ADDIS ABABA UNIVERSITY

ADDIS ABABA INSTITUTE OF TECHNOLOGY

SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING

Analysis and Modeling the impact of Road Network Typology on the Macroscopic Fundamental Diagram

A Thesis for the Partial Fulfillment of the Master of Science in Road and Transport Engineering

BY: TILANEH TESFAHUN MEKONNEN

ADVISOR: YONAS MINALU (Dr.Eng)

June 8, 2024

ADDIS ABABA, ETHIOPIA

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The undersigned have examined the thesis entitled **“**Analysis and Modeling the impact of Road Network Typology on the Macroscopic Fundamental Diagram” presented by **Tilaneh Tesfahun Mekonnen**, a candidate for the degree of **Master of Science** and hereby certify that it is worthy of acceptance.

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Tilaneh Tesfahun Mekonnen

Acknowledgment

First I would like to thank my God for blessing me with the health and resilience. Next I would like to express my deepest gratitude to Dr. Yonas Minalu for his unwavering support, invaluable guidance, and relentless encouragement throughout this journey. His expertise and mentorship have been instrumental in shaping this thesis.

I am also deeply thankful to my family for their unwavering love, encouragement, and understanding during this demanding period. Their constant support has been my pillar of strength.

Special thanks to the members of the progress seminar committees, including Dr.Getu Segni, Dr. Fitsum Teklu, Dr. Robeam Solomon, Dr. Abel Kebede, Emnete Tadesse and Tamru Tilahun. Your constructive feedback and insightful comments during the seminars were instrumental in refining my research and guiding it towards completion.

Last but not least, I am grateful to all those who directly or indirectly contributed to this work, whether through discussions, feedback, or moral support. Your contributions have not gone unnoticed and are sincerely appreciated.

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List of Acronyms

ANOVA	Analysis of Variance
AVL	Automatic Vehicle Location
DUE	Dynamic User Equilibrium
GIS	Geographic Information System
GPS	Global Positioning System
GTP	Grid Tree Pattern
FD	Fundamental Diagram
MAPE	Mean Absolute Percentage Error
MFD	Macroscopic Fundamental Diagram
MLR	Multiple Linear Regression
MTT	Marginal Travel Time
OD	Origin Destination
OSM	Open Street Map
RMSE	Root Mean Square Error
SO	System Optimum
SUMO	Simulation of Urban Mobility
SUE	Stochastic User Equilibrium
TAZ	Traffic Analysis Zone
UE	User Equilibrium

Abstract

The population and traffic in cities increased consistently due to the increase in urbanization, economic growth, and increased welfare. This trend necessitates changes in city road network structure in order to satisfy the growing travel demand. This research investigates the relationship between road network typology and the macroscopic fundamental diagram (MFD) in Addis Ababa city road network.

The macroscopic fundamental diagram (MFD) refers to the relationship between density, flow, and speed at the network level. The macroscopic fundamental diagram is important in the field of transportation and urban planning. By illustrating the relationship between travel speeds, traffic flow rates, and vehicle density in an urban setting, it gives a macro-level understanding of how urban transportation networks work.

The objective of the study is to understand how different road network typologies affect the overall traffic flow and the macroscopic fundamental diagram. Sixty-one 2km by 2km road networks extracted from OpenStreetMap were analyzed using simulation of urban mobility (SUMO) with consistent Origin-Destination (OD) data. The study used geographic information system (GIS) software to gather road network typological data (i.e. road network connectivity indexes, network density, primary road proportion, and trafficable area). Whereas, the maximum flow data were extracted from a simulation of urban mobility output.

An exponential regression model was developed to assess the impact of network typological factors on the MFD. The regression model yielded significant results, with an adjusted R square value close to one, indicating a strong correlation between network characteristics and macroscopic traffic flow dynamics. Factors such as alpha, degree centrality, primary length proportion, and network density were found to be statistically significant in influencing the aggregated maximum flow. The study aims to provide insights into how road network characteristics influence macroscopic traffic flow dynamics, aiding in the optimization of transportation systems and urban planning strategies. The findings will offer valuable information for urban planners and decision-makers to enhance transportation efficiency and network design in Addis Ababa City. The research highlights the importance of understanding MFD for optimizing transportation systems and suggests a shift towards holistic urban traffic management strategies based on macroscopic variables for sustainable urban development.

Key words: Aggregated maximum flow, GIS, City structure, Road network typology, Macroscopic fundamental diagram, Simulation of urban mobility, Transportation efficiency, Urban planners.

Chapter One: Introduction

1.1. Background

In recent years, urbanization, economic growth, and increased welfare have led to a consistent rise in both urban populations and urban traffic, particularly in developing nations (Guojing Hu, 2020). This trend has necessitated significant changes in the structure and layout of cities to accommodate this growing travel demand. While modern transportation advancements have enhanced travel in terms of safety, speed, reliability, and convenience, they have also brought about several negative consequences, such as traffic congestion, accidents, and environmental pollution (Lele Zhang Z. Y., 2020).

Macroscopic traffic flow models for urban networks describe how traffic variables at the network level behave and interact. This description of traffic behavior holds significance in assessing the quality of traffic service in a network as well as in conducting diagnostic, monitoring, and evaluation tasks over time and space (James C. Williams). The MFD represents a fundamental cornerstone in the fields of transportation engineering and urban planning. It offers a macro-level perspective on how urban transportation systems perform, illustrating the relationship between vehicular density, traffic flow rates, and travel speeds within an urban environment (Yi Yu1*, 2020). Understanding the MFD provides critical insights into congestion patterns, transportation efficiency, and the overall performance of a city's transportation infrastructure.

As urban populations continue to grow, and with them the ownership of vehicles in large cities, the MFD becomes an invaluable tool for city planners, traffic engineers, and policymakers. It offers the potential to optimize transportation systems, reduce congestion, enhance safety, and minimize environmental impacts. However, the factors influencing the shape and behavior of the MFD and their significance are multifaceted and complex, encompassing a wide array of urban design, traffic management, and technological elements.

Many researchers studied factors affecting the macroscopic fundamental diagram. (Ting-ting Zhao1, 2012), studies the influence of traveler information on the macroscopic fundamental diagram using the simulation software TransModeler to model and simulate the dissemination of traveler information as well as the drivers' route choice behaviors that have been affected by the information. The influences of several model parameters, including the informed percentage, the reroute time interval, and the acceptable delay level, are also examined. (Jong, 2012) Studied the effect of network structure and signal setting on the macroscopic fundamental diagram and concluded that the structure of a network in itself does not have a strong influence on the shape of the MFD. He concludes that the difference in MFDs comes from the different characteristics of the links, like length, speed, and capacity, and the intersections of the network. Regarding the effect of signal setting, (Jong, 2012) concludes that a strong relationship exists between the MFD of the subnetwork and its perimeter. A town traffic model employing a two-fluid framework has been created by extending concepts derived from a previous kinetic theory of multilane traffic (Prigogine, 1979). The two fluids are defined as the set of moving cars and those halted due to traffic conditions.

Recently the performance of a network or part of it can be represented by a macroscopic fundamental diagram (MFD) using aggregated data for flow and density (Jong, 2012). Like a conventional link fundamental diagram three states are demonstrated in macroscopic fundamental diagram.

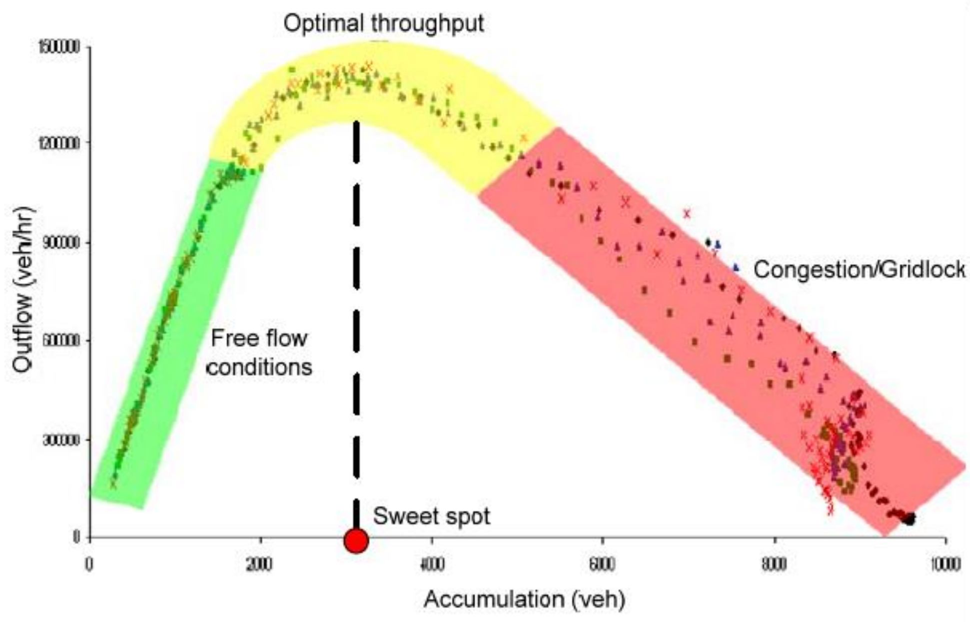


Figure 1 Macroscopic fundamental diagram (Qian, 2009)

The first part is when there are a few vehicles in the network, where the network is in a free flow condition and the outflow is small. With the increase in the number of vehicles, there is an accumulation (density) at which the flow (production) reaches maximum point. As the number of vehicles further increases in the network beyond this point, spillback (congestion) starts to occur and finally the network reaches a state of gridlock. Therefore, to optimize traffic flow in a network, the number of vehicles should be around this optimum accumulation level. In this study, we are going to identify the typological factors that affect this maximum flow of the network.

Recent advancements in data gathering technologies, such as the global positioning system (GPS) and geographic information system (GIS), have enabled more accurate and efficient collection of traffic and topological data within a network. This breakthrough has opened up avenues for investigating how traffic performance and behavior are influenced by network typologies in innovative ways. By using these technologies, we can understand the underlying mechanisms that shape traffic flow patterns. Specifically, examining how different network typologies impact the structure and properties of the macroscopic fundamental diagram (MFD) which provides valuable insights into traffic dynamics.

This research endeavors to contribute to the advancement of more efficient and sustainable transportation systems through a comprehensive analysis of network typological metrics and their impacts on the macroscopic fundamental diagram (MFD). By unraveling the intricate interactions between road network typologies and traffic dynamics, this study aims to establish a solid foundation for evidence-based decision-making in urban planning and also the formulation of effective traffic management strategies.

In the following chapters, we will embark on a comprehensive exploration of the macroscopic fundamental diagram and the myriad factors that influence its shape and behavior. We will consider the implications of these findings for urban planners, traffic engineers, and policymakers, ultimately aiming to propose a model for predicting the situation.

1.2. Statement of the problem

Traffic congestion, and environmental pollution remain a significant and pressing challenge in urban areas, resulting in increased travel times, economic costs, and environmental consequences. Effective traffic management and congestion mitigation are paramount for sustainable urban development. The macroscopic fundamental diagram (MFD), a fundamental concept in traffic flow theory, offers a critical framework for comprehending and optimizing traffic flow within urban transportation networks. However, the MFD's shape, characteristics, and performance are not static; they evolve dynamically in response to various factors. These factors include network typology, traffic demand patterns, roadway geometry, traffic management measures, and a host of interdependencies. Despite the acknowledged significance of these factors, a comprehensive analysis of their individual contributions, significance and interactions affecting the MFD metrics has not been well studied.

The main problem that this research aims to solve is the lack of comprehensive understanding regarding how and how much network typologies affect the macroscopic fundamental diagram (MFD) and overall network performance. The study aims to provide insights into the core elements influencing network behavior by examining the clear relationship between network typologies and MFD parameter. This research contributes to filling the gap in knowledge about the relationship between network typology and traffic flow dynamics, ultimately aiding in the optimization of transportation systems and urban planning strategies.

1.3. Objectives

1.3.1. General objective

The general objective of the thesis is to investigate the relationship between road network typology and the macroscopic fundamental diagram of the road network.

1.3.2. Specific objective

The primary objectives of this study are as follows:

- To investigate the relationship between road network connectivity, centrality, density and proportion of primary roads with macroscopic fundamental diagram.
- To develop a prediction model that assesses the impact of road network typology on macroscopic flow.
- Provide insights and recommendations for urban planners on how network typologies influence macroscopic traffic flow, facilitating informed decision-making in initial urban land use planning and network redesign.

1.4. Research Question

Research questions have been developed in order to help us address the objectives of the study. These questions will help us focus on what we need to find out. They guide us to the solutions we seek.

- ➢ Which methods have been used to analyze road transport network structure, and how can they be used for the evaluation of road network performance?
- ➢ How does road network connectedness impact road network performance?
- ➢ How does the road network infrastructure impact the macroscopic fundamental diagram?
- ➢ Is road network typology a significant factor in road network macroscopic performance?

1.5. Significance of the study

The research primarily focuses on modeling and identifying the key typological factors that influence the macroscopic fundamental diagram (MFD). Modeling and analysis of factors affecting the macroscopic fundamental diagram will use urban planners and engineering practitioners to create more efficient and sustainable transportation systems in initial land use planning and network redesign by aligning the transportation infrastructure with the anticipated traffic demand, which will contribute to better mobility and reduced congestion.

Decision-makers can also formulate effective policies based on a clear understanding of the significant factors. The established relationships will also offer a simple, fast, and straightforward alternative for MFD estimations that allows efficient prediction of traffic flow patterns, simplifying the process of analyzing and optimizing urban transportation systems.

The current urban traffic management mainly involves congestion transfer based on microscopic traffic control principles. However, by considering macroscopic factors like overall traffic flow patterns, we can develop strategies that optimize the entire traffic system. This approach allows for a more holistic understanding of urban traffic dynamics, potentially reducing congestion and improving overall transportation facility efficiency.

Understanding influential variables aids in informed infrastructure planning. City planners can prioritize investments in areas that have the most substantial impact on the MFD, ensuring that resources are allocated efficiently for sustainable urban development. The insights gained also contribute to sustainable urban development by fostering transportation systems that align with the city's growth. This includes designing road layouts that can accommodate the increasing population and economic activities.

Finally, optimized traffic flow resulting from understanding significant factors can contribute to reduced fuel consumption and lower emissions, thereby mitigating the environmental impact of transportation in the city.

1.6. Thesis Outline

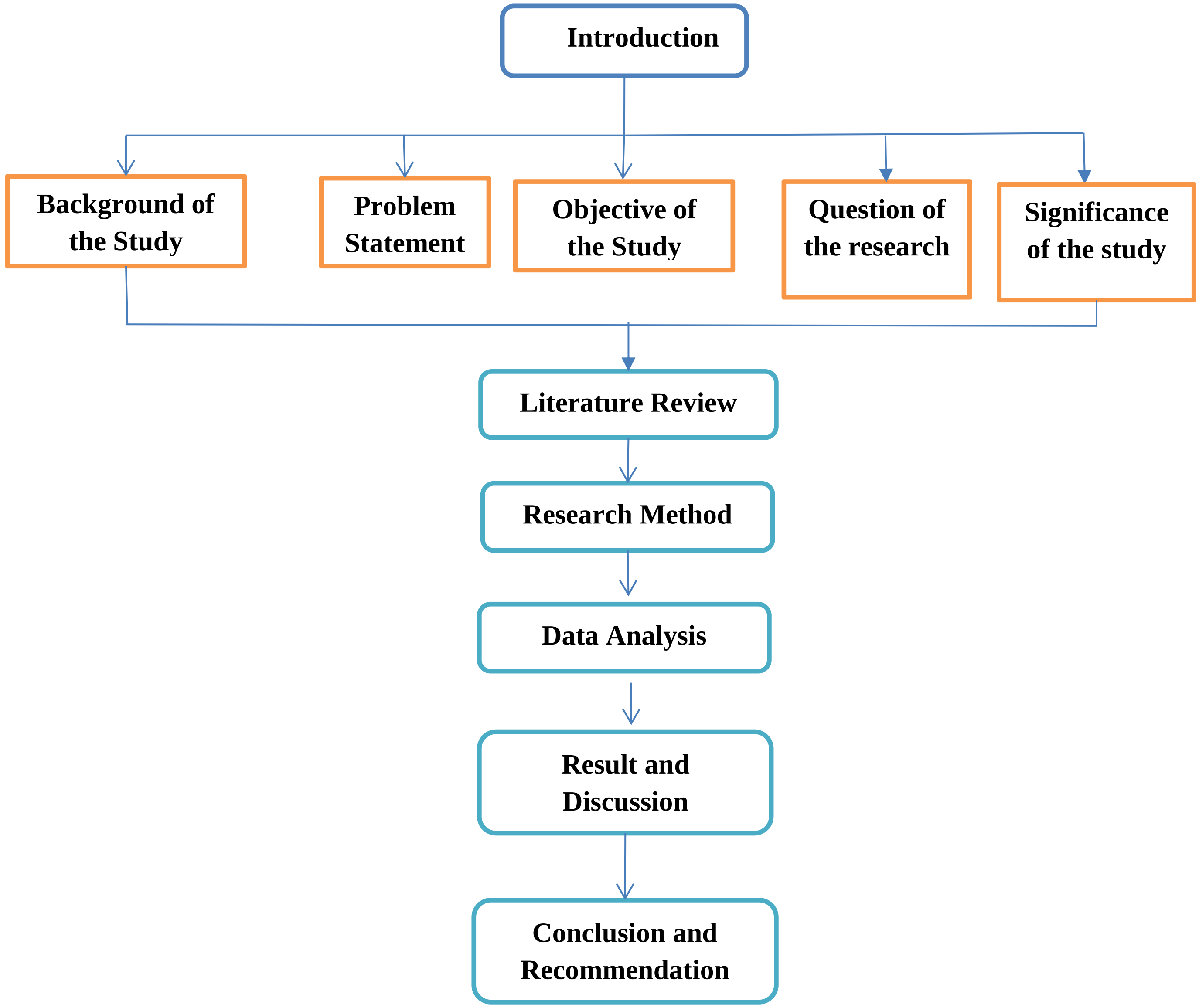


Figure 2 Thesis outline

Introduction: This chapter contains the background of the study, the problem statement, the objective, the hypothesis, and the significance of the study.

Literature review: This chapter will review literature related to factors affecting the macroscopic fundamental diagram (MFD). The definition and concept of the macroscopic fundamental diagram (MFD), historical development and key theories, previous works on factors affecting MFD, gaps in existing literature, and others will be reviewed.

Methodology: In this chapter, I will discuss the methodology, data collection, analysis, and simulation.

Data analysis: In this part, the data gathered from urban mobility simulations (SUMO) and GIS extraction are analyzed and organized to be suitable for modeling.

Result and discussion: In this part, research results, which include interpretation and theoretical implications, practical implications for transport planning, and a predictable model, were discussed.

Conclusion and recommendation: Finally, in this section, summarizing the main findings, their significance, reflection on the limitations, policy implications, and areas for further research are discussed.

Chapter Two: Literature review

2.1. Fundamental Theory of Traffic Flow

Traffic flow represents the traffic load on a transportation system, and the interaction between these loadings and the facility capacity determines the operational performance of the system (May, 1990). Traffic flow theory involves the development of mathematical relationships among the primary elements of a traffic stream: flow, density, and speed. These relationships help the traffic engineer in planning, designing, and evaluating the effectiveness of implementing traffic engineering measures on a highway system (Garber, 2009).

There are three basic approaches to traffic analysis. These traffic analysis models (approaches) study how traffic flows operate by either considering the time-space actions of individual drivers influenced by nearby vehicles (microscopic models), observing drivers' behavior without explicitly distinguishing their time-space actions (mesoscopic models), or examining the overall flow of vehicles as a collective (macroscopic models) (Hoogendoorn, 2001). The definition and example for each type of traffic model are discussed below.

2.1.1. Microscopic

A microscopic model of traffic flow attempts to analyze the flow of traffic by modeling driver-driver and driver-road interactions within a traffic stream, which respectively analyzes the interaction between a driver and another driver on a road and between a single driver on the different features of a road (Jabeena, 2013). This model focuses on the detailed study of individual vehicle interactions within a traffic stream. Unlike macroscopic analysis, which considers collective traffic behavior, microscopic analysis delves into the intricacies of factors such as acceleration, deceleration, lane changes, and driver decision-making processes. This method employs simulation models to simulate the movement of individual vehicles, contributing to a granular understanding of traffic flow and safety considerations. Microscopic analysis is instrumental in optimizing traffic flow, enhancing safety, and informing strategies for intersection management. It is particularly relevant in the context of emerging technologies like connected and autonomous vehicles, where the impact on individual vehicle behavior is a key consideration.

Car-following models: This model is generally based on how one vehicle follows another vehicle in an uninterrupted flow. Various models were formulated to represent how a driver reacts to changes in the relative positions of the vehicle ahead.

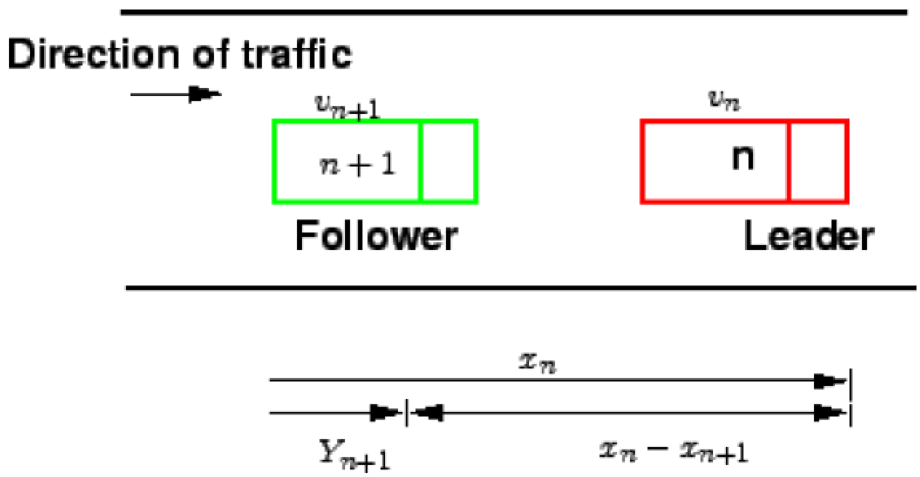


Figure 3 Car following concept (Jabeena, 2013)

A number of theories have been proposed for modeling car-following behavior, and these concepts may be categorized into four groups according to behavioral assumptions:

- Stimulus response models,
- Safety distance or collision avoidance models,
- Action point models, or psycho-physical models,
- Optimal velocity models

The initial car following model was put out as a stimulus-response idea, assuming that the driver of the following vehicle properly senses and responds to the speed and spacing difference between the lead and following cars.

The second class of models is based on the driver's tendency to keep a safe following distance. It has the advantage that it explicitly accounts for differences between acceleration and deceleration phases of driving.

The psycho-physical or action point models, which constitute the third class of traffic flow models, aim to capture more realistic driving behavior by considering imperfect perception and discontinuous responses based on thresholds related to visual angle, speed, spacing, and other factors (Jabeena, 2013). These models introduce the concept of different driving modes, such as free driving, approaching, following, and braking. Drivers transition between these modes as they reach specific thresholds determined by factors like speed difference and headway distance. The main challenge of these models is estimating and calibrating the individual threshold values.

The fourth category of models encompasses optimal velocity models, which operate under the assumption that a driver tailing another vehicle adjusts their speed based on the variance between their current speed and the optimal or desired speed they aim to achieve. Generally, these models have drawbacks such as not guaranteeing entirely collision-free scenarios and sometimes yielding unrealistically high accelerations. Some well-known microscopic models within this category include the Response-Stimulus Model (RSModel), Intelligent Driver Model (IDM, 1999), Van Aerde Model, Velocity Difference Model (VDIFF), Wiedemann Model (1974), and GIPPS Model (1981).

2.1.2. Mesoscopic

Mesoscopic traffic analysis involves studying the behavior of groups of vehicles within a road system, providing an intermediate perspective between macroscopic and microscopic approaches. This method focuses on understanding how vehicles form clusters, navigate lanes, merge, and interact as groups. Mesoscopic analysis contributes insights into platoon dynamics, intersection behavior, and overall road network efficiency. It often employs simulation models to simulate the behavior of these vehicle clusters, offering a detailed yet intermediate-level understanding of traffic flow and patterns.

2.1.3. Macroscopic

Macroscopic traffic analysis is a conceptual framework that provides a holistic understanding of traffic dynamics on a large scale. This approach involves observing and describing the collective behavior of traffic flow without getting into the intricacies of individual vehicle interactions. It encompasses a wide range of aspects, including overall traffic patterns, density, and movement across a road network. By focusing on high-level observations, macroscopic analysis is instrumental in informing transportation planning, evaluating road capacity, and shaping effective traffic management policies. Through the examination of statistical data and the utilization of simulation models, this approach aids decision-makers in making informed choices about infrastructure development and optimizing traffic efficiency at a systemic level.

Various macroscopic models have been explored in this context. Among the well-known steady-state speed-density functional forms are Greenshield's model, Greenberg's model, Underwood's model, Drake's model, the modified Greenshield model, Pipe's generalized model, Underwood's model with Taylor series expansion, and Drake's model with Taylor series expansion.

Greenshield’s Model (1935): Macroscopic flow models show how one aspect of traffic flow changes in relation to another. The most important relationship is between speed and density. Greenshield was the first to propose a basic connection. This model is essential for understanding how traffic flows without interruptions and predicting and explaining real traffic patterns. Greenshield suggested that speed and density are related in a straight line (a linear relationship).

