AGILE: GIScience Series, 5, 4, 2024. https://doi.org/10.5194/agile-giss-5-4-2024
Proceedings of the 27th AGILE Conference on Geographic Information Science, 4–7 Sept. 2024.
Editors: Alison Heppenstall, Mingshu Wang, Urska Demsar, Rob Lemmens, and Jing Yao.
This contribution underwent peer review based on a full paper submission.

The Impact of Traffic Lights on Modal Split and Route Choice: A use-case in $Vienna$

Ioanna Gogousou[1], Manuela Canestrini[1], Negar Alinaghi[1], Dimitrios Michail[2], and Ioannis Giannopoulos[1]

[1]TU Wien, Department of Geodesy and Geoinformation, Vienna, Austria
[2] National and Kapodistrian University of Athens, Greece

Abstract. The transportation dynamics within a European city, $Vienna$, are examined using a multi-graph representation of the city's network. The focus is on time-optimized routing algorithms and the effects of altering the average waiting penalty at traffic lights. The impact of these modifications, whether an increase to 60, 90, or even 150 seconds or a decrease to 10 seconds, is observed in the selection of transportation modes and routes for identical origin and destination pairs. The investigation also extends to whether routes shift towards secondary street networks to avoid traffic lights as the waiting penalty increases. Experimental variations in average waiting time for cars aim to uncover detailed effects on transportation mode choices, route length and time changes, and variations in human energy expenditure. These findings could provide valuable insights into the transportation network and its possibilities and help in urban planning and policy development. The results indicate a shift in transportation mode as the waiting penalty for cars at traffic lights increases, and in some instances, routes are redirected to roads of lower importance such as residential or service roads.

Keywords. Traffic Lights, Urban Mobility, Transportation Networks, Public Transport, OpenStreetMap

1 Introduction

Looking deeper into the complex dynamics of urban transport and the resulting impact of traffic lights on vehicle movements, it is obvious that the preferred mode of transport is by car when it comes to travel duration (Hitge and Vanderschuren, 2015; Liao et al., 2020). The complexities of waiting times at traffic lights, congestion, and parking difficulties in city centers expose areas where improvements could enhance the overall experience of urban mobility. Complementary to research efforts that explore ways to minimize and optimize average waiting times at traffic lights for cars (Rida et al., 2018; Rida and Hasbi, 2018), our study focuses on investigating the impact of such changes on average waiting times using the complex network of $Vienna$ as a use case. Adopting an innovative approach, to observe the plain transportation network, we systematically change the average waiting times for cars whenever traffic lights are present. The goal is to reveal the resulting changes in transportation patterns, with a particular focus on routes optimized for time efficiency.

In 2023, $Vienna$ was ranked first in the world for quality of life, and its transportation network played an important role. Wiener Linien, the city's public transport operator, runs 5 underground lines, 29 tram lines, and 127 bus routes. The subway of the city, operates throughout the night on weekends and public holidays, ensuring continuous service for passengers. With a fleet comprising over 500 tramcars and 450 buses, Wiener Linien boasts a robust transportation system, making $Vienna$ an ideal urban environment for this study.

Especially within cities, routing services are integral to our daily lives, often employed when navigating to a destination. Whether for new or familiar routes, individuals frequently utilize these services to generate efficient routes. Even when a routing query seems unnecessary for well-known routes, people often rely on previously generated routes. Consequently, the algorithmic output of routing services serves as a viable proxy for actual routes between an origin and destination. This allows for a comprehensive analysis of transportation patterns within a city.

The primary objective of this study is to determine the effects of manipulating average traffic light waiting penalties for cars, on randomly generated routes of various lengths across the city. By adjusting the average waiting times at traffic lights for cars, meaning the red part of the traffic signal cycle, we can observe how the same Origin-Destination (OD) pair route is changing. In addition, we examine the results of such a penalty for average traffic light waiting times on the length of the route and human energy expenditure.

Using a comprehensive representation of $Vienna$'s urban network and randomly selected OD pairs spanning various distances across the city, our study introduces a unique approach. We first decrease the waiting penalty *for cars* from an average of 30 seconds to 10 seconds in order to observe if we get any modal change in this best-case scenario. Then we gradually increase the waiting penalty, from 30 seconds to 60, 90, and even the extreme case of 150 seconds *for only the car* as a mode of transportation. This approach, without using traffic data, presents the optimal scenario in terms of transportation within a city. In essence, we want to observe if the mode of transport will change when we assign a higher or smaller average waiting penalty to the fastest option, the car (Hitge and Vanderschuren, 2015; Liao et al., 2020). Given the extensive research already conducted in the transportation field regarding traffic lights and enhancing the driving experience, we were inspired to go deeper into this topic. Our motivation came from a desire to explore a spectrum of potential modifications within this optimal scenario and analyze their impact on modal share. At the same time, with this average increase or decrease in waiting time for the traffic lights for cars, we try to determine if the choice of roads changes and "smaller" roads are preferred by the algorithm. By altering the average traffic light waiting penalty for car mode, the objective is to observe changes in routes between the same OD pairs and assess their broader impact on the entire transportation network. It is important to emphasize again that our approach is algorithmic, excluding congestion or any other real time data. However, during the route generation phase, additional filters are incorporated in order to approximate human behavior with respect to travel choices according to the existing literature.

This approach allows us to focus on the inherent characteristics of the transportation network, observing and understanding changes in the network in its fundamental state, before introducing the complexities associated with additional factors. This initial step is the foundation for subsequent analyses that may involve more complex elements like traffic data.

The present study underscores the dominance of the car modality as the fastest mode of transportation, which is in line with relevant works (Hitge and Vanderschuren, 2015; Liao et al., 2020), highlighting the need for targeted interventions to improve public transportation options and efficiency. This is especially crucial in well-designed cities such as the one in this work, where the routing algorithm consistently favors individual car travel, indicating areas for necessary improvements and adjustments in urban mobility planning. Individual cars offer greater speed and flexibility compared to public transportation or alternative modes of transport (Hitge and Vanderschuren, 2015). Routing algorithms optimized by time, prioritize speed in reaching the destination, and cars often provide the fastest means of travel. Furthermore, cars offer door-to-door service, which plays a huge role as opposed to public transportation routes that may involve transfers or longer walking distances to reach the destination. For these reasons, even in well-designed cities with extensive transportation networks, routing algorithms that are optimized by time in this best-case scenario most often suggest individual cars as the fastest mode.

The findings of this research can have substantial environmental implications, potentially used to reduce congestion and promote greater adoption of eco-friendly transport options. Such changes in transportation preferences can offer valuable insights for policymakers and urban planners (Tennøy, 2010). By understanding algorithmic considerations in mode choices, authorities can formulate improved policies for infrastructure and urban development.

Prior to exploring the specifics of our research, it is crucial to clarify certain aspects. Firstly, it is worth noting that conducting such a study in real-life conditions presents significant challenges, primarily due to the fact that it represents a scenario, which may either be impractical or excessively costly to implement. Secondly, our approach focuses on the manipulation of parameters in the static baseline modeled transportation network. We then observe the outcomes resulting from these alterations. Consequently, the basis for our validation process involves the accuracy of our baseline scenario modeling in relation to the actual transportation network. Our dataset is coming from OpenStreetMap (OSM), supplied by the Vienna government, ensuring the correctness of the geometries within our multi-graph. Additionally, the public transport timetables are sourced from Wiener Linien, another trusted governmental source, and have been integrated into our model across all public transportation modes making them correspond to reality.

The rest of the paper is organized as follows. Section 2 provides an overview of related work and introduces the existing literature. Section 3 analyzes the methodology employed in this study, providing insights into the research approach. Section 4 shows the results of the experiments carried out, presenting a detailed view of the results. Section 5 discusses the presented findings, providing an in-depth exploration of their consequences and significance. In conclusion, Section 6 provides a summary and proposes future research.

