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Human Centric Routing Algorithm for Urban Cyclists and the Influence of Street Network Spatial Configuration

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Human Centric Routing Algorithm

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Street Network Spatial Configuration

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Abstract

Understanding wayfinding behavior of cyclist aid decision makers to design better cities in favor of this sustainable active transport. Many have modelled the physical influence of building environment on wayfinding behavior, with cyclist route choices and routing algorithm. Incorporating cognitive wayfinding approach with Space Syntax techniques not only adds the human centric element to model routing algorithm, but also opens the door to evaluate spatial configuration of cities and its effect on cyclist behavior. This thesis combines novel Space Syntax techniques with Graph Theory to develop a reproducible Human Centric Routing Algorithm and evaluates how spatial configuration of cities influences modelled wayfinding behavior. Valencia, a concentric gridded city, and Cardiff with a complex spatial configuration are chosen as the case study areas. Significant differences in routes distribution exist between cities and suggest that spatial configuration of the city has an influence on the modelled routes. Street Network Analysis is used to further quantify such differences and confirms that the simpler spatial configuration of Valencia has a higher connectivity, which could facilitate cyclist wayfinding. There are clear implications on urban design that spatial configuration with higher connectivity indicates legibility, which is key to build resilience and sustainable communities. The methodology demonstrates automatic, scalable and reproducible tools to create Human Centric Routing Algorithm anywhere in the world. Reproducibility self-assessment (https://osf.io/j97zp/): 3, 3, 3, 2, 1 (Input data, Preprocessing, Methods, Computational Environment and Results).

Keywords

Routing Algorithm

Space Syntax

Graph Theory

Spatial Configuration

Bikeability

Cyclist Route Choice

Reproducibility

Acronyms

Artificial Intelligence	AI
Application Programming Interface	API
Computer Aid Design	CAD
European Petroleum Survey Group	EPSG
Geographic Information System	GIS
Global Positioning System	GPS
Origin and Destination	OD
OpenStreetMap	OSM
Portable Document Format	PDF
Street Network Analysis	SNA
Street Network Functions	SNF
Visual Basic .Net	VB.NET
World Geodetic System	WGS

Contents

Figures

Tables

Chapter 1

Introduction

1.1. Background

Cycling is an emerging means of active transport which is widely supported by sustainable transport in many cities all over the world. It is deemed to be a silver-bullet to urban problems, in order to reduce carbon emissions, traffic congestion and has been increasingly associated to multitude health, society, and economical benefits (Nordström & Manum, 2015).

This modal shift has been widely promoted in many cities in United Kingdom (UK) and some European Union Member states, where governments rolled out policies and provide budgets to improve cycling infrastructure and education program, there had seen a 200% increase of commuters opting for cycling as their usual commuting choice (e.g. in United States 62% increase in 4 years) (Liu et al., 2016).

Urban dwellers are opting for cycling to navigate through spaces to perform daily activities, from home to daily destinations, as well as unfamiliar places. Wayfinding in unfamiliar places could be a challenge to some, and wayfinding strategy could vary from person (Hrncir et al., 2014). Some would consider a more direct path and safety to be the best, while some might take distance and speed into consideration. Finding an optimal path which considers the wide variety of factors is not an easy task, therefore cyclists turn to route planners for support.

Cyclist route planner, in other words Routing Algorithm is a challenging Artificial Intelligence (AI) problem (Hrncir et al., 2014), due to its multiple routing scenarios and data representation required to model road network features as well as cyclists needs and preference. Routing Algorithm is widely utilized in many urban mobility studies. To verify cyclist route choices derived from GPS tracks and questionnaires, scholars generate routes based on origins and destinations for comparison with real life data, predict mobility flow and incorporating them into *geosimulation* or agent-based modelling (Filomena, Manley, & Verstegen, 2019; Manum et al., 2017; Raford, Chiaradia, & Gil, 2001). In another case, customized routing algorithm can be used along with Space Syntax on accessibility measures such as closeness centrality and betweenness centrality (Nourian, Van Der Hoeven, et al., 2015).

1.2. Motivation

It is clear that the built environment influences wayfinding strategy of pedestrians and cyclists, however there has been dividing views on how it influences their paths. Traditional transport planning and cyclist routing applications focused on shortest distance, slope, while some novel ones take into account the comfort level of the path or the amount of cycling infrastructure it provides (Hrncir et al., 2017). Another school in urban planning – the *Space Syntax* community highlighted the importance of cognitive wayfinding strategy: angular change, argued that it is the crucial element that explains the actual human wayfinding patterns (Shatu, Yigitcanlar, & Bunker, 2019), (Manum, Nordström, & Gil, 2018).

Despite the wide research on *Bikeability* with Space Syntax measures which are in turn based on street network analysis (SNA), the existing routing algorithm implemented with both physical and cognitive parameters are very limited. Even so, the available routing algorithm with Space Syntax measures are using outdating techniques: for example, axial mapping (Lee & Ryu, 2007), which is implemented mainly for pedestrians, does not take into account the importance of directionality in the algorithm (Nourian, Van Der Hoeven, et al., 2015) .

There exist difficulties in integrating street network physical variables with cognitive variables since the notion of graph theory is interpreted differently. In a geometrical street network, which is the traditional standard of transportation studies, street network is presented in a Junction-to-Junction graph where streets are links and junctions as nodes (Porta 2006). Whereas in Space Syntax which describes street network cognitively, the notion of navigation is on streets instead of junctions, using a Street-to-Street representation. The advantage of the cognitive spatial network representation is that it is the closer to the way people perceive their location in cities, also allowing modelling cognitive factors such as angular change easily (Raford, Chiaradia, & Gil, 2007).

The increasing availability of street network data had made the comparison of large scale city street layout possible (Boeing, 2019). The importance to study a diverse pattern of street network is also stated by Shatu *et al.*, who suggested American and Australian cities are mainly of a grid pattern, which could show less interesting and varied results (Shatu, Yigitcanlar, & Bunker, 2019). The study of street network was once deemed complex due to the large amount of data and lengthy data cleansing process (Boeing, 2016). Thanks to the emergence of reproducible tools to work with street network data,

it has been a lot easier extracting and comparing street network data of a large scale, as seen in recent urban studies with large sample sizes spanning across countries and continents (Abad & van der Meer, 2018; Boeing, 2018a). Apart from the benefits of reproducibility, the larger sample size avoids generalization and provides more robust interpretability of urban structures; The study of Boeing compared city orientation through street network and discovered polarising difference between European cities – which is barely a grid, a result of organic growth laid down way before urban planning existed; VS American cities which observed a grid structure, a result of modern large-scale master plans(Boeing, 2018b). Apart from visual classification, he developed a set of metrics for quantifying these differences of street networks such as connectivity, centrality, complexity etc., and suggested how these street patterns contribute to the movement of people.

1.3. Research Questions

Inspired by a new comprehensive geodesic method for active transport develop by Nourain *et al.* (Nourian, Rezvani, et al., 2015), the authors modelled street network in a dual directed representation which takes into account both physical impedance of length, slope and cognitive angular change in each street segment. This algorithm is embedded in a plugin developed on CAD Grasshopper environment, which could be hardly replicated and further integrated into available Urban Analytics libraries. This thesis aims at creating a human centric routing algorithm which models physical properties and cognitive parameters, with open source tools guiding by reproducibility approach, which could be applied to many cities. This brings about research questions as follows:

What are the major cyclist route choices both physically and cognitively?

How to model physical and cognitive cyclist route choices in routing algorithm?

How does the routing algorithm perform when applying on different cities with different spatial configuration?

The overall objectives are:

1. To identify relevant cyclist route choices through literature review,
2. To create a routing algorithm with graph theory which applies both physical and cognitive cyclist route choices,
3. To apply the routing algorithm on different European cities,
4. To compare the routes generated by routing algorithm with visual and statistical methods, and
5. To discuss if some city configuration favours or inhibits cyclist behaviour.

1.4. Section Summary

This thesis is organized in the following sequence:

Chapter 2 presents relevant literature related to routing algorithm and Space Syntax concept linked to wayfinding approach. It introduces the foundations of graph theory, Space Syntax, and describes its deeper connection to cyclist route choices and common parameters exist in routing algorithm.

Chapter 3 illustrates the methodology on creating a human centric routing algorithm through extending various Python libraries based on graph theory and Space Syntax, with full documentation on Jupyter Notebook.

Chapter 4 displays the results of the routing algorithm and evaluates by comparing bikeability metrics. It further illustrates the routes evaluation process by visual identification of spatial configuration and statistical approach, then further quantified SNA.

Chapter 6 discusses routes evaluation, the implications of spatial configuration on cyclist wayfinding and connects the findings to the bigger picture of future urban planning practices.

Chapter 7 summarises the work of the thesis and suggests the limitations and future possible work.

Chapter 2

Literature Review

The creation of a Routing Algorithm that models both human cognition and physical aspects, it is a multi-disciplinary approach that combines theories of Mathematics, Computation, and also aspects of Environmental Psychology – *Spatial Cognition* and urban design in terms of the way the build environment influences wayfinding behaviour. This section of literature review illustrates and connects the underlying concepts of these schools of disciplines, and helps frame this thesis into context.

Modelling a Human Centric Routing Algorithm, one needs to have an understanding of the underlying theory of Street Network Modelling, including Graph Theory and Street Network Representation, which is underlined in section 2.1. Section 2.2 focuses on the bigger picture of Wayfinding behaviour in respective to Spatial Cognition to brings out the importance of adding Space Syntax techniques – angular change into routing algorithm, and further review important cyclist route choices revealed by *Bikeability* research. Section 2.3 reviews existing literature on cyclist routing algorithm and their methodology. Lastly section 2.4 states the recent advancements of *Reproducibility* in urban analytics hence its importance in this thesis.

2.1. Concepts on Street Network Modelling

2.1.1. Graph Theory

The network approach has been widely used to model social, biological, and man-made systems (Porta, Crucitti, & Latora, 2006; Sergio Porta et al., 2006). In particular, urban studies use transportation networks to model the complex relationships exhibit in the city, such as traffic flows and urban growth patterns (Porta, Crucitti, & Latora, 2006). The study of networks is built upon the foundation of graph theory, a branch of mathematics. Below are introducing some basic concept of graph theory which are used throughout this thesis.

Graph, Nodes and Edges: Graph (G) is an abstract representation of a system consisting of elements and connections. Elements are called nodes and drawn as a point, while the connections between them represented by lines, are called edges. Nodes and Edges are the basic units which constructs a graph. Edges could be undirected or directed.

Undirected and Directed graph: In undirected graph, edges could be transverse in both directions, while in a directed graph, or digraph has directed edges. U$\rightarrow$ v represents the direction of edge, while u is the origin (from) node and v is the destination (to) node. Graphs can also have multiple edges between the same nodes. Such graphs are called multigraphs, or multidigraphs if they are directed.

Weighted graph: A weighted graph's edges is assigned with an attribute to quantify some value, such as importance or impedance between connected nodes. A common weight is distance, and a path could be routed through an order of directed sequence of edges that connects to an ordered sequence of nodes.

Street network: a street network could be categorized as a complex spatial network, which is a complex network which has neither a fully regular nor fully random configuration, with nodes and edges embedded in space.

2.1.2. Representation of Street Network

Street networks have been traditionally represented as a primal graph, since this node-to-node representation is the simplest way to capture distance, one of the most crucial geographic components. It was first introduced in the early sixties, and is still widely used in many transportation studies (Porta, Crucitti, & Latora, 2006). As long as places and junctions are points and relations are edges, distance can easily be associated with edges as a weight.

While in contrast, the dual graph inverts this representation, displaying city streets as nodes and intersections as edges. This method was introduced by a group urban designers and planners who studied Space Syntax, a method to model how humans interact with the built environment (Manum et al., 2017). Through representing intersections as edges, this Street-to-Street representation makes dual graph unique in a way that it stores relationships between two streets possible, such as angular change.

Figure 1 illustrates the process of deriving dual graph from a fictional street network. Dual graph stems from an axial map (figure 1b), where each straight space (line of sight) is represented by one single straight line, an axial line. A dual connectivity

graph is then derived, each axial line is turned into a node, while each pair of connected axial nodes are linked with an edge. As seen in Figure 1b&c, street centreline 1 is connected to street 2,3,4, as presented in Figure 1c, represented in a non-metric way. The dual connectivity graph uses nodes to represent an axial line that is regardless of its metric length, and the measurements of accessibility could be calculated on the basis of a non-geographic distance called step-distance, giving the potential to help forecast movement activity in the city.
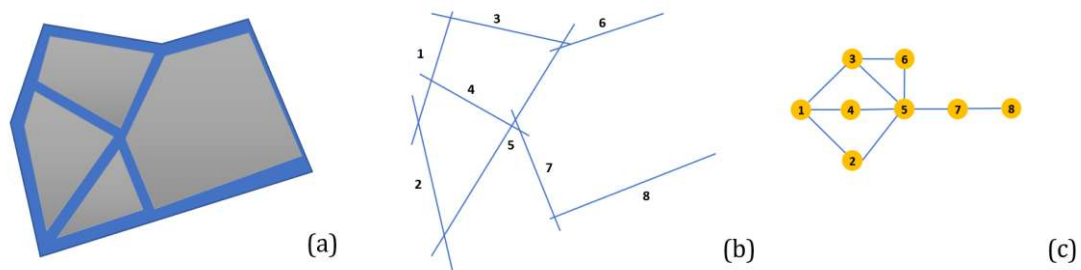
Figure 1: Derivation of Dual Graph representation in Axial Map Method: (a) Fictive street network, with grey as building blocks and blue as streets (b) Axial map representation (b) Dual connectivity map. An adaptation of street network presentation by Porta *et al.* (Porta, Crucitti, & Latora, 2006)

Dual connectivity graph brought about from Space Syntax Study is constructed with axial lines (Dalton 2001) however, there raised a new syntactic representation of street network which integrates both topological and geometric configurations of space – Segments map. This is particularly useful in cities with uniform structure, in particular American cities such as Broadway in Manhattan, which displays a grid like structure with very less disruption and smooth linear streets that cross regular streets diagonally (K. Al Sayed et al., 2018). Furthermore some criticized on the difficult integration of axial lines into GIS, that even there has been continuous effort to automate the axial lines generation process, there still requires manual interference to decide if certain feature is important in the map (Turner, 2007; Jiang, Claramunt, & Klarqvist, 2002).

Instead of a continuous straight axial line, segments map breaks each axial line down into its individual street segment. For example in edge 1 as displayed in Figure 1b, it is represented in a segments map in Figure 2a as 2 edges: (1,2), and edge 5 is split into 2 edges: (6,7) Segments have geometric properties marking the angular change between each pair of intersecting streets, which is a useful method to analyse angular depth that can find the least angular path through the network. Then through representing the centroid of streets into nodes and the connection as edge, a dual segments graph is formed, as seen in Figure 2b.
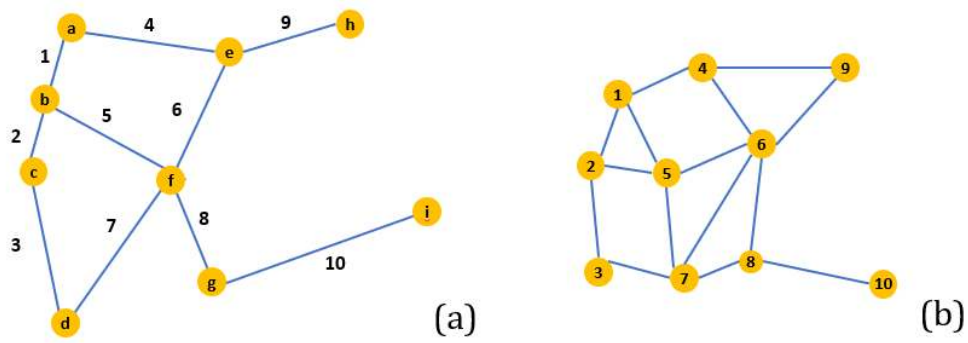
Figure 2: Derivation of Dual Graph representation through Segments Map Method: (a) Primal Segments Graph (b) Dual Segments Graph

In this study, both the primal segments graph (as primal graph) and dual segments graph are opted for the routing algorithm. Primal graph takes into account geographic elements such as distance and elevation, and the original representation of street dataset available; while dual graph allows to model angular change, which is crucial element to analyse human activity in building environment.

