Incorporating Cycling in Ottawa-Gatineau Travel Forecasting Model

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Abstract:
The paper presents an approach that goes beyond the traditional travel modeling paradigm by incorporating cycling as an explicitly defined mode alternative in the recently updated model for Ottawa-Gatineau. Current models tend to operate with greatly simplified cycling Level-of-Service (LOS) measures (most often an arbitrary specified average speed across the entire network) and do not model details associated with actual cycling routes and facilities. Also, current models largely ignore the cross-modal impacts which cyclists and motorised traffic place upon each other. As a result, policies that affect cycling conditions, for example cycling lanes and/or related traffic regulations cannot be evaluated with the current models. The proposed innovative cycling simulation model for Ottawa-Gatineau, is based on a cycling route choice model that is designed to be sensitive to a wide range of LOS measures including time, speed, level-of-stress, turn conditions at intersections, area type effects etc. This route choice model serves as basis for a regional cycling assignment model. This regional assignment model is integrated into the overall regional travel model that predicts the share of cycling trips versus other auto, transit, and other non-motorized modes for different types of trips and population segments.

1. Introduction

Bicycling is on the rise in bike friendly communities (BFCs) like Ottawa-Gatineau. For example, according to the 2011 TRANS[1] Origin-Destination (O-D) Survey, compared to 2005, bicycling has grown by 40% in the Ottawa-Gatineau region. Given the steady increase of bicycling, especially in BFCs, it is essential to study and model the impacts of bicycling on the region's traffic congestion and travelers' mode choice. The recent advances in transportation planning with respect to bicycle environment and ever-increasing computational resources have made it possible to incorporate bicycling into the travel demand modeling paradigm. This paper describes the approach to incorporate bicycling as an explicitly defined mode alternative in the recently updated regional model for Ottawa-Gatineau.

While there exist mode choice models that include biking as a "mode" (for example, San Francisco and Portland regional models developed by the local Metropolitan Planning organizations), these models still treat bicycles in the network assignment in a simplified fashion. In particular, these current models tend to operate with greatly simplified bicycling LOS measures (most often an arbitrary specified average speed across entire network) and do not model details associated with actual bicycling routes and facilities. Also, current models largely ignore the cross-modal impacts which bicyclists and motorised traffic place upon each other.

In order to address these issues, this paper takes a three-pronged approach: (a) Develop a bicycling route choice model that is designed to be sensitive to a wide range of LOS measures including time, speed, level-of-stress, turn conditions at intersections, and area type effects; (b) Develop an integrated regional bicycle assignment -- traffic assignment model that will generate realistic routes and LOS characteristics for the bicycle trips, and (c) Embed (a) and (b) within the overall travel demand model so that mode choice would be affected by experienced travel times and would predict the share of cycling trips versus other auto, transit, and other non-motorized modes for different types of trips and population segments.

Ottawa-Gatineau Travel Forecasting Model

Figure 1.1 shows the overall framework of the travel forecasting model developed for Ottawa-Gatineau. The model structure includes daily tour-based travel generation and spatial distribution sub-models implemented in an aggregate manner, in a commercial transportation software package EMME. The model draws heavily from the authors' experience in implementing many advanced microsimulation Activity-Based Models (ABMs) in the United States and Canada. Some of the advanced features, in particular, related to trip chaining and time-of-day choice, proved to be possible to incorporate in the aggregate model framework.

Some unique features of the developed model compared to other aggregate travel models include:

[1] TRANS is a joint technical committee established in 1979 to co-ordinate efforts between the major transportation planning agencies of Ottawa's National Capital Region and includes all three levels of government. Member agencies include the National Capital Commission, the Ministère des Transports du Québec, the Ministry of Transportation of Ontario, Ville de Gatineau, the City of Ottawa, and the Société de transport de l'Outaouais.

a) Incorporation of Trip Chaining. Considering individual's trips as part of the trip chain in which they are made, constitutes the most advanced practice in travel modeling today. Accounting for trip linkages within the chain brings several important benefits. First of all, it allows for better and

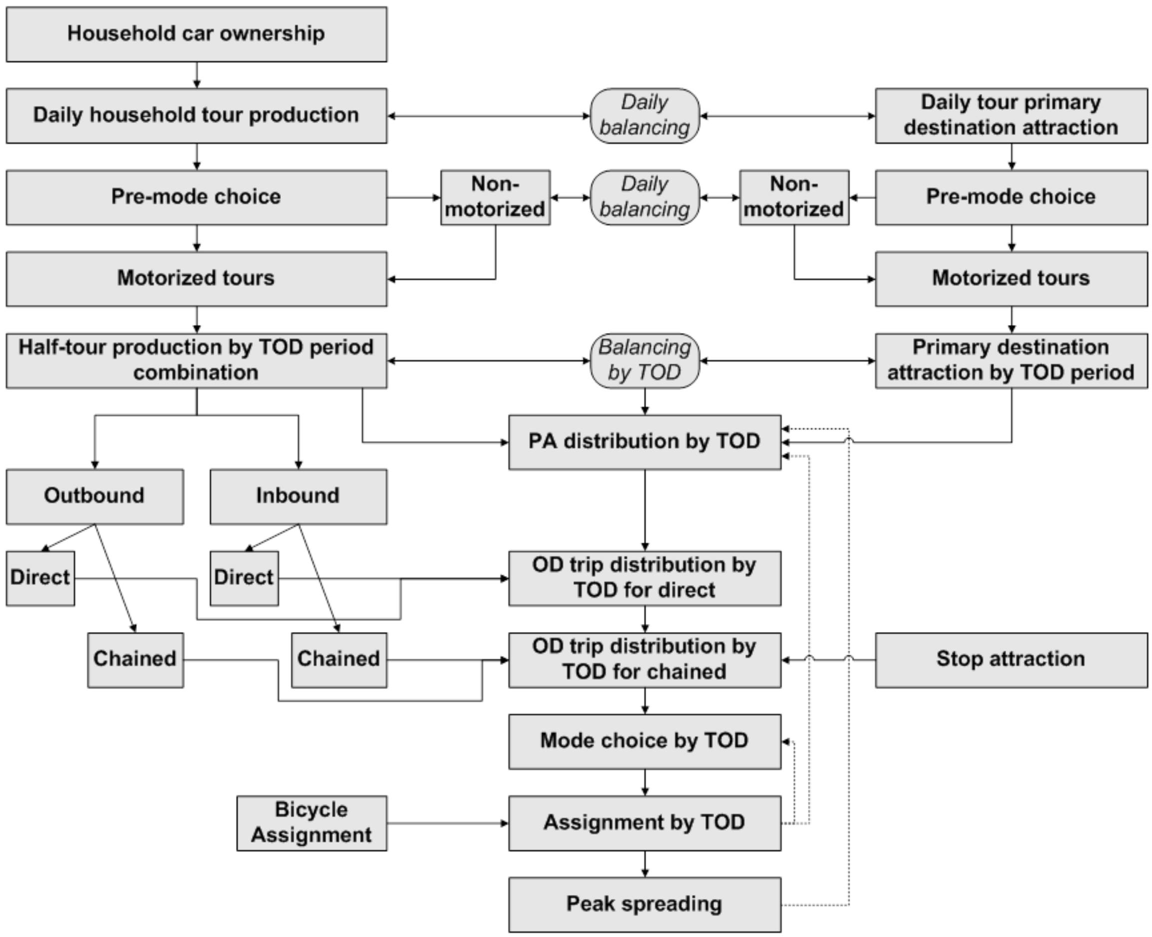

Figure 1.1: Ottawa-Gatineau Regional Travel Model

more consistent modeling of non-home-based trips (that account for approximately 30% of the total daily trips). Secondly, it ensures a logical consistency across trips included in the same tour in terms of their destinations, time-of-day, and mode choice.