2 Related Work

Reducing waiting times and optimizing traffic light operations to alleviate congestion are key concerns in urban transportation management. In this section, we review relevant literature on these topics providing a framework for our approach, which focuses on assessing the impact of average waiting time at traffic lights on transportation mode choices on routing algorithms. There are numerous studies about traffic lights and how the waiting time can actually be reduced using state-of-the-art models and techniques.

In recent decades, traffic signal management has become an important concern within the research community. A notable paper by Wiering et al. (2000) presents in detail the application of multi-agent reinforcement learning (RL) algorithms to develop intelligent traffic light controllers, with the goal of minimizing the collective waiting time for vehicles within urban environments. The RL system was designed to learn value functions, estimating the expected waiting times for cars based on diverse configurations of traffic lights. Following this work, further RL techniques for traffic light control emerged (Wiering et al., 2004; Prabuchandran et al., 2014; Zhu et al., 2023).

Subsequently, novel techniques were employed to address the challenges associated with traffic light control. Shinde (2017) created a new technique called Adaptive Traffic Light Control System (ATLCS). The proposed system uses sensor networks for efficient traffic control by adjusting traffic light timings to minimize wait times, optimizing road capacity, saving travel time, and preventing congestion. Younes and Boukerche (2016) presented the Intelligent Traffic Light Controlling (ITLC) algorithm, which improved isolated traffic light efficiency by 30% compared to the Online Algorithm (OAF). They also introduced the ATL algorithm, demonstrating a 70% enhancement in traffic flow for arterial street coordination. In addressing the increasing global issue of traffic congestion, the work of Verma et al. (2022) presents a novel system model that employs the AnTabu routing algorithm and a traffic light control system based on fuzzy logic to effectively manage traffic flow, significantly reducing the average vehicle travel time and improving the throughput of the roads intersection. Furthermore, numerous attempts have already been made to simulate traffic networks, incorporating the operational dynamics of traffic lights in various models (Wen, 2008; Harahap et al., 2019).

Congestion is a problem that is highly related to traffic lights, thus, many recent papers try to model the transportation network and observe the effect of congestion (Ben-Dor et al., 2022). There is also existing research on traffic control, which deals with traffic control recognition at junctions (traffic lights, stop, priority, and right of way rules) using crowd-sensed GPS data (vehicle trajectories), as well as features extracted from OpenStreetMap (Zourlidou et al., 2022).

Previous research has highlighted the significant impact of traffic lights on the behavior of both drivers and pedestrians (N. Speisser and Lab, 2018). In a study conducted in five cities, a clear correlation was observed between waiting times and the rate of running red lights. The findings suggest potential modifications to existing regulations, especially for drivers at tram crossings. The study also underscores the importance of considering pedestrian acceptability and credibility thresholds, proposing a recommended maximum waiting time of less than 90 seconds.

Much research has also been done on fuel consumption and the total cost of traveling by employing routing algorithms. The work of Ehmke et al. (2018) examines routing methodologies, comparing the impact of minimizing distance or travel time against considerations of total cost, fuel consumption/emissions, distance, and travel time, advocating for comprehensive cost models and adaptable routing algorithms as essential to effectively minimize overall expenses. Wen et al. (2014) introduced two heuristic methods that address the complex issue of solving the minimum cost path problem within a time-varying road network that includes congestion charges. Their study aimed to offer practical solutions for finding the minimum cost path between node pairs in such dynamic environments. They compared these heuristic methods against an alternative exact approach utilizing real-time traffic data.

In addition, we identified studies that use graphs to optimize waiting times at traffic lights. More specifically, Lusiani et al. (2020) introduced a method to optimize traffic light waiting times at congested crossroads using compatible graphs. The approach simplifies traffic flow systems, identifies sub-graphs with minimal cliques, and calculates waiting times based on a 60-second cycle assumption. Applied to Pasteur crossroads in Bandung, it reduces the average waiting time from 282 seconds every hour to an optimal 135 seconds an hour. Following the aforementioned study, recent research was conducted to explore the application of the Compatible Graph and Webster methods for optimizing the traffic light arrangement in Jepara (Asih et al., 2023). They employed compatible graph modeling to optimize traffic flow and used the Webster method to determine traffic light cycle times. Taking into account variables such as the number of vehicles, road width, and different traffic densities in the morning and afternoon, the study proposes a solution with a three-phase cycle, resulting in effective cycle times of 98 seconds for the morning session and 155 seconds for the afternoon session, as validated through simulation using PTV Vissim software.

In summary, related studies presented various effective approaches to alleviate traffic congestion, improve traffic light control, and optimize transportation modes. However, most existing studies are heavily dependent on real-time data or modeling of real-time data for their analyses, with a primary emphasis on aspects related to traffic management.

It is important to note that our algorithmic approach diverges from the current studies by not incorporating real-time data on congestion or traffic light operation. Instead, our method operates at a higher level, analyzing the impact of average traffic light waiting penalties on transportation mode choices and route changes towards lower-importance streets across the city. Through the utilization of a) the complete network structure derived from the open-source database, OpenStreetMap (OpenStreetMap contributors), and b) the NetworkX library (Hagberg et al., 2008) for the computation of time-efficient routes across various OD pairs using Dijkstra's algorithm (Dijkstra, 1959), we can observe the influence that traffic lights have on the entire transportation network. Once more, it is crucial to emphasize that our primary focus lies on the transportation network itself. Specifically, we are interested in examining how adjustments to the average traffic light waiting penalties will influence the routes within the baseline scenario.

As noted previously, conducting studies of this nature in real-world settings is either infeasible or very expensive. Therefore, our approach enables us to assess the effects of modifications to the transportation network within this optimal scenario. We operate under the assumption that if the observed outcomes fail to align with the desired results, implementing such changes in more complex models or even in reality, may prove pointless.

3 Methodology

3.1 Data and Software Availability

The transportation network in $Vienna$, which includes public transportation, walking, biking, and driving a car, was initially derived from the Open Street Map (OSM) dataset (OpenStreetMap contributors). Especially for $Vienna$, we have access to accurate and reliable data directly provided by local authorities in OpenStreetMap (OSM) format. The Overpass API is utilised for downloading the data. Roadways in each network are represented as edges, with nodes representing junctions and public transport stations. This comprehensive representation accurately depicts $Vienna$'s transportation system through a multi-graph model.

The OSM bicycle network primarily comprises bicycle lanes, which are relatively sparse. To overcome this limitation and adhere to $Vienna$'s Highway Code, a bicycle graph was constructed through the intersection of pedestrian and car graphs. By establishing connections among the shared nodes in each network, the multi-layer transportation network was formed. Additionally, it is important to note that in this multi-graph representation, it is allowed to change from one node to another with zero cost if, in the very same node, more than one mode of transportation is available. There is only one exception that needs to be mentioned. Private modes of transport (bike and car) are only available at the beginning of a route. Thus, this approach does not incorporate car and bike sharing facilities.

It is also important to consider the human energy expenditure during travel. By focusing not only on the choices of transport modes but also on the energy expended by people using these modes, we gain a holistic understanding of the impact of traffic light operations on human energy expenditure. Kölbl and Helbing (2003) suggests that energy expenditure is a more effective factor in explaining individuals' mobility choices. As individuals move around the city, they possess some energy that is closely tied to travel time. This can potentially serve as a more precise indicator of the mobility choices. Furthermore, we also observe the potential change in the length of the route. According to these findings, appropriately scaled daily travel time distributions for different transportation modes, such as walking, cycling, bus or car driving, follow a universal functional relationship similar to a canonical-like energy distribution. Furthermore, Kölbl et al. (2023) approximated these energy functions through an extensive human-subject survey study that spans more than two decades in multiple countries. This dataset holds significant value and can be used to estimate average energy expenditure for any transportation mode within a network using publicly available data sources.

