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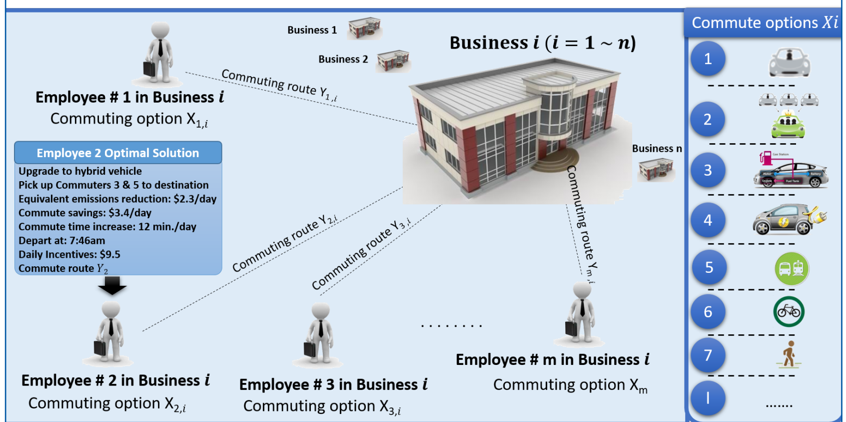
Multi-Business Commute Optimization System: System Development and Pilot Case Study



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16. Abstract

This report focuses on the development of an innovative Multi-Business Commute Optimization System (MBCOS) to contribute to reducing negative environmental impacts of the transportation sector. MBCOS consists of three integrated components, a website (www.commuteopt.com), a travel attributes model, and a multi-objective optimization model. The website is designed to facilitate the collection of travel data and delivery of recommended plans. The travel attributes model is designed to calculate attributes such as travel time, cost, GHG and air pollution emissions, energy use, and calories for all commuting options. MBCOS is designed to model commute options, including drive alone, carpool, use of public transit, bike, walk, and combination of these modes. The optimization model is designed to identify optimal commute plan for each employee in a business to minimize GHG and air pollution emissions while complying with commute needs, preferences and convenience. A case study of 47 employees is presented to evaluate system performance and demonstrate its capabilities. Results show that the developed system is capable of reducing the total GHG and air pollution emissions up to 23.4% compared to reported commute behavior. Furthermore, recommendations generated by the model show promising and practical solutions that can successfully contribute in reduction of transportation emissions. Finally, brief widespread application of the system in Colorado and USA is analyzed to document its potential benefits to businesses in USA.

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ABSTRACT

The transportation sector in the United States is currently dealing with several challenges, such as greenhouse gas (GHG) and air pollution emission increases, parking facility costs, congestion, and energy consumption. The present report focuses on the development of an innovative multi-business commute optimization system (MBCOS) to provide a new means of resolving the aforementioned challenges and increase efficiency in transportation systems. MBCOS consists of three integrated components: a website (www.commuteopt.com), a travel attributes model, and a multi-objective optimization model. The website is designed to facilitate the collection of travel data and delivery of recommended plans. The travel attributes model is designed to calculate attributes such as travel time, cost, GHG and air pollution emissions, energy use, and calories for all commuting options. MBCOS is designed to model commute options, including drive-alone, carpool, use of public transit, bike, walk, and combinations of these modes. The optimization model is designed to identify optimal commute plans for each employee in a business to minimize GHG and air pollution emissions while complying with commute needs, preferences, and convenience. A case study of 47 employees is presented to evaluate system performance and demonstrate its capabilities. Results show that the developed system is capable of reducing the total GHG and air pollution emissions up to 23.4% compared with reported commute behavior. Furthermore, recommendations generated by the model show promising and practical solutions that can successfully contribute to a reduction of transportation emissions. Finally, brief widespread application of the system in Colorado and the United States is analyzed to document its potential benefits on a large-scale application.

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1. INTRODUCTION

The United States transportation sector has been dealing with several challenges, including traffic congestion, air pollution, greenhouse gas (GHG) emissions, and increasing energy and infrastructure costs. The transportation sector is reported as the largest and fastest-growing source of GHG emissions in the United Stated at 28% (Environmental Protection Agency, 2018). Furthermore, the transportation sector is the major source of air pollution, smog, and air toxins, accounting for over 55% of total NO_X emissions in the United States. Moreover, the congestion of urban road networks costs the United States about $85 billion per year, accounting for delays due to extended travel time, reduced mobility, increased vehicle operating costs, and environmental degradation (Department of Transportation, 2009). A considerable part of transportation challenges comes from the drive-alone commute mode, which is reported in 2016 as the predominant commute mode at 76.3%; this is significantly higher than the modal shares of carpool at 9%, use of public transit at 5.1%, and walking at 2.7% (U.S. Bureau of the Census, 2016). Free/subsidized parking cost at workplaces, relatively low price of fuel, inefficient public transit systems, urban sprawl, commuter time constraints and intermediate stop needs, along with the absence of inequivalent subsidizations for alternative commute modes, are the major causes of the high drive-alone modal share. This shows the pressing need for effective transportation planning and programs that could reduce the drive-alone mode to address the aforementioned challenges. Practical and smart solutions are needed to reduce transportation related emissions while satisfying the commute preferences, convenience, and needs of commuters.

Several motives exist to minimize the vehicle mile travel (VMT) and GHG emissions. They vary from environmental concerns to energy dependency, public health, air and noise pollution, and urban sprawl. For example, it is shown that the use of public transit systems can save an equivalent of 4.2 billion gallons of gasoline, resulting in a reduction of 37 million metric tons of CO_2 emissions (Bailey et al., 2008). To achieve this vital goal of reducing the United States VMT, departments of transportation (DOTs) are consistently active to reduce GHG emissions from the transportation sector using tools and guidelines such as: (1) mixed land-use and public transit development; (2) multimodal transportation systems; and (3) active-transportation modes. Currently, trips by business employees and commuters with shared destinations are not optimized in terms of environmental impacts and costs; rather they rely mainly on personal convenience, cost, and time constraints.

2. LITERATURE REVIEW

Studies and policies addressing commute travel behavior have received particularly high attention. This may be partially because traffic challenges are specifically prevalent during peak traffic hours, and because morning and evening commutes represent a significant proportion of trips during peak traffic hours. It may also be partially because commute trips are relatively monotonically repetitive and stable compared with other types of trips, which increases the potential effects and success chances of the developed policies (Bureau of Transportation Statistics, 2015). Outcomes of such research efforts have resulted in the development of many policies and programs. Accordingly, another part of the literature focused on the development and assessment of the effectiveness of these programs. The following sections discuss these studies and policies in more details.

2.1 Factors Influencing Commute Mode Choice

Several statewide and community-level surveys are conducted to identify factors influencing commute mode choice by collecting travel-related data such as mode of transportation, duration, distance, and trip purpose (Federal Highway Administration, 2011; Yang et al., 2015). These surveys document the volumes and patterns of passenger transportation. The surveys can support identifying the shortcomings of existing transportation systems and provide insights on commuting needs for expansion of transportation services. Results of the surveys show that the motivations of commute modal share include: (1) individual determinants such as lifestyle, physiological characteristics, gender, and age; (2) natural environment such as air and weather; (3) built environment such as land-use patterns, urban design, and transportation facilities; and (4) social environment such as culture and social equity (Yang, 2015).

Donald et al. studied the psychological factors affecting commute mode choice using the travel behavior data of 827 participants in the UK. The study showed that commuters are more concerned with environmental impacts for driving mode rather than other factors, including habitual, social, and moral factors (Donald et al., 2014). Accordingly, providing information of commute environmental impacts can motivate travelers to reduce the modal share of driving. In another study, Legrain et al. studied the impacts of commuting stress on commute mode choice using a large-scale university travel survey to compare commuter stress across three modes of transportation: walking, driving, and public transit. The outcome of the study showed that driving is the most stressful mode of transportation when compared with walking and public transit (Legrain et al., 2015). In another research, St-Louis et al. studied the levels of satisfaction across six transportation modes, including walking, bicycle, automobile, bus, metro, and train to promote their use over automobile. This study showed commuters that use public transit or bike are more satisfied with their trips compared with drivers and bus users, mainly due to the commute time unreliability factor, which results in early or late arrival (St-Louis et al., 2014).

2.2 Impacts of Commute Mode Choice

The lower rates of modal shares for public transit, walk, and bike use is partially due to inefficient transportation planning policies that fail to identify the impacts of commute mode choices. Commute mode choice has impacts on reducing environmental impacts such as GHG and air pollution emissions, reducing energy demand, improving public health, reducing noise and congestion, reducing parking facility costs, and achieving savings in commute cost and time. Frequently, transportation programs only focus on reducing the commute times, overlooking other important socio-environmental and economic benefits of alternative commute mode choice to driving. This results in underinvestment in alternative commute modes, such as walking, biking, and using public transit.

Handy and Mokhtarian conducted a review of existing research on the correlation among urban development, travel, and CO_2 emissions by vehicles in the United States. The analysis indicated that using public transportation instead of driving can reduce GHG emissions by 30% of work commute travels (Handy & Mokhtarian, 2008). In another similar study, Zahabi et al. estimated that increasing public transit accessibility by 10% would cause a 3.5% reduction in households' GHG emissions (Zahabi et al., 2012). In another study, Anderson focused on the benefits of using public transit using the data from the 2003 Los Angeles transit workers strike. It is estimated that the annualized congestion relief benefit of operating the Los Angeles transit system is nearly $2.6 billion (Anderson, 2014). The health impacts of commute mode choices were studied by Deenihan and Caulfield, who showed that increasing the modal share of biking from 1.72% to 2.5% reduces the number of deaths per year from 3.4 to 17.9 (Deenihan & Caulfield, 2014).

2.3 Existing Commute Mode Choice Evaluation Tools

Literature on commuter mode choice is rich; yet, tools that businesses can utilize to identify optimum policies and incentives, and associated benefits, are limited. Three available tools include CUTR_AVR model (University of South Florida, 1998), Business Benefits Calculator (Center for Urban Transportation Research, 2002), and Commuter Choice Decision Support System (CCDSS) (Federal Highway Administration, 2003). CCDSS is supported by the USDOT and US EPA. It is designed to help employers determine the most appropriate types of commuter choice options for their worksite. Business Benefits Calculator, developed by the US EPA, is a web-based calculator that helps business owners evaluate financial, environmental, traffic-related, and other benefits of workplace transportation programs. CUTR_AVR Model, by the Center for Urban Transportation Research at the University of South Florida, was developed based on a large, real-world dataset and uses an artificial neural network to predict mode share and average vehicle ridership by inputting attributes of the employer-based transportation program. All these tools provide businesses with generalized recommendations for commuting policies and estimates on benefits (e.g., GHG emissions reduction). They base their recommendations and estimates on aggregate measures of commute data, rather than individualized commute information and individual-specific incentives.

The outcome of existing studies and the limited success of existing policies reveal a pressing need to develop a new approach for identifying the optimal selection of commute alternatives that simultaneously minimize businesses commute emissions as well as commute time and cost of individual commuters. This new approach requires modeling employees' constraints, preferences, and footprint coupled with monetary and health incentives to generate practical solutions that are capable of changing existing commute behavior and maximizing sustainability of the transportation systems.

3. RESEARCH OBJECTIVES & METHODS

This report presents the development of a new multi-business commute optimization system (MBCOS), which is designed to identify optimal commute plans of employees at multiple businesses that are co-located or employees of a business with different work locations. MBCOS is designed to minimize the total GHG and air pollution emissions while maintaining preferences and convenience of business commuters. MBCOS is designed to achieve the vital goal of reducing business commute GHG and air pollution emissions by changing the commute behavior of each employee from drive alone to alternative commute modes, such as using public transit, carpooling using existing vehicle, biking, walking, or using combinations of these modes. Monetary incentives can be provided by business owner(s) to motivate employees to follow the recommended commute plans and to cover the extensions in commute duration due to use of public transit, walk, bike, and carpool, all of which usually take longer. The present model extends the capabilities of the previously developed single business commute optimization system (BCOS) (Abdallah et al., 2019) by considering multiple businesses that are co-located. This allows MBCOS to identify more carpooling options to further reduce the GHG and air pollution emissions from business commutes.

MBCOS consists of a web-based travel survey, a geographical information system (GIS) network, and an optimization model. A website is designed to facilitate the collection of travel survey data, including employees commute information such as origin and destination addresses, arrival and departure times to/from work, and original commute method. The GIS model is designed to calculate GHG and air pollution emissions, travel time, cost, energy consumption, and calories burned for every possible commute mode, including drive-alone using existing vehicle, use of public transit, bike, walk, and carpool with other commuters. The optimization model is designed to identify the optimal commute behavior change of employees from drive-alone to alternative commute modes that result in minimum total GHG and air pollution emissions. To evaluate the performance of the developed system and demonstrate its new capabilities, a case study of 47 employees to nine different work locations is analyzed. The following sections discuss the details of MBCOS components.