2.2. Cyclist Route Choices: through Spatial Cognition and Bikeability

The urban built environment to some extent can facilitate or limit one's wayfinding behaviour depending on the structure and characteristics of the physical element of the city. Lynch developed the idea of an *Imageable City* (Vaez, Burke, & Alizadeh, 2016). A strong imageable city is an environment that has an apparent clarity or *legibility*, which could facilitate human wayfinding due to its ease to be organized into a coherent pattern. Imageability is crucial for spatial cognition, since suggested by Montello, people acquire spatial knowledge from their environment and construct cognitive maps to aid their wayfinding task (Montello, 2010).

The cognitive behaviour of wayfinding by cyclist and pedestrians in unfamiliar environments are very similar, which is largely influenced by the spatial configuration of the network layout (Emo et al., 2012). People tend to choose well-connected paths and legible layouts which is easy to understand, in order to create a cognitive map which aids navigation. Spatially, one might say that an orthogonal grid with street segments of equal lengths to be an ideal urban configuration, since the line of sight is continuous and navigation space is constant. While an irregular grid has a lack of geometric order which blocks lines of sight and access, and therefore less intelligible (Hillier et al., 1993).

Space Syntax theory and methodology provides theory and quantitative tools to describe and measure spatial configuration of urban space. This method is used by urban planners to model how human interact with the built environment (Manum et al., 2017). There are numerous Space Syntax Measures - which is also called Street Network Analysis (SNA) (Depthmap, 2005) such as Integration, Connectivity, Angular Segment Analysis and Betweenness Centrality etc., in particular many of these measurements use angular shortest path as a major input to calculate human movement flows. Instead of topological shortest distance path, angular shortest path was found to be highly associated with wayfinding behaviour (Manum et al., 2017; Turner, 2009; Raford, Chiaradia, & Gil, 2007). This is related to how people perceive distance, Turner suggested that one requires higher cognitive load for memory when memorizing turns, therefore people are more likely to minimise cognitive distance as they walk through a foreign environment (Hillier & Iida, 2005).

Apart from a legible spatial configuration aids spatial cognition, a simpler route could also enhance cyclist wayfinding performance.

Finding routes that properly consider all the above criteria is not an easy task, therefore cyclists can turn to navigation aids for route suggestion. Unlike driving navigation aids,

there are a limited number of options for cyclists wayfinding. De Waard et al., (2017) explored the influence on spatial cognition by cyclist navigation aid, and suggested that the use of visual map to provide cyclist navigation support is useful to build spatial knowledge. Cyclist support with visual map based on spatial memory could lead to errors and require the highest spatial cognition ability. While turn-to-turn navigation cyclist support by smartphones is more mentally demanding comparing to drivers support, which could be similar to texting and reading while driving, leading to safety concerns. In the light of spatial cognition in building a cognitive map to aid cyclist navigation, the motivation of providing the simplest and easiest path as optimal is crucial for cyclist to acquire route and survey knowledge and therefore reduce error when performing navigation tasks.

While there is another school of transport modelling where studies try to understand wayfinding behaviour, in another words route choices models or bikeability. Most of these studies are carried out in search of local insights in cyclist volume and identify locations where operational improvements would benefit the greatest number of cyclists. Studies suggested that individual traces are difficult to predict subject to a wide range of variables (Raford, Chiaradia, & Gil, 2001), however it is not always random and there is an emerging order of factors which influence cyclists route choices. There has been researches on cyclist behaviour had introduced more influencing environmental factors on cyclist route choices, such as presence of slope, bike lanes, pleasantness, weather factors, cyclist safety and air pollution, etc (Law, Sakr, & Martinez, 2014) (Hrncir et al., 2014) (Hood, Sall, & Charlton, 2011). A study in San Fracisco California revealed that steep slopes, length and turns were disfavoured, and the presence of bike lanes are preferred (Hood, Sall, & Charlton, 2011). The significance of cycling infrastructure is also highlighted by a research in Copenhagen, where cyclists prefer to cycle on shorter distances and segregated bikeways (Skov-Petersen et al., 2018). Many cases the product in these studies is a map with bikeability index displaying the suitability of street network for cycling. These insights are useful input for urban mobility and routing computational studies in providing factors on how cyclist find their way.

2.3. Routing Algorithm

2.3.1. Current cyclist routing applications & their algorithms

In the current landscape of cyclist routing problem, a majority of publicly available and popular routing applications mainly incorporates physical factors. Google maps supports bicycle trip planning in some areas, it does not allow setting up any cycling preferences and mainly provide route parameters of distance time and elevation. Komoot, a specialized outdoor experience route planning tool incorporates urban biking emphasizes on the route type, surface and elevation, provides an interactive display for various parameters (Komoot, 2020). Hrncir *et al.* developed a Multi-criteria Bicycle Routing Algorithm which allows user defined choice preferences and incorporated comfort level through the effect of route surfaces and traffic level (Hrncir et al., 2014). However, these routing algorithms are created solely focusing on physical parameters, and as suggested by many cyclist route choice studies, they have not accounted for angular change as a crucial component in human wayfinding.
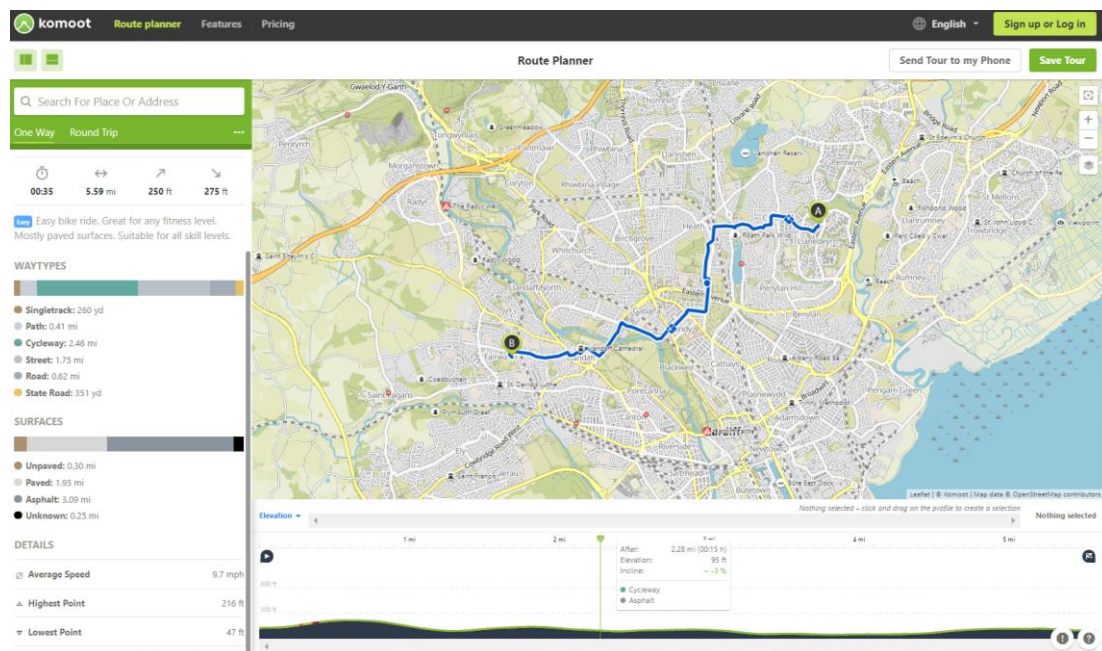
Figure 3: Web interface of route planner Komoot

The cognitive aspects involved in wayfinding through street networks can be modelled with Space Syntax methods, as mentioned in previous chapter, by means of dual graph representation. Due to the limited number of studies focusing only on cognitive cyclist routing algorithm, cognitive pedestrians routing algorithm are also reviewed. Lee & Ryu developed a shortest path algorithm incorporating cognitive element through Axial Map (Lee & Ryu, 2007). The algorithm incorporated mean depth of nodes in terms of visited turns, discovered that axial mapping cannot incorporate direction which could be not

suitable for vehicle routing. Duckhman highlighted the importance of having least number of turn as a parameter and created a simplest path routing algorithm for pedestrians which however, it does not take into account geographic distance and created routes that are 50% longer than the corresponding shortest path (Duckham & Kulik, 2003). In a study of cyclist behaviour in London , axial map and segments map are used to find the fastest cognitive route, and compared the computer routes with cyclist traces, the authors discovered that cyclists tend to follow routes with least angular change (Raford, Chiaradia, & Gil, 2007). In 2015 Nourain extended the study of Duckhman, and designed a novel comprehensive geodesic algorithm to find 'easiest path' for walking and cycling, i.e. a path that is short, flat and cognitively simple. The algorithm used a using a directed dual graph to take into account both physical impedance of length, slope, direction and angular change of each street segment (Nourian, Rezvani, et al., 2015).

Many of these approaches are mainly designed for pedestrians since it is relatively easier to model the street network as un-directed graph. This implies that the graph created could be traversed from u→v and vice versa. Although for cyclist there is also less limitation regarding direction, safety constitutes a crucial factor to take into account. Furthermore, in order to model the behaviour of slopes, direction is crucial. Therefore, one can argue that the existing studies are not reproducible and have to be readjusted to cater for cyclist needs.

2.3.2. How studies integrate weights

To turn route choice of different units (degree, number of bike path, length (m) and slope (%)) into meaningful weights, merely just adding up the numbers are not enough. There have been various methods to combine routing weights.

Impedance is used in many urban analytics studies as a measurement to combine parameters of different units. Impedance is a transport analysis term derived from physics, indicating the resistance to movement (Manum & Nordstrom, 2013).

In the multi criteria cyclist routing algorithm deployed in Prague by Hrncir *et al*., in order to capture the unique topology of the city, the algorithm allows users to choose the weights on travel time (s), comfort (coefficient) and flatness (coefficient) (Hrncir et al., 2014). These three criteria have their own units, and are not combined as a single weight, but the algorithm finds a route with edges that gives the lowest value in every criterion. Travel time is defined by two functions which returns a value in time (seconds). One is a

slowdown function, which returns the slowdown in seconds given by crossings, while change in elevation is defined by a speed acceleration which penalize uphill rides. The comfort criteria capture a preference towards comfortable roads with good quality surfaces and low traffic, derived from type of road and number of junctions, which returns a coefficient. The importance of elevation is modelled again as the last criteria by giving a coefficient on the flatness of the edge. One challenge reflected in this study is that to gather various criteria data from a single source in geographic format is difficult, furthermore features are stored separately in edge and nodes. For example to model comfort, OSM tags mapping is utilized for surface type which is stored in edges, and combine it with obstacles which are features that slow down cyclist, that are stored as nodes (Hrncir et al., 2017).

To model the easiest paths by Nourian *et al.*, the study combined physical and cognitive impedance and used a weighted sum model to model the total impedance of each edge (Nourian, Rezvani, et al., 2015). This method is used since it is simple and the only way that was found to combine angular change with other impedance.

2.4. Reproducibility of Urban Studies

Reproducibility is stressed as a fundamental principle in science by many GIScientists. Computers and computational analysis become an indispensable part of research, and they argued that the results and workflow should be reproduced, challenged and tested by other researchers (Nüst et al., 2018).

In many urban street network studies, they often adopt of industry specific platforms and software such as transportation modelling tools and proprietary software such as CAD and ArcGIS. While such tools can provide a graphical interface for experts from various backgrounds, yet a major limitation is the lack of consistent, open-source and easy-to-use research tools, making other researchers in replicating and further develop on the study a difficult task (Boeing 2015). For instance, street network dataset is a core component of many of these urban studies, however there is yet to be a standard workflow or tool that offers a 'consistent, scalable, configurable method' to collect street network data for anywhere in the world and assemble it into graph theoretic objects.

Nourian developed a 'easiest path algorithm' as a plugin tool in C# and VB.NET for Rhinoceros CAD software application (Nourian, Rezvani, et al., 2015). While Manum utilizes ArcGIS Network Analysis tool and SDNA+ for network creation and bicycle flow

estimation (Manum et al., 2019). Comparing to a script which could provide full documentation of the workflow a study, the above studies are often not open source and could not be easily replicated.

Given the limitation in this area of research, Boeing developed OSMnx a Python package for easy acquisition and analysis of street networks everywhere around the world. It allows automated downloading of urban data from OpenStreetMap (OSM), network simplification, convert into a multidigraph, perform route searches, visualization and saving them into interoperable formats (Boeing, 2017). The library utilizes NetworkX, another Python package for general network analysis. Figure 4 illustrates the ease to extract street network from anywhere in the world.
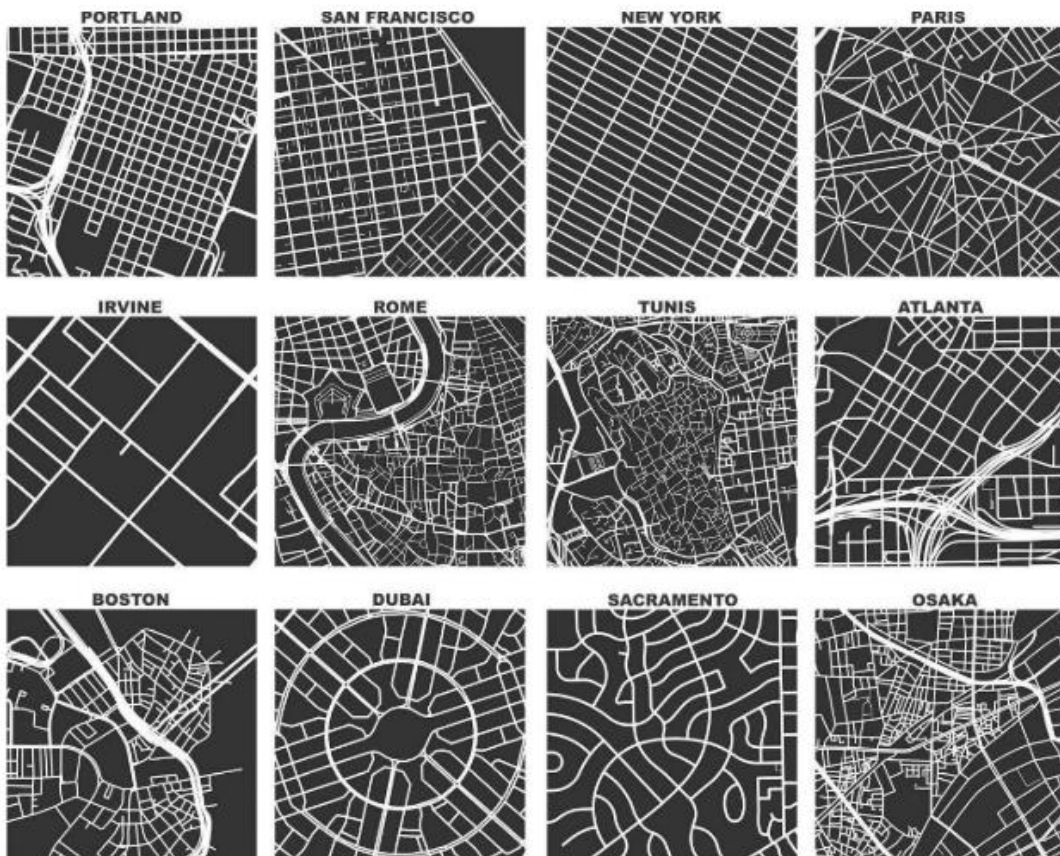
Figure 4: Excerpt of 1 square mile street network of world cities (Boeing 2017)

Chapter 3

Methodology

There are many routing algorithms available and developed in various platforms (see section 2.3.1). However, these studies are difficult to replicate at areas outside of the study area due to the wide range of data required and inconsistent data sources and street network formats. The aim of this thesis is to tap into the new source of geospatial data from OSM, which has considered as increasingly reliable due to its completeness and accuracy in European countries.