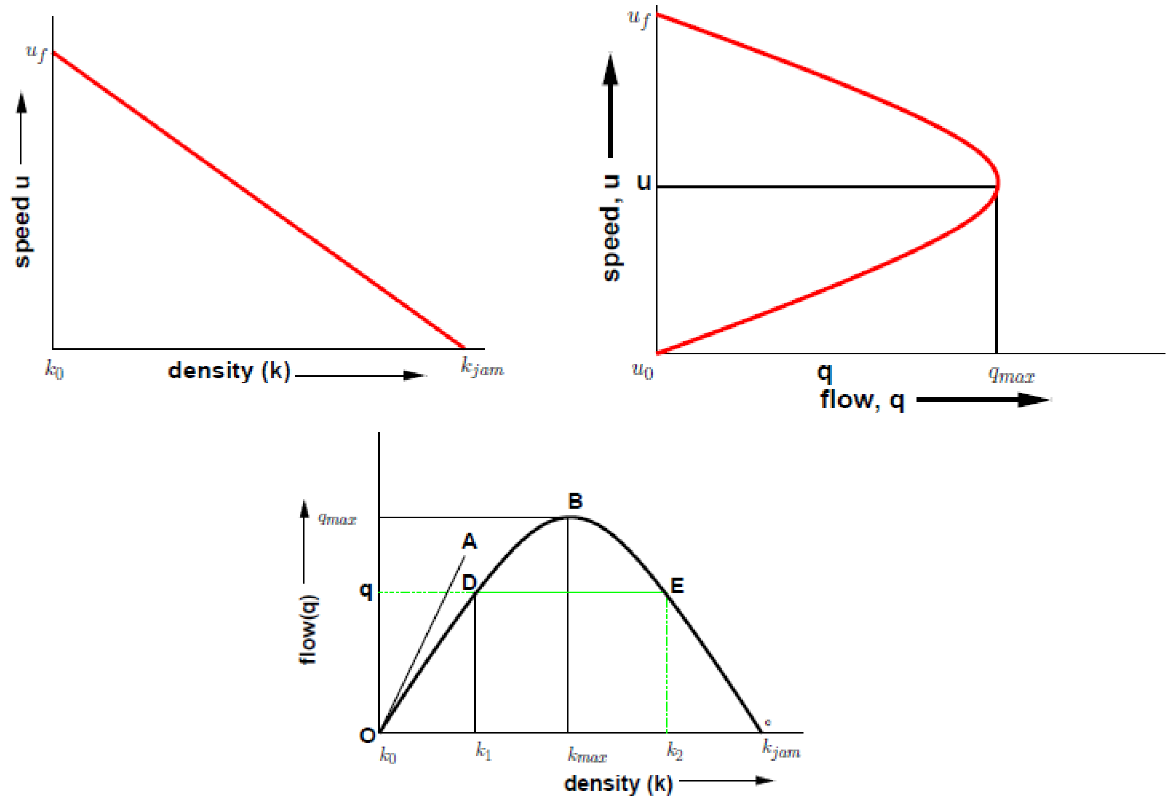


Figure 4 Fundamental traffic flow diagrams (Jabeena, 2013)

$$\mathrm{v} = v_f - \frac{v_f}{k_j} * k$$

$$q = k * v$$

$$k_o = \frac{k_j}{2}$$

$$v_o = \frac{v_f}{2}$$

$$q_{max} = \frac{v_{f*k_j}}{4}$$

Where v_f is free flow speed, k_j is the jam density, K is field density, k_o is optimum density, v_o is optimum speed, and q_{max} is the maximum flow.

Greenberg's logarithmic model (1959): Greenberg used a fluid-flow analogy concept and proposed a logarithmic speed-density relationship.

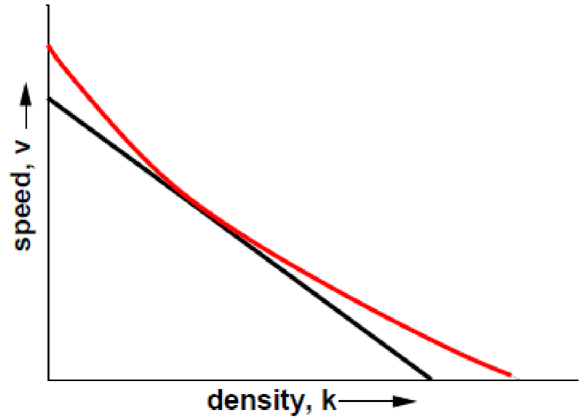


Figure 5 Speed density relationship by Greenberg (Jabeena, 2013)

$$V = v_o * Ln * \frac{k_j}{k}$$

Greenberg's model has become popular because it can be determined analytically and generally provides a better fit compared to Greenshield's model. However, a major criticism is that it cannot accurately predict lower density speeds. As density goes to zero, according to this model, speed increases infinitely, which is not realistic. Another shortcoming is that it violates boundary conditions, as zero density would theoretically require an infinitely high speed.

Underwood exponential model (1961): This model is an exponential relationship between speed and density. Underwood is devising a model based on this exponential function in an effort to address the shortcomings of the Greenberg model.

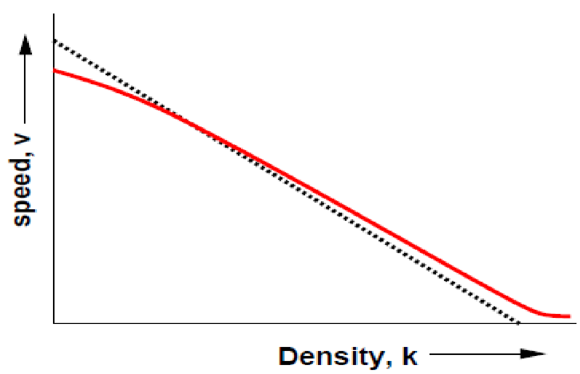


Figure 6 Speed density relationship by underwood (Jabeena, 2013)

$$v = v_f * e^{\frac{-k}{k_{cri}}}$$

The Underwood model has a tendency to underestimate speeds in free-flowing phases but overestimate them in congested areas. Its main drawback is that speed reaches zero only when density approaches infinity; this makes it unsuitable for predicting speeds at high densities. While the model is better than the Greenshield and Greenberg models in uncongested conditions, it does not provide a good fit for congested conditions.

2.2. Understanding the Macroscopic Fundamental Diagram

The macroscopic fundamental diagram (MFD) is a concept in urban planning that describes the relationship between traffic flow, density, and speed at a city or regional scale. It is a macro-level representation of traffic dynamics.

The MFD is a graphical representation showing how flow (measured in vehicles per hour or number of vehicles left) changes with variations in traffic density (vehicle per unit of road space or number of vehicles in the network) and speed. The MFD graph has an optimal density at which traffic flow will reach its maximum. Densities greater than this optimal density will cause congestion, as a result, speed and flow will decrease. The flow of traffic on the road network is less than its capacity below this threshold.

In order to manage and optimize transportation networks (road networks), especially in urban areas, it is important to understand the MFD because it can be used to inform decisions regarding traffic signal timing, route planning, and infrastructure upgrading that will increase system efficiency and improve congestion.

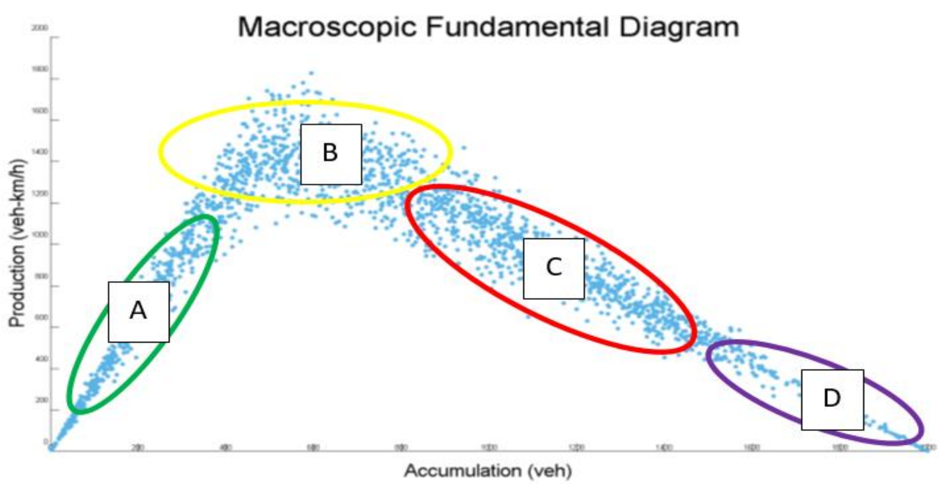


Figure 7 Typical macroscopic fundamental diagram showing all possible regions (Jong, 2012)

Production represents the cumulative flow of vehicles across all links in the network. The accumulation represents the total number of vehicles in that network. The figure shows different traffic states and shows that production declines after a certain threshold for accumulation is reached.

In the first part (A) of the graph (before the maximum threshold is reached), there is a direct and proportional relationship between accumulation (density) and production (flow). In this part, as traffic density increases, traffic flow also increases in a linear manner, indicating that the transportation network is operating efficiently (Jong, 2012).This state of MFD indicates the network is not yet congested, and there is available capacity for additional vehicles in practical terms. It means that, as more vehicles enter the network, they can do so without significant reductions in speed or increases in congestion.

The second part (B) of the MFD typically represents a region where traffic congestion starts. In this segment, as traffic density increases further beyond the linear part, traffic flow reaches its maximum capacity, and additional vehicles cause congestion and reduce flow.

Key characteristics of this region (region B) are:

I. **Congestion**: this is the region in which the road network reaches the optimum flow, and congestion starting point if the density increases further. The region corresponds to the critical traffic density due to which vehicles start to experience slower speeds, stop and go conditions, and lower flow.

II. **Capacity limit**: In this area, the flow of traffic reaches its maximum capacity; adding additional vehicles to the road network will lead to decreasing flow rates.

III. **Increased travel times**: travel times will become more unpredictable, and the transit system will become less reliable.

The third part (C) of the macroscopic fundamental diagram (MFD) can be named the spillback or queue formation region. It is the region where traffic congestion becomes so high that other areas beyond the initial congested area start to become congested, and queues or backups on upstream sections of the transportation network start.

Key characteristics of this region are:

1. **Backups**: in this region, traffic congestion is so high that queues are formed. These queues can extend back along the roadway, affecting areas that were previously operating without congestion.
2. **Delays**: vehicles in queues experience a higher delay, and travel times can become highly unpredictable. The spillback region shows that congestion has reached a critical level, and that the road network capacity has been exceeded.

The last part of the MFD graph (D) is the gridlock region, in which severe forms of traffic congestion exist (traffic comes to a complete stop) and vehicles cannot go in any direction.

The main characteristics of this region in the MFD graph include:

a) **Total stagnation:** this indicates a total or entire disruption of traffic flow. Vehicles are basically unable to move (stop) due to high congestion. Intersections become blocked, and roadways become fully congested.

b) **Total capacity**: the gridlock region signifies that the transportation network has reached its absolute capacity and is unable to accommodate any more vehicles.

c) **Significant disruption**: gridlock leads to significant disruption in traffic patterns. It can be initiated by accidents, poorly timed traffic signals, and inadequate infrastructure.

2.3. The Emergence of Macroscopic Fundamental Diagram

Many versions of the macroscopic fundamental diagram (MFD) exist today, employing different types of data to illustrate the relationship between flow and density. However, all MFDs fundamentally relate to the original concept of the fundamental diagram (FD). This diagram depicts how flow, density, and speed interact on transportation links and has been around for over 85 years. It was first introduced by (Greenshields, 1935), and over the years, numerous mathematical formulations have been developed to describe its shape.

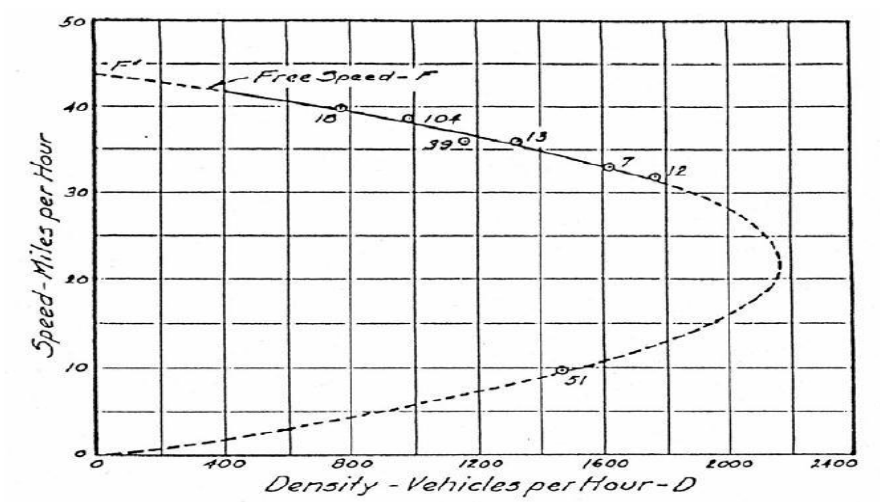


Figure 8 First fundamental diagram (density vs speed) (Greenshields, 1935)

Macroscopic fundamental diagrams (MFDs) illustrate the empirically observed performance characteristics of networks by establishing connections between space mean speed, traffic density, and flow. Due to their significant potential advantages in various applications, MFDs have quickly gained global popularity since their initial demonstration, which relied on empirical data collected from Yokohama (Geroliminis & Carlos, 2008). The study used both detectors and mobile vehicle probes for data collection. Due to fixed detectors, they may not represent the whole network data from GIS-equipped taxis used for analysis. While (Geroliminis & Carlos, 2008) were the first convincing empirical evidence for the existence of MFD, (Hani Mahmassani, 1984) tried to explore the aggregate flow density relationships from microscopic simulation.

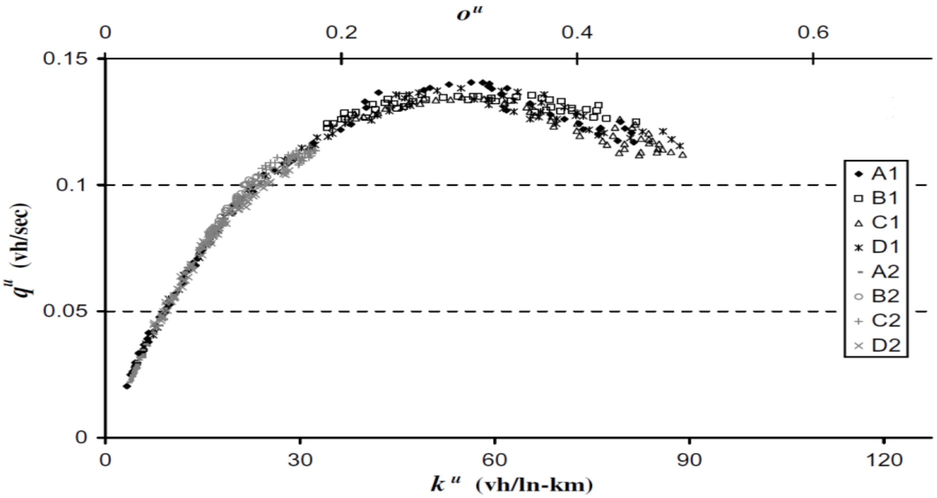


Figure 9 MFD from the Yokohama experiment, over 8 different time periods (Geroliminis & Carlos, 2008)

Recently, (Wai Wong, 2021) studied network topological effects on a macroscopic fundamental diagram using empirical data as evidence to examine the explicit connections between network topologies and the parameters of a specific MFD in the form of a macroscopic Underwood's model. Junction and network density were used as factors of topology for the 63 1km by 1km networks.

2.4. Macroscopic Fundamental Diagram Estimation Methods

The current methods of obtaining MFDs for transportation networks are analytical derivation and experimental analysis. Experimental analysis may be based on either simulated or measured data.

2.4.1. Analytical estimation method

This method has been developed for urban corridors with well-balanced flows at intersections, meaning the difference between inflows and outflows is close to zero. This method is applicable for homogeneous and equal urban corridors in stationary situations, either to the upstream demand (during free flow) or to the downstream supply (during congestion) (Ludovic Leclercq, 2014).

2.4.2. Edie method

This method needs full trajectories of vehicle information, so when vehicle trajectories are available, it is possible to calculate average network flow, density, and speed using Edie's generalized definition. Edie's method has two steps. First, the average flow (Q) and density (K) for each link for the given time interval (t+Δt) are calculated.

$$Q_i = (\sum_k d_k)/l_i \triangle t \text{ and } K_i = (\sum_k \tau_k)/l_i \triangle t$$

Where d_k=distance traveled

τ_k=the time spent by vehicle k within the space–time window S_w defined by link i and time interval [t, t + Δt], Second flow (Q), and density (K) can be calculated by averaging the link values of the whole network

$$\mathrm{Q} = (\sum_k Q_I\, l_I)/\mathrm{l} \text{ and } \mathrm{K} = (\sum_k K_I\, l_I)/\mathrm{l} \text{ and}$$

Where V=Q/K

Edie's method is only applicable in practice when the data source is from a traffic simulator. It is the only unbiased method to determine the relationship between flow and density and to estimate the macroscopic fundamental diagram of the road network.

2.4.3. Loops Methods

Loop detectors are the most common source of field traffic data, offering localized snapshots of traffic states. These snapshots are frequently utilized as surrogates for link traffic states when estimating the macroscopic fundamental diagram (MFD). This method depends on or gives results from subnetworks equipped with loop detectors. However, if the equipped links provide a representative picture of the whole network, it can be used as an estimate for the total network MFD (Ludovic Leclercq, 2014).

2.4.4. Probes Method

The probe method, or probe vehicle data, involves collecting information from vehicles equipped with GPS devices or other tracking technologies. These vehicles act as probes moving through the transportation network, and from these vehicles, we can find the average network speed. Probe vehicle data only provides V (Ludovic Leclercq, 2014).

$$\mathrm{V} = (\sum_k d_k)/\sum_k \tau_k$$

d= distance traveled by vehicle k

τ=time spent by vehicle k during time interval (t+Δt)

So the loops method has to be applied to find the flow (Q) from loops. This method too has restrictions; it only covers the observational area available.

2.5. Reviewing the macroscopic fundamental diagram's influencing factors

The most important factors that affect the macroscopic fundamental diagram are (Lele Zhang Z. Y., 2020)

- Traffic factors,
- Network settings,
- Control settings, and
- Route choice behaviors.

Following this, each factor will be discussed separately.

2.5.1. Traffic Factors

Numerous studies indicate that elements like traffic demand, turning patterns, and modes of travel play a crucial role in influencing both traffic density and the configuration of the macroscopic fundamental diagram (MFD). (Carlos F. Daganzo a, 2008) Assumed low number of turning traffic would not have much impact on the distribution of traffic in a homogenous network; as a result, it would have no effect on traffic networks MFD. However, (Nikolas Geroliminis B. B., 2012) found the turning effect on MFD, and as we can see on the MFD figures below, the turning movements significantly decrease the performance of a signalized intersection as they interrupt signals and reduce the storage capacity of the links.

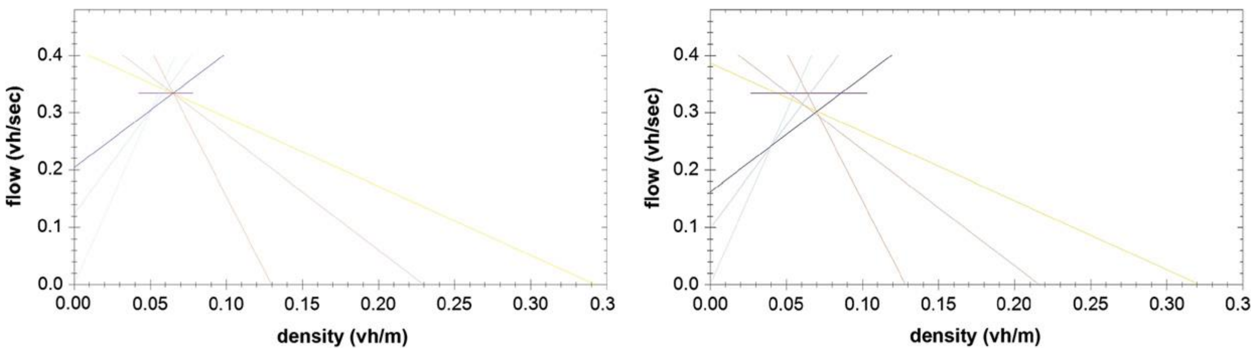


Figure 10 MFD without turns (left) and with turns (right) (Nikolas Geroliminis B. B., 2012)

(J. DePrator, 2017) examines how treating left turns affects the performance of the network using macroscopic performance measures and reveals that prohibiting left turns increases a network’s maximum trip completion rate, especially when trips are long. However, prohibiting left turns in very light or heavy traffic conditions reduces efficiency. So, a dynamic strategy of allowing left turns for light traffic and heavy congestion and prohibiting for moderate congestion allows the network to operate with the highest efficiency.

Most urban road networks are multimodal transport systems. Investigating the impact of different transport modes on network performance was done by different researchers. (Allister Loder, 2017) Uses loop detector data, automatic vehicle location device (AVL) trajectories of public transport vehicles, and vehicle occupancies (i.e., number of passengers per vehicle) to study the impact of different transport modes on the network performance for the city of Zurich, Switzerland. (Allister Loder, 2017) Find that every additional vehicle (either public transport or a car) has a negative effect on the average speed of the car. However, they revealed that the marginal effect of one public transport vehicle is more than ten times greater than the marginal effect of a car. In (Chiabaut, 2015) the focus was on examining passenger MFD, which links passenger accumulation with passenger density. The study underscored how passengers' choices of mode and routes, such as system optimum (SO), user equilibrium (UE), and stochastic user equilibrium (SUE), influence the shape of the passenger MFD. It was found that the relationship between capacity and mode ratio was not consistently increasing or decreasing; instead, there was an optimal mode ratio. While routing mechanisms didn't impact the congested portion of the MFD, they did affect capacity and the corresponding critical density, with SO showing the most effective performance, followed by SUE and UE.

The possibility of aggregated relationships in describing the performance of urban bimodal networks with buses and cars sharing the same road infrastructure and how this performance is affected by the relationship between modes and the effect of location and number of bus stops was studied based on simulation data by (Nikolas Geroliminis N. Z., 2014). The result of the study shows that the network's vehicle flow decreases with the number of buses serving in the network, while passenger throughput is maximized at a non-zero accumulation of buses.

2.5.2. Network Settings

The road network setting can significantly influence the shape and parameters of the macroscopic fundamental diagram (MFD). Factors like road geometry, number of lanes, connectivity between different parts of the network, road space distribution, and bus lanes all play a role in the shape and parameter values of MFD. (Allister Loder, 2017) confirms that having a larger portion of exclusive lanes decreases the impact of public transport vehicles on car speeds. Additionally, this resulted in a decrease in the capacity of the road network, leading to a lower maximum value for the macroscopic fundamental diagram. (Nan Zheng, 2013) Studies the influence of spatial allocation of modes and interaction among them on network traffic performance. They also studied how space allocation (static, dynamic, and dynamic space allocation with congestion pricing) affects performance, and they revealed that in static space allocation, the performance of the network system significantly increases when 10% and 15% of the space in the center region is dedicated to bus lanes, compared to the basic scenario where buses and cars share the whole network system without bus lanes. Space efficiency also increases with dynamic space allocation.

Several scholars thought that converting a one-way network to a two-way network would reduce the network's serving capacity due to the fact that intersections in two-way networks can serve fewer vehicles per unit time than their one-way counterparts. However, (Daganzo, 2012) presents an analytical model to compare one-way and two-way networks. He found that two-way networks can serve more trips per unit time than one-way networks when average trip lengths are short. He also found that two-way networks, in which left-turn movements are banned at intersections, can always serve more trips than one-way networks, even when trips are long. Thus, the trip-serving capacity of a one-way network can actually be increased when converting to two-way operation by simply banning left turns.

(Nikolas Geroliminis B. B., 2012) Studies show that shorter link lengths are more sensitive to the green ratio. Even though variations in link length will decrease the capacity, shorter links are more vulnerable to poor signal coordination. (Wai Wong, 2021) Also studies the effect of network topology on macroscopic fundamental diagrams using networks extracted from dense urban areas of Hong Kong based on taxi GPS data. He revealed that the free flow speed of the network decreased with the number of junctions per unit distance, and the optimal density of the network decreased with the degree density normalized by trafficable area, which represents the intensity of the conflicts between traffic streams. However, (Jong, 2012) studied the structure of the network itself, which does not have a strong influence on the shape of the macroscopic fundamental diagram but on the different characteristics of links (length, speed, and capacity).

2.5.3. Control Settings

The signal control strategy employed directly impacts the macroscopic fundamental diagram (MFD). A better signal control method will increase traffic flow and give a more stable MFD with consistent flow-density-speed relationships. Conversely, inefficient strategies may result in congestion, deviations from typical MFD patterns, and reduced network performance. Since traffic signal systems are a major factor in determining network performance and have an impact on MFD shape, their selection could be utilized as a general performance indicator.

(Xinkai Wua, 2010) Argues that large scatter in the macroscopic fundamental diagram is due to signal coordination, green time ratios, turning movements, and he says low capacity is primarily caused by turning traffic and poor synchronization. (Weike Lu, 2020) Studies the effect and characteristic values of the network under four control modes (fixed-time, actuated, adaptive, and adaptive coordinated control) using four metrics (maximum throughput, critical accumulation, gridlock accumulation, and the degree of homogeneity) based on a macroscopic fundamental diagram. The result of the research shows that adaptive coordinated control is the best by three metrics. (Jong, 2012) Also signal setting has a strong relationship with the shape of the macroscopic fundamental diagram.

Locally adaptive traffic signals improve network stability in moderately congested conditions by increasing flows and reducing gridlock likelihood because they allocate green times proportionally to upstream approach densities. However, their impact is reduced in heavily congested networks, where adaptive driver routing may be more effective (Vikash V. Gayah, 2014).

