A MULTI-CLASS, MULTI-CRITERIA BICYCLE TRAFFIC ASSIGNMENT MODEL

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ABSTRACT

Cycling is gaining popularity both as a mode of travel in urban communities and as an alternative mode to private motorized vehicles due to its wide range of benefits (health, environmental, and economical). However, this change in modal share is not reflected in current transportation planning and travel demand forecasting modeling processes. The existing practices to model bicycle trips in a network are not sophisticated enough to describe the full cyclist experience in route decision-making. This is evident in the existing practices' methodology: the all-or-nothing assignment uses single attributes such as distance, safety, or a composite measure of safety multiplied by distance. The purpose of this paper is to develop a multi-class and multi-criteria bicycle traffic assignment model that not only accounts for multiple user classes by acknowledging that there are different types of cyclists with varying levels of biking experience, but also for relevant factors that may affect each user classes behavior in route choice decisions. The multi-class, multi-criteria bicycle traffic assignment model is developed in a two-stage process. The first stage examines key criteria to generate the set of non-dominated (or efficient) routes for each user class, and the second stage determines the flow allocation to efficient routes by user class. Numerical experiments are then conducted to demonstrate the two-stage approach for the multi-class, multi-criteria bicycle traffic assignment model.

Keywords: Traffic assignment; multi-objective shortest path; multi-class; cyclist route choice; bicycle

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1 INTRODUCTION

The recent rise in cycling in many cities can be attributed to municipal efforts to promote the health, environmental, and economical benefits of non-motorized modes (Yang and Zacharias, 2016; Zhu and Diao, 2018). Cycling's increased mode share consequently leads to a higher demand for reliable bicycle traffic assignment methodology. Unfortunately, there is only a limited quantity of tools and methods available for modeling bicycle trips in a network. Only a few research efforts focus on network analysis for bicycle trips (e.g., Klobucar and Fricker, 2007; Broach et al., 2011; Mekuria et al., 2012). While these methods do provide pioneering efforts to develop traffic assignment methods for bicycle trips, they are too simplistic. Given an origin-destination (O-D) trip table that describes the travel demand pattern within a study area, the traffic assignment problem is to determine the flows by assigning the O-D trip table to routes in a transportation network according to some behavioral route choice rules. However, current methods are based simply on the all-or-nothing (AON) assignment method, which uses a single attractiveness measure such as distance, safety, or a composite measure of safety multiplied by distance. This is problematic because cyclists travel not only on one route, but on many different routes based on different levels of biking experience and based on different preferences which impact the combinations of criteria for selecting a bicycle route. The AON simplistic modeling of cyclists' route choice will affect the bicycle traffic assignment results and may influence investment decisions for bicycle infrastructures. Therefore, it is imperative to incorporate heterogeneous cyclist route choice behaviors in the bicycle traffic assignment model in order to enhance the accuracy of bicycle traffic forecasts.

The route choice model for bicycles is much more complex than the model for private motorized vehicles because there are many influential factors affecting cyclist route choice decisions. According to empirical studies on bicycle route analysis, cyclists choose routes based on any number of criteria that may include distance, number of intersections, road grade, bicycle facility, and safety. In identifying the factors that affect cyclist route choice decisions, Stinson and Bhat (2003), Hunt and Abraham (2007), and Broach et al. (2011) discovered travel distance/time was significant while Hopkinson and Wardman (1996), Akar and Clifton (1996), Dill and Carr (2009) and Winters et al. (2011) revealed safety was likewise influential. Sener et al. (2009) confirmed that the travel distance/time and safety were important factors in cyclist route choice. Mekuria et al. (2012) suggested that stress is an important factor in cyclist trip-making behavior. Handy and Xing (2011) analyzed the key factors in commuting trips in six small U.S. cities, while Heinen and Handy (2012) compared the factors with respect to health, environmental friendliness, and travel enjoyment in bicycle cities like Davis in the United States and Delft in the Netherlands.

In route choice modeling, one of the major difficulties is the choice set generation (Prato, 2009). In bicycle route choice modeling, many empirical studies have indicated that cyclists choose routes based on several criteria (e.g., distance, number of intersections, road grade, bike facility, safety, etc.). Hence, a few papers using empirical data for bicycle route choice set generation have been developed in the literature. For example, Hood et al. (2011) adopted the doubly stochastic method of Bovy and Fiorenzo-Catalano (2007) to pre-generate a bicycle route set, while

Menghini et al. (2008) used a breadth-first search link elimination method to generate a bicycle route set. Both studies used GPS tracking data to generate the bicycle route choice set, albeit different in methodologies, for the bicycle traffic assignment procedure. Ehrgott et al. (2012) developed a bi-objective routing model as an alternative to determining the route choice set for commuter cyclists based on two criteria, i.e., travel time and suitability of a route for cycling. As mentioned by the authors, their study serves as a starting point for the bicycle traffic assignment problem with the aim that it can be used as part of the travel demand forecasting procedure. Recently, Wang et al. (2018) applied the bi-objective routing model to examine the trade-off between travel time and pollutant dose as a means to support healthy route choice for commuter cyclists. In a similar vein, Ryu et al. (2018) developed a two-stage bicycle traffic assignment model for a single user class with only two criteria (i.e., distance related attributes and safety related attributes).

While it is important to analyze the various criteria that affect cyclist decision making, it is also critical to consider multiple user classes in a bicycle traffic assignment model. According to a study on Portland cyclists (Geller, 2006), residents can be categorized into four types of cyclists: "*the strong and the fearless*", "*the enthused and the confident*", "*the interested but concerned*", and "*no way no how*". Each group has distinct relationships and attitudes with bicycle transportation that may affect their preferences in route choice. Feizi et al. (2019) acknowledged the need to consider different cyclists' skill levels by developing an instrumented probe bicycle equipped with various sensors to measure the relationship between cycling dynamic performance and characteristics of roadway environment. Consequently, the purpose of this research is to build on these existing studies by developing a multi-class and multi-criteria bicycle traffic assignment model that explicitly considers multiple user classes and multiple criteria affecting cyclist route choice decisions for estimating bicycle volumes on a transportation network. The multi-class component aims to model the different types of cyclists by segmenting them into multiple user classes according to the cyclists' characteristics, while the multi-criteria component aims to model the relevant factors (e.g., least elevation gain route, shortest distance route, safest route, least accident route, bike friendly route, lowest pollution route, route with green space, etc.) that affect each user classes behavior in making route choice decisions. By integrating both the multi-criteria and multi-class components into the model, this research seeks to gain a more comprehensive understanding of cyclist decision making and of bicycle network analysis. Specifically, the multi-class, multi-criteria bicycle traffic assignment model extends the two-stage process developed by Ryu et al. (2018) to not only account for multiple user classes by acknowledging that there are different types of cyclists with varying levels of biking experience, but also for relevant factors that may affect each user classes behavior in route choice decisions. The first stage adopts a multi-objective shortest path algorithm to generate a set of non-dominated (or efficient) routes for each user class based on multiples criteria (i.e., route distance, route safety, and route pollution), and the second stage uses a path-size logit (PSL) model as a multi-path traffic assignment method to determine the flow allocation to efficient routes by user class. The main difference lies in the choice set generation method (i.e., different empirical-based methods versus a multi-objective shortest path algorithm). Note that the two-stage process developed in this paper can be extended to include congestion effect similar to the stochastic user equilibrium (SUE) traffic assignment method for motorized vehicles (Prashker and Bekhor, 2004; Chen et al., 2012).

The remainder of this paper is organized as follows. After the introduction, the multiple bicycle user classes and criteria are described, followed by the presentation of the two-stage traffic assignment procedure, a numerical experiment to demonstrate the features and applicability of the proposed two-stage procedure, and some concluding remarks.

2 METHODOLOGY

This section describes the methodology for modeling the multi-class, multi-criteria bicycle traffic assignment procedure as shown in Figure 1. There are two stages in this procedure: (1) route generation for determining individual route choice sets based on the relevant criteria for each user class, and (2) traffic assignment for allocating flows to routes of each user class. The multi-class, multi-criteria bicycle traffic assignment model assigns the bicycle O-D matrices of multiple user classes (assumed to be given from the mode choice step of a four-step travel demand forecasting model) based on the path-size logit (PSL) stochastic traffic assignment model using the relevant individualized route sets to obtain the bicycle traffic flow pattern on the network.

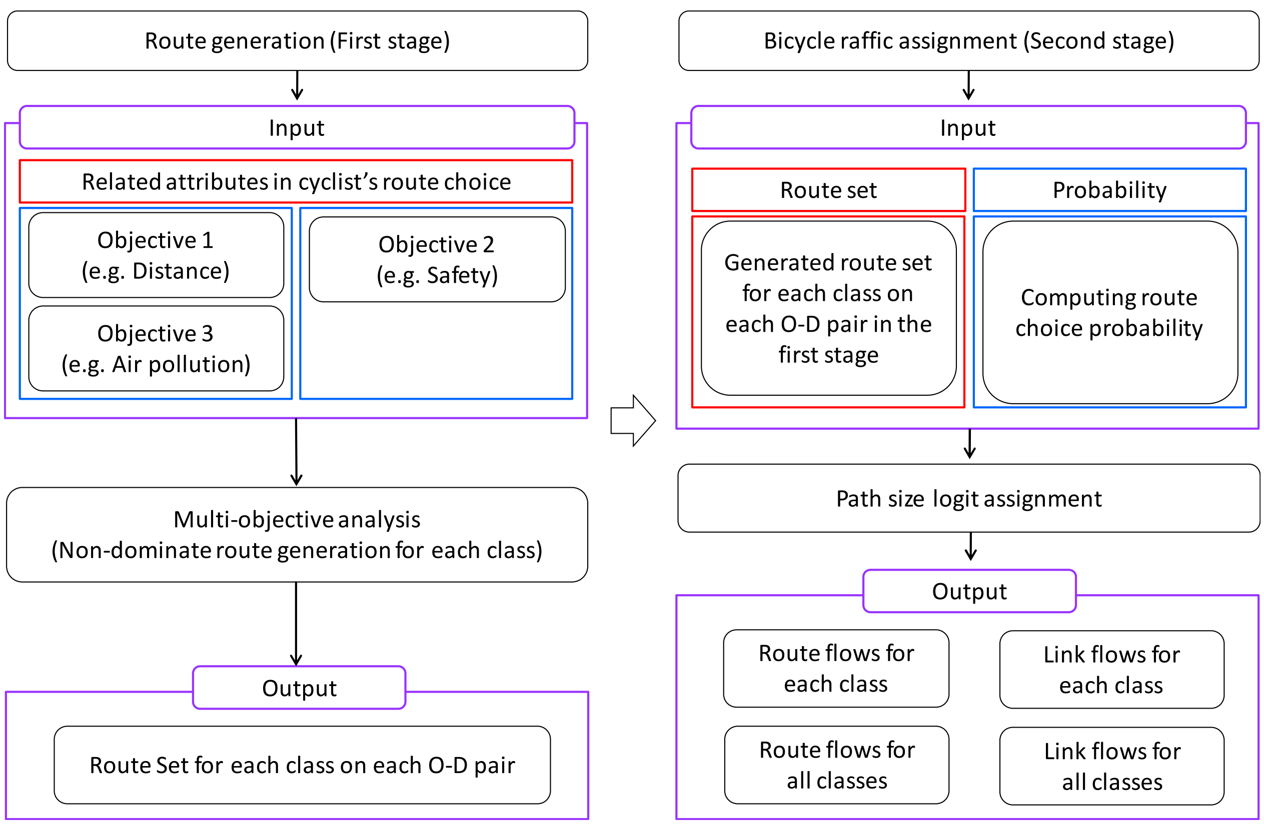


Figure 1. Multi-class, multi-criteria bicycle traffic assignment procedure

The following subsections describe the multiple user classes, the multiple criteria affecting cyclists' route choice decisions, the multi-objective shortest path algorithm, and the PSL stochastic traffic assignment model for flow allocations to the efficient routes.