In addition, the complex architecture and proprietary software used in many urban analytics studies have slowly seen a shift in computational workflow, into an easier-to-use Python environment. The shift to an easier computational environment can also prompt more interest and usage from wide range of users and researchers. This thesis observed such a trend, integrate various available Python based libraries and created a workflow that could be easily replicated and extended, especially with the use of Jupyter Notebooks (Millman & Pérez, 2019).

The first two parts of the methodology provide a detailed description on the steps taken to create the human centric routing algorithm, through graph creation and modelling impedances. Next, based on research on the influence of the built environment on wayfinding, the routing results are generated and contrasted between two cities: Valencia and Cardiff. Lastly the generated routes are evaluated with statistics approach in relation to the quantitative results from the SNA.

3.1. Diagram & Workflow

The diagram in Figure 5 illustrates the stepwise methodology of the computational workflow. The workflow is separated into three parts: 1: Graph Creation, 2: Impedance Model which are based on Python, and Route Creation & Analysis on Python, ArcGIS Pro, R and Excel.
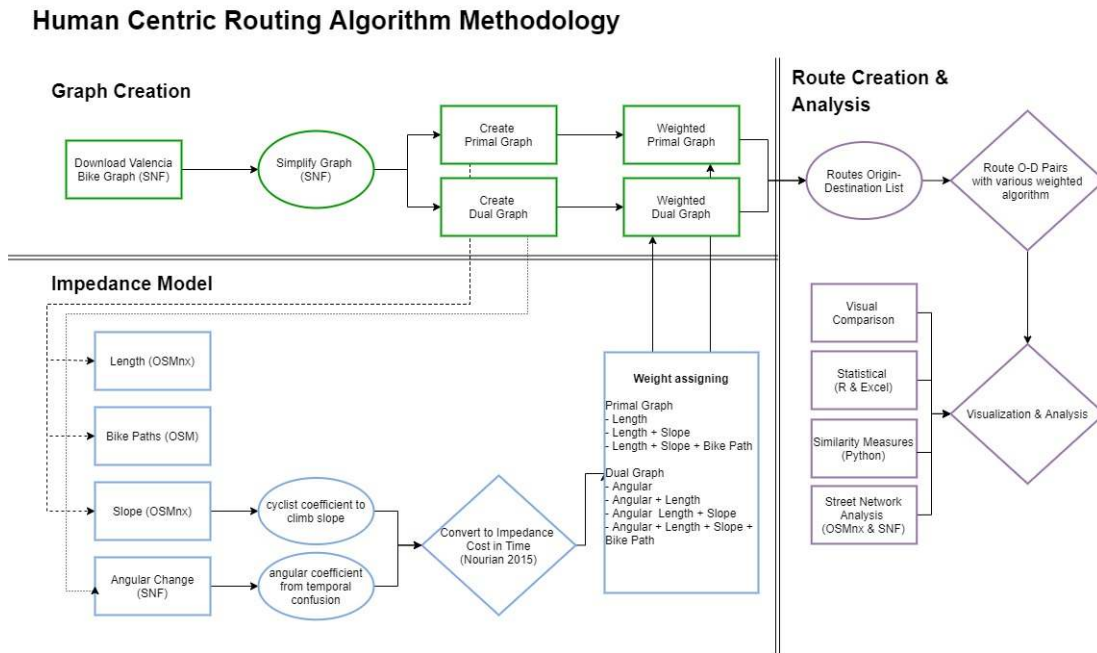
Figure 5: Methodology workflow diagram of human centric routing algorithm

Firstly, Graph creation is described at section 3.4, a street network is downloaded with OSMnx and resulted with a primal street network. Then at section 3.5 the Primal Graph is then further processed to add various impedances with data from the street network, such as presence of bike paths. The primal graph is converted into a dual graph with reference to Street Network Functions (SNF). Then various weights are calculated based on an impedance model and the two graphs are ready to route, as described at section 3.6.

Next in Route Creation and Analysis of sections 3.7 & 3.8, origins and destinations (OD) are picked, routes are created from respective graphs. Lastly the routes are visualized with matplot lib and ArcGIS Pro, data tables are created with geopandas and exported to excel as csv to create charts. For further interpretation of spatial configuration of the city, SNA is used also in Python.

3.2. Software & Platform

The computational workflow runs mainly in Python, integrating various libraries and recreating functions to create routing algorithm. The main part of analysis workflow such as similarity measures and SNF are in Python, while the comparison of parameters is with R.

Python, Jupyter Notebook, Anaconda

Python is a scripting language with simple and easy to learn syntax emphasising readability, making it attractive to beginners and professionals alike to write clear and logical code for small- and large-scale projects. The extensive modules and packages supported allows users to program in a modular style such that code could be reused across a variety of projects; in order words, code developed in this language is highly scalable and reproducible (Python Software Foundation).

To program with Python, one requires a computational environment. For this thesis, the Jupyter Notebook environment was chosen due to its interactivity and its ability to display stepwise workflows and easy-to-readiness. Jupyter Notebook is an open-source web application which allows programmers to edit, display, run and visualize code in each cell, add text and comments, making code prototyping and sharing very easy (Seltzer, 2017). Python version 3.7 is used with the following packages.

The Python Libraries used in this thesis is explained below.

Street Network Functions

SNF is the underlying code of the human centric routing algorithm. This Python library was developed by Gabriele Filomena for a study "Computational approach to *The Image of City*" using street network to extract cognitive map with network analysis measures (Filomena, Verstegen, & Manley, 2019). It utilised packages such as OSMnx and GeoPandas, which integrated the ability to model street networks as graph objects that preserves relationship between networks, and the flexibility of Pandas dataframe. One of the most valuable functions borrowed this thesis is the creation of dual graph and angular measurements. Other functions such as street network downloading, simplification and primal graph creation were also employed in this thesis.

OSMnx

OSMnx is a Python package for working with OSM street network data, from downloading, graph creation, network simplification, SNA and visualization. OSMnx can download OSM street network data and construct it into NetworkX graphs. This package made it possible to apply the algorithm in any city around the world since it utilizes OSM data as a central repository of street network data, and quickly construct it into a graph – which could have been inconsistent and difficult in the past for researchers.

NetworkX

NetworkX is a free and open-source Python Package which is the core of OSMnx, supports graph-theoretic network analysis, in particular keeping track of connections between networks (Hagberg, Swart, & Schult, 2008). Apart from graph creation, it is also the library that provide a series of routing algorithm to compute paths with weights in a directed graph.

Pandas & GeoPandas

Pandas is a powerful Python library for data analysis, while GeoPandas is a Python module which is built on top of Pandas extending its ability to work on spatial data. It stores data in DataFrame (df) or GeoDataFrame (gdf), a table like object which is flexible to select and work with large amount data (Tenkanen, 2017).

Similarity Measures

Frechet distance is used to support the visual similarity of routes, by providing a minimum distance to connect two generated routes. The Github library similarity measures is used for the algorithm (Jekel et al., 2019).

Routing Functions

Routing Functions (rf) are created to compile code from various libraries as a result of this thesis. Functions include graph download, routes generation, visualization and analysis.

R GGally

GGally, a package built upon GGPlot that combines various plots into matrix for correlation (Schloerke et al., 2017).

3.3. Case study area

This thesis aims to create a human centric routing algorithm based on reproducibility standards, therefore by applying on different cities can test the usability of the algorithm and also compare its performance base on different spatial configuration and street network properties. Two European cities of similar size are chosen as the case study area: Valencia in Spain and Cardiff in Wales, UK.

With over 700,000 inhabitants, Valencia is one of the major cities of Spain with a size of 150 km^2 where active transport is widely support. More than 50% of interior commuting is made by walking and cycling (Valencia, 2017). In particular cycling takes up 5% of total daily commuting means, had seen a 20% increment in 3 years ((Valencia, 2013)p16) In Valencia's sustainable Mobility Development Plan, it shows the transparency and open attitude of the city towards data and smart mobility, therefore with its database and the city size, it is a very suitable city as a case study area.

Cardiff is the capital of Wales, also its largest city of 140 km^2 is home of 400,000 inhabitants. Due to its ongoing government initiative in supporting cycling, 6% of the daily commuting is made with cycling, which is the highest in Wales (Welsh Government, 2019; Cardiff Council & Freshfield Foundation, 2017).

The two European cities have quite opposite spatial configuration. Valencia built around the historic centre outside the ring road regulated on a grid pattern by Francisco Mora. The grid pattern developed by Francisco Mora an architect in the 18th century is named the Ensanche Plan, the layout was an orthogonal grid within a grid, marking an urban unit of houses bordered by perpendicular streets (Torreño Calatayud, 2005). While Cardiff exhibits a distinctive pattern, described as a fan-like or similar to a 'hand and fingers' layout. The city has a relatively flat bay area at the centre, with development extending outwards towards the hills, some argues that its physical geography poses challenges for future growth (Neil Harris, 2018).

3.4. Graph Creation

The aim of this thesis is to create a routing algorithm which considers both physical aspect of streets (distance and slope), bike path and angular change. To define the graphs required in a deeper level, a primal directed graph and a dual directed graph are needed to generate the most optimal routes.

The reason of requiring both primal and dual graphs are illustrated in section 2.1.2: primal graph representation is required to faithfully retain all geographic, spatial metric information essential to urban form of street networks. On the other hand, a dual graph representation can be deployed to represent angular relationships between street segments, and it allows to compute further topological measures. Both graphs are required since the dual graph is derived from the primal graph, and when the routes are created across the dual graph, the primal graph is employed to map the routes back from a dual representation to a primal network.

The creation of primal graph uses OSMnx to convert gdfs to graph. A directed graph is created which preserves directionality, that is crucial in the next step when calculating the slope of the streets, and also to prevent routing in the other direction in a one-way street.

Creation of dual graph take reference of SNF and NetworkX. SNF provides the possibility to create a dual graph, however, it was originally created for pedestrian SNA, requirements are simpler since pedestrian has no restrictions and ignores one-way directionality, and connect adjacent nodes with reciprocal directed edges. Therefore, the code was modified to only create links between edge of the same direction, calculate angular change between two streets, and create graph.

3.4.1. Street Network data download

From the SNF module, there are a few methods to download a street network from OSMnx and save them as gdfs. The street networks are primal with street name, type and preserve directionality. Street networks could be downloaded through a shapefile, directly from an OSM Polygon, or on the basis of distance from a given address. The latter approach is used since it gives a uniform area from a bounding box which could be easily visualized. There are various types of networks to be downloaded, to name a few:

drive: get drivable public streets (but not service roads)
walk: get all streets and paths that pedestrians can use (this network type ignores one-way directionality by always connecting adjacent nodes with reciprocal directed edges)
bike: get all streets and paths that cyclists can use
all: download all (non-private) OpenStreetMap streets and paths

Then the graph is given a projection system in EPSG code, in this case we are using WGS 84 which is a standard world coordinate system. Since graph object is difficult to access and manipulate in Python street network graphs are converted into gdfs. Then the network is simplified and cleaned. Below is the edges of the two cities, Valencia and Cardiff.

Figure 6: Primal edge of two cities. Left: 4km graph of Valencia, Right: 5km graph of Cardiff

Here is a header of Valencia edges. It presents streetID, the length, oneway, type of street, origin (u) and destination (v). The column 'key' is also added since this column is necessary to run OSMnx functions.

Figure 7: Gdf header from Jupyter Notebook, displaying the primal edges of Valencia

3.4.2. Create Primal Graph

When the graph is downloaded, it is composed of two gdfs: nodes (street junctions) and edges (street segments). This makes modifying parameters of the graph much easier. The graph is then simplified to ensure nodes only exist when intersections between different street segment exist; this is crucial when transforming primal graph into a dual graph.

Next, to ensure the graph preserves directionality, edges that can be routed both ways are copied, and the UVs are flipped by using the function rf.copy_DiEdges.

This ensures that when such edges are used to calculate slope in the next section, slopes from u→v and v→u can be assigned to the respective edges. Originally before such a function was created, when slope is calculated for edges that could be routed both ways, since there is only one edge present, only one direction of slope is calculated. However, in reality the slope is different while going upwards and downwards at the same edge.

3.4.3. Create Dual Graph

Dual Graph is derived from Primal Graph based on its parameters and spatial features. It involves two steps – 1: creating dual edges gdf from primal edges gdf, and then combining it into a dual graph, and 2: mapping the weights back to a dual graph.

As mentioned, the SNF library was created for pedestrians, which could be routed in both directions. Therefore, when creating dual edges, the original function disregarded directions and created dual connection edges for all adjacent edges. However, in the case of routing algorithm, directions has to be respected, therefore changes were made to the function.

First, centroids are created for each edge segment. Then instead of mapping all possible interactions with a 'OR' clause, possible interactions are found ONLY if the 'to' street's origin node 'u' is the same with the destination node 'v' of the 'from' street.

Table 1: Modified Code snippet for creating dual graph

```
ORIGINAL SNF
possible_intersections = centroids_gdf.loc[(centroids_gdf['u'] ==
from_node) | (centroids_gdf['u'] == to_node) | (centroids_gdf['v']
 == to_node) | (centroids_gdf['v'] == from_node)]

MODIFIED RF
possible_intersections = centroids_gdf.loc[(centroids_gdf['u'] ==
to_node) & (centroids_gdf['v'] != from_node)]
```

Then the weights computed for each street are added to the centroids (i.e. original edges) based on the matching edgeID. Afterwards connecting edges (i.e. nodes, or intersections) are created between two centroids.

3.4.4. Graph Statistics & Visualization

Below is a diagram of some basic statistics of the primal and the dual graph of Valencia and Cardiff respectively. Note that despite the city area is similar, the graph taken for Valencia is from a 4000km buffer, while from Cardiff is a 5000km buffer, yet the size of the cycling Graph in Cardiff is smaller than that of Valencia by almost a half.

