<u>OPTIMIZATION MODELING FOR URBAN STREET DESIGN</u>

by

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A Dissertation
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of
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of
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Civil Environmental and Infrastructure Engineering

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Master of Science
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DEDICATION

This is dedicated to my daughter Ioana and my husband Laurence.

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I would like to thank Dr. Aimee Flannery for her continuous support and inspiration. The interesting and educational journey at George Mason University began with a class taught by Dr. Flannery and it is ending with her being the Dissertation Director.
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ABSTRACT

OPTIMIZATION MODELING FOR URBAN STREET DESIGN

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For decades transportation legislation actions have demonstrated the desire to plan, design and operate multi-modal surface transportation systems (National Complete Streets Coalition [NCSC], 2009). The push for multi-modal operations stems from several key concerns including environmental impacts, natural resource scarcity, rising fuel costs and dependency on foreign oil, and the declining health of Americans due to their reliance on personal automobile travel. The introduction of legislation for multi-modal surface transportation designs reflects the desire of the public and decision makers to provide greener designs that reduce our dependency on foreign oil and effects on the environment while improving air quality and the health of travelers. However, it has been determined that the methods needed by engineers and planners to design such facilities are currently lacking in their ability to reflect traveler perceptions of service by mode which is needed to successfully design such multi-modal transportation systems.

In addition, design guidance does not include methods by which engineers and planners can weigh the range of potential alternative designs to optimize the design of streets to comfortably accommodate all modal travelers.

The purpose of this dissertation was to develop a Multi-objective Optimization Model to support the design of Complete Streets and to identify optimal urban street designs that achieve a pre-defined level of service rating for travelers on an urban arterial including auto, pedestrian and bicycle modal users, while meeting geometric design standards. To achieve this goal, Cumulative Logit Level of Service (LOS) Models were developed for the pedestrian and bicycle modes that incorporate traveler's perceptions of Level of Service and provide a distribution of perceived LOS to assist decision makers. Next, a Multi-objective Optimization Model was developed that can provide an optimal right of way design to accommodate the auto, pedestrian and bicycle modes at a pre-defined LOS that also adhere to geometric design standards.

Building on a national research study database, the probabilities of road user perceptions of Level of Service (LOS) for the pedestrian and bicycle modes were developed using the Cumulative Logit Modeling technique. An existing auto cumulative logit LOS model was utilized and the transit mode was not included due to lack of similar data. These models used variables found to be statistically significantly correlated to traveler's perception of LOS including: *Space Mean Speed* and *Median Presence* for the auto mode; *Number of Traffic Lanes, and Sidewalk Width* for the pedestrian mode and *Number* *of Traffic Lanes, Bike/Shoulder Width and Posted Speed Limit* for bicycle mode. These newly developed Cumulative Logit LOS Models for the pedestrian and bicycle modes provide a distribution of LOS ratings based on traveler perceptions of LOS and require minimal data collection on the part of the engineer or planner without a significant reduction in model accuracy which should spur the use of the methodology.

Next, these Cumulative Logit LOS Models were used in the development of a four-step Multi-objective Optimization Model that provides designers with a set of urban street characteristics that optimize modal traveler perceptions of service. The objective function was to balance the perceived LOS for each of the three modes subject to street characteristic constraints. Several scenarios of Right of Way (ROW) width for the Multi-objective Optimization Model were created to demonstrate the usefulness of the modeling approach. It was observed that fewer number of through lanes and the presence of a raised median, sidewalk and bike lane result in higher user rating of LOS for all three modes. These findings reflect the findings of previous studies conducted in-vehicle, through surveys, and through focus groups (Pecheux et al., 2004; Petritsch et al., 2005).

The findings of this study support the use of Cumulative Logit Modeling techniques to model ordered categorical traveler perception LOS data with a reduced set of independent variables for the pedestrian and bicycle modes on urban streets as compared to previous data intensive models (Dowling (NCHRP report 616). In addition, this study provides a new method for designing Complete Streets that seeks to optimize the perceived performance of urban streets by the auto, pedestrian, and bicycle modes while adhering to existing design standards.

CHAPTER 1: INTRODUCTION

1.1 Problem Statement

The greening of the surface transportation system in the United States (US) has been driven by two main influences: the rapid increase in fuel costs and the increased desire for many travelers to reduce their carbon footprint through the use of more sustainable transportation modes. This societal shift has resulted in an increased awareness of the need to design sustainable street systems that can accommodate alternative transportation modes alongside personal automobiles safely and efficiently. While the US is considered a rich and well educated country, for many years the development of a sustainable surface transportation system has not been a priority due in part to the heavy reliance on personal automobile travel (Buehler, 2009). The affordability of automobiles and the convenience they bring to personal travel has resulted in an increase in automobile usage and decrease in the presence of competing modes on most highway facilities, including urban streets for decades (Buehler, 2009). In contrast to the benefits that automobiles provide to individual users are the negative effects including air, water, and noise pollution; use of non-renewable fossil fuels; and traffic congestion (Buehler, 2009).

The perceived negative impact of automobile presence on pedestrians and bicycles on streets is another reason for the decrease in the use of alternative modes of transportation on urban street facilities.

Legislative actions reflect the attention that decision makers have given to their constituents' desire for sustainable surface transportation solutions to green urban street networks. To address this societal shift, this dissertation study developed a multi-objective optimization tool which will allow transportation engineers and planners to design sustainable streets that accommodate all modes that meet design standards at an acceptable level of service.

1.1.1 Legislative Action

To combat the negative effects of private automobile use, recent transportation legislation calls for the inclusion of multi-modal planning, design, and operation of surface transportation systems that receive federal funding. The Inter-modal Surface Transportation Efficiency Act (ISTEA), enacted by Congress in 1991, required state level plans for transportation to consider all transportation modes and all possible connections between them (USDOT, 2009). The Transportation Equity Act for the 21st Century (TEA-21), implemented in 1998, was a continuation of the ISTEA that placed the emphasis on statewide transportation planning processes. Among the areas to be considered was an emphasis on the integration and connectivity of the transportation system, across and between modes, for people and freight. TEA-21 also required a multi-modal statewide transportation planning process to involve federal, state and regional agencies and the public (USDOT, 2009).

The Safe Accountable Flexible Efficient Transportation Equity Act: A Legacy for Users (SAFETEA-LU) followed TEA-21 in 2005 and represented the largest surface transportation investment to date at $244.1 billion. SAFETEA-LU addressed challenges of the transportation system including increasing intermodal connectivity and improving safety for all modes. The passage of legislation in the past several decades that incorporates a multi-modal emphasis demonstrates the desire of the public and decision makers to reduce the dependency on foreign oil; improve air quality; reduce impact on the environment; and improve the health of travelers (FHWA, 2005).

Locally, the Commonwealth of Virginia has developed, with the concurrence of the Secretary of Transportation and through four state transportation modal agencies, a multi-modal long-range transportation plan called VTrans2025 (VDOT, 2009). The Statewide Multi-modal Long-Range Transportation Plan is in compliance with federal and state legislative requirements to ensure continuation of federal funding for transportation programs and projects. VTrans2025 is a multi-modal effort that is and will continue to engage the expertise of specialists from each modal sector to meet the objectives of the long range plan (VDOT, 2009).

Following on the heels of these landmark pieces of legislation, the concept of Complete Streets has emerged that envisions streets that will accommodate all transportation modes and users of urban streets facilities. The concept is tailored to the needs and context of each community and provides a connected transportation network that promotes sustainable development and alternative transportation modes (Robinson, 2009). The Complete Street Act of 2009, S.584, is a bill, that was introduced to the US Senate on March 12, 2009, written to require that all transportation modes be safely and conveniently accommodated on and across federally funded streets and highways (Harkin, 2009). The Act has not yet been signed into law as of the time of this dissertation publication, however, if signed into law, it will require that all federally funded transportation projects take into account the safety and convenience of all transportation facility users from project planning to land development phases of projects (Harkin, 2009).

Finally, on March 11, 2010, Secretary of Transportation Ray LaHood issued a Policy Statement on Bicycle and Pedestrian Accommodation Regulations and Recommendations (USDOT, 2010). The policy emphasizes the support of the US Department of Transportation (USDOT) for the development of fully integrated transportation networks where bicyclists and pedestrians are included by transportation agencies in policy, planning, funding and implementation of improvements (USDOT, 2010).

The extent of legislation related to multi-modal planning, design, and operations of streets and highways demonstrates the need for analysis tools and methods to assist engineers and planners in their pursuit of multi-modal facilities.

1.1.2 Analysis Methods

While the motivation and policy is in place to consider all modal users when designing urban streets, the methods by which engineers and planners analyze their designs have yet to be fully developed. Typically when preparing new designs, planners and engineers utilize many methods to assess the impact of their designs ranging from estimating safety performance; operational performance; determining air quality issues; addressing human factors considerations; and finally estimating the cost of the proposed design. Engineers and planners often turn to the *Highway Capacity Manual* and *Software* to analyze the operational performance of surface transportation investments (TRB, 2000). The current state-of-the-art methodology for urban street operational analysis is provided by the *Highway Capacity Manual*, (HCM) fourth edition, 2000 has been deemed incomplete by numerous studies and it will be replaced by a new version of the *Highway Capacity Manual* currently scheduled for release in 2010 (Cristei et al., 2005; Dowling et al., 2009; Flannery et al., 2008). The forthcoming 2010 urban street methodology will greatly improve the tools engineers and planners can use to analyze the operational performance of urban streets; however, it does not provide a method to optimize their proposed designs to meet perceived level of service on urban streets.

A few studies have been conducted that sought to model traveler perceptions of service on urban streets; however, the methods identified in the studies did not address the optimal design for all users on urban streets (Dowling et al., 2008; Ali et al., 2009; Washburn et al., 2004; Petritsch et al., 2006). This dissertation provides a method for practitioners to design optimal facilities for bicycle, pedestrian and auto users within an available right of way for development or redevelopment to obtain an acceptable level of user satisfaction on urban streets.

1.2 Motivation and Contribution to State of the Knowledge

The study utilizes concepts of quality of service set forth in the *Highway Capacity Manual* and an existing national database of traveler perceived level of service ratings for urban streets (TRB, 2000; TRB, 2009). The inclusion of traveler perceived level of service through cumulative logit modeling technique is intended to provide decision makers with a better understanding of the public's perception of service on urban streets which should improve the decision making process. In addition, the use of a multi-objective optimization method, as presented further in this dissertation, will allow engineers, planners, and decision makers to optimize the components of an urban street and obtain the perceived level of service across all modes on urban streets within a given right of way.

Specifically this study:

1. Identifies existing methods to incorporate traveler perception of level of service on urban streets into the decision making process.
2. Develops models to incorporate pedestrian and bicycle perception of level of service on urban streets into the decision making process.
3. Develops an optimization model to design an optimal Complete Urban Street to meet a minimum modal traveler perception of service for the auto, bicycle and pedestrian modes.

The contribution of the new model provides practitioners with a tool that will allow them to design streets that will accommodate three transportation modes, auto, pedestrian and bicycle, concomitantly at a level of service that is satisfactory for all three modes. A review of the existing literature did not reveal an optimization approach to urban street multi-modal design. Previous research studies focused on analyzing each transportation mode independently and providing insight on how modal users perceive the arterial roadway environment. The methods developed in this dissertation incorporate traveler's perceptions of service while providing optimal designs to achieve optimal modal level of service on urban streets.

1.3 An Overview of the Study Approach

The tasks accomplished in this dissertation study are presented in Figure 1.1. The main effort of this dissertation was to create a Multi-objective Optimization Model to use in the design of urban Complete Streets. The objectives were to optimize a given right of way on urban streets while simultaneously achieving an acceptable auto, pedestrian and bicycle traveler perceived level of service.

To accomplish these objectives, an existing national database of traveler perceptions of level of service on urban streets was utilized to develop an optimization model that attempts to surpass the previously created models that analyzed the level of service for different modes of transportation in isolation.

The street characteristics for the roadway facilities identified in the data set have been analyzed for correlation with the study participant rated level of service for the pedestrian and bicycle modes. The street characteristics identified as highly correlated with traveler perception of service have been used to develop cumulative logit models for the pedestrian and bicycle modes to determine modal level of service. The cumulative logit modeling technique was used for its ability to estimate ordered categorical data and a distribution of LOS ratings. An existing cumulative logit model for the auto mode has been utilized for this dissertation (Dowling, 2009). The model includes variables that are suitable for the modeling process in this dissertation. And finally, the results of the three models have been used as objective functions in a multi-objective optimization model for the design of Complete Streets.