2.5.4. Route Choice Behavior

The driver's route choice, whether adaptively responding to current traffic conditions or not, has a significant impact on the distribution of vehicle density across the road network. This distribution of traffic density is important in forming the macroscopic fundamental diagram (MFD), which is the relationship between flow, density, and speed at a network level. Adaptive routing, where drivers change their routes in real-time based on traffic conditions, tends to lead to a more balanced density, which will result in higher overall network flow and greater efficiency. Conversely, non-adaptive routing may result in localized congestion and suboptimal network performance due to concentrated traffic flow on certain routes. (Ludovic Leclercqa, 2013) Studies the influence of route choice in the MFD for a network of parallel routes under different traffic conditions, static and dynamic cases for user equilibrium and system optimum. They revealed that, especially in congested part system optimum static and dynamic approaches provide different results. They also revealed that, under a dynamic approach, MFDs for user equilibrium and system optimum are very close when congested in the decreasing part of the curve. So, even when SO is applied in congested conditions, the saving is small, but SO can provide a large improvement in static conditions even in congested conditions.

2.6. Applications of MFD

The macroscopic fundamental diagram (MFD) proves to be a suitable and valuable macro-level metric for assessing network performance. A comprehensive grasp of the MFD enables its integration into models that are utilized for traffic analysis, control, and assessment.

2.6.1. Traffic Control

Traffic control is one of the main applications of macroscopic fundamental diagrams and MFD-based models. It involves the development of traffic control algorithms for the purposes of increasing network performance and reducing congestion. Macroscopic fundamental diagrams give researchers and traffic engineers a useful tool for modeling aggregated dynamics of urban transportation networks and putting intelligent traffic management tactics into practice. One of the most widely used strategies is perimeter control, which tries to maximize the network's overall performance by regulating the entrance and outflow across protected region borders. The MFD serves as a valuable tool to gauge the impact of new control strategies or infrastructure changes, as alterations in the MFD format indicate the success or effectiveness of implemented measures. It is important to remember that the size of the area we are looking at is important. Assessing the impacts within a small area may give the wrong results, as observed changes could be artifacts of the limited scope. For instance, the implementation of a new traffic control system at one intersection may have an impact at another intersection, depending on the driver's route choices. To avoid such misinterpretations, it is recommended to analyze results within a larger area using the MFD. As stated in (Mehdi Keyvan-Ekbatani a, 2012), even though the research on MFD is still active, the level of knowledge gained is a good and reliable base for traffic control strategies.

2.6.2. MFD based Evaluation

The macroscopic fundamental diagram provides a holistic view of road network performance, aiding in congestion management, infrastructure planning, and traffic signal optimization. In (Geroliminis & Carlos, 2008) work, the use of the outflow rate derived from the Macroscopic Fundamental Diagram (MFD) is suggested for assessing a city's accessibility and identifying opportunities for improvement.

MFD is also used in urban development, where it aids in the effective and sustainable design of urban areas by using traffic patterns available. The macroscopic fundamental diagram can also be used to control traffic in emergency situations like evacuations or accidents. MFD can also be used for infrastructure improvement as well as public transport integration. The idea of a macroscopic fundamental diagram is also helpful for the creation of intelligent transportation systems because it permits real-time, data-driven, dynamic modifications to traffic management plans, improving the performance of the road network entirely. Essentially, the Macroscopic Fundamental Diagram is a flexible instrument that helps planners of transportation in a variety of fields make well-informed judgments.

(Lele Zhang T. M., 2013) Uses MFD curves to evaluate different types of adaptive traffic signal systems under various boundary conditions and compare their performance against a highly adaptive system of self-organizing traffic signals that is designed to uniformly distribute the network density. The result shows that the MFD of the self-organizing traffic signals lies above the MFD for the realistic systems. So, MFDs can be used to evaluate and compare different control systems based on their research.

2.6.3. Pricing

An additional application of the macroscopic fundamental diagram (MFD) is stated in (Levinson, 2009). They discuss the utilization of MFD in modeling periodic congestion within a network to formulate a congestion pricing strategy. Their investigation gives MFD the opportunity to design a congestion pricing plan based on the network, and this plan was tested at the same location studied by (Geroliminis & Carlos, 2008) during the morning peak congestion period in Yokohama, Japan. The result shows that the congestion pricing, or toll case, demonstrated significant efficiency compared to the scenario without tolls.

2.6.4. Routing Strategies

The macroscopic fundamental diagram (MFD) has applications in routing strategies. By examining how different routes impact road network efficiency and traffic flow through MFDs, we can evaluate the overall network performance. Combining MFDs from various routes into one allows us to gauge the effects of different routing strategies under conditions like user equilibrium and system optimum. This analysis provides insight into how route choices affect congestion, travel times, and network capacity. Additionally, it aids in optimizing traffic and enhancing the efficiency of transportation networks.

The macroscopic fundamental diagram (MFD) is used to compare routing strategies in simple networks. The study investigates how different routing strategies affect network performance under various conditions, including user equilibrium and system optimum, by estimating MFDs on different routes and aggregating them into a unified network MFD (Ludovic Leclercqa, 2013). This analysis provides insights into the implications of route choices on traffic flow patterns and network efficiency, making the MFD a better tool for evaluating and comparing routing strategies in relation to network traffic management.

2.7. Road Network Typology

The term network describes the structure of pathways within a system of identified locations known as nodes. It is also defined as an arrangement of intersecting lines. A route is a single link between two nodes that are part of a larger network. Networks of transportation facilitate the movement of people and products. Indicators are employed to quantify network form and structure in order to comprehend the complex structure of networks. The network's performance is ascertained using this. There is a need to know what is being measured in order to understand the dynamics of transport networks. The structure and arrangement of roads within a city's road network affect the city's overall structure and function. Because of their geographical characteristics, roads are often spatial networks with nodes and edges integrated into space. In relation to road networks, edges refer to road segments that connect two intersections, whereas nodes are the intersections in the network.

2.7.1. Graph Theory

Graph theory is a branch of mathematics that studies graphs. Graphs are mathematical structures consisting of nodes (intersections) that are connected by edges (road segments). It is used to model and analyze relationships between objects. It has many applications in multiple fields of study, such as computer science, engineering, social sciences, and operations research. Finding the shortest paths, determining connectivity between nodes, and analyzing network flow are studied by graph theory.

According to graph theory, a link is defined as an imaginary straight line representing a finite length of road route. Whereas a node is defined as an imaginary point where links intersect, it represents transport network intersections.

2.7.2. Road Network Typology Indices and measurements

Road network indices and measures are used for the evaluation of road network properties and performances. Quantifiable indicators enable the exploration of structure from a spatial perspective and can abstract the features of complicated network systems. Indices are employed in the evaluation of a network graph's attributes. The connection metric is one indication used to assess network performance. Any transportation network's main goal is to provide connectivity because it connects the destinations that users desire to go to.

I. Network density

Network density measures the territorial occupation of a transport network in terms of km of links per square kilometers of surface. It also refers to the number of roads or road segments within a given area, typically measured in kilometers of roads per square kilometer of land area. It is a measure of how well-developed the road network is in a particular region. A higher road density generally indicates better accessibility and connectivity within the area**.**

$$ND = L/A$$

Where ND refers to network density (Km/Km^2).

L is the total length of the transport network (Km).

A is the area of the transportation network (Km).

The unit of measurement will be km/km^2 for big networks and long infrastructure, whereas for small networks, it is possible to use m/m^2 or other measurement units.

II. Eta index (η)

In a traffic network, the eta index (η) is used to measure the average edge length in the network and as a measure of speed. The Eta index provides insight in to the typical distance between intersections or nodes in the network which can be used as a measure of road network connectivity.

Here is the formula.

$$\eta = \frac{L(G)}{E}$$

Where η is Eta index (unit less)

L(G) refers to the summation of all edges in the network measured in kilometers

E refers to the number of edges in the network

As discussed above, the Eta index is the measure of speed in the road network because it is assumed that the shorter the edges in the network, the more difficult it is to ensure the maximum speed of the segment concerned, and the longer the edges in the network, the better it is to ensure the maximum speed. So, for longer edges, adding a new link will decrease the Eta index as the average length per link reduces.

III. Beta index (β)

The beta index, also known as the link-node ratio, calculates the degree of connectedness in a graph by dividing the total number of nodes by the number of links. Nodes refer to transport network intersections, and edges are connections between nodes. The beta value for trees and simple networks is less than one. A beta value for a network that is connected and has one cycle is equal to one.

$$\beta = \frac{E}{N}$$

Where β is beta index (unit less)

E refers to the number of edges of the network

N refers to the number of edges in the network

IV. Alpha index (α):

Alpha index is a measure of connectedness that compares a network's cycle count (a finite, closed path starting and ending at a single node) to its possible maximum cycle count (Edward Karl Morlock, 1967). A network is more linked the higher its alpha index. Simple networks and trees will have a value of 0. A network that is fully connected has a value of 1.

$$\boldsymbol{\alpha} = \frac{\text{E}-\text{N}+1}{2N-5}$$

Where α is alpha index

E is the number of edges and N is the number of nodes

The value of the alpha index is between zero and one. As the alpha index increases, the level of connectivity also rises. Simple networks will have zero alpha values. A value of alpha equal to one signifies a more connected network where all conceivable links exist among different nodes. However, in certain cases, the alpha index might be negative, indicating insufficient connectivity within the transportation networks of the study area.

V. Gamma index ($\boldsymbol{\gamma}$)

Gamma index is a measure used to evaluate the level of connectivity in a network. It considers the relationship between the number of observed links (edges) and the total number of possible links (edges) that could exist between nodes in the network. The gamma index ranges between 0 and 1. A value of 1 indicates that every possible link between nodes in the network is present, resulting in a fully connected network. However, achieving a gamma value of 1 is typically considered highly unlikely in real-world scenarios because it would mean that every node in the network is directly connected to every other node. Conversely, a gamma value closer to 0 suggests a network with fewer observed links relative to the total possible links, indicating lower connectivity. This might occur in networks with sparse connections or where certain nodes are isolated from others.

$$\boldsymbol{\gamma}=\frac{\text{E}}{3(N-2)}$$

Where $\boldsymbol{\gamma}$ refers to gamma index

E refers to number of edges

N refers to number of nodes

VI. Grid tree pattern (GTP)

Road network patterns are assessed using a metric called the Grid-Tree Pattern (GTP), which measures how much a network resembles a grid or a tree structure. The GTP value of 1 indicates excellent connectivity and numerous route possibilities in a strictly grid-based road network. Alternatively, the GTP value approaches 0 in a road network that resembles a tree and consists of roadways branching out from a central point with few or no intersections, indicating a hierarchical and linear structure. A road network's overall connectivity and redundancy can be easily assessed using the GTP metric.

$$GTP=\frac{E-N+1}{(\sqrt{N}-1)2}$$

Where GTP is grid tree pattern

E refers to number of edges and N is the number of nodes

VII. Network centrality

Road centrality refers to the measure of importance or prominence of a particular road within a road network. It typically considers factors by which certain roads are capable of providing a critical connection for others. Roads with high centrality are often critical for efficient transportation and may play a significant role in connecting various parts of a region or city. Centrality measures include degree, betweenness, and closeness centrality, in which they quantify how central or important each node or link is inside a network, so that these measures are appropriate to describe the difference between pattern types (Yuanyuan Zhang).

A. Degree centrality

Degree centrality is the most intuitive, natural, and computationally efficient measure to describe the importance of a given intersection. This centrality measure is used in the analysis of the spatial networks of urban streets (Paolo Crucitti, 2006). A node's degree of centrality indicates how many direct connections it has in a network. It is determined by adding up all of the edges that are connected to a node, which indicates how connected it is. It represents, in a normalized manner, the percentage of potential connections a node may have in the network. A basic statistic called degree centrality is used in network research to identify the most connected nodes and highlight important hubs of impact, interaction, or possible bottlenecks. The identification of nodes having substantial connections or influence within a network is a typical application across multiple domains.

For a network consisting of N number of nodes and E number of edges and a single node (n) and edge (e), the degree centrality for node n is

$$C(_D)n=deg(n)$$

Where C(d)n is degree centrality of node n

So the degree centrality of the whole network becomes (C.Freeman, 1978/79)

$$C_D(G)=\frac{\sum_{i=1}^{N}(C_D(n^*)-C_D(n_i)}{(N)^2-3N+2}$$

Where $C_D(G)$ is the general degree centrality of a network

$(C_D(n^*)$ is the node with maximum degree centrality

N is the number of nodes

B. Closeness centrality

Closeness centrality is a measure used in network analysis to assess the centrality of a node within a network. It quantifies how close a node is to all other nodes in the network. In the context of a road network, closeness centrality measures how quickly a particular road or intersection can reach all other locations in the network. Roads or intersections with high closeness centrality are typically well-connected and can efficiently access other parts of the network. Closeness centrality is in fact defined as the reciprocal of farness. The inverse of farness is actually closeness centrality, and the higher a node's closeness centrality value, the more probable it is to be closer and central to the other nodes in the network. A larger value of closeness centrality represents that node being more central and closer to other nodes in a network (Selim Reza, 2010). The basic parameter to calculate the closeness centrality is the shortest path distance between a node and all other nodes in the network.

$$C_C(n_i)=\frac{1}{\sum_{i=1}^{N} d(n_j,n_i)}$$

Where $d(n_j, n_i)$ is the distance between node n_j and all other nodes n_i

C. Betweenness centrality

It quantifies the number of shortest paths between pairs of nodes in the network that pass through a particular node. In the context of a road network, betweenness centrality measures how many of the shortest routes between different locations traverse a specific road or intersection. Roads or intersections with high betweenness centrality are crucial for connecting various parts of the network and facilitating efficient travel between them. A road of low centrality is not easily accessible to other nodes by the shortest paths. If g_{v1v2} is the number of shortest paths connecting node 1 and 2 and $g_{v1v2}(n)$

$$C_B(n)=\sum_{v1\neq v2\neq v}\left(\frac{g_{v1v2}(\mathrm{n})}{g_{v1v2}}\right)$$

Chapter Three: Methodology

The research methodology chapter outlines the approach employed to address the research objectives and questions presented in this study. To achieve the objectives, the chapter started from the research flow of the study. It then provides an overview of network sampling and testing methods. The initial decision involves determining the available testing methods and determining the most appropriate one for achieving the research objectives. After deciding the test method, the discussion will continue with an explanation of how it will be used. Finally, the type of data used and the collection method will be discussed.

3.1. Research flow

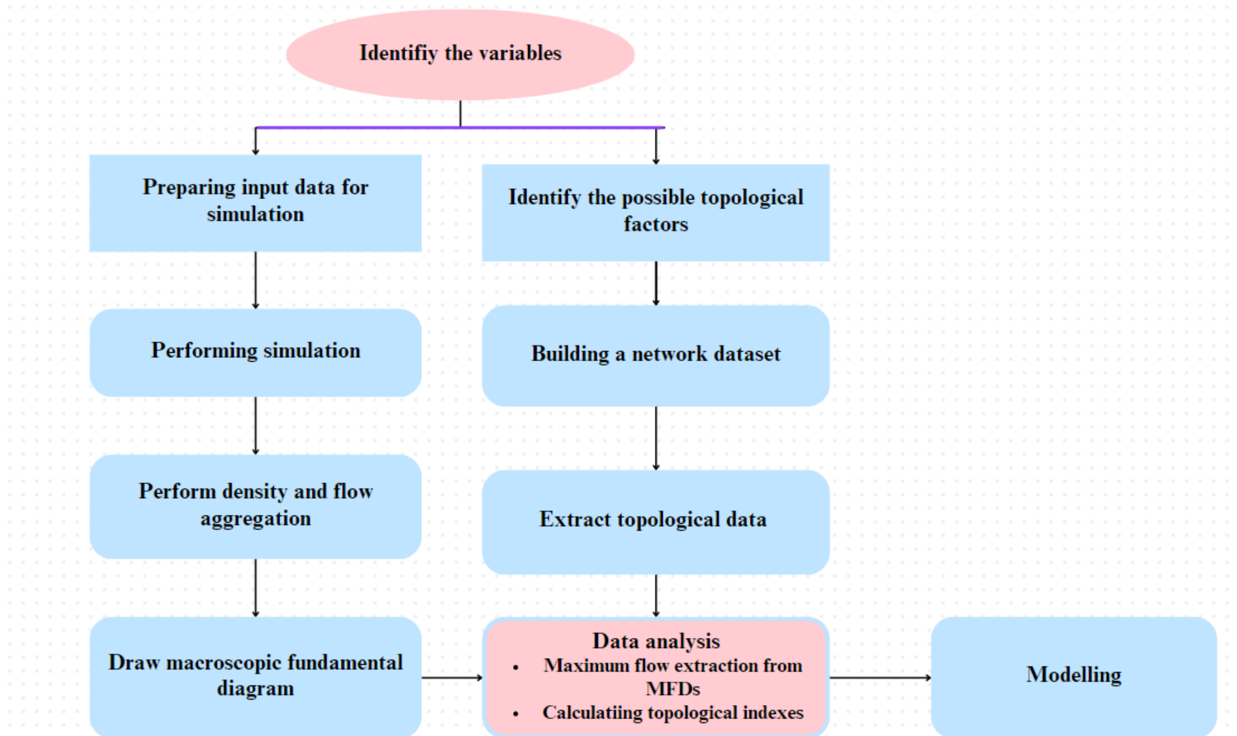


Figure 11 Research flow

This initial step involves the extraction and preparation of all relevant data needed for the simulation. This includes extraction road network, and editing the networks. Once the input data is prepared, the simulation is conducted using simulation of urban mobility (SUMO) software. This simulation models the traffic flow and following the simulation, the data is aggregated to calculate density and flow metrics, which are crucial for understanding the macroscopic behavior of the network. This aggregated data is then used to draw the macroscopic fundamental diagram (MFD), providing a visual representation of the relationship between traffic density and flow in the network.

Regarding the independent variables the first step involves identifying the structural characteristics of the road networks that might influence its performance. This includes examining various network typologies, such as grid patterns, radial designs, and other configurations. Understanding these topological factors is essential as they play a significant role in determining traffic flow efficiency and network resilience. After identifying the key typological factors, the next step is to construct a comprehensive network dataset. This dataset includes detailed information on the network's structure, such as node connectivity, edge lengths, network density, and centrality.

With the network dataset and simulation results in hand, the next step involves a thorough analysis of the data. This includes extracting maximum flow values from the MFDs and calculating key typological indices, such as the alpha, beta and gamma indexes. The final step is to use the insights gained from the data analysis to develop predictive models. These models aim to forecast the impact of different typological configurations on traffic flow performance. By simulating various network typologies, these models help in optimizing the layout and management strategies of road networks.

3.2. Sample size

Sampling of road networks takes place in Addis Ababa which is the largest urban center and capital city of Ethiopia located approximately 9.1° N latitude and 38.7° E longitude, with an elevation of around 2,355 meters above sea level. Determining the sample size in the context of researching how network typology affects the aggregated maximum flow (performance) of a road network requires a number of crucial stages. First, from the broader network, the selection of 2*2-kilometer square road networks is done. The size of the area of extracted road network is chosen to have broad typological variation in the study area and to have a consistent controlled network size. The network sampling section below provides guidelines for this extraction method. These guidelines were taken into account things like variety, representativeness, and the requirement to include a range of network structure types in the research region. Once the study area chosen, the next step involves calculating the number of samples needed for the study. This calculation is crucial for ensuring the statistical power and reliability of the analysis.

As shown in the figure below the whole area of Addis Ababa is 538.326 square kilometers. But it is known that certain areas have no road infrastructure, and some others are not very heavily urban and the networks are not well connected since every origin-destination pair have to be connected.

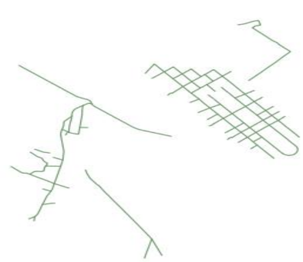


Figure 12 Less urbanized area topology

As a result, these less urbanized and rural regions are not included in determining the size of the research sample, which means they are not included in the study. Consequently, the entire area under consideration for this study is reduced to 384 square kilometers. As a result, this adjusted area is the basis for calculating the sample size.

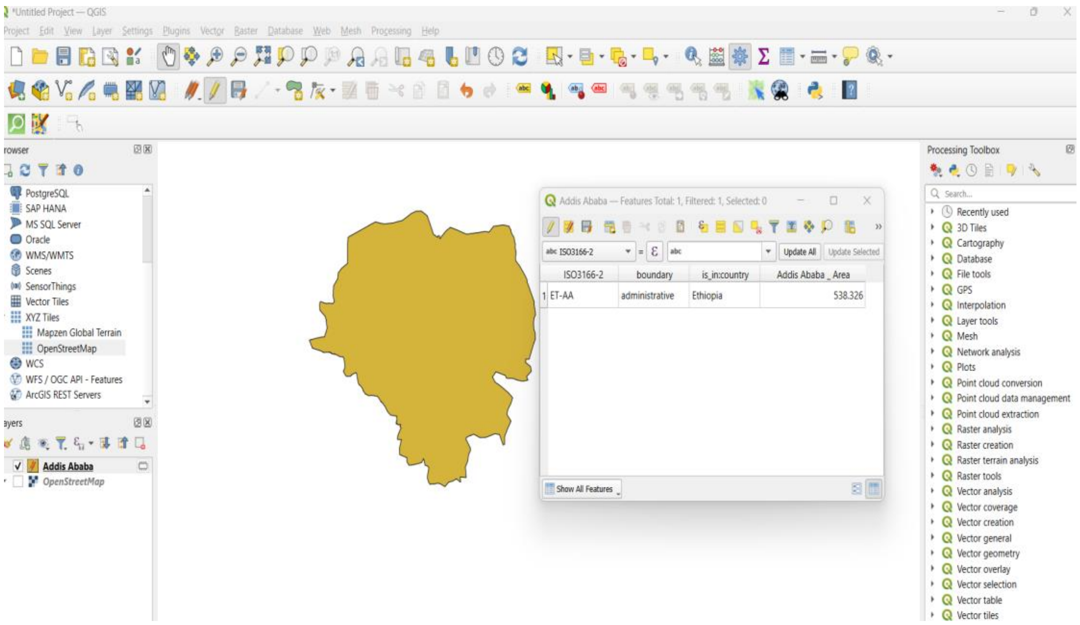


Figure 13 Total area of Addis Ababa

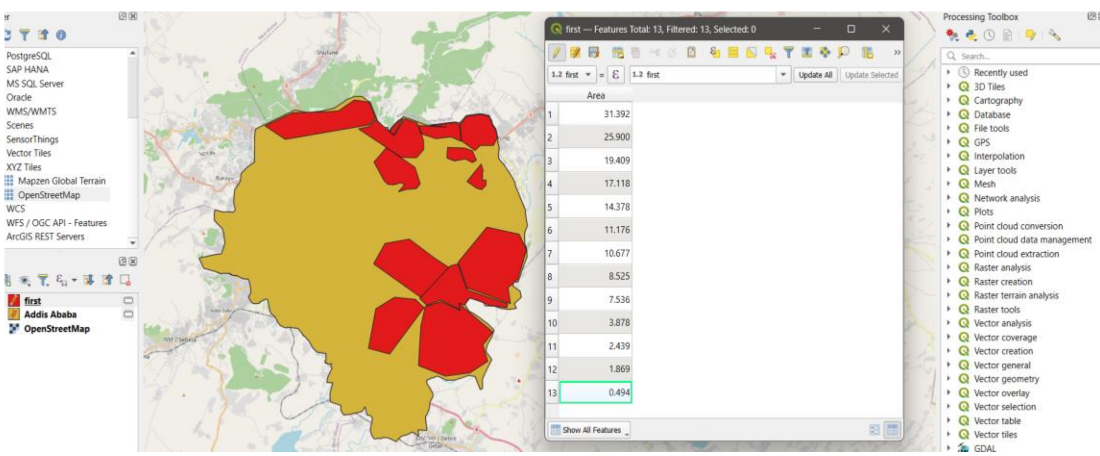


Figure 14 Areas deducted from study area

A formula that was designed to meet the needs of the research was applied to estimate the sample size. This formula takes into account variables including population size, the margin of error, and the required degree of confidence. So, the total population size of the study area will be 96 (i.e., 384/4)

$$\text{Sample size} = n = \frac{m}{1+\frac{z^2 * p(1-p)}{e^2 * N}}$$

Where z is the z score for 95% confidence interval =1.96

E is the margin of error =0.05

N is the population size=96

P is the population proportion =0.88

M is the unlimited population size

$$\mathrm{m} = \frac{z^2 * p(1-p)}{e^2}$$

$$\mathrm{m} = \frac{1.96^2 * 0.88(1-0.88)}{0.05^2}$$

$$\mathrm{m} = 162.269$$

$$\mathrm{n} = \frac{162.269}{1 + \frac{1.96^2 * 0.88(1-0.88}{0.05^2 * 96}}$$

$$\mathrm{n} = 60.31 = 61$$

3.3. Network sampling

The network of Addis Ababa city roads is used to model and investigate the factors affecting the macroscopic fundamental diagram (road network performance). Sixty-one 2km by 2km network areas covering the densest area of the city were sampled according to the following criteria:

1) To enable observation of a broad range of relationships between the parameters of the MFD and the network typological metrics, they had to cover as many urbanized areas as possible.

