Modeling multi-modal network equilibrium with active transportation and shared mobility

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To my parents, my wife, Yanting Shi, and my two sons, Michael and Leonard.

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Abstract

The imbalance between increasing travel demand by passengers and the stagnant growth of transportation infrastructure capacity, particularly in urban areas, has caused dramatic impacts on traffic condition, the environment, public health, and energy consumption. Consequently, the development of sustainable and resilient transportation systems has become an increasingly challenging task. Travel demand management (TDM) is a set of strategies aimed at redistributing travel demand in time or space to alleviate the imbalance between travel demand and available infrastructure capacities. Active transportation (AT), which includes walking and cycling, has emerged as a popular TDM approach in modern urban areas, with the potential to reduce vehicular travel (VT) demand and alleviate traffic congestion. However, potential barriers such as longer commuting times and adverse health effects, including exposure to hazardous air pollution and traffic injuries, often dissuade travelers from choosing AT. Therefore, understanding the complex relationship between AT and VT demand is crucial, especially when considering the health effects associated with these modes of transportation, such as the negative impact of air pollution and the benefits of physical activity.

Nevertheless, it is important to acknowledge that modeling active transportation in urban areas without considering the influence of Transportation Network Companies (TNCs), particularly the effects of enhancing vehicle occupancy through e-pooling and express pool services, can lead to biased findings. Hence, this study model the AT and VT traveling modes in a multi-modal network problem taking into account TNC services, such as, e-hailing, e-pooling, and express pool. The objective is to analyze passengers' choices among active transportation, solo driving, and TNC services, considering various trade-offs related to health, monetary, time, and inconvenience costs, and their subsequent impacts on traffic network performance. Given the non-separable and asymmetric nature of the disutility functions associated with multi-modal travel modes, the problem is formulated as a mixed complementarity problem. Accordingly, the discussion the existence and uniqueness of solution(s) are conducted based on the properties of equilibrium models in my dissertation.

By utilizing the proposed mathematical model, the study aims to assess the market share of active transportation, solo driving, and TNC modes at the equilibrium state, provid-

ing valuable insights for policymakers seeking to enhance mobility, energy efficiency, public health, and environmental outcomes. These components are integral to the establishment of a sustainable transportation system.

Chapter 1

Introduction

1.1 Research Background

The imbalance between the increasing travel demand of passengers and the stagnant growth of transportation infrastructure capacity (especially in urban areas) causes dramatic impacts on traffic congestion, air pollution, public health, and energy consumption [Afrin and Yodo, 2020, Mihyeon Jeon and Amekudzi, 2005]. From 1982 to 2017, the value of wasted fuel and delays due to traffic congestion increased from $15 billion to $179 billion in 494 U.S. urban areas [Schrank et al., 2019]. On- and off-road vehicle emissions contributed to more than 75% of carbon monoxide (CO) and 60% of nitrogen oxides (NOx), with as much as 90% of local CO emissions in large urban areas [Gately et al., 2017]. The urgency of balancing vehicle travel demand and transportation facility capacity has become a critical challenge in developing sustainable and resilient transportation systems.

Travel Demand Management (TDM) has emerged as a key strategy in these circumstances. TDM is a set of strategies, aiming to rebalance the scales between travel demand and the capacity of existing infrastructure by redistributing travel demand across time and space.[Luten, 2004]. Typical applications or policies of TDM strategies include carsharing, ridesharing, and bike or walking support programs.

Active transportation (AT), such as walking and cycling, is an important TDM strategy that can reduce vehicle travel demand and provide numerous benefits such as improved mobility, energy efficiency, and environmental sustainability [Gopalakrishna et al., 2012]. Additionally, AT also promotes public health by providing an opportunity for incidental physical activity in daily routines [Frank and Engelke, 2001]. When used in conjunction with pooling applications (e.g., express pool) in urban areas, AT can further improve vehicle utilization rates and save additional vehicle routing miles due to its ability to take advantage of shortcuts that vehicles cannot access. These benefits make AT a desirable commuting mode for sustainable transportation systems.

However, travelers may be hesitant to choose AT, despite its mobility and environmental benefits, due to potential longer commuting times and adverse health effects such as hazardous air pollution exposure and traffic injuries [Stinson and Bhat, 2004]. Furthermore, as users shift from AT to Vehicular Transport (VT), it can increase VT demand, resulting in higher hazardous air emissions and heightened injury risks that further discourage travelers from choosing AT for travel. However, as vehicular traffic congestion intensifies due to increased traffic flows, vehicular commuters may be incentivized to shift to AT, leading to less vehicular travel demand, reduced vehicle emissions, fewer potential traffic injuries, and decreased traffic congestion. The tradeoff between AT and VT can create a feedback loop cycle where the adoption of one mode affects the demand and attractiveness of the other.(see Figure 1.1.)

Figure 1.1. A cycle diagram illustrating affects between AT and VT

Given the interesting and complex relationship between AT and VT, it is critical to form a better understanding of the interactions between VT and AT in order to develop a sustainable transportation system. Yet, it is important to acknowledge that modeling active transportation in urban areas without considering the influence of Transportation Network Companies (TNCs), particularly the effects of enhancing vehicle occupancy through e-pooling and express pool services, can lead to biased findings.

The adoption of mobile technologies, such as smartphones and global positioning systems (GPS), has significantly reduced the matching and operation costs (i.e., detour) associated with shared mobility transportation services. As a result, emerging services such as ridesourcing and ridesharing have become increasingly popular among travelers. It is worth noting that the impacts of shared mobility on the transportation system can vary depending on the context and specific characteristics of each mode. For instance, carpooling and vanpooling have been found to have positive impacts on reducing vehicle miles traveled, fuel consumption, and greenhouse gas emissions [Shaheen et al., 2018].Additionally, three research papers [Xu et al., 2015, Ma et al., 2020, Li et al., 2020a] have developed theoretical models to explore the behaviors of drivers and passengers in ridesharing markets and analyze the impacts of network congestion. On the other hand, the impacts of ridesourcing services (i.e., Transportation network companies (TNCs)) on the transportation system are more complex and still under debate. The study by [Ban et al., 2019] develops models that integrate ridesourcing services into network equilibrium problems, and some other papers, such as [Di and Ban, 2019] and [Gu et al.], have combined ridesharing and ridesourcing services in theoretical studies. Recently, some empirical studies (e.g., [Hoffmann et al., 2016, Pan and Qiu, 2022, Jin et al., 2019]) have documented that ridesourcing attracts travelers who initially chose public transport for travel, potentially intensifying traffic congestion[Sutherland, 2019, Roy et al., 2020]. Based on this literature, recent studies (e.g., [Sun and Szeto, 2021, Li et al., 2018, 2020b]) have extended the equilibrium model and explored policy implications related to shared mobility, including solo driving and public transportation systems. However, the pooled ridesourcing services (such as e-pooling and express pool), with the potential to enhance vehicle occupancy, have not been thoroughly explored. Therefore, it is critical to form a better understanding of the interactions between VT and AT, taking into account the TNC services in order to develop a sustainable transportation system.

To address this research theme, my dissertation proposes a multi-modal network equilibrium model that includes AT and VT modes (including TNC services) to study user behaviors and the resulting impacts on traffic network congestion, environment, energy, and public health. The model can be calibrated using real-world data and used to explore efficient policies to curb vehicular travel demand and advance traffic sustainability. The problem is formulated as a complementarity problem due to the non-separable and asymmetric nature of the disutility functions associated with multi-modal travel modes. My study explores the existence and uniqueness of solution(s) based on the properties of equilibrium models. For the numerical study, the classical Sioux Falls network [Ukkusuri and Yushimito, 2009] is utilized, and open-sourced data or published behavior study results are referenced to set up the coefficients of associated terms for sensitivity analyses in order to observe the outcomes of traffic performance.

1.2 Motivation

The booming sharing economy advocates "mobility as a service" as a popular travel mode [Ho et al., 2018]. In the last few years, there has been a resurgence of interest in the investigation of shared mobility systems' impact on network equilibrium. Shared mobility(SM) potentially enables drivers to utilize vehicles and energy more efficiently and reduce traffic congestion accordingly through higher vehicle occupancy. Meanwhile, with the development of modern technologies, such as GPS and smartphones, the matching cost was reduced significantly, as did the operational cost. Therefore, app-based on-demand e-hailing and e-pooling services have started to emerge and prosper, and a possible shift from car ownership to "mobility as a service" is gaining attention among transportation scholars ([e.g., Xu et al., 2015, Ban et al., 2019, Di and Ban, 2019]).

However, the decreasing price of ride-sourcing introduces a possible competitive dynamic between SM and other more affordable travel modes, such as public transportation and active transportation. Several studies [Hoffmann et al., 2016, Pan and Qiu, 2022, Jin et al., 2019] have documented the competitive relationship between ride-sourcing and public transit in urban areas, particularly in city centers. These studies highlight that ride-sourcing services attract more travelers to on-road traffic, resulting in increased congestion levels and exacerbating traffic congestion issues. AT serves as another TDM application, offering significant benefits in terms of mobility, energy efficiency, and environmental impact, AT stands out due to its characteristics, including low space requirements and zero emissions, which contribute to reducing congestion and environmental pollution. Moreover, AT promotes public health, setting it apart from non-active transportation modes. However, in recent years, AT has been relatively overlooked in studies on the impact of vehicle networks, especially considering shared mobility (SM) applications, leaving the interaction among VT, AT, and SM largely unexplored. Recognizing this gap, my dissertation aims to fill this void by developing a comprehensive theoretical model that captures the intricate relationship among VT, AT, and SM. Through this model, this study delves into the complexities of their interaction and intend to derive policy insights that can enhance network performances and promote sustainable transportation practices.

To shed more light on the possible interactions between VT and AT, the proposed model is constituted for both the substitution (i.e., competition) and the complementary (i.e., cooperation) relationships between SM and AT. While AT may compete with VT for a trip, it can also become part of the trip and facilitate travelers' transfers from their origins to their destinations (e.g., express pool), complementing VT. The proposed analytical tool in my dissertation enables a comprehensive understanding of the complex interactions between different modes of transportation, including walking, cycling, solo driving, ride-sourcing, ride-pooling, and their combinations. Policymakers can calibrate the model with real-life data to assess the impact of specific policy changes in market shares of various traffic modes on aggregate vehicle mileages, network congestion, emissions, energy consumption, and public health outcomes. Thus, my research can inform potential policies to enhance the efficiency of existing transportation infrastructure and land use, promoting vehicle mobility, environmental sustainability, and public health, all crucial components of a sustainable transportation system.

1.3 Research Questions

By formulating mathematical models and conducting numerical analyses, my dissertation seeks to provide insights into the following inquiries:

- How will traveler preferences (in terms of values of time and etc.) change the market share of different transportation modes (e.g., bike, walk, solo driving, carpooling, ride-sourcing, ride-pooling, and their combinations) at a new equilibrium? Correspondingly, how will VMT, congestion, emissions, and public health performance change at the new equilibrium?

- In the cooperation scenario, upon the introduction of AT into the trip, how would the overall route mileage and congestion level of SM change? Does this impact vary depending on the stage at which AT is introduced in the trip, such as in the beginning, at the end, or in the middle?

- When considering both the benefits of increased physical activity and the negative effects of exposure to polluted air, how would the overall public health metric be influenced in cooperation or competition scenarios?

- Based on the insights gained from answering the previous questions, what policy implications can be drawn to promote an environmentally friendly, energy-efficient, and sustainable transportation system? For instance, would subsidizing walking or cycling trips contribute to improved public health outcomes and reduced VMT?

Chapter 2

Literature Review

The traffic assignment problem (TAP), also known as the problem of finding the Wardrop equilibrium [Wardrop, 1952] flow pattern over a given urban transportation network, refers to the challenge of determining the optimal travel demand distribution over network links, given a fixed supply of transportation infrastructure and a link performance function [Sheffi, 1985]. The Wardrop user equilibrium is achieved when the travel cost of each used path between the same origin and destination is minimized and equal for all modes, ensuring that no traveler has an incentive to deviate from their current mode or route selection. At equilibrium, the demand distribution over network links can be observed, providing insight into potential impacts on traffic congestion, as well as associated consequences related to the environment, public health, and energy consumption.

Beckmann et al. [1956] formulated a convex optimization problem in order to investigate traffic flow at user equilibrium. (see Equation 2.1)

$$\text{minimize} Z(x) = \sum_{a \in A} \int_0^{x_a} t_a(s) ds \tag{2.1a}$$

subject to

$$\sum_k f_k^\omega = q^\omega, \quad \forall \omega \in N \times N, \tag{2.1b}$$

$$f_k^\omega \geq 0, \tag{2.1c}$$

$$\sum_\omega \sum_k f_k^\omega \delta_{a,k}^\omega = x_a, \quad \forall a \in A, \tag{2.1d}$$

$$\delta_{a,k}^\omega = \begin{cases} 1, & \text{if route } k \in K^\omega \text{ uses link a} \\ 0, & \text{otherwise} \end{cases} \tag{2.1e}$$

where x_a is the flow on arc a, t_a is the travel time function of arc a. Let ω denote an O-D pair (o, d) for passengers, K is a path connecting the O-D pair ω and K^ω is a set of paths connecting the O-D pair ω, f_k^ω is the flow on path k connecting the O-D pair ω, C_k^ω is the travel time on path k connecting the O-D pair ω, q^ω is the travel demand of the O-D pair ω, $\delta_{a,k}^\omega = 1$ indicates if a link a is on path k between O-D pair ω, otherwise 0.

This formulation is the sum of the integrals of link performance functions $t_a(.)$, which take links' flow as variables. The equation Equation 2.1b indicates the summation of all the paths' flows between the O-D pair ω is equal to the demand q^ω. The equation Equation 2.1d indicates the relationship between path flow f_k^ω and link flow x_a through indicator variable $\delta_{a,k}^\omega = 1 \; or \; 0$. This formulation doesn't have intuitive economic or behavior interpretation but is constructed and utilized to solve the user equilibrium problem [Sheffi, 1985].

The Lagrangian transformation of the equivalent minimization problem with respect to the constraints in Equation 2.1 can be formulated as:

$$L(\mathbf{f}, \mathbf{u}) = Z[\mathbf{x}(\mathbf{f})] + \sum_\omega \eta_\omega (q^\omega - \sum_k f_k^\omega) \tag{2.2}$$

where η_ω is the dual variable associated with the demand constraints for O-D pair ω. Taking the first derivative of the Equation 2.2, the optimality condition of the convex formulation

Equation 2.2 can be expressed as:

$$f_k^\omega (C_k^\omega - u_\omega) = 0 \quad \forall k, \omega \tag{2.3a}$$

$$C_k^\omega - u_\omega \geq 0 \quad \forall k, \omega \tag{2.3b}$$

$$\sum_k f_k^\omega = q^\omega \quad \forall \omega \tag{2.3c}$$

$$f_k^\omega \geq 0 \quad \forall k, \omega \tag{2.3d}$$

The derivation process can be found in [Sheffi, 1985, chapter 3.2]. The equation of Equation 2.3 constitutes a complimentarity relationship [Facchinei and Pang, 2003]

$$\begin{aligned} 0 \leq f_k^\omega \perp C_k^\omega - u_\omega \geq 0 \quad \forall \omega \\ \sum_k f_k^\omega = q^\omega \quad \forall \omega \end{aligned}$$

so that:

$$\begin{cases} f_k^\omega > 0 \rightarrow C_k^\omega = u_\omega & \text{at equilibrium if the path k of the O-D pair } \omega \text{ has flow,} \\ & \text{then the travel time of path } k \text{ is the minimum travel time} \\ & \text{of the O-D pair } \omega. \\ f_k^\omega = 0 \rightarrow C_k^\omega \geq u_\omega & \text{at equilibrium if the path k of the O-D pair } \omega \text{ has no flow,} \\ & \text{then the travel time of path } k \text{ is greater than or equal to the} \\ & \text{minimum travel time of the O-D pair } \omega. \end{cases} \tag{2.4}$$

The model presented in Equation 2.1 is widely used in transportation studies because of its simplicity and easy interpretability. Moreover, its cartesian product structure allows for efficient solution algorithms using matrix operations. However, since the model does not consider link capacity constraints, the predicted traffic volumes on certain links may be excessively high [Sender, 1970]. This limitation reduces the usefulness of the model in helping policymakers and transportation professionals address urban planning problems.

2.1 Side constraints

An interesting variant is the user equilibrium model with side constraints. The side constraint was introduced to describe limitations on the availability of scarce resources (e.g., link capacities [Hearn, 1972]) to avoid exaggerated traffic volume prediction on links or to provide a numerical relationship between flows of different modes (e.g., favorable condition of certain travel mode as described in [Larsson and Patriksson, 1999]). The general form of the side constraint per link is

$$g_a(x) \leq 0 \tag{2.5}$$

which is added to the formula Equation 2.1 to form the general User equilibrium model with side constraints.

The Lagrange multipliers (i.e., auxiliary variables) of the inequality constraints Equation 2.5 are the shadow prices for the side constraints, which can be interpreted as the monetary cost that the traffic flow (i.e., travelers) willingness to pay (or earn) when the side constraints hold. Assuming (x^*, f^*) is a solution to a side-constrained traffic assignment problem. The derivative of $g_a(x)$ on a certain link a would equal to 1, if there is a flow on the link a at equilibrium. Since the shadow cost η_a^* has the complementarity relationship with side constraints $g_a(x) \leq 0$, such that $0 \leq g_a(x) \perp \eta_a \geq 0$, the cost of path k of the OD pair ω regarding the shadow price (i.e., resource limitation) can be expressed as:

$$\sum_{a \in k} \eta_a^* \left(\sum_{a} \delta_{a,k}^{\omega} \frac{\partial g(x^*)}{\partial x_a} \right) \tag{2.6}$$

Let's denote $f_k(f^*)$ as the path travel cost, the general cost (travel cost + cost (i.e., Lagrange multiplier)) could be expressed as:

$$\underbrace{F_k}_{\text{general cost}} = \underbrace{f_k(f^*)}_{\text{travel cost}} + \underbrace{\sum_{a \in k} \eta_a^* \left(\sum_{a \in k} \delta_{a,k}^{\omega} \frac{\partial g(x^*)}{\partial x_a} \right)}_{\text{cost due to resource limitation}} \tag{2.7}$$

Therefore, Equation 2.4 can be reformulated as:

$$0 \leq \underbrace{f_k(f^*)}_{\text{travel cost}} + \underbrace{\sum_{a \in k} \eta_a^* \left(\sum_{a \in k} \delta_{a,k}^{\omega} \frac{\partial g(x^*)}{\partial x_a} \right)}_{\text{cost due to source limitation}} \perp C_k^{\omega} - u_{\omega} \geq 0 \tag{2.8}$$

The shadow price (multipliers) are determined endogenously by giving the total demands (for fixed demand studies).