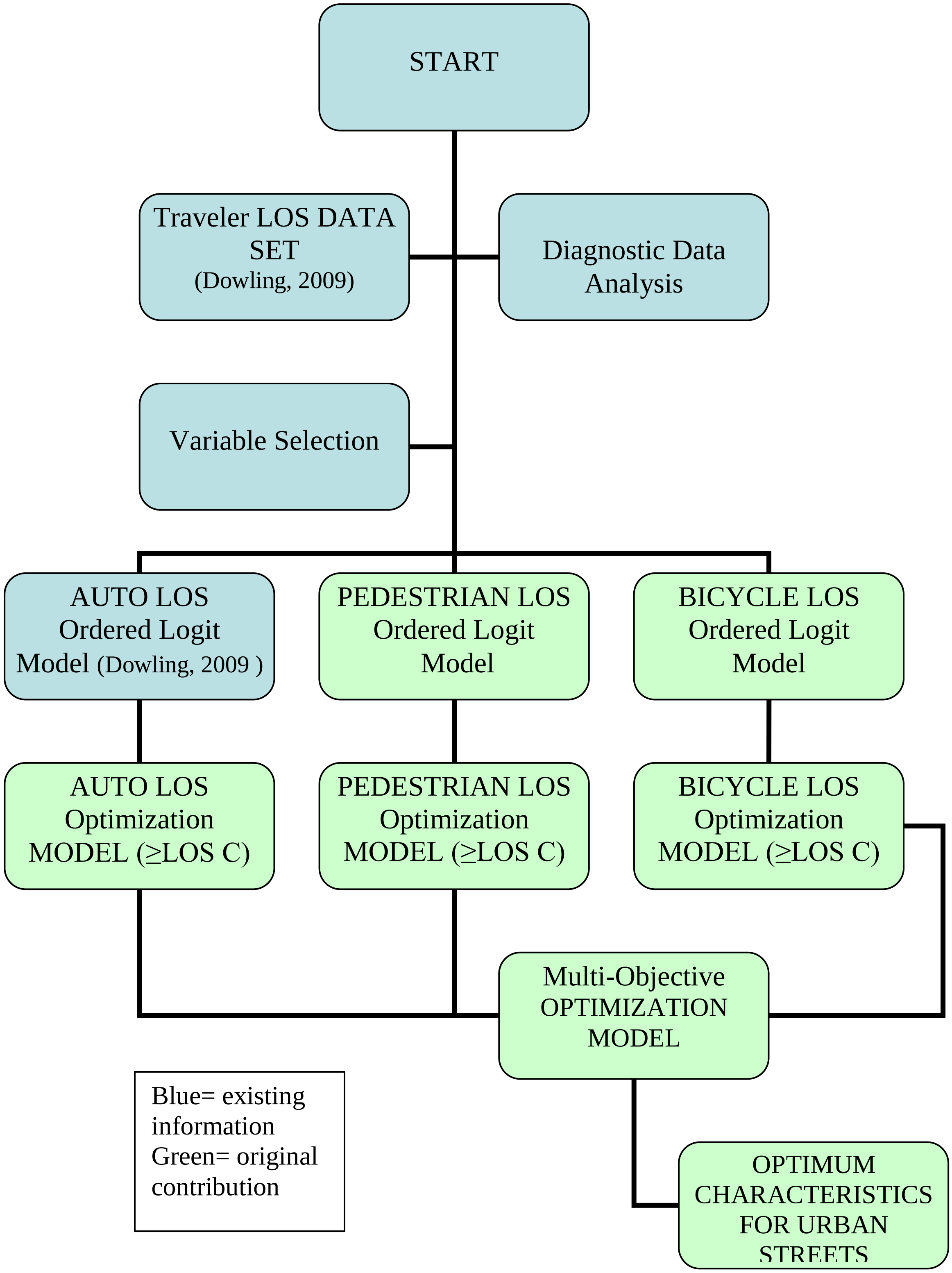

Figure 1.1 An overview of the study approach

This dissertation is organized as follows: Chapter 2 provides a literature review with summaries of journal articles on related research objectives. The study methodology is included in Chapter 3. Chapter 4 presents the models used to estimate traveler perceived LOS for the pedestrian and bicycle modes and the creation of a Multi-objective Optimization Model. Chapter 5 presents the validation of the Cumulative Logit Models and a sensitivity analysis of a Multi-objective Optimization Model. Chapter 6 provides conclusions of study and finally Chapter 7 provides recommendations for future research.

CHAPTER 2: LITERATURE REVIEW

In this literature review, a brief overview of the methods contained in the *Highway Capacity Manual* (HCM) 2000 is provided along with a review of the definitions of quality of service and level of service as given in the *HCM* 2000. In addition, a brief background on the HCM is provided to readers who are unfamiliar with transportation standards and guides used for operational analysis in the U.S. and internationally. Next, studies that analyzed Quality of Service (QOS) and LOS are introduced. Several journal articles that utilize a variety of modeling techniques for traveler perceived level of service are summarized. Next, the concept of Complete Streets is presented to outline the emerging multi-modal urban streets policies. Finally, optimization modeling techniques are reviewed and considered for their ability to model the Complete Street design environment. Finally, the literature review is summarized with a review of the relevance of the identified studies to this dissertation research.

The literature review has been presented in the following order:

1. *Highway Capacity Manual* review
2. Quality of Service and Level of Service research studies
3. Quality of Service and Level of Service Modeling Techniques
4. Complete Streets review
5. Optimization modeling techniques.

6. Conclusions

2.1 *Highway Capacity Manual* – QOS and LOS Methods and Uses

To better understand the function of the *Highway Capacity Manual* in the context of the engineer and planner toolbox, a review of the *HCM*'s widespread use and impact is provided here. In addition, a review of the definitions of QOS and LOS are provided.

The *Highway Capacity Manual* will soon be released in its fifth edition, the *Highway Capacity Manual* 2010. The *HCM* is published by the Transportation Research Board and is widely viewed by transportation professionals as the source of operational analysis methods for surface transportation systems. The most recent version of the *HCM*, *HCM* 2000, sold over 13,200 copies in 68 countries in the first three years of publication which demonstrates the wide use of the methods contained in the Manual. While not a national standard of design, many state and local jurisdictions have adopted the *Highway Capacity Manual* and the methods contained in it as a standard for analyzing operational performance of surface highway systems (TRB, 2005).

One of the most widely recognized uses of the *HCM* is the ability of the Level of Service methods contained in the Manual to synthesize information obtained from complex deterministic, empirically based models into a stratification of performance levels. These performance levels are referred to as Level of Service or LOS. For most analysis methods, a single Measure of Effectiveness (MOE) has been selected by the Highway

Capacity and Quality of Service Committee to represent the quality of the performance of a facility, and that single measure is stratified into six categories of performance, A-F (A being the best performance; F being the worst performance). For example, the MOE for signalized intersections for vehicles is average control delay, with LOS A achieved when average control delay is 10 seconds and LOS F achieved when average control delay exceeds 80 seconds (TRB, 2000). A quick search on the Internet reveals that many agencies have adopted the stratification of LOS A to F as their means to assess the performance of roadway segments, intersections, and facilities (AHDT, 2009; FDOT, 2007; VDOT, 2004). Often jurisdictions require new developments to meet or exceed a particular LOS on the neighboring transportation facility or new developments are often required to mitigate the impact through transportation impact fees which are placed into a fund for future transportation improvement projects.

Over the past decade the Highway Capacity and Quality of Service Committee (HCQOS), which is a volunteer organization that oversees and adopts the methods contained in the *HCM*, has begun to address the limits of the use of LOS. In particular, surveys and focus groups held with user groups (engineers, planners, decision makers), has revealed that many felt that while the LOS methods were useful to explain complex transportation modeling results to non-technical decision makers, they also felt LOS methods needed refinement to better reflect travelers experiences (Flannery et al., 2004). To address these concerns, the HQCS Committee began to request funding for research studies to better relate LOS thresholds and MOEs to travelers' experiences on various facility types. One recently completed study, National Cooperative Research Program Project 3-70 (NCHRP 3-70), Multimodal LOS for Urban Streets, has been reviewed as part of the literature review (Dowling et al., 2009).

2.2 Quality of Service and Level of Service Studies

NCHRP 3-70 Multimodal Level of Service for Urban Streets

The quality of service provided to travelers on urban streets has been the focus of several recent research studies (Dowling et al., 2008; Flannery et al., 2008; Petritsch et al., 2006). One study in particular was developed under the National Cooperative Highway Research Program (NCHRP) during a six year period beginning in 2003, NCHRP 3-70, Multimodal Level of Service for Urban Streets (Dowling et al., 2009). This study developed a method for analyzing the level of service for multimodal streets which included auto, fixed route transit bus, pedestrian and bicycle modes. The study developed a tool that allows practitioners in the transportation field to assess the effect of various characteristics of the urban streets based on perception of QOS by the auto, bus, pedestrians and bike riders. The study was developed using a video laboratory methodology for auto, pedestrian and bicycle modes where video clips were created then shown to research subjects in a survey setting. Transit data collection, however, took place in the field and on various bus routes to better capture the transit experience. The results of the study are important due to the inclusion of street characteristics that have not been used previously by the *HCM* methodologies for computing LOS on urban streets and the inclusion of the ratings of service by the traveling public to determine factors that influence service ratings and thresholds of service (Dowling et al., 2009).

In NCHRP 3-70 data collection efforts took place in two phases. Phase I of the data collection tested the feasibility of video laboratory settings to gather traveler perceptions of level of service. To test the feasibility, video clips were filmed and created that captured the auto driver's view of a variety of urban street cross-sections and conditions in the Washington, DC area. Additionally, field surveys with participants who also viewed and rated video clips that depicted auto were conducted. The ratings of LOS provided by a small group of participants who participated in both the video laboratory and the field studies were compared to ratings of the existing HCM auto LOS methods for urban streets. A review of the differences between traveler perceived LOS and HCM estimated LOS was deemed acceptable and video laboratory settings were selected as the method of data collection for the larger efforts which took place in Phase II (Dowling et al., 2009).

Video clips were created for the pedestrian, bicycle, and auto modes as part of NCHRP 3-70. Transit LOS ratings were gathered from users of the transit systems in several locations in the US; however, the transit methods and findings are not included here as the transit mode was not included in this overall study. The transit mode was not included in this study due to two primary reasons:

- Level of service ratings were not collected using the same methods as the other modes
- Level of service ratings were collected only from users of the transit systems which limited the ability to capture the perceived service by both riders and non-riders, unlike the auto, pedestrian, and bicycle modes.

Video clips were created for the auto mode by using:

- Rented vehicle
- Two video cameras
- A Global Positioning System (GPS) unit

The team filmed urban street scenes from the driver's perspective then extracted the video clips creating a total of 35 clips showing the scene from driver's perspective including a view of the speedometer. An important characteristic of the selected routes was a consistent cross section, including the same number of through travel lanes on the video clip. All taping sessions took place during daylight hours and dry conditions. The auto clip characteristics have been summarized in table 2.1 and have been presented in detail in Appendix 1 (Dowling et al., 2009).

Pedestrian video clip creation was also accomplished in two phases where in Phase I eight video clips were created and shown to 45 participants. The video clip collection was continued in Phase II and was enhanced by adding combinations of conditions. All video clips were created during daylight hours and during dry conditions with the "moving camera" approach. Taping was accomplished with a "steady camera" unit and 32 video clips were created. The ranges of pedestrian clip characteristics have been presented in Table 2.2.

Table 2.1 Roadway Characteristics in Auto Clips

Street Characteristics	Range
No of Through Lanes	1-3 Lanes
Presence of median	0, 1, 2, 3*
Total Travel Time (sec)	48-471
Space Mean Speed (mph)	3.8-41.9
Ped on sidewalk	0,1,2**
# of stops (below 5 mph)	0-4
Total # of Signals	1-9
Pres of Excl LT L Signals	0,1***
Presence of RTL Signals	0,1***
Tree Presence	1,2,3****
Average Lane Width (ft)	10-14
Width of Median (ft)	0-54
Right Shoulder Width (ft)	0,4,8
Left Shoulder Width (ft)	0,2,3,4
Width of Parking Lane (ft)	0,7,8,10
Width of sidewalk (ft)	0-14
Sep ROW to Sidewalk (ft)	0-10
Width of Bike Lane (ft)	0,5,6

The codes used to define categories for different variables are discussed blow:

*Presence of median
0 = no separation between opposing traffic streams
1 = no opposing traffic stream (one-way street)
2 = two way left turn lane
3 = raised median (curbs between opposing traffic streams)

**Pedestrians on sidewalk
0= few or none
1= some
2= many

*** Pres of Excl LT or RTL at Signals
0 = none present
1 = present

****Tree Presence
1= few or none
2= some

Table 2.2 Roadway Characteristics in Pedestrian Clips

Street Characteristics	**Range**
Sidewalk Width (ft)	No Sidewalk, <4, >4
Separation of Walkway From Traffic	Yes, No
Traffic Speed (mph)	<30, 30-40, >40
Traffic Volume Outside Lane (vph)	<400, 400-800, >800
Pedestrian Volumes (pph)	Low(<300), Medium(300-1000), High(>1000)
Number of lanes crossed	2, >4
Signal Delay (sec)	<30, >30

The creation of bicycle video clips was accomplished in one phase. The street characteristics for the bicycle study have been presented in Table 2.3. The video simulation with "moving camera" approach was used to create the video clips depicting bicycling conditions along various arterial streets in which the bicyclists utilized shoulders or bicycle lanes and traveled along the arterial as a vehicle. Thirty video clips were created and shown to study participants (Dowling et al., 2009).

Table 2.3 Roadway Characteristics in Bicycle Clips

Street Characteristics	Range
Width of Outside Lane (ft)	<12, >12
Presence/Width of Bike Lane (ft)	No lane, ≤4, >4
Vehicle Flow in Outside Lane (vph)	<400, 400-800, >800
Speed Limit (mph)	<30, 30-40, >40
Crossing width (ft)	<36, 36-60, >60
Control Delay (s)	No stop, <40, >40

The video clips created for each mode were presented to 145 participants in four different locations in the US: New Haven, CT; Chicago, IL; Oakland, CA and College Station, TX. For each of the three modes, participants were asked to watch 10 video clips and rate them on a six-point scale (A through F, A being the best and F the worst) as a commuter.

Of the ten video clips per mode shown to study participants, six unique clips per mode per location were shown and rated by participants and four clips for each mode were shown at all four locations, which provided a robust set of data to be utilized in part in the validation of the models developed in the study. The Appendix provides tables with the numbering and assignment of the video clips presented at each survey location (Dowling et al., 2009).

Modeling Results – NCHRP 3-70

The data collected were used in NCHRP 3-70 to develop traveler perceived LOS models for each of the modes. The auto LOS model was developed as follows. First, a correlation analysis was conducted to establish the relationship between the dependent variable, the LOS rating by each participant, and the independent variables or their transformations. The results of the analysis were that 69 of the 78 variables were statistically significantly correlated to the dependent variable. Linear regression techniques were considered for the auto mode, however, researchers responsible for the development of the auto LOS model believed that the categorical ordered nature of LOS ratings by participants pointed towards the use of the cumulative logistic modeling techniques to estimate the percentage of participants that would rate a facility LOS A, B, C, D, E, or F versus the average rating of LOS as would be estimated by a traditional linear regression model (Dowling, et al, 2009).

The logit model for cumulative probability P(Y≤j|x) is defined as follows (Agresti, 2007):

$$Ln[P(Y < j|x)/1 - P(Y < j|x)] = \beta'(x) \text{, or} \qquad \text{Equation 2.2.1}$$

$$P(Y < j|x) = \exp(\beta'(x))/[1 + \beta'(x)] \qquad \text{Equation 2.2.2}$$

Each cumulative probability has a different intercept α_j but the same coefficients β. Which means that each independent variable will have one β parameter but it will not change when the α parameter changes (Agresti, 2007). For the purpose of this dissertation study, the auto model selected from NCHRP 3-70 included the independent variables *Median Presence and Space Mean Speed* of the vehicle driven in the video clips. A Cumulative Logistic Model was developed and the Maximum Likelihood Estimates Parameters have been presented in Table 2.4.

Table 2.4 Maximum Likelihood Estimate Parameters for Traveler Perceived Auto LOS Model

Parameter	**Estimate**
Intercept LOS F, $\alpha1$=	-1.192
Intercept LOS E, $\alpha2$=	-0.2
Intercept LOS D, $\alpha3$ =	0.706
Intercept LOS C, $\alpha4$=	1.801
Intercept LOS B, $\alpha5$=	3.617
Space Mean Speed (mph), $\beta1$ =	-0.084
Median Presence (0-3) , $\beta2$ =	-0.224

The study also created a Cumulative Logit Model using the number of stops per mile on the facility and the presence of exclusive left turn lanes at intersections. Table 2.5 presents the results of the Maximum Likelihood Estimate for Ordinal Regression applied to automobile LOS (Dowling et al., 2009).