3.1 Web-based Travel Survey

A website that can be accessed at www.commuteopt.com has been designed and developed to facilitate the collection of employee travel data. Users who participated in this study were required to create an account on the website. After registration, users filled out commute information and needs surveys on the website. These surveys were designed to collect data on existing commute information, such as departure and arrival times, existing commute method, origin and destination, type of vehicle, parking location and its cost, available access to commute methods, and commuter flexibility and convenience.

3.2 Geographical Information System Network

The GIS network is designed to analyze feasible commute methods, such as drive existing vehicle alone, carpool with another commuter, using public transit, bike, and walk based on the data collected from the website. After that, the GIS network will generate outputs of each commute method, which includes the commute time, cost, distance, GHG emissions, air pollution, burned calories, and energy consumption. The GIS model is composed of model inputs, model process, and model outputs, which are discussed as follows:

3.2.1 Model Inputs

The MBCOS GIS model inputs are:

1) Travelers' info: While a business's human resources office typically keeps records of employee home addresses and office locations, the web-based travel survey explained in the previous section was designed and utilized to capture additional and up-to-date information, such as departure times, required intermediate stops, parking location, parking cost, and other information.
2) Existing transportation network: This includes identifying a model of the structure and properties of the transportation network for all modes of transportation considered in the developed GIS network. This step also includes understanding the assumptions and limitations of the model (e.g., walk speed and maximum transit walk radius). The four primary transportation modes considered are walk, bike, transit, and drive.
3) Travel attributes. This set includes identifying the travel attributes the business desires in optimizing or measuring (e.g., travel times, travel costs, energy, emissions, and calories). Eight travel attributes could be selected for modeling, including travel time, travel distance, travel cost, CO_2 emissions, NO_x emission, VOC emissions, energy, and calories.

3.2.2 Model Process

The GIS computations are composed of the following steps:

1) Geocoding origins and destinations. This step entails transforming the travelers' origins and destinations (usually in text format) into geo-referenced data points in the GIS model.
2) Editing the transportation network. This step entails ensuring the suitability of the utilized transportation network in computing representative travel times and distances of all commute trips and using all possible travel modes. For example, the step involves ensuring appropriate travel speeds for the different travel modes, as well as ensuring the suitability of the adopted network in producing multimodal travel attributes of multimodal trips, e.g., walk, bus, and wait travel characteristics of walk-transit trips.
3) Identifying the travel attribute parameters. In this step, parameters required to compute travel attribute values from travel times and distances are identified (e.g., a parameter that estimates travel cost from travel distance, such as cost per mile) for every transportation mode. Table 3.1 lists the attribute parameters utilized in the GIS module.
4) Identifying the travel alternatives. This step identifies the travel alternatives that are required to be considered. As mentioned above, four primary transportation modes were considered in this work. However, six travel alternatives were identified: walk, bike, walk-transit, bike-transit, drive-alone, and carpool.
5) Developing the attributes functions. This step develops the different functions for calculating the attribute values associated with every commute trip using every travel alternative. As mentioned earlier, the travel attributes are a function of travel times and travel distances.

Table 3.1 Attribute parameters adopted in the GIS module

Mode	Travel Attributes					
	CO_2	NO_X	VOC	Cost	Energy	Calories
Walk	85.3 g/mi	0	0	0	0	85 cal/mi
Bike	88.01 g/mi	0	0	0.1 ₵/mi	0	48 cal/mi
Transit + Walk	294.6 g/mi	1.643 g/mi	0.039 g/mi	Fare $1.25	0.04049 gal/mi	1.133 cal/min + 85 cal/mi
Transit + Bike	294.6 g/mi	1.643 g/mi	0.039 g/mi	Fare $1.25 + 0.1 ₵/mi	0.04049 gal/mi	1.133 cal/min + 85 cal/mi
Drive	368.4 g/mi	0.693 g/mi	1.034 g/mi	59.2 ₵/mi + Parking Fee	0.04049 gal/mi	1.133 cal/min + 85 cal/mi

3.2.3 Model Output

As mentioned earlier, the objective of the GIS is to compute the commute footprints of every employee using every possible mode of travel. Accordingly, the GIS outputs include the measured travel attributes for every commuter and for every commute alternative.

3.3 Optimization Model

The optimization model is designed to identify the optimal selection of commute alternatives of employees with multiple work destinations based on the data collected from the website and travel attributes measured in the GIS network. The optimization model minimizes the total negative environmental impacts of employees while complying with the available business budget for incentives and commuter convenience and flexibility. The optimization model is developed in two main steps: (1) model formulation, which identifies decision variables and formulates objective functions and constraints; and (2) model implementation, which executes the computations to identify the optimal values of decision variables that result in the minimum transportation emissions.

3.3.1 Model Formulation

Four types of decision variables were identified to model all possible commute modes for each commuter, as shown in Figure 3.1. $\bar{X}_{i,j}$ and $\bar{\bar{X}}_{i,j}$ are binary decision variables used to model six types of commute alternatives for outgoing and return trips, respectively, as shown in Figure 3.1. These commute alternatives include drive alone, use of public transit and walk, use of public transit and bike, bike only, walk only, and carpool picked up by another commuter; where i represents a business commuter and ranges from 1 to number of commuters (NC) and j represents the type of transportation mode and ranges from 1 to 6, as shown in Figure 3.1. $\bar{Y}_{k,l}$ and $\bar{\bar{Y}}_{k,l}$ are binary decision variables used to model all carpooling options of two commuters; where commuter k picks up commuter l for outgoing and return trip, respectively, as shown in Figure 3.1.

The outgoing trip legs for commuter k to pick up commuter l include (1) driving from commuter k home location to commuter l location; (2) driving from commuter l home location to commuter l work location; (3) driving from commuter l work location to commuter k parking location; (4) searching for parking spot at commuter k parking location; and (5) walking to commuter k work location. Likewise, the return trip legs for commuter k to pick up commuter l include (1) walking from commuter k work location to commuter k parking location; (2) driving from commuter k parking location to commuter l work location; (3) driving from commuter l work location to commuter l home location; and (4) driving from commuter l home location to commuter k home location.

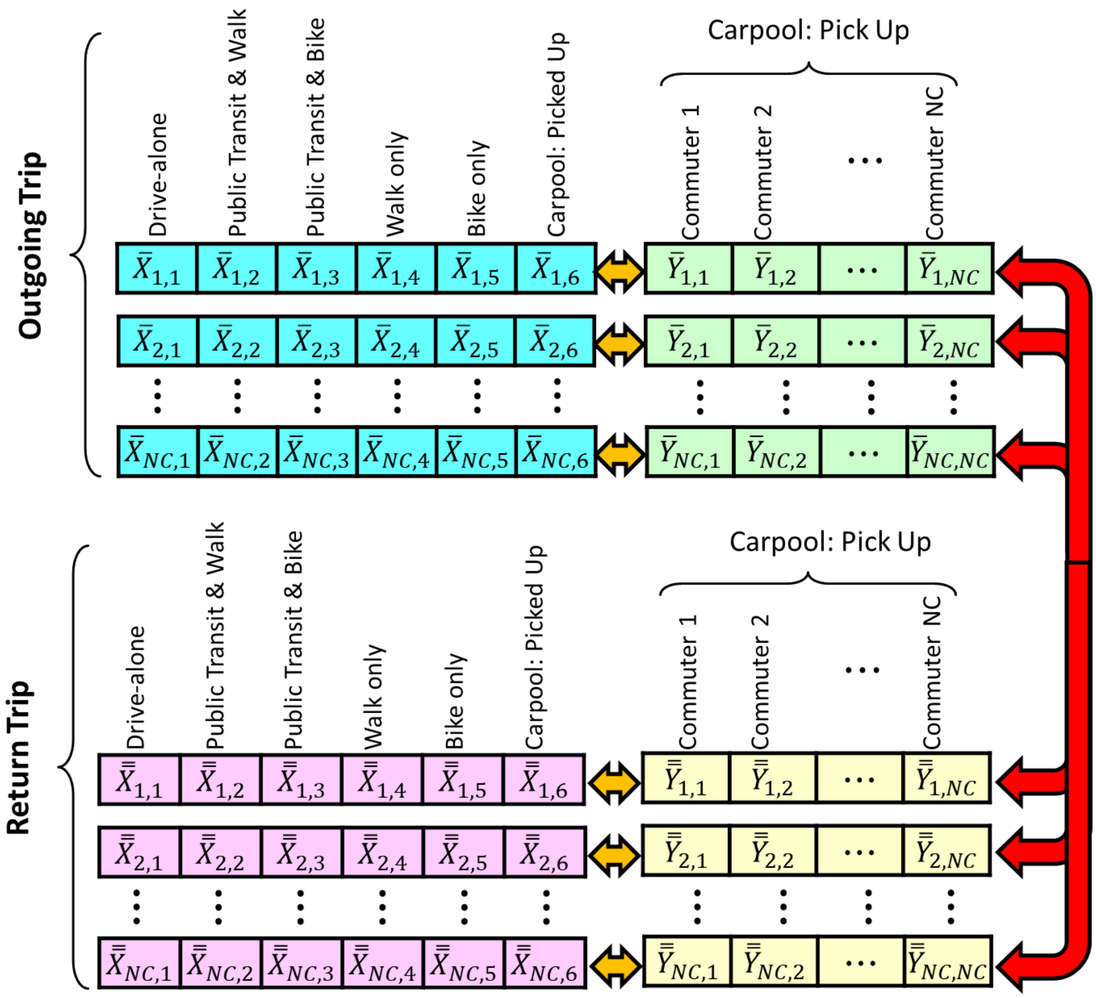

Figure 3.1 Identified decision variables to model commute options

The objective function is designed to quantify and minimize the total equivalent social cost of GHG and air pollution emissions, as shown in Eq. (1). The objective function can be minimized by reducing the selection of drive alone options, where convenient to commuters and based on the model constraints.

$$\text{Minimize } TCE = \sum_{i=1}^{NC}\sum_{j=1}^{6}[\bar{X}_{i,j}+\bar{\bar{X}}_{i,j}]\times[C_{i,j}+N_{i,j}+V_{i,j}]+\sum_{k=1}^{NC}[\bar{Y}_{k,l}+\bar{\bar{Y}}_{k,l}]\times[C_{k,l}+N_{k,l}+V_{k,l}] \quad \text{Eq. (1)}$$

$$C_{i,j}=CE_{i,j}\times F_{CO_2} \quad \text{Eq. (2)}$$

$$N_{i,j}=NE_{i,j}\times F_{NO_X} \quad \text{Eq. (3)}$$

$$V_{i,j}=VE_{i,j}\times F_{VOC} \quad \text{Eq. (4)}$$

$$C_{k,l}=CE_{k,l}\times F_{CO_2} \quad \text{Eq. (5)}$$

$$N_{k,l} = NE_{k,l} \times F_{NO_X} \quad \text{Eq. (6)}$$

$$V_{k,l} = VE_{k,l} \times F_{VOC} \quad \text{Eq. (7)}$$

Where: TCE is the total equivalent social cost of GHG and air pollution emissions. $C_{i,j}$, $N_{i,j}$ and $V_{i,j}$ are the equivalent social cost of CO_2, NO_X and VOC emissions for commuter i using transportation mode j, respectively, which are calculated as in Eqs. (2-4). Similarly, $C_{k,l}$, $N_{k,l}$ and $V_{k,l}$ are the equivalent social cost of CO_2, NO_X and VOC emissions for commuter k using carpool and pick up commuter l, respectively, which are calculated as in Eqs. (5-7). $CE_{i,j}$, $NE_{i,j,}$ and $VE_{i,j}$ are the CO_2, NO_X, and VOC emissions in grams for commuter i using transportation mode j, respectively, which are the GIS model output. $CE_{k,l}$, $NE_{k,l}$, and $VE_{k,l}$ are the CO_2, NO_X, and VOC emissions in grams for commuter k using carpool and pick up commuter l, respectively, which are the GIS model output. F_{CO_2}, F_{NO_X}, and F_{VOC} are equivalent social cost of 1-gram emission of CO_2, NO_X, and VOC, which are $\$40 \times 10^{-6}$, $\$10.3 \times 10^{-9}$, and $\$2.4 \times 10^{-9}$, respectively (Environmental Protection Agency, 2014; Victoria Transport Policy Institute, 2013).