There is a series of papers [Larsson and Patriksson, 1994, 1995, Patriksson and Larsson, 1997, Larsson and Patriksson, 1999] that introduce the side constraints properties, solution algorithms, and application in transportation studies. Hearn [1972], as an early example, used side constraints to model link capacity for adding concrete link capacity effects:

$$l_a \leq x_a \leq u_a \tag{2.9}$$

$$l_a - x_a \leq 0 \ \text{ or } \ x_a - u_a \leq 0, \quad l_a, u_a \in \mathbb{R}^+ \tag{2.10}$$

where x_a is the traffic volume of link a, l_a is the required minimum traffic flow for link a, and u_a is the volume capacity of link a. Equation 2.9 can be normalized as a general form:

$$g(x_a) = x_a - \mu_a \leq 0, \quad \mu_a \in \mathbb{R} \tag{2.11}$$

where g(.) is convex (sometimes even affine) and continuously differentiable in general. μ_a is the general link-dependent capacity (a scalar). The complementarity condition is:

$$0 \leq x_a - \mu_a \perp \eta_a \geq 0 \tag{2.12}$$

Where, the η_a is the Lagrange multiplier (i.e., shadow price), which indicates the willingness to pay to have one more if $x_a = \mu_a$. According to different studies, the multiplier could have different interesting interpretations, they can be seen as link queuing length, tolls, or delays.

There are also applications that describe a favorable situation for public transits[Patriksson and Larsson, 1997], and the constraint is formulated as:

$$\gamma_a x_a^{pr} \le x_a^{pu},\ \gamma_a \ge 0 \tag{2.13}$$

Where, x_a^{pu} denotes the traffic flow of public transit on the link a, x_a^{pr} denotes the traffic flow of private vehicles, and γ_a is a preferred volume ratio of public transit to private vehicles. The multiplier could be interpreted as compensation to travelers to have this volume relationship.

Recently, Xu et al. [2015] proposed using the inequality side constraints to describe the integrated relationship between rideshare drivers and rideshare passengers on a link:

$$x_a^{rd} \le x_a^{rr} \le Cap\ x_a^{rd} \tag{2.14}$$

Where Cap is the capacity of a vehicle. The inequality constraints were used to ensure that the rideshare rider is at least served by one rideshare driver; the total number of rideshare riders on a serving vehicle is less than the vehicle's capacity. The innovative reformulation shed light on modeling ridesharing problems with an interesting interpretation of multipliers. The complementarity conditions are:

$$0 \le \eta^+ \perp x_a^{rd} - x_a^{rr} \ge 0 \tag{2.15}$$

$$0 \le \eta^- \perp Cap\ x_a^{rr} - x_a^{rd} \ge 0 \tag{2.16}$$

Further, the multipliers (η^+, η^-) of these two inequality constraints can be seen as the compensation (or penalty) for the limitation of ridesharing passenger volume.

Later, Ban et al. [2019] proposed using inequality constraints to describe the relationship between the supply and demand of TNCs' services at a node. The complementarity condition is described as:

$$0 \le \eta_i^{tnc} \perp \sum_{j \in D} Z_{ji}^{tnc} - Q_i^{tnc} \ge 0 \tag{2.17}$$

Where Z_{ji}^{tnc} is the number of available TNC vehicles driving from other trips destination j to the new origin of the new request i, Q_i^{tnc} is the demand of TNC vehicles at node i, and multiplier η_j^{tnc} was interpreted as the surge price that used to balance the supply and demand.

The introduction of side constraints enables modeling limitation of scarce resources and paves the road for complex network modeling problems. However, the Cartesian product structure of the feasible set in the original Beckman transformation [Sheffi, 1985] was lost while including side constraints in the formulation. Further, it is challenging to formulate the problem as an optimization problem while modeling the interaction between vehicles of different types. Therefore, it is desirable to formulate a computationally efficient model.

2.2 Variational Inequality

Variational inequality was initially developed to deal with equilibrium problems [Facchinei and Pang, 2003] and focuses on understanding and modeling the optimality or equilibrium condition instead of objectives and constraints. VI has found extensive practical applications, including traffic network equilibrium problems, due to its rich mathematical theory, effective solution algorithms, and numerous interesting connections to various disciplines[Facchinei and Pang, 2003].

Given a subset K of the Euclidean n-dimensional $\mathbb{R}^n$ and a mapping $F : K \to \mathbb{R}^n$, the variational inequility, denoted as $VI(K, F)$, is to find a vector $x \in K$ such that

$$(y - x)^T F(x) \geq 0, \quad \forall y \in K \tag{2.18}$$

A simple example of an application using VI is a convex optimization. Given a subset K of the Euclidean n-dimensional $\mathbb{R}^n$, for $x \in K$ and its feasible moving direction set: $S_{feasible}(x) = \{s \in \mathbb{R}^n : s = x' - x, x' \in K\}$ and the gradient descent set is $S_{descent}(x) = \{s \in \mathbb{R}^n : s^T \nabla f(x) < 0\}$, knowing that x^* is the solution, so that $\nabla f(x^*)^T (x' - x^*) \geq 0$ holds for the vector x^* at the optimal condition, which also means that $S_{feasible}(x^*) \bigcap S_{descent}(x^*) = \emptyset$.

In the context of optimization, a mixed complementarity model (MiCP) is a variation of the VI that incorporates both equality and inequality constraints with non-negative variables, and can be used to model a variety of real-world problems such as traffic equilibrium and market competition. The MiCP can also be formulated as a system of nonlinear equations with complementarity conditions, where the solution satisfies the equations and ensures that the complementary slackness conditions hold. The MiCP problem is defined as, for given vector-valued functions F: $\mathbb{R}^{m+n} \rightarrow \mathbb{R}^n$ and G:$\mathbb{R}^{m+n} \rightarrow \mathbb{R}^d$, the MCP is that of finding a pair of vectors $(x, y) \in \mathbb{R}^{n+m}$ satisfying $0 \leq x \perp F(x, y) \geq 0$ and $G(x, y) = 0$ with the former meaning the three conditions $x \geq 0, F(x, y) \geq 0$, $x^T F(x, y) = 0$, and y is free.

$$x \geq 0, F(x, y) \geq 0, x^T F(x, y) = 0, \; and \, G(x, y) = 0$$

Linearly constrained VI is commonly applied in network modeling studies because the network flow is usually positive and the demand function is usually assumed to be fixed or follows a linear relationship with a minimum travel time of an OD pair. In [Larsson and Patriksson, 1999], the authors proved the equivalence between linearly constrained VI and MiCP Equation 2.4. This equivalence provides network equilibrium modelers with a rich set of properties and computational tools (see [Dirkse and Ferris, 1995]).

2.3 Modeling Ridesharing in user equilibrium model

Xu et al. [2015] creatively used the inequality side constraint in the rideshare equilibrium study. The paper [Xu et al., 2015] focused on understanding the relations among ridesharing, solo driving, and network congestion in an open marketplace. The paper developed a general multiple-origin to multiple destinations network equilibrium model and initially proposed using inequality side constraints:

$$x_a^{rd} \leq x_a^{rr} \leq Cap \; x_a^{rd} \tag{2.19a}$$

$$\Rightarrow x_a^{rd} \leq x_a^{rr} \tag{2.19b}$$

$$\Rightarrow x_a^{rr} \leq Cap \; x_a^{rd} \tag{2.19c}$$

to describe the flow relationship between rideshare riders and rideshare drivers. The Equation 2.19b ensures if there is a rideshare rider at least there is a rideshare passenger; Equation 2.19c ensures the total number of rideshare riders on a serving vehicle is less than the vehicle's capacity. Due to the asymmetric disutility functions of passengers in these three travel modes, travelers have different route choice preferences according to network geometry and accordingly affect travel mode choices. To capture the vehicle routing result from different modes, the network was duplicated for three copies where each copy represents one traveler class (i.e., solo driver, rideshare driver, and rideshare rider). Because it is assumed that the system operates as an open marketplace and thus the ridesharing price will be determined by the market (without a central control agent) so that the carpool drivers are free to choose their routes on the network. Due to the asymmetric disutility function, the author formulated the model as a MiCP, and the existence and uniqueness of the problem were discussed accordingly in that paper.

In a pioneering work, [Ban et al., 2019] modeled the e-hailing service within a network equilibrium problem, and explored the competition relations between e-hailing and driving alone travel mode. The study modeled the e-hailing mode as a for-profit traveling mode and set the e-hailing service platform's goal as maximizing the total profit of the TNC company instead of maximizing monetary income for each TNC driver. By introducing the destination-to-origin demand, the model could capture the deadhead miles that e-hailing vehicles drive from the previous customer's destination to the origin of the upcoming customers. The paper made a significant contribution by developing a model to explore the complex competition and cooperation relationships between two distinct groups: solo drivers (treated as a group) and Transportation Network Companies (TNCs). The competition relation between solo drivers involves the maximization of their own benefits, while TNCs operate with a cooperation relation among all e-hailing drivers to achieve the goal of maximizing total profit. Another novel contribution of the paper was to model the relation between TNC demand and vacant available TNC vehicles as a side inequality constraint $\sum_{j\in D} Z_{ji}^{tnc} - Q_i^{tnc} \geq 0$, and interpret and apply the multiplier η_j^{tnc} (i.e.g, shadow price) of a side constraint as the additional monetary payment (i.e., surge price) in traveler's disutility function for equilibrium studies.

$$0 \leq \eta_j^{tnc} \perp \sum_{j\in D} Z_{ji}^{tnc} - Q_i^{tnc} \quad \Rightarrow \quad \begin{cases} \sum_{j\in D} Z_{ji}^{tnc} - Q_i^{tnc} = 0 & \eta_j^{tnc} > 0 \\ \sum_{j\in D} Z_{ji}^{tnc} - Q_i^{tnc} > 0 & \eta_j^{tnc} = 0 \end{cases} \tag{2.20}$$

Later, [Di et al., 2018] introduced the average vehicle occupancy ratio for riding fare calculation, which was calculated based upon the volume of rideshare passengers in [Xu et al., 2015]. Another contribution of the paper to rideshare equilibrium modeling is that it reformulated the rideshare equilibrium model, proposed in [Xu et al., 2015], into a link-node-based model. The reformulated model cut off the steps of iterating all paths from a pair of origin and destination, thereby reducing the computational burden in the pre-processing step. The existence and uniqueness of the reformulated model were proven using the properties of the complementarity models [Facchinei and Pang, 2003]. Di's paper also further explores the benefits of using High Occupancy Toll (HOT) lanes in a rideshare environment, which provides policy insights for policymakers on the pricing scheme considering rideshare travel mode.

[Di and Ban, 2019] incorporated both carpool and Ride-sourcing modes into the traffic equilibrium problem and reformulated the link-path-based model into the link-node-based model to comprehensively understand the interaction among solo driving, carpooling, and e-hailing travel modes.

Instead of using the aggregated link flows relations of rideshare drivers and passengers to represent the matching relationship roughly, [Li et al., 2020a] explicitly formulates the one-to-one matching decisions of ridesharing riders and drivers in an equilibrium problem in road networks. By adding both the passenger and rider's scripts on the control variables (i.e., path flow variable), the model could describe a driver who either travels as a solo driver between OD pairs or serves as an e-hailing driver to pick up which passenger along his path. However, the paper doesn't consider pooling or transfer mechanisms due to the significant increase in computational complexity.

Not like [Xu et al., 2015], which uses inequality constraints to describe the capacity relations between carpool vehicles and carpool passengers, [Ma et al., 2020] proposed a matching constraint to describe the restriction of shared riding seats, thereby each type of rideshare drivers (e.g., with one passenger, two passengers, etc.) is matched with a corresponding integer number of riders.

The waiting time (i.e., vehicle pick-up time) is critical for passengers in choosing travel mode. The inconvenience cost in [Xu et al., 2015] included the waiting penalty. Since the authors assume that more passengers mean more waiting and detours (i.e., inconvenience cost), inconvenience cost is positively associated with rideshare passenger flow. [Li et al., 2020a] followed setting of inconvenience cost in [Xu et al., 2015] for their equilibrium model. Furthermore, [Ban et al., 2019, Di et al., 2018, Di and Ban, 2019] used the routing time of vacant vehicles as the waiting time to explore the new equilibrium. However, due to the significant increase in complexity, these papers applied the average waiting time of the entire network in the disutility function instead of using the time that a specific person spent waiting for the matched vehicle. Noruzoliaee [2018] modeled equilibrium with a mixed autonomous/human driving environment. In the paper, the authors assumed that passengers need to match with vehicles with seats available at any transfer point; thereby, two kinds of waiting for penalties, search friction cost and extra waiting cost, are considered in their study. The search friction cost followed the literature [Yang et al., 2010] used the number of available taxis or customers at a node to derive the meeting rate m for search friction cost and the multiplier of the inequality between requesting customers and available taxis at a node to represent the extra waiting cost for customers. [Chen and Di, 2021] adopted this setting in their paper for congestion tolling study. Later, Noruzoliaee and Zou [2022] extended the study into a pooling-allowed (many-to-many matching) scenario.

Recently, [Gu et al.] developed a traffic equilibrium with shared mobility services coupling morning-evening commutes together. This paper pioneers considering the interrelationship between morning and evening travel demand. For example, considering only driving, carpooling, and ride-sourcing choices, travelers who have taken a carpool or ride-sourcing for a morning commute can only choose carpool or ride-sourcing traveling back to their houses. Therefore, the choice of evening traveling highly depends on the mode travelers took for the morning itinerary. In the ridesharing equilibrium model, they added the equality constraint

$$\sum_m q^m_{i,morning} = \sum_m q^m_{i,afternoon} \quad m \in \{ridesourcing, carpooling\} \tag{2.21}$$

$$q^{solo}_{i,morning} = q^{solo}_{i,afternoon} \tag{2.22}$$

to describe the demand relations between morning and afternoon commutes. The study provided insights into the equilibrium problem with both spatial and temporal demand restrictions.

[Li et al., 2018] added public transit into the rideshare (i.e., carpool) user equilibrium; thereby, the model includes solo driver, rideshare driver, rideshare passengers, and transit passengers. For public transit passengers, disutility is defined as the summation of travel time, bus fare, and bus crowdedness impact. The crowdedness impact mainly reflects the passengers' discomfort while in a crowded bus or subway carriage. Later, [Li et al., 2020b] added subsidy or monetary penalty on pooling or solo drivers, respectively, to represent the HOT lane setting in the network. The big difference between this paper to the rest of the papers that study rideshare user equilibrium is that this paper assumed the path cost is not simply the summation traversed link cost [Gately et al., 2015] (e.g., not a linear function of the total travel time). This nonadditive problem was raised in [Gabriel and Bernstein, 1997]. The consideration of nonlinear cost function stems from observations of New Jersey highway tolls. Because time and monetary costs (tolls) are the main contributors to travel costs, there is no linear relationship between high-speed tolls and distance traveled. Later, [Sun and Szeto, 2021] proposed a logit-based multi-class stochastic ridesharing user equilibrium model. In their study, the model incorporates different policies such as car restrictions, cordon tolling, and subsides. The paper used a formulation similar to the classic BPR model with different parameter settings to describe the relationship between the number of passengers and public transportation travel time. There are also other studies that focus on the interaction among solo driving, rideshare, and public transit. However, in these studies, public transit is assumed to have constant cost, which is associated with the length of the travel route.

In conclusion, there are two pioneering works, Xu et al. [2015] and Ban et al. [2019], in modeling rideshare and ride-sourcing modes in the network equilibrium context. There are also variants focusing on different aspects of the study, such as scenario setting (i.e., [Gu et al.]), passenger to capacity ratio (i.e., [Ma et al., 2020]), detail routing info (i.e., [Li et al., 2020a]), and even interactions among different shared mobility modes (i.e.,[Di and Ban, 2019]). However, there is a void in the literature regarding the interaction between AT and VT (including SM) modes.

2.4 Modeling active transportation

Cycling and walking are considered sustainable and environmentally friendly modes of transportation that can help reduce traffic congestion, greenhouse gas emissions, and air pollution in urban areas. In transportation modeling, cyclists or pedestrians are often represented as an integrated flow on links, reflecting the fact that they share infrastructure with other modes of transportation.

For example, [Liu et al., 2019] defined link bicycle flow as variables and assumed bicycle paths are on or adjacent to roadways but are physically separated from motorized traffic within the existing urban network. The paper focused on the optimal network design problem of bike paths. The problem seeks to maximize the total route utilities of cyclists and capture their actual route choice behavior using a path-based logit model. A mixed-integer nonlinear nonconvex model was developed for the problem and was reformulated and linearized into a mixed-integer linear program. The program is solved with a global optimization method and a metaheuristic. Results are provided to illustrate the performance of these methods and the model properties.

With the emergence of bike-sharing programs, the usage of bikes increased, which gave rise to the attention of designing bike-sharing systems. To investigate the cyclists' behavior while facing the different bike-sharing operating rules or pricing mechanisms, researchers proposed cycling or pedestrian disutility functions by taking the volume of cyclists or pedestrians as input. Stinson and Bhat [2004] conducted an internet-based survey analysis and documented that the distance between home and work location, region of residence, and season have important effects on the propensity to commute by bicycle. Individuals residing and working in more dense areas (urban areas) have a higher likelihood of commuting to work by bicycle, presumably because of better bicycle-related infrastructure. Some other papers, such as [Heinen et al., 2013, Winters et al., 2011, Fukushige et al., 2021, Ferri-García et al., 2020], confirmed these findings. Therefore, travel time is assumed to be the main concern when choosing a bike for travel. For example, [Zhang and Liu, 2021] studied the strategic interaction and potential integration between bike sharing and the metro system, including walking as an alternative. A bi-level model was proposed to investigate the interaction as the upper level for system-wise optimization and the lower level as a static user equilibrium model. For the utility function, both walking and bike cost are assumed to increase monotonically as the volume of the walker or cyclist increases. The analytical and numerical results show that bike-sharing and metro systems are complementary to each other, that bike-sharing systems raise the attraction of metro systems, and metro system can help reduce the total social cost even if the operator maximizes its profit. However, under the elastic demand assumption, the system has a significant welfare loss when the bike-sharing system maximizes its profit.

[Zhang et al., 2019] studied dynamic pricing scheme for rebalancing bike sharing system. A negative pricing strategy (i.e., monetary subsidy) was introduced to incentivize bicycle riders to ride bikes from oversupplied to undersupplied areas. If the bike trip starts from an oversupplied area to an under-supplied one, the negative price will apply; otherwise, the normal positive price will be adopted. Different from [Zhang and Liu, 2021], the disutility for active transportation considered travel time, discomfort, and monetary cost (no monetary cost on walk link) three aspects. Especially for the travel time disutility, the paper adopted the bi-direction flow interaction impedance that was proposed in [Wu and Lam, 2003]. Discomfort cost is the travel time times a coefficient. A variational inequality model was proposed to explore the dynamic of traffic assignment on the network. The study result indicated that the free price and the negative price could both attract more users due to the low cost compared to the positive price. Free prices could only speed up the bike usage rate but further enlarge the gap between supply and demand at the same time, which is challenging for operators to improve service quality. In particular, travelers will change their paths and modes under NP to relocate the bikes, which decreases the average trip distance. Indeed, the number of used links and the average trip distance is both the smallest for NP implementation.