Table 2.5 Maximum Likelihood Estimate Parameters for Automobile LOS

Parameter	**Estimate**
Intercept LOS F, $\alpha1$	-2.919
Intercept LOS E, $\alpha2$	-1.827
Intercept LOS D, $\alpha3$	-0.853
Intercept LOS C, $\alpha4$	0.283
Intercept LOS B, $\alpha5$	2.094
Stops per mile, $\beta1$=	0.203
Pres of Ex LT Lane, $\beta2$=	-0.522
Tree Presence, $\beta3$=	-0.338

Comparison of the *HCM* 2000 and the stops per mile model developed in NCHRP 3-70 revealed that the *HCM* 2000 was only able to estimate 50 percent of the observed mean clip LOS while the NCHRP 3-70 stops model was able to estimate 83 percent of the observed mean clip LOS (Dowling et al., 2009). The space mean speed model was used in this dissertation for its ability to contribute to the multi-objective optimization model.

A bicycle LOS model was developed in NCHRP 3-70 as an aggregate model, by using the outputs from existing segment and intersection LOS models in order to obtain the arterial LOS instead of an agglomerate model which uses the independent street characteristics to calculate the arterial bicycle LOS. Further, a linear regression model was considered by the researchers responsible for the bicycle mode to be more appropriate given the existing bicycle regression LOS models that have been developed in the past. Given the use of linear regression techniques to estimate bicycle user perceived LOS, researchers determined the mean LOS rating of each video clip and regressed against that mean rating a combination of conditions present on the video clip. This approach means that of the 1413 observations of bicycle LOS ratings, only 28 mean ratings were used in the modeling process which represents the number of bicycle clips shown to study participants.

Using Pearson correlation analysis relevant variables were selected and used for two sub-models of the same form but with different predictor variables. Bicycle Model # 1 is shown in equation 2.2.3 and Bicycle Model # 2 is shown in equation 2.2.4.

$$BikeLOS\#1 = 0.160*(ABSeg) + 0.011*(\exp(ABInt) + 0.035*(Cflt) + 2.85 \qquad \text{Equation 2.2.3}$$

$$BikeLOS\#1 = 0.20*(ABSeg) + 0.03*(\exp(ABInt) + 0.05*(Cflt) + 1.40 \qquad \text{Equation 2.2.4}$$

Where

$ABSeg$ = The length weighted average segment bicycle score,

Exp = The exponential function, where e is the base of the natural logarithms,

$ABInt$ = Average intersection bicycle score

$Cflt$ = Number of unsignalized conflicts per mile, i.e., the sum of the number of driveways per mile.

The disadvantage of the bicycle LOS models created was that they are not able to generate an estimate of the entire distribution of LOS rating as a Cumulative Logit Model would have. In addition, the dependent variable, participant perceived bicycle LOS, was not collected as a continuous variable, instead participants were restricted to rating their perceived LOS in categories ranging from A to F. Therefore, the conversion of the LOS categories into a mean participant rating is necessarily the mathematically correct approach to modeling categorical data.

The models developed in NCHRP 3-70 for the bicycle mode were compared to the mean LOS as per the *HCM* 2000 bicycle LOS methodology. Researchers reported that the two newly formed models did a better job of estimating traveler perceived bicycle LOS than the methodology in *HCM* 2000. It was reported that the *HCM* 2000 bicycle LOS methodology predicted 15 percent of the observed mean LOS ratings while the two models created by NCHRP 3-70 predicted 27 and 46 percent of the observed mean LOS rating respectively.

The pedestrian model development process was similar to the bicycle model development in that the model was developed to estimate the mean LOS observed by pedestrians along an urban street. The level of service for the facility was selected between two computed LOS as presented in equation 2.2.5.

$$PedestrianLOS = Worse\_of\,(PedestrianDensity\_or PedOtherLOS) \quad \text{Equation 2.2.5}$$

Where

$PedLOS$ = The letter grade level of service for the urban street combining density and other factors,

$PedDensityLOS$ = The letter grade level of service for sidewalks, walkways, and street corners based on density,

$PedOtherLOS$ = The letter grade level of service for the urban street based on factors other than density.

The approach taken by the NCHRP 3-70 research team for the pedestrian mode was to provide the analyst with two methods by which to estimate pedestrian LOS. The first, which is based on the *HCM* 2000 methodology, was used to determine the pedestrian density for the sidewalk and waiting areas at signalized intersections street corners. Pedestrian density can then be used to estimate pedestrian LOS in areas where pedestrian traffic is very high. Alternatively, the analyst can utilize the pedestrian LOS for the facility which was developed in NCHRP 3-70 using linear regression and traveler's perceptions of pedestrian LOS. The NCHRP 3-70 research team developed two linear regression models to estimate pedestrian LOS as presented in the following equations:

Pedestrian LOS Model #1

$$OtherPLOS(\#1) = (0.318PSeg + 0.220P\text{int} + 1.606) * (RCDF) \quad \text{Equation 2.2.6}$$

Pedestrian LOS Model #2

$$OtherPLOS(\#2) = (0.45PSeg + 0.30P\text{int} + 1.30) * (RDCF) \quad \text{Equation 2.2.7}$$

Where

$OtherPLOS$ =Pedestrian non-density (other factors) LOS,

$PSeg$ =Pedestrian segment LOS value,

$P\text{int}$ =Pedestrian intersection LOS value,

$RCDF$ =Roadway crossing difficulty factor.

Since the first model did not produce LOS F, the second model was created to produce a full LOS range. The two models predicted the mean video clip rating 43 percent of the time while the *HCM* 2000 methods predicted the mean video clip rating correctly only 25 percent of the time. Thus, again there was an improvement in predicting the mean pedestrian LOS, however, again the full robustness of the 1400 individual data points for pedestrian LOS ratings was not utilized in the modeling process by the NCHRP 3-70 team and will be addressed in this dissertation.

NCHRP 3-70 Model Performance

The fit of the auto, bicycle, and pedestrian models developed in NCHRP 3-70 were compared to the existing *HCM* 2000 models for each mode respectively. Table 2.6 presents the results of the correlation analysis of the HCM LOS, observed LOS and auto model LOS. The auto model has a superior correlation to the mean video clip ratings, explaining approximately 82 percent of the variation in mean observed LOS ratings.

Table 2.6 Correlation Coefficients of Auto LOS Model

Models Compared	**Pearson Correlation Coefficient**
HCM LOS to Mean Observed LOS	0.499
Model LOS to Mean Observed LOS	0.825

Similarly, Tables 2.7 and 2.8 include the results of the correlation analysis for the pedestrian and the bicycle LOS models. Both models are better able to estimate the observed mean LOS for the video clips as compared to the *HCM* 2000 methodologies. .

The pedestrian model developed in NCHRP 3-70 is able to explain approximately 70 percent of the variation in mean observed LOS ratings and the NCHRP 3-70 bicycle model is able to explain approximately 50 percent of the variation in the mean LOS ratings.

Table 2.7 Correlation Coefficients of Pedestrian LOS Model

Models Compared	**Pearson Correlation Coefficient**
HCM LOS to Mean Observed LOS	0.016
Model LOS to Mean Observed LOS	0.709

Table 2.8 Correlation Coefficients of Bicycle LOS Model

Models Compared	**Pearson Correlation Coefficient**
HCM LOS to Mean Observed LOS	0.059
Model LOS to Mean Observed LOS	0.468

As noted previously, the robustness of the perceived traveler LOS data for the bicycle and pedestrian modes is believed to have not been fully utilized in the NCHRP 3-70 modeling effort. Efforts were taken in this dissertation research to develop cumulative logit models for the pedestrian and bicycle modes to estimate the entire distribution of traveler ratings. The Cumulative Logit Model for the auto mode developed as part of NCHRP 3-70 has been utilized in this dissertation research.

The NCHRP 3-70 methodology addresses the perceived LOS by auto, pedestrian, bicycle and transit modal users separately while attempting to capture the multimodal interaction between modes when applicable. The study provides engineers and planners with four models to assess the perceived traveler service provided to fixed route on-street transit systems; on-street bicycle facilities; roadside pedestrian facilities; and auto facilities for the primary through movement on urban streets, however, no methodology was provided that will allow an analyst to perform an optimization design for urban streets (Dowling et al., 2009).

A follow-on study developed with the data from NCHRP 3-70 modeled pedestrian LOS using a cumulative logistic regression modeling approach was recently completed (Ali et al., 2009). The street characteristics that were strongly correlated with the individual LOS rating were used for developing the model included: number of traffic lanes, sidewalk width, posted speed and traffic volume. The results of the correlation analysis are presented in Table 2.9.

Table 2.9 Results of Correlation Analysis of Independent Variables with LOS Ratings

Variable	τ Rank Correlation Coefficient	Significance p-value
Sidewalk Width	**0.335**	0
Pedestrian Flow Rate	0.201	0
Outside Lane Width	0.121	0.007
Shoulder Width	-0.277	0
On Street Parking	0.246	0
Barrier	0.314	0
Buffer Width	0.111	0.005
Same Direction Traffic Volume	**-0.182**	0
Number of Through Lanes	**-0.291**	0
Speed Limit	**-0.161**	0
Traffic Volume/Lane	-0.028	0.465

The model predicted the probability of rating for each of the six LOS levels. Table 2.10 presents the results of the Maximum Likelihood Estimates for Ordinal Regression for the pedestrian mode as developed by Ali et al.

Table 2.10 Maximum Likelihood Estimate Parameters for Pedestrian Mode

Parameter	**Estimate**
Intercept LOS F, α1=	-3.497
Intercept LOS E, α2=	-2.020
Intercept LOS D, α3 =	-1.108
Intercept LOS C, α4=	0.014
Intercept LOS B, α5=	2.283
Sidewalk Width (>5 ft), β1 =	0.562
Num of Through Lanes , β2=	-0.601
Directional Volume (H), β3=	1.293
Directional Volume (L), β4=	0.457
Speed Limit (>40) , β5 =	-0.674

Figure 2.1 presents the cumulative probability curves for the pedestrian LOS model created by Ali et al. where the number of traffic lanes is depicted for one to four lanes while the traffic volume varies between 0-500 vph, the sidewalk width is less than 5 ft and the posted speed limit varies between 20-40 mph. On the X axis of Figure 2.1 the pedestrian LOS categories are depicted as follows: A=6 and F=1.

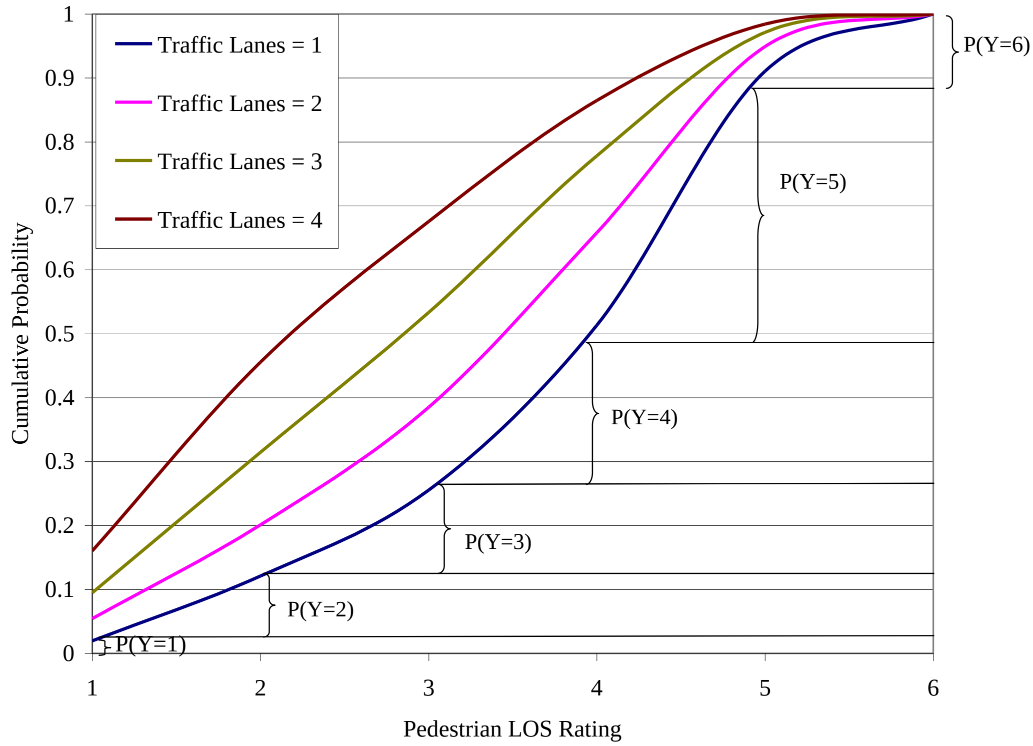

Figure 2. 1 Cumulative Probability Curves for Pedestrian LOS Rating (Ali et al., 2009)

The study also provided a validation for the proposed pedestrian cumulative logit model which is presented in Figure 2.2. Similarly with Figure 2.1 the X axis represents pedestrian LOS categories as A=6 and F=1. The authors noted the model validation demonstrated that the participants' ratings of service were closely predicted by the model (Ali et al., 2009).