To ensure that the identified commute plans of employees are practical, four types of constraints are integrated in the model. These constraints are (1) model logic constraints, (2) consistency constraints, (3) convenience constraints, and (4) incentive constraints. The model logic constraints are used to ensure the possibility of identified commute modes. For example, for every commuter, only one commute mode should be selected in each outgoing and return trip, as shown in Eq. (8-9). Consistency constraints ensure rationality of the optimal commute plans of employees. For example, a commuter who bikes in the outgoing trip can only be recommended to bike or use public transit and bike in the return trip, as shown in Eq. (10). Convenience constraints are used to maintain the convenience of commuters. For example, commute modes that extend travel time of commuters more than their specified time tolerances are identified as infeasible in the model, as shown in Eqs. (11-12). Lastly, the incentive constraint ensures that the total monetary incentives for all commuters will not exceed the business incentives budget.

$$\sum_{j=1}^{6} \bar{X}_{i,j} + \sum_{l=1}^{NC} \bar{Y}_{k,l} = 1 \qquad i = k = 1,2, \dots, NC \qquad \text{Eq. (8)}$$

$$\sum_{j=1}^{6} \bar{\bar{X}}_{i,j} + \sum_{l=1}^{NC} \bar{\bar{Y}}_{k,l} = 1 \qquad i = k = 1,2, \dots, NC \qquad \text{Eq. (9)}$$

$$\sum_{j \in \{3,5\}} \bar{X}_{i,j} - \sum_{j \in \{3,5\}} \bar{\bar{X}}_{i,j} = 0 \qquad i = 1,2, \dots, NC \qquad \text{Eq. (10)}$$

$$\sum_{j=1}^{6} \bar{X}_{i,j} \times \bar{T}_{i,j} - OCT_i \leq OTT_i \qquad i = 1,2, \dots, NC \qquad \text{Eq. (11)}$$

$$\sum_{j=1}^{6} \bar{\bar{X}}_{i,j} \times \bar{\bar{T}}_{i,j} - RCT_i \leq RTT_i \qquad i = 1,2, \dots, NC \qquad \text{Eq. (12)}$$

Where: OCT_i and RCT_i are the outgoing and return trip existing commute time, respectively, for commuter i. OTT_i and RTT_i are the outgoing and return trip extended commute time tolerances, respectively, of commuter i.

3.3.2 Model Implementation

The developed optimization model is implemented in three steps: (1) collecting input data from the GIS network and travel survey data to the optimization model; (2) executing the model computations using open-source Gurobi IntLinProg solver built-in interface for Matlab®2019a; (3) generating the individualized optimal commute plans. The calculated travel attributes for each commute mode for both outgoing and return trips by the GIS network, along with the commute preference and needs from the travel survey data, are fed into the optimization model. The optimization model is coded based on a problem-based optimization programming feature introduced in Matlab®2017b, where the decision variables, objectives, and constraints are symbolically defined. Compared with the conventional solver-based optimization programming, the problem-based optimization is easier to create and debug, and it is convertible to the solver-based version. The mixed integer linear programing is used since it guarantees the global optimum within a reasonable computational time. Finally, the optimization model organizes the model output and summarizes the results by generating commute plan recommendations for each employee based on the identified solution. The recommended commute solutions are designed to include detailed plan information such as commute mode, reduction in GHG and air pollution emissions, savings in commute time, cost, and energy, monetary incentives, and increase in burned calories.

3.4 Performance Evaluation

A case study of a student community was analyzed to evaluate the performance of the developed MBCOS and demonstrate its new capabilities. Case study data were collected using an online survey instrument developed by the authors. The data documented real-world commute behavior for 21 undergraduate engineering students as they commuted to/from the university. Input data included information about transportation mode choice, arrival and departure times, and commute origin and destination. Figure 3.2 demonstrates the origins and destination of the student commuters. In the morning event, the origins (shown in green) represent residences, and they are identical to the destinations (shown in red) in the afternoon commutes. The university is represented by the destinations (shown in red) in the morning commutes and the origins (shown in green) in the afternoon commutes. The general location of the university can be identified on the map by the cluster of points (destinations in the morning commute and origins in the afternoon commute) on the map. All the events display similar patterns of trip ends, with a few differences. A few points digress from the expected patterns, which represent the differences in a commuter travel plan. For example, a commuter's set afternoon trips consisted of going to work from the university in one event and to home in the other event. Table 3.2 shows the 21 students' individual commuter departure and arrival times and main transportation modes, which were collected using the online survey.

(a) Monday AM (b) Monday PM

Figure 3.2 Geographical distribution of 21 students

Commuters' origin and destination data were input into the GIS model component of MBCOS. Table 3.3 and Table 3.4 show samples of all trip attribute values for commuting-alone and carpooling options for commuter 1 that are generated using the GIS model. Such data represent input data for the multi-objective optimization model component of MBCOS.

Table 3.2 Commuter departure and arrival times and transportation modes of 21 students

Commuter	Morning Commute			Afternoon Commute		
	Departure time	Primary Transportation Mode	Arrival time	Departure time	Primary Transportation Mode	Arrival time
1	9:01 AM	Drive car	9:05 AM	5:56 PM	Drive car	6:00 PM
2	8:23 AM	Ride bike	8:25 AM	9:58 AM	Ride bike	10:00 AM
3	9:46 AM	Drive car	9:55 AM	2:01 PM	Drive car	2:10 PM
4	8:16 AM	Drive car	8:20 AM	6:25 PM	Drive car	6:30 PM
5	12:07 PM	Drive car	12:23 PM	3:54 PM	Drive car	4:10 PM
6	8:39 AM	Drive car	8:46 AM	10:57 AM	Drive car	11:00 AM
7	8:11 AM	Walk	8:12 AM	2:59 PM	Walk	3:00 PM
8	7:34 AM	Carpool	7:43 AM	6:22 PM	Carpool	6:30 PM
9	8:52 AM	Drive car	9:00 AM	11:53 AM	Drive car	12:00 PM
10	8:11 AM	Drive car	8:15 AM	8:11 PM	Drive car	8:15 PM
11	7:37 AM	Ride bike	7:40 AM	3:58 PM	Ride bike	4:00 PM
12	8:05 AM	Carpool	8:15 AM	10:51 PM	Carpool	11:00 PM
13	7:35 AM	Drive car	7:40 AM	7:36 PM	Drive car	7:40 PM
14	7:57 AM	Drive car	8:01 AM	9:56 AM	Drive car	10:00 AM
15	8:51 AM	Drive car	9:02 AM	1:55 PM	Drive car	2:00 PM
16	9:59 AM	Walk	10:00 AM	12:08 PM	Walk	12:10 PM
17	6:10 PM	Drive car	6:14 PM	7:56 PM	Drive car	8:00 PM
18	4:30 PM	Walk	4:32 PM	9:28 PM	Walk	9:30 PM
19	9:43 AM	Drive car	9:55 AM	9:53 PM	Drive car	10:05 PM
20	10:59 AM	Walk	11:00 AM	4:59 PM	Walk	5:00 PM
21	8:08 AM	Drive car	8:20 AM	4:48 PM	Drive car	5:00 PM

Table 3.3 Values of trip attributes for commuting-alone options (Sample GIS model output for commuter #1)

$m = 1$	Commute alternatives	Performance Measures			
		Commute Time ($CT_{m,n}$)	Commute Distance ($CD_{m,n}$)	Commute Cost ($CC_{m,n}$)	Equivalent Social Cost of Emissions
		minutes	miles	$	$
n = 1	Walking only	33.3	1.8	0.0	0.000
n = 2	Biking only	10.7	1.8	0.0	0.000
n = 3	Skateboarding only	13.3	1.8	0.0	0.000
n = 4	Driving-alone	3.0	1.8	1.9	0.044
n = 5	Walking and riding bus	15.0	1.9	0.0	0.035
n = 6	Biking and riding bus	6.5	1.9	0.0	0.035
n = 7	Skateboarding and riding bus	7.5	1.9	0.0	0.035

Table 3.4 Values of trip attributes for carpooling options (Sample GIS model output for commuter #1**)**

$m = 1$	Pick up commuter l	Performance Measures			
		Commute Time ($CT_{m,l}$)	Commute Distance ($CD_{m,l}$)	Commute Cost ($CC_{m,l}$)	Equivalent Social Cost of Emissions
		minutes	miles	$	$
	$l = 2$	2.1	1.9	1.8	0.043
	$l = 3$	6.8	8.5	4.0	0.093
	$l = 4$	5.0	5.7	3.7	0.088
	$l = 5$	13.9	18.4	9.8	0.231
	$l = 6$	7.6	11.3	6.5	0.153
	$l = 7$	2.7	1.7	1.6	0.038
	$l = 8$	6.3	11	6.0	0.142
	$l = 9$	6.4	12.4	6.0	0.141
	$l = 10$	5.2	5.1	3.9	0.091
$n = 8$	$l = 11$	0.6	1.9	0.8	0.029
	$l = 12$	7.9	13	7.0	0.165
	$l = 13$	4.9	5.7	4.0	0.095
	$l = 14$	4.1	4.7	3.2	0.075
	$l = 15$	9.0	13.3	6.4	0.151
	$l = 16$	2.5	2	2.6	0.060
	$l = 17$	4.7	4.7	3.2	0.075
	$l = 18$	3.1	2.1	2.3	0.055
	$l = 19$	9.5	19.6	10.4	0.246
	$l = 20$	2.7	1.7	1.6	0.038
	$l = 21$	12.8	17.6	10.4	0.245

3.4.1 Analysis of Performance Results of the System

Based on the collected data, the optimization model component calculated total commute time at 325.15 minutes as well as equivalent cost of GHG and air pollution emissions of the existing commute scenario at $3.45. MBCOS is then used to identify the optimal selection of commute alternatives that generate optimal tradeoffs among the two optimization objectives of (1) minimizing equivalent social cost of GHG and air pollution emissions, and (2) minimizing total commute time of the business transportation network.

To run the optimization analysis, additional input data were fed into MBCOS, including convenient commute time limits for biking and walking, commuter hourly rates, available daily incentives that can be used to incentivize commuters to implement the recommended commute plan, carpooling departure/arrival time tolerance, commute-duration tolerance, and increments for identifying Pareto optimal solutions. The value of students' time was set at a rate of $18 per hour (based on average university student pay rates) and the business budget for incentives was set in this case study at a maximum monetary incentive of $200 per day. The daily convenient commute times for biking and walking are set in MBCOS up to 38.6 minutes and 23 minutes, respectively, according to the American Commuting Survey Report (McKenzie, 2014). The carpooling departure/arrival time tolerance was set in the model to 180 minutes, which allows carpooling only for commuters who do not have differences in their arrival time in the morning commute and departure time in the afternoon commute greater than 180 minutes. A large value was set for the carpooling departure/arrival time tolerance in order to allow carpooling of four occupants per vehicle and show the capabilities of the designed system; otherwise, limited carpooling options could be identified due to the students' variance in their departure/arrival times.

The full range of the optimization objectives depends on the value of commute time tolerance. For example, the full range of the total commute time of the student community was identified at 221.8 minutes for a 25-minute commute time tolerance and, accordingly, the Pareto-optimal solutions are generated using 0.01 minutes as increments of ε (i.e., 0.45% of the full range of the travel time objective). Based on the selected increments, a total of 22,181 single objective optimization problems were solved, or individually solved in 0.46 seconds. The optimization model completed the model computations for the 21 students within 2.83 hours on a personal computer (Intel Core i7-4770 M with CPU 3.4 GHz with 16 GB memory). Regarding the large search space of the case study, the computational time is reasonable and shows that the designed optimization model is efficient in generating Pareto-optimal solutions. MBCOS is capable of generating Pareto optimal solutions for a larger number of commuters. For example, MBCOS can identify the optimal solutions for a business of 100 employees in 8.45 hours. It should be noted that increasing the size of the increments (ε) can significantly reduce the computational time and identify a sufficient variety of the Pareto optimal solutions.

The optimization model was designed to first identify the minimum and maximum total commute times for 5-, 10-, 15-, and 25-minute commuter tolerance for extended commute duration per trip. For every value of ε_i, the two-objective optimization problem was converted into a single-objective optimization problem, where the total travel time was incorporated into the optimization problem as a constraint and then the minimum total equivalent social cost of GHG and air pollution emissions was identified. Initially, ε_1 was set to the minimum value of the total commute time, which was obtained in the previous step, and the optimization model was solved to find the corresponding minimum total equivalent social cost of GHG and air pollution emissions. In order to generate the rest of Pareto-optimal solutions, the optimization model was solved for different values of ε_i with a fixed increment of 0.01 minutes (*i.e.*, $\varepsilon_i = \varepsilon_{i-1} + \epsilon$) up to the maximum total commute time. Accordingly, MBCOS generated Pareto-optimal solutions for the two aforementioned optimization objectives for each specified commuter's tolerance, as shown in Figure 3.3. Based on the results of MBCOS, the identified Pareto-optimal solutions were expanded and higher reductions in emission and total commute time were achieved as the commuter tolerance increased. Specifically, for a commuter tolerance of 25 minutes per trip, the equivalent social cost of GHG and air pollution of the business commute can be reduced to \$2.4 (≈ 30.4% reduction), as shown in Figure 3.3 for solution "S_4." Solutions S_1, S_2, S_3, and S_4 show the extreme solutions with greatest reduction of GHG and air pollution emissions and longest commute time for 5-, 10-, 15-, and 25-time extension tolerance per trip, as shown in Figure 3.3. In contrast, solution S_0 shows the solution with the greatest GHG and air pollution emissions but shortest commute time, as shown in Figure 3.3.