b) Daily Tour Generation. The new production and attraction sub-models operate with tours and provide daily trip numbers of which time-of-day-specific numbers are derived in a consistent way based on the time-of-day choice model. The tour production model does not focus on the individual person rates but rather on the household as a whole and on its composition (number of workers, number of non-workers, etc.), dwelling type, and car ownership. The tour (primary destination) attraction model is also daily (with subsequent time-of-day choice). It is formulated as a zonal model and is based on the socio-economic and land-use variables.

c) Daily tour distribution of which TOD-specific trip matrices are derived in a consistent way. The distribution of tours is first modeled for the entire day in the so-called Production-Attraction format that provides an aggregate regional picture of major traffic flows (commuting to work being the most important of them). Further on, tours and half-tours are broken by time-of-day periods. At the final stage, half-tours are converted into trips, by types of half-tours. Direct half-tours represent a single trip each. Chained half-tours are converted into two successive trips each by insertion of an intermediate stop. It should be noted that this technique is principally different from just having independent time-of-day-specific models. In the proposed structure, TOD-specific trip matrices are consistently derived from the same source and dependent on the same input variables.

d) Detailed mode choice procedures to support TRANS planning needs. The implemented mode choice sub-model explicitly incorporates a variety of transit modes (regular bus, express bus, Transitway, rail/LRT) and access options (walk, park & ride, kiss & ride) as well as distinguishes between auto driver and passenger modes. Further on the current research, mode choice was extended to include bicycle as a separate mode.

e) Incorporation of accessibility effects in tour generation: Incorporation of accessibility measures in tour generation and overall model equilibration allows for analysis of accessibility impacts on so-called "induced or suppressed" demand. This will account for Travel Demand Management (TDM) policies including road tolling and parking fares. Figure 1.2 provides further details.

f) Multi-class auto assignment with cross impacts of auto, commercials, trucks, and bicycles: Cross impacts of bicycles and auto modes on traffic conditions along with their impact on mode choice is modeled. This is a substantial improvement and an innovative feature that has not been yet incorporated in even the most advanced travel models in practice. This will be discussed in detail in subsequent sections.

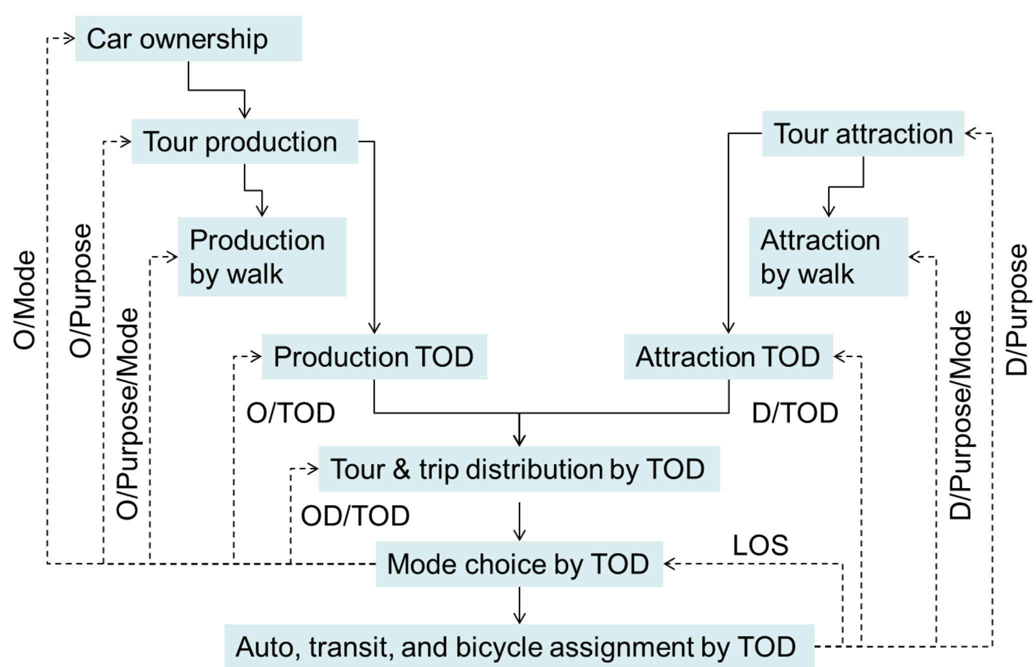

Figure 1.2: Incorporation of accessibility effects in tour generation

Organization

The rest of the paper is organized as follows. Section 2 contains a brief literature review of the current bicycle models and bicycle LOS measures. Some insights, with respect to bike usage, gained from the analyses of the 2011 TRANS O-D survey data is described in Section 3. Section 4 explains the bicycle route choice and assignment model and how it is incorporated into the travel forecasting framework. Some conclusions and scope for future research is reported in Section 5.

2. Literature Review

While there are many papers that deal with quantifying LOS variables for bicyclists and bicycle facilities, the authors found practically no literature on bicycle routing and bicycle assignment models. Contributions of a few relevant papers are discussed below.

Landis et al. *(1)* developed a statistically calibrated Bicycle Level-of-Service (BLOS) model. This model was based on real-time perceptions from bicyclists traveling in actual urban traffic and subject to roadway conditions. The study included a regression analysis of BLOS measures as a function of roadway and traffic characteristics and concluded that heavy vehicles, vehicular speeds, and vehicular access directly affect a roadway's "bike-ability".

The FHWA developed a Bicycle Compatibility Index (BCI) to evaluate the capability of urban and suburban roadway sections to accommodate both motorists and bicyclists *(2)*. Bicyclists' perceptions were recorded by having them view a number of videotaped roadway segments. The segments were then rated based on how comfortably the bicyclist would be able to ride on it, given the operational and geometric features of the roadway. Some of the features that defined the BCI included the presence of a bicycle lane, curb lane width, presence of a parking lane, and traffic speed.