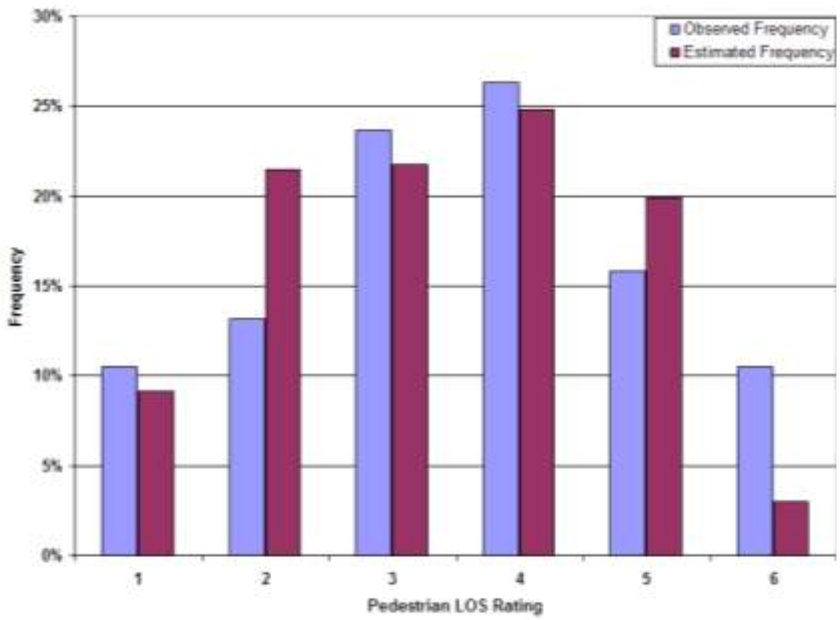

Figure 2. 2 Pedestrian Model Validation – Observed versus Estimated Pedestrian LOS Ratings for Clip 226 (Ali et al., 2009)

Other large-scale studies have been conducted to determine traveler perception of service on rural freeways in Florida (Washburn et al., 2004). A study based on a field survey based approach collected data related to driver and passenger perception of quality of service on rural freeways. The participants selected the performance measures that were the most important to them when traveling on rural freeways. The top four factors were determined to be: the ability to maintain desired speed (Factor 1), ability to travel at speed limit (Factor 2), ability to change lanes and pass easily (Factor 3), and good road surface conditions (Factor 4). An ordered probit model was later developed to determine the statistical importance of facility characteristics to drivers' ratings of service. The model was formulated as presented by equation 2.2.9 and it provides the goodness-of-fit measure, corrected ρ^2.

$$\bar{\rho}^2 = 1 - \frac{L^*(\hat{\beta}) - (\frac{k}{2})}{L^*(0)} \qquad \text{Equation 2.2.9}$$

Where:

$L^*(\hat{\beta}) =$ log likelihood at model convergence

$L^*(0) =$ log-likelihood at zero,

k = number of coefficients in the model

The initial log-likelihood, the log-likelihood at convergence and the corrected goodness-of-fit measure for the four factors are presented in table 2.11(Washburn et al., 2004).

Table 2.11 Results of the Ordered-Probit Model Estimated Results

	Factor 1	Factor 2	Factor 3	Factor 4
Initial log-likelihood	-491.94	-472.8	-501.55	-540.94
Log-likelihood at convergence	-282.35	-322.33	-315.77	-350.43
Corrected goodness-of-fit measure ($\bar{\rho}^2$)	0.420	0.313	0.364	0.348

It was concluded that travelers think multi-dimensionally with regards to quality of service and not one dimensionally as is typically the case with most HCM LOS methods.

A majority of the study participants considered three or more characteristics as extremely important when rating the service quality of their trip (Washburn et al., 2004).

The *HCM* 2000 LOS concept has also been analyzed in a study performed in Indiana (Choocharukul et al., 2003). The study provided statistical evidence that travelers perceived LOS differs from the LOS defined by the Manual. The researchers recruited a pool of 195 study participants from five occupational groups: 84 graduate and undergraduate students, 32 transportation professionals, 14 environmental management professionals, 35 truckers and 30 clerical staff from state agencies. Additional, socio-demographic attributes were also gathered about the participants. Two groups were formed: group one included the students, transportation professionals and the environmental professionals; group two included the truckers and the clerical staff. The collected data were from two locations near Chicago and five locations in and around Indianapolis and resulted in two sets of 12 video clips. Each set contained two clips for each LOS; one clip from the lower end of the threshold and the second from the upper end. The study was developed in a laboratory setting where a group-administered survey procedure was chosen. This setting allowed the two participating groups to view the video clips simultaneously. The participants were shown 12 video clips and were asked to rate their perception of LOS from A to F. The data collected were used in statistical model development.

The ordered probability model was derived by defining a variable, *z*, for the perception of LOS rankings:

$$z = \beta X + \varepsilon \qquad \text{Equation 2.2.9}$$

Where *X* is a vector of variables for perceived LOS, *β* is a parameter and *ε* is a random disturbance (Choocharukul et al., 2003). Observed LOS was written as follows:

$$\begin{aligned}
&y = 1______if\ _\ z \le \mu_1 \\
&y = 2______if\ _\ z \le \mu_2 \\
&y = 3______if\ _\ z \le \mu_3 \\
&y = 4______if\ _\ z \le \mu_4 \\
&y = 5______if\ _\ z \le \mu_5 \\
&y = 6______if\ _\ z \le \mu_6
\end{aligned}$$

Where LOS A corresponds to $y = 1$ and LOS F corresponds to $y = 6$; μ are estimable parameters that define y. The ordered probit model was written as:

$$\begin{aligned}
&P(y = 1) = \phi(-\beta X) \\
&P(y = 2) = \phi(\mu_2 - \beta X) - \phi(\beta X) \\
&P(y = 3) = \phi(\mu_3 - \beta X) - \phi(\mu_2 - \beta X) \\
&P(y = 4) = \phi(\mu_4 - \beta X) - \phi(\mu_3 - \beta X) \\
&P(y = 5) = \phi(\mu_5 - \beta X) - \phi(\mu_4 - \beta X) \\
&P(y = 6) = 1 - \phi(\mu_5 - \beta X)
\end{aligned} \qquad \text{Equations 2.2.10}$$

Where $\phi(.)$ is the cumulative normal distribution,

$$\phi(u) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{u} e^{-\frac{1}{2}w^2}\, dw \qquad \text{Equation 2.2.11}$$

The model was estimated by random effects ordered probability model with traffic density as the only independent variable. The parameter estimation results are presented in Table 2.12.

Table 2.12 Parameter Estimation Results for Density Threshold Values (t-statistics in parenthesis)

Independent Variable	Model 1 STU	Model 2 TPP	Model 3 ENV	Model 4 TRK	Model 5 CLK	Model 6 ALL
Constant	-0.535 (-3.84)	-1.156 (-3.05)	-1.218 (-1.87)	-0.715 (-1.73)	-0.504 (-1.93)	-0.658 (-7.09)
Traffic Density In pc/mi/ln	0.107 (30.46)	0.107 (9.12)	0.122 (14.13)	0.103 (19.60)	0.080 (18.39)	0.099 (52.48)
Threshold μ_2	1.445 (11.53)	1.250 (6.41)	1.663 (3.08)	1.386 (5.76)	1.328 (8.08)	1.366 (21.55)
Threshold μ_3	3.016 (23.21)	2.884 (9.31)	3.069 (6.76)	2.467 (9.16)	2.424 (13.15)	2.741 (38.39)
Threshold μ_4	4.704 (27.26)	4.389 (9.48)	4.505 (8.08)	4.077 (14.25)	3.573 (17.03)	4.222 (47.36)
Threshold μ_5	8.333 (26.75)	6.854 (6.60)	7.363 (8.26)	8.255 (18.94)	6.546 (17.91)	7.440 (47.08)
Std Dev of Rand Eff	0.573 (9.88)	0.636 (4.16)	0.815 (1.21)	0.540 (3.84)	0.507 (4.16)	0.580 (12.99)
Num of Obs	1008	384	168	420	360	2340
Log Likelihood at zero	-1728.08	-641.59	-293.71	-712.01	-622.71	-4029.21
Log Likelihood at convergence	-938.88	-377.90	-151.86	-410.92	-406.20	-2343.50
ρ^2	0.46	0.41	0.48	0.42	0.35	0.42

The acronyms in Table 2.12 are: STU=University Students, TPP=Transportation Professionals, ENV=Environmental Management Professionals, TRK=Truckers, CLK=Clerical Staff, and ALL=All subgroups.

The results show that the density and the threshold estimates are statistically significant, as indicated by the *t*-statistic and the goodness-of-fit is reasonable. A comparison of the *HCM* 2000 density range and the estimates was performed. It showed that the perceived LOS did not closely follow the *HCM* 2000 in many areas. Table 2.13 presents the comparison of LOS.

Table 2.13 Comparison of Level of Service Criteria

LOS	Perceived Density Range (pc/mi/ln)						
	Model 1 STU	Model 2 TPP	Model 3 ENV	Model 4 TRK	Model 5 CLK	Model 6 ALL	HCM
A	0-5	0-11	0-10	0-7	0-6	0-7	0-11
B	>5-19	>11-23	>10-24	>7-20	>6-23	>7-21	>11-18
C	>19-34	>23-38	>24-35	>20-31	>23-37	>21-34	>18-26
D	>34-49	>38-52	>35-47	>31-47	>37-51	>34-49	>26-35
E	>49-83	>52-75	>47-70	>47-87	>51-89	>49-82	>35-45
F	>83	>75	>70	>87	>89	>82	>45

The conclusion of this study was that the *HCM* 2000 thresholds do not correspond with the perceived thresholds of LOS and that factors other than density influence driver perceived LOS. Among factors that were found to influence driver perception of LOS were freeway visibility, average speeds, number of lanes, percent of trucks and standard deviation of headway (Choocharukul, 2003).

A study, conducted in the greater Washington DC area, used video presentation to assess the facility characteristics that influence driver's perception of quality of service on urban streets (Cristei, 2005). Nineteen videotaped clips were created on urban streets having the driver perspective and the speedometer images combined into one. The deficiency of the study was that the video clips created did not cover the entire array of urban street category and LOS. However, the study analyzed the demographic data and concluded that there was no statistically significant difference between male and female ratings at 0.05 confidence level, but there was a statistically significant difference of the ratings of three age groups (18-27, 28-55, over 55). Further the study provided statistical evidence that driver ratings of LOS were not well represented by the HCM LOS. The study created and analyzed box plots for each arterial type and provided evidence that driver perception of LOS may be biased by local conditions. One of the conditions referred to the landscaped arterials that were consistently rated higher than the HCM LOS and the second referred to the fact that the greater Washington DC area has congested traffic conditions on a daily basis therefore lowering driver's expectations.

The study provided a launching board for future research by suggesting data collection to obtain a set of video clips that cover the entire array of arterial category and LOS and further analysis by creating a categorical model to predict the LOS ratings distribution. The importance of the study also consists of the suggestion that understanding the characteristics of the participants may facilitate a better understanding of their ratings (Cristei, 2005).

The roadway lane designation among variable modes was analyzed in a study at University of Maryland (Elshafei, 2006)). The study was based on assigning three different lane scenario to a fixed given right-of-way width in an urban transportation network setting. The measures of performance used in the study were:

- travel speed,
- travel time,
- delay time and users' cost for each mode,
- operating cost,
- bicycle compatibility index (BCI) comparisons,
- mobility,
- accessibility and
- safety and environmental impacts.

The average travel speed, as well as travel times and delays, for each mode in each of the three scenarios were determined using the traffic simulation software VISSIM (Verkehr in Städten – Simulation, or "traffic in towns – simulation") (Elshafei, 2006). VISSIM is a microscopic, behavior-based multi-purpose traffic simulation program. The software is capable of integrating pedestrian and vehicle simulations.

The cost of travel and delays, operating costs, effectiveness for mobility accessibility, safety and environmental impacts were calculated using the VISSIM output data. The multi-objective decision-making framework consisted of a collection of charts each presenting the result of each objective in each of the three different scenarios. Each charts' top and bottom values represented unlabeled constraints for the model. The study's main question regarding the impact on performance of the change in lane distribution and modes was to be answered – if necessary - by performing a sensitivity analysis. The three selected scenarios for the 26-foot width were:

- Scenario # 1 with two 13-foot mixed traffic lanes.
- Scenario # 2 one 12-foot mixed traffic lane and one 14-foot exclusive bus lane.
- Scenario # 3 two 10.5-foot mixed traffic lanes and one 5-foot bicycle lane.

The case study conducted showed that in scenario #1 the performance levels for all objectives were higher than the other two scenarios; however it was acknowledged that bicycle safety is the major drawback of this scenario. Scenario #3 had the second best set of performance levels. The drawback of this model was the high number of accidents predicted.

The study went on to analyze the impact of lane width modification and travel time and it concluded that lane width increase results in travel time decrease (Elshafei, 2006). The lack of statistical analysis is a weakness of the study; however the findings are helpful for the scope of this dissertation by showing that street characteristics influence user's performance levels, and not only free flow speed, as used in the *HCM* methodology.

Some of the previously summarized studies provide statistical evidence that additional facility characteristics, as well as driver demographics, are important when attempting to determine user's level of satisfaction with transportation facilities. The *HCM* 2000 methodology for calculating the LOS has been challenged for it does not include facility characteristics in equations computing the LOS and does not appear to represent travelers' perceptions of service well.

2.3 Modeling Techniques for LOS data

The LOS data gathered to date consists of discrete ordered data reflecting traveler's perception of the quality of service on highway facilities for auto, bicycle, transit or pedestrian modes. Several modeling techniques, including linear and non-linear regression and Cumulative Logit modeling have been used to estimate the LOS of travelers. These modeling techniques are described in several examples here.

2.3.1 Linear Regression

A study conducted in Florida developed a LOS model to represent pedestrians' satisfaction and perception of LOS on sidewalks along urban arterials (Petritsch et al., 2006). The focus of the study was on pedestrians' response to walking in real-life conditions which was part of a larger study including video laboratory surveys. Approximately 100 people, both volunteers and paid participated in what was referred to as the "Walk for Science 2004" participated in the study. The participants were a mix of sex, age, geographic origin, and many were also active walkers. Half of the participants were assigned to a segment study and the other half to an intersection study. Each participant was provided with a score card and received two briefings, a video briefing and a course briefing, before starting their walk individually. The data collected were analyzed to determine how well distributed were the ratings. Three major hypotheses were tested:

- Participants' scores would be differentiated by demographic characteristics,
- The pedestrian LOS model, as provided in *HCM* 2000, for street segments does not adequately predict users' satisfaction,
- Paid participants will not score differently than volunteer participants

The first hypothesis was tested using a student *t*-test and determined that demographic characteristics did not influence participants' ratings. The second hypothesis was tested, for parallel segments and for perpendicular segments, also using a student *t*-test. The pedestrian LOS model, as provided in *HCM* 2000, was used to compute the LOS for the street segments selected and compared with the LOS ratings of the participants. The results of the test demonstrated that there was a large statistically significant difference between the calculated LOS and the rated LOS and that there was a need for an improved pedestrian LOS model.

The third hypothesis was also tested using a student *t*-test and the findings provided evidence that there was no difference in the ratings of volunteer and paid participants.

Further it was concluded that additional studies could be successfully conducted by using volunteer and/or paid participants.

The study went on to build a model to determine which characteristics influence pedestrians' perception of QOS. Three steps were followed. The first step was to identify the relevant variables by using a Pearson correlation analysis. The second step was to test for the best configuration for each variable and the third was to establish the coefficients for the variables to be introduced in the best-fit regression model. The independent variables selected in the preliminary list were:

- Pedestrian proximity to travel lanes,
- Pedestrian perceived conflicts at intersections,
- Pedestrian perceived threat exposure when crossing roadways or driveways,
- Pedestrian delay at intersections.