Primal Graph   Dual Graph
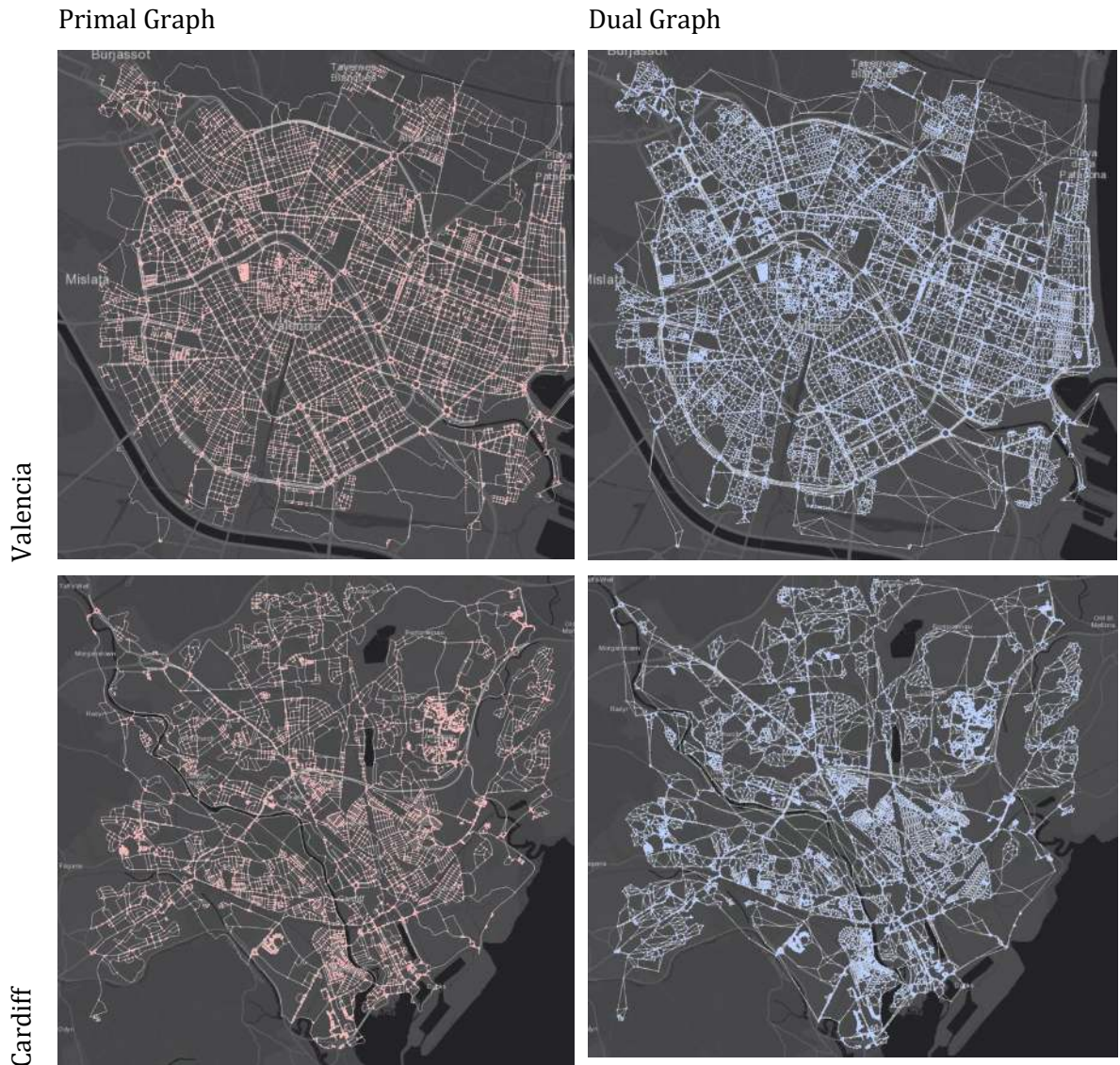
	Nodes	Edges
Valencia primal graph	11,349	26,061
Valencia dual graph	26,061	50,721
Cardiff primal graph	6,509	18,605
Cardiff dual graph	18,605	38,641

Figure 8: Graphs and statistics of Valencia and Cardiff

3.4.5. Mapping Weights

One might ask how to map the weights on a primal graph onto a dual graph, since the notion of edges on a primal graph is the same with real life which edges are streets and the physical properties are stored on the same edge. While on a dual graph the edges indicates the connection between two streets or segments. An important method to note is that in a dual graph, value of the to-primal-street (v) is mapped on the connected edge. An example could be seen in the below figure. The dual edge(1,4) takes the value of edge 4. A function created to automate this process is rf.mapCol_dual.
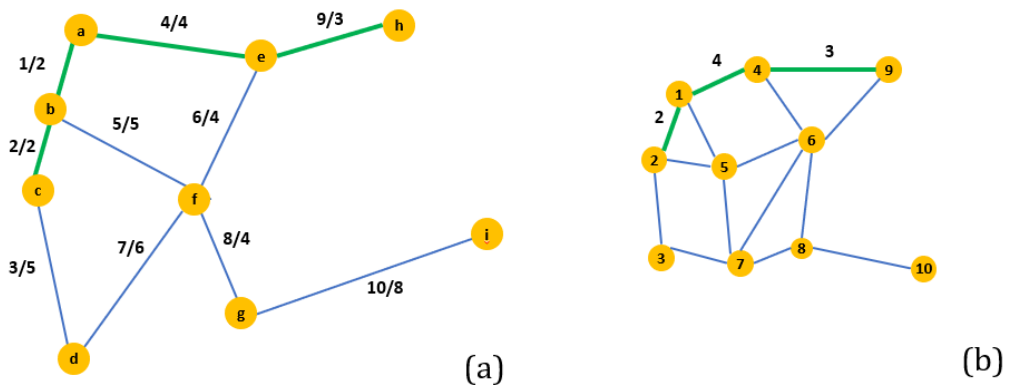
Figure 9: Illustrates how weights are being mapped from a primal graph to a dual graph. (a) is a directed primal graph with a route going from node c to h in one direction. For instance the label '1/2': the number in the front indicates the edgeID, while the number at the back indicates the weight on the edge. E.g. edgeID 1 has a weight of 2, while edgeID 9 has a weight of 3. (b)On a dual graph the directed connection between edge1&4 gets the weight of edge4 instead of edge1, since it marks the decision point of going towards the next edge.

3.5. Impedance Modelling

This part entails the modelling of impedance that is extracting the parameters from OSM and calculating impedance in the light of Nourian's research (Nourian, Rezvani, et al., 2015).

3.5.1. Parameters Calculation

From the literature review of cyclist route choices at section 2.2, distance, slope, angular change and bike path are considered in this thesis as an parameters for the routing algorithm. For distance and slope, primal graph is employed, whereas angular change is calculated with dual graph.

Distance

Edge length is calculated with osmnx.add_edge_lengths to add length between nodes u and v in meters.

Slope (from Elevation)

Next to find the slope for each edge, functions from OSMnx are used.

Firstly, a primal graph is passed to osmnx.add_node_elevations, to find the elevation on each node and added it to the node as an attribute. It takes a google maps elevation API, and therefore an API key is created for this function.

Next, osmnx.add_edge_grades is used to add the grade of each edge. It calculates the difference in elevation from origin(u) to destination(v), then divides by the edge length. This function creates two attributes, grade and grade_abs, where grade contains negative values (as in going downhill) and positive (uphill), while grade_abs contains the absolute value of grade.

As a part of the exploratory results, the average and median street grade is as follows. Average street grade in Valencia is 1.2%, Median street grade in Valencia is 0.8%. While That of Cardiff is 2.1% and 1.2% respectively.
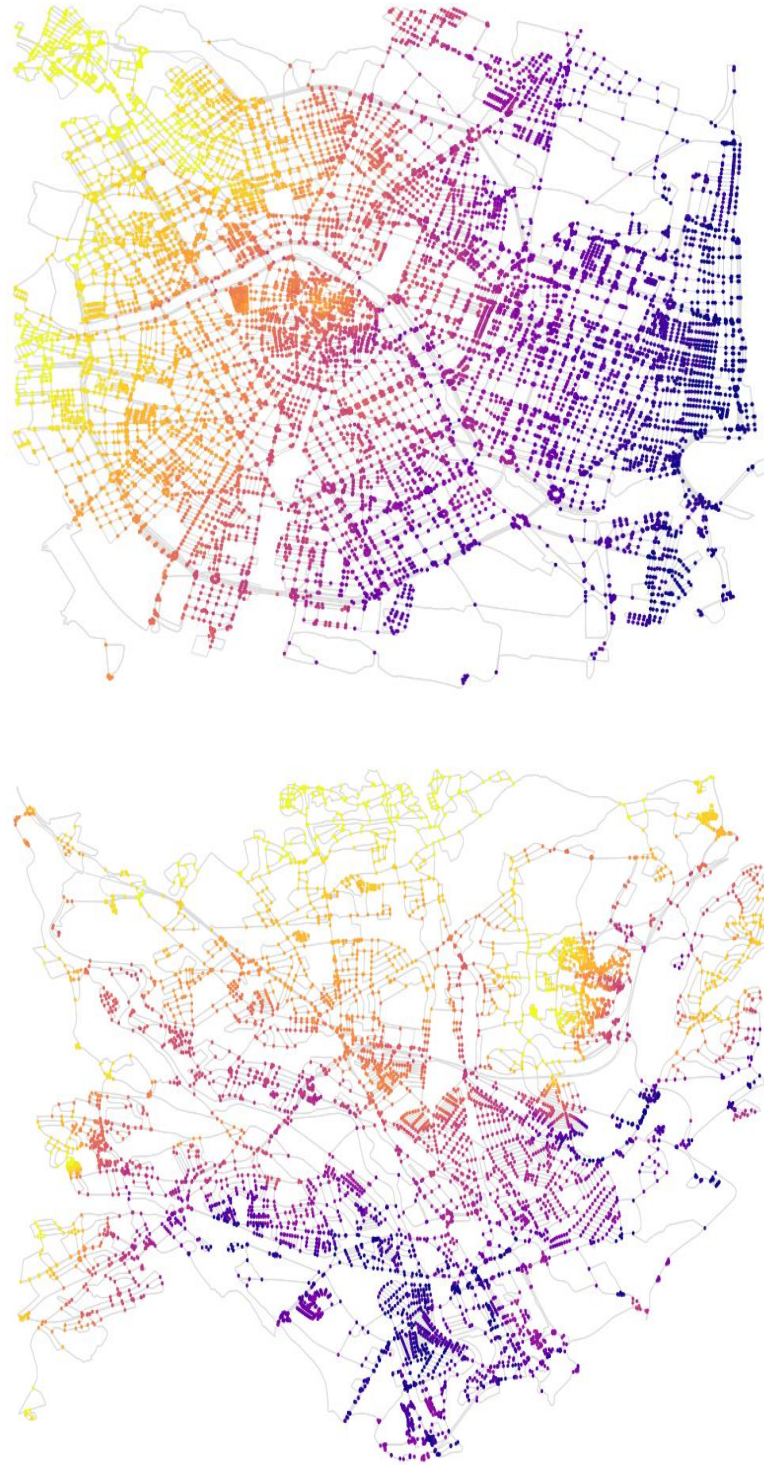
Figure 10. Maps of nodes with elevation. Top: Valencia, bottom: Cardiff. Gradual increment of elevation from blue to red to yellow

Bike path

Street classification tags such as primary, secondary, pedestrian and bike path etc., is provided in the OSMnx dataset, therefore there was not a need for extra data merging. A column 'hasBikeP' is added to define if the edge allows the passage of cyclists.

Below shows a map of paths that are identified as bike path. Bike paths from Valencia are compared with GIS data from Valencia Open Data Portal (Valencia's Transparency and Open Data Portal, 2020), which displays a high accuracy of data. Whereas the only data source of bike path in Cardiff is in pdf format (Cardiff Council, 2018), despite it displayed a slightly more connected bike path map, it remains fairly scarce as shown at Figure 11.

Figure 11. Maps of bike paths in OSM data. Left: Valencia, right: Cardiff

Angular Change

In order to calculate the angular change of a route, a dual graph is required. (see section 3.4.3). The angle between two streets are calculated and stored at the connected edge of dual graph with a modified formula taken from SNF. The deflection angle is a positive degree from 0 to 180. It is also converted to radians for further processing.

The parameters are added to the graph, and weights are assigned through a uniform unit of time.

	u	v	geometry	deg	rad	key	slopeCost	hasBikeP	length
0	26061	11705	LINESTRING (-0.34306 39.48010, -0.34352 39.48023)	0.003	0.000	0	14.777	0.000	41.446
1	26061	11704	LINESTRING (-0.34306 39.48010, -0.34320 39.48035)	98.637	1.722	0	13.265	0.000	44.510
2	26060	11702	LINESTRING (-0.34283 39.48006, -0.34274 39.48024)	0.026	0.000	0	8.803	0.000	39.436
3	26060	11701	LINESTRING (-0.34283 39.48006, -0.34236 39.47994)	80.362	1.403	0	18.941	0.000	84.854
4	26059	2660	LINESTRING (-0.34300 39.47975, -0.34264 39.47933)	100.085	1.747	0	22.510	1.000	100.845

Figure 12: Weighted gdf from Jupyter Notebook

3.6. Impedance Calculation

To turn these parameters of different units (degree, number of bike path, length (m) and slope (%)) into meaningful weights, merely just adding up the numbers is not enough. There has been various methods to combine routing weights.

Impedance is used in many urban analytics studies as a measurement to combine parameters of different units. Impedance is a transport analysis term derieved from physics, indicating the resistance to movement (Manum & Nordstrom, 2013).

In this thesis, the method of a weighted sum model proposed by Nourain is taken as a reference to model both physical slope impedance and cognitive angular confusion (Nourian, Van Der Hoeven, et al., 2015). The weighted sum model takes all impedances: length, slope, bike path and angular confusion, and model them in terms of time (seconds) – which is a commensurate unit, and therefore is possible to model the total impedance of various weight combination.

3.6.1. Physical Difficultly: Slope and Length Impedance

Physical strength is required heavily when a person is cycling. Depending on the steepness and the length of a street this effects the speed of cyclying, and becomes a ccontributing factor on the willingness of whether or not to take certain routes. The speed could be calculated by taking into account the effect of slope per each road segment, and the physical power a person could sustain. In a case where 2 edges have the same distance, the algorithm penalizes higher slope angle and favours the edge with a smaller slope, which in turns requires less time to be traversed.
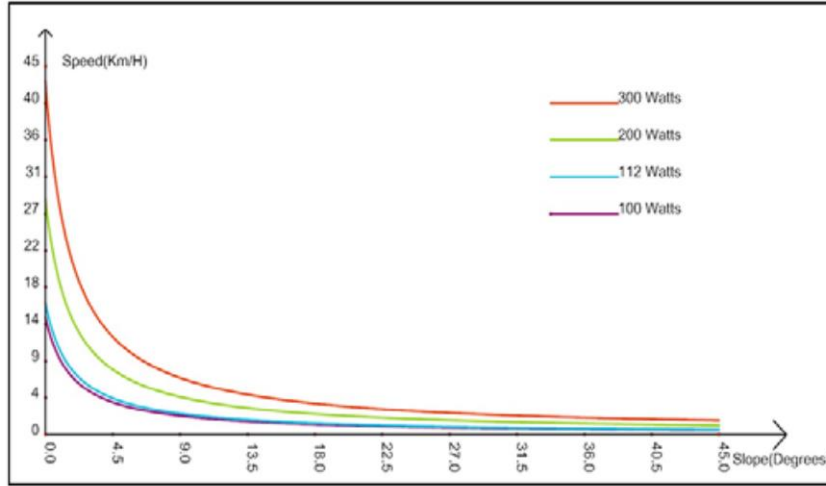
Figure 13: A plot of the model of cycling speed from Nourian (Nourian, Van Der Hoeven, et al., 2015), a function of slope at the constant power of 112 Watts. Note that the slope is display as degrees, where in our original data slope is in %.