2.1 Multiple User Classes

Based on the Portland study (Geller, 2006), it has been suggested that there are four types of cyclists as indicated in Figure 2. These four types of cyclists are: (1) strong and fearless, (2) enthused and confident, (3) interested but concerned, and (4) no way no how. Strong and fearless cyclists represent less than 1% of the population; they are the rare daily commuters who "*will ride regardless of roadway conditions.*" Enthused and confident cyclists represent 7% and are semi-regular cyclists who are "*comfortable sharing the roadway with automotive traffic, but they prefer to do so operating on their own facilities*" (e.g., bicycle lanes and bicycle boulevards). The interested but concerned cyclists, who represent 60% of the population, are irregular cyclists who are "*curious about cycling*" but are concerned with riding a bicycle. Lastly, no way no how travelers represent 33% and are simply "*not interested in bicycling at all, for reasons of topography, inability, or simply a complete and utter lack of interest*". The study also noted that "*the separation between these four broad groups is not generally clear-cut*". However, this classification with percentages for each user class serves as a good foundation to develop a multi-class version of the multi-criteria bicycle traffic assignment model.

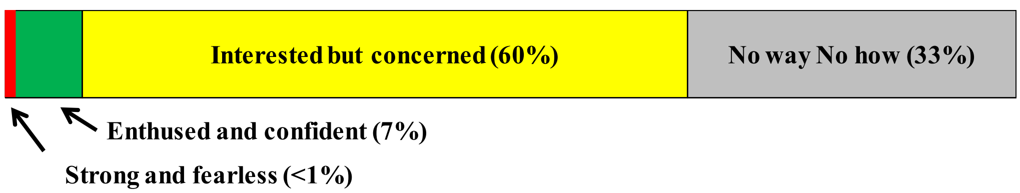


Figure 2. Four types of cyclists in Portland (Geller, 2006)

2.2 Criteria Affecting Cyclists' Route Choice

Empirical studies on bicycle route choice analysis indicate that cyclists choose routes based on a number of criteria. Examples of key criteria include travel distance or time (Stinson and Bhat, 2003; Hunt and Abraham, 2007; Broach et al., 2011, Chen et al., 2018), safety (Hopkinson and Wardman, 1996; Akar and Clifton, 2009; Dill and Carr, 2003; Winters et al., 2011, Lee and Abdel-Aty, 2018), stress (Mekuria et al. 2012), travel distance/time and safety (Sener et al., 2009), etc. Willis et al. (2015) summarized the influential factors that may affect bicycle travel with 24 relevant papers published between 2005 and 2015. Route planners acknowledge the diversity and quantity of influential factors by providing a variety of bicycle routes that optimize different factors (e.g., least elevation gain route, shortest distance route, safest route, least accident route, bike friendly route, lowest pollution route, route with green space, etc.) to serve the needs of different cyclists.

In this study, three key criteria (e.g., route distance-related attributes, route safety-related attributes, and route pollution-related attributes) are adopted to develop the multi-class, multi-criteria bicycle traffic assignment model. These criteria are composed of many factors identified in the literature for modeling bicycle route choice decisions. For example, criterion related to route safety incorporates many of the cyclist safety concerns that Hopkinson and Wardman (1996), Akar and Clifton (2009), Dill and Carr (2003) and Winters et al. (2011) uncovered in their research regarding route choice. Figure 3 provides a summary of the different factors by organizing them into four groups and showing how the factors contribute to the three key criteria used to model cyclists' route choice decisions for different user classes. The four factor category groups include (a) motorized traffic related data (e.g., traffic volume, proportion of heavy vehicles, speed limit, etc.) used in the Highway Capacity Manual (HCM, 2010), (b) network topology (e.g., link distance, slope, intersection configuration, etc.), (c) bicycle facility (e.g., bike lane, bike path, bike parking, etc.), and (d) user preferences (e.g., road cognition, environmental impact, bike friendliness, etc.). These factors are further combined into the three key criteria (distance-related attributes, safety-related attributes, and air pollution-related attributes) to determine cyclist route choice decisions for different user classes. The details of these three key criteria are described in the following subsections.

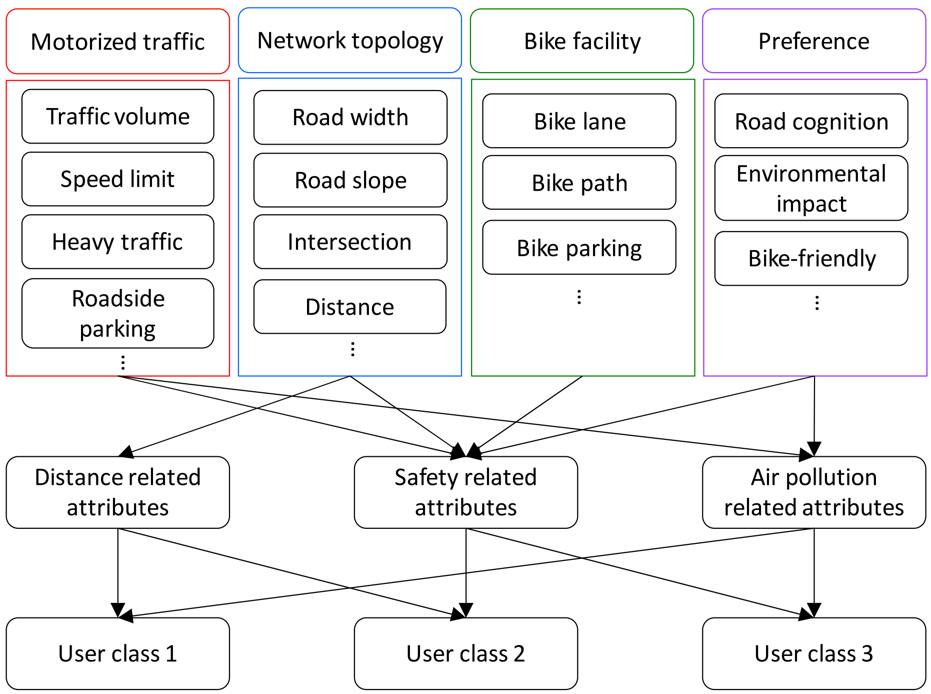


Figure 3. Three key criteria affecting cyclists' route choice decisions

Route distance

As a composite measure, route distance is composed of both the sum of link distances along the route and the turning delays at intersections that the route passes through. Intersection delays are especially significant for cyclists; they have been shown to be a major deterrent against route choice. To address the unit incompatibility problem between link length and intersection turning delay (link length measures length in meters while intersection turning delay measures time in seconds), delay is converted to an equivalent distance unit with an appropriate conversion factor. The route distance can be computed as follows:

$$d_k^{rs} = \sum_{a \in A} l_a \delta_{ka}^{rs} + \sum_{a \in IN_i} \sum_{b \in OUT_i} cf_i^t d_i^t \delta_{ka}^{rs} \delta_{kb}^{rs}, \quad \forall k \in \mathrm{K}_{rs}^m, rs \in \mathrm{RS} \tag{1}$$

where d_k^{rs} is the distance (in meters) on route k connecting O-D pair rs; l_a is the length (in meters) on link a; δ_{ka}^{rs} (δ_{kb}^{rs}) is the route-link indicator; 1 if link a (b) is on route k between O-D pair rs and 0 otherwise; cf_i^t is the delay conversion factor to an equivalent distance unit (in meters/second) for turning movement t at intersection i; d_i^t is the delay (in seconds) of turning movement t at intersection i; A is the set of links; IN_i and OUT_i are the sets of links terminating into and originating out of intersection i; RS is the set of O-D pairs; and K_{rs}^m is the set of routes connecting O-D pair rs of class m. The route distance in Eq. (1) can be computed by summing the link distances (first term) and the intersection turning delays (second term) on that path. Note that the first term can further include other attributes such as penalty for links with elevation gain, restriction on gradient, or any attribute that has an impact on the physical geometry of the link. On the other hand, the second term can further include signalized delays at intersections. Note that using two consecutive route-link indicators $\delta_{ka}^{rs}\delta_{kb}^{rs}$ (i.e., link a and link b along route k between origin r and destination s), turning movement penalty (left, through, and right) can be appropriately added to the route cost without the need to expand the network to represent turning movements for all approaches of each intersection (Chen et al., 2012).

