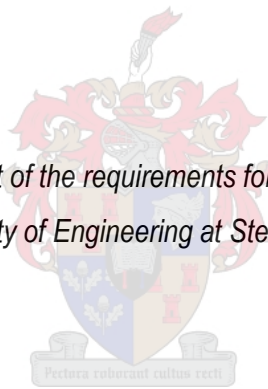# THE CHARACTERISATION OF NON-MOTORISED TRANSPORTATION ON THE STELLENBOSCH CAMPUS

By Hans-Peter Klink

Thesis presented in fulfilment of the requirements for the degree of Master of Engineering in the Faculty of Engineering at Stellenbosch University

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March 2020

DECLARATION

By submitting this thesis electronically, I declare that the entirety of the work contained therein is my own, original work, that I am the sole author thereof (save to the extent explicitly otherwise stated), that reproduction and publication thereof by Stellenbosch University will not infringe any third party rights and that I have not previously in its entirety or in part submitted it for obtaining any qualification.

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Hans-Peter Klink

March 2020

ABSTRACT

This thesis aims to understand and characterise how non-motorised transport (NMT) users transverse the Stellenbosch campus of Stellenbosch University. In establishing the behaviour of these users, initiatives in which the data could not only benefit local infrastructure planning but be used as a means to improve current and future transportation services could be identified, especially from a Mobility-as-a-Service perspective.

Data was collected in the form of logged signals from Bluetooth devices using 44 custom build Bluetooth sensors. These sensors were placed across the campus area for three periods, which consisted out of four weekdays. From the logged signals, common trends in the form of typical travel paths and detections levels could be determined. The collected data was filtered using Microsoft Excel in order to distinguish between signals logged from motorised and non-motorised transportation users. From the filtering process, a dataset which estimated the behaviour of NMT users in the forms of detection levels and origin and destination (O/D) matrices was created. Graphs depicting the level of NMT activity over a typical 24 hour period and, heatmaps and O/D maps could be then be designed.

Once the data was visualised, it could then be analysed and findings could be formed based on current transportation services and the development of NMT related infrastructure. Major findings in this regard included identifying where micromobility services and the local minibus taxi industry could stand to benefit from the space/time characterisation of NMT behaviour.

OPSOMMING

Hierdie tesis is daarop gemik om die gebruikers van nie-gemotoriseerde vervoer (NGV) oor die Stellenbosch-kampus van die Universiteit Stellenbosch te verstaan en te karakteriseer. Deur die gedrag van NGV-gebruikers te bepaal, kan inisiatiewe geïdentifiseer word waarin die data nie net plaaslike infrastruktuurbeplanning bevoordeel nie, maar ook die beplanning van huidige en toekomstige vervoerdienste, veral vanuit 'n Mobiliteit-as-'n-Diens-perspektief.

Data is versamel in die vorm van aangetekende seine vanaf Bluetooth-toestelle met behulp van 44 spesiaal gemaakte Bluetooth-sensors. Hierdie sensors is gedurende drie periodes, wat vier weeksdae insluit, oor die kampusgebied geplaas. Vanuit die aangetekende seine kan algemene neigings in die vorm van tipiese reispaaie en aantekeningsvlakke bepaal word. Die versamelde data is met behulp van Microsoft Excel gefiltreer om te onderskei tussen seine wat van gemotoriseerde en nie-gemotoriseerde gebruikers van vervoer gebruik is. Vanaf die filterproses is 'n datastel geskep wat die gedrag van NMT-gebruikers in die vorm van aantekeningsvlakke en oorsprong- en bestemmingsmatrikse (O/B) vertoon. Grafieke wat die vlak van NGV-aktiwiteit oor 'n tipiese periode van 24 uur uitbeeld, sowel as hittekaarte en O/B-kaarte is daarna ontwerp.

Nadat die data gevisualiseer is, kon dit ontleed word. Bevindinge kon gevorm word op grond van huidige vervoerdienste en die ontwikkeling van NMT-verwante infrastruktuur. Belangrike bevindings in hierdie verband sluit in die identifisering van waar mikromobiliteitsdienste en die plaaslike minibustaxibedryf kan baat by die ruimtelike/tydse karakterisering van NGV-gedrag.

ACKNOWLEDGEMENTS

I am now more than ever convince that we were not designed to overcome challenges on our own, but through the support we receive from those around us. It is with this revelation, that I would like to acknowledge the following people with whom I shared the journey of completing this thesis:

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Lastly, I need to acknowledge my Creator. A being which I know is greater than any earthly sorrow which I have or may yet suffer. In all the challenges that is still to come, I know that in comparison to who You are, they are small. I know this journey is still far from over, but every day I know that I am growing stronger and better.

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LIST OF ACRONYMS

ACL	–	Asynchronous Connection-Less
CITP	–	Comprehensive Integrated Transport Plan
CSV	–	Comma Separated Value
GPS	–	Global Positioning System
FHWA	–	Federal Highway Association
ITS	–	Intelligent Transportation Systems
L2CAP	–	Logical Link Control and Adaption Protocol
MAC	–	Media Access Control
MaaS	–	Mobility-as-a-Service
MT	–	Motorised Transportation
NMT	–	Non-Motorised Transportation
O/D	–	Origin/Destination
ODM	–	Origin/Destination Matrix
PAN	–	Personal Area Network
REC	–	The Research Ethics Committee at Stellenbosch University
RF	–	Radio Frequency
SDF	–	Spatial Development Framework
SIG	–	Special Interest Group (*Bluetooth*)
SSML	–	Stellenbosch Smart Mobility Lab
SoC	–	System-on-Chip
SU	–	Stellenbosch University

LIST OF SYMBOLS

m	–	metres
mW	–	megawatts
km	–	kilometres
s	–	seconds
h	–	hours
km/h	–	kilometre per hour

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Non-motorised transportation (NMT) can be described as any mode of transportation powered by humans. It is the opposite to fuel or electric based modes of mobility, which, falls under the category of motorised transportation (MT). Common NMT modes include walking, cycling, and activities as skateboarding. Traditionally, the hierarchy within transportation places MT above NMT, although efforts to promote NMT, especially within urban planning, is steadily taking place (Neun, 2018). When considering transportation planning, considerably less attention is given to NMT than to MT. Where the planning of road networks, bus routes, station logistics and so forth is usually associated with the detailed collection of data and the development of large-scale models, the attitude towards development of NMT infrastructure and logistics often rides on the back end of these models (Schneider *et al.*, 2005). Little consideration is given to how NMT users move, when, this should arguably be the cornerstone on which the planning of travel services and infrastructure be based. Although the development of NMT infrastructure is of importance, the understanding of NMT travel characteristics has other benefits. It is thus argued that it is by gaining a proper understanding of NMT characteristics that a foundation can be designed which aims to complement the transportation industry, especially in finding manners in which the characterisation of NMT could compliment MT.

When considering how data can be used to complement different transportation services, one has to consider relatively new concepts such as Mobility-as-a-Service (MaaS). MaaS is a platform from which several transport modes can be accessed, and is seen as a means to solve greater transportation challenges (Goodall *et al.*, 2017). With a focus on NMT data, the question is raised, that if we consider mobility as a *service*, what role the characterising of NMT, a commonly 'free' means of travel, plays within this paradigm shift. Is NMT only a means of accessing MaaS service points or can NMT be incorporated into a MaaS centred system in order to holistically optimise the overall mobility of the network by understanding local NMT peaks and demands.

When taking NMT to a local level, one questions to what extent a town such as Stellenbosch could benefit from understanding NMT. When considering Stellenbosch, locals will immediately point to the number of MT users traveling from outside the town towards the town, the lack of parking within the town, and the growing student population. In addition, Stellenbosch is generally frequented by many tourists which adds pressure to existing transportation challenges. By analysing the daily movement patterns of NMT users on the Stellenbosch campus of Stellenbosch University (SU) and laying them out for examination, this research study aims to prove the benefit of understanding NMT within the larger transportation planning field by utilising data collection methods which coincide with the development of new technologies.

Considering the integration of technology into our daily lives (take for example smart phones, of which ownership in South Africa had increased to 51% in 2017 (Silver and Johnson, 2018)), movement data is suddenly available in abundance and accessible to any transportation engineer or urban designer who needs it. This research study will show with relative ease how NMT data can be collected and be incorporated into the planning and design of travel infrastructure and services to such a degree as to nullify reasons often given for the lack of attention given to the proper designing and planning of NMT infrastructure (Schneider, Patten and Toole, 2005). This is done by means of Bluetooth technology in the form of sensors. By using Bluetooth sensing it is possible to trace the travel patterns of both NMT and MT users and then have the ability to visualise the general travel activity taking place over the course of a typical day. By collecting NMT data in this manner and analysing the behaviour of NMT users across a study area such as Stellenbosch University, it becomes possible to measure current and predict future transportation initiatives and services.

Two services are considered specifically for this study, namely, the provision of micromobility services, which commonly includes transport services such as bicycles, e-scooters, and e-bicycles sharing, and the incorporation of the minibus taxi industry. The collected NMT data will thus be used to identify the distribution of NMT peaks over the study area in order to analyse the space/time behaviour of NMT users with regard to these two services. The provision of micromobility services will be considered on a conceptual level, whereas the incorporation of the minibus taxi industry will be considered more practically in its implementation and operation. The aim, however, remains to display the usefulness of NMT data as a means to design a holistic and optimal MaaS driven system by considering how the data complements the planning of other transportation services. From these findings it is envisaged that this study will indicate

that transportation planning should be viewed as starting not from the ignition of an engine, but from when a person sets their feet on the ground as the morning sun rises.

1.2 Research objective

The first objective of this study was to investigate NMT trends within and on the periphery of the Stellenbosch campus of SU. In collecting NMT data with the use of Bluetooth sensors it was anticipated that the spread of typical NMT behaviour over a 24 hour period across the campus could be elucidated in order to understand NMT behaviour. From this characterisation of NMT behaviour, comes secondary objectives, namely, to identify manners in which NMT data could be used in spatial and transportation planning in order to optimise and provide better NMT experiences. Lastly, the final objective was to examine how existing and future transportation services in the forms of micromobility and the minibus taxi industry could benefit from understanding the space/time characterisation of NMT behaviour in and around the campus.

1.3 Research scope

Stellenbosch, a town located in the south western region of South Africa and which is situated about 50 km east of Cape Town, acted as the testbed for this study. The town had a population of about 176 523 in 2018 which is estimated to rise by 8% to 190 680 by 2023 (Sustainability Institute, 2017). With this level of consistent growth, and given the existing transportation challenges within Stellenbosch, the proper planning of transportation facilities and the need for new innovative ideas are of the utmost importance. Within Stellenbosch, east of the town centre, lies one of the five campuses of Stellenbosch University, which is illustrated in Figure 1.1 on the next page. It is within the confines of this campus where the study took place. The University is a public research university which caters for around 31 000 students based on the 2018 annual University census. Of the 31 000, an estimated 25 000 students attend classes on the Stellenbosch campus, of which an estimated 6 700 reside in Stellenbosch (Mlitwa, 2019). Classes at SU start at 08:00 and end at 17:00, with a standard lecture period of 50 minutes to allow for students to move between lecture venues if necessary. Because a high number of individuals moves around the campus environment daily, as well as the provision of NMT infrastructure generally associated with campus environments (which limit MT), the potential exists to collect a rich set of mobility data. Similar studies have previously also considered using campus settings to collect and analyse the movement patterns of pedestrians (Malinovskiy and Wang, 2012; Malinovskiy, Saunier and Wang, 2012). Although provision was made for NMT in

the forms of pedestrian-only zones, such as Jan Marais Square, known as the Red Square, there was still a heavy presence of road users within this environment, as was evident by traffic on a two-lane dual carriage way (Merriman Road) which split the campus. In addition to Merriman Road, various other streets were also open to MT users.
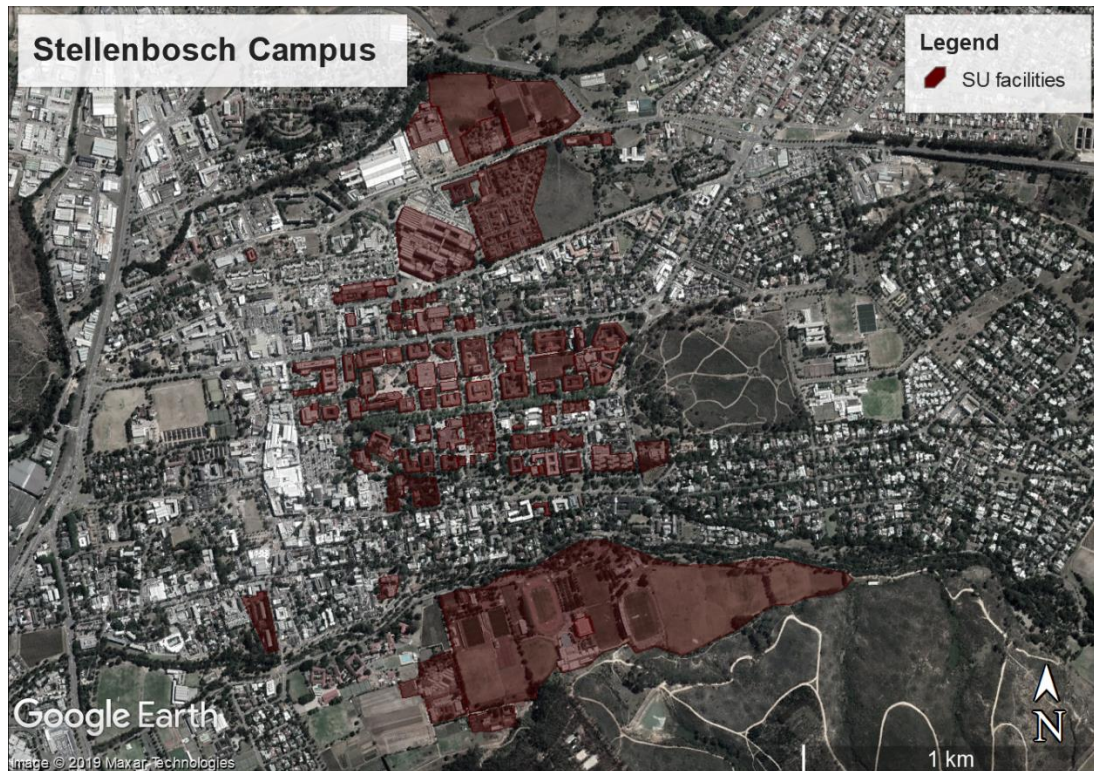
Figure 1.1: Stellenbosch campus (Google Earth Pro, 2019)

Various data collection options existed, of which Bluetooth technology was one. Due to its relatively low costs and ease of implementation it was decided that Bluetooth sensors would be used for this study. Data was collected using 44 custom-made Bluetooth sensors over the period of nine days in order to get an estimation of the daily travel patterns of NMT users. With the data collected from the sensors aided by the use of Microsoft Excel, PTV Visum, and Google Fusion Tables, it was possible to measure the level of NMT activity taking place on the campus throughout a typical 24 hour day, to identify areas on the campus where activity was taking place, and to identify the typical route choices made by NMT users.

1.4 THESIS OUTLINE

The literature review was considered to be the theoretical foundation on which this study was based and aimed to provide the necessary context on which knowledge was formed. Chapter 2 will discuss various pieces of literature pertaining to the different aspects of this study, such as

how NMT is viewed, what relationship it has with MaaS, and various aspects regarding the collection of NMT data. Following from this, the methodological process pertaining to the collection, filtering, and presentation of the data is described in Chapter 3. Chapter 4 then discusses the overall quality of the data, the validation of the cleaning process, as well as the final dataset which was used for this study. The interpretation and findings which is based on this final dataset is then discussed in Chapter 5. Here it is revealed how the trends observed could be applied to various scenarios. Consideration is given to how other role players in the urban environment could use the collected data and trends to optimise the planning of various services and infrastructure before narrowing the focus down to the potential of using the data in optimising future and current mobility services. The conclusion and opportunities for future research are then discussed in Chapter 6.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

The aim of this literature review is two-fold: first, the typical role of NMT within the transportation sector has to be understood, specifically in the context of a MaaS driven system, and secondly, the method by which data would be collected for this study, i.e. Bluetooth tracking, had to be investigated. To comment on NMT, one has to understand the various perceptions of and attitudes towards NMT within the broader transport field. It was thus necessary to delve into the various reasons often given for the collection of NMT data. The role NMT models had within transportation planning and design was also considered. Typically, what was of concern was the level of detail to which authorities usually implemented policies and design in regard to NMT. The financial emphasis and constraints on the collection of data on NMT, compared to that of MT, was also studied, especially regarding the methods by which mobility data was collected and used.

Since it was predetermined that Bluetooth tracking would be used for this study, a comparative overview of Bluetooth tracking, compared to other mobility data collection methods had to be established. By doing so, a broad sense of the advantages and limitations regarding Bluetooth tracking could be established. It was, however, still vital to form a deeper understanding of how Bluetooth technology operates. This understanding would then allow for clear communication with the technical team constructing and designing the Bluetooth hardware used for this study.

This chapter is thus structured as follows: Section 2.2 discusses NMT, where attention is placed on the typical roles of this mode of transport within the transportation field. In addition, MaaS was also studied in order to understand the extent to which the collecting of NMT data and the understanding of NMT movement has been considered within the planning and design of MaaS systems. Moving on to Section 2.3, typical data collection methods pertaining to NMT are discussed. An understanding was formed of the advantages and drawbacks of the different collection methods. Emphasis was then placed-on Bluetooth tracking in Section 2.4. This section dissects and analyses the various concerns regarding Bluetooth tracking as a mobility data collecting tool. As part of the conclusion of this chapter, Section 2.5 summarises the various points discussed in this chapter.

2.2 NMT AND MaaS

NMT is best understood in its definition as described by Neun (2018) in his paper on *Fusion Mobility*. Here Neun described NMT as the opposite to fuel or electric based modes of mobility (MT). Thus, common modes of NMT would include walking, cycling, and such activities as skateboarding. In addition, Neun mentions modes which he regards as hybrids between MT and NMT, such as e-bicycles and e-scooters. For the purpose of this study, these modes will be considered as NMT modes. Common reasons given for considering the role of NMT within the transportation planning field were: the efficient planning and analysis of NMT infrastructure (Tanaboriboon and Guyano, 1991; Hood, Sall and Charlton, 2011; Royal HaskoningDHV, 2016), understanding the travel behaviour of NMT users for commercial or public facility designs (Tanaboriboon and Guyano, 1991; Buckland and Jones, 2008; Hood, Sall and Charlton, 2011; Malinovskiy and Wang, 2012; Malinovskiy, Saunier and Wang, 2012; Ryus *et al.*, 2014), promoting the health benefits associated with NMT and working towards solving challenges associated with MT (Royal HaskoningDHV, 2016; Wegener *et al.*, 2017).

Although reasons given for the promotion of NMT included the relief aimed at MT challenges, other paradigm shifts within the transportation sector also strive towards to same goal. Recently, the concept of MaaS has been promoted as a means to solve common urban mobility challenges (Karlsson, Sochor and Strömberg, 2016; Goodall *et al.*, 2017; Pangbourne *et al.*, 2018). MaaS is referred to as a central serving point from which users could access their transportation needs, commonly in the form of mobile applications. The foundation on which a successful MaaS system can be operated is dependent on various factors, including the cooperation between public and private sectors and transportation service providers, as well as subsidies to support the system (Goodall *et al.*, 2017; Pangbourne *et al.*, 2018). This relationship is best illustrated by Pangbourne *et al.* (2018) in Figure 2.1 which identifies and explains the typical roles and partnerships of the various entities participating within a MaaS driven system. In regard to Stellenbosch, a MaaS app/system would thus be operated by the municipality in partnership with transportation service providers such as Metrorail, MyCiti, Golden Arrow, Uber, Taxify, Mellowcabs, etc. The potential also exists that transportation services which would be offered by SU to students could be incorporated into such an app/system. Currently, no NMT services exist around Stellenbosch, except for Maties bicycles which students at SU can hire for an academic year (Stellenbosch University, 2019).
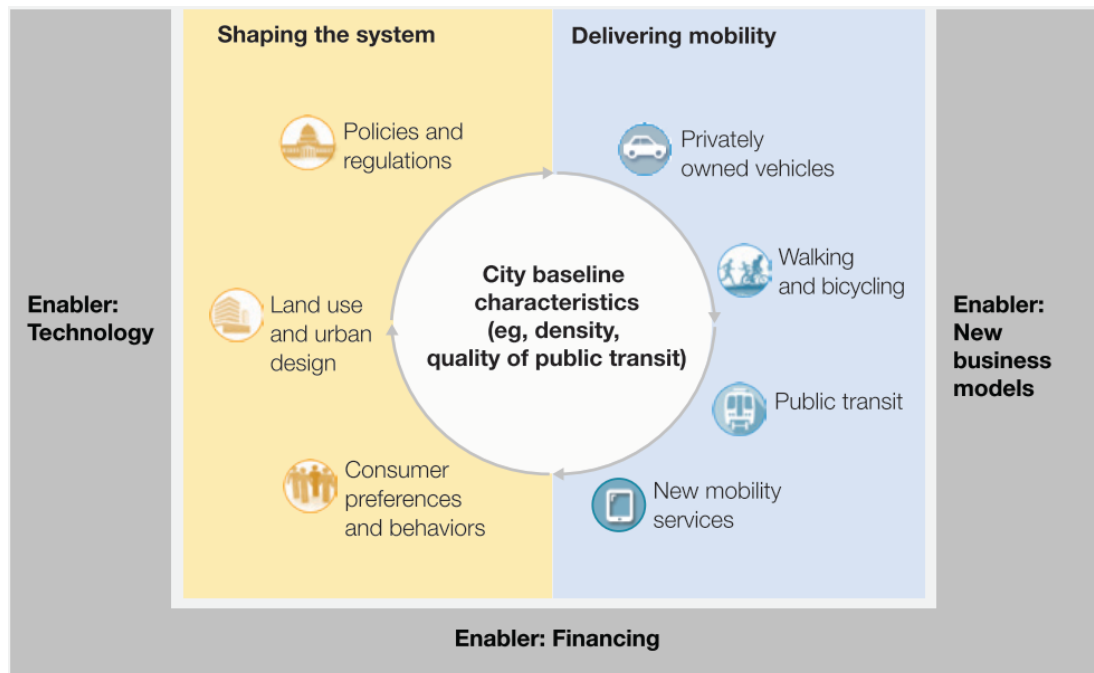
Figure 2.1: A framework for understanding urban mobility (Bouton *et al.*, 2015)

Although MaaS is viewed by many as a favourable transportation system, it was found that little attention was given to NMT modes as part of this system. Commonly, NMT only came into play in the form of bicycle sharing (Karlsson, Sochor and Strömberg, 2016; Goodall *et al.*, 2017). To this end, it was concluded that a possible reason for this lack of promotion of NMT (especially in the form of walking) was that a high level of financial and technical support was required to operate a MaaS system. As NMT does not generate high levels of revenue, it was thus not justifiable to support it compared to other means of transportation (Pangbourne *et al.*, 2018).

However, the potential of the use of NMT hybrid modes (Neun, 2018), such as e-bicycles and e-scooters, was currently being investigated with emphasis on their role within micromobility (Reed, 2019). Reed argues that the concept of MMaaS may have beneficial impact on urban mobility in the sense of making travel more efficient, accessible, and convenient. He further argues that these benefits stem from these modes' higher efficiency in terms of energy and space. Considering the transportation network and urban layout of Stellenbosch, one should then consider what NMT patterns could reveal in terms of providing micromobility services as alternatives to traditional NMT modes. Perhaps, as Reed argues, the use of these modes, which highlights consumer and commercial appeal in countries such as the United States, United Kingdom, and Germany could be used favourably in an urban setting such as Stellenbosch by students, residents, workers, and visitors.

2.3   MOBILITY AND DATA

Although it was decided that Bluetooth will be used as the main method of collecting the travel behaviour of NMT, various other data collection methods exist. In order to fully understand the limitations, advantages and disadvantages associated with Bluetooth technology, it was necessary to examine these different methods in order to compare them.

The first and most basic form of collecting mobility data is counts. The counting of transportation modes is well known within the transportation field. With the advances of technology, counts today can be done either manually (by means of counting officers) or automatically (by means of infrared scanners, inductive loops, and even computer vision technology) (Schneider *et al.*, 2005; Semanjski and Gautama, 2016; Kurkcu and Ozbay, 2017). Generally, counts will not necessarily reveal travel patterns (with the exception of computer vision), however, counts are generally useful in terms of determining traffic flow rates, traffic volumes, and traffic densities. Counts are generally considered to be a costly exercise, however, the advantages pertaining to manual counts is that multiple modal forms can be incorporated in a counting session. As there are several reasons for conducting or not conducting counts compared to other data collection methods, Table 2.1 summarises the general findings regarding manual and automatic counts.

Table 2.1: Advantages and disadvantages of counts

Manual counts	Advantages	- Can be integrated with other transport modes - Leaves less room for error - Categorises transport modes
	Disadvantages	- Costly - Labour intensive
Automatic counts	Advantages	Reduces labour costs
	Disadvantages	- Positioning of devices are crucial in minimising error - Only computer vision can distinguish transport modes - People are still required for post-processing of data - Maintenance and implementation costs are high - Outside factors, such as rain and low-lit areas, influence the accuracy of counts

As counts focus mainly on quantifying mobility, other data collection methods seek to understand the associated behaviour. In this regard, many often use travel surveys (Schneider, Patten and Toole, 2005). Surveys have various forms, including household travel surveys, and national census. Surveys often provide authorities with a base-line dataset. Surveys are considered labour intensive and costly and generally represent a limited number of mobility

users (Schneider, Patten and Toole, 2005). Ideally, surveys should represent a sample of a target population from whom the data is collected. Commonly, the data collected from surveys is used for modelling purposes which focus on determining trip origins and destinations, trip frequencies, purposes, and preferred travel modes. Semanjski and Gautama (2016) found that NMT is generally underrepresented in surveys.

With the advancements of mobile technologies, such as the smart phone, as well as with improvements regarding GPS, new innovative manners exist in which mobility data can be collected. In regard to the use of GPS and mobile phones in conjunction with NMT, various studies explore the feasibility of this data collection method (Hood, Sall and Charlton, 2011; Semanjski and Gautama, 2016; Lue and Miller, 2019). With the creation of apps which cater for cyclists, GPS data as well as data often collected via surveys, can be collected and used to plan cycling paths. The use of such an application, however, revealed a user bias which favoured the cycling enthusiast. This resulted in a skewed perception that could exist where investment in the development of cycling infrastructure should be prioritised. (Hood, Sall and Charlton, 2011). A general problem encountered in the use of mobile applications to determine NMT route choices was the willingness of persons to interact with the applications. Commonly the effect of the app on a phone's battery life, as well as the use of personal information, deterred users from downloading applications (Lue and Miller, 2019). Consideration should thus be given to how invasive data collection methods of this nature are. In this regard, Semanjski and Gautama (2016) identified two types of data collection methods, one being a passive manner of data collection and the second being active.

Passive data collection apps will collect data in the background. Commonly, these apps will log GPS data, but will not require the user to physically interact with the app. Active data collection apps require users, for example, to create profiles as part of the process of using the app. The advantage associated with this method is that a richer set of data is obtained. When considering the concept of MaaS in this regard, the active data collection method could easily be incorporated into a MaaS application. Given that the data collected from such an application would belong, most likely, to a local government, it would empower such a government to better plan for transportation infrastructure and initiatives. Commonly, the data collected from applications allows for the estimation of route choices, travel speeds, as well as providing a higher resolution to the spatial and temporal data collected (Semanjski and Gautama, 2016).

Touching briefly on the use of Bluetooth and Wi-Fi as a means to collect movement data, most often the reason for using these two methods lies within their 48-bit Media Access Control (MAC) address (Wasson, Sturdevant and Bullock, 2008; Fabron, 2016). This address is unique for any Bluetooth or Wi-Fi enabled device, meaning that, by applying matching algorithms across a Bluetooth sensing environment, it is possible to track the movement patterns of a specific Bluetooth device. Using Bluetooth and Wi-Fi technology in the form of sensors is also considered relatively cheap (Malinovskiy and Wang, 2012; Malinovskiy, Saunier and Wang, 2012; Dunlap *et al.*, 2016; Lesani and Miranda-Moreno, 2018). The use of Bluetooth technology specifically is discussed in more detail under Section 2.4 below.

This understanding of the various data collecting methods can best be summarised using Table 2.2 adapted from the United States Federal Highway Administration (2013) and Kurkcu and Ozbay (2017). Here the various methods are placed in order of the term of their usage and their associated costs. Consideration was also given toward pedestrian detection. It should be noted that some methods mentioned below were not discussed as part of this literature review due to: 1) the data collection method being applicable to only one NMT mode and 2) the feasibility of implementing the method for this study was unlikely.

Table 2.2: Available pedestrian counting technologies (Federal Highway Administration, 2013; Kurkcu and Ozbay, 2017)

	Technology	Bicyclist only detection	Pedestrian only detection	Cost
Permanent	Wi-Fi and Bluetooth sensors	●	○	R
	Inductive loops	○	N/A	RR
	Magnetometer	○	N/A	R - RR
	Pressure sensor	○	○	RR
How long?	Radar sensor	○	○	R - RR
	Seismic sensor	○	○	RR
	Video imaging: automated	○	○	R - RR
	Infrared sensor: active or passive	○	●	R - RR
	Pneumatic tubes	●	N/A	R - RR
Temporary or short term	Video imaging: manual	○	○	R - RRR
	Manual observations	●	●	RR - RRR
Note: ○ = what is technologically possible; ● = a common practice; R, RR, and RRR indicate relative cost per data point. Video imaging and computer vision are one and the same				

2.4   BLUETOOTH TECHNOLOGY

2.4.1   Overview

In order to understand the limitations of using Bluetooth as a means to collect spot data, it was necessary to understand how Bluetooth functioned on a conceptual level. Fabron (2016) refers to Bluetooth as a wireless communication specification operating on the unlicensed 2.4 GHz band. This frequency is shared by other wireless communication specifications, including Wi-Fi, microwave ovens, and drones. The frequency is unlicensed in many areas of the world, however, under the guidance of the Bluetooth Special Interest Group (SIG), it is regulated in regard to the units of power (Watts) which may be transmitted over the frequency, the modulation schemes used, and unintentional out-of-band radio frequency (RF) interference. In order for devices to communicate with each other, Bluetooth uses wireless personal area networks (PANs). As part of the communication process, devices using Bluetooth require a transmitter, a receiver and modem-like control chips which modulate and demodulate digital signals. These components are frequently integrated into one System-on-Chip (SoC) which commonly includes a receiver, an antenna, and a control chip.

Bluetooth operates by communicating over a small network (piconet). The simplest form is a point-to-point piconet where one Bluetooth device acts as the primary device and another as the secondary device. In the case of a multipoint-to-point piconet, up to seven secondary devices can be connected to one primary device. The primary device is responsible for initiating a piconet. The universal method shown in Figure 2.2 below, is commonly used to establish connections.
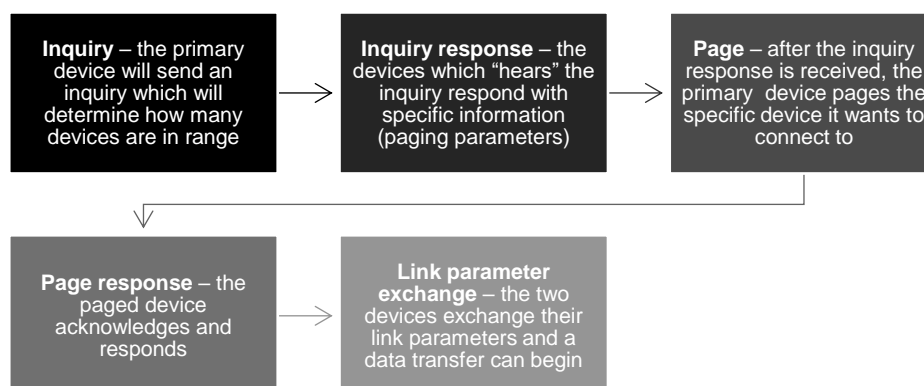
Figure 2.2: Establishing a link between Bluetooth devices

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A Bluetooth device can be in several states, depending on the type of operation expected of it or the command it has received. Figure 2.3 shows these various states as well as their relationship towards one another. For this study, however, the inquiry, inquiry scan, and inquiry response state were what was of importance, since the sensors main purpose is only to identify devices and log these devices. No connection was thus necessary between any two devices.
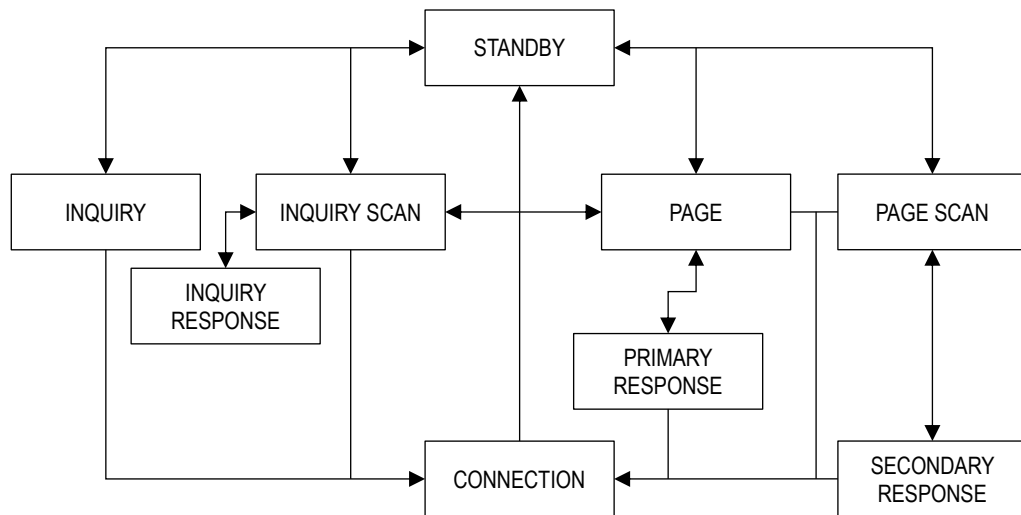
Figure 2.3: Different states of Bluetooth (Gene Fabron, 2016)

A detailed explanation of the RF transmission modulation techniques falls outside the scope of this research project. However, when considering the limitations of using Bluetooth as a means to collect transport data, it is important to consider the transmitter characteristics of Bluetooth devices. Based on their highest output power capabilities, Bluetooth devices are characterised according to Table 2.3. The signal range can be disturbed by various interferences, classified as either physical obstructions (such as walls), other Bluetooth piconets, or other protocols on the 2.4 GHz band. Additionally, it should be noted that for this study the transmission range of the sensors was not of any importance, since the sensor would only be receiving signals, not transmitting them.