Two of the listed variables were highly correlated with the dependent variable and were included in the model development: the separation between the motor vehicles and the pedestrians and the total number of lanes crossed. The model format for pedestrian LOS for arterials with sidewalks was as shown by equation 2.3.1.1.:

$$Pedestrian\_LOS = a_1(Xing\_width/mi) + a_2(vol15) + C \quad \text{Equation 2.3.1.1}$$

Where

a_1 *and* a_2 = coefficients for Xing width/mi and vol 15 respectively;

$XingWidth/mi$ = total width of crossing at conflict locations [sum/mi of the crossing widths in ft of all driveways and intersection, signalized and unsignalized;

$vol15$ = average 15-min volume on adjacent roadway; and

C = a constant.

The results of the stepwise analysis are presented in Table 2.14, including the terms, coefficients and *t*-statistic for the model. The model coefficient determination shows a good fit of the model with the collected data.

Table 2.14 Model Coefficients and Statistics Developed by Using Field "Walk for Science Data"

Model Terms	Coefficient	t-Statistic
Crossing width/mi	0.001	2.314
Vol 15 (average 15-min volume on adjacent roadway)	0.008	2.923
Constant	1.43	3.373
Model coefficient of determination (R^2)	0.70	

The study emphasized the applicability of the model and its limitations. The first limitation of the developed model was that it can only be applied to roadways with sidewalks. A second limitation was that the participants walked along roadways with a maximum of four lanes and all crossed intersections were not wider than four lanes. And a third limitation was that none of the participants were physically or visually impaired. The study presents a good applicability of the stepwise regression analysis to the context of LOS analysis studies, however, it should be noted that only the mean ratings of service for segments and intersections were used to determine the pedestrian LOS model. This modeling approach may not fully utilize the robustness of the individual participate ratings (Petritsch et al., 2006).

Another study conducted in Florida focused on LOS for pedestrians at signalized intersections (Petritsch et al., 2007b). The participants dedicated to the intersection study, 50 people of 100 selected, were a mix of gender, age and geographic origin. The walking course was approximately 5 km in length and included 23 intersection crossings of which 21 had pedestrian signals. The data collection was also accomplished by distributing score cards with numbers for each intersection and a map with the intersection numbers noted. The participants were given a video simulation briefing and a course briefing and were instructed to obey the traffic signals when crossing the intersections.

The hypotheses tested prior to model development were:

- Participants' scores will be differentiated by demographic characteristics,

- Pedestrians crossing with traffic (in the same direction as traffic in the adjacent lanes parallel to the crosswalk) would score the intersection differently than pedestrians crossing against traffic.
- The *HCM* 2000 pedestrian LOS model for roadway segments does not adequately predict how well intersections serve pedestrians.
- Paid participants will not score differently than volunteer participants.

The first hypothesis was tested using a student *t*-test and it was found that at a significance level of 0.05, the differences between participants' scores by demographic characteristics were not statistically significantly different.

The second hypothesis was also tested using a student *t*-test. Four intersections were selected and it was found that the pedestrians crossing with traffic did not score the intersection LOS differently than pedestrians who crossed against traffic. The third hypothesis which stated that the *HCM* 2000 model does not predict how well intersections serve pedestrians was determined to be correct and it was concluded that a model has to be developed specifically for the pedestrian LOS. The fourth hypothesis was also accepted indicating that volunteer participants can be selected for this study.

A pedestrian LOS model was developed to mathematically represent the level of satisfaction of pedestrians that engage in crossing an intersection. Three steps were followed. The first step was to identify the relevant variables by using a Pearson correlation analysis. The second step was to test for the best configuration for each variable and the third was to establish the coefficients for the variables to be introduced in the best-fit regression model.

The factors that influence pedestrians perception of level of exposure selected for the model were as follows:

- Right-turn-on-red volumes for the street being crossed;
- Permissive left turns approaching from the street parallel to the crosswalk;
- The motor vehicle volume on the street being crossed;
- The speed of vehicles on the street being crossed;
- The number of lanes being crossed;
- Pedestrians' delay.

The model for pedestrian LOS for signalized intersections was formulated as presented by equation 2.3.1.2:

$$PedestrianLOS = a_1(RTOR + PermLefts) + a_2(PerpTrafVol * PerpTrafSpeed) + a_3(LanesClosed^{0.514}) + a_4 \ln(PedDelay) + C$$

Equation 2.3.1.2

Where

$RTOR + PermLefts$ = sum of number for right-turn-on-red vehicles and the number of motorists making a permitted left turn in a 15-min period,

$PerpTrafVol * PerpTrafSpeed$ = product of the traffic volume in the outside through lane of the street being crossed and the midblock 85th percentile speed of the traffic on the street being crossed in a 15-min period,

$LaneCrossed$ = the number of lanes being crossed by the pedestrian,

$PedDelay$ = average number of seconds that the pedestrian is delayed before being able to cross the intersection,

C = a constant.

The results of the stepwise correlation conducted are shown in Table 2.15.

Table 2.15 Model Coefficients and Statistics

Model Terms	**Coefficient**	**t-Statistic**
RTOR+PermLefts	5.689E-03	8.474
PerpTrafVol*PerpTrafSpeed	1.274E-04	27.955
$\text{LanesCrossed}^{0.514}$	0.6810	17.579
ln(PedDelay)	4.011E-02	7.527
Constant	0.5997	6.756
Model coefficient of determination (R^2)	0.770	

The researchers concluded that the model developed with their study was highly reliable, due to the relatively high coefficient of determination, and the fact that it had been calibrated and applied in many US metropolitan areas (Petritsch et al., 2007b). This study provided insight into pedestrian perception of level of service at signalized intersections, and the statistical analysis provided evidence that the *HCM* 2000 pedestrian LOS model does not predict pedestrian perception of LOS at intersections well. It is not the focus of this dissertation to analyze pedestrian perception of LOS at intersections; however, the findings of this study can be useful for future research.

A different study, also developed in Florida, focused on bicycle LOS for arterials (Petritsch et al., 2007a). The purpose of the study was to build on an existing model that estimated bicycle LOS for segments and intersections to create a model that would be applicable to entire arterial sections. The data for this study were collected during an event called "Ride for Science 2005" sponsored by the Florida Department of Transportation which took place in Tampa Florida. The participants were volunteers of various levels of bicycling experience, age, gender and the number of years that they lived in the Metropolitan Tampa Area.

The bicycling course was selected to include roadways with two, four, and six lanes conditions with and without shoulders and bike lanes with various speed limits and vehicle mix. The course also included signalized and unsignalized intersections and it was approximately 20 miles long. The participants received score cards at the beginning of the ride and were asked to rate their experience on an A to F scale. 700 data points were collected as part of the study which were converted to numerical scores with LOS of A=1 and LOS of F=6. The second part of the study consisted of a video laboratory survey. The participants were asked to watch a video simulation; some watched the video then rode the course while others first rode the course then watched the video. The ratings between the two groups did not differ statistically significantly according to the authors. The participants were then asked to give three reasons for their ratings. The answers that were most common pertained to the presence or lack of bicycle lanes, traffic volume, pavement condition and available space (Petritsch et al., 2007a).

The study tested an existing linear regression for bicycle segment LOS model with equation 2.3.1.3:

$$BicycleSegmentLOS = a_1 \ln(vol_{15} / L + a_2 SP_t (1 + 10.38 HV)^2 + a_3 (1/PC_5)^2 = a_4 (W_e)^2 + C$$

Equation 2.3.1.3

Where

vol_{15} = volume of directional traffic in a 15-min time period,

L = total number of through lanes,

SP_t = effective speed limit [where SP_t=1.12 ln(SP_p-20)+0.81 and SP_p is the posted speed limit in mph,

HV = percentage of heavy vehicles,

PC_5 = FHWA's five-point surface condition rating,

W_e = average effective width of outside through lane,

C = a constant, and

a_1 to a_5 = coefficients (a_1=0.507;a_2=0.199; a_3=7.066; a_4=-0.005; and C=0.760).

The explanatory power of this model was R^2=0.53 which was considered strong however the researchers developed a new model through the described effort to improve the existing one. A correlation analysis was conducted to determine the relationship between the independent variables and the dependent variable. Three variables were tested: the number of driveways per mile, signalized intersections per mile and unsignalized intersections per mile. The number of unsignalized intersections per mile was selected as a variable that was highly correlated with the traveler perceived LOS data and was introduced in the new regression model as shown in equation 2.3.1.4 as follows:

$$BicycleFacilityLOS = a_1(avsegLOS) + a_2(numunsigpm) + C \qquad \text{Equation 2.3.1.4}$$

Where

$avsegLOS$ = distance-weighted average segment bicycle LOS along the facility,

$numunsigpm$ = the number of unsignalized intersection per mile along the facility,

C = a constant.

The results of the model are presented in Table 2.3 and are considered an improvement over the initial model by the authors (Petritsch et al, 2007).

Table 2.16 Model Coefficients and Statistics Developed by Using Field "Ride for Science Data"

Model Terms	Coefficient	*t*-Statistic
AvSeg LOS	0.797	6.648
NumUnsigpm	0.131	4.061
Constant	1.370	4.074
Model correlation (R^2)	0.717	

It was not clear how the variables included in the model were selected in the preliminary stage of the study. The modeling approach was not fully documented in the papers by not including the provenience of all coefficients and the reasoning behind variable selection and model format. The use of natural logarithm and the combination of variables using summation or multiplication was not fully explained or justified. These models predicted only the mean LOS rating for a mode of transportation that in turn had to be compared to a mean of the participants' LOS ratings. The researchers utilized only the mean rating of bicycle LOS by all participants and as a result it was difficult to estimate the full range of LOS ratings from A to F. In addition, the variables and weights for variables were transformed in order to obtain the six LOS levels. This approach to modeling categorical data is questionable.

2.3.2 Cumulative Logit

The Cumulative Logit Modeling technique has been used to analyze a data set for automobile driver's perception of LOS in an effort to determine which facility characteristics were important in determining driver's perception of LOS (Flannery et al, 2008). This technique is one type of binomial regression based on a generalized linear model. The data collection approach was video laboratory and it included video clips depicting several different segments of urban streets under various operating conditions. Given the traditional use of LOS methodologies, which typically do not include weather or lighting conditions, all videos were taped during daylight hours and dry weather conditions. Participants in the study were asked to watch the video clips and rate each of them on a scale from LOS A to LOS F with A being the best and F the worst. Then these ratings were converted into numerical values where A=6 and F=1. The factors that were highly correlated with driver's perception of service included:

- Presence of median (yes or no)
- Landscaping (yes or no)
- Progression (no progression is stopped and more than 50 percent of signals), and
- Posted Speed (surrogate for arterial type)

These factors were used in selecting the facilities that were video taped and used in the full nation-wide study. The modeling process was preceded by a heuristic selection of the explanatory variables. Five variables were selected as follows:

- Stops per mile,
- Median Type,
- Width of parking lane,
- Presence of Exclusive Left Turn Lanes,
- Presence of Trees.

A stepwise cumulative logistic model was developed and resulted in a set of three variables used for the final model: stops per mile, presence of exclusive left turn lanes and presence of trees. The Maximum Likelihood Estimates of parameters for the model have been presented in Table 2.17

Table 2.17 Maximum Likelihood Estimate of Parameters for Cumulative Regression Model Applied to Automobile LOS

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr>ChiSq
Intercept α1	1	-2.919	0.227	164.405	<.0001
Intercept α2	1	-1.827	0.207	77.519	<.0001
Intercept α3	1	-0.853	0.201	18.025	<.0001
Intercept α4	1	0.283	0.201	1.995	0.1578
Intercept α5	1	2.094	0.209	100.300	<.0001
Stops per mile β1	1	0.203	0.018	122.336	<.0001
Pres of Ex LT Ln β2	1	-0.522	0.111	22.063	<.0001
Tree Presence β3	1	-0.338	0.061	30.476	<.0001

The study concluded that the cumulative logit models matched the ratings at a much higher rate (71 percent) than the *HCM* methodology did (17 percent) and that additional factors: stops per mile, presence of exclusive left turn lane and presence of trees, currently not considered by the *HCM* methodology contribute to the explanatory power of the methodology (Flannery et al., 2008).

The studies summarized here that use the regression analysis as the modeling tool are actually creating models of low to moderate strength. These models predicted only the mean LOS rating for a mode of transportation that in turn had to be compared to a mean of the participants' LOS ratings, meaning that the studies did not use the full range of data but the mean rating. Due to this process of compressing the data, it was difficult to estimate the full range of LOS ratings from A to F, therefore the linear regression models were considered to be less suitable for analyzing the LOS data.

The studies that used Cumulative Logit Modeling provided a base for the modeling approach utilized for this dissertation. Cumulative Logit Modeling is ideal for modeling categorical data with hieratical categories. This modeling approach also uses the entire range of the data collected and creates models that provide the distribution of the traveler perceived LOS ratings. Cumulative Logit Modeling has been utilized in this dissertation to model bicycle and pedestrian LOS.

2.4 Complete Streets

The concept of Complete Streets has gained interest in recent years. Policy makers, planners, and engineers are investing energy into promoting the idea of urban streets that accommodate bicycles, pedestrians and mass transit along with automobiles. Advocates of the concept envision that people of all ages will be provided with more transportation options that will significantly improve their lifestyle. Despite the appeal of Complete Streets to many, critics have made their opinions known. Their main concern is that there will be no funds to be allocated to the new concept and the projects that would spring from it. Other critics fear that the automobile traffic will not decrease; instead it will be redistributed to other streets defeating the main purpose of the concept (NCSC, 2009).

The Complete Street Act of 2009, S.584 has been introduced to Congress and it may become law. The bill defines Complete Streets as roadways that accommodate all travelers safely and efficiently. The bill stipulates that the concept of Complete Streets must be implemented starting with the planning phase and be sustained through the development phase. The safety and convenience of all users is the main focus of the concept (Harkin, 2009). Previous legislation has suggested the need for multimodal planning and design which support the current Complete Streets legislation.

Across the US fourteen states, six counties, ten regional governments and fifty two cities have implemented Complete Street policies as related by the National Complete Street Coalition (NCSC, 2009). This fact points to the desire by many agencies to improve multimodal options for travelers on urban streets.