Additionally, the traffic lights, extracted from OSM as node objects, were assigned to the nearest edges. Within our directed multi-graph structure, some edges allow movement in both directions. If a traffic light exists in one direction and not the other, this information was incorporated into the graph, reflecting as 'True' at the junction of the former direction and 'False' at the junction of the latter concerning the traffic light presence.

A traffic light penalty of 30 seconds for $Vienna$, was used as a baseline. This value is commonly used as an average waiting penalty OpenSourceForEver (2021); Caquot (2022). This penalty was initially applied to construct our multi-graph representation. Consequently, every node featuring a traffic light is assigned a 30-second penalty for car, pedestrian, and bike modes. In this study, each layer is equipped with its own set of traffic lights, each operating independently. Changes in the average waiting traffic light penalty are specifically related to the car mode, while the average penalties for pedestrians or cyclists remain constant. It is important to note that buses and trams, given priority in $Vienna$, are exempted from this traffic light penalty, and other forms of public transport in the city do not encounter traffic lights.

Regarding speed limits, cars were assigned values based on the OSM 'max speed' tag. In instances where this tag is absent, a default value of 30 km/h is assigned. This maximum speed value was multiplied by 0.75. This value gives an estimate of acceleration and deceleration on a segment. Then the time value is obtained by dividing the length of the segment by the adjusted speed value. Public transport schedules are sourced from Wiener Linien's GTFS (General Transit Feed Specification) data (https://www.data.gv.at/katalog/dataset/wiener-linien-fahrplandaten-gtfs-wien), which are publicly available timetables. Utilizing this data, we can determine the average time it takes to travel from one station to another, considering that travel times between stations may vary throughout the day.

Regarding the bike speed, it is consistently set at 11.5 km/h. For walking, the speed on flat surfaces and uphill is 3.5 km/h (Levine and Norenzayan, 1999),(Kassim et al., 2020). The uphill is actually reflected through the energy value, and the higher the elevation, the more energy is consumed. The downhill walk is set at 5 km/h. During the computation of human energy expenditure for both biking and walking, the slope of the terrain is taken into account. This factor is considered to provide a more comprehensive assessment of the energy expenditure associated with these

OSM tags	Joined Tags
motorway motorway link trunk trunk link primary primary link secondary secondary link tertiary tertiary link	Primary Streets
unclassified residential service living street	Secondary Streets

Table 1. Open Street Map tags and categorized tags for the Primary and Secondary Street Network.

modes of transportation, taking into account the impact of varying terrain conditions. All these values for human energy expenditure were obtained from the table 1.0.2 and 1.1 from the book of Spitzer et al. (1982).

Finally, OpenStreetMap (OSM) tags were utilized to observe if routes change toward less important streets. Table 1 presents the various tags and how these OSM tag definitions were used to classify the streets into the *Primary Street Network* and the *Secondary Street Network*. In addition to the existing tags, we introduced a new tag labeled "no car segment" to emphasize instances where a mode transition occurs from car to another mode.

The data and code for this work are both accessible from our website [1]. We used Python programming language (Version 3.10) for processing the data, creating the multigraph, the routing process and analyzing the results.

3.2 Route Generation and Processing

Our sampling strategy works as follows. Origin-Destination pairs (OD) were randomly selected across $Vienna$, 1000 pairs for 21 different length categories were used for the experiment, resulting in more than 20000 routes. These categories range from short distances, such as 100m to 500m for the first category, to long distances, such as 19001m to 20000m (e.g. 501m to 1000m for the second category, 1001m to 2000m for the third and so on). Each length category initially comprises 1000 generated OD pairs. Dijkstra's algorithm (Dijkstra, 1959) using time as a cost function instead of the shortest path was employed to calculate these routes using the NetworkX library (Version 3.0) (Hagberg et al., 2008). Additionally, each route retains records of both the total human energy expenditure and the total distance traveled.

[1] https://geoinfo.geo.tuwien.ac.at/resources/

Table 2. Filters for Realistic Route Scenarios based on Literature

Mode of Transport	Filters
Car	≥ 1 km
Walk	≤ 1.5 km
Bike	≤ 5 km
Overall transfers	≤ 4 + Walking

To guarantee realistic routes and approximate human behavior, we applied specific filters in the routing algorithm to generate feasible routes. Feasible routes are the ones that adhere to certain human criteria, such as the acceptable walking distance and the number of transitions between modes humans are willing to follow. Routes with a total walking distance exceeding 1500m (Walton and Sunseri, 2010), (Fonseca et al., 2021) were filtered. Furthermore, following Daniels and Mulley (2013), our approach involves using a car as a mode of transportation exclusively for trips greater than 1km. This decision aligns with the idea that distances ranging from 400m to 800m are considered walkable. Additionally, the total biking distance was restricted to less than 5km (Larsen et al., 2010; Chillón et al., 2016), and the overall transfers from one mode to another were limited to less than 5. Zha et al. (2019) used mobile phone GPS data to pinpoint transfer points between various transportation modes within individual journeys. This is used as the foundation for trip mode segmentation and the recognition of individual trip mode chains. The authors processed a dataset comprising 1,863 valid trips, and within this dataset, they identified and utilized 8,243 records of transfer points from one mode to another. This yields an average of approximately four transitions per trip. In our research, we implemented a constraint of four transfers in addition to walking. As walking is already considered a mode with its own filter, we excluded it from the count of four transfers. This decision was based on the rationale that walking is an inherent component of transitioning between different modes. To dynamically implement these filters, we modified Dijkstra's algorithm for determining the shortest path, adapted specifically for optimizing time efficiency in our context. This adaptation ensures that the algorithm outputs a "feasible" route, aligning more closely with a realistic representation of the situation.

It is important to note that our length categories are initially defined based on shortest paths. However, after the implementation of the feasibility change, routes may deviate from the shortest paths, potentially resulting in longer distances. For instance, if a route between a given OD pair is originally classified in a 2km distance bin according to the shortest path but is considered infeasible according to the literature criteria, the alternative feasible route may have a greater distance.

Table 2 provides an overview of all applied filters. This representation aims to illustrate the key parameters and conditions utilized in the study.

After constructing the multi-graph representation of the transportation network and incorporating route generation with a 30-second waiting penalty for car, bike, and walking modes, we performed an evaluation of feasible routes. Our analysis explored the average time spent per length category, the average route length per category, and the average human energy expenditure across the entire length spectrum. Additionally, we explored the distribution of modes within each length category (i.e., the resulting modes based on the routing algorithm). The findings revealed that algorithmically optimized for time efficiency in route selection, the car mode is favored across all transportation modes and length categories.

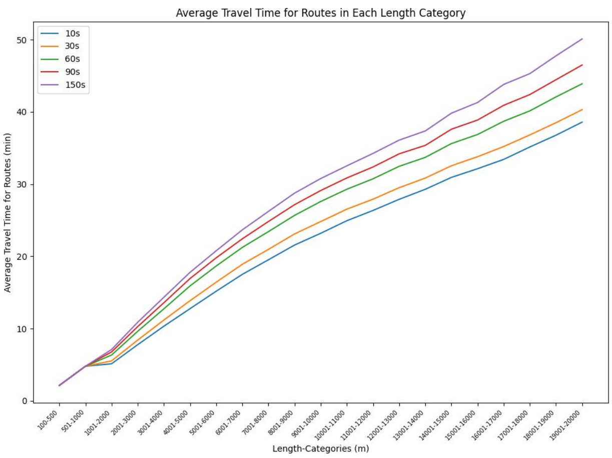


Figure 1. Average travel time in each length category for different average waiting times at traffic lights.