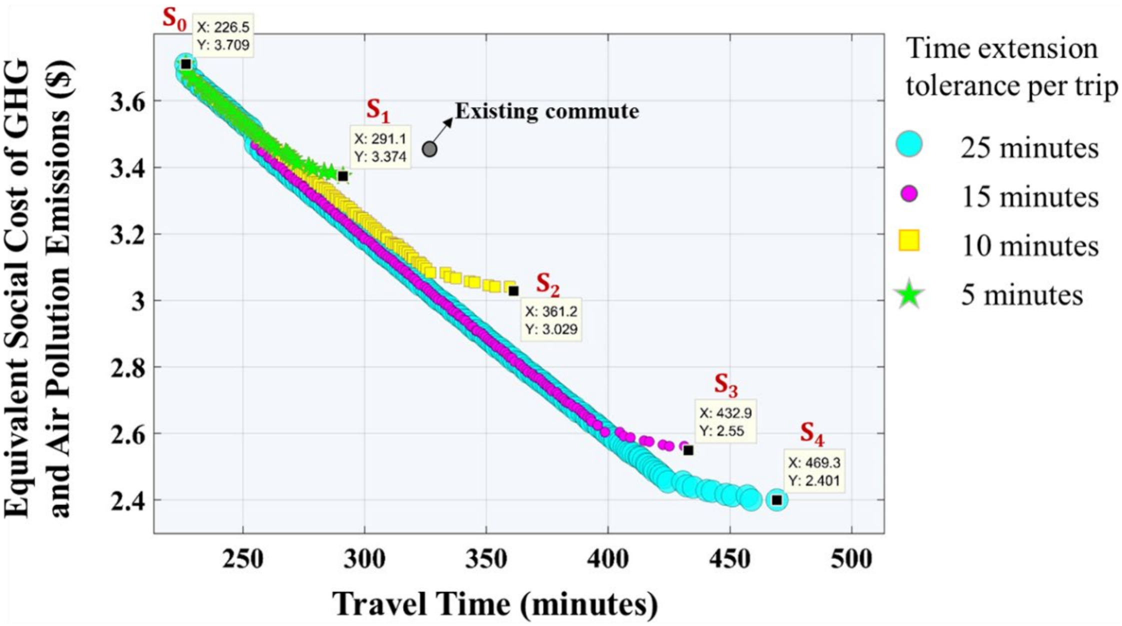

Figure 3.3 Pareto-Optimal solutions of MBCOS for various commuter's tolerance

Several Pareto-optimal solutions that MBCOS generated have lower total commute time and equivalent social cost of GHG and air pollution emissions as compared with the existing commute scenario, as shown in Figure 3.3. Furthermore, Figure 3.3 shows that a much higher reduction of emissions can be achieved if the commute tolerance is increased; however, total commute increases. The Pareto-optimal solutions that were identified for each commuter tolerance include two extreme solutions with (1) minimum possible negative environmental impacts and (2) minimum possible total commute time. Additionally, several solutions are identified between the two extreme solutions, which represent non-dominated solutions as discussed in the implementation phase. For example, 205 Pareto-optimal solutions could be identified for a commute tolerance of 25 minutes, as shown in Figure 3.4. Solution S_1 shows the Pareto-optimal solution with the least total commute time and the maximum equivalent social cost of GHG and air pollution emissions. In contrast, solution S_{205} is the solution with the highest total commute time and minimum total equivalent social cost of GHG and air pollution emissions. Eight other non-dominated solutions as well as the existing commute are highlighted in Figure 3.4. Figure 3.4 shows the frequency of commuters using drive-alone, public transportation, bike, walk, and carpool for the identified solutions from S_1 to S_{205}. For example, solution S_1, which has the least total commute time, identified one commuter drives alone, 10 commuters pick up 10 other commuters, while no commuters use public transportation, biking, or walking as they will result in increasing the total commute time. In addition, S_{205}, which has the least equivalent cost of GHG and air pollution emissions, identified three commuters drive alone, five commuters use public transportation, and 13 commuters use biking. It should be noted that the selection of driving cars option decreases and the selection of biking option increases as the model moves from S_1 (minimum commute time) to S_{205} (minimum emissions), as shown in Figure 3.4.

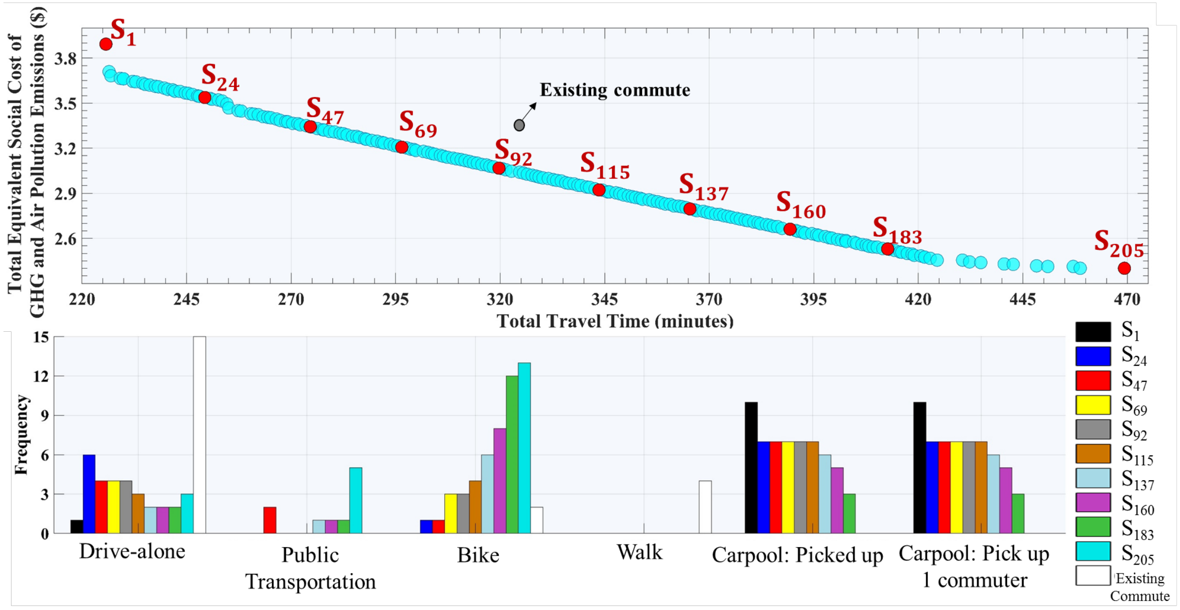

Figure 3.4 Frequency of commuters for solutions S_1 to S_{205}.

The optimization model is designed to generate a commute plan, which includes individual-specific commute recommendations, differences in commute times, and available incentives, as shown in Table 3.5 for solution S_{103} with commuter's tolerance of 25 minutes per trip. The results show that MBCOS recommended commute mode, daily commute duration and difference from existing commute time, equivalent social cost of GHG and air pollution emissions, daily commute cost, and individualized monetary incentive. The results of this solution show negative values for the difference in commute time for commuters 2, 7, 16, 18, and 20. These negative values resulted because these commuters originally walked, except for commuter 2, who originally biked, and the model recommended that commuter 2 bike or drive to work, resulting in a shorter commute time. The model is designed to calculate the incentives for commuters based on the increase in their commute time proportional to their hourly rate ($18/hour for this case study). For example, the commute time of commuter 5 increased by 28.2 minutes as a result of using public transit and bike. Such a change resulted in a monetary incentive of (28.2/60) × $18 = $8.5, as shown in Table 3.5. Furthermore, MBCOS is designed to identify reduction in environmental impacts expressed in equivalent social cost of GHG emissions and air pollution, as shown in Table 3.5. Finally, findings in Table 3.5 demonstrate that the optimization model solution extended trip duration of only four commuters (commuters 4, 5, 10, and 13) out of 21. Accordingly, 12 commuters were not impacted or potentially had their commute time reduced while 7.7% of emission reduction was achieved. It should be noted that solution S_{115} is a mid-solution and further reductions in GHG and air pollution emissions can be achieved as the solutions get closer to the extreme solution S_{205}.

Table 3.5 Selected commute alternatives and their difference in commute time and incentives of a mid-solution, S_{103}, for 25-min commuter's tolerance

Commuters	Original commute mode	Recommended commute mode	Daily commute time (min)	Difference in the daily commute time (min)	Reduction of equivalent social cost of GHG and air pollution emissions	Daily commute cost	Incentive ($)	Reduction in commute cost
1	Drive-alone	Drive-alone	6.0	0.0	0%	$3.7	-	0%
2	Bike	Drive-alone	3.5	-7.6	NA	$1.9	-	NA
3	Drive-alone	Drive-alone	16.9	0.0	0%	$8.5	-	0%
4	Drive-alone	Bike	31.2	20.5	-100%	-	$6.9	-37%
5	Drive-alone	Public Transportation + Bike	59.8	28.2	-46%	$0.3	$8.5	56%
6	Drive-alone	Drive-alone	9.2	0.0	0%	$6.3	-	40%
7	Walk	Bike	5.0	-10.5	NA	-	-	NA
8	Drive-alone	Drive-alone	15.5	0.0	0%	$12.4	-	1%
9	Drive-alone	Drive-alone	14.4	0.0	0%	$10.9	-	12%
10	Drive-alone	Drive-alone	23.0	15.9	-100%	-	$4.8	-20%
11	Bike	Bike	13.2	0.0	NA	-	-	NA
12	Drive-alone	Drive-alone	18.7	0.0	0%	$14.4	-	0%
13	Drive-alone	Bike	28.6	25.2	-100%	-	$6.2	8%
14	Drive-alone	Drive-alone	6.4	0.0	0%	$3.9	-	0%
15	Drive-alone	Drive-alone	15.1	0.0	0%	$10.1	-	22%
16	Walk	Bike	2.4	-12.1	NA	$1.4	-	NA
17	Drive-alone	Bike	7.4	0.0	0%	$3.9	-	0%
18	Walk	Bike	4.0	-30.3	NA	$1.9	-	NA
19	Drive-alone	Drive-alone	22.7	0.0	0%	$21.3	-	0%
20	Walk	Bike	5.0	-10.4	NA	-	-	NA
21	Drive-alone	Drive-alone	23.6	0.0	0%	$15.8	-	0%

3.4.2 Sensitivity Analysis

A sensitivity analysis was conducted to analyze the sensitivity of the model results to variations in (1) optimization model parameters to generate Pareto-optimal solutions, (2) commuters' origin and departure times, and (3) commuter home addresses. The number of Pareto-optimal solutions that can be identified using ε-constraint method is dependent on the selected increments (ε value). Selecting small value of ε (*i.e.,* ε = 0.00045% = 0.001 minutes of the optimization objective range) will result in a large number of single objective optimization problems, which will require long computation time and effort. On the other hand, selecting large value of ε (i.e., ε = 4.5% =10 minutes of the optimization objective range) will result in a limited number of single-objective optimization problems with short computation time. However, the quality of the obtained Pareto-optimal solutions might be jeopardized, as many of the Pareto-optimal solutions might be overlooked.

To analyze the sensitivity of MBCOS to time increments in identifying optimal solutions, various ε values (10, 1, 0.1, 0.01, and 0.001 minutes) were used to identify the number of Pareto-optimal solutions for 5-, 10-, 15- and 25-minute commute time tolerances, as shown in Figure 3.5. For example, when the incremental steps are set to 10 minutes, only 23 Pareto-optimal solutions are identified for a commute time tolerance of 25 minutes, as shown in Figure 3.5. As the incremental steps decrease to 0.001 minutes, 209 Pareto-optimal solutions are identified, as shown in Figure 3.5. However, the computational time to generate these Pareto-optimal solutions is 28.6 hours, as shown in Table 3.6. Selecting incremental steps 10 times larger than 0.001 minutes will result in the 205 number of Pareto-optimal solutions, only missing four solutions; while the computational time is significantly reduced to 2.83 hours, as shown in Table 3.6. Accordingly, the minimal ε value to generate all Pareto-optimal solutions for the community of 21 students is 0.001 minutes. It should be noted that an ε value of 0.10 minutes identified the majority of Pareto-optimal solutions (189 solutions), as shown in Figure 3.5, and with computational time of 0.211 hours. Furthermore, decision makers can identify a good variety of Pareto-optimal solutions with short computational time for ε value of 10 minutes or 1 minute, as shown in Figure 3.5.