Route bicycle level of service (BLOS)

The safety aspect of bicycle facilities (or the suitability for bicycle travel) can be assessed by a variety of different measures. Lowry et al. (2012) reviewed thirteen methods used in the research community and found that most measures score the perceived safety of bicycle facilities by using a set of variables to represent conditions of the roadway and environment that affect a cyclist's comfort level. To account for the different attributes contributing to the safety of bicycle routes in this paper, we decided to use the Highway Capacity Manual's (2010) bicycle level of service (BLOS) measure as a surrogate measure. The BLOS measure is a state-of-the-art bicycle safety measure that is widely used as a guide for bicycle facility design across the United States; therefore, we consider BLOS to be a reasonable method for measuring bicycle safety. It should be noted that the BLOS measure is not the only measure of bicycle safety and that other bicycle safety measures can be easily substituted into our proposed framework for modeling cyclists' route choice behavior. The route BLOS measure is a composite measure based on the average segment bicycle score on a route (*ABSeg*), the average intersection bicycle score on a route (*ABInt*), and the average number of unsignalized intersections or the number of driveways per mile on a route (*Cflt*). Based on the HCM (2010), the route BLOS score can be computed as follows.

$$BLOS_k^{rs} = 0.200 \cdot (ABSeg_k^{rs}) + 0.030 \cdot \left(\exp(ABInt_k^{rs})\right) + 0.050 \cdot (Cflt_k^{rs}) + 1.40 \quad \forall k \in \mathrm{K}_{rs}^m, rs \in \mathrm{RS} \qquad (2)$$

where $BLOS_k^{rs}$ is the bicycle level of service on route k between O-D pair rs; $ABSeg_k^{rs}$ is the length weighted average segment bicycle score on route k between O-D pair rs ($ABSeg_k^{rs} = \left(\sum_{a \in A} l_a \cdot Bseg_a \cdot \delta_{ka}^{rs}\right) \Big/ \left(\sum_{a \in A} l_a \cdot \delta_{ka}^{rs}\right)$); $ABInt_k^{rs}$ is the average intersection bicycle score on route k between O-D pair rs ($ABInt_k^{rs} = \sum_{i \in I} \sum_{a \in IN_i} \sum_{b \in OUT_i} IntBLOS_i \delta_{ka}^{rs} \delta_{kb}^{rs} \Big/ N_k^{rs}$); N_k^{rs} is the number of intersections on route k between O-D pair rs; $Cflt_k^{rs}$ is the number of unsignalized intersections or the number of driveways per mile on route k between O-D pair rs; $Bseg_a$ and $IntBLOS_i$ are respectively the bicycle scores on link a and intersection i provided in Eqs. (3) and (4).

$$\begin{aligned} BSeg_a = 0.507 \ln\left(\frac{v_a}{4 \cdot PHF_a \cdot La_a}\right) + 0.199 Fs_a \left(1 + 10.38 \cdot HV_a\right)^2 + \\ 7.066\left(\frac{1}{PC_a}\right)^2 - 0.005(We_a)^2 + 0.76 \end{aligned} \tag{3}$$

$$IntBLOS_i = -0.2144 \cdot Wt_i + 0.0153 \cdot CD_i + 0.0066\left(\frac{Vol15_i}{L_i}\right) + 4.1324 \tag{4}$$

where

PHF_a : peak hour factor of link a

HV_a : proportion of heavy motorized vehicles of link a

We_a : average effective width on outside through lane of link a (m)

Fs_a : effective speed factor on link a

La_a : total number of directional through lanes on link a

v_a : directional motorized vehicle volume on link a (vph)

PC_a : *FHWA's* five-point pavement surface condition rating on link a

Wt_i : width of outside through lane plus paved shoulder (including bike lane where present) of intersection i

CD_i : crossing distance, the width of the side street (including auxiliary lanes and median) of intersection i

$Vol15_i$: volume of directional traffic during a 15-minute period of intersection i

L_i : total number of directional through lanes of intersection i

The details of the BLOS score development can be found in NCHRP Report 616 (Dowling et al. 2008). The calculation of segment and intersection BLOS scores requires volume and speed of motorized vehicles, proportion of heavy motorized vehicles, pavement surface condition, configuration of intersection layout, such as average effective width of outside through lane, crossing distance, number of directional through lanes, etc. The motorized traffic data are obtained exogenously by solving the multi-class traffic assignment problem with multiple vehicle types. See Figure 3 for an illustration of the factors used to compute the BLOS score.

Route pollution

In some cities where air quality is inadequate, cyclists may prefer a route that avoids pollution. For simplicity, we choose carbon monoxide (CO), which has been shown as an important indicator for the level of atmospheric pollution, as a representative attribute of air quality. In addition, CO is a convenient measure because methodologies have been developed for computing the network-wide CO pattern and empirical data is available for analysis. However, other pollutants can be modeled in a similar manner (see Pankow *et al.* (2014) for a more detailed evaluation of cyclists' exposure to traffic related air pollution). In this study, the route pollution is computed as follows:

$$CO_k^{rs} = \sum_{a \in A} g_a(v_a) \cdot \delta_{ka}^{rs}, \quad \forall\, k \in \mathrm{K}_{rs}^m, rs \in \mathrm{RS} \tag{5}$$

where $g_a(v_a)$ is the amount of CO pollution in grams per vehicle (g/veh) on link (or segment) a. To estimate the amount of CO pollution, we adopt the nonlinear macroscopic model of Wallace et al. (1998):

$$g_a(v_a) = 0.2038 \cdot t_a(v_a) \cdot \exp\left(\frac{0.7962 \cdot l_a}{t_a(v_a)}\right) \tag{6}$$

where v_a is the motorized vehicle volume on link a (note that bicycle link flows are denoted by x_a); $t_a(v_a)$ is the travel time (in minutes) of link a; and l_a is the length (in kilometers) of link a. To calculate the amount of CO pollution, $g_a(v_a)$, the traffic volume, v_a, and travel time, $t_a(v_a)$, of motorized vehicles need to be estimated for each link in the network. This is done by a multi-class traffic assignment procedure for motorized vehicles (see Section 4.2 on the characteristics of the Winnipeg network). Note that the above CO measure has also been adopted as a proxy for air quality in Yin and Lawphongpanich (2006), Nagurney et al. (2010), Chen and Xu (2012), Chen and Yang (2012), Chen et al. (2011), Ng and Lo (2013), Xu et al. (2013, 2015), and Szeto et al. (2014).

2.3 Multi-Objective Shortest Path Procedure

The three key criteria identified in Section 2.2 will be used in the multi-objective shortest path procedure to generate non-dominated (or efficient) routes relevant to each user class. The solution procedure for multiple objective shortest path problems involves the generation of a set of non-dominated (or Pareto) routes because there may not be a single optimal route that dominates all other routes in all objectives. This detail makes the solution procedure for the multi-objective shortest path problem distinct from that of the single objective shortest path problem. In the literature, there are several solution procedures that have been developed for solving the multi-objective shortest path problem, including the label correcting approach (Skriver and Andersen, 2000), the two-phase method (Ulungu and Teghem, 1995), the label setting approach (Tung and Chew, 1992), and the ranking method (Climaco and Martins, 1982). See Raith and Ehrgott (2009) for a comparison of different solution strategies for solving the bi-objective shortest path problem.

Note the multi-objective shortest path procedure used to generate the set of efficient bicycle routes for each user class needs to handle a non-additive route cost structure. Of the objectives (or criteria) considered for bicycle route generation, route BLOS is non-additive. It is a composite measure based on the average segment bicycle score (*ABSeg* given in Eq. (3)) on a route, the average intersection bicycle score (*ABInt* given in Eq. (4)) on a route, the average number of unsignalized conflicts/driveways per mile on a route (Cflt), and the route constant (1.40). The route constant in Eq. (2) is an empirically calibrated constant by HCM, and it is assumed to be the same for all routes and all O-D pairs. These four terms (*ABSeg*, *ABInt*, *Cflt*, and 1.40) are non-additive despite that the sum is additive. Hence, the overall route BLOS is not additive along a route. Also note that the numerical value of BLOS is to be minimized (i.e., a smaller value means a better LOS) when using the multi-objective shortest path algorithm.

In this paper, the ranking method proposed by Climaco and Martins (1982) was modified for solving the multi-objective shortest problem with a non-additive route cost structure. In the ranking method, no weights are needed since the method explicitly generates the set of non-dominated routes. It should be noted that using a weighted-sum approach, which converts multiple objectives into a single objective, can only generate one optimal route for a given weight combination. Although multiple routes can be generated by varying the weight combinations, it is well known in the literature that some non-dominated routes in the duality gap may not be generated by any weight combinations (Daskin, 1995). See Section 3.1 for the implementation details of the modified ranking procedure.

2.4 Path-Size Logit Stochastic Traffic Assignment

In the stochastic traffic assignment problem, route overlapping is one of the major concerns in modeling route choice decisions (see Prashker and Bekhor (2004) and Chen et al. (2012) for a detailed description of the different approaches for handling the route overlapping problem). In this paper, the path-size (PS) factor (Ben-Akiva and Bierlaire, 1999) is adopted to handle the route overlapping problem due to its simplicity and relatively better performance compared to other closed-form models (e.g., cross-nested logit (CNL) model and paired combinatorial logit (PCL) model). The PS factor accounting for different path sizes is determined by the length of links within a route and the relative lengths of routes that share a link as follows:

$$PS_k^{rs} = \sum_{a \in k} \left(\frac{l_a}{L_k^{rs}} \right) \cdot \left(\frac{1}{\sum_{l \in \mathrm{K}_{rs}^m} \delta_{la}^{rs}} \right), \qquad \forall \ rs \in \mathrm{RS}, k \in \mathrm{K}_{rs}^m \tag{7}$$

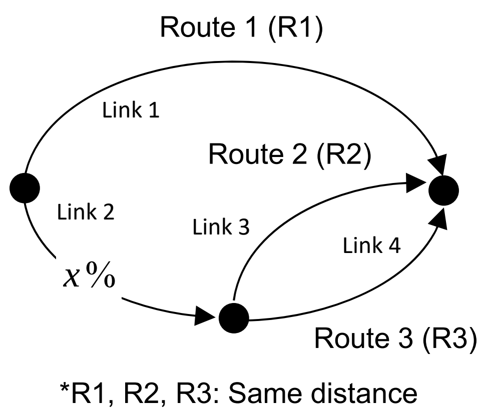
where PS_k^{rs} is the PS factor of route k between O-D pair rs; l_a is the length of link a; and L_k^{rs} is the length on route k between O-D pair rs. Routes with a heavy overlapping with other routes have a smaller PS value, while routes that are more distinct have a larger PS value. For other functional forms of the PS factor, see Bovy et al. (2008) and Prato (2009). With the derived PS value in Eq. (7), the PS-logit (PSL) probability for the stochastic traffic assignment problem can be expressed as

$$P_k^{rs} = \frac{PS_k^{rs} \cdot \exp\left(U_k^{rs}\right)}{\sum_{j=1}^{n} PS_j^{rs} \cdot \exp\left(U_j^{rs}\right)}, \quad \forall \ rs \in \mathrm{RS}, k \in \mathrm{K}_{rs}^m \tag{8}$$

where U_k^{rs} is the utility of route k between O-D pair rs. A possible way to define the utility is as follows:

