenveld would be recovered, the total recovery yield, based on this quantification method would be approximately € 145.000 at the price of € 3,50 / kg and € 0,80 / kg for recycled copper and aluminium respectively. But since there is more metal actually available, the actual yield would be approximately € 164.000, meaning almost € 20.000 more than calculated. This is not even taking into account cables that are not registered by network operators, tram lines and public lighting.

A final conclusion can be drawn that the current methodology does provide a new way to approximate the minimum quantity of metals in electricity cables in the low voltage networks. However, this methodology is not suitable for finding the exact spot to start digging, because locational accuracy is too low. For the Amsterdam municipality and maybe even the Netherlands, this means there is a lot to gain in terms of recoverable metals, if certain areas are being redeveloped and new networks have to be laid. And if the future becomes more and more wireless, it might be even possible to recover more cables when areas are redeveloped, contributing to a more sustainable and more circular future.

9.1.1 Sub-questions

The other research questions in addition to the main question were:

1. *What data on underground infrastructure is already available?*

It turned out that although network operators have a database containing every cable in their possession, municipalities have little or no clue about what is underneath their feet. The **KLIC** has this data and sells it whenever excavation work is conducted, but for other purposes, such as urban mining, this data is very expensive. The municipality of Rotterdam can be set as an example for other municipalities, because of their own initiative to create a database with all underground infrastructure.

2. *Is graph theory fit to approximate an electrical network from a design perspective?*

From the literature review in Chapter 2 it was found that graph theory has been used to optimally model electrical networks. This design perspective showed that there are uses for graph theory in finding optimal networks and could therefore be used to find the minimum length of cables needed to connect buildings in a network. Modelling the cable network in geometric space had not been done before and this thesis showed that it is possible,

although manual generation of the topological network is difficult.

3. What input data and methods are necessary for creating a topological network?

From the experiments with a multitude of datasets it was found that manually generating topological skeletons is a arduous process, no matter the input data. But with a topological skeleton to start from, such as the **NWB**, the results resemble reality more closely and quantification of underground urban mines becomes possible, although there is a trade-off between location accuracy and quantification accuracy. From the assessment of validation data, it was found that Alliander does not provide the data on their network as open data, given the sensitive nature of the electrical networks, whereas Enexis, another network operator, does share their data. Fortunately, Alliander shared their data for this research. Without it, network analysis would not have been possible.

Furthermore, the method proposed in this thesis was a result of an iterative search for the most suitable combination of datasets and accompanying methods. Various datasets and methods have been experimented with and this resulted in the final datasets and method presented in this thesis. Although the **NWB** provides very good results and accuracy while not overestimating the quantity, better datasets could improve this method even more. This is discussed in more detail in section 9.2.

4. How can the resulting location and quantities be validated?

The validation process of the location of previous methods showed that the location of cables can be predicted relatively well, given that the spatial distribution of buildings is not too complex. In complex spatial distributions the location of cables is simply too difficult to predict with an automated algorithm. However, when using the **NWB** as topological skeleton, locational accuracy is decreased in order to increase quantitative accuracy, resulting in a systematic error between reality and computed cable location. This systematic error continues to influence the quantity, as validation of the quantity showed. By comparing computed metal contents with the validation data, the accuracy of the quantification could be determined. Furthermore, by using three different methods for connecting buildings and transformers to the **NWB** skeleton, validation could be compared across three methods, which showed that the 'Connect to Closest Junction Vertex' method outperformed the others.

5. How can challenges in data management be overcome if the research is scaled up?

The current datasets can be stored without problems in separate shapefiles. However, if this research were to be scaled up to the size of a city, use of a spatial database is advised, because the data would become too vast to handle in shapefiles and process in Python with the current methods. By using spatial databases with spatial indices and clustering methods, data can be accessed more easily and processing would not take up as much time as current methods. Furthermore, by storing the quantity not as a number for every edge but as a string, showing the full quantification, the results can be used in further research and visualization is possible.

9.2 DISCUSSION

As was expected, not all approaches in this research are without failure. An assessment of the methods and results is necessary to determine the contribution to the particular research field. This section first discusses the used data and its limitations and then continues with possible flaws in the used methods.

9.2.1 Review of datasets

Some of the problems that occur in this research are due to the limitations of the used datasets. Other problems that are initially not due to the data, could be solved by using different datasets. This subsection discusses the limitations and possibilities of the datasets that have been or could have been used.