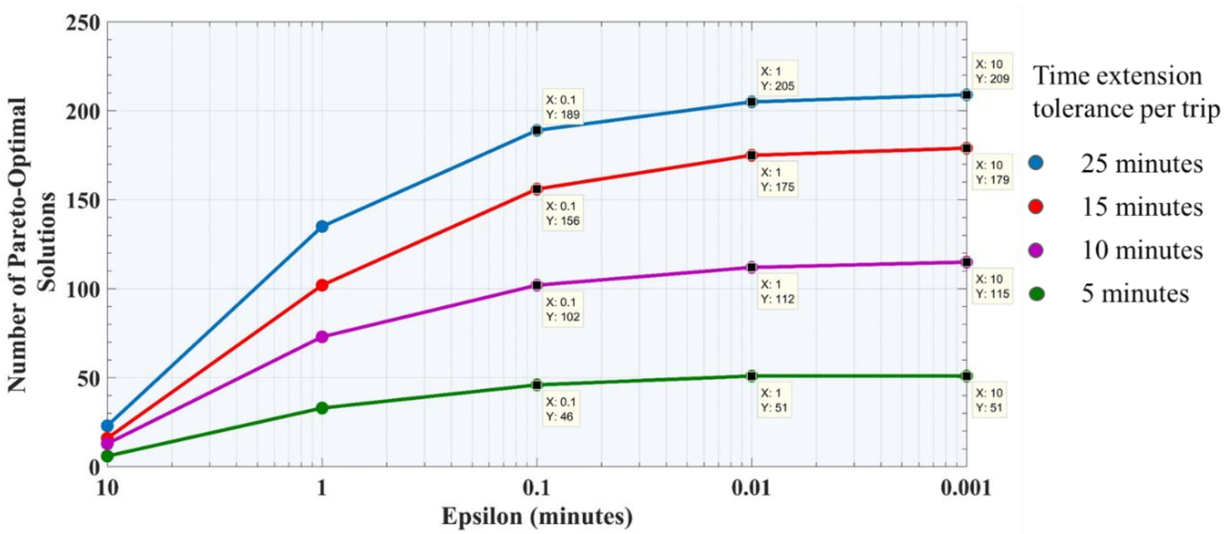

Figure 3.5 Sensitivity analysis for different values of ε

Table 3.6 Computational time of different values of increments (ε)

Increments (minutes)	ε = 10	ε = 1	ε = 0.1	ε = 0.01	ε = 0.001
Computational Time (hrs.)	0.011	0.026	0.211	2.83	28.6

To analyze the sensitivity of the optimization model to the input data of commuters in terms of home addresses, the home address for commuters 3 and 11 were changed where their travel time was reduced by 50%. After identifying the Pareto-optimal solutions for the case of 25 minutes' commute time tolerance, the average total commute time for all the Pareto-optimal solutions was identified at 284.6 minutes, which is a reduction of ≈ 14.2% compared with the average total commute time for all Pareto-optimal solutions identified in the original case study (331.7 minutes). Furthermore, the average equivalent social cost of GHG and air pollution emissions was reduced from $3.01 to $2.23, representing a 26% reduction in negative environmental impacts. It should be noted that when commuter home addresses are closer to the destination, not only does the contribution of these commuters to GHG and air pollution emissions reduce when either driving or public transportation, it also makes green commute modes, such as biking and walking, more feasible and thus presents opportunities for greater reductions in negative environmental impacts.

Finally, to analyze the sensitivity of the optimization model to the departure and arrival times of the commuters, these times were changed in the morning and afternoon to make them the same for commuters 3 and 11 as commuter 1. This change allowed commuters 1, 3, and 11 to be able to carpool, which was not feasible in the original case study. This change resulted in an 18.5% reduction of the average total commute time for all the Pareto-optimal solutions as compared with the original case study.

Furthermore, the reduction in the negative environmental impacts was calculated at 19.2%, which is less than the reduction achieved by changing the commuters' home addresses. The reason for this difference is that changing the departure times of commuters 3 and 11 resulted in more feasible carpooling options, which still contribute to the GHG emissions of the commuters; however, changing the home location of commuters 3 and 11 closer to the business location allowed biking and walking, which are associated with zero emissions, to be feasible.

3.4.3 Discussion of System Performance

In general, with increases in commuter tolerance and allowing for greater flexibility in departure and arrival times, the model recommends switching from riding in cars to carpooling, biking, or public transit and biking to minimize negative environmental impacts. The model generally recommends biking over walking and skateboarding; however, the multi-objective optimization seeks to minimize environmental impacts simultaneously with total commute time, and biking is faster than either walking or skateboarding. It should be noted that skateboarding may appear to be a relatively minor mode of transportation, but it was included in this case study as an intermediary transportation option relevant to a community of students and allowed greater granularity for the optimization model in the context of the analyzed case study.

One notable observation based on the study's findings is that the social cost of negative environmental impacts is small compared with the value of people's time. Specifically, as discussed before, the model assigned social costs as estimated by the EPA and Victoria Transport Policy Institute for GHG, NO_X, and VOC emissions (Environmental Protection Agency, 2014; Victoria Transport Policy Institute, 2013). As can be seen in Figure 3.3 and Figure 3.4, the social cost of the negative environmental impacts is undervalued as compared with commuter's value of time. For example, social cost of negative environmental impacts is reduced up to \$3.45 per day for increase in the students commute time up to 470 minutes. However, the model assigns a value of \$18/60 minutes of people's time based on student hourly pay rates at the university. Accordingly, the results of the developed model show that the estimated social costs of the negative environmental impacts by EPA and Victoria Transport Policy Institute for GHG, NO_X, and VOC emissions are undervalued as compared with commuters' value of time. Finally, it should be noted that the model identifies the importance of GHG, NO_X, and VOC emissions according to their reported social cost by EPA and Victoria Transport Policy Institute; however, different evaluations of the social costs for GHG, NO_X, and VOC emissions could lead to different model results, and may, in fact, be desirable based on differing perceived importance from business owners or governments.

4. CASE STUDY

A case study of government employees was analyzed to evaluate the performance of the system. The department of human resources sent an invitation email to all employees who worked in the county buildings. The invitation email asked the employees to create user accounts and fill out commute information and commute needs surveys on the website (www.commuteopt.com). The employees were provided with video tutorials on how to use the MBCOS website to specify their commute information and needs. The case study was designed to be performed in a four-week duration. Employees were given two weeks to fill out the surveys; the authors then performed the system computations and uploaded the results to the website, and lastly, employees took one week to check the system recommended commute plans. Forty-seven participants filled out the two surveys specifying their home and work addresses, existing commute mode, willingness to change their commute behavior, ranges of their departure and arrival times, intermediate stops, and parking information. Figure 4.1 shows 47 commuters' home locations with nine distinctive work locations.

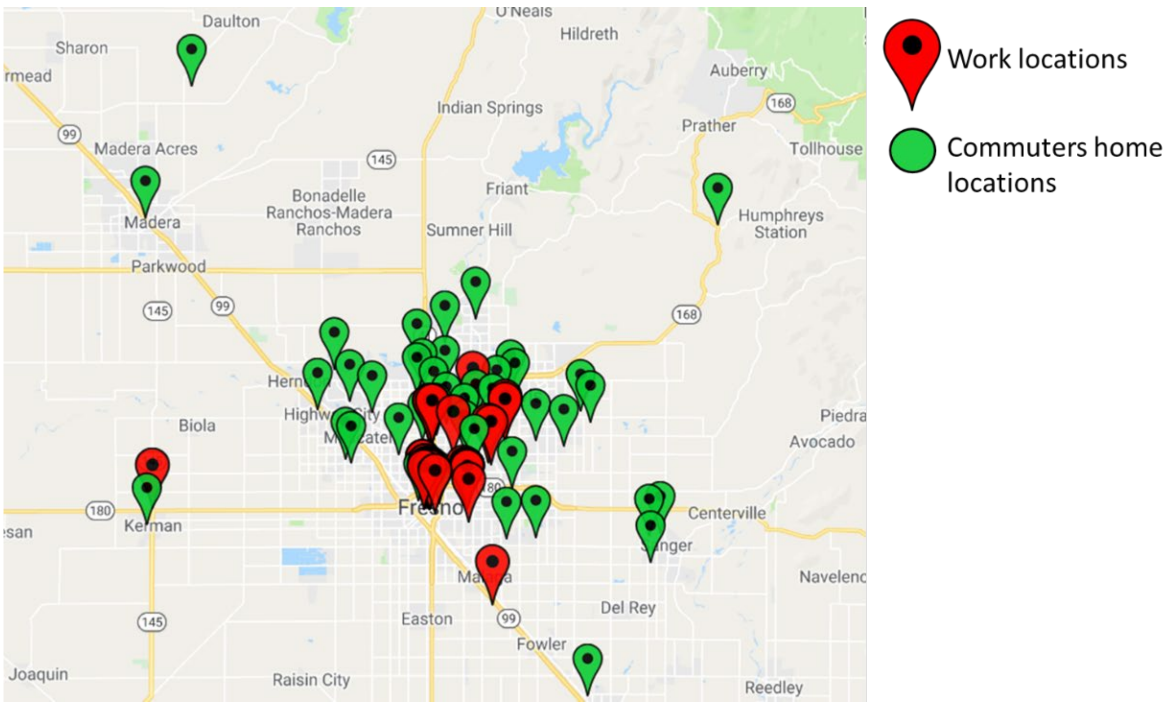

Figure 4.1 Commuters' home and work locations

Travel survey data of commuters collected from the website were fed into the GIS network to calculate the travel attributes of each employee, including the travel time, distance, cost, and equivalent social cost of GHG and air pollution emissions from the origin to destination addresses for outgoing and return trips, and for every commute mode, as shown in Table 4.1.

Table 4.1 Sample of calculated outgoing travel attributes for Commuter 1 by the GIS network

	Travel Attributes	Commute Alternatives				
		Drive alone	Public Transit & Walk	Public Transit & Bike	Walk only	Bike only
Commuter 1	Travel Time (min.)	36.2	161.7	136.3	314.9	100.3
	Travel Distance (mile)	15.0	16.0	16.0	14.6	14.7
	Energy Consumption (gallons of gasoline)	0.6	0.6	0.6	0.0	0.0
	Equivalent Social Cost of GHG and Air Pollution Emissions ($)	0.6	0.6	0.6	0.0	0.0
	Travel Cost ($)	9.9	1.3	1.4	0.0	1.5

The decision variables of the optimization model were used to model all the commute modes, including drive-alone, use of public transit and walk or bike, bike only, walk only, and carpool with one employee. The four types of constraints, model logic constraints, consistency constraints, convenience constraints, and incentive constraints were integrated in the model based on the commute preferences and needs collected from the travel surveys on the website. The constraints were formulated based on the employees' required arrival time in the outgoing trip and departure time in the return trip, preferred transportation alternatives, possibility of carpooling, flexibility in extending commute time, and business incentive budget. The objective function was designed to identify the optimal selection of commute modes for each employee to minimize the total GHG and air pollution emissions. The computations of the optimization model were then executed on a personal computer, the Intel Core (TM) i5 2.5GHz processor and 8GB RAM. The computations of the optimization model, including the modeling of optimization problem, identifying the optimal solution, and generating the results took approximately four minutes.

Figure 4.2a shows the percentage reduction in GHG and air pollution emissions compared with the existing commute behavior for weekdays and based on commute tolerance of 20 minutes. The reason that the reductions in GHG and air pollution emissions vary from one day to another is due to employees' different commute needs on each day. For example, two employees might be recommended to carpool on Monday since their required arrival time at work is less than a specified tolerance. However, these two employees cannot carpool on Tuesday due to significant difference in their arrival times. On average, the total reduction of GHG and air pollution emissions was calculated at 23.4%, as shown in Figure 4.2a. The resultant change in the employees' commute behavior can lead to reductions in the total commute time, cost, distance, and energy, as shown in Figure 4.2b. The greatest reduction was achieved in the total commute cost at 25% since the employees can save the driving cost, including the fuel consumption, maintenance, and parking cost, by changing their commute behavior.