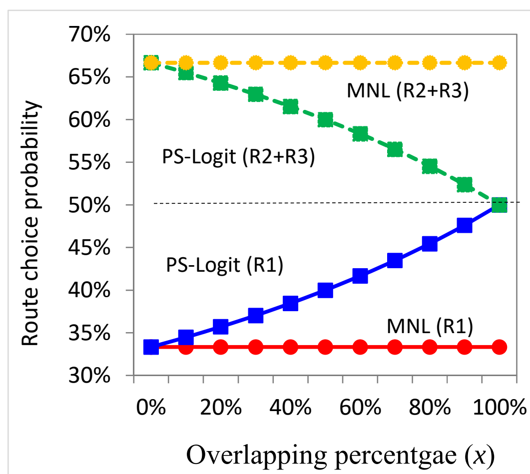
$$U_k^{rs} = -\left(\left(d_k^{rs}\right)^{\alpha} \cdot \left(BLOS_k^{rs}\right)^{\beta} \cdot \left(CO_k^{rs}\right)^{\gamma} \right), \ \forall \ rs \in \mathrm{RS}, k \in \mathrm{K}_{rs}^m \tag{9}$$

where α, β and γ are parameters of the utility function. Figure 4 provides an illustration of how the PSL model resolves the route overlapping problem using the loop-hole network. This network, shown in Figure 4(a), consists of three routes. Route 1 (R1: link 1) is an independent route (i.e., no overlapping with other routes), while Route 2 (R2: link 2 and link 3) and Route 3 (R3: link 2 and link 4) share an overlapping percentage (x%) on link 2 between the two routes. All three routes are assumed to have the same distance (e.g., 100% for the purpose of illustration). For example, if x=20%, the PS values of route 2 and route 3 are 0.9 (i.e., $PS_2 = \left(\frac{l_2}{L_2} = 0.2\right)\left(\frac{1}{2}\right) + \left(\frac{l_3}{L_2} = 0.8\right)\left(\frac{1}{1}\right) = 0.9$), whereas the PS value of route 1 is always 1.0 (i.e. $PS_1 = \left(\frac{l_1}{L_1} = 1.0\right)\left(\frac{1}{1}\right) = 1.0$) since R1 is an independent route. The route choice probability with different percentages of route overlapping is shown in Figure 4(b). As can be seen, the PSL model gives the same choice probability as the multinomial logit (MNL) model when there are no route overlaps (x=0%). In this case, the independence assumption (i.e., the three routes are distinct without any overlap) is fully satisfied, and the PSL model degenerates to the MNL model at x=0%. However, when there are route overlaps (x>0%), the PSL choice probability of the two overlapping routes (R2+R3) becomes smaller with an increasing x value (i.e., shown in the green line), which is more reasonable compared to the constant MNL choice probability results (i.e., R1 shown in the red line and R2+R3 shown in the yellow line) for all x values.



x%: percentage of route overlapping between route 2 and route 3

(a) Loop-hole network



(b) Route choice probability

Figure 4. Illustration of the PSL model in resolving the route overlapping problem

The PSL stochastic traffic assignment model is used to allocate the multi-class O-D demands based on different types of cyclists described in Section 2.1 using the combined utilities of multiple criteria via the PSL probability expression in Eq. (8).

3 SOLUTION PROCEDURE

The overall procedure for solving the multi-class and multi-criteria bicycle traffic assignment model follows a two-stage process, which is described in Figure 1. This section describes the implementation details of these two stages.

3.1 Stage 1: Multi-Objective Route Generation

As mentioned in Section 3.2, the modified ranking method is adopted for generating efficient route sets for multiple user classes by considering relevant criteria that may affect each user classes' route choice decisions. The overall modified ranking procedure with three criteria for a single user class is described in Figure 5.

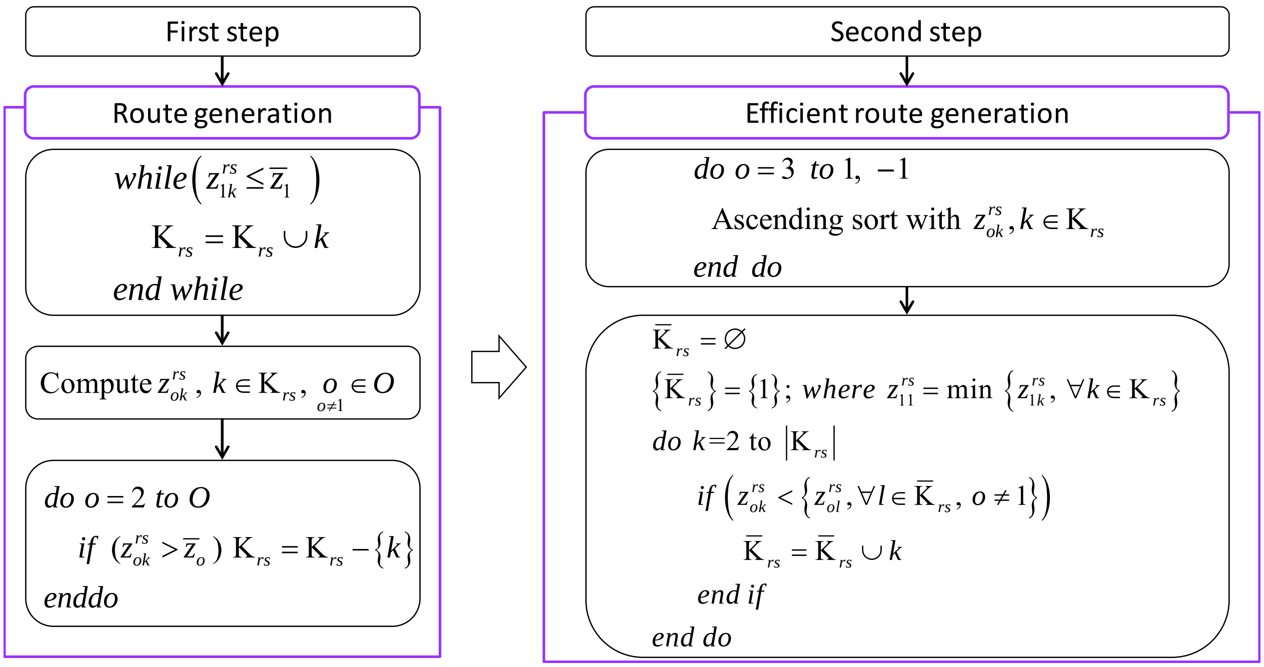


Figure 5. Modified ranking method for generating efficient routes for a single class

Using the three key criteria as an example for illustration purposes, the first step of the modified ranking analysis uses the distance-related attributes (i.e., route distance) z_{1k}^{rs} to generate a set of realistic routes without exceeding the maximum allowable bound ($\bar{z}_1$); then the corresponding safety-related attributes (i.e., route BLOS) z_{2k}^{rs} and pollution-related attributes (i.e., route CO) z_{3k}^{rs} are computed. If the route attributes are higher than the upper bounds (e.g., $\bar{z}_2$ and $\bar{z}_3$), the routes are excluded from the route set. With these generated routes, the second step sorts the objective values in an ascending order from the third objective to the first objective. From the ascending order procedure, the route with smaller route BLOS and route CO values are located on left (i.e., left to right order) when multiple minimal distance routes exist in the route set. Next, the first route in the set is the minimum distance route and serves as the first efficient route with the minimum distance. Then, the next route is compared to the routes in the efficient route set to determine whether it satisfies the non-dominated route condition. If the route is satisfied, the route will remain in the efficient route set; otherwise, the route is excluded in the route set. The process is repeated for the remaining routes in the route set. This procedure is repeated for each user class with its own set of criteria.

In the multi-class, multi-criteria bicycle traffic assignment procedure, each user class has its own efficient route set that considers the tradeoffs among the multiple criteria that are important to the users in each class. The route generation procedure extends the modified ranking method to determine multiple efficient route sets for multiple user classes. To reduce the intensive memory requirements of storing efficient routes, a universal efficient route set is designed to store the efficient routes for all user classes without the need to separately store efficient routes for each individual user class (i.e., an efficient route can be shared or used by multiple user classes). A binary (true/false) indicator in each user class is used to determine the individual class efficient route set out of the universal efficient route set. This simple scheme can help reduce the memory requirements by eliminating the storage of redundant efficient routes for each user class. Figure 6 provides an example of the individual class efficient route set and the universal efficient route set for all classes with three criteria obtained from the route generation procedure in Stage 1.

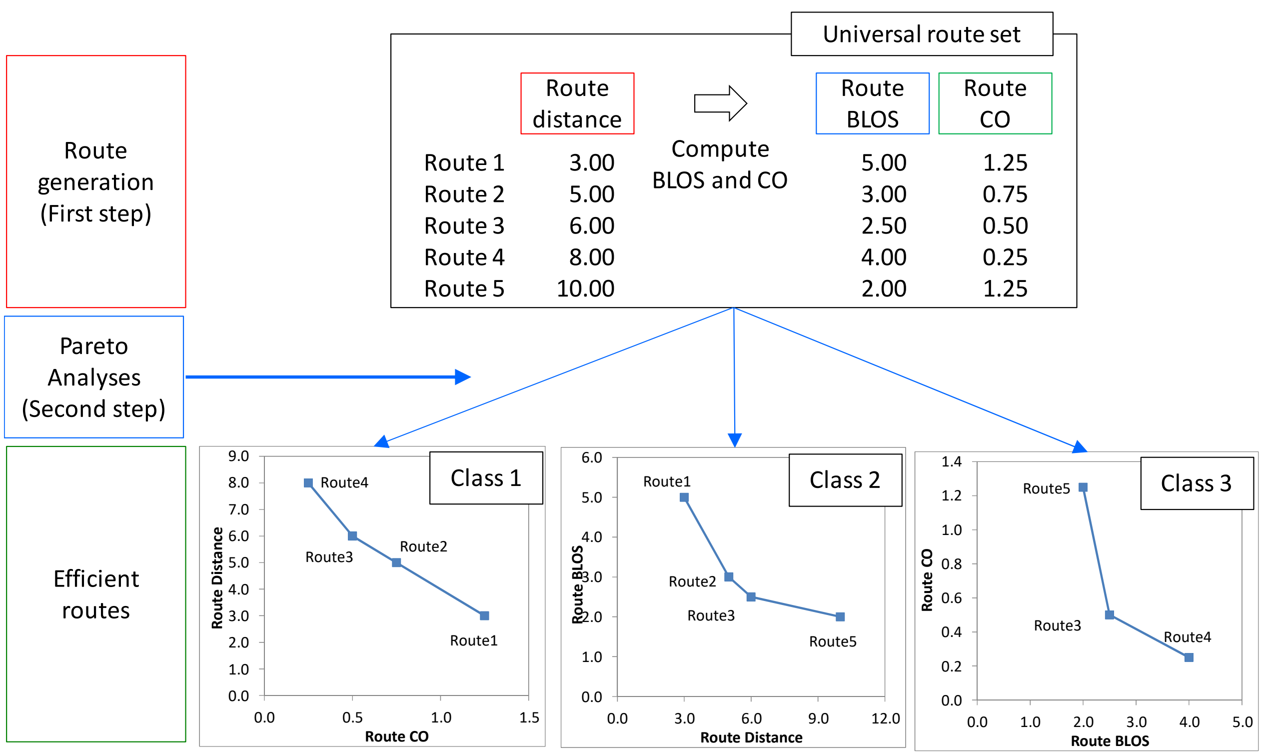


Figure 6. Example of individual class efficient route set and the universal efficient route set

3.2 Stage 2: Multi-Path Traffic Assignment Method

In Stage 2, a path-size logit (PSL) model is used as a multi-path traffic assignment method to determine the flow allocation to efficient paths by user class. The main steps include: (1) computing the path-size factor and utility for each efficient route identified in stage one for each user class according to Eqs. (7) and (9); (2) calculating the route probability based on the PSL model for each user class according to Eq. (8); (3) assigning the demand to the efficient routes according the PSL probabilities for each user class; and (4) outputting the bicycle flow pattern on the network, which includes individual class route and link flows as well as aggregate route and link flows of all classes.

