ADOPTING MICRO-MOBILITY FOR URBAN PEOPLE AND FREIGHT TRANSPORTATION

By

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Civil Engineering - Doctor of Philosophy

2020

ABSTRACT

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Oil-dependent transportation is an enormous burden on the United States in varied areas. One recognized approach to addressing transportation oil-dependency and corollary emissions, and to promoting sustainability, is shared mobility. One form of shared mobility is shared micro-mobility, which is based on shared use of low-speed transportation modes such as regular and electric bicycles or scooters. The most common types of shared micro-mobility are bike-sharing and scooter sharing systems. Despite growing attention to shared micro-mobility in the literature, understanding potential users' choice of this emergent transportation mode, and thus insights into potential markets of shared micro-mobility, are noticed as a major knowledge gap. Furthermore, design frameworks for shared micro-mobility which can help authorities better reflect the benefits and costs associated with these systems is another knowledge gap. On the other hand, understanding measures and contexts in favor of micro-mobility for urban freight delivery is also a gap to bridge. This research sets out to address these discerned knowledge gaps in three major directions.

First, users' stated commute mode choices, from options in a mixed fleet bike-sharing system as well as conventional alternatives, were captured through an online survey. The survey presented respondents, who were a sample of commuters to Michigan State University, with hypothetical commute scenarios introducing quantified health benefit values and emission costs of offered commute modes, as well as conventionally considered travel costs and travel context specification. Through discrete choice models developed with the collected data, travel time and

dominant topography of the commute path were found to significantly affect commute mode choice. This observation indicates necessity of incorporating electrically assisted micro-mobility, namely electric bikes and scooters, to ensure success of shared micro-mobility schemes in hilly terrain, or shared micro-mobility programs anticipated to support long trips.

Next, a multi-objective optimization problem is proposed, which encompasses operational and societal costs of a conventional urban transportation network incorporating a mixed fleet bike-sharing system. This framework addresses the tradeoff between authoritarian perspectives influencing transportation and user perspectives. Through a hypothetical case study and a proposed metaheuristic solution algorithm, varied analyses found pedal-assist electric bike (pedelec) and bus to be the most popular public modes. Results show that more authoritarian emphasis on public health or emission results in more pedelecs and less bus and e-scooter ridership in the system. Also, in cases of increased inactivity-related health care expenditure or higher emission costs, the design framework would provide more pedelecs to serve the demand.

Lastly, a framework is formulated to provide insights into policy implications and operational insights in favor of micro-mobility for last mile freight transportation. Analyses of a hypothetical delivery instance in downtown Chicago indicate that electric cargo bikes and tricycles always serve as the optimal fleet when customers are within 3 mi of their assigned distribution center. In this case, increase in delivery sizes shifts the optimal fleet towards electric cargo tricycles. On the other hand, in case of customers lying beyond 3 mi of the distribution center, electric micro-mobility would not be an optimal choice; however, when customers are over 12 mi from the distribution center, or within 6 mi of the distribution center while pollution tax is in place, another sustainable alternative, namely electric van, constitutes the optimal delivery fleet.

“This dissertation is lovingly dedicated to my mother, **Narges,**
for her love, encouragement, and support.”

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to my advisor, Dr. Neeraj Buch, for his guidance, support, and patience. I also would like to extend my heartfelt appreciation to the rest of my dissertation committee, Dr. Srinivas (Sri) Talluri, Dr. Peter Savolainen, and Dr. Timothy Gates, for their valuable directions and insights. Finally, I wish to thank my dear parents, sisters, friends, and all who have been my sources of love, motivation, and strength.

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CHAPTER 1. INTRODUCTION

1.1 Motivation

Oil-dependent transportation is an enormous burden on the United States in varied areas; the U.S. incurs: 1) oil purchase cost of approximately $1 billion per day which can also inflict an extra $45 billion per year due to oil price volatility, and 2) emission costs of over $55 billion annually manifested in health and other deteriorations [1], [2]. U.S. Department of Transportation (USDOT) has set out goals to reduce oil dependency and transportation-related emissions, and to promote sustainable practices [3]. The generally unanimous definition of sustainability is “meeting the needs of the present without compromising the ability of future generations to meet their own needs.” [4]. Sustainability in transportation practices are considered accomplishable partly by means of transportation planning and operations [5].

One currently recognized approach to transportation sustainability is shared mobility. Shared mobility is known as concurrent or successive use of transportation services by users, without ownership burdens [6]. In this line, shared micro-mobility is an innovative strategy that draws on low-speed transportation modes, such as regular and electric bicycles and scooters [7]. In addition to promoting sustainability, shared micro-mobility promises also enhanced urban mobility, economic development, and public health. Bike-sharing is among the most popular shared micro-mobility options particularly in urban areas. In bike-sharing systems, users can rent a bike from a station near their origin, ride it over to their destination, and drop it off at a station near their destination. Bike-sharing systems, which are a form of public transit, provide the benefits of biking to the users, without having to incur ownership complications [8]. There are multiple benefits associated with bike-sharing systems, including flexible mobility, reduction of greenhouse gas emissions, personal savings, health benefits, mitigated traffic congestion, reduced fuel consumption, and support for multimodal transportation networks [8], [9]. In fact, bike-sharing systems are viewed as a means of public transportation whose ultimate goal is to be integrated into urban transportation networks [10]. Achieving this goal can lead to more efficient transportation systems.

As aforementioned, electric bicycles, commonly referred to as e-bikes, are also among alternatives that can be deployed for shared micro-mobility. E-bikes boast enhanced performance compared to conventional bicycles through the ability to travel longer distances and at higher operating speed, and providing more convenience particularly in hilly settings [9]. In general, e-bikes are classified into two major types of bicycle style e-bikes (BSEB) and scooter style e-bikes (SSEB); BSEB is partially electric and still requires pedaling, and thus can yield health benefits, whereas SSEB is fully electric [11]. Owing to the mentioned superiorities, e-bikes are costlier than conventional bicycles and there is a cost barrier to e-bike adoption. Incorporating e-bikes in bike-sharing systems has been proposed as a solution to overcome the cost barrier [12]. E-bike-sharing systems are generally anticipated to draw users from competing personal and motorized travel modes, and elevate the environmental and social benefits of conventional bike-sharing systems [13].

Freight activities form another major contributor to transportation emissions in the United States. It is projected that the U.S. will undergo a 23.5% increase in freight transportation by 2025, and another 20% growth by 2040. In accordance, it is expected that, within this time frame, freight transportation related emissions will surpass those from other transportation sectors, such as passenger transportation [14]. On the other hand, according to 2015 statistics, U.S. trucking industry incurs approximately over $56 billion due to congestion in urban settings [15]. Additionally, illegal parking and unloading exposes delivery companies to fine costs and causes road congestion [16]. In this respect, there is a growing micro-mobility trend for last-mile freight transportation, and cargo cycles are increasingly recognized for alleviating shortcomings of conventionally motorized urban freight activities, owing to environmentally-friendly and mobility-enhancing attributes [17][18].

Aware of the growing attention to micro-mobility for passenger and freight transportation, this dissertation aims to address some of the related gaps. Bridging these gaps can help cast light on detailed design of shared micro-mobility systems as a public transportation option, and realizing contexts in which last-mile logistics can benefit from cargo cycles.

1.2 Knowledge Gaps

Literature indicates that shared micro-mobility, as a public transportation option, and cargo cycles, as a micro-mobility trend in urban logistics, have been recognized in appreciation of economic, environmental, and health benefits. However, there exist lacks of:

- understanding users' view of shared micro-mobility in light of elaborate benefits and costs awareness;
- design frameworks and associated decision-making tools for shared micro-mobility systems that accurately reflect the benefits and costs; and,
- understanding measures and settings that can drive urban logistics to deploy cargo cycles, considering a freight company's costs as well as societal benefits, in one exhaustive framework.

This dissertation intends to address the above-mentioned gaps and contribute to the evolving trend of integrating the rising awareness of transportation sustainability with decision-making procedures by both urban authorities and freight movers.

1.3 Problem Statement

This dissertation provides insights into passenger and freight transportation focusing on emerging micro-mobility technologies, and considering authoritarian and user perspectives of operational specifications and quantified visions of benefits and costs. To present an overview of the present study, the following constituent chapters are briefly introduced here.

Chapter 2 titled "Investigating Users' Commuting Mode Choice from Intended Shared Micro-Mobility Integrated with Typical Options", addresses the knowledge gap as to users' commuting mode choice when given the shared micro-mobility alternative in a typical transportation network. To this end, this chapter sets out to develop discrete choice models through data from a self-designed online survey, which accounts for quantified health benefit values and emission costs of modes, as well as conventionally considered travel costs and travel context specifications. The objective of this chapter is to develop transport mode choice models, as a transportation planning tool, and to uncover significantly influential factors in commuting mode choice, when both conventional and novel factors are presented to users.

Chapter 3 titled "A Multi-Modal Public Transportation System Offering Shared Micro-mobility" attends to the lack of shared micro-mobility design frameworks that account for detailed benefits and costs aspects. In other words, the objective of this chapter is to present a framework that can help in more informed decision making when planning sustainable and active urban mobility, and thus proposes a multi-objective optimization problem entailing operational and societal costs of a typical urban transportation network incorporating a mixed fleet bike-sharing system. This framework addresses the tradeoff between authoritarian perspectives influencing transportation, as well as users' standpoints, considering quantified emission costs and health benefit values along operational costs of the system.

Chapter 4 titled "Micro-Mobility and Electrification to Support Sustainable Urban Freight Delivery" gets to understanding emission policies and urban contexts in favor of electric cargo cycles and electric vans for logistics. To do so, chapter 4 presents a complex mathematical formulation reflecting a trade-off between operational costs of a freight delivery company and the societal costs imposed by the company on the society. The objective of this chapter is to comprehend policy implications and operational insights in terms of when and how green modes of transportation can be deployed for network sustainability enhancement.

Chapter 5 recapitulates the present study and recommends directions to address its caveats, and to complement it through future research.

1.4 Expected Contributions

This dissertation intends to address the aforementioned knowledge gaps through the defined objectives, and contribute to the existing literature on adopting micro-mobility for passenger and freight transportation. Accordingly, Chapter 2 is expected to illuminate what factors, among detailed benefit and costs associated with commuting alternatives in a typical transportation network offering shared micro-mobility, significantly influence commuters' mode choice, and to yield transportation mode choice models developed in light of detailed considerations. Through these contributions, the direction and findings of Chapter 2 are expected to be informative to transportation decision-makers and planners contemplating shared micro-mobility alternatives. Next, Chapter 3 presents a design framework for multimodal transportation networks incorporating shared micro-mobility, considering detailed benefits and costs, through the eyes of both planners and users. This contribution, in response to a recognized gap in the literature, is anticipated to help informed planning of shared micro-mobility systems in urban transportation networks. Finally, Chapter 4 attends to micro-mobility adoption for last-mile logistics through a mathematical modeling framework that accounts for operational freight transportation costs as well as emission taxes, in a real-world transportation network. The contribution of Chapter 4 is to discern policy implications and urban contexts that can spur the uptake of electric micro-mobility as well as electric vans, thereby helping support sustainable urban freight delivery through micro-mobility and electrification.

CHAPTER 2. INVESTIGATING USERS' COMMUTING MODE CHOICE FROM INTENDED SHARED MICRO-MOBILITY INTEGRATED WITH TYPICAL OPTIONS

2.1 Overview

Bike-sharing is an increasingly evolving concept across the globe, offering diverse benefits such as flexible mobility, reduced fuel use, the corollary reductions in emissions, and increased physical activity levels [8]. Essentially, bike-sharing enables users to enjoy the advantages of biking as an active mode of transportation, without the complications of private bike ownership (i.e. purchase and regular maintenance). On the other hand, another rapidly growing aspect of today's transportation is represented by e-bikes [9]. In general, there are two major types of e-bikes [11]: 1) bicycle style e-bikes (BSEBs) which resemble conventional bicycles in both appearance and operation; one type of BSEB which is referred to as pedelec requires the rider to constantly keep pedaling while assisting the rider through electric assistance to the pedals, and 2) Scooter style electric bicycles (SSEBs) which share many similar features to gasoline-fueled scooters, while essentially relying on electric power. Figure 2-1 portrays examples of BSEB and SSEB [19]. As opposed to pedelecs, scooter style electric bicycles do not require pedaling. E-bikes are superior to conventional bicycles in many respects, such as the ability to traverse longer distances and reach higher speeds, and being more convenient, especially over hilly terrains. Also, even though less than conventional bikes, pedelecs would still provide health benefits by engaging the rider in the physical activity of pedaling, despite the electric assistance [9]. In the United States, the requirements for e-bikes are defined as a two-/three-wheeled vehicle with operating pedals, whose speed is limited to 20 mph when ridden exclusively on electric power, and with 750w of power or less [20].

a) BSEB or pedelec

b) SSEB

Figure 2-1 Examples of major e-bike types (10)

Beside the variety of benefits e-bikes have in comparison to conventional bicycles, they are also costlier. To overcome the cost barrier to e-bikes adoption, inclusion of e-bikes in bike-sharing systems has been proposed [12]. This solution also has the potential to attract more users from other transportation modes and contribute to the social benefits that conventional bike-sharing systems [21]. In general, e-bike-sharing systems are anticipated to contribute to reduced single occupancy trips by cars, improve air quality through reduced CO_2 emissions, enhance public health by increasing physical activity levels, improve roadway mobility and safety especially for cyclists due to more cyclists than car users, support local economies and tourism and, at larger scales, the societal quality of life [13].

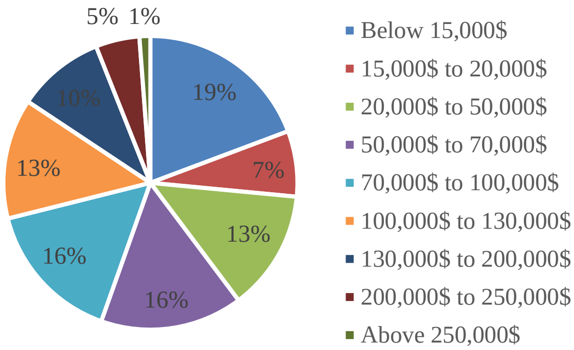
As of 2007, many cities in the United States have made the acquaintance of bike-sharing concept as a means to overcome urban transportation challenges such as congestion, air pollution and public health concerns [22]. The Capital Bikeshare launched in 2010 in Washington D.C. was the first major bike-sharing system in the United States [23]. Today, the American bike-sharing systems vary in scale, from a very small program in Des Moines, Iowa, consisting only of twenty-five bikes and three docking stations, to the large scale program in New York City with six thousand bikes and three hundred stations [24]. Most of the current literature on American bike-sharing systems are retrospective, and have travel logs data or user surveys. Among the investigated systems, Capital Bikeshare is supposed to be the most studied program, mostly owing to the free access to the usage data of this system [25], [26]. In a similar trend, studies with broader global scopes also majorly investigate the already implemented bike-sharing programs with various objectives such as identification of usage patterns, exploration modal shifts, or determination of influential factors in system uptakes [27].

There are few studies in the literature attending to intended bike-sharing systems and their anticipated markets [28]–[33]. This scarcity is even more noticeable when it comes to e-bike-sharing or mixed fleet bike-sharing [34]. To address this knowledge gap in terms of shared micro-mobility, Chapter 2 of this dissertation investigates users' preferences in a typical transportation network which is to offer a mixed fleet bike-sharing system. It must be noted that presenting users with quantified health benefit values and emission costs associated with available modes to choose from is a novel approach in favor of public awareness and its influences on travel mode choice. To this end, an online survey was designed and distributed to a sample of Michigan State University faculty, students and staff to collect their current travel patterns, demographics and outlooks on an intended mixed fleet bike-sharing system. With use of the collected data set, discrete choice models are developed employing both classic variables of travel time and travel cost, and novel factors such as emission cost and health benefit values associated with the offered modes.

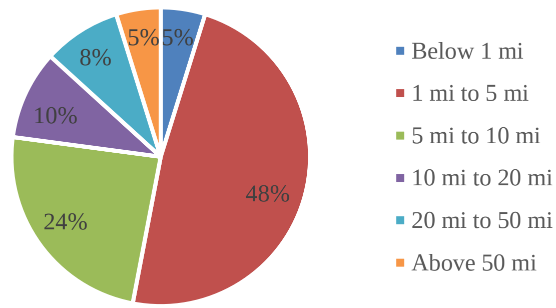
2.2 Data

In this study, an online survey about morning commutes to Michigan State University (MSU) was conducted. This survey was running from April to July of 2018, to which 114 participants from MSU responded, including faculty, staff and students. The modes considered in this study are private modes including, walking, private regular bike, motorcycle, and private automobile, as well as shared modes, such as regular bike, shared pedelec, shared electric scooter (E-scooter), and bus. These mode choices take place in different proposed contexts of commuting distance (5 instances of 1 mi, 5 mi, 10 mi, 20 mi, and 50 mi) and topography (mostly flat, mostly mildly hilly, and mostly steeply hilly). As contributions, the survey reflects each mode's contribution to societal emission cost and the health benefit values. For this purpose, modes' quantitative characteristics are displayed in Table 3-1, whose values are based on the average values in the United States. The detailed calculation values for health benefit quantification and fare calculations are presented in Appendices A and C, and the survey is presented in Appendix F. It must be briefly noted that the emission costs and health benefit values are only specific to operation whiles of each mode. Accordingly, as an example, since biking emits no emission while operation, it would have emission costs equal to zero, while biking engages the rider in pedaling and is an active mode while operation, and therefore has health benefit values.

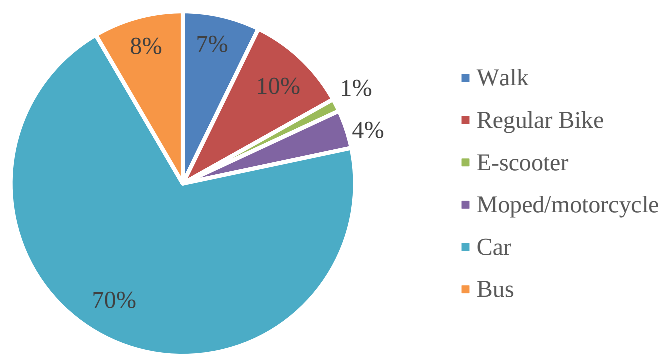
After removing the incomplete responses to the survey, 83 respondents are retained, each having completed 15 distance-topography scenarios. Accordingly, a total of 1,245 observations are obtained. Figure 2-2 and Table 2-1 present overview of the collected data. As can be seen in Figure 2-2-b, the nearly half of the commuting distances to MSU lie within 1 mi to 5 mi. Also, Figure 2-2-c shows that the dominant current commuting mode is private automobile.



a) Annual income level



b) Commuting distance



c) Current regular commuting modes

Figure 2-2 Overview of the demographics and travel choices

According to Table 2-1, female and male respondents constitute 42% and 58%, respectively. It should be noted that in this table and under *Occupation* variable, Professional student signifies a student who majors in a professional degree, which includes but is not limited to: doctor of education, doctor of veterinary medicine, law, dentistry, medicine, doctor of physical therapy, nursing, pharmacy, etc. Lifelong student/ learner is defined as a voluntary, constant self-motivated pursuer of knowledge for personal of career-related reasons [35].

Table 2-1 Data overview

Categorical Variable			Frequency	Percentage
Gender	Female		35	0.42
	Male		48	0.58
Occupation	Undergraduate Student		22	26.83
	MSc Student		2	2.44
	PhD student		4	4.88
	Professional Student		0	0.00
	Lifelong Student		1	1.22
	Faculty: Assistant Professor		7	8.54
	Faculty: Associate Professor		7	8.54
	Faculty: Professor		10	12.20
	Staff		29	35.37
Responsible for children	Yes		12	17
	No		71	83
Private automobile	Yes		74	89
	No		9	11
Motorcycle	Yes		7	8
	No		76	92
Pedelec	Yes		1	98
	No		82	2
E-scooter	Yes		1	98
	No		82	2
Commuting path	Mostly Flat		68	82
	Mostly Mildly Hilly		15	18
Continuous Variable	**Min.**	**Max.**	**Median**	**Average**
Age	18	72	39	40.62
Commuting time (min)	1	75	15	18.68
Number of people respondent commutes with	0	3	0	-

State commuting mode choices across the distance-topography scenarios are shown in Figure 2-3. Figure 2-3 indicates that private car is the predominantly selected mode for commute. However, at commuting distance of 1 mile, walking is a competing alternative. When commuting distance increases to 5 -10 miles, mixed fleet bike sharing alterantives, namely shared bike, shared pedelec, and shared E-scooter, overtake private motorcyc in almost all the circumstances. Even at commuting distance of 20 miles, when topography is mostly flat, mixed fleet bike-sharing alternatives are chosen as frequently as is private motorcycle. It can also be observed that, up to 20 miles of cummuting distance, users choose mixed fleet bike-sharing over bus, except for when topography is mostly steeply hilly at 20 miles of commuting ditance.

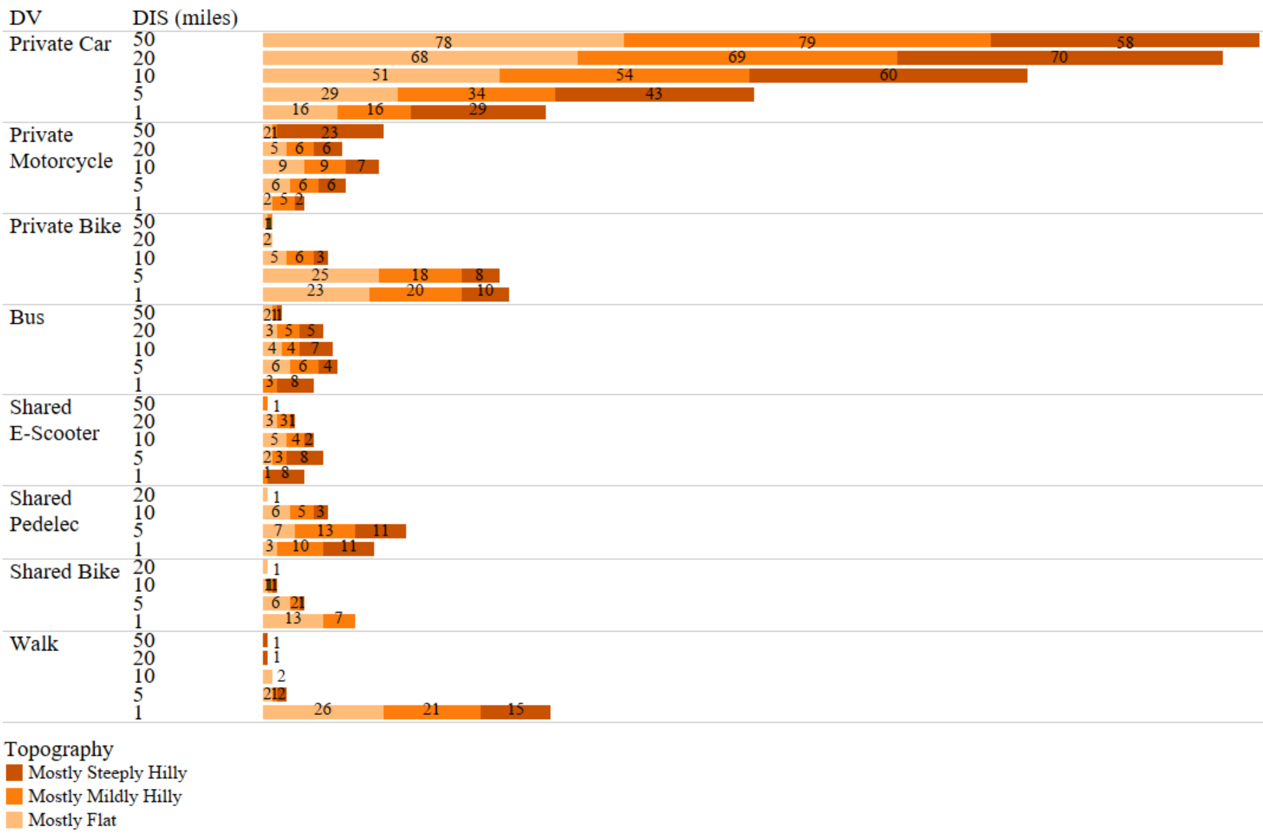


Figure 2-3 Stated commuting mode choices across distance-topography scenarios

2.3 Methodology

In this study, the R studio® software "mlogit" package intended for developing multinomial logit (MNL) regressions is used [36], to test a variety of discrete choice models based on the above presented dataset; the aim is to explore influential factors in commute mode choice and to develop predictive models. For this purpose, novel explanatory variables, namely quantified health benefit values and emission costs of commuting alternatives, as well as the more common variables such as travel time, travel cost, and travel distance are considered. Since the proposed alternatives include also active modes whose choice is affected by topography, this variable is also incorporated in this study. The factors considered when developing discrete choice models include, but are not limited to, correlation of the predictive variables, reasonableness of the signs of coefficients which are statistically different from zero, and the Log-Likelihood value.

2.4 Results

In regards to the predictor/explanatory variables, two main categories are defined: 1) alternative specific variables with generic coefficients, and 2) individual specific variables with alternative specific coefficients. Alternative specific variables with generic coefficients are specific to each mode/alternative, but essentially have the same influence on mode choice regardless of the intended alternative's characteristics. For example, it is considered that commuting duration has the same influence on commuter's choice, irrespective of the alternative's specifications. Similarly, the monetized health benefit value is an advantage that a commuter could derive by opting for an active mode regardless of which specific active mode has been selected. Accordingly, travel time, travel cost, health benefit value, and emission cost (belong to this category. On the other hand, individual-specific variables with alternative-specific coefficients are specific to each commuter/ observation, regardless of the selected mode. However, such variables provoke different perceptions in association with the selected mode. Topography is thus an individual-specific variable reflecting the distance that each commuter traverses, which affects the choice of each mode differently. This classification indicates the fact that varied modes would induce particular notions/ feelings (e.g. comfort) in different topographical contexts. Accordingly, Topography is considered an individual variable with alternative specific coefficients. The notations for the considered predictor variables are presented in Table 2-2. It should be noted that the variable DisPowered is the adjusted values of distance, in which distance value is taken to the power of 2 if the selected mode is among walking, private regular bike, shared regular bike, and shared pedelec, and to the power of 1 for other modes. This is to reflect the difficulty of traversing distance for the active modes in comparison to the other relatively more convenient options.

Table 2-2 Notations of the considered predictor variables

Predictor/Explanatory Variable	Notation
Distance	Dis
Topography	Topo
Adjusted distance	DisPowered
Travel time	TT
Travel cost	TC
Emission cost	EmissionCost
Health benefit value	HealthValue

2.4.1 Correlations and Covariates

In order to come up with a well-trained regression model, correlations of the covariates for the entire 1,245 observations (the 83 participants each responding to 15 trip scenarios) were explored at the outset. The Pearson correlations matrix as well as p-values can be seen in Table 2-3. In each cell, the p-value can be seen in parenthesis next to the associated Pearson correlation coefficient.

Table 2-3 Pearson correlation coefficients and respective p-values

	Dis	Topo	TT	TC	EmissionCost	HealthValue	DisPowered
Dis	1.00	0.00 (1.00)	0.78 (0.00)	0.46 (0.00)	0.95 (0.00)	-0.04 (0.17)	0.21 (0.00)
Topo	0.00 (1.00)	1.00	-0.01 (0.68)	0.005 (0.06)	-0.01 (0.67)	-0.03(0.24)	-0.02 (0.56)
TT	0.78 (0.00)	-0.01 (0.68)	1.00	0.14 (0.00)	0.62 (0.00)	0.52 (0.00)	0.59 (0.00)
TC	0.46 (0.00)	0.05 (0.06)	0.14 (0.00)	1.00	0.59 (0.00)	-0.32 (0.00)	-0.06 (0.03)

Table 2-3 Pearson correlation coefficients and respective p-values (cont'd)

	Dis	Topo	TT	TC	EmissionCost	HealthValue	DisPowered
EmissionCost	0.95 (0.00)	-0.01 (0.67)	0.62 (0.00)	0.59 (0.00)	1.00	-0.19 (0.00)	0.06 (0.04)
HealthValue	-0.04 (0.17)	-0.03 (0.24)	0.52 (0.00)	-0.32 (0.00)	-0.19 (0.00)	1.00	0.79 (0.00)
DisPowered	0.21 (0.00)	-0.02 (0.56)	0.59 (0.00)	-0.06 (0.03)	0.06 (0.04)	0.79 (0.00)	1.00

2.4.2 Multinomial Logit Models

An exhaustive set of standard multinomial logit (MNL) models, presented in Appendix G, are developed either with single covariates, or, according to Table 2-3, with covariates that are not highly correlated, i.e. the ones with p-values greater than 0.05. It is noteworthy that the MNL models are developed using R's mlogit package which enables defining generic as well as alternative specific coefficients. Among covariates, "Dis" and "Topo" are travel-context-related and independent of alternatives. i.e. transport modes in this study; for such covariates, alternative-specific parameters/coefficients must be introduced in the models, to reflect the fact that these covariates affect the choice of each alternative differently. The other covariates, however, are alternative-dependent, and can be considered with generic or alternative-specific parameters/coefficients. The first alternative, i.e. *Walk* is set as the reference alterative in the model development. The fitted models and their summaries are presented in Appendix G. Along with standard MNL models, whenever there are continuous covariates, i.e. *TT*, *TC*, *EmissionCost*, and *HealthValue*, random parameter (mixed) logit models are also tested.

The best model found through MNL analyses (presented in Appendix G), is concluded to be the mixed logit model in which TT (Travel Time) has random generic parameters, and Topo (Topography) has alternative-specific parameters.