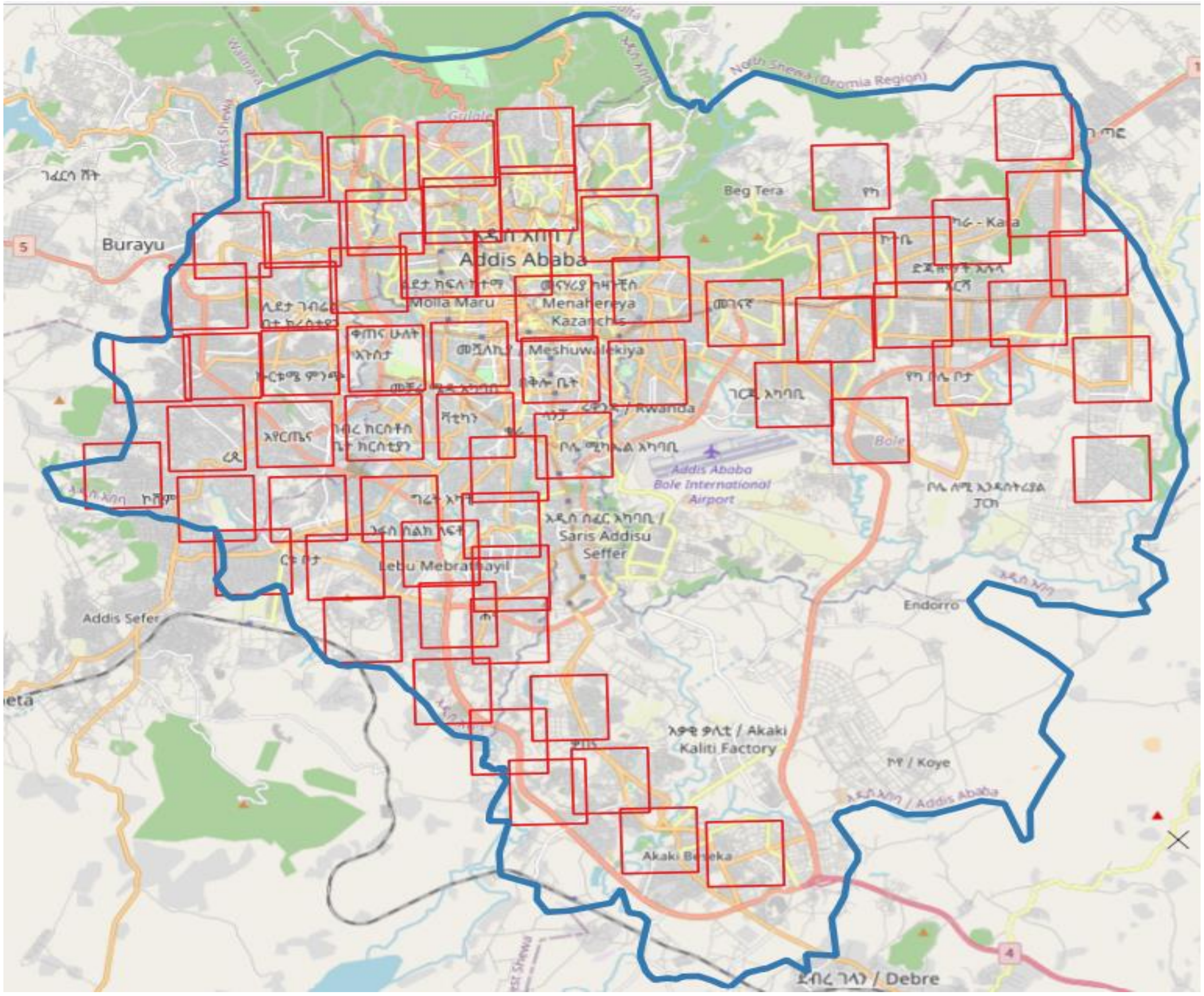


Figure 15 Network sampling

2) For each sampled network's typological properties to be unique and exclusive, the overlapping areas have to be reduced as much as possible.

3) For the limits of a sampling network, it was restricted, wherever possible, to run along a road's centerlines or to cross a junction. For instance if the centerline of roundabout junction is used as a limit of the sample some parts of the roundabout will be missed and the roundabout is no longer functional as roundabout junction.

In order to determine the correlation between the network typologies and the selected MFD's shape, a variety of urban shapes and network structures were considered when selecting the sampling locations. A varied set of topological properties can be seen throughout these sampled networks, which were built and planned in accordance with unique typological patterns and terrestrial features. For example, some networks consist solely of roads with comparatively long link lengths, whereas others are grid networks with very small link lengths.

3.4. Possible Methodologies

Network wide aggregated macroscopic variables (flow, density and speed) can be found by the following three possible methodologies;

- Using real traffic data collected by authorities/organizations
- Mathematical method
- Simulations

All the methods have both advantage and disadvantages. The advantages and disadvantages of each method and the reason of the chosen method will be discussed below.

3.4.1. Real Life Data

Using real-world data is the most representative method, free from assumptions and simulations. However, real-life data comes with several significant limitations. To investigate the impacts of different factors that affect MFD, the data should ideally originate from a network where such systematic changes have been made. However, none of these datasets and detectors are available in the city.

3.4.2. Mathematical Method

While the mathematical approach may be inherently systematic, the derived equations still need validation, either through real-life data or simulation. The first drawback is that it contains a large number of assumptions and often does not take network dynamics into account explicitly. The other drawback is the complexity of deriving these formulations and the need for mathematical expertise.

3.4.3. Simulations

While simulations also rely on numerous assumptions, they frequently incorporate network dynamics more comprehensively compared with a mathematical approach. Moreover, simulations provide the advantage of maintaining constant parameters, except for the ones under evaluation, making them suitable.

So the unavailability of real-life datasets makes the real-life data approach out of choices. The complexities of the formulations and their need for calibration with real-life data also make the mathematical approach difficult to consider in my methodology. Due to those difficulties and the flexibility of the simulation, the simulation approach is my test method. In addition, it allows a degree of experimental control that is not practical in actual traffic systems, as well as the ability to explore a wider range of situations than can be observed in field work.

Simulation of Urban Mobility (SUMO) software will be used to analyze the effect of network typology on the macroscopic fundamental diagram of the road network. A dynamic simulation environment using the SUMO software will be configured.

3.5. Simulation of Urban Mobility (SUMO)

Simulation of Urban Mobility (SUMO) is an open source, highly portable, microscopic, and continuous traffic simulation package designed to handle large networks (Alvarez Lopez, 2019). It enables the detailed modeling and analysis of traffic dynamics within road networks, particularly in urban environments. SUMO facilitates the simulation of individual vehicles' movements, interactions, and behaviors, including lane changes, acceleration, and deceleration. It is mainly developed by employees of the Institute of Transportation Systems at the German Aerospace Center.

3.5.1. Extraction and SUMO network (SUMO Network)

Networks used for simulation by SUMO should be converted in to SUMO network and edited to treat all networks equally. Here are the steps to extract a sumo network;

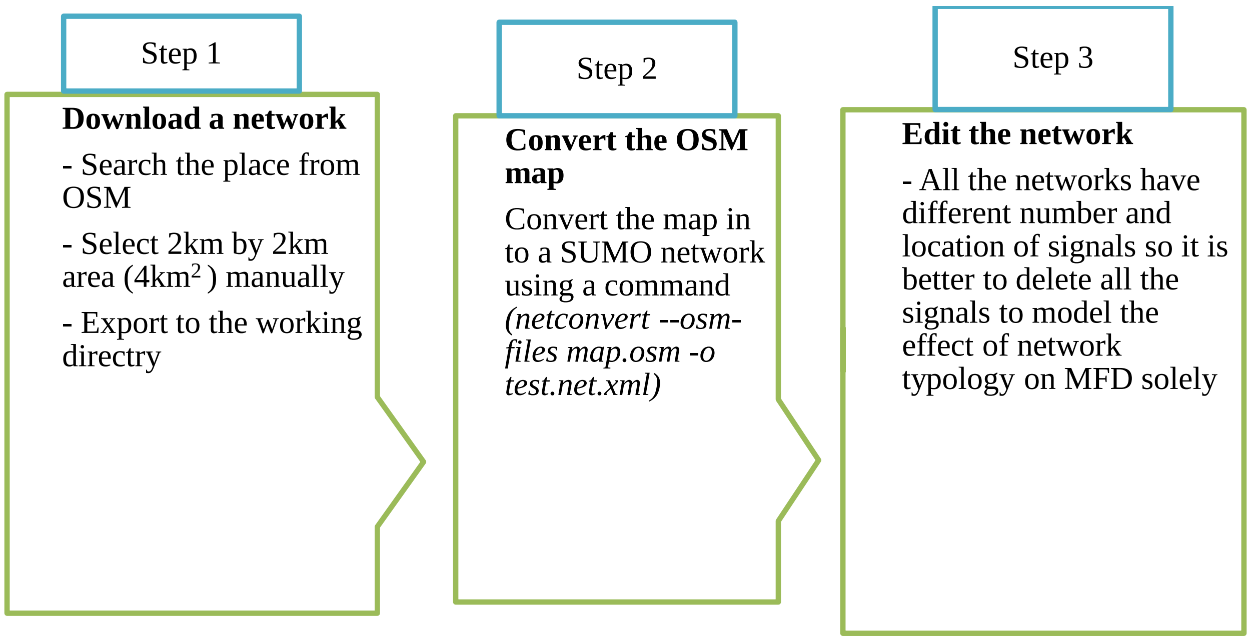
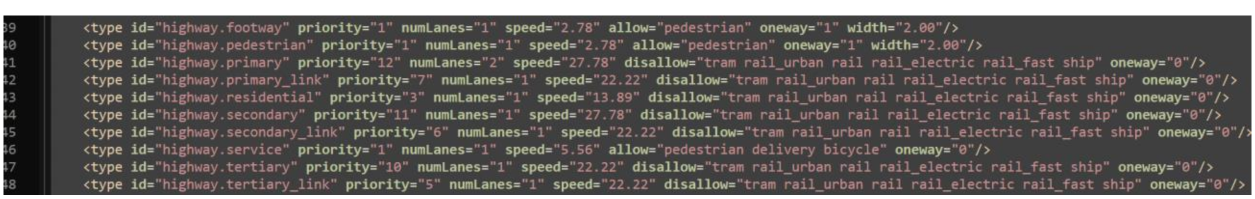


Figure 16 SUMO network extraction

SUMO network is the road network file consists of road network characteristics mainly;

- Road hierarchy
- Number of lane and way
- Speed limit and width of the road



```
<type id="highway.footway" priority="1" numLanes="1" speed="2.78" allow="pedestrian" oneway="1" width="2.00"/>
<type id="highway.pedestrian" priority="1" numLanes="1" speed="2.78" allow="pedestrian" oneway="1" width="2.00"/>
<type id="highway.primary" priority="12" numLanes="2" speed="27.78" disallow="tram rail_urban rail rail_electric rail_fast ship" oneway="0"/>
<type id="highway.primary_link" priority="7" numLanes="1" speed="22.22" disallow="tram rail_urban rail rail_electric rail_fast ship" oneway="0"/>
<type id="highway.residential" priority="3" numLanes="1" speed="13.89" disallow="tram rail_urban rail rail_electric rail_fast ship" oneway="0"/>
<type id="highway.secondary" priority="11" numLanes="1" speed="27.78" disallow="tram rail_urban rail rail_electric rail_fast ship" oneway="0"/>
<type id="highway.secondary_link" priority="6" numLanes="1" speed="22.22" disallow="tram rail_urban rail rail_electric rail_fast ship" oneway="0"/>
<type id="highway.service" priority="1" numLanes="1" speed="5.56" allow="pedestrian delivery bicycle" oneway="0"/>
<type id="highway.tertiary" priority="10" numLanes="1" speed="22.22" disallow="tram rail_urban rail rail_electric rail_fast ship" oneway="0"/>
<type id="highway.tertiary_link" priority="5" numLanes="1" speed="22.22" disallow="tram rail_urban rail rail_electric rail_fast ship" oneway="0"/>
```

Figure 17 Converted SUMO network file

3.5.2. Origin Destination Matrix

In SUMO, an Origin-Destination (OD) matrix represents the flow of traffic between different origin and destination pairs within a transportation network. It is a fundamental component used in transportation planning and traffic analysis to understand the patterns of travel demand and to model the movement of vehicles between various locations. It uses OD matrices to define the demand for travel between different zones or areas within the simulated network. This information is essential for generating realistic traffic scenarios and conducting various analyses.

The OD matrix is defined by SUMO as the figure below

```
$O;D2
* From-Time To-Time
0.00 1.00
* Factor
1.00
*
* some
* additional
* comments
          1   2   200
          1   3   200
```

Figure 18 Origin-Destination definition

Where numbers (1 and 2) were the name of the traffic analysis zones and the amount of traffic have written in the third column (200).

The origin and destination locations of each network have the same coordinates. The consistency allows for each network to be treated equally, used for accurate comparisons and analysis of traffic flows across different networks. The origin and destination from each traffic analysis zone are shown in the figure below.

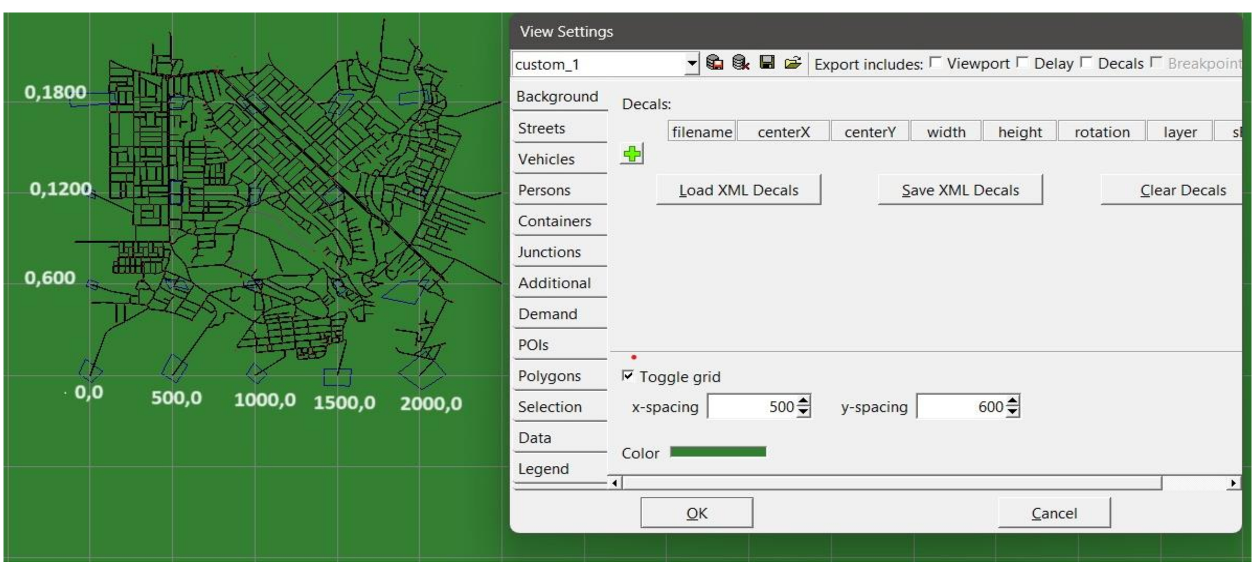


Figure 19 Grid bases Origin-Destination

Traffic analysis zone (TAZ) represents a sub section of the whole network in which it defines the area of vehicle destination and origin location. A traffic assignment zone (traffic analysis zone), or TAZ, is described by its id (an arbitrary name) and lists of source and destination edges (Alvarez Lopez, 2019). The traffic analysis zone is defined as;

```
<tazs>
   <taz id="<TAZ_ID>" edges="<EDGE_ID> <EDGE_ID> ..."/>
   ... further traffic assignment zones (districts) ...
</tazs>
```

A TAZ must have a minimum of one source edge and one destination edge, each identified by its unique ID, and it uses a probability called weight herein. Vehicles can be loaded into or removed from the network using these edges accordingly. Following loading, the probability sums for each source and destination list are adjusted.

3.5.3. Trip Generation

Trip generation is the process of creating virtual trips within a simulated transportation network. These trips represent the movement of vehicles or individuals from one location (origin) to another (destination) within the network. Trip generation is a crucial step in simulating travel demand and assessing the performance of transportation systems. Od2trips produces a collection of trips for a given network (the traffic analysis zones specified in netedit, TAZ-files) and the OD matrices prepared, splitting them into single vehicle trips in Sumo. It accomplishes this by selecting source and destination edges defined in traffic analysis zones.

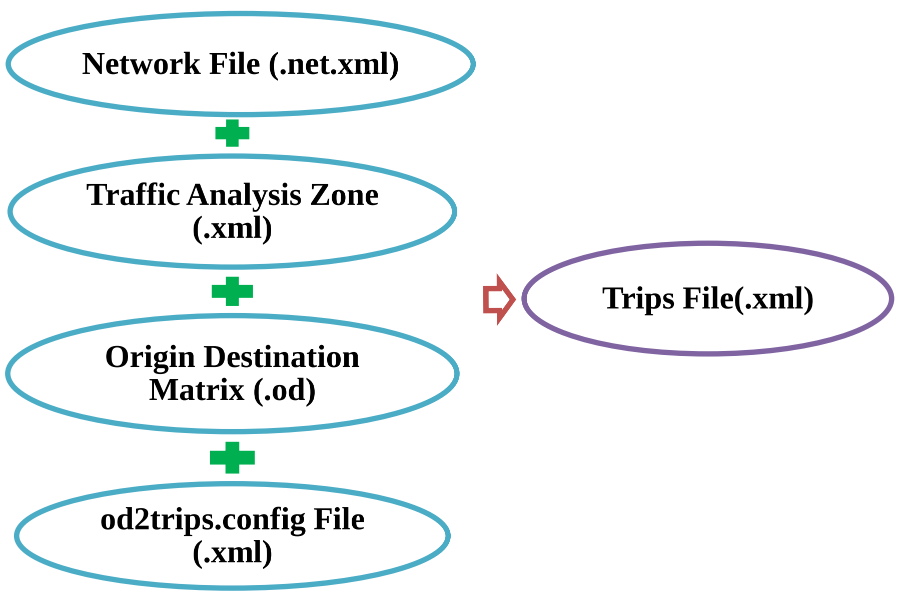


Figure 20 Trip generation

```xml
<trip id="41720" depart="0.14" from="-42974936#2" to="-49911398" fromTaz="19" toTaz="9" departLane="free" departSpeed="max"/>
<trip id="26602" depart="0.15" from="-591705536" to="-27909790#0" fromTaz="16" toTaz="1" departLane="free" departSpeed="max"/>
<trip id="47531" depart="0.23" from="1102769393" to="-532919286#0" fromTaz="20" toTaz="18" departLane="free" departSpeed="max"/>
<trip id="53962" depart="0.29" from="104503673#1" to="566687832#1" fromTaz="4" toTaz="12" departLane="free" departSpeed="max"/>
<trip id="32500" depart="0.30" from="-39208505" to="-8104351#12" fromTaz="17" toTaz="2" departLane="free" departSpeed="max"/>
<trip id="41582" depart="0.32" from="-42974936#2" to="532339579#0" fromTaz="19" toTaz="8" departLane="free" departSpeed="max"/>
<trip id="67760" depart="0.34" from="567112712" to="43456240#2" fromTaz="7" toTaz="5" departLane="free" departSpeed="max"/>
<trip id="46626" depart="0.34" from="1102769393" to="-568874848#1" fromTaz="20" toTaz="14" departLane="free" departSpeed="max"/>
```

Figure 21 Trips file

3.5.4. Route Assignment

Traffic assignment is the term used to describe the process of assigning a certain set of trip interchanges to a particular transportation system. Replicating the pattern of vehicle movements that would be seen on the transportation system when the trip matrix, or matrices, to be assigned represents the travel demand is the primary goal of the trip assignment procedure.

(Alvarez Lopez, 2019) The simulation must identify routes through the network (list of edges) that are utilized to reach the destination from the origin edge for a given set of vehicles with origin-destination relations (trips). The easiest way to locate these routes is to use routing algorithms to calculate the shortest or quickest paths across the network. Since the number of cars in the network affects the travel time, these techniques require assumptions about the travel time for each network edge, which are typically unknown prior to the simulation. The problem of determining suitable routes that take into account travel times in a traffic-loaded network is called user assignment. A frequent problem with naive user assignment is that all vehicles take the fastest path under the assumption that they are alone in the network and are then jammed at bottlenecks due to the sheer amount of traffic.

Iterative Assignment (Approximating System Optimum): The idea of reaching system optimality in SUMO centers on substituting path marginal travel time (MTT) for the conventional path travel time metric. For the system to operate as efficiently as possible, this switch is essential for optimizing traffic flow. It has two methods to calculate marginal travel time. The first method, global approximation, takes a holistic approach, assessing the cumulative effect of adding a vehicle to a specific path on the total system travel time over a designated time interval. In contrast, the local approximation method zooms in on the individual path itself, analyzing how the addition of an extra vehicle influences travel time within that specific route. This localized perspective provides a detailed understanding of how changes in traffic conditions affect individual routes, enabling more precise adjustments to optimize system-wide performance. Through these methods, SUMO strives to refine traffic management strategies and move closer to achieving system optimality in urban mobility simulations.

Iterative Assignment (Dynamic User Equilibrium): Duarouter imports different demand definitions and computes vehicle routes that may be used by Sumo using shortest path computation; when called iteratively, Duarouter performs dynamic user assignment (DUA). This is facilitated by the tool duaiterate.py, which converges to an equilibrium state (DUE). Duarouter has two main purposes: computing the fastest or optimal routes directly as well as iteratively in the context of dynamic user assignment.

The Gawron algorithm in SUMO computes probabilities for choosing from a set of alternative routes for each driver. The following values are considered to compute these probabilities:

- The travel time along the route used in the previous simulation step
- The sum of edge travel times for a set of alternative routes
- The previous probability of choosing a route

The other is the Logit mechanism, which applies a fixed formula to each route to calculate the new probability. It ignores old costs and old probabilities and takes the route cost directly as the sum of the edge costs from the last simulation.

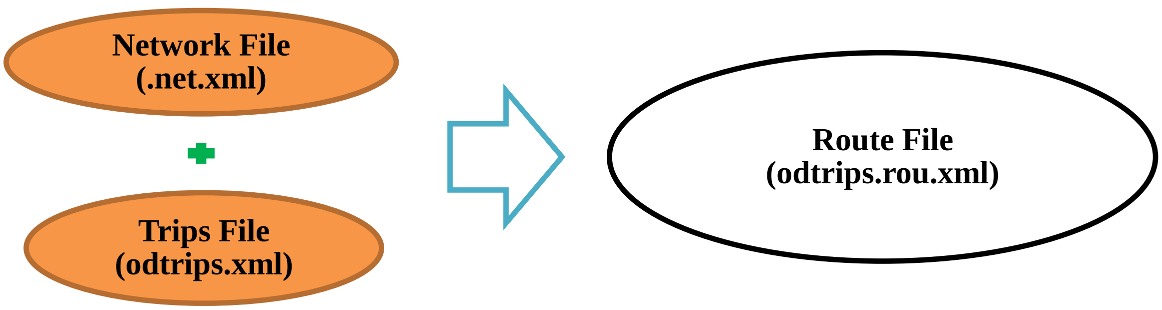


Figure 22 Trip assignment

```
<vehicle id="41720" depart="0.14" departLane="free" departSpeed="max" fromTaz="19" toTaz="9">
    <routeDistribution last="0">
        <route cost="119.11" probability="1.00000000" edges="-42974936#2 -42974936#1 -42974936#0 -200620481 -200620483 -35338719#2 -35338719#1 -353
    </routeDistribution>
</vehicle>
<vehicle id="26602" depart="0.15" departLane="free" departSpeed="max" fromTaz="16" toTaz="1">
    <routeDistribution last="0">
        <route cost="130.90" probability="1.00000000" edges="-591705536 158326844#2 49911421#1 567873515 27909851#0 27909851#1 -27909813#7 -2790981
    </routeDistribution>
```

Figure 23 Vehicle route file

Sumo can use other methods like iterative assignment (mixing DUE and SO), one-shot assignment in which at the moment of departure, each car will calculate its quickest route, preventing all vehicles from recklessly entering the same traffic bottleneck, and marouter, which uses a capacity constraint function based on the infrastructure capacity (speed limit, number of lanes, edge priority, etc.) to calculate travel times.

Although SUMO provides a number of route assignment techniques, the Dynamic User Equilibrium (DUE) assignment approach was used for this study. The dynamic user equilibrium (DUE) assignment approach is used because it more closely resembles real-world situations. In the end, it reflects the dynamic character of traffic flow by simulating the actions of individual drivers looking for the best routes in the face of changing traffic circumstances.

3.6. Data collection

3.6.1. Edge based flow and density

All the input data that are used to draw the macroscopic fundamental diagram (aggregated flow and aggregated density) are extracted from the data output from the simulation for each network. Despite multiple researchers demonstrating the independence of the macroscopic fundamental diagram from origin-destination (OD) demand, this thesis adheres to a consistent OD matrix across all networks in the simulation. Consequently, the significance of the OD matrix lies in achieving maximum flow in the output of the simulation's macroscopic fundamental diagram, rendering the quantity of the OD matrix inconsequential for the purposes of this study. Therefore, each traffic analysis zone will witness the departure of 200 vehicles to all other zones, ensuring a uniform and controlled distribution of traffic throughout the network under examination. This standardized approach facilitates a clearer assessment of the impact of other variables on the macroscopic fundamental diagram, allowing for more robust conclusions to be drawn regarding traffic flow dynamics and network performance.

The simulation steps used to find edge based data are summarized below.