4 NUMERICAL RESULTS

To demonstrate the multi-class, multi-criteria bicycle traffic assignment problem, three classes of cyclists are adopted to develop the numerical experiments for examining the effects of multiple user classes and multiple criteria on the bicycle traffic assignment results. The three cyclist classes are as follows: the "*strong and fearless*" cyclist class (who compose of less than 1% of the population), the "*enthused and confident*" cyclist class (7% of the population), and the "*interested but concerned*" cyclist class (60% of the population). The "*no way no how*" cyclist class, who compose of 33% of the population, are not included in the numerical experiments because this user class does not consider cycling as a potential mode. The two-stage bicycle traffic assignment procedure is coded in Intel Visual FORTRAN XE and runs on a 3.60GHz processor and 16.00GB of RAM. The total computational effort required was 603 seconds, of which 95% is spent in the first stage of the multi-class, multi-criteria bicycle traffic assignment procedure.

4.1 Description of the Network and Scenarios

A real network in the City of Winnipeg, Canada is used to demonstrate the applicability of the two-stage procedure for performing the multi-class, multi-criteria bicycle traffic assignment problem. Figure 7 provides an illustration of the Winnipeg network, which consists of 154 zones, 1,067 nodes, 2,555 links (1,943 links without centroid connectors), and 4,345 O-D pairs for motorized vehicles. The network structure, O-D trip table for motorized vehicles, and link performance parameters are from the Emme/4 software (INRO Consultants, 2013). The bicycle network is assembled based on information obtained from the City of Winnipeg (2013). 541 of the 2,555 links are bikeways. The bicycle O-D demand is created based on the gravity model with the gamma impedance function using 2006 census data (City of Winnipeg, 2006). Note that trip lengths greater than 10 km are excluded in generating the skim trees for the gravity model. To create the multi-class bicycle O-D trip tables, the bicycle O-D demand is segmented into the three user classes mentioned above (i.e., strong and fearless cyclists, enthused and confident cyclists, and interested but concerned cyclists). Table 1 provides a summary of the generated bicycle O-D demand for each user class and the total demand for bicycle trips. Figure 8 presents the trip length frequency distribution (TLFD) for the bicycle trips using route distance to define the trip categories.

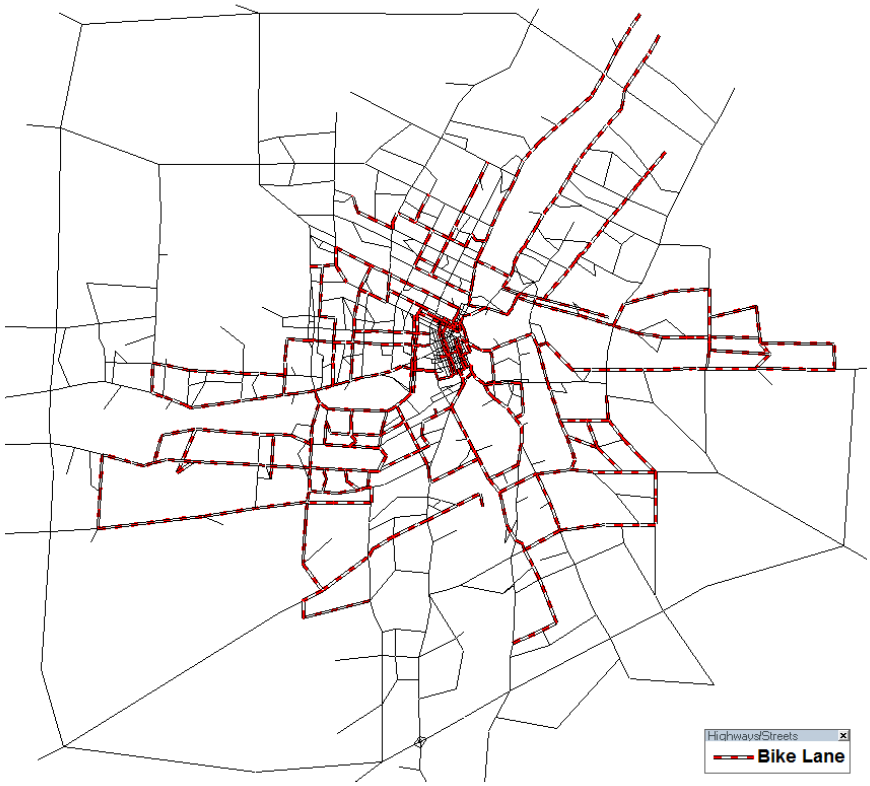


Figure 7. Winnipeg network with bike lanes

Table 1. Generated bicycle demand for each user class

Class #	Type	Proportion	Total demand
1	Strong and Fearless	1.5%	82.0
2	Enthused and Confident	10.3%	573.9
3	Interested but Concerned	88.2%	4919.1
Total		100.0%	5575.0

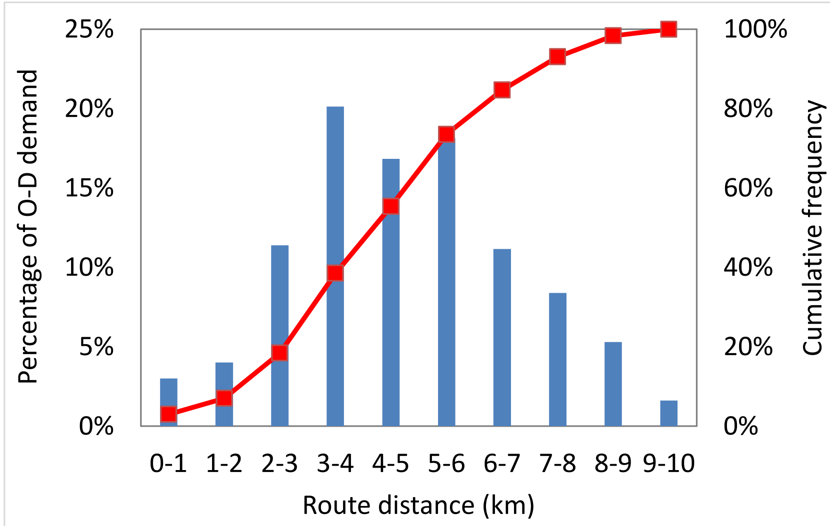


Figure 8. Bicycle trip length frequency distribution

Two scenarios are set up to examine the effects of using different number of criteria in the utility function on the multi-class bicycle traffic assignment model. Table 2 provides a summary of the two scenarios. Scenario 1 assumes all user classes adopt two criteria for the utility function, but the two criteria are different for each user class. On the other hand, Scenario 2 assumes the following: Class 1, the strong and fearless cyclist class, is only concerned with route distance; Class 2, the enthused and confident cyclist class, uses both route distance and route BLOS; and Class 3, the interested but concerned cyclist class, adopts all three criteria (route distance, route BLOS, and route CO) for route choice decisions.

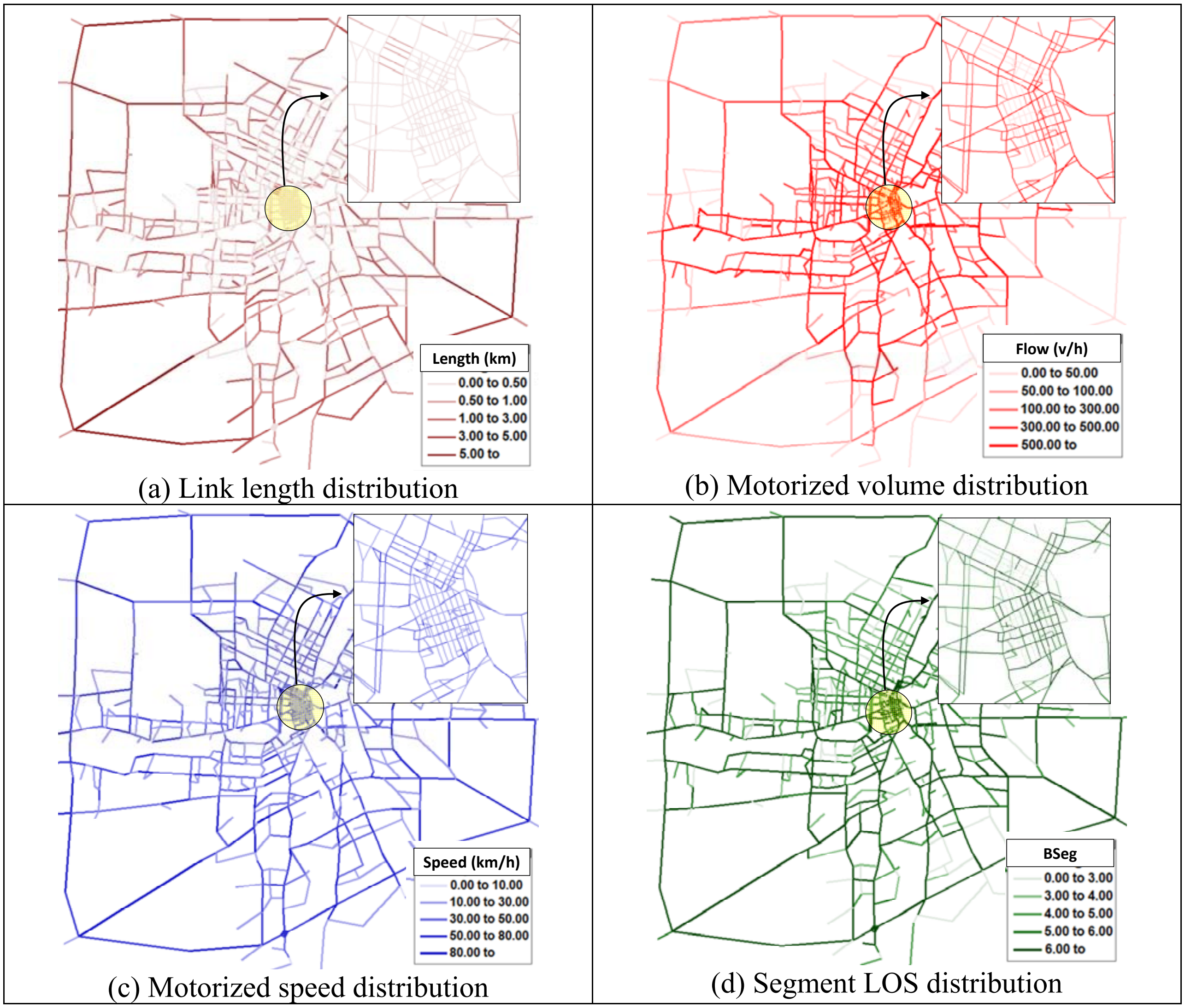
Table 2. Summary of criteria used for the utility function of each user class in the two scenarios