Table 2-4 Best MNL model determined

Model	Model Coefficients' Specifications Note: Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Mixed (Random parameter) MNL Model with covariates:

- TT with generic random parameter/coefficient
- Topo with alternative-specific parameters/coefficients

Model Fit:

- Log-Likelihood: -1380.3
- McFadden R^2: 0.21145
- Likelihood ratio test : chisq = 740.27 (p.value = < 2.22e-16)

	Estimate	z-value	Signif.
Shared bike:(intercept)	-1.59	0.00	**
Shared pedelec:(intercept)	-3.38	0.00	***
Shared e-scooter:(intercept)	-4.49	0.00	***
Bus:(intercept)	-3.52	0.00	***
Private bike:(intercept)	-1.17	0.00	**
Private Motorcycle:(intercept)	-6.77	0.00	***
Private car:(intercept)	-3.89	0.00	***
TT	-0.06	0.00	***
Shared bike:Topo	-0.63	0.06	.
Shared pedelec:Topo	0.62	0.01	**
Shared e-scooter:Topo	0.82	0.00	**
Bus:Topo	0.69	0.00	**
Private bike:Topo	-0.06	0.77	
Private Motorcycle:Topo	1.09	0.00	***
Private car:Topo	0.79	0.00	***
sd.TT	0.21	0.00	***

random coefficients	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
TT	-inf	-0.20	-0.06	-0.06	0.08	Inf

The criteria to select this model are the largest log-likelihood values among the investigated models, sensible parameter/coefficient signs, and the fact that almost all of the parameters/coefficients are statistically significantly different from zero. Mixed logit or random parameter models address both repeated measurements due to successive scenarios presented to survey respondents, and Independence of Irrelevant Alternatives (IIA). Accordingly, the drastic improvement from standard MNL with TT and Topo covariates, to the mixed logit variant with random TT parameter is understandable. However, a nested logit version derived from the standard MNL is also developed for comparison purposes.

2.4.3 Multinomial Nested Logit Model

To derive the nested logit model, the first step is to discern the hidden nests. To do so, a random alternative, in this case E-scooter, is chosen, and its travel time is altered to 70% of the previous values; accordingly, a new dataset was generated based on the actual data set to test IIA. To this end, the actual data set and fitted function in R studio mlogit package are used to obtain old probabilities (OProb), and the new IIA test dataset and predict function in mlogit package are used for developing new probabilities (NProb). After testing ratios of NProb for alternative private car over each of the other alternatives, except E-scooter, it was found out that alternatives private car and private motorcycle form one nest, which is called private motorized modes (*PrivMotorModes*); all other alternatives are one nest, which is called environmental modes (*EnvironmentModes*). Figure 2-4 displays the structure of the multinomial nested logit model.

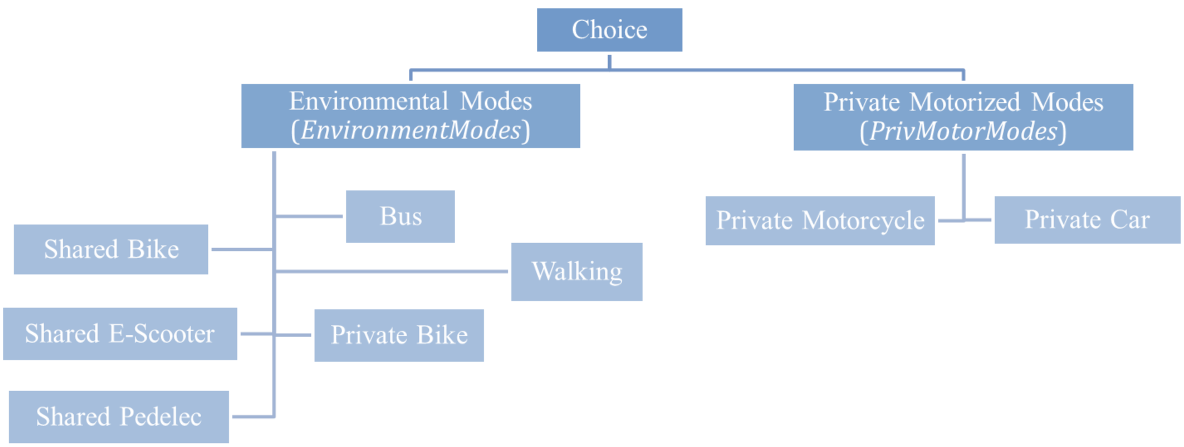


Figure 2-4 Visualization of the Multinomial Nested Logit Model

After discerning the two nests, nested logit model with TT and Topo was developed (results presented in Table 2-5). It was realized that this newly fitted model has smaller log-likelihood value than that of the mixed MNL model, which indicates better performance of the mixed MNL model in addressing issues with discrete choice modeling; this is a reasonable observation in light of mixed logit model relaxing IIA assumption and addressing panel data due to repeated measurements.

Table 2-5 Nested Logit Model developed with TT and Topo covariates

Model	**Model Coefficients' Specifications** Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '			
Multinomial Nested Logit Model with Covariates: ▪ TT with generic parameter ▪ Topo with alternative-specific parameters **Model Fit:** ▪ Log-Likelihood: -1511.4 ▪ McFadden R^2: 0.1366		**Estimate**	**z-value**	**Signif.**
	Shared Bike:(intercept)	-0.67	0.46	
	Shared pedelec:(intercept)	-3.24	0.00	***
	Shared e-scooter:(intercept)	-4.88	0.00	***
	Bus:(intercept)	-3.79	0.00	***
	Private bike:(intercept)	0.01	0.99	
	Private motorcycle:(intercept)	-160.00	0.35	
	Private car:(intercept)	-3.45	0.51	

	TT	-0.03	0.00	***
	Shared bike:Topo	-1.32	0.02	*
	Shared pedelec:Topo	0.78	0.04	*
	Shared e-scooter:Topo	1.07	0.01	*
	Bus:Topo	0.93	0.02	*
	Private bike:Topo	-0.33	0.32	
	Private motorcycle:Topo	15.30	0.21	
	Private car:Topo	-1.30	0.40	
	iv:EnvironmentMod	1.70	0.00	***
	iv:PrivMotorModes	58.70	0.38	

2.4.4 Mixed logit (Random Parameter) Model with Aggregated Alternatives

In line with developing multinomial nested logit, and in order to address both IIA issue, revolving hidden nests of alternatives, and the panel data, repeatedly collected from same respondents, another approach is aggregating alternatives in one nest into one single alternative and developing mixed logit model. For this purpose, the two upper level nests in the multinomial nested logit method, namely private fossil fuel driven modes (*PrivFossilFuelModes*) and environmental modes (*EnvironmentModes*) are considered. In terms of predictor variables, i.e. TT and Topo (see Table 2-2 for all notations), as TT is an alternative-specific variable, different approaches of aggregation were tested; for each mode choice scenario, the aggregate TT value of each nest is calculated through mean, median, or 85th percentile of alternatives' TT values in that nest, for that specific scenario. Results of the three mixed logit models are presented in Table 2-6.

Table 2-6 Mixed logit models with aggregated alternatives

Mixed logit model	Summary

Mixed (Random Parameter) MNL Model with Covariates: ▪ TT (Median) with random generic parameter ▪ Topo with alternative specific parameters **Model Fit:** ▪ Log-Likelihood: -410.71 ▪ McFadden R^2: 0.47253 ▪ Likelihood ratio test : chisq = 735.85 (p.value = < 2.22e-16)		**Estimate**	**z-value**	**Signif.**
	FossilFuelModes:(intercept)	-5.25	0.00	***
	TT_combinedAlt	-0.31	0.00	***
	FossilFuelModes:Topo_combinedAlt	0.81	0.00	***
	sd.TT_combinedAlt	0.74	0.00	***

Table 2-6 Mixed logit models with aggregated alternatives (cont'd)

Mixed logit model	**Summary**			
Mixed (Random Parameter) MNL Model with Covariates: ▪ TT (Mean) with random generic parameter ▪ Topo with alternative specific parameters **Model Fit:** ▪ Log-Likelihood: -414 ▪ McFadden R^2: 0.4683 ▪ Likelihood ratio test : chi sq = 729.26 (p.value = < 2.22e-16)		**Estimate**	**z-value**	**Signif.**
	FossilFuelModes:(intercept)	-5.34	0.00	***
	TT_combinedAlt	-0.14	0.00	***
	FossilFuelModes:Topo_combinedAlt	0.82	0.00	***
	sd.TT_combinedAlt	0.52	0.00	***

Mixed (Random Parameter) MNL Model with Covariates:

- TT (85th percentile)
- with random generic parameter
- Topo with alternative specific parameters

	Estimate	z-value	Signif.
FossilFuelMode:(intercept)	-5.45	0.00	***
TT_combinedAlt	-0.10	0.00	***
FossilFuelMode:Topo_combinedAlt	0.84	0.00	***
sd.TT_combinedAlt	0.45	0.00	***

Model Fit:

- Log-Likelihood: -413.99
- McFadden R^2: 0.46831
- Likelihood ratio test : chi sq = 729.29 (p.value = < 2.22e-16)

According to Table 2-6, all the aggregation approaches result in drastic improvement in model fit. The largest improvement, or increase in the Log-Likelihood value is obtained through aggregate nests and median TT values in each scenario.

2.4.5 K-fold Cross Validation

Concluded from the previous sections and the model development processes, the best disaggregate model is the mixed multinomial logit model with TT and Topo covariates, and the aggregate mixed multinomial logit model, with medan value of TT, leads to substantial improvement to the disaggregate model. The analyses so far have focused on in-sample performances, as we have been trying to find the best fits to the data (indicated by largest Log-Likelihood values), as well as reasonable and statistically meaningful models (based upon model parameters/coefficients). In the modeling procedure, out-of-sample performance is also of importance, as we wish to know how the model performs on unseen data, or data that has not been used for training. Therefore, any trained model needs to be validated so that its out-of-training-set performance and transferability are evaluated. For this purpose, K-fold cross validation is a robust validation approach, which consists of the following steps:

1. The dataset is randomly split into K subsets/folds;
2. One subset is reserved as the validation set, and the remaining subsets are used for training;
3. The trained model is then tested on the reserved validation set; it is noteworthy that metrics such as root mean squared error (RMSE) and mean absolute error (MAE) and correlation between predicted and actual values (R2) are recorded as indicators of model performance;
4. The procedure is repeated until each subset serves as a validation set once;
5. The average of the K recorded metrics (RMSE, MAE, and R2) are then calculated to reflect model's anticipated performance on any dataset.

The caret package in R is capable of conducting K-fold cross validation with a wide variety of model structures, but models with multinomial dependent. Accordingly, to validate the best disaggregate and aggregate models found in this study, the mentioned steps were scripted in R, and the built-in RMSE, MAE, and R2 functions in the caret package were used to record model performance each time. In this study, the common value of $K = 10$ is selected. It is also noteworthy that, technically, the used model performance metrics, i.e. RMSE, MAE, and R2, benchmark the model-based fitted/predicted probability of choosing the selected mode by the respondent, against the actual probability of choosing that mode, which is 100%. Accordingly. There is no variation among the actual probabilities as they are all 1.00, and thus correlation metric (R2) is not applicable. However, RMSE and MAE can be used, yielding differences between the predicted probabilities by the models and the actual probabilities, i.e. 1.00. The 10-fold cross validation results for the best disaggregate and aggregate mixed multinomial logit models are presented in Table 2-7 and Table 2-8.

Table 2-7 10-fold cross validation metrics for the best disaggregate mixed multinomial logit model

	RMSE_Validatiom	MAE_Validatiom	RMSE_Training	MAE_Training
1	0.73	0.70	0.70	0.67
2	0.69	0.66	0.70	0.67
3	0.68	0.64	0.69	0.65
4	0.64	0.59	0.66	0.61
5	0.69	0.66	0.68	0.64
6	0.62	0.53	0.62	0.53
7	0.61	0.52	0.61	0.52
8	0.66	0.62	0.66	0.62
9	0.72	0.69	0.67	0.64
10	0.62	0.53	0.62	0.54
Avg	0.67	0.62	0.66	0.61

Table 2-8 10-fold cross validation metrics for the best aggregate mixed multinomial logit model (with medain TT value)

	RMSE_Validatiom	MAE_Validatiom	RMSE_Training	MAE_Training
1	0.43	0.40	0.44	0.41
2	0.43	0.41	0.44	0.41
3	0.45	0.40	0.43	0.39
4	0.45	0.35	0.40	0.31
5	0.39	0.29	0.40	0.31
6	0.39	0.31	0.40	0.30
7	0.45	0.41	0.44	0.40
8	0.44	0.42	0.44	0.40
9	0.42	0.39	0.44	0.40
10	0.42	0.39	0.43	0.38
Avg	0.43	0.38	0.43	0.37

Logically, ideal value for RMSE and MAE are zero, as we aim to minimize the errors or differences between fitted/predicted values and actual values. According to Table 2-7 and Table 2-8, the average values of each model performance metric for training and validation sets are close, and this observation indicates appropriate similar in- and out-of-sample performances; in other words, the models do not suffer from overfit to the training set, or underfit to the validation set. Eventually, it can be seen that the aggregate mixed multinomial logit model evinces better fits and predictive power in comparison to the disaggregate variant.

According to the best model summarized in Table 2-6, only travel time (TT) and topography (Topo) have statistically significant influence on transportation mode choice of the survey respondents. As expected, increase in travel time results in decreased utility of any mode. It can also be seen that as the topography becomes unfavorable, i.e. travel path becomes hilly(ier), private fossil fuel propelled modes, namely private motorcycle and private care would become more utilitarian than other modes. More specifically, with each level of increase in hilliness, private fossil fuel driven modes become 2.24 ($= e^{0.81}$) times more likely to be selected.

2.5 Conclusion

This study is organized according to three main aspects: 1) the increasing popularity of bike-sharing and e-bike-sharing, 2) the necessity of investigating potential users' preferences in an intended mixed fleet system, and 3) the shortage of such research, particularly in the North America. To this end, an online survey was distributed to a sample of commuters to Michigan State University (MSU), including faculty, staff and students. This survey was running from April to July of 2018, and inquired about travel patterns, demographics and outlooks on an intended mixed fleet bike-sharing system. The collected data was then used to develop utility functions and capture users' perspectives as to an intended transportation system.

This study accounts for classic variables predominantly existent in discrete choice models, i.e. travel time and travel costs, accompanied by variables indicating dominant topographical condition of commuters' travel paths. Moreover, contributory determinants with quantified health benefit values and emission costs associated with proposed travel modes are incorporated. After exploring numerous discrete choice models, the best mode in terms of fit, reasonableness, and predictive power is obtained. Results suggested that the most influential factors in transport mode choice are travel time and travel path topography. The best [disaggregate] model shows that increase in terrain hilliness leads to less selection likelihood of bikes (either shared or private) for commute, in comparison to walking. It is an interesting finding which reveals users perceive walking to be more utilitarian (or perhaps more convenient) than biking when topography portends more hilliness. Also, this observation points out the necessity of including e-bikes to ensure success of shared micro-mobility in hilly settings.

Another finding is that, unexpectedly, presenting respondents with quantified emission costs and health benefit values associated with transport mode choice, does not result in significant shift towards shared mobility. This observation can be due to the fact that the predominantly car-driving respondents do not find the less polluting and more health-enhancing attributes of shared micro-mobility encouraging enough. Another explanation can be the organization of presented scenarios in the designed survey. The hypothetical scenarios are organized with distances of 1 mi, 5 mil, 10 mil, 20 mi, and 50 mi, which can be not sufficiently accommodating to intervals more in favor of micro-mobility. This brings up a caveat to the present study which can be addressed in future so as to enrich the travel survey and obtain statistically stronger findings. Another caveat of the present study is the small sample size which can be addressed through modification to the survey and redistributing it.

The findings of this study can help in-depth research and/or planning of sustainable transportation systems offering bike-sharing and e-bike-sharing services. More studies in similar contexts, i.e. commutes to CBDs, will help enrich the findings and provide a more solid foundation. Also, more accurate analyses can be performed with more precise consideration of emission costs (e.g. by considering cradle-to-grave emission rather than running emission cost, and electricity generation source) and health benefit values (e.g. by incorporating health benefits of walking to/from public or shared modes' stations). Continuation of research in this line can assist in promoting and deploying sustainable and active transportation systems with conventional and electric bikes, hopefully in more shared mobility contexts with further individual and societal benefits.

CHAPTER 3. A MULTI-MODAL PUBLIC TRANSPORTATION SYSTEM OFFERING SHARED MICRO-MOBILITY

3.1 Overview

Bike-sharing has been receiving growing attention and expanded drastically across the globe; in the late 1990s there existed only a handful of bike-sharing programs, while there are currently beyond 400 functional bike-sharing systems worldwide [37]. This drastic growth owes to the underlying factors of raised public and government awareness about the downsides of car use, as well as the affordability of the bike-sharing service [38].

There are numerous studies in the literature on bike-sharing systems, which predominantly focus on the existing bike-sharing systems and investigate the spatial-temporal performances or mobility patterns of these systems through data mining methods [39]–[42]. However, attention to network and facility location design of bike-sharing systems from strategic planning perspectives is not as common. Lin and Yang [43] formulated a mathematical model for a bike-sharing system design problem. They consider both users' and investors' perspectives, respectively by considering the level of service, in terms of demand coverage, and system setup costs. There are a number of studies focusing on hub location inventory models. However, application of these models to bike-sharing system has not received enough attention [44]. Another important concern of planners when designing bike-sharing systems is the locations of bike stations, as a key determinant of its success [45]–[47]. In addition to optimum locations of stations, fleet sizes and distribution of supply, considering the relocation of bikes to maximize the served demand, has been an interest to researchers [48]–[51].

Despite the conceptual foundations for e-bike-sharing systems and high hopes for their promising advantages, few studies have attended to the design of such systems. In a pilot research at the campus of University of Tennessee, Knoxville, a small bike-sharing system offering both regular and electric bikes was set up. This campus was considered a good candidate for implementation of an e-bike-sharing system, due to the hilly terrain and the vast spatial expanse of the campus and was shown to have attracted more users to cycling [52].

Aware of the shortage of studies on the design of e-bike-sharing systems, this study aims to bridge this gap by introducing a design framework for a public transportation system which offers e-bikes as well as regular bikes and buses. The main contribution of this study is considering the tradeoff between user preference, investment cost and social costs/benefits. The multifaceted objective is to minimize the investment cost, along with other social costs, such as emission cost; while maximizing the revenue and health benefits of the system. Quantification of these costs and benefits in an intended mixed fleet bike-sharing system offering both conventional bikes, e-bikes of both pedelec and e-scooters, as well as a bus system for a target area, is required. This contributory aspect to the present research helps investors and transportation planners to strike a trade-off between different facets of their decision on initiating a multi-modal transportation system. Moreover, another major contribution of this study is considering user choice through a utility function, added as a constraint to the proposed mathematical model.

3.2 Mathematical Formulation

This study considers a transportation system, including the shared or public modes (i.e. bikes, pedal-assist electric bicycles or pedelecs, e-scooters, and buses), as well as the private modes (i.e. cars and motorcycles), available to the users in the target area. Let I denote the set of the transportation modes, and $|I| = N_I$. Figure 3-1 depicts a schematic sketch of a target area, divided into numerous user groups with specific populations, in such a way that each group contains users with the same financial power for their daily transportation, and the same distance from the destination which is the central business district (CBD). Let J denote the set of the user groups, with $|J| = N_J$. We assume that the transportation modes ($i \epsilon I$) are numbered from 1 to N_I, and the user groups ($j \epsilon J$) are numbered from 1 to N_J.

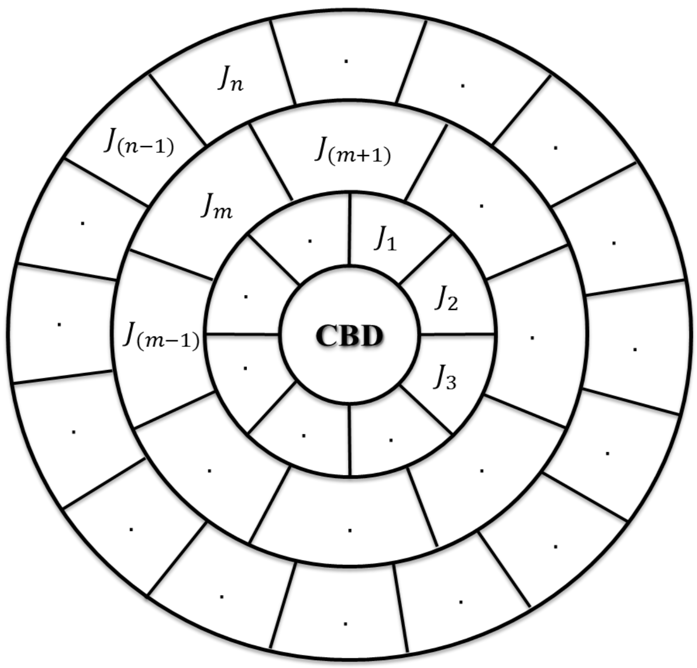


Figure 3-1 Sketch of the study area; each cell represents a user group (J_j), with a specified financial power and at a specific commuting distance from CBD

Each user group is at a certain distance from the destination or CBD, denoted by d_j, with a total demand for transportation denoted by Ψ_j, and the financial power denoted by F_{P_j}.

The characteristics of each mode considered in this study are as follows. The capacity of each mode is denoted by Ω_i. Each mode *i* has an average speed represented by v_i. The expense of using mode i by a member of user group j is denoted by $C_{u_{ij}}$ expressed in dollars. The user cost or $C_{u_{ij}}$ would be the fare for public modes denoted by C_{r_i}, and would be the daily cost of ownership (C_{p_i}) and fuel cost for the private modes ($C_{f_{ij}}$). The comfortable traveling distance by mode i is denoted by D_i in miles. The fuel consumption rate of mode i is denoted by F_i which CO_2 signifies the amount of fuel that mode consumes to traverse unit of distance (i.e. gallons per mile). The purchase and maintenance costs of mode i, are respectively denoted by C_{p_i} and C_{m_i}. In this study we focus on as the dominant emission; the amount of CO_2that mode i emits is denoted by G_i expressed in grams of CO_2produced per unit fuel (i.e. gallon). The monetary value of the health benefit gained from an hour of using mode i, which is associated with the physical activity level of mode i, is denoted by h_i. It is worth noting that only bike and pedelec are considered to involve physical activity and thus other transportation modes are assumed to not provide any health benefits. The procedure of calculating h_i is provided in Appendix A.

The fuel price and fuel tax are respectively denoted by C_l and C_t. Our objective in this study is multifaceted. Primarily, we consider both the entire system's perspective and the users' perspective. From the entire system's viewpoint, we intend to minimize the system costs, while maximizing the system gains. From the users' standpoint, we develop a utility function that considers various aspects of users' decision-making. The utility function accounts for the mode choice behavior of the users in each user group.

Having introduced the parameters used in this study, we are ready to present our mathematical model:

$$\underset{N_i}{Minimize} \quad Z = \sum_i(\gamma_c C_{s_i} + \sum_j(\left(\gamma_e E_{ij} - \gamma_h H_{ij} - \gamma_r C_{v_{ij}}\right) \Gamma_{ij} + \gamma_c \rho_{ij} \left(\Psi_j \pi_{ij} - \left(\frac{\pi_{ij}\Psi_j}{\sum_{j\in J}(\pi_{ij}\Psi_j)} \right) N_i\, \Omega_i \right))) \tag{2-1}$$

such that

$$C_{s_i} = \begin{cases} 0 & if\ i \in \{\text{car, motorcycle, walking, private bike}\} \\ N_i C_{p_i} + N_i C_{m_i} & if\ i \in \{\text{shared bike, pedelec, e} - \text{scooter, bus}\} \end{cases} \tag{2-2}$$

$$E_{ij} = \begin{cases} \frac{d_j\, F_i\, G\, C_f}{\Omega_i} & if\ i \in \{\text{car, motorcycle, bus}\} \\ 0 & if\ i \in \{\text{walking, shared/private bike, pedelec, e} - \text{scooter}\} \end{cases} \tag{2-3}$$

$$H_{ij} = \begin{cases} 0 & if\ i \in \{\text{e} - \text{scooter, car, motorcycle, bus}\} \\ h_i \frac{dj}{v_i} & if\ i \in \{\text{walking, shared/private bike, pedelec}\} \end{cases} \tag{2-4}$$

$$C_{v_i j} = \begin{cases} C_{t_i} d_j F_i & if\ i \in \{\text{car, motorcycle}\} \\ C_{r_i} & if\ i \in \{\text{shared bike, pedelec, e} - \text{scooter, bus}\} \end{cases} \tag{2-5}$$

$$\Gamma_{ij} = \begin{cases} \Psi_j\, \pi_{ij} & if\ N_i\, \Omega_i > \sum_{j\in J} \Psi_j\, \pi_{ij} \\ \left(\frac{\pi_{ij}\Psi_j}{\sum_{j\in J}(\pi_{ij}\Psi_j)} \right) N_i\, \Omega_i & if\ N_i\, \Omega_i \leq \sum_{j\in J} \Psi_j\, \pi_{ij} \end{cases} \quad \forall i \in I, j \in J \tag{2-6}$$

$$\rho_{ij} = \begin{cases} 0 & if\ N_i\, \Omega_i > \sum_j \Psi_j\, \pi_{ij} \\ D_{ui}.\, d_j & if\ N_i\, \Omega_i \leq \sum_j \Psi_j\, \pi_{ij} \end{cases} \quad \forall i \in I, j \in J \tag{2-7}$$

$$D_i - d_j \leq \mu_{ij} M \quad \forall i \in I, j \in J \tag{2-8}$$

$$D_i - d_j > (\mu_{ij} - 1)M \quad \forall i \in I, j \in J \tag{2-9}$$

$$C_{p_i} - F_{p_j} \leq \xi_{ij}\, M \quad \forall i \in I, j \in J \tag{2-10}$$

$$C_{p_i} - F_{p_j} > (\xi_{ij} - 1)M \quad \forall i \in I, j \in J \tag{2-11}$$

$$U_{ij} = \beta_0 + \beta_1 d_j^{\eta_{1i}} + \beta_2 N_i \Omega_i + \beta_3 T^{\eta_{2i}} + \beta_4 \frac{d_j}{v_i} + \beta_5 C_{u_{ij}} + \beta_6 (1 - \mu_{ij}) + \beta_7 (1 - \xi_{ij}) + \beta_8\, E_{ij} + \beta_9\, H_{ij} \quad \forall i \in I, j \in J \tag{2-12}$$

$$C_{u_{ij}} = \begin{cases} C_{p_i} + C_{f_{ij}} & i \in \{\text{car, motorcycle, private bike}\} \\ C_{r_i} & i \in \{shared\ \text{bike, pedelec, e} - \text{scooter, bus}\} \end{cases} \tag{2-13}$$

$$C_{f_{ij}} = C_l\, d_j\, F_i \quad \forall i \in I, j \in J \tag{2-14}$$

$$\pi_{ij} = \frac{e^{U_{ij}}}{\sum_x e^{U_{xj}}} \quad \forall i \in I, j \in J \tag{2-15}$$

$$\sum_{i\in I} \pi_{ij} = 1 \quad \forall j \in J \tag{2-16}$$

$$\sum_{i\in I} C_{p_i} N_i \leq \text{B} \quad \forall i \in \{shared\ \text{bike, pedelec, e} - \text{scooter, bus}\} \tag{2-17}$$

$\mu_{ij} \in \{0,1\}$ $\quad \forall i \in I, j \in J$ (2-18)

$\xi_{ij} \in \{0,1\}$ $\quad \forall i \in I, j \in J$ (2-19)

$\pi_{ij} \in [0,1]$ $\quad \forall i \in I, j \in J$ (2-20)

$$\mathrm{N_i} \geq \begin{cases} m_b & i \in \{shared \text{ bike}\} \\ 0 & i \in \{\text{ pedelec, e} - \text{scooter, bus}\} \end{cases} \qquad (2\text{-}21)$$

The objective of this study is to minimize the investor's costs, while maximizing the systems revenue, minimizing environmental (CO_2 emission) concerns, maximizing societal health benefits, and minimizing the entire systems unserved demand cost. Accomplishing this objective is under consideration of importance/weight factors for each term, i.e. $\gamma_c, \gamma_e, \gamma_h, and\ \gamma_r$. The decision variables in this problem are the numbers of public modes $(\text{i.e. } N_{i\,,} \forall i \in \{\text{bike, pedelec, e} - \text{scooter, bus}\})$.

C_{s_i} denotes the investment cost for mode i, defined by the normalized purchase cost C_{p_i}, plus the maintenance cost C_{m_i} of the mode (Constraint 2-2). In fact, the investment cost is incurred by the authority implementing the public transportation system. E_{ij} is the emission cost function for mode i adopted by group j. The emission production cost for each user is a function of the group's distance from destination (d_j), the fuel consumption rate of the mode (F_i), the CO_2 production rate of mode i (G_i), the $CO2$ burden cost (C_f), divided by the capacity of the mode(Ω_i) (Constraint 2-3). H_{ij} is the health benefit value function of mode *i* used by group *j*, which is a product of hourly value of adopting a mode (h_i) and the time needed to reach the destination by that mode (Constraint 2-4). It is noteworthy that health benefit values in this study are calculated as inactivity costs forgone as a result of engaging in physical activity. In other words, inactivity costs for American adults are considered to be avoided if individuals are active per physical activity guideline for Americans [53]. $C_{v_{ij}}$ is the revenue function, which is the fare of a mode if it is a public mode of transportation, and the fuel tax if the mode is private (Constraint 2-5). The calculations of the fares are explained in the Appendix C.