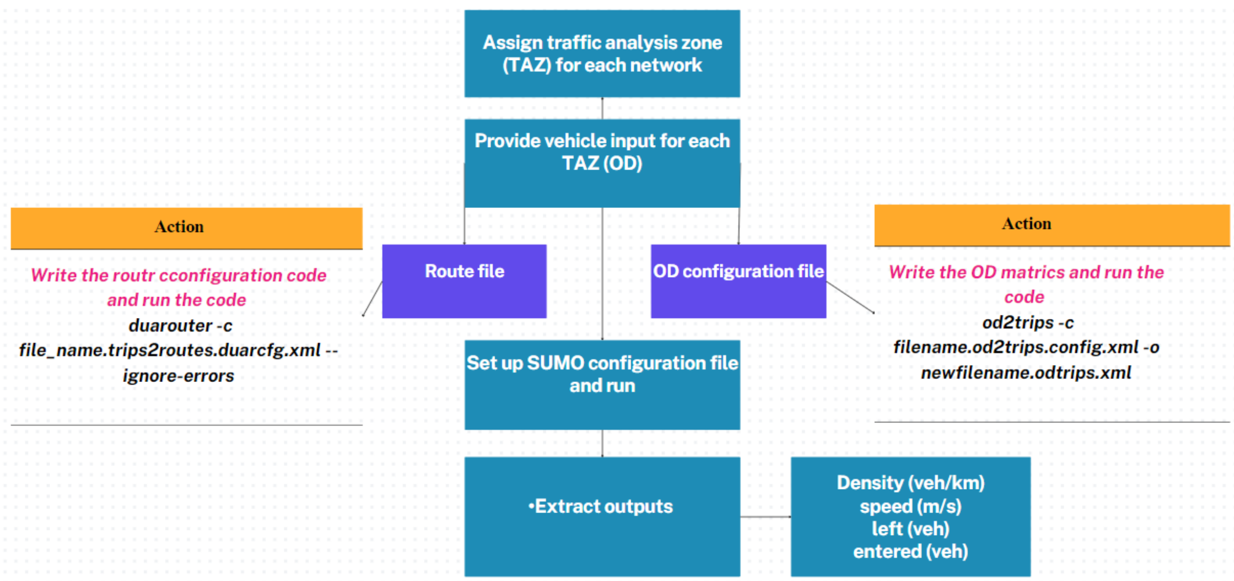


Figure 24 Data extraction flow chart from SUMO

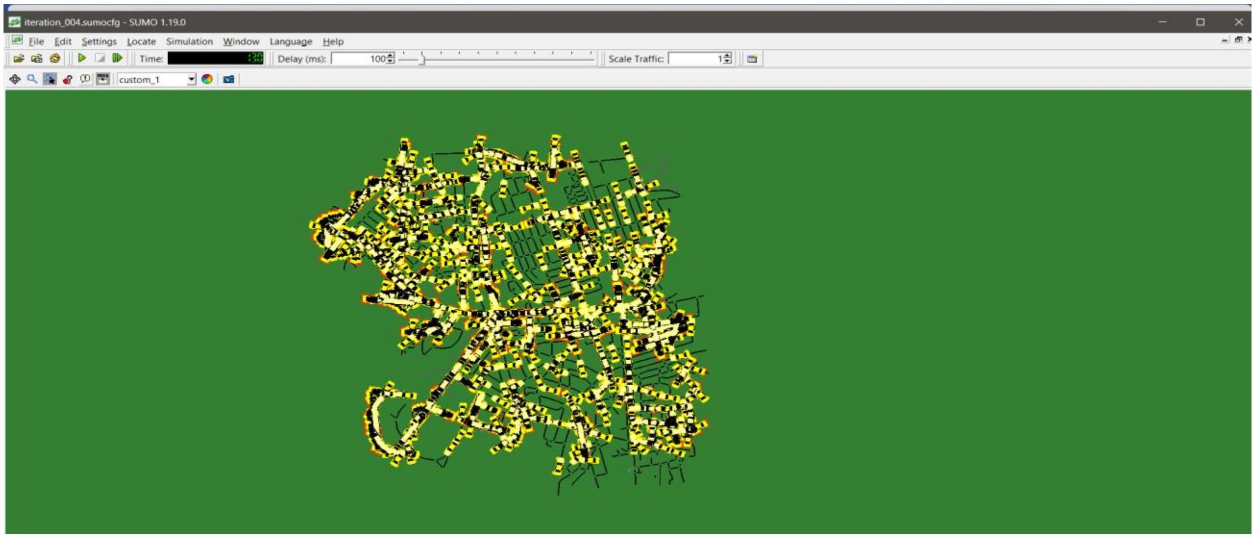


Figure 25 Simulation running in sumo (SUMO interface)

Simulation of Urban Mobility (SUMO) output values can be either lane-based, edge-based, or groups of edges-based. They describe the situation in the network in terms of traffic science by giving macroscopic values such as the mean vehicle speed and density.

Some of the outputs of the edge based simulation are

- Density (vehicle density on the edge in veh/km)
- Left (the number of vehicles that have left the edge by moving downstream)
- Entered (the number of vehicles that have entered the edge by moving from the upstream)
- Speed (the mean speed on the edge with in the reported interval) or an average over time and space (space mean speed) (m/s)

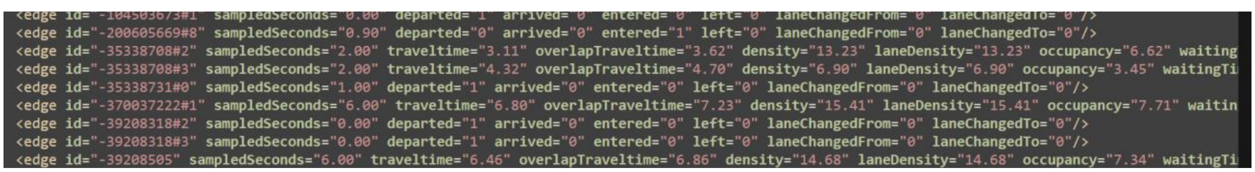


Figure 26 Simulation output

In order to aggregate (spatial aggregation) over multiple edges for a long time, the density can be averaged. However, it is not as easy, especially if they are consecutive, because each vehicle generates data on each lane it is on, even if it is on multiple lanes. So, for long and slow vehicles, it is not possible to aggregate simply, but for short and fast-moving vehicles, the error is negligible. In every network, outputs are aggregated at consistent time intervals throughout a 1000-second simulation period. These aggregated results are then displayed at 5-second intervals, resulting in a total of 200 aggregation points.

3.6.2. Typology indices and measures

Road networks are extracted from OpenStreetMap, and various typological metrics and indices are derived using GIS software. These metrics serve as crucial indicators of network structure and connectivity, providing valuable insights into the spatial characteristics of the road system under analysis. By utilizing data from OpenStreetMap and GIS software, this study ensures the accuracy and reliability of the network representation, enabling a comprehensive exploration of the relationships between network typology and macroscopic traffic flow (MFD) behavior. Road typology indices and measures are collected through GIS analysis, encompassing a range of metrics that elucidate the structural properties of the road network. These measures include, but are not limited to, network density and connectivity.

The following typological data are extracted from GIS software:

- ➢ Network density
- ➢ Proportion of primary roads
- ➢ Trafficable area
- ➢ Number of nodes
- ➢ Number of edges
- ➢ Degree centrality

The extraction of road network typological data using GIS follows those simplified steps.

Trafficable area: it is simply the multiplication of the width and the length of the road. The number of lanes and width of the road network data can be found in converted road network and the length of the road can be extracted by the GIS software by the following steps.

- ✓ Load saved road file to GIS
- ✓ Open the attribute table
- ✓ Add new length field calculator
- ✓ Set the desired precision and the decimal number
- ✓ Choose length and calculate the length

Network density and primary road proportion: they can also found from GIS software by putting the road hierarchy and length of the road in different columns.

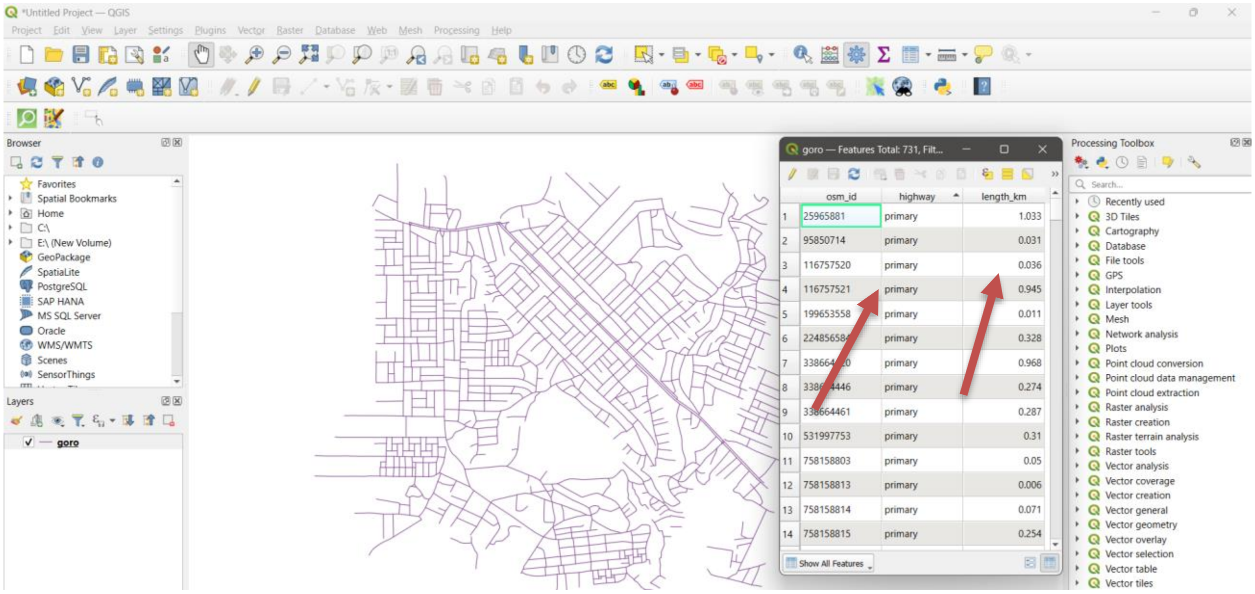


Figure 27 Road network length calculation (edge lengths)

Number of edges: in GIS edge (link) is a linear connection between two nodes in a network. The number of edges of a network can be extracted by the following simplified steps;

i. Load OSM data to GIS**:** The map extracted from OpenStreetMap is a collection of different types of features, including highways, buildings, parks, and other elements. To extract highways, only the other elements are deleted from the layer.

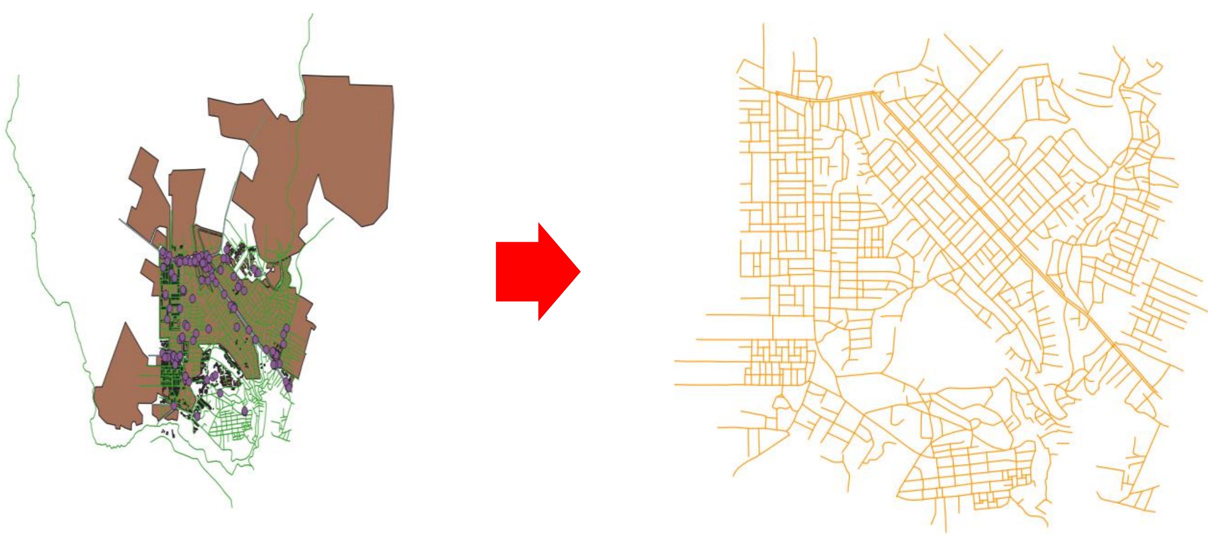


Figure 28 Loading Roads to GIS

ii. Load saved road file**:** after the road file is saved as a shape file from OSM, the next step is to reload it to the GIS for further analysis. This process allows us to work only on road networks, focusing on road network topology and excluding other features.

iii. Dissolving**:** in this step, road features of the same characteristics are merged or combined.

iv. Multipart to single part**:** in this process, multipart geometries are converted into single-part geometry. For example, if a road has curves and a straight road in one road segment, QGIS considers each of the curves and the straight parts as a different road segment. So using the multipart-to-single-part tool, the segment was treated as a single part. In this step, the number of total edges (road segments) is obtained.

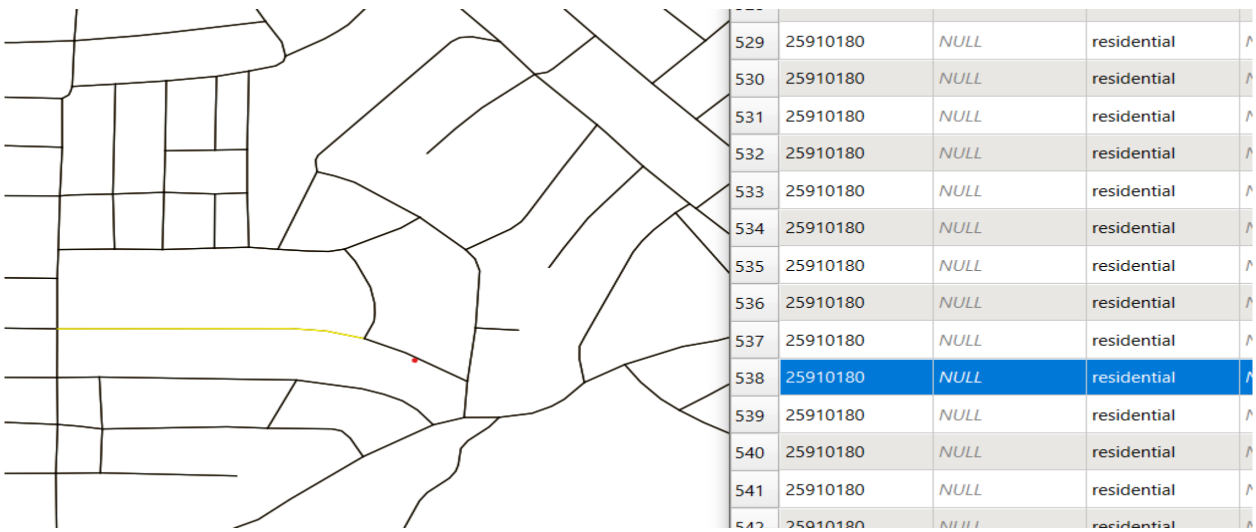


Figure 29 Road network edge

Number of nodes: the number of nodes (connections) a network can be extracted after the multiple road segments are changed into a single road segment, line intersection is used to find the point where two or more road segments (edges) intersect.

Figure 30 Road Network Junctions

Finally, redundant and identical features are removed. This step is crucial to ensuring data accuracy and preventing errors in analysis. The number of road junctions is obtained by this step.

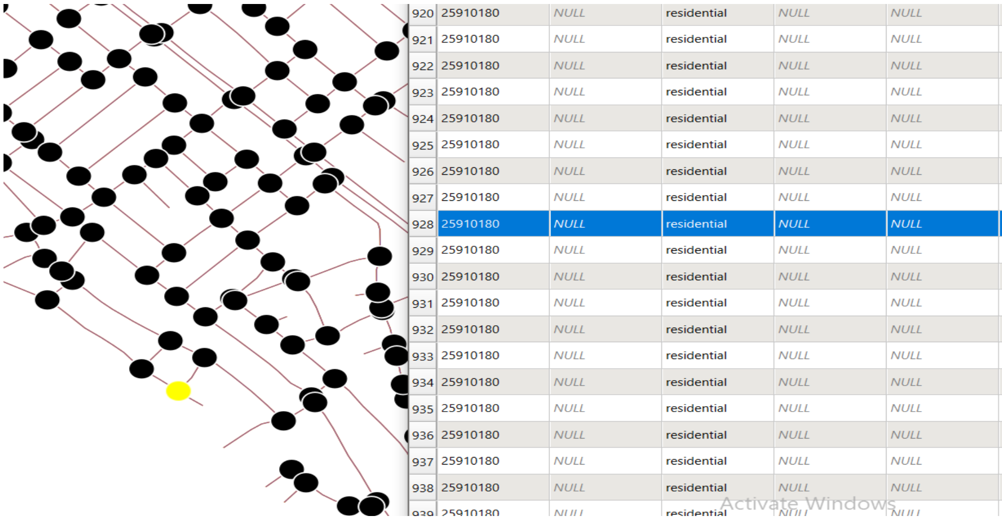


Figure 31 Cleaned road junction

Degree centrality: It is the number of edges connected to a node. This is calculated in ArcMap as follows;

i. Load the shape file in ArcMap

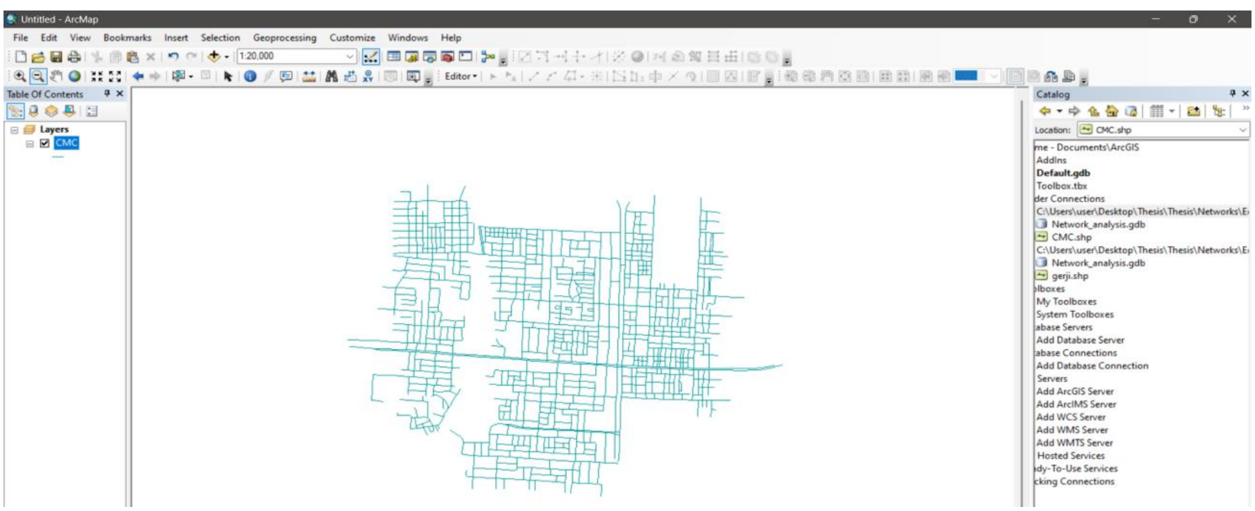


Figure 32 Loaded road network in ArcMap

ii. Create a new feature dataset: it is a collection of related feature classes that share a common coordinate system. Feature datasets used to facilitate controller datasets such as topology, or utility network and parcel fabric

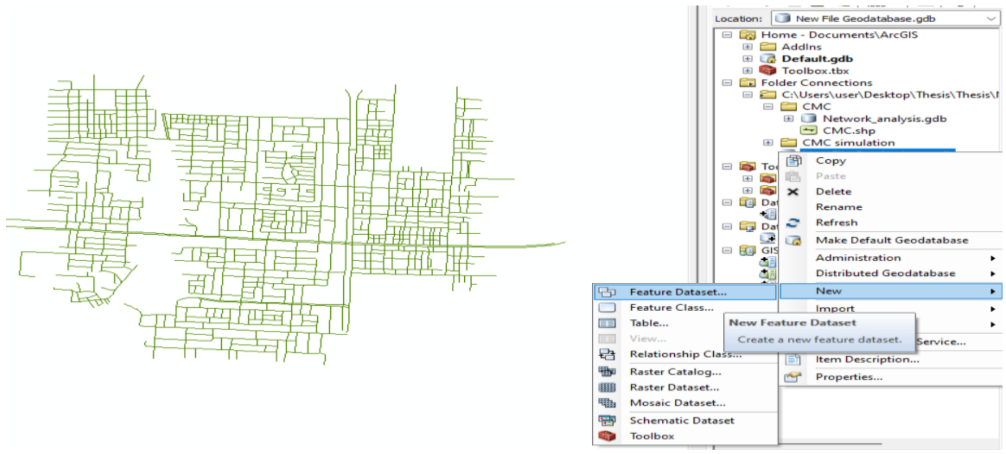


Figure 33 Feature dataset

iii. Save the layer dataset as geodatabase feature class

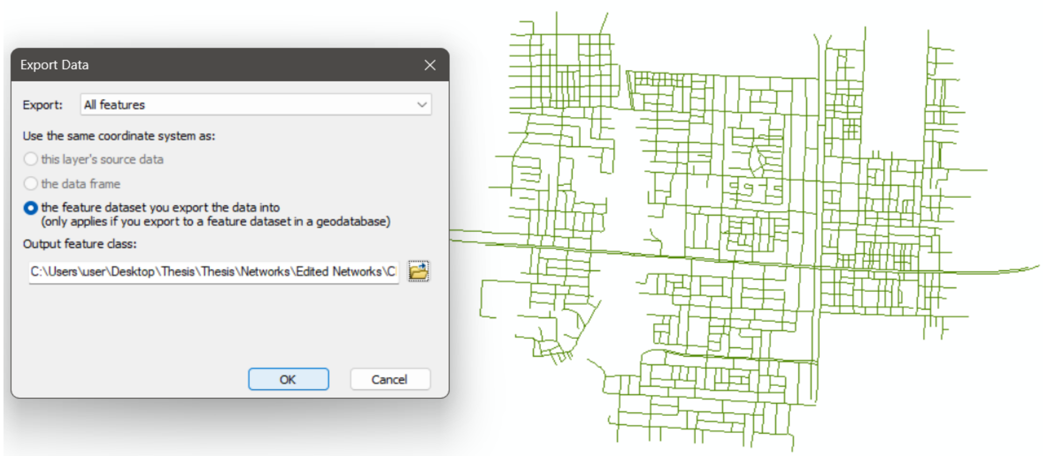


Figure 34 Geodatabase feature class

iv. Create a new network dataset and join based on common attribute: a network in GIS is a set of points and lines that represent a possible routes from one location to another. A network dataset are used to model transportation networks. They are created from the source features (lines and points) and they store the connectivity of source features. Network analysis is always done in network dataset

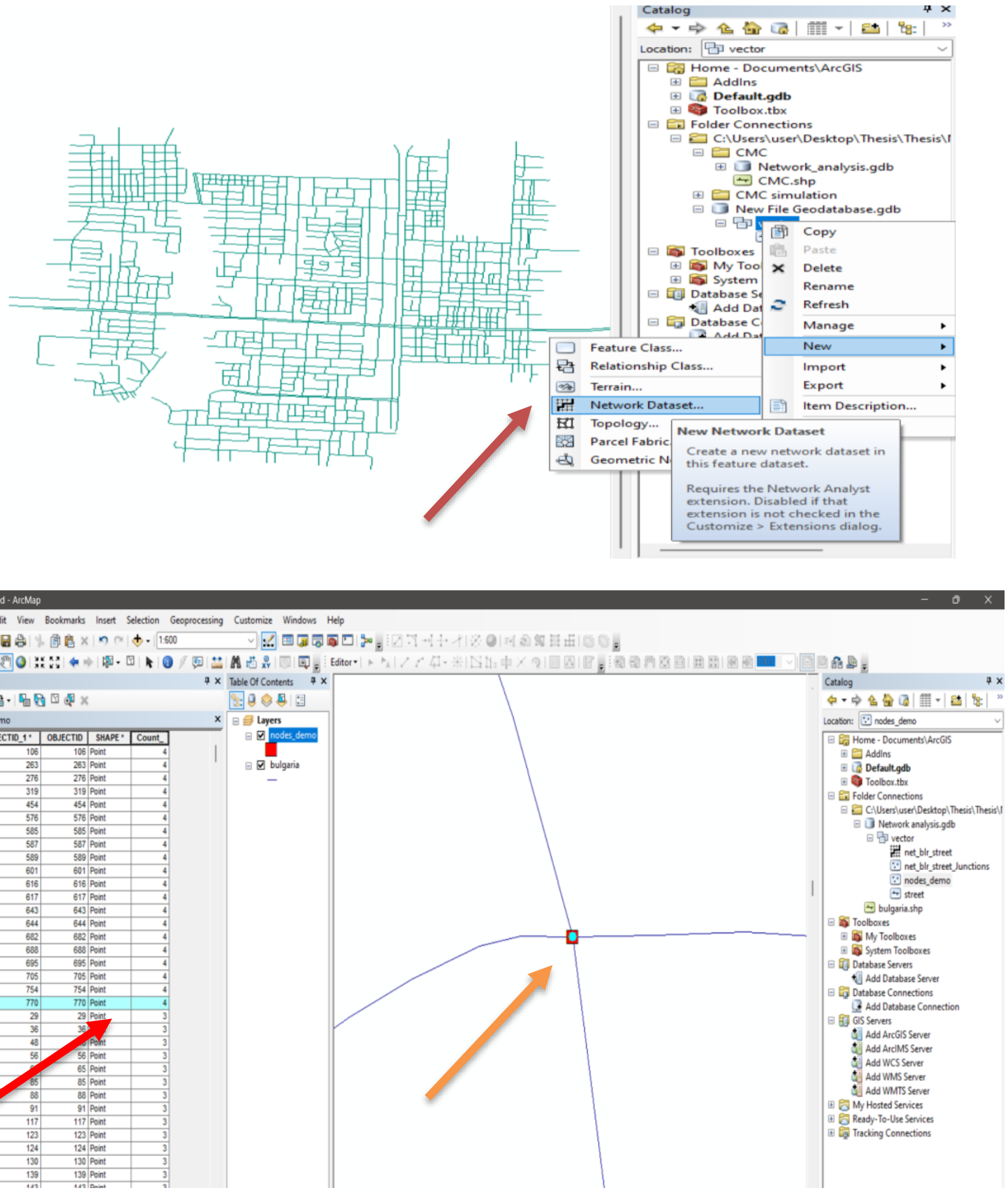


Figure 35 Number of edges connected to a single node

Chapter Four: Data Analysis

In this section, the data collected from simulations of urban mobility (SUMO) and GIS extraction are analyzed and arranged in a way suitable for the modeling.