	Scenario 1			Scenario 2		
	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
Route Distance	X	X		X	X	X
Route BLOS		X	X		X	X
Route CO	X		X			X

4.2 Characteristics of the Winnipeg Network

Figure 9 shows the characteristics of the Winnipeg network that are used to compute the three key route choice criteria described in Section 2.2. Figure 9(a) depicts the link length distribution used for computing the three route choice criteria; Figure 9(b) and Figure 9(c) plot the motorized volume and speed distributions obtained from the multi-class motorized vehicle traffic assignment results provided by the Emme/4 software (INRO Consultants, 2013); Figure 9(d) and Figure 9(e) show the computed bicycle segment and intersection LOS distributions based on Eqs.

(3) and (4); and Figure 9(f) plots the link CO distribution based on the nonlinear macroscopic model of Wallace et al. (1998) given in Eq. (6). A segment with a high motorized vehicle volume typically gives a higher BLOS value, while links with a larger effective width on the outside lane typically gives a lower BLOS value. In addition, a segment with a high motorized vehicle volume typically yields a large value for CO due to the congestion effect. These characteristics of the Winnipeg network serve as the input factors for calculating the three route criteria: route distance, route BLOS, and route pollution.

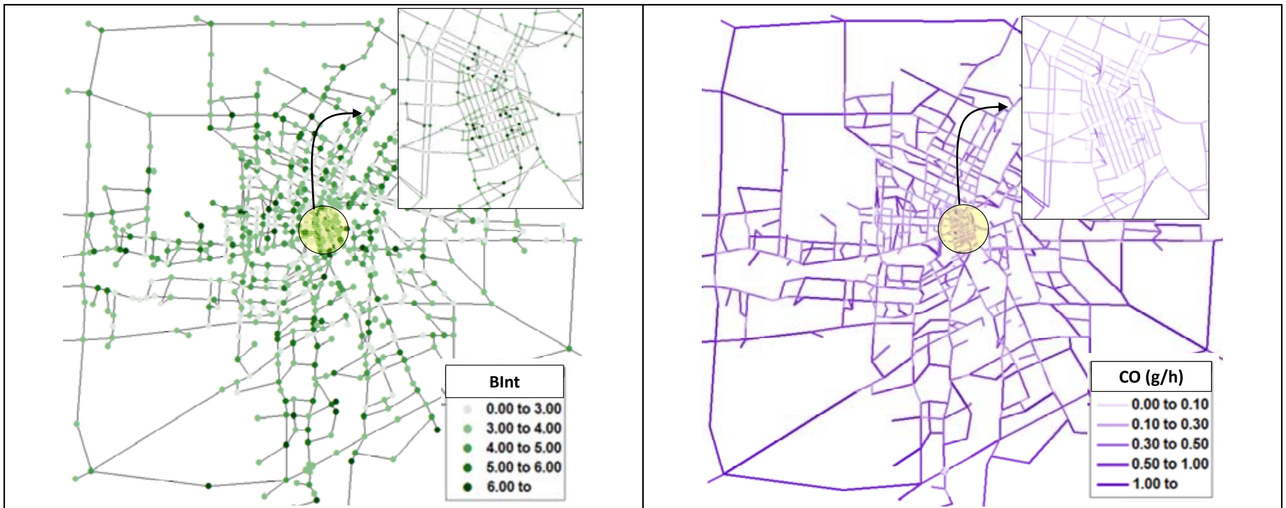


(a) Link length distribution

(b) Motorized volume distribution

(c) Motorized speed distribution

(d) Segment LOS distribution



(e) Intersection LOS distribution | (f) Link CO distribution

Figure 9. Characteristics of the Winnipeg network

4.3 Route Generation Results from Stage One

Based on the characteristics of the Winnipeg network shown in Figure 9, Stage 1 uses the modified ranking method to generate the set of efficient routes for each user class according to the criteria adopted in the two scenarios. To prevent generating unreasonable routes for the above three criteria, the upper bounds are set up for each criterion (i.e., 10.0 km route distance, 7.0 for bicycle level of service, and 25 g/veh for route pollution). Note that the 10.0 km bound for route distance is based on the bicycle commute trip length suggested by Aultman-Hall et al. (1997).

Figure 10 provides a sample of the results of the route distribution using three criteria for Class 3 in Scenario 2 and a comparison of the total number of efficient routes between the two scenarios. Specifically, Figures 10(a), (b) and (c) show the route distribution using distance, BLOS, and CO, respectively, while Figure 10(d) compares the total number of efficient routes for each user class in each of the two scenarios. Note that the average number of efficient routes per O-D pair is relatively small. For Class 3 in Scenario 2, the total number of efficient routes is 50,994 with an average of 6.92 routes per O-D pair (there are 7,368 O-D pairs overall in the Winnipeg network). Longer distance O-D pairs typically have more efficient routes, while shorter distance O-D pairs have fewer efficient routes. In terms of the route distribution, most routes are between 5 to 8 km in terms of distance, 3 to 4 for BLOS values, and 5 to 8 CO g/veh for pollution. As for the comparison between the two scenarios, the number of efficient routes depends on the number of criteria and the specific criteria used to generate the efficient routes.

In Scenario 1, all three user classes use two criteria with different combinations of criteria as shown in Table 2, but the numbers of efficient routes generated are quite different as shown in Figure 10(d). In Scenario 2, it is clear that as the number of criteria increases, the number of efficient routes increases. This is generally expected for the multi-objective optimization problem (i.e., the number of non-dominated solutions increases exponentially as the number of criteria increases (Ehrgott, 2005). Between the two scenarios, users from Class 1 have the least number of efficient routes (with either using route distance only as in Scenario 2 or using both route distance and route pollution as in Scenario 1). On the other hand, users from Class 3 have the most number of efficient routes with using either all three route criteria as in Scenario 2 or just two criteria (i.e., route BLOS and route pollution) as in Scenario 1.