The National Highway Co-operative Research Program published a report that developed a methodology to calculate LOS for various modes on urban streets. The recommended Bicycle LOS model is a weighted combination of the bicyclists' experiences at intersections and on street segments in between the intersections *(3).* Some of the features that defined the BLOS included Peak Hour Factor, total number of through lanes, pavement surface conditions, and directional traffic volume. Table 2.1 shows the BCI, BLOS, and bicycle compatibility levels for *(2)* and *(3).*

Letter LOS	BCI Range (FHWA)	BLOS Range (NCHRP)	Compatibility Level
A	< 1.51	< 2.00	Extremely High
B	1.51 - 2.30	2.00 - 2.75	Very High
C	2.31 - 3.40	2.75 - 3.50	Moderately High
D	3.41 - 4.40	3.50 - 4.25	Moderately Low
E	4.41 - 5.30	4.25 - 5.00	Very Low
F	> 5.30	> 5.00	Extremely Low

Table 2.1: BCI associated with BLOS and Letter LOS for an average adult bicyclist

The Mineta Transportation Institute *(4)* developed a BLOS model based on people's tolerance for traffic stress. The following three classes of bicyclists by level of experienced traffic stress were defined:

- A = Advanced cyclists whose greater skill enables them to share roads with motor traffic. Moreover, they are unwilling to sacrifice speed for separation from traffic stress.
- B = Basic adult cyclists, who lack the "skill" to confidently integrate with fast or heavy traffic.
- C = Children cyclists, less capable than class B at negotiating with traffic and more prone to irrational and sudden movements.

Based on these definitions, the authors created a network connectivity metric which defined the level of connectivity (from an origin to a destination) for different classes of users. The objective was to develop metrics for low-stress connectivity, or the ability of a network to connect travelers' origins to their destinations without subjecting them to unacceptably stressful links.

The bicyclist's ability to use a certain type of facility has a huge bearing on the route making behavior of that bicyclist. The roadway features as well as personal attributes affect this route making behavior. In addition to the Mineta study, Dill et al. *(5)* and Stimson and Bhat *(6)* also classified bicycle users. Table 2.2 shows the classification and their shares in the U.S. and city of Portland.

Type	Description	City of Portland	United States
Strong and Fearless	Very Comfortable without bike lanes	6%	4%
Enthused and Confident	Very comfortable with bike lanes	9%	9%
Interested but Concerned	Not very comfortable, interested in biking more; Not very comfortable, currently bicycling for travel	60%	56%
No Way No How	Physically unable; Very uncomfortable on paths; Not interested	25%	31%

Table 2.2: Distribution by Cyclist Type *(5)*

The proposed model uses these classifications to develop BLOS that are segmented based on cyclist type. The BLOS is then used in the route choice model that is used in the bicycle assignment and generates route level skims that affect mode choice. The route level skims are similar to the ones studied by Hood et al. *(7)*

3. Statistical Analysis

In 2011, TRANS conducted a Travel Origin-Destination Survey. In all, 25,374 households representing 62,897 people were surveyed. Of these, 30,454 (48%) respondents were male and the remaining (52%) were female. The average age of the respondents was 41 years. The modes of travel reported by the respondents can be divided into seven main categories. These are cars/motorcycles, car passengers/taxis, buses/para-transit, O-train, walk, bicycle, and school bus. Close to 2% of the trips were reported to be made using bicycles.

Table 3.1 shows the average age of the respondents by mode type. The table also shows the average trip distance and duration for each mode. As expected, car is the quickest mode, while walking is the slowest mode. Also, logically, people tend to travel longer distances using cars or transit, but prefer to walk or bike for shorter distances.

Mode	Trip Duration (Mins)	Trip Distance (Kms)	Age
Car/Motorcycle Driver	18	11	49
Car Passenger/Taxi	16	9	36
Other buses/Para-transit	43	11	37
O-Train	37	11	36
Walk	12	1	38
Bike	22	5	41
School Bus	42	8	11

Table 3.1: Average age, trip duration, and trip distance by mode

Table 3.2 shows the mode usage by gender, and the gender preference for a mode. Of the total number of people that use cars and motorcycles as a driver, 51% are male and 48% are female (an almost equal split). For car passengers and taxi riders, the split is skewed towards females: 35% are male and 64% are female. The other skewed modes are the O-Train and biking (both towards male). 67% of the bike users are male and only 32% are female.

Table 3.2 also shows the modal split by gender. Of all the males that make trips, 2.5% use bikes, only 1.1% of all females that make trips use bikes. From the gender and mode split, it can be concluded that males have a general proclivity to bicycling compared to females. Additionally, it can also be stated that females tend to be car passengers/use taxis more than males.

	Gender Split for each Mode		Modal Split for each Gender	
Mode	**Male**	**Female**	**Male**	**Female**
Car/Motorcycle Driver	51.52%	48.48%	61.52%	53.43%
Car Passenger/Taxi	35.78%	64.22%	12.18%	20.17%
Other buses/Para transit	45.05%	54.95%	9.39%	10.57%
O-Train	59.77%	40.23%	0.27%	0.17%
Walk	45.21%	54.79%	9.46%	10.58%
Bike	67.26%	32.74%	2.48%	1.11%
School Bus	51.81%	48.19%	4.31%	3.70%

Table 3.2: Mode by Gender for all Trips

Table 3.3 further explores the trip characteristics of bicyclists by grouping them into different age categories. As expected, children below 15 years of age make the shortest trips and ride the least amount of time per trip. Adults between 35-65 years of age make the longest bicycle trips. On average, the trips made by this age group are also the longest. The total number of reported bicycle trips was also the highest for the 35-65 years age group.

Age	Trip Distance (Kms)	Trip Duration (mins)	#Trips
Less than 15	3	10	343
15 - 20	5	22	185
20 - 35	5	21	512
35 - 50	6	23	848
50 - 65	6	25	725
Greater than 65	4	18	179

Table 3.3: Bicycle Trip Characteristics grouped by Age

Table 3.4 shows the time of day during which the different available modes were used. The proportion of bikes used during each of the time periods is somewhat similar. However, there is a slight spike in the AM peak period between 8:30 AM to 9:30 AM. Similarly, during the PM period between 4:30 PM to 6:30 PM there is a slight spike in bike usage. Bike usage seems to be more during the tapering shoulder of the peak period than during the peak hour itself.

The total daily modal split is, as expected, that cars are the most commonly used mode. 57% of all trips are made using cars, compared to 10% walking trips, and 2% bike trips.