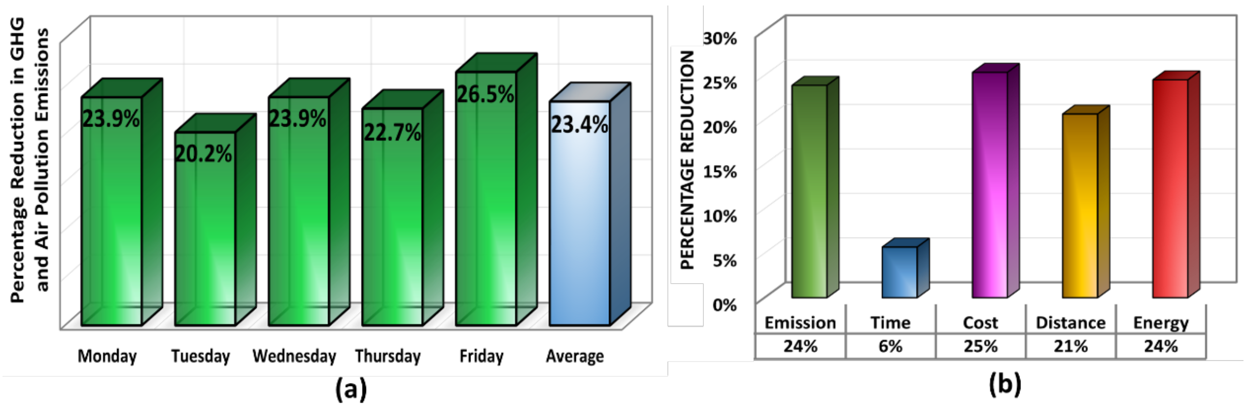

Figure 4.2 Percentage reductions – (a) in GHG and air pollution emissions for weekdays; (b) breakdown of total travel time, cost, distance and energy for Monday

Figure 4.3 shows the frequency of the recommended optimal commute modes, and the existing commute behavior on Monday. Out of the 45 employees who need to commute on Monday, 43 employees originally drive alone, while only one employee uses public transit and walks, and one employee walks to the work destination. Based on the generated solution by MBCOS, 15 employees are recommended to drive alone to maintain their convenience. For example, an employee who is not flexible to extend his/her commute time more than 20 minutes cannot receive a recommendation that increases his/her commute more than 20 minutes. Furthermore, MBCOS recommended 11 employees to carpool. The two employees who previously walked and used public transit and walked were recommended to commute the same as their existing commute behavior. The rest of the recommended commute plan is shown in Figure 4.3.

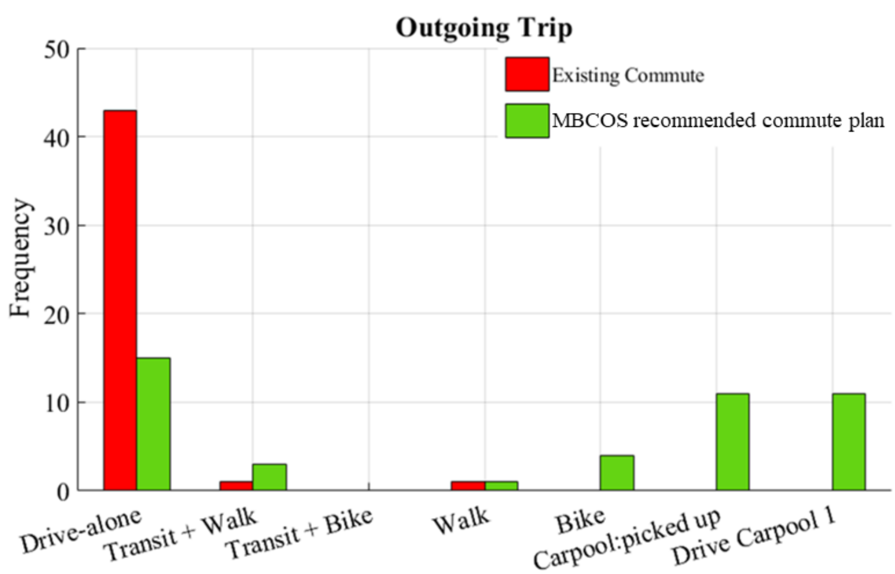

Figure 4.3 Frequency of the recommended commute modes

As mentioned in model implementation step, the optimization model generates individualized commute plans for employees of the business. The individualized commute plans show details of recommended commute mode for each employee, changes in commute time, monetary incentives and cost savings, as well as changes in daily commute footprints, as shown in Table 4.2 and Table 4.3 for Monday commute. It should be noted that recommended commuting options for outgoing and return trips can be different. For example, commuter 43 is recommended to drive alone for the outgoing trip, but for the return trip, he/she is recommended to carpool and pick up commuter 39, as shown in Table 4.2.

Table 4.2 Sample of recommended commute modes and commute time impacts

#	Existing Mode	Recommended Mode		Outgoing Trip			Return Trip		
		Outgoing Trip	Return Trip	Existing Travel Time (min.)	Recommended Travel Time (min.)	Reduction in Travel Time (min.)	Existing Travel Time (min.)	Recommended Travel Time (min.)	Reduction in Travel Time (min.)
1	DRIVING	'Carpool: Picked up by commuter 2'	'Carpool: Picked up by commuter 2'	36**	19**	17	35	20	15
2	DRIVING	'Carpool: pick up commuter 1'	'Carpool: pick up commuter 1'	36	38	-2	31	32	-1
3	DRIVING	'Driving alone'	'Driving alone'	20	20	0	20	20	0
4	DRIVING	'Driving alone'	'Driving alone'	26	26	0	19	19	0
5	DRIVING	'Driving alone'	'Driving alone'	26	26	0	23	23	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
43	DRIVING	'Driving alone'	'Carpool: pick up commuter 39'	56	56	0	56	70	-14
44	TRANSIT + WALKIN G	'Transit + Walk'	'Transit + Walk'	69	69	0	61	61	0
45	DRIVING	'Carpool: pick up commuter 10'	'Driving alone'	36	50	-14	35	35	0
46*				[]					
47	DRIVING	'Driving alone'	'Driving alone'	28	28	0	26	26	0

* Commuters 35 & 46 do not need to commute on Monday

** Commuter reported a 15-minute walk from parking to work address and a 2-minute search for a parking spot

Table 4.3 Sample of monetary incentives and savings, and commute impacts of employees

#	Monetary Incentives and Savings ($)						Recommended Commute Footprint			Existing Commute Footprint			Reductions		
	Monetary incentives from riders outgoing	Monetary incentives from riders return	Monetary incentives to driver outgoing	Monetary incentives to driver return	Outgoing saving	Return saving	Cost ($)	Time (min.)	Emissions ($)	Cost ($)	Time (min.)	Emissions ($)	Cost ($)	Time (min.)	Emissions ($)
1	0.0	0.0	5.9	5.5	3.9	3.2	11.8	39.5	0.0	19.0	71.5	0.5	7.1	32.0	0.5
2	5.9	5.5	0.0	0.0	5.9	5.3	8.1	70.6	0.5	19.5	66.3	0.5	11.4	-4.3	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	11.6	39.8	0.3	11.6	39.8	0.3	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	8.6	45.1	0.2	8.6	45.1	0.2	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0	0.0	11.1	48.8	0.3	11.1	48.8	0.3	0.0	0.0	0.0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
43	0.0	14.8	0.0	0.0	0.0	12.7	43.2	125.7	1.4	55.9	111.4	1.4	12.7	-14.4	0.0
44	0.0	0.0	0.0	0.0	0.0	0.0	2.5	129.7	0.1	2.5	129.7	0.1	0.0	0.0	0.0
45	9.5	0.0	0.0	0.0	6.6	0.0	24.6	85.2	0.8	31.2	70.5	0.8	6.6	-14.7	-0.1
46*							[]								
47	0	0	0	0	0	0	10.26	53.23	0.23	10.26	53.23	0.23	0	0	0

* Commuters 35 & 46 do not need to commute on Monday

5. WIDESPREAD APPLICATIONS AND IMPACTS

U.S. DOTs are focusing on promoting and developing transportation programs that can reduce VMT per capita. Therefore, it is essential to analyze the widespread applications and impacts of the developed transportation programs or systems based on estimated reductions in VMT per capita. The analysis of widespread impacts of the system provides clear understanding of the efficiency of developed systems to achieve the GHG and air pollution emissions reduction targets. Furthermore, the analysis provides a clear vision on the resultant impacts of the developed system and therefore supports the transportation planners and decision makers in promoting the use of the developed system.

The widespread applications and impacts of transportation programs or systems can be analyzed by generalizing the obtained results from the case studies. However, because of their limited number, the case studies may be extended by randomly generated problems, which can be a good representation of the entire population. Accordingly, randomly generated problems can be verified by the results of the case studies. The objective and methodology of analyzing widespread impacts are next discussed in detail.

5.1 Objectives and Methodology of Analyzing Widespread Applications

The primary objective is to analyze the widespread applications and impacts of the developed system by generalizing the obtained results from the case studies across the United States. The analysis of widespread application of MBCOS focuses on estimating the reduced VMT per employee of businesses with different numbers of employees. Additionally, the analysis of widespread application of MBCOS can lead to a clear understanding of reductions in transportation GHG and air pollution emissions, total commute cost, time, distance, and energy.

Two case studies were analyzed to estimate the reductions in VMT per employee. The reduction of VMT per employee as a result of using MBCOS at businesses of different numbers of employees is calculated. The reduction in VMT per employee of using MBCOS at businesses with different numbers of employees was estimated for each case study, as shown in Table 5.1. For case study one, 5, 15, and 23 employees were randomly selected, and the IR was estimated. For example, the IR of using MBCOS for randomly selecting five employees in the case study is 0.9 VMT per employee in a single day, as shown in Table 5.1. As the number of employees increases, more carpooling options become available and thus more reduction in VMT can be achieved along with IR increases. Similarly, the IR for 5, 15, 25, and 35 employees was estimated for case study 2, as shown in Table 5.1.

Table 5.1 Estimated reduction of VMT per employee for different numbers of employees in the case studies

Case study 1 (single business)		Case Study 2 (multi-business)	
Number of employees	VMT reduction per employee	Number of employees	VMT reduction per employee
5	0.90	5	0.48
15	1.98	15	1.09
23	2.60	25	1.61
		35	1.96

Due to the limited number of employees in the case studies, and to generalize the VMT reduction per employee for businesses with greater number of employees, several single business problems up to 160 employees are randomly generated and verified by the results of the case studies. Each generated problem consists of employees randomly selected from the 160 employees, as shown in Figure 5.1. Accordingly, the average reduction in VMT per employee of each problem is calculated for businesses of 1, 10, 60, and 160 employees, as shown in Table 5.2.

Table 5.2 Average reduction in VMT per employee of businesses with different numbers of employees

Randomly generated single business problems	
Number of employees	Reduced VMT per employee
1	0
10	1.35
60	3.86
160	4.13

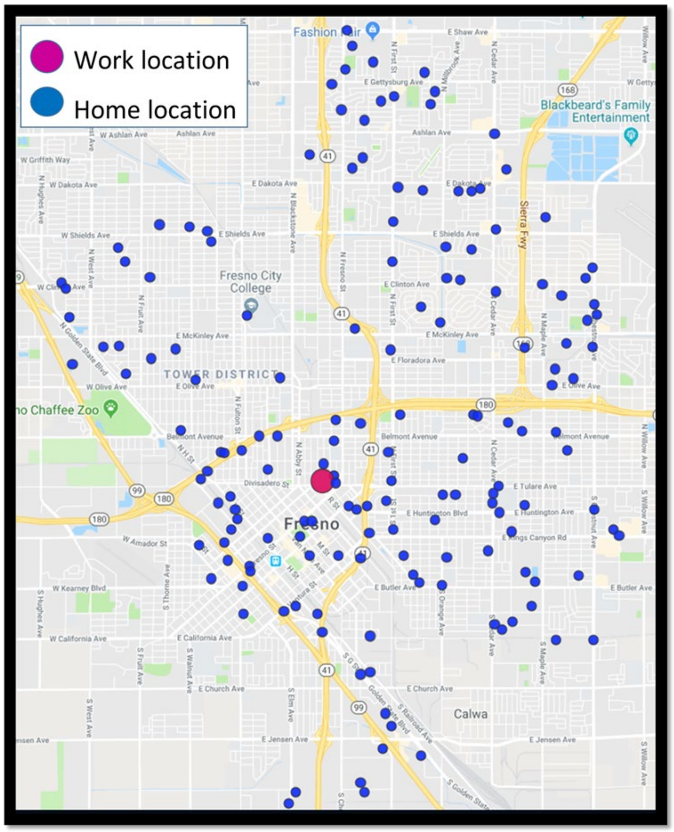

Figure 5.1 Randomly generated single business problem of 160 employees

To generalize the estimated reductions of VMT per employee for businesses of different sizes, a logarithmic function is fitted to the IR values of randomly generated problems, as shown in Figure 5.2. To verify the estimated reductions in VMT per employee of the randomly generated problem, the results of the case studies are shown in Figure 5.2. The logarithmic function fitted to the IR values shows that as the number of employees increases in a business, the IR increases and reaches a plateau. This IR estimation function based on the randomly generated problems is $y = 0.7952\ln(x) - 0.2482$ where x is the number of employees who participate in the use of MBCOS and follow the recommendations. Accordingly, for businesses of different sizes, the IR is calculated using the same function.