Γ_{ij} (Constraint 2-6) represents the adoption of mode i by user group j. When the demand for mode i in group j is less than the availability, the number of users, experiencing the societal costs and generating the revenue equals the demand. However, in case the demand exceeds the availability, the number of users, experiencing the societal costs and generating the revenue, would be restricted to availability and there would be unserved demand. In case there is unserved demand, there would be penalty, also known as the inconvenience cost of remaining unserved, which is denoted by ρ_{ij} (Constraint 2-7). In this study, it is assumed that the unserved demand for shared/public modes would have to rely on Taxi/Uber to make the commute; the average unit cost is thus calculated as D_u. The calculation of this cost is explained in the Appendix E.

Constraints 2-8 through 2-9 stipulate distance feasibility of each mode for each user group. If mode i is feasible for user group j, from the distance comfortability perspective, which means if the group's distance to CBD is less than the comfortable distance of the mode, μ_{ij} would equal 1; otherwise, μ_{ij} would be zero. Similarly, Constraints 2-10 and 2-11 investigate financial feasibility. U_{ij} denotes utility of mode i for group j (Constraint 2-12). The utility of each mode for each user group depends on the factors such as distance, mode availability, topography of the area, travel time, user expenses, distance and financial feasibilities, emissions costs and health benefits. The coefficients of utility function are derived from literature [54], [55].

User expenses that is denoted by $C_{u_{ij}}$would be the fare if i is a public mode. In case i is a private mode (i.e. private bikhe, motorcycle, car), use expenses would entail normalized daily purchase cost of the relevant mode, and if the private mode is motorcycle or car, the fuel cost ($C_{f_{ij}}$) incurred by user group j to make the the commute to the CBD is also included. A private mode's fuel cost denoted by $C_{f_{ij}}$ is product of fuel price, the vehicles consumption rate and the user's distance from destination (CBD) (Constraints 2-13 and 2-14). π_{ij} which is the probability of group

j using mode i is calculated based upon logit model and the utility function U_{ij} (Constraint 2-15). Constraint 2-16, ensures that the sum of probabilities across the modes for each group j equals unity. Constraint 17, mandates that the cost of purchasing the modes of the shared and public system not be greater than the total system implementation budget (B). Constraints 2-18 through 2-21 are feasibility constraints. It is noteworthy that, in Constraint 21, a minimum number of shared bikes are considered in the system which is derived from managerial insights.

This problem is a formulated as an integer programming. Moreover, the probability function used for users' mode choice modeling, is a nonlinear function of the mode counts. As the probability function is a component of the objective function and one of the constraints as well, the problem is of non-linear nature.

3.3 Solution Algorithm

Due to the nonlinearity of the utility function, the optimization model is computationally challenging for the available commercial solvers. Thus, a metaheuristic based upon Simulated Annealing (SA) is proposed and modified to fit the proposed model. There are a number of transportation-related studies (i.e. facility location models) in the literature which have adopted SA-based algorithms to solve flow capturing mixed integer programs (MIPs) [56], [57]. Proven efficiency of SA algorithm for these types of problems inspired our proposed solution algorithm. SA-based metaheuristic is inspired by annealing in metallurgy. The iterative process resembles the heating and controlled cooling of a solid material to increase the size of its crystals and reduce their defects. At the cooling stage, an equilibrium state should be achieved at each temperature before moving to a lower temperature. The final solution is achieved at the minimum or final temperature.

An SA-based algorithm typically has two main steps. In the first, it searches over the feasible set of the integer solutions, starting from a current feasible solution and then moving to a neighbor feasible solution. The second step compares the objective functions of the current and the new solutions, and based on the difference, replaces the current solution with the new one with a probability. The probability is gradually reduced as the solution process proceeds. SA schemes allow larger objective function values (worse solutions) relative to the current solution be accepted, which offers a mechanism to avoid getting trapped in local optimum solutions. This feature is very useful when the problem is known to have multiple local optima.

The initial solution used in this study which is derived from a series of sensitivity analyses, is set to be one vehicle for each public mode. The pseudo-code of the deployed solution algorithm presented as follows.

Input: Maximum number of temperature changes K_0, Maximum number of inner iterations at each temperature K_1, different costs, vehicle and user characteristics, utility function parameters.
Output: $N_i^* \in \mathrm{N}$
Initialize:
Set the current temperature stage $t = 0$, choose initial temperature u_t
Set a state variable $\xi = 1$, which indicate that a mode count should be added. $\xi = 0$ when a mode count should be removed.
Initialize $N_i^t \in \mathrm{N}$
While $t < K_0$, **do**
    Set inner iteration index $k = 0$. Set $N_i^k = N_i^t$
    While $k < K_1$ **do**
        Calculate U_{ij}
        Calculate Γ^k
        Set Λ be a weighted matrix of different modes (assumed to have the same values).
        Set a random number $\gamma = u[0,1]$.
        If $\Lambda > \gamma$ **then**
            $\xi = 0$
        else
            $\xi = 1$
        end if
            If $\xi = 1$ **then**

$N_i^k = N_i^k + 1$
If $B_c \geq B$ **then**
$N_i^k = N_i^k - 2$
end if
else
$N_i^k = N_i^k - 1$
If $N_i^k = 0$ **then**
$N_i^k = N_i^k + 2$
end if
end if
Set Γ^k and Γ^{k-1} be the objective function values associated with the perturbed and current solutions respectively
Set k=k+1 and the perturbed solution as N_i^k. Draw a random number $\gamma = u[0,1]$.
If $\Gamma^k < \Gamma^*$ **then**
$\Gamma^* = \Gamma^k$, $N_i^* = N_i^k$
end if
If $\Gamma^k > \Gamma^{k-1}$ and $\exp\left(\frac{\Gamma^{k-1} - \Gamma^k}{u_t}\right) > \gamma$ **then**
Discard the perturbed solution, i.e. set $N_i^k = N_i^{k-1}$.
end if
end while
Set $t = t + 1$ and and $u_t = \theta u_0$, where $\theta = 0.85$.
end while
$\Gamma^*$and N_i^*

3.4 Numerical Example

In this section, a hypothetical numerical example is presented solution assessment. In this respect, the metaheuristic solution algorithm is tested, pareto frontier is investigated considering different factors for objective function components, and sensitivity analyses are performed on a number of parameters or example specifications to explore solutions under varied scenarios.

3.4.1 Case study

The proposed model has the ability to capture a variety of modes and user groups. However, a case study based on a hypothetical network is fabricated which encompasses walking, biking (private and shared), pedelec, e-scooter, bus, motorcycle and car, to be used by six user groups. The modes' characteristics used for our case study are displayed in Table 3-1, whose values are based on the average values in the United States. The detailed calculation values and procedures are presented in Appendices A through E. The configuration of the user groups is available in Table 3-2. Among the public modes, buses have the highest comfortable travelling distance. Thus, it is decided that the farthest user group is at a distance that users can at least use buses to commute to the central business district (CBD).

The health benefit hourly values in this study are calculated following an approach proposed by Trubka et al. [58], and based upon the inactivity costs in the United States [59]; in this approach it is assumed that the inactivity costs would be avoided if one abides by the physical activity guideline for Americans (24). Another noteworthy aspect in the proposed modelling framework, is that the utility function determines the desirability of a mode based upon various factors including distance from the CBD, mode availability, topography of the area, travel time, user expenses, distance and financial feasibilities, emissions costs and health benefits. Among these factors, the only varying component is the mode availability which is defined in this study as the mode counts multiplied by the capacity of a specific mode. Public mode counts are the decision variables and intended to be optimized in the objective function which considers a trade-off between the implementation cost and unserved demand cost. Considering this trade-off, the system chooses to incur unserved demand cost in lieu of providing more of a specific public mode, if the cost of provision is greater than the unserved demand cost. Therefore, if any of the modes considered in the modeling framework were acceptable to the users and if the investment cost was comparable to the inconvenience cost of unserved demand, the users would have been assigned to one of the existing modes. However, depending on the various characteristics of each mode (mentioned above), it is not always the optimum decision to serve all the users in the system with the public modes discussed in the model. In such instances, a user who is unserved, has to opt out for another mode that is not included in the public transit system. Therefore, we assumed this mode as taxi/Uber. The unserved demand cost, D_{u_i} can be further adjusted for each specific mode i for improved accuracy. Another insight incorporated in this framework is a minimum number of shared bikes in the system based upon managerial insights. For the numerical example purposes, average station density (7.3 ($stations/sq\ mi$)) and a minimum number of bikes per station are considered [60]. Additionally, the average population density of Ingham and Clinton counties, which equals 1,454 (pp/sq mi) [61], is considered for obtaining coverage areas for each population sector.

Table 3-1 Characteristics of common modes used for commuting

Characteristics	walking	Bike (shared/ private)	Pedelec	E-Scooter	Car	Bus	Motorcycle
Comfortable travelling distance (mi) (D_i)	1[62]	3.8[62]	5.01	6.2	12.1 [62]	10.2[62]	12.1[62]
Average speed (mph) (v_i)	3.5[62]	10[62]	12	13.4	28.9 [62]	11.4[62]	29.5[62]
Average daily cost of ownership ($) ($C_{p_i}$)	-	0.28	1.6	1.03	5.75	68.5	1.52
Average daily maintenance cost ($) ($C_{m_i}$)	-	0.34	1.94	1.25	3.85	1.1	2.07
Health benefit hourly value ($/h)	14.44	15.2	14.06	-	-	-	-
Trip cost of public modes (Fare)	-	0.22($\frac{\$}{hr}$)	1.4($\frac{\$}{hr}$)	2.58($\frac{\$}{hr}$)	-	$1.25 [63]	-
Fuel cost ($/gallon) ($C_l$)	-	-	-	-	2.485 [64]	2.485	2.485
Fuel consumption rate (gallon/mi) (F_i)	-	-	-	-	0.043 [65]	0.307 [65]	0.023[65]

Table 3-1 Characteristics of common modes used for commuting (cont'd)

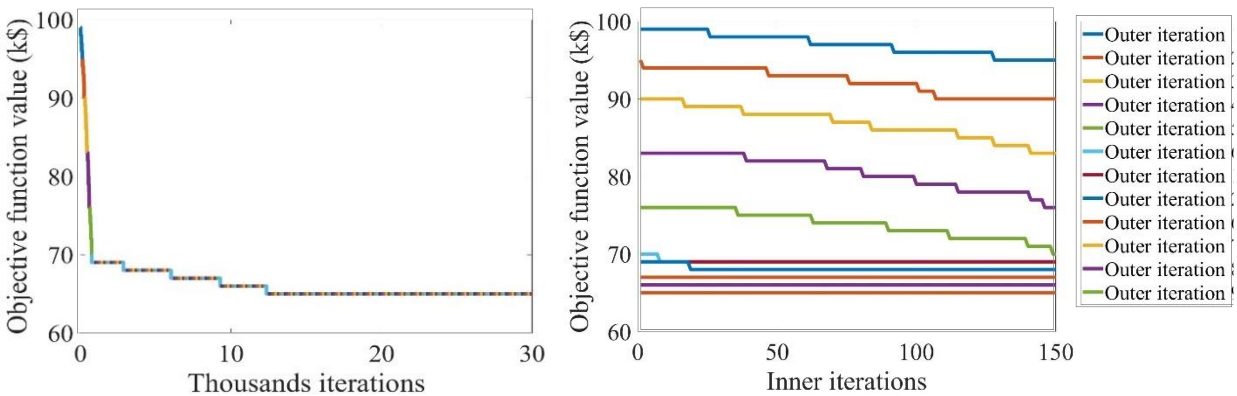
Characteristics	walking	Bike (shared/ private)	Pedelec	E-Scooter	Car	Bus	Motorcycle
Emission production rate (grams of CO_2/gallon) (G)	-	-	-	-	8,887 [66]	8,887	8,887
Financial burden of emission (\$/grams of CO_2) (C_f)	-	-	-	-	0.0002	0.0002	0.0002 [54]
Fuel tax (cents /gallon) (C_t)	-		-	-	26.3 [67]	26.3	26.3

Table 3-2 Hypothetical user class specifications

User group	1	2	3	4	5	6
Distance from CBD area (mi)	1	1	5	5	10	10
Financial power ($/commute)	2.6	12	2.6	12	2.6	12
Population	1,000	1,000	1,000	1,000	1,000	1,000

3.4.2 Algorithm Performance

Considering a budget of $15,000, equal importance/weight factors ($\gamma_c = \gamma_e = \gamma_h = \gamma_r = 1$), setting the inner iteration to 150 and the outer iteration to 200, and starting with an initial solution of 1 shared bike, 1 pedelec, 1 e-scooter and 1 bus, the algorithm successfully converges for our case study after 90 outer iterations. The algorithm performance can be seen in Figure 3-2. The optimum mode counts are determined as 156 shared bikes, 1,928 pedelecs, 27 e-scooter and 105 buses, having consumed almost 69% of the budget, namely $10,348.



a) General trend of the objective function

b) Objective function trend for different inner and main (outer) iterations

Figure 3-2 SA algorithm performance

3.4.3 Pareto Front Investigation

In multi-objective optimization, essentially, different incorporated objectives can have varied importance/weight in decision making process. In the framework of this problem, investment and unserved demand cost (γ_c), emission cost (γ_e), health benefit value (γ_h), and system revenue (γ_r) are represented by the associated factors/weights in the objective function. The underlying reason is the fact that importance of investment cost and system revenue, emission cost, and health benefit, may differ in the eyes of the decision makers. In this numerical example, sensitivity analysis is performed on different values of the above-mentioned factors in order to prepare a pareto front with a-priori weights.

To come up with a basis for factors, relative importance of different terms are considered. For this purpose, total public transit investment equaling \$24.38 billion [68], [69], vehicle tailpipe $CO2$ emission cost in urban areas equaling \$56.99 billion, and the average annual inactivity-related health care expenditure equaling \$66.14 billion, are considered. Based upon these total costs, and setting the importance factor of investment cost to 1, relative importance factors of emission cost and health benefit values would be 2.3 and 2.7, respectively. Table 3-3 presents pareto front sensitivity analysis scenarios and the determined optimal mode counts for each scenario. Note that optimal mode counts show the number of each public mode that the system optimally provides, and not the demand for each mode. The pareto frontier derived from sensitivity analysis on the importance factors can be seen in the Figure 3-3. The axes indicate setup and investment cost, and emission cost, and the colors show magnitude of health benefit values in the system corresponding to each scenario.

Table 3-3 Pareto front sensitivity analysis scenarios and associated optimal mode counts

Scenario	**Decision Factors [Investment Emission Health]**	**Optimal Mode Counts**
'S1'	[1.00 1.00 1.00]	shared Bike: 156, Shared pedelec:1928, shared E-scooter:26, Bus:105
'S2'	[1.00 1.00 1.70]	shared Bike: 156, Shared pedelec:2005, shared E-scooter:0, Bus:100
'S3'	[1.00 1.00 2.70]	shared Bike: 156, Shared pedelec:2000, shared E-scooter:0, Bus:100
'S4'	[1.00 1.00 3.50]	shared Bike: 156, Shared pedelec:2000, shared E-scooter:0, Bus:100
'S5'	[1.00 1.00 4.00]	shared Bike: 156, Shared pedelec:2000, shared E-scooter:0, Bus:100
'S6'	[1.00 1.50 1.00]	shared Bike: 156, Shared pedelec:1935, shared E-scooter:26, Bus:105
'S7'	[1.00 1.50 1.70]	shared Bike: 156, Shared pedelec:2005, shared E-scooter:0, Bus:100
'S8'	[1.00 1.50 2.70]	shared Bike: 156, Shared pedelec:2000, shared E-scooter:0, Bus:100
'S9'	[1.00 1.50 3.50]	Shared Bike: 156, Shared pedelec:2000, shared E-scooter:0, Bus:100
'S10'	[1.00 1.50 4.00]	shared Bike: 156, Shared pedelec:2000, shared E-scooter:0, Bus:100
'S11'	[1.00 2.30 1.00]	shared Bike: 156, Shared pedelec:1944, shared E-scooter:26, Bus:105
'S12'	[1.00 2.30 1.70]	'shared Bike: 156, Shared pedelec:2005, shared E-scooter:0, Bus:100'
'S13'	[1.00 2.30 2.70]	'shared Bike: 156, Shared pedelec:2000, shared E-scooter:0, Bus:100'
'S14'	[1.00 2.30 3.50]	'shared Bike: 156, Shared pedelec:2000, shared E-scooter:0, Bus:100'

'S15'	[1.00 2.30 4.00]	'shared Bike: 156, Shared pedelec:2000, shared E-scooter:0, Bus:100'

Table 3-4 Pareto front sensitivity analysis scenarios and associated optimal mode counts (cont'd)

Scenario	**Decision Factors [Investment Emission Health]**	**Optimal Mode Counts**
'S16'	[1.00 3.00 1.00]	'shared Bike: 156, Shared pedelec:1952, shared E-scooter:27, Bus:104'
'S17'	[1.00 3.00 1.70]	'shared Bike: 156, Shared pedelec:2005, shared E-scooter:0, Bus:100'
'S18'	[1.00 3.00 2.70]	'shared Bike: 156, Shared pedelec:2000, shared E-scooter:0, Bus:100'
'S19'	[1.00 3.00 3.50]	'shared Bike: 156, Shared pedelec:2000, shared E-scooter:0, Bus:100'
'S20'	[1.00 3.00 4.00]	'shared Bike: 156, Shared pedelec:2000, shared E-scooter:0, Bus:100'
'S21'	[1.00 4.00 1.00]	'shared Bike: 156, Shared pedelec:1961, shared E-scooter:27, Bus:104'
'S22'	[1.00 4.00 1.70]	'shared Bike: 156, Shared pedelec:2005, shared E-scooter:0, Bus:100'
'S23'	[1.00 4.00 2.70]	'shared Bike: 156, Shared pedelec:2000, shared E-scooter:0, Bus:100'
'S24'	[1.00 4.00 3.50]	'shared Bike: 156, Shared pedelec:2000, shared E-scooter:0, Bus:100'
'S25'	[1.00 4.00 4.00]	'shared Bike: 156, Shared pedelec:2000, shared E-scooter:0, Bus:100'

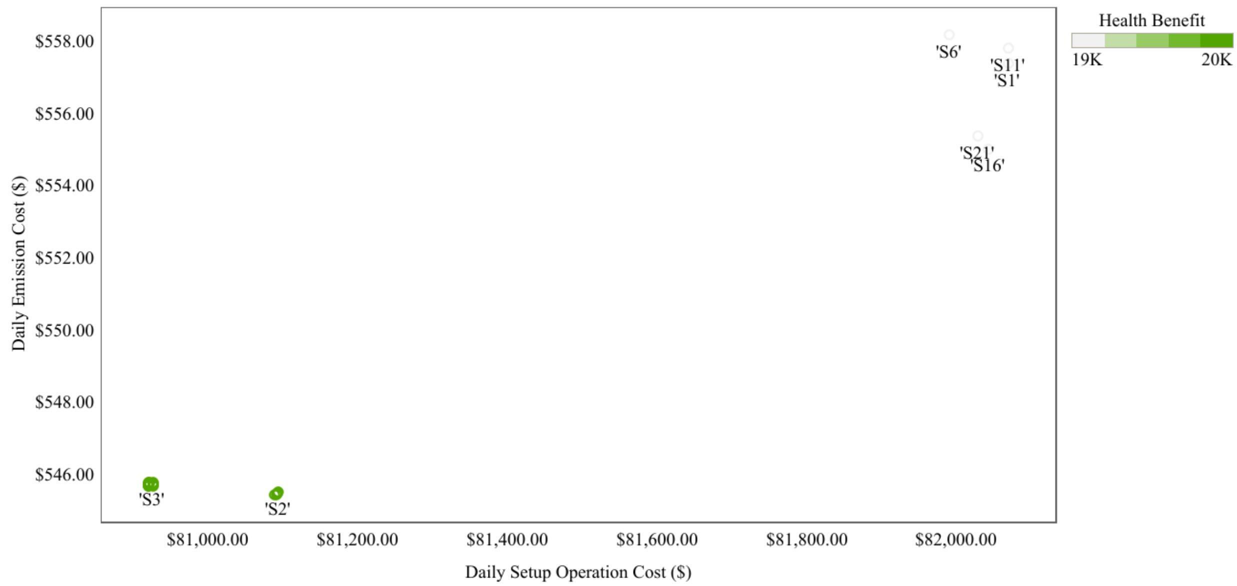


Figure 3-3 Pareto frontier (importance/weight factor sensitivity analysis)

According to Figure 3-3, different analyzed importance/weight factors do not result in substantial changes in the associated values. Some of the scenarios even share very close costs/values such that overlaps are seen in Figure 3-3; specifically, there are overlaps between scenarios 3, 4, 5, 8, 9, 10, 12, 13, 14, 15, 18, 19, 20, 23, 24, and 25, and between scenarios 2, 7, 17, and 22. However, this trend can be observed in Table 3-3 that, with increase in emission cost weight, the system turns away from bus to pedelec. This means that in case of rising emission burden cost, pedelec competes with, and manages to replace, bus ridership. On the other hand, increase in health importance factor leads to decrease in the adoption of both bus and e-scooter, namely the inactive public modes. Overall, pedelec is a desirable mode in the system that sompete with e-scooter and bus due to its health benefits and zero running emission.

3.4.4 Cost Sensitivity Analysis

This section focuses on investigating the effects of different costs on the users' mode choice and optimum configuration of public modes. Thus, various scenarios are investigated for financial burden of emission, health benefit value, trip cost, and fuel cost. It is noteworthy that all importance/weight factors are assumed to equal 1 in the following analyses.

3.4.4.1 Financial Burden of Emission

The sensitivity of the model is tested for four scenarios of financial burden of emission: scenario 1 with \$$2\times 10^{-6}$/grams of CO_2, scenario 2 with \$$2\times 10^{-4}$/grams of CO_2 (base case), scenario 3 with \$0.01/grams of CO_2, and scenario 4 with \$0.02/grams of CO_2. The optimum mode counts and demand percentages for each mode under each of the four scenarios are shown in **Error! Reference source not found.**-a and **Error! Reference source not found.**-b, respectively. As the financial burden of emission increases, the system would provide fewer buses, to a point that in the fourth scenario the system does not provide any buses. In return, more pedelecs are provided. Looking into the changes in demands across the scenarios in **Error! Reference source not found.**-b, it can be observed that demand for bus declines with the rise of emission burden cost, and the users turn to pedelec as a primary choice, followed by walking. The ability of pedelec to cover longer trips is the reason users prefer to choose pedelec over walking and biking, when buses are not a utilitarian option due to being pollutant.

3.4.4.2 **Health Benefit Hourly Values**

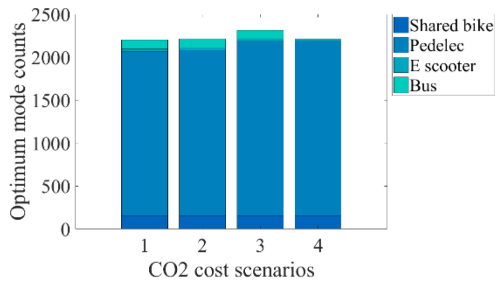
Four scenarios were implemented to investigate the model's sensitivity to the value of health benefits. In these four scenarios, the health benefit hourly value for each of the active modes were respectively multiplied by factors of 0.1, 1, 2 and 5. The optimum mode counts and demands for each modes across the scenarios are shown in **Error! Reference source not found.**-c and **Error! Reference source not found.**-d, respectively. As expected, with the increase of health benefit hourly values (i.e. hospital or other illness treatment costs increases), the demand for bus and e-scooter which are assumed to have no health benefit value decline. On the other hand, more users would choose pedelec and walking due to their increased health benefit values. It is also observed that demands for both shared and public bikes decrease as well, even though biking has a higher health benefit value than the other active modes, namely pedelec and walking. The reason people would prefer walking over biking in particular, is the distance coverage of the two modes and the groups' distance configuration of the first two user groups. These groups would choose to walk more because it is free of charge and would also provide comparable health benefits to biking. On the other hand, users at the distance of 5 mi from campus would predominantly choose to ride pedelec since pedelec accounts for longer comfortable travelling distance than bike, and is less costly than e-scooter. The last two groups would mainly depend on bus as it is feasible for them from distance perspective, while also being more affordable than car and motorcycle. Based upon the approach in this study for calculating health benefit hourly values, increase in the health benefit hourly values of the modes results from increase in the inactivity costs including the doctor and hospital fees. As a result of this increase, the public transportation system should provide more pedelecs as they enjoy both reasonable comfortable ranges and health benefit values, while reducing the numbers of shared bikes, e-scooters and buses.

3.4.4.3 **Trip Cost**

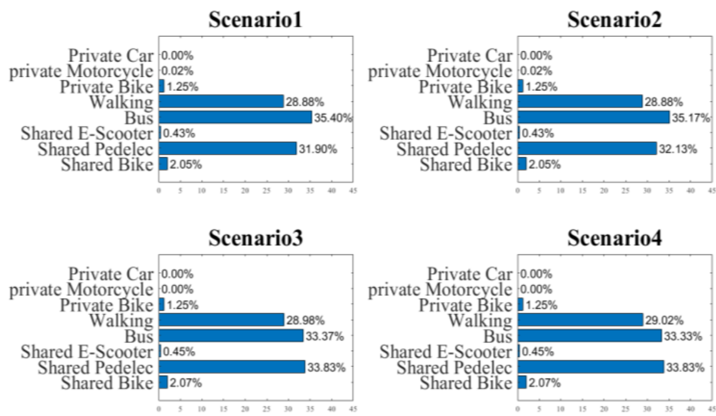
To investigate the sensitivity of the user groups to the public modes' fares, four scenarios are arranged such that the trip costs/fares of the base case are multiplied by factors of 0.5, 1, 1.5, and 2.5. **Error! Reference source not found.**-f shows that as the trips costs increase, more users would choose pedelec and the demands for the other public modes drop. Also, the number of users who choose to walk increases. The underlying reason is that users from the first two groups whose commuting distances are within the comfortable distance of walking would choose to walk in order to avoid costs of increasingly expensive public modes. The third and fourth groups' users also would prefer pedelec more as it is a feasible choice which is less costly than e-scooter and bus. Aligned with the demand trends, the optimum count of pedelec increases as trip costs increase, but the system reduces the number of buses and shared bikes (**Error! Reference source not found.**-e) while still satisfying the demands. Only in the first scenario there is unserved demand for e-scooter as the system does not provide e-scooter in the first scenario. The reason here is that the system decides to leave the demand for e-scooter unserved in this case, rather than incurring the cost of providing the demanded e-scooters, due to the large investment costs. Another important finding by trip cost sensitivity analysis was that increasing public modes' fares by above 150% would prevent users from choosing public modes.

3.4.4.4 **Fuel Cost**

Four fuel cost scenarios are considered to analyze the sensitivity of the model to fuel cost. In the four scenarios, the current fuel cost is multiplied by 0.1, 1, 2, and 10, respectively. Under these changes, the optimum mode counts and demand percentages remain unvarying. This suggests the insensitivity of our model to fuel cost. The reason is that due to the limited travel distances of user groups the fuel dependent modes are not very popular even in the base case condition of fuel cost. In other words, for example, the first two groups would normally prefer walking due to being both free of charge and also health beneficial, the third and fourth groups tend to opt for pedelec as it would be less costly than other modes while also providing health benefits, and the last two groups would be inclined to use bus as the comfortable range of bus accommodates the distances of the last two groups from the CBD and is more affordable than the other modes. Under these circumstances, further changes in fuel cost only affect a relatively small percentage of system's demand, so the changes are not visible.

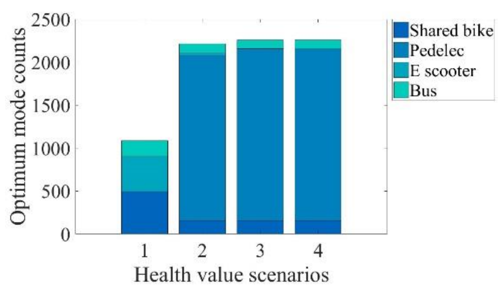


a) Optimum mode counts (numbers of each public mode) for CO_2cost scenarios

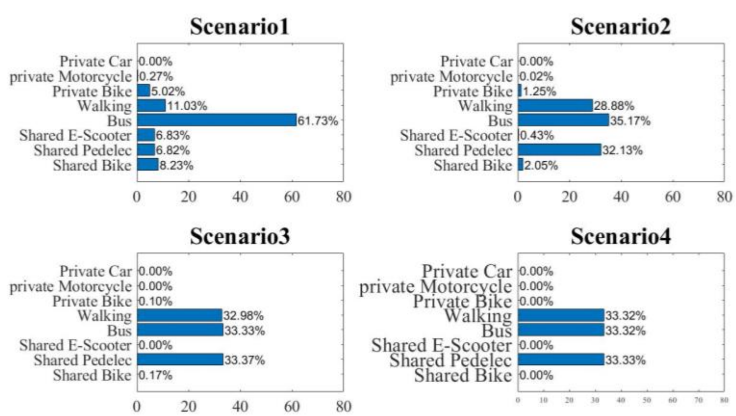


b) Demand percentages for CO_2cost scenarios

Values of CO_2burden cost are the four scenarios are as follows: scenario 1 with \$2× 10^{-6}/grams of CO_2, scenario 2 with \$2× 10^{-4}/grams of CO_2 (base case), scenario 3 with \$0.01/grams of CO_2, and scenario 4 with \$0.02/grams of CO_2.



c) Optimum mode counts (numbers of each public mode) for health benefit hourly value scenarios

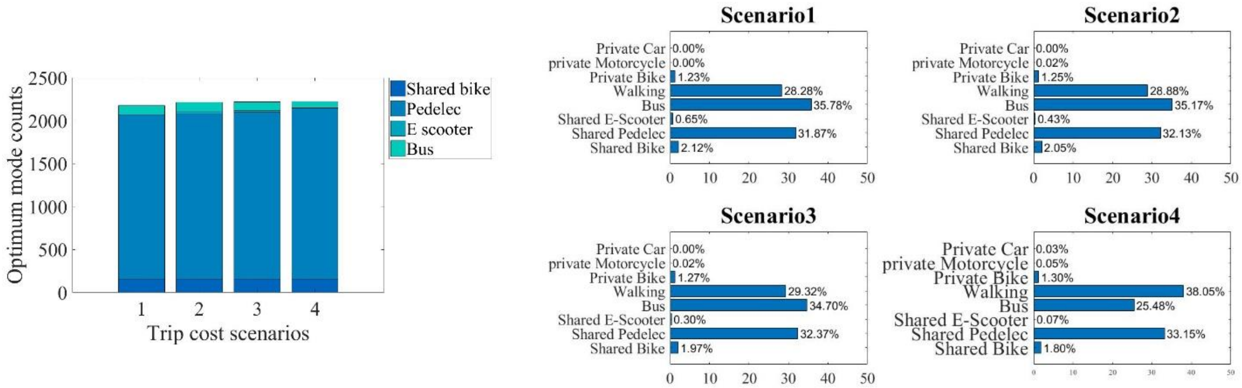


d) Demand percentages for health benefit hourly value scenarios

The four health benefit scenarios, health benefit hourly values of each of the active modes were multiplied by factors of 0.1, 1, 2 and 5, respectively.