4.1. Aggregated Flow and Density

The flow and density data from all 61 simulated networks have been aggregated. Aggregated flow represents the total volume of traffic passing through all road segments, while aggregated density reflects the overall concentration of vehicles across the networks for a certain time interval. By examining these aggregated measures, different macroscopic fundamental diagrams for each sampled network found. The output of each simulated network looks like the table below.

Table 1 Sample output of a network around Megenagna

Begin (sec)	End (sec)	ID (edge id)	ID2 (edge id)	Arrived (veh)	Entered (veh)	Left (# veh)	Density (veh/km)	Lane Density (veh/km)	Time Loss (sec)	Speed (m/s)
0	5	dump_5	-1188407059#3	0	0	0				
0	5	dump_5	-1214461661#1	0	0	0				
0	5	dump_5	-1214747969#4	0	0	0	2.56	2.56	0.05	11.52
0	5	dump_5	-160475035	0	0	0	13.09	13.09	1.77	9.47
0	5	dump_5	-162714210#2	0	0	0	4.15	4.15	1.31	16.18
0	5	dump_5	-198120535#0	0	0	0				
0	5	dump_5	-198258742	0	0	0	19.16	19.16	0.67	11.25
0	5	dump_5	-369549764#5	0	0	0				
0	5	dump_5	-42974861#8	0	0	1	23.75	23.75	0.66	11.81
0	5	dump_5	-48505874	0	0	0	21.57	21.57	1.15	9.42
0	5	dump_5	-49870368	0	0	0				
0	5	dump_5	-534602171#2	0	0	0	5.3	5.3	0.14	14.64
0	5	dump_5	-567530373#1	0	0	0	19.91	19.91	1.26	8.15
0	5	dump_5	-568334074	0	0	0	1.8	1.8	0.04	15.35
0	5	dump_5	-568334106#0	0	0	0	18.35	18.35	0.81	11.32
0	5	dump_5	-568381633	0	0	0	4.83	4.83	1.48	9.87
0	5	dump_5	-584583919#0	0	0	0	6.87	6.87	0.2	12.2
0	5	dump_5	-585005948#7	0	0	0	3.11	3.11	0.17	12.99
0	5	dump_5	1188407059#3	0	0	0	2.52	2.52	0.07	21.64
0	5	dump_5	1214461661#1	0	0	0	29.57	29.57	1.54	10.4
0	5	dump_5	1214747969#4	0	0	0	7.97	7.97	1.55	9.07
0	5	dump_5	160475035	0	0	0	10.97	10.97	0.57	12.22

The sample output table above shows that the number of vehicles left a single edge (flow) and the edge density in a five-second interval. This edge-based data has to be aggregated to draw the macroscopic fundamental diagram of the network in a five-second interval.

Table 2 Aggregated flow and density values for the first few seconds

Begin (sec)	End (sec)	Aggregated Density (veh)	Aggregated Flow (veh/5sec)	Begin (sec)	End (sec)	Aggregated Density (veh)	Aggregated Flow (veh/5sec)
0	5	299	2	165	170	32227	543
5	10	1723	41	170	175	31010	498
10	15	3056	73	175	180	31615	497
15	20	4028	109	180	185	31444	473
20	25	4641	136	185	190	32588	492
25	30	5959	186	190	195	33322	471
30	35	7203	236	195	200	33900	465
35	40	8351	282	200	205	33713	483
40	45	9522	306	205	210	35093	511
45	50	10728	335	210	215	36672	506
50	55	11903	369	215	220	37083	518
55	60	12687	392	220	225	36241	499
60	65	13503	416	225	230	36248	473
65	70	14887	414	230	235	36670	485
70	75	15843	470	235	240	36966	486
75	80	16797	463	240	245	38625	487
80	85	17419	458	245	250	38957	487
85	90	18267	476	250	255	38736	465
90	95	18797	498	255	260	38997	476
95	100	19834	512	260	265	39814	460
100	105	21030	494	265	270	39335	486
105	110	21746	570	270	275	39380	459
110	115	23098	583	275	280	40239	461
115	120	24624	562	280	285	40580	452
120	125	24177	551	285	290	40480	442
125	130	24724	534	290	295	40524	431
130	135	26540	525	295	300	41217	395
135	140	26696	502	300	305	41466	394
140	145	27049	511	305	310	41682	384
145	150	27555	505	310	315	41203	356
150	155	28167	486	315	320	42519	380
155	160	28246	486	320	325	42203	381
160	165	28682	500	325	330	41951	358

The simulation output was aggregated for the whole simulation period of 1000 seconds. As a result, there are 200 aggregated flow-density points for a single network.

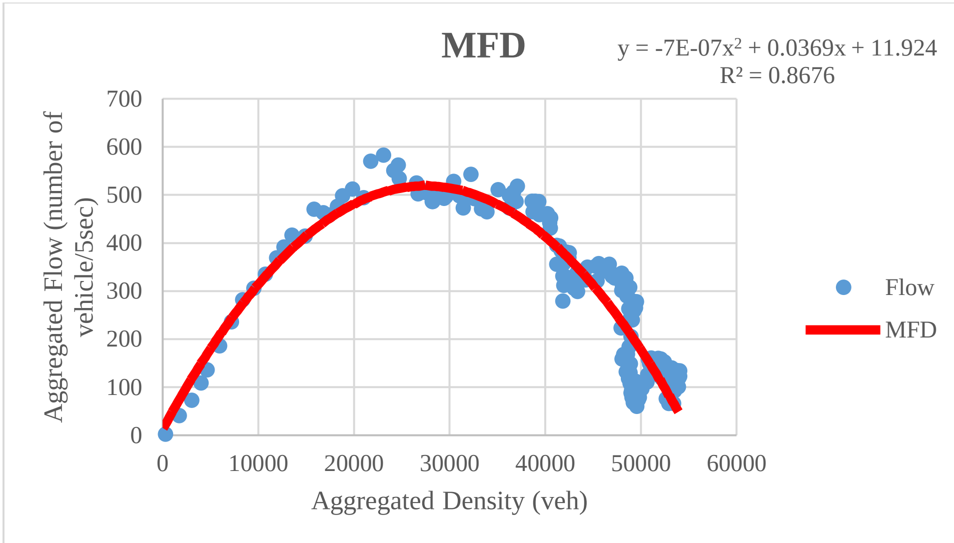


Figure 36 MFD for a single network

The flow and density data from all networks are aggregated over 5-second intervals. Using this aggregated data, macroscopic fundamental diagrams were plotted for each network in order to visualize and analyze traffic behavior across the networks.

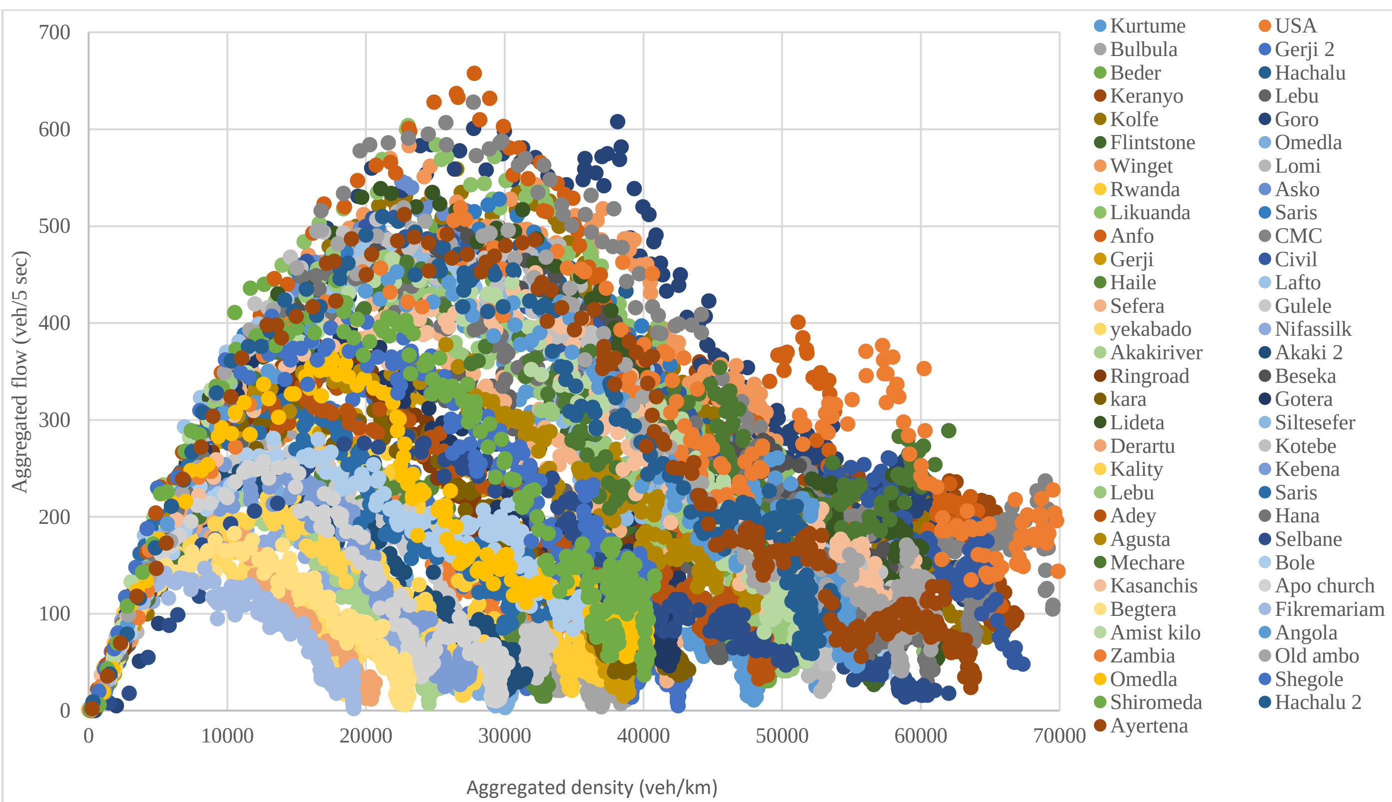


Figure 37 Scatter plot MFDs of all networks

4.1.1. Maximum Flow

In traffic flow analysis, the critical density represents the point at which traffic flow reaches its maximum capacity, leading to congested conditions. The maximum flow corresponds to the highest achievable traffic flow rate at this critical density. To find the maximum flow and the corresponding critical density, first the aggregated flow and density are fitted to drive the equation of the macroscopic fundamental diagram. Once the equation of the MFD is obtained, the next step will be calculating its derivative with respect to density. This derivative represents the rate of change of flow with respect to density and is crucial for identifying critical points. The critical density is calculated by setting the first derivative equal to zero and finding the density value. Finally, substitute the critical density values into the original MFD equation to find the corresponding flow rates, which is the maximum flow rate. The maximum flow rate value obtained represents the maximum flow achievable in the system.

Table 3 Maximum flow of each network

Network	Maximum Flow (veh/5sec)	Network	Maximum flow ((veh/5sec))	Network	Maximum Flow (veh/5sec)
1	368	25	191	49	201
2	274	26	390	50	198
3	352	27	387	51	319
4	351	28	317	52	477
5	322	29	258	53	421
6	375	30	374	54	346
7	357	31	253	55	413
8	395	32	203	56	459
9	387	33	126	57	450
10	386	34	182	58	214
11	189	35	138	59	230
12	215	36	223	60	234
13	384	37	379	61	353
14	252	38	380		
15	263	39	260		
16	384	40	406		
17	341	41	280		
18	222	42	433		
19	303	43	426		
20	222	44	416		
21	349	45	433		
22	179	46	393		
23	148	47	227		
24	132	48	418		

4.2. Network Typology

The typology of each network was extracted from GIS to understand its structure and density. Using GIS, the following types of data were extracted:

- Number of nodes
- Length of the road
- Number of edges
- Trafficable area
- Network density
- Degree centrality

4.2.1. Road network typological indices and measures

In the preceding subsections, typological data were extracted for sampled networks using a set of basic topological information, including the quantity of junctions (nodes) and edges (links), the spatial configurations of nodes and links, and the trafficable area connected to the sampled networks. In order to achieve this, the sampled networks were transformed into the node-link form. Road segments are represented as edges and intersections as nodes in the primal representation, which is an instinctive and natural method.

Alpha index (α): A measure of connectivity which evaluates the number of cycles in a graph in comparison with the maximum number of cycles. The higher the alpha index, the more a network is connected. Trees and simple networks will have a value of 0. A value of 1 indicates a completely connected network.

$$\alpha = \frac{(E-N+1)}{(2N-5)}$$

Where E is the number of edges

N is the number of nodes

Eta index (μ): Average length per link. Adding new nodes will cause a decrease of Eta as the average length per link declines. Complex networks tend to have a low eta value.

$$\mu = \frac{L(G)}{E}$$

Where L(G) is total length of links

E is the number of edges

Beta index (β): Measures the level of connectivity in a graph and is expressed by the relationship between the numbers of links over the number of nodes. Trees and simple networks have Beta value of less than one. A connected network with one cycle has a value of 1.

$$\beta = \frac{E}{N}$$

Degree centrality (C_D(G): measure the number of links connected a node

$$C_D(G)=\frac{\sum_{i=1}^{N}(C_D(n^*)-C_D(n_i))}{(N)^2-3N+2}$$

Where $C_D(G)$ is the general degree centrality a network

$(C_D(n^*)$ is the node with maximum degree centrality

$C_D(n_i)$ is the degree centrality of nodes

N is the number of nodes

Grid tree pattern (GTP): Measures how much a network resembles a grid or a tree structure. A GTP close to 1 indicates a grid network whereas a GTP close to 0 indicates a tree network.

$$GTP=\frac{E-N+1}{(\sqrt{N}-1)2}$$

Where E is the number of edges

N is the number of nodes

Gamma index (γ): A measure of connectivity that considers the relationship between the number of observed links and the number of possible links. The value of gamma is between 0 and 1 where a value of 1 indicates a completely connected network and would be extremely unlikely.

$$\gamma=\frac{E-N+1}{(\sqrt{N}-1)2}$$

Table 4 Road network connectivity indexes

Network	Eta	Alpha	Gamma	GTP	Beta	Degree centrality
1	0.071	0.330	0.554	0.419	1.658	0.001
2	0.095	0.352	0.569	0.444	1.698	0.002
3	0.090	0.360	0.574	0.444	1.715	0.002
4	0.087	0.374	0.583	0.457	1.742	0.002
5	0.092	0.382	0.588	0.466	1.757	0.002
6	0.091	0.401	0.601	0.479	1.796	0.002
7	0.088	0.330	0.554	0.421	1.656	0.001
8	0.066	0.306	0.537	0.400	1.608	0.001
9	0.086	0.349	0.566	0.436	1.694	0.002
10	0.079	0.387	0.591	0.462	1.769	0.002
11	0.047	0.368	0.580	0.466	1.725	0.005
12	0.134	0.425	0.617	0.504	1.837	0.004
13	0.071	0.325	0.550	0.415	1.647	0.001
14	0.113	0.356	0.571	0.449	1.706	0.003
15	0.094	0.346	0.564	0.437	1.686	0.002

Network	Eta	Alpha	Gamma	GTP	Beta	Degree centrality
16	0.076	0.342	0.562	0.430	1.680	0.001
17	0.098	0.353	0.569	0.442	1.702	0.002
18	0.114	0.376	0.585	0.472	1.740	0.005
19	0.097	0.376	0.584	0.459	1.747	0.002
20	0.085	0.344	0.563	0.441	1.680	0.003
21	0.135	0.360	0.574	0.449	1.715	0.002
22	0.150	0.342	0.562	0.442	1.677	0.003
23	0.157	0.398	0.600	0.497	1.777	0.007
24	0.184	0.418	0.614	0.534	1.800	0.012
25	0.123	0.420	0.615	0.500	1.790	0.003
26	0.072	0.346	0.564	0.435	1.687	0.002
27	0.063	0.309	0.540	0.402	1.615	0.001
28	0.102	0.358	0.572	0.445	1.711	0.002
29	0.114	0.380	0.587	0.467	1.751	0.002
30	0.081	0.337	0.558	0.426	1.669	0.002
31	0.090	0.369	0.580	0.452	1.733	0.002
32	0.115	0.364	0.577	0.466	1.716	0.005
33	0.145	0.369	0.580	0.469	1.724	0.005
34	0.140	0.363	0.577	0.475	1.709	0.007
35	0.163	0.381	0.589	0.489	1.743	0.007
36	0.097	0.377	0.585	0.477	1.739	0.005
37	0.058	0.340	0.560	0.432	1.675	0.002
38	0.062	0.326	0.551	0.416	1.650	0.001
39	0.063	0.347	0.565	0.443	1.687	0.003
40	0.061	0.352	0.568	0.434	1.701	0.001
41	0.055	0.354	0.570	0.453	1.698	0.004
42	0.058	0.362	0.575	0.441	1.722	0.001
43	0.057	0.317	0.545	0.406	1.632	0.001
44	0.063	0.332	0.555	0.420	1.662	0.006
45	0.067	0.348	0.566	0.435	1.692	0.002
46	0.065	0.333	0.556	0.424	1.663	0.002
47	0.080	0.346	0.565	0.444	1.685	0.003
48	0.064	0.341	0.561	0.432	1.678	0.002
49	0.181	0.410	0.605	0.420	1.801	0.002
50	0.072	0.320	0.547	0.427	1.631	0.004
51	0.068	0.329	0.553	0.421	1.654	0.002
52	0.063	0.327	0.551	0.415	1.650	0.001
53	0.056	0.317	0.545	0.408	1.632	0.001

Network	Eta	Alpha	Gamma	GTP	Beta	Degree centrality
54	0.062	0.313	0.542	0.408	1.621	0.002
55	0.054	0.309	0.540	0.401	1.616	0.001
56	0.056	0.320	0.547	0.411	1.638	0.001
57	0.059	0.362	0.575	0.446	1.719	0.002
58	0.051	0.341	0.561	0.439	1.674	0.003
59	0.057	0.328	0.552	0.429	1.648	0.003
60	0.062	0.360	0.574	0.454	1.712	0.003
61	0.057	0.306	0.537	0.406	1.606	0.002

The road network infrastructure data extracted for analysis encompasses key metrics, including network density, primary road proportion, and trafficable area. These metrics are derived from geographic information system (GIS) data, utilizing length measurements, while network width data is sourced from a converted SUMO network. They served as critical indicators for assessing the spatial characteristics and functionality of road networks. Network density quantifies the concentration of road segments within a given area, providing insights into the amount of infrastructure constructed. Primary road proportion highlights the proportion of major roads within the network, which often play a crucial role in facilitating efficient traffic flow. The trafficable area delineates the usable surface area within the road network, influencing vehicular movement and infrastructure utilization.

Table 5 Network infrastructure size metrics

Network	Length (km)	Length of Primary roads (km)	Proportion of primary roads	Trafficable Area	Network density
1	102.843	8.146	0.079	0.388	25.711
2	70.121	10.100	0.144	0.245	17.530
3	97.98	5.218	0.053	0.385	24.495
4	79.686	4.374	0.055	0.294	19.922
5	68.635	16.235	0.237	0.297	17.159
6	66.69	10.747	0.161	0.271	16.673
7	109.103	3.005	0.028	0.432	27.276
8	95.344	13.156	0.138	0.380	23.836
9	95.344	8.869	0.093	0.365	23.836
10	89.823	33.890	0.377	0.433	22.456
11	20.259	5.000	0.247	0.071	5.065
12	61.806	5.943	0.096	0.264	15.452
13	106.225	17.130	0.161	0.467	26.556
14	75.658	8.955	0.118	0.325	18.915

Network	Length (km)	Length of Primary roads (km)	Proportion of primary roads	Trafficable Area	Network density
15	80.88	12.378	0.153	0.347	20.220
16	95.224	7.948	0.083	0.377	23.806
17	89.88	17.108	0.190	0.398	22.470
18	47.999	2.600	0.054	0.168	12.000
19	85.96	26.800	0.312	0.395	21.490
20	53.683	0.000	0.000	0.188	13.421
21	112.74	61.311	0.544	0.609	28.185
22	84.887	0.000	0.000	0.297	21.222
23	46.396	0.000	0.000	0.162	11.599
24	28.113	0.000	0.000	0.098	7.028
25	69.771	4.371	0.063	0.259	17.443
26	71.754	0.000	0.000	0.251	17.939
27	98.47	14.289	0.145	0.345	24.618
28	98.382	18.324	0.186	0.423	24.596
29	70.372	4.412	0.063	0.266	17.593
30	96.21	10.887	0.113	0.375	24.053
31	93.54	6.437	0.069	0.373	23.385
32	44.293	0.000	0.000	0.155	11.073
33	56.143	0.000	0.000	0.197	14.036
34	37.924	0.000	0.000	0.133	9.481
35	42.014	0.000	0.000	0.147	10.504
36	34.914	0.000	0.000	0.122	8.729
37	54.689	0.528	0.010	0.193	13.672
38	89.793	5.009	0.056	0.347	22.448
39	41.195	1.980	0.048	0.144	10.299
40	98.292	30.000	0.305	0.362	24.573
41	27.335	0.000	0.000	0.096	6.834
42	95.067	24.875	0.262	0.368	23.767
43	113.892	29.283	0.257	0.432	28.473
44	98.086	0.339	0.003	0.372	24.522
45	76.06	19.652	0.258	0.279	19.015
46	74.849	0.000	0.000	0.262	18.712
47	46.984	4.771	0.102	0.195	11.746
48	65.561	17.631	0.269	0.229	16.390
49	78.123	0.000	0.000	0.097	19.531
50	34.969	0.000	0.000	0.122	8.742
51	75.749	1.869	0.025	0.279	18.937

Network	Length (km)	Length of Primary roads (km)	Proportion of primary roads	Trafficable Area	Network density
52	98.594	22.198	0.225	0.368	24.649
53	90.096	19.500	0.216	0.334	22.524
54	69.946	0.184	0.003	0.266	17.487
55	89.591	25.140	0.281	0.351	22.398
56	80.961	15.322	0.189	0.300	20.240
57	62.644	10.825	0.173	0.219	15.661
58	32.204	0.523	0.016	0.115	8.051
59	35.356	0.000	0.000	0.124	8.839
60	36.389	3.042	0.084	0.138	9.097
61	47.081	5.238	0.111	0.183	11.770

4.3. Modelling

The modeling process involves selecting the appropriate statistical techniques to analyze the relationship between a dependent variable and independent variables. To select the best model, I will follow the trends and patterns through visualization and descriptive statistics of the dependent and independent variables. Depending on the nature of the trend (linear, exponential, power, etc.), the possible model types will be selected. By using insights gained from the trends of each dependent and independent variable, the best fit trends of all independent variables will be tested, and the best fit model will be selected as the research model. The best model will be selected based on model significance, goodness of fit (adjusted R^2), parsimony, simplicity, and interpretability. In addition to selecting a model based on statistical methods, I will provide high weight to reviewing literature (theories) to develop a theoretical understanding of the independent variables, their relationship with the dependent variable, and the expected coefficient signs and effect magnitudes.

4.3.1. Multiple linear regression

Multiple regression is a statistical method for examining the connection between one dependent variable and several independent variables. Using known values for the independent variables to forecast the value of the single dependent variable is the goal of multiple regression analysis. Each predictor value is weighed, with the weights denoting their relative contribution to the overall prediction. Multiple linear regression has the following form;

$$y = a_0 + a_1x_1 + a_2x_2 + a_3x_3 \dots a_nx_n$$

Where y is the dependent variable,

$x_1, x_2, x_3, \dots x_n$ are the independent variables.

a_0 is the y-intercept.

a_1, a_2, a_3,…a_n are the coefficients (weights) of the independent variables

4.3.2. Power regression

Power regression model is an example of nonlinear regression model which has a form of;

$y = a_0 {x_1}^{a_1} {x_2}^{a_2} {x_3}^{a_3} \dots {x_n}^{a_n};$

Where y is the dependent variable,

x_1, x_2, x_3, …x_n are the independent variables.

a_0 is the y-intercept.

a_1, a_2, a_3…a_n are the coefficients (weights) of the independent variables

In order to fit a power regression we take natural log (ln) on both sides of the equation and the equation becomes linear equation of the form;

$lny = lna_0 + a_1 lnx_1 + a_2 lnx_2 + a_3 lnx_3 \dots a_n lnx_n$

The equation shows the equation of linear regression model, and it is called log-log regression model. So, by transforming the data in to ln x and ln y we can use the multinomial regression concept. However, the final equation and the interpretation is different

$y = e^{lny} = a_0 e^{a_1 lnx_1 + a_1 lnx_1 + a_2 lnx_2 + a_3 lnx_3 \dots a_n lnx_n}$ If simplified it will give the original equation

4.3.3. Exponential regression

Exponential regression is also an example of nonlinear regression which has the form

$$y = e^{a_0 + a_1 x_1 + a_2 x_2 + a_3 x_3 \dots a_n x_n}$$

Where y is the dependent variable,

x_1, x_2, x_3, …x_n are the independent variables.

a_0 is the y-intercept.

a_1, a_2, a_3…a_n are the coefficients (weights) of the independent variables

As discussed in power regression model above, when take natural log (ln) on both sides of the equation becomes linear equation of the form;

$$lny = a_0 + a_1 x_1 + a_2 x_2 + a_3 x_3 \dots a_n x_n$$

The equation shows the equation of linear regression model, and it is called log-level regression model. So, by transforming the dependent variable y in to (ln y) we can use the multinomial regression concept. However, the final equation and the interpretation is different.