The aim is to obtain a model of temporal cost of traversing an edge in terms of its slope angle. The temporal cost is considered as cycling impedance and is denoted as SI_k, of the kth edge, which is illustrated in equation 1. Since time equals to distance divided by speed, therefore d_k is the distance of edge k, while s is the speed. While speed could be further break down as power P divided by m mass of an average person assumed to be $85kg$ and g for gravitational acceleration equals to $9.81 m/s^2$, a_k as in the slope angle of the kth edge, and F_f denoting a nominal force of friction that is to be counteracted by the bicyclist which is 25.

$$SI_k = \frac{d_k}{s} = \frac{d_k(mg \times a_k + F_f)}{P} = \frac{d_k(85 \times 9.81 \times a_k + 25)}{112} \qquad \text{- Equation 1}$$

$$a_k = grade \times 100 \times 0.57 \times rad = grade \times 100 \times 0.57 \times \frac{\pi}{180°} \qquad \text{- Equation 2}$$

The slope angle of the kth edge a_k is caculated from grade, illustrated in equation 2. The grade calculated from OSMnx is in %, it is then converted into a decimal angle, where each grade is equals to 0.57° (Engineering ToolBox, 2009). Then the angle is converted into radians by multiplying it to $\frac{\pi}{180°}$.

The cost SI_k is computed in terms of seconds it takes to traverse an edge. This algorithm calculates the temporal cost to traverse a uphill slope, which is defined as grade > 0. However in case of a downhill slope where the grade < 0, this algorithm does not take into account the higher speed of cyclist, and assumes the speed is the same as cyclist cycling on a flat street where grade equals to 0.

3.6.2. Cognitive Difficulty: Angular Impedance

Based on the underlying theory of wayfinding, a route which has the least angular change is easier to remember and to traverse without falling into errors. Moreover people tend to remember straighter paths since they form the main roads in a cognitive map (Shatu, Yigitcanlar, & Bunker, 2019).

This equation disregarded the original part applied by Nourian (Nourian, Van Der Hoeven, et al., 2015), that the angular confusion is calculated only if the streets of degree is and larger than 2, which is not the angular degree but the number of neighbouring streets the edge leads to. Street degree is valid in the original equation since it splits a street centerline into equal segments. However in the case of this thesis, such segments is already simplified in eliminated, therefore edges are only segmented when there are junctions in real situation, meaning that all the decision points (nodes) are real life decision junctions.

The calculation of Angular impedance could be referred to equation 3. Angular impedance is denoted as AI_k, which is composed of the angular change to traverse from one edge to another, multiply by τ, an arbitary 'angular confusion' coefficient of time. Angular confusion is introduced in Nourian (2015), which indicates the time in seconds a person and in this case cyclist would take to decide which is the next street to take. The maxmium τ, time taken to decide the next link is 10 seconds in the case of maximum change of direction. While square sine of theta $sin^2 \frac{\theta_k}{2}$ is a sigmoid function that could accept arguments in radians and can work consistently as a relative impedence function. The angle is converted from degree to radians as a dimensionless number, since as seen in Figure 14, the changing direction in negative or positive degree does not make any difference in angular confusion in seconds.

$$AI_k = \tau \, sin^2 \frac{\theta_k}{2} \qquad \text{- Equation 3}$$
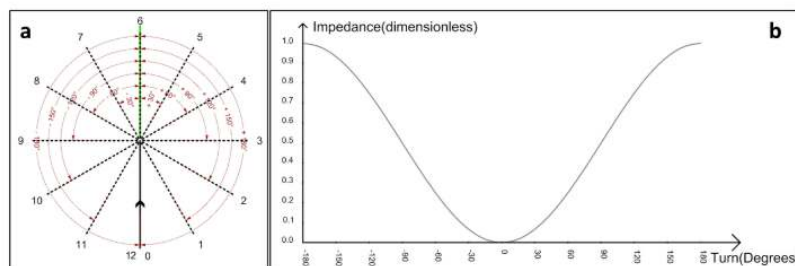
Figure 14: Adapted from Nourian (Nourian, Van Der Hoeven, et al., 2015), (a) shows the angles computed based on the incoming direction of the cyclist. (b) shows a plot of the cognitive impedance as a dimensionless number despite the positive or negative angle

3.6.3. Comfort: Bike Path

The prescence of cyclist infracstructure can enhance the performance of a cyclist, and hence sustain a higher speed. By comparing two paths of the same distance, cyclist could sustain a higher speed at a bike path than on an average street either pedestrian or car roads. There are many benefits to choose bike paths than a sidewalk or main road. First, it could be paved with a surface that is well maintained, and it avoids separates cyclist and traffic which induce safeness (Manum et al., 2017).

This criteria is an addition to Nourian's routing algorithm. The prescence of bike path is added as an impedance to reduce time required to traverse the edge.

$$BI_k = d_k \beta = \frac{d_k}{100} \times 4 \qquad \text{- Equation 4}$$

In equation 4, BI_k is the comfort impedance as a temporal cost in seconds. It is hypothesized that on an edge without bike path, the time will increase by 4 seconds every 100m. The distance of the edge k is d_k. The coeficient of slowing down due to the absecen of bike path is β, which could be defined as 0.04.

3.6.4. Weighted sum model

At this stage all individual weights are calculated with a commensurate unit of time, they are inputed into a weighted sum model to model the total impedance of each edge. Equation 5 shows the calculation of weightA4, which is hypothesized to give the most optimal route.

$$weightA4_k = SI_k + AI_k + BI_k \qquad \text{- Equation 5}$$

Table 2 summarises the weights indicating the combination of impedance for each weight. The weights for distance, slope and bike path are calculated originally on a primal graph, giving weightP1 to P4. Then the weights are mapped onto a dual graph (illustrated in section 3.4.5). While the weights are summed with the impedance of angular change, giving weightsA1 to A4, with weightA4 according to our hypothesis as the weight which may give the most optimal route, namely the flatest, easiest and the most comfortable path.

Table 2: Naming of routes generated based on different weights and the graph routed

Primal Graph	Impedence	Dual Graph	Impedence
WeightP1	Distance	*WeightA1*	Angular Change
WeightP2	Distance Slope	*WeightA2*	Angular Change , Distance
WeightP3	Distance, Slope, Bike Path	*WeightA3*	Angular Change, Distance & Slope
WeightP4	Bike Path	*WeightA4*	Angular Change, Distance, Slope, Bike Path

3.7. Routes Creation & Visualization

This section entails the methodology on picking origins and destinations to be imported into the routing algorithm, routes generation and visualization of the data.

3.7.1. Origin Destination List

In order to have comparable results between the two cities and analyse the performance within the city, 3 origin and destination (OD) pairs are picked around the major districts or landmarks in the city. ODs separated by an average of 5000m (Euclidean distance) are chosen for consistency in distance.

The coordinates of the origin-destination pairs are taken from OSM and stored as points which will be used directly in the routing algorithm.
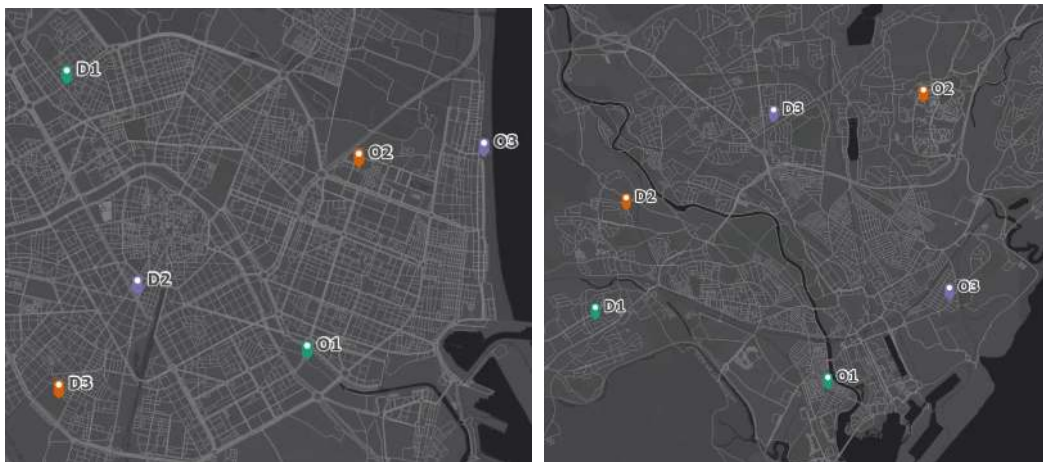
Figure 15: Locations of the three pairs of origin and destinations in Valencia (left) and Cardiff (right)

3.7.2. Routing Algorithm

To find the most optimal path in mathematical terms, one could use Graph Theory. Path finding could also be referred to routing problem, and the most common and traditional is the shortest path problem.

Dijkstra Algorithm is a widely used method to find the shortest path in a network (Dijkstra, 1959). It considers a certain cost (e.g. distance) and iterates through the whole network to find the single path with the lowest cost. There are major rules to the Dijkstra algorithm: cannot revisit nodes, only consider positive weights and search adjacent nodes with the lowest cost.

Figure 16 helps to illustrate the path finding problem. Each node N in the graph is associated with a temporary label, for example nodes c and h (yellow nodes). We need to find the shortest path between nodes c and h. Started with node c, the algorithm can choose to go to b or d. The value of edge to node b is smaller (2), and is picked, and so on until the path reaches node h. So the path can be formed with the nodes {c,b,a,e,h}, and edges {(cb), (ba), (ae), (eh)}, with the shortest distance 11(2+2+4+3). The path finding algorithm from NetworkX is utilized, and gives a string of nodes which denotes the routed path.
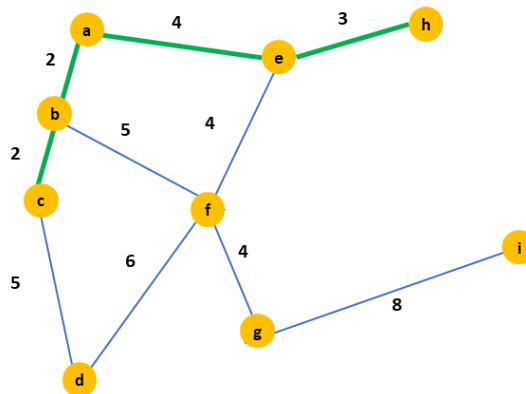
Figure 16: Path routed with Dijkstra Algorithm, greenline indicates the routed path

There are many efficient routing algorithms to solve this problem such as Dijkstra, Bellman-Ford, A*, Genetic, etc., in this study Dijkstra Algorithm will be used since it is the default routing method of the graph theory library NetworkX.

The methodology of routing on both primal graph and dual graph is similar. However, for routing on a dual graph, the nearest node in the dual graph is different from the nearest node in a primal graph, therefore the first edge of the primal route is used to as the origin node, and last edge will be used as the destination node of a dual graph.

3.7.3. Mapping routes

Routes are generated with Dijkstra Algorithm with different weights, and mapped accordingly to their original representations. As seen at Figure 17, if primal and dual routes are directly compared, the dual routes will be different from the normal street network since they are based on a virtual graph. Furthermore, the dual representation is different from how people conceptualise street networks and it may therefore be difficult to comprehend. Therefore, the dual routes are mapped on a primal graph, the red line is the same route on a primal graph which follows all the detailed bends of a normal path.
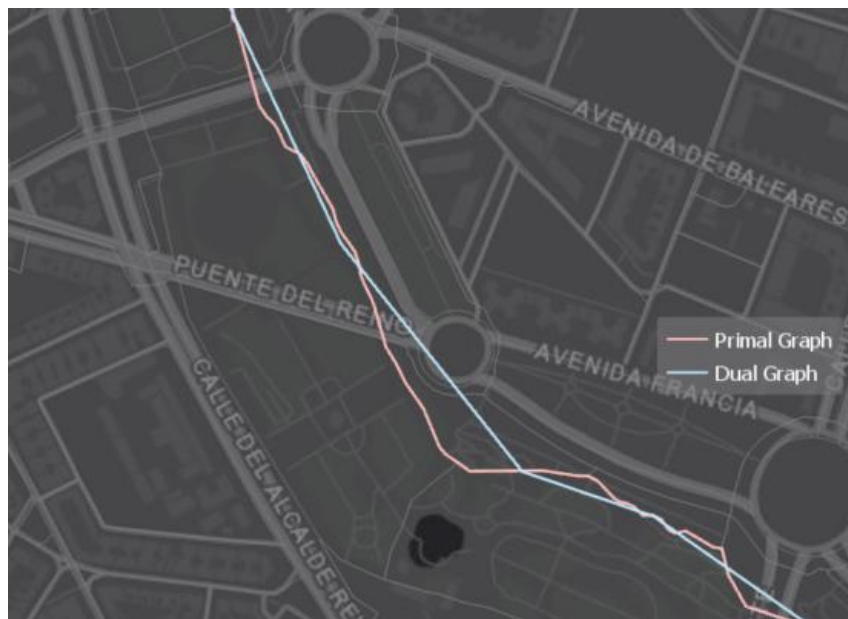
Figure 17: Map of Valencia OD 3, optimal route. Blue is the dual route, while red is the dual route mapped on a primal graph

Table 3 shows the methods and function created to map various routes. The reason behind mapping primal routes on dual edges is to find the angular confusion of the road, which could be an important parameter when evaluating the performance of algorithm.

Table 3: Function employed to map routes for various parameters

P Node string →P node pair → = P edge (rf.map_Rto_primalE)
D Node string → = P edge
P Node string → P node pair → = P edge → edgeID = D node → D node pair → = D edge (rf.map_PRto_dualE)
D Node string → D node pair → = D edge (rf.map_Rto_dualE)

3.7.4. Visualization

There are two ways of visualization: first is to visualize routes on Jupyter Notebook with matplotlib for exploratory analysis. Second way is to use ArcGIS Pro to create nice graphics for presentation uses.

3.8. Routing Algorithm Analysis

This part of the thesis aims to address the last research question: How does the routing algorithm performs on an individual level and based on the influence of the spatial configuration of two cities.

A number of exploratory comparison analysis are adopted for evaluation. Routes are compared visually, and examined statistically through parameters correlation and similarity measures. To quantify the street network configuration of cities, SNA is adopted.

Through these comparison analyses, it is aimed to answer the following hypothesis:

1. Shortest distance path will have a higher angular change
2. How does the presence of bike path influence other parameters
3. Which route is the optimal path most similar to
4. Valencia with a concentric gridded pattern will favour cyclist wayfinding than Cardiff with a complex street configuration

3.8.1. Visual Comparison

The routes generated based on the influence of various weights are compared to find similarities in pattern. They are further compared in a bigger picture to find if the spatial configuration of the city influences the generated route patterns. This process is conducted in ArcGIS Pro, and maps are created.

3.8.2. Quantitative Comparison

Parameters Statistics

The aim of calculating parameter statistics of routes would be useful in identifying route characteristics. Functions are created to automate the process in Python. The rf.stats_toTable is created with different calculations.

Parameters such as length, uphill, downhill and percentage of bike path for the route are calculated by summing up the individual weights of a route. Yet for angular change, it has to query the dual edges of the route in order to find the seconds in angular confusion. While for cycling time, it is the sum of the routed weight, however in cases of bike path and angular change, since they are not routed based on distance, the weight of the original weight of distance is used to find the time.