Buildings The **BAG** contains all the buildings in the Netherlands. It functions properly and has the required information for the particular use in this research. However, when there is more than one address point assigned to a building, these points are distributed randomly. This makes distinction of the building point closest to the boundary an erroneous process. It would be very useful if the **BAG** included a building point for every building that was at the location of the distribution board, maybe through cooperation with network operators.

Streets The **NWB** provides the street data in this research. The streets are already topologically consistent and ready to use as topological network. However, as the dataset does not correctly represent the streets, in this research, a more accurate location for the cables is necessary. Therefore, this dataset is only useful to a certain extent. Furthermore, there is a slight mismatch between **BGT** geometry and **NWB** geometry. The latter is not always at the same location, or within the geometry of the **BGT**, making it unfit to spatially join with the **BGT** to add street names to polygons.

Transformers The methods in this research are very dependent of location data of transformers. For this research, Alliander was able to provide the location of these transformers, but without these, network analysis is not possible.

9.2.2 Critical review of used methods

The **NWB** as a topological network to perform network analysis on is a functional method for extracting quantities of underground urban mines. Nevertheless, there are imperfections that could be improved upon to increase accuracy. The most important imperfection is the fact that the **NWB** is a simplification of the electrical network. Only the center lines of the road are considered, while most electrical cables are located on both sides of the street. This design flaw results in less edges to quantify and less accurate results. Currently, this flaw is compensated by doubling the quantified amount, but a better solution would be to adjust the network to closer resemble reality.

Furthermore, the three different methods that are used to connect buildings and transformers to the network are topologically slightly different

and leave the methodology prone to errors. Although the maximum error in the 'Connect to Closest Junction Vertex' network is 75 meter due to its subdivision of edges into segments of 75 meters, the other two methods can contain errors not so easily quantifiable.

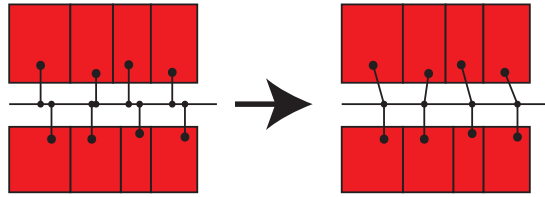


Figure 9.1: Possible performance increase for 'Connect to Closest Point' method.

Currently, the 'Connect to Closest Point' method, adds a new node for every building or transformer that has to be connected. By comparing the three methods, it was immediately clear that the 'Connect to Closest Point' had the most vertices in all methods. This flaw could be overcome if a vertex is only added if there are no other vertices within a certain threshold, similar to Figure 9.1.

Although the 'Iteratively Connect to the Closest Junction Vertex' method seems to be a well-designed method and presents in both cable length as well as quantity a good result, the topology of the method is sometimes incorrect. Figure 9.2 shows how a row of houses could be connected using the 'Iteratively Connect to the Closest Junction Vertex' method. In this method, one vertex represents a hub, connecting other buildings. Even though this was how electricity was divided in history, this is not the case anymore, since each building should be separately connected to the LV network.

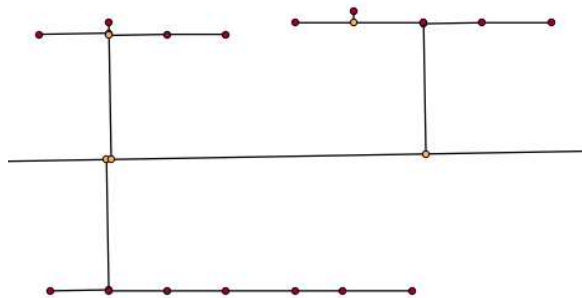


Figure 9.2: Errors in topology with 'Iteratively Connect to the Closest Junction Vertex' method.

Additionally, the quantity of metal is divided into kilograms copper and kilograms aluminium by using the ratio in which they are distributed in the environment according to the literature. This approach was necessary, since it is nearly impossible or very improbable to automatically estimate whether a cable consists of copper or aluminium veins. Therefore, the distinction was not made in this particular thesis, but it does decrease the certainty with regards to the quantity of metal.