However, the literature has largely neglected the important influence of biking's health effects. A survey conducted in [Stinson and Bhat, 2004] found that the primary motivations for commuting by bicycle were the health and fitness benefits, the enjoyment of using a bicycle, and the perception of contributing to environmental concerns. Another study [Akar and Clifton, 2009] carried out a web-based survey to investigate the travel patterns and concerns of cyclists on the University of Maryland campus, and found that raising awareness of the health benefits of cycling may encourage more people to view cycling as an opportunity for exercise.

2.5 Modeling health impact in equilibrium models

As we delve into the impact of active transportation on health, it is essential to comprehensively examine both positive and negative facets of health-related changes. One critical negative aspect is the exposure to polluted air, which poses a significant health risk to those who engage in active transportation. The issue of urban air pollution has gained traction due to its contribution to over 4.2 million deaths annually, as reported by the World Health Organization [World Health Organization (WHO), 2021]. Numerous studies have indicated that exposure to vehicular emissions can lead to severe health problems, including headaches, respiratory diseases, and cardiovascular diseases, even when pollutant concentrations are below government-mandated thresholds [Xing et al., 2016, Burnett et al., 2018, Burns et al., 2020, Di et al., 2017]. Therefore, understanding the relationship between urban traffic emissions and human health is crucial in determining the net health impact of active transportation.

In [Zhang and Batterman, 2013], traffic congestion increases vehicle emissions and degrades ambient air quality, and recent studies have shown excess morbidity and mortality for drivers, commuters, and individuals living near major roadways. The study applied simulation modeling to predict hazardous emissions. The simulation model applied both the Comprehensive Modal Emissions Model (CMEM) and MOBILE6.2 in the estimation of NO_x. The NO_x was chosen as the emission measurement since traffic is its major contributor. The California Line Source Dispersion Model version 4 (CALINE4) was applied to understand the emission damage to both travelers and residents near the congestion area due to the dispersion. The study results showed that additional traffic could significantly increase risks, especially for an arterial road; incremental risks increased sharply for both on- and near-road populations as traffic increased. The study also suggested evaluations of risk associated with congestion must consider travel time, the duration of rush-hour, congestion-specific emission estimates, and uncertainties. Pm 2.5 is another very critical emission component, but both CMEM nor MOBILE6.2 did not cover the impact of Pm 2.5, which could be a future work within this literature.

[Tan et al., 2021] developed a dynamic framework that integrated a time-dependent macroscopic emission model that was proposed in Wallace et al. [1984], the double-queue model [Ma et al., 2014] and the extended Gaussian dispersion model of a line source that developed based upon [Benson and CALIN, 1984]. A dynamic system optimization problem that considers the impacts of vehicular emissions on human health (DSO-HE) is established to minimize the total emission exposure. A numerical study result proves that dynamically managing network traffic can reduce regional emission exposure. Further, the result also indicates that traffic congestion and emissions (exposure) can be minimized simultaneously may not be true under any conditions, and traffic professionals need careful consideration to leverage the tradeoff between congestion and emissions. Nevertheless, the network system's performance may be affected by the omission of additional factors in the objective function, beyond congestion and emissions.

[Sun et al., 2018] proposed a different scenario that assumes there are three types of travelers that one type only consider travel time as their disutility and behave selfishly, the second type of travelers are also selfish player, but environmental advocates and their route decisions are based on travel time, and emission exposures and the third type of travelers behaved as a group, and the goal is to minimize the total cost. The experimental results showed that the route choice behaviors had been changed by considering the emission exposure cost in the cost function. Further, at a certain level of concern (by adjustment of exposure parameters), cooperative behaviors lead to better system performance.

In conclusion, as an emerging TDM strategy, shared mobility has been studied in different scenarios, such as with solo drivers and interaction between Carpooling and e-hailing services, using VI with side constraints. However, there is a void in the literature regarding the complex interaction between shared mobility and active transportation modes, especially when jointly considering the health effects. Understanding the interactions between two traffic modes sheds light on policies aiming to curb traffic congestion and advance traffic sustainability. Therefore, this study would fill this gap by modeling the AT and SM using VI models and provide policy implications for an environmentally friendly, energy-efficient, and more sustainable transportation system.

Chapter 3

Same OD pairs models

In this chapter, a game-theoretic model is proposed to capture the interaction among active transportation, vehicular transport(including shared mobility modes), and network performance. The game comprises two stages: mode choice and route choice. Unlike previous studies, the impact of total VMT on vehicle emissions is considered, which in turn affect health outcomes. Therefore, the disutility (i.e., general cost) associated with mode and route choice accounts for both network congestion and health effects (see Figure 3.1 as a reference). This approach allows for a more comprehensive assessment of the costs and benefits of different modes and routes.

Assuming that participants are rational and self-interested, they will choose the most economical mode and route that minimizes their disutility. The game will converge to an equilibrium where no one has the incentive to deviate from their current choices. By considering the health effects of pollution exposure and the relationship between VMT and emissions, the model provides a framework for evaluating the net health impact of active transportation under different policies.

In this study, a fixed demand scenario is considered, where a predetermined amount of travel demand must be assigned to the network for each origin-destination (OD) pair. Travelers are required to choose a single travel mode to meet their travel demand. This study focuses on the demand for cyclists as the active transportation mode, specifically examining flows that utilize roadway space instead of pedestrian sidewalks. Regarding shared mobility, the analysis centers on ride-sourcing services in urban areas, since the other important shared moibility application, carpooling, has the relatively low market share (Ellis et al.,

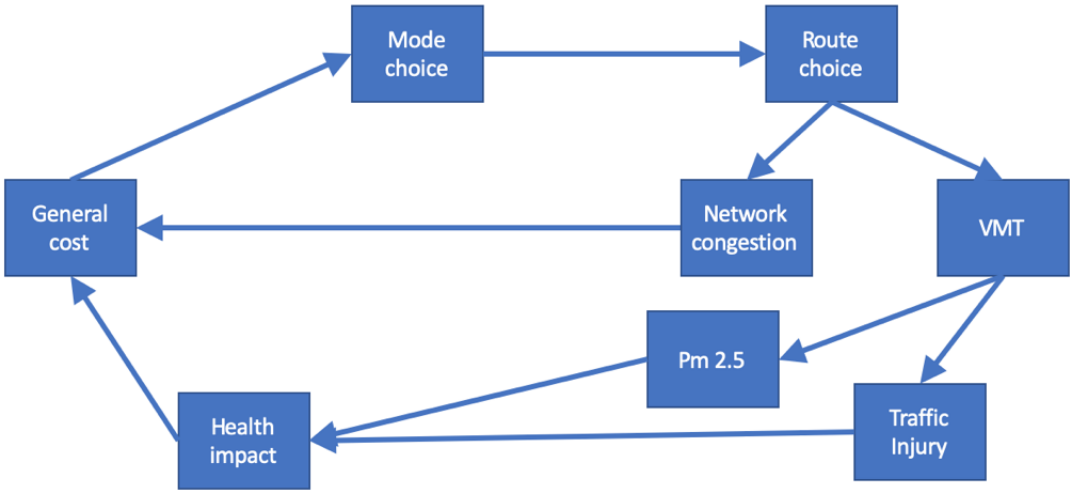

Figure 3.1. The influence diagrams

2019). Consequently, three travel modes are considered in this study: driving alone, taking a Transportation Network Company (TNC) vehicle, and cycling.

3.1 Problem Description

Given a directed network G(N,A) with a set of nodes, N, and a set of arcs A. Let W denote a set of O-D pair (o, d) for passengers, where $(o, d) \in N \times N$, $o \neq d$, $o \in O$, where O is a set of origin nodes and $O \subseteq N$, $d \in D$, where D is a set of destination nodes and $D \subseteq N$. ω is one pair of O-D pairs, where $\omega \in N \times N$ and $\omega \in W$, and K^ω is the set of simple paths connecting the O-D pair ω, and each simple path k is composed of a sequence of arcs that has no cycles. $\delta^\omega_{a,k}$ is the arc-path incidence indicator that $\delta^\omega_{a,k} = 1$ indicates the link a is part of the link k, otherwise $\delta^\omega_{a,k} = 0$.

Given the total demand q^ω of an O-D pair ω, the f^ω_k is the traffic flow on path k, and $f^{\omega,m}_k$ is the traffic flow of travel mode m, the path traffic flow and the travel demand of the OD pair of ω has:

$$q^\omega = \sum_k f^\omega_k = \sum_m \sum_k f^{\omega,m}_k, \quad k \in K^\omega \tag{3.1}$$

Let x_a denotes the flow on arc a, and x_a^m denotes the flow of travel mode m on arc a, then,

$$x_a = \sum_m x_a^m = \sum_\omega \sum_{k \in K^\omega} \delta_{a,k}^\omega f_k^{\omega,m} \tag{3.2}$$

By defining the link travel time function as $c(.)$, then link travel cost C_a is expressed as:

$$C_a = c(x_a), \quad a \in A \tag{3.3}$$

And a path travel cost C_k^ω of a certain O-D pair ω:

$$C_k^\omega = \sum_a \delta_{a,k}^\omega C_a, \quad k \in K^\omega \tag{3.4}$$

Therefore, a flow pattern $E(q)$ compatible with the above equations is in equilibrium if :

$$f_k^{\omega,m} > 0 \rightarrow C_k^{\omega,m} = u_\omega \tag{3.5}$$

$$f_k^{\omega,m} = 0 \rightarrow C_k^{\omega,m} \geq u_\omega \tag{3.6}$$

Where u_ω is the minimum travel cost of the OD pair ω.

3.2 Scenario Settings and Assumptions

In this chapter, the primary focus is on three modes of transportation: solo driving, TNC services, and bicycling. However, within the category of TNC services, there are three distinct types of services that are examined:

- **Normal ride** The normal ride service involves one vehicle serving one request, where the request can have multiple passengers but not exceeding the vehicle's capacity. Trips under this mode typically have a single origin and destination, and there is no requirement for passengers to walk.

- **Pooling** The pooling strategy matches multiple groups of riders to one vehicle that is heading in a similar direction at the same time.

- **Express pooling** The express pool option is similar to the pooling strategy but incentivizes riders to walk to a designated meeting point instead of being picked up directly at their requested location. In exchange for their walking distance, riders receive monetary rewards.

Several other assumptions are taken into consideration in this study:

- TNCs are assumed to be readily available throughout the network, allowing travelers to be promptly served upon requesting a ride, without the need to wait for a TNC vehicle to arrive from other nodes.

- TNC drivers have the flexibility to choose among offering normal rides, pooling rides, or express pooling rides at the start of a trip but cannot change the type of service during the trip. Once a trip begins, drivers are not allowed to pick up or drop off any passengers in the middle of their route.

- In this part of the analysis, all travelers are assumed to possess bicycles and have the choice to travel as cyclists for their trips. Since the focus is solely on flows that utilize roadway space, cycling is considered as the only active transportation mode that facilitates travel from origin to destination.

- Similar to the active transportation settings, all travelers are assumed to have private vehicles and have options to travel as solo drivers for their trips.

- The total number of travelers of any origin-destination (OD) pair remains constant.

- Cyclists have access to dedicated cycling lanes that are separated from vehicular traffic lanes, which means that their travel time is only dependent on the distance of the route they choose.

- All TNC vehicles are homogeneous with a vehicular capacity of two.

3.3 Notations

Below is a list of notations used to formulate the problem in this study:

Table 3.1. Basic Notation

$G : \{N, A\}$	a graph G with numbered nodes, N, and numbered arcs, A
O,	set of origin nodes; $O \subseteq N$
D,	set of destination nodes; $D \subseteq N$
ω	one pair (o,d) for passengers, where $\omega \in W$
W	a set of O-D pair (o,d) for passengers $\subseteq N \times$ N, $o \in O$, and $d \in D$.
where $o \neq d$	
k^ω	the path k of the O-D pair ω
K^ω	a set of paths connecting the O-D pair ω
q^ω	demand of the O-D pair ω for participants
q^ω_m	demand of the O-D pair ω for participants using mode m
f^m_k	flow on path k by using travel mode m
x_a	link flow on the link a
x^m_a	link flow on the link a using mode m
c^m_a	link cost of link a by using travel mode m
l_a	length of the link a
$\delta^\omega_{a,k}$	link-path incidence indicator between link and path
Δ^ω	incidence matrix where $\Delta^\omega = \{\delta^\omega_{a,k}, a \in A, k \in K^\omega, \omega \in W\}$
t^0_a	free flow travel time of link a
CAP_a	capacity of link a
A, B	coefficients of the BRP model
Cap	vehicle capacity by assuming vehicles are
	all homogeneous in terms of transport capacity

3.4 Participants and relations

The network is duplicated into multiple layers to accommodate the traffic flow of the following participants:

- solo driver
- cyclist
- normal passenger on one-passenger vehicles
- normal pool passengers on two-passenger vehicles
- express passenger on one-passenger vehicles

- express pool passenger on two-passenger vehicles

Let x_a^s and x_a^c reflect the flow of solo driver and the flow of cyclist on link a, respectively. Accordingly, let $x_a^{nr,i}$ and $x_a^{er,i}$ each denote normal passenger and express pool passengers on a vehicle with i number of passengers. Given the assumption that all TNC vehicles are homogeneous with a maximum capacity of two passengers, an occupied TNC vehicle would have either one or two passengers for normal ride or pooling ride services, respectively. let's denote $x_a^{rd,i}$ as the volume of TNC vehicles or drivers working as normal rides when $i = 1$; and as pooling rides when $i = 2$. A similar setting applies to express pool services. Therefore, the matching relationship between TNC passengers and TNC vehicles can be described as follows:

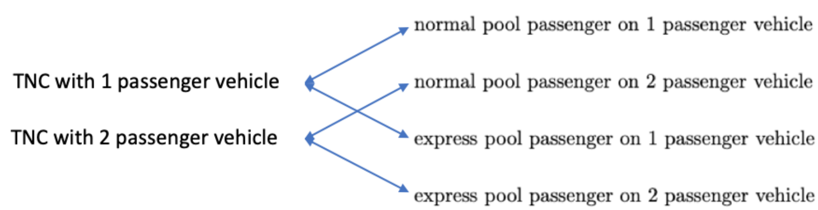

Figure 3.2. Matching relationship between passengers and vehicles of TNC

Let $x_a^{r,i}$ denote the total number of passengers on one passenger TNC vehicle on link a. For each link, the total number of passengers can be described as $x_a^{r,i} = x_a^{nr,i} + x_a^{er,i}$. Because i is used to indicate the number of passengers on a certain type of TNC vehicle, the relationship can be expressed as follows:

$$x_a^{nr,i} + x_a^{er,i} = x_a^{r,i} = i \cdot x_a^{rd,i} \tag{3.7}$$

Since bicycles are assumed to use separate lanes, only vehicles contribute to the vehicle traffic flow and congestion. Therefore, the traffic flow of link a consists of both TNC drivers and solo drivers:

$$x_a = \sum_i x_a^{rd,i} + x_a^s \tag{3.8}$$

and

$$x_a = \sum_m x_a^m = \sum_\omega \sum_k \delta_{a,k}^\omega f_k^{m,\omega}, m \in \{(rd,1),(rd,2),s\}\ , k \in K^\omega. \tag{3.9}$$

3.5 Arc travel time cost function

In this study, the classic BPR (Bureau of Public Roads) function is utilized as the arc travel time function.

$$t_a(x_a) = BPR(x_a) = t_a^0[1 + A(\frac{x_a}{CAP_a})^B] \tag{3.10}$$

$$\tag{3.11}$$

The amount of flow on arc a is the sum of the number of drivers (both TNC and solo drivers) x_a on arc a

$$x_a = \sum_i x_a^{rd,i} + x_a^s \tag{3.12}$$

So, the link travel time can be expressed as:

$$t_a(x_a) = BPR(x_a) = t_a^0[1 + A(\frac{\sum_i x_a^{rd,i} + x_a^s}{CAP_a})^B] \tag{3.13}$$

Furthermore, from Equation 3.7, one can derive:

$$x_a^{rd,i} = x_a^{r,i}/i = (x_a^{nr,i} + x_a^{er,i})/i \tag{3.14}$$

Therefore,

$$t_a(x_a) = BPR(x_a) = t_a^0[1 + A(\frac{x_a^s + \sum_i(x_a^{nr,i}/i + x_a^{er,i}/i)}{CAP_a})^B] \tag{3.15}$$

Unlike normal TNC or solo drivers, the express pool mode has a distinct impact on congestion. [Stiglic et al., 2015] have explored the benefits of picking up passengers at meeting points instead of letting passengers wait at the requesting point(i.e., express pool). The findings indicate that the use of express pool reduces vehicle mileage by decreasing the detour of picking up passengers, resulting a lower contribution to congestion. Based on their results, It is assumed that an increase in the number of express pool vehicles leads to reduced congestion due to fewer vehicle detours. To capture this effect, the following modified travel time function is used:

$$t_a^e(x_a) = BPR(x_a) = t_a^0[1 + A(\frac{\gamma^i(x_a^s + \sum_i(x_a^{rr,i}/i + x_a^{er,i}/i))}{CAP_a})^B],\ 0 < \gamma^i \leq 1 \tag{3.16}$$

where γ^i is the coefficient of vehicle flow on arc a.

It is assumed that express passengers walk to the picking-up point (see figure Figure 3.3). Accordingly, $t_a - t_a^e$ represents the time spent by express passengers on walking outdoors. To minimize the waiting time at the picking-up point by either the vehicle or by the express passenger, it is natural to assume that the walking time is equivalent to the time saved by the vehicle, as it doesn't have to travel to the passenger's original requesting point. Where walking time t_a^w is:

$$\begin{aligned} t_a^w =& t_a(x_a) - t_a^e(x_a) && (3.17) \\ =& t_a^0[1 + A(\frac{(x_a^s + \sum_i(x_a^{rr,i}/i + x_a^{er,i}/i))}{CAP_a})^B] - t_a^0[1 + A(\frac{\gamma^i(x_a^s + \sum_i(x_a^{rr,i}/i + x_a^{er,i}/i))}{CAP_a})^B] && (3.18) \end{aligned}$$

where $0 < \gamma^i \leq 1$.