Figure 3-4 Cost sensitivity analysis

Figure 3-4 Cost sensitivity analysis (cont’d)



e) Optimum mode counts (numbers of each public mode) for trip cost scenarios

f) Demand percentages for trip cost scenarios

In the four trip cost scenarios, trip costs/fares of the base case are multiplied by factors of 0.5, 1, 1.5, and 2.5, respectively.

3.4.4.5 **Budget Sensitivity Analysis**

Changes in the budget on hand considerably affects the investment power in public modes. To explore the sensitivity of our model to the initial budget, this section considers four scenarios which change the initial budget of our numerical experiment, respectively by factors of 0.5, 0.75, 1, and 1.5. As can be seen in Figure 3-5, the optimum mode counts of scenarios 2-4 are identical as the budget constraint is not binding. The percentages of used budget versus the initial budget are 99.99%, 91.89%, 68.92%, 45.95% for scenarios 1-4, respectively. It can be observed the best investment strategies, irrespective of the available budget, is to circumvent investing in e-scooters, unless the cost and characteristics of this mode changes.

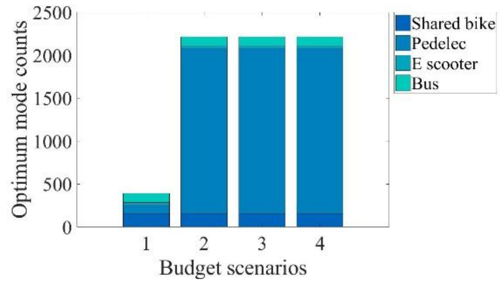


Figure 3-5 Budget sensitivity analysis

3.4.4.6 **Distance Sensitivity Analysis**

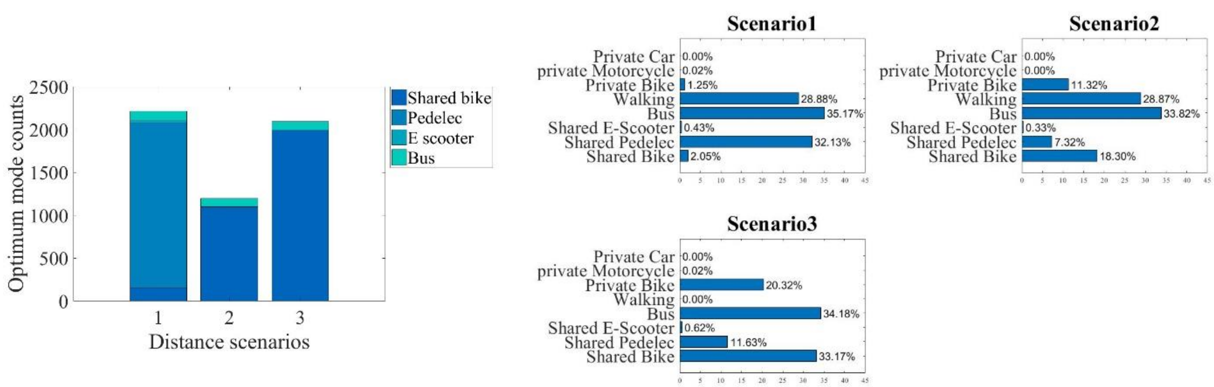
To analyze the sensitivity of the model to user groups' travel distance distribution, three different scenarios were tested as shown in

Table **3-4**.

Table 3-4 Distance Sensitivity Analysis Scenarios

Scenario1			Scenario 2			Scenario 3		
User group	Distance from CBD	Financial power	User group	Distance from CBD	Financial power	User group	Distance from CBD	Financial power
1	1	2.6	1	1	2.6	1	2	2.6
2	1	12	2	1	12	2	2	12
3	5	2.6	3	3	2.6	3	2.5	2.6
4	5	12	4	3	12	4	2.5	12
5	10	2.6	5	10	2.6	5	10	2.6
6	10	12	6	10	12	6	10	12

Optimum mode counts and demand percentages for the three scenarios are presented in Figure 3-6. In the first scenario, which is our base case scenario in this study, the most popular public modes are bus and pedelec. The reason is that these two modes (bus and pedelec) are less expensive and have the ability to traverse longer distances in comparison to similar modes (i.e. e-scooter/car and bike). The other popular mode in the first scenario is walking for the first two user groups that are located closer to CBD area. In scenario 2, the percentage of the users who choose to walk, remains almost invariant as walking remains a feasible mode for the first two user groups. Bus would still be the most popular public mode, and shared bike competes to take pedelec's place. The reason is that the users in this scenario are distributed closer to CBD. In particular, distances from the CBD of the users in the third and fourth group fall within the comfortable range of bike in the second scenario. Therefore, as shared bike is less expensive than pedelec, users reasonably switch from pedelec to shared bike. In scenario 3, walking becomes an infeasible mode for all the groups, as the distances from CBD has increased. As a result, the demand for shared bike significantly increases, as shared bike becomes the feasible and affordable mode for the first four groups. The demand for private bike also significantly increases, as private bike is also feasible for the first four groups as well as being more affordable than the other modes.



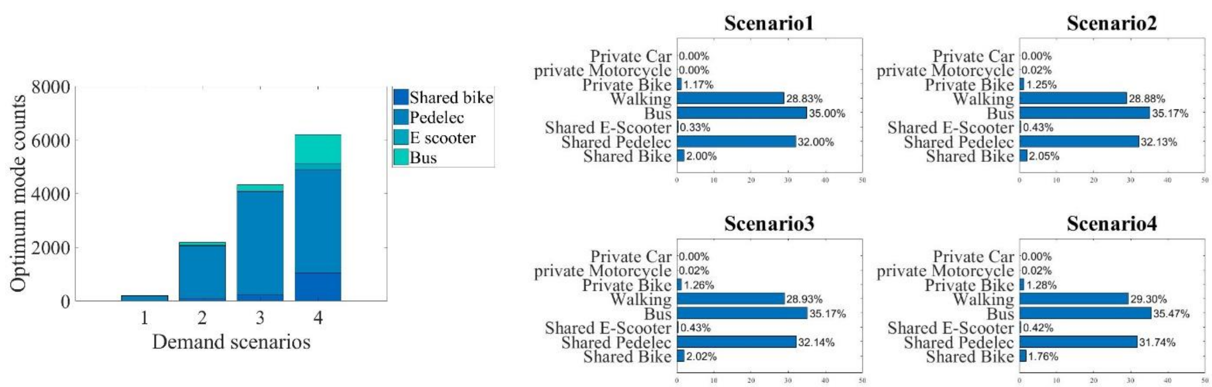
a) Optimum mode counts (numbers of each public mode) for different distance scenarios

b) Demand percentages for different distance scenarios

Figure 3-6 Distance sensitivity analysis

3.4.4.7 **Demand Sensitivity Analysis**

In this section, four scenarios are arranged to explore the sensitivity of the model to the demand. In the base case scenario, each user group has a population of 1000. For the scenarios 1-4 for the demand sensitivity analysis, we consider demand variations by factors of 0.1, 1, 2 and 10. In addition, the initial budget is also increased to a high value ($150,000) to ensure that budget constraint would not be violated. The optimum mode counts and demand percentages are shown in Figure 3-7. As the modal demand distribution is a function of mode characteristics and not the total demand, demand percentages/distributions for different modes remain unchanged across the scenarios as expected (Figure 3-7-b). According to Figure 3-7-a, the optimum mode counts seem to have high correlation with demand except for pedelec in scenario 4. This phenomenon is due to the fact that increasing pedelec up to 10 times of the base case optimum value would not justify the associated benefits, and thus at this scale, the system decides to have unserved demand for pedelec, because the unserved demand cost is less than the cost that would be incurred to satisfy the demand.



a) Optimum mode counts for demand scenarios

b) Demand percentages for demand scenarios

Figure 3-7 Demand sensitivity analysis

3.5 Conclusion

While bike-sharing is an increasingly thriving concept across the globe, there is a shortage in the literature on bike-sharing design framework. To address this shortage, a contributory approach is taken in this study, to account for users' perspectives through a utility function and complement it by considering investors viewpoint and societal concerns/costs and benefits in the multi-faceted objective function. The costs of the system entail implementation and maintenance costs as well as emission costs, while the benefits include quantified health benefits and system revenue. The problem is formulated as a nonlinear integer programming problem. Due to the non-linearity in the mathematical framework, a metaheuristic based on simulated annealing (SA) algorithm is proposed to solve the problem. This algorithm showed successful convergence through a hypothetical numerical example, which ensures an optimal solution; it must be noted, however, that as with any metaheuristic, this optimal solution can be a sub-optimum and not necessarily the global optimum. The main findings derived from the hypothetical numerical example are as follows:

- Giving more importance/weight to health benefit results in more pedelecs and less bus and e-scooter ridership in the system; also, more importance/weight of emission burden cost would lead to switching from bus to pedelec;
- As the value of health benefit increases, the system requires more pedelecs, while reducing the numbers of shared bikes, e-scooter and buses.
- The most popular public modes are bus and pedelec, because these two modes (bus and pedelec) can traverse longer distances in comparison to walking and biking which are free of charge and more affordable, respectively. On the other hand, bus and pedelec are less expensive than e-scooter, motorcycle and car.

- Increasing financial burden of emission was found to reduce the demand and the optimum mode counts for bus while increasing the demand and optimum mode counts for pedelec.
- For small communities with short travel distances, as users would not choose fuel consuming modes, the model is insensitive to fuel cost.
- Similarly, when trip costs/fares of the public modes are raised, demands for bus and e-scooter would decline in general, and users would choose to walk or ride pedelec instead.

It is noteworthy that the findings rely on the hypothetical case study and the parameters are estimated based on the average values in the United States. In fact, the flexible modeling framework and successful solution algorithm suggest that the proposed framework can be deployed by related authorities in decision-making organization such as metropolitan planning organization (MPO), municipality departments, etc.

The utility function in this study is premised upon the existing literature and the coefficients are estimated. One of the next steps of Chapter 3 would be to incorporate the utility functions from Chapter 2 and analyze the results. Eventually, the performance of the proposed metaheuristic algorithm can be tested using an analytical solution method or other metaheuristics, such as genetic algorithm. In other words, as metaheuristics do not guarantee global optimum solutions, analytical methods can be tested to investigate possible improvement of the results by the proposed metaheuristic, i.e. SA algorithm, or other metaheuristics can be employed for comparison purposes in terms of both computation time and solution quality.

One of the limitations of this study is disregarding the last mile of travel, which affects the health benefits provided by walking to bike-sharing stations or public transit mode. However, it has been consistently disregarded for both modes should not affect the main findings of the study.

This can simply be addressed, by adjusting the parameter values in accordance with planners' intentions.

Another extension to this study can be considering the rebalancing of the mixed fleets of the proposed bike-sharing system. This process is normally executed using motorized vehicles which lead to emission generation and disregarding it could overrate bike-sharing as a clean and emission-less transportation mode. Similarly, emissions from electricity production can also be considered. Another concern regarding biking and e-bike riding that has not been addressed in this study is their safety. In fact, there are safety concerns about using these modes on roadways since they are not as protected as motorized transportation modes. However, these modes are known to be safer for the other users in the system. In terms of solution algorithm, this study employs a metaheuristic algorithm due to non-linearity in the mathematical framework imposed by one of the constraints incorporating the probability function. One direction for further analysis is to linearly approximate the probability function to relax the non-linearity in the associated constraint, and investigate the optimality gap and compare computation complexities with the metaaheuristic approach.

CHAPTER 4. MICRO-MOBILITY AND ELECTRIFICATION TO SUPPORT URBAN FREIGHT DELIVERY

4.1 Overview

Freight delivery makes up a large portion of urban daily traffic and is indispensable to economic vitality in cities. While intercity freight delivery undergoes longer travel distances, the last miles of freight delivery inside urban areas suffer from significant inefficiency [70]. An underlying factor in this inefficiency is that urban freight delivery can contribute to congestion and increased travel time, such that the cost of delay for commercial vehicles in the United States in 2010 is estimated to be $23 billion [71]. Trucks, for example, comprise only 6% of urban traveled distances but incur 26% of the gross congestion cost [72]. Another operational problem that motorized delivery vehicles encounter is parking and unloading. This process can lead to browsing for a parking spot and eventually illegal parking, which results in roadway blockage and congestion, as well as exposing delivery companies to major fine costs [16]. Moreover, motorized freight delivery can affect urban life by air and noise pollution, as well as posing safety concerns [73]. In fact, the large delivery vehicles particularly on narrow urban streets can lead to the perception of unsafe roadways.

In order to address the side effects of motorized urban freight delivery, cargo cycles are currently gaining recognition. Cargo cycles are commonly known as freight bikes, but can also refer to three-wheeled vehicles for carrying people or goods [70]. Cargo cycles have been around since the nineteenth century and were initially used by tradesmen, grocers, milkmen, and messenger boys [74]. However, they have only recently been recognized as a means for urban freight delivery. One of the contexts in which cargo cycles have proven to be successful are urban areas with high congestion levels and limited on-street parking [75]. In a before-and-after study on a trial in London, an office supplies company replaced its delivery diesel vans with electric tricycles in addition to electric vans (e-van) [76]. This shift led to per package total distance reduction by 14% while decreasing CO_2 emission reduction by 55%. In a study in Manhattan, New York, the feasibility of cargo cycles for delivery in urban areas was investigated [77]. It was suggested that micro-consolidation centers in urban areas makes cargo cycles an appropriate alternative to urban freight trucks. In another study, small businesses that are not willing to expand their practices are identified as barriers to further growth of cargo logistics. The geographical context is another important factor influencing the uptake of cargo cycles, in the sense that high density urban contexts and the presence of narrow streets make cargo cycles more appealing. It is suggested in this research that several measures can be taken to facilitate adoption of cargo cycles; the recommended measures encompass: improved infrastructure for cycles, incentives/subsidies to spur companies to deploy cargo cycles in their supply chain, deregulation of electrically assisted cycles, and policies such as zero emission zones or drive-through traffic reduction [78]. In a set of pilot projects in Italy from April 2013 to March 2016, electric bikes and electric scooters were found to result in CO_2 reduction and energy savings [79]. Cargo cycles are legally allowed to use bicycle lanes in many urban areas and can thus avoid mixing with roadway traffic and circumvent congestions [80]. Moreover, they can park both on- and off-street which is another superiority over motorized urban freight delivery vehicles (particularly trucks). Another asset to cargo cycles is that they do not yield local air and noise emissions [81]. This is a major benefit with the increasing awareness of environmentally friendly transportation. In this line, subsidization of cargo cycles and electric vans is suggested as a policy solution to significantly reduce last-mile freight delivery emissions [82]. Influences of other policies such as pollution charges/taxes remain to be explored to further complement the literature.

There are studies in the literature that formulate single depot problems where distance and temporal duration constraints are based on approximations of vehicle routing problem [83], [84]. Classic vehicle routing problem (VRP) algorithms try to optimize the cost of distributing goods from a storehouse to a set of customers by several vehicles, each allowed to serve only one route. The problem was firstly presented by modeling the fleet of homogenous trucks seeking to minimize their travel distance from a center to several gas stations [85]. Then, the problem was extended to incorporate more than one vehicle with varying capacities in the formulation [86]. In the more recent studies of VRP, each of the variants strive to include more real-world aspects of logistics. Among these, periodic VRPs [87], dynamic VRPs [88], VRP with Time Windows (VRPTW) [89], [90], VRP with Pickup and Delivery (VRPPD) [91], and vehicle routing with split deliveries [92] can be mentioned. Use of heterogeneous fleet of vehicles is another variant of the classical VRP. In other words, the classical VRP utilizes identical vehicles, and this limitation is relaxed in studies on the heterogeneous fleet VRP (HFVRP) [93]–[97]. Another relatively recent and increasingly evolving variant of VRP is knows as Green vehicle routing problem (G-VRP), which revolves around environmental aspects. Based upon literature, G-VRP chiefly branches into either fuel consumption reduction, or refueling/recharging of alternative fuel vehicles [98]. In order to address environmental issues associated with vehicle routing problems, the most straightforward action is to reduce fuel consumption, which results in emission reduction and environmental benefits [99]–[101] . The other major approach to G-VRP is to target driving range and refueling infrastructure scarcity [102]–[104].

In an effort to bridge the literature gap as to influential policies and urban settings in cargo cycles adoption for freight delivery, we propose a heterogeneous fleet G-VRP (HF G-VRP) in this study. In our HF G-VRP, we aim to illuminate influences of pollution taxes and realistic urban routing on selection of alternative delivery fleets, particularly cargo cycles. To this end, the proposed HF G-VRP aims to minimize delivery costs including enforced pollution taxes. In order to explore impacts of pollution taxes on optimal delivery fleet composition, the HF G-VRP needs to be solved for various scenarios. Since HF G-VRP is a variant of the classic VRP, it is an NP-hard problem, and the exact solution to this problem, or the global optimum, becomes exponentially intractable with problem size increase. In practice, numerical experiments demonstrate that, not only commercial solvers encounter difficulty in finding the solution to even small instances of the proposed HF G-VRP problem, but even a recently developed metaheuristic approach in the literature, known as variable neighborhood search (VNS) cannot provide the optimal solution within reasonable computation time. Therefore, a new metaheuristic algorithm is also developed in this study to address computational difficulties. Also, rigorous and realistic parameter estimations for various specifications of vehicle types are conducted in this study; a thorough literature review in addition to logical assumptions provide all of these specifications in one table. Finally, the numerical experiments are provided for a large-scale realistic case study of downtown Chicago.

This chapter is structured as follows. The next section provides problem statement and model formulation including objective function, decision and state variables, parameters, and constraints. This section is followed by proposing solution algorithms to solve the problem of interest in this study. The next section provides the numerical experiments including case study definition, parameters estimation, and numerical results for comparing the solution methods and sensitivity analyses. The last section provides the concluding remarks of this study.

4.2 Mathematical Formulation

In this study, a heterogeneous fleet of delivery vehicles including diesel and electric vans, as well as electric pedal-assist bikes and trikes, and moped-style bikes and trikes are considered, which total to h_M =6 types, i.e. $h \in H = (1, \dots, h_M)$. $V = (1, \dots, z_M)$ in this problem represents the set of the network vertices/nodes, and $A = (1, \dots, e_M)$ indicates the network links. Note that in V, $z = 1$ denotes the depot, and $(2, \dots, z_M)$ indicate customers. l represents the vector of link lengths, such that the length of link e would be specified by l_e . The matrix t indicates vehicle travel time for each link in the network, i.e. t_{eh} denotes the travel time of vehicle type h on link e. The volume capacity and mass capacity of each vehicle type are denoted in vectors Q and PL, respectively. In these vectors, Q_h indicates the volume capacity and PL_h denotes the mass capacity of vehicle type h. Another considered vehicle property, namely range, is represented by the vector R, wherein R_h denotes the range of vehicle type h on full tank in miles (diesel or electricity). The purchase price (expressed in $ per day over the average life of the vehicle) and maintenance cost (expressed in $ per mile) of vehicles are shown by vectors C_p and C_m, such that C_{ph} is the normalized daily purchase price and C_{mh} is the maintenance cost of vehicle type h. Fuel consumption rates (expressed in $ per miles) are denoted by vector CF; CF_h is the fuel consumption rate of vehicles of type h. The inversed average density of the transported cargo is denoted by CD (expressed in ft^3/ton). The driver's labor cost is represented by CL, i.e. CL_h denotes the labor cost of driving vehicle type h (expressed in $ per hour). The societal costs of CO_2 emission and noise (in $ per miles) are denoted by $Ccost$ and $Ncost$, respectively; $Ccost_h$ and $Ncost_h$ indicate the societal CO_2 emission cost and noise cost of vehicle type h, respectively.

The time window within which all deliveries must be made is denoted by T. The required time to unload delivery demand at each customer's location, i.e. the service time, is denoted by ST_z, wherein z is a customer, i.e. z $\in (2, \dots, z_M)$. Matrix E indicates the entering links to each vertex $z \in (1, \dots, z_M)$ as a binary variable, such that E_z^e takes the value of 1 if node z is the downstream node of link e, and zero otherwise. Similarly, matrix O depicts the outgoing links from network nodes, where O_z^e equals 1 if node z is the upstream node of the link e and zero otherwise.

In this HF G-VRP, we introduce taxes for CO_2 emission and noise pollution into the objective. For each vehicle type, i.e. $\forall h \in H$, $CTax_h$ and $NTax_{\ h}$ denote tax on CO_2 emission and noise, respectively, both of which are expressed in $ per miles. Thus, the delivery company would adjust its fleet choice and routing in response to taxes, as a result of which the generated CO_2 emission and noise pollution imposed on the society are affected.

The decision variable in our problem is the binary variable x that allocates each customer (downstream node of each link) to a certain vehicle type to be served by, i.e. x_{eh} equates to 1 when a vehicle type h traverses link e and serves the customer located at the downstream of link e. Variable y is a state variable, where y_h expresses the number of deployed vehicles of type h to serve the delivery demand. L is another state variable introduced to track vehicle loads; L_{eh} denotes the remaining volume in vehicle type h, traversing link e. In order to track traveled distance of deployed vehicles up to and after a link, state variables R^u and R^d are defined, respectively. This variables ensure feasibility of an assigned tour to a vehicle type in terms of the vehicle range. ${R^u}_{eh}$ and ${R^d}_{eh}$ are thus continuous state variables respectively indicating the distances a vehicle type h has traversed up to the upstream and downstream nodes of link e. Similarly, to track the travel times of deployed vehicles up to and after a link, state variables T^u and T^d are introduced, respectively. Accordingly, $T^u{}_{eh}$ and $T^d{}_{eh}$ show the elapsed travel times of a vehicle type h up to upstream and downstream of link e, respectively in a tour that is traversed by vehicle type h. The total cost of the delivery company is represented by variable F and the company margin of benefit is depicted as α. Table 4-1 recapitulates the notations and definitions of the model parameters and variables.

Table 4-1 Notations and definitions of model parameters/ variables

Parameter/ variable	**Definitions**
V	Set of network vertices
A	Set of network links
H	Set of vehicle types
l_e	The length of link e
t_{eh}	The travel time of vehicle type h on link e
Q_h	The volume capacity of vehicle type h
PL_h	The mass capacity of vehicle type h
R_h	The range of vehicle type h on full tank in miles (diesel or electricity)
C_{ph}	The normalized daily purchase price of vehicle type h
C_{mh}	The maintenance cost of vehicle type h
CF_h	The fuel consumption rate of vehicles type h
$CL_{\ h}$	
CD	Inversed average density of the transported cargo (expressed in ft^3/ton).
$Ccost_h$	The societal CO_2 emission cost of vehicle type h
$Ncost_h$	The societal noise cost of vehicle type h
T	The time window within which all deliveries must be made
ST_z	The required time to unload delivery demand at customer z's location, i.e. The service time at customer z
E_z^e	A binary variable: 1 if node z is the downstream node of link e and zero otherwise
O_z^e	A binary variable: 1 if node z is the upstream node of the link e and zero otherwise
CTax_h	Tax on CO_2 emission
$\mathrm{NTax}_{\ h}$	Denote tax on noise emission
TD_{total_h}	The total distance traveled by vehicle type h
x_{eh}	A binary decision variable equating to 1 when a vehicle type h traverses link e and serves the customer located at the downstream of link e
L_{eh}	The remaining volume in vehicle type h, traversing link e
$R^u{}_{eh}$	A continuous state variable indicating the distances a vehicle type h has traversed up to the upstream node of link e
$R^d{}_{eh}$	A continuous state variable indicating the distance a vehicle type h has traversed up to the downstream node of link e
$T^u{}_{eh}$	The elapsed travel time of a vehicle type h up to upstream of link e by vehicle type h

Table 4-1 Notations and definitions of model parameters/ variables (cont'd)

Parameter/ variable	Definitions
$T^d{}_{eh}$	The elapsed travel time of a vehicle type h up to downstream of link e by vehicle type h

Equations (1-27) display the objective function and constraints of our model, which would be explained subsequently.

$$\underset{x,y,L,R^u,R^d,T^u,T^d}{Minimize} \; F = \sum_{h=1}^{h_M} y_h \, C_{p_h} + \sum_{h=1}^{h_M} \sum_{e=1}^{e_M} (\, l_e x_{eh} \left(C_{m_h} + CF_h + CTax_h + \; NTax_{\,h} \right) + CL_{\,h} t_{eh} x_{eh}) \tag{1}$$

such that

$$\sum_{h=1}^{h_M} \sum_{e=1}^{e_M} \; E_z^e x_{eh} = 1 \quad , \quad \forall \, z \in \{2, \dots, z_M\} \tag{2}$$

$$\sum_{h=1}^{h_M} \sum_{e=1}^{e_M} \; O_z^e x_{eh} = 1 \quad , \quad \forall \, z \in \{2, \dots, z_M\} \tag{3}$$

$$\sum_{e=1}^{e_M} E_z^e x_{eh} = \sum_{e=1}^{e_M} O_z^e x_{eh} \quad , \quad \forall \, z \in \{1, \dots, z_M\}, \forall h \in \{1, \dots, h_M\} \tag{4}$$

$$\sum_{e=1}^{e_M} \; O_1^e x_{eh} = y_h \quad , \quad \forall h \in \{1, \dots, h_M\} \tag{5}$$

$$\sum_{e=1}^{e_M} \; O_1^e L_{eh} = \sum_{z=2}^{z_M} \sum_{e=1}^{e_M} E_z^e x_{eh} \, q_z \;, \; \forall h \in \{1, \dots, h_M\} \tag{6}$$

$$\sum_{h=1}^{h_M} \sum_{e=1}^{e_M} E_z^e L_{eh} - \sum_{h=1}^{h_M} \sum_{e=1}^{e_M} O_z^e L_{eh} \; = \; q_Z, \quad \forall \, z \in \{2, \dots, z_M\} \tag{7}$$

$$L_{eh} \leq \; x_{eh} \min\{Q_h, PL_h \; CD\} \quad , \quad \forall e \in \{1, \dots, e_M\}, \quad \forall h \in \{1, \dots, h_M\} \tag{8}$$

$$\sum_{e=1}^{e_M} E_1^e L_{eh} = 0 \quad , \quad \forall h \in \{1, \dots, h_M\} \tag{9}$$

$$\sum_{e=1}^{e_M} O_1^e \; R^u{}_{eh} = 0 \quad , \quad \forall h \in \{1, \dots, h_M\} \tag{10}$$

$$\sum_{e=1}^{e_M} E_z^e R^d{}_{eh} \; = \; \sum_{e=1}^{e_M} O_z^e R^u{}_{eh} \quad , \quad \forall h \in \{1, \dots, h_M\}, \;\; \forall \, z \in \{2, \dots, z_M\} \tag{11}$$

$$R^u{}_{eh} \; + l_e x_{eh} = R^d{}_{eh} \quad , \quad \forall \, e \in \{1, \dots, e_M\}, \; \forall h \in \{1, \dots, h_M\} \tag{12}$$

$$R^u{}_{eh} \; \leq \; x_{eh} R_h \quad , \quad \forall \, e \in \{1, \dots, e_M\}, \; \forall h \in \{1, \dots, h_M\} \tag{13}$$

$$R^d{}_{eh} \; \leq \; x_{eh} R_h \quad , \quad \forall \, e \in \{1, \dots, e_M\}, \; \forall h \in \{1, \dots, h_M\} \tag{14}$$

$$\sum_{e=1}^{e_M} O_1^e \; T^u{}_{eh} = 0 \quad , \quad \forall \, e \in \{1, \dots, e_M\}, \; \forall h \in \{1, \dots, h_M\} \tag{15}$$

$$\sum_{e=1}^{e_M} E_z^e T^d{}_{eh} + ST_z = \sum_{e=1}^{e_M} O_z^e T^u{}_{eh}, \ \forall h \in \{1, \dots, h_M\}, \ \ \forall z \in \{2, \dots, z_M\} \tag{16}$$

$$T^u{}_{eh} + t_{eh} x_{eh} = T^d{}_{eh} \quad , \quad \forall e \in \{1, \dots, e_M\}, \ \forall h \in \{1, \dots, h_M\} \tag{17}$$

$$T^u{}_{eh} \le x_{eh}\, T \quad , \quad \forall e \in \{1, \dots, e_M\}, \ \forall h \in \{1, \dots, h_M\} \tag{18}$$

$$T^d{}_{eh} \le x_{eh}\, T \quad , \quad \forall e \in \{1, \dots, e_M\}, \ \forall h \in \{1, \dots, h_M\} \tag{19}$$

$$x_{eh} \in \{0,1\} \quad , \quad \forall e \in \{1, \dots, e_M\}, \ \forall h \in \{1, \dots, h_M\} \tag{20}$$

$$L_{eh} \ge 0 \quad , \quad \forall e \in \{1, \dots, e_M\}, \ \forall h \in \{1, \dots, h_M\} \tag{21}$$

$$R^u{}_{eh} \ge 0 \quad , \quad \forall e \in \{1, \dots, e_M\}, \ \forall h \in \{1, \dots, h_M\} \tag{22}$$

$$R^d{}_{eh} \ge 0 \quad , \quad \forall e \in \{1, \dots, e_M\}, \ \forall h \in \{1, \dots, h_M\} \tag{23}$$

$$T^u{}_{eh} \ge 0 \quad , \quad \forall e \in \{1, \dots, e_M\}, \ \forall h \in \{1, \dots, h_M\} \tag{24}$$

$$T^d{}_{eh} \ge 0 \quad , \quad \forall e \in \{1, \dots, e_M\}, \ \forall h \in \{1, \dots, h_M\} \tag{25}$$

$$S_C = \sum_{h=1}^{h_M} \sum_{e=1}^{e_M} l_e x_{eh} \left(Ccost_h + Ncost_h \right) \tag{26}$$

$$S_R = \sum_{h=1}^{h_M} \sum_{e=1}^{e_M} l_e x_{eh} \left(CTax_h + NTax_h \right) \tag{27}$$