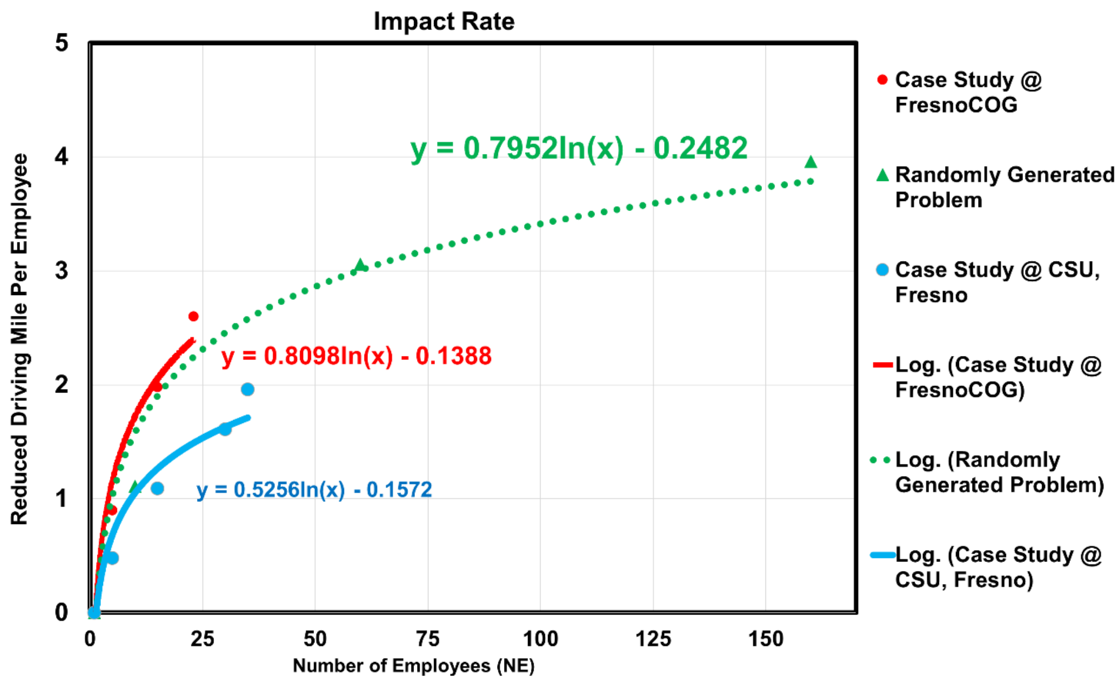

Figure 5.2 Estimated reductions in VMT for businesses of different number of employees

5.2 Analysis of Widespread Application of MBCOS

The widespread application (WSA) of MBCOS is analyzed in three different phases: (1) Phase 1: short-term WSA, 1 – 3 years; (2) Phase 2: medium-term WSA, 3 – 6 years; and (3) Phase 3: long-term WSA, 6 – 9 years. The number of businesses using MBCOS and participation rates of employees who use MBCOS increase over time; however, the number of employees who follow the MBCOS recommendations is assumed to be fixed. In Phase 1, the number of businesses using MBCOS is estimated at 35%, where 20% of their employees participate in the use of MBCOS and 50% of them follow the recommended commute plans of MBCOS, as shown in Figure 5.3. In Phase 2, the number of businesses using MBCOS increases to 55%, where 40% of their employees participate in the use of MBCOS and 50% of them follow the recommended commute plans of MBCOS, as shown in Figure 5.3. In Phase 3, the number of businesses using MBCOS increases to 75%, where 60% of their employees participate in the use of MBCOS and 50% of them follow the recommended commute plans of MBCOS, as shown in Figure 5.3.

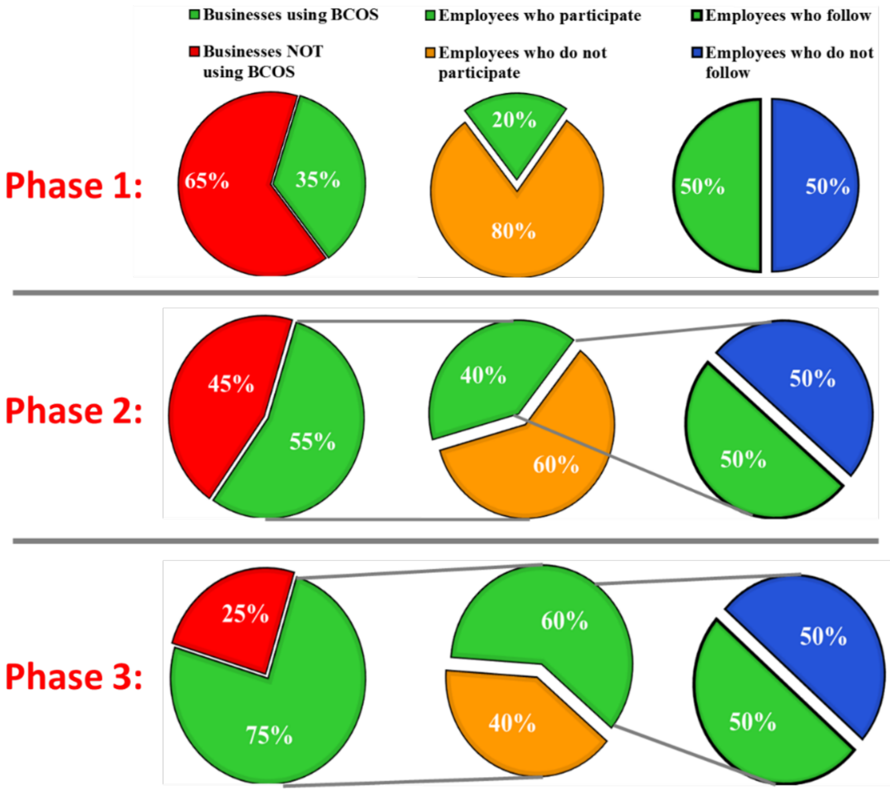

Figure 5.3 Three phases of widespread application of MBCOS

The number of businesses with different numbers of employees for all counties across the United States are obtained from United States Bureau of Labor Statistics, which categorizes businesses in every county to less than 20 employees, 20 – 99 employees, 100 – 499 employees, and more than 500 employees (U.S. Bureau of Labor Statistics, 2018). For example, Table 5.3 shows the data of number of businesses and their employees in Denver, CO.

Table 5.3 Data of number of businesses and their employees in Denver, CO

State Name	County Name	Firm size	Number of firms	Total number of employees	Average number of employees per business
Colorado	Denver	Fewer than 20 employees	15,530	58,366	10
Colorado	Denver	20 – 99 employees	1,950	66,020	60
Colorado	Denver	100 – 499 employees	809	60,855	300
Colorado	Denver	500+ employees	1,412	214,503	500

The IR of businesses of different sizes is calculated based on the average number of employees of the businesses that participate and follow the MBCOS recommendations and logarithmic trendline for randomly generated problems. Table 5.4 shows the calculated IR at businesses in Denver with different sizes for the three different phases. For businesses of less than 20 employees, IR would be zero during the first two phases, while it is expected to be increased to 0.48 VMT per employee per day in the third phase.

Table 5.4 VMT reduction per employee using MBCOS

County Name	Firm Size	Impact Rates (IR)		
		Phase 1	Phase 2	Phase 3
Denver	Fewer than 20 employees	0	0	0.48
Denver	20-99 employees	0.41	1.5	2.18
Denver	100-499 employees	1.94	3.04	3.72
Denver	500+ employees	2.44	3.53	4.21

Based on the calculated IR for every firm size, and the number of employees who participate and follow the MBCOS recommendations, the total reduced VMT is calculated. Figure 5.4 shows the estimated annual reduction of VMT in Denver, CO, for businesses of different numbers of employees and throughout the three phases. During the first phase of WSA, the total reduction in VMT is 10K reaching to 110K and 382K in the second and third phases, respectively.

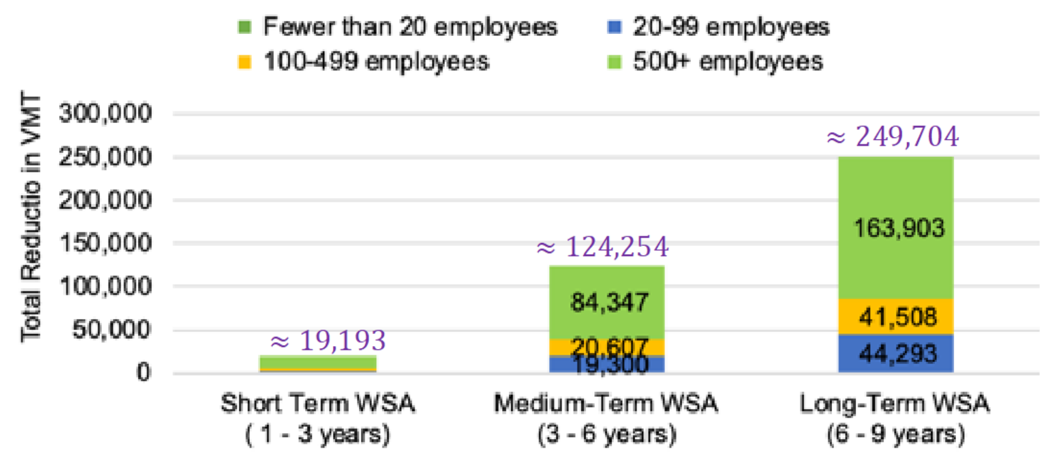

Figure 5.4 Estimated annual reduction of VMT in Denver, CO

The existing business-related VMT is calculated by multiplying the number of employees and the average business VMT per employee. The average business VMT per employee based on the randomly generated problems is 16 miles per day for every employee. For example, if a business has 100 employees, the existing VMT of the business is 100×16 miles $= 1{,}600$ miles. The percentage reduction in VMT compared with the existing VMT shows the percentage reduction in business commute emissions. Figure 5.5 shows the percentage reduction in business commute emissions, based on different firm sizes and across the three phases.

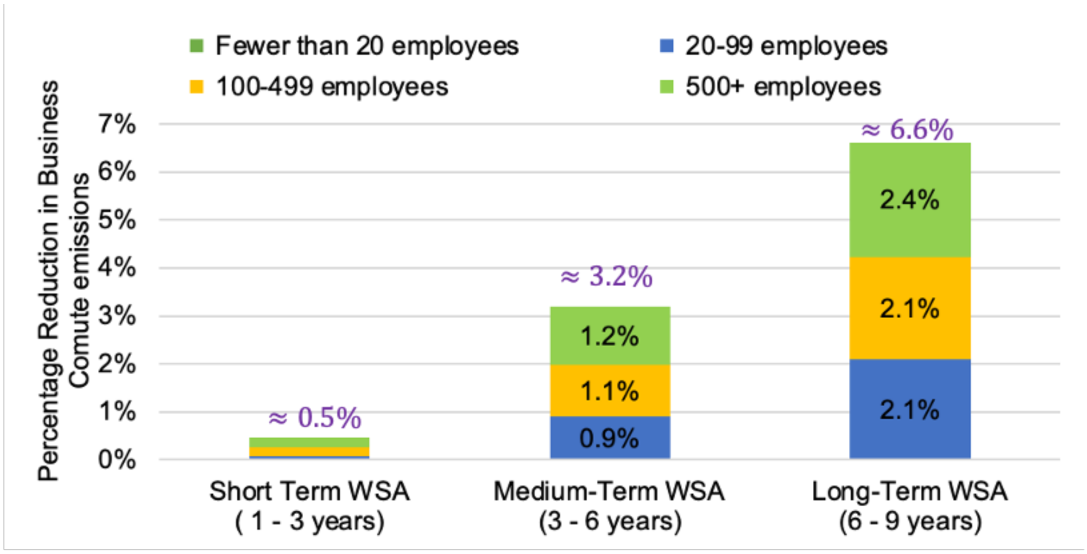

Figure 5.5 Percentage reduction in business commute emissions

Similarly, the annual VMT reduction in Colorado, USA, can be estimated. Figure 5.6 shows the estimated annual reduction of VMT in Colorado, USA, for businesses of different numbers of employees and throughout the three phases. During the first phase of WSA, the total reduction in VMT is 0.1 million, and it increases to 1.4 million in second phase, and 4 million in the third phase.