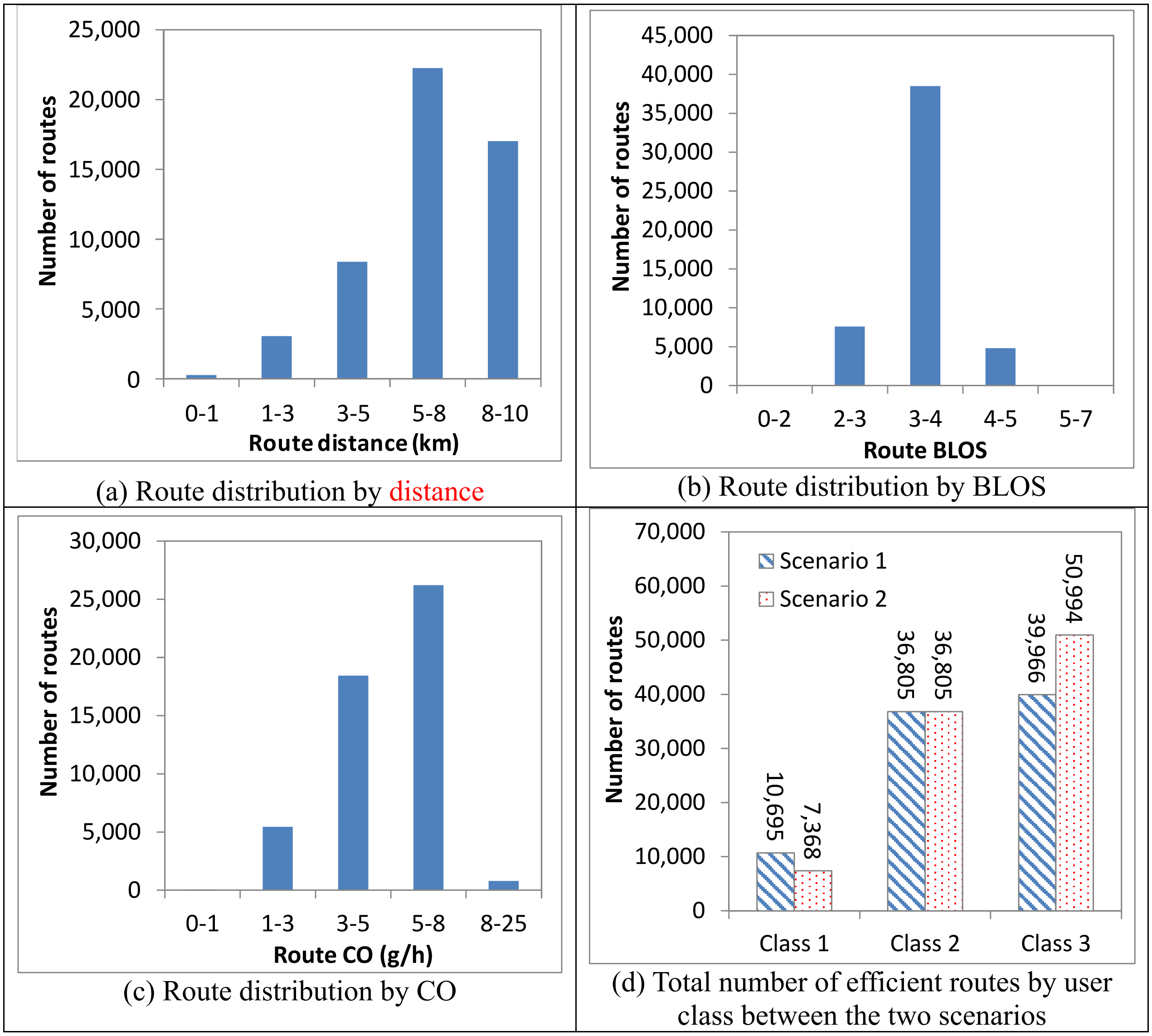
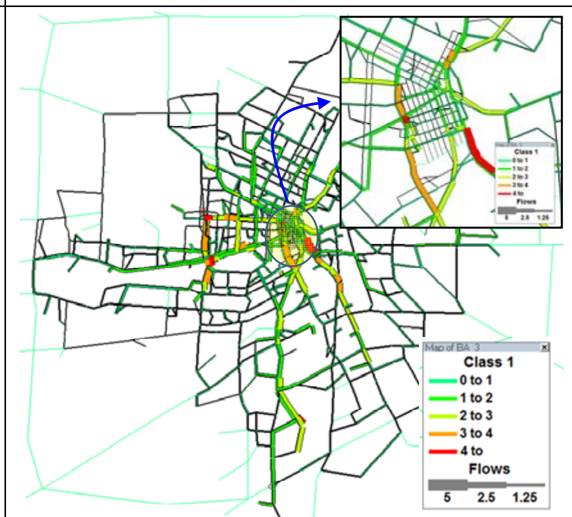
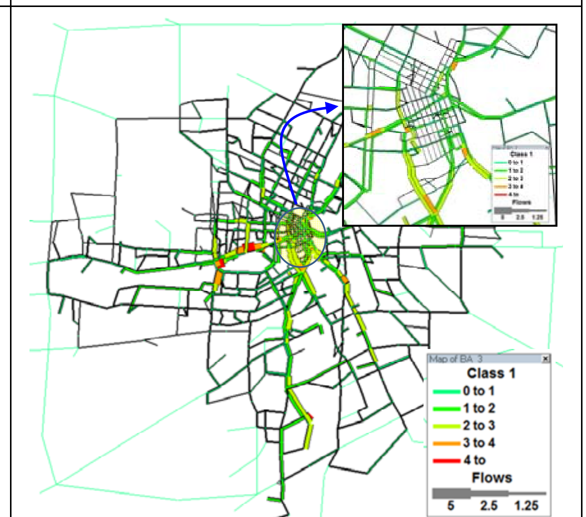
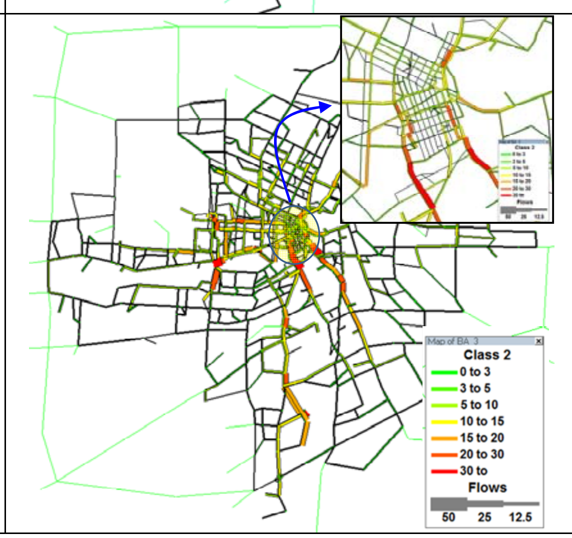
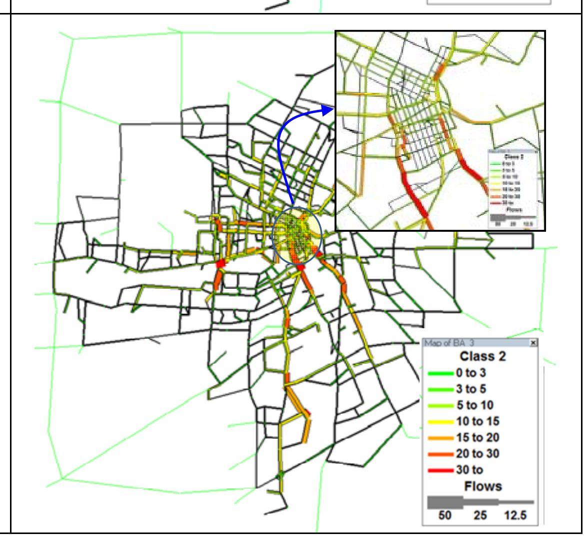


Figure 10. Route distribution by route criterion for class 3 of scenario 2 and total number of efficient routes by user class between the two scenarios

4.4 Bicycle Traffic Assignment Results from Stage Two

Using the efficient routes generated from the first stage for all user classes, we perform the customized path-based loading for assigning the multi-class bicycle O-D trip tables to the network according to the PSL stochastic loading method. In this study, the following parameters are used for the utility function in Eq. (9): $\alpha = 0.862; \beta = 0.117$; (these two values are obtained from Kang and Fricker, 2013), and $\gamma = 0.05$ (this value is assumed). Figure 11 depicts the link flow pattern of each user class for both scenarios. Note that the magnitude of the link flow is color coded and represented by the thickness of the line. For the link flow pattern of Class 1 in Scenario 1, the total number of efficient routes (using the criteria route distance and route pollution) is 10,695. Conversely, in Scenario 2 (which uses route distance as the sole criterion), the total number of efficient routes is 7,368. Therefore, the link flow patterns between the two scenarios are quite different since different numbers and route utilities are being used to assign the O-D demand of Class 1. On the other hand, Class 2 users of both scenarios use the same two objectives (route distance and route BLOS) to compute the route utilities, and consequently yield the same link flow pattern. As for Class 3, the two scenarios adopt different objectives (i.e., route BLOS and route pollution for Scenario 1 and all three route criteria for Scenario 2) and generate different numbers of efficient routes (See Figure 10(d)). However, the resulting link flow patterns are visually similar as this class has the largest amount of O-D trips (88% of total demand or 4919 trips out of 5575 trips) compared to 656 trips or less than 12% in Class 2 and Class 3 (See Table 1).

Class	Scenario 1	Scenario 2
1		
2		

3

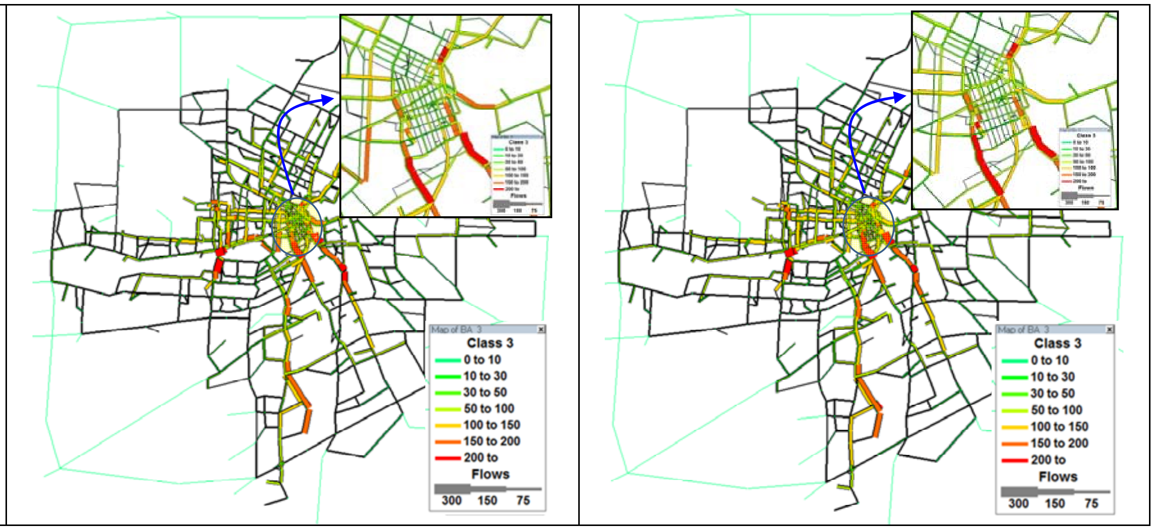


Figure 11. Link flow pattern of each user class for both scenarios

For the aggregate network measures, Table 3 provides the average traveled distance, the average traveled BLOS, and the average traveled CO for each user class computed according the following equations:

Average traveled distance: $$ATD^m = \sum_{rs\in RS}\sum_{k\in K_{rs}^m} d_k^{rs} f_{mk}^{rs} \Big/ \sum_{rs\in RS}\sum_{k\in K_{rs}^m} f_{mk}^{rs}, \quad \forall\ m\in M \tag{10}$$

Average traveled BLOS: $$ATB^m = \sum_{rs\in RS}\sum_{k\in K_{rs}^m} BLOS_k^{rs} f_{mk}^{rs} \Big/ \sum_{rs\in RS}\sum_{k\in K_{rs}^m} f_{mk}^{rs}, \quad \forall\ m\in M \tag{11}$$

Averaged traveled CO: $$ATC^m = \sum_{rs\in RS}\sum_{k\in K_{rs}^m} CO_k^{rs} f_{mk}^{rs} \Big/ \sum_{rs\in RS}\sum_{k\in K_{rs}^m} f_{mk}^{rs}, \quad \forall\ m\in M \tag{12}$$

Table 3. Average traveled distance, BLOS and CO for each user class and all user classes

		Class 1	Class 2	Class 3	All
Scenario 1	Route distance (km/h)	**4.808**	**5.129**	5.423	5.384
	Route BLOS	3.863	**3.612**	**3.566**	3.575
	Route CO (g/h)	**3.999**	4.221	**4.335**	4.318
Scenario 2	Route distance (km/h)	**4.787**	**5.129**	**5.136**	5.130
	Route BLOS	3.847	**3.612**	**3.639**	3.640
	Route CO (g/h)	4.022	4.221	**4.198**	4.198