Over-sizing of cables could be another explanation for the difference between computed and actual metal mass. From an interview with the company Phase2Phase it was found that usually standard cables are used when a new cable is to be laid, whether there is one or ten buildings to be connected, as long as there is sufficient capacity. Often, this results in cables with lots of overcapacity. This overcapacity is useful when an area is redeveloped and more buildings are connected to the grid. The philosophy is that paying once for a bigger cable is economically better than paying costs for excavation twice, since these costs are the conclusive factors. But this over-sizing of cables makes realistic modelling of the underground urban mine much more difficult.

Performance-wise, the analysis process of finding all shortest paths from buildings to transformers take a lot of processing time. A large case study area such as Slotervaart, with more than 5000 nodes, can take up to an hour to find all shortest paths. Although the three different methods each slightly vary in processing time due to different amounts of nodes, there is a lot of processing time to be gained if this process could be optimized. Performance increases could start by using a spatial database as discussed in Chapter 8, even for the case study areas.

9.3 FUTURE RESEARCH AND RECOMMENDATIONS

As the previous section has shown, there are flaws to overcome and improvements to be made to get better results. Therefore, recommendations for future research are made to improve this research.

- **The location of cables** could be improved by adapting the **NWB** with edges, generated by offsetting lines from the original lines. These lines could still be topologically consistent, while being more true to the location of the actual cables. Alternatively, one could use not the **NWB**, but the centrelines of roads and/or pavements to build a topological skeleton and use that skeleton to offset to construct a more realistic network. Additionally, the 'Connect to Closest Junction Vertex' method is now divided into segments of 75 meters. Further research could investigate whether a different segment length could positively influence the accuracy.
- **Public lighting** is not taken into account in the current research, although a large part of the cable network exist of cable that connect public lighting fixtures to the electrical network. In terms of **UUM**, it would be very interesting to be able to add these cables to the total sum of cables. Lighting fixtures are included in the **BGT** dataset, therefore only a connection from these points have to be made to the constructed topological network.
- **Public trams** are also supplied with electricity, although it uses **DC** instead of **AC**. But because of their function, locating the cables would be much easier. The **BGT** might be able to distinguish roads with tram lines that can be used. Otherwise external sources will have to be found. Furthermore, the constant power requirement of trams allows for generalization of cables into one thickness, making complicated quantification calculation unnecessary.

- **Other materials** such as metal pipes for gas and optical fibres could be included in the Underground Urban Mining process, since these cables are usually located close to electrical cables.

In addition to these recommendations for future research into this topic, there might be possibilities in cooperation of BAG and network operators. Network operators know the location of distribution boards in buildings, because that is where their cable ends, and if they could share this information with the BAG, the data of address points could be enriched with information on the location of distribution board and entrances. However, it might not be economically interesting enough to make this connection.

As pointed out in the discussion of used methods, this methodology has showed that accurate locations cannot be achieved. If not quantification but locating underground cables is the main goal, other methods might prove more useful. However, these methods are often time and cost ineffective. But in the near future, self driving cars or possibly robot could overcome this barrier. By fitting a self driving car with a GPR, accurately mapping the underground infrastructure could become a closer reality.

Furthermore, as visualization was left out of the scope of this research, there might be opportunities for visualization of supply paths for each building. The QGIS plugin that was built to ensure correct paths from buildings to transformers could be updated to further investigate the data from a pure visualization perspective.

9.4 REFLECTION

In the Geomatics programme at the TU Delft, five aspects of data are discussed: 1) Data Acquisition, 2) Data Storage, 3) Data Analysis, 4) Data Visualization and 5) Data Quality. Initially, all five aspects were part of this research, but due to time limitations, the visualization of the results was chosen as a topic for further research and left out for this research.

Combining datasets such as BAG and BGT is both part of Data Acquisition as Data Quality, since both datasets have to work together in order to generate results, although they do not work as good together as was desired. Furthermore, Chapter 7 ensures that the results are validated as part of Data Quality. Similarly, the Data Storage is discussed in Chapter 8.

Furthermore, the problems that arise in Chapters 4, 5 and 6 and the solutions to the problems, show the Data Analysis process. Topics such as Network Analysis, Computational Geometry and Topology have been handled in the courses on GIS and 3D Modelling (GEO1002 and GEO1004) in the Geomatics Programme. Moreover, the topic of Electrical Network Design as an application field to the above-mentioned topics turned out to be very challenging and interesting. I think that I can successfully conclude the MSc Geomatics with this thesis, having deployed several skills in all of the above aspects of Geomatics. I was most intrigued by the vast complexity of the electrical network and it even motivated me to apply for a traineeship at Alliander.

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COLOPHON

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