Chapter Five: Result and Discussion

The objective of this section is to present the research study's findings and go over what they mean. Identified trends, patterns, and correlations, contextual interpretations are evaluated using the gathered data analysis. Moreover, the hypotheses or research questions are evaluated with the findings and finally a prediction model developed

5.1. Typological characteristics of road networks

Alpha index: an assessment of connectedness that compares a graph's cycle count to its maximum cycle count. A network is more linked the higher its alpha index. Simple networks and trees will have a value of 0. A network that is fully connected has a value of 1.

Table 6 Summary of alpha index

Topological Metric	*Alpha*
Minimum	0.306
Maximum	0.425
Mean	0.352
SD	0.028

Beta index: the beta index, sometimes referred to as the link-node ratio, divides the total number of nodes in a graph by the number of links in order to determine the degree of connectivity. Nodes are the intersections of transport networks, and edges are the links that connect nodes.

Table 7 Summary of beta index

Topological Metric	**Beta**
Minimum	1.606
Maximum	1.837
Mean	1.697
SD	0.052

Gamma index: a metric used to assess how connected a network is. It takes into account the correlation between the total number of potential links (edges) that could connect any two nodes in the network and the number of links (edges) that have been seen. The value of the gamma index is between 0 and 1. A network that is fully connected has all possible links between its nodes present, as indicated by a value of 1.

Table 8 Summary of gamma index

Topological Metric	**Gamma**
Minimum	0.537
Maximum	0.617
Mean	0.568
SD	0.019

Eta index: the average length per connection is known as the eta index. As the average length per link decreases, adding more nodes will result in a decrease in Eta. Low eta values are typical of complex networks.

Table 9 Summary of eta index

Topological Metric	Eta index
Minimum	0.047
Maximum	0.184
Mean	0.087
SD	0.033

Network density: it calculates the number of kilometers of links per square kilometer of surface that a transportation network occupies. In a particular area, it also denotes the quantity of roads or road segments, usually expressed in kilometers of roads per square kilometer of land area. It is an indicator of the level of development of the road system in a specific area.

Table 10 Summary of network density

Topological Metric	Network density
Minimum	5.064
Maximum	28.473
Mean	18.002
SD	6.198

Trafficable area: this refers to the designated areas within a given place that are open to traffic or transportation. In an urban context, trafficable zones are essential for promoting connectedness and movement.

Table 11 Summary of trafficable area

Topological Metric	Trafficable area
Minimum	0.070
Maximum	0.609
Mean	0.276
SD	0.114

Grid tree pattern: an indicator of how much the road network resembles a grid or a tree is called the Grid-Tree Pattern (GTP), which is a statistic used to analyze it. A grid-type road network will have a GTP of 1. Roads radiate off of a central point with fewer junctions, indicating a more hierarchical design, in a network that resembles a tree when the GTP value is close to 0.

Table 12 GTP summary

Topological Metric	Grid tree pattern (GTP)
Minimum	0.400
Maximum	0.534
Mean	0.443
SD	

Proportion of primary road: Primary roads are the main thoroughfares in a network of roads; they are usually built to accommodate large amounts of traffic and link important locations. The proportion of primary roads in a given road network is calculated by dividing the network's total length of primary roads by total length.

Table 13 Summary of proportion of primary roads

Topological Metric	Proportion of primary roads
Minimum	0.000
Maximum	0.544
Mean	0.071
SD	0.100

Degree centrality: A node's degree, or the total number of edges it possesses, is its degree centrality. The node is more central the higher the degree. Given that many nodes with high degrees also have high centrality.

Table 14 Summary of degree centrality

Topological Metric	Degree centrality
Minimum	0.001
Maximum	0.012
Mean	0.002
SD	0.0019

5.2. The Effect of Road Network Typology on Macroscopic Traffic Flow

5.2.1. Alpha index

As discussed in the previous sections, the alpha index measures the redundancy and connectivity of a graph or road network and computes the ratio between the actual number of cycles (closed loops) in a network and the maximum number of cycles that can exist. A less linked, more linear structure is indicated by a lower alpha index, whereas a higher alpha index denotes a more connected network with numerous paths.

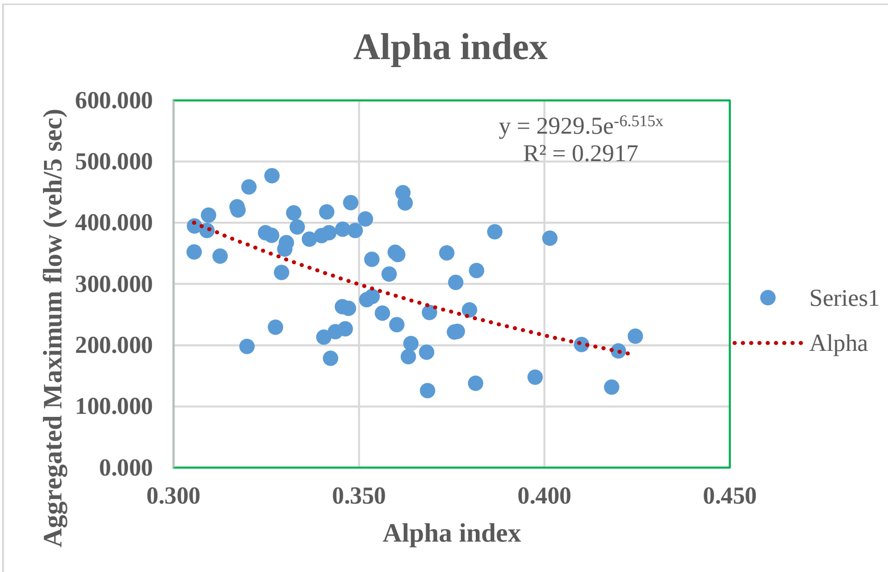


Figure 38 Relationship between Alpha Index and Network Maximum Flow

As we can see in the plot of alpha index and aggregated maximum flow, as alpha index increases, the network wide aggregated flow decreases. As the alpha index refers to the connectedness of the road in the network, its trend is the same as the number of junctions. So, the main reason behind the decrease in aggregated network maximum flow as the alpha index increases will be the decrease in speed and the waiting time at connection points (junctions). Vehicles are free to go at their normal speeds in light traffic, with no restrictions imposed by other cars or traffic congestion. However, vehicles must stop or slow down as they approach a roundabout or priority intersection due to safety concerns and traffic laws.

No matter how different junction types handle conflicts, traffic congestion typically occurs at junctions when traffic loads are higher than they can handle. The long stopping time and reduced speed will result in congestion close to intersections where local concentrations are comparatively higher. As a result of these variations, the traffic upstream experiences even more variations in speed, which worsens the congestion. As a result, a network's maximum flow capacity will be lower, start declining, and finally go into gridlock.

5.2.2. Beta index

Based on graph theory, the ratio of edges (also known as links) to nodes (also known as vertices) in a graph is expressed as the beta index. As discussed in the literature review section, the beta index, which shows the density of links within the network, is a straightforward indicator of connectedness (the average degree of the junctions) in the context of road networks.

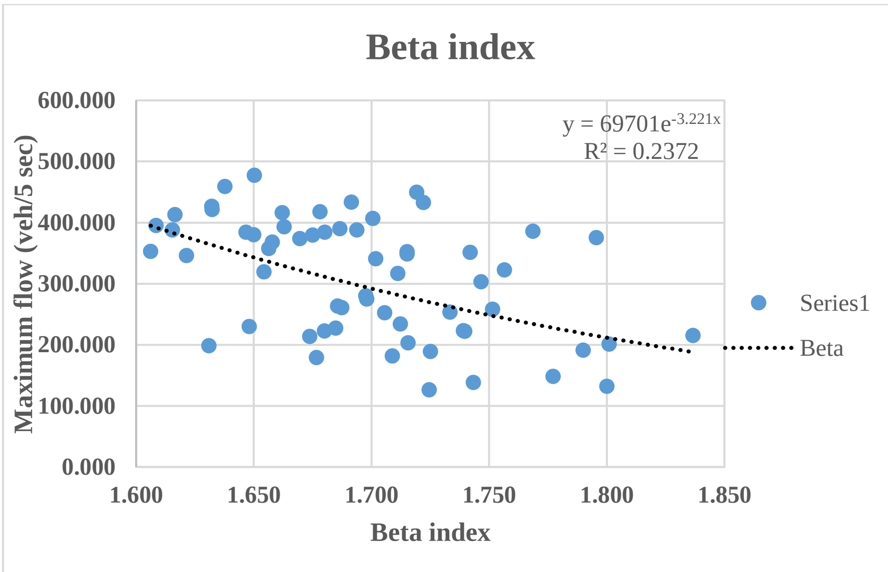


Figure 39 Relationship between Beta Index and Aggregated Network Maximum Flow

As can be seen in the figure above, when the beta index, which measures the average degree of junctions, increases, the total maximum flow within a road network tends to drop. Numerous variables related to the increasing complexity at junctions with enhanced connections can explain this adverse association.

Basically, the more links or roads that converge at a single junction in a network, the higher the beta index and the more complex the vehicle traffic at these intersections. There is a greater likelihood of traffic interference when cars turn or when there are more connections. Due to the additional roads that meet at the junction, this increased complexity might result in longer wait times and more challenging turning maneuvers due to the larger turning angles. The aggregated flow over the road network may decline overall as these delays (due to longer waiting times) accumulate and congestion worsens. Higher beta index networks are more likely to encounter bottlenecks and disturbances, which slow traffic flow across these crucial nodes in the network.

Therefore, even if a network with a higher beta index might be more connected and possibly have more redundancy, a network with more complicated junctions have less efficiency due to operational difficulties. This, in turn, contributes to a lower aggregated maximum flow (lower performance).

5.2.3. Gamma index

As discussed previously, the gamma index is used to measure a network's level of connectedness. It measures the difference between the total number of edges (links) in a network and the maximum possible number of edges. It can also be used to evaluate the completeness and density of a road network.

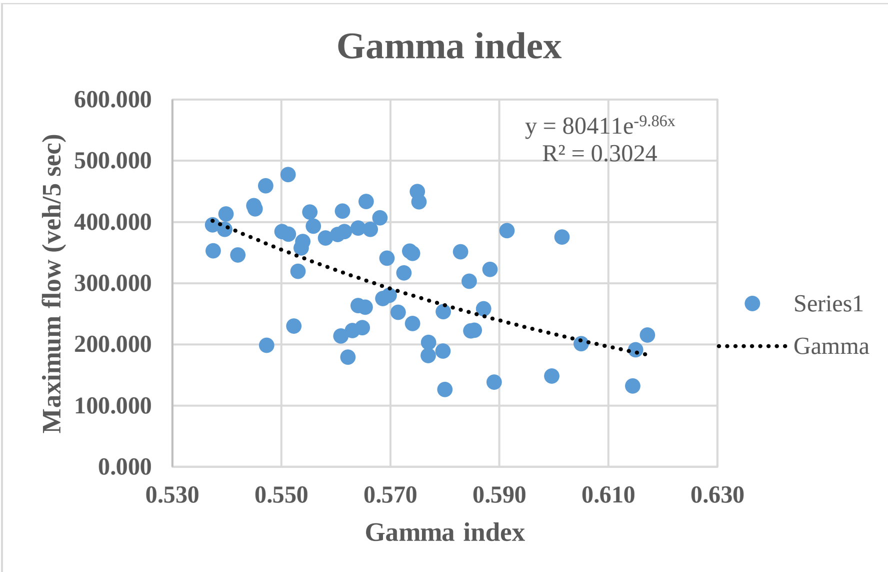


Figure 40 Relationship between Gamma index and Aggregated Maximum Flow

There are usually more junctions and intersections with a higher gamma index (higher level of connectedness), which results in more locations where traffic converges or crosses. As a result of cars waiting to join or cross, there will be more potential for congestion, which would slow down traffic flow throughout the network. Longer wait times result from more junctions.

5.2.4. Degree centrality

The number of direct connections a node has inside a network is indicated by its degree of centrality. A node's degree of connectivity may be determined by adding up all of the edges that link to it. It shows the fraction of possible connections a node could have in the network in a normalized way.

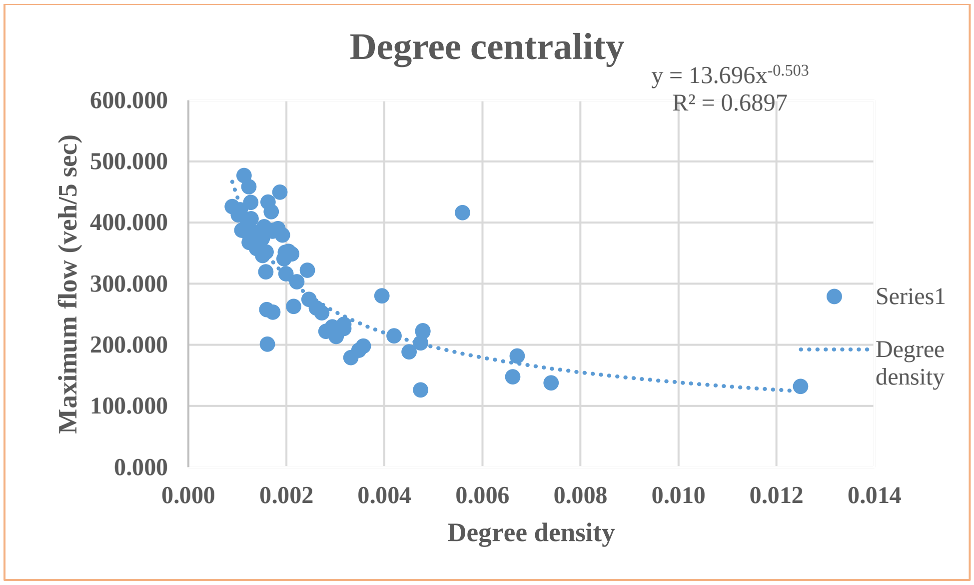


Figure 41 Relationship between Degree Densities and Aggregated Maximum Flow

Longer wait times due higher number of conflict points and more challenging turning maneuvers due to the larger turning angles are the cause of a decreased maximum flow when the degree density of the network increases.

5.2.5. Grid tree pattern

An indicator of a road network's structure that places it on a spectrum between tree patterns and grid patterns is the Grid-Tree Pattern (GTP) metric. It has a value between 0 and 1, where 0 denotes a pure tree pattern, where roads branch out of arterial or central thoroughfares with few to no loops or cycles, and 1 denotes a pure grid design, where roads intersect regularly to form numerous pathways and cycles. Higher values reflect a more interconnected grid-like structure, while lower values indicate a simpler, more hierarchical tree-like structure. Intermediate values show networks with a combination of grid and tree elements.

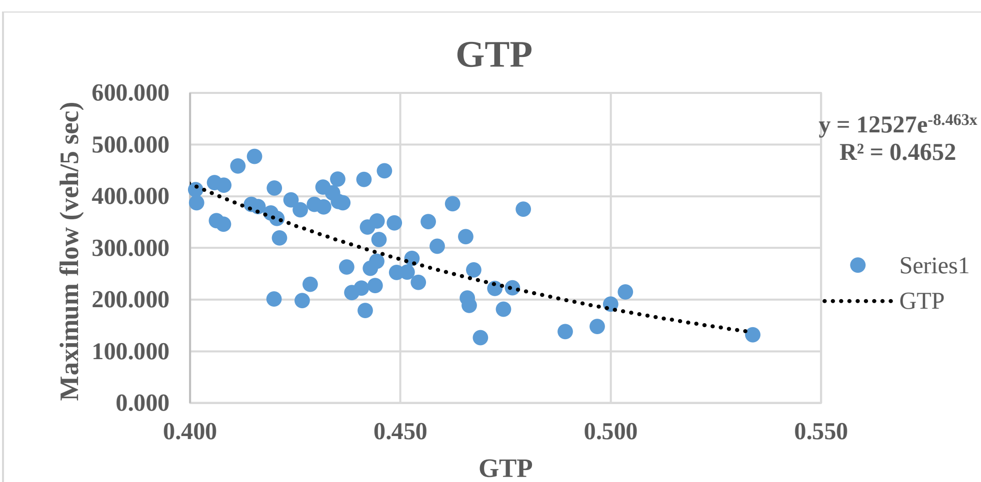


Figure 42 Relationship between GTP and Aggregated Maximum Flow

Because there are more intersections, there are more traffic conflicts, necessitating the need for longer waiting times. These extra crossings may result in traffic jams and bottlenecks, which would lower the network's overall performance.

Reduced aggregated flow is also a result of grid-based networks' slower average speed. In comparison to tree-based networks, grid-based networks often have lower average vehicle speeds due to the increased number of intersections. Grid-based patterns are less effective for heavy traffic volumes and result in longer journey times because of this speed reduction and the resulting increase in traffic conflicts that affect the aggregated flow.

5.2.6. Trafficable area

The whole surface area of a road or other paved surface that is appropriate for vehicular traffic. This dimension, which includes all lanes that are components of the road, is normally computed by multiplying the length of the road by its width. It is a vital indicator of road transportation development in the network.

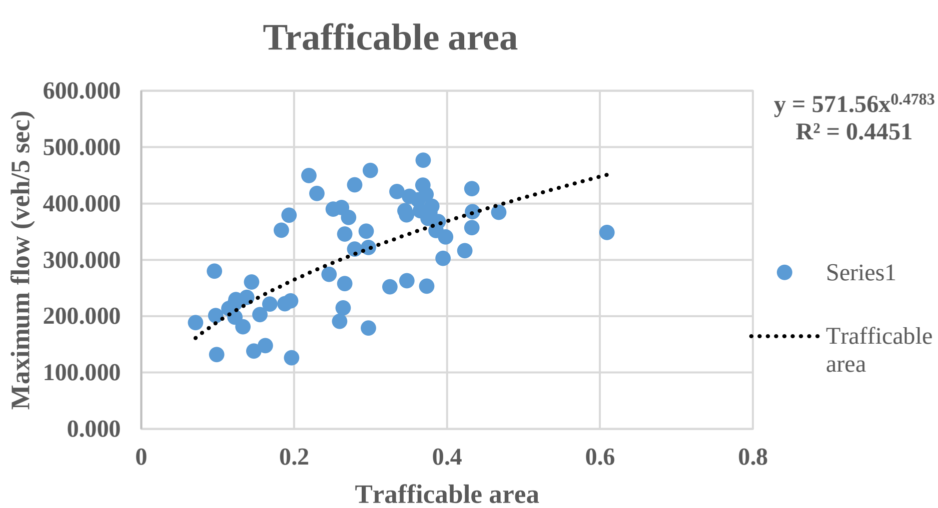


Figure 43 Relationship between trafficable area and aggregated maximum flow

For a number of reasons, the aggregated maximum flow of a road network rises with the trafficable area, or the entire area of the road. The trafficable area affects road capacity, vehicle movement, and total traffic flow. So, an increase in trafficable area enhances the flow of the road network. A larger trafficable area generally means more space for vehicles. This increased capacity allows for more traffic lanes, directly contributing to a road's ability to accommodate a greater volume of vehicles. As a result, the network can handle higher traffic loads, leading to an increase in aggregated maximum flow. Larger areas provide more space for cars to move around, which can lessen traffic and the possibility of bottlenecks. The extra space allows cars to spread out, make better use of several lanes, and avoid traffic bottlenecks.

5.2.7. Network density

As it was discussed previously, it is calculated as the ratio of the total length of all road links to the surface area they cover. This is a statistic that measures how much of a given region is occupied by a transport network. Usually, it is expressed in terms of linkages per square kilometer of land. This measure gives an idea of how intensively developed a transportation network is in a certain location. Greater network density is indicative of a more fully developed transportation system, which is typically found in cities with extensive road networks. Conversely, a lower network density, which is more common in rural or underdeveloped areas, can indicate fewer transit linkages and a more dispersed network.

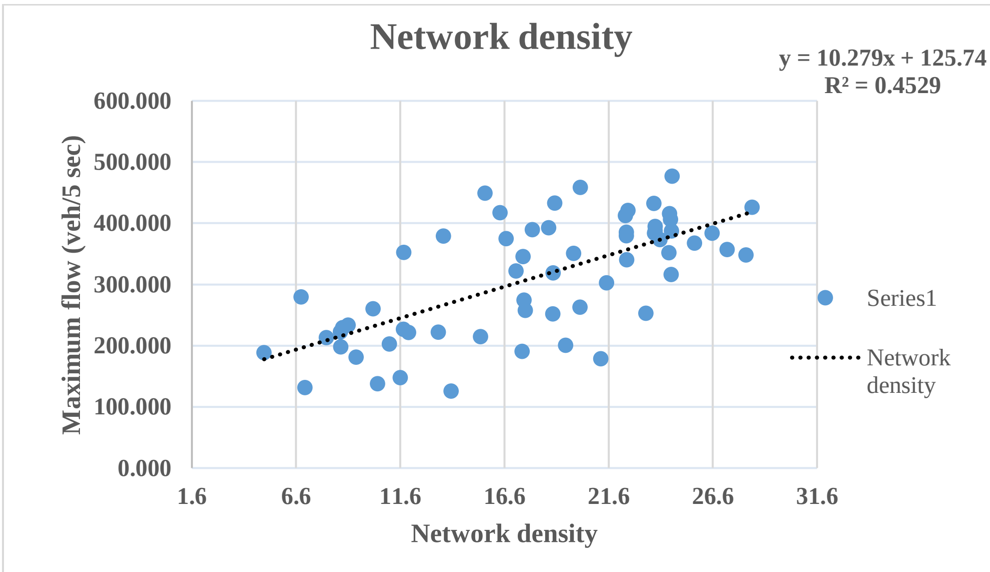


Figure 44 Relationship between network density and aggregated maximum flow

A transport network's aggregated flow generally increases as network density rises, mostly as a result of network development's direct influence. The overall length of highways grows when new ones are built or old ones are extended, providing more room for cars to go. Higher aggregated flow results from the network's ability to handle more traffic due to this growth. More roads and lanes provide greater freedom for traffic to flow, which eases congestion and makes travel easier. By decreasing reliance on certain roads or crossings, the number of other routes increases, resulting in improved traffic distribution. Consequently, the probability of bottlenecks and congestion diminishes, resulting in enhanced traffic flow. Drivers have more alternatives when they may select from a variety of routes, which improves the transport network's overall efficiency and flexibility.

5.2.8. Primary road proportions

In a hierarchy of road networks, primary roads are the highest levels. These roads often have multiple lanes, higher speed limits, and reliable infrastructure to accommodate higher traffic flow since they are built to manage large amounts of traffic. Primary roads link important local areas and promote mobility. Their capacity, layout, and strategic significance in a transportation network set them apart from secondary and local roads, serving as the main hub for traffic flow over a large region.

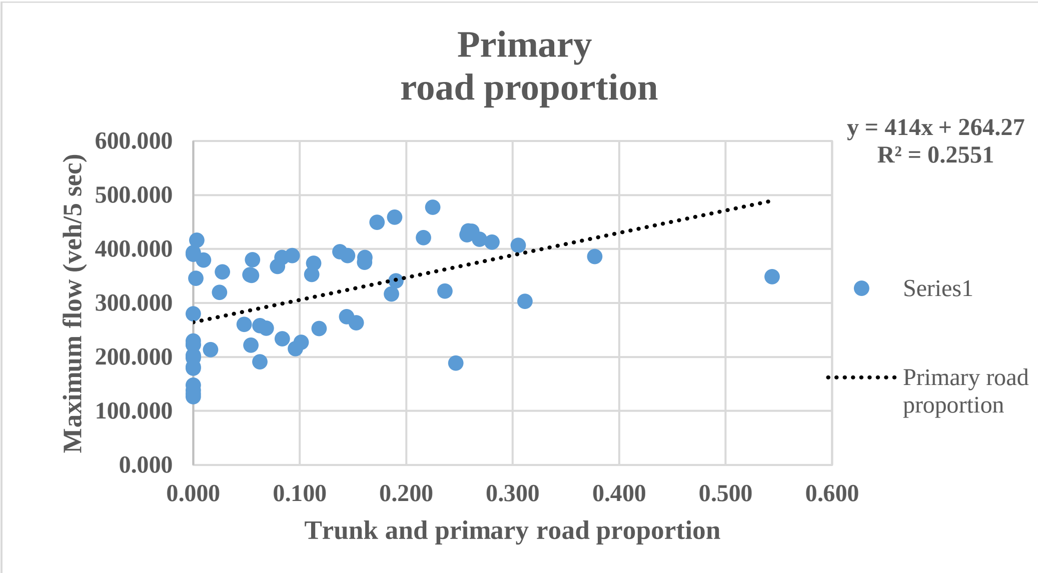


Figure 45 Trunk and primary road proportion

As the figure of proportion of roads and aggregated maximum flow illustrates, a road network's aggregated flow gets increased by increasing the percentage of primary roads. Since these high-capacity roads are built to handle heavy traffic, expanding their number on the network increases its total capacity. Consequently, a greater flow for a given traffic density might be shown by an upward shift in the MFD caused by larger ratios of primary roads.

By providing more lanes and faster travel speeds, primary roads reduce the risk of bottlenecks and allow traffic to move more efficiently. This efficient traffic distribution helps maintain a smoother flow, reducing congestion and delays.