Table 2.3: Bluetooth device classes (Fabron, 2016; Bluetooth SIG Proprietary, 2019)

Class	Maximum output power	Signal range
1	100 mW	~ 100 m
2	2.5 mW	~ 10 m
3	1 mW	~ 1 m

2.4.2 Bluetooth tracking

It was found that Bluetooth was commonly employed along road corridors in order to determine travel times along these corridors (Wasson, Sturdevant and Bullock, 2008; Malinovskiy and Wang, 2012; Malinovskiy, Saunier and Wang, 2012). Increasingly, Bluetooth or Wi-Fi (which also makes use of unique MAC addresses) sensors were being used at bus or train terminals, or the modes themselves, as a means to estimate O/D demands and establish waiting times (Dunlap *et al.*, 2016; Shlayan, Kurkcu and Ozbay, 2016).

While some studies have considered using Bluetooth as a means of tracking shopper activity or for crowd control (Utsch and Liebig, 2012; Oosterlinck *et al.*, 2017; Yoshimura *et al.*, 2017), only a few studies have considered using Bluetooth for the purpose of NMT infrastructure planning. Consideration was, however, not given in these studies to how NMT data could potentially be used as a means to complement other transport services. It was found by Malinovskiy *et al.* (2012a) that by using static Bluetooth sensors, specifically at the ends of travel corridors, travel behaviour could be determined by estimating travel and dwell times of pedestrians at the Universities of Washington and Montreal. Although a low penetration rate of 2% and 5% was established, it was remarked that it was still possible to examine general trends. Concern was mentioned for scenarios with low pedestrian volumes as it was assumed that low volumes would result in little Bluetooth activity. Additionally, it was remarked that a bias could potentially exist towards the use of Bluetooth sensors in preference to other types of collection methods. Malinovskiy *et al.* (2012a) mention a study which conducted tests at bus stops across Seattle which indicated higher Bluetooth activity within less affluent neighbourhoods. Similarly, Malinovskiy *et al.* (2012b) considered examining travel behaviour of students by turning individuals into travel sensors by means of mobile sensor. The mobile sensor consisted of a smartphone with an application which logged the time and place where Bluetooth devices were detected. A low penetration rate (roughly 2.25%) was again observed with this study.

When considering using Bluetooth sensors across such a wide network, where various modes of transportation exist, the question is raised of how one should apply modal classification. Single detections would not reveal a modal choice, but given the travel time between at least two sensors, a modal choice needs to be estimated. Unfortunately, little consideration is given in the research on how the use of Bluetooth within transportation planning helps towards modal differentiation. It is thus necessary that other factors, such as where a signal was recorded (arterial or NMT-only spaces) or the travel characterises of signals logged at different sensors,

be considered in differentiating between travel modes of users. In Bathaee's 2014 study, methods are presented explaining how one could classify modes using various clustering methods. These methods were, however, applied to a restriction of at least two to three sensors along a corridor, with the use of counts as a means of supporting the clustering methods (Bathaee, 2014). Thus, the study cannot be compared to this research project, which examines 44 sensors, as the expected movement will vary from sensor to sensor and the time to conduct extensive counts was also not available. Some research also considered using logit models as a means of classifying modes (Lesani and Miranda-Moreno, 2018) where calibration in the forms of counts, as well as video footage, were again needed to reduce margins of the error. Similarly, to the previous study, this method was also applied to data collected by only three sensors. Although a proper investigation into a modal classification model would be of immense value, the exercise of creating such a model falls outside the scope of this research study. Thus, for simplicity, and roughly based on the two studies mentioned above, modal classification will be based on travel time in the simplest terms, where the counts at individual sensors will be used to validate the modal classification across the dataset.

2.4.3   Limitations

From what was studied regarding Bluetooth as a data collection means, the following limitations could be identified. The majority of Bluetooth devices can be regarded as Class 2 devices, meaning a transmission signal range of up to 10 m can be assumed (Fabron, 2016). Additionally, the penetration rate associated with Bluetooth sensing can fluctuate between 2-12% due to either a lack of persons carrying Bluetooth devices or persons who have put their Bluetooth off (Wasson, Sturdevant and Bullock, 2008; Malinovskiy and Wang, 2012; Malinovskiy, Saunier and Wang, 2012; Shlayan, Kurkcu and Ozbay, 2016; Kurkcu and Ozbay, 2017; Lesani and Miranda-Moreno, 2018). Due to this low penetration rate, volumes cannot be accurately determined, although, using correction models, it would be possible to estimate volumes. This, however, would require that sufficient counts also be collected in order to correctly calibrate the models for the various sensors (Lesani and Miranda-Moreno, 2018). Finally, it was established that modal classification is not an easily automated process and it would require much more time to create an appropriate model for a study area of this size in order to correctly classify travel modes (Bathaee, 2014; Lesani and Miranda-Moreno, 2018).

Although not a limitation in the sense of those discussed above, literature on the use of Bluetooth as a data collecting tool has highlighted the privacy concerns of individuals

(Malinovskiy, Saunier and Wang, 2012; Kurkcu and Ozbay, 2017; Oosterlinck *et al.*, 2017). In these studies, the common concern raised was that because MAC addresses are registered to individual devices, it would be possible (albeit through a lot of effort) to track individuals. From these three studies a consensus was reached that in order to avoid scrutiny of any of the data collected during the research period, an automatic system would need to be put into place which anonymised logged MAC addresses and issued them with new identifiers which could not be traced back to an individual. This process was used in order to gain the necessary approval from the Research Ethics Committee (REC) at Stellenbosch University for this research study.

2.5 CONCLUSION

This chapter has served as the basis on which knowledge will be built throughout the study. In order to understand the context of NMT within transportation engineering, a brief overview of NMT was first provided. From this, the reasons as to why engineers and planners had traditionally collected NMT data was examined. It was found that, commonly, NMT data is crucial for the maintaining and planning of NMT facilities, as well as promoting NMT for its health and sustainability benefits (Tanaboriboon and Guyano, 1991; Buckland and Jones, 2008; Hood, Sall and Charlton, 2011; Malinovskiy and Wang, 2012; Malinovskiy, Saunier and Wang, 2012; Ryus *et al.*, 2014; Royal HaskoningDHV, 2016; Wegener *et al.*, 2017).

Given the prevalence of MaaS and the aim of the study, which is to understand NMT in the hopes of identifying how NMT trends could be used to complement other transportation services, a typical understanding of MaaS as the integration of various forms of transport services into a single mobility service, accessible on demand, was desired. It was established that commonly, NMT in the form of walking does not serve as a major mode within MaaS systems, given that for a MaaS system to operate effectively, financial support is crucial – which generally comes from MT service operators (Pangbourne *et al.*, 2018). Nonetheless, walking would still be required as a means of travel between service points within a MaaS system. With the development of bicycle sharing, as well as NMT hybrid modes in the form of e-bicycles and e-scooters, it appeared that these modes, however, would be favourably accepted for a MaaS system (Reed, 2019).

With an understanding formed of what to consider in the dissecting of NMT data from a MaaS perspective, consideration was given to the manners in which NMT data could be collected. Although it was decided that, given the convenience of Bluetooth technology, Bluetooth sensors

would be used to collect spot data, an overview of other methods was still required to understand the benefits and limitations of using Bluetooth for this study. Various methods were evaluated, such as counts, surveys, and apps which collected movement data. Commonly, it was established that financial constraints regularly affected the choice of data collection method. Given the evaluation of these various methods, it was concluded that the Bluetooth sensors would suffice for this study.

Although the use of Bluetooth sensors compared to other data collection methods was examined, an understanding of the technical operations of Bluetooth technology was still desired in order to ensure that the research could be carried out as effectively as possible. For this study, the focus was placed on how Bluetooth devices communicated, the typical range over which these devices can communicate, and how Bluetooth was commonly used by transportation engineers and planners in practice. Limitations could thus be identified, which were incorporated into the methodological process. This also enabled clear communication between the research team and the technical team which provided the Bluetooth sensors and additional services.

CHAPTER 3

METHODOLOGY

3.1 INTRODUCTION

Since the goal of this study is to analyse the typical NMT behaviour of persons moving about on SU's Stellenbosch campus, it is important that this study be non-invasive. The data collection process thus incorporated 44 sensors which was procured with additional services from Bridgiot, a local start-up company based in Stellenbosch. The sensors logged the Bluetooth signals of Bluetooth enabled devices traveling within the boundaries of the study area. It was important that these sensors be placed effectively across the study area in order to collect NMT user data efficiently.

Although the placement of the sensors would ideally detect NMT users, the data collected nevertheless represented only Bluetooth devices and not NMT users. Thus, travel modes (NMT or MT) could not be determined. To distinguish between NMT and MT users, various filters were coded to not only remove unnecessary data, but to create an ultimate NMT dataset. As part of this filtering process the data was configured into formats familiar to persons using traditional transportation engineering methods to analyse mobility, such as origin/destination (O/D) Matrices. Once the data was presentable, the analysis and validation of the data collection and data filtering processes could be commenced. The final dataset could then also be placed under the necessary scrutiny. Ultimately, the data could then be applied, and findings could be established. The overall process used for this study is illustrated in Figure 3.1.

Collect data → Filter data → Analyse data → Apply data

Figure 3.1: Basic description of methodological process

The layout of this chapter is presented as follows: Section 3.2 briefly describes the research design used for this study. Ethical considerations and the process of obtaining ethical clearance is discussed in Section 3.3. Section 3.4 deals with the data collection tools and software used

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during the course of this study. Following from this, the data filtering process is described in Section 3.5. Due to the various assumptions, limitations, and constraints across the methodological process, Section 3.6 aims to summarise and discuss them in detail. Section 3.7 then serves as the conclusion for the chapter.

3.2   RESEARCH DESIGN

The research design for this study can be described as descriptive. The data collected during the course of this study was obtained without any direct intervention from the researcher. Research periods were also chosen in such a way as to minimise the impact of external factors and events on the typical movement patterns within the study area.

3.3   ETHICAL CLEARANCE

Since the potential existed for the tracking of persons moving around the study area, it was necessary to receive ethical clearance from the REC at SU. This process entailed providing measures to ensure that no person could be traced during the course of this study and that no person's privacy could be affected. Additionally, the collected data had to be stored in a secure and restricted location.

Regarding the anonymisation process, the Bluetooth sensors were designed to log the MAC address of any device whose Bluetooth settings were on. Since MAC addressed are unique for every Bluetooth equipped device, the logged MAC addresses were immediately stripped and given new unique IDs. These IDs could not be traced back to their original MAC addresses, thus ensuring anonymity. This process was conducted similarly to the process in studies mentioned in Section 2.4.3 (Malinovskiy, Saunier and Wang, 2012; Kurkcu and Ozbay, 2017; Oosterlinck *et al.*, 2017).

Once the data was received from Bridgiot, the data was uploaded to a computer lab which could be reached only through three card-accessible doors. Only Civil Engineering staff and graduate students have access to the first two doors, while the last door could be accessed only by staff and students affiliated with the Stellenbosch Smart Mobility Lab (SSML).

Once the necessary protocol had been completed, ethical clearance was received from the REC.

3.4 RESEARCH INSTRUMENTS

The toolset used for this study consisted of Bluetooth technology (for data collecting purposes), Microsoft (MS) Excel (for data filtering, visualisation, and analysis purposes), Google Fusion Tables, and PTV Visum (both used for visualisation and analysation purposes). The various assumptions, limitations and constraints relating to the research instruments are discussed in more detail under Section 3.6.

3.4.1 Bluetooth sensors

The Bluetooth sensors used consisted of a Raspberry Pi computer board (referred to as simply Pi) and a battery pack. The hardware can be seen in Figure 3.2. The choice of Bluetooth technology was based on its capabilities as discussed in Chapter 2 as well as being relatively inexpensive. Bridgiot, a local start-up company based in Stellenbosch assisted in manufacturing the hardware, as well as providing additional services. Given the limited budget, the sensors were optimised in their design and number. Ideally, the sensors could have been built to provide real-time data. For this, a constant power supply and internet connection was required. Nonetheless, the sensors were connected to battery packs which would supply power for between three to four days depending on the amount of data collected. Internet connection was supplied in the form of a Wi-Fi hotspot created from a smartphone. The sensor was thus only connected to the hotspot just before a collecting period and afterwards, the first connection was used to set-up the internal clock of the Pi and the second to upload the collected data to a database. To conserve additional power, the Pi model used was the Pi Zero which uses Bluetooth Low Energy (BLE). BLE is designed for short bursts of small data packets over a longer range in order to conserve the battery life of the devices using it.

In reference to Chapter 2 on the workings of Bluetooth technology Fabron (2016), the sensors in effect sniffed for other Bluetooth devices. Once the sensors identified other visible devices, they were programmed to log the time of the detection, the MAC address of the detected device (which was anonymised), and the time at which the device was no longer detected. This information was then stored in a Comma Separated Values (CSV) file. Further data enrichment, which included the temperature, weather, and sunlight conditions took place once the data had been uploaded to the data server.

Although it had been envisioned to have 45 sensors, one sensor was removed due to vandalism, and hence only 44 sensors were used to collect data during the three main data collecting

periods. In order to deter vandalism and to comply with guidelines set out by Stellenbosch Municipality and SU's Facilities Management, the boxes in which the sensors were installed were mounted on metal straps at a height of 2.5 m.

Figure 3.2: Bluetooth sensor

Due to the number of sensors, a mesoscopic approach was taken in choosing the locations of the points where data was collected. This meant that sensors were placed in locations neither too far from nor too near to each other. Should the sensors have been placed at greater distances, it was assumed that the data collected would be limited to only detections and it would not be possible to distinguish trips i.e. an origin-destination pair. However, should the sensors have been placed too close to each other, only a small area could have been studied. The final locations are shown in Figure 3.3. The study area consisted of an area traversed mainly by students. Although NMT infrastructure is present within the study area, cars have a heavy presence as well. The boundary of the study area was chosen by considering how movement took place around the campus. Five main observations were made in this regard. First, the location of recreational areas frequently visited by students was considered. These areas are located mostly to the south west of campus, and thus, sensors were placed along Andringa, Plein, and Van Riebeeck Streets. Shops, restaurants, pubs, and nightclubs are located mostly to the west and south of these streets. Secondly, the Coetzenburg sports facilities

and mountain trails were considered. Sensors along the eastern side of Van Riebeeck Street were placed to collect movement between the campus and these areas. Residential activity, however, would also have been collected as Van Riebeeck Street is one of the few routes residents (predominantly non-students) from the south eastern side of campus could take to travel from their houses towards the town centre and out of town. Thirdly, the Engineering Faculty and its surrounding area was considered. The Engineering Faculty is situated at the northern side of campus and can be viewed as being on the boundary of the campus. Banghoek Street (along which the faculty is situated) was thus chosen as the northern boundary line along which sensors were placed. It was argued that movement further north and west of this street would not be applicable to the study area and hence was not applicable to this study. Fourthly, the area situated directly to the north east of campus, which comprises mostly private student accommodation, was considered. It was thus assumed that travel interactions would take place between this area and the campus and that, due to a lack of recreational facilities in this area, travel activities within the area itself were regarded as irrelevant. Lastly, the locations of the common parking areas around the campus were considered along with the aforementioned considerations. Parking was a known problem within Stellenbosch; thus, it was assumed that movement to and from these parking areas would correlate with movement to and from campus.

With the boundaries determined, empirical observations regarding the movement of NMT users were used to place the remaining sensors. Sensors were thus placed, for example, between lecture halls, and coffee shops. Additionally, consideration was given to the road network and infrastructure, such as pedestrian crossings, one-way roads, and NMT-only facilities, as well as the locations of the various construction sites during the time of this study.

3.4.2   MS Excel, PTV Visum, and Google Fusion Tables

MS Excel was used because of to its built-in functions with which data can be analysed and its programming platform, Visual Basic for Application (VBA). With the use of VBA, macros were developed with which the data was filtered, and formatted. Macros consist of programming a series of actions which can be written up and performed in MS Excel. The data was visualised in MS Excel by means of graphs. Along with these graphs, maps would also be generated. Using PTV Visum and the O/D matrices, O/D maps could be visualised which also displayed detections at sensors. In addition, Google Fusion Tables could be used to translate the detections to geographical intensities in the form of heatmaps.

3.5 METHODOLOGICAL PROCESS PERTAINING TO THE DATA

3.5.1 Background

Data was collected for three different periods. The periods were selected in such a manner as to avoid any events which might disrupt typical daily travel patterns, such as a Varsity Cup game and SU's Open Day. These selected periods would thus reflect a typical day of movement on the Stellenbosch campus which could be used to base findings on. In order to ensure that typical behaviour was captured, the days which the periods were based on were Tuesdays to Fridays. The reasoning behind why these days were chosen will be explained hereafter. The three periods are summarised in Table 3.1.

Table 3.1: Data collection periods

Period	Start date	End date	Effective period length
1	09 April 2019	12 April 2019	2
2	23 April 2019	26 April 2019	2
3	30 April 2019	03 May 2019	2

Effectively the sensors collected data for two weekdays, when disregarding the day on which the sensors were placed and removed. The days of the week which were chosen as collecting periods: 1) were based on reflecting the general daily movement patterns of persons within the study area and 2) were based on the time it took to recharge the batteries of the sensors. In regard to collecting typical movement patterns, it was important that Wednesdays be included as part of the data collection period, since it is known that on Wednesday evenings students often visit the local pubs and nightclubs in and around Stellenbosch.

Having made the decision to include Wednesdays, it was then decided that the batteries had to be collected before the start of the weekends in order to have them fully charged before the start of the next week. The assumptions, limitations, and constraints pertaining to the selection of the data collection periods, as well as the data filtering process, is described in detail under Section 3.6.
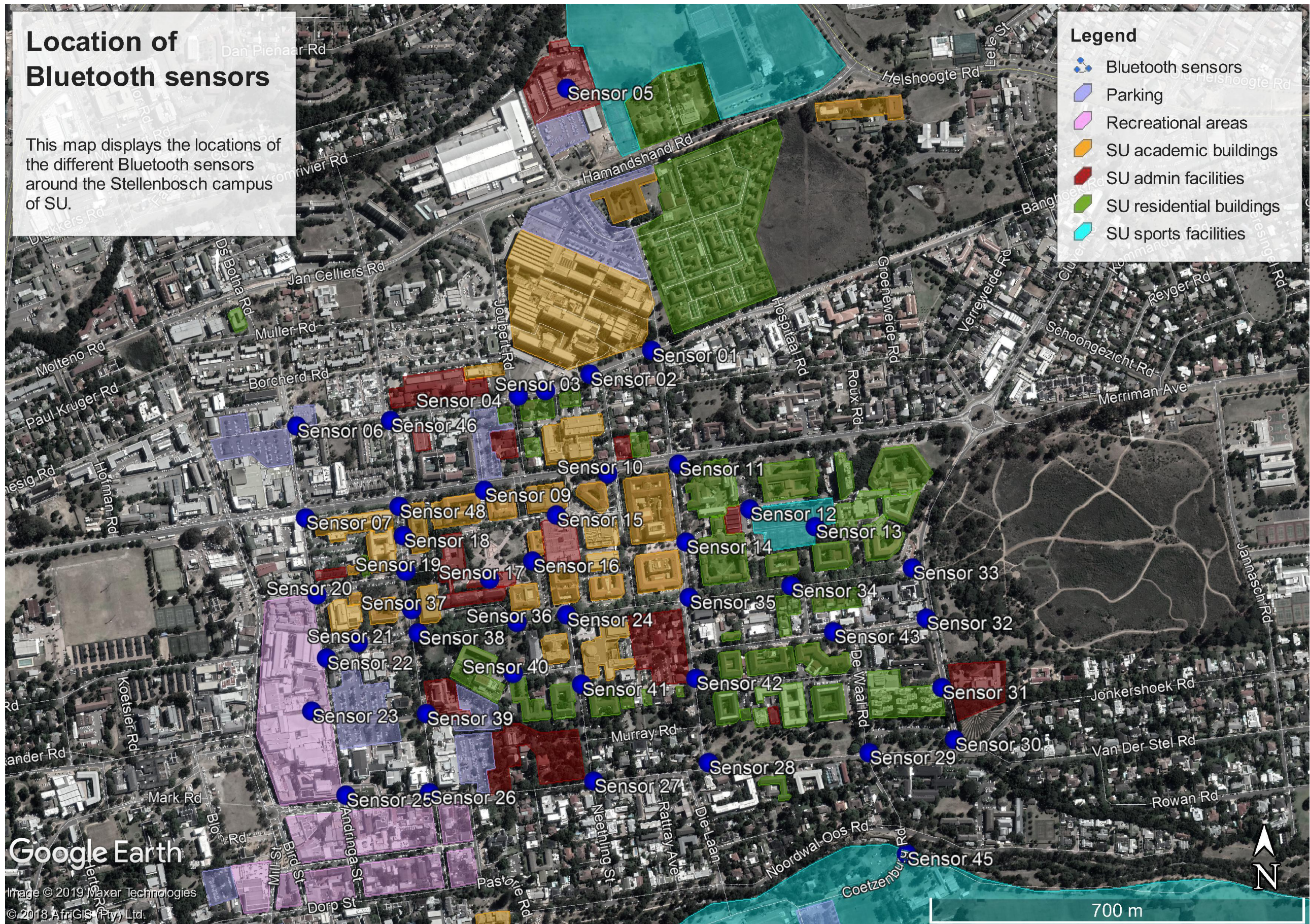
Figure 3.3: Sensor locations (Google Earth Pro, 2019)

3.5.2 Filtering methodology

The following methodology (Figure 3.4) pertaining to the filtering process was developed and is described below. Due to the vast amount of data under consideration (the raw data consisted of three MS Excel sheets worth of data), it was important to have a solid step-by-step approach which could be applied consistently. Additionally, to ensure that little room for error existed with the development of the macro codes, no data could be fully deleted during the filter process.
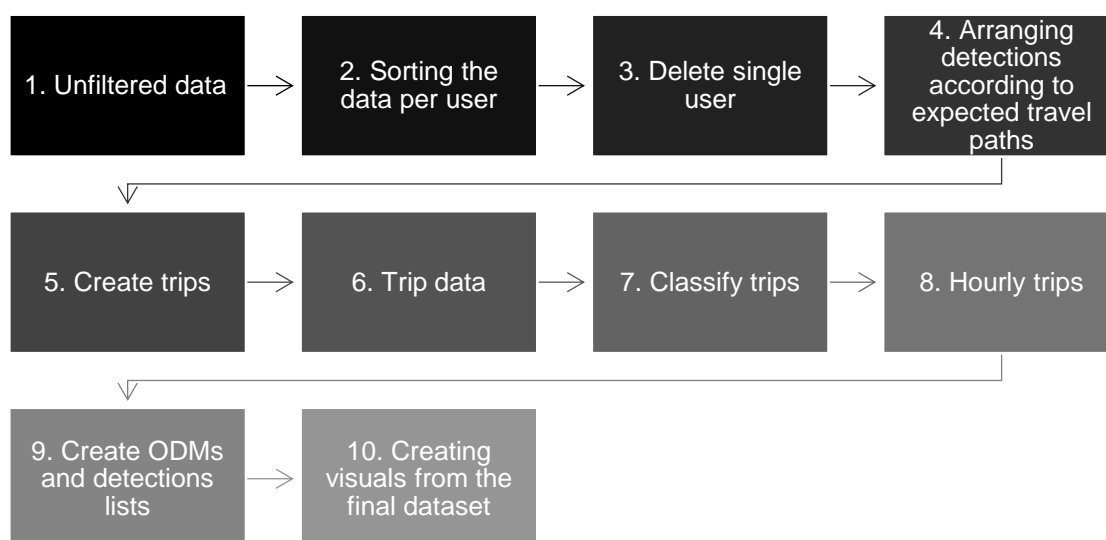
Figure 3.4: Data filtering methodology

Figure 3.4 indicates the 10-step methodological process used to filter the data. The coded filters were designed with this process in mind. This process is considered comprehensive in its consideration of how to translate the data received via logged Bluetooth MAC addresses to NMT movement patterns. Given the size and complexity of these codes, a CD can be found attached to the copies of this thesis meant for examination which contains one of the three macro-enabled filtered Excel files. The macros can thus be viewed using this file. The macros which are relevant to certain steps will be indicated in **blue** in order for the reader to identify the step in the Excel file. It should be noted that the macros were run in alphabetical order and that some macros are not mentioned in the process below given that the process described the general approach followed. Any request for the macros for digital readers can be directed to the author of this thesis. The filtering process can then be described as follow:

1. **Unfiltered data**: The raw data was received from Bridgiot as a CSV file. The data was then converted to a macro-enabled workbook format (.xlsm). This format allowed for the writing of macros using Excel.

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2. **Sorting the data per user**: The data was originally grouped per sensor. In order to ensure that the Macros functioned efficiently, the data was manually regrouped chronologically by User IDs.

3. **Remove single users**: Since it could not be established whether users who were only detected at a single sensor were traveling by NMT or MT means, these users were removed from the datasets. To establish whether a user travelled by NMT or MT means, detections between two sensors were required to determine travel characteristics. *Macro A: DeleteOneSensorUsers()*

4. **Arranging detections according to expected travel paths**: A complication emerged during the data filtering where it was found that the data was only stamped per minute and not per second. This meant that it was not possible to determine the chronological order of a user's detections if those detections were logged by various sensors in the same minute. In order to overcome this, the distances between the 44 sensors were measured according to the longest path which could be travelled between two sensors by means of walking. These distances were stored on a separate sheet. A macro was then written to read the distance between sensors which was recorded in the same time frame and, depending on which sensor was the closest, predecessors and successors could be established and the data could be arranged accordingly. From here, the users chronological travel pattern between sensors could be arranged. *Macro B: SortTimeStampSensors()*

5. **Create trips**: A new sheet was created where the data was reformatted to reflect single trips between sensors, i.e. establishing O/D movements. *Macro C: CreateTrips()*

6. **Trip data**: A sheet containing the travel distance was created in Step 4. Using this sheet, general travel characteristics could be determined for each trip. This included, determining travel time between sensors, as well as travel speeds. These characteristics were populated for all the trip. *Macro D: FillTrips()*

7. **Classify trips**: Travel speed was the main criterion used to classify users as NMT or MT. However, two other criteria were also used. As mentioned in Section 3.3.1, sensors were placed in such a manner as to maximise the collecting of NMT movement. As such, certain sensors were positioned at locations where only NMT users could travel. Thus, trips which were detected at these sensors could immediately be classified as NMT trips. Secondly, sensors were placed at two one-way streets. An assumption could thus be made that any trip detected between sensors in the opposite direction of the one-way streets could also

automatically be classified as NMT trips. After these filters had been applied, a macro was written which would classify the trips according to travel speeds. *Macros E & F: SensorClassification() & F_LinkClassification()*

It should be mentioned that trips were not regarded as single events, but as part of bigger trips thus, should a trip's destination and time at destination be the same as the next trip's origin and time departing from origin, the two individual trips were regarded as one larger trip. Two speed categories were established. The first speed category classified any trip with a travel speed of 5 km/h or less as a trip by a pedestrian. This is supported by the Guidelines for human settlement planning and design (CSIR, 2005), which states that walking speeds are typically around the order of 5.25 km/h (1.5 m/s). In addition, although little design information exists to support the use of 10 km/h as an upper limit to faster NMT users, such as cyclists, it was decided that based on the average, a cycling speed of 19 km/h (Road Bike, 2019) would be used as guidance. However, should this speed have been used, it was assumed many MT users would accidentally be classified as NMT users. Hence, given that little cycling activity was observed in the study area, it was decided that a 10 km/h cap would be sufficient. Trips with a travel speed greater than 10 km/h were then classified as trips produced by MT users.

The influence of the speed filter would be evaluated with counts. As part of this process, the sensitivity of the parameters were tested by changing the upper limit for pedestrian travel speed to 2.5 km/h and the upper limit for cyclists to 5 km/h (from here, the first travel speed filter will be referred to as the 10 km/h filter and the second filter as the 5 km/h filter as it was decided that focus would be placed solely on NMT users as a whole, regardless of the type of NMT user – meaning pedestrian vs cyclist). By doing this, the counts could be used to evaluate which results from the two filters best reflected the ratios defined by the counts. After this evaluation, which is discussed in detail under Section 4.3, it was decided that the 10 km/h filter would be used to classify users as either NMT or MT.

Macro H3: SpeedClassification2()

8. **Group trips**: It was decided that trips would be grouped in hourly periods, i.e. trips occurring between 07:00 – 08:00 am would be grouped together. The reason being that the data could still be displayed per minute graphically and hourly periods would be sufficient for creating O/D maps and heatmaps later on. A new spreadsheet was created to group the trips. Within this sheet, trips were organised according to their origin time and

their destination time. A macro was then created to categorise a trip according to the hourly period in which the trip occurred.

Macros J: HourlyTrips() & Periods()

9. **Creating ODMs and detection lists**: Spreadsheets for each hour were generated via macros. Thus, in total, 24 new spreadsheets containing the trips which occurred for during hour of a typical day were created. As part of this macro, O/D matrices were generated for each hour, also the number of detections per minute within a specific hourly period, as well as the total detections for an hourly period. The detections were also summarised for each sensor. The final O/D matrices and detection lists were then created by consolidating all the datasets with corresponding weekdays and hours. To ensure that the data was not skewed for a specific day or a specific hour, and to ensure that a typical day was represented by the data, special consideration was given to how the data was combined. This process is explained in detail under Section 4.2.

Macros K & L: CreateSheets() & ODMData()

10. **Creating visuals from the final dataset:**

Finally, with the final datasets completed, the data was configured into graphs and maps. Graphs could be produced based on the number of detections per minute or per hour for each sensor or for the entire study area (were the detections from all the sensors were added together). The horizontal axis of the graphs would indicate the time of day whereas the vertical axis would display the number of detections for the given time of day (per minute or per hour) as a ratio of the overall maximum number of detections recorded. This would make the graphs easier to read should they be used to compare trends between modes.