In this mathematical formulation, the objective, formulated in Equation (1), is to minimize the freight delivery company’s costs, inclusive of fleet purchase and maintenance expenses, fuel costs (electricity and gas), CO2 and noise emission taxes, and labor costs associated with the fleet drivers. Constraints (2) and (3) ensure that each customer is served exactly once (using one incoming link and one outgoing link). Constraint (4) ascertains the conservation flow to make sure each vehicle that serves a customer location would subsequently exit to serve another customer or go back to depot, while both sides of the constraint are equal to one. For vehicle types that do not serve the customers both sides of the constraint are equal to zero. Constraint (5) determines the number of deployed vehicles of each type. Constraints (6-9) track the load of selected vehicle to serve the customers in the delivery network and make sure that no vehicle exceeds its capacity. Constraint (6) mandates that vehicles of each type depart the depot with a total volume (summed over all the vehicles of that type) of the customers’ demands that are served by that particular vehicle type. This constraint loads the total required delivery demand for each vehicle type, which needs to be distributed between selected tours for that vehicle type. Constraint (7) reduces the load tracking state variable by amount of customer demand for selected vehicle type and tour to serve those customers. Constraint (8) makes sure that the load on any selected vehicle to serve customers is not exceeding its capacity. Note that if customers at upstream and downstream nodes of a link are not served by a certain vehicle type, then the load tracking state variable would be set to zero. Constraint (9) stipulates that all selected vehicles of different types return to the depot empty. Constraints (10-14) track the traveled distance by each selected vehicle and make sure it does not exceed its maximum range. Constraint (10) initializes the traveled distance to zero for all selected vehicles while departing the depot. Constraint (11) indicates that the traveled distance by any selected vehicle to serve a customer is the same right before and after serving the customer. Constraint (12) states that the traveled distance for a selected vehicle downstream of a link equals to its traveled distance up to the upstream node of the link plus the link length. Note that if the customers downstream and upstream of a link are not served with a certain vehicle type, then the traveled distance would not change. Constraints (13) and (14) ensure that traveled distances of selected vehicles do not exceed their associated range. Constraints (15-19) ensure that all customers are served during a given time window. Constraint (15) sets the travel time of all selected vehicles for delivery to zero while departing the depot. Constraint (16) states that travel time of each vehicle right after serving a customer is equal to travel time right before serving the customer plus the required time to drop off the delivery demand. Constraint (17) indicates that travel time of each selected vehicle downstream of a link in its tour equals to the travel time of that vehicle upstream of the link plus the time it takes for the vehicle to traverse that particular link. Constraint (18) and (19) ascertain that travel times of each selected vehicle along its tour is limited to the delivery time window at all times. It also sets the travel time to zero for non-selected vehicle types to serve customers of each link (upstream and downstream customers). Constraint (20) states that the decision variable x is binary. Constraints (21-25) state that the state variables associated with the load, traveled distance, and travel time are non-negative continuous values. Equation (26) determines the cost-benefits to the society due to the company's delivery activity, and thus entails both the societal costs of emission, and the pollution tax revenues.

4.3 Solution Algorithm

The proposed problem is solved with three approaches; a commercial solver, an existing metaheuristic approach in the literature, and a modified metaheuristic approach incorporating Simulated Annealing (SA) concept. The first approach, i.e. the commercial solver, is not able to address large scale applications due to computational complexities. The second approach, developed in the literature, can be applied to large scale applications, but it fails to find the optimal solutions in a reasonable time. Therefore, the third approach, a modified version of the second approach, is proposed in this study to address the computational efficiency challenge and provide a better solution to the problem of interest.

4.3.1 Commercial Solver

In the first approach, a commercial optimization software (CPLEX® solver using AMPL®) is applied to solve the problem of interest in this study. Commercial solvers such as CPLEX® are used widely to find the exact solution of problems. However, once a problem is NP-hard, the problem size grows exponentially with increase in the number of customers, and commercial solvers are either unable to find the exact solution, or fail to do so within a computationally reasonable time. Vehicle Routing Problem (VRP) and its variants, which can be reduced to a classical VRP, are known to be NP-hard [105]. Therefore, our proposed problem formulation, which is a Heterogeneous Fleet Vehicle Routing Problem (HFVRP), cannot be solved using commercial solvers for case studies with large number of customers, as it is shown in the numerical results section. However, smaller size problems are solved using the commercial software to provide benchmarks to assess the performance of the metaheuristic algorithms that are used in this study.

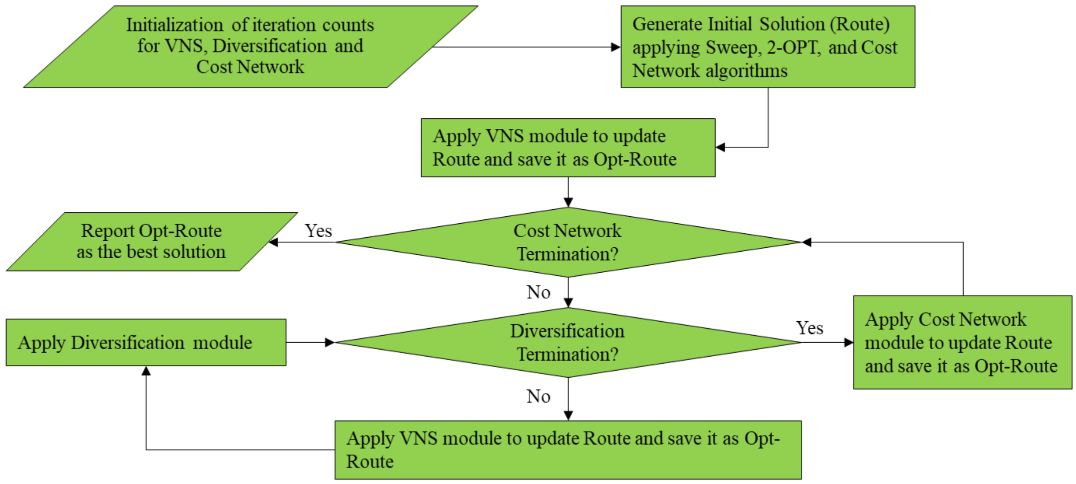
4.3.2 Variable Neighborhood Search (VNS-Based) Metaheuristic

To overcome the computational efficiency challenge for large scale applications, we opted for a metaheuristic approach based on variable neighborhood search (VNS) algorithm proposed by Salhi et al. [105] with certain minor modifications to adapt it for the problem of interest in this study. The VNS-based metaheuristic algorithm is proposed for combinatorial optimization problems, which has evinced successful performances [106], [107]. This metaheuristic algorithm is portrayed in Figure 4-1.

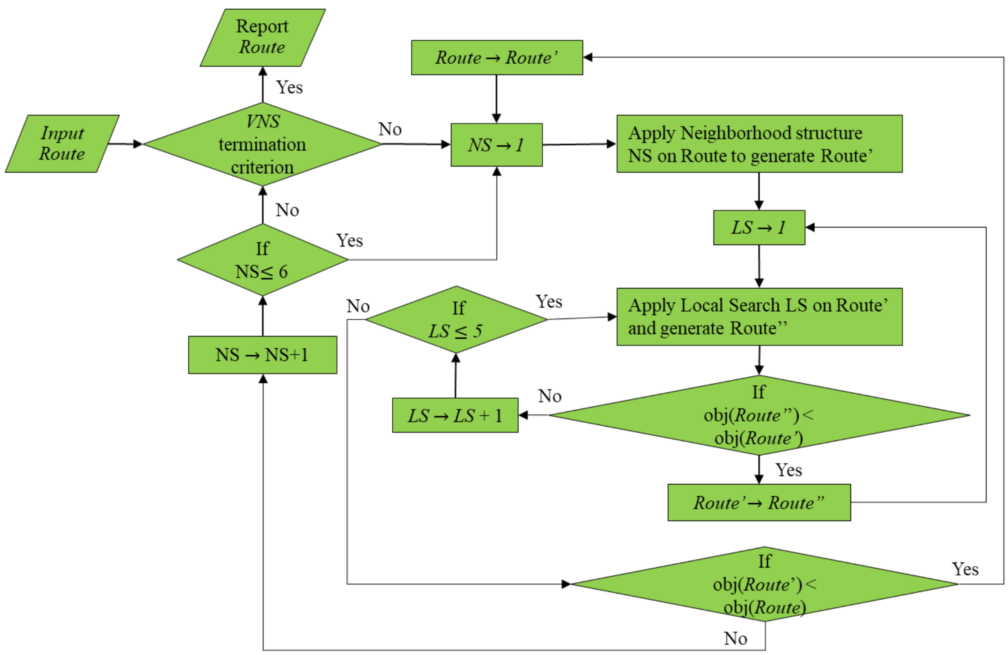
As can be seen in Figure 4-1, an initial solution is built up through the sweep algorithm [108] and is improved by the 2-opt procedure [109]. Next, following Salhi et al. [105], a cost network is constructed for the built tours by 2-opt algorithm, to which the Dijkstra algorithm is applied. The selected shortest path in the proposed cost network provides final tours and vehicle type allocation to each tour resulting from the initial solution. In this study, the cost network construction proposed by Salhi et al. [105] is adjusted in accordance with the proposed problem formulation. In this regard, for any given solution (tours), all tours are combined into one route to form a giant tour, which begins from the depot and covers all k customers with a known order in the given giant tour. Then, a cost network is built for this giant tour, in which every link ij would have a cost C_{ij} (minimum sum of the operating cost to serve costumers i to j by one tour over different available vehicle types) calculated as shown in Equation (4-27):

$$C_{ij} = \min_{h} C_{p_h} + \ (C_{m_h} + CF_h + \mathrm{CTax_h} + \ \mathrm{NTax}\ _h)(D_{d,i} + \sum_{k=i}^{j-1} D_{k,k+1} + D_{j,d}) + CL_h\ (t_{(d,i)h} + \ \sum_{k=i}^{j-1} t_{(k,k+1)h}\ + \ t_{(j,d)h}) \qquad (4\text{-}27)$$

In Equation 4-27, h represents feasible vehicle types that can serve customers on the link ij (*ij* tour) of the cost network. $D_{m,n}$ is the distance from node *m* to node *n,* and $t_{(m,n)h}$ is the travel time from node *m* to *n* using vehicle *h*. Each node represents a customer or the depot. Unlike the proposed approach by Salhi et al. [105], which starts from the smallest capacity vehicle considering only purchase and maintenance costs to serve the customers in each hypothetical link of the cost network, the present study takes advantage of all components of the multi-faceted objective function to find a vehicle resulting in the least objective function value. Once the cost network is built, the Dijkstra shortest path algorithm is used to determine the tours and their assigned vehicle types resulting in the least objective function value.



a) VNS-based metaheuristic



b) VNS module

Figure 4-1 Visualized VNS based metaheuristic

Subsequently, the VNS module is applied following Salhi et al. [105] proposition (shown in Figure 4-1-b) to further enhance the initial solution. In each iteration of the VNS module, the so-called shaking steps are taken based upon insertions and exchanges, known as neighborhood structure (NS) operators, in order to reach a feasible neighbor solution. An insertion consists of taking out a random customer node from a randomly selected tour and inserting it into another randomly chosen tour. On the other hand, an exchange includes selecting a random set of nodes from a random tour, and trading it with another random set from another random tour. After shaking a route to a feasible neighbor solution, local search (LS) operators are performed to find an improved solution. Iterative applications of these neighborhood structures and performing various local searches on each neighbor solution converges to a good solution for the problem of interest, without ensuring optimality. Note that in each neighborhood structure a random solution is found, while in the local search all possible options are searched and the best option is selected. Note that the order of the neighborhood structure or local search operators matters. At any instant that the current solution is improved in one of the neighborhood structure or local search steps, the current solution would be updated and the neighborhood structure or local search step would be reinitiated to the first step. This means at each iteration all steps are repeated until no improvement is observed in the current solution incorporating all NS and LS operators, orderly.

Six NS operators, which are provided in the study by Salhi et al. [105], are used in this algorithm (NS_{max} denotes the maximum number of NS operators) within each iteration of the VNS module. These neighborhood structures, in the order proposed and implemented by Salhi et al. [105], are briefly explained as follows:

- $NS = 1$; "1-1 interchange" in which a random customer is chosen from a randomly selected tour, and is systematically switched with customers from all other tours, until a feasible swap (in terms of vehicle capacity and range) is constructed.
- $NS = 2$; "type-1 2-0 shift" in which two consecutive random customers chosen from a randomly selected tour are checked for a feasible insertion in other tours.

- $NS = 3$; “2–1 interchange” in which two consecutive random customers from a randomly selected tour are swapped with another customer in another tour ensuring the feasibility.
- $NS = 4$; “type-1 perturbation” in which one randomly chosen customer is removed from one tour and relocated to another randomly selected tour, while one another customer is also relocated from the second tour to a third randomly selected tour considering feasibility in the updated (second and third) tours.
- $NS = 5$; “type-2 perturbation” which is similar to “type-1 perturbation”, relocating two consecutive customers instead of one customer.
- $NS = 6$; “type-2 2-0 shift” which is similar to “type-1 2-0 shift”, checking two consecutive random customers for feasible insertions into two different tours.

The successive multi-level local searches performed within each of the six neighborhood structure (NS) operators of the VNS module are briefly explained as follows:

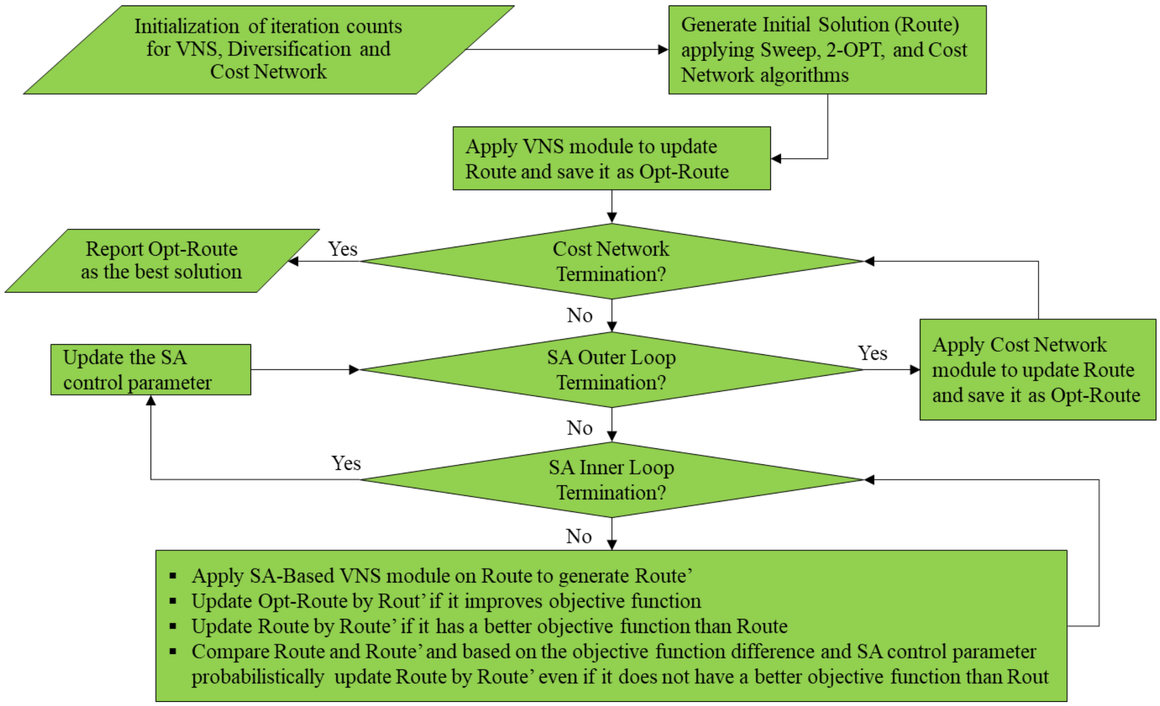
- $LS = 1$; “inter-tour 1-insertion” in which a customer is removed from a tour and checked for insertion in another tour, while maintaining feasibility.
- $LS = 2$; “2-opt algorithm” which is applied to each tour of the current solution (see [109] for more details).
- $LS = 3$; “intra-route swap” in which a pair of customers are swapped within each tour.
- $LS = 4$; “intra-tour 1-insertion” in which a customer is removed from its position in a tour and relocated to another position in the same tour.
- $LS = 5$; “intra-tour 2-insertion” which is similar to “intra-tour 1-insertion”, relocating two consecutive customers.

Once the initial VNS module is implemented, the major loop of the metaheuristic algorithm begins. Within the major loop, a similar VNS module is repeated, where the input route to this module is updated by two other modules, namely, diversification and cost network. The cost network module is described as part of the initial solution generation process earlier. The cost network module is applied until no improvement in the current solution is observed, while the diversification module is implemented for a given number of iterations [105]. The diversification module gets the latest current solution generated over the VNS iterations as an input. Combining the proposed tours in this current solution, the module generates a giant tour based on certain rules. Then, an optimization approach breaks this giant tour and allocates the best vehicle type to each tour. This process is performed to alter the current solution in order to search for a different possible solution satisfying the same customer orders generated by the VNS module. Once all the iterations of the diversification module are performed, a final cost network application searches for an improved solution. If the improved solution is found, the diversification loop would be repeated, while if there is no improvement, then the best solution is found by the algorithm. For more details on the solution algorithm for this metaheuristic algorithm please see Salhi et al. [105]. We also propose to modify the heuristic approach in our study based on the concept of simulated annealing (SA) to prevent trapping into a local optimal solution.

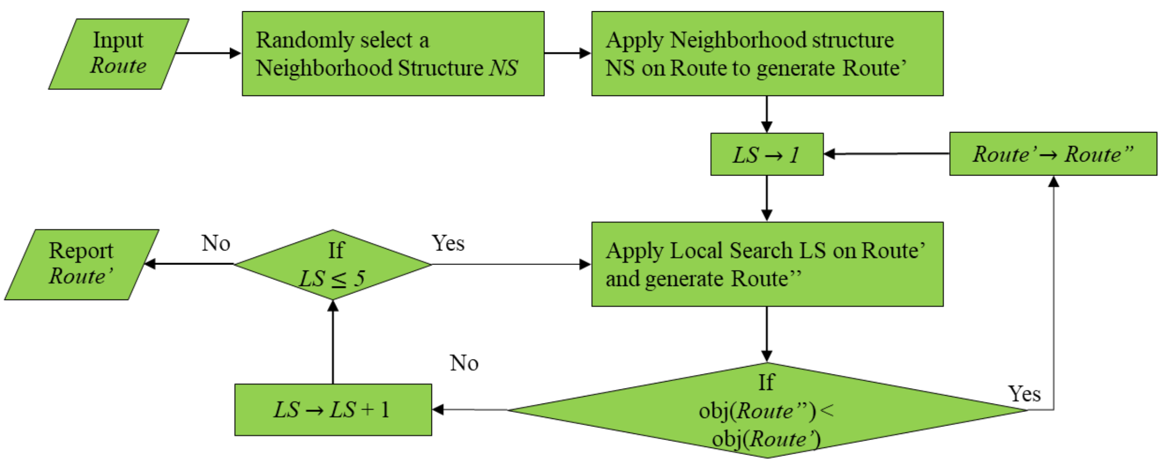
In an effort to prevent trapping in locally optimal solutions, we propose incorporating simulated annealing (SA) concept into the VNS-based metaheuristic. In general, an SA-based algorithm, inspired by annealing phenomenon in metallurgy [110], typically consists of two main steps. In the first step, the algorithm starts from a current solution and perturbs it to a neighboring feasible solution. Subsequently, the second step compares the objective function value of the current and the feasible solution obtained from the first step, and replaces the current solution with the new one under a probabilistic condition, which is one for a better solution and a certain probability based on the objective function difference between two solutions, even for worse neighbor solutions. The acceptance probability of the worse solutions reduces gradually as the solution process proceeds using a control parameter that would be updated after certain number of iterations. The rationale behind accepting worse solutions probabilistically is to avoid being trapped in local optima. However, to ensure convergence of the algorithm, the probability of accepting worse solutions is reduced as the number of iterations proceeds. SA-based metaheuristics have proven efficiency in transportation studies [56], [57], [111]. The SA-based VNS metaheuristic algorithm proposed by this study is depicted in Figure ***4-2***.

According to Figure ***4-2***-a, the initial solution is fabricated through the same procedure as the one in the VNS-based metaheuristic. Therefore, the main difference between the VNS-based metaheuristic and the SA-based VNS metaheuristic lies in the major loops. In the SA-based VNS metaheuristic, we deploy VNS as the first step of the SA algorithm, which searches for a new feasible solution to be compared with the current solution. Additionally, as can be seen in Figure ***4-2***-b, we made changes to the VNS procedure proposed by Salhi et al. [105]; first, we employ the diversification procedure as an NS operator, and thus there are seven NS operators (i.e. $NS_{max} = 7$). Second, the NS operators do not follow the trend proposed by Salhi et al. [105]; rather, in each VNS procedure iteration, one NS operator is selected at random, instead of repeating all NS operators until no further improvement is found. Accordingly, each modified VNS procedure iteration would be faster compared to the VNS procedure iteration conforming to Salhi et al. [105]. Once all local search operators are orderly repeated for a randomly selected neighborhood structure, until no improvement in the updated solution is captured, this solution would be considered as the neighbor solution and would be compared with the current solution at the SA level, which is also the input to the VNS module.

If the neighbor solution is better than the current solution, it would update the current solution with probability of one. However, even if the neighbor solution is worse than the current solution in terms of the objective function, probabilistically it might replace the current solution. Note that the probability of accepting a worse solution depends on the objective function difference between the neighbor and current solution (i.e., how much worse it is) in addition to a control parameter. This control parameter is kept fixed over inner loop iterations, and is decreased at each outer loop iteration. This control parameter and its variations allow to find an equilibrated solution at each outer loop iteration and assists the algorithm to converge to a final solution over the outer loop iterations. The modified VNS module is repeated until the maximum number of SA iterations is reached (Outer iterations). Then, the cost network procedure is applied as the extra refinement, identically to the VNS-based metaheuristic algorithm. The SA would be repeated if the cost network module can find a better solution, otherwise the algorithm would be terminated. The flow of SA-based VNS metaheuristic can be seen in Figure **4-2**.



a) SA-Based VNS metaheuristic



b) The modified VNS module

Figure 4-2 Visualized SA-based VNS metaheuristic

Random-SA-VNS is another variant of SA-based VNS metaheuristic that is proposed and tested here. In this variant, similar to Neighborhood Structures, the Local Searches are also selected randomly instead of going through the entire structure. This is expected to improve the computational efficiency.

4.4 Numerical Experiments

In this section, a case study is inputted into the mathematical formulation along with model parameters, and the solution algorithms are tested. Subsequently, sensitivity analyses are performed on emission taxes and package sizes to investigate their impacts on delivery activities.

4.4.1 Case Study

The Chicago downtown network is considered to be the case study for the numerical results. This network is bound from the west and the east by O'Hare Airport and Lake Michigan, respectively [112]. This network includes downtown Chicago and some western and northern suburban cities of Chicago, and contains 1,578 nodes, 4,805 links, and 218 zones. Figure 4-3 depicts the configuration of the Chicago downtown network. The size and level of congestion and the downtown structure makes this network a great case study to implement the proposed framework.

As our aim is to solve a single depot HFVRP, we assume that the depot in our problem of interest is located at the location of a UPS® store in downtown Chicago. 100 randomly selected nodes are considered to be the maximum number of customers that need to be served by this one single depot. These 100 customers are categorized into five levels each consisting of 20 customers. The levels represent customers within 3 miles (level 1), between 3 miles and 6 miles (level 2), between 6 miles and 9 miles (level 3), between 9 miles and 12 miles (level 4), and beyond 12 miles (level 5) of distance from the depot.

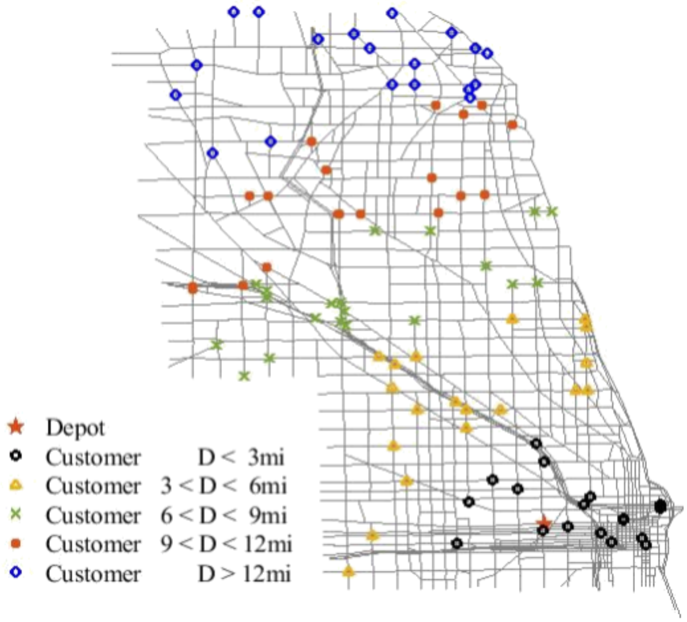


Figure 4-3 Configuration of Customers and Depot in Chicago Downtown Network

4.4.2 Assumptions and Model Parameters

This study intends to investigate policy implications on freight delivery activities in urban areas and realize how more sustainable transportation modes can be deployed to this end. We assume that our hypothetical company aims to choose from a set of delivery vehicles including conventional cargo vans, electric vans, pedal-assist and all electric cargo bikes, as well as pedal-assist and all electric cargo trikes. The specifications of the alternatives are presented in Table 4-2.

In order to calculate the normalized daily maintenance cost for an electric van, 5-year maintenance cost [113], i.e. $4870, is divided by the average of vehicle miles traveled (VMT) for delivery trucks and light trucks [114], i.e. average annual VMT of 12,414 miles. For the social carbon cost, we use the average of EPA proposed values for 2015 and 2020 [115], which have been calculated in 2007 USD, and convert the amount to 2018 USD [116], which yields $47.23 per ton of CO_2. To obtain emission cost for conventional cargo van, we use the specifications of

Ford® Transit Connect [117]. Using the city gas mileage of 24 mi/gal [118], and the amount of carbon dioxide produced when burning a gallon of gasoline, i.e. 9071.85 g/gal, the emission cost of conventional cargo van is estimated to be \$0.0178 per mile. Note that for cargo vans we have considered only operational emission generation. However, for other modes, the well to wheel emission is considered. Regarding the electric van, we use the average emission production rate of Nissan Leaf, i.e. 149 g/mi [119]. The emission production rate of all cargo cycles are assumed to be equal to 35.2 g/mi [120]. In terms of fuel cost, the national average gas price of \$2.73 per gallon is used [121], and together with the city gas mileage of 24 mi/gal [118], the fuel cost of conventional cargo van is estimated at \$0.11 per mile. The average electricity cost for the transportation sector is \$0.0958 per kWh [122]. With use of each electric vehicle's battery size and range and the average electricity cost, we calculate the associated fuel costs. It must be noted that the battery size for pedal-assist bike and trike is assumed to be 0.418 kWh with the resultant range of 50 mi, while the electricity mileage of all electric bike and trike is assumed to be 0.024 kWh/mi [123]. The labor cost in this study is assumed to be equal to the average delivery driver wage in the United States, i.e. \$17 per hour [124]. In terms of customer demands, we assume an average package size of 1.22 ft^3, and weight of 14.6 Ibs. The average package size is calculated assuming 60% of an average urban delivery truck's capacity is utilized each day, which is equivalent to 500 identically-sized packages. To capture the weight of each package, dimensional weight is calculated with the divisor for domestic shipments, i.e. 166 [125]. It is also assumed that the delivery truck is a 20' carrier with the capacity of 1,016 ft^3 [126]. Table 4-2 presents the considered parameters for the mathematical framework in section 4.2.