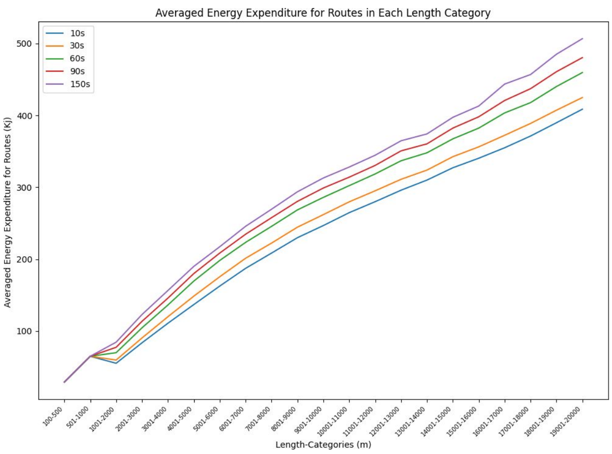


Figure 2. Average energy expenditure in each length category for different waiting times at traffic lights.

Then, we retained the same Origin-Destination pairs and started the generation of multi-graph representations from the beginning, with this time-adjusted average waiting times at traffic lights for only the car as a mode of transportation. The penalties for biking and walking remained unchanged throughout the process. We explored variations in average waiting times for cars, meaning that we only changed the red phase of the traffic light cycle and not the length of the cycle, by adjusting them to 60s, 90s, and 150s, and then decreasing them to 10s. This approach enables us to readily observe travel mode changes, route variations, and discrepancies in average travel length, travel time, and average human energy between all routes in this best-case scenario across the different traffic light penalties.

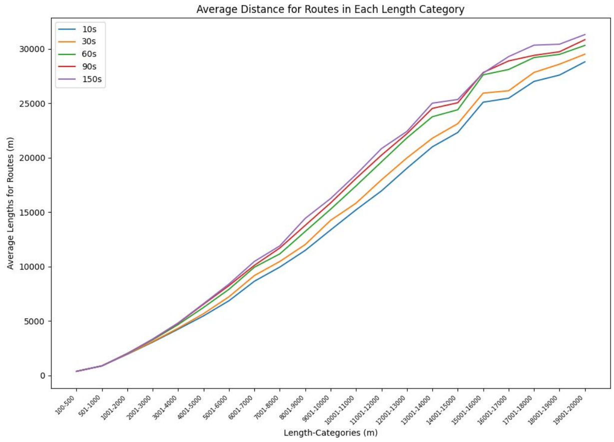


Figure 3. Average travel distance in each length category for different waiting times at traffic lights.

4 Results

In this section we present the results of experiments involving average waiting times (red light waiting) for the car mode at traffic lights. Table 3 provides an overview of the average modal split corresponding to different average waiting time penalties at traffic lights.

In Figure 1 the average travel times for the same OD pairs are presented, using time as a cost function. It is evident that travel time increases as the waiting time at traffic lights increases. In addition, the car is the preferred mode when the algorithm optimizes for time.

Furthermore, the results of the average values for energy expenditure are also presented in Figure 2. These routes, as before, are also plotted according to different length category bins. In conclusion, the average length traveled for all routes is shown in Figure 3.

Table 3. Average percentage of each mode for different average waiting time values for car mode across all length spectrum.

Mode	10s	30s	60s	90s	150s
Bus	7.29%	8.91%	12.50%	14.50%	17.37%
Walk	0.58%	0.73%	1.20%	1.61%	2.12%
Bike	8.89%	9.03%	9.79%	10.79%	12.28%
Car	81.12%	77.84%	68.70%	61.56%	51.74%
Tram	0.17%	0.23%	0.56%	0.95%	1.46%
Subway	0.86%	1.67%	3.84%	5.52%	7.50%
Train	1.09%	1.58%	3.41%	5.07%	7.53%

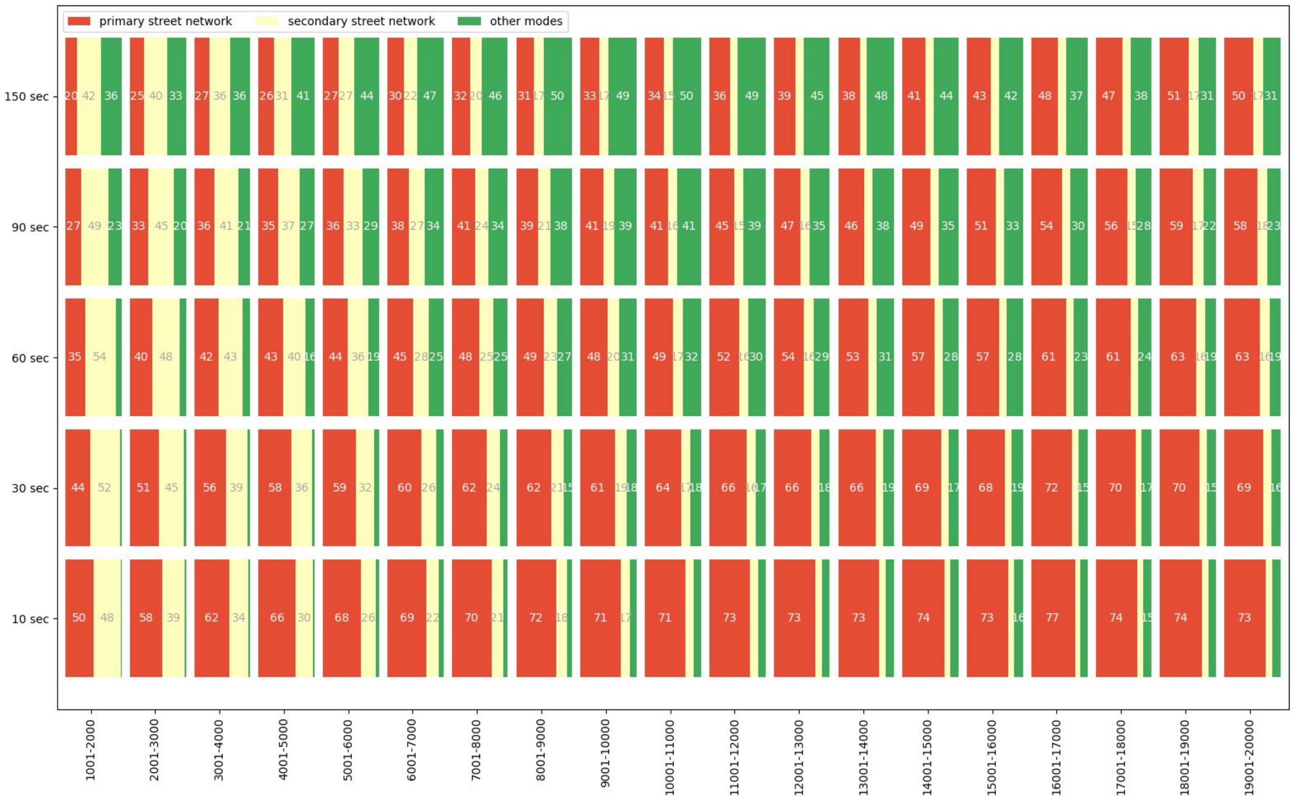


Figure 4. This figure illustrates the distribution of OpenStreetMap (OSM) tag labels among the routes within each length category. The numbers inside the bars represent averaged results for each category. The Primary Street Network is depicted in red, the Secondary Street Network in yellow, and other means of transport are represented in green. The y-axis represents the different waiting penalties for cars (seconds), and the x-axis represents the different length categories (meters).