Time of Day	Car/Motorcycle Driver	Car Passenger/Taxi	Other buses/ Para-transit	O-train	Walk	Bike	School Bus	Proportion of Bikes
5:30 AM to 6:30 AM	1863	229	431	7	89	26	2	0.98%
6:30 AM to 7:30 AM	5048	1143	1241	18	335	100	251	1.23%
7:30 AM to 8:30 AM	8138	2384	2460	36	1665	346	1819	2.05%
8:30 AM to 9:30 AM	5867	1373	1300	21	1604	357	1007	3.09%
9:30 AM to 12:30 PM	13224	2739	1599	52	2363	328	183	1.60%
12:30 PM to 3:30 PM	14640	3575	2502	55	3433	384	1470	1.47%
3:30 PM to 4:30 PM	8278	2357	1752	26	1954	296	1247	1.86%
4:30 PM to 5:30 PM	9128	2610	1845	40	1263	332	268	2.14%
5:30 PM to 6:30 PM	6687	2471	1060	29	912	262	36	2.28%
6:30 PM to 7:30 PM	5364	2194	465	14	722	129	10	1.45%
7:30 PM to 9:00 PM	5166	2303	343	13	725	93	1	1.07%
9:00 PM to 5:30 AM	6513	2176	757	30	729	121	19	1.15%
Modal Split	57.47%	16.33%	10.07%	0.22%	10.10%	1.77%	4.04%	

Table 3.4: Trip Time-of-Day by Trip Mode

Table 3.5 further explores the bicycle trips made by time of day. Most trips are made around the AM and PM peak periods. The average trip duration is around 22 minutes (24 hour period). However, the trips made between 7:30 PM to 9:00 PM are especially longer with an average travel time of 22 minutes.

Trip Time	Trip Duration (mins)	#Trips	%Trips
5:30 AM to 6:30 AM	20	30	0.94%
6:30 AM to 7:30 AM	27	124	3.60%
7:30 AM to 8:30 AM	22	405	12.47%
8:30 AM to 9:30 AM	21	310	12.87%
9:30 AM to 12:30 PM	19	304	11.82%
12:30 PM to 3:30 PM	17	411	13.84%
3:30 PM to 4:30 PM	21	300	10.67%
4:30 PM to 5:30 PM	25	357	11.97%
5:30 PM to 6:30 PM	23	235	9.44%
6:30 PM to 7:30 PM	21	110	4.65%
7:30 PM to 9:00 PM	22	83	3.35%
9:00 PM to 5:30 AM	23	114	4.36%

Table 3.5: Bicycle Trip Characteristics grouped by Time-of-Day

Table 3.6 studies the modal splits of bicyclists and non-bicyclists. Persons who reported at least one bike trip are labeled bicyclists. Of the 62,897 people included in the survey sample, 1,229 were bicyclists. Bicyclists make up 2% of the entire survey sample. Non-bicyclists have no reported bike trips. Non-bicyclists tend to use cars for most of their trips. 74% of the trips made by non-bicyclists are either using cars or taxis. On the other hand, bicyclists use bicycles for 63% of their trips and cars for about 21% of their trips. Walk trips constitute about 10% of the total bicyclists and non-bicyclists trips.

	Trips			Modal Split		
Mode	**All Persons**	**Bicyclists**	**Non-Bicyclists**	**All Persons**	**Bicyclists**	**Non-Bicyclists**
Unknown	505	20	485	0.32%	0.45%	0.32%
Car/Motorcycle Driver	90538	692	89846	57.31%	15.74%	58.50%
Car Passenger/Taxi	25809	302	25507	16.34%	6.87%	16.61%
Other buses/Paratransit	15808	98	15710	10.01%	2.23%	10.23%
O-Train	343	1	342	0.22%	0.02%	0.22%
Walk	15865	461	15404	10.04%	10.48%	10.03%
Bike	2792	2792	0	1.77%	63.50%	0.00%
School Bus	6313	31	6282	4.00%	0.71%	4.09%

Table 3.6: Modal Split of Bicyclists and non-Bicyclists

The next section discusses the bike-auto assignment methodology in detail.

4. Auto – Bicycle Assignment Model

As stated previously, while a large number of qualitative studies and initial modeling efforts for bicycle assignment exist, no study to date has attempted to develop LOS measures that can be used in a bike assignment model; further, no study has examined the cross modal impacts of vehicular and bike movements in the equilibrium network assignment framework. The auto-bike assignment model developed in this section fills that gap in both the state of art and state of practice.

The methodology presented here first describes a framework for calculating the generalized cost and volume delay functions for both bicycles and motorized vehicles using the LOS variables. Next, an auto-bicycle assignment equilibrium framework is outlined.

Segmentation of Variables

As stated by *(4)* and *(5)*, bicyclists can be categorized based on their biking ability and inclination towards biking. This in turn implies that these users experience different travel times and also have different impacts on the travel times of motorized vehicles. Furthermore, bike facility type also affects the bicyclist's travel time and the travel times of motorized vehicles. For example, a novice bicyclist using a bike separated facility will not impact motorized vehicle as much as a novice bicyclist using a mixed-traffic lane. This suggests segmentation along user classes as well as bicycle facility type. In other words, the LOS variables will be segmented by User Class and their impact will be dependent on the bike facility type. Figure 4.1 lists the bicycle facility types and the user classes.

Figure 4.1: Bicycle user classes and bike facility types

Impact on Travel Time (Bicycles)

Different variables affect the bicycle level of service. This BLOS can be interpreted as the additional time required for traversing a link compared to free flow conditions. For example, if it takes 6 minutes to traverse a link on a bike under *ideal* free flow conditions, then in the presence of vehicular traffic, it will take more time. This additional time to traverse that link can be interpreted as the BLOS. Assume that BLOD for link (i,j) for a bicyclist of type m is defined as LOS_{ijm}. Then, the delay experienced by that bicyclist is given by:

$$\text{Link Delay}_{ijm} = \text{LDF}_{ijm} \times \text{Free Flow Time} \qquad \forall (i,j) \in A \;\; \forall m \in M$$

Where, the link delay factor (LDF) is defined as:

$$LDF_{ijm} = 1 + LOS_{ijm} \qquad \forall (i,j) \in A \;\; \forall m \in M$$

In turn, LOS_{ijm} is defined as:

$$LOS_{ijm} = \text{Max}\{f(A_{ij},\ P_i,\ \ P_j,\ M_m \times A_{ij}),\ 0\}$$

Where,
A_{ij}: Link specific variables
P_i: Downstream node-specific variables
P_j: Upstream node-specific variables
$M_m \times A_{ij}$: Link-user specific interaction variables