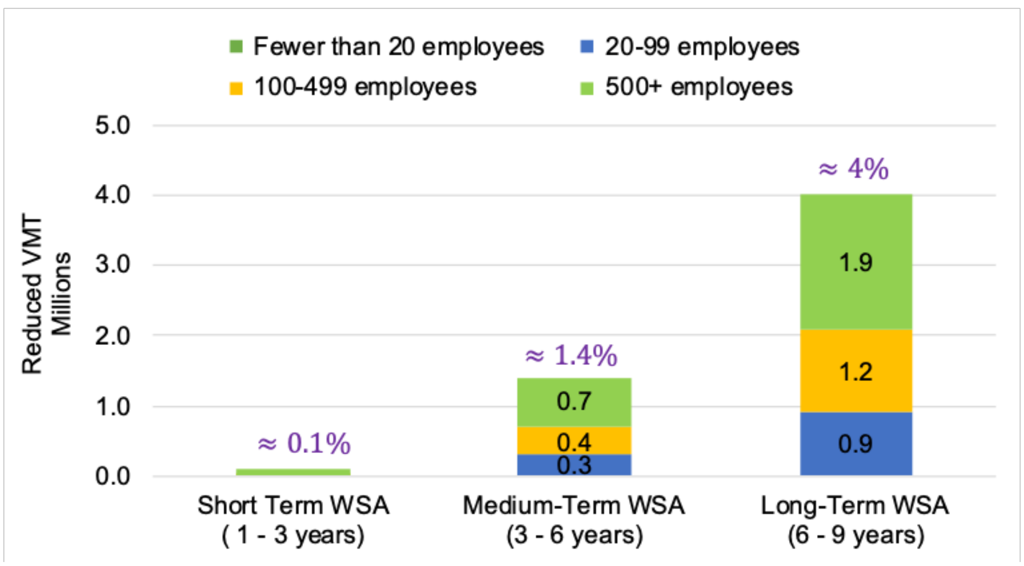

Figure 5.6 Estimated annual VMT reduction in Colorado, USA

Figure 5.7 shows the percentage reduction in business commute emissions in Colorado, USA, based on different firm sizes and across the three phases. In the first phase, the percentage of business commute emissions is limited to 0.02% compared with the existing business commute emissions. However, in the second phase, the percentage of business commute emissions increases to 1%, and in the third phase it increases to nearly 9.3%.

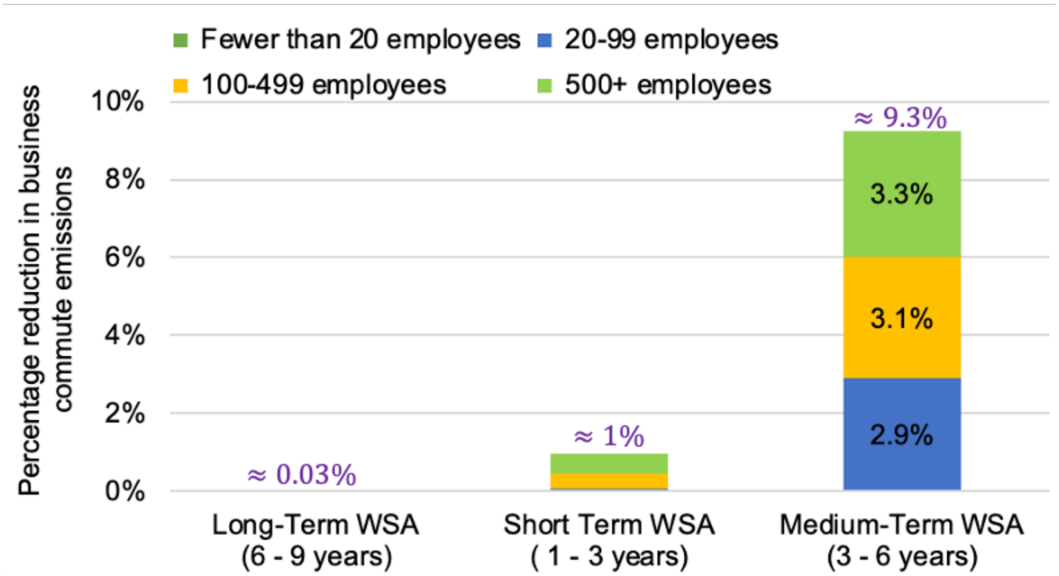

Figure 5.7 Percentage reduction in business commute emissions, Colorado, USA

The total reduction in transportation GHG emissions due to the WSA of MBCOS in the United States can be estimated based on the expected reductions in VMT of all U.S. states. Figure 5.8 shows the percentage reduction in total transportation GHG emissions as a result of WSA of MBCOS. In the first phase, the percentage of reduction in total transportation GHG emissions is 0.06%, 0.25% in the second phase, and 0.57% in the third phase, as shown in Figure 5.8.

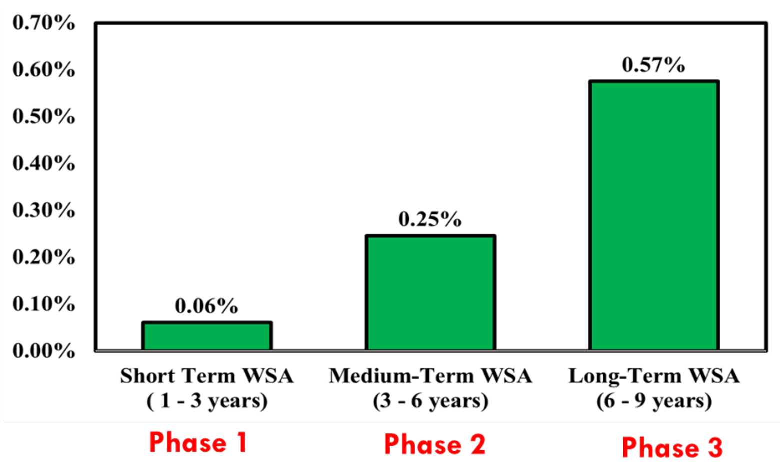

Figure 5.8 Estimated reduction in total transportation GHG emissions, United States

Based on the estimated reduction in VMT across the entire United States, the total reduction in total commute cost, time, and energy consumption can be estimated. Figure 5.9 shows the annual reduction in total commute cost, time, and energy consumption as well as the total annual reduction in VMT.

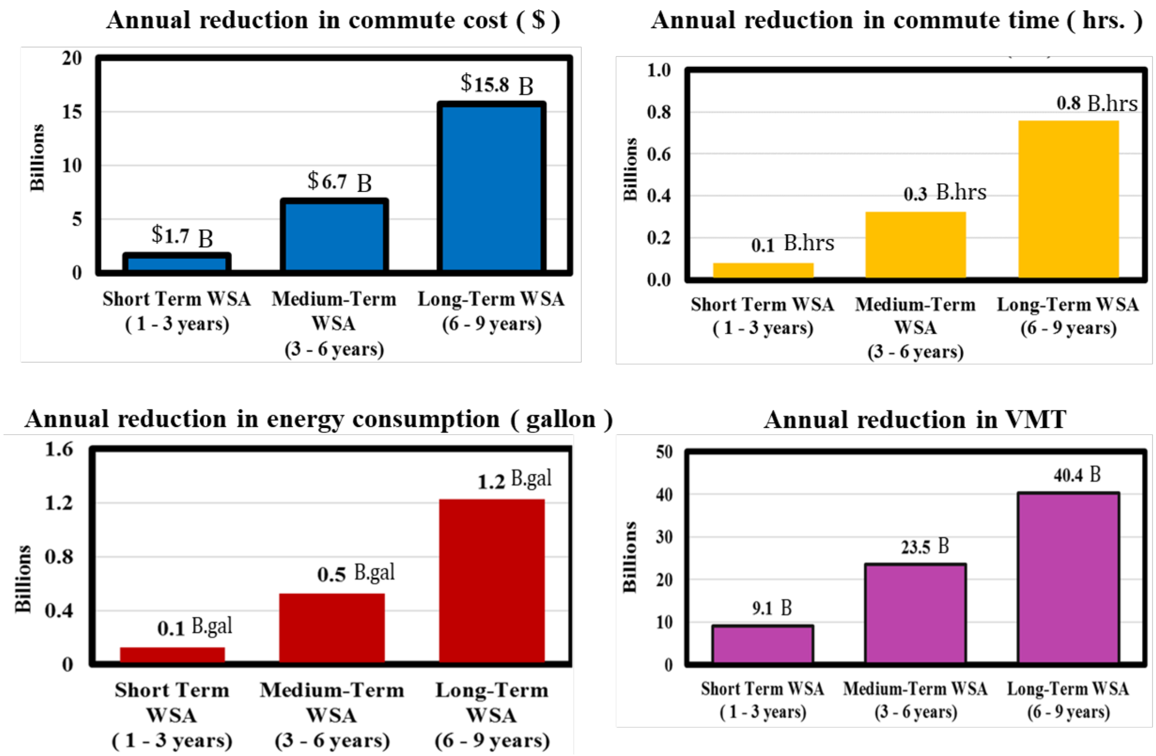

Figure 5.9 Estimated reduction in total commute cost, time, energy and VMT, United States

The widespread application of MBCOS was analyzed considering three different phases, short-term (1 – 3 years), medium-term (3 – 6 years), and long-term (6 – 9 years). The number of businesses and number of employees who participate in using MBCOS is assumed to be increased over time, while the number of employees who follow the optimal recommended commute plans of MBCOS is assumed to be fixed at 50%. These assumptions are dependent on the support of U.S. DOTs. The analysis shows that MBCOS is capable of reducing the business commute emissions by 9.3% in Colorado, USA, after the third phase of the widespread application of MBCOS. The reductions at larger size businesses in terms of number of employees seem to be greater. Additionally, MBCOS is effective in reducing the total transportation emissions by 0.57% in the third phase of widespread application of the system. Furthermore, MBCOS is effective in reducing the total commute cost, time, and energy consumption. For example, in the second phase of widespread application of the system the reduced annual total commute cost is $6.7 billion, which is nearly four times larger than that in the first phase, and $15.8 billion in the third phase.

6. DISCUSSION & CONCLUSIONS

This report presented the development of an innovative Multiple Business Commute Optimization System (MBCOS) designed to identify optimal commute plans of employees at multiple businesses that are co-located or employees of a business with different work locations. MBCOS minimizes the total GHG and air pollution emissions while maintaining preferences and convenience of business commuters. MBCOS is designed to reduce emissions by influencing and incentivizing commuters at businesses to change their behavior from drive alone to alternative commute modes, such as using public transit, carpooling using existing vehicle, biking, walking, or using a combination of these modes. MBCOS is designed to provide monetary incentives from business owners to incentivize employees to follow recommended commute plans. The monetary incentives are provided to support business commuters in changing their existing commute behavior, and to cover the inconvenience of commuters due to extended commute time of using alternative commute modes, such as bike, walk, carpool, and use of public transit. This new system consists of a web-based travel survey, GIS network, and an optimization model. The web-based travel survey includes a website, www.commuteopt.com, which is designed to facilitate the collection of travel survey data. These data include employees' commute information such as origin and destination addresses, arrival and departure times to/from work, and original commute method. The GIS network focuses on calculating the travel attributes, including GHG and air pollution emissions, tleravel time, cost, energy consumption, and burned calories for every possible commute mode, such as drive-alone using existing vehicle, use of public transit, bike, walk, and carpool with other commuters. The optimization model is designed to identify optimal commute behavior change of employees from drive-alone to alternative commute modes that result in minimum total GHG and air pollution emissions. To evaluate the performance of the developed system and demonstrate its unique capabilities, a case study was analyzed. The results of the case study, based on 47 employees, showed that the GHG and air pollution emissions can be reduced by 23.4% on average while allowing up to 20 minutes time extension to existing commute behavior of the employees. Additional reductions can be achieved in other case studies if the following conditions exist: (1) better access for employees to public transit systems, which will allow more feasible alternatives for public transit use, and (2) higher parking costs, which can promote the use of carpooling and public transit use due to commute savings. Furthermore, it is believed that as the number of participating employees increases, more carpooling options can be identified and thus more commute cost savings and reductions in GHG and air pollution emissions can be achieved.

The widespread application of MBCOS is analyzed for its potential application in Colorado and the United States. The authors are currently working on expanding the capabilities of the developed MBCOS to model more alternative commute modes, such as using Uber or Lyft, upgrading to hybrid and electric vehicles, and carpooling with two or three employees. These new capabilities can achieve higher reductions in GHG and air pollution emissions.

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