Two sets of maps were created based on detections and trips over hourly periods. The first set of maps were the O/D maps. These maps were created in PTV Visum and showcased the intensity of detections at each sensor over a given hour as well as the intensity of trips between sensors. Since having to display 44 by 44 possible trip combinations (1 936 trips) would make visual analysis difficult, it was decided to cluster sensors according to similar land-use characteristics. Ten zones were thus established which reduced the number of trips combinations between zones to 100. These zones are displayed in Figure 3.5 below and the sensors included in each zone is summarised in Table 3.2 which follows.
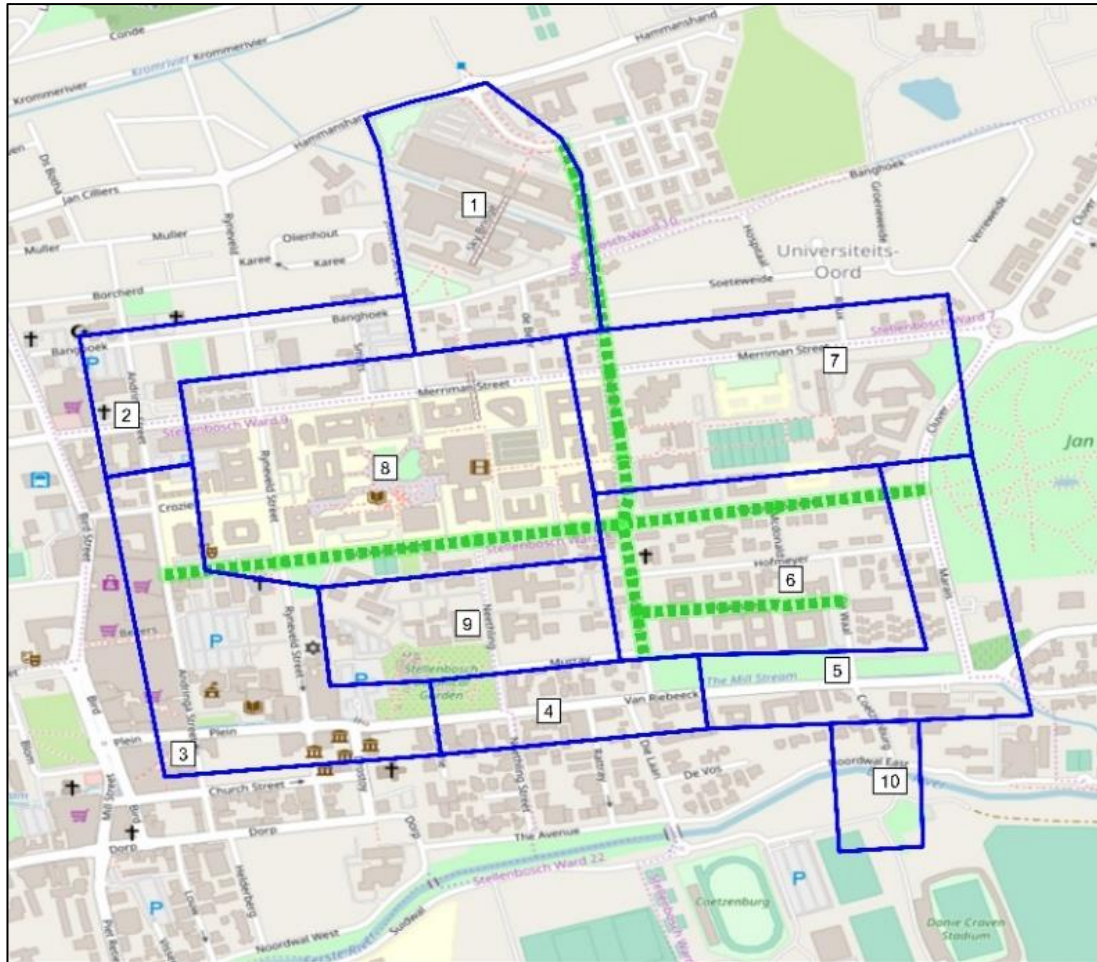
Figure 3.5: O/D zones (PTV Visum, 2019)

Table 3.2: O/D zone sensor composition

Zone	Sensors	Reasoning for grouped sensors
1	01, 02, 03, 04	Overall movement to/from the Engineering complex
2	06, 07, 46	Overall movement to/from the north western region
3	20, 21, 22, 23, 25, 26, 39	Overall movement to/from the commercial region south west of the campus
4	27, 28	Overall movement to/from the southern boundary
5	29, 30, 31, 32, 33	Overall movement to/from the south eastern boundary
6	34, 35, 42, 43	Overall movement to/from the residences located to the south of Victoria street
7	11, 12, 13, 14	Overall movement to/from the residences located to the north of Victoria street
8	09, 10, 15, 16, 17, 18, 19, 24, 37, 38, 48	Overall movement to/from the Red Square and the surrounding academic buildings
9	36, 40, 41	Overall movement to/from residences located south of the Red Square
10	45	Movement to/from Coetzenburg

3.6 ASSUMPTIONS, LIMITATIONS, AND CONSTRAINTS

Various impacts had to be considered while executing this study. A large number of these considerations pertain specifically to the use of Bluetooth sensors as a means of collecting spot data. As mentioned in Chapter 2, Bluetooth devices transmit signals at either 1 m, 10 m or 100 m ranges based on the class of the device. Since the sensor logged only transmitted signals, there was no effective way to identify the class of the device, which was logged, since the logging of a device was determined only be whether it could be sniffed out. A limitation thus existed in the form the difficulty or impossibility of calculating the traveling speed of devices. Should, for example, a device has a transmission range of 100 m, it was possible that two sensors which were spaced close to one another could log the same device either at the same time, or within a short interval. Should this device have been carried by an NMT user, the macro created to classify the user would most likely (based on the calculated travel speed) classify the user as a MT user. Since the aim of this study was to focus on NMT users (hence it had been necessary to derive only typical NMT trends), it was decided that this limitation would be discarded. It was thus assumed that a sufficient number of trips would be classified as NMT for the purpose of this study. In addition to calculating the speed of users, as the time stamps were executed per minute, it was assumed that where a trip occurred in the same minute, 60 seconds would be used to calculate the travel speed. Again, the possibility of incorrectly classifying trips existed. Nonetheless, the same assumption was used to justify why this could be disregarded.

Given that various devices are Bluetooth enabled (smartphones, smartwatches, earphones, etc.) it was possible that a single person would be logged as two or three users. Unfortunately, no successful method was found of distinguishing between someone carrying one or more Bluetooth enabled devices. Hence, under the circumstances it was decided to speculate that a clear majority of users would only be carrying one Bluetooth enabled device. This was based on observations made during counts where a limited number of persons were identified carrying more than one device such as smartwatches or Bluetooth earphones. Regarding motor vehicles carrying more than one device, it was again argued that this concern fell outside of the scope of this study, since emphasis was placed on NMT users.

Lastly, regarding the concerns raised in respect to Bluetooth technology, it was observed during counts that a small number of buses and minibuses carrying groups of people drove within the confines of the study area. It is difficult to assess what effect these groups had on the number of detections at sensors, as no effect could be seen when analysing the counting data compared

to the sensor data which was logged during the same counting periods. Hence it was assumed that the effect of these groups was negligible.

Pertaining to the consolidation of the data over similar days and hours, a limitation presented itself in that the time it took to place the sensors and collect the sensors meant that the data collected on these days could not be used to create the final dataset. Additionally, given that the sensors were custom-made, the sensors were also prone to malfunction. Luckily, this occurred with two sensors, and it was decided that this could be ignored.

Finally, the study area also presented constraints. As SU and the town is in a state of renewal in order to keep up with growing populations and advanced technology, construction was taking place at various points within the study area. Fortunately, only one construction site would have an impact during the data collection period, namely, the site where the new Teaching and Learning facilities for SU are to be situated. Sensors were thus placed to incorporate the diverted movement caused by this site.

3.7 CONCLUSION

The research design for this study was described as descriptive, since the data collection and evaluation processes did not require any direct intervention from the researcher. Given the nature of the study in its use of Bluetooth technology as a means to collect spot data, ethical clearance was required. Clearance was provided by REC based on the assurance that the anonymisation process which was used would ensure that the collected data could in no manner be traced back to any specific individual.

Various assumptions, limitations, and constraints were highlighted during the literature review and in the investigation of the study area. Of these, it was important to consider the transmission range of Bluetooth signals, the time stamp of the logged signals, the number of Bluetooth devices carried by users, and the layout of the campus during construction. Most of these could be disregarded by reassigns that the possible negative effects which could result could be regarded as minimal when considering that the end product of this study was solely to identify patterns and trends.

The tools that were used for this study included 44 Bluetooth sensors (hardware), MS Excel, PTV Visum, and Google Fusion Tables (all three of which are regarded as software). The sensors were designed and operated by a local start-up company, namely, Bridgiot to log

Bluetooth signals with time stamps by which these logs could be accessed using MS Excel. The hardware used in the design of the sensors consisted of Raspberry Pi Zeros powered by mobile battery packs, which could connect to the internet by means of a wireless hotspot. The data collection periods were limited by the three-day lifespan of the battery packs. The data would thus be collected over three days starting on Tuesdays, before which the battery packs would be charged over the weekends. It was additionally assumed that the total data collected over these three days would adequately represent a typical day on the campus. The sensors were placed at fixed locations across the study area. Sensors were placed at positions which would limit the detection of MT users, such as sensors located between SU residences or on the Red Square.

MS Excel was used to code the filters which would create a final NMT dataset. The main coded filter considered the travel speed of users between sensors when classifying a user as travelling by means of NMT or MT. In order to validate the use of this filter, counts were also commenced in parallel to the sensors collecting Bluetooth data. During the counts, travel modes were recorded which would then be used to certify the ratios expressed by the filters. Two speed parameters were used to test the sensitivity of using travel speed as a means of classifying travel modes, namely a 5 km/h and a 10 km/h parameter. Any user traveling at a speed below these parameters was classified as an NMT users. The conclusion of the validation process, however, is discussed in Chapter 4. Once the final NMT data was compiled, the data was transformed into lists of detections and O/D matrices.

Using the final datasets, graphs could be designed in MS Excel and Google fusion sheets as well as PTV Visum could be used to display movement on the campus. In MS Excel, graphs could be created, displaying how users move over a typical 24 hour day. The O/D matrices could be used to create O/D maps from which trip intensities between sensors could be distinguished in hourly periods. Additionally, using the hourly detections and Google Fusion Tables, heatmaps could be created which displayed the intensity of NMT detections. With the data translated visually, the results could then be discussed and analysed.

CHAPTER 4

DATA RESULTS AND ANALYSIS

4.1 INTRODUCTION

The data will be presented and the results will be discussed in this chapter. Given the vast amount of data collected during the course of this study, it was necessary to put the data under scrutiny to validate the data collection and filtering processes. As described in Chapter 3, using MS Excel, filters were created which was used to produce a final dataset. As part of the filtration process, detection data was translated into trips which were then classified as belonging to either MT or NMT users based mainly on travel speeds. By doing this, the detections used to create the trips were automatically classified as well. In order to analyse the effectiveness of the filters, the resultant data was evaluated according to the MT and NMT classifications obtained. It should be noted that this chapter references detections mainly with regard to the validation of the data, and not trips.

In Section 4.2 the filtration process will be discussed. The various aspects of the filtration process are viewed with specific emphasis placed on the effect each process had on the resultant data, on which the findings and analysis would be based. The processes involved in validating the final dataset are discussed in Section 4.3. First, the effect of using Bluetooth devices as a means of exploring NMT behaviour was considered in terms of penetration rates. Following this, the process used to classify trips and detections, was examined by comparing the counts completed at sensors with the resulting classified detections. Lastly, a comparison was made of the trends observed from the counts and the trends gained from the detections. Once the filtering process had been placed under critical review, the form in which the data is presented in Chapter 5 is introduced and discussed in Section 4.4. Here, emphasis is placed on how the data is represented. Section 4.5 serves as the conclusion which will summarise the key points raised in this chapter.

4.2 FILTRATION PROCESS

As mentioned in Chapter 3, data was collected over three periods (Table 3.1). The sensors collected data based on the time from the detection of a Bluetooth device until the same device was undetectable. The basic format is shown in Table 4.1 below with *Time In* indicating the time

at which a device was detected and *Time Out* showing the time the detection was lost. Each detection was given a special user ID, in order to track the movement of the detected device between the sensors. As described in Section 3.5.2, the data was stamped per minute, which slightly influenced the accuracy of the filtering process in determination of the travel speeds. In addition to the data parameters shown in Table 4.1, parameters, such as weather, temperature, and day or night were recorded.

Table 4.1: Data format

User	Sensor	Date	Time In	Time Out
User 0000060	Sensor 06	2019/04/09	10:55:00	10:55:00
User 0000060	Sensor 48	2019/04/09	10:59:00	10:59:00
User 0000060	Sensor 09	2019/04/09	10:59:00	10:59:00
User 0000060	Sensor 02	2019/04/09	11:00:00	11:00:00
User 0000060	Sensor 01	2019/04/09	11:01:00	11:01:00
User 0000060	Sensor 11	2019/04/09	12:36:00	12:36:00
User 0000060	Sensor 35	2019/04/09	12:36:00	12:36:00
User 0000060	Sensor 14	2019/04/09	12:37:00	12:37:00
User 0000060	Sensor 34	2019/04/09	12:37:00	12:37:00
…	...	…	…	…

Over the three collecting periods (Table 3.1), a total of 2.1 million detections were recorded. The sensors were vulnerable to weather conditions such as heat and water exposure, which affected the lifespan of individual sensors. This influenced not only the number of sensors used during Periods 2 and 3, but also the quality of data collected as explained further in this section. As described under Section 3.5.2, the filtering process comprised various stages. The first of these was to remove detections of users which occurred at a single sensor only, meaning that a user was registered at only one of the 44 sensors. The reasoning behind this, as described in Section 3.5.2, was that these users could not be classified as either MT or NMT since no information existed to determine their modal nature. An estimated 270 000 detections were removed during this process, leaving further estimated 1.9 million detections.

Detections were then transformed into trips. An estimated 1.5 million unfiltered trips were produced. It was then necessary that the non-trips be filtered out. Non-trips were defined as consecutive detections at the same sensor and trips where the travel time exceeded 30 minutes (as explained in Section 3.5.2). An estimated 140 000 non-trips were removed during the filtering process leaving approximately 1.4 million trips which could be filtered as either MT or NMT based on travel speed.

As mentioned in Chapter 3, in order to test the sensitivity of using travel speed as a means to classify trips, two separate speed parameters (5 km/h and 10 km/h) were used to classify trips above or below those parameters as NMT. The results of using these filters are discussed in detail under Section 4.3.2 which deals with the validation of the filtering process. However, in order to provide context for this section, it should be noted that all final results were based on the 10 km/h speed filter, as this filter provided the best dataset for the analysis of NMT trends.

Two additional filters were also applied in conjunction with the speed filters. These filters categorised trips solely on the position of the sensors. The first of these filters categorised users detected at specific locations as NMT users, since no other mode of transport could travel past these sensors. This filter was called the *Sensor Filter*. The second filter, the *Link Filter*, categorised users as NMT based on a travel direction opposing the two one-way streets which formed part of the testbed. It was assumed that any movement in the opposite direction belonged to NMT users.

Although a large amount of data was collected, and in order to represent a typical day on the Stellenbosch campus, a choice had to be made as to which datasets should be accumulated in order to represent the final dataset. To do this, data could only be merged based on the least common shared days and times. Thus, for example, data was collected for each Tuesday for Periods 1 – 3. However, the time at which data was collected on Tuesdays was dependant on when the sensors were turned on, thus, data only started to reflect from between 07:00 and 09:00. Effectively, Tuesdays could thus not be incorporated into the final dataset as they would add value only to the hours from 07:00 to the end of the day. Table 4.2 shows the days and hourly period for which data was collected. From this, two options were identified as to how the data should be accumulated. It was first noted that data was collected for three full Thursdays, meaning that these three data sets could be accumulated. However, the data would at best reflect only a typical Thursday and only three days' worth of data would be used. Secondly, it was noted that a full Wednesday and Thursday's worth of data was collected for Periods 1 and 2. The accumulation of these four days would better represent typical NMT behaviour, and an additional day's worth of data could also be added. It was thus decided to finalise all results based on the second option. The results pertaining to the applied filters, along with the filters used previously, produced the results which are summarised in Table 4.3.

Based on the consolidated NMT detections, Figures 4.1 – 4.6 were produced. Figures 4.1 and 4.2 show detections per minute and the ratio of NMT and MT detections per hour

respectively. In addition, the filtered detections, based on the 10 km/h speed filter, are also shown. Figures 4.3 – 4.6 shows the total unfiltered and total filtered detections geographically, based on where the sensor were positioned (refer to Figure 3.3 for the geographical position of each sensor) in the form of a heatmap. Figures 4.3 and 4.4 are based on a 100 m zoom, whereas Figures 4.5 and 4.6 are based on a 200 m zoom.

Due to the density of the sensor network, it was expected that a number of users would be collected by only a single sensor, and that results would be limited regarding trips between different sensors. This is evident from Figures 4.1 and 4.2, where a general drop in detections was observed across the 24 h period. From the heatmaps (Figure 4.3 – 4.6) it is also observed that the intensity of detections to the south east of campus also reduced once the filters had been applied. Regarding Figure 4.1, where an overall peak was observed between 11:45 and 14:00 regarding the unfiltered detections. This peak flattens and stretches from 07:45 to 14:00 after filtration. Although a large number of detections had been filtered out, the remaining number was still enough to efficiently analyse travel behaviour.

In addition, it was found that upon closer inspection of Figure 4.2, that the ratio between MT and NMT users changed between the periods of 14:00 to 07:00 and 07:00 to 14:00. For the period between 14:00 and 07:00, it was observed that the majority of trips were categorised as MT, whereas the opposite occurred during the 07:00 and 14:00 period.

From the heatmaps (Figures 4.3 – 4.6) it was also evident that the majority of detections which were removed, had been detected at the sensors on the border of the study area, especially to the north west and south east of campus. Furthermore, at the centre of the campus, where sensors were spaced closer to one another, the intensity shown on the heatmap increased. This finding could most likely be attributed to the decreased number of detections elsewhere on the map as a result of the filtering process removing redundant data. It could thus be concluded that the filtration process performed sufficiently in removing data which would not reflect the movement of the general NMT population. The detailed validation of the results is to be discussed in the following section. Preliminary observations of the data collected suggest that the data could be used to draw adequate conclusions, although some areas of concern were identified, which will be discussed at length when examining the results.

Table 4.2: Datasets collected

Period starting at:	Period 1				Period 2				Period 3:				Total:			
	Tue:	Wed:	Thu:	Fri:	Tue:	Wed:	Thu:	Fri:	Tue:	Wed:	Thu:	Fri:	Tue:	Wed:	Thu:	Fri:
00:00	0	1	1	1	0	1	1	1	0	0	1	1	0	2	3	3
01:00	0	1	1	1	0	1	1	1	0	0	1	1	0	2	3	3
02:00	0	1	1	1	0	1	1	1	0	0	1	1	0	2	3	3
03:00	0	1	1	1	0	1	1	1	0	0	1	1	0	2	3	3
04:00	0	1	1	1	0	1	1	1	0	0	1	1	0	2	3	3
05:00	0	1	1	1	0	1	1	1	0	0	1	1	0	2	3	3
06:00	0	1	1	1	0	1	1	1	0	0	1	0	0	2	3	2
07:00	1	1	1	1	0	1	1	1	0	0	1	0	1	2	3	2
08:00	1	1	1	1	1	1	1	0	1	0	1	0	3	2	3	1
09:00	1	1	1	1	1	1	1	0	1	0	1	1	3	2	3	2
10:00	1	1	1	1	1	1	1	0	1	0	1	1	3	2	3	2
11:00	1	1	1	0	1	1	1	0	1	1	1	0	3	3	3	0
12:00	1	1	1	0	1	1	1	0	1	1	1	0	3	3	3	0
13:00	1	1	1	0	1	1	1	1	1	1	1	0	3	3	3	1
14:00	1	1	1	0	1	1	1	1	1	1	1	0	3	3	3	1
15:00	1	1	1	0	1	1	1	0	1	1	1	0	3	3	3	0
16:00	1	1	1	0	1	1	1	0	1	1	1	0	3	3	3	0
17:00	1	1	1	0	1	1	1	0	1	1	1	0	3	3	3	0
18:00	1	1	1	0	1	1	1	0	1	1	1	0	3	3	3	0
19:00	1	1	1	0	1	1	1	0	0	1	1	0	2	3	3	0
20:00	1	1	1	0	1	1	1	0	0	1	1	0	2	3	3	0
21:00	1	1	1	0	1	1	1	0	0	1	1	0	2	3	3	0
22:00	1	1	1	0	1	1	1	0	0	1	1	0	2	3	3	0
23:00	1	1	1	0	1	1	1	0	0	1	1	0	2	3	3	0

The left axis is labelled: Number of data sets per hour

Concluding options on how best to use the data:
1) Use only data collected on Thursdays –three days' worth of data
2) Use data collected on the Wednesdays and Thursdays or Period 1 and 2 – four days' worth of data

Data was collected over three periods	Data was collected over two periods	Data was collected over one period	No data was collected

Table 4.3: Filtration results

RAW DATA				
	Period 1	**Period 2**	**Period 3**	**Total**
Total unfiltered detections	851 426	766 971	500 669	**2 119 066**
Single users	*(93 838)*	*(87 225)*	*(85 875)*	*(266 938)*
Total filtered detections	757 588	679 746	414 794	**1 852 128**
Total unfiltered trips	624 844	556 052	339 581	**1 520 477**
Non-trips filtered	*(67 065)*	*(56 490)*	*(47 483)*	*(171 038)*
Total filtered trips	557 779	499 562	292 098	**1 349 439**

APPLICATION OF SPEED FILTERS								
	Results based on 5 km/h filter				Results based on 10 km/h speed filter			
	Period 1	Period 2	Period 3	Total	Period 1	Period 2	Period 3	Total
MT trips	352 546	295 365	157 745	**805 656**	312 015	252 852	140 093	**704 960**
Sensor NMT filter	52 397	68 700	49 385	**170 482**	52 397	68 700	49 385	**170 482**
Link NMT filter	5 222	3 109	2 349	**10 680**	5 222	3 109	2 349	**10 680**
NMT trips	147 614	132 388	82 619	**362 621**	188 145	174 901	100 271	**463 317**
Total NMT trips	205 233	204 197	134 353	**543 783**	245 764	246 710	152 005	**644 479**

CONSOLIDATION OF FINAL DATA BASED ON 10 km/h RESULTS	
MT trips	410 307
NMT trips	356 308
Total trips	**766 615**
MT detections	506 062
NMT detections	457 563
Total detections	**963 625**
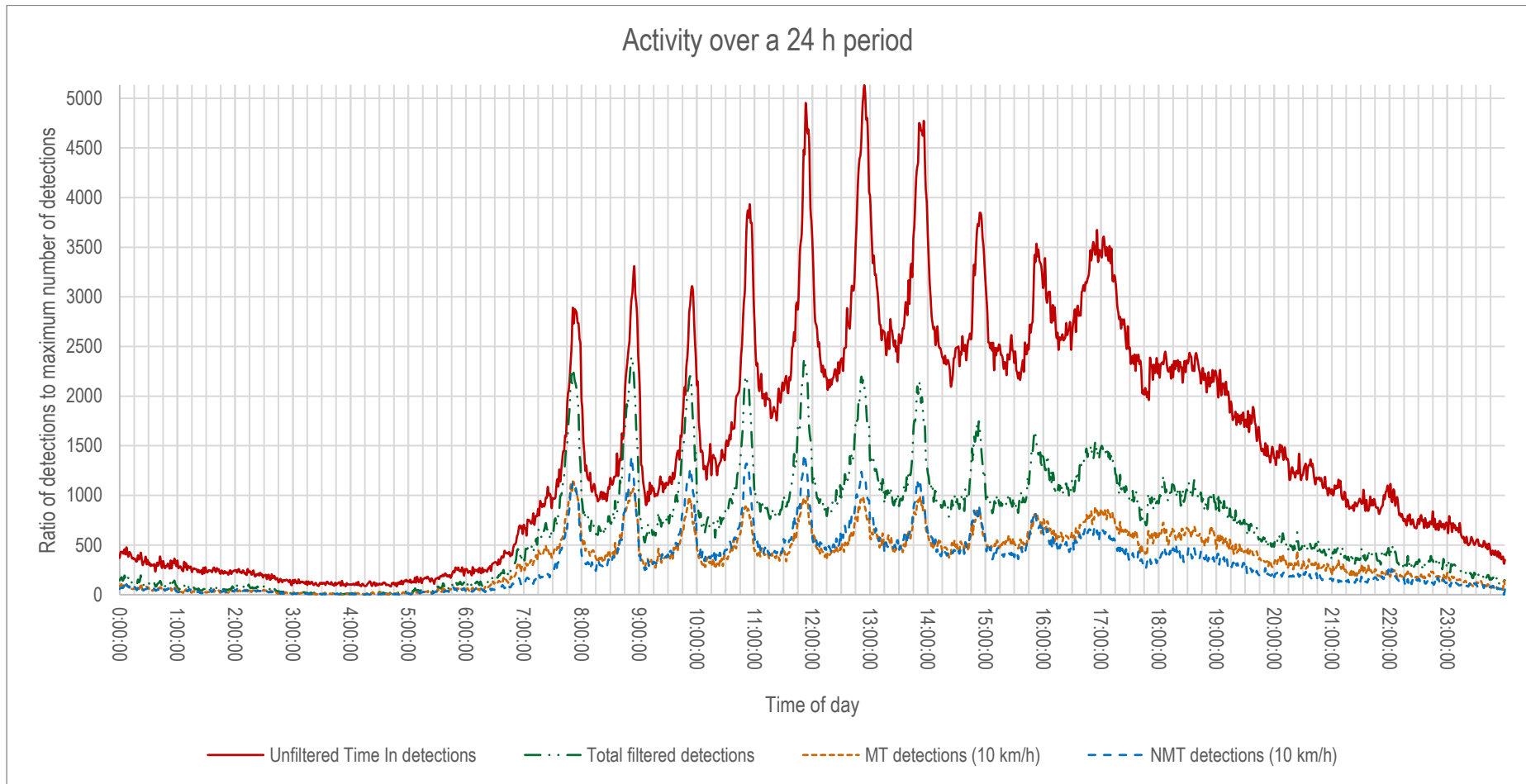
Figure 4.1: Number of detections over a 24 h period based on *Time In* detections
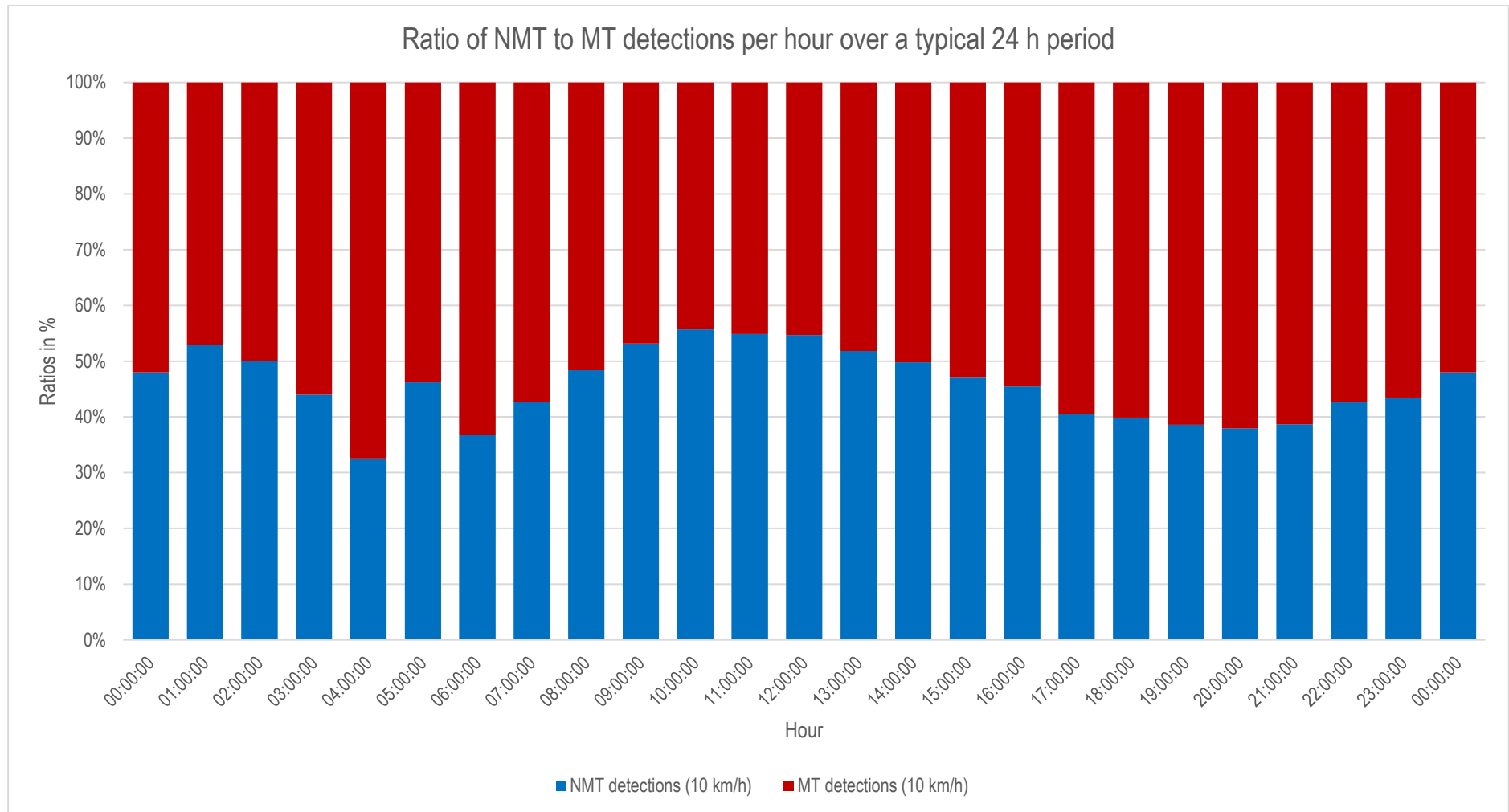
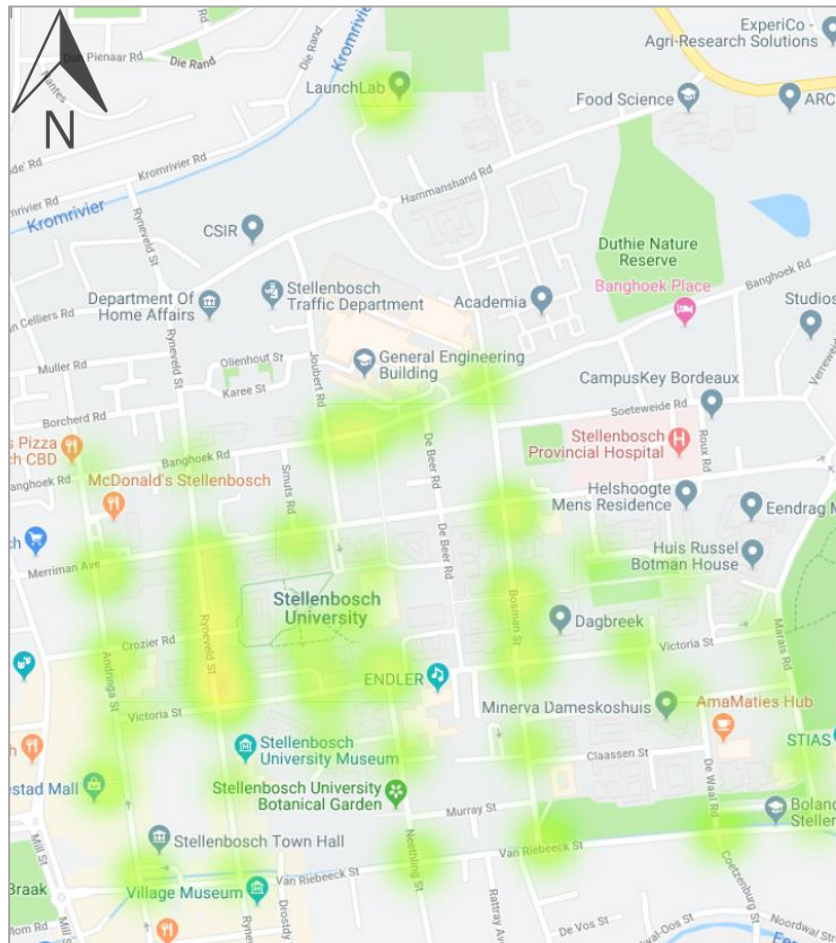Figure 4.2: Ratio of MT and NMT detections per hour