The fact that policy makers in the US are investing their efforts into proposing legislation dedicated to the design and deployment of Complete Streets is encouraging. How to design and operate these Complete Streets has yet to be determined and it is the focus of this dissertation research to provide the tools needed by engineers and planners to assess the effect of their designs on traveler perceived LOS on urban Complete Streets.

2.5 Optimization Techniques

The proposed approach for this dissertation research is to utilize a multi-objective optimization technique to determine the division of urban street right of way to optimize and normalize the perceived LOS by pedestrians, bicyclists, and through movement auto drivers at the same time. To understand better the appropriateness and the requirements of the proposed multi-objective optimization model and the ordered logistic model development process, a review of optimization techniques and multi-objective optimization methods is included here.

2.5.1 Introduction to Optimization

Mathematical optimization has its roots in calculus but took a major leap forward with the advent of Operations Research beginning in the 1940s (Agresti, 2007). During World War II, groups of scientists and mathematicians in Great Britain and the United States were assigned to support field commanders in solving an array of complex strategic and operations problems, thus deriving the term “operational research” or “operations research”. Following World War II, the techniques of operations research were applied throughout the public and private sectors to address planning, design, and management problems. Operations research became a discipline in academic curricula and optimization is considered to be a chapter of this discipline. Optimization techniques now are able to address linear and nonlinear problems including discrete and continuous variables. Optimization problems have a specific structure where an objective function is maximized (e.g. profit, revenue) or minimized (e.g. environmental harm, mortality) subject to a set of constraints that define the set of feasible solutions. The optimal solution is given by the best value (maxima or minima) of the objective function that also satisfies the constraint set (Agresti, 2007).

Successful, large-scale commercial products have been developed and used to solve single and multi-objective optimization problems. These commercial products include CPLEX , SOLVER and LINGO.

2.5.2 Multi-objective Optimization

Most of the real-world decision-making problems are multi-objective where the objectives are conflicting. Solving a multi-objective optimization problem brings three enhancements to the single-objective problem solving approach. First, the planners and decision-makers have more appropriate implications in the optimization process. Second, more alternatives are indentified during the optimization process. Third, and a more realistic image of the problem is perceived by the analysts (Cohon, 1978).

A multi-objective optimization problem has two or more objective functions which are expressed differently than in single-objective problems. The general form of a multi-objective optimization function with *n* decision variables, *m* constraints and *p* objectives is:

Maximize:

$$Z(x_1, x_2, \ldots, x_n) = [Z_1(x_1, x_2, \ldots, x_n), Z_2(x_1, x_2 \ldots, x_n), \ldots, Z_p(x_1, x_2, \ldots, x_n)]$$

Equation 2.5.2.1

Subject to:

$$g_i(x_1, x_2, \ldots, x_n) \leq 0, \quad i = 1, 2, \ldots, m$$ Equation 2.5.2.2

$$x_j \geq 0\,,\; j = 1,2,...,n \qquad \text{Equation 2.5.2.3}$$

Where $Z(x_1, x_2,..., x_n)$ is the multi-objective objective function and $Z_1(\ )$, $Z_2(\ )$,…,$Z_p(\ )$ are the *p* individual objective functions.

To solve multi-objective optimization problems several techniques can be applied that can be grouped as follows:

- Generating Techniques which include the Weighting Method, the Constraint Method, the Derivation of a functional relationship for the noninferior set method and the Adaptive Search Method.
- Prior Articulation of Preferences Techniques which include: Goal Programming, Assessing Utility Functions, Estimation of optimal Weights and Surrogate Trade off Method.
- Progressive Articulation of Preferences Techniques which include the Step Method, the Iterative Weighting Method and the Sequential Multi-objective Problem Solving Method (Cohon et al., 1975).

The Generating Techniques will not be discussed further in this dissertation.

The Prior Articulation of Preferences Techniques are based on the selection of a complete ordering of alternatives to eliminate most of the noninferior solutions, therefore reducing the computational burden, prior to computing the solution to the multi-objective problem.

The noninferiority concept can be defined as finding the noninferior solution when no other feasible solution can be found that can produce increase to one objective without causing decrease in any of the other objectives.

Progressive Articulation Preferences Technique have the following general approach: first find a noninferior solution then present he solution to decision makers and modify it according to their comments. Further, the same process is repeated until satisfaction is achieved or a termination rule is applied. This algorithm is applies to all techniques listed for this method (Cohon et al., 1975).

This dissertations scope is to create one objective for each of the three modes considered: auto, pedestrian and bicycles. The objective functions are conflicting and are based on the perceived LOS by each mode's users. In order to find an optimum solution the three objectives have to be balanced where the perceived level of satisfaction for each mode can not fall below a minimum established value and it will be further explained in Chapter 4.

2.5.3 Goal Programming

Goal Programming (GP) is a well known multi-objective method proposed by Charnes and Cooper that was applied primarily to private sector problems during 1970's (Cohon, 1978). The distinguishing characteristic of GP is the specification of goals by decision makers. An optimal solution will produce the target values for all objectives simultaneously. Pre-emptive programming is used where there exists a priority in goal achievement amongst the goals. If there needs to be a direct comparison of the objectives, non pre-emptive programming should be used, where unwanted deviations are multiplied by weights which reflect their relative importance (Cohon, 1978). The three primary means of developing the objective function under Goal Programming are:

• Preemptive (lexicographic) – where the goals are ordered into a priority level, with each level being substantially higher than the next.

• Non-preemptive (weighted) – where the goals are given a relative weight. Goal achievement is normalized to achieve direct comparison.

• Minmax (balanced) – The achievement function seeks to minimize the maximum unwanted deviation, or, alternatively, to maximize the minimum progress towards all objectives (Cohon, 1978).

2.5.4 Balancing Multiple Objectives

In a study conducted by Liner in 2009, he addressed conflicting goals of economical, environmental and social issues. These multiple non-commensurate objectives were considered equally important for the optimization of the water supply planning process. The study focused on a balanced achievement function and preemptive methods.

The goal programming process for the water supply plan was structured to accomplish a definition of requirements followed by an evaluation of alternatives and then by the development and execution of the model.

Under the definition of requirements the demand baseline was established first by introducing conservation programs, followed by baselining the utility financials and the water supply capacity. This step was followed by evaluating the alternatives where the evaluation goals for performance were defined to include Performance Measure Definitions, Magnitude and Direction of Goodness and Relative Weighting of Measure within Goal. The Goals for the Evaluation Menu were established by the specific needs facing the utility and included:

- Economic Goal Measures to include cost of water supply alternative, net income, operating ratio and average water rate;
- Environmental Goal Measures to include percentage of water from renewable sources, wastewater reuse percentage, total waste discharge and energy usage;
- Social Goal Measures to include average water bill/median household income, hours of service lost due to water main breaks, minimum demand utility, expected duration to meet minimum demand on backup power after power loss and hours of service lost due to sewer collapses.

The potential alternatives were defined in terms of capacity, cost and contribution to performance.

Frame Decision Variables were established to determine the need for an alternative to be introduced. The Constraints were established in relationship with uniqueness and capacity.

Following the Goal Definition the Baseline Balance, and Relax Goal Achievement were the next steps and were accomplished by maximizing each goal individually and balancing the goal achievement as presented in equations 2.4.2.1 to 24.2.4.

Maximize $Z_{Balance} = z$

Subject to:

$$z \leq \sum_{j=1}^{n} c_{jEconomics} x_j / G_{Economics}$$ Equation 2.4.2.1

$$z \leq \sum_{j=1}^{n} c_{jSocial} x_j / G_{Social}$$ Equation 2.4.2.2

$$z \leq \sum_{j=1}^{n} c_{jEnvironmental} x_j / G_{Environmental}$$ Equation 2.4.2.3

$$\sum_{j=1}^{n} a_{ij} x_j \leq b_i \text{, for i=1,…,m}$$ Equation 2.4.2.4

Where:

z = deviation variable for the goal achievement,

G_k = maximum goal achievement threshold for k $\in$ {Economic, Environmental and Social},

a_{ij} = technological coefficients representing unit usage by x_j,

b_i =right hand side coefficient,

m = number of constraints such as supply, demand and budget.

Capacity constraints were defined for each of the goals and state-of-the art software was used to maximize the minimum goal achievement, $Z_{Balance}$, for all three goals.

The hypothesis for this study, that an integrated water resource plan can accomplish balance between three components, was demonstrated using GP. It was demonstrated that a balance can be achieved for the three objective goals (Liner, 2009).

The objectives established for this study were conflicting, non-commensurate, and each had to be considered by decision makers to achieve the most politically and technically feasible set of solutions. To accommodate all of the objectives, the decision was made to evaluate how measures with a social aspect can be incorporated in a mathematical model. This has been accomplished by identifying consistent and useful social indicators that can be incorporated into decision analysis methodology. Each goal was first defined with unweighted components. The problem was then defined by a composite goal where all components were given equal importance for the final goal. The overall goals have been balanced; however, the components inside the goal were weighted to allow for the more important components to outweigh the less important components.

Another study developed in Chicago in 1979 used a global optimization model to develop a comprehensive land use plan (Bammi & Bammi, 1979). This study optimized the allocation of land throughout the county required for different uses (e.g. residential, commercial, open space) in response to a forecasted significant increase in county population over the next twenty years. A rural county was undergoing urbanization and needed a land use plan that would accommodate new residents and businesses as well as established farms in a coherent and efficient way. The goal was to avoid haphazard or unplanned growth by providing an overall land use plan that would focus new development in economically, socially, and environmentally reasonable ways.

The objective functions included in the optimization process were:

- Conflict - minimized the negative impacts of adjacent land uses,

- Transportation - minimized the distance traveled in all new trips,
- Tax Impact - minimized the overall tax cost index,
- Environmental Impact – minimized the cost to the environment,
- Community Facilities – minimized capital costs for providing services to the residents.

The objectives were conflicting, non-commensurate, and each had support from decision makers. To accommodate all of the objectives, the decision was made to find a land use plan that achieved balance in achievement of all objectives. Each objective function was first optimized by itself to find its best possible value without concern for the values of any other objective. Because all of the objectives were to be minimized, these objective values represent not only best values but also lower bounds for each objective. Any land use plan that accommodates one objective will necessarily result in a worse value for some other objective, higher than that objective's lower bound. Forming ratios of each objective's value to its lower bound (or best possible value) normalizes all of the objectives and ratios are commensurate (they are all unitless). Minimizing the maximum of these ratios results in a land use plan with all objectives being achieved at approximately the same proportion to their best values. Thus, balance is achieved between all of the objectives (Bammi & Bammi, 1979).

Balancing competing objectives or performance measures by first normalizing the different measures to a single scale, and then minimizing the maximum of their normalized values has been used in real-time reservoir operations (Houck, 1982; Nzewi & Houck, 1995). The goal in these cases was to find an operating policy that maximized total net benefits from a multi-purpose reservoir system. The competing uses of the reservoir for flood control, water supply, and recreation made the identification of a usable real-time operating policy difficult. The derivation of the real-time operating policy involved these steps:

1. Find the optimal operations for an extended period (e.g. 365 days) using historical streamflow data and economic benefit and loss functions for all uses of the reservoir-river system.
2. From the optimized operations for the extended historical period, estimate the cumulative distribution functions of storages, releases, and any other physical measures desired.
3. The real-time operating policy is determined by solving an optimization model at the beginning of any day. The objective of the optimization model is to minimize the maximum CDF value for storages, releases, or other physical measures used in step 2, that are forecasted to occur during the next one or more days included in the optimization model.

Remarkably, tests demonstrated that this balancing of the physical attributes of the operations within a real-time operations policy resulted in better long term performance of the reservoir-river system than other real-time operating policies.

The scope of this dissertation matches the problems confronted by Liner (2009), Bammi and Bammi (1979), and is similar to those discussed by Houck (1982), and Nzewi and Houck (1995). It encompasses multiple, noncommensurate, conflicting objectives that are difficult to accommodate in a different manner than the one used in these studies. The Complete Streets mandate is to balance the objectives at hand. Hence, attempting to make the ratios of actual achievement to best possible values equal for all objectives is a reasonable approach.

2.6 Conclusions

The literature review provided background information regarding the *Highway Capacity Manual*, Level of Service and Quality of Service studies, Complete Streets and Optimization Modeling Techniques. This information has been utilized in this dissertation study in the following chapters.

CHAPTER 3: METHODOLOGY

The purpose of this dissertation is to create a method that will allow practitioners to design a new facility or retrofit the existing design by optimizing the geometrical characteristics by balancing the level of service for several modes utilizing a Multi-objective Optimization Model. A brief description of the data collection efforts undertaken in NCHRP 3-70 study is provided in Chapter 2 as these data were utilized n this study. Appendix 1 is provided for additional background information.

The approach taken to develop the multi-objective optimization model is described in Figure 3.7 at the end of this chapter. As shown in Figure 3.7, the steps taken in the development of the multi-objective optimization model were:

- Develop Cumulative Logit Model for the pedestrian mode
- Develop Cumulative Logit Model for the bicycle mode
- Develop Multi-objective Optimization Model for urban streets

The following sections describe the efforts undertaken to develop the Cumulative Logit LOS Models for the pedestrian and bicycle modes and the development of the multi-objective optimization model for urban streets.

3.1 Use of NCHRP 3-70 LOS Models and Data

The NCHRP 3-70 datasets had individual traveler ratings of LOS for the auto, pedestrian and bicycle modes that were used in this dissertation. As noted is Chapter 2, the auto cumulative logit traveler perceived LOS model developed in NCHRP 3-70 was utilized in this dissertation. The Cumulative Logit Model developed with NCHRP 3-70 was found to be superior to the existing *HCM 2000* models (Flannery et al., 2008). As was noted in Chapter 2, the linear regression pedestrian and bicycle LOS models developed in NCHRP 3-70 did not capture the ordered categorical nature of the ratings of LOS. This dissertation research developed cumulative logit models for the pedestrian and bicycle modes to estimate the entire distribution of traveler ratings instead of using linear regression techniques as was the case in NCHRP 3-70 for the pedestrian and bicycle modes. The next section of this chapter describes the efforts to select the variables for pedestrian and bicycle LOS models.

3.2 Data Exploration and Variable Selection for Pedestrian and Bicycle Modes

Pedestrian Mode

A new model for the pedestrian mode was developed by using the NCHRP 3-70 data, this dataset consists of 1410 useable traveler perceived LOS data points. Using a random number generator, the data were separated into two groups: two-thirds of the data were reserved for modeling, 931 data points, and one-third of the data were reserved for validation, 471 data points. Box plots were developed to understand the thresholds of the data which could be categorized such as *Sidewalk Width* and *Through Lanes* as shown in Figures 3.1 and 3.2. Figure 3.1 shows an overlap in the data for the two sidewalk categories; however there is a difference of one LOS category between the mean ratings of the two sidewalk categories therefore the two selected categories were used in the Cumulative Logit Model. In Figure 3.2 the perceived LOS by pedestrians overlaps for facilities with two and three lanes; however, a portion of the data for the three lane category was below the two lane category. A difference was also observed for the pedestrian ratings for facilities with one lane therefore three categories were used for the variable *Through Lanes*.