Parameters Correlation

Through correlation of parameters one could identify if some parameters could influence other parameters. There are a few hypotheses that correlation could answer.

One of the underlying theories fuelling this thesis is that the shortest path usually has a high angular change, therefore there is a need to minimize angular change while predicting human movement in built environment (Shatu, Yigitcanlar, & Bunker, 2019).

The correlation between bike path and speed could also be spotted, since in the algorithm it is modelled that with the presence of bike path, there could be a negative relation where if there is more bike path, the speed could be reduced.

Lastly, there is also hypothesized that there could be a correlation between angular confusion and bike path, and that it could give some insight if bike path would inhibit or favours cyclist cognitive wayfinding by minimizing angular change.

Similarity Measures

In order to back up the observations through visualizing routes, similarity is quantified by means of Frechet distance. Frechet distance is a measure that takes the continuity of shapes into account, and therefore is more suitable in calculating similarity of curves than Hausdorff distance (Pankaj K. Agarwal, 2007). The measure could be illustrated as a man walking a dog, where the compared curve is the trajectory of the two. Frechet distance of the two curves is the minimum length of leash to connect the pair.

3.8.3. Street Network Analysis

Street Network Analysis is a method to quantify spatial configuration of street networks within the study of Space Syntax. This analysis is conducted to provide a statistical backup on the visualized city configuration.

Firstly, a series of SNA are calculated with Boeing's library: OSMnx (Boeing, 2018a). The library covers more than 20 street network measurements, from basic network statistics such as segment lengths, to connectivity measures. In order to have a better interpretation of the data, SNA metrics on United States (US) cities are used as a reference.

The focus of this thesis is not to study the city configuration of the city, but to interpret emerging routes patterns in relation to the configuration and the morphology of a specific case-study area.

Chapter 4

Results & Analysis

This chapter present and discuss the routes created from the routing algorithm, then evaluate the performance through applying Human Centric Routing Algorithm in two European cities: Valencia and Cardiff. Section 4.1 provide visualization of all the routes and evaluate the performance at a origin and destination level. While section 4.2 present the empirical results of the performance in each city and interpret how parameters and SNA influence the results.

4.1. Routes visualization

Routes visualization is separated into two parts. Section 4.1.1 is a continuation of the Jupyter Notebook on routes visualization, where future users will be able to reproduce the workflow from beginning (data download) to the end (visualization). However due to the limitation of the plotting functionalities and time, routes are visualized in a deeper level on ArcGIS Pro. Section 4.1.2 presents the generated routes and its related metrics.

4.1.1. Visualization on Jupyter Notebook

On completion of the whole routing algorithm creation, visualization was added into Jupyter Notebook. It allows future users of the notebook a complete view of the routing algorithm therefore visualization is provided as an overview of the routes, and for further interpretation, the routes as gdf could be downloaded as shapefile and analysed in ArcGIS Pro.
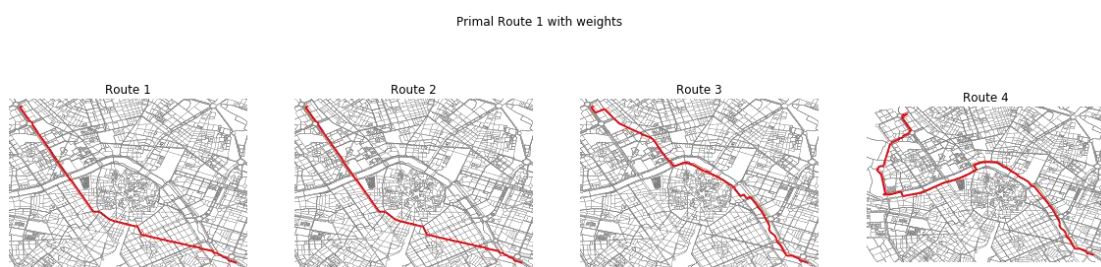
Figure 18: Routes visualization on Jupyter Notebook with matplotlib, example of Valencia OD1

4.1.2. Routes Comparison

As mentioned in Section 3.7.1, three origin destination pairs are routed per city with eight different weights, while the below sections displays the five most discreet routes that are weighted with only one single parameter: distance, slope, angular change and bike path, and in comparison to the optimal weighted route, one which incorporates all the weights.

VAL OD1	length (m)	time (min)	uphill (m)	angConf (s)	bikeP (%)
Distance	6258.88	23.28	36.91	33.31	45.94
Slope	6264.19	27.82	36.59	36.83	49.55
Bike Path	9163.89	34.09	36.9	57.43	98.74
Angular	7515.31	27.21	35.61	12.35	13.34
Optimal	6447.25	28.38	36.83	37.55	91.59
average	6821.99	27.42	36.71	33.14	58.17

Figure 19: Routes result of Valencia OD1. Top is a map of the major routes, bottom is a table of parameter results, X-axis are the parameters of each route and y-axis are the name of the routes

In Valencia OD 1 at Figure 19, the average length is 6822m, and average time is 27 min. There is 37 m of uphill slopes, angular confusion of an average of 33 seconds and an 60% bike path coverage.

The most optimal path is the most similar to distance and slope, which requires 1283m to connect the paths, which could be different visually from that of the map where the optimal path is the most similar to bike path (with similarity value of 1902m) with almost 70% overlap at the beginning of the route. Similarity statistics could be referred to Table 5 and Annex.

VAL OD2	length (m)	time (min)	uphill (m)	angConf (s)	bikeP (%)
Distance	6374.14	23.56	26.64	38.83	5.31
Slope	6374.14	26.85	26.64	38.83	5.31
Bike Path	8586.72	31.94	32.47	114.32	95.2
Angular	10885.3	40.48	41.48	21.43	7.51
Optimal	6530.7	30.17	33.79	44.85	66.7
average	7235.64	29.18	30.18	51.89	29.31

Figure 20: Routes result of Valencia OD2

In Valencia OD 2 at Figure 20, The average distance of paths is 7245m, takes 29.2min to cycle, with 30m of uphill path, 51.2 seconds of angular confusion and 30% of bike path coverage. Routes of different weights performed differently and displays a dispersed pattern, which could be tell by the largest connected distance between Angular and Bike Path, of 4774m which is 3.5 times of the average connected distance. Visually the optimal route is not similar to any of the routes, whereas Frechet distance found the closest route to the optimal route to be distance and slope, of 1200m; while the most different route is with angular change, of 2652m.

In this route, the angular optimized path performs the worst in parameters since it had a huge detour instead of getting a direct route towards the destination, and resulted with the longest in length, time taken and slope. Bike path still has the largest angular change of 114 seconds.

VAL OD3	length (m)	time (min)	uphill (m)	angConf (s)	bikeP (%)
Distance	6731.39	25.04	15.86	111.36	59.12
Slope	6792.54	26.76	12.07	84.25	34.73
Bike Path	9331.52	34.72	13.74	71.21	100
Angular	9859.1	36.32	22.29	20.22	19.38
Optimal	6841.13	28.42	16.65	54.89	80.08
average	7478.77	29.00	15.83	68.50	59.78

Figure 21: Route results of Valencia OD3

OD 3 of Valencia at Figure 21 has an average length of 7478m, takes 29 min with an average of 16m uphill, angular confusion of average 70 seconds and 60% bike path.

The optimal path is the most similar to slope path of only 613m of distance. It is the most different from bike path of 2691m.

The angular optimized path displays the highest metrics of being 25% longer than the average path, longest time and largest uphill path. However, despite distance being the shortest path, the angular change is highest of 111 sec, of almost 60% higher than the average.

In this example bike path and angular change are equally long in length, and follow a similar direction which goes along the coast. In this Origin Destination, the route which favours bike path could be the most suitable for visitors, since it goes around the coast and also crossing the park then enters the city centre.
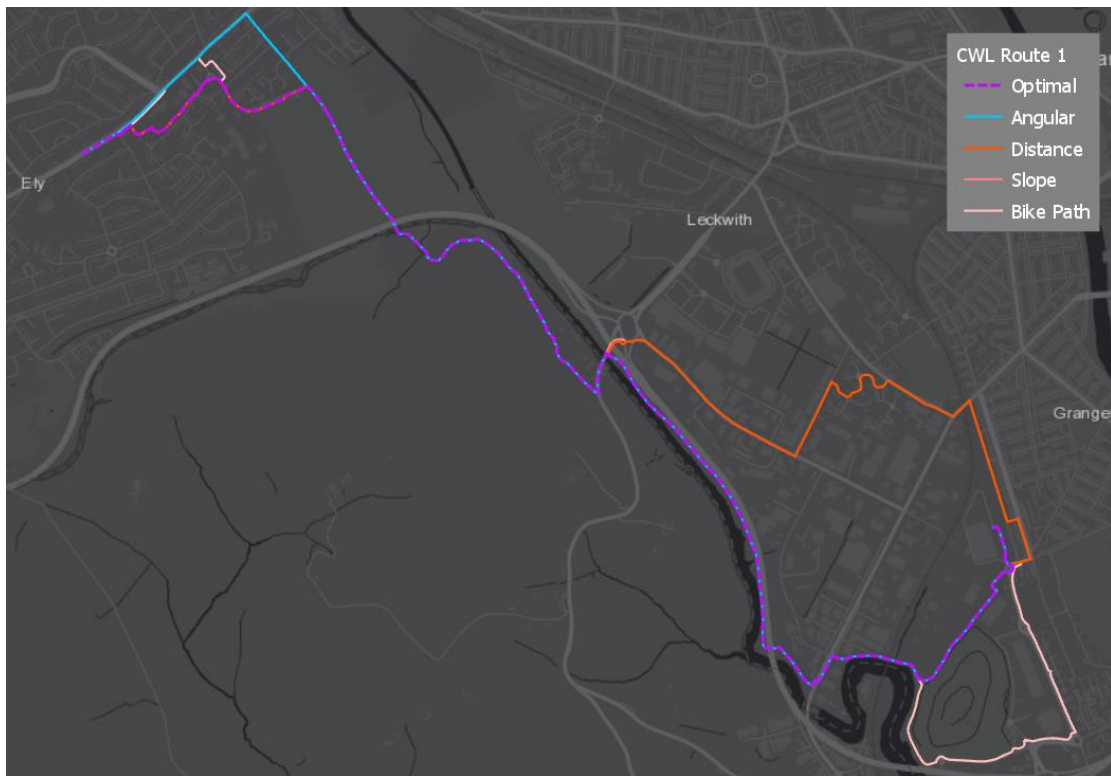
CWL OD1	length (m)	time (min)	uphill (m)	angConf (s)	bikeP (%)
Distance	5823.29	21.66	24.03	54.13	3.05
Slope	5834.55	24.61	23.53	44.23	1.3
Bike Path	7059.13	26.26	27.81	53.59	59.86
Angular	6042.96	22.11	26.09	17.26	36.19
Optimal	5839.44	25.97	24.36	26.22	38.75
average	6014.75	24.12	24.86	34.24	31.60

Figure 22: Route results of Cardiff OD1

In Cardiff OD1 at Figure 22 , the average distance is 6014m, with an average time of 24 min, uphill of 25m, angular confusion of 34 seconds and 32% of bike path.

The routes of this OD is very similar that all the paths overlapped midway, as seen on the passage which follows the bend that enters the a small park. The optimal path is the most similar to the angular path, of only 291m connected distance. Angular confusion of the distance and bike path routes are the highest by 60% more than the average.
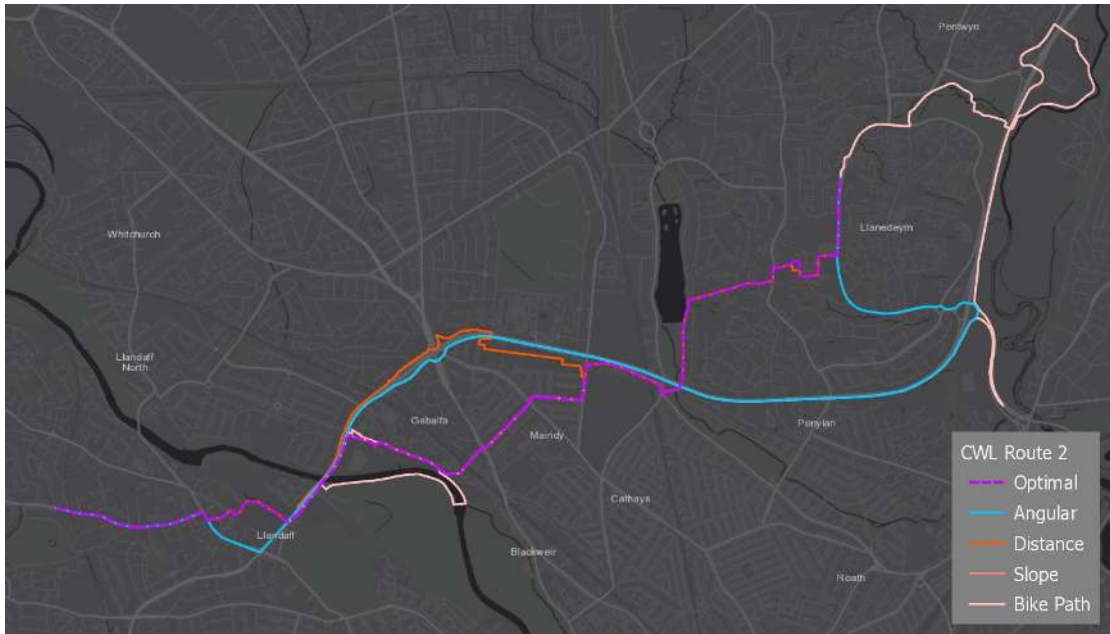
CWL OD2	length (m)	time (min)	uphill (m)	angConf (s)	bikeP (%)
Distance	7630.36	28.39	70.41	123.98	24.55
Slope	7660.17	36.45	64.42	93.47	16.18
Bike Path	14908.33	55.46	90.89	106.76	31.76
Angular	8947.33	30.56	63.50	17.58	0.00
Optimal	7695.24	37.76	64.32	75.33	17.29
average	8751.91	36.26	69.16	88.82	19.10

Figure 23: Route results of Cardiff OD2

Cardiff OD2 at Figure 23 displays the following behaviour. It has a relatively long average length of 8751m, takes 36 min with average of 70m uphill, angular confusion of 88seconds and only 20% of bike path.

In this OD, the results are quited skewed in particular for bike path which started with a completely different direction and results with its 70% longer in length than that of average, and respectively increased time and uphill. Despite the bike path took a detour of almost double of the distance, it only has 30% of bike route, and the angular confusion 106 s is not as high as the distance route of 124s.