Figure 4.3: Unfiltered heatmap at 100 m zoom (Google Fusion Tables, 2019)
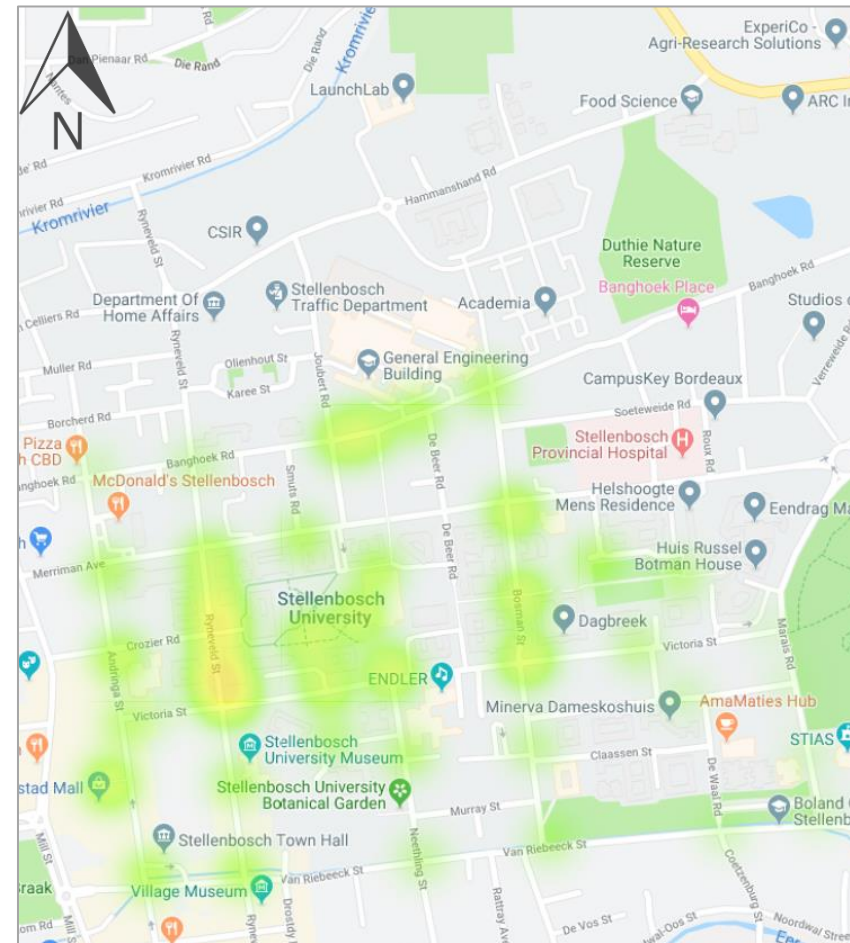
Figure 4.4: Filtered NMT heatmap at 100 m zoom (Google Fusion Tables, 2019)
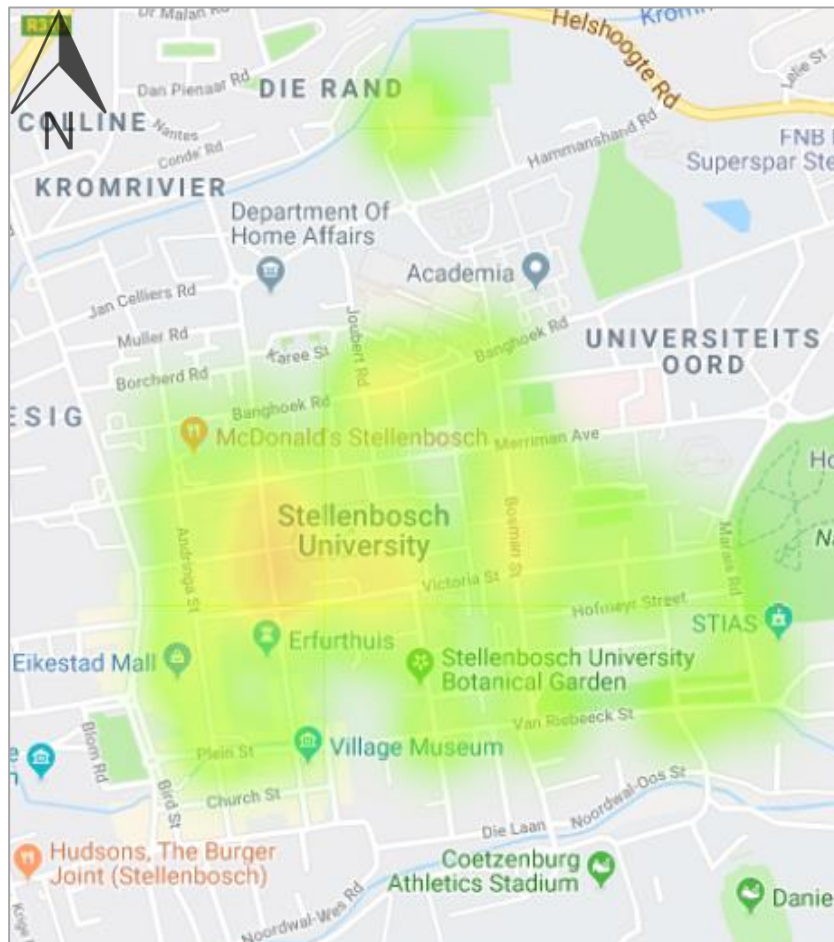
Figure 4.5: Unfiltered heatmap at 200 m zoom (Google Fusion Tables, 2019)
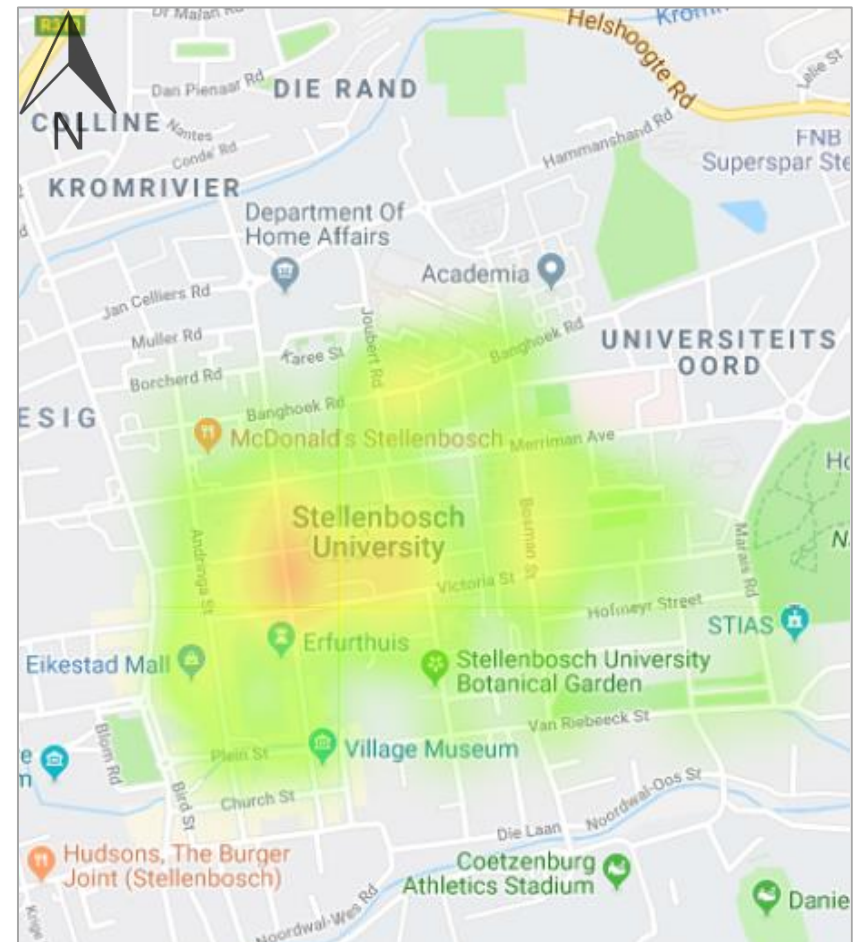
Figure 4.6: Filtered NMT heatmap at 200 m zoom (Google Fusion Tables, 2019)

4.3 DATA VALIDATION

In order to validate the data collecting process as well as the results it yielded, counts were done at a select number of sensors based on their position on the campus. Counts were done for hourly periods at 10-minute intervals. By using 10-minute intervals instead of the more traditional 15-minute intervals, more detail was able to be collected on how volumes fluctuated during the hour in which counts were completed. Counts took place mainly between the hours of 10:00 – 11:00 and 12:00 – 13:00, to allow for time to travel between counting stations and to incorporate the daily tasks of the research team. Additionally the results, as discussed in the previous section, revealed peaks during 08:00 – 14:00 on an hourly basis, which justified the limited counting periods. Overall, 10 sensors were chosen. The position of these sensors is shown in Figure 4.7 and discussed in Table 4.4 below.

Figure 4.7: Counting locations

Table 4.4: Counting station positions

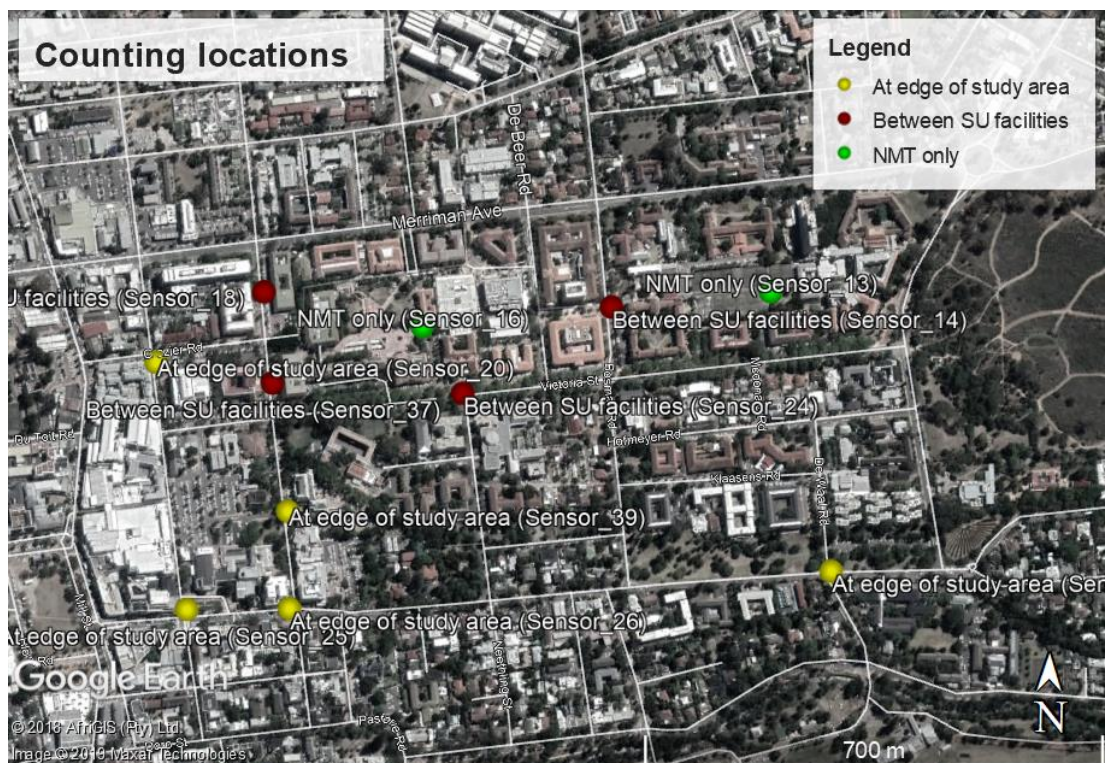| Sensor:	Location and reasoning:		Accessibility:
Sensor 13	-	Located near SU student housing	NMT
	-	To observe NMT users	
Sensor 16	-	Red Square between SU facilities	NMT
	-	To observe NMT users	
Sensor 18	-	Pedestrian crossing between SU facilities.	MT & NMT
	-	To observe the relationship between MT and NMT users	
Sensor 20	-	Situated at an intersection with a four-way stop with pedestrian crossings on the campus border	MT & NMT
	-	To observe the relationship between MT and NMT users on the edge of the study area	
Sensor 24	-	Situated near a pedestrian crossing between SU facilities	MT & NMT
	-	To observe the relationship between MT and NMT users	
Sensor 25	-	Situated at a one-way street close to shopping facilities on the edge of the study area	MT & NMT
	-	To observe the relationship between MT and NMT users on the edge of the study area	
Sensor 26	-	Situated at a one-way street on the edge of the study area	MT & NMT
	-	To observe the relationship between MT and NMT users on the edge of the study area	
Sensor 29	-	Situated at an intersection with a three-way stop with limited pedestrian infrastructure	MT & NMT
	-	To observe the relationship between MT and NMT users on the edge of the study area	
Sensor 37	-	Pedestrian crossing between SU facilities	MT & NMT
	-	To observe the relationship between MT and NMT users	
Sensor 39	-	Situated at a one-way street leading to the edge of campus	MT & NMT
	-	To observe the relationship between MT and NMT users on the edge of the study area	

4.3.1 Penetration rate

In parallel to the counts, sensors were also deployed. By doing so, the penetration rate of the sensors could be determined as a percentage of the Bluetooth detections of the counted population. Table 4.5 below summarises the results derived from the counts.

Table 4.5: Counts

Sensor:	Period:		NMT users	MT users:	Total users:	Bluetooth detections:	Penetration rate (%):
	From:	To:					
Sensor 14*	12:00	13:00	940	499	1439	164	**11.4%**
Sensor 18	10:00	11:00	1180	389	1569	31	**2.0%**
Sensor 20	12:00	13:00	457	523	980	33	**3.4%**
Sensor 24	10:00	11:00	502	566	1068	42	**3.9%**
Sensor 25	10:00	11:00	622	320	942	14	**1.5%**
Sensor 37	10:00	11:00	794	470	1264	76	**6.0%**
Sensor 39	12:00	13:00	555	315	870	49	**5.6%**

*Although not initially included, counts at 15-minute intervals were done at Sensor 14. These counts could, however, be used only for the validations of the penetration rate and the filtering process since 10-minute intervals were used for the remaining sensor.

Although 10 counts were conducted along with the sensors, unforeseen events which did not reflect typical traveller behaviour within the study area, influenced the outcome of the Bluetooth data collected at Sensors 13, 16, 26, and 29. The results of these counts could thus not be added due to a lack of confidence in their accuracy. This was unfortunate given that the counts at Sensors 13 and 16 were the only counts which could be used to determine a penetration rate in NMT-only spaces. Nonetheless, the penetration rates produced from the counting fell within the ranges reported by the studies discussed in Chapter 2, specifically, between 2% and 12% (Wasson, Sturdevant and Bullock, 2008; Malinovskiy and Wang, 2012; Malinovskiy, Saunier and Wang, 2012; Shlayan, Kurkcu and Ozbay, 2016; Kurkcu and Ozbay, 2017; Lesani and Miranda-Moreno, 2018).

4.3.2   User classification

4.3.2.1   *Validation of filters*

MT and NMT modes were classified during the counting process. By categorising users, ratios could be determined, which were used to evaluate the ratios produced from the filtering processes, as described in Section 4.3. From this evaluation, the accuracy with which the speed filter, specifically, categorised trips could be determined. Tables 4.6 and 4.7 below summarise these findings. Here, the sensitivity of the filters was analysed by comparison to the difference in filter ratios to the ratios from the counts. Since Sensors 13 and 16 were located in NMT-only areas, their counts are not represented in these tables, therefore it could not be used to validate the filter.

Table 4.6: MT and NMT ratios based on 5 km/h speed filter

Sensor	Period		5 km/h filter			Counts			NMT/MT$_{filter}$ - NMT/MT$_{counts}$
	From	To	NMT users	MT users	NMT/ MT	NMT users	MT users	NMT/ MT	
Sensor 14*	12:00	13:00	971	1465	**0.66**	940	499	**1.88**	**-1.22**
Sensor 18	10:00	11:00	1518	1329	**1.14**	1180	389	**3.03**	**-1.89**
Sensor 20	12:00	13:00	768	748	**1.03**	457	523	**0.87**	**0.15**
Sensor 24	10:00	11:00	1460	1807	**0.81**	502	566	**0.89**	**-0.08**
Sensor 25	10:00	11:00	624	595	**1.05**	622	320	**1.94**	**-0.90**
Sensor 26	10:00	11:00	479	655	**0.73**	189	564	**0.34**	**0.40**
Sensor 29	12:00	13:00	161	1279	**0.13**	184	878	**0.21**	**-0.08**
Sensor 37	10:00	11:00	2370	1832	**1.29**	794	470	**1.69**	**-0.40**
Sensor 39	12:00	13:00	500	357	**1.40**	555	315	**1.76**	**-0.36**
Mean:									**-0.49**
Variance:									**0.53**

*Although not initially included, counts at 15-minute intervals were done at Sensor 14. These counts could, however, be used only for the validations of the penetration rate and the filtering process since 10-minute intervals were used for the remaining sensor.

Table 4.7: MT and NMT ratios based on 10 km/h speed filter

Sensor	Period		10 km/h filter			Counts			NMT/MT$_{filter}$ - NMT/MT$_{counts}$
	From	To	NMT users	MT users	NMT/ MT	NMT users	MT users	NMT/ MT	
Sensor 14*	12:00	13:00	1643	1386	**1.19**	940	499	**1.88**	**-0.70**
Sensor 18	10:00	11:00	1687	1053	**1.60**	1180	389	**3.03**	**-1.43**
Sensor 20	12:00	13:00	967	651	**1.49**	457	523	**0.87**	**0.61**
Sensor 24	10:00	11:00	1368	1302	**1.05**	502	566	**0.89**	**0.16**
Sensor 25	10:00	11:00	679	267	**2.54**	622	320	**1.94**	**0.60**
Sensor 26	10:00	11:00	687	446	**1.54**	189	564	**0.34**	**1.21**
Sensor 29	12:00	13:00	213	1228	**0.17**	184	878	**0.21**	**-0.04**
Sensor 37	10:00	11:00	2535	1441	**1.76**	794	470	**1.69**	**0.07**
Sensor 39	12:00	13:00	827	424	**1.95**	555	315	**1.76**	**0.19**
Mean:									**0.07**
Variance:									**0.59**

*Although not initially included, counts at 15-minute intervals were done at Sensor 14. These counts could, however, be used only for the validations of the penetration rate and the filtering process since 10-minute intervals were used for the remaining sensor.

As expected, the number of trips classified as NMT increased when the travel speed filter was increased from 5 km/h to 10 km/h since the increase in travel time would increase the number of users classified as NMT. From Tables 4.6 and 4.7 a general variance of 0.53 for the 5 km/h filtering process and 0.59 for the 10 km/h process was observed. When considering the outliers, -1.89 and 0.40 for the 5 km/h process and -1.43 and 1.21 for the 10 km/h process, and the means, -0.49 for the 5 km/h process and 0.07 for the 10 km/h process, the variance in the

data would indicate that the filtering process has no bearing on estimating an accurate user type. This was, however, expected. Although the influence of the filtering process on the classification of trips could be regarded as insignificant, nevertheless, the results from the 10 km/h speed filter produced the lowest mean, and thus it was decided that the results produced from this filter will be used further.

In addition to the findings summarised in these tables, a regression analysis was performed to evaluate the relationship between the detection of Bluetooth devices and the number of MT and NMT users. Although the results of this analysis would not have any bearing on the filtering process, it was hoped that these results could indicate whether or not it would be possible to calibrate a model which would more accurately portray the modal differentiation. It should be noted however, that the classification of trips and users remains a very complicated process which is seldom expounded on in literature. Alongside this, studies conducted in the past (Bathaee, 2014; Lesani and Miranda-Moreno, 2018), considered only small groups of sensors with extensive counts when analysing how to apply modal classification to Bluetooth data. Due to the sample size constraints these findings may not be applicable to this study. The results from the regression analysis is summarised in Table 4.8 and Figure 4.8.

From the regression analysis, it can be concluded that both MT and NMT contribute to produce Bluetooth detections, however, when considering the adjusted R-square values, neither contributed significantly. Hence the filtering process does not accurately represent the mode differentiation taking place on the campus. It is assumed that one factor which may play a role, is the range of the Bluetooth signals emitted, as discussed in Chapter 2 (Fabron, 2016). This range, which can vary from a Class 1 device which emits at a range of ~100 m range to a Class 3 device which emits at a range of ~1 m, could easily have a major impact on the travel speeds of users and thus influence how they are classified. Nonetheless, it was decided that the results produced from the 10 km/h speed filter would be used. Although this speed filter had the lowest mean, as regards difference in user classification ratios, of those observed during the counts (Table 4.7), the variance in these differences still leaves room for criticism as this should not be the final basis on which such a conclusion should be drawn.

Table 4.8: Regression analysis

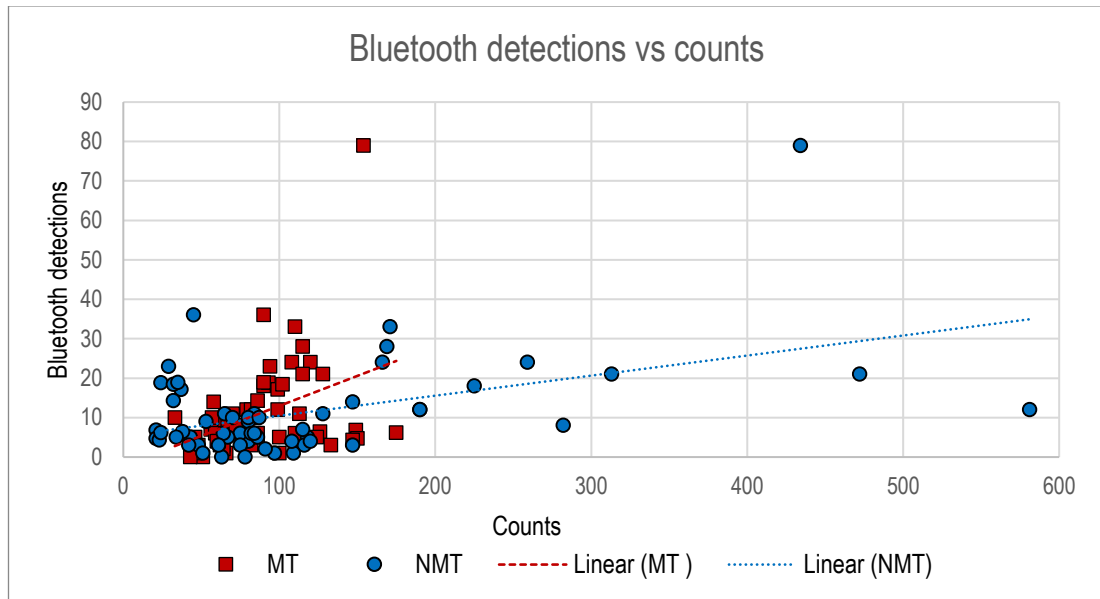|	t-stat	P-value	R-square:	Adjusted R-square:
MT:	3.24	2.00 E-03	0.16	0.14
NMT:	3.96	2.12 E-04	0.22	0.20

Figure 4.8: Linear regression

In order to then justify the use of this filter, focus is shifted to the aim of this thesis which seeks to analyse NMT behaviour. Hence, the question is thus raised as to how well the NMT data represents the observations made during counts. Validation is then required to confirm whether the results produced by the application of the 10 km/h filter to the Bluetooth data follows the same pattern as those observed during counts.

4.3.2.2 *Validation of patterns observed*

As mentioned at the start of this section, counting stations were chosen in such a manner as to give a good representation of how NMT behaviour could vary across the study area. Thus, Sensors 18, 24, and 37 were chosen to consider movement between SU facilities, Sensors 20, 25, 29, and 37 would consider movement at the edge of the testbed, and Sensors 13 and 16 considered movement at locations accessible only to NMT users. With the focus now on how the results showed up on producing patterns of NMT users similar to those observed during counts, Figures 4.9 to 4.12 were produced based on the filter results and the counts. The figures were produced in a similar manner to Figures 4.1 and 4.2. By accumulating the detections from both the results and the counts over 10-minute intervals and then dividing these detections or counts by the maximum number recorded, the two data sets could easily be compared.

Figure 4.9 has already revealed that the NMT filter results assume the same curvature as those produced by the counts. What is noticeable is that the MT counts tend to follow a straight line, which is in stark contrast to the MT filtered results. This already reflects a bias of the results towards the NMT pattern, meaning that a good number of NMT users were mistakenly classified as MT users based on their travel speeds.
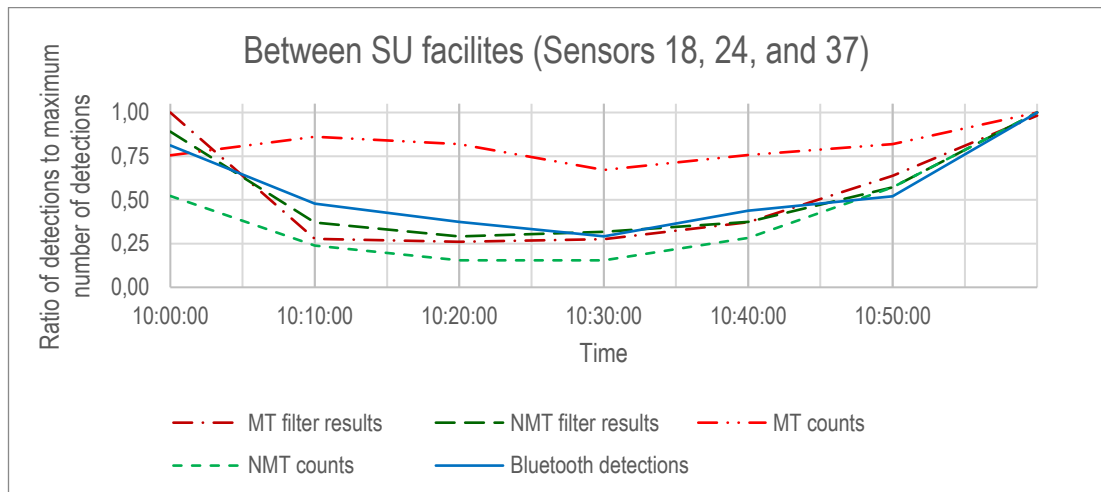

Figure 4.9: Detections near SU facilities (Sensors 18, 24, and 37)

Although, not exactly similar to the relationship seen in Figure 4.9, the NMT filter results shown in Figure 4.10 tend to follow the patterns produced from the counts. It cannot be stated that a relationship exists between the MT filter results and the MT counts. Additionally, the trend of the Bluetooth detections was particularly interesting, as it did not follow of the patterns produced by either the MT or the NMT counts.
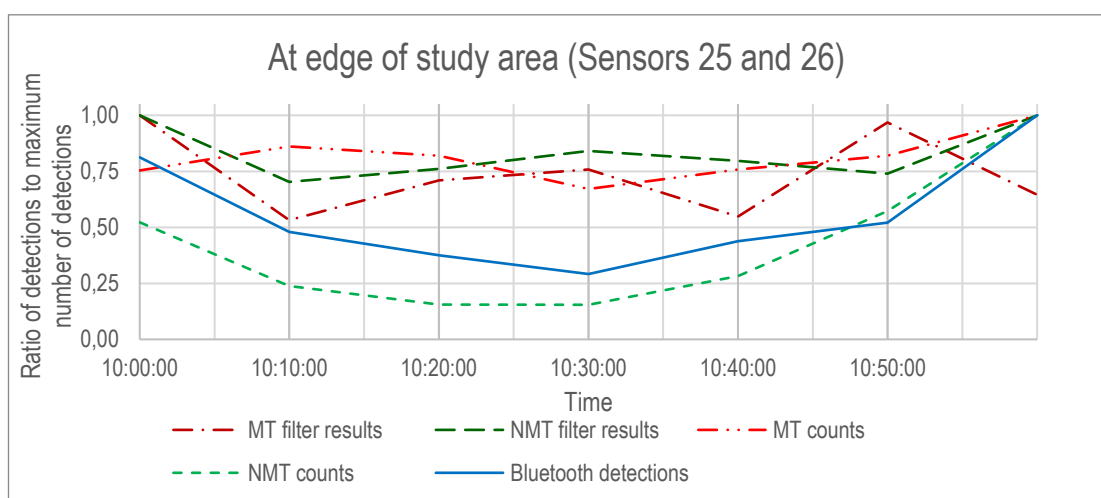

Figure 4.10: Detections at the edge of study area (Sensors 25 and 26)

From Figure 4.11 it is noted that both the MT and NMT filter results tend to follow the same pattern produced from their respective counts. It is, however, also observed that the filter results do not follow these patterns exactly. Again, an observation is made on the Bluetooth detections which does not correlate to either of the patterns produced by the MT or NMT counts.
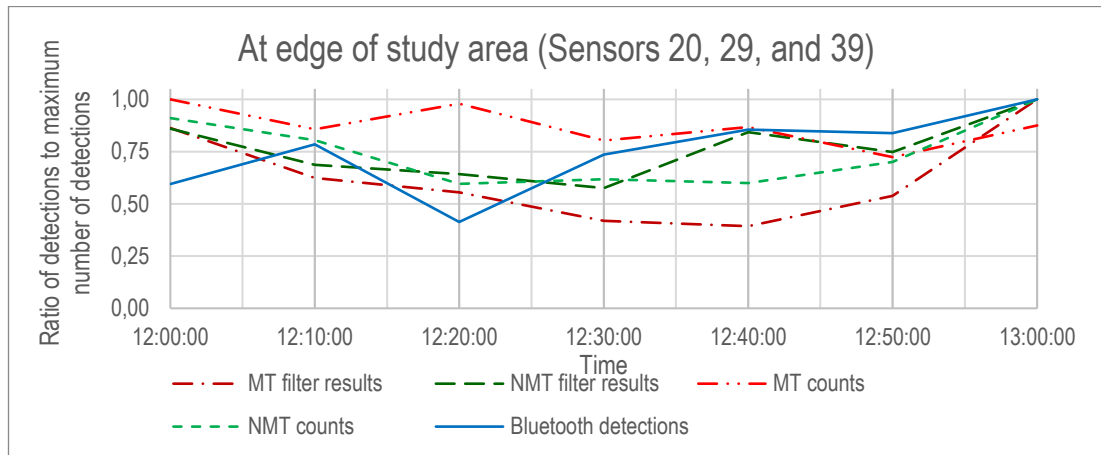

Figure 4.11: Detections at the edge of study area (Sensors 20, 29, and 39)

Although confidence in the Bluetooth data collected during the counting at Sensors 13 and 16 was lacking, the data was nevertheless incorporated to compare the general trends, as shown in Figure 4.12. Given the travel patterns of NMT users during the course of an academic day, which peaks before class, then drops significantly before peaking again, the pattern observed during counts indicated a sufficient reflection of the data. Given the location of these two sensors towards the more central part of the campus, which is largely exposed to students, assurance is given in that the data reflects the typical behaviour of NMT users.
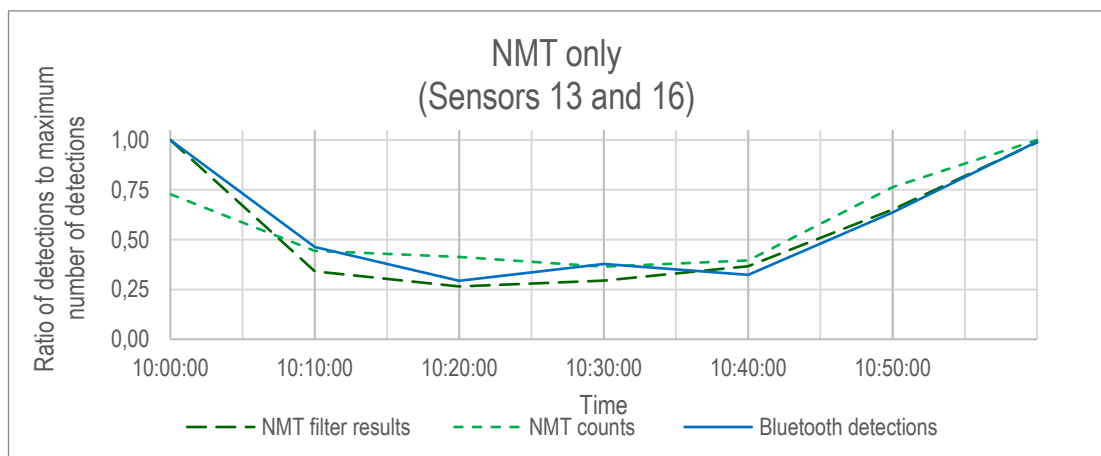

Figure 4.12: Detections at sensors accessible only to NMT users (Sensors 13 and 16)

It can thus be concluded that when focusing solely on the NMT filter results, the patterns produced from these results tend to follow those produced from NMT counts. Based on these observations, it is thus argued that the filtered results could be useful in investigating NMT behaviour on Stellenbosch campus.

4.3.3 Summary

Following the validation process, key findings were made. It was concluded that the penetration rates are similar within the bounds of those reported by other studies, specifically between 1.5% and 11.4% compared to 2% and 12%. Unfortunately, due to unforeseen circumstances, a penetration rate at NMT-only locations could not be determined. Nonetheless, the use of Bluetooth as a means of collecting spot data was considered favourably, on that mobility patterns could be produced. Regarding the methods used to filter the data, a more complex filtering process would be required in order to distinguish between MT and NMT users when using Bluetooth as a data collecting method. Classification based solely on speed does not reflect the empirical observations and the use of regression as a method to classify users requires a significant amount of counting data. In order to classify trips with the help of regression, more advanced techniques would be required, and thus, given the scope of this research project, it is recommended that the classification of mass amounts of Bluetooth data be studied further. However, for the purposes of this study, the filtered data was deemed as adequate, since it was shown that the NMT patterns produced by the results tend to mimic those produced from counts.