Variables	Units	Strong Bicyclist			Enthusiastic Bicyclist			Interested Bicyclist		
		Value	Effect	Multiplier	Value	Effect	Multiplier	Value	Effect	Multiplier
Link-Level										
Bicycle Lane (yes/no)	N/A	1	Decrease	-1.25	1	Decrease	-1.12	1	Decrease	-1.05
Bike Lane Width	Feet	5	Decrease	-0.41	5	Decrease	-0.4	5	Decrease	-0.395
Curb Lane Width	Feet	10	Decrease	-0.0498	10	Decrease	-0.0498	10	Decrease	-0.0498
Traffic Speed	Mph	35	Increase	0.022	35	Increase	0.022	35	Increase	0.022
Curb Lane Volume	Vph	700	Increase	0.002	700	Not Good	0.002	700	Not Good	0.002
Other Lane Volume	Vph	1400	Increase	0.0004	1400	Not Good	0.00045	1400	Not Good	0.0004
Parking Lane (yes/no)	N/A	1	Increase	0.52	1	Increase	0.506	1	Increase	0.506
Residential Area (yes/no)	N/A	1	Decrease	-0.364	1	Decrease	-0.359	1	Decrease	-0.32
% HV Volume	Ratio	15	Increase	0.034	15	Increase	0.034	15	Increase	0.034
Frequency of NVA	N/A	3	Increase	0.019	3	Increase	0.019	3	Increase	0.019
Pavement Condition (good/bad)	0-4	0	Increase	0.05	0	Increase	0.05	0	Increase	0.05
Node-Level										
Signal	N/A	1	Increase	0.011	1	Increase	0.011	1	Increase	0.011
Stop Sign	N/A	0	Increase	0.005	0	Increase	0.005	0	Increase	0.005
Cross Street Width	Feet	15	Increase	0.02	15	Increase	0.0153	15	Increase	0.0153
Pedestrian Crossing	N/A	1	Increase	0.05	1	Increase	0.07	1	Increase	0.09
LOS		0.016			0.2065			0.2905		
Free Flow Travel Time	Mins	6			6			6		
Delayed FF Travel Time	Mins	**6.096**			**7.239**			**7.743**		

Table 4.1: An Example showing Bicycle LOS computation

Table 4.1 shows an example of the LOS computation with the initial parameters set by the authors based on the literature review. The free flow time for traversing a 1 km long link at 10 km/hr is 6 min. However, the external link and node level factors have different impacts on the bicyclist types. As a result, a strong bicyclist takes 1.016 times the free flow time to traverse the link. An enthusiastic bicyclist takes 1.2065 times and an interested bicyclist takes 1.2905 times the free flow travel time. Note that the BLOS calculation includes the motorized vehicular traffic and accounts for its cross impacts too.

Link Volume Delay Function (Bicycle)

The link delay factor does not account for the delay caused due to traffic congestion at a link. To account for these delays, the link volume delay function is defined. The following factors affect delays experienced by bicyclists:

- **Auto volume** – high V/C ratio for autos implies a steeper bicycle VDF as they have to navigate through high congestion for mixed-traffic
- **Bicyclist type** – Stronger bicyclists have higher free flow time and lower sensitivity to congestion and auto traffic
- **Bike lane type** – Easier to navigate through dedicated bike lane than mixed traffic
- **Total effective capacity** – effective capacity available to bikes conditional on the modeled traffic volumes

A link-based bike VDF that accounts for these factors is proposed for the current research. Let the capacity of the link be C, the auto volume on that link be V_a, the bicycle free flow travel time be t_0, and the link delay factor be LDF. In addition, a few calibration parameters are also defined -- α_b, β_b, γ, θ, μ, ν, ζ_b. The need for these parameters will be explained later. Now, the travel time on a link with bike volume $V_b$is given by $t(V_b)$ and is defined as:

$$t(V_b) = ACF \times \left(1 + \zeta_b \left(\frac{V_b}{C_{eff}}\right)^{Exp_{eff}}\right)$$

Where,

$$Exp_{eff} = \max\left\{\gamma, \min\left\{\left(\frac{C}{V_a + \epsilon}\right)^{\theta}, \beta_b\right\}\right\}$$

Effective Capacity, $C_{eff} = \max\{C - V_a,\ \alpha_b C\}$

Auto Congestion Factor: $\boldsymbol{ACF} = LDF \times t_0 \times \left(1 + \mu \left(\frac{V_a}{C}\right)^{\nu}\right)$

Figure 4.2 shows the bicycle VDF for three levels of auto congestion and for all three bicyclist types. The VDF shown is when the bikes move with mixed-traffic. For the cases where the bike use a dedicated (and grade separated) bike facility, the calibration parameters must be changed accordingly.

The strongest bicyclists are least affected by auto volumes and other link delay factors. Hence, the strong bicyclist curves are the least steep. Conversely, the interested bicyclist curves are the steepest. Moreover, cross impacts of auto congestion are incorporated into this VDF using the auto congestion factor (ACF). It is also assumed that, given the auto traffic, the bikes only have the remaining capacity available to route through the links. For separated bike lanes, this variable will change accordingly.