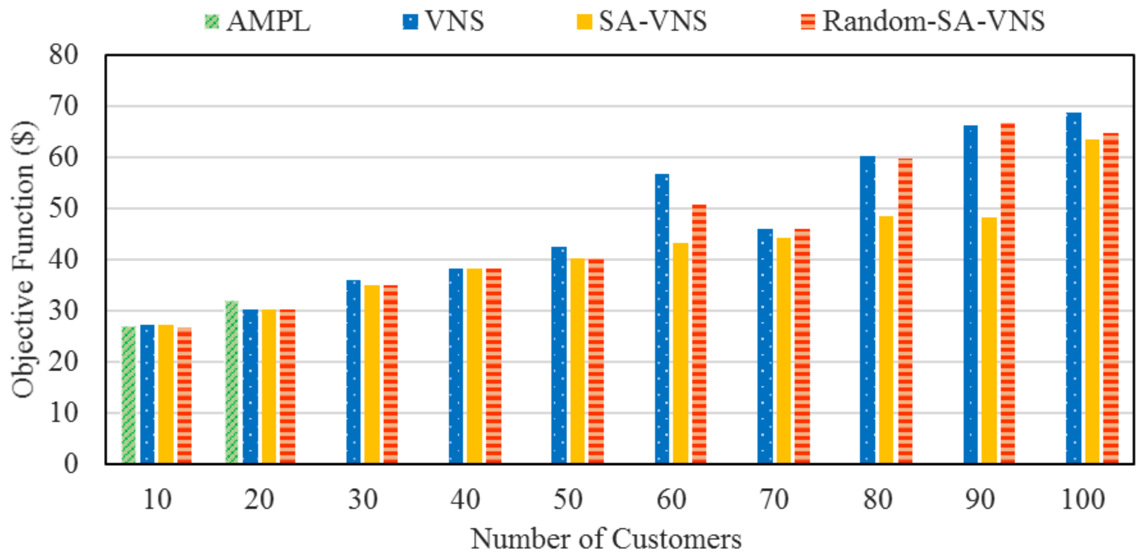
One of the main steps in developing and adopting metaheuristic algorithms is calibrating the parameters of the algorithm. These parameters for SA algorithm are numbers of inner and outer iterations, as well as the parameters defining the probability. Based on previous studies by the same authors regarding applications of SA in various problems, 30 inner and 30 outer iterations are considered in this study for the SA approach *(35-39)*. For the VNS metaheuristic approach, the suggested values by Salhi et al. [105] are used.

Table 4-2 Input parameters into the proposed mathematical formulation (section 4.2)

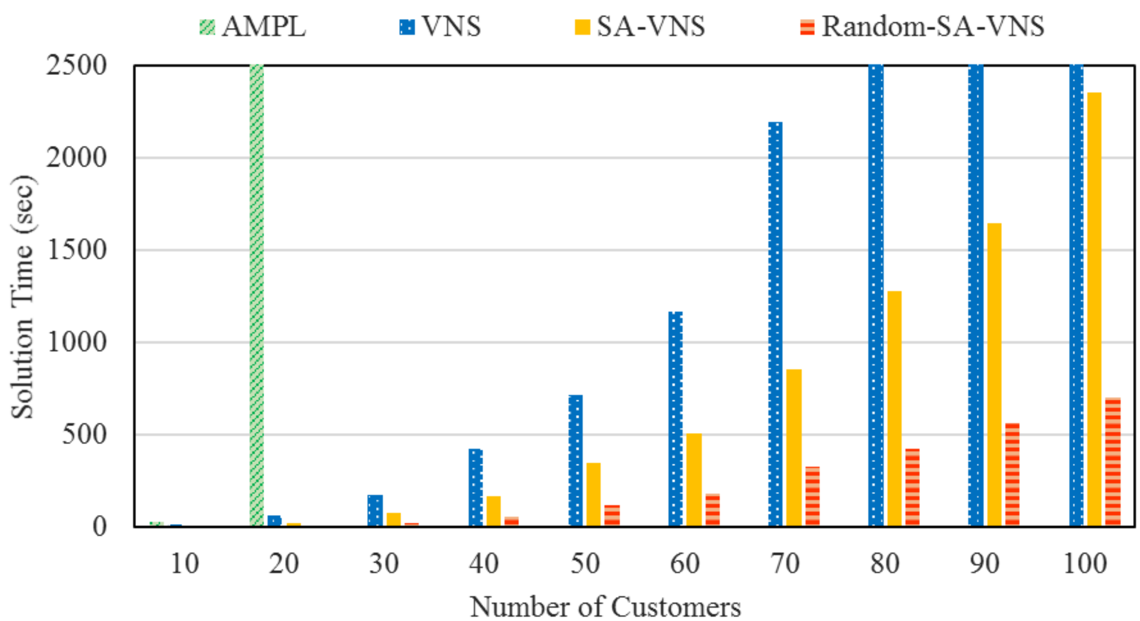
Specifications	Cargo van	Electric Cargo Van	Pedal-assist bike	All electric bike	Pedal-assist trike	All electric trike
Life Span (years)	12 [127]	10 [127]	5 [70]	5 [70]	5 [70]	5 [70]
Purchase price ($)	24,275 [117]	38,481 [128]	1,244 [70]	4,058 [70]	6,491 [70]	11,236 [70]
Normalized daily purchase cost ($/day)	5.54	10.54	0.68	2.22	3.55	6.15
Normalized daily maintenance cost ($/mi)	0.08 [113], [114]	0.12 [70]	0.02 [70]	0.02 [70]	0.02 [70]	0.02 [70]
Single charge/fueling range (comfortable range for bikes and trikes) (mi)	379 [118]	173 [128]	50 [129]	49 [130]	50 [129]	49 [130]
Volume capacity (ft^3)	123 [117]	148 [70]	5 [70]	5 [70]	49 [70]	49 [70]
Payload (lb)	1549 [117]	1,697 [70]	200 [70]	200 [70]	550 [70]	550 [70]
Max operating speed (mph)	30 [131]	30 [131]	10 [70]	15.5 [70]	10 [70]	15.5 [70]
Emission Cost ($/mi)	0.0178	0.00704	0.00166	0.00166	0.00166	0.00166
Noise cost ($/mi)	0.01 [132]	0	0	0	0	0
Fuel cost ($/mi)	0.11	0.023	0.0008	0.0022	0.0008	0.0022

4.4.3 Comparison of Different Methods

In this section, the exact solution method using a commercial solver is compared with the proposed methods of VNS, SA-VNS, and Random-SA-VNS for various problems with different number of customers that are randomly selected from the entire 100 customer pool. The results are presented in Figure 4-4 and confirm that a metaheuristic is required to solve the larger problems, since a commercial solver is unable to provide a solution as the size of the problem grows (more than 20 customers). Also, it can be observed that the proposed SA-VNS has the ability to increase computational efficiency significantly compared to VNS algorithm providing solutions with much lower objective functions. SA-VNS even showed better performance in finding the optimal solutions for larger problems. It is worth noting that even though Random-SA-VNS provides solution closer to VNS rather than SA-VNS, its computational efficiency is much better than the other approaches. Another observed pattern is the increasing pattern of the solution time and objective function value. This is expected, since larger number of customers increases the number of variables and tour sizes, as a result of which operational costs and solution times would increase.



(a) Objective function



(b) Solution time

Figure 4-4 Comparison of different solution methods

In order to find the optimum policy to minimize the cost to the society, a variety of sensitivity analyses are performed in this section. The sensitivity to emission and noise tax multiplication factors for different package sizes and distance levels are presented in Table 4-3. Results are presented for select distance levels 1, 3, and 5 to provide meaningful variations in the solution set. The emission and noise tax factors are multiplied by societal costs of emission (i.e. CO_2) and noise to represent the tax amounts. It can be observed that for small distances (0-3 miles from depot) bikes and trikes form the optimal fleet. As the package size grows, trikes are required to substitute bikes so as to handle larger-sized packages. For long distances, i.e. distance level 3 representing customers at 6-9 miles of distance from depot, and for lower levels of emission tax, the optimum option is regular van; however, as the amount of tax grows, electric vans form the optimal fleet. At higher distance levels (level 5, beyond 12 miles from depot) electric vans are always the optimum option, since lower fuel and maintenance costs of these vehicles compensate for the higher purchase price when traveling longer distances.

Table 4-3 Sensitivity to emission and noise tax

Distance from Depot	Package Size Factor	Costs and Vehicles Types	Emission and Noise Tax Factor		
			0	1.5	2
Level 1 (0-3 miles)	0.5	Company Cost	4.87	4.95	5.04
		Emission Cost	0.08	0.08	0.08
		Tax Revenue	0	0.08	0.15
		Vehicle Type	3 Bikes	3 Bikes	3 Bikes
	1	Company Cost	5.70	5.76	5.82
		Emission Cost	0.06	0.06	0.06
		Tax Revenue	0	0.06	0.12
		Vehicle Type	Trike	Trike	Trike
Level 3 (6-9 miles)	0.5	Company Cost	24.24	26.15	27.12
		Emission Cost	4.16	0.97	0.97
		Tax Revenue	0	0.97	1.94
		Vehicle Type	Van	E-Van	E-Van
	1	Company Cost	24.24	26.15	27.12
		Emission Cost	4.16	0.97	0.97
		Tax Revenue	0	0.97	1.94
		Vehicle Type	Van	E-Van	E-Van

Table 4-3 Sensitivity to emission and noise tax (cont'd)

Distance from Depot	Package Size Factor	Costs and Vehicles Types	Emission and Noise Tax Factor		
			0	1.5	2
Level 5 (>12 miles)	0.5	Company Cost	28.73	30.02	31.31
		Emission Cost	1.29	1.29	1.29
		Tax Revenue	0	1.29	2.58
		Vehicle Type	E-Van	E-Van	E-Van
	1	Company Cost	28.73	30.02	31.31
		Emission Cost	1.29	1.29	1.29
		Tax Revenue	0	1.29	2.58
		Vehicle Type	E-Van	E-Van	E-Van

4.5 Conclusion

The objective of this study is to find the optimum configuration of freight delivery fleet in urban areas. The optimization includes minimizing both the company and the societal costs in a bi-level optimization model. A metaheuristic solution algorithm is developed to solve the bi-level optimization problem efficiently. The numerical results on a large-scale case study (Chicago downtown network with up to 100 customers) compare different solution algorithms and demonstrates superiority of the proposed solution method in this study in terms of solution time and optimality. Furthermore, a thorough sensitivity analysis on the average package size, customers' distance relative to the depot, and the emission tax values are presented. The following concluding remarks are noted:

- CPLEX® as a commercial solver cannot solve large size problems;
- SA-VNS that is developed in this study is superior to VNS that is developed in the literature in terms of both solution time and objective function value. In the numerical experiments of this study, SA-VNS provides at most 27% lower objective function relative to VNS, and with 50% to 80% lower solution times;

- Random SA-VNS (a variant of SA-VNS) provides solutions close to VNS in terms of objective function with much better computational efficiency even relative to SA-VNS (up to 70%);
- At short distances, bikes and trikes are selected. The average package size may switch the optimal solution from bikes towards trikes;
- At long distances, bikes and trikes are not feasible. Due to longer distances that need to be covered, the operational costs dominate purchase cost of vehicles and as a result, E-van is selected;
- At medium distances, operational costs cannot dominate the purchase cost and as a result cargo van is selected. In this case, once the emission taxes are introduced, the model switches from cargo van to E-van;

This study provides a modeling framework along with a proper solution algorithm to develop a sustainable urban freight delivery system considering various vehicle types. In addition to the methodological contributions, our study provides insights into how and when, which modes are selected for delivery, and what the societal outcomes are. Despite the significant environmental benefits of the presented framework and computational benefits of the solution algorithm, there are still some limitations that can be considered for future research. For example, the presented modeling framework and solution algorithm can be extended to a dynamic and stochastic model in the future studies. In addition, we propose a multiple-depot freight delivery problem for future studies. Locating optimal points for depot(s) (single or multiple) can be another future research direction.

CHAPTER 5. OVERALL CONCLUSIONS, CONTRIBUTIONS, AND RECOMMENDATION

Growing awareness of the downsides to the heavily fossil fuel driven transportation in the U.S. has led to sustainable transportation planning and operations. For this purpose, recognition of emerging technologies for transportation of passengers and freight is on the rise. Light two-/three-wheeled electric vehicles, increasingly known as micro-mobility, are gaining attention due to numerous advantages such as environmental-friendliness, mobility improvement, and health benefits. This dissertation explores incorporation of micro-mobility into urban transportation networks, through the lenses of authorities as well as users. The highlights and contributions of this dissertation are as follows:

- An online survey is designed to capture users' stated mode choice in different commuting settings. The aim is to determine influential factors, among conventional as well novel attributes, in commute mode choice.
    - Analysis of discrete choice models suggest that alternatives' travel time and travel path topography have significant influence on commute mode choice.
    - Offering e-bikes can help increase bike-sharing attractiveness when the terrain is hilly, or when user looks for a faster option;
    - Urban settings like areas around CBDs and university campuses with essentially short trips are proper candidates for mixed fleet bike-sharing systems;
- A design framework for a multi-modal transportation system is introduced, focusing on a mixed fleet bike-sharing system. The mixed fleet bike-sharing system is to offer both

conventional and electric bikes, and is intended within a typical transportation network for commuting to a CBD. Considering quantified health benefit values and emission costs of commuting modes is a contribution in this study. Another major contribution is striking a trade-off between authoritarian and user perspectives. Conclusively, the proposed design framework is capable of determining optimal fleets, accounting for detailed societal and individual costs. Through a hypothetical numerical example with relatively short commuting distances, the following main findings are derived:

- Generally, bus and pedelec are the most popular modes due to the trade-off between affordability and range;
- With increase in health benefit values, pedelc becomes the dominant public transportation mode for commuting;
- As emission cost increases, commuters find pedelec more utilitarian than bus;
- Increasing financial burden of emission was found to reduce the demand and the optimum mode counts for bus while increasing the demand and optimum mode counts for pedelec;
- As a result of the relatively short commuting distances and general inclination for non-fuel consuming modes, the model is essentially insensitive to fuel cost;
- Increasing fares or trips costs would drive users more towards pedelec and walking.

▪ Deploying electric cargo cycles, as well as electric and conventional vans for urban freight delivery is investigated. The main findings of this research include, but are not limited to, the following:

- When delivery distances from depot are relatively short, bikes and trikes are selected for freight transportation; under these circumstances, as the package size increases, optimal fleet would deploy more bikes than trikes;
- At medium delivery distances, in a trade-off between purchase and operating costs, cargo vans constitute the optimal fleet; in this case, E-vans replace cargo vans if emission taxes increase;
- In instances with long delivery distances from depot, bikes and trikes are not feasible; also, the operational costs dominate purchase costs as a result of longer distances, and thus E-van becomes the optimal choice;

In terms of future studies, revising the travel survey and incorporating social marketing strategies can yield interesting insights into impacts of public awareness of emission and health aspects of transportation modes and micro-mobility. Moreover, exploring covariates not investigated in the present study can help improve the deterministic portions of the models thus reduce error terms, thereby illuminating influences of unexplored factors. Enhancing the quantitative calculations of mode attributes can be another research direction for more accurate findings.

With improved mode choice models, the design framework for shared micro-mobility can be enhanced. Other extensions to the shared micro-mobility design framework can be detailed formulation looking into candidate shared micro-mobility station locations, micro-mobility fleet rebalancing, and quantified safety aspects adopting shared micro-mobility. In terms of micro-mobility for urban freight transportation, more realistic variants of vehicle routing problem can be deployed to incorporate multiple depots, optimal locating of depot(s), deliveries with time windows, dynamic vehicle routing, and so on. Furthermore, the problem can be extended to explore large scale impacts of deploying micro-mobility for urban freight transportation, and investigate varied policy scenarios.

APPENDICES

APPENDIX A. HEALTH VALUES

For public health promotion, Pate [133] recommends that American adults must engage in at least 30 minutes of moderate-intensity physical activity on most or preferably all weekdays. To determine intensity of physical activity, the index of Metabolic Equivalent of Task (MET) is commonly used. A compendium presenting MET values for a wide range of physical activities was developed in 1989 by Ainsworth et al. [134] and was published in 1993. This compendium was updated in 2000 [135] and underwent a second update in 2011 [136]. Pate [133] states that METs of moderate-intensity physical activities are from 3 to 6 and refer researchers to the compendium [134] for examples of moderate intensity physical activities. Another important point of the paper by Pate et al. is that they articulate "physical activity is any bodily movement produced by skeletal muscles that results in energy expenditure" and " ... is closely related to, but distinct from, exercise and physical fitness." According to physical Activity Guidelines for Americans in 2008, for substantial health benefits, adults need to do at least: (a) two hours and 30 minutes (150 minutes) each week of moderate-intensity aerobic activity (e.g. brisk walking), or (b) one hour and 15 minutes (75 minutes) each week of vigorous-intensity aerobic activity (e.g. jogging or running, or (c) an equivalent mix of moderate- and vigorous-intensity aerobic activity. Note that every session of physical activity must be no shorter than 10 min for advantage gain. Also, the index that shows intensity is abbreviated as MET which stands for metabolic equivalent of task.

In transportation discipline, active transport (AT), basically including walking and cycling, is associated with less dependence on car use and higher levels of physical activity and is thus supposed to provide substantial health benefits [137], [138]. By incorporating a bike share system, with both conventional and electric bikes, into existing transportation systems, our research also aims to contribute tobli public health and minimize the financial burden physical inactivity could put on society’s shoulders.

For the purpose of our study, we need to first) know the MET value for e-biking, and second) quantify the price of biking and e-biking.

In a study, Simons et al. [139] aimed to evaluate the potential of e-biking as a means for providing substantial health benefits. Twelve normally active adults volunteered and were asked to traverse a path of 4.3 km length as they would normally ride for commuting, with e-bikes at three modes of no support, low or eco support, and high or power support. Mean speeds and mean intensities of the activities are as follows:

Table A-1 Findings from the study by Simons et al. [130]

Mode	Mean speed	Mean intensity (MET)
No support	12.25 mph	6.1
Eco (light) support	13.2 mph	5.7
Power (high) support	14.6 mph	5.2

Even though e-bikes, when ridden without electric assistance or at "no support" mode, are harder to manoeuver than conventional bikes, we assume that e-biking with no support is equivalent to regular biking.

The average biking speed for commuting to work in the United States is 10.8 mph [62]. Based upon this value and the study by Simons et al. [139], the speed of riding pedelec in the United States would be scaled to 11.6 mph, which is assumed to be 12 mph in our study. On the other hand, we assume the biking to work speed is 10 mph, consistently with the compendium of physical activities [136], and thus the MET of biking to work is 4. Accordingly, the MET of riding pedelec to work would be 3.7. In terms of walking to work in the U.S., the average speed is 3.7

mph [62]. Consistently with the compendium of physical activities [136], we assume that walking speed is 3.5 mph with the MET of 3.8.

To come up with average commuting distance with pedelec, as well as the average commuting speed and distance by SSEB, we deployed the results from [140]. In this paper, pedelec riders were found to speed 17% higher and reach distances 32% farther, as compared to regular bikes. With extrapolation, we assume in our study that SSEB riders would speed 34% higher and traverse 64% longer distances than regular bike commuters do. Accordingly, we assume that average commuting distance by pedelec would be 5.01 mi, and the average commuting distance and speed by SSEB would respectively be 6.2 mi and 13.4 mph in the United States.

In order to quantify monetary values of moderate-intensity physical activities, in a study conducted in Australia, [58] decided that inactivity costs can be avoided if Australian physical activity guideline is met. The calculations were done as follows:

They initially consider annual direct cost of inactivity in Australia. Additionally, indirect costs are also addressed and thus the total economic burden of inactivity is determined. Next, they deduce that if the inactive adult population participate in physical activity as the recommendations in guideline, the costs would be avoided, and on this basis, they mention that an adult is required to perform at least 2.5 hours of moderate-intensity physical activity in each of the 52 weeks of the year. Finally, they calculate monetary value of an hour of moderate physical activity based on these considerations. Following [58], we calculated physical activity value in the United States with a similar approach. We first obtained the extra mean per capita expenditure on health care that an able-bodied, inactive American adult has to make annually, compared to health care expenditure of an active adult from the study by [59]. Note that this value of $ 1,015 does not consider indirect costs. According to a Canadian ratio, 54.3% of total cost would be indirect portion which concerns issues such as productivity losses due to premature death. Thus, the total financial burden equals \$ 2,221. Per capita monetary value of an hour of moderate-intensity physical activity id determined when the total cost is divided by 130 hours, that is:

Per capita monetary value of an hour of moderate-intensity physical activity = $\$17.08\ /hr$

In this approach, the calculated value applies to the generic term of "moderate intensity physical activity". In other words, there is no difference between prices of biking and e-biking for example. As we are trying to determine numbers of fleets partially based upon their financial benefits, it matters to us to differentiate in this study. For this purpose, we assume that the \$ 17.08 is the value of an hour of a physical activity with intensity of 4.5 METs, which is the mean value in the range of "3 ≤ MET ≤ 6". We assume that, in this range, there is linear relationship between intensity and value which is represented by a line that passes through the origin. Therefore, as we have coordinates of one point on this line, that is (4.5, 17.08), we can calculate the slope, which is $\$3.79/\ h.MET$, and obtain varied values for moderate activities with different intensities.

With the formula "Y = 3.8.X", where Y is the hourly value and X is the intensity, and the MET values provided in the [136] and [139] we have the following values:

Table A-2 Estimated health benefit hourly values

Commuting mode	MET	Mean Speed (mph)	Value (\$/hr)
walking	3.8	3.5	14.44
Biking	4	10	15.2
E-biking (pedelec)	3.7	12	14.06

APPENDIX B. AVERAGE DISTANCE AND SPEED FOR THE COMMON COMMUTING MODES

Table B-1 Modes' distances and speeds

Commuting Mode	Mean Speed (mph)	Average Commuting distance (mi)
walking	3.5	1
Biking	10	3.8
Pedelec	12	5.01
E-scooter	13.4	6.2
Bus (public transit)	11.4	10.2
Motorcycle	29.5	12.1
Car	28.9	12.1

APPENDIX C. FARE CALCULATIONS

To calculate the fares for the shared/public modes in this study, we relied on the bike-sharing system [141] and the electric scooter sharing system [142] in Vancouver, BC, Canada. Also, the fares are charged for 30-minute interval uses.

First, based upon the annual pass for the bike-sharing system, we determined the monthly pass value at almost $11/mo. Next, assuming average biking commute distance of 3.8 mi, we came up with the average daily biking commuting distance (to and from work) of 7.6 mi. Thus, the value of biking in Vancouver would be: $(\$11/mo)\ /\ (228\ mi/mo)\ =\ \$0.05/mi$ Considering the biking speed of 10 mi/h, we would obtain: $0.05/mi *10 mi/h = $0.5/h = $ 0.25/(.5h) in Canada. Based upon the value of Canadian dollar against the American dollar on July 4th, 2017, (One Canadian dollar cost 0.77 U.S. dollar), the bike-sharing fare in Canada was adjusted at "US$ 0.19 /(.5h) ". Next, in order to conjecture the fare for a bike in the intended system in East Lansing, Michigan, the ratio of bus fares in Vancouver to East Lansing was calculated as U.S. $ 2.19/ 1.25 = 1.76. Accordingly, the bike fare in East Lansing was set to $0.11/(0.5h).

Based on the electric scooter fare in Vancouver, the monthly pass 15 Canadian dollars, as well as 40 cents per mile. Considering the average commuting distance with electric scooter at 6.2 mi, and thus 12.4 mi per day, we would have: ($15/mo) / (372 mi/mo) = $ 0.04 /mi. In total, the fare would be $ 0.04 /mi + $0.4 /mi = $0.44/mi. Next, considering the average speed of 13.4 mph, the fee would be $5.9/h, or $2.95/ (.5 h) in Canada, and thus US$ 2.27/ (.5h). With use of the bus fare ratio of 1.76, the e-scooter sharing fee in East Lansing would be: $1.29/(.5h). In this study, we assume that the fare for pedelec would be the average of regular bike and electric scooter fares, namely $0.7/(.5h).

APPENDIX D. DAILY COSTS OF OWNERSHIP AND MAINTENANCE

For a regular bike, either shared or private, we assume the average purchase price as $350 [143]. For pedelec, we assume the base price of $1500 in the U.S. [13]. To have an estimate of the base price for an SSEB, we rely on a ratio of SSEB price to pedelec price in china [11] and estimated a base price of $2600 for SSEB in the U.S.

Based upon the life expectancies of regular bike, pedelec and SSEB as 9375 mi, 9375 mi and 31250 mi respectively [144], and with a similar approach to Appendix C by assuming that an average commuting distances of 7.6 mi/day, 10.02 mi/day and 12.4 mi/day for regular bike, pedelec and SSEB respectively, the expected life cycle of regular bike, pedelec and SSEB would respectively be 1234 days, 925 days and 2520 days. Accordingly, the daily cost of ownership for regular bike, pedelec and SSEB are estimated as $0.28, $1.6, and $1.03. Assuming the annual maintenance cost of a bicycle at $125 [145], the daily maintenance cost of regular bike would be $0.34. If we assume that the ratio of daily maintenance cost to daily ownership cost of regular bike applies to pedelec and SSEB, the daily maintenance costs of pedelec and SSEB would be $1.94 and $1.25 respectively. For bus, the average purchase price is $300,000 over a lifespan of 12 years [146], which yields the daily cost of ownership of $68.5. The average daily maintenance cost of bus is assumed to be $1.1 according to the annual bus maintenance cost of $400 [147].

For a motorcycle, we assume an average purchase price of $7500 [148], over an average lifespan of 13.5 years [149], and thus the average motorcycle ownership cost is estimated at $1.52. Daily motorcycle maintenance cost is assumed to be $2.07 [150]. For a car, the average purchase price is assumed to $21,000 enduring for 10 years, and thus the average daily ownership cost would be $5.75 [54]. The daily maintenance cost of car is considered to be $3.85.

APPENDIX E. UNSERVED DEMAND COST

When the demand for one of the shared/public modes is greater than the availability, we assume that the unserved demand turns to Taxi/ Uber for their commute. As we are presenting hypothetical user group configurations in East Lansing, Michigan, we initially estimated the Taxi fare for a commuting distance of 4 mi, as $17.77, with use of (https://www.taxifarefinder.com/main.php?city=Lansing-MI). Considering the distance, we then calculated the per mile trip cost when taking Taxi as $4.5/mi. Next, estimating the Uber fare for the same distance ($10.2), the per mile trip cost with Uber was calculated as $2.55/mi. Thus, the fare per mile cost was averaged to $3.53/mi.

APPENDIX F. SURVEY: DEVELOPMENT OF COMMUTE MODE CHOICE MODELS

Please read through the following must-know concepts for this survey:

- **Bike-sharing systems:** Bike-sharing systems are majorly intended for urban trips and are composed of stations across varied locations offering bicycles to customers for pickup, as well as empty docks to customers who are returning the rented bicycles. A customer can pick up a bicycle at a station near their origin, travel to a station near their destination and return the bicycle.
- **Electric bicycles (Pedelecs):** Pedelecs are similar to regular bicycles in appearance and function and require the rider to keep pedaling. However, pedelecs assist the rider in pedaling through the electric power they administer to the pedals, and make riding less physically demanding. Thus, pedelecs enable the rider to reach higher speeds, traverse longer distances and hilly (upgrade) topographies more easily.
- **Electric scooters:** Electric scooters do not need the rider to pedal and can be ridden as a gasoline-powered scooter would be, with the difference that electric scooters rely on electric power.

Electric bicycle (Pedelec)
Source:
Jonathan Weinert, Joan Ogden, Dan Sperling, Andrew Burke, The future of electric two-wheelers and electric vehicles in China, Energy Policy, Volume 36, Issue 7, 2008, Pages 2544-2555, ISSN 0301-4215,http://dx.doi.org/10.1016/j.enpol.2008.03.008. (http://www.sciencedirect.com/science/article/pii/S0301421508001298)

Electric scooter
Source:
Jonathan Weinert, Joan Ogden, Dan Sperling, Andrew Burke, The future of electric two-wheelers and electric vehicles in China, Energy Policy, Volume 36, Issue 7, 2008, Pages 2544-2555, ISSN 0301-4215,http://dx.doi.org/10.1016/j.enpol.2008.03.008. (http://www.sciencedirect.com/science/article/pii/S0301421508001298)

Figure F- 1 Pedelec and electric scooter examples

- In the following section, please select the appropriate answer:
    - Do you own a private car?
        - Yes
        - No
    - Do you own a private motorcycle/moped?
        - Yes
        - No
    - Do you own a private electric bike (pedelec)?
        - Yes
        - No
    - Do you own a private electric scooter?
        - Yes
        - No
- In the following section, please answer the questions as to your <u>**regular morning commute**</u> from **your residence** to **Michigan State University**:
    - Please select the range within which your commute distance (in miles) falls:
    - Below 1
    - 1 to 5
    - 5 to 10
    - 10 to 20
    - 20 to 50
    - Above 50

▪ Please enter your approximate *in vehicle* commute travel time (in minutes):

▪ How do you regularly commute to campus?

○ Walk

○ By Regular Bicyle

○ By Electric Bike (Pedelec)

○ By Electric Scooter/Moped

○ By Motorcycle/Moped

○ By Private Car

○ By Bus

○ By Taxi/ Uber

▪ How would you describe the topography of your commuting path?