The optimal route is the most similar to the slope path with only 502m of distance.
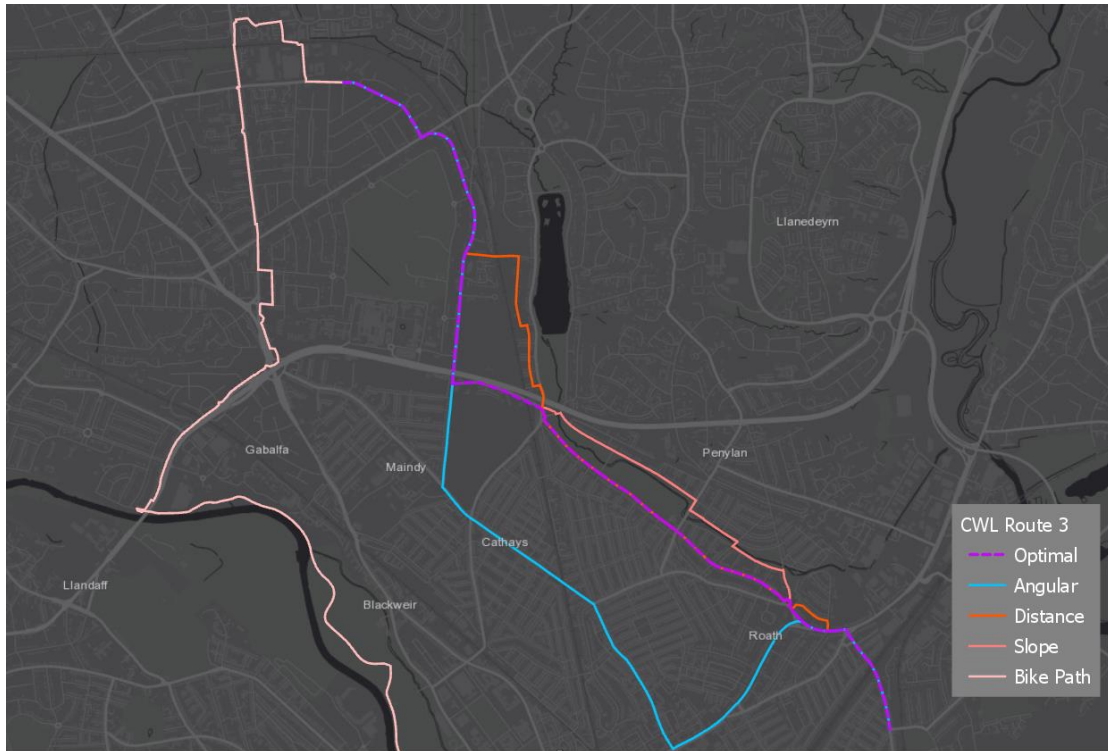
CWL OD3	length (m)	time (min)	uphill (m)	angConf (s)	bikeP (%)
Distance	5539.30	20.61	22.44	54.57	0.00
Slope	5666.03	23.13	16.60	96.58	0.00
Bike Path	14046.03	52.25	48.41	153.07	71.82
Angular	6831.43	24.83	21.42	13.84	0.00
Optimal	5615.20	26.38	20.04	31.35	0.00
average	6824.30	27.19	23.20	63.59	8.98

Figure 24: Route results of Cardiff OD3

In Cardiff OD3 at Figure 24, it has an average distance of 6824m, 27min, uphill of 23.2m, average angular confusion of 64s and only 9% of bike path.

In this route, bike path also behaved drastically different which routed out of the map, and does not overlap with any of the paths, resulting with highest values in all parameters.

The most optimal route is the most similar to both slope and distance of 443m.

Disregarding bike path, the angular confusion is the highest as seen by distance of 96s.

This route has the lowest percentage of bike path coverage, in which all the paths has 0% despite the route weighted with bike path.

5.1. Routes Statistics

Through commuting parameter statistics, patterns and trends emerged on the relations of these routes. In particular, routes with the highest angular confusion could be identified. Table 4 provides a summary of routes with the highest angular confusion at each origin destination. It could be seen that distance and bike route both has the highest angular confusion. It was hypothesized that paths of higher angular change has a longer distance, people would tend to minimize distance instead and take a path of higher angular change. It is true that angular route itself could be 10% longer than the shortest path route. Moreover, it is not necessarily true that longer routes will have higher angular change, which could be seen in OD1 and OD2 of Cardiff. At both OD, bike path optimized paths are two to three times longer than the average distance, yet it still has a lower angular confusion than that of the distance route.

Table 4: Summary of routes with highest angular confusion parameter, at each origin destination

	highest angConf		2nd angConf	
VAL OD1	bike	57.00	optimal	37.50
VAL OD2	bike	114.00	optimal	44.00
VAL OD3	dist	111.00	slope	84.00
CWL OD1	dist	54.00	bike	53.00
CWL OD2	dist	123.00	bike	106.00
CWL OD3	bike	153.00	slope	97.00

Finding similarity between routes is a major focus of this thesis, a summary of the results are displayed in Table 5, and the full results can be found at Annex 1. Frechet distance was used to find the distance to connect two curves, where a lower value indicates a higher similarity while higher value indicates a lower similarity. Values for slope and distance is the most similar, where 5 out of 6 routes has distance and slope routes being the most similar. At Valencia OD2 the distance and slope route is 100% the same with 0m of distance. While angular and bike path are showing the largest difference of 3 out of 6.

Table 5: Results of similarity measures by Frechet distance in meters, first two columns are the most similar and different routes for each origin destination, the last two columns are the most similar and different routes in comparison to the optimal route

	Overall similar		Overall different		Optimal similar		Optimal different	
VAL OD1	dist&slope	51.46	ang&bike	2129.02	dist&slope	1283.22	ang	2108.31
VAL OD2	dist&slope	0.00	ang&bike	4744.93	dist&slope	1200.35	ang	2652.66
VAL OD3	dist&slope	332.91	bike&opt	2691.85	slope	613.67	bike	2691.85
CWL OD1	dist&slope	44.64	slope&bike	1200.08	ang	291.79	dist&slope	1090.16
CWL OD2	slope&optimal	502.07	ang&bike	1928.07	slope	502.07	bike	1928.07
CWL OD3	dist&slope	211.60	slope&bike	2891.17	dist&slope	443.53	bike	2874.94

5.1.1. Parameters Correlation

In order to find if parameters could be related and influenced one to another, especially in certain street network configuration. The parameters are then analysed in R to find statistical correlation between parameters in different cities.

Figure 25: Correlation pairs between parameters. It shows scatter plot and distribution of the metrics. Numbers are correlation: black is correlation of 2 metrics for all data points, data points in blue are that from Valencia, reds are from Cardiff. There is a total of 48 routes, 24 routes per city

Despite length and speed which have a direct correlation, the following pairs of parameters has a notable correlation: uphill & length (0.556), angular confusion & length (0.414), angular confusion & uphill (0.343) and bike path & angular confusion (0.246).

Angular confusion and length exhibit a moderate correlation of 0.414, which is tested significant with p-value of 0.0034. The correlation could be explained by the correlation of Cardiff of 0.575, where longer paths has more angular change. However in Valencia, that is not the case and displays a slight negative correlation, in which when the length of path is longer it does not necessarily has a higher angular change.

At the correlation between angular confusion and uphill, there exists an opposite correlation, which Cardiff has a positive correlation, while Valencia has a negative

correlation. Both correlations are significant at a 0.005 value. This significant difference could be answered by the network configuration. In Valencia, the lowlands are closer to the coast on the east where there are ports and historic city centre, elevation increases gradually towards the west where newer developments are made. At the historic city centre there lies more of a organic growth therefore has a more complex pattern, while the new settlements are designed in a grid and simpler pattern. While in Cardiff, it is a relatively newer city and the low lands are dictated by irregular grid patterns where the city centre is, the higher irregular hills scattered in the north are residential areas which displays a 'loop and lollipop' pattern which exists in the residential suburbs design in the US (Boeing, 2018a) and categorized by Boeing as low connectedness, thus higher angular confusion leading to more turns to get to the destination.

And lastly the total correlation between angular confusion and bike path is 0.25, which is slightly significant of 0.09, yet the correlation of the two parameters in Valencia has a 0.52 correlation at a 0.01 confidence level. This correlation could suggest when routes contain more bike path, the angular confusion is higher, and in opposite, when routes has a lower angular confusion, there is a lower % of bike path. This finding leads to a question that requires further discussion: Are bike paths built in a way that aligns with cognitive wayfinding behaviour?

5.1.2. Street Network Analysis

A phenomenon emerged by visualizing routes in the two cities, that routes in Valencia is more diverged and spread out, while routes in Cardiff has a higher percentage of overlay and similarity. As mentioned in the above section, the city configuration is described and provide reasoning on the differences.

To quantify the configuration of SNA is used. The SNA function of Boeing provides more than 20 measurements, relevant metrics are extracted in the table below. It is in reference to the metrics ran by the same function, in a case study of urban street networks in all cities in the US (Boeing, 2018a).

Table 6: Results of SNA of both cities in comparison with results in the US from (Boeing, 2018a)

Street Network Analysis	VALENCIA	CARDIFF	US CITY (BOEING)
Streets per node avg	4.060	3.412	2.850
Edge length avg	62.149	84.055	144.000
Circuity	1.039	1.07	1.080
Connectivity	1.00	1.00	N/A
Clustering coefficient avg	0.063	0.111	0.040
Betweenness centrality	0.006	0.009	N/A
Max Betweeness centrality	0.015	0.02	N/A

Average streets per node quantifies the connectedness in terms of average number of edges adjacent to its nodes in a physical form. It could be seen that Valencia has a relatively higher value than Cardiff, than that of a US city.

The *Average edge length* gives an estimation of the average block size is. Valencia has the smallest block size, then Cardiff. In the average US city it has double of the block size as it is in Europe. It could be linked to the bikeability and walkability of the city, as suggested by the large block size in the US which is designed for automobile, while that of the city has a smaller block size (Boeing, 2018a).

Circuity measures the curvilinearity of the street network. It is the ratio of edge lengths to the great-circle distance between the nodes the edges connect. The lower it is the more grid-ness the street network displays. This metric shed light on why the routes in Cardiff has a higher angular confusion. Valencia has a lower value than that of Cardiff due to its more gridded pattern and more direct paths, comparing to the highly dwindling paths Cardiff displays, however in comparison to the value of 1.080 in the US which is supposed to be the lowest, such difference requires deeper investigation.

In terms of connectivity measures, *connectivity* shows the resilience of the network. This is a highly reflective indicator on how connected a network is. Average node connectivity

is the mean number of paths between each pair of nodes in the graph, representing the expected number of nodes to remove from a network to disconnect a route. The higher the connectivity of a network is, the higher average node connectivity will be. However, in the case of this thesis, it did not give any meaningful results.

Apart from connectivity, there are other measures of connectedness such as centrality and clustering.

Clustering coefficient displays a ratio of the number of neighbouring edges a node is connected and the maximum number of links that exists between its neighbours. If the node's neighbours are all connected it gives a value of 1, while if its none is 0. It could be seen that Valencia is not as connected with its neighbours as Cardiff is in terms of the average, which could be due to the gridded pattern and the directionality it displays.

While *betweenness centrality* measures how many network's shortest paths pass through some node to indicate its importance. The higher the average betweenness centrality, the more the street network is prone to failure due to a single choke point, while the lower betweenness centrality provides a larger number of route choices. The higher value in Cardiff suggests that most of the shortest path would pass through a number of major streets, while in Valencia it could be suggested that the flow is more dispersed in a larger number of streets resulting a lower value. This is further proved in calculating the *maximum betweenness centrality* of the two cities. In Valencia, there is a lower maximum betweenness centrality of 0.015, comparing to that of Cardiff – 0.02.
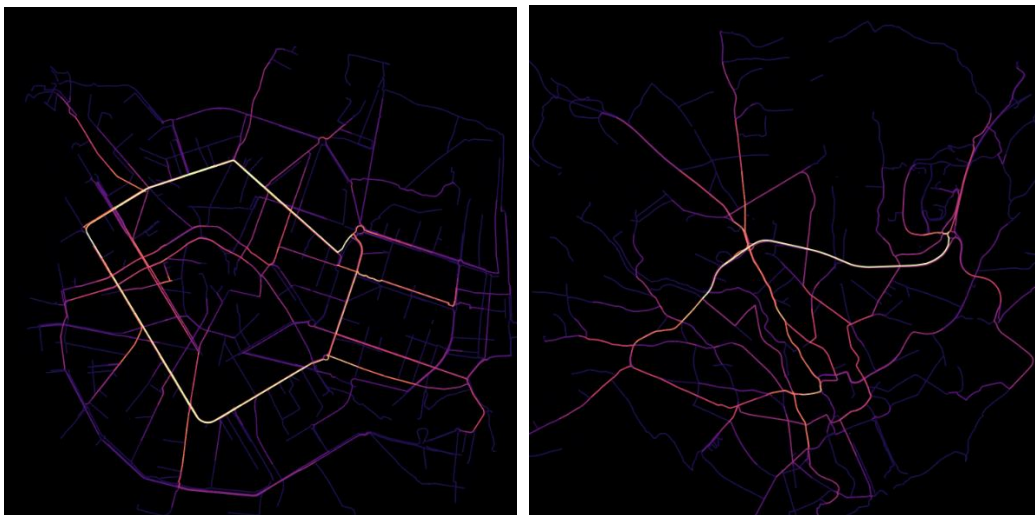
Figure 26: Degree betweenness centrality measure, left (a): Valencia, right (b): Cardiff

By visualizing the edges betweenness centrality based on angular change, it is possible to discover popular routes and predict movement flow. Comparing the two cities, it is easier to depict the spatial configuration of Valencia than that of Cardiff. Furthermore,

the cyclist flow illustrated by betweenness centrality could accurately predict the popular routes as generated by routing algorithm. The high similarity of routes from Valencia OD2 (Figure 20) are very similar to the edges of highest betweenness centrality (the bright yellow paths) as displayed in Figure 26 (a).

It could be concluded that two out of four SNA suggests Valencia has a higher connectivity than Cardiff, which reinforced the results and hypothesis that there is an underlying difference in the connectivity of street network which leads to how the routing algorithm performs.

Chapter 6

Discussion

6.1. Route Characteristics

This thesis provides a method by analysing generated routes through evaluation of route characteristics, which was not precedented in previous researches. It is the aim to create a human centric routing algorithm which uses distance, slops, bike path and angular confusion to model routes that are closest to cyclist wayfinding behaviour, and uses these parameters to evaluate if certain characteristics would inhibit other parameters.

One of the motivations is the paradox of shortest path and angular change, that people tend to choose paths of least angular change than shortest distance. The generated route results do show that in half of the origin destination, paths of shortest distance display the highest angular change. This phenomenon is particularly true in Cardiff, where the path has a stepping pattern to navigate through its irregular street configuration. This finding is supported by (Cooper, 2017), that cyclists 'here cyclists must occasionally overcome their aversion to twisty routes if they wish to pick the shortest path'.

The other routes with high angular change are the ones that optimize bike paths. The high correlation of angular change and bike path particularly in Valencia suggests that bike paths are dwindling, which could inhibit the cognitive wayfinding behaviour of cyclist. This is due to the change in direction is seen as a cognitive cost, and hence increases the mental distance. In a research of the spatial configuration of cycling landscape in London (Law, Sakr, & Martinez, 2014), it also pointed out the importance to consider Space Syntax measures while planning for cyclist infrastructure. Since cyclist flow tend to aggregate at locations of higher connectivity but without bike path, rather than choosing locations that are safer with designated cycling facilities.

However there is an opposing argument brought by D'Acci that curvy streets stimulate curiosity and mystery (given that it is a direct path without decision points) which people tend to choose it over 'boring' straight paths (D'Acci, 2019). This is true for the case of people who know the environment well, or that they are exploring the area. Furthermore, based on personal experience, Bike Paths are usually annotated with signages, which

would ease the cognitive demand on wayfinding. As illustrated by the bike path and optimal path of Valencia OD1, despite it being dwindling with high angular confusion, one could steer towards these paths more based on the attractiveness.

	length (m)	speed(m/s)	uphill (m)	downhill (m)	angConf (s)	bikeP (%)	similar(m)
AVG (VAL)	7178.80	251.48	27.58	21.91	51.18	49.08	1391.55
AVG(CWL)	7196.99	248.15	39.07	51.50	62.21	19.89	976.21

Table 7 displays the average parameters of routes in two cities. The variation of slope (uphill and downhill) suggested that Cardiff could have a higher difference due to its hilly elevation. Whereas angular confusion is higher in Cardiff by 10%, which could be due to the irregular pattern that exists.