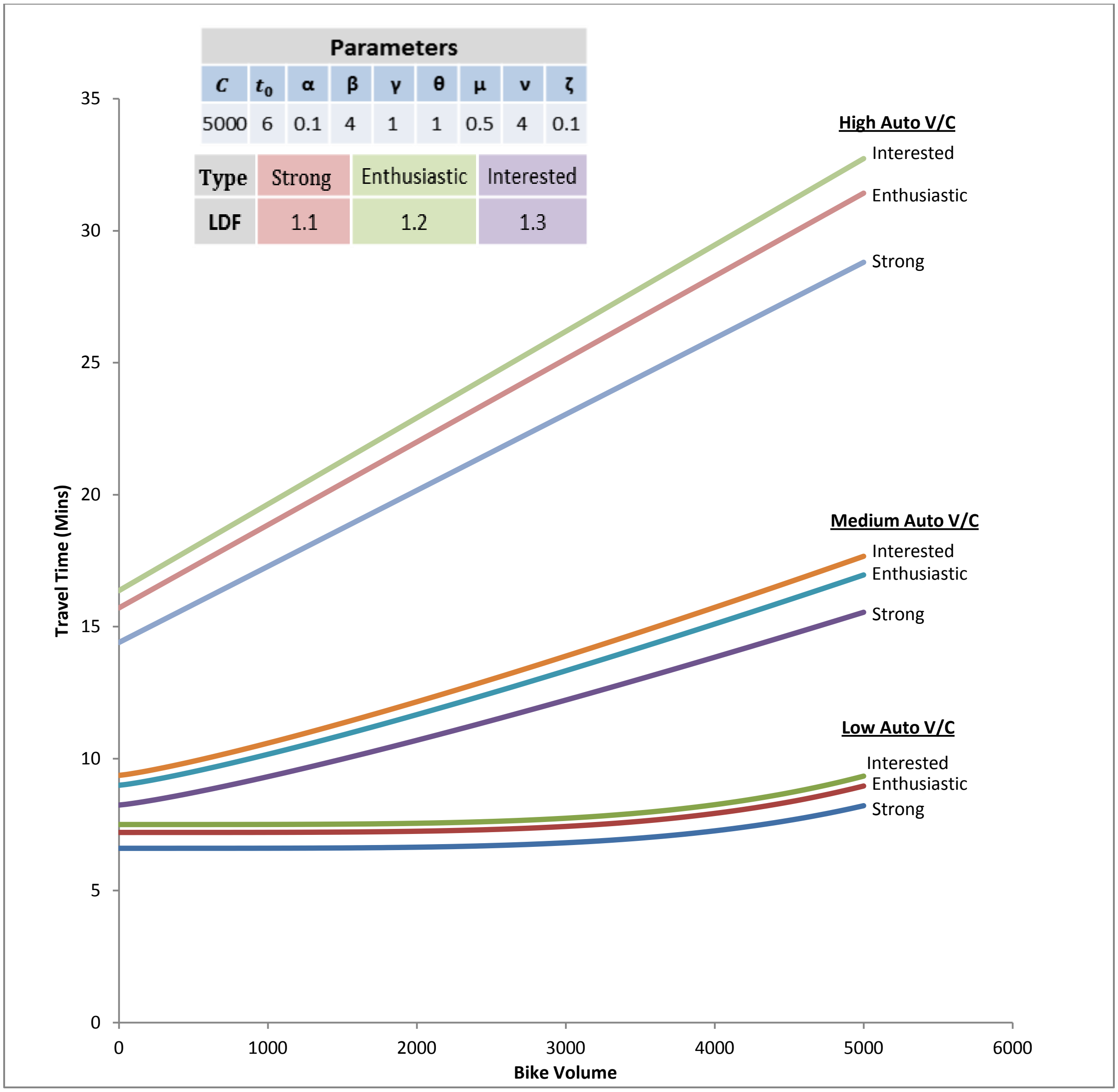

Figure 4.2: Bike VDF for different levels of congestion and different users

Link Volume Delay Function (Auto)

In addition to examining how auto traffic affects bicycle congestion, one also needs to examine the effect bicycles have on auto congestion and link travel times. In short, bicycles affect auto travel times and autos affect bicycle travel times. This is, of course, in addition to the other exogenous factors that also affect their travel times.

Auto travel times increase due to the presence of bicycles. Bicycles take up capacity, and since they move slower than autos, they take up more capacity than their physical dimensions. Moreover, the amount of effective capacity a bicyclist takes up depends on their type. For example, novice bicyclists tend to slow down autos more than experienced bicyclists. Thus, the travel time delay motorized vehicles experience because of the presence of bicycles can be accounted by the amount of effective car capacity bicycles take up. In other words, expressing bicycles in terms of passenger car equivalents (PCEs) and making only the remaining capacity available to cars for traversing the link.

Mathematically, this can be expressed as follows. Let the capacity of the link be C, the bike volume on that link be V_b, the auto free flow travel time be t_0, the link factor be LF, let PCE for bike user b and link type *l* be p_{b_l}. In addition, a calibration parameters β_a, ζ_a are also defined. The link factor is a parameter whose value is dependent on the link type (mixed-traffic, bike lane etc.). Now, the travel time on a link with auto volume $V_a$is given by $t(V_a)$ and is defined as:

$$t(V_a) = t_0 \times LF \times \left(1 + \zeta_a \left(\frac{V_a + \sum_b p_{b_l} V_b}{C}\right)^{\beta_a}\right)$$

Figure 4.3 shows the auto VDF for three levels of bike congestion and for two types of bike facilities.

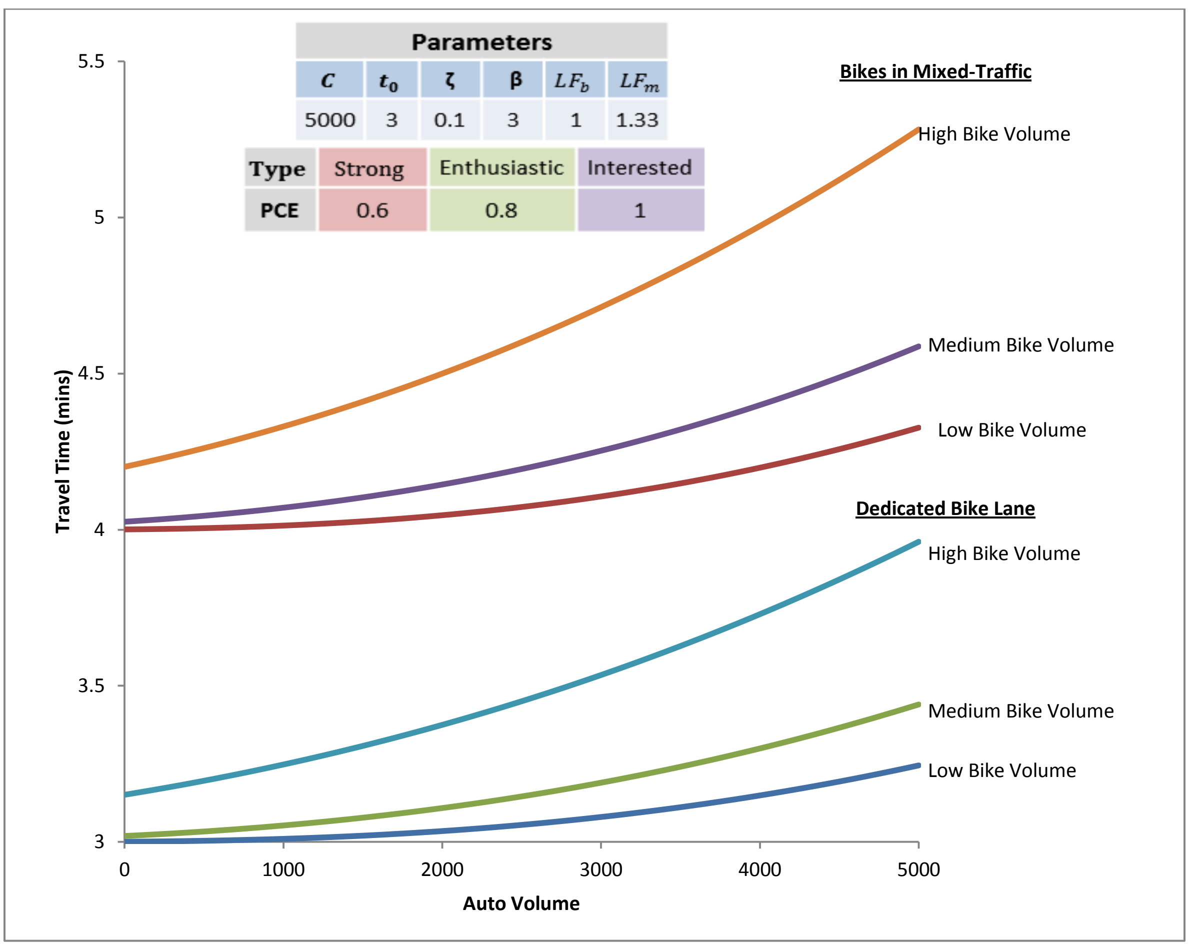

Figure 4.3: Auto VDF for different bike facilities and bike volumes

Turn Penalties

Turning movements and conditions at intersections have a strong impact on bicycle and auto travel times. Turning bikes increase auto travel times and turning autos increase bike travel times. In addition, proportion of bikes (autos) turning also directly affect bike (auto) travel times. Lastly, turning and through traffic in other directions also adversely impact travel times. These factors have to be taken into consideration while incorporating turn penalties.