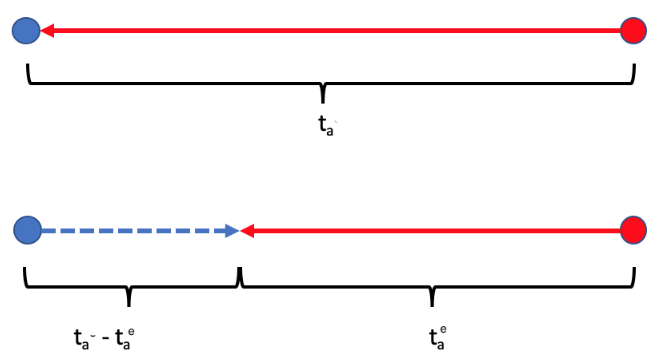

Figure 3.3. The illustration of meeting point for express pool

3.6 Emission cost function

In line with the prevalent approach in health model studies, a linear relationship between vehicle miles traveled (VMT) and emission levels is assumed in this study. This assumption is widely adopted due to its commonality and allows for a straightforward analysis of the relationship between these factors. Specifically, the emissions from vehicles on a particular link, denoted as E_a, are modeled to be directly related to the number of vehicles present on that link:

$$\underbrace{E_a}_{\text{vehicle emission}} = \epsilon_e f_a l_a, \tag{3.19}$$

where ϵ_e is the conversion coefficient, f_a is the traffic flow on link a, and l_a is the link length.

3.7 General cost functions for travelers

Solo driver

It is assumed that each traveler has the option to drive alone using their private vehicle. As a result, their cost of traveling consists of both a travel time-based cost and a distance-based cost, which are described as follows:

$$C_a^s = \underbrace{\alpha_1^d t_a}_{\text{travel time based cost}} + \underbrace{\beta_1^d l_a}_{\text{distance based cost}} \tag{3.20}$$

Where t_a is the travel time of link a, and α_1^d and β_1^d are respective conversion factors from travel time and travel distance to cost for solo drivers.

Normal pool passenger

For normal pool passengers, it is assumed that they wait indoors to minimize their exposure to air pollution. As a result, their general cost function does not include a term that captures their disutility from being exposed to emission pollution.

$$C_a^{nr,i} = \underbrace{\alpha_1^r t_a}_{\text{travel time based cost}} + \underbrace{\alpha_2^n t_a}_{\text{travel time based fare}} + \underbrace{\beta_2^n l_a}_{\text{distance based fare}} + \underbrace{(i-1)\lambda^{nr} t_a}_{\text{inconvenient cost}} \tag{3.21}$$

where i is a constant describing the number of passengers in the car, α_1^r is the conversion factor from travel time to cost for normal pool passengers, α_2^n and β_2^n are time- and distance-based riding fare rate for normal pool passengers, and λ^{nr} is a conversion factor from time to cost. The inconvenience cost captures the impatience of passengers regarding the picking up and dropping off of other fellow travelers during the trip. Since passengers only experience delays during the pick-up and drop-off of other fellow travelers, a $i-1$ multiplier is included in the inconvenient cost. This multiplier accounts for the additional inconvenience caused by additional pick-up or drop-off along the route .

The four aforementioned cost elements can be further categorized into two groups: travel time-associated cost and travel distance-associated cost, as follows:

$$C_a^{nr,i} = \underbrace{t_a(\alpha_1^r + \alpha_2^n + (i-1)\lambda^{nr})}_{\text{Travel time associated cost}} + \underbrace{\beta_2^n l_a}_{\text{Travel distance associated cost}} \tag{3.22}$$

Express pool passenger:

Unlike normal passengers, express passengers take walks to the meeting points instead of waiting at the requested points. Outdoor walking generates health benefits for express poll passengers but also exposes them to harmful vehicle emissions. Therefore, the express pool passenger's general cost function is described as follows:

$$\begin{aligned} C_a^{er,i} = & \underbrace{\alpha_1^r t_a}_{\text{travel time based cost}} + \underbrace{\alpha_2^e t_a}_{\text{travel time based fare}} + \underbrace{\beta_2^e l_a}_{\text{distance-based cost}} + \underbrace{(i-1)\lambda^{er} t_a}_{\text{inconvenient cost}} - \underbrace{\epsilon_w^b (t_a - t_a^e)}_{\text{PA benefit}} \\ & + \underbrace{\epsilon_w^e E_a (t_a - t_a^e)}_{\text{Pollution exposure}} \end{aligned} \tag{3.23}$$

where α_1^r is a conversion factor from time to cost for express pool passengers, α_2^e and β_2^e are the time- and distance-based riding fare rates for express pool passengers. λ^{er} is a conversion factor from time to cost. A similar logic for the inconvenient cost of normal pool passengers is applied to the inconvenient cost of express pool passengers here. ϵ_w^b is a conversion factor from health benefits to monetary gain. This kind of conversion was first proposed in the Health economic assessment tool (HEAT) [Kahlmeier et al., 2011]. ϵ_w^e is an exposure factor that converts the air pollution exposure to cost. E_a is the vehicle emission on link a.

Assuming that the total damage of exposure to air pollution depends on the time spent outdoors, the disutility for express pool passengers due to air pollution exposure during their walks is modeled using the time traveled outdoors and the conversion factor ϵ_w^e. This factor represents the impact of air pollution exposure on their overall disutility. However, walking also generates health benefits due to physical activities. Furthermore, it is assumed that the health benefit is linearly associated with walking time. Therefore, the total benefit due to walking is expressed as $\epsilon_w^b(t_a - t_a^e)$, where ϵ_w^b represents the conversion factor from health benefits to monetary gain, t_a denotes the actual walking time, and t_a^e denotes the expected walking time.

The cost can also be separated into travel time associated cost and travel distance associated cost:

$$C_a^{er,i} = \underbrace{t_a(\alpha_1^r + \alpha_2^e + (i-1)\lambda^{er} + (t_a - t_a^e)(-\epsilon_w^b + \epsilon_w^e E_a))}_{\text{Travel time associated cost}} + \underbrace{\beta_2^e l_a}_{\text{Travel distance associated cost}} \tag{3.24}$$

Cyclist:

It is assumed that each traveler has a bike, providing them with the option to ride a bicycle from their origins to their destinations. Riding bicycles, similar to walking outdoors, generates health benefits but also exposes travelers to polluted air. The commuting time plays a crucial role in travelers' decision to choose whether to travel by bicycle, as highlighted by Stinson et al. (2004) in their study on the frequency of bicycle commuting. In this study, it is assumed that cyclists ride at a constant speed throughout the entire trip. Therefore, the travel time is linearly associated with the travel distance, and it can be expressed as $t_a^c = C_b l_a$, where C_b represents the conversion factor from distance to time for cycling, and l_a denotes the travel distance.The distance-based cost would not be considered in cyclists' disutility function to avoid duplication. Therefore, the general cost function of a cyclist is

$$C_a^c = \underbrace{\alpha_1^c t_a^c}_{\text{travel time based cost}} - \underbrace{\epsilon_c^b t_a^c}_{\text{PA benefit}} + \underbrace{\epsilon_c^e E_a t_a^c}_{\text{exposure to pollution}} \tag{3.25}$$

Where, α_1^c is a conversion factor from time to cost. ϵ_c^b and ϵ_c^e are conversion factors of health benefits and emission health damage. E_a is the vehicle emission on link a.

Similar to express pool passengers, cyclists have both physical activity benefits and polluted air exposure risks, but different conversion magnitude due different level of physical movement intensity. Further, unlike vehicles, cyclists do not emit toxic air pollutants. Therefore, the level of air pollution exposure for cyclists is solely determined by the flow of vehicles.

The cost of cyclists can be separated into two parts: travel time-associated and vehicles volume-associated cost, as follows:

$$C_a^c = \underbrace{t_a^c \alpha_1^c - t_a^c \epsilon_c^b}_{\text{cyclist travel time associated cost}} + \underbrace{\epsilon_c^e E_a t_a^c}_{\text{vehicles volume associated cost}} \tag{3.26}$$

3.7.1 Mixed Complementarity model

The proposed equilibrium model follows the classic Wardrop equilibrium principle, which is, all travelers would have the minimum and equal travel cost across different travel modes and route selections for all chosen modes and routes. By applying Equation 3.4, one can derive:

$$C_k^{m,\omega} = \sum_a \delta_{a,k}^{\omega} C_a^m, \quad k \in K^{\omega}, \quad m \in \{s, c, (nr, i), (er, i)\}, i \in \{1, 2\} \tag{3.27}$$

where $C_k^{m,\omega}$ denotes the path cost of mode m of the O-D pair ω. Let u_ω denote the minimum travel cost between the OD pair ω, and with the equations above, then:

$$\begin{cases} f_k^{m,\omega} > 0 \Rightarrow C_k^{m,\omega} = u_\omega \\ f_k^{m,\omega} = 0 \Rightarrow C_k^{m,\omega} \geq u_\omega \end{cases} \tag{3.28}$$

Therefore, the path-based MiCP model aims to find the values of $f_k^{m,\omega}$ and u_ω that satisfy the following goals:

$$0 \leq f_k^{m,\omega} \perp C_k^{m,\omega} - u_\omega \geq 0, \; k \in K^{\omega} \tag{3.29}$$

$$u_\omega \text{ free} \perp q^{\omega} - \sum_{k \in K^{\omega}} \sum_m f_k^{m,\omega} = 0 \tag{3.30}$$

The MiCP Equation 3.29 and Equation 3.30 formulate the network user equilibrium conditions with active transportation and ridesharing services. Equation 3.29 demonstrates that at the equilibrium, the generalized travel costs for cyclists, solo drivers, and TNC passengers on all used paths of a certain OD pair are equal to the minimum generalized travel cost u_ω; all unused paths of a certain OD pair has higher generalized travel cost than u_ω. Furthermore, Equation 3.30 demonstrates that the travel demand between OD pairs must be satisfied if the minimum generalized travel costs are achieved.

3.8 Existence and Uniqueness

3.8.1 Existence

The linearly constrained variational inequality (VI) is equivalent to the MiCP from [Facchinei and Pang, 2003]. By denoting $\mathbf{\Phi}(\mathbf{f}) = C_k^{m,\omega}$ where $m \in \{s, c, (nr, i), (er, i)\}$ and $i \in \{1, 2\}$, the goal is to find a vector $\boldsymbol{f}^*$ that satisfies the following conditions:

$$\Phi(\mathbf{f}^*) \cdot (\mathbf{f} - \mathbf{f}^*) \geq 0, \forall \mathbf{f} \in \Omega \tag{3.31}$$

where the domain Ω is bounded by:

$$f_k^{m,\omega} \geq 0 \tag{3.32}$$

$$q^\omega - \sum_{k \in K^\omega} \sum_m f_k^{m,\omega} = 0 \tag{3.33}$$

Since all the constraints are linear, the given subset Ω is closed and convex. The cost functions are continuous in the given domain Ω. According to [Facchinei and Pang, 2003, 1.2.1 Proposition], there exists at least a solution for the VI formulation. The existence of a link flow solution is guaranteed due to the fact that link flows are induced by path flows.

3.8.2 Uniqueness

Given the link-based utility function $C_a^m(x_a)$ as follows:

Solo driver

$$C_a^s(x_a) = \underbrace{\alpha_1^d t_a(x_a)}_{\text{travel time based cost}} + \underbrace{\beta_1^d l_a}_{\text{distance based cost}} \tag{3.34}$$

Normal Pool Passenger

$$C_a^{nr,i}(x_a) = \underbrace{t(x_a)(\alpha_1^r + \alpha_2^n + (i-1)\lambda^{nr})}_{\text{travel time based cost}} + \underbrace{\beta_2^n l_a}_{\text{distance based cost}} \tag{3.35}$$

where $t(.)$ is the BPR function as the aforementioned link travel time function, which is a strictly monotone on link flow v_a. Since $\alpha_1^d > 0$, $\beta_1^d l_a > 0$ and $l_a > 0$ are constants, Equation 3.34 is strictly monotone. Given $\alpha_1^r > 0, \alpha_2 > 0, i \in \{1, 2\}$, then $\alpha_1^r + \alpha_2 + (i - 1)\lambda^{nr} > 0$, Equation 3.35 is strictly monotone.

For the cyclists, the general cost function is:

$$C_a^c(x_a) = \underbrace{\alpha_1^c t_a^c(x_a)}_{\text{travel time based cost}} - \underbrace{\epsilon_c^b t_a^c(x_a)}_{\text{PA benefit}} + \underbrace{\epsilon_c^e E_a t_a^c(x_a)}_{\text{exposure to pollution}} \tag{3.36}$$

where t_a^c is linearly associated with the length of the link a, l_a, which is a positive constant, thereby $\alpha_1^c t_a^c(x_a)$ and $\epsilon_c^b t_a^c(x_a)$ are constants. Since $E_b = \epsilon_e f_a l_a$, and e_c^e and $t_a^c(x_a)$ are constants, and when $a_1^c - \epsilon_c^b > 0$ then Equation 3.36 is strictly monotone.

For the express pool, the general cost function is:

$$\begin{aligned} C_a^{er,i}(x_a) = & \underbrace{\alpha_1^r t_a(x_a)}_{\text{travel time based cost}} + \underbrace{\alpha_2^e t_a(x_a)}_{\text{travel time based fare}} + \underbrace{\beta_2^e l_a}_{\text{distance-based cost}} + \underbrace{(i-1)\lambda^{er} t_a(x_a)}_{\text{inconvenient cost}} \\ & - \underbrace{\epsilon_w^b (t_a(x_a) - t_a^e(x_a))}_{\text{PA benefit}} + \underbrace{\epsilon_w^e E_a(t_a(x_a) - t_a^e(x_a))}_{\text{Pollution exposure}} \\ = & t_a(x_a)(\alpha_1^r + \alpha_2^e + -\epsilon_w^b + (i-1)\lambda^{er}) + \beta_2^e l_a + \epsilon_w^b t_a(x_a) + \epsilon_w^e E_a(t_a(x_a) - t_a^e(x_a)) \end{aligned} \tag{3.37}$$

where:

$$t_a^e(x_a) = t_a^0(x_a)[1 + A(\frac{\gamma^i x_a}{CAP_a})^B],\ 0 < \gamma^i < 1 \tag{3.38}$$

$$t_a(x_a) = BPR(x_a) = t_a^0(x_a)[1 + A(\frac{x_a}{CAP_a})^B] \tag{3.39}$$

and

$$t_a(x_a) - t_a^e(x_a) = (1 - \gamma^i)A(\frac{x_a}{CAP_a})^B \tag{3.40}$$

$$= (1 - \gamma^i)(BPR(x_a) - t_a^0(x_a)) \tag{3.41}$$

Since BRP is strictly monotone, and $\epsilon_w^e > 0$ and $E_a > 0$, so $\epsilon_w^e E_a(t_a(x_a) - t_a^e(x_a))$ is a monotonic increasing function. Furthermore, the $\beta_2^e l_a$ is a constant, $i \in \{1, 2\}$, so when $\alpha_1^r + \alpha_2^e - \epsilon_w^b > 0$, Equation 3.37 is strictly monotone.

According to the theorem [Facchinei and Pang, 2007, 2.3.3], if F is strictly monotone on K, the $VI(K, F)$ has at most one solution. As the existence of the result was proven in the previous section, it is concluded that there exists a unique solution with respect to the link flow.

3.9 Numerical Study

3.9.1 The Braess's network study

In this section, the proposed model is tested using the Braess network. The Braess network is employed as a test case to validate the correctness of the proposed model. The graph has four nodes $N = \{1, 2, 3, 4\}$ with five directed arcs $A = \{\{1, 2\}, \{1, 3\}, \{2, 3\}, \{2, 4\}, \{3, 4\}\}$. Only one OD pair is considered for the Braess network numerical study, where the demand q of the OD pair $\{1, 4\}$ is $q^{1,4} = 30$.

The network parameter settings are listed in Table 3.2. To account for additional factors such as parking, which is a significant concern for solo drivers, a deliberate decision has been made to assign a higher time cost to solo driving in comparison to other travel modes. This adjustment aims to capture the overall travel experience and provide a more comprehensive representation of the costs associated with solo driving. In general, the bicycle's speed is assumed to be 8 mph, which is much slower than automobiles. Therefore, the value of a conversion from distance to time of cyclists is assumed to be high.

Cycling is qualified as a moderate-intensity physical activity [Sperlich et al., 2012, Fishman et al., 2015] and has a higher Metabolic Equivalent of Task (MET)-hours [World Health Organization et al., 2010]. However, it is important to note that passengers usually rush to walk to the pick-up spot and thus may also experience high MET. In this study, it is assumed that pedestrians have slightly higher health benefits than cyclists.

Table 3.2. Parameters settings for Braess's network

Parameters	Constants	Values
Link length	$l_a, a \in \{1, 2, ..., 5\}$	1
Link capacity	$CAP_a, a \in \{1, 2, ..., 5\}$	5
Link free flow travel time	$t_a^0, a \in \{1, 2, ..., 5\}$	1
BRP coefficient	A, B	0.15, 4
Value of time	α_1^d, α_1^r	2.2, 1.6
In convenient cost	$\lambda^{nr}, \lambda^{er}$	0.12, 0.11
Fare of time for TNC	α_2^n, α_2^e	0.6,0.5
Fare of distance for TNC	$\beta_1^d, \beta_2^n, \beta_2^e$	2, 0.6, 0.5
Coefficient of physical activity	$\epsilon_w^b, \epsilon_c^b$	0.01, 0.009
Coefficient of pollution exposure	$\epsilon_w^e, \epsilon_c^e$	0.001, 0.0009
Converter from distance to time	α_1^c	20

With the only OD pair (1,4), the are three paths 1

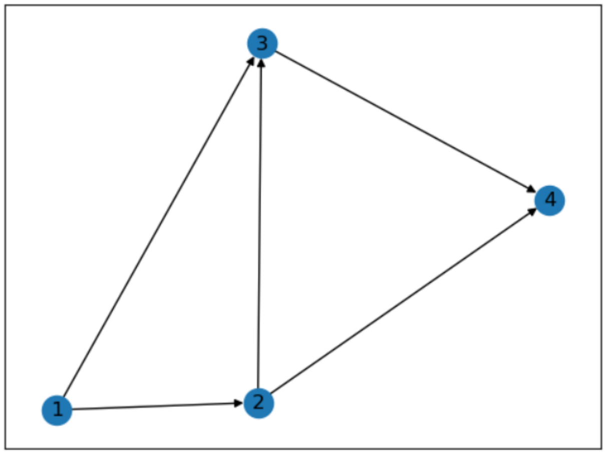

Figure 3.4. Braess's network

1. "$1 \rightarrow 2 \rightarrow 4$"

2. "$1 \rightarrow 3 \rightarrow 4$"

3. "$1 \rightarrow 2 \rightarrow 3 \rightarrow 4$"

The capacity and free flow time of all links in the road network is set to be the same for the convenience of verifying the validity of the model. With this setting, the route "$1 \rightarrow 2 \rightarrow 3 \rightarrow 4$" would not have any flow on it since the general cost of this path would be strictly higher than the other two paths. Furthermore, travelers on the same mode would be evenly distributed on route "$1 \rightarrow 2 \rightarrow 4$" and "$1 \rightarrow 3 \rightarrow 4$" because of the same geometric settings and equal general costs that it may generate for travelers.