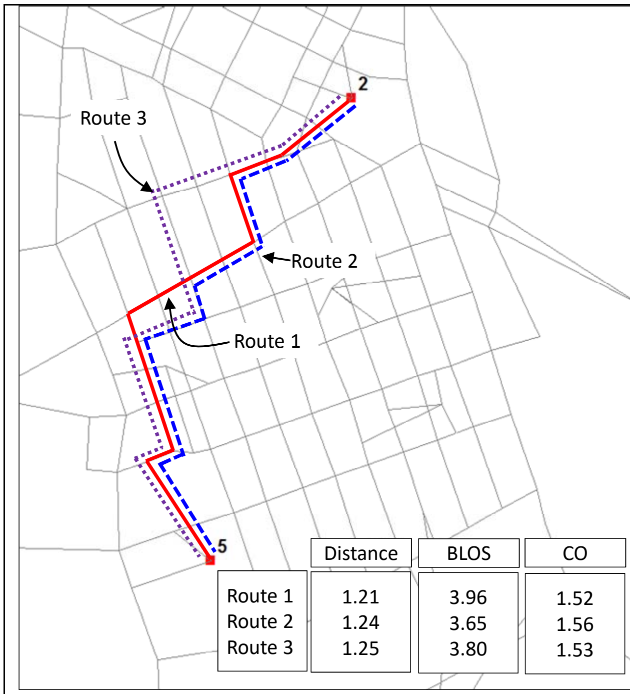
** bold and red fonts indicate the criteria used for the specific user class*

A cursory glance at Table 3 would reveal several obvious patterns in aggregate network measures. Firstly, the table shows that route distance seems to have a higher impact when comparing the two scenarios (i.e., Class 1 and Class 3). This is particularly obvious in Scenario 2: Class 1, which uses route distance as its only criterion, has the lowest average traveled distance among the three user classes and in both scenarios. Lastly, the table shows a positive correlation between route distance and route CO. Minimizing route distance implicitly reduces the value of route CO (see Eqs. (5) and (6)).

A closer inspection of Table 3 would reveal the effects of using multiple criteria in the calculation of the aggregate network measures. The effect can be readily observed in Scenario 1 by examining the values for route BLOS and route CO for Class 2 and 3. Since Class 2 focuses on minimizing route distance and route BLOS while Class 3 focuses on minimizing route BLOS and route CO, we might expect that Classes 2 and 3 would have lower values for their respective criteria of focus. However, Table 3 shows that Class 3's value for route CO is higher than Class 2's value for route CO even though route CO was minimized in Class 3 and not in Class 2. These unexpected results may be attributed to the parameter values used in the utility function. For example, the parameter value for route BLOS was higher than that of route CO, which results in the average route BLOS being more minimized than that of the average route CO.

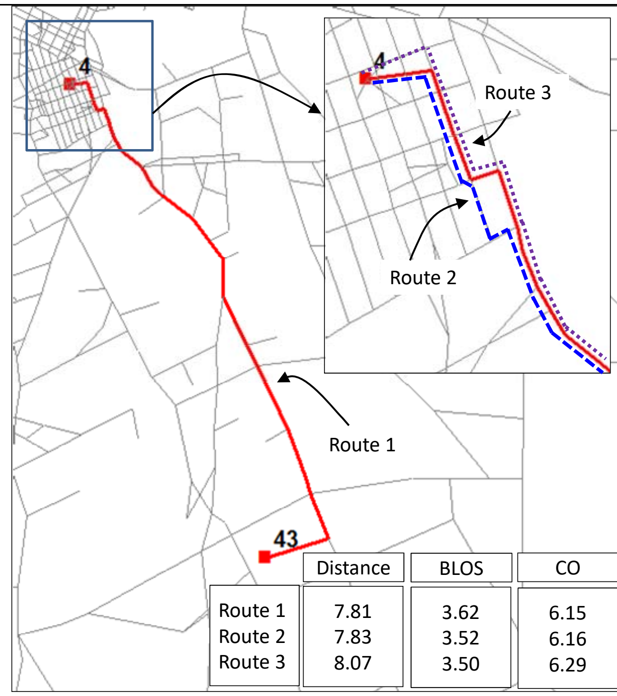
For the disaggregate analysis, we examine the effect of multi-class and multi-criteria considerations on the route choice probabilities. For the single user class, two different utility functions are used for comparison; the first utility function uses two criteria (route distance and route BLOS), and the second utility function uses three criteria (route distance, route BLOS, and route pollution). For the multiple user classes, we continue to use the setup from the two scenarios. For demonstration purposes, we use O-D pairs (5-2) and (43-4) to respectively represent a short O-D pair and a long O-D pair in the Winnipeg network. Figure 12 shows three efficient routes for each O-D pair and the route choice probabilities. Note that these three efficient routes carry majority of the flows. For both O-D pairs, Route 1 is the shortest-distance route among three efficient routes, while the other two are efficient routes (but these routes do not necessarily have the best value in the other two criteria). For the short O-D pair (5-2), Figure 12(a) shows that the single user class with a bi-criteria utility function assigns a higher probability for all three routes compared to those of the single user class with a three-criteria utility function and both scenarios of the multiple user classes. The reason is that the number of efficient routes generated for the short O-D pair using the single user class with bi-criteria utility function is much less compared to the other cases. Therefore, it assigns a higher probability to these efficient routes. Figure 12(b) shows that there is less disparity in the assigned probabilities to the three efficient routes for the long O-D pair (43-3) compared to the short O-D pair (5-2). Also, Scenario 2 assigns a higher probability to Route 1 since it only uses the route distance as the objective for generating efficient routes, while Scenario 1 considers both route distance and route pollution.

From Figure 12(c), we can observe that the route choice probabilities of each class are significantly different in the multi-class analysis. Cyclists from Class 1 travel only on the shortest route in both scenarios. Although Scenario 1 considers two objectives, the network generates only one efficient route because both objectives (i.e., route distance and route CO) are highly correlated. There are a few notable differences in route choice probabilities within individual user classes. In the long O-D pair (43-4) analysis, the probabilities between Routes 1 and 3 for Class 2 cyclists in both scenarios differ by 4.4 percentage points. For Class 3 cyclists, there is little variance in route choice probability for all three routes in Scenario 1. However, in Scenario 2, Class 3 cyclists experience greater variance in route choice probability; the probabilities between Routes 2 and 3 differ by 5.1 percentage points.



	Single-class		Multi-class	
	Bi-obj.	Tri-obj.	Scenario 1	Scenario 2
Route 1	18.1%	12.1%	13.0%	14.0%
Route 2	17.8%	11.9%	11.6%	12.3%
Route 3	17.3%	11.5%	11.6%	11.9%

(a) O-D pair (5-2)



	Single-class		Multi-class	
	Bi-obj.	Tri-obj.	Scenario 1	Scenario 2
Route 1	27.8%	28.2%	26.3%	29.2%
Route 2	27.9%	28.3%	25.0%	27.9%
Route 3	23.4%	23.2%	24.5%	22.9%

(b) O-D pair (43-4)

O-D	Route #	Multi-class					
		Scenario 1			Scenario 2		
		Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
(5-2)	Route 1	100%	18.1%	11.0%	100%	18.1%	12.1%
	Route 2	-	17.8%	11.1%	-	17.8%	11.9%
	Route 3	-	17.3%	11.1%	-	17.3%	11.5%
(43-4)	Route 1	100%	27.8%	24.9%	100%	27.8%	28.2%
	Route 2	-	27.9%	25.0%	-	27.9%	28.3%
	Route 3	-	23.4%	25.0%	-	23.4%	23.2%

(c) Route choice probablities of each class in both scenarios

Figure 12. Effect of multi-class and multi-criteria considerations on route choice probabilities

5 CONCLUDING REMARKS

In this paper, we present the development of a multi-class, multi-criteria bicycle traffic assignment model that explicitly considers multiple user classes and multiple criteria affecting cyclist route choice decision-making for estimating bicycle volumes on a transportation network.

The multi-class component incorporates defined cyclist classes with differing levels of cycling experience and interest, while the multi-criteria component incorporates relevant factors that affect each user class' behavior in route choice decision-making. The overall procedure for developing the multi-class and multi-criteria bicycle traffic assignment model follows a two-stage process. The first stage considers key criteria (e.g., one or more factors relevant to each user class) to generate a set of non-dominated (or efficient) routes for each user class, while the second stage determines the flow allocation to each user's set of efficient routes using a path-size logit model. After the development of the model, we tested the model on a real network in Winnipeg, Canada, to demonstrate the applicability of the model.

The results of the Winnipeg experiment reveal that the integration of multiple user classes and multiple criteria into the bicycle traffic model yield variable outcomes. There are three main reasons that explain the variability in outcomes. First, each user class has different route choice preferences that affect the attributes used in the analysis. Second, the route choice probabilities are highly sensitive to the number of criteria used in the analysis (e.g., two objectives in the Scenario 1 and three objectives in the Scenario 2). Also, the aggregate network measures for route distance, route BLOS, and route CO are highly sensitive to the number of criteria used in the utility function, to the weighting of each criterion in the calculation process, and to each specific user class. Finally, the flow patterns between the single class model and multi-class models are significantly different because the single class model is incapable of using different combinations of criteria to match the specific preferences of each user class.

This paper is based on three key criteria: route distance-related attributes, route safety-related attributes, and route pollution-related attributes. While the route distance attribute is fairly straightforward, we had to choose surrogate measures for the route safety and route pollution criteria. For our analysis, we chose to use route BLOS as a surrogate measure for modeling cyclists' perception of safety and route CO as a surrogate measure for air pollution. There are other possibilities for surrogate measures; for example, it may be helpful to consider measures such as the bicycle compatibility index (Harkey et al. (1998)) or route stress (Mekuria et al., 2012) as a substitute for perception of safety. Other criteria, such as route cognition based on the concept of space syntax (Raford et al., 2007) from the field of urban planning, may also provide more insight. More numerical tests should be conducted with different network topologies, bicycle facilities, and cyclist characteristics. Note that the current two-stage bicycle traffic assignment model did not consider the effect of congestion (i.e., link travel times are independent of flows). It would thus be necessary to consider a flow-dependent model to capture the effects of congestion and safety in terms of motorized traffic in the bicycle traffic assignment procedure, i.e., similar to the stochastic user equilibrium (SUE) traffic assignment method for motorized vehicles (see Prashker and Bekhor, 2004; Chen et al., 2012). In addition, the two-stage approach could be extended to consider other travel choice dimensions (e.g., mode choice, destination choice, and travel choice). One example is to consider mode choice in addition to route choice in a multi-modal road network (Li et al., 2015). Destination choice and travel choice could also be considered in a similar manner to create different combined travel demand models involving non-motorized modes.

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