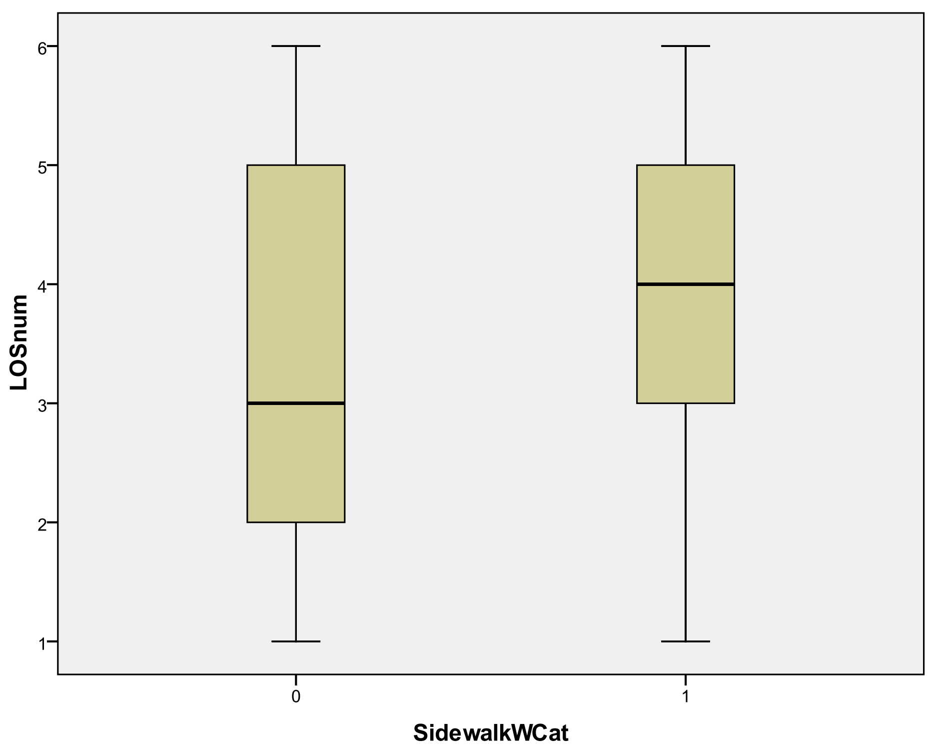

Figure 3.1 Box Plot of Categorized Sidewalk Width for Pedestrian Mode

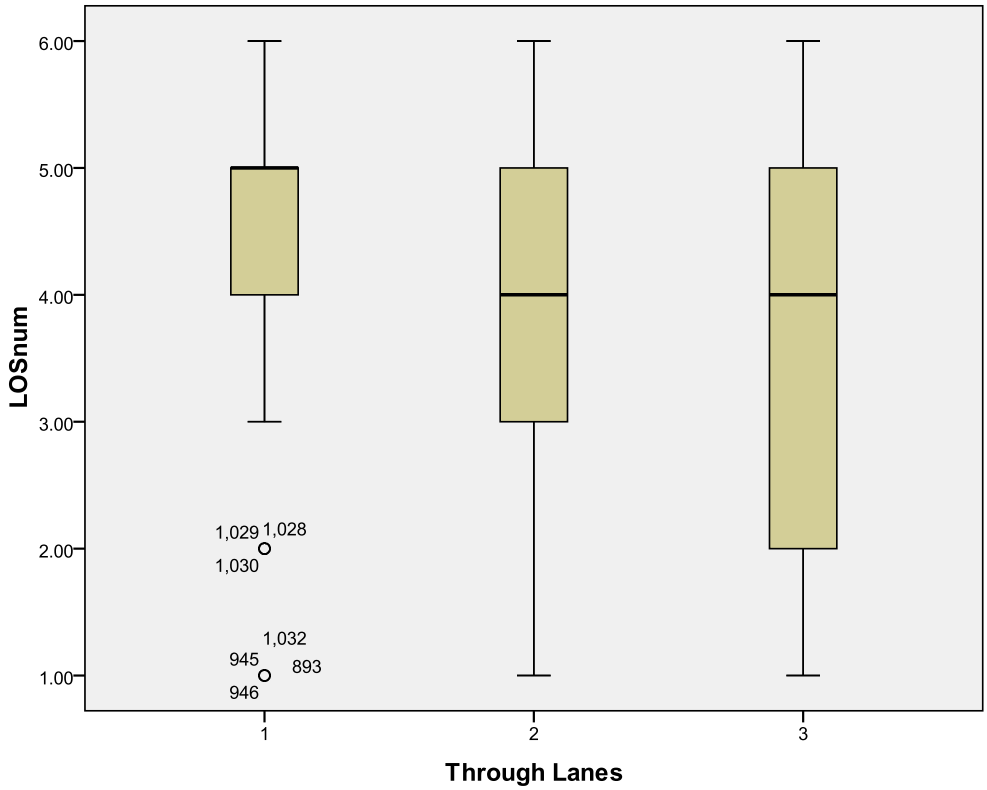

Figure 3.2 Box Plot of Categorized Speed Limit for Pedestrian Mode

The categories for the variables selected and presented in Figures 3.1 and 3.2 are:

- *Sidewalk Width*

  $< 5\,ft = 0, > 5\,ft = 1$

- *Number of Through Lanes*

  1, 2, 3

Next, to better understand the relationship between traveler perceptions of LOS and the independent variables collected through NCHRP 3-70, a correlation analysis was conducted. A Kendall Tau Correlation analysis was selected to be conducted due to the ordinal variables present in the data. A Kendall-tau coefficient is a non-parametric correlation coefficient used to assess and test correlations between non-interval scaled ordinal variables, while Pearson correlation provides a measure of the strength and direction of the linear relationship between two variables (Bolboaca et al., 2009).

Table 3.1 contains the results of the Kendall correlation analysis between participant ratings of LOS and a variety of geometric and traffic characteristics for the pedestrian mode. This analysis was conducted by Ali et al. in a published study discussed in Chapter 2, this analysis was further refined as part of this dissertation.

Table 3.1 Results of Correlation Analysis with Participant Rating of Pedestrian LOS (Ali et al., 2009)

Variable	τ Rank Correlation	Significance p-value
Sidewalk Width	**0.335**	0
Pedestrian Flow Rate	0.201	0
Outside Lane Width	0.121	0.007
Shoulder Width	-0.277	0
On-street Parking	0.246	0
Barrier	0.314	0
Buffer Width	0.111	0.005
Same Direction Traffic Volume	-0.182	0
Through Lanes	**-0.291**	0
Posted Speed Limit	-0.161	0
Traffic Volume/Lane	-0.028	0.465

Table 3.1 reveals that several variables including *Sidewalk Width; Pedestrian Flow Rate; Shoulder Width; On-street Parking; Barrier* and *Through Lanes* have some correlation with participant rating of LOS. However, further analysis as shown in Table 3.2 which provides the correlation between variables, reveals that all variables except T*hrough Lanes* were highly correlated with *Sidewalk Width.* Therefore, the variables selected from the set of variables found to be correlated with participant rating of pedestrian LOS and considered to be significant contributors to the development of the multi-objective optimization model were *Sidewalk Width* and *Through Lanes.*

Table 3.2 Results of Correlation Analysis between Variables for Pedestrian Mode

Variable/Correlation Coefficient	**Sidewalk Width**	**Pedestrian Flow Rate**	**Outside Lane Width**	**Shoulder Width**	**On-street Parking**	**Barrier**	**Buffer Width**	**Same Direction Traffic Volume**	**Traffic Lanes**
Sidewalk Width	1.000								
Pedestrian Flow Rate	0.491	1.000							
Outside Lane Width	0.455	0.511	1.000						
Shoulder Width	-0.296	-0.415	-0.271	1.000					
On-street Parking	0.563	0.594	0.454	-0.485	1.000				
Barrier	0.627	0.692	0.608	-0.540	0.897	1.000			
Buffer Width	0.400	0.050	0.044	0.057	0.207	0.196	1.000		
Same Direction Traffic Volume	-0.336	-0.291	-0.039	0.418	-0.201	-0.247	-0.119	1.000	
Through Lanes	-0.041	-0.200	-0.044	0.537	-0.331	-0.362	-0.136	0.500	1.000
Posted Speed Limit	-0.173	-0.076	0.159	0.555	-0.165	-0.194	0.026	0.552	0.387

Bicycle Mode

The bicycle model also has been developed with the data collected from the NCHRP 3-70 Study. Box plots for each of the variables that could take a categorical form and that would be useful for the Multi-objective Optimization Model were developed next.

Figures 3.3 through 3.5 present the relationships between LOS and each of the selected variables. Figure 3.3 shows lower LOS ratings for facilities without bicycle lanes while the ratings increase for facilities with bicycle lanes between four and eight ft.
The bicyclists LOS ratings for facilities with one lane, as shown in Figure 3.4, are higher as compared to the ratings for facilities with two or three lanes indicating that the potential of multiple vehicles to the left of the bicyclists is reducing bicyclist perception of LOS. It appears that the facilities with one lane only are differentiated from facilities with two lanes. Although there is some overlap of the data between the facilities with two and three lanes a difference in LOS ratings was observed and therefore three categories were used for *Through Lanes*.

In Figure 3.5 the *Posted Speed Limit* has been categorized and plotted against the bicyclists LOS ratings. A difference between the bicyclists ratings of LOS for facilities with *Posted Speed Limit* <30 mph and >30 mph was observed.

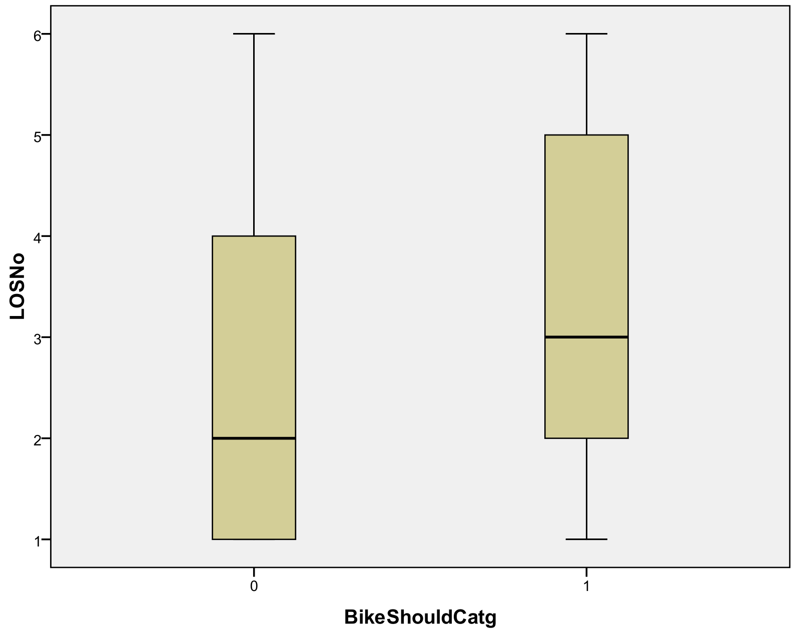

Figure 3.3 Box Plot of Relationship between *Bike/Shoulder Width* and LOS

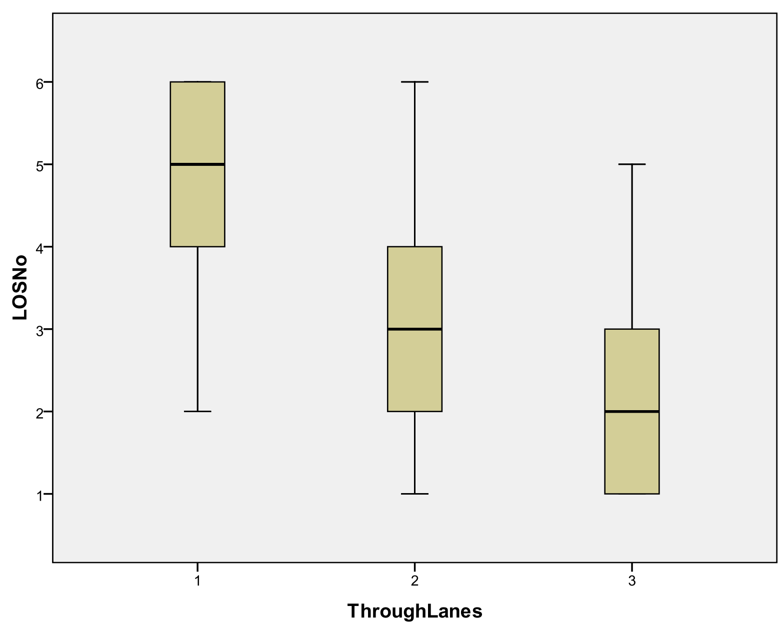

Figure 3.4 Box Plot for Relationship between *Number of Through Lanes* and LOS

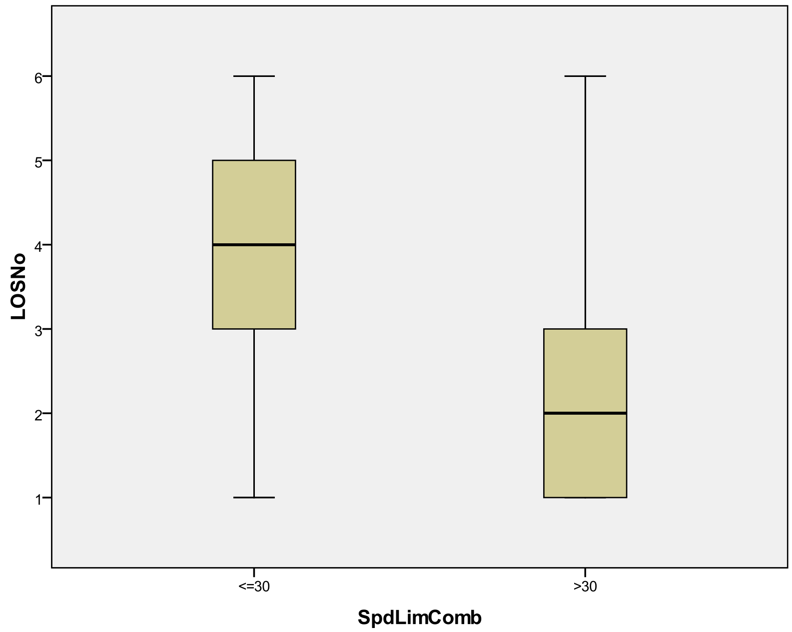

Figure 3.5 Box Plot for Relationship between *Posted Speed Limit* Category and LOS

Based on the data diagnosis, the independent variables were categorized as follows:

- *Bike/Shoulder Width*

  $0\,ft = 0, 4-8\,ft = 1$

- *Speed Limit*

  $20-30mph = 0, 30-55mph = 1$

- *Number of Through Lanes*

  1, 2, 3

A Kendall correlation analysis was next conducted in order to determine the variables that were statistically significantly correlated to individual traveler LOS ratings. The results of the correlation analysis between the independent variables and participant bicycle LOS are presented in Table 3.3 and the results of the correlation analysis between variables shown in Table 3.4.