At the equilibrium status, the minimum general cost of the OD pair (1,4) is 5.07. As shown from Table 3.3, with ten travel demand of OD pair (1,4), 5.87 of 30 total travelers choose to take express service, 6.93 travelers choose to take express service and pool with another passenger, and 17.20 travelers choose to take normal e-hailing service and pool with another passenger. The result of passengers' route choices are consistent with the expectation. After selecting the travel mode, travelers are distributed evenly between routes "$1 \rightarrow 2 \rightarrow 4$" and "$1 \rightarrow 3 \rightarrow 4$".

Table 3.3. Computational results of the Braess's network

Mode	Route	Volume
Cyclist	1,3,4	0.00
Cyclist	1,2,3,4	0.00
Cyclist	1,2,4	0.00
Expresspoll with one passenger	1,2,3,4	0.00
Expresspoll with one passenger	1,2,4	2.94
Expresspoll with one passenger	1,3,4	2.94
Expresspool with two passengers	1,3,4	3.46
Expresspool with two passengers	1,2,4	3.46
Expresspool with two passengers	1,2,3,4	0.00
Normalpool with one passengers	1,2,3,4	0.00
Normalpool with one passengers	1,3,4	0.00
Normalpool with one passengers	1,2,4	0.00
Normalpool with two passengers	1,2,4	8.60
Normalpool with two passengers	1,3,4	8.60
Normalpool with two passengers	1,2,3,4	0.00
Solo driver	1,2,4	0.00
Solo driver	1,3,4	0.00
Solo driver	1,2,3,4	0.00

3.9.2 Sioux Falls network study

In this section, the model is tested with the Sioux-Falls network. The Sioux-falls network has been studied extensively in the transportation network modeling literature. The data set contains 24 nodes, 76 links, and 528 OD pairs. The parameters of the network, such as link length and capacity, can be found at [bstabler, 2023] on Github, so the introduction of network parameters is omitted here. The original data contains 528 OD pairs with around 360000 travel demands at total. See Figure 3.5 as a reference.

However, the original data set (24 nodes, 76 links, and 528 OD pairs) leads to a large problem that is computationally expensive to solve. Therefore, the geometry of the network is kept but the problem size is reduced by taking a subset of the OD pairs by referencing the study settings from [Xu et al., 2015, Ban et al., 2019]. There are five nodes (1,2,11,13,20) are selected as origins and another five nodes (10,15,16,17,19) as destinations, in which the total OD pairs is 25The total travel demand in the original network is 360,000, and it is evenly distributed among the origin-destination (OD) pairs, resulting in 14,400 units of demand for each OD pair. For simulation purposes, the nodes (10, 15, 16, 17, 19) are selected as

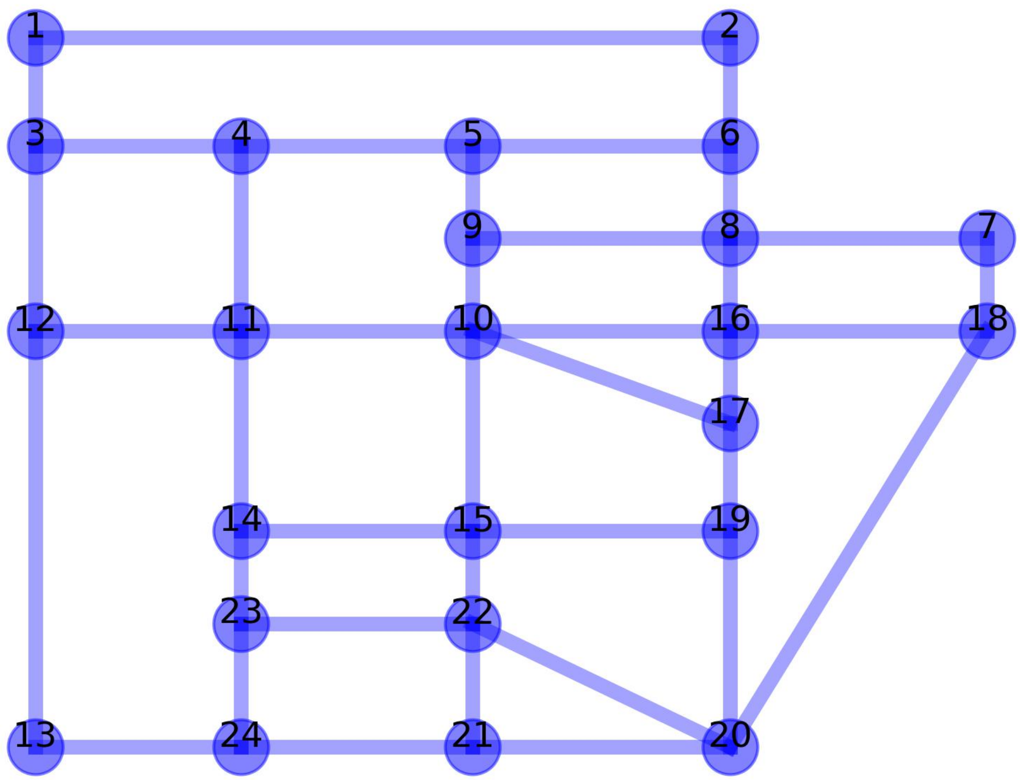

Figure 3.5. Sioux Falls's network

destinations to represent a Central Business District (CBD) scenario. See Figure 4.3 as a reference.

To further reduce the size of the problem, the distances of the links are utilized as weights and the k-short shortest path algorithms [Yen, 1971] is applied to select the ten shortest paths between the selected OD pairs.Therefore, for the numerical study, the path-based model described in Equation 3.29 and Equation 3.30 is utilized, resulting in a total of 1500 variables. the proposed model and the network Sioux Falls are coded in Julia language with PATH solver[Steven Dirkse, Michael C. Ferris, and Todd Munson, 2023]. With a 3.6 GHz and 16 GB memory PC, the problem is solved in 12.9 seconds.

To capture the changes in the network, the following measurements are considered:

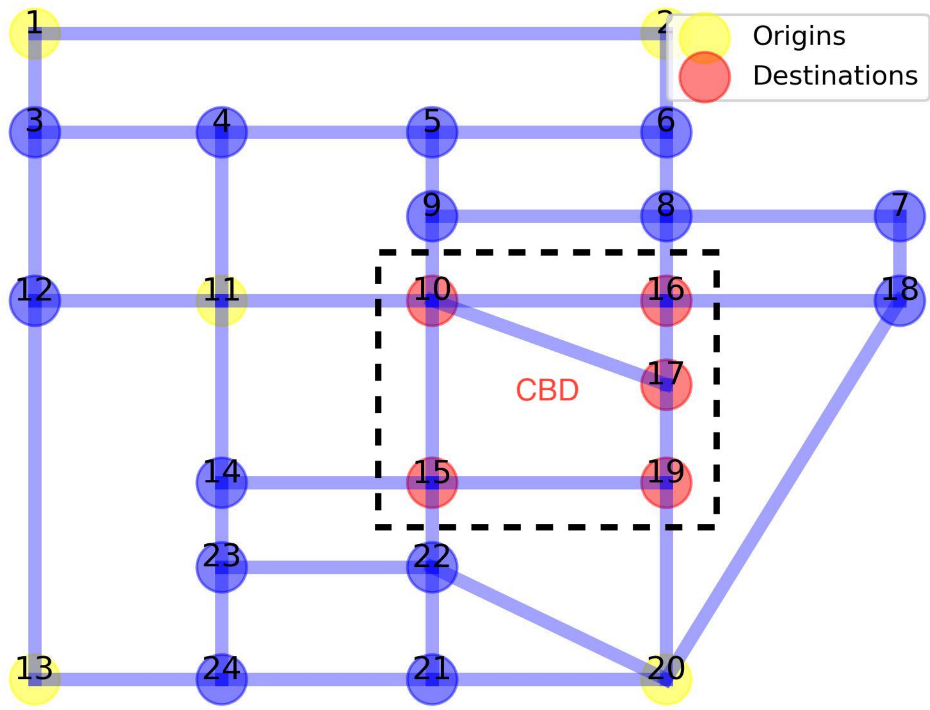

Figure 3.6. Locations of origins and destinations

1. The congestion level CL (total link travel time) :

$$\mathrm{CL} = \sum_{a \in A} t_a \tag{3.42}$$

2. The total vehicle miles traveled(VMT):

$$\mathrm{VMT} = \sum_{a \in A} l_a x_a^{rd} \tag{3.43}$$

3. The total cyclist miles traveled(CMT):

$$\mathrm{CMT} = \sum_{a \in A} l_a x_a^{c} \tag{3.44}$$

4. The total physical benefit (PB):

$$\text{PB} = \sum_i \sum_a \epsilon_w^b (t_a - t_a^e) x_a^{er,i} + \sum_a \epsilon_c^b l_a x_a^c \tag{3.45}$$

5. The total pollution exposure (PE):

$$\text{PE} = \sum_i \sum_a \epsilon_w^e E_a (t_a - t_a^e) x_a^{er,i} + \sum_a \epsilon_c^e l_a E_a x_a^c \tag{3.46}$$

6. The total vehicle time traveled(VHT):

$$\text{VHT} = \sum_a t_a x_a^{rd} \tag{3.47}$$

By applying the parameters specified in Table 3.2, the model outputs are obtained for various values of the value of time for solo drivers. The following are the results for different value of time scenarios:

Table 3.4. The results of changing time-based cost for solo driver

time_cost	PB	CMT	VMT	CL	PE	VHT
2.02	3.54	1159216.62	4629403.65	6928.39	394.67	244057669.63
2.04	4.68	1165237.23	4622351.28	6879.54	520.72	241828664.30
2.06	5.79	1171086.13	4615760.85	6831.84	645.57	239665135.47
2.08	6.91	1176950.43	4609021.13	6784.72	769.01	237529658.81
2.10	8.00	1182895.02	4601447.14	6738.12	888.60	235411923.38
2.12	9.08	1188777.59	4593946.99	6692.25	1007.00	233332177.58
2.14	10.17	1194600.73	4586505.06	6647.10	1125.60	231289510.66
2.16	11.14	1199157.40	4570201.87	6600.20	1232.48	229405399.47
2.18	11.37	1199442.55	4562602.25	6582.35	1246.84	228966918.32
2.20	11.37	1199442.55	4562602.25	6582.35	1246.84	228966918.32

The results presented in Table 3.4 demonstrate the impact of varying time-based costs for solo drivers on the various performance metrics of the Sioux Falls network. These performance measures include physical activity benefits, cyclist miles traveled, vehicle miles traveled, congestion levels, exposure to air pollution, and vehicle time traveled. The data reveals a clear trend: as the time-based cost for solo drivers increases, there are notable changes in network performance. Specifically, there is an increase in physical activity benefits and cyclist miles traveled, indicating a shift towards more active transportation modes. Additionally, exposure to air pollution also increases, as more travelers choose the AT modes. Regarding vehicular traffic, the findings reveal a decrease in congestion levels and vehicle hours traveled as the time-based cost for solo drivers increases. This implies that higher costs associated with solo driving encourage the adoption of alternative modes of transportation, resulting in reduced congestion and overall travel time for vehicles.

One interesting observation from the table is that the output values for time-based cost of 2.18 and 2.2 are the same. This suggests that there may be a saturation point where further increases in time-based cost of solo drivers may not significantly affect the network performances, as all solo drivers have probably switched to the other traffic modes.

Table 3.5. The results of changing physical activity coefficients of walking and cycling

health coeffcients (walk, bike)	PB	CMT	VMT	CL	PE	VHT
1.1,1.09	8.12	1184601.55	4600211.42	6730.24	888.21	235295830.13
1.2,1.19	16.14	1191077.78	4596172.29	6702.97	892.39	234139528.71
1.3,1.29	24.30	1197403.7	4591771.08	6666.4	897.73	232684010.92
1.4,1.39	32.76	1204415.8	4583868.69	6639.31	901.94	231059892.45
1.5,1.49	41.21	1214312.32	4577115.53	6593.71	905.17	229453289.78
1.6,1.59	49.84	1222773.55	4567158.91	6552.77	909.56	227920303.27
1.7,1.69	58.53	1232281.55	4561600.43	6515.08	914.01	226044694.53
1.8,1.79	67.44	1238770.85	4553464.91	6477.4	918.48	224546036.94
1.9,1.89	76.41	1247016.4	4545369.1	6436.72	923.04	222406157.71
2.0,1.99	85.61	1254634.07	4538516.83	6398.04	928.62	221194314.17

To explore the relationship between physical activity benefits and the coefficients for walking and cycling, a sensitivity analysis is conducted. Specifically, by simultaneously adjusting both coefficients, the effects on the network can be observed. This allows for analyzing the impacts of different combinations of coefficients on various aspects of the network. The outcomes of this analysis are presented in Table Table 3.5, which highlights the associated changes in physical activity benefits, cyclist miles traveled, vehicle miles traveled, congestion levels, pollution exposure, and vehicle hours traveled across different levels of the health coefficient.

With an increase in the health coefficient for walking and cycling, several notable trends emerge. Firstly, there is a consistent rise in physical activity levels and cyclist miles traveled, accompanied by a corresponding decrease in vehicle miles traveled. This suggests that promoting active modes of transportation can lead to increased physical activity and a reduction in reliance on private vehicles. However, it is important to note that there is a tradeoff between physical activity and exposure to pollution. As physical activity increases, so does the exposure to pollution. This implies that individuals who engage in active transportation may experience higher levels of pollution exposure compared to those using other modes of transportation.

On a positive note, the increase in the health coefficient is also associated with a decrease in congestion levels, pollution exposure, and vehicle hours traveled. This suggests that promoting active transportation can help alleviate traffic congestion and reduce overall pollution levels in the network. In summary, the results indicate that encouraging active modes of transportation can have several benefits, including increased physical activity and reduced vehicle miles traveled. However, there is a need to address the potential negative impact of increased pollution exposure. Implementing strategies to mitigate pollution, such as improving air quality or designing bike/walk routes with lower pollution levels, can help strike a balance between promoting active transportation and ensuring public health and well-being.

Even though the sensitivity analysis shows PE continues to increase as the PB increases, it is important to note that PB increases faster than PE. This is because when the number of vehicles drops, each pedestrian or cyclist's pollution exposure also drops, thus establishing a positive circulation system so that more and more travelers choose to use active transportation modes without concern of air pollution exposure.

Last, to investigate the influence of air pollution exposures on the traffic network, a sensitivity analyses is conducted by adjusting the pollution exposure coefficients for pedestrians and cyclists simultaneously. The exposure coefficients represent the level of exposure to air pollutants experienced by individuals engaging in walking and cycling.

The results, presented in Table 3.6, demonstrate interesting patterns. As the exposure coefficient increases, there is a noticeable decrease in cyclist miles traveled (CMT) and physical activity benefits, suggesting a reduced preference for active transportation modes. This implies that as individuals are exposed to higher levels of air pollution, they are less likely

Table 3.6. The results of changing pollution exposure coefficients of walking and cycling

exposure coefficient (walk, bike)	PB	CMT	VMT	CL	PE	VHT
0.001 ,0.0015	8.00	1182895.02	4601447.14	6738.12	888.60	235411923.38
0.002, 0.0025	4.26	1033207.20	4742104.18	7659.44	977.84	278039118.04
0.003, 0.0035	2.99	920628.05	4838693.12	8524.90	1057.65	318384021.25
0.004, 0.0045	2.36	827211.79	4929727.62	9376.15	1140.19	360048531.05
0.005, 0.0055	1.98	749253.56	4992667.08	10209.07	1221.08	402130442.00
0.006, 0.0065	1.72	679182.75	5053432.30	11022.16	1301.78	444252301.54
0.007, 0.0075	1.54	629475.14	5110419.51	11779.45	1377.52	486563595.36
0.008, 0.0085	1.40	582505.62	5164026.27	12573.98	1459.51	532360698.39
0.009, 0.0095	1.30	541365.87	5211999.78	13379.51	1545.71	580198616.17
0.01, 0.0105	1.21	503074.52	5257120.89	14179.61	1626.64	628077464.89

to choose walking or cycling as their preferred modes of transportation.

Furthermore, the increase in exposure coefficients is accompanied by an increase in congestion, vehicle miles traveled, air pollution exposure, and vehicle hours traveled. These findings indicate that higher levels of air pollution have detrimental effects on the traffic network, leading to increased congestion, greater VMT, heightened exposure to air pollutants, and longer travel times.

In summary, data in Table 3.6 highlights the impact of air pollution exposures on pedestrian and cyclist behavior, as well as on the overall traffic network. As exposure coefficients increase, there is a decrease in active transportation usage, such as walking and cycling. However, this shift is coupled with negative consequences such as increased congestion, VMT, air pollution exposure, and VHT. Therefore, mitigating air pollution can play a crucial role in alleviating the adverse effects on the traffic network and promoting sustainable transportation choices.

3.10 Concluding remarks

In this chapter, a network equilibrium model was developed to analyze the societal impacts of travelers having the option to use AT or VT (including TNC services) for their travel needs. The model consists of three interconnected parts: mode choice, route choice, and network congestion. To reduce computational expenses, the problem was modeled as a mixed complementarity problem and used the equivalent variational inequality model to establish the existence and uniqueness of the solution. However, the unique solution only applies to the link-based model, not the path-based model [Sheffi, 1985]. By taking into account health impacts, such as physical activity benefits and air pollution exposure, my model can be utilized by transportation planners and environmental scientists to understand the interaction between active transportation and ridesharing modes, providing valuable insights into the potential benefits of promoting active transportation.

Additionally, the numerical study results suggest that solo drivers are highly sensitive to travel time costs; as the time-based cost for solo drivers increases, physical activity benefits, cyclist miles traveled, and exposure to air pollution increase, while congestion and vehicle hours traveled decrease. However, there may be a saturation point where further increases in time-based cost of solo drivers may not significantly affect the network performances. The results also demonstrate that promoting active transportation can alleviate all negative impacts on the network, such as congestion, vehicle miles traveled, air pollution exposure, and vehicle hours traveled. This indicates that active transportation can be a viable solution for transportation planners and environmental scientists to achieve sustainable urban mobility.

In this study, it was assumed that passengers and TNC vehicles can only be matched if they share the same origin and destination. Additionally, it was assumed that TNC services are available at any node on the study network, and all participants have their own bicycles or vehicles. To gain further insights, future research can relax these assumptions by limiting the supply of TNC services or bikes at certain nodes. By doing so, it would be possible to observe the real effects of waiting and detouring and to better understand the impact of active transportation on TNC services. Furthermore, while many studies have investigated the competition between TNC services, taxis, and public transit in central urban areas with a high population density, few studies have explored the combined effects of these traffic modes with active transportation. Relaxing these assumptions could provide valuable insights to transportation planners, helping them to improve travel demand management strategies.