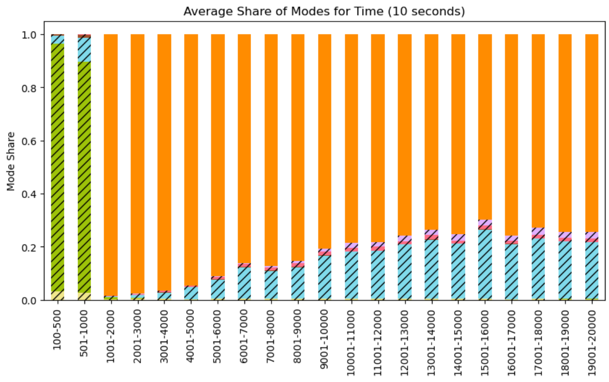
These results provide valuable insights regarding the influence of the average traffic light waiting penalties on both route length and human energy expenditure, next to time. The presented figures offer details on the output of the routing algorithm under different average waiting time scenarios for the mode car, contributing to a more comprehensive understanding of their influence on modal split and route choice.

As previously noted, the algorithm often prioritizes the car as the fastest option when optimizing for time efficiency. Nevertheless, increasing average waiting times for cars redirects traffic from main roads toward alternative transportation modes, such as active modes or public transport. This is obvious in Figure 4 which illustrates 19 length categories associated with car usage in the routes. The x-axis represents these 19 length categories, while the y-axis displays varying waiting penalties for cars ranging from 10 to 150 seconds. The Primary Street Network is depicted in red, while the Secondary Street Network is represented in yellow. The green color is used to denote other modes of transportation, including both active modes and public transport. The numerical values within the color bars represent the average percentages corresponding to each respective street tag based on the length category to which they belong. This figure facilitates the observation of how the algorithm redirects traffic flow towards streets of lower categories and promotes the utilization of more "eco-friendly" transportation modes.

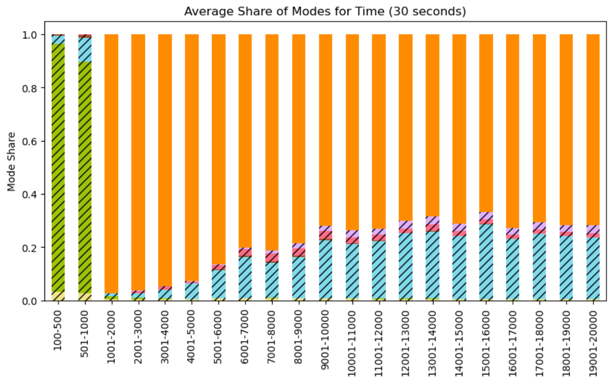
Additionally in Figure 5, the modal share across the entire length spectrum is depicted. The sub-figures present modal distributions for average waiting times for cars of 10, 30, 60, 90, and 150 seconds, showcasing the various modes of transportation utilized across the routes. The active modes and public transport data are depicted at the bottom of the illustration with a texture as a grouping factor.

5 Discussion

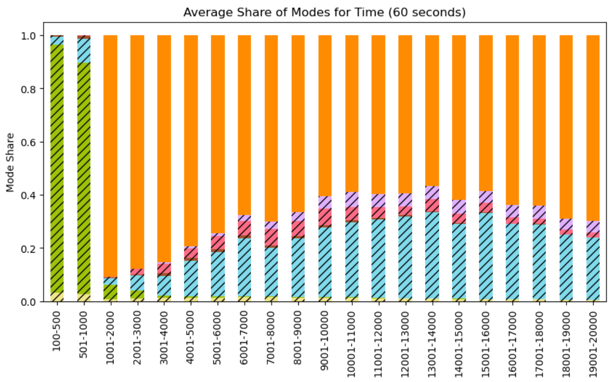
This section discusses the results obtained during changes to the average waiting penalty for traffic lights for the mode car. Table 3 illustrates the impact of different waiting times on the suggested mode of transportation. $Vienna$ has a highly developed transportation system, and traditionally, the car has been considered the fastest option, even with an efficient public transport network since, most of the time, it offers greater speed, flexibility, and door-to-door approach along with an extensive network .(Hitge and Vanderschuren, 2015; Liao et al., 2020). However, our findings reveal an interesting pattern: as the average waiting penalty for traffic lights for cars increases, the algo-



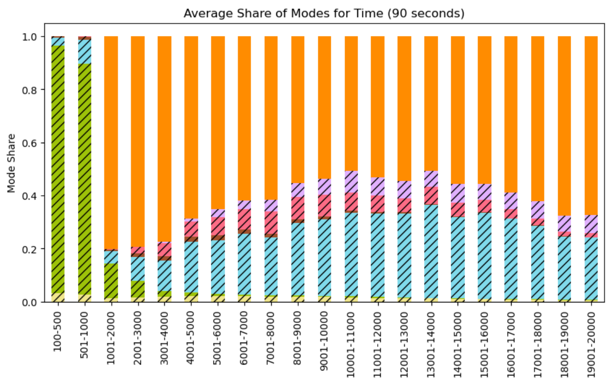
(a) Mode distribution for 10s average waiting time for cars



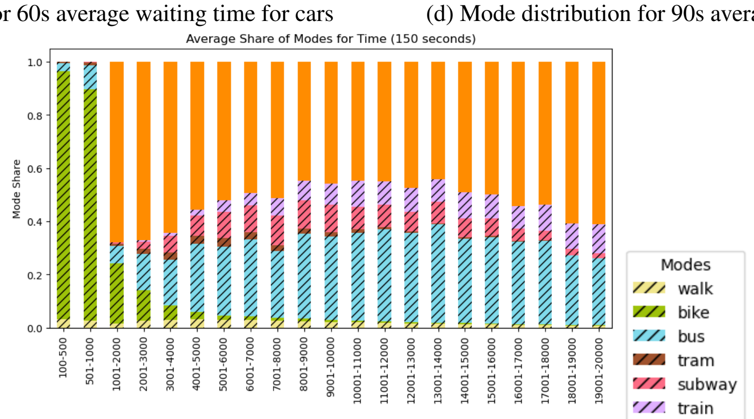
(b) Mode distribution for 30s average waiting time for cars



(c) Mode distribution for 60s average waiting time for cars



(d) Mode distribution for 90s average waiting time for cars



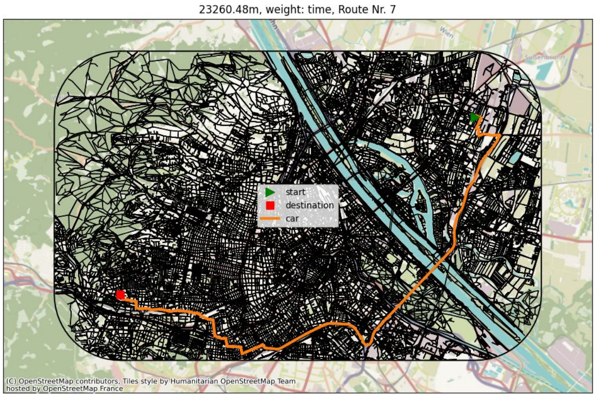
(e) Mode distribution for 150s average waiting time for cars

Figure 5. Distribution of modal share across the different length categories. In the x-axis, the normalized mode share is presented, and in the y-axis, the different length categories are depicted (meters). As the average waiting penalty increases, the car mode decreases (orange color), and other modes increase (colors with line hatch). Legend is the same for all subfigures and represents the color for different modes of transportation.