It could then be concluded that by the process of validating the data and the filtering process all aspects of the data may be considered as critiqued. Although many aspects of the filtering process could be improved upon, the data was still considered useful in analysing the overall movement patterns of NMT users on the Stellenbosch campus.

4.4 FILTRATION RESULTS

The results produced by the 10 km/h filtration process was configured into graphs, heatmaps, and O/D maps. Reference has been made on numerous occasions within this chapter to detections, whereas little emphasis has been placed on the filtered trips. The reason for this is that, when it came to validate the data, the detections were effectively the only means on which validation could be based. It thus bears repeating that detections were categorised based on the trips produced from them, as described in Chapter 3. The trips, however, played their role

in producing the O/D matrices. Given the vast amount of data, the majority of results can be viewed in Appendix A. Key aspects of the results are discussed in this section.

Figure 4.12 shows detections over hourly periods (NMT detections per hour) and, detections over one-minute periods (NMT detections per minute). Figure 4.14 and 4.15 show the activity taking place at various sensors over a typical 24 hour day in a similar manner as Figure 4.13, though with the use of a surface graph instead of a line graph. It should be noted that a surface graph would work better had the sensors been placed along a single corridor as a means to show how movement along the corridor changed. Nonetheless, this was an easy way to show-case how the level of NMT activity differs for each sensor. In order to effectively compare the data trends in Chapter 5 it was necessary to convert the detections into ratios, as was done Section 4.3.2.2. These ratios are products of the number of detections per minute/hour over the overall maximum number of detections per minute/hour.

Figures 4.16 and 4.17 below show examples of the maps produced from the filtered results for the periods between 05:00 – 06:00 and 08:00 – 09:00. The map on the left was created with PTV Visum using the O/D results, and the heatmap on the right was created using Google fusion tables, using the number of detections per minute within an hour. It should be noted that the O/D matrices are not included in Appendix A, as the maps produced from the matrices contributed more in analysing NMT mobility. The data can, however be viewed electronically should it be requested. The elements used in the O/D maps are: blue circles which represent the number of detections at a sensor; and lines of various thickness between sensors, which represent the number of trips taking place between sensors in the given hour. The element used in the heatmap is essentially a colour scale based on the number of detections at each sensor, which accumulate based on the level of zoom. The heatmap is based on a 200 m zoom. Where green is displayed on the heatmap, small numbers of detections were recorded. As the number of detections increase, the colour shifts from green to yellow and finally to red, which represents the highest number of detections. Unfortunately, the element's size and intensity is based on the number of detections within the analysed hour and not the overall detections. This is seen when comparing Figures 4.16 and 4.17 where, although lower detections were recorded from the period between 05:00 - 06:00 than for the period between 08:00 - 09:00, the same size and intensity is displayed. To compasate for this, graphs similar to Figure 4.13 were added below the maps, which should be viewed in conjunction with the maps. These graphs are based on the NMT detections per hour from Figure 4.13. In order to simplify the figures, the period under consideration is highlighted instead of adding an axis.
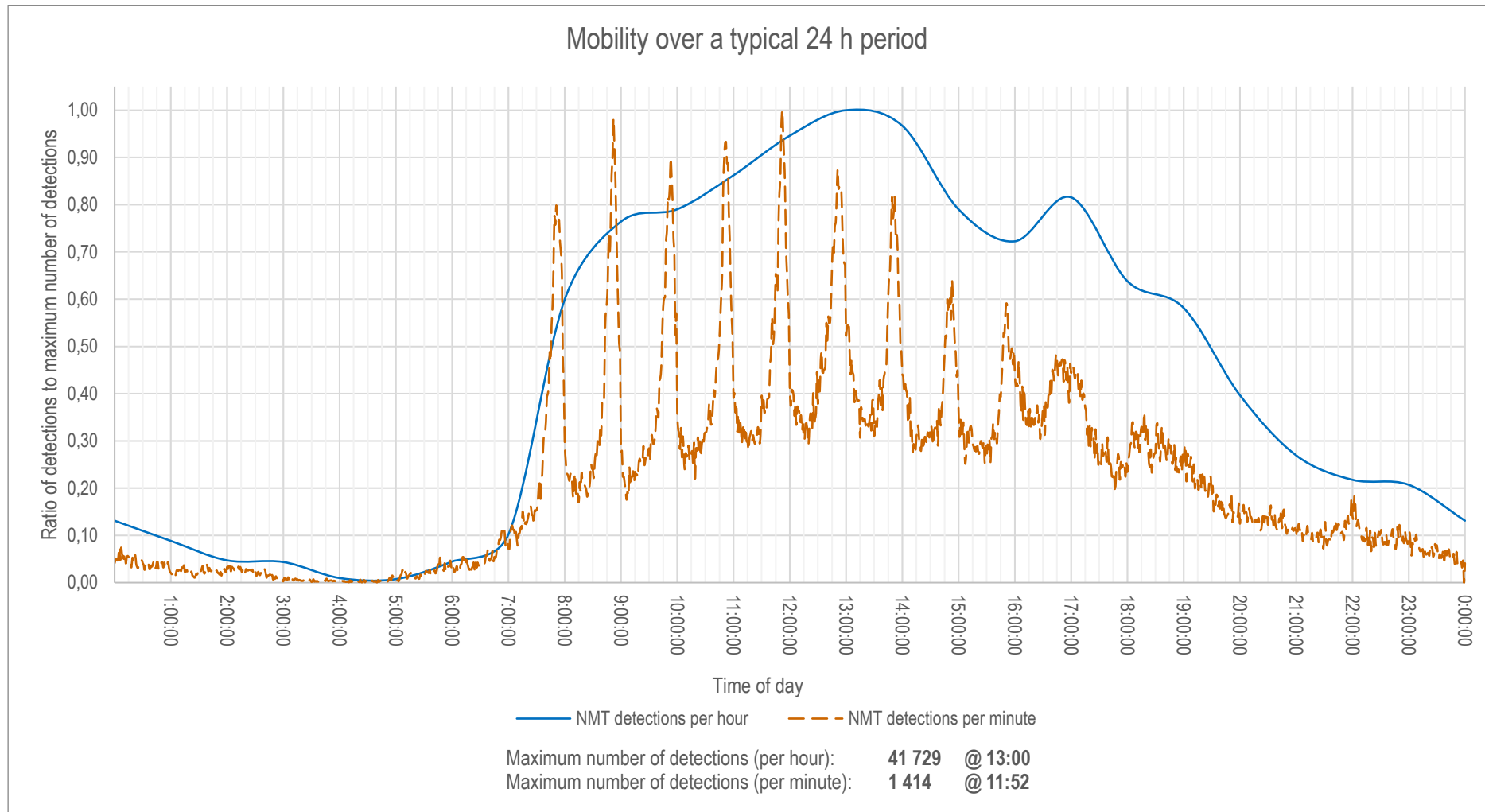
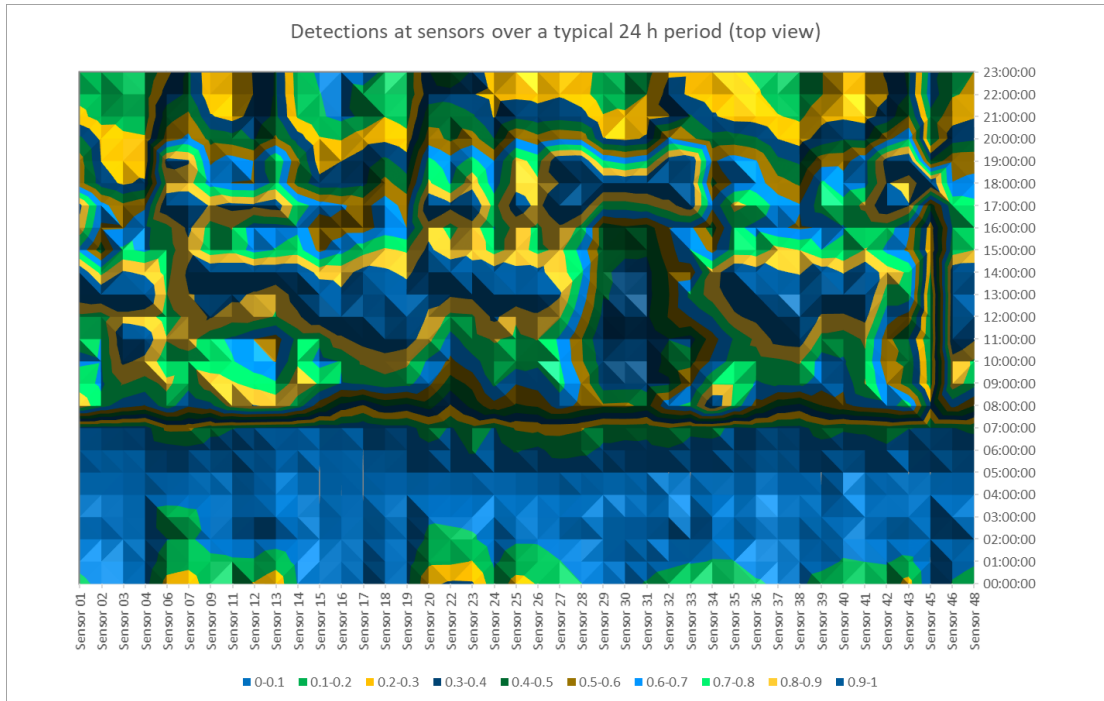Figure 4.13: Detections over a typical 24 h day

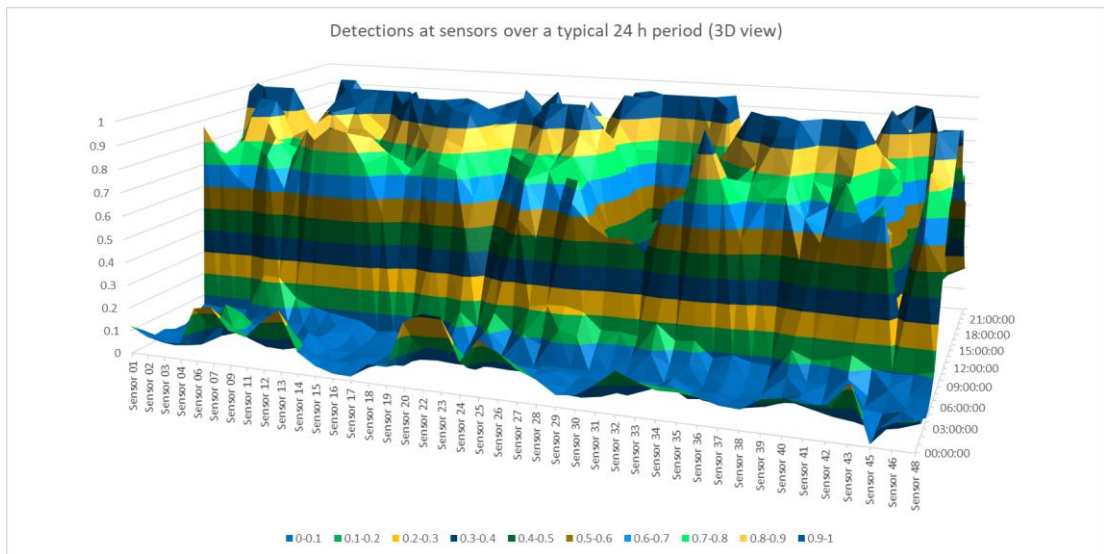Figure 4.14: Detections at sensors over a typical 24 h period (top view)

Figure 4.15: Detections at sensors over a typical 24 h period (3D view)
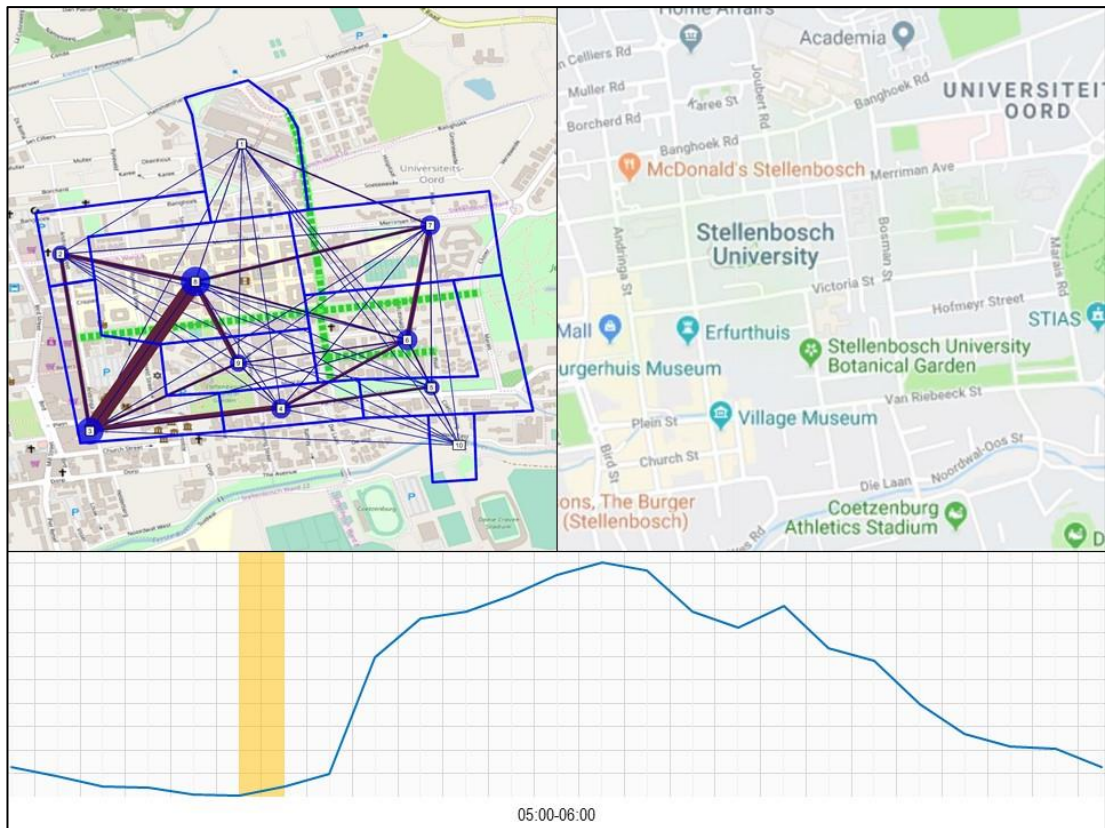
Figure 4.16: Activity maps for 05:00-06:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

Figure 4.17: Activity maps for 08:00-09:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

4.5 CONCLUSION

This chapter placed emphasis on evaluating, critiquing, and representing both the data and the processes used to filter the data. As with any study of this nature, it was necessary to place all these under tight scrutiny. As a starting point, the filtration process used to obtain a final group of NMT detections and trips was discussed and analysed. It was found that before the process, 2.1 million detections had been recorded over the three data collecting periods. From this, final estimates of 360 000 NMT trips and 460 000 NMT detections were obtained which were used for analysis. Although a large number of detections went unused, the resultant trips and detections nevertheless contributed greatly, enabling the production of graphs and figures on which the findings in Chapter 5 could be based.

In order to understand the shortcomings of the data collecting method (i.e. Bluetooth sensors), the penetration rate of the sensors and the classification filter used to distinguish between MT and NMT users were assessed. It was found that the penetration rate fluctuated between 1.5% and 11% across the counting stations. It was concluded that the penetration rate could be deemed as acceptable, based on literature which estimated rates between 2% and 12% (Wasson, Sturdevant and Bullock, 2008; Malinovskiy and Wang, 2012; Malinovskiy, Saunier and Wang, 2012; Shlayan, Kurkcu and Ozbay, 2016; Kurkcu and Ozbay, 2017; Lesani and Miranda-Moreno, 2018).

When considering the same counts as a means to determine NMT to MT ratios, it was found that, although the use of a 10 km/h speed filter to distinguish between MT and NMT users based on trip travel times produced the lowest mean in terms of ratio differences from the filtering results and the counts, the variance in data still revealed the inconsistent nature of results based on the use of this filter alone. It was thus concluded that since the design of an effective manner to distinguish between users fell outside the scope of this study, it could be suggested that further research be conducted to better establish how one could determine different types of user when using Bluetooth as a means to analyse mobility.

Although the filtering process was deemed insufficient in effectively differentiating between MT and NMT users, the patterns produced from the counts and those produced from the filtering results indicated that the approximated NMT trends based on the filtering results could be regarded as an accurate representation of NMT mobility on the SU campus. It was thus decided that the data would nonetheless be used for analyses and to base findings on.

Lastly, the manner in which the NMT data would be presented so as best to analyse it, was discussed. Based on the data, which took the forms of detections per sensor and trips between sensors, it was deemed that the appropriate manner in which to present the data would be in the form of graphs for overall detections per minute and hour, heatmaps for detections per hour, and O/D maps for trips between sensors.

CHAPTER 5

DATA INTERPRETATION AND FINDINGS

5.1 INTRODUCTION

As the aim of this study is to understand NMT movement in order to identify means by which NMT data could be incorporated in the planning of efficient transportation services, focus will now be placed on the interpretation of the results and how the results can be analysed to base findings on. To do this, data was collected and configured in the form of graphs and maps which were used to visualise NMT trends and patterns. First, mobility graphs were generated indicating the activity levels of NMT users over a typical 24 hour period. The NMT activity levels represent the Bluetooth detections per minute and/or detections per hour as a fraction of the total detected Bluetooth signals for the corresponding 24 hour period. Similarly, the second visualisation tool used activity levels per hour to create heatmaps using Google Fusion Tables. These heatmaps indicated the intensity of detections over the area being used for the study. Lastly, by converting the detections into trips between sensors, O/D matrices were constructed showing not only the activity levels but also the movement between sensors per hour.

Whilst the findings should revolve around the main objective of this study, some minor outcomes are highlighted in order to illustrate other means in which the data could be used. Various applications of the data and results are thus considered as part of this chapter, including elements discussing how the data could be used for planning by various institutions in Stellenbosch.

In Section 5.2 the data was interpreted by investigating the relationship between the location of the sensors and the NMT trends recorded by the sensors. Section 5.3 further investigates the findings in regard to the SU's Green Route and shuttle service and how they could be used by SU to assist their transport services and transport infrastructure development. From here, the findings are evaluated in terms of how they could be used by Stellenbosch Municipality with regard to NMT facility planning in Section 5.4. Next, in Section 5.5, the data and findings are assessed by considering how a MaaS driven transportation system could benefit from understanding NMT movement. Here, the emphasis is placed specifically on the integration of up-and-coming and traditional transport services. The summary of all these observations can be found in Section 5.6.

5.2   TREND INVESTIGATION

Considering the campus environment in which thus study was executed, an *a priori* expectation was expressed that a 10-minute NMT peak would occur 10 minutes prior to each lecture period and be repeated throughout the day. It was also expected that this hourly peak might subside or be less pronounced in the afternoon, since more practicals or tutorials are likely to be scheduled in the afternoon, resulting in longer class periods. Figure 4.11 provided sufficient evidence to recognise the formerly deduced expectation as accurate. The confirmation of this assumption reinforces the application capabilities of the study by showing that data obtained in this manner could be used to base observations on and therefore provide valuable information, about the movement of NMT users specifically.

In order to make the interpretation process run more smoothly, it was decided that the following two-step methodology would be used to analyse the observed trends before interpreting the trends as a whole: first, the data collected by the various sensors would be grouped according to shared location and land-use traits. This will be done twice, first for the position of the sensors based on their proximity to the campus, which is described in Section 5.2.1, and secondly based on shared land-use properties, such as their proximity to lecture halls, was described in Section 5.2.2. Once the investigation of how NMT trends differ, based on their location on the campus area is completed, an overall interpretation on how NMT users move in the study area for a typical 24 hour period is detailed in Section 5.2.3. By first analysing the relationship between NMT trends and location, it is hoped that an explanation for these trends may be deduced and later aid in interpretation of these results.

Figures 5.1 and 5.2 show the grouping of data based on the location of sensors. The first grouping consisted out of an inner campus group and an outer campus group. The inner group would thus consider the parts of the study area which were related to the campus itself, whereas the outer group considered the sensors at the periphery of the campus towards the town. Here, an investigation was conducted on whether the overall trend observed in Figure 4.11 was limited to the campus only. From this, a relationship between the inner and outer parts of the campus could be discovered and explained. The second grouping split the sensors based on their proximity to land-use. Three groups were identified, namely, sensors located near SU classes and facilities, sensors located near SU residences, and sensors located near shops, clubs, pubs, and restaurants. Moreover, a detailed investigation of the effect of the land-use on NMT trends was performed. The aim of this grouping process was to identify possible explanations

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for the trends observed, as this might give valuable insight on how these facilities interacted with movement patterns.
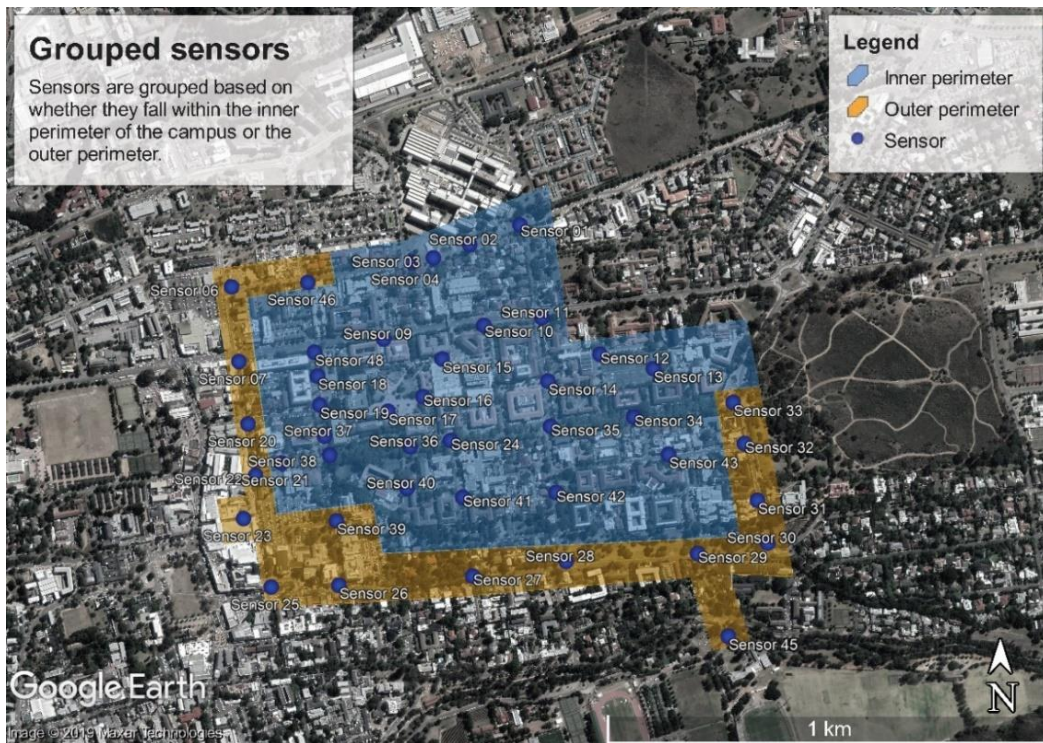

Figure 5.1: Sensors grouped according to their proximity to the inner and outer perimeter of the campus (Google Earth Pro, 2019)
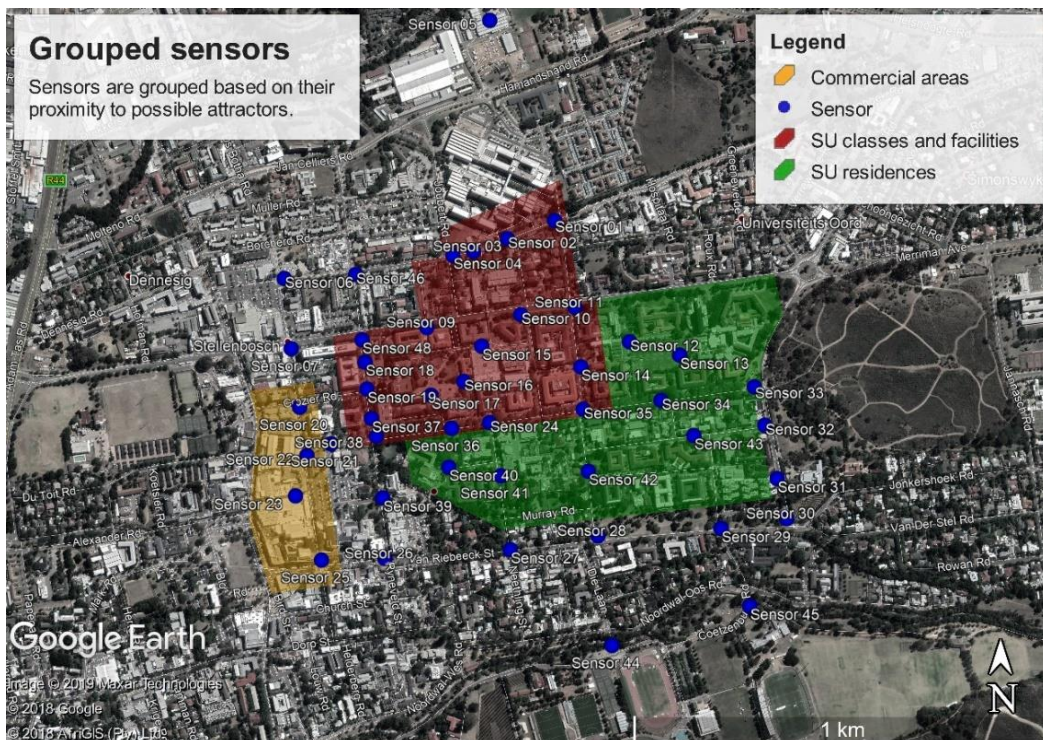

Figure 5.2: Sensors grouped according to their proximity to possible attractors (Google Earth Pro, 2019)

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5.2.1 Perimeter trends

In addition to the results already included in Appendix A, detection graphs, similar to Figure 4.11, have also been produced. First, graphs comparing the number of detections per hour, to the hour, with the maximum number of detections. Figure 5.3 shows the detections for the sensors located in the inner and outer perimeters. The sensors were grouped according to their relative position with respect to the campus. The sensors grouped under the outer perimeter category were most often located off the campus, where it was assumed that more non-student NMT users would be located during the day, whereas the inner perimeter sensors were located at spots where student NMT users were expected to travel during the day.
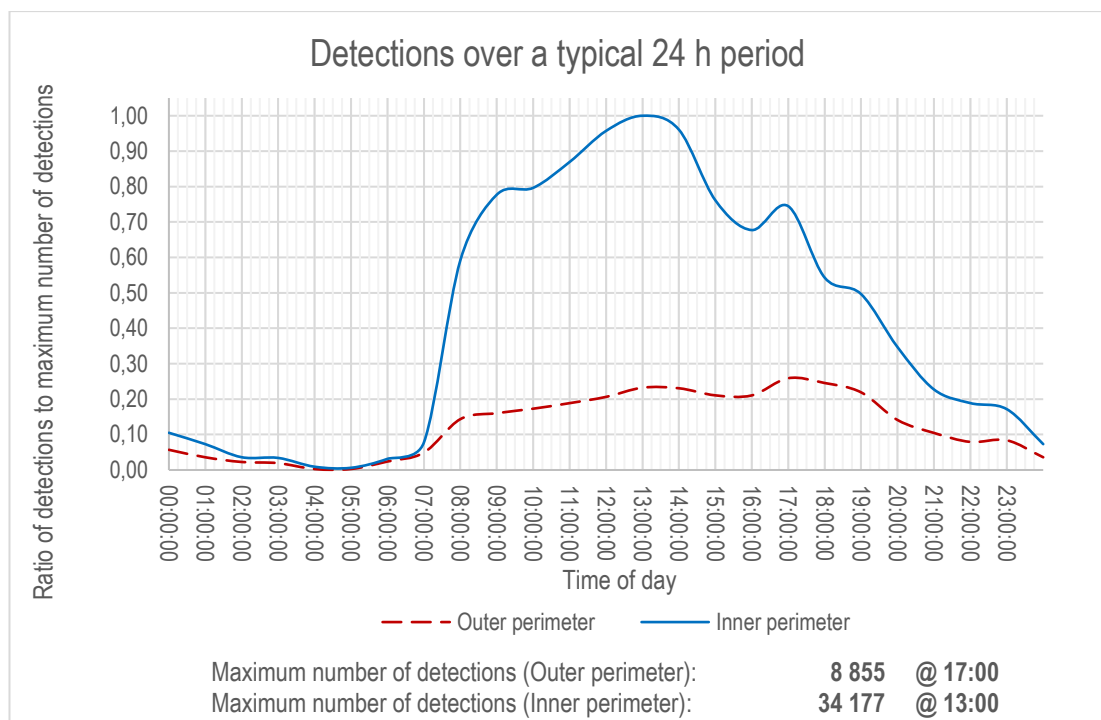

Figure 5.3: Detections over a typical 24 h period - comparing activity in the inner and outer perimeters of the study area

As a point of departure into the investigation of how the level in NMT activity differs between the two perimeters, it was first noted that in general, the two graphs followed similar trends. Both showed a steep climb in activity from 07:00 – 08:00 and both showed a steady decline in activity between 17:00 – 22:00. This was likely due to the presence of NMT users starting and ending their day. As mentioned in Chapter 1, 25 000 students attend to classes on the Stellenbosch campus, of which only 6 700 reside on or near the campus. When considering the NMT trends, it can be assumed that the spike in detections between 07:00 and 08:00 could be caused by the arrival of ±18 300 students. Similarly, the drop in detections in the late afternoon could be

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attributed to the departure of these students. This observation is true for all of the trends discussed hereafter.

When considering the O/D maps and heatmaps in Appendix A, in addition to Figure 5.3, the shift in NMT activity between the campus and the town becomes immediately evident. A peak is observed during 12:00 – 14:00 for NMT activity in the inner perimeter of campus, whereas a peak in NMT activity is observed in the outer perimeter between 16:00 – 18:00. When considering Figures 5.4 to 5.7 on the next page, a shift in activity is noted. Given the land-use of the study area, the conclusion can be drawn that the peak which occurs in the inner perimeter is likely to be due to a lunch break which generally starts at 12:00 and ends at 14:00. Given the location of the Eikestad shopping mall in proximity to the outer perimeter, it can also be assumed that the peak observed between 16:00 – 18:00 could be a result of afternoon activities such as persons doing shopping, going to the gym after work/class, etc. Given that SU classes usually end from 16:00 onwards, and that working people could be off work from 16:30 onwards, it would make sense that a peak would be observed near the mall during this timeslot. It should be noted that when comparing these peaks with Figure 4.11, a correlation was found for these time periods (12:00 – 14:00 and 16:00 – 18:00).

NMT activity in the early mornings are present in both the inner and outer perimeters. A likely cause is attributed to the nightlife activities which take place at the outer perimeter of campus. No restaurants, pubs, or clubs are located within the inner perimeter of the campus; however, social activities could still be present. Between 04:00 and 05:00 the level of NMT activity basically decreases to a negligible value. Considering that most of the clubs and pubs close at 02:00 (*Stellenbosch Nightlife - 15 Bars & Clubs*, 2019) and that the occasional house party would probably not last past 04:00, it is expected that the level of NMT activity would fall dramatically.

5.2.2   Trends according to possible attractors

When grouping the sensors in proximity to possible attractors for NMT activity (Figure 5.2), the trends in Figure 5.8 are observed. Three possible attractors were identified, according to which sensors were grouped, namely, SU academic facilities, SU student residences, and commercial areas (such as shops, clubs, pubs, and restaurants).