Chapter 4

Multiple OD pairs models

In the previous chapter, the ride-hailing services only matched riders with drivers who have the same origin-destination (OD) itinerary. In this chapter, the problem is redefined into a multiple origin-destination (OD) scenario. This new scenario allows for a more flexible and dynamic representation of the transportation network, where passengers from different OD pairs can share a ride on a TNC vehicle for a portion of their trips. To analyze travelers' behavior, the original traffic network is replicated, and a separate network for walking is created, allowing passengers to traverse it by themselves.

To facilitate the analysis of travelers' behavior, a separate network for walking is created by replicating the original traffic network. This additional network enables passengers to navigate it independently without affecting vehicle or cyclist traffic flow. By relaxing these constraints, one can explore the selection of pick-up and drop-off locations under varying levels of traffic congestion. Additionally, this relaxed model provides insights into the potential role of walking in mitigating congestion near pick-up and drop-off points. The study also takes into account the impact of physical activity benefits and air pollution exposure from vehicle emissions on health, aiming to gain a better understanding of traveler preferences.

Like walking, cycling is also an essential sustainable and healthy mode of transportation, and thus we also consider alleviating constraints regarding cyclists in this scenario. A similar assumption made in the previous chapter was also applied to bicycles here, where bikes are assumed to be available across the entire network without capacity limits. Accordingly, this study evaluates the potential benefits of cycling, such as reducing vehicle emissions and providing physical activity health benefits, and its role in mode selection (vehicular vs. active transportation) and the selection of pickup or drop-off spots for express pool passengers. By considering factors related to both walking and cycling, this chapter's findings offer valuable insights for policymakers aiming to promote sustainable and efficient transportation systems while minimizing negative societal consequences.

4.1 Problem Description

Given a directed network G(N,A) with a set of nodes, N, and a set of arcs A. Let W denote a set of O-D pair (o, d) for passengers, where $(o, d) \in N \times N$, $o \neq d$, $o \in O$, where O is a set of origin nodes and $O \subseteq N$, $d \in D$, where D is a set of destination nodes and $D \subseteq N$. ω is one pair of O-D pairs, where $\omega \in N \times N$ and $\omega \in W$, and K^ω is the set of simple paths connecting the O-D pair ω, and each simple path k is composed of a sequence of arcs that has no cycles. $\delta^\omega_{a,k}$ is the arc-path incidence indicator that $\delta^\omega_{a,k} = 1$ indicates the link a is part of the link k, otherwise $\delta^\omega_{a,k} = 0$.

Given the total demand q^ω of an O-D pair ω, the f^ω_k is the traffic flow on path k of the O-D pair ω and $f^{\omega,m}_k$ is the traffic flow of travel mode m, and path link relationships from Equation 3.1,Equation 3.2, Equation 3.3,Equation 3.4 the path traffic flow and the travel demand of the OD pair of ω has the following flow pattern $E(q)$ compatible with the above equations is in equilibrium if both of the following conditions are satisfied:

$$f^{\omega,m}_k > 0 \rightarrow C^{\omega,m}_k = u_\omega \tag{4.1}$$

$$f^{\omega,m}_k = 0 \rightarrow C^{\omega,m}_k \geq u_\omega \tag{4.2}$$

where u_ω is the minimum travel cost of the OD pair ω.

The major difference between single OD and multiple OD scenarios is the equation Equation 4.3, which allows participants to switch traveling modes from link to link. Then, the flow conservation relation is:

$$\sum_m \sum_{a \in \mathrm{IN}\{i\}} x^m_a - \sum_m \sum_{a \in \mathrm{OUT}\{i\}} x^m_a = 0, m \ \in \ \{er, nr, w\} \tag{4.3}$$

4.2 link-based disutility function

For the link-based disutility function, according to their different link performance, participants are categorized into four groups: pedestrians, riders, drivers (both solo drivers and vacant TNC drivers), and cyclists.

Pedestrian

For pedestrians' disutility function, the same format as cyclists' disutility function in a single OD pair scenario is adopted in this chapter. However, the relaxation of the assumption and the inconvenience generated by waiting and detouring can be explicitly modeled. Assuming the average walking speed is constant, then the travel time-based cost, distance-based cost, PA benefits, and exposure to pollution damage are all associated with walking distance. Therefore, the walking disutility function is formulated as follows:

$$\begin{aligned} C_a^w &= \underbrace{\alpha_1^w l_a}_{\text{travel time based cost}} + \underbrace{\beta_1^w l_a}_{\text{distance based cost}} - \underbrace{\epsilon_w^b l_a}_{\text{PA benefit}} + \underbrace{\epsilon_w^e E_a l_a}_{\text{exposure to pollution}} && (4.4) \\ &= \underbrace{l_a(\alpha_1^w + \beta_1^w - \epsilon_w^b)}_{\text{distance base cost}} + \underbrace{l_a \epsilon_w^e E_a}_{\text{vehicle flow based cost}} && (4.5) \end{aligned}$$

where α_1^w and β_1^w are conversion factors from time to cost and from distance to cost for pedestrians, respectively. ϵ_w^b is the conversion factor from health benefits to monetary gain. ϵ_w^e is the conversion factor from air pollution exposure to monetary gain. E_a is the vehicle emission associated with the number of vehicles on this link. By assuming the relationship between VMT for a certain area and emission levels are linear, the emission of a link a can be epxressed as:

$$\underbrace{E_a}_{\text{vehicle emission}} = \epsilon_e f_a l_a, \tag{4.6}$$

where ϵ is the conversion coefficient, f_a is the traffic flow on link a, and l_a is the link length.

Pedestrians derive physical benefits from engaging in walking activities, although they also expose themselves to the outdoor environment. Additionally, pedestrians can enjoy reduced monetary costs throughout their trips. Commuting time and monetary incentives play pivotal roles in pedestrians' decision-making process when considering whether to incorporate walking into certain parts of their trips.

Riders

TNC passengers encounter both time-based costs and monetary costs (i.e., ride fares) during their trips. As the walking and riding phases are modeled separately, the disutility structure remains the same for both normal pool and express pool riders, with the only distinction being the coefficients applied. Consequently, the disutility function for TNC riders is formulated as follows:

$$C_a^{rr} = \underbrace{\alpha_1^{rr} t_a}_{\text{travel time based cost}} + \underbrace{\alpha_2^{rr} t_a}_{\text{travel time based fare}} + \underbrace{\beta_2^{rr} l_a}_{\text{distance based fare}} \tag{4.7}$$

where α_1^{rr} is the conversion factor from travel time to cost for TNC passengers, α_2^{rr} and β_2^{rr} are time- and distance-based riding fare rates for TNC passengers.

Solo Drivers and vacant TNC drivers

Similar to the same OD scenario assumption, it is assumed each traveler has the option to driver alone with their private vehicle.

$$C_a^{s} = \underbrace{\alpha_1^{d} t_a}_{\text{travel time based cost}} + \underbrace{\beta_1^{d} l_a}_{\text{distance based cost}} \tag{4.8}$$

Where t_a is the travel time of link a, and α_1^d and β_1^d are respective conversion factors from travel time and travel distance to cost for solo drivers.

Furthermore, the pickup cost of vacant TNC vehicle could also be modeled through solo drivers since the trips that a vacant TNC vehicle traveling from the destination of the previous trip to the origin of the current trip has no passengers. However, the cost is different since this deadhead trip is part of the service, which TNCs financially support, and no parking cost is added to the disutility. Thereby, the coefficient of TNC vehicle is different from solo drivers, and can be modeled as

$$C_a^v = \underbrace{\alpha_1^v t_a}_{\text{travel time based cost}} + \underbrace{\beta_1^v l_a}_{\text{distance based cost}} \tag{4.9}$$

.

Where α_1^v and β_1^v are respective conversion factors from travel time and travel distance to cost for picking up vehicles.

Cyclists

Similar to the disutility function for cyclists in the same OD scenario, cyclists derive benefits from physical exercise while incurring costs due to exposure to polluted air and the overall travel time.

$$C_a^c = \underbrace{\alpha_1^c t_a^c}_{\text{travel time based cost}} - \underbrace{\epsilon_c^b t_a^c}_{\text{PA benefit}} + \underbrace{\epsilon_c^e E_a t_a^c}_{\text{exposure to pollution}} \tag{4.10}$$

Where, α_1^c is a conversion factor from time to cost. ϵ_c^b and ϵ_c^e are conversion factors of health benefits and emission health damage.

4.3 Path-based disutility function

In this study, participants are classified into three groups based on the path-based disutility function: solo drivers, TNC passengers, and cyclists. Solo drivers and cyclists are assumed to travel from their origins to destinations without switching modes, so the path cost is simply the summation of the cost of traversed links. On the other hand, for TNC passengers, their trip is typically composed of walking, riding the TNC vehicle, or a combination of both modes. In addition, there are two simplifing assumptions:

1. TNC vehicles can accommodate a maximum of one passenger at a time.

2. Passengers are not concerned about the waiting time for the vacant TNC to arrive and pick them up.

Path-based disutility is simply the accumulation of iterated links of the path for solo drivers and cyclists. Considering whether the passengers or the TNC vehicle need to move to pick up location, there are the following four possibilities:

1. A vacant TNC vehicle that is instantly available at passenger's origin.

2. A vacant TNC vehicle that is not instantly available at passenger's origin. The vehicle moves to the passenger's origin for pickup.

3. A vacant TNC vehicle that is not instantly available at passenger's origin. Passenger walks to the vehicle's position.

4. A vacant TNC vehicle that is not instantly available at passenger's origin. The passenger and vhicle both move to a meet-up point for pickup.

It is assumed that only vacant TNC vehicles are available to serve passengers. This simplification is made to avoid the computational complexity that would arise if we were to consider the pickup location choice of TNC vehicles that already have one passenger onboard. Taking into account this choice would significantly increase the number of possible scenarios and the computational burden of the problem.

The path-based disutility is simply the summation of the disutility of iterated links. Therefore, the path-based general cost can be written as follows:

$$\begin{aligned} C_k^{n,\omega} = &\sum_{a \in A_{vacant}^k} (\underbrace{\alpha_1^d t_a + \beta_1^d l_a}_{\text{Vacant traveling}}) + \sum_{a \in A_{occupied}^k} \underbrace{(\alpha_1^{rr} t_a + \alpha_2^{rr} t_a + \beta_2^{rr} l_a)}_{\text{occupied traveling}} \\ &+ \sum_{a \in A_{walking}^k} \underbrace{(\alpha_1^w l_a + \beta_1^w l_a - \epsilon_w^b l_a + \epsilon_w^e E_b l_a)}_{\text{walking}} \end{aligned} \tag{4.11}$$

where n indicates the type of possibilities in the previous section, A_{vacant}^k, $A_{occupied}^k$, and $A_{walking}^k$ are the set of arcs of vacant vehicle, occupied vehicle, and walking sections for the path k, respectively.

For instance, as mentioned in type 1 in the previous section, when a passenger requests a ride and a vehicle is immediately available at the passenger's origin, both the "vacant traveling" and "walking" costs are reduced to zero. Consequently, the "occupied traveling" cost becomes the sole remaining factor in the disutility function for this passenger:

$$C_k^{1,\omega} = \sum_{a \in A_{occupied}^k} (\underbrace{\alpha_1^{rr} t_a + \alpha_2^{rr} t_a + \beta_2^{rr} l_a}_{\text{occupied traveling}}) \tag{4.12}$$

Another example, as mentioned in type 3 possibility, if a passenger requests for a ride, and the vehicle is not instantly available at the passenger's origin, and passenger walks to the vehicle's position, both "occupied traveling" and "walking" sections are non-zero this situation. In this case, the disutility function for this passenger can be expressed as:

$$C_k^{3,\omega} = \sum_{a \in A^k_{occupied}} \underbrace{(\alpha_1^{rr} t_a + \alpha_2^{rr} t_a + \beta_2^{rr} l_a)}_{\text{occupied traveling}} + \sum_{a \in A^k_{walking}} \underbrace{(\alpha_1^{w} l_a + \beta_1^{w} l_a - \epsilon_w^b l_a + \epsilon_w^e E_b l_a)}_{\text{walking}} \tag{4.13}$$

It is important to note that these four possibilities involve both normal TNC and express TNC services and whether the trip includes a walking component. The coefficients for these services are different to reflect the differences in their operations and offerings.

4.4 Mixed Complementarity model

The proposed equilibrium model follows the classic Wardrop equilibrium principle, all travelers would have the minimum and equal path-based travel cost across different travel modes and route selections. Let u_ω denote the minimum travel cost between the OD pair ω, and including the equations above, then:

$$\begin{cases} f_k^{n,\omega} > 0 \Rightarrow C_k^{n,\omega} = u_\omega \\ f_k^{n,\omega} = 0 \Rightarrow C_k^{n,\omega} \geq u_\omega \end{cases} \tag{4.14}$$

The link-based disutility function has been introduced in the previous section.

Therefore, the path-based MiCP model is proposed, and the goal is to find $f_k^{n,\omega}$ and u_ω such that:

$$0 \leq f_k^{n,\omega} \perp C_k^{n,\omega} - u_\omega \geq 0,\ k \in K^\omega, n \in \{1, 2, 3, 4, c, s\} \tag{4.15}$$

$$u_\omega \text{ free} \perp q^\omega - \sum_{k \in K^\omega} \sum_n f_k^{n,\omega} = 0 \tag{4.16}$$

The MiCP Equation 4.15 and Equation 4.16 formulate the network user equilibrium conditions with active transportation and ridesharing services. Equation Equation 4.15 demonstrates that at the equilibrium, the generalized travel costs from cyclists, solo drivers, and TNC passengers on all used paths of a certain OD pair are equal to the minimum generalized travel cost u_ω; all unused paths of a certain OD pair has higher generalized travel cost than u_ω. Furthermore, Equation 4.16 demonstrates that the travel demand between OD pairs must be satisfied if the minimum generalized travel costs are achieved.

4.5 Existence and Uniqueness

4.5.1 Existence

The linearly constrained variational inequality (VI) is equivalent to the MiCP from [Facchinei and Pang, 2003]. By denoting $\mathbf{\Phi}(\mathbf{f}) = C_k^{n,\omega},\ n \in \{1, 2, 3, 4, c, s\}$, it intends to find a vector $\mathbf{f}^*$ that can satisfy:

$$\Phi(\mathbf{f}^*) \cdot (\mathbf{f} - \mathbf{f}^*) \geq 0, \forall \mathbf{f} \in \Omega \tag{4.17}$$

where the domain Ω is bounded by:

$$f_k^{n,\omega} \geq 0 \tag{4.18}$$

$$q^\omega - \sum_{k \in K^\omega} \sum_m f_k^{n,\omega} = 0 \tag{4.19}$$

Since all the constraints are linear, the given subset Ω is closed and convex. The cost functions are continuous in the given domain Ω. According to [Facchinei and Pang, 2003, 1.2.1 Proposition], there exists at least a solution for the VI formulation. Therefore, the existence of a link flow solution is guaranteed due to the fact that link flows are induced by path flows.

4.5.2 Uniqueness

For link-based disutility functions:

$$\begin{cases} C_a^s(x_a) & = a_1^d t_a(x_a) + \beta_1^d l_a(x_a) \quad \text{solo driver} \\ C_a^v(x_a) & = a_1^v t_a(x_a) + \beta_1^v l_a(x_a) \quad \text{vacant vehicle} \\ C_a^c(x_a) & = a_1^c t_a^c(x_a) - \epsilon_c^b t_a^c(x_a) + \epsilon_c^e E_a t_a^c(x_a) \quad \text{cyclist} \\ C_a^{rr}(x_a) & = \alpha_1^{rr} t_a + \alpha_2^{rr} t_a + \beta_2^{rr} l_a \quad \text{rider} \\ C_a^w(x_a) & = \alpha_1^w l_a + \beta_1^w l_a - \epsilon_w^b l_a + \epsilon_\omega^e E_a l_a \quad \text{ped} \end{cases} \tag{4.20}$$

All coefficients are positive to provide meaningful interpretations of the model's results. The BPR function was adopted in this study, which is strictly monotone. Therefore, when $a_1^c - \epsilon_c^b > 0$, there is at most one solution. Since we proved the existence of solutions, there would be only one unique link-based solution for this proposed model.

4.6 Numerical Study

4.6.1 A small network model

The graph has ten nodes $N = \{1, 2, 3, 4, 5, 6, 7, 8, 9, 10\}$ with fourteen bi-direction arcs(see Figure 4.1 as the reference). For simplicity, only one OD pair is considered for the simple numerical study, where the demand D of the OD pair $\{9, 10\}$ is $q^{9,10} = 50$. Passengers can choose to drive alone, bike, or take TNC services. Passengers are set to have the option to walk to the adjacent nodes for express pool options. For example, for a passenger at node 9, if the passenger chooses to use the express pool, the origins would be among {1,2,7,8} other than 9.

The network parameter settings are listed in Table 4.1. Compared with other modes of travel, driving alone is assigned a higher time cost due to depreciation of the vehicle value and parking costs of driving alone.

At the equilibrium status, with 50 travel demands from node 9 to node 10, the minimum general cost of the OD pair (9,10) is 31.96. 37.9 travelers choose to use normal pool services, half of 37.9 travelers take the route {9,2,3,10}, and the other half take the route {9,7,6,10}. This service doesn't require passengers to walk to the meet-up point. Instead, TNC vehicles

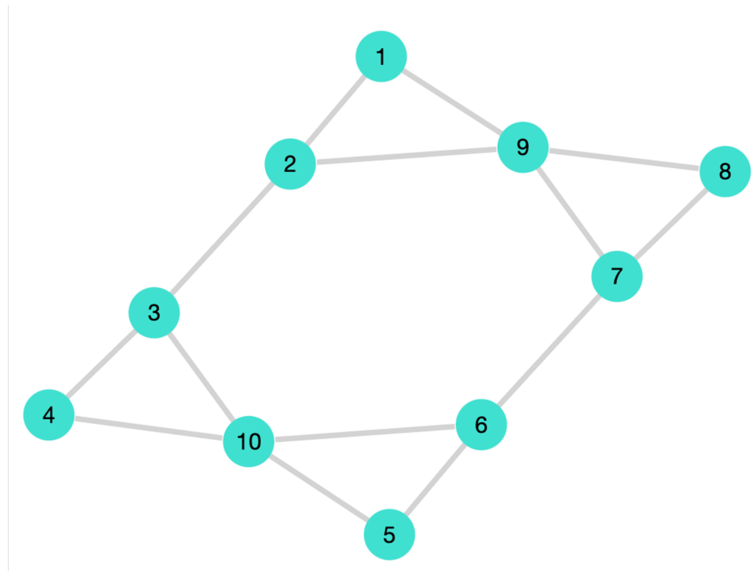

Figure 4.1. numerical study model

Table 4.1. Parameters settings for 10 nodes network

Parameters	Constants	Values
Link length	$l_a, a \in \{1, 2, ..., 28\}$	1
Link capacity	$CAP_a, a \in \{1, 2, ..., 28\}$	5
Link free flow travel time	$t_a^0, a \in \{1, 2, ..., 28\}$	1
BRP coefficient	A, B	0.15, 4
Value of time	$\alpha_1^w, \alpha_1^c, \alpha_1^d, \alpha_1^v, \alpha_1^{rr}$	5, 5, 2, 0.5, 1
Fare of time for TNC	$\alpha_2^v, \alpha_2^{rr}$	0.5, 1
Fare of distance for TNC	β_2^v, β_2^{rr}	0.5, 1
distance cost	β_1^w, β_1^d	5,2
Coefficient of physical activity	$\epsilon_w^b, \epsilon_c^b$	1,1
Coefficient of pollution exposure	$\epsilon_w^e, \epsilon_c^e$	0.5 ,0.5

from node 1 drive to node 9 to pick up passengers at their requested spots (i.e., origins). 12.09 travelers decided to choose express pool service and take the route {1,2,3,4,10} for their trip. For the express pool service, the passengers are required to walk to a meet-up spot. For this route, passengers walked to node 2 and meet with the required TNC express pool vehicles to pick up and are sent to destination 10 (see Table 4.2 as the reference).