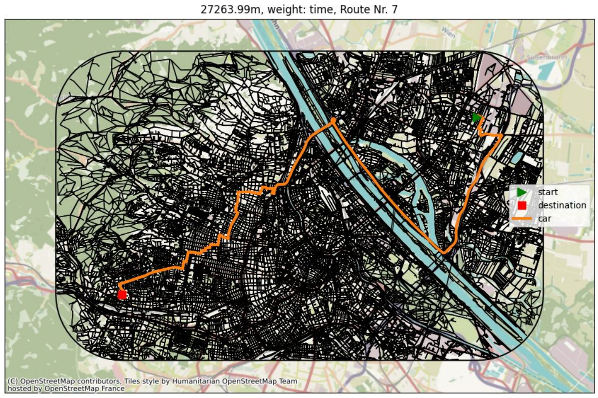
rithm also favors modes of transportation other than cars when it tries to find the time-efficient path.

The averaged results presented in Table 3 align with the information depicted in Figure 4. We initially compare the impact of reduced average waiting penalty for cars (from 30 to 10 seconds), followed by an analysis of the effects of increased waiting penalties (from 30 to 60, 90, 150 seconds). It is important to clarify that the modification applies solely to the duration of the red phase in the traffic light cycle and also average traffic lights waiting penalties for bikes and pedestrians remained the same.

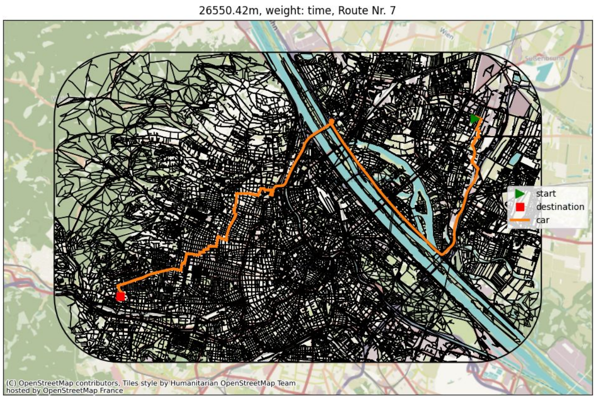
As anticipated, when the traffic light penalty decreases from 30 to 10 seconds, there is an observable increase in the utilization of the Primary Street Network (depicted in red). This indicates that the routes mainly follow paths that primarily traverse larger streets within the city. This trend gets more intense when the route length increases. Furthermore, a decrease in the traffic light waiting penalty for cars does not promote the adoption of eco-friendly modes of transport. The green category in Figure 4, representing active modes and public transportation, has a minor change as the length category increases. This suggests that a reduction in the average waiting penalty, in the best-case



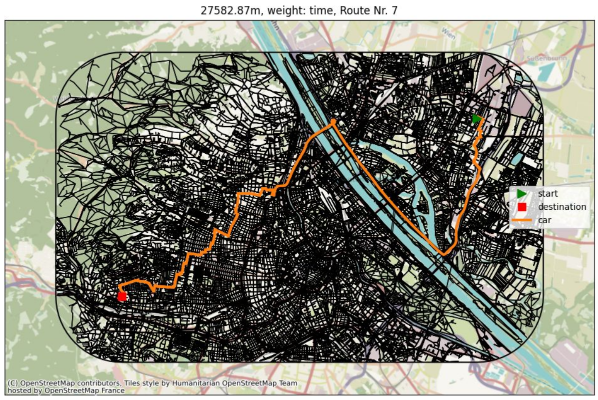
(a) Route for 10s Waiting Time



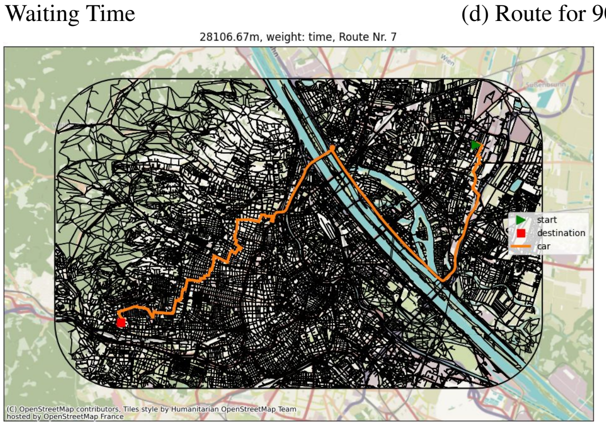
(b) Route for 30s Waiting Time



(c) Route for 60s Waiting Time



(d) Route for 90s Waiting Time

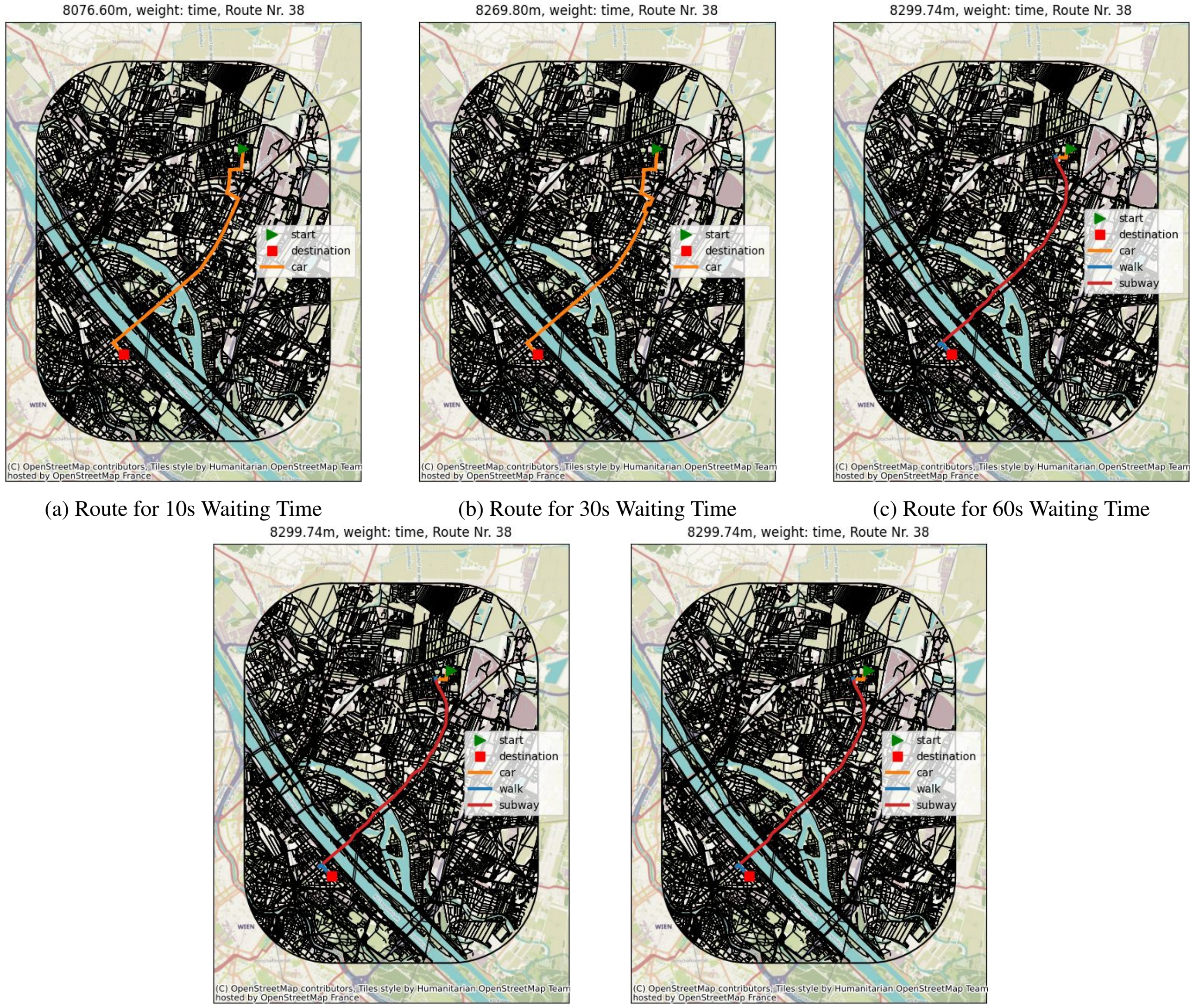


(e) Route for 150s Waiting Time

Figure 6. Route 7 with the same Origin-Destination pairs across different waiting penalties at traffic lights. In this example route, the mode remains the same between all traffic light penalties. The algorithm exports the most time-efficient route.

scenario, will not result in notable changes in terms of the time-efficient path and the mode of transportation.