○ Mostly Flat

○ Mostly Mildly Hilly

○ Mostly Steeply Hilly

- In the following questions, please assume that a bike-sharing system is readily available and easily accessible from your residence and offers regular bikes, pedelecs, and electric scooters. You can rent any of the three types to make your morning commute from your residence to your destination, which is assumed to be Michigan State University in this survey. Also, assume that there is a station near your destination on campus to which you can return the regular bike/ pedelec/ electric scooter you rent. In addition, please assume that you can also own both private motorcycles and private cars.

  Please be advised that each question is specific in terms of the presented distance and the resulting characteristics of each mode (i.e. travel time, fare, emission burden cost, and health value), and/or the topography condition.

  Considering the above-mentioned information and assuming that you are making your morning commute from your residence to Michigan State University, please answer the following questions:

- Please assume that it is **a mild day with no precipitation**, and your **commute distance is about 1 mi,** and the trip costs and benefits are as shown in Table F-1:

  Note: Please be advised that the active modes which yield health benefits involve different levels of physical activity. In fact, each person in the United States would incur $2,221 annually for being physically inactive, and the active modes help save a portion of this amount, depending on trip length and the mode used. The health benefits presented in the table below, for each mode, represent the amount that can be saved by each trip.

  Also, the emission burden cost values are the amounts of financial burden that each fuel-driven vehicle imposes on the environment on each trip due the CO_2 gas emission.

Table F- 1 Trip costs and benefits of modes when commuting distance is 1 mi

	Travel Time (min)	Cost/Fare ($)	Emission Burden Cost ($)	Health Benefit Values ($)
Walking	18	0	0	4.13
Bike-Sharing: Bike	6	0.11	0	1.52
Pedelec	5	0.7	0	1.17
Electric Scooter	5	1.29	0	0
Bus	6	1.25	0.03	0
Private Regular Bike	6	0.62	0	1.52
Private Motorcycle	3	3.65	0.04	0
Private Car	3	9.71	0.08	0

- Now, assuming that the **topography** of your commuting path is **mostly flat**, which of the following modes would you select?
  - Walking
  - Bike-sharing: Regular bike
  - Bike-sharing: Pedelec
  - Bike-sharing: Electric scooter
  - Bus transit

- Private regular bike
- Private Motorcycle
- Private car

- In the previous question, if the **topography** of your commuting path is **mostly mildly hilly**, which of the following modes would you select?
  - Walking
  - Bike-sharing: Regular bike
  - Bike-sharing: Pedelec
  - Bike-sharing: Electric scooter
  - Bus transit
  - Private regular bike
  - Private Motorcycle
  - Private car
- In the previous question, if the **topography** of your commuting path is **mostly steeply hilly**, which of the following modes would you select?
  - Walking
  - Bike-sharing: Regular bike
  - Bike-sharing: Pedelec
  - Bike-sharing: Electric scooter
  - Bus transit
  - Private regular bike
  - Private Motorcycle
  - Private car

- Please assume that it is **a mild day with no precipitation**, and your **commute distance is about 5 mi**, and the trip costs and benefits are as shown in Table F- 2:

  Note: Please be advised that the active modes which yield health benefits involve different levels of physical activity. In fact, each person in the United States would incur $2,221 annually for being physically inactive, and the active modes help save a portion of this amount, depending on trip length and the mode used. The health benefits presented in the table below, for each mode, represent the amount that can be saved by each trip.

  Also, the emission burden cost values are the amounts of financial burden that each fuel-driven vehicle imposes on the environment on each trip due the CO_2 gas emission.

Table F- 2 Trip costs and benefits of modes when commuting distance is 5 mi

	Travel Time (min)	**Cost/Fare ($)**	**Emission Burden Cost ($)**	**Health Benefit Values ($)**
Walking	86	0	0	20.63
Bike-Sharing: Bike	30	0.11	0	7.6
Pedelec	25	0.7	0	5.86
Electric Scooter	23	1.29	0	0
Bus	27	1.25	0.14	0
Private Regular Bike	30	0.62	0	7.6
Private Motorcycle	11	3.88	0.20	0
Private Car	11	10.13	0.38	0

- Now, assuming that the **topography** of your commuting path is **mostly flat**, which of the following modes would you select?
  - Walking
  - Bike-sharing: Regular bike
  - Bike-sharing: Pedelec
  - Bike-sharing: Electric scooter
  - Bus transit

- Private regular bike
- Private Motorcycle
- Private car

- In the previous question, if the **topography** of your commuting path is **mostly mildly hilly**, which of the following modes would you select?
  - Walking
  - Bike-sharing: Regular bike
  - Bike-sharing: Pedelec
  - Bike-sharing: Electric scooter
  - Bus transit
  - Private regular bike
  - Private Motorcycle
  - Private car

- In the previous question, if the **topography** of your commuting path is **mostly steeply hilly**, which of the following modes would you select?
  - Walking
  - Bike-sharing: Regular bike
  - Bike-sharing: Pedelec
  - Bike-sharing: Electric scooter
  - Bus transit
  - Private regular bike
  - Private Motorcycle
  - Private car

➢ Please assume that it is **a mild day with no precipitation**, and your **commute distance is about 10 mi**, and the trip costs and benefits are as shown in Table F-3: **Note:** Please be advised that the active modes which yield health benefits involve different levels of physical activity. In fact, each person in the United States would incur $2,221 annually for being physically inactive, and the active modes help save a portion of this amount, depending on trip length and the mode used. The health benefits presented in the table below, for each mode, represent the amount that can be saved by each trip. **Also,** the emission burden cost values are the amounts of financial burden that each fuel-driven vehicle imposes on the environment on each trip due the CO_2 gas emission.

Table F- 3 Trip costs and benefits of modes when commuting distance is 10 mi

	Travel Time (min)	**Cost/Fare ($)**	**Emission Burden Cost ($)**	**Health Benefit Values ($)**
Walking	172	0	0	41.26
Bike-Sharing: Bike	60	0.22	0	15.2
Pedelec	50	1.4	0	11.72
Electric Scooter	45	2.58	0	0
Bus	53	1.25	0.27	0
Private Regular Bike	60	0.62	0	15.2
Private Motorcycle	21	4.16	0.41	0
Private Car	21	10.67	0.76	0

- Now, assuming that the topography of your commuting path is mostly flat, which of the following modes would you select?
  - o Walking
  - o Bike-sharing: Regular bike
  - o Bike-sharing: Pedelec
  - o Bike-sharing: Electric scooter
  - o Bus transit

- Private regular bike
- Private Motorcycle
- Private car

▪ In the previous question, if the **topography** of your commuting path is **mostly mildly hilly**, which of the following modes would you select?

- Walking
- Bike-sharing: Regular bike
- Bike-sharing: Pedelec
- Bike-sharing: Electric scooter
- Bus transit
- Private regular bike
- Private Motorcycle
- Private car

▪ In the previous question, if the **topography** of your commuting path is **mostly steeply hilly**, which of the following modes would you select?

- Walking
- Bike-sharing: Regular bike
- Bike-sharing: Pedelec
- Bike-sharing: Electric scooter
- Bus transit
- Private regular bike
- Private Motorcycle
- Private car

- Please assume that it is **a mild day with no precipitation**, and your **commute distance is about 20 mi**, and the trip costs and benefits are as shown in Table F-4:

  Note: Please be advised that the active modes which yield health benefits involve different levels of physical activity. In fact, each person in the United States would incur $2,221 annually for being physically inactive, and the active modes help save a portion of this amount, depending on trip length and the mode used. The health benefits presented in the table below, for each mode, represent the amount that can be saved by each trip.

  Also, the emission burden cost values are the amounts of financial burden that each fuel-driven vehicle imposes on the environment on each trip due the CO_2 gas emission.

Table F- 4 Trip costs and benefits of modes when commuting distance is 20 mi

	Travel Time (min)	**Cost/Fare ($)**	**Emission Burden Cost ($)**	**Health Benefit Values ($)**
Walking	343	0	0	82.51
Bike-Sharing: Bike	120	0.44	0	30.4
Pedelec	100	2.8	0	23.43
Electric Scooter	90	3.87	0	0
Bus	106	1.25	0.55	0
Private Regular Bike	120	0.62	0	30.4
Private Motorcycle	41	4.16	0.82	0
Private Car	42	10.67	1.53	0

- Now, assuming that the **topography** of your commuting path is **mostly flat**, which of the following modes would you select?
  - Walking
  - Bike-sharing: Regular bike
  - Bike-sharing: Pedelec
  - Bike-sharing: Electric scooter
  - Bus transit

- Private regular bike
- Private Motorcycle
- Private car

- In the previous question, if the **topography** of your commuting path is **mostly mildly hilly**, which of the following modes would you select?
  - Walking
  - Bike-sharing: Regular bike
  - Bike-sharing: Pedelec
  - Bike-sharing: Electric scooter
  - Bus transit
  - Private regular bike
  - Private Motorcycle
  - Private car
- In the previous question, if the **topography** of your commuting path is **mostly steeply hilly**, which of the following modes would you select?
  - Walking
  - Bike-sharing: Regular bike
  - Bike-sharing: Pedelec
  - Bike-sharing: Electric scooter
  - Bus transit
  - Private regular bike
  - Private Motorcycle
  - Private car

- Please assume that it is **a mild day with no precipitation**, and your **commute distance is about 50 mi**, and the trip costs and benefits are as shown in Table F-5:
  Note: Please be advised that the active modes which yield health benefits involve different levels of physical activity. In fact, each person in the United States would incur $2,221 annually for being physically inactive, and the active modes help save a portion of this amount, depending on trip length and the mode used. The health benefits presented in the table below, for each mode, represent the amount that can be saved by each trip.
  Also, the emission burden cost values are the amounts of financial burden that each fuel-driven vehicle imposes on the environment on each trip due the CO_2gas emission.

Table F- 5 Trip costs and benefits of modes when commuting distance is 50 mi

	Travel Time (min)	Cost/Fare ($)	Emission Burden Cost ($)	Health Benefit Values ($)
Walking	858	0	0	206.29
Bike-Sharing: Bike	300	1.1	0	76
Pedelec	250	6.3	0	58.58
Electric Scooter	224	10.32	0	0
Bus	264	1.25	1.36	0
Private Regular Bike	300	0.62	0	76
Private Motorcycle	102	4.16	2.04	0
Private Car	104	10.67	3.82	0

- Now, assuming that the **topography** of your commuting path is **mostly flat**, which of the following modes would you select?
  Walking
  - Bike-sharing: Regular bike
  - Bike-sharing: Pedelec
  - Bike-sharing: Electric scooter
  - Bus transit

- Private regular bike
- Private Motorcycle
- Private car

▪ In the previous question, if the **topography** of your commuting path is **mostly mildly hilly**, which of the following modes would you select?

- Walking
- Bike-sharing: Regular bike
- Bike-sharing: Pedelec
- Bike-sharing: Electric scooter
- Bus transit
- Private regular bike
- Private Motorcycle
- Private car

▪ In the previous question, if the **topography** of your commuting path is **mostly steeply hilly**, which of the following modes would you select?

- Walking
- Bike-sharing: Regular bike
- Bike-sharing: Pedelec
- Bike-sharing: Electric scooter
- Bus transit
- Private regular bike
- Private Motorcycle
- Private car

- In the following section, please select your preferred mode under different weather conditions:
- Please select what mode you would choose for your regular daily morning commute under each of the weather conditions:

	Walking	Bike-sharing: Regular bike	Bike-sharing: Pedelec	Bike-sharing: Electric Scooter	Bus	Private regular bike	Private Motorcycle	Private Car
Rainy	○	○	○	○	○	○	○	○
Snowy	○	○	○	○	○	○	○	○
Cloudy (Temperature = 70°F)	○	○	○	○	○	○	○	○
Cloudy (Temperature = 25°F)	○	○	○	○	○	○	○	○
Sunny (Temperature = 70°F)	○	○	○	○	○	○	○	○
Sunny (Temperature = 25°F)	○	○	○	○	○	○	○	○

- In the following section, please select your preferred mode under different **air quality conditions:**
  - Please select what mode you would choose for your daily morning commute under each of the air quality conditions:

	Walking	Bike-sharing: Regular bike	Bike-sharing: Pedelec	Bike-sharing: Electric Scooter	Bus	Private regular bike	Private Motorcycle	Private Car
Air quality: Low pollution levels	○	○	○	○	○	○	○	○
Air quality: Medium pollution levels	○	○	○	○	○	○	○	○
Air quality: High pollution levels	○	○	○	○	○	○	○	○

- In the following section, you will be offered questions centered on **your attitude** towards the **transportation mode** you choose for your **regular daily morning commute**:
  - Please specify how important each of the following factors are in your commuting mode choice:

	Not at all important	Slightly important	Moderately important	Very important	Essential
Commuting distace	○	○	○	○	○
The availability of the transportation mode	○	○	○	○	○
The topography of the commuting path	○	○	○	○	○
The commuting travel time	○	○	○	○	○
The cost of the transportation mode	○	○	○	○	○
Environmental concerns	○	○	○	○	○
Health-related concerns	○	○	○	○	○

- Please specify your gender:
  - Male
  - Female
- Please enter your age

- Please select your occupation:
  - Undergraduate student
  - M.Sc. student
  - Ph.D. student
  - Professional student
  - Lifelong student
  - Faculty: Assistant Professor
  - Faculty: Associate Professor
  - Faculty: Professor
  - University Staff
- Please select the range within which your annual income level before tax (in dollars) falls:
  - Below 15,000
  - 15,000 to 20,000
  - 20,000 to 50,000
  - 50,000 to 70,000
  - 70,000 to 100,000
  - 100,000 to 130,000
  - 130,000 to 200,000
  - 200,000 to 250,000

- Above 250,000

- Please enter the number of people you typically commute with, excluding yourself (e.g. dropping siblings/parents/friends/etc. off, carpooling, etc.):

  ____

- Are you responsible for driving anyone under the age of 16?
  - Yes
  - No

APPENDIX G. INVESTIGATED MULTINOMIAL LOGIT (MNL) MODELS

The fitted models and their summaries are presented in Table G-1; the alternatives are as follows: “1” is walking, “2” shared bike, “3” is pedelec, “4” is E-scooter”, “5” is bus, “6” is private bike, “7” is motorcycle, and “8” is private car. Along with standard MNL models, whenever there are continuous covariates, i.e. TT, TC, EmissionCost, and HealthValue, random parameter (mixed) logit models are also tested.

Table G-1 Investigated MNL models

<table>
<tr><td colspan="5">Base Covariate: Dis</td></tr>
<tr><td>Model</td><td colspan="4">Model Coefficients’ Specifications
Note: Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1</td></tr>
<tr><td rowspan="16">MNL model with Covariate(s):
▪ Dis with alternative-specific parameters

Model Fit:
▪ Log-Likelihood: -1516
▪ McFadden R^2: 0.13397
▪ Likelihood ratio test : chisq = 469.01 (p.value = < 2.22e-16)</td><td></td><td>Estimate</td><td>z-value</td><td>Signif.</td></tr>
<tr><td>2:(intercept)</td><td>-1.10</td><td>0.00</td><td>***</td></tr>
<tr><td>3:(intercept)</td><td>-0.70</td><td>0.00</td><td>**</td></tr>
<tr><td>4:(intercept)</td><td>-1.95</td><td>0.00</td><td>***</td></tr>
<tr><td>5:(intercept)</td><td>-1.85</td><td>0.00</td><td>***</td></tr>
<tr><td>6:(intercept)</td><td>-0.14</td><td>0.51</td><td></td></tr>
<tr><td>7:(intercept)</td><td>-2.01</td><td>0.00</td><td>***</td></tr>
<tr><td>8:(intercept)</td><td>-0.05</td><td>0.79</td><td></td></tr>
<tr><td>2:Dis</td><td>0.11</td><td>0.10</td><td></td></tr>
<tr><td>3:Dis</td><td>0.20</td><td>0.00</td><td>***</td></tr>
<tr><td>4:Dis</td><td>0.31</td><td>0.00</td><td>***</td></tr>
<tr><td>5:Dis</td><td>0.34</td><td>0.00</td><td>***</td></tr>
<tr><td>6:Dis</td><td>0.20</td><td>0.00</td><td>***</td></tr>
<tr><td>7:Dis</td><td>0.38</td><td>0.00</td><td>***</td></tr>
<tr><td>8:Dis</td><td>0.38</td><td>0.00</td><td>***</td></tr>
</table>

Table G-1 Investigated MNL models (cont'd)

<table>
<tr><th>Model</th><th>Model Coefficients' Specifications
Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1</th></tr>
<tr><td>MNL model with Covariate(s):
▪ Dis & Topo with alternative-specific parameters

Model Fit:
▪ Log-Likelihood: -1487.2
▪ McFadden R^2: 0.15042
▪ Likelihood ratio test : chisq = 526.62 (p.value = < 2.22e-16)</td><td>

	Estimate	z-value	Signif.
2:(intercept)	0.16	0.78	
3:(intercept)	-1.68	0.00	***
4:(intercept)	-3.43	0.00	***
5:(intercept)	-3.20	0.00	***
6:(intercept)	0.14	0.74	
7:(intercept)	-3.59	0.00	***
8:(intercept)	-1.03	0.01	**
2:Dis	0.10	0.14	
3:Dis	0.21	0.00	***
4:Dis	0.32	0.00	***
5:Dis	0.34	0.00	***
6:Dis	0.20	0.00	***
7:Dis	0.38	0.00	***
8:Dis	0.39	0.00	***
2:Topo	-0.76	0.01	*
3:Topo	0.48	0.03	*
4:Topo	0.71	0.01	**
5:Topo	0.65	0.00	**
6:Topo	-0.16	0.42	
7:Topo	0.76	0.00	***
8:Topo	0.48	0.01	**

</td></tr>
<tr><td>MNL model with Covariate(s):
▪ Health benefit value (generic parameter)
▪ Dis (alternative-specific parameters)

Model Fit:
▪ Log-Likelihood: -2485.4
▪ McFadden R^2: -0.41984
▪ Likelihood ratio test : chisq = (p.value = 1</td><td>

	Estimate	z-value	Signif.
2:(intercept)	-0.01	0.95	
3:(intercept)	0.00	1.00	
4:(intercept)	-0.01	0.95	
5:(intercept)	-0.01	0.97	
6:(intercept)	0.02	0.89	
7:(intercept)	-0.01	0.97	
8:(intercept)	0.09	0.57	
HehValue	3.43	0.88	
2:Dis	8.94	0.88	
3:Dis	10.13	0.88	
4:Dis	14.15	0.88	
5:Dis	14.15	0.88	
6:Dis	8.94	0.88	
7:Dis	14.15	0.88	
8:Dis	14.16	0.88	

</td></tr>
</table>

Table G-1 Investigated MNL models (cont'd)

<table>
<tr><th>Model</th><th>Model Coefficients' Specifications
Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1</th></tr>
<tr><td>MNL model with Covariate(s):
▪ Health benefit value (generic parameter)
▪ Dis & Topo with alternative-specific parameters

Model Fit:
▪ Log-Likelihood: -2484.5
▪ McFadden R^2: -0.41935
▪ Likelihood ratio test : chisq = (p.value = 1)</td><td>

	Estimate	z-value	Signif.
2:(intercept)	-0.01	0.99	
3:(intercept)	-0.01	0.97	
4:(intercept)	-0.02	0.94	
5:(intercept)	-0.02	0.95	
6:(intercept)	0.04	0.91	
7:(intercept)	-0.03	0.93	
8:(intercept)	0.07	0.82	
HehValue	3.43	0.88	
2:Dis	8.94	0.88	
3:Dis	10.13	0.88	
4:Dis	14.15	0.88	
5:Dis	14.15	0.88	
6:Dis	8.94	0.88	
7:Dis	14.15	0.88	
8:Dis	14.16	0.88	
2:Topo	0.00	0.99	
3:Topo	0.01	0.96	
4:Topo	0.01	0.96	
5:Topo	0.01	0.96	
6:Topo	-0.01	0.96	
7:Topo	0.01	0.94	
8:Topo	0.01	0.94	

</td></tr>
</table>

Table G-1 Investigated MNL models (cont'd)

Base Covariate: Topo				
Model	**Model Coefficients' Specifications** Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1			
MNL model with Covariate(s): ▪ Topo with alternative-specific parameters Model Fit: ▪ Log-Likelihood: -1725.6 ▪ McFadden R^2: 0.014186 ▪ Likelihood ratio test : chisq = (p.value = 1.6814e-08)		**Estimate**	**z-value**	**Signif.**
	2:(intercept)	0.49	0.34	
	3:(intercept)	-0.83	0.07	.
	4:(intercept)	-1.72	0.00	**
	5:(intercept)	-1.18	0.01	*
	6:(intercept)	0.92	0.01	*
	7:(intercept)	-0.85	0.05	*
	8:(intercept)	1.83	0.00	***
	2:Topo	-0.77	0.01	*
	3:Topo	0.41	0.05	.
	4:Topo	0.58	0.02	*
	5:Topo	0.50	0.02	*
	6:Topo	-0.21	0.26	
	7:Topo	0.56	0.00	**
	8:Topo	0.27	0.08	.
MNL model with Covariate(s): ▪ Topo with alternative-specific parameters ▪ TT introduced with generic parameter Model Fit: ▪ Log-Likelihood: -1516.8 ▪ McFadden R^2: 0.13348 ▪ Likelihood ratio test : chisq = (p.value = < 2.22e-16)		**Estimate**	**z-value**	**Signif.**
	2:(intercept)	-0.80	0.13	
	3:(intercept)	-2.36	0.00	***
	4:(intercept)	-3.38	0.00	***
	5:(intercept)	-2.63	0.00	***
	6:(intercept)	-0.37	0.34	
	7:(intercept)	-3.67	0.00	***
	8:(intercept)	-0.96	0.01	*
	TT	-0.03	0.00	***
	2:Topo	-0.72	0.02	*
	3:Topo	0.49	0.02	*
	4:Topo	0.66	0.01	**
	5:Topo	0.57	0.01	*
	6:Topo	-0.15	0.44	
	7:Topo	0.71	0.00	***
	8:Topo	0.42	0.02	*

Table G-1 Investigated MNL models (cont'd)

Model	Model Coefficients' Specifications Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

MNL model with Covariate(s):

- TT & Topo with Alternative-specific parameters

Model Fit:

- Log-Likelihood: -1487.1
- McFadden R^2: 0.15045
- Likelihood ratio test : chisq : (p.value = < 2.22e-16)

	Estimate	z-value	Signif.
2:(intercept)	0.12	0.84	
3:(intercept)	-1.70	0.00	***
4:(intercept)	-3.36	0.00	***
5:(intercept)	-3.12	0.00	***
6:(intercept)	0.11	0.80	
7:(intercept)	-3.37	0.00	***
8:(intercept)	-0.85	0.08	.
2:Topo	-0.76	0.01	*
3:Topo	0.48	0.03	*
4:Topo	0.71	0.01	**
5:Topo	0.65	0.00	**
6:Topo	-0.16	0.42	
7:Topo	0.76	0.00	***
8:Topo	0.48	0.01	**
1:TT	-0.05	0.23	
2:TT	-0.13	0.29	
3:TT	-0.14	0.36	
4:TT	-0.13	0.44	
5:TT	-0.11	0.46	
6:TT	-0.12	0.35	
7:TT	-0.26	0.50	
8:TT	-0.25	0.50	

Table G-1 Investigated MNL models (cont'd)

<table>
<tr><th>Model</th><th>Model Coefficients' Specifications
Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1</th></tr>
<tr><td>MNL model with Covariate(s):
▪ Topo with Alternative-specific parameters
▪ TC with generic parameter

Model Fit:
▪ Log-Likelihood: -1722.2
▪ McFadden R^2: 0.016131
▪ Likelihood ratio test : chisq = (p.value = 2.2812e-09)</td><td>
<table>
<tr><th></th><th>Estimate</th><th>z-value</th><th>Signif.</th></tr>
<tr><td>2:(intercept)</td><td>0.53</td><td>0.30</td><td></td></tr>
<tr><td>3:(intercept)</td><td>-0.57</td><td>0.21</td><td></td></tr>
<tr><td>4:(intercept)</td><td>-1.33</td><td>0.02</td><td>*</td></tr>
<tr><td>5:(intercept)</td><td>-1.04</td><td>0.03</td><td>*</td></tr>
<tr><td>6:(intercept)</td><td>0.99</td><td>0.01</td><td>**</td></tr>
<tr><td>7:(intercept)</td><td>-0.39</td><td>0.41</td><td></td></tr>
<tr><td>8:(intercept)</td><td>3.03</td><td>0.00</td><td>***</td></tr>
<tr><td>TC</td><td>-0.11</td><td>0.01</td><td>*</td></tr>
<tr><td>2:Topo</td><td>-0.77</td><td>0.01</td><td>*</td></tr>
<tr><td>3:Topo</td><td>0.41</td><td>0.05</td><td>*</td></tr>
<tr><td>4:Topo</td><td>0.58</td><td>0.02</td><td>*</td></tr>
<tr><td>5:Topo</td><td>0.50</td><td>0.02</td><td>*</td></tr>
<tr><td>6:Topo</td><td>-0.21</td><td>0.26</td><td></td></tr>
<tr><td>7:Topo</td><td>0.56</td><td>0.00</td><td>**</td></tr>
<tr><td>8:Topo</td><td>0.27</td><td>0.08</td><td>.</td></tr>
</table>
</td></tr>
<tr><td>MNL model with Covariate(s):
▪ Emission cost with generic parameter
▪ Topo with Alternative-specific parameters

Model Fit:
▪ Log-Likelihood: -1560.3
▪ McFadden R^2: 0.10862
▪ Likelihood ratio test : chisq = (p.value = < 2.22e-16)

➢ Model does not make sense in terms of Emission cost sign</td><td>
<table>
<tr><th></th><th>Estimate</th><th>z-value</th><th>Signif.</th></tr>
<tr><td>2:(intercept)</td><td>0.49</td><td>0.34</td><td></td></tr>
<tr><td>3:(intercept)</td><td>-0.83</td><td>0.06</td><td>.</td></tr>
<tr><td>4:(intercept)</td><td>-1.73</td><td>0.00</td><td>**</td></tr>
<tr><td>5:(intercept)</td><td>-1.50</td><td>0.00</td><td>**</td></tr>
<tr><td>6:(intercept)</td><td>0.92</td><td>0.01</td><td>*</td></tr>
<tr><td>7:(intercept)</td><td>-1.36</td><td>0.00</td><td>**</td></tr>
<tr><td>8:(intercept)</td><td>0.45</td><td>0.19</td><td></td></tr>
<tr><td>EmissionCost</td><td>1.43</td><td>0.00</td><td>***</td></tr>
<tr><td>2:Topo</td><td>-0.78</td><td>0.01</td><td>*</td></tr>
<tr><td>3:Topo</td><td>0.41</td><td>0.05</td><td>*</td></tr>
<tr><td>4:Topo</td><td>0.58</td><td>0.02</td><td>*</td></tr>
<tr><td>5:Topo</td><td>0.51</td><td>0.02</td><td>*</td></tr>
<tr><td>6:Topo</td><td>-0.21</td><td>0.26</td><td></td></tr>
<tr><td>7:Topo</td><td>0.58</td><td>0.00</td><td>**</td></tr>
<tr><td>8:Topo</td><td>0.32</td><td>0.05</td><td>*</td></tr>
</table>
</td></tr>
</table>

Table G-1 Investigated MNL models (cont'd)

<table>
<tr><th>Model</th><th>Model Coefficients' Specifications
Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1</th></tr>
<tr><td>MNL model with Covariate(s):
▪ Health value with generic parameter
▪ Topo with alternative-specific parameters

Model Fit:
▪ Log-Likelihood: -1516.2
▪ McFadden R^2: 0.13381
▪ Likelihood ratio test : chisq = (p.value = < 2.22e-16)

➢ Model does not make sense in terms of Health value sign</td><td>

	Estimate	z-value	Signif.
2:(intercept)	-0.55	0.30	
3:(intercept)	-2.12	0.00	***
4:(intercept)	-4.64	0.00	***
5:(intercept)	-4.11	0.00	***
6:(intercept)	-0.12	0.75	
7:(intercept)	-3.77	0.00	***
8:(intercept)	-1.09	0.00	**
HehValue	-0.12	0.00	***
2:Topo	-0.71	0.02	*
3:Topo	0.50	0.02	*
4:Topo	0.78	0.00	**
5:Topo	0.71	0.00	**
6:Topo	-0.14	0.46	
7:Topo	0.77	0.00	***
8:Topo	0.48	0.01	**

</td></tr>
<tr><td>MNL model with Covariate(s):
▪ Topo & DisPowered with alternative-specific parameters

Model Fit:
▪ Log-Likelihood: -1485.5
▪ McFadden R^2: 0.15134
▪ Likelihood ratio test : chisq = (p.value = < 2.22e-16)</td><td>

	Estimate	z-value	Signif.
2:(intercept)	0.44	0.41	
3:(intercept)	-0.95	0.04	*
4:(intercept)	-3.18	0.00	***
5:(intercept)	-2.96	0.00	***
6:(intercept)	0.77	0.04	*
7:(intercept)	-3.36	0.00	***
8:(intercept)	-0.79	0.04	*
2:Topo	-0.77	0.01	*
3:Topo	0.43	0.04	*
4:Topo	0.69	0.01	**
5:Topo	0.63	0.01	**
6:Topo	-0.19	0.31	
7:Topo	0.74	0.00	***
8:Topo	0.46	0.01	**
2:DisPowered	0.00	0.46	
3:DisPowered	0.00	0.00	***
4:DisPowered	0.23	0.00	***
5:DisPowered	0.26	0.00	***
6:DisPowered	0.00	0.00	***
7:DisPowered	0.30	0.00	***
8:DisPowered	0.30	0.00	***

</td></tr>
</table>

Table G-1 Investigated MNL models (cont'd)

Model	**Model Coefficients' Specifications**
	Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