5.3. Exploring Variable Correlations

Analyzing correlations between variables is a crucial stage in data analysis before moving on to modeling. It aids in the detection of multicollinearity, which is the result of strong correlations between independent variables. Particularly in linear regression models, multicollinearity can result in unstable regression coefficients, exaggerated standard errors, and untrustworthy findings. The best variables for a model are selected through correlation analysis. Knowing the relationships between variables is essential when creating predictive models in order to select the ones that have the most influence on the target variable. Strong correlations between variables and the target variable make them excellent candidates for inclusion in a model since they may contain valuable predictive information.

Table 15 Summary of Variable Correlations

Factor	*Primary length proportion*	*Eta*	*Trafficable Area*	*Alpha*	*Gamma*	*GTP*	*Degree centrality*	*Beta*	*Network density*	*Maximum Flow*
Primary length proportion	1.00									
Eta	-0.24	1.00								
Trafficable Area	0.60	-0.17	1.00							
Alpha	-0.06	0.70	-0.27	1.00						
Gamma	-0.07	0.70	-0.28	1.00	1.00					
GTP	-0.16	0.66	-0.39	0.89	0.90	1.00				
Degree centrality	-0.40	0.61	-0.56	0.50	0.52	0.74	1.00			
Beta	-0.02	0.66	-0.23	0.99	0.99	0.87	0.45	1.00		
Network density	0.47	-0.15	0.94	-0.30	-0.31	-0.51	-0.63	-0.26	1.00	
Maximum Flow	0.51	-0.67	0.63	-0.53	-0.54	-0.66	-0.71	-0.48	0.67	1.00

The variables alpha, degree centrality, primary road proportion, and network density were chosen for the model as they are not multicollinear, and maintaining significant correlations with the target variable, maximum flow. In a dataset with highly correlated variables, it's critical to find a set of predictors that do not unduly impact each other's coefficients. In this context, Alpha, Degree Centrality, and Network Density demonstrated a balance between maintaining unique, reliable contributions to the model and avoiding redundancy. Alpha has a moderately negative correlation with maximum flow, indicating its potential for predicting flow rates. With a somewhat negative connection to maximum flow, Alpha shows promise in terms of flow rate prediction. While network density has a high positive association with maximum flows, degree centrality is the variable with the largest negative correlation to maximum flow. Degree centrality captures the influence of the number of edges connected to a node on the maximum flow of the road network. A more stable and understandable model is produced when these four variables are combined because they offer a thorough understanding of the variables affecting maximum flow without adding the complications of high multicollinearity.

5.4. Prediction Model

The prediction model helps to quantify the relationships between the independent variables (alpha, network density, degree centrality, proportion of primary roads) and the dependent variable (maximum flow). It reveals the impact of change in each independent variable on the macroscopic fundamental diagram. So once the model created, it can make predictions about maximum flow in scenarios where there are values for the independent variables but want to estimate the corresponding maximum flow.

A predictive model was created using multiple linear regression (MLR), and exponential regression to forecast the maximum flow within a network at a macroscopic level. Due to power regression requires all independent variables values to be non-zero, and there is zero values in some independent variables testing power regression was not possible. The data analysis tool employed for this purpose was the MS-Excel Data Analysis Tool Pak. The model was constructed using several variables: primary road proportion, alpha, road network density, and degree centrality were considered explanatory factors, while the network's macroscopic maximum flow served as the dependent variable. A dataset consisting of 61 networks, as outlined in the table below, was utilized to formulate and refine this predictive model.

Table 16 Summary of independent and dependent variables

Network	Primary length proportion	Degree centrality	Alpha	Network density	Maximum Flow
1	0.079	0.001	0.330	25.711	367.730
2	0.144	0.002	0.352	17.530	274.435
3	0.053	0.002	0.360	24.495	352.063
4	0.055	0.002	0.374	19.922	351.094
5	0.237	0.002	0.382	17.159	322.128
6	0.161	0.002	0.401	16.673	375.100
7	0.028	0.001	0.330	27.276	357.425
8	0.138	0.001	0.306	23.836	395.040
9	0.093	0.002	0.349	23.836	387.496
10	0.377	0.002	0.387	22.456	385.653
11	0.247	0.005	0.368	5.065	188.700
12	0.096	0.004	0.425	15.452	214.972
13	0.161	0.001	0.325	26.556	384.175
14	0.118	0.003	0.356	18.915	252.365
15	0.153	0.002	0.346	20.220	262.985
16	0.083	0.001	0.342	23.806	384.073
17	0.190	0.002	0.353	22.470	340.625
18	0.054	0.005	0.376	12.000	221.626
19	0.312	0.002	0.376	21.490	303.020
20	0.000	0.003	0.344	13.421	222.318
21	0.544	0.002	0.360	28.185	348.543
22	0.000	0.003	0.342	21.222	178.969
23	0.000	0.007	0.398	11.599	147.935

Network	Primary length proportion	Degree centrality	Alpha	Network density	Maximum Flow
24	0.000	0.012	0.418	7.028	131.927
25	0.063	0.003	0.420	17.443	191.017
26	0.000	0.002	0.346	17.939	389.957
27	0.145	0.001	0.309	24.618	387.468
28	0.186	0.002	0.358	24.596	316.525
29	0.063	0.002	0.380	17.593	257.780
30	0.113	0.002	0.337	24.053	373.685
31	0.069	0.002	0.369	23.385	253.455
32	0.000	0.005	0.364	11.073	203.049
33	0.000	0.005	0.369	14.036	126.195
34	0.000	0.007	0.363	9.481	181.560
35	0.000	0.007	0.381	10.504	137.993
36	0.000	0.005	0.377	8.729	222.996
37	0.010	0.002	0.340	13.672	379.410
38	0.056	0.001	0.326	22.448	379.845
39	0.048	0.003	0.347	10.299	260.487
40	0.305	0.001	0.352	24.573	406.392
41	0.000	0.004	0.354	6.834	280.050
42	0.262	0.001	0.362	23.767	432.880
43	0.257	0.001	0.317	28.473	426.330
44	0.003	0.006	0.332	24.522	416.190
45	0.258	0.002	0.348	19.015	433.256
46	0.000	0.002	0.333	18.712	393.168
47	0.102	0.003	0.346	11.746	227.040
48	0.269	0.002	0.341	16.390	417.761
49	0.000	0.002	0.410	19.531	201.100
50	0.000	0.004	0.320	8.742	198.127
51	0.025	0.002	0.329	18.937	319.275
52	0.225	0.001	0.327	24.649	476.985
53	0.216	0.001	0.317	22.524	421.168
54	0.003	0.002	0.313	17.487	345.900
55	0.281	0.001	0.309	22.398	412.720
56	0.189	0.001	0.320	20.240	458.786
57	0.173	0.002	0.362	15.661	449.590
58	0.016	0.003	0.341	8.051	213.600
59	0.000	0.003	0.328	8.839	229.650
60	0.084	0.003	0.360	9.097	233.610

Network	Primary length proportion	Degree centrality	Alpha	Network density	Maximum Flow
61	0.111	0.002	0.306	11.770	352.830

For exponential regression, transformation of the data were performed and then we used the usual multiple linear regression using the transformed data. Finally the equation found from multiple linear regression were rearranged to have an exponential equation.

Multiple linear regression, and exponential regression models equations can be expressed as:

$$y = a_0 + a_1x_1 + a_2x_2 + a_3x_3 \ldots\ a_nx_n \quad \text{(MLR)}$$

$$lny = a_0 + a_1x_1 + \ a_2x_2 + \ a_3x_3 \ldots a_nx_n \quad \text{(Exponential)}$$

Where y is the dependent variable.

x_1, x_2, x_3, ….x_n are the independent variables.

a_0 is the y-intercept.

a_1, a_2, a_3………, a_n are the coefficients of the independent variables.

Table 17 Multiple linear regression output summary

Regression Statistics	
Multiple R	0.818783445
R Square	0.67040633
Adjusted R Square	0.646863925
Standard Error	56.73348392
Observations	61

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	366628.463	91657.11575	28.4765439	6.30152E-13
Residual	56	180246.5391	3218.688198		
Total	60	546875.0021			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	296.80383	28.10825594	10.55931149	6.13071E-15	240.4962271	353.1114328	240.4962271	353.1114328
Primary length proportion (x1)	105.3702771	39.85911319	2.643568024	0.010621168	25.52287853	185.2176756	25.52287853	185.2176756
Degree centrality (x2)	-159.4453081	64.42970405	-2.474717375	0.01638842	-288.5135147	-30.37710141	-288.5135147	-30.37710141
Alpha (x3)	-113.971656	35.75761029	-3.187339843	0.002349804	-185.6027569	-42.34055504	-185.6027569	-42.34055504
Network density (x4)	107.3621281	37.11989152	2.892307161	0.005436741	33.00204991	181.7222063	33.00204991	181.7222063

Table 18 Multiple linear regression output summary using transformed data

Regression Statistics	
Multiple R	0.84133988
R Square	0.707852794
Adjusted R Square	0.686985136
Standard Error	0.193910617
Observations	61

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	5.101905593	1.27548	33.92104696	2.26635E-14
Residual	56	2.105674344	0.0376		
Total	60	7.207579937			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	6.631116408	0.361686965	18.3339	2.46232E-25	5.906570353	7.355662464	5.906570353	7.355662464
Primary length proportion (x1)	0.624470407	0.250432603	2.49357	0.015627325	0.12279362	1.126147195	0.12279362	1.126147195
Degree centrality (x2)	-68.81214133	18.35130807	-3.7497	0.000421388	-105.5742289	-32.05005375	-105.5742289	-32.05005375
Alpha (x3)	-3.056108745	1.027031256	-2.9757	0.004309827	-5.113499577	-0.998717913	-5.113499577	-0.998717913
Network density (x4)	0.013687459	0.005420065	2.52533	0.014416719	0.002829764	0.024545155	0.002829764	0.024545155

The fitted regression model gives the equation for multiple linear regression

$$\mathrm{y} = a_0 + a_1x_1 + a_2x_2 + a_3x_3 \ldots\ a_nx_n$$

$$\mathrm{y} = 296.80383 + 105.370x_1 - 159.445x_2 - -113.971x_3 + 107.362x_4$$

The fitted exponential model equation becomes

$$lny = 6.631 + 0.624x_1 - 68.812x_2 - 3.056a_3 + 0.013x_4$$

$$y = e^{6.631+0.624x_1-68.812x_2-3.056x_3+0.013x_4}$$

$$y = e^{6.631} * e^{0.624x_1} * e^{-68.812x_2} * e^{-3.056x_3} * e^{0.013x_4}$$

$$y = 758.24 * e^{0.624x_1} * e^{-68.812x_2} * e^{-3.056x_3} * e^{0.013x_4}$$

$$\mathrm{y} = \frac{758.24e^{0.624x_1} * e^{0.013x_4}}{e^{68.812x_2} * e^{3.056x_3}}$$

Where y is the dependent variable (maximum flow veh/5sec),

x_1 is primary road proportion (km/km)

x_2 is degree centrality

x_3 is alpha index of road connectivity

x_4 is network density (km/km^2)

After the analysis conducted which involves two different regression models i.e. exponential, and multiple linear regression model the best model chosen. Each model were assessed based on goodness of fit, interpretability and significance of independent variables. Based on the criteria exponential regression model have greater adjusted R^2 value than multiple linear regression. This indicated that the exponential regression model explained a larger proportion of the variance in the dependent variable compared to multiple linear regression. As a result exponential regression model were selected to predict the effect of primary road proportion, degree centrality, alpha and network density on aggregated maximum flow of the road network.

The results of the comprehensive exponential regression analysis reveal two correlations. Firstly, there is a positive correlation between primary road proportion and network density, indicating that an increase in either of these variables corresponds to a rise in the network's maximum flow. This suggests that a higher proportion of primary roads, which typically serve as major traffic arteries, along with a denser network structure, contribute positively to the efficiency of traffic flow within the network. Conversely, there is a negative correlation observed between the alpha index of road connectivity and degree centrality with the network maximum flow. This implies that as the alpha index, reflecting the network's connectivity, or the degree centrality, representing the number of connections per node, increases; the maximum flow through the network tends to decrease. These findings underscore the importance of considering various network typology characteristics in understanding and optimizing traffic flow dynamics, with primary road proportion and network density playing facilitative roles, while higher levels of road connectivity and degree centrality decrease optimal flow.

From the regression output statistics, the multiple R value was found to be 0.84, representing the multiple correlation between the response (dependent) variable and the four explanatory (independent) variables. This indicates the strength of combined set of predictor variables and the response variable i.e. correlation is between the dependent variable and a linear combination of the predictors, not just any one of them. The value 0.84 which is close to 1 indicate there is strong relationship between combined set of independent variables and response variable.

R square value, which is calculated as (Multiple R) ^{2} = $(0.84)^2$= 0.7. The R2 value of 0.7 (70%), which is closer to 1 (100%), tells us how well of the variation in network maximum flow can be explained by the alpha of road connectivity, degree centrality, primary road proportion, and network density. One limitation of R^2 is that it increases by adding independent variables to the model, which is misleading since some of the added variables might be useless with minimal significance. Adjusted R^2 overcomes this issue by adding a penalty if the added independent variable does not improve the model. The adjusted R square, which is equivalent to 0.68, takes

68% of the four independent variables in the model into account and corrects for bias. This adjusted R square value of 0.68 is very helpful in correcting biases when independent variables are greater than 1. This model have independent variable more than one. So, adjusted R^2 were used to evaluate the goodness of fit of the model. The root mean square error (RMSE) and mean absolute percentage error also calculated. As we can see below the values of both RMSE and MAPE, the average magnitude of error produced by a model (MAPE) and the average difference between values predicted by a model and the actual value are small. All RMSE, MAPE and adjusted R^2 tells the independent variables are good in explaining the dependent variables.

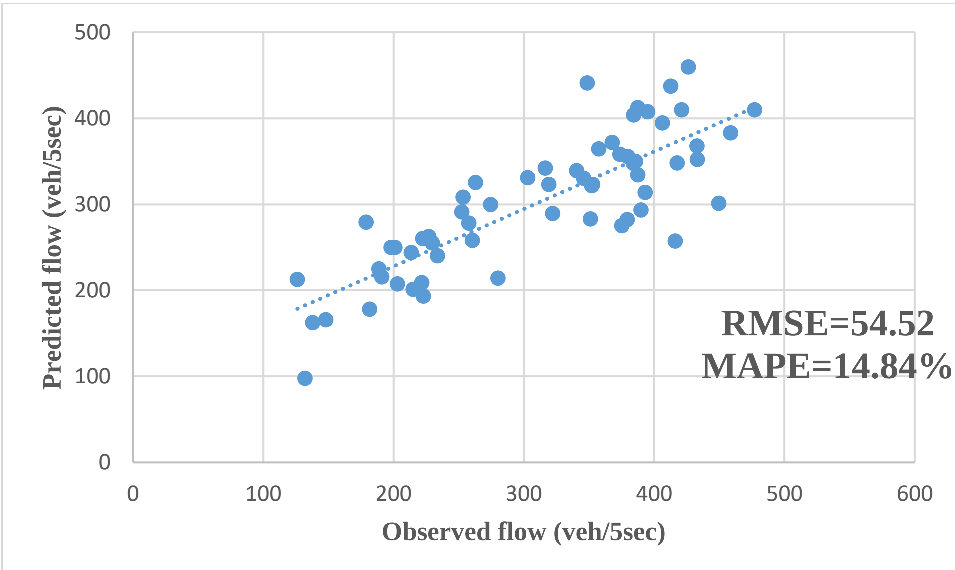


Figure 46 Predicted vs observed plot

From the ANOVA output, the significance F-value is 2.26635E-14, which is less than 0.05. This suggests that the model is statistically significant. Additionally, the p-values of all the independent variables are also less than 0.05. This implies that the independent variables (alpha index, primary road proportion, network density, and degree centrality) in the model are statistically significant for predicting the maximum flow.

The coefficients of the exponential regression, on the other hand, show that, the rate at which the respective independent variables (network density, degree centrality, alpha index and primary road proportion) affect the dependent variable (aggregated maximum flow). As a result the road density and primary road proportion increases there effect on the maximum flow exponentially at a rate of 0.013 and 0.624 respectively. The reason behind this is the network's ability to handle more traffic as a result of the infrastructure expansion, and more roads and lanes provide greater freedom for traffic to flow. Conversely, the increase of alpha index of road connectivity and degree centrality of the network will reduce the maximum flow of the network exponentially at a rate of 3.056 and 68.812 respectively. This is due to the increase in waiting time, speed and the difficulty during turning.

To examine how the maximum flow changes when only two independent variable is changed while the others are held constant, 11 values within the collected data range were tested. The observed trends (increase or decrease) are summarized in the table and the figure below. As the color transitions towards red in the figure, the maximum flow increases, demonstrating the impact of increasing network density and primary road proportion on maximum flow. Whereas increasing alpha index and degree centrality will reduce the maximum flow.

Table 19 Effect of altering a single independent variable on maximum flow

Independent Variable Values				*Maximum flow (only x_1 increases)*	*Maximum flow (only x_2 increases)*	*Maximum flow (only x_3 increases)*	*Maximum flow (only x_4 increases)*
x_4	x_3	x_2	x_1				
6	0.3	0.001	0.1	277	295	297	236
7	0.31	0.002	0.15	286	275	289	240
8	0.32	0.003	0.2	295	257	280	243
9	0.33	0.004	0.25	304	240	271	246
10	0.34	0.005	0.3	314	224	263	249
11	0.35	0.006	0.35	324	209	255	252
12	0.36	0.007	0.4	334	195	248	256
13	0.37	0.008	0.45	345	182	240	259
14	0.38	0.009	0.5	356	170	233	262
15	0.39	0.01	0.55	367	159	226	266
16	0.4	0.012	0.6	379	138	219	269

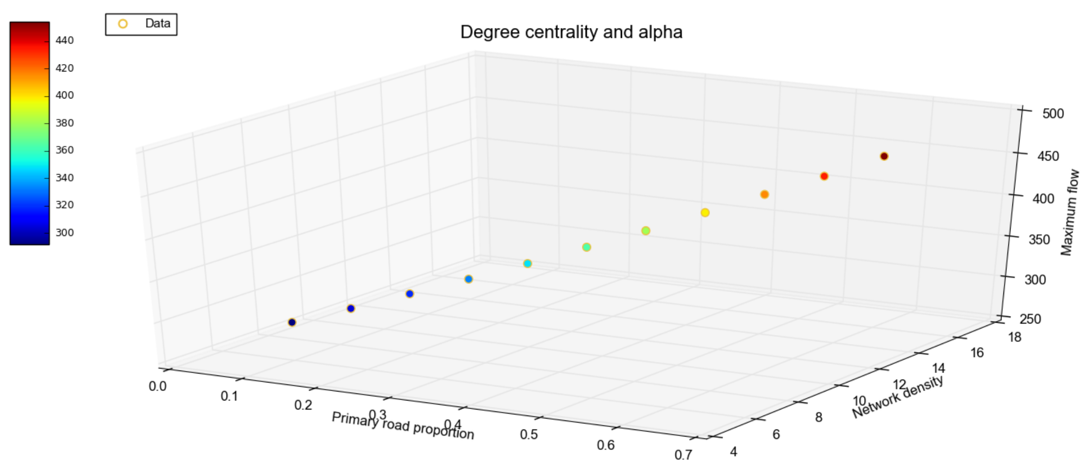


Figure 47 Effect proportion of primary roads and network density on maximum flow

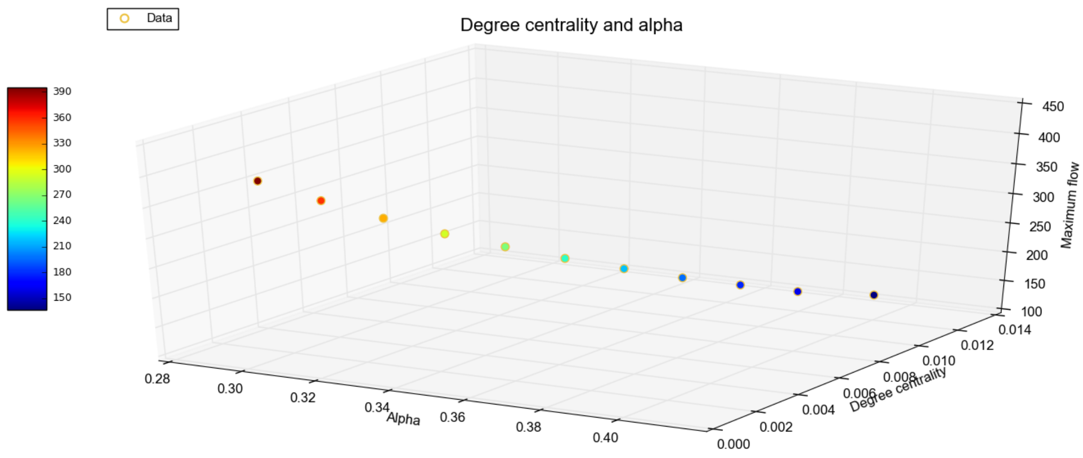


Figure 48 Effect of degree centrality and alpha on maximum flow

Chapter Six: Conclusion and Recommendation

6.2. Conclusion

The objective of this study were investigating the impact of road network connectivity, network density, degree centrality and proportion of primary roads on the macroscopic fundamental diagram (MFD), develop prediction models for planning decisions, and provide insights for urban planners on how network typologies influence traffic flow dynamics. After analysis, exponential regression modelling approach used to evaluate the factors affecting the macroscopic fundamental diagram.

In this study sixty one 2km by 2km road networks were extracted from OpenStreetMap and using the same OD data for all networks simulation by simulation of urban mobility (SUMO) were performed. Using the simulation outputs (maximum flow) and the network typological data extracted from the GIS software exponential regression model has been developed.

Through an in-depth analysis of factors impacting the MFD on Addis Ababa City Transportation Network, this research has revealed key findings including the significant influence of road network connectivity, network density, degree centrality and proportion of primary roads on the MFD. In which it will possibly use to enhance traffic management and optimize network performance. The findings of this research also underscore the critical importance of understanding the MFD in optimizing transportation systems in urban areas. By identifying key variables that affect traffic flow patterns, this study will offer a foundation for developing more efficient and sustainable transportation strategies for Addis Ababa's transportation network. For instance Government agencies may use to evaluate the impact of proposed changes in road network density (such as adding new roads or modifying existing ones) on maximum flow of the road network. Predictions can guide decisions on where and how to invest in infrastructure improvements.

In conclusion the findings of the study indicate that the network maximum flow will increase as the proportion of primary roads increases. This is attributed to the characteristics of primary roads, which are higher capacity roads with more lanes, and higher speed limits. As a result, vehicles have more room to maneuver and greater freedom to flow, leading to improved network maximum flow. Moreover, an increase in network density results in a higher maximum flow due to the network's ability to accommodate a larger volume of vehicles.

On the other hand, the study reveals that an increase in degree centrality and alpha index leads to a decrease in network flow. This is attributed to factors such as a higher number of conflict points, increased stopping (waiting) time at junctions, challenging turning maneuvers, and decreased speed. These aspects negatively impact upstream traffic flow and network flow. For instance as vehicles are delayed or come to a stop at junctions in downstream, the vehicles start to queued and the queue of vehicles waiting to pass through these intersections can extend back along the upstream intersection. If the spacing between intersections is short, the congestion at downstream junctions can propagate upstream, affecting the flow of traffic at subsequent intersections.

6.2. Recommendation and Gaps

To optimize the transportation network in Addis Ababa and similar urban environments, it is recommended to prioritize infrastructure investments based on the significant impact of different factors that affect the macroscopic flow of the road network. Continuous data collection and analysis of traffic patterns, coupled with the development of advanced prediction models, can enhance decision-making for urban planning and infrastructure development.

- The current urban traffic management mainly involves congestion transfer based on microscopic traffic control principles. However, it is recommended that urban traffic management strategies should be shifted towards a more holistic approach that considers macroscopic variables such as overall traffic flow, density, and speed patterns. By using these variables into traffic management frameworks, cities can develop strategies that optimize the entire traffic system, leading to reduced congestion and improved transportation facility efficiency. This shift will enable decision-makers to address urban traffic dynamics more comprehensively, ultimately contributing to sustainable urban development. For instance, if a certain intersection experiences high congestion, the government considers constructing a new road to alleviate this problem. The added new road will change factors like degree centrality, alpha, network density, and the proportion of primary roads. By evaluating how these indexes change, the overall impact on network flow can be assessed. This evaluation helps predict the broader impacts of the new road, ensuring it does not only transfer congestion to another area but genuinely improves the overall traffic flow and performance.
- Urban planners and policy makers in initial land use planning and network redesign should prioritize investments in areas that have the most substantial impact on the macroscopic flow, ensuring that resources are allocated efficiently for sustainable urban development. The insights gained from this research will used to increase sustainable urban development by creating transportation systems that align with the city's growth. This includes designing road layouts that can accommodate the increasing population and economic activities. For instance, governments can evaluate proposed road layouts for new cities, such as those planned cities around the Grand Ethiopian Renaissance Dam (GERD) and the Geda economic zones. By analyzing how different road network layouts impact overall traffic flow from the outset, planners can design layouts that minimize future congestion and ensure efficient transportation.

In addition, despite the statistical significance, the relatively small variation in Addis Ababa road hierarchy still limits the range of relationships between the MFD parameters and the network typological metrics observed in this study. Future research should focus on exploring other jurisdictions with a wider range of road hierarchies and other important factors affecting the shape of MFD, apart from network typology, are expected to be traffic control parameters such as signal timing plan and speed limits and route selection. So, investigating and incorporate their effect into the MFD structure another interesting future research direction. In addition, it is generally assumed that the identification of typological features and the investigation of their effects on the distribution of MFD will be an interesting future research direction, as network typology may affect the distribution of macroscopic fundamental diagram (MFD).

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