When comparing the average 30-second waiting penalty for cars with the increased average penalties (60, 90, and 150 seconds), an interesting conclusion arises. Initially, by increasing the waiting penalty for cars up to a certain point, the routes are redirected towards lower category streets (yellow category), particularly for shorter routes (up to 5-6km). This suggests that the algorithm is trying to avoid traffic lights, favors smaller streets, most likely ones that do not include traffic lights (Figure 4). However, beyond this particular threshold, we observe a notable increase in the green category, representing public transport and active modes. This increase persists until approximately the 9-10km category, after which it gradually declines. It is evident that in the extreme case of a 150 second waiting penalty for cars, the percentage distribution between the car mode and all other modes becomes nearly equal (50-50). This implies that even in the absence of congestion data, in the optimal scenario where the average traffic light waiting penalty for cars increases, we observe that for shorter travels within the city, public transportation and active modes become nearly as time-efficient as car travel.



(a) Route for 10s Waiting Time

(b) Route for 30s Waiting Time

(c) Route for 60s Waiting Time

(d) Route for 90s Waiting Time

(e) Route for 150s Waiting Time

Figure 7. Route 38 with the same Origin-Destination pairs across different waiting penalties at traffic lights. In this example route, the mode remains the same between the 10s and 30s penalty. However, after that penalty, the modality is changing. The algorithm again exports the most time-efficient route.

Figure 6 depicts a specific Origin-Destination pair with its corresponding routes under different waiting times at traffic lights. As the waiting penalty changes, we can also observe the change in route. Each sub-figure represents a unique path chosen by the algorithm to optimize for time efficiency. The total travel length is shown on top of each sub-figure. By observing the total length traveled between the sub-figures, it is evident that the algorithm adjusts the route by covering more distance to reach the destination in the most time-efficient manner. It is important to observe that the mode of transportation selected still remains the car, which means that it remains the fastest mode.

An intriguing example is evident when examining Figure 6. Despite Figure 6b depicting a scenario with a 30-second penalty, Figure 6c presents a route with a shorter length even though the traffic light waiting time is increased (60s). This shows that in the case of Figure 6c, the route has fewer traffic lights and most probably lower speed limits. Otherwise, the algorithm in the first case would have chosen it.

In Figure 7, another example of the same OD pair is presented across the different average waiting penalties at traffic lights. It is evident that the modality is changing in this case. Figures 7a and 7b have the car as the fastest option to reach the destination. However, when the traffic light penalty for cars increases to 60 seconds, we can clearly observe the change in the modality. In the first two, Figures 6a and 6b, a slight alteration in the route is noticeable, likely indicating an effort to avoid traffic lights. However, when the waiting penalty for cars is doubled (60 seconds), the car is no longer the fastest option.

While traffic congestion is not modeled in the current approach, our methodology provides valuable insights by presenting a "raw" representation of the transportation network. Optimizing for the best-case scenario, our model deliberately ignores factors such as parking search times, congestion and waiting times in public transport.

In this optimized best-case scenario, the results confirm the belief that cars remain the fastest mode of transportation (Hitge and Vanderschuren, 2015; Liao et al., 2020). Surprisingly, when the average waiting penalty for the mode car increases, the algorithm prefers to follow an alternative route by following routes in secondary streets, instead of changing the modality. This means that the car is still the faster option even if it requires some extra kilometers to travel in order to reach the destination point. However, with a significant increase in the traffic light waiting penalty for cars, it can be observed that other modes become nearly as fast as cars. In Figure 5 the average mode distribution share is depicted. There, for each average waiting penalty for cars, we can observe the average modal share. As mentioned earlier, in trips with a length of approximately 9 to 10 km, cars and other modes of transportation are utilized equally. In these plots, it is evident how public transport emerges as the waiting penalty increases, particularly in middle-range trips.

Aligning with the findings in existing literature, our exploration led us to identify a "feasible" path, a theoretically viable route for individuals traveling between an origin and destination point. Even when the average waiting time at traffic lights was increased, the car remained the preferred mode , meaning the fastest mode when the algorithm used time as a cost function. In Figures 1, 2 and 3 it is obvious that as the average waiting penalty increases, the red light time, the values in averaged results also slightly increase. The plots of all travel time, distance, and energy expenditure for routes look very similar, something that is expected as time, distance, and human energy expenditure are highly correlated. However, based on the values observed on the y-axis, it is obvious that there is no substantial difference in the average values for time, distance, and human energy. Therefore, it can be concluded that an increased or decreased average waiting penalty for cars can be considered as noticeable when one analyzes the longer distances, implying that the time, distance, and human energy spent to reach the destination increase. On the contrary, when all distance bins are analyzed together and averaged, these differences remain relatively consistent, revealing probably negligible differences resulting mostly from the small impact on short routes.

6 Conclusion and Future Work

In summary, this research focuses on a best-case scenario for $Vienna$ and models its multi-modal transportation network. By decreasing (10 seconds) or increasing (60, 90, and 150 seconds) the average red time waiting penalty for the *car mode*, we investigated modal changes and observed variations in time-efficient routes (including OSM tags for primary and secondary streets, average travel length, average travel time, and human energy expenditure). Our research within this best-case scenario uncovered that as the average traffic light penalty increases, there is a significant shift towards eco-friendly modalities. We recognize that our research has certain limitations, as it does not incorporate traffic congestion data and models an ideal situation for traveling around the city. Nevertheless, this optimal best-case scenario provides valuable insights into the underlying transport network. By specifically focusing on this optimized scenario, city planners and policy-making authorities can obtain valuable insights for immediate practical applications. It is important to first examine this best-case scenario before going into more complex modeling.

As an extension to this research, future work could delve into incorporating traffic data as an additional parameter to further improve the model's accuracy. By integrating real-time traffic conditions into the algorithm, the transportation network's responsiveness could be enhanced, providing a more dynamic and realistic representation of travel. Additionally, conducting more experiments using existing models, rather than approximating waiting penalties, could contribute to the precision of the algorithm. Furthermore, broadening this research by applying the same test to other cities would offer valuable insights into how modality changes may vary across different urban landscapes. This comparative analysis could uncover city-specific patterns.

References

Asih, T. S. N., Hidayati, S. N., Mulyono, M., and Rosyida, I.: Application of Compatible Graph and Webster Methods for Traffic Light Arrangement in Jepara, JTAM (Jurnal Teori dan Aplikasi Matematika), 7, 999–1010, 2023.

Ben-Dor, G., Ogulenko, A., Klein, I., and Benenson, I.: Modeling the Effect of Congestion Charge and Parking Pricing on Urban Traffic: Example of Jerusalem, AGILE: GIScience Series, 3, 26, https://doi.org/10.5194/agile-giss-3-26-2022, 2022.

Caquot, A.: Traffic light management to improve urban traffic, Master's thesis, Máster Universitario en Ingeniería Mecánica, https://oa.upm.es/71316/1/TFM_ALBAN_CAQUOT.pdf, 2022.

Chillón, P., Molina-García, J., Castillo, I., and Queralt, A.: What distance do university students walk and bike daily to class in Spain, Journal of Transport & Health, 3, 315–320, 2016.