A significant difference is the average amount of bike path the city provides, where Valencia has 1.5 times more of what Cardiff displayed. In fact, Valencia has 20.8% of bike path out of the whole street network, while Cardiff only has 9.72%. It is surprising that just 10% of the amount of bike path could make such a difference in routes. However the edges with highest degree betweenness centrality of Valencia is not covered with bike path, despite that it is predicted by algorithm that it would have the highest cyclist flow.

6.2. Spatial Configuration of cities and its influence

From visualizing the patterns of routes, it is apparent that city configuration does influence how the routes behaved. Valencia is a concentric gridded city, while Cardiff has more of a decentralized irregular pattern. The pattern and variability of the routes in the cities are quite different.

From the maps, routes in Valencia are very dispersed and does not seem to overlap; while in Cardiff, routes are highly overlapped especially in OD1. From similarity measures, Valencia displays an average similarity of 1391m, which is 30% higher than Cardiff of 976m, indicating that routes in Cardiff are more similar than that of Valencia. This could be due to the concentric grid pattern that Valencia displays, where streets are on average more connected and therefore provide more route choices. While in Cardiff, it could be seen that routes pass through the same edge more often.

The connectivity measures of SNA provides further proof that the street network of Valencia has a higher connectivity than Cardiff. In which the highly dispersed routes is due to the extensive route choices the concentric grid pattern provides. In particular

betweenness centrality gives a numerical proof that the dispersed routes of Valencia could be due to the extensive route choices the street network offers, that to go from one point to another there could be numerous ways to achieve, implying that there would be a smoother flow of traffic and has a lower chance of traffic jam.

In light of the performance of the routing algorithm on the variability of route choices, angular change of the city and the legibility of the spatial configuration, one could conclude that the simpler gridded planned spatial configuration of Valencia could be more favourable for cyclists than the complex pattern of Cardiff.

The simplicity of urban form could be associated with legibility – by which people can understand the layout easily. It was first proposed by Lynch in the image of city. Lynch described a legible city as easily identifiable and streets are easily grouped into an overall pattern. He advised that a well-planned city is more memorable and imageable for city dwellers, providing a simple wayfinding process (Vaez, Burke, & Alizadeh, 2016). Weisman (1981) built on his theory, that well-differentiated urban elements makes wayfinding easier since the unique characteristics of cities tends to be more memorable and aids wayfinding. While on the contrary, navigation and wayfinding in areas where layouts are complicated, in particular at pre-modern cities is more difficult and confusing which is seen in Cardiff and the city centre of Valencia. By understanding the urban layout easily, people can easily construct cognitive maps. This finding is supported by Kim (Young Ook Kim & Penn, 2004) that cognitive maps drawn by people living in areas with a high value of legibility are better representors of their surroundings comparing to the cognitive maps drawn by residents of an area of lower legibility.

A legible urban layout facilitates wayfinding performance, yet the over simplification of layout as illustrated in modern urban policy is argued to have deteriorating effect on wayfinding. Jane Jacobs suggested the organic disorder of old cities provides a more liveable environment for urban users. She pointed out the important role of messy complexity and condemned the gridded urban image of modern US cities that is automobile oriented, and that spatial cognition of urban users are affected negatively due to the reliance on driving (Vaez, Burke, & Alizadeh, 2016). Complexity in urban design is deemed to contribute to walkable and healthy neighbourhoods, which has implication of sustainability towards a resilient, connected and robust community (Boeing, 2018b). However there has to be a fine balance between simplicity and complexity; structure and variety, in order to build a resilience and sustainable city that is resistant to the increasing urban problems that cities are going to face in the future.

6.3. Reproducibility

One of the novel contributions of the thesis is to develop a reproducible library that future users can benefit in terms of prerequisite knowledge and the computational environment to recreate their own human centric routing algorithm. The original methodology of a Easiest Path Routing Algorithm as inspired by Nourian et al (Nourian, Van Der Hoeven, et al., 2015) was developed as a plugin for Grasshopper with C# and VB.Net, which could be a proprietary environment that inhibits future users who are not familiar with the environment.

This section is to evaluate the reproducibility of this thesis according to three major criteria on reproducibility evaluation (Nüst et al., 2018): Input data, Methods (Preprocessing, methodology and computational environment) and Results. Each criterion has four levels ranging from 0 (not reproducible) to 3 (fully reproducible).

- Input data: 3
- Methods - Preprocessing: 3
- Methods - Methodology/analysis/processing: 3
- Methods - computational environment: 2
- Results: 1

This thesis could be ranked at a overall level of 2.6 out of 3, since in the data part only open source data from OSM is retrieved, and the development platform is on Jupyter Notebook which provides a detailed description and rationale of the knowledge applied in the algorithm. However, at computational environment, there is a high dependency based on the stability of the Anaconda environment. For instance, during the development of this thesis the whole Python environment had to be reinstalled due to the broken paths after Windows update. Reproducibility of results is given a 2, since analysis is compared visually due to the nature of street configuration studies which could subject to objectivity. Efforts is given to provide quantitative support on the visualization with similarity measures and SNA. The notebooks and code are transparently published on GitHub and could be found at https://github.com/sinki-blau/humanCentricRA_final.

6.4. Limitations & Recommendations

The development of a routing algorithm is an A.I. problem, there are a myriad of dependencies on an accurate prediction of cyclist route choice that are not simply influenced by the built environment. Parameters such as perceived safety, pleasantness, road surface quality, amenities on the way, and even herd effect could influence wayfinding behaviour. Incorporating more relevant parameters and its extent of influence could yield a better prediction.

Although the data quality of OSM data is deemed accurate in a general level, in the case of bike paths in Cardiff, data is not sufficient and updated. This highly influence how the routing algorithm performs as seen in the results of routes.

The case study area selection also contributes significantly to the study results. Valencia is a city that the authors are familiar with, therefore it was chosen as the case study area. Given its characteristics for being a relatively flat area and a distinct concentric grid pattern, another city of contrasting elements is chosen. Visually Cardiff is a hilly city with contrasting city configuration, it is further backed up by related study and has a similar size as Valencia, hence chosen as the comparison city. It was assumed that routes generated of various criteria: slope, angular change and bike path would have distinct results. However, routes of distance and slope still remained very similar, which could be seen that five out of six most similar routes are distance and slope routes, hence the importance of having slope as a major parameter is downplayed. Therefore, it is crucial to apply this analysis to a series of worldwide cities of distinct spatial configuration, to avoid arbitrary generalization.

Another concern rises from the evaluation methodology. There still lacks robust research on the area of routing algorithm and comparison of spatial configuration, which resulted in a number of efforts and methods trying to make sense of the results. In particular, despite that SNA provides powerful prediction to human movement flow, the implementation of SNA provided to results that could be hardly interpreted and referenced to. To make sense of the results, Boeing highlighted the importance to identify significant configuration indictors and cluster cities into morphological types (Boeing, 2019). In this thesis, the spatial configuration of the two cities were derived visually, there could be hidden patterns that could only be identified through correlation with morphological clusters.

In this thesis, the evaluation methodology is based on the comparison between computed routes of various parameters, which is not verified with real world examples. It was not the intention of this thesis to conduct the lengthy data collection process, but to focus on the related development and analysis. Two real world evaluation methods are proposed. Firstly, is to compare actual routes with the generated routes to find the extent of similarity, and see if there are any local parameters which influences route choices. The second method is related to the influence of spatial cognition, in which is to provide the optimal route to cyclist to evaluate if such routes are deemed easier and that it reduces navigation errors. It is recommended by Duckham that such experiment with human subjects could test the hypothesis that cognitively optimal routes are preferable comparing to route instructions based on shortest path (Duckham & Kulik, 2003).

Chapter 6

Conclusion

This paper has two primary purpose. First is to develop a reproducible human centric routing algorithm for cyclists, and second is a discuss in the influence of spatial configuration of city on routing algorithm and its wider contribution to urban design.

This thesis reached the aim to develop a novel reproducible methodology on a human centric routing algorithm which models human wayfinding behaviour both cognitively and physically. It overcame the challenges of the difficulty to incorporating both cognitive (angular change) and physical (distance, slope and bike path) parameters, and also introduced directionality to the routing algorithm. Routes were created based on various criteria, and results showed that the optimal weighted routes could optimize angular change, slope, distance and maximize bike path. By analysing and comparing the routes created on the both cities, there came to 3 major findings: 1) Cardiff has a significantly lower % in bike paths than Valencia, 2) Cardiff has a higher average angular change than Valencia, 3) routes in Valencia is more wide spread and less similar than Cardiff.

Based on the motive that wayfinding is guided by building environment, the spatial configuration of city is calculated with statistical measures and street network analysis for a quantitative approach. Metrics of connectivity are possible measures to verify the higher connectedness Valencia displays, due to the simple concentric gridded pattern.

It is worth noting that spatial configuration of cities plays an important role in dictating wayfinding behaviour of cyclist, however this research was just an exploratory effort to test the relationship. Future research can further explore a robust evaluation methodology between spatial configuration and cyclist wayfinding, which will have significant implications to compare bikeability index of worldwide cities. Furthermore, a classification to methodologically sort city configuration into clusters could be very beneficial on future research, in particular how these patterns influence mobility patterns and behaviours, which could help urban planners to enhance features that aid active transport and build resilience and sustainable cities.

Chapter 7

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Annex

Similarity Measures with Frechet Distance

Valencia OD1

	PR1w1	PR1w2	PR1w3	PR1w4	DR1w1	DR1w2	DR1w3	DR1w4
PR1w1	0.00	51.46	1282.10	1420.49	1140.79	154.82	154.82	1283.22
PR1w2	51.46	0.00	1282.10	1420.49	1136.21	154.82	154.82	1283.22
PR1w3	1282.10	1282.10	0.00	1967.12	2129.02	1271.24	1279.19	263.18
PR1w4	1420.49	1420.49	1967.12	0.00	2129.02	1408.57	1412.94	1902.46
DR1w1	1140.79	1136.21	2129.02	2129.02	0.00	1143.50	1143.50	2108.31
DR1w2	154.82	154.82	1271.24	1408.57	1143.50	0.00	33.63	1272.66
DR1w3	154.82	154.82	1279.19	1412.94	1143.50	33.63	0.00	1280.61
DR1w4	1283.22	1283.22	263.18	1902.46	2108.31	1272.66	1280.61	0.00

Valencia OD2

	PR2w1	PR2w2	PR2w3	PR2w4	DR2w1	DR2w2	DR2w3	DR2w4
PR2w1	0.00	0.00	130.79	1324.76	3654.71	333.48	333.48	1200.35
PR2w2	0.00	0.00	130.79	1324.76	3654.71	333.48	333.48	1200.35
PR2w3	130.79	130.79	0.00	1328.55	3652.76	333.48	333.48	1200.35
PR2w4	1324.76	1324.76	1328.55	0.00	4744.93	1322.30	1322.30	2426.36
DR2w1	3654.71	3654.71	3652.76	4744.93	0.00	3654.45	3654.45	2652.66
DR2w2	333.48	333.48	333.48	1322.30	3654.45	0.00	0.00	1283.86
DR2w3	333.48	333.48	333.48	1322.30	3654.45	0.00	0.00	1283.86
DR2w4	1200.35	1200.35	1200.35	2426.36	2652.66	1283.86	1283.86	0.00

Valencia OD3

	PR3w1	PR3w2	PR3w3	PR3w4	DR3w1	DR3w2	DR3w3	DR3w4
PR3w1	0.00	332.91	317.48	2415.59	1863.99	332.84	332.84	780.91
PR3w2	332.91	0.00	236.40	2622.73	1863.99	235.22	235.22	613.67
PR3w3	317.48	236.40	0.00	2611.23	1863.99	128.98	269.87	587.49
PR3w4	2415.59	2622.73	2611.23	0.00	1074.31	2621.61	2621.61	2691.85
DR3w1	1863.99	1863.99	1863.99	1074.31	0.00	1863.77	1863.77	1863.77
DR3w2	332.84	235.22	128.98	2621.61	1863.77	0.00	256.54	526.84
DR3w3	332.84	235.22	269.87	2621.61	1863.77	256.54	0.00	614.82
DR3w4	780.91	613.67	587.49	2691.85	1863.77	526.84	614.82	0.00

Cardiff OD1

	PR1w1	PR1w2	PR1w3	PR1w4	DR1w1	DR1w2	DR1w3	DR1w4
PR1w1	0.00	44.64	1100.25	1200.08	1090.16	1090.16	1090.16	1090.16
PR1w2	44.64	0.00	1100.25	1200.08	1090.16	1090.16	1090.16	1090.16
PR1w3	1100.25	1100.25	0.00	677.87	801.43	801.43	801.43	801.43
PR1w4	1200.08	1200.08	677.87	0.00	801.43	801.43	801.43	801.43

DR1w1	1090.16	1090.16	801.43	801.43	0.00	291.79	291.79	291.79
DR1w2	1090.16	1090.16	801.43	801.43	291.79	0.00	0.00	19.42
DR1w3	1090.16	1090.16	801.43	801.43	291.79	0.00	0.00	19.42
DR1w4	1090.16	1090.16	801.43	801.43	291.79	19.42	19.42	0.00

Cardiff OD2

	PR2w1	PR2w2	PR2w3	PR2w4	DR2w1	DR2w2	DR2w3	DR2w4
PR2w1	0.00	794.01	1346.32	1853.28	1036.80	788.50	788.50	788.50
PR2w2	794.01	0.00	1346.32	1853.28	1036.80	502.07	502.07	502.07
PR2w3	1346.32	1346.32	0.00	1916.87	1692.79	1342.43	1342.43	1342.43
PR2w4	1853.28	1853.28	1916.87	0.00	1928.07	1928.07	1928.07	1928.07
DR2w1	1036.80	1036.80	1692.79	1928.07	0.00	1064.58	1064.58	1064.58
DR2w2	788.50	502.07	1342.43	1928.07	1064.58	0.00	92.12	92.12
DR2w3	788.50	502.07	1342.43	1928.07	1064.58	92.12	0.00	0.00
DR2w4	788.50	502.07	1342.43	1928.07	1064.58	92.12	0.00	0.00

Cardiff OD3

	PR3w1	PR3w2	PR3w3	PR3w4	DR3w1	DR3w2	DR3w3	DR3w4
PR3w1	0.00	211.60	211.60	2868.38	1051.98	443.53	443.53	443.53
PR3w2	211.60	0.00	0.00	2891.17	1051.98	443.53	443.53	443.53
PR3w3	211.60	0.00	0.00	2891.17	1051.98	443.53	443.53	443.53
PR3w4	2868.38	2891.17	2891.17	0.00	2240.00	2874.94	2874.94	2874.94
DR3w1	1051.98	1051.98	1051.98	2240.00	0.00	1045.31	1045.31	1045.31
DR3w2	443.53	443.53	443.53	2874.94	1045.31	0.00	0.00	0.00
DR3w3	443.53	443.53	443.53	2874.94	1045.31	0.00	0.00	0.00
DR3w4	443.53	443.53	443.53	2874.94	1045.31	0.00	0.00	0.00

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