Figure 5.4: Activity maps for 12:00 - 13:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

Figure 5.5: Activity maps for 13:00 - 14:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

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Figure 5.6: Activity maps for 16:00 - 17:00 (Google Fusion Tables, 2019; PTV Visum, 2019)
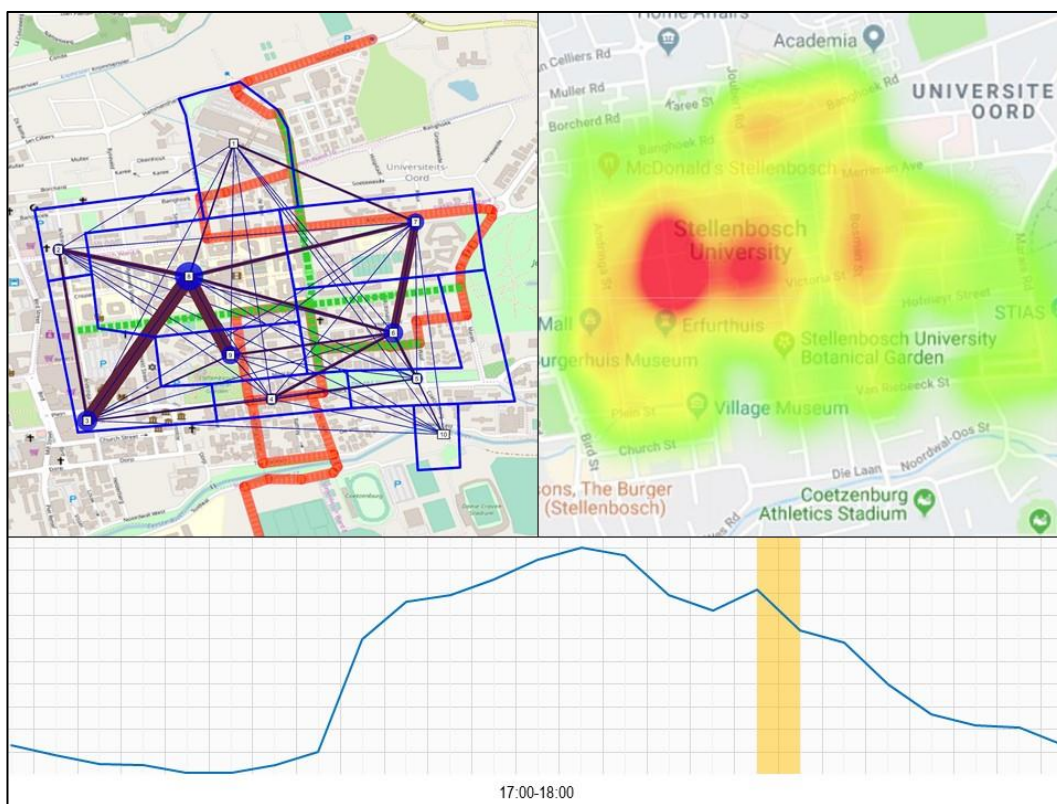

Figure 5.7: Activity maps for 17:00 - 18:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

First, the sensors located near SU classes and facilities were grouped together, next, the sensors located close to SU residences were grouped and last, the sensors near shops, clubs, pubs, and restaurants. As mentioned in Section 5.2.1, the steep increase and steady decrease in NMT activity most likely correlates with the influx and efflux of students to and from the town, which can also be observed within the data; NMT activity taking place near SU classes and facilities far exceeds the NMT activity taking place near other land-use groupings. This is also likely to be due to the number of students arriving from outside Stellenbosch. This assumption is supported by the notion that only 5500 SU students (roughly 22% of the total student population) reside in student accommodation. This number correlates with the 0.22 peak observed for NMT activity in close proximity to SU residences. Note that this ratio is derived from the ratio of NMT detections per hour to total detections per hour, respectively. Additionally, from this observation, it can be assumed that the majority of NMT users detected were students.
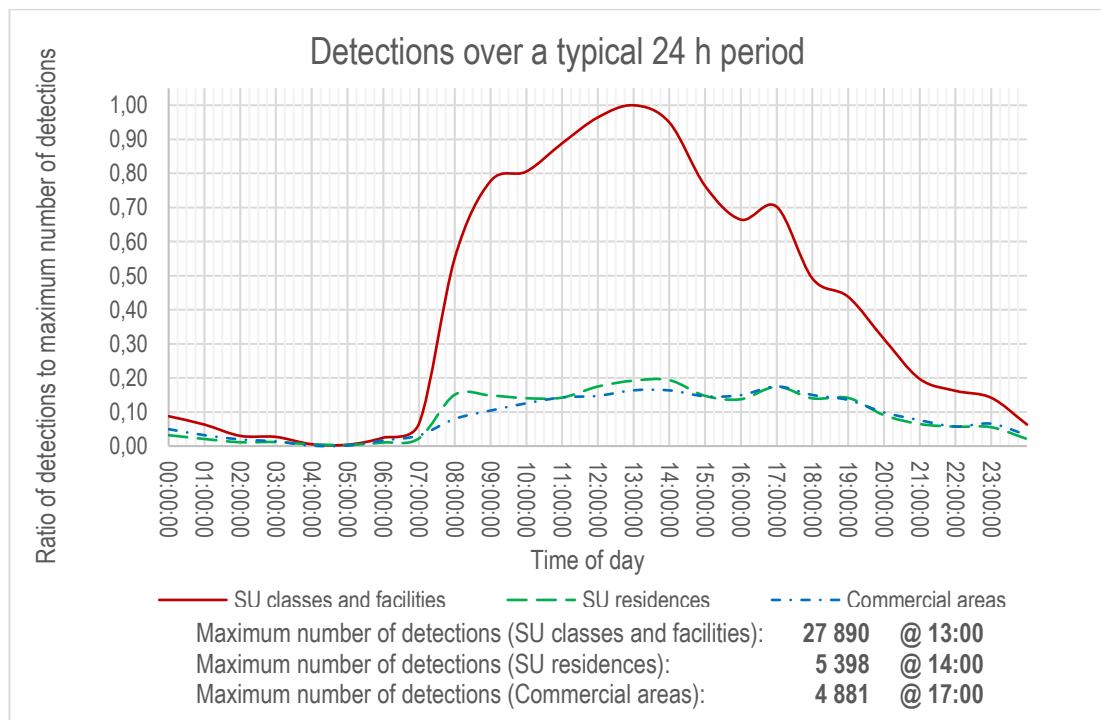
Figure 5.8: Detections over a typical 24 h period - comparing activity by considering possible attractors

When considering SU classes and facilities, it is noted that the peak is spread across the period between 08:00 – 15:00, where from 13:00 a steady decline in NMT activity is observed. Although the last classes usually start at 16:00 and end at 17:00, it is expected that activity near these facilities will slowly attenuate after 14:00 From empirical observation, the downward trend from 14:00 – 16:00 could be attributed to practical and tutorials classes usually being scheduled in the afternoons. These classes do not always continue for the entire allotted time of 2 to 3 hours.

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The small peak observed at 17:00 is then easily explained by considering the end of formal classes for the day, and thus students leaving the academic facilities.

Three peaks are observed when focusing on the SU residences. The first peak takes place around 08:00, the second between 13:00 – 14:00, and the last at 17:00. When considering the daily activity of students, these peaks most probably correlate with students going to class, returning to residences for lunch and afterwards returning to class, and lastly, students returning from their final classes for the day and/or taking part in extra-mural activities. A small peak is also observed at around 19:00. A cause for this peak is most likely associated with students socialising among their residences on campus or students heading to town.

The last trend observed is that of NMT activity in close proximity to shops, clubs, pubs, and restaurants. This trend follows a pattern nearly identical to the one produced for NMT activity near SU residences from 15:00 – 04:00. Given that it is likely that after class hours, activity will take place between SU residences and the town, this relationship is expected. It is also expected that peaks will not be present in the morning and afternoon for NMT activity near shops, clubs, pubs, and restaurants, as this activity would steadily increase throughout the day. The peak observed at 17:00 most probably correlates with students leaving class and moving towards the commercial side of the town.

5.2.3   Interpretation of trends

Following the analysis of how NMT trends differ across the study area based on the inner and outer perimeters of the campus and land-use characteristics, an overall interpretation on NMT movement across the study area can now be described in detail. Using Table 5.1 (page 68), the movement of NMT users is interpreted for hourly periods which share the same movement patterns and intensities as revealed in Figure 4.11, and the overall results as presented in Appendix A (specifically, the O/D maps and heatmaps which reveal travel patterns and detection intensities).

It was observed from Appendix A that between 08:00 – 17:00, NMT users generally travelled around Sensors 01, 02, 03, and 04, which were located in close proximity to the Engineering Faculty, Sensors 11, 12, 13, and 14, which were in close proximity to university residences and classes, Sensors 9, 15, 16, and 17, which are located on the Red Square of the campus, Sensors 48, 18, 19, 37, and 38, which are located on the section of Ryneveld Street where classes are located to the west and the red square is located to the east, and lastly at Sensors

36, 24, and 35, which are located in Victoria Street, where classes are located to the northern side and some residences to the south. Figure 5.9 shows the maps for 08:00 – 09:00 which resemble the other hourly periods during this time span. During this time frame, trips are generated mainly between sensors located near university residences, the Engineering Faculty, the Red Square, and the classes located along Ryneveld and Victoria Streets. A spike in detections takes place between 07:00 – 08:00, just before this observed peak, due to, as mentioned beforehand, the influx of students traveling to the campus and classes.

From 17:00 onwards movement shifts towards the western side of the campus. This can be attributed to the proximity of the Eikestad Mall as well as other commercial properties. As classes formally end at 17:00, it can be assumed that this shift in detections could stem from persons moving towards the commercial side of town to engage in typical afternoon activities (as mentioned, these could include shopping and/or going to the gym) Figure 5.10 shows the NMT activity between 17:00 – 18:00.

Regarding movement to the Coetzenburg sport facilities to the south of campus, a peak was noted during the 17:00 and 18:00 period between Sensors 28, 29, 30, 31, and 45. Effectively only Sensor 45 collected data moving towards Coetzenburg, given its position to the southern side of the Eerste River (no other sensor was positioned on this side of the Eerste River). This peak can be attributed to sport training taking place between these periods (such as rugby and athletics). This period is also generally accepted as the time during which NMT users would be taking part in other training activities such as jogging or hiking.

From 19:00 to roughly 23:00, a shift occurs again. Although, from Figure 4.11, the level of NMT activity is steadily declining, higher mobility levels are noted at the western edge of the study area, as well as along the western part of Victoria Street and parts of Plein and Van Riebeeck Streets. Figure 5.11 shows the activity taking place between 20:00 – 21:00. This can be attributed to the restaurants, pubs, and clubs located in close proximity to these sensors. Movement is also observed between Sensors 12 and 13, as well as other sensors located around them. This can be attributed to the activity of students moving between dining halls, the tennis courts, or the taking part in typical student activities between residences and other university venues.

The level of NMT activity continues to decline until it reaches a minimum value between 23:00 – 06:00. Although some activity is still observed between 23:00 – 03:00, it is assumed

that these movements belong to students moving from the town back towards SU residences. From 06:00 – 07:00 a steady climb in activity is observed, most likely belonging to early risers and joggers, before the spike in activity takes place between 07:00 – 08:00. Figure 5.12 shows the activity maps for 04:00 – 05:00.

Table 5.1: NMT mobility explained based on possible attractors

Time frame:	Level of activity based on Figure 4.12:	Sensors affected most base on O/D maps and heatmaps in Appendix A:	Possible attractors based on Figure 5.2:	Possible reasons for activity:
07:00–08:00	Steep rise in activity	Overall	SU classes and facilities	Student traveling to campus
08:00-17:00	General peak spread over this period	01, 02, 03, 04	SU classes (Engineering Faculty)	Classes
		11, 12, 13, 14	SU classes and facilities and SU residences	Classes
		09, 15, 16, 17	SU classes and facilities	Classes or off-periods
		18, 19, 37, 38, 48	SU classes and facilities	Classes
		23, 35, 36	SU classes and facilities and SU residences	Classes
17:00-19:00	Gradual decline in activity	07, 20, 22, 23, 25, 26	Commercial areas	Shopping and/or gym
		12, 13	SU classes and facilities	Tennis practice and socialising between residences
		09, 11, 14, 16, 17, 18, 19, 24, 35, 36, 37, 38, 48	SU classes and facilities	After class studying
19:00-23:00	Gradual decline in activity	09, 11, 14, 16, 17, 18, 19, 24, 35, 36, 37, 38, 48	SU classes and facilities	Studying
		12, 13, 34, 40 ,41, 42, 43	SU residences	Socialising between residences or studying
		07, 20, 22, 23, 25, 26	Commercial areas	Partaking in nightlife activities
23:00-03:00	Gradual decline in activity	07, 20, 22, 23, 25, 26	Commercial areas	Partaking in nightlife activities
		11, 12, 13, 14, 35	SU residences	Socialising between residences or studying
03:00-06:00	Lowest	12, 13, 24, 36, 40	SU residences	Students returning home or
06:00-07:00	Steady rise	Overall	N/A	People exercising

Figure 5.9: Activity maps for 08:00 - 09:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

Figure 5.10: Activity maps for 17:00 - 18:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

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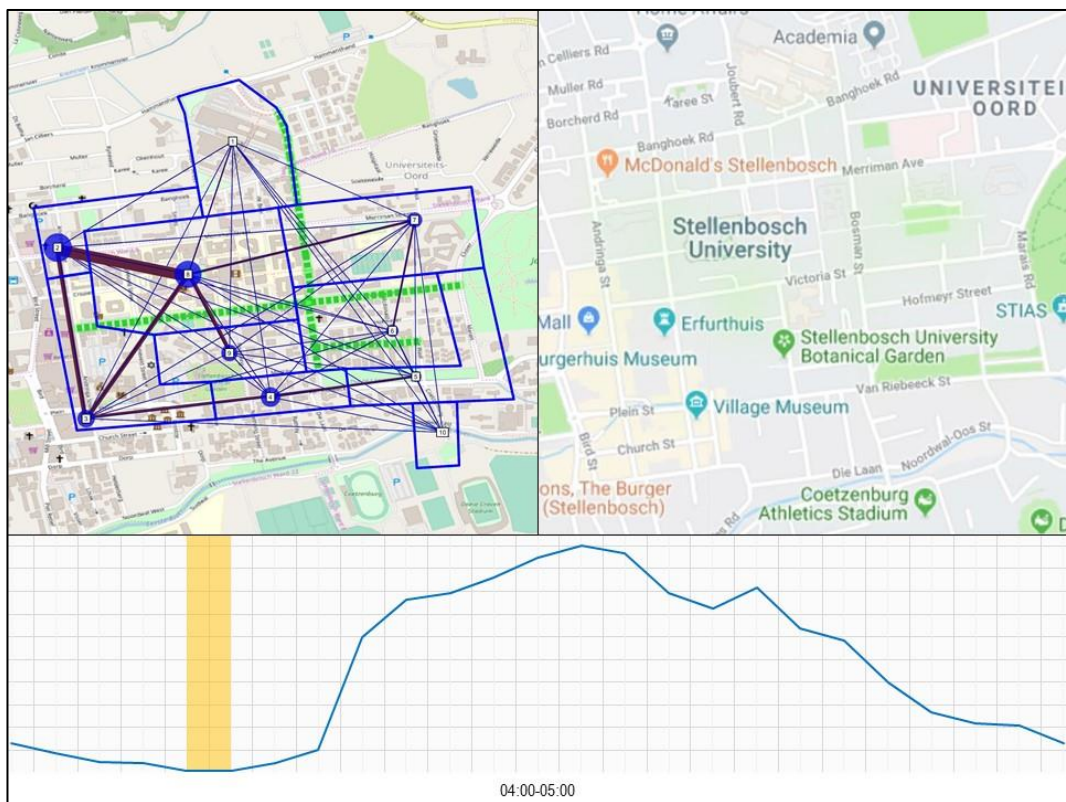Figure 5.11: Activity maps for 20:00 - 21:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

Figure 5.12: Activity maps for 04:00 - 05:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

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5.3   APPLICATION TO SU CAMPUS

The results have promising opportunities pertaining to the planning and delivering of transportation and safety services by SU. Two existing services which could benefit from this study are the SU Green Route safety initiative and the SU shuttle service.

The Green Route is a route which was identified and marked by SU and is monitored by Campus Security. This route has to be accessible to security personnel by means of NMT and MT modes. By comparing the position of this route to the intensity of NMT activity from the maps in Appendix A, especially during non-peak periods, an understanding can be formed as to whether this route needs to be extended. For example, considering NMT movement which takes place from 18:00 onwards, it could be suggested that the Green Route be extended along parts of Banghoek and Andringa Streets and Merriman Avenue where SU facilities are located as indicated in Figure 5.13.
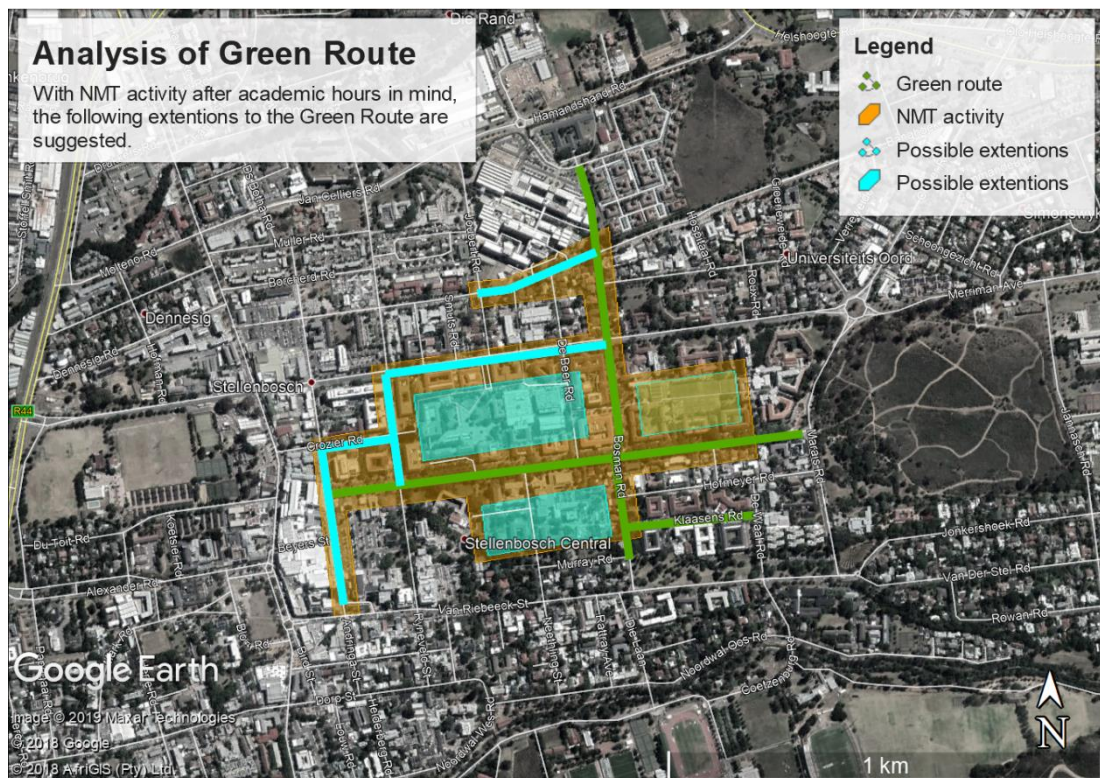

Figure 5.13: Suggested extensions to Green Route (Google Earth Pro, 2019)

Regarding the SU transport service, three shuttle service plans are provided to students and staff on and around the campus. Of these, attention will be focused on the day shuttle which operates on fixed routes during the course of the academic day. The orange route shown on the maps (Appendix A) between 07:00 and 18:00 represents the day shuttle route. The findings

could ideally be used to maximise the use of the day shuttle. It should be noted, however, that since sensors were not located along this route or in close proximity to this route, that the analysis of this route should be considered as indicative. When considering the position of the shuttle route and the shuttle stops, it is observed that where NMT movement mainly occurs on the parts of Ryneveld, Victoria, and Bosman Streets where many lecture halls are located in close proximity, no shuttle stops are provided or the shuttle stops are positioned further away from where the NMT activity is taking place. It is suggested that the shuttle route be extended to these areas, or that stops be moved to these areas, as indicated in Figure 5.14. This recommendation is also supported by observations made when counts were undertaken at sensors located along these streets, where it was noted that during the 10-minute peak period before the start of lectures, many vehicles stopped to pick-up or drop-off students, which obstructed traffic. In addition, it is recommended that should it not be feasible to extend the shuttle service, some streets be converted to one-way streets, which should allow for pick-up and drop-off facilities similar to those at Cape Town International airport.
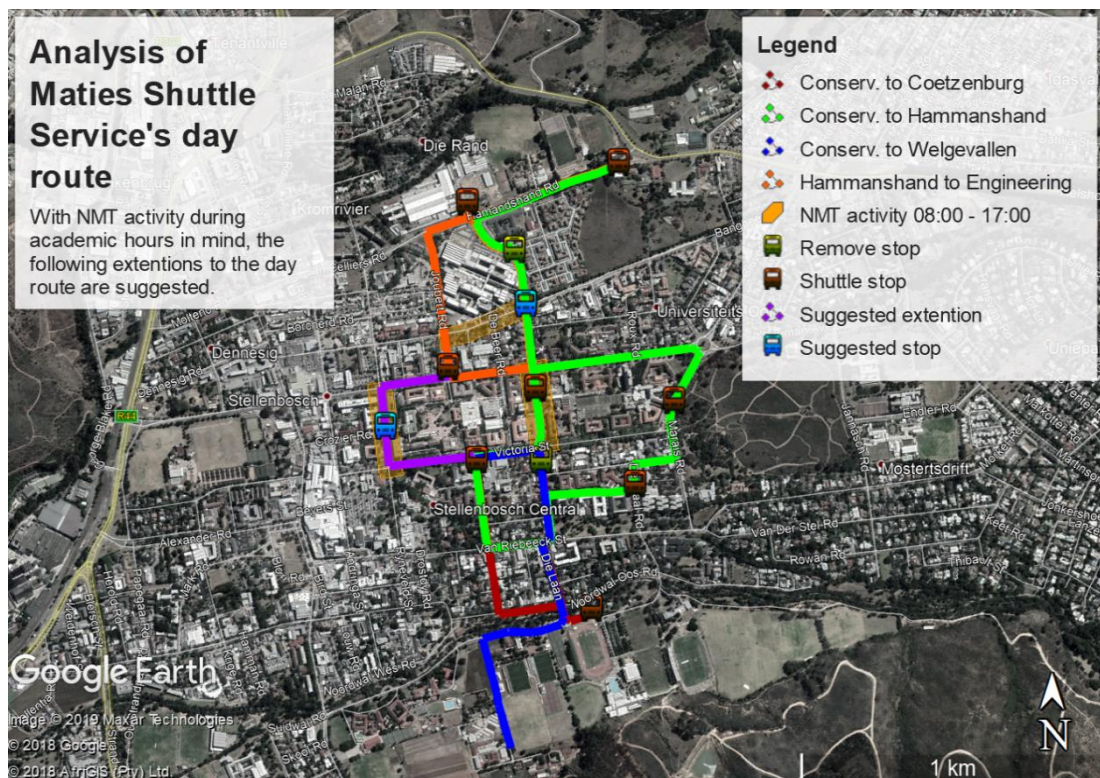

Figure 5.14: Analysis of the Maties Shuttle Service day route (Google Earth Pro, 2019)

5.4 APPLICATION TO LOCAL NMT INFRASTRUCTURE DEVELOPMENT

Given recommendations from the municipality's own Spatial Development Framework (SDF) (Stellenbosch Municipality, 2019) and Comprehensive Integrated Transport Plan (CITP) (Royal HaskoningDHV, 2016), and given a study concerning the development of a comprehensive cycle plan for Stellenbosch (Gordge, Laing and Wentzel, 2015), it can be recommended that this research study could assist in supporting the development of NMT infrastructure as a means to identify where NMT infrastructure development should take place. It was noted by Gordge *et al.* that the potential exists, given various social factors, for Stellenbosch to facilitate the growth of cycling into a major travel mode. This fits in with the findings of Chapter 2, where it was found that, commonly, NMT data is collected for the purposes of understanding NMT travel behaviour in order to understand where and how local governments should invest in planning and designing these facilities (Tanaboriboon and Guyano, 1991; Buckland and Jones, 2008; Hood, Sall and Charlton, 2011; Malinovskiy and Wang, 2012; Malinovskiy, Saunier and Wang, 2012; Ryus *et al.*, 2014; Royal HaskoningDHV, 2016).

A study conducted by Randall (2015) would suggest that given the results from surveys conducted on why employees in South Africa do not use cycling as a main transport mode, a correlation exists with the lack of provision of cycling infrastructure. With this in mind a similar observation is made to that of Malinovskiy *et al.* (2012b) where they note that two questions regarding NMT mobility is of specific interest to the US Federal Highway Association (Schneider *et al.*, 2005), namely: 1) Where is pedestrian and bicycle activity taking place, and 2) what effect does facility construction have on levels of bicycling and walking. They argue that 'the questions themselves are a product of the available means of data collection.' Hence, although land-use plays a role in attracting NMT activity, it can be argued that where NMT activity already takes place, NMT infrastructure should be provided, and moreover, when NMT infrastructure is accessible, NMT activity will be promoted.

Thus, the findings presented in this chapter, i.e. where NMT activity is taking place, indicates areas surrounding the campus where opportunities exist for developing NMT infrastructure. Although a low incidence of cycling activity was observed, it is argued that investment in cycling infrastructure along road corridors with high levels of NMT activity, would promote cycling the same time.

5.5 TOWARDS A MaaS DRIVEN TRANSPORTATION SYSTEM

As this study aims to understand NMT movement in order to identify means by which NMT data could be incorporated into planning efficient transportation services, an investigation on how the findings and interpretation of the data can be used in a MaaS context will now be done. As a starting point, micromobility services will briefly be considered as a new transportation service which could benefit from the results and findings. From here, considering that a manner now exists by which to analyse and understand NMT data, the question is then asked how other existing transportation services could benefit from this understanding. The travel patterns of an existing public transport service, in the form of minibus taxis operating in and around Stellenbosch, are considered in this regard. By comparing the patterns of the collected data to those of minibus taxi activity, it is hoped that a gap could be identified which could be used in order to improve mobility on the campus.

When considering micromobility, one considers modes such as shared bicycles, e-bicycles, and e-scooters (Reed, 2019). SU currently provides for the renting and storing of bicycles via their Matie Bike and bicycle sheds initiatives (Stellenbosch University, 2019). The effectiveness of the Matie Bike campaign is, however, currently unknown. Four sheds are currently provided where bicycles (Matie Bikes and personal bicycles) can be stored (Figure 5.15). The sheds are not located near parking lots, but rather close to academic facilities. This is highlighted, since it is assumed that should this service be offered as a means to reduce the use of private cars within the perimeter of the campus, it would make sense that a modal shift should occur with ease, hence, as close as possible to where students with private cars park. From Figure 5.15, however, it is noted that some of the sheds are located near areas where NMT activity is at its highest intensity (indicated in orange).

Since this study was not explicitly focused on the effectiveness of the offering of bicycle, e-bicycle, or e-scooter services, it is difficult to form arguments as to how, with the use of the collected data, these services could be introduced or offered differently. What is, however, evident from the trends, is that a major offering could take place between 08:00 – 17:00. Additionally, the promotion of these services would greatly benefit from infrastructure changes which promoted their use. It is suggested that, based on the activity maps in Appendix A, that a change in street layouts in parts of Andringa Street, Ryneveld Street, Victoria Street, Bosman Street and Merriman Avenue would be favourable. These streets should be altered to accommodate NMT modes as they were noted as presenting the highest intensities of NMT

detections. Additionally, SU could also incorporate infrastructural changes to its campus to facilitate and promote these modal services.

Figure 5.15: Location of SU bicycle sheds and parking lots in comparison to the area where greatest level of NMT intensities were recorded (Google Earth Pro, 2019)

An opportunity to incorporate minibus taxis as a means of providing mobility services also presents itself when considering the trends observed in this study with minibus taxi and light vehicle counts obtained from Stellenbosch Municipality. By combining the NMT detections with these two datasets, Figure 5.16 was developed. It should be noted that the counts were derived from across the town and have been converted to ratios similar to the ratios used for the detections. The counts were only done to collect activity over the course of a typical working day, thus from 06:00 – 18:00.

From this figure, findings could first be made regarding the utilisation of the local minibus taxi industry as a means of providing a service to students and staff around the campus. A morning and afternoon peak were observed in minibus taxi activity. Between these two peaks, a slump in the activity took place. Considering that it is in this period where a high level of NMT activity was observed, it could be suggested that routes dedicated to minibus taxis be established which would serve students and staff in support of the Matie Shuttle service. Again, infrastructure development could assist in facilitating and promoting this service. It is interesting to note that

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while the morning peak regarding minibus taxi activity occurs from 06:00, the spike in NMT activity only occurs near 08:00. From this, the question thus arises as to what impact a shift in these patterns would have in optimising the transportation system in Stellenbosch in ensuring that mobility is used effectively and efficiently. Could a new opportunity be created in regard to MaaS by shifting the feeder routes of the local minibus taxi industry into the campus area, or perhaps by shifting the morning peaks of NMT activity?

In order to provide additional context as to how other modes of transport interact around the study area, the activity of light vehicles around Stellenbosch were also included in Figure 5.16. It is observed that similarly to the minibus taxis, a morning and afternoon peak is present. Again, it is noted that the morning peak starts at 06:00. Since the presence of light vehicles is substantial throughout a typical working day, it is challenging to identify a correlation between the trend observed from the light vehicles and those of NMT users. It is, however, noticed that where the light vehicle's morning peak starts to decline, the spike in NMT activity and the first NMT peak starts. This could correlate with students and workers arriving at their destinations and then traveling by means of NMT modes. The drop in NMT activity in the afternoon again correlates with the afternoon peaks in private vehicle activity. Since it was shown that the peaks observed in NMT activity (NMT detections per minute) correlates with the changes in classes over the hours of 08:00 – 17:00, the question is raised as to what effect a change in class hours or class durations would have on the overall system. It is assumed that by pushing the start of the academic day to 08:30, a definite reduction in the morning peak on the roads would be experienced in general.
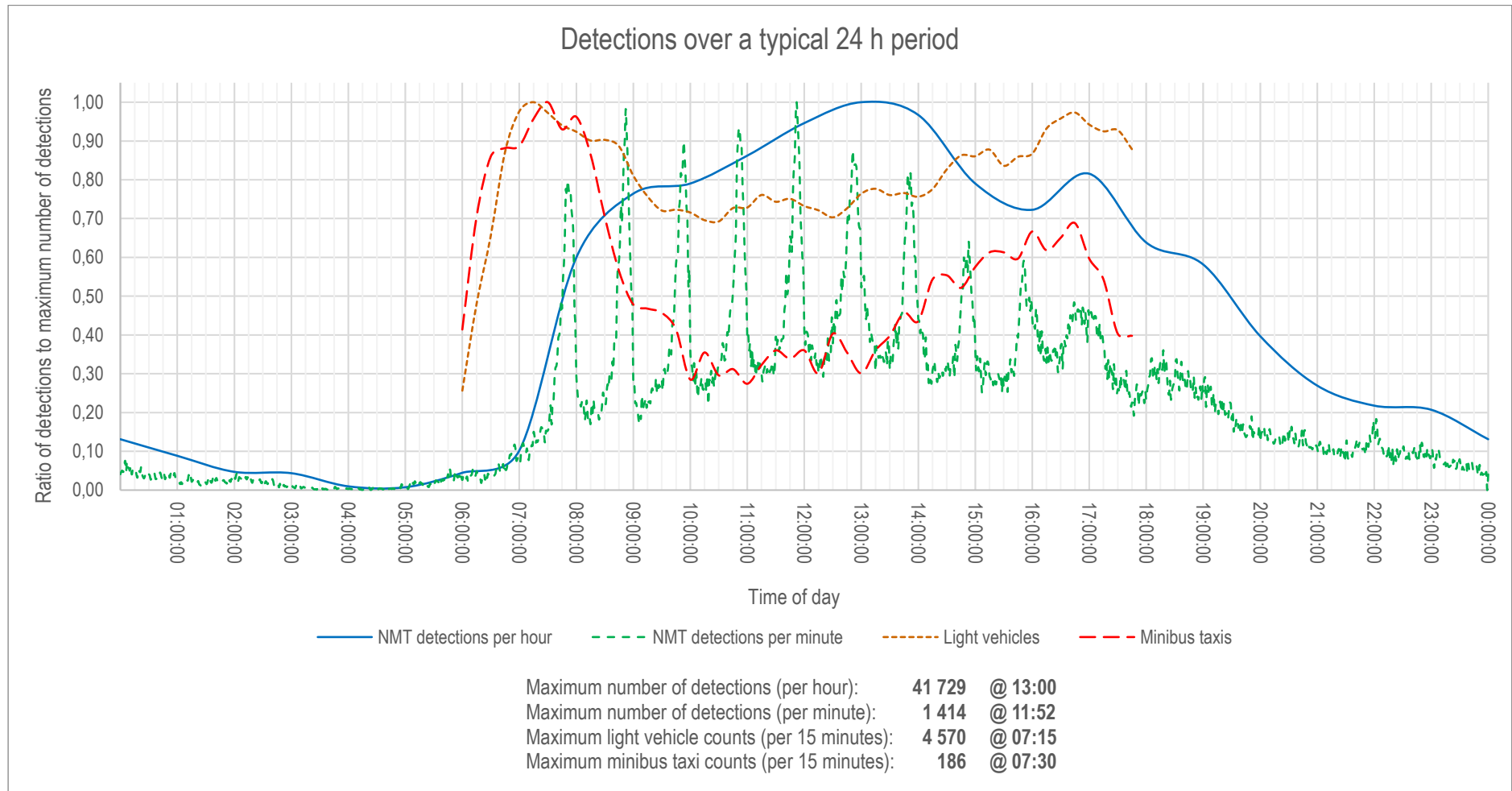
Figure 5.16: Detections over a typical 24 h period – other transportation modes included

5.6 CONCLUSION

5.6.1 Summary

Before the data could be used to formulate findings and to identify how the data could be used to benefit a MaaS centred transportation system, the data needed to be interpreted. The data was interpreted by considering what the effect of location has on NMT trends. Emphasis was placed on the differing NMT trends in the inner and outer perimeters of the campus by dividing the data based on their sensor's location in respect to the campus. Here, it was revealed that the majority of NMT trips occur within the inner perimeters of the campus. It is also these users who contribute the most to the overall trend as shown in Figure 4.11. In addition, by analysing the peaks of each perimeter, it was concluded that the general peak observed for NMT activity in the inner perimeter was likely due to the campus-wide lunch break which takes place between 13:00 – 14:00, although some might already be off around 12:00. The second peak for activity within the inner perimeter correlates with the peak observed in the level of activity in the outer perimeter. It was concluded that this is likely due to a shift in movement from the campus towards the town, most likely for the purpose of shopping activities.