Daniels, R. and Mulley, C.: Explaining walking distance to public transport: The dominance of public transport supply, Journal of Transport and Land Use, 6, 5–20, http://www.jstor.org/stable/26202654, 2013.

Dijkstra, E. W.: A Note on Two Problems in Connexion with Graphs., in: Numerische Mathematik, vol. 1, pp. 269–271, 1959.

Ehmke, J. F., Campbell, A. M., and Thomas, B. W.: Optimizing for total costs in vehicle routing in urban areas, Transportation Research Part E: Logistics and Transportation Review, 116, 242–265, https://doi.org/10.1016/j.tre.2018.06.008, 2018.

Fonseca, F., Conticelli, E., Papageorgiou, G., Ribeiro, P., Jabbari, M., Tondelli, S., and Ramos, R.: Levels and Characteristics of Utilitarian Walking in the Central Areas of the Cities of Bologna and Porto, Sustainability, 13, https://www.mdpi.com/2071-1050/13/6/3064, 2021.

Hagberg, A., Swart, P. J., and Schult, D. A.: Exploring network structure, dynamics, and function using NetworkX, https://www.osti.gov/biblio/960616, 2008.

Harahap, E., Darmawan, D., Fajar, Y., Ceha, R., and Rachmiatie, A.: Modeling and simulation of queue waiting time at traffic light intersection, in: Journal of Physics: Conference Series, vol. 1188, p. 012001, IOP Publishing, 2019.

Hitge, G. and Vanderschuren, M.: Comparison of travel time between private car and public transport in Cape Town, Journal of the South African Institution of Civil Engineering, 57, 35–43, 2015.

Kassim, A., Tayyeb, H., and Al-Falahi, M.: Critical review of cyclist speed measuring techniques, Journal of Traffic and Transportation Engineering (English Edition), 7, 98–110, https://doi.org/10.1016/j.jtte.2019.09.001, special Issue: Modeling and detecting traffic dynamics: granular, pedestrian and vehicular flow, 2020.

Kölbl, R., Kozek, M., and Jakubek, S.: A Framework for Modal Split and Implications on Transport Growth and Travel Time Savings, Available at SSRN 4399513, uNDER REVIEW, 2023.

Kölbl, R. and Helbing, D.: Energy laws in human travel behaviour, in: New Journal of Physics, vol. 5, p. 48, 2003.

Larsen, J., El-Geneidy, A., and Yasmin, F.: Beyond the quarter mile: Re-examining travel distances by active transportation, Canadian Journal of Urban Research, 19, 70–88, 2010.

Levine, R. V. and Norenzayan, A.: The pace of life in 31 countries, J of cross-cultural psychology, 30, 178–205, 1999.

Liao, Y., Gil, J., Pereira, R. H., Yeh, S., and Verendel, V.: Disparities in travel times between car and transit: Spatiotemporal patterns in cities, Scientific reports, 10, 4056, 2020.

Lusiani, A., Sartika, E., Binarto, A., and Habinuddin, E.: Compatible Graphs on Traffic Lights Waiting Time Optimization, in: Proceedings of the International Seminar of Science and Applied Technology (ISSAT 2020), pp. 467–471, Atlantis Press, https://doi.org/10.2991/aer.k.201221.077, 2020.

N. Speisser, C. D. and Lab, S.: Impact of waiting times on pedestrians' and car drivers' behaviour at signalised intersections, in: Collection of open conferences in research transport (2018), 2018.

OpenSourceForEver: Penalty for traffic lights #675, https://github.com/osmandapp/OsmAnd-resources/pull/675, 2021.

OpenStreetMap contributors: OpenStreetMap, https://www.openstreetmap.org.

Prabuchandran, K., Hemanth Kumar, A., and Bhatnagar, S.: Multi-agent reinforcement learning for traffic signal control, in: 17th International IEEE Conference on Intelligent Transportation Systems (ITSC), pp. 2529–2534, https://doi.org/10.1109/ITSC.2014.6958095, 2014.

Rida, N. and Hasbi, A.: Traffic Lights Control Using Wireless Sensors Networks, in: Proceedings of the 3rd International Conference on Smart City Applications, SCA '18, Association for Computing Machinery, New York, NY, USA, https://doi.org/10.1145/3286606.3286791, 2018.

Rida, N., Ouadoud, M., Hasbi, A., and Chebli, S.: Adaptive Traffic Light Control System Using Wireless Sensors Networks, in: 2018 IEEE 5th International Congress on Information Science and Technology (CiSt), pp. 552–556, https://doi.org/10.1109/CIST.2018.8596620, 2018.

Shinde, S. M.: Adaptive traffic light control system, in: 2017 1st International Conference on Intelligent Systems and Information Management (ICISIM), pp. 300–306, 2017.

Spitzer, H., Hettinger, T., and Kaminsky, G.: Tafeln für den Energieumsatz bei körperlicher Arbeit, Beuth, 1982.

Tennøy, A.: Why we fail to reduce urban road traffic volumes: Does it matter how planners frame the problem?, Transport Policy, 17, 216–223, https://doi.org/10.1016/j.tranpol.2010.01.011, 2010.

Verma, A., Tandon, R., and Gupta, P. K.: TrafC-AnTabu: AnTabu routing algorithm for congestion control and traffic lights management using fuzzy model, Internet Technology Letters, 5, e309, https://doi.org/10.1002/itl2.309, 2022.

Walton, D. and Sunseri, S.: Factors Influencing the Decision to Drive or Walk Short Distances to Public Transport Facilities, International Journal of Sustainable Transportation, 4, 212–226, https://doi.org/10.1080/15568310902927040, 2010.

Wen, L., Çatay, B., and Eglese, R.: Finding a minimum cost path between a pair of nodes in a time-varying road network with a congestion charge, European Journal of Operational Research, 236, 915–923, https://doi.org/10.1016/j.ejor.2013.10.044, vehicle Routing and Distribution Logistics, 2014.

Wen, W.: A dynamic and automatic traffic light control expert system for solving the road congestion problem, Expert Systems with Applications, 34, 2370–2381, https://doi.org/10.1016/j.eswa.2007.03.007, 2008.

Wiering, M., Vreeken, J., van Veenen, J., and Koopman, A.: Simulation and optimization of traffic in a city, in: IEEE Intelligent Vehicles Symposium, 2004, pp. 453–458, https://doi.org/10.1109/IVS.2004.1336426, 2004.

Wiering, M. A. et al.: Multi-agent reinforcement learning for traffic light control, in: Machine Learning: Proceedings of the Seventeenth International Conference (ICML'2000), pp. 1151–1158, 2000.

Younes, M. B. and Boukerche, A.: Intelligent Traffic Light Controlling Algorithms Using Vehicular Networks, IEEE Transactions on Vehicular Technology, 65, 5887–5899, https://doi.org/10.1109/TVT.2015.2472367, 2016.

Zha, W., Guo, Y., Li, B., and Liu, D.: Individual Travel Based Transportation Mode Transfer Points Analysis and Identification, in: 2019 Chinese Automation Congress (CAC), pp. 2997–3002, https://doi.org/10.1109/CAC48633.2019.8996211, 2019.

Zhu, R., Li, L., Wu, S., Lv, P., Li, Y., and Xu, M.: Multi-agent broad reinforcement learning for intelligent traffic light control, Information Sciences, 619, 509–525, https://doi.org/10.1016/j.ins.2022.11.062, 2023.

Zourlidou, S., Golze, J., and Sester, M.: Traffic Regulation Recognition using Crowd-Sensed GPS and Map Data: a Hybrid Approach, AGILE: GIScience Series, 3, 22, https://doi.org/10.5194/agile-giss-3-22-2022, 2022.