Figure 4.4 shows the different turn movements when going from upstream node *i* through node *j* to node k. Three movements are available, $i-j-k$, $i-j-\overline{k}$, and $i-j-\underline{k}$. So, the turn penalty for bicycles for turn $i-j-k$ is a function of the auto and bike volumes in all the directions and movements:

$$TP_{b_{ijk}} = f\left(V_{a_{ijk}}, V_{b_{ijk}}, V_{a_{ij}}, V_{b_{ij}}, f_k(V_a, V_b, \ldots), f_{\overline{k}}(V_a, V_b, \ldots), f_{\overline{k}}(V_a, V_b, \ldots)\right)$$

Similarly, the turn penalty for autos is given by:

$$TP_{a_{ijk}} = f\left(V_{a_{ijk}}, V_{b_{ijk}}, V_{a_{ij}}, V_{b_{ij}}, f_k(V_a, V_b, \ldots), f_{\overline{k}}(V_a, V_b, \ldots), f_{\overline{k}}(V_a, V_b, \ldots)\right)$$

These turn penalties are dynamic because they change with traffic volume. Jeihani et al. *(8)* developed a similar intersection delay function which can be easily adapted to this context. The turn penalties can be added as a fixed delay to the link Volume Delay Function, and then they can be iteratively recalculated in the overall equilibrium framework.

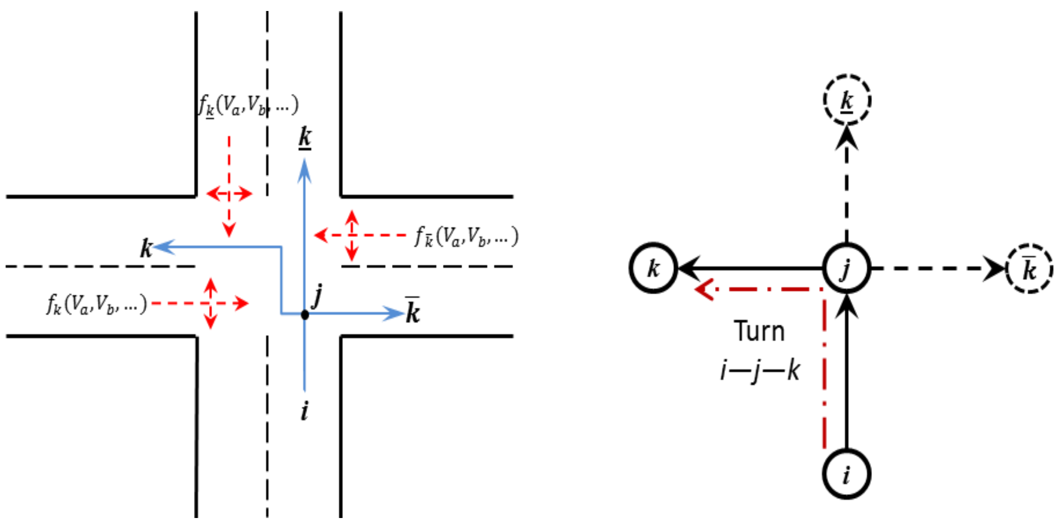

Figure 4.4: Turn movements and turn penalties

Iterative Implementation of Equilibrium Bicycle-Auto Assignment

The final goal of defining the LOS variables, VDFs, and turn penalties is to study the effects bicycles have on vehicular traffic and vice-versa in a coherent equilibrium framework. This objective is met by iteratively assigning bicycles and autos onto the network with the linkage between them. That is, while assigning bikes, we assume that the auto traffic on the links and turns is a given input to calculate the bike LOS and bike VDFs. Once bike assignment is completed, we assume that, during auto assignment, the bike traffic on the links and turns is a given input. The process iterates between these two assignments until the stopping criteria (equilibrium) is obtained. While doing one type of assignment, we assume that the flows obtained from the other assignment type are fixed and eventually reach equilibrium. It should be noted that a possible alternative way is to assign both auto and bicycle trips as different sets of vehicle classes in one multi-class assignment procedure. However, this would restrict the way different turn penalties would be calculated since in each single assignment turn penalties should be fixed for each class. The proposed iterative framework captures the important cross-impact of auto traffic and bicycle traffic on each other for each turn movement specifically.

Figure 4.5 explains the layout of the procedure. The algorithm first calculates the required inputs for the assignment process by segmenting the bicycle users based on their ability and the links based on their "bike-ability". The corresponding LOS variables, turn penalties, and VDFs are calculated. The LOS and link delay factors are also calculated. In the first step, auto assignment is carried out assuming that there are no bikes on the network. After auto assignment, the auto traffic is "preloaded" onto the network and bike assignment is carried out; note that bike VDFs will be calculated at this stage. The resulting traffic flows and travel times are used as input parameters. If the stopping criterion is met, the OD skims are passed on to the mode choice model.

Overall, there are three levels of equilibration: (a) bike and auto assignment each one separately; (b) equilibrium between bike and auto assignments achieved by iterations between them; (c) demand model equilibrium (passing OD skims to mode choice and other demand models). The algorithm framework is given below.