Once these conclusions had been reached, the focus was placed on the land-use within the study area. The collected data was again divided, this time into three groups, namely, the proximity of the sensors to SU classes and facilities, SU residences, or commercial areas. From this, Figure 5.8 was produced. Again, it was revealed that the majority of NMT activity taking place on the campus occurs between SU classes and facilities. The relationship between the trends related to the level of activity near SU classes and facilities and SU residences was of special interest. Here, the movement between residences and classes could easily be identified when observing that a morning, lunch, and afternoon peak occurs for both groups which is probably a good indication of how students move between their residences to classes. Regarding the trend observed for NMT activity taking place near shops, clubs, pubs and restaurants, it was noted that a steady climb takes place from the morning, until near the afternoon, when the trend starts to follow the same pattern as that of the other two groups. This most likely correlated with students leaving the campus area to move towards the town either for shopping or to participate in night life activities later in the evening.

Considering how the trends differed across the study area led to an overall interpretation of the data being formed. It was concluded that NMT activity heavily increased in the hour before the

academic day started (07:00 – 08:00), most likely due to the influx of off-campus students. Furthermore, by considering the detections per minute, peaks in NMT activity levels occurred in the 15-minute periods before each hourly scheduled class (08:00 – 17:00). Thereafter, a steady decline in NMT activity was observed. Numerous explanations exist for this; however, it can be assumed that during this period NMT users are either leaving town (students living outside of Stellenbosch), going shopping, or going out of town. A dead period was observed between 03:00 – 05:00 where virtually no NMT activity took place.

From the overall interpretations, findings could be produced by considering how the data might benefit SU and the local NMT infrastructure developments, and eventually a MaaS driven transportation system. As a point of departure, the Green Route, a route the use of which is promoted by SU, especially in the evenings, was analysed. Along this route, students will often find campus security officials on patrol. When considering the layout of the route with where NMT activity is taking place in the non-academic portion of a typical day, it was suggested that the layout of the Green Route be extended along parts of Banghoek and Andringa Street and Merriman Avenue. Furthermore, the Maties shuttle service's day route was also examined with regard to where NMT activity takes place. Although the service could not sufficiently be analysed due to a lack of sensors placed along the route, it was suggested that when comparing the shuttle stops with where NMT activity is actually taking place, the stops be repositioned in order to catch a larger pool of users.

On how the data could benefit local NMT infrastructure planning, attention was drawn to current NMT plans in the form of Stellenbosch's Spatial Development Framework and Comprehensive Integrated Transport Plan. Here the need for NMT modes and infrastructure is highlighted. Based on common reasons as to why governments collect NMT data, gleaned from Chapter 2, it was suggested that the data from this study could be used by Stellenbosch Municipality as a means to identify and support the development of its NMT infrastructure.

Lastly, when considering how the data could be used within a MaaS driven transportation system, three concepts were brought forward. First, a look into micromobility indicated that SU currently provides for shared bicycles in the form of the Matie Bike. Additionally, SU provides bicycle sheds where these bicycles as well as private bicycles can be stored. Although little could be said regarding the effectiveness of promoting the Matie Bike concept, comment was reserved to the current locations of the bicycle sheds when considering where NMT activity is taking place across the campus. In addition to suggesting that the locations of the sheds be

moved or more sheds be added, it was proposed that infrastructural changes be considered as a means to promote the use of bicycles as well as e- bicycles and e-scooters. By considering the main time frame during which NMT activity is at its highest, temporary road closures could perhaps be considered instead of changing physical infrastructure.

In addition to these micromobility modes, it was also suggested that the local minibus taxi industry be incorporated into an on-campus mobility service option. When considering that during the peak observed in NMT activity on campus and the drop in the level of minibus taxi activity over a typical working day, it was proposed that the routes be dedicated towards minibus taxis on which a transport service could be offered in conjunction with SU's shuttle service. This would allow students and staff to travel with ease across the campus. In addition to observing the trend in minibus taxi activity, the trend in the activity of light vehicles (often in the form of private cars) was also investigated. From this the question was posed, that considering the relationship between where the level of activity measured for light vehicles starts to decline after the morning peak and the fact that during this time the level in NMT activity starts to climb, what effect a shift in the starting time of SU's academic day would have on the traffic trends around the town? Although this question could not be answered, it was hypothesised that a shift in 30 minutes (meaning that classes would start at 08:30 instead of 08:00) could perhaps lighten the level of congestion in and around Stellenbosch.

5.6.2 Findings

Following from the summary of this chapter, minor findings regarding the usefulness of characterising NMT behaviour can be compiled as follow:

- NMT data in the form of visualised trips and detections (the O/D maps and heatmaps) can be used as a means to facilitate the planning of NMT facilities across the campus, especially given the space/time characterisation of the data;
- In addition, the data can be used as a means to improve non-transport related spatial planning aspects of the campus environment, such as the extension of the Green Route and overall safety after hours;
- From a local government point of view, areas which have the potential of being pedestrianised or which could facilitate cycling can be identified;
- Regarding transportation services, the NMT data shows how the Matie's Shuttle service can use the data in determining service points across the campus;

Following from these findings and considering the main objectives of this study as described in Chapter 1, the major findings of this study can be listed as:

– That NMT data, when effectively characterised in a space/time manner, such as was done in this thesis, clearly shows potential in that area and times can be identified which would benefit the introduction towards micromobility services, such as bicycle, e-scooter, and e-bicycle sharing. From the O/D maps, trend lines also serve to show popular routes on the campus, whereas the heatmaps would indicate the spaces which should be reserved for service points;

– Furthermore, in understanding the fluctuation in the level of NMT activity over a typical 24 hour day, the local minibus taxi industry also stands to benefits in that the potential to provide on-campus transportation services at times where their typical clients are not active can be identified and utilised.

CHAPTER 6

CONCLUSION AND OPPORTUNITIES FOR FUTURE RESEARCH

6.1 THESIS SUMMARY

This thesis sought to understand the travel behaviour of NMT users in an attempt to assess whether NMT data could be used as a means to benefit the efficiency of future and traditional transportation services. As part of this attempt, other opportunities in which the type of NMT data collected from this study could be used were also identified as by-products. The Stellenbosch campus of SU was used as the study area upon which NMT data was collected and analysed. Bluetooth technology was used as the means to collect spot data and derive mobility trends. From the data, it was then possible to create visuals which were used to analyse the travel patterns of NMT users in the study area over what was deemed a typical 24 hour period.

The study started off by investigating the literature available on the workings of NMT within the transportation sector. Attention was placed on why authorities typically collect NMT data. Given the rising presence of MaaS, literature was reviewed which highlighted current MaaS systems, how these systems operated and the typical role of NMT within these systems. To discover to what end a MaaS system could benefit from and use the understanding of NMT travel behaviour was also a goal. Once a clear foundation had been formed regarding NMT, focus was shifted towards the manner in which NMT data could be collected. Although Bluetooth technology was used for this study, because of the ease of its implementation, it was still necessary to consider the advantages and drawbacks of Bluetooth compared to other methods of collecting NMT movement data. Common methods which had been considered for this study were reviewed, which confirmed that the Bluetooth sensors would be sufficient in their abilities to collect spot data from which trends could be analysed. Consequently, literature regarding the technical aspects of Bluetooth technology and its workings within the transportation engineering field was reviewed. This was done in order to garner a full understanding of the technical limitations associated with using Bluetooth signals as a means to determine travel behaviour. Additionally, this assisted in the communication between the researcher and the technical team involved in developing the Bluetooth sensors which were used for this study.

With a firm foundation on the theoretical aspects of the thesis, the methodological process had to be designed. The study comprised four general stages, namely, the collection of data, the filtering of raw data, the analysis of the final dataset, and the application of the data to real world scenarios. With these four stages defined, focus could then be placed on the development of the data collection process. Forty four sensors were procured for this study. In order to efficiently collect data on the movement of NMT users, sensors were placed in such a manner as to limit the detection of MT. Sensors were limited to sidewalks and NMT-only spaces, such as the walkways between SU residences and the Red Square on the campus. Sensors were also placed in accordance with how NMT users typically traversed the Stellenbosch campus, which was based on empirical observations as well as land-use. With the locations of the sensors finalised, the data collection periods were determined. These periods were chosen so as to effectively represent a typical day on the campus. This meant that the periods could not include days such as public holidays or days on which unusual events took place on the campus setting, as this would disrupt the final dataset. Given the nature of the sensors, the periods comprised four days each, two of which were dedicated to installing the sensors and later collecting them in order to recharge the mobile battery packs.

The raw data was received from Bridgiot in the form of .CSV files compatible with MS Excel. Given the amount of data (three stand-alone MS Excel files which were too large to merge), a proper systematic process was designed to filter through the datasets. This 10-step process entailed the organising of the data in order to translate it from single detections to trips, as well as classifying the trips according to possible modes of travel, mainly NMT and MT, in accordance with this study. Various assumptions had to be incorporated in part of this process, such as the number of Bluetooth devices likely to be carried by users, and the use of travel speed to classify user modes.

Given that classification was based mainly on travel characteristics of trips between sensors, it was necessary that this filter be properly validated. Counts were thus done parallel with the operation of a Bluetooth sensor. This allowed for validation of the modal classification based on the observed ratios of NMT to MT users with those derived from the filter. Furthermore, penetration rates could also be determined which could be compared with similar studies and the counts could further be used to validate the NMT patterns observed in the final dataset. It was found, however, that simply using travel speed as a means to classify modes was not sufficient. It was recommended that other techniques be explored which could be used to classify Bluetooth data according to possible travel modes. Nonetheless, it was established that

the travel patterns of NMT users during counts were nearly identical to those derived from the filtered Bluetooth data. Hence, as this study's aim was to understand to behaviour of NMT users, it was decided that the final dataset could still be used to this end. It was thus assumed that the final dataset contained a sufficient number of NMT datapoints.

With the final dataset completed, the data was transformed visually for analysis purposes. Graphs depicting the detections of NMT users over a typical 24 hour period were created for the entire network of sensors, as well as individual sensors. These graphs represented detections on either an hourly basis or a per minute basis based on the maximum number of detections over the given analysis period. In addition to these graphs, maps were also created which represented NMT activity across the campus. The first set of maps was created using PTV Visum. O/D matrices were created as part of the data filtering process, from which the desire lines could be drawn based on the movement between sensors over a given hourly period. The thickness of these lines would then indicate the number of trips occurring between two sensors. In addition, circles whose sizes were a function of the number of detections at a sensor within the analysis period were also incorporated. In addition, using Google Fusion Tables, heatmaps were generated whose colour scale indicated the intensity of detections at sensors across the campus over an hourly period. The graphs ultimately revealed the manner in which NMT users moved over a 24 hour period. The maps could also reveal how mobility shifted geographically as the level of detections changed over a typical day.

From the findings of this study, the following conclusions could be reached. As a by-product, the potential of this data collection method of revealing NMT mobility trends is underrated in regard to its possibility to assist in the planning of NMT infrastructure and supportive services. One such example showed how the NMT data could be used to evaluate the layout of the SU Green Route, a route patrolled by campus security after hours. It was shown that additional roads on the boundaries of the campus could benefit by extending the route layout of the Green Route. However, the major findings pertaining to the goal of this thesis was found in the analysis of the manner in which future and traditional transportation services could benefit from the NMT travel behaviour on the Stellenbosch campus it revealed.

Consideration was firstly given to the current Maties Bike service. In understanding where NMT activity was taking place, the effectiveness of this service in the provision of bicycle sheds and bicycle routes could be evaluated. It was found current initiatives to promote the use of renting a Maties Bike most likely fall short, in that the service is not provided in areas which attract NMT

activity. Additionally, the infrastructure where NMT activity is currently taking place does not support convenient travel. Additionally, in considering micromobility services, a gap was identified which could benefit from the results of this thesis. It should, however, be noted that as stated in literature, a correlation was found between the promotion of NMT or NMT hybrid modes and the infrastructure supporting these modes. Thus, certain streets were identified as a means of indicating where the necessary development should occur in the hopes of promoting micromobility on the Stellenbosch campus.

Finally, the NMT data was compared to other existing transportation modes and services, specifically, the minibus taxi industry. It was revealed that in understanding the travel patterns of NMT users across the campus, new opportunities were revealed which could benefit not only the minibus taxi industry, but greater mobility across Stellenbosch. The graphs which indicated the number of NMT detections across the study area was compared to counts collected from minibus taxis around Stellenbosch. Here, it was evident that the peaks observed between the two modes, complemented each other in the sense that where a peak occurred in NMT travel, a drop in minibus taxis was observed. It is based on this observation that a conclusion could be reached that the collection and analysis of NMT data can serve in identifying manners in which the greater transportation system can operate both more effectively and more efficiently.

In conclusion, it is generally accepted that travel in the 21st century does not occur by only one travel mode. Travel, however, can also not start before any physical activity has taken place. It is thus imperative that the transportation system become more holistic, starting with our planning of transportation services and infrastructure. It is thus also imperative that the most basic form of travel, namely NMT, not be pushed aside in our aim to innovate, but that we understand how this simple form of movement can and should be used as the building block for the any revolutionary transport initiatives. As seen, it is in our understanding of how people move in the most basic sense, that we can identify new means by which to provide better services as we strive to create an improved travel experience for most, if not all, persons.

6.2   CONCLUSION

First, this thesis set out to characterise the behaviour of NMT users across the Stellenbosch campus. From this characterisation, clear travel paths and high NMT activity points were determined. In interpreting the data in regard to the space/time characteristics of NMT users over a typical 24 hour weekday, minor and major suggest could be made which wold indicate

the usefulness in understanding NMT behaviour. To proof this, various minor and major findings were deduced which used the final dataset as a tool to assess not only transportation related issues, but spatial aspects of the study area as well.

To present the general usefulness in understanding NMT data, the following minor findings were summarised in Section 5.6.2 which showed that:

- NMT data in the form of visualised trips and detections (the O/D maps and heatmaps) can be used as a means to facilitate the planning of NMT facilities across the campus, especially given the space/time characterisation of the data;
- In addition, the data can be used as a means to improve non-transport related spatial planning aspects of the campus environment, such as the extension of the Green Route and overall safety after hours;
- From a local government point of view, areas which have the potential of being pedestrianised or which could facilitate cycling can be identified;
- Regarding transportation services, the NMT data shows how the Matie's Shuttle service can use the data in determining service points across the campus;

From here, emphasis was then placed on the impact of NMT data, as collected and characterised in this thesis, on a MaaS driven system. These major findings, also summarised in Section 5.6.2, included analysing how micromobility services and the local minibus taxi industry stands to benefit from the NMT data. It was shown that:

- NMT data, when effectively characterised in a space/time manner, such as was done in this thesis, clearly shows potential in that areas and times can be identified which would benefit the introduction towards micromobility services, such as bicycle, e-scooter, and e-bicycle sharing. From the O/D maps, trend lines also serve to show popular routes on the campus, whereas the heatmaps would indicate the spaces which should be reserved for service points;
- Furthermore, in understanding the fluctuation in the level of NMT activity over a typical 24 hour day, the local minibus taxi industry also stands to benefits in that the potential to provide on-campus transportation services at times where their typical clients are not active can be identified and utilised.

6.3 OPPORTUNITIES FOR FUTURE RESEARCH

This thesis has touched on various subjects worth researching. The first of these pertains to the data collection method, namely, the use of Bluetooth sensors as a means to collect and analyse NMT mobility. Specifically, a method to determine the type of mobility of users, given a vast number of sensors collecting data across a study area, should be studied. As mentioned in the literature review, current models focus on only a limited number of sensors and use extensive counts to calibrate them. It should be considered, given the advancements in mobile devices, whether other innovative manners exist to collect NMT data? Although various data collection methods were reviewed, there is still room for improvement in how NMT data can be collected and used.

Furthermore, the aim of this study was not to identify a relationship between NMT and MT, although it was argued that by understanding NMT mobility, MT services stand to benefit. Nonetheless, in regarding the mobility patterns of light vehicle users with respect to those of NMT users in Section 5.5, the question was raised as to what effect a shift in class time could have on the road network around Stellenbosch. Should SU agree to shift classes by half an hour for at least one term, the effects of this decision on the road and the campus could be researched and the results documented. It would be fascinating to see whether the effects of this change would be similar to those on traffic to and from Cape Town's CBD since the introduction of flexitime.

Regarding future transport initiatives, the potential of using real-time NMT data in cooperation with autonomous vehicles should be investigated, especially regarding road safety. It is often debated when considering the legality of crashes with pedestrians how autonomous vehicles should be programmed in responding to scenarios where an accident is unavoidable between a vehicle and one of many pedestrians. It is argued, that should an autonomous vehicle be programmed with the capabilities of being fed real-time pedestrian data, the vehicle could perform functions which, should it not be able to avoid the accident, it could at least avoid a fatality or any serious injuries.

Lastly, it is suggested that should this study be repeated, it would be beneficial to consider a denser network of sensors. This would allow for a better representation of trips across the study area. From this, a clearer indication could also be garnered on where people are moving. Should

this study be repeated, it could also be suggested that a different setting, such as the CBD of Cape Town, be considered.

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APPENDIX A

GRAPHS AND ACTIVITY MAPS

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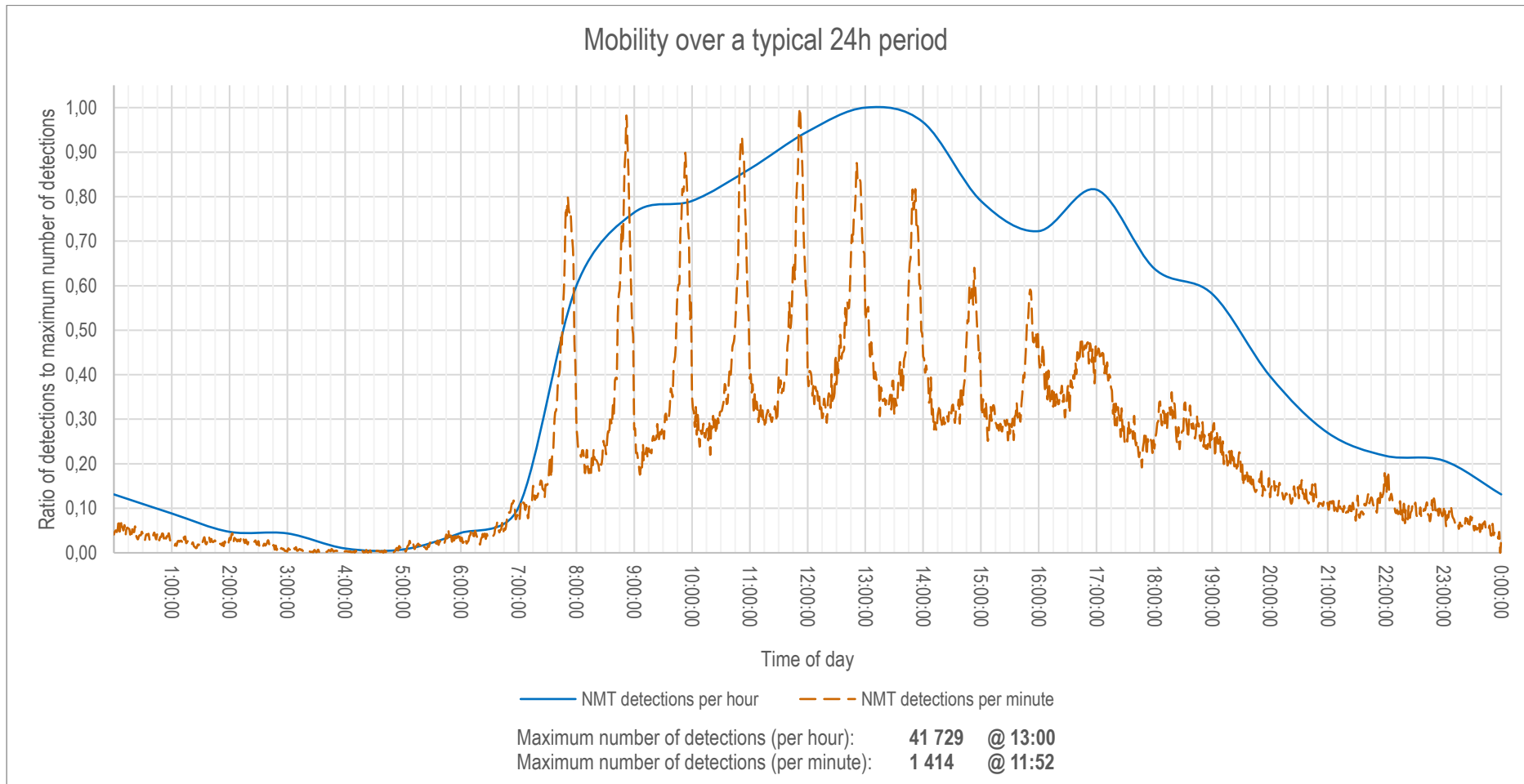
Figure A-1: Detections over a typical 24 h period
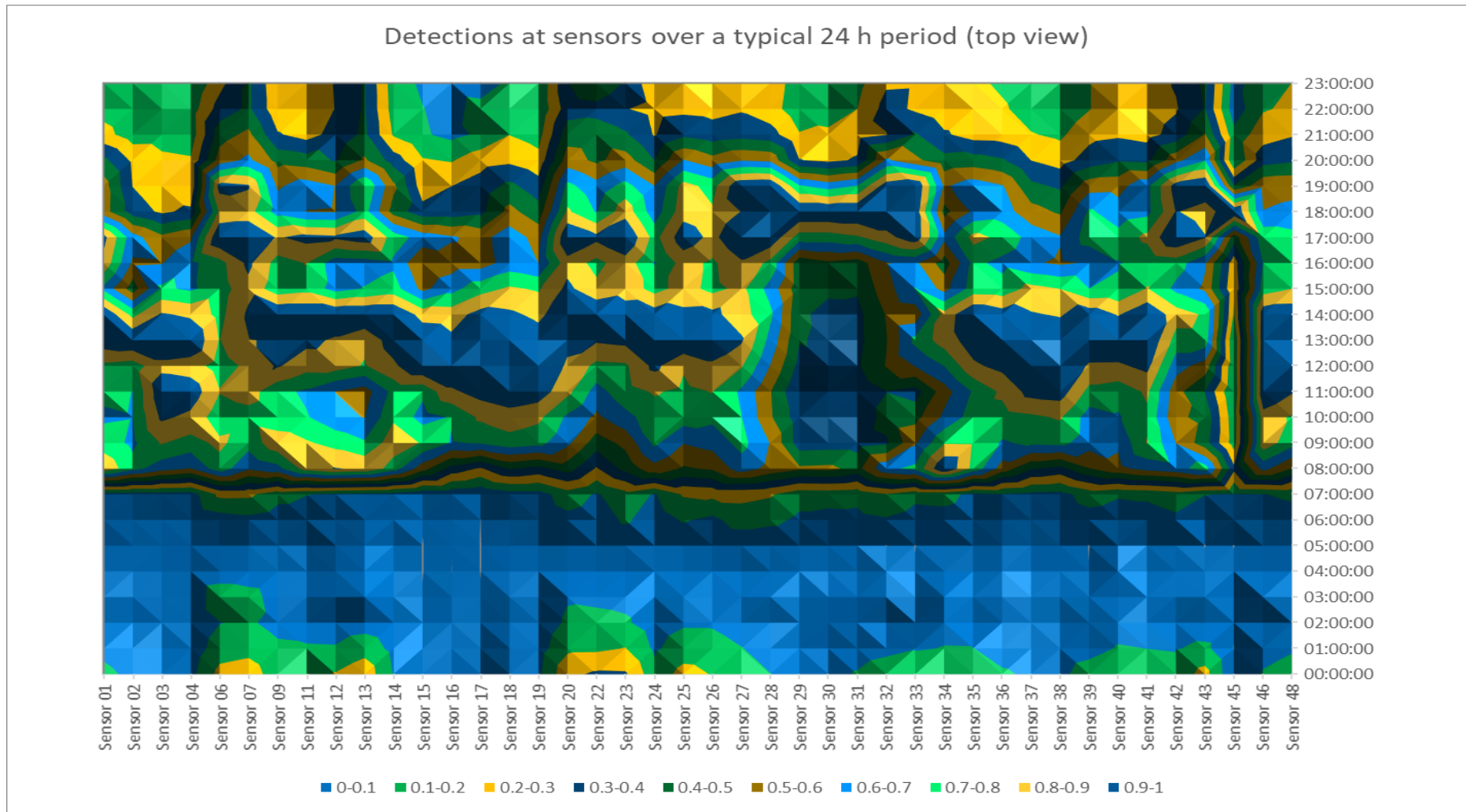
Figure A-2: Sensor detections over a typical 24 h period
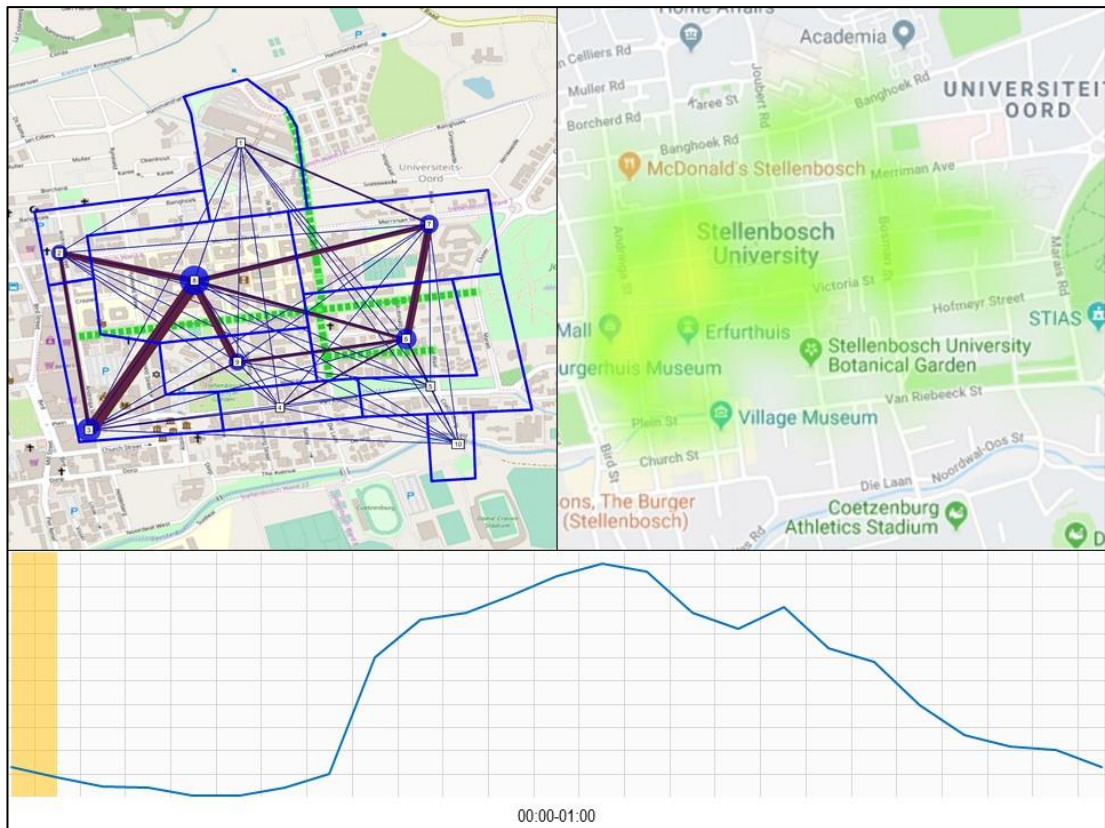
Figure A-3: Activity maps for 00:00 - 01:00 (Google Fusion Tables, 2019; PTV Visum, 2019)
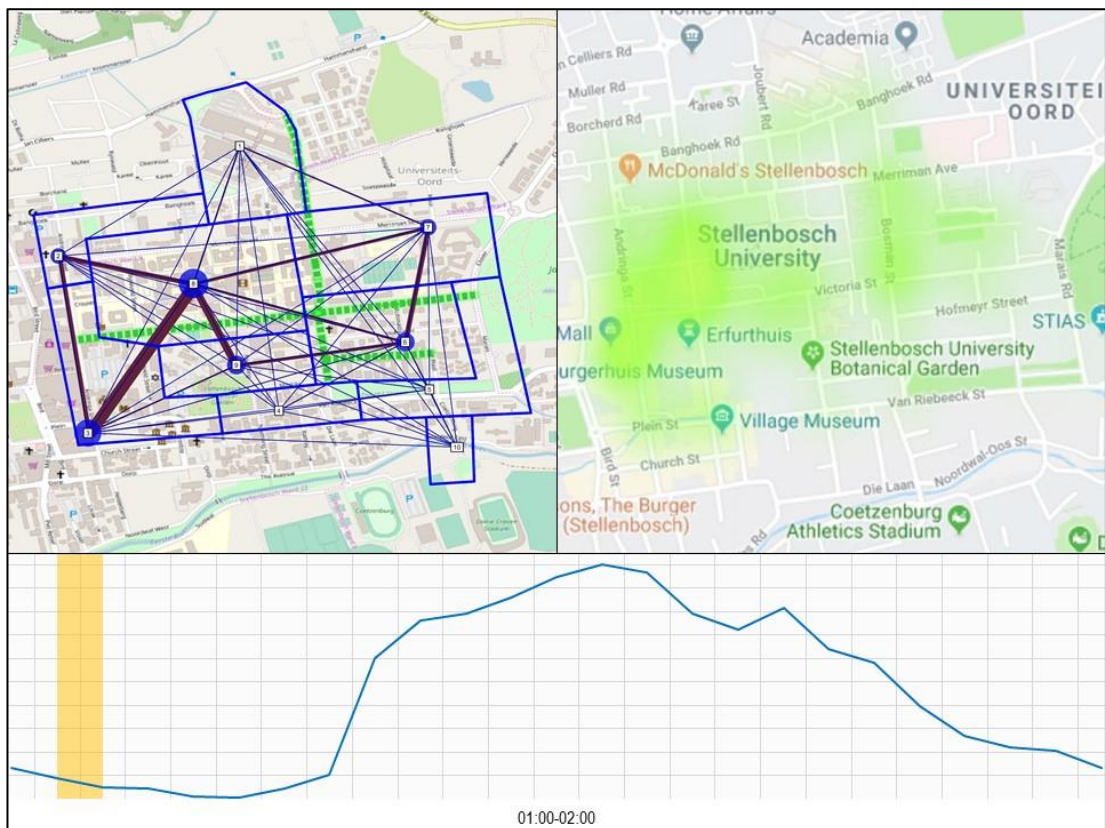
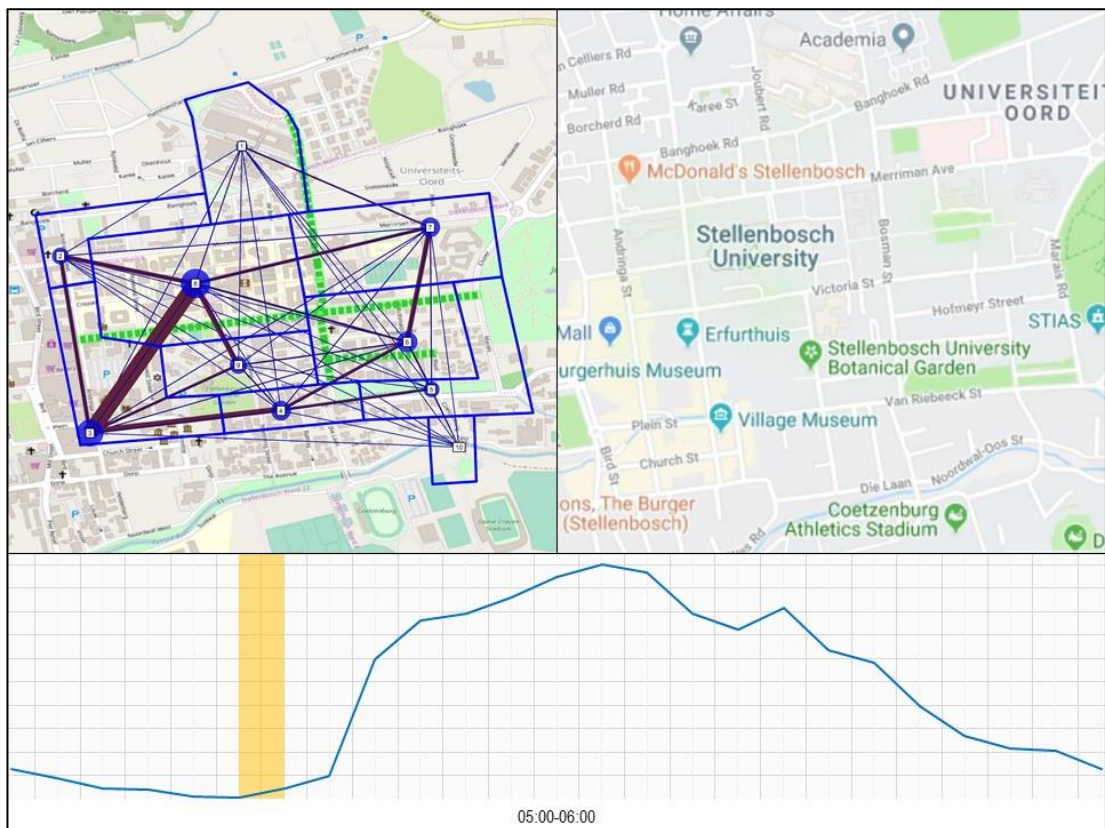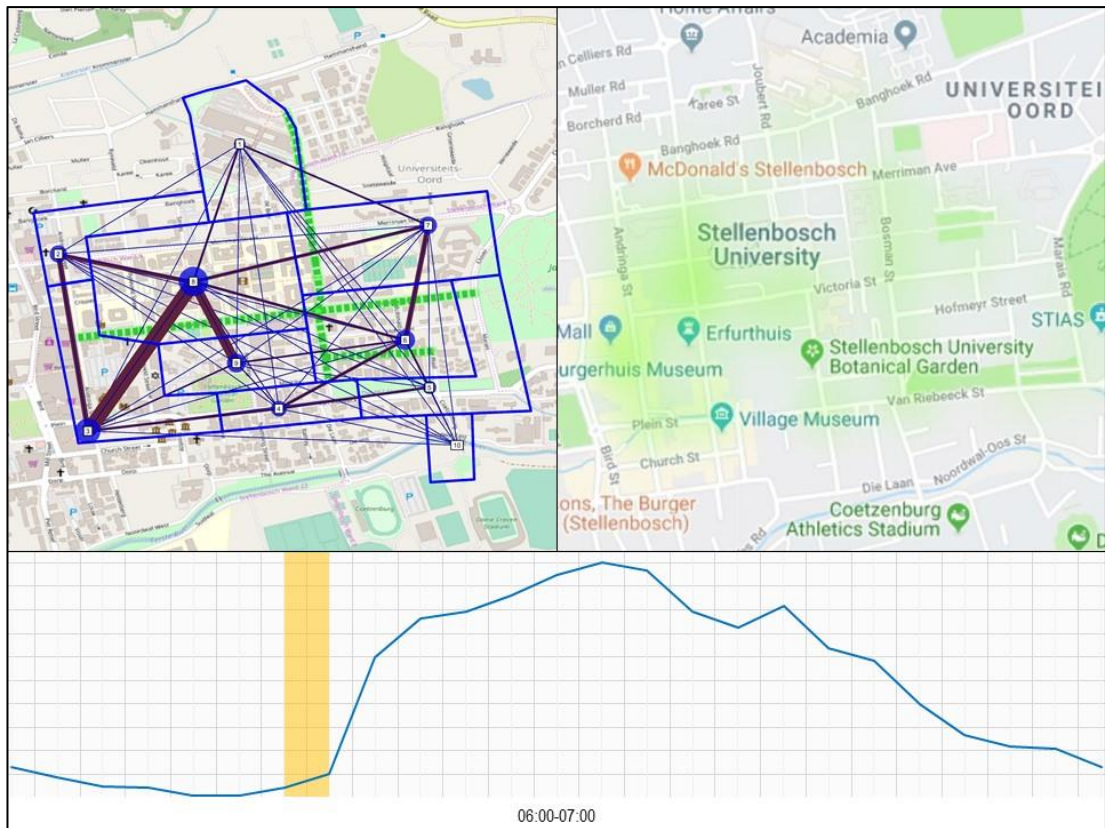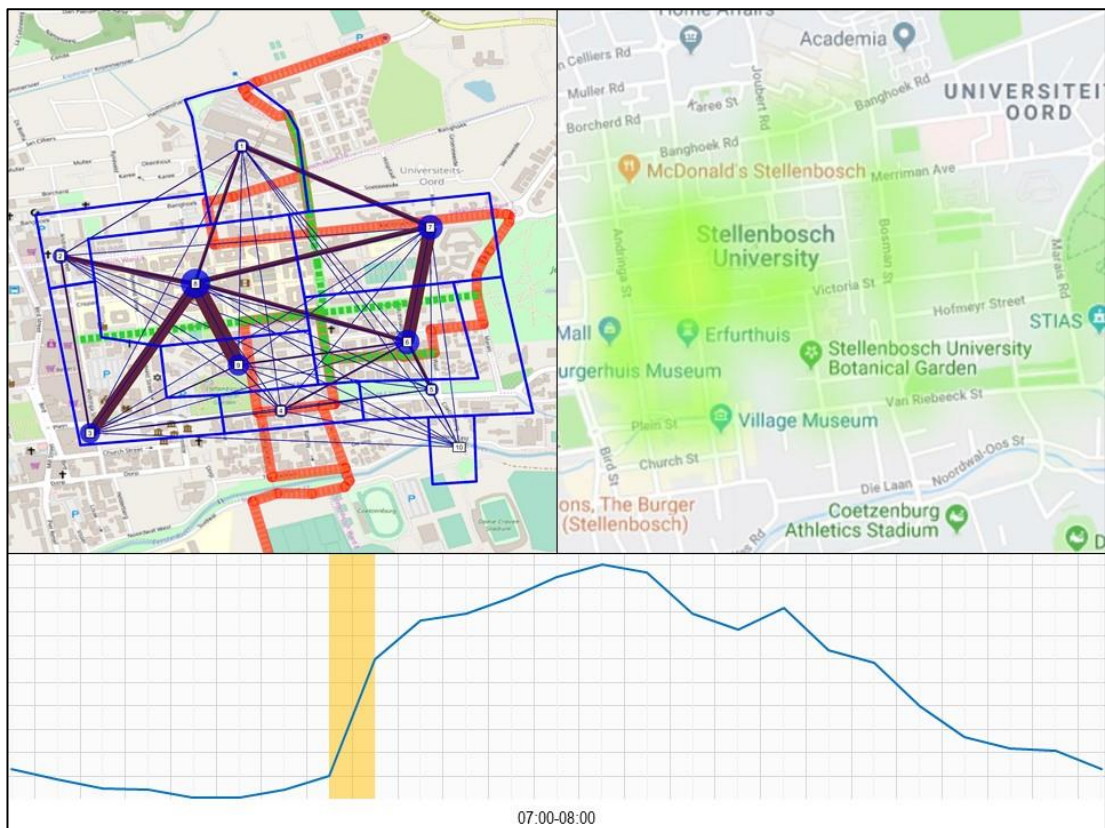Figure A-4: Activity maps for 01:00 - 02:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