MNL model with Covariate(s):

- Topo with alternative-specific parameters
- DisPowered with generic parameter

Model Fit:

- Log-Likelihood: -1585
- McFadden R^2: 0.094502

	Estimate	**z-value**	**Signif.**
2:(intercept)	0.50	0.34	
3:(intercept)	-0.83	0.06	.
4:(intercept)	-2.80	0.00	***
5:(intercept)	-2.26	0.00	***
6:(intercept)	0.92	0.01	*
7:(intercept)	-1.92	0.00	***
8:(intercept)	0.76	0.02	*
DisPowered	-0.01	0.00	***
2:Topo	-0.78	0.01	*
3:Topo	0.41	0.05	*
4:Topo	0.66	0.01	**
5:Topo	0.58	0.01	**
6:Topo	-0.21	0.26	
7:Topo	0.64	0.00	**
8:Topo	0.36	0.03	*

MNL model with Covariate(s):

- Topo with alternative-specific parameters
- Emission cost with generic parameter

Model Fit:

- Log-Likelihood: -1560.3
- McFadden R^2: 0.10862

➢ Model does not make sense in terms of Emission cost sign

	Estimate	**z-value**	**Signif.**
2:(intercept)	0.49	0.34	
3:(intercept)	-0.83	0.06	.
4:(intercept)	-1.73	0.00	**
5:(intercept)	-1.50	0.00	**
6:(intercept)	0.92	0.01	*
7:(intercept)	-1.36	0.00	**
8:(intercept)	0.45	0.19	
EmissionCost	1.43	0.00	***
2:Topo	-0.78	0.01	*
3:Topo	0.41	0.05	*
4:Topo	0.58	0.02	*
5:Topo	0.51	0.02	*
6:Topo	-0.21	0.26	
7:Topo	0.58	0.00	**
8:Topo	0.32	0.05	*

Table G-1 Investigated MNL models (cont'd)

<table>
<tr><th>Model</th><th>Model Coefficients' Specifications
Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1</th></tr>
<tr><td>MNL model with Covariate(s):
▪ Topo with alternative-specific parameters
▪ Emission cost & Health value with generic parameter

Model Fit:
▪ Log-Likelihood: -1496
▪ McFadden R^2: 0.14537
▪ Likelihood ratio test : chisq = (p.value = < 2.22e-16)

➢ Model does not make sense in terms of Emission cost & Health value sign</td><td>

	Estimate	z-value	Signif.
2:(intercept)	-0.39	0.46	
3:(intercept)	-1.91	0.00	***
4:(intercept)	-3.76	0.00	***
5:(intercept)	-3.48	0.00	***
6:(intercept)	0.04	0.92	
7:(intercept)	-3.30	0.00	***
8:(intercept)	-1.10	0.00	**
EmissionCost	0.64	0.00	***
HehValue	-0.09	0.00	***
2:Topo	-0.72	0.02	*
3:Topo	0.49	0.02	*
4:Topo	0.72	0.00	**
5:Topo	0.66	0.00	**
6:Topo	-0.15	0.42	
7:Topo	0.73	0.00	***
8:Topo	0.47	0.01	**

</td></tr>
</table>

Table G-1 Investigated MNL models (cont’d)

Model	Model Coefficients’ Specifications
	Note: Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

MNL model with Covariate(s):

- Topo & DisPowered with alternative-specific parameters
- Emission cost with generic parameter

Model Fit:

- Log-Likelihood: -1485.5
- McFadden R^2: 0.15139
- Likelihood ratio test : chisq = (p.value = < 2.22e-16)

	Estimate	z-value	Signif.
2:(intercept)	0.44	0.40	
3:(intercept)	-0.95	0.04	*
4:(intercept)	-3.15	0.00	***
5:(intercept)	-2.91	0.00	***
6:(intercept)	0.77	0.04	*
7:(intercept)	-3.33	0.00	***
8:(intercept)	-0.78	0.04	*
EmissionCost	-9.04	0.70	
2:Topo	-0.78	0.01	*
3:Topo	0.43	0.04	*
4:Topo	0.69	0.01	**
5:Topo	0.63	0.01	**
6:Topo	-0.19	0.31	
7:Topo	0.74	0.00	***
8:Topo	0.46	0.01	**
2:DisPowered	0.00	0.50	
3:DisPowered	0.00	0.00	**
4:DisPowered	0.23	0.00	***
5:DisPowered	0.50	0.42	
6:DisPowered	0.00	0.00	***
7:DisPowered	0.66	0.48	
8:DisPowered	0.99	0.57	

Table G-1 Investigated MNL models (cont'd)

Model	Model Coefficients' Specifications Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

MNL model with Covariate(s):

- Topo & DisPowered with alternative-specific parameters

Model Fit:

- Log-Likelihood: -1485.5
- McFadden R^2: 0.15134

	Estimate	z-value	Signif.
2:(intercept)	0.44	0.41	
3:(intercept)	-0.95	0.04	*
4:(intercept)	-3.18	0.00	***
5:(intercept)	-2.96	0.00	***
6:(intercept)	0.77	0.04	*
7:(intercept)	-3.36	0.00	***
8:(intercept)	-0.79	0.04	*
2:Topo	-0.77	0.01	*
3:Topo	0.43	0.04	*
4:Topo	0.69	0.01	**
5:Topo	0.63	0.01	**
6:Topo	-0.19	0.31	
7:Topo	0.74	0.00	***
8:Topo	0.46	0.01	**
2:DisPowered	0.00	0.46	
3:DisPowered	0.00	0.00	***
4:DisPowered	0.23	0.00	***
5:DisPowered	0.26	0.00	***
6:DisPowered	0.00	0.00	***
7:DisPowered	0.30	0.00	***
8:DisPowered	0.30	0.00	***

Table G-1 Investigated MNL models (cont'd)

Model	**Model Coefficients' Specifications** Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
MNL model with Covariate(s): ▪ Topo & DisPowered with alternative-specific parameters ▪ TC with generic parameter Model Fit: ▪ Log-Likelihood: -1484.4 ▪ McFadden R^2: 0.15199 ▪ Likelihood ratio test : chisq = (p.value = < 2.22e-16) ➢ Model does not make sense in terms of TC sign	See coefficients below

	Estimate	**z-value**	**Signif.**
2:(intercept)	0.40	0.44	
3:(intercept)	-1.21	0.01	*
4:(intercept)	-3.33	0.00	***
5:(intercept)	-3.27	0.00	***
6:(intercept)	0.56	0.16	
7:(intercept)	-4.58	0.00	***
8:(intercept)	-4.22	0.06	.
TC	0.35	0.13	
2:Topo	-0.78	0.01	*
3:Topo	0.43	0.04	*
4:Topo	0.68	0.01	**
5:Topo	0.63	0.01	**
6:Topo	-0.20	0.30	
7:Topo	0.74	0.00	***
8:Topo	0.46	0.01	**
2:DisPowered	0.00	0.56	
3:DisPowered	0.00	0.20	
4:DisPowered	0.16	0.01	**
5:DisPowered	0.24	0.00	***
6:DisPowered	0.00	0.00	***
7:DisPowered	0.28	0.00	***
8:DisPowered	0.28	0.00	***

Table G-1 Investigated MNL models (cont'd)

Base Covariate: TT

Model	**Model Coefficients' Specifications** Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
MNL Model with Covariate(s): ▪ TT with generic parameter Model Fit: ▪ Log-Likelihood: -1543.7 ▪ McFadden R^2: 0.11811 ▪ Likelihood ratio test : chisq = alue = < 2.22e-16)	see table below
Random Parameter MNL Model with Covariate(s): ▪ TT with random parameter ▪ random coefficients: Min. 1st Qu. Median Qu. Max. TT -Inf -0.1886656 -0.0583696 -0.0583696 0.07192638 Inf Model Fit: ▪ Log-Likelihood: -1413.4 ▪ McFadden R^2: 0.19254 ▪ Likelihood ratio test : chisq = (p.value = < 2.22e-16)	see table below

	Estimate	**z-value**	**Signif.**
2:(intercept)	-1.93	0.00	***
3:(intercept)	-1.38	0.00	***
4:(intercept)	-2.03	0.00	***
5:(intercept)	-1.48	0.00	***
6:(intercept)	-0.62	0.00	***
7:(intercept)	-2.22	0.00	***
8:(intercept)	-0.12	0.49	
TT	-0.03	0.00	***

	Estimate	**z-value**	**Signif.**
2:(intercept)	-2.49	0.00	***
3:(intercept)	-2.08	0.00	***
4:(intercept)	-2.77	0.00	***
5:(intercept)	-2.07	0.00	***
6:(intercept)	-1.19	0.00	***
7:(intercept)	-4.41	0.00	***
8:(intercept)	-2.17	0.00	***
TT	-0.06	0.00	***
sd.TT	0.19	0.00	***

Table G-1 Investigated MNL models (cont'd)

Model	Model Coefficients' Specifications
	Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Random Parameter MNL Model with Covariate(s):

- TT with random parameter
    - random coefficients

  Min. 1st Qu. Median :
  Qu. Max.
  TT -Inf -0.2006971 -0.06206938 -(
  0.07655838 Inf
- Topo with alternative-specific parameter

Model Fit:

- Log-Likelihood: -1380.3
- McFadden R^2: 0.21145
- Likelihood ratio test : chisq = 740.27
  (p.value = < 2.22e-16)

	Estimate	z-value	Signif.
2:(intercept)	-1.59	0.00	**
3:(intercept)	-3.38	0.00	***
4:(intercept)	-4.49	0.00	***
5:(intercept)	-3.52	0.00	***
6:(intercept)	-1.17	0.00	**
7:(intercept)	-6.77	0.00	***
8:(intercept)	-3.89	0.00	***
TT	-0.06	0.00	***
2:Topo	-0.63	0.06	.
3:Topo	0.62	0.01	**
4:Topo	0.82	0.00	**
5:Topo	0.69	0.00	**
6:Topo	-0.06	0.78	
7:Topo	1.09	0.00	***
8:Topo	0.79	0.00	***
sd.TT	0.21	0.00	***

TC

Model	Model Coefficients' Specifications
	Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

MNL Model with Covariate(s):

- TC with generic parameter
- DisPowered with alternative-specific parameter

Model Fit:

- Log-Likelihood: -1513.4
- McFadden R^2: 0.13542
- Likelihood ratio test : chisq =
  (p.value = < 2.22e-16)

➢ Model does not make sense in terms of TC sign

	Estimate	z-value	Signif.
2:(intercept)	-0.86	0.00	***
3:(intercept)	-0.35	0.14	
4:(intercept)	-1.89	0.00	***
5:(intercept)	-1.95	0.00	***
6:(intercept)	0.22	0.29	
7:(intercept)	-3.02	0.00	***
8:(intercept)	-3.29	0.15	
TC	0.35	0.13	
2:DisPowered	0.00	0.46	
3:DisPowered	0.00	0.32	
4:DisPowered	0.14	0.01	*
5:DisPowered	0.23	0.00	***
6:DisPowered	0.00	0.00	***
7:DisPowered	0.27	0.00	***
8:DisPowered	0.27	0.00	***

Table G-1 Investigated MNL models (cont'd)

Model	Model Coefficients' Specifications Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Random Parameter MNL Model with Covariate(s):

- TC with random parameter
  - random coefficients
    - random coeff

Min. 1st Qu. Median M
Max.
TC -Inf 1.26584 1.469072 1.4
1.672303 Inf

- ➢ DisPowered with alternative-specific parameter

Model Fit:

- Log-Likelihood: -1326
- McFadden R^2: 0.24249
- Likelihood ratio test : chisq =
  (p.value = < 2.22e-16)

➢ Model does not make sense in terms of TC sign

	Estimate	z-value	Signif.
2:(intercept)	-1.0	0.0	***
3:(intercept)	-1.1	0.0	***
4:(intercept)	-2.9	0.0	***
5:(intercept)	-3.5	0.0	***
6:(intercept)	-0.4	0.1	.
7:(intercept)	-7.4	0.0	***
8:(intercept)	-15.1	0.0	***
TC	1.5	0.0	***
2:DisPowered	0.0	0.3	
3:DisPowered	0.0	0.8	
4:DisPowered	0.0	0.4	
5:DisPowered	0.3	0.0	***
6:DisPowered	0.0	0.0	***
7:DisPowered	0.3	0.0	***
8:DisPowered	0.4	0.0	***
sd.TC	0.3	0.0	***

Table G-1 Investigated MNL models (cont'd)

<table>
<tr><th>Model</th><th colspan="4">Model Coefficients' Specifications
Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1</th></tr>
<tr><td rowspan="23">MNL Model with Covariate(s):
▪ Topo and DisPowered with alternative-specific parameter
▪ TC with generic parameter

Model Fit:
▪ Log-Likelihood: -1484.4
▪ McFadden R^2: 0.15199
▪ Likelihood ratio test : chisq = !
(p.value = < 2.22e-16)

➢ Model does not make sense in terms of TC sign</td><td></td><td>Estimate</td><td>z-value</td><td>Signif.</td></tr>
<tr><td>2:(intercept)</td><td>0.41</td><td>0.44</td><td></td></tr>
<tr><td>3:(intercept)</td><td>-1.21</td><td>0.01</td><td>*</td></tr>
<tr><td>4:(intercept)</td><td>-3.33</td><td>0.00</td><td>***</td></tr>
<tr><td>5:(intercept)</td><td>-3.27</td><td>0.00</td><td>***</td></tr>
<tr><td>6:(intercept)</td><td>0.56</td><td>0.16</td><td></td></tr>
<tr><td>7:(intercept)</td><td>-4.58</td><td>0.00</td><td>***</td></tr>
<tr><td>8:(intercept)</td><td>-4.22</td><td>0.06</td><td>.</td></tr>
<tr><td>TC</td><td>0.35</td><td>0.13</td><td></td></tr>
<tr><td>2:DisPowered</td><td>0.00</td><td>0.56</td><td></td></tr>
<tr><td>3:DisPowered</td><td>0.00</td><td>0.20</td><td></td></tr>
<tr><td>4:DisPowered</td><td>0.16</td><td>0.01</td><td>**</td></tr>
<tr><td>5:DisPowered</td><td>0.24</td><td>0.00</td><td>***</td></tr>
<tr><td>6:DisPowered</td><td>0.00</td><td>0.00</td><td>***</td></tr>
<tr><td>7:DisPowered</td><td>0.28</td><td>0.00</td><td>***</td></tr>
<tr><td>8:DisPowered</td><td>0.28</td><td>0.00</td><td>***</td></tr>
<tr><td>2:Topo</td><td>0.78</td><td>0.01</td><td>*</td></tr>
<tr><td>3:Topo</td><td>0.43</td><td>0.04</td><td>*</td></tr>
<tr><td>4:Topo</td><td>0.68</td><td>0.01</td><td>**</td></tr>
<tr><td>5:Topo</td><td>0.63</td><td>0.01</td><td>**</td></tr>
<tr><td>6:Topo</td><td>-0.20</td><td>0.30</td><td></td></tr>
<tr><td>7:Topo</td><td>0.74</td><td>0.00</td><td>***</td></tr>
<tr><td>8:Topo</td><td>0.46</td><td>0.01</td><td>**</td></tr>
</table>

Table G-1 Investigated MNL models (cont'd)

Model	**Model Coefficients' Specifications** Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Random Parameter MNL Model with Covariate(s):

- Topo and DisPowered with alternative-specific parameter
- TC with random parameter
  - random coefficients
    Min. 1st Qu. Median M
    Max.
    TC -Inf 1.275938 1.486062 1
    6185 Inf

Model Fit:

- Log-Likelihood: -1291.4
- McFadden R^2: 0.26223
- Likelihood ratio test : chisq = 918
  (p.value = < 2.22e-16)

- Model does not make sense in terms of TC sign

	Estimate	**z-value**	**Signif.**
2:(intercept)	0.27	0.62	
3:(intercept)	-2.03	0.00	***
4:(intercept)	-4.67	0.00	***
5:(intercept)	-5.23	0.00	***
6:(intercept)	-0.12	0.79	
7:(intercept)	-9.59	0.00	***
8:(intercept)	-16.90	0.00	***
TC	1.49	0.00	***
2:DisPowered	0.00	0.42	
3:DisPowered	0.00	0.96	
4:DisPowered	0.07	0.27	
5:DisPowered	0.32	0.00	***
6:DisPowered	0.01	0.00	***
7:DisPowered	0.37	0.00	***
8:DisPowered	0.40	0.00	***
2:Topo	-0.77	0.02	*
3:Topo	0.48	0.03	*
4:Topo	0.79	0.00	**
5:Topo	0.78	0.00	***
6:Topo	-0.17	0.38	
7:Topo	0.98	0.00	***
8:Topo	0.75	0.00	***
sd.TC	0.31	0.00	***

Table G-1 Investigated MNL models (cont'd)

Base Covariate: EmissionCost

Model	**Model Coefficients' Specifications** Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
MNL Model with Covariate(s): ▪ Topo with alternative-specific parameter ▪ Emission cost with generic parameter Model Fit: ▪ Log-Likelihood: -1560.3 ▪ McFadden R^2: 0.10862 ▪ Likelihood ratio test : chisq = (p.value = < 2.22e-16) ➢ Model does not make sense in terms of Emission cost sign	see table below

	Estimate	**z-value**	**Signif.**
2:(intercept)	0.49	0.34	
3:(intercept)	-0.83	0.06	.
4:(intercept)	-1.73	0.00	**
5:(intercept)	-1.50	0.00	**
6:(intercept)	0.92	0.01	*
7:(intercept)	-1.36	0.00	**
8:(intercept)	0.45	0.19	
EmissionCost	1.43	0.00	***
2:Topo	-0.78	0.01	*
3:Topo	0.41	0.05	*
4:Topo	0.58	0.02	*
5:Topo	0.51	0.02	*
6:Topo	-0.21	0.26	
7:Topo	0.58	0.00	**
8:Topo	0.32	0.05	*

Random Parameter MNL Model with Covariate(s): ▪ Topo with alternative-specific parameter ▪ Emission cost with random parameter ▪ random coefficients Min. 1st Qu. Me 3rd Qu. Max. EmissionCost -Inf 2.344622 4.858 4.858723 7.372825 Inf ▪ Model Fit: ▪ Log-Likelihood: -1446.3 ▪ McFadden R^2: 0.17375 ▪ Likelihood ratio test : chisq = (p.value = < 2.22e-16) ➢ Model does not make sense in terms of Emission cost sign	see table below

	Estimate	**z-value**	**Signif.**
2:(intercept)	0.50	0.35	
3:(intercept)	-0.84	0.07	.
4:(intercept)	-1.73	0.00	**
5:(intercept)	-1.64	0.00	***
6:(intercept)	0.92	0.01	*
7:(intercept)	-1.61	0.00	***
8:(intercept)	-0.78	0.04	*
EmissionCost	4.86	0.00	***
2:Topo	-0.78	0.02	*
3:Topo	0.42	0.05	.
4:Topo	0.58	0.02	*
5:Topo	0.53	0.02	*
6:Topo	-0.21	0.26	
7:Topo	0.62	0.00	**
8:Topo	0.42	0.02	*
sd.EmissionCost	3.73	0.00	***

Table G-1 Investigated MNL models (cont'd)

Model	**Model Coefficients' Specifications** Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

MNL Model with Covariate(s):

- DisPowered with alternative-specific parameter
- Emission cost with generic parameter

Model Fit:

- Log-Likelihood: -1514.5
- McFadden R^2: 0.13482
- Likelihood ratio test : chisq = (p.value = < 2.22e-16)

	Estimate	z-value	Signif.
2:(intercept)	-0.82	0.00	***
3:(intercept)	-0.09	0.58	
4:(intercept)	-1.69	0.00	***
5:(intercept)	-1.58	0.00	***
6:(intercept)	0.43	0.00	**
7:(intercept)	-1.77	0.00	***
8:(intercept)	0.17	0.33	
EmissionCost	-9.56	0.68	
2:DisPowered	0.00	0.40	
3:DisPowered	0.00	0.01	**
4:DisPowered	0.21	0.00	***
5:DisPowered	0.50	0.42	
6:DisPowered	0.00	0.00	***
7:DisPowered	0.67	0.47	
8:DisPowered	1.02	0.56	

Random Parameter MNL Model with Covariate(s):

- DisPowered with alternative-specific parameter
- Emission cost with random parameter
- random coefficients

Min. 1st Qu. Median Qu. Max.
EmissionCost -Inf 72.9959 75.5333 78.07084 Inf

Model Fit:

- Log-Likelihood: -1405.2
- McFadden R^2: 0.19722
- Likelihood ratio test : chisq = (p.value = < 2.22e-16)

	Estimate	z-value	Signif.
2:(intercept)	-0.78	0.00	***
3:(intercept)	-0.05	0.80	
4:(intercept)	-1.23	0.00	***
5:(intercept)	-1.69	0.00	***
6:(intercept)	0.47	0.00	**
7:(intercept)	-1.81	0.00	***
8:(intercept)	-0.51	0.01	**
EmissionCost	75.50	0.00	**
2:DisPowered	0.00	0.88	
3:DisPowered	0.00	0.61	
4:DisPowered	0.13	0.00	***
5:DisPowered	-1.76	0.01	**
6:DisPowered	0.00	0.00	***
7:DisPowered	-2.70	0.01	**
8:DisPowered	-5.27	0.00	**
sd.EmissionCost	3.76	0.00	***

➢ Model does not make sense in terms of Emission cost sign

Table G-1 Investigated MNL models (cont'd)

Model	**Model Coefficients' Specifications** Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

MNL Model with Covariate(s):

- DisPowered & Topo with alternative-specific parameter
- Emission cost with generic parameter

Model Fit:

- Log-Likelihood: -1485.5
- McFadden R^2: 0.15139
- Likelihood ratio test : chisq = (p.value = < 2.22e-16)

	Estimate	**z-value**	**Signif.**
2:(intercept)	0.44	0.41	
3:(intercept)	-0.95	0.04	*
4:(intercept)	-3.15	0.00	***
5:(intercept)	-2.91	0.00	***
6:(intercept)	0.77	0.04	*
7:(intercept)	-3.33	0.00	***
8:(intercept)	-0.78	0.04	*
EmissionCost	-9.04	0.70	
2:DisPowered	0.00	0.50	
3:DisPowered	0.00	0.00	**
4:DisPowered	0.23	0.00	***
5:DisPowered	0.50	0.42	
6:DisPowered	0.00	0.00	***
7:DisPowered	0.66	0.48	
8:DisPowered	0.99	0.57	
2:Topo	-0.78	0.01	*
3:Topo	0.43	0.04	*
4:Topo	0.69	0.01	**
5:Topo	0.63	0.01	**
6:Topo	-0.20	0.31	
7:Topo	0.74	0.00	***
8:Topo	0.46	0.01	**

Table G-1 Investigated MNL models (cont'd)

Model

Model Coefficients' Specifications
Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Random Parameter MNL Model with Covariate(s):

- DisPowered & Topo with alternative-specific parameter
- Emission cost with random parameter
  - random coefficients

Min. 1st Qu. Median 3rd Qu. Max.
EmissionCost -Inf 74.80909 77.411 80.01327 Inf

Model Fit:

- Log-Likelihood: -1374.8
- McFadden R^2: 0.21459
- Likelihood ratio test : chisq = (p.value = < 2.22e-16)

➢ Model does not make sense in terms of Emission cost sign

	Estimate	**z-value**	**Signif.**
2:(intercept)	0.50	0.36	
3:(intercept)	-0.89	0.07	.
4:(intercept)	-2.63	0.00	***
5:(intercept)	-3.08	0.00	***
6:(intercept)	0.83	0.03	*
7:(intercept)	-3.55	0.00	***
8:(intercept)	-1.61	0.00	***
EmissionCost	77.40	0.00	**
2:DisPowered	0.00	0.94	
3:DisPowered	0.00	0.55	
4:DisPowered	0.14	0.00	***
5:DisPowered	-1.80	0.01	**
6:DisPowered	0.00	0.00	***
7:DisPowered	-2.76	0.01	**
8:DisPowered	-5.40	0.00	**
2:Topo	-0.79	0.02	*
3:Topo	0.42	0.05	.
4:Topo	0.66	0.01	**
5:Topo	0.66	0.01	**
6:Topo	-0.20	0.29	
7:Topo	0.82	0.00	***
8:Topo	0.52	0.00	**
sd.EmissionCost	3.86	0.00	***

Table G-1 Investigated MNL models (cont'd)

Base Covariate: HealthValue

Model	**Model Coefficients' Specifications** Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Mnl.HealthValueandDis MNL Model with Covariate(s): ▪ Health value with generic parameter ▪ DisPowered with alternative-specific parameter Model Fit: ▪ Log-Likelihood: -2485.4 ▪ McFadden R^2: -0.41984 ▪ Likelihood ratio test : chisq = (p.value = 1)	see table below
Random Parameter MNL Model with Covariate(s): ▪ Health value with random parameter ▪ DisPowered with alternative-specific parameter ➢ Model does not run due to matrix singularity issues	

	Estimate	**z-value**	**Signif.**
2:(intercept)	-0.01	0.95	
3:(intercept)	0.00	1.00	
4:(intercept)	-0.01	0.95	
5:(intercept)	-0.01	0.97	
6:(intercept)	0.02	0.89	
7:(intercept)	-0.01	0.97	
8:(intercept)	0.09	0.57	
HehValue	3.43	0.88	
2:Dis	8.94	0.88	
3:Dis	10.10	0.88	
4:Dis	14.20	0.88	
5:Dis	14.20	0.88	
6:Dis	8.94	0.88	
7:Dis	14.20	0.88	
8:Dis	14.20	0.88	

Table G-1 Investigated MNL models (cont'd)

Model	**Model Coefficients' Specifications** Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

MNL Model with Covariate(s):

- Health value with generic parameter
- Topo with alternative-specific parameter

Model Fit:

- Log-Likelihood: -1516.2
- McFadden R^2: 0.13381
- Likelihood ratio test : chisq = (p.value = < 2.22e-16)

➢ Model does not make sense in terms of Health value sign

	Estimate	**z-value**	**Signif.**
2:(intercept)	-0.55	0.30	
3:(intercept)	-2.12	0.00	***
4:(intercept)	-4.64	0.00	***
5:(intercept)	-4.11	0.00	***
6:(intercept)	-0.12	0.75	
7:(intercept)	-3.77	0.00	***
8:(intercept)	-1.09	0.00	**
HehValue	-0.12	0.00	***
2:Topo	-0.71	0.02	*
3:Topo	0.50	0.02	*
4:Topo	0.78	0.00	**
5:Topo	0.71	0.00	**
6:Topo	-0.14	0.46	
7:Topo	0.77	0.00	***
8:Topo	0.48	0.01	**

Random Parameter MNL Model with Covariate(s):

- Health value with random parameter
- Topo with alternative-specific parameter

➢ Model does not run due to matrix singularity issues

Table G-1 Investigated MNL models (cont'd)

<table>
<tr><th>Model</th><th>Model Coefficients' Specifications
Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1</th></tr>
<tr><td>MNL Model with Covariate(s):
▪ Health value with generic parameter
▪ Topo & Dis with alternative-specific parameter

Model Fit:
▪ Log-Likelihood: -2484.5
▪ McFadden R^2: -0.41935
▪ Likelihood ratio test : chisq = (p.value = 1)</td><td>
<table>
<tr><th></th><th>Estimate</th><th>z-value</th><th>Signif.</th></tr>
<tr><td>2:(intercept)</td><td>-0.01</td><td>0.99</td><td></td></tr>
<tr><td>3:(intercept)</td><td>-0.01</td><td>0.97</td><td></td></tr>
<tr><td>4:(intercept)</td><td>-0.02</td><td>0.94</td><td></td></tr>
<tr><td>5:(intercept)</td><td>-0.02</td><td>0.95</td><td></td></tr>
<tr><td>6:(intercept)</td><td>0.04</td><td>0.91</td><td></td></tr>
<tr><td>7:(intercept)</td><td>-0.03</td><td>0.93</td><td></td></tr>
<tr><td>8:(intercept)</td><td>0.07</td><td>0.82</td><td></td></tr>
<tr><td>HehValue</td><td>3.43</td><td>0.88</td><td></td></tr>
<tr><td>2:Topo</td><td>0.00</td><td>0.99</td><td></td></tr>
<tr><td>3:Topo</td><td>0.01</td><td>0.97</td><td></td></tr>
<tr><td>4:Topo</td><td>0.01</td><td>0.96</td><td></td></tr>
<tr><td>5:Topo</td><td>0.01</td><td>0.96</td><td></td></tr>
<tr><td>6:Topo</td><td>-0.01</td><td>0.96</td><td></td></tr>
<tr><td>7:Topo</td><td>0.01</td><td>0.94</td><td></td></tr>
<tr><td>8:Topo</td><td>0.01</td><td>0.95</td><td></td></tr>
<tr><td>2:Dis</td><td>8.94</td><td>0.88</td><td></td></tr>
<tr><td>3:Dis</td><td>10.10</td><td>0.88</td><td></td></tr>
<tr><td>4:Dis</td><td>14.20</td><td>0.88</td><td></td></tr>
<tr><td>5:Dis</td><td>14.20</td><td>0.88</td><td></td></tr>
<tr><td>6:Dis</td><td>8.94</td><td>0.88</td><td></td></tr>
<tr><td>7:Dis</td><td>14.20</td><td>0.88</td><td></td></tr>
<tr><td>8:Dis</td><td>14.20</td><td>0.88</td><td></td></tr>
</table>
</td></tr>
<tr><td>Random Parameter MNL Model with Covariate(s):
▪ Health value with random parameter
▪ Dis &Topo with alternative-specific parameter

➢ Model does not run due to matrix singularity issues</td><td></td></tr>
</table>

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