<u>**Assignment Inputs:**</u>

1. Auto VDF: $t(V_a) = t_0 \times LF \times \left(1 + \zeta_a \left(\frac{V_a + \sum_b p_{b_l} V_b}{C}\right)^{\beta_a}\right)$
2. Bike VDF: $t(V_b) = ACF \times \left(1 + \zeta_b \left(\frac{V_b}{C_{eff}}\right)^{Exp_{eff}}\right)$
3. Turn Penalties
4. Trip Tables

<u>**Procedure:**</u>

1. Initialize flow vectors, $\boldsymbol{V}_b^0 = 0$ and $\boldsymbol{V}_a^0 = 0$; and travel time vectors, $\boldsymbol{T}_a^0 = [t_0 LF]$ and $\boldsymbol{T_b^0} = [\boldsymbol{ACF}]$.
2. For any n^{th} iteration:

While $\sum_{rs} \frac{T_{b_{rs}}^n - T_{b_{rs}}^{n-1}}{T_{b_{rs}}^n} > \epsilon$ do:

   a. Assign autos on network using $t(V_a)$
   b. Resulting Auto flow, $V_a^n = \frac{n-1}{n} V_a^{n-1} + \frac{1}{n}\left(|V_a^n - V_a^{n-1}|\right)$
   c. Calculate link Delay Factor and new $t(V_b)$

d. Assign bicycles on network using $t(V_b)$
e. Resulting bike flow, $V_b{}^n = \frac{n-1}{n} V_b^{n-1} + \frac{1}{n}\left(|V_b^n - V_b^{n-1}|\right)$

Outputs

1. Bicycle flows, bicycle link travel times fed to auto assignment
2. Average OD skims for mode choice (detailed later)

5. Conclusions

The paper presents an approach that goes beyond the traditional travel modeling paradigm by incorporating cycling as an explicitly defined mode alternative in the recently updated model for Ottawa-Gatineau. While there are many papers that deal with quantifying LOS variables for bicyclists and bicycle facilities, the authors found practically no literature on bicycle routing and bicycle assignment models. The adopted approach overcomes the limitations of the existing travel models in practices that operate with greatly simplified bicycling LOS measures and do not model details associated with actual cycling routes and facilities.

The designed model framework addresses specifics of auto LOS and bicycling LOS and the associated cross-modal impacts which cyclists and motorised traffic place upon each other. The proposed model will be able to evaluate specific policies that affect cycling conditions, for example dedicated cycling lanes and/or related traffic regulations that cannot be evaluated with the current models. This is important particularly for the City of Ottawa (TRANS Member Agency) that is currently considering several large-scale programs to further promote bicycle use and improve conditions for bicycling.

The proposed innovative cycling simulation model for Ottawa-Gatineau, is based on a cycling route choice model that is designed to be sensitive to a wide range of LOS measures including time, speed, level-of-stress, turn conditions at intersections, area type effects etc. This route choice model serves as basis for a regional cycling assignment model. The cycling assignment model is equilibrated with the auto assignment. That is, while assigning bikes, we assume that the auto traffic on the links and turns is a given input to calculate the bike LOS and bike VDFs. Once bike assignment is completed, we assume that, during auto assignment, the bike traffic on the links ad turns is a given input. The process iterates between these two assignments until the stopping criteria (equilibrium) is obtained. The proposed iterative framework captures the important cross-impact of auto traffic and bicycle traffic on each other for each turn movement specifically. This regional assignment model is integrated into the overall regional travel model that predicts the share of cycling trips versus other auto, transit, and other non-motorized modes for different types of trips and population segments.

By the time of the conference the model development will have evolved and we will be able to present all results of model validation, calibration, and application for various scenarios. We plan to present sensitivity of the bicycle ridership to the bicycle network improvements (in particular, further development of dedicated bike lanes) and the corresponding impact on regional travel conditions and congestion levels.

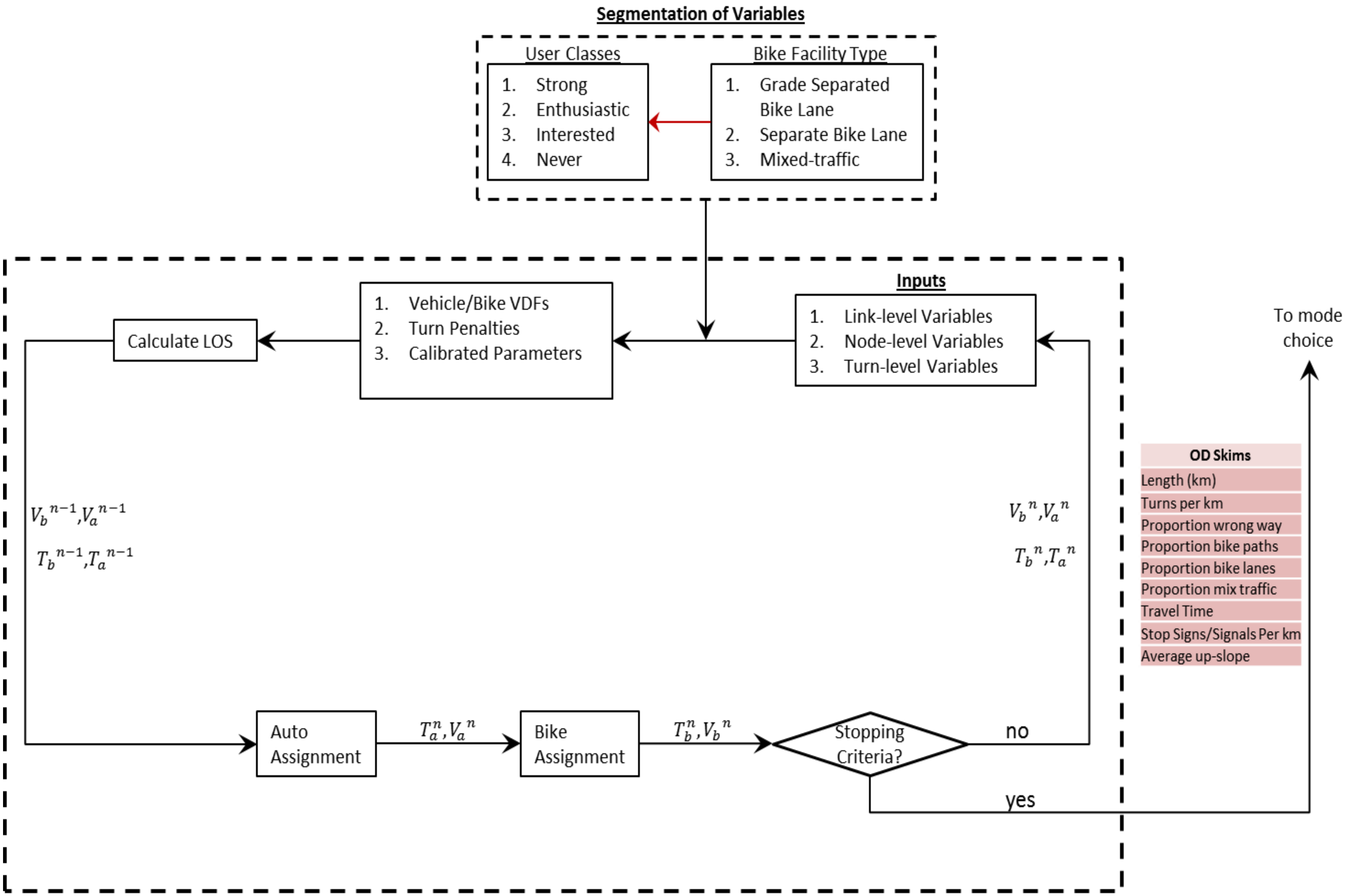

Figure 4.5: The Complete Bike Mode Choice and Assignment Framework

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