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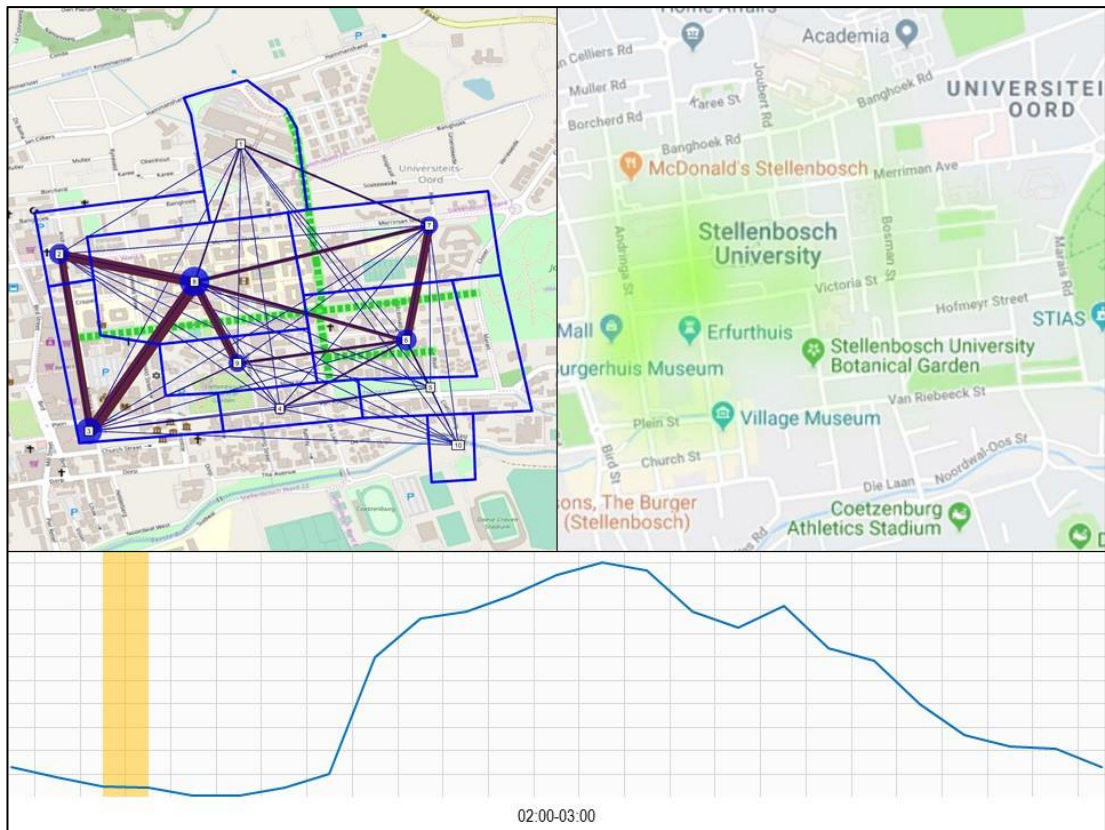
Figure A-5: Activity maps for 02:00 - 03:00 (Google Fusion Tables, 2019; PTV Visum, 2019)
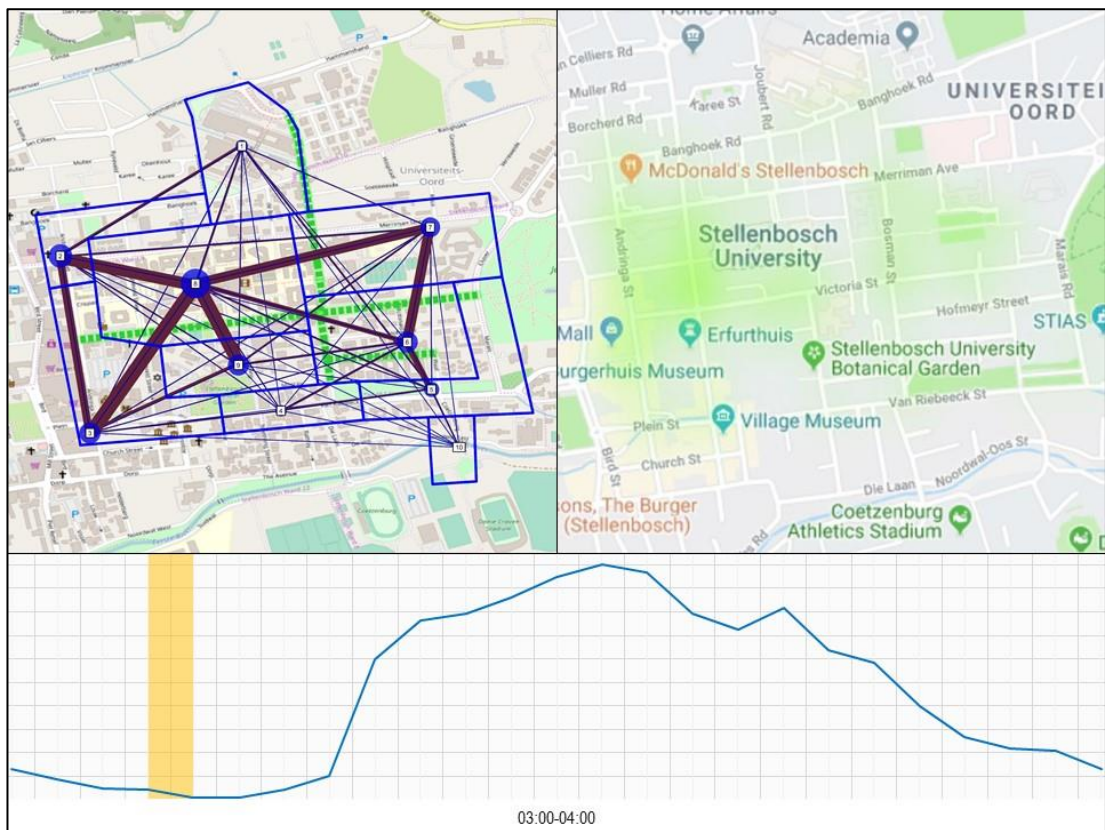
Figure A-6: Activity maps for 03:00 - 04:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

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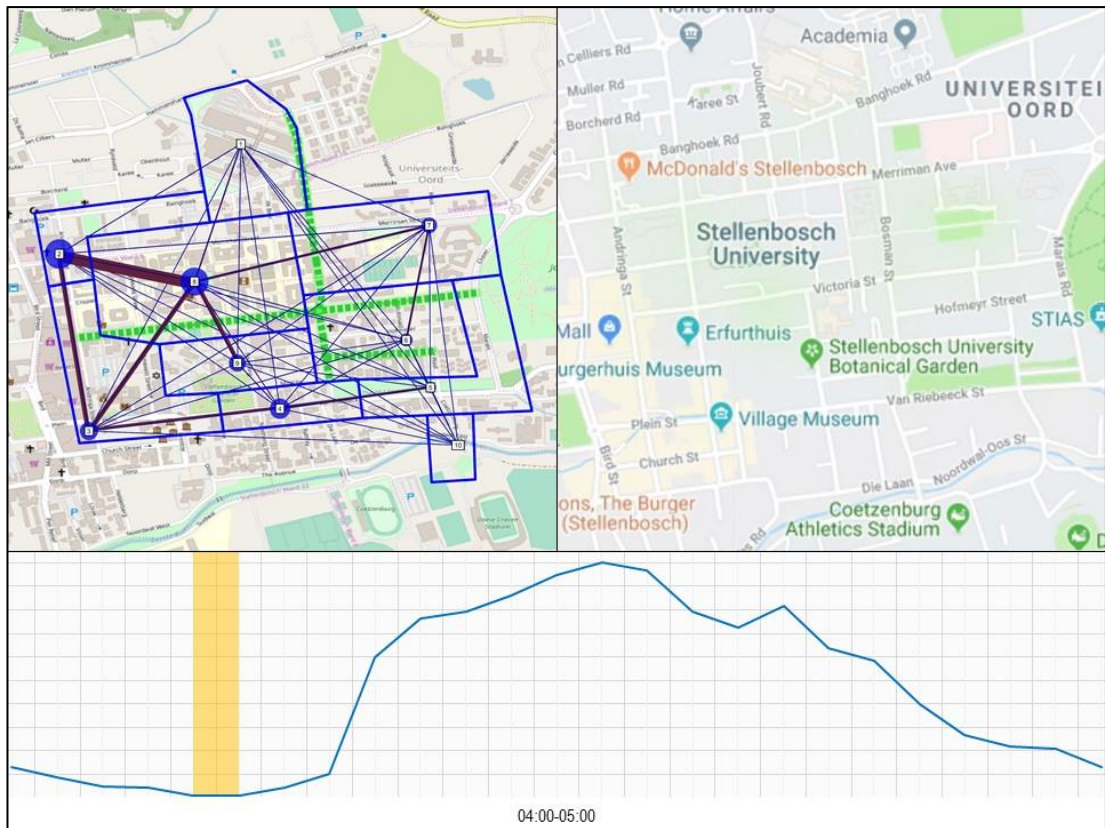
Figure A-7: Activity maps for 04:00 - 05:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

Figure A-8: Activity maps for 05:00 - 06:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

Figure A-9: Activity maps for 06:00 - 07:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

Figure A-10: Activity maps for 07:00 - 08:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

Figure A-11: Activity maps for 08:00 - 09:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

Figure A-12: Activity maps for 09:00 - 10:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

Figure A-13: Activity maps for 10:00 - 11:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

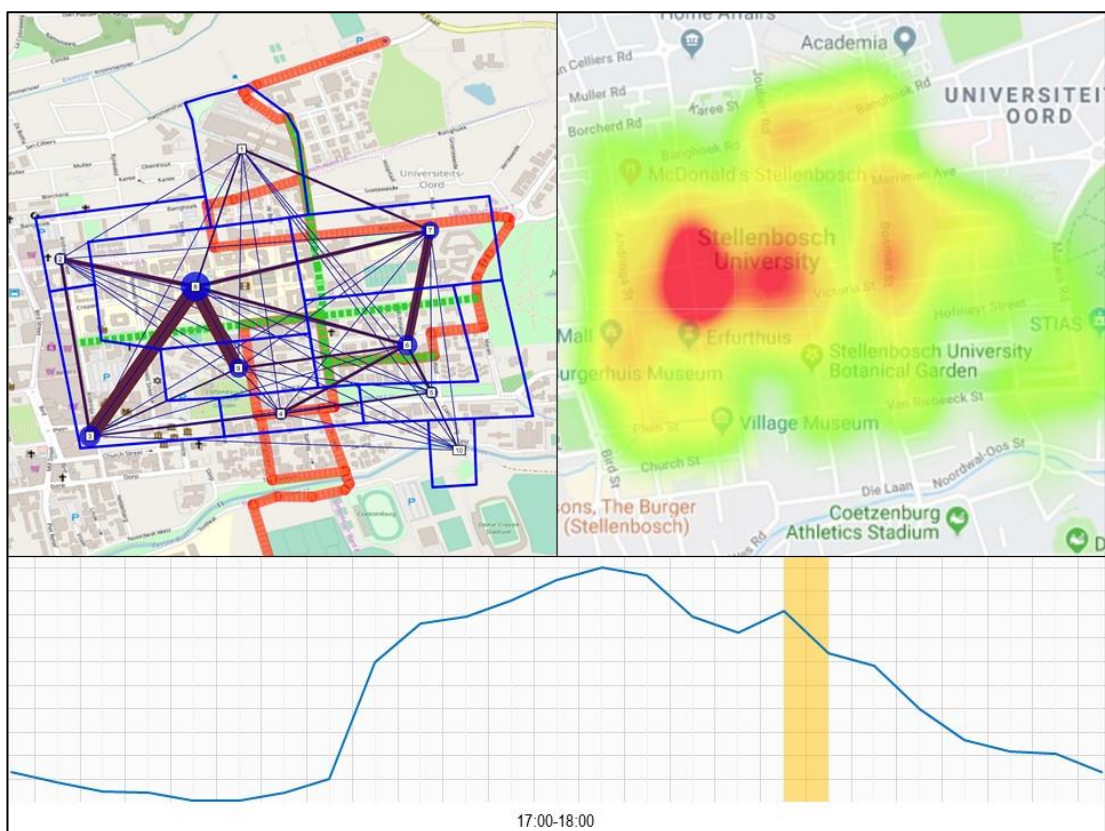Figure A-14: Activity maps for 11:00 - 12:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

Figure A-15: Activity maps for 12:00 - 13:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

Figure A-16: Activity maps for 13:00 - 14:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

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Figure A-17: Activity maps for 14:00 - 15:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

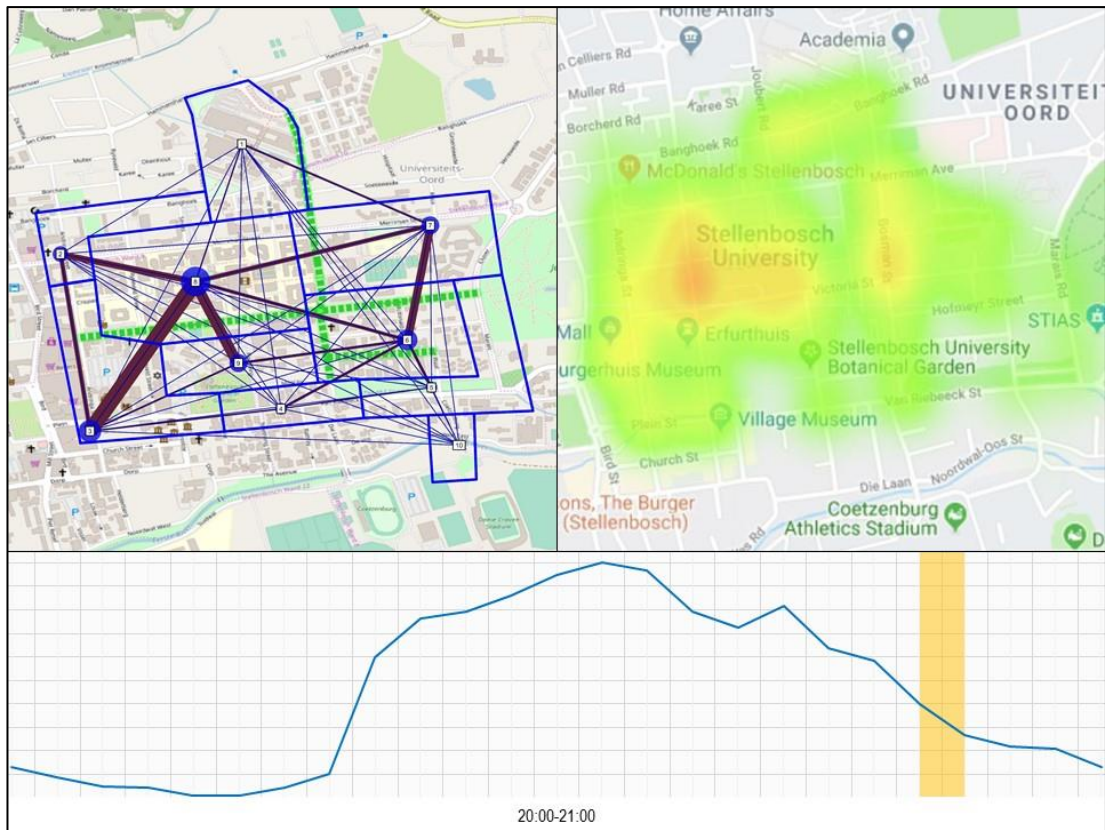Figure A-18: Activity maps for 15:00 - 16:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

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Figure A-19: Activity maps for 16:00 - 17:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

Figure A-20: Activity maps for 17:00 - 18:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

Figure A-21: Activity maps for 18:00 - 19:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

Figure A-22: Activity maps for 19:00 - 20:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

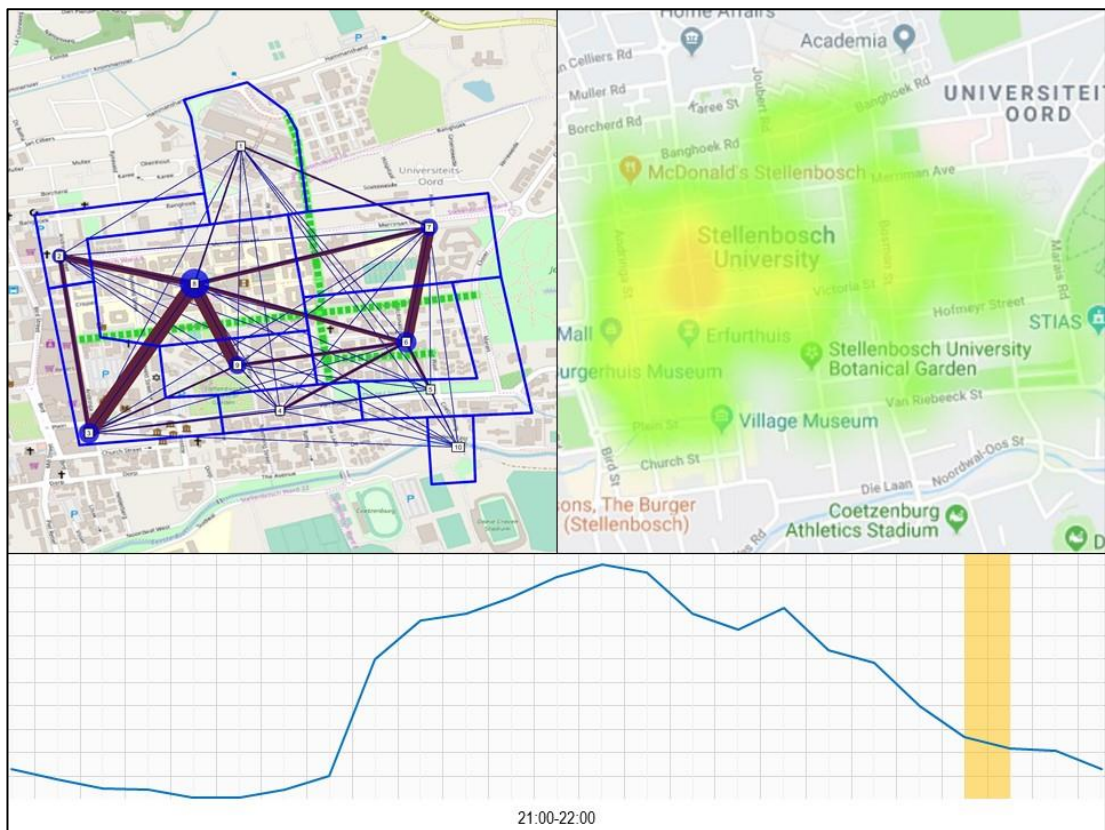Figure A-23: Activity maps for 20:00 - 21:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

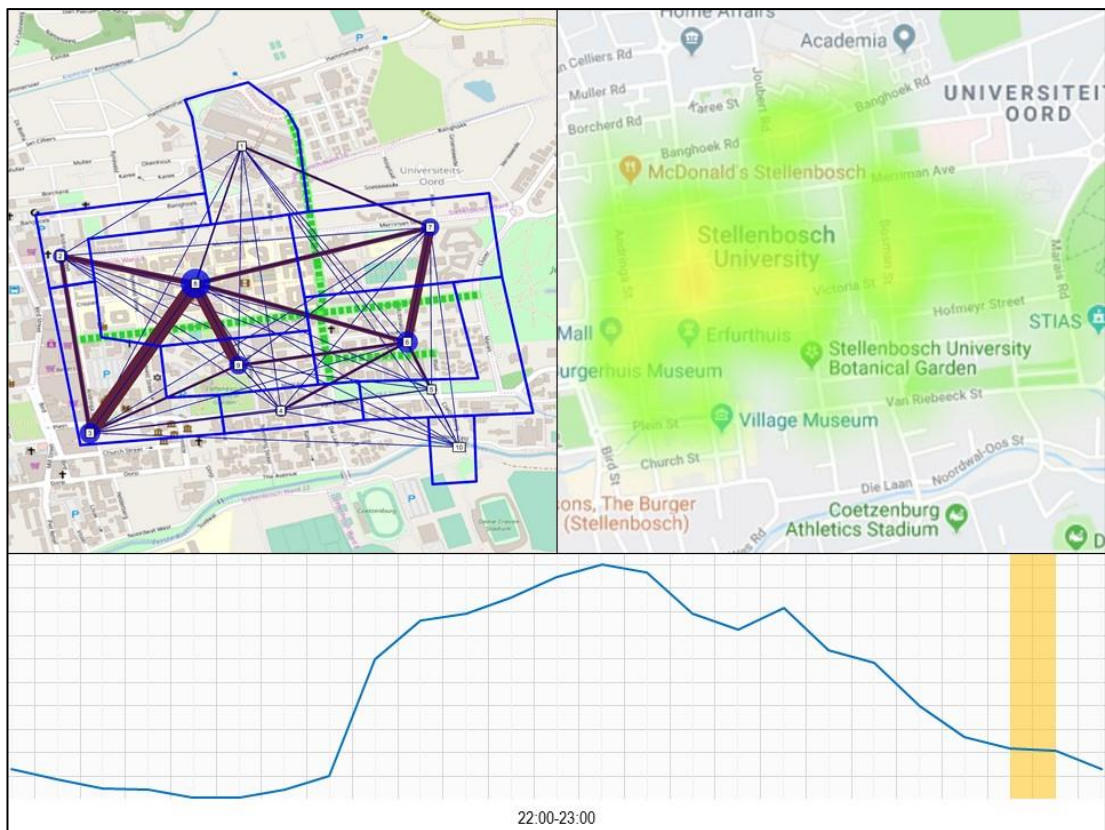Figure A-24: Activity maps for 21:00 - 22:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

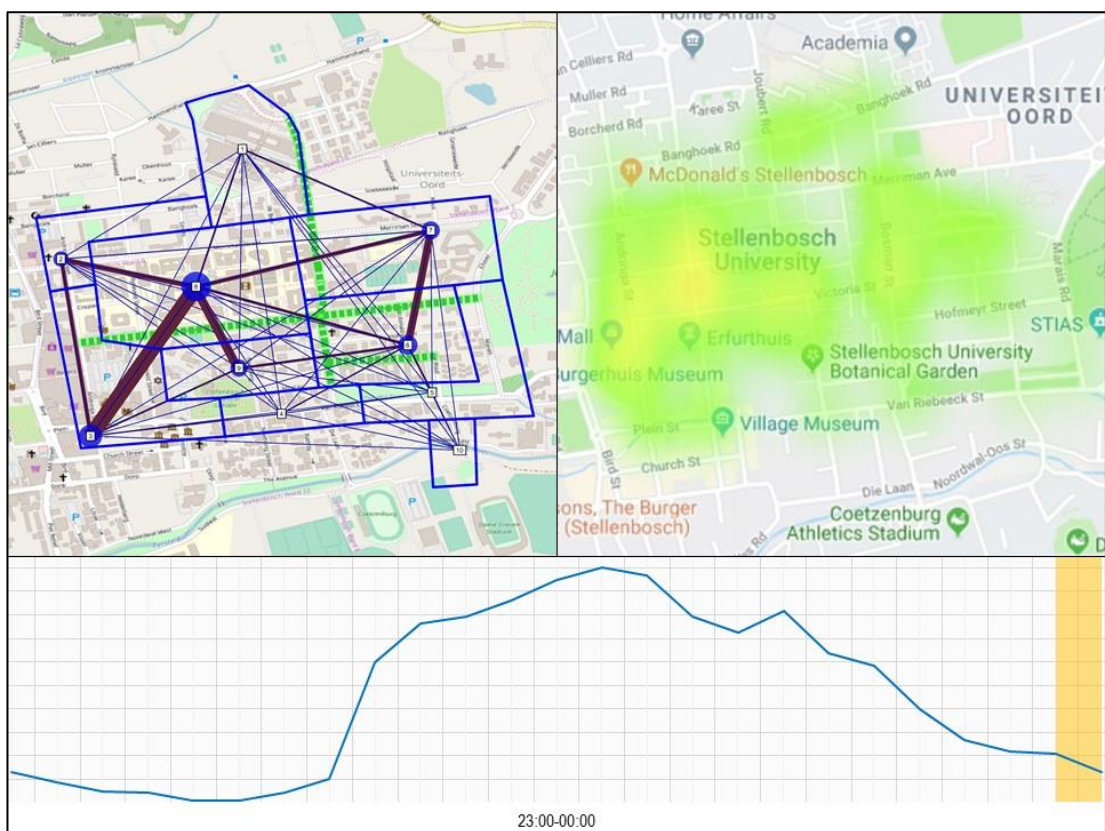Figure A-25: Activity maps for 22:00 - 23:00 (Google Fusion Tables, 2019; PTV Visum, 2019)

Figure A-26: Activity maps for 23:00 - 00:00 (Google Fusion Tables, 2019; PTV Visum, 2019