Table 4.2. Computational results of the 10 nodes network

Mode	Path	Meet-up point	Volume
Normal POOL	1,9,2,3,10	9	18.95
Normal POOL	1,9,7,6,10	9	18.95
Express POOL	1,2,3,4,10	2	12.09

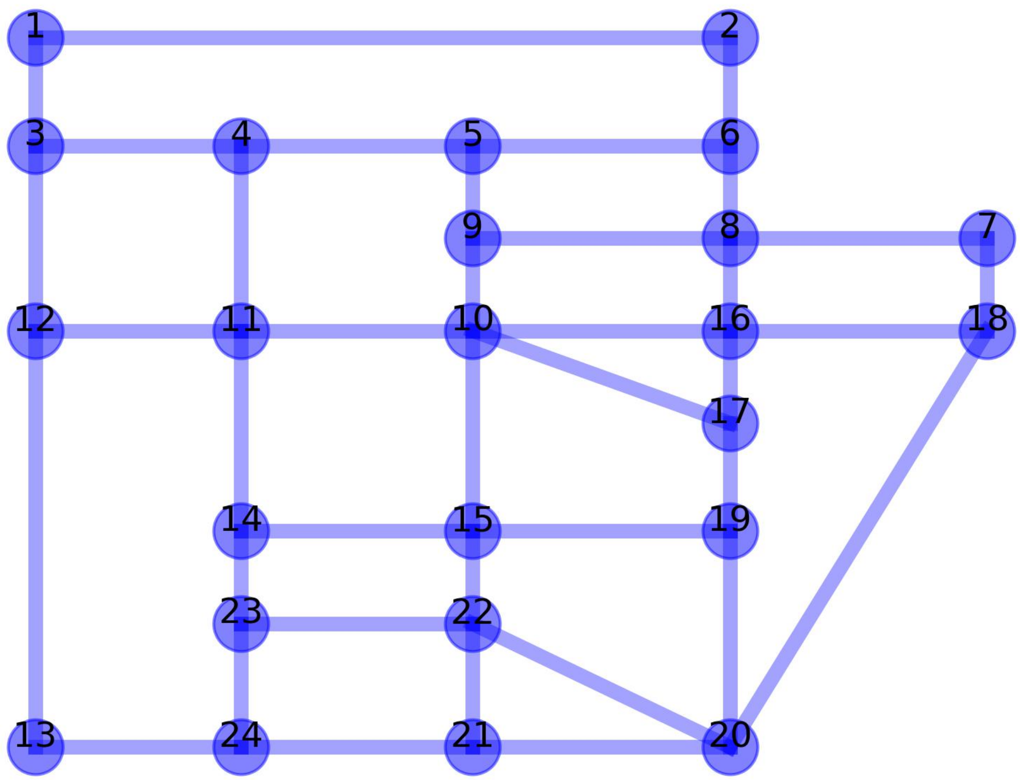

Figure 4.2. Sioux Falls's network

4.6.2 Sioux Falls

In this section, the model is tested using the Sioux-Falls network, which consists of 24 nodes, 76 links, and 528 OD pairs. The network parameters, such as link length and capacity, can be found in the [bstabler, 2023] repository on Github, so they are not included in this analysis. The original dataset contains around 360,000 travel demands for the 528 OD pairs, as shown in Figure 4.2.

However, to reduce the complexity of the problem while maintaining the significance of the results for the proposed model, the specific nodes for passenger requests and vehicle origins are carefully selected. For the passenger requests, five nodes (1, 2, 11, 13, 20) are selected as origins and another five nodes (10, 15, 16, 17, 19) as destinations. nodes

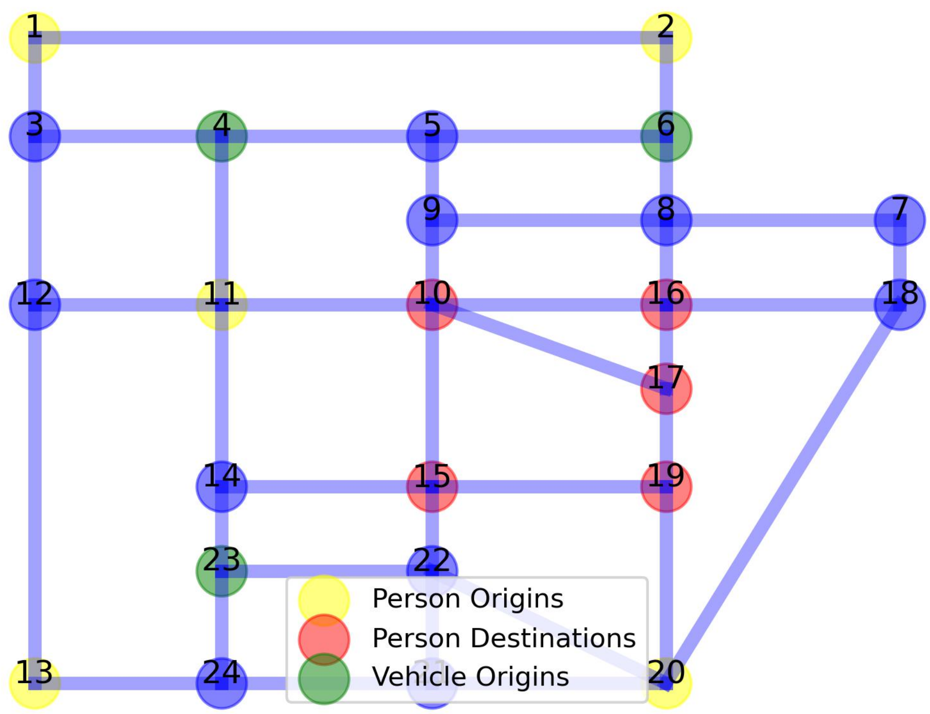

Figure 4.3. Locations of origins and destinations of passenger's requests and vehicles

(10,15,16,17,19) are selected as destinations to simulate a Central Business District (CBD). See Figure 4.3 as a reference. Three nodes (4, 6, 23) are selected as for the vehicle origins. These selections are based on the study settings from previous works such as [Xu et al., 2015, Ban et al., 2019].

To further reduce the problem size, the links' distances are used as the weights and applied the k-short shortest path algorithms [Yen, 1971] to select the ten shortest paths between the selected OD pairs. Therefore, the path-based model Equation 4.15 and Equation 4.16 is proposed for the numerical study with 1500 variables. The model and the network Sioux Falls are coded in Julia language with PATH solver[Steven Dirkse, Michael C. Ferris, and Todd Munson, 2023]. With a 3.6 GHz and 16 GB memory PC, the problem is solved in 6.2 seconds.

To capture the changes of the network, the following measurements are considered as introduced in the previous chapter:

1. The congestion level CL (total link travel time) :

$$\mathrm{CL} = \sum_{a \in A} t_a \tag{4.21}$$

2. The total vehicle miles travel(VMT):

$$\mathrm{VMT} = \sum_{n} \sum_{a \in A^k_{occupied}} l_a x^n_a \quad n \in \{1, 2, 3, 4\}, \quad k \in \bigcup^{\omega} K^{\omega} \tag{4.22}$$

3. The total cyclist miles travel(CMT):

$$\mathrm{CMT} = \sum_{a \in A} l_a x^c_a \tag{4.23}$$

4. The total physical benefit (PB):

$$\mathrm{PB} = \sum_{n} \sum_{a \in A^k_{walking}} \epsilon^b_w(l_a) x^n_a + \sum_{a} \epsilon^b_c t^c_a x^c_a \quad n \in \{3, 4\}, \quad k \in \bigcup^{\omega} K^{\omega} \tag{4.24}$$

5. The total pollution exposure (PE):

$$\mathrm{PE} = \sum_{n} \sum_{a \in A^k_{walking}} \epsilon^e_w(l_a) x^n_a E_a + \sum_{a} \epsilon^e_c t^c_a x^c_a E_a \quad n \in \{3, 4\}, \quad k \in \bigcup^{\omega} K^{\omega} \tag{4.25}$$

Table 4.3 presents the results of the selected network performances, which were obtained by varying the time-based cost of solo drivers. The network performance indicators considered in the analysis include physical activity (PB), cyclist miles traveled (CMT), vehicle miles traveled (VMT), congestion (CL), and exposure to air pollution (PE). The findings indicate that as the time-based cost of solo drivers increases, there is an increase in cyclist miles traveled (CMT), suggesting that higher costs associated with solo driving encourage greater usage of cycling as an alternative mode of transportation. Furthermore, both phys-

Table 4.3. The results of changing time-based cost of solo drivers

time-based cost of solo driver	VMT	CMT	CL	PB	PE
2.1	5951834.0	451164.8	27837.19	451478.8	50177.45
2.2	5953355.6	451889.9	27871.36	452203.9	50264.47
2.3	5954834.4	452603.2	27905.23	452917.2	50350.06
2.4	5956272.4	453305.0	27938.8	453619.0	50434.28
2.5	5957671.4	453995.7	27972.06	454309.7	50517.16
2.6	5959033.0	454675.5	28005.01	454989.5	50598.74
2.7	5960358.9	455344.9	28037.67	455658.9	50679.06
2.8	5960569.5	456493.0	28105.09	456807	50816.84
2.9	5961541.7	457917.6	28213.71	458231.6	50987.79
3	5963565.1	459313.9	28321.5	459627.9	51155.34

ical activity benefits and air pollution exposure show an upward trend as the time cost of solo driving increases.

It is important to note that the increase in the time-based cost of solo drivers leads to an increase in vehicle miles traveled (VMT) and congestion (CL). This can be attributed to factors such as the presence of e-hailing services and express pool, which contribute to additional miles traveled by vehicles and potentially worsen traffic congestion. These observations align with the findings of Ban et al. [2019] and various empirical studies, highlighting the impact of e-hailing services on VMT and congestion in urban areas.

In order to delve deeper into the effects of express pool on the performance, a scenario without the possibility of passengers' walking is constituted. Specifically, there is a significant increase in pollution exposure for pedestrians while keeping the other model parameters consistent with the previous scenario. As a result of this adjustment, the cost of pollution exposure became too high for passengers who wanted to walk, effectively eliminating their preference for the express pool as a mode of travel. The results obtained in Table 4.4 reveal important insights about the impact of express pool modes on vehicle miles traveled (VMT), congestion, and the choice of transportation modes. When express pool modes are not available, the study found that both VMT and congestion experience even greater increases compared to the scenario where passengers have the option to walk. Specifically, congestion nearly doubles in magnitude compared to the scenario with the express pool. This suggests that the presence of express pool modes can help alleviate congestion to some

Table 4.4. The network performances without express pool

time-based cost of solo driver	VMT	CMT	CL	PB	PE
2.1	7030874.2	542942	48187.08	543256	65190.72
2.2	7032236.5	543589.3	48214.85	543903.3	65268.39
2.3	7033462.7	544230.1	48240.35	544544.1	65345.29
2.4	7034496.3	544846.4	48262	545160.4	65419.25
2.5	7035503.8	545461.1	48283.71	545775.1	65493.01
2.6	7040406.3	546386.4	48339.08	546700.4	65604.04
2.7	7046063.8	547392.4	48403.79	547706.4	65724.77
2.8	7052332.9	548673.2	48486.9	548987.2	65878.46
2.9	7063951.6	551651.3	48683.24	551965.3	66235.84
3	7074818.8	554613.7	48880.04	554927.7	66591.32

extent. Interestingly, the study also observed an increase in cyclist miles traveled. One possible explanation for this observation is that the absence of the express pool result in a worse VMT and congestion condition, and the higher levels of VMT and congestion motivate individuals to switch from vehicular transportation to active transportation modes, such as cycling, as a means to avoid road congestion.

4.7 Conclusion

In this chapter, several important modifications were made to the assumptions and methodology used in the previous chapter. Firstly, the initial assumption of ride-hailing services matching riders exclusively with drivers sharing the same origin-destination itinerary was eliminated. Instead of relying on estimated values, this study utilized actual vehicle routing to accurately calculate the inconveniences resulting from detours. By incorporating actual network magnitude, the measurement of physical benefits and air pollution exposure was enhanced for more precise evaluation.

Furthermore, the study recognized the possibility of vehicles not being available at all locations within the network. This acknowledgment was crucial in assessing the implications of vacant vehicle routing, which can result in increased vehicle miles traveled (VMT) and congestion throughout the entire network. By incorporating these adjustments into the analysis, the study offers a more comprehensive and realistic understanding of the impacts of ride-hailing services and express pool options on transportation networks. This enhanced analysis provides valuable insights for transportation planners and policymakers in effectively managing and optimizing the performance of these services within the existing transportation infrastructure.

The study presented in this chapter has important implications for transportation planners and policymakers. The tool developed in this study can be used to evaluate policies that aim to manage travel demand using active transport and TNC services for urban areas. In future work, it would be valuable to investigate the application of this tool in different urban settings to achieve specific goals, such as reducing total vehicle miles traveled, minimizing emissions, and alleviating congestion. Additionally, pooling services, such as express pool, could be added to the model to investigate potential routing savings when utilizing these services. The further saving on VMT would benefit both environment and public health.

Chapter 5

Network Design Problem: Pricing for sustainability

Driving alone, commonly referred to as single-occupancy vehicles (SOVs), significantly contributes to traffic congestion and has adverse environmental and public health impacts. The continuous rise in the number of individuals choosing to drive alone leads to increased vehicle volume on roadways, exacerbating traffic congestion, fuel consumption, and pollution emissions[Afrin and Yodo, 2020]. To address these challenges and foster a more sustainable transportation system, it is crucial to effectively manage vehicular travel demand.

Efficient management of vehicular travel demand is paramount to ensure that transportation infrastructure aligns with the needs of individuals while maintaining a harmonious balance with the environment. Several strategies have been developed to achieve this goal, with shared mobility and active transportation modes, such as walking and cycling, playing integral roles. These strategies aim to reduce reliance on single-occupancy vehicles by promoting higher vehicle occupancy and encouraging the adoption of alternative transportation modes. By enhancing vehicle occupancy and prioritizing active transportation, these strategies contribute to reducing traffic congestion levels, decreasing greenhouse gas emissions, and improving air quality.

In addition to shared mobility and active transportation, pricing strategies, including congestion pricing, have proven effective in managing vehicular travel demand. Congestion pricing involves implementing charges for utilizing specific roadways or areas during peak hours. The objective is to incentivize individuals to opt for public transportation, carpooling, or other sustainable modes of transportation, thereby reducing traffic congestion and promoting a greener environment.

In addition to congestion pricing strategies, parking pricing mechanisms have also demostrated potential in reducing vehicular traffic [Victoria Transport Policy Institute, 2019]. Implementing an efficient parking pricing strategy can yield numerous benefits, including increased turnover of parking spaces, improved user convenience, cost savings for parking facilities, reduced traffic congestion, and increased revenue [Litman, 2010].

A well-designed parking pricing system can address various challenges associated with parking, thereby contributing to more efficient transportation. Appropriately setting parking prices has the potential of alleviating issues such as the frustrating and time-consuming task of circling around in search of an open spot. Moreover, parking cost can motivate drivers to consider alternative transportation modes, such as public transit, walking, or cycling, thereby reducing the overall demand for parking spaces and further alleviating traffic congestion in urban areas.

Although previous studies indicate the potential of parking pricing to reduce traffic volumes and improve transportation efficiency [Litman, 2010], there remains a gap in research regarding the effectiveness of integrating parking pricing with other demand management strategies like shared mobility and active transportation. This chapter presents a study that seeks to fill this research void and provide valuable insights to policymakers.

The primary objective of this chapter is to examine the synergistic effects of combining parking pricing with other demand management strategies. By investigating the integration of parking pricing with shared mobility and active transportation, my analysis aims to uncover potential benefits, challenges, and optimal approaches for achieving sustainable and livable urban environments.

Specifically, we present a bi-level mathematical model that aims to identify the parking pricing scheme for low-occupied vehicles, in order to incentivize ridesharing and active transportation and contribute to urban sustainability. For the upper level, we take parking price as a control variable and consider multiple societal objectives, such as roadway congestion, vehicle miles travel, cyclist miles traveled, physical activity, and pollution exposures, while the lower level is a network equilibrium problem, where each traveler selects their optimal routes based on their general cost and no one can improve their benefits by deviating from their chosen routes. Therefore, the pricing of parking serves as the catalyst for altering traffic patterns on transportation networks.

5.1 Bi-level model

Bilevel optimization refers to a specific type of optimization problem that encompasses two distinct sets of variables and objectives. It involves an embedded structure where one problem, known as the upper-level problem or the leader, incorporates another problem referred to as the lower-level problem or the follower [Dempe, 2002].

In this hierarchical optimization framework, the upper-level problem (i.e.,"leader") represents the main objective or goal, while the lower-level problem(i.e., "follower") is nested within it and acts as a constraint or sub-problem. The leader aims to optimize its objective while considering the decisions made by the follower, who aims to optimize their own objective based on the leader's decisions. This hierarchical structure leads to inter-dependencies and interactions between the upper-level and lower-level variables.

A bilevel program is usually expressed as:

$$Min_x \ f(x, y) \tag{5.1}$$

$$s.t. \ g(x, y) \leq 0 \tag{5.2}$$

$$min_y \ F(x, y) \tag{5.3}$$

$$s.t. \ G(x, y) \leq 0 \tag{5.4}$$

Where x, y are the decision variables. Noted that if $F(x, y)$ is an equilibrium problem, which is also known as a mathematical programming model with equilibrium constraints (MPEC)[Luo et al., 1996]. In this case, the problem can be expressed as:

$$Min_x \ f(x, y) \tag{5.5}$$

$$s.t. \ g(x, y) \leq 0 \tag{5.6}$$

$$VI(K, F(x, y)) \tag{5.7}$$

Where x is the upper-level variable and y is the lower-level variable, and x are parameters in VI and $y \in K$, where K is a closed convex set.

5.2 Methodology

In this study, we assume there are five parking lots that are operated by the government, and each of them is located at a different destination. First of all, the government wants to maximize revenue and minimize societal impacts by choosing the optimal parking price. In the scenario of my study, we assume that only solo drivers have the willingness to park at their destinations. Therefore, for a given parking pricing scheme, travelers minimize their traveling costs by determining of traveling mode and traveling route. Therefore, we model the problem as a bi-level optimization problem. The upper level consists of the government's objectives and constraints, and the lower level consists of participants' objectives and constraints.

Following the network setting and game design from Chapter 3 and Chapter 4, the government could have multiple monetary and societal objectives, such as revenue, roadway congestion, vehicle miles traveled, cyclist miles traveled, physical activity, and pollution exposures. we denote p_d as the parking price of the place d, hence the upper-level multi-objective problem is formulated as:

$$\begin{aligned} objective =&\alpha \cdot congestion + \beta \cdot VMT + \gamma \cdot CMT + \delta \cdot physical\ activity \\ &+ \zeta \cdot pollution\ exposure + \theta \cdot revenue \qquad (5.8a) \\ =&\alpha \sum_{a \in A} t_a + \beta \sum_{a \in A} l_a x_a^{rd} + \gamma \sum_{a \in A} l_a x_a^c + \delta(\sum_i \sum_a \epsilon_w^b (t_a - t_a^e) x_a^{er,i} + \sum_a \epsilon_c^b l_a x_a^c) \\ &+ \zeta(\sum_i \sum_a \epsilon_w^e E_a (t_a - t_a^e) x_a^{er,i} + \sum_a \epsilon_c^e l_a E_a x_a^c) + \theta \sum_{d,a:sn(a)=d} x_a^s p_d \qquad (5.8b) \end{aligned}$$

where, $m \in \{s, nr-1, nr-2, er-1, er-2, c\}$, and $sn(.)$ denote a node of the arc a.

For the lower-level study, it is a multi-modal network equilibrium problem. we use the proposed model in Chapter 3, so the equilibrium problem is formulated as:

$$0 \leq f_k^{\omega,m} \perp C_k^{\omega,m} - u_\omega \geq 0 \qquad (5.9a)$$

$$u_\omega \text{ free} \perp q^\omega - \sum_{k \in K^\omega} \sum_m f_k^{\omega,m} = 0 \qquad (5.9b)$$

Therefore, by combining the upper-level problem Equation 5.8 and the lower-level problem Equation 5.9, the goal is to search for a flow pattern that is compatible with both constraints of the lower problem and the objectives from the upper-level at equilibrium.

5.3 Algorithm

we utilize a Genetic Algorithm (GA) based heuristic optimization approach to solve the proposed multi-objective optimization problem. GA is a stochastic optimization algorithm. It is widely used in multi-objective optimization problems because of its flexibility, robustness, and easy implementation. GA uses selection, crossover, and mutation to create new solutions, which are evaluated and selected for the next generation. Through these iterations, GAs converge on a set of better-performed solutions. Following [Hou and Lee, 2018], the Latin Hypercube sampling (LHS) method was applied to select initial points to facilitate the searching process.

For this study, a set of parking prices for all destinations is defined as a chromosome. For each generation, chromosomes are evaluated by Equation 5.9. The chromosomes are ranked according to evaluation results. Then, several groups of two high-ranked random chromosomes are selected for crossover. The length of crossover is randomly defined. For every generation, there is also a small chance that a chromosome may mutate (See Algorithm 1 as a reference below)

Input : Sets of parking prices p_d, population size *popsize*, crossover probability *pc*, mutation probability *pm*, tournament size *ts*, maximum number of generations *max_gen*

Output: Best solution and its corresponding objective value

$d \leftarrow$ dimension of decision variable space;

num_seeds $\leftarrow$ number of runs to execute;

st $\leftarrow$ matrix to store the best objective values;

Initialize P with a population of *popsize* random floats of length d using Latin-Hypercube sampling;

for *seed* $\leftarrow 1$ *to num_seeds* **do**

  Set *gen* $\leftarrow 0$, *s_best* $\leftarrow$ None, *x_best* $\leftarrow$ None;

  while *gen* $<$ *max_gen* **do**

    Evaluate each individual in P using the function $value(x, v, w, W)$;

    if *s_best is None or the maximum value in s is greater than s_best* **then**

      Set *s_best* $\leftarrow$ the maximum value in s and *x_best* $\leftarrow$ the corresponding individual;

    end

    Initialize a new population Q of size *popsize* by selecting pairs of parents from P using the function $tournament\_selection(P, s, ts)$ and applying crossover and mutation with the function $cx\_and\_mut(P1, P2, pc, pm)$;

    Set $P \leftarrow Q$;

    Store *s_best* in $st[seed, gen]$;

    Increment *gen*;

  end

  Print *x_best* and *s_best*;

end

Algorithm 1: LHS initialed Genetic Algorithm for parking price problem

5.4 Numerical study

The Sioux Falls network is chosen for the numerical study in this section. The network contains 24 nodes and 76 links. For simplicity, we only choose 25 OD pairs that originated from (1,2,11,13,20) to (10,15,16,17,19). we have a total travel demand of 360000 from the original network, and we evenly distribute the travel demand to OD pairs, resulting in 14400 for each OD pair. we used link distance as the weights and applied the k-short shortest path algorithms [Yen, 1971] to select the ten shortest paths between the selected OD pairs. The nodes (10,15,16,17,19) are chosen as destinations to simulate a Central Business District (CBD). we assume each destination has a parking lot, and the parking fees are added to observe the changes in traffic patterns. See Figure 5.1 as a reference.

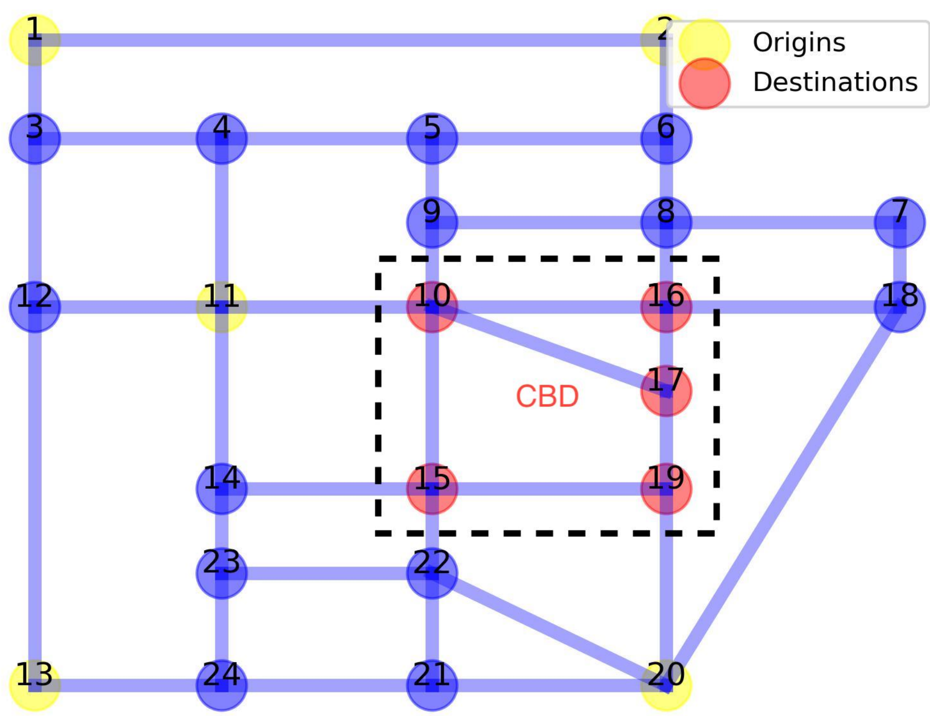

Figure 5.1. Locations of origins and destinations

Although policymakers, in reality, may have preferences for different objectives, it is crucial to note that revenue optimization remains a critical factor in maintaining the parking facility. Therefore, in this numerical study, we set the optimization objective as the revenue plus another negative societal impact (VMT). For this optimization objective, we set $\theta = 1, \beta = 2$ and the other coefficients are set to be equal to zero.

For the GA algorithm, we choose to have ten random seeds, and a population of 300 with 80% better chromesome for crossover and 10% mutation rate. As shown in Figure 5.2, the

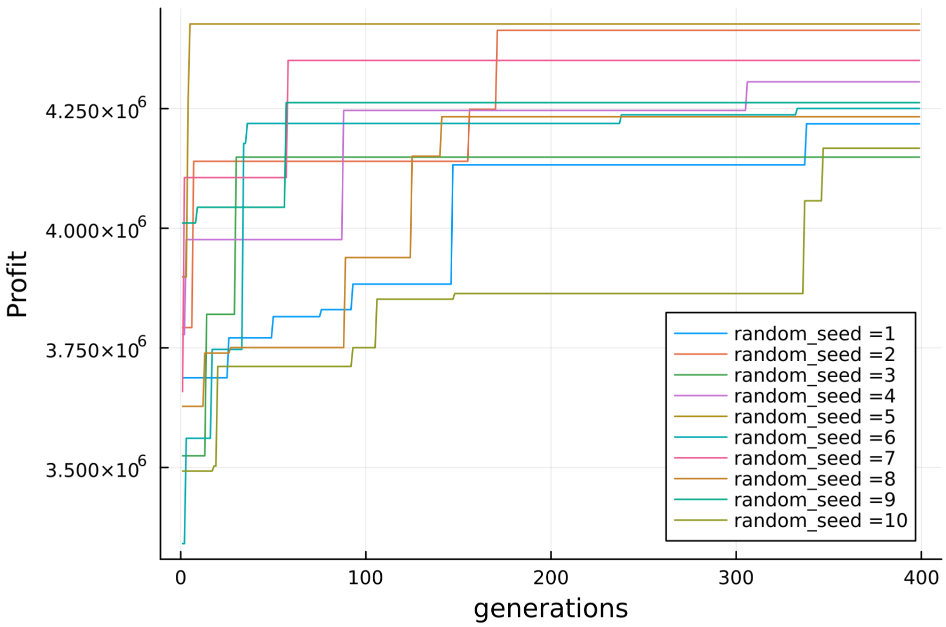

Figure 5.2. Performances changes by GA

10 random seeds converge quickly, and become stable after 400 generations. The final result of these 10 random seeds are

Seed number	Total revenue
Random seed 1	4218270.00
Random seed 2	4413700.00
Random seed 3	4148650.00
Random seed 4	4306040.00
Random seed 5	4426880.00
Random seed 6	4250350.00
Random seed 7	4350730.00
Random seed 8	4233100.00
Random seed 9	4262520.00
Random seed 10	4167240.00

By averaging the results of these ten random seeds, we have 4277748 revenue as the optimal solution with 95592 standard deviation, where the parking prices are 22.74 at destination 10, 23.67 at destination 15, 26.98 at destination 16, 29.194 at destination 17, and 29.638 at destination 19.

Regarding the network performances, we apply the same measurements proposed in chapter three:

1. The congestion level CL (total link travel time) :

$$\mathrm{CL} = \sum_{a \in A} t_a \tag{5.10}$$

2. The total vehicle miles traveled(VMT):

$$\mathrm{VMT} = \sum_{a \in A} l_a x_a^{rd} \tag{5.11}$$

3. The total cyclist miles traveled(CMT):

$$\mathrm{CMT} = \sum_{a \in A} l_a x_a^{c} \tag{5.12}$$

4. The total physical benefit (PB):

$$\mathrm{PB} = \sum_{i} \sum_{a} \epsilon_w^b (t_a - t_a^e) x_a^{er,i} + \sum_{a} \epsilon_c^b l_a x_a^c \tag{5.13}$$

5. The total pollution exposure (PE):

$$\mathrm{PE} = \sum_{i} \sum_{a} \epsilon_w^e E_a (t_a - t_a^e) x_a^{er,i} + \sum_{a} \epsilon_c^e l_a E_a x_a^c \tag{5.14}$$

Table 5.1. The average results of the multi-objective optimization

Stats	VMT	CMT	CL	PB	PE
Mean of “with parking price”	2752852	2071151	10559.1	12.54	1359.24
values of “without parking”	2756638	2067361	10595.26	11.4	1340.57
Differences of “with - without”	-3786	3790	-36.16	1.14	18.67

Table Table 5.1 presents a statistics comparison of the “with parking price” and “without parking price” conditions. In this table, physical activity (PB), cyclist miles traveled (CMT), vehicle miles traveled (VMT), congestion (CL), and exposure to air pollution (PE) are analyzed for network performance. Under the "with parking price" condition, the mean values indicate that the average VMT is slightly lower compared to the "without parking price" condition. This suggests that the presence of parking prices may further discourage excessive vehicle usage and thereby results in a reduction in overall travel distance. Furthermore, the Congestion Level (CL) experiences a slight decrease, indicating that parking pricing may have a positive effect on alleviating congestion.

For the health and environmental related impacts, the "with parking price" condition shows a higher mean value for Physical Benefit (PB) compared to the "without parking price" condition. This is consistent with the pattern of CMT, which also shows a increase under the "with parking price" condition. Both results imply that the presence of parking pricing can encourage individuals to engage in more physically active modes of transportation, such as walking or cycling.

Additionally, PE demonstrates a higher mean value under the "with parking price" condition, implying that the implementation of parking prices may lead to an increase in pollution exposure. Consistent with the findings in Chapter 3 and Chapter 4, this increase reflects a trade-off between the health benefits from active transportation and the harm of inhaling more air pollutants by cyclists or pedestrians.

5.5 Conclusion

This chapter explores the impact of integrating a parking pricing scheme with other travel demand management strategies, specifically SM and AT. The focus is on implementing parking pricing exclusively for solo drivers at various destinations. To address the inherent characteristics of the problem, a bilevel optimization model is examined, which captures the government's high-level decision-making process regarding parking pricing, as well as the lower-level decision-making process of travelers based on similar general cost functions discussed in Chapter 3.

The findings of the analysis indicate that the introduction of higher-level parking pricing schemes effectively reduces the number of underutilized vehicles on the road. Furthermore, it provides additional incentives for travelers to choose ridesharing and active transportation options, thereby contributing to the overall sustainability of urban areas.

These findings highlight the potential benefits of incorporating parking prices as a strategy to reduce vehicle travel distance, alleviate congestion, and promote physical activity. By influencing travel behavior and encouraging the use of sustainable transportation options, such as walking, cycling, or public transit, parking pricing strategies can contribute to the creation of more sustainable and livable cities. Policymakers and urban planners can consider these insights to design effective parking policies and transportation management strategies that prioritize sustainability and public health.

The future work would include the sensitivity analysis of different aspects of the parking pricing scheme. For example, under different travel demand conditions, one can explore the effects of varying parking prices on travel behavior and mode choices. In addition to the sensitivity analysis of the parking pricing scheme, future work can also focus on evaluating the effectiveness of collaborative policies to improve the overall sustainability of the transportation system. This can involve simulating changes in gas prices and adjusting the cost associated with solo driver distance. By examining the impact of these policy adjustments on travel behavior, mode choice, and overall travel demand, we can gain insights into how different policy levers can be utilized to promote sustainable transportation practices.

Chapter 6

Conclusion

In my dissertation, we developed two novel network equilibrium models to study the relationship among AT, VT, and TNC services. For TNC services, we consider e-hailing, e-pooling and express pool applications. By considering health effects, these models allow me to study the impact of these strategies on the entire transportation system and identify potential trade-offs and synergies between different transportation modes.

In chapter two, my dissertation presents an extensive literature review focused on network modeling that incorporates shared mobility modes and active transportation. The review covers the utilization of inequality constraints to capture the dynamics between passengers and service vehicles with limited capacities. To enhance computational efficiency, the literature employs mixed complementarity models. This knowledge serves as a foundation for my proposed network models and provides valuable insights for readers seeking to understand the advancements in modeling shared mobility and active transportation using the mixed complementarity approach and inequality constraints.

In chapter three, by assuming passengers can only match with drivers for a trip if they have the exact same origin and destination, we developed a network equilibrium model to study the many aspects of the network, such as congestion performance and vehicle miles traveled, when travelers have the alternatives of using active transportation and TNC services for their travel. The model comprises three interconnected components: general cost, mode choice, and network congestion. To address computational efficiency, we formulate the problem as a mixed complementarity problem and establish an equivalent variational inequality model to demonstrate the existence and uniqueness of the solution. Note that the unique solution is applicable to the link-based model since different combination path flows may have the same link flow solution. However, in reality, link flow is easy to observe and provides practical insights. By incorporating health impacts such as physical activity benefits and air pollution exposure, my model contributes to the understanding of the interplay among components of network congestion, vehicle emission, air pollution exposure, physical activity benefits, mode choice, and route choice. This makes it a valuable tool for transportation planners and environmental scientists seeking to analyze and optimize the network performance, including these two sustainable transportation options active transportation and TNC modes.

In chapter four of my dissertation, we present an extended network equilibrium model that relaxes certain assumptions made in previous chapters. Specifically, we consider the scenario where passengers have the choice to walk to their nearest meet-up spots on the network,locating on adjacent nodes, for pickup by TNC vehicles. This allows for a more realistic representation of passenger behavior and introduces the associated health and pollution effects into the model. Additionally, the model accommodates the presence of drivers operating without passengers (i.e., deadhead miles), which aligns more closely with real-world conditions and allows for the observation of passengers' responses to inconvenience. This extended model serves as a valuable tool for evaluating policies aimed at managing travel demand through active transportation and shared mobility options. The insights obtained from this study can aid transportation planners and policymakers in making informed decisions about how to effectively promote and integrate active transportation and shared mobility initiatives within their cities.

In chapter five, a parking pricing scheme to regulate vehicular travel demand is introduced. A bilevel optimization model is developed to address the issue of on-road low-occupied vehicles, with the aim of promoting ridesharing and active transportation and contributing to urban sustainability. The findings highlight the potential benefits of using parking prices as a strategy to reduce vehicle travel, alleviate congestion, encourage physical activity, and mitigate pollution exposure. By influencing travel behavior and incentivizing the use of sustainable transportation options, such as walking and cycling, parking pricing strategies can play a significant role in creating more sustainable and livable cities.

To sum up, this study provides a nuanced view of the transportation system that was overlooked in the past. The future work of my dissertation could be extended to include public transit for study. Many studies revealed the competition or cooperation relationship between shared mobility and public transit, but no literature theoretically reveals the connection between these two modes. Especially when active transportation is involved, the relationship among these three components could be more very complex, which is worth further study to investigate.

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