Table 3.3 Results of Correlation Analysis

Variable	τ Rank Correlation	Significance p-value
Outside Lane Width	-0.160	0.000
Bike/Shoulder Width	**0.188**	**0.000**
Through Lanes	**-0.417**	**0.000**
Peak hour Volume	-0.107	0.000
Heavy Vehicles	-0.100	0.001
Speed Limit	**-0.457**	**0.000**
Pavement Rate	0.054	0.078
On Street Parking	0.090	0.000
Signalized Intersections Distance	-0.127	0.000
Unsignalized Conflicts per Mile	-0.276	0.000

The variables found to be correlated with participant rating of bicycle LOS and considered to be significant contributors to the development of the Multi-objective Optimization Model were: *Bike/Shoulder Width, Speed Limit* and *Through Lanes.* The *Bike/Shoulder Width* variable was found to be positively correlated with the dependent variable indicating that an increase in lane width results in an increase in traveler perceived LOS rating therefore an increase in comfort level for bicyclists. While the *Number of Through Lanes* and *Posted Speed Limit* were negatively correlated with the traveler perceived LOS indicating that an increase in the number of lanes and speed limit results in worse ratings of LOS by study participants. The number of through lanes and posted speed limit are also indicators that an increase in auto activity results in a worse LOS rating for the bicycle mode.

The correlation analysis conducted between variables shows that the *Bike/Shoulder Width* and the *Through Lanes* variable are not highly correlated. Similarly, *Bike/Shoulder Width* and *Speed Limit Category* are not correlated. However there appears to be a relationship between *Through Lanes* and Speed *Limit Category* which has been further explored in the development of the Cumulative Logit Model.

Table 3.4 Results of Correlation Analysis between Variables for Bicycle Mode

Variable/ Correlation Coefficient	OLW	**B/SW**	**TL**	PHV	HV	**SL**	PR	OSP	SID
Outside Lane Width	1.000								
Bike/Shoulder Width	0.483	1.000							
Through Lanes	0.084	-0.066	1.000						
Peak hour Volume	0.445	0.584	0.043	1.000					
Heavy Vehicles	0.109	-0.241	0.104	-0.182	1.000				
Speed Limit	0.668	0.223	0.477	0.666	0.163	1.000			
Pavement Rate	-0.105	-0.021	0.077	0.176	-0.513	0.033	1.000		
On Street Parking	0.143	0.272	0.070	0.322	-0.059	0.215	0.057	1.000	
Signalized Intersections Distance	-0.071	-0.172	0.268	-0.392	0.005	0.016	0.155	-0.085	1.000
Unsig Conflicts per Mile	0.431	0.204	0.387	0.155	-0.022	0.345	0.034	-0.104	-0.273

The Multi-objective Optimization Model has been built to provide the street elements for each mode: traffic lanes, bicycle lanes, sidewalks, median and grass strips. The *Bike/Shoulder Width* for the bicycle mode is the facility characteristic that is part of the ROW width, therefore contributing to the Multi-objective Optimization Model. Similarly, the *Sidewalk Width* and the *Through Lanes* contribute to the Multi-objective Optimization Model for the auto and pedestrian modes. The auto mode has been connected with the bicycle mode through the *Average Space Mean Speed* variable which is influenced by the *Posted Speed Limit*, and the bicycle mode has been connected to the pedestrian mode through the *Through Lanes.*

3.3 Proposed Modeling Approach

The process of variable selection was followed by the development of an optimization function. The main purpose of the optimization function was to include one objective for each of the three modes: auto, bicycle and pedestrian. Each mode's objective was to determine a design that will produce a traveler perceived LOS equal to or greater than a chosen level. For this study, the chosen level of LOS was D which may allow for a comfortable and acceptable level of satisfaction for the three modes concomitantly, however, an analyst could choose any LOS as desired. Also, all three modes carry an equal weight in the optimization model. Figure 3.6 represents a potential design of a Complete Street with a 70 ft right of way width consisting of two 12 ft auto lanes; two 5 ft bicycle lanes; a 10ft median; and two 5 ft sidewalks on either side of the street. The purpose of the proposed optimization model is to allow engineers and planners to manipulate the design of each of the modal facilities to optimize LOS for all modes. For example, reducing the auto lane width to 11 ft would allow for a wider bike lane which may improve bicycle LOS.

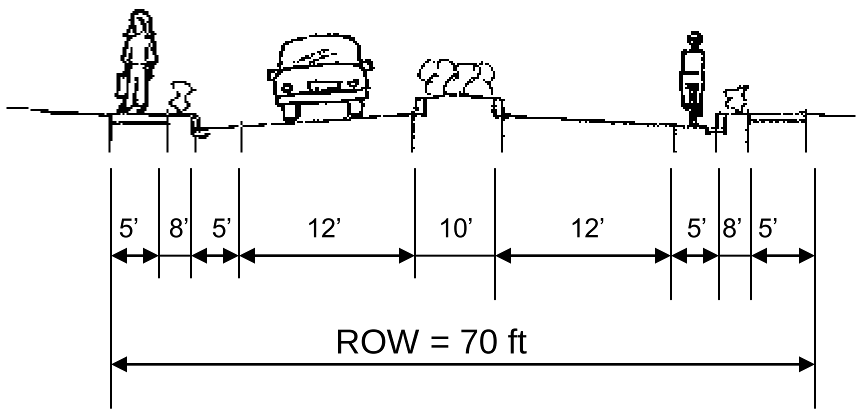

Figure 3.6 Example Complete Street Design Cross-Section

The sequence of steps followed in the modeling process is presented below. The first three steps of the process consisted of creating three LOS Optimization Models for the three modes: auto, pedestrians and bicycles where the objective functions were cumulative logit equations for the selected LOS level. The fourth step consisted of creating a Multi-objective Optimization Model where the three Optimization Models created in steps 1 through 3 were combined and optimized simultaneously.

3.3.1 Cumulative Logit Model

The Cumulative Logit Model is a type of binomial regression model and it has been selected for use in this dissertation for its capability of treating variables as if they were measured on an ordinal scale and was developed by using equation 3.3.1.1 (Agresti, 2007).

$$Logit[P(Y \leq j)] = \alpha_j - \beta_x, \qquad \text{Equation 3.3.1.1}$$

Where:

j=1, ……,J-1

The α_j were the intercepts for each category and β was a constant parameter for each independent variable that remained unchanged for all logit functions. The cumulative probabilities for each of the response variable categories were obtained with equation 3.3.1.2.

$$\Pr ob(event \leq j) = \frac{1}{(1 + e^{-(\alpha j - \beta j)})} \qquad \text{Equation 3.3.1.2}$$

Then the individual probabilities were calculated using the following equation:

$$\Pr ob(event = j) = \Pr ob(event \leq j) - \Pr ob(event < j) \text{ (Agresti, 2007)} \qquad \text{Equation 3.3.1.3}$$

The intercepts and the constant parameters for pedestrian LOS ratings were computed using the Maximum Likelihood Estimation (MLE).

3.3.2 Optimization modeling

The generalized reduced gradient method was used for the development of the auto, pedestrian and bicycle Optimization Models (Flystra et al., 1998). Each of the three modes was set into an Optimization Model with the objective to minimize the probability of obtaining LOS ratings of D or less. The optimization models are discussed in Chapter 4.

3.3.3 Multi-objective Optimization Modeling

A Multi-objective Optimization Model has been developed for Complete Street design. The objective constraints have been established based on the facility characteristics included in the Cumulative Logit Models for each mode. The model has been built in four steps. The first three steps established the minimum values for the probability of obtaining LOS D or less, thus establishing the low threshold for each of the three modes as follows:

$$\text{Minimize} \begin{cases} P_{auto \le} \text{ LOS D} & \text{Equation 3.3.3.1} \\ P_{pedestrian \le} \text{ LOS D} & \text{Equation 3.3.3.2} \\ P_{bicycle \le} \text{ LOS D} & \text{Equation 3.3.3.3} \end{cases}$$

Step 1: Minimize P1 for auto mode, resulting in P1* as the optimized value;

Step 2: Minimize P2 for pedestrian mode, resulting in P2* as the optimized value;

Step 3: Minimize P3 for bicycle mode, resulting in P3* as the optimized value;

Step 4: Bring the three modes together into one optimization model as shown in equations 3.3.3.4 and 3.3.3.5.

$$Minimize Z4 = X \qquad \text{Equation 3.3.3.4}$$

Subject to:

$$X \le Pi / Pi^{*} \quad \text{i=1,2,3} \qquad \text{Equation 3.3.3.5}$$

The steps to be followed in obtaining the Optimization Model are described in more detail in Chapter 5. The selection of the models to be used for this study for each of the three modes is described in Chapter 4. A schematic of the approach to the Multi-objective Optimization Model is presented in Figure 3.7.

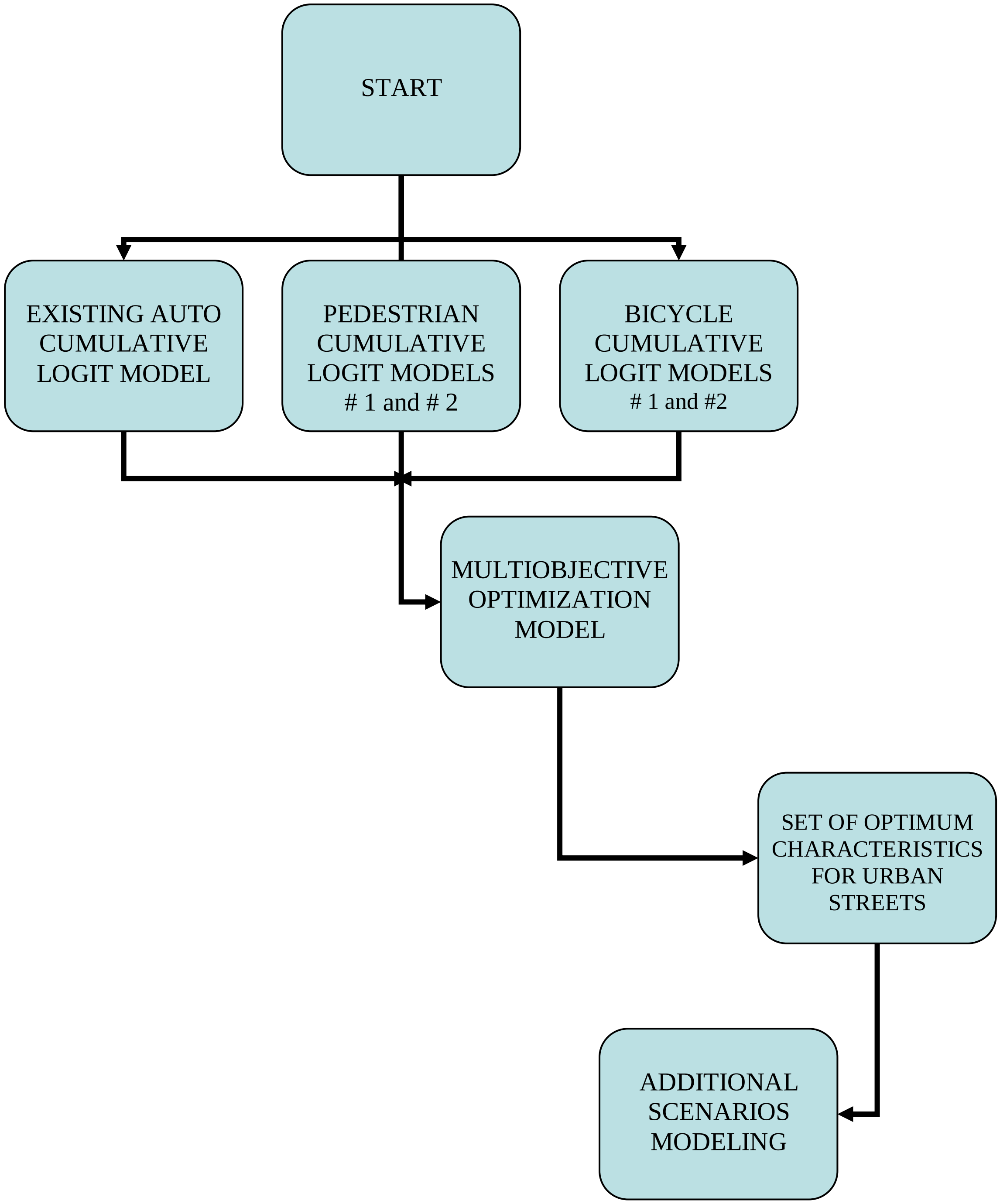

Figure 3. 7 Schematic of Modeling Approach

CHAPTER 4: COMPLETE ROADWAY INTEGRATION STUDY TO EFFECT IMPROVEMENT (CRISTEI) MULTI-OBJECTIVE OPTIMIZATION MODEL

Complete Street design can be accomplished by providing optimal facilities for all the modes expected to be present on urban arterials. Ideally a transportation engineer or planner will utilize the modeling approach presented here in the preliminary design stage of a new facility or in the redevelop process of an existing cross section of urban arterial. The modeling approach presented takes into account the level of perceived service of pedestrians, bicyclists, and through auto drivers; the available right of way; and required design standards.

Three transportation modes have been included in this study: the auto mode, the pedestrian mode, and the bicycle mode. A standard urban street will have, or will most likely have mass transit. This transportation mode has not been included in the modeling effort due to the method used to collect traveler perceived LOS data for the transit mode. In NCHRP 3-70, participants who rated the performance of the transit mode were surveyed in-route on fixed-route surface street systems unlike the auto, pedestrian, and bicycle modes which were surveyed through a video laboratory setting. In addition, the decision to use the transit mode was made as participants were using the transit system, as compared to participants who rated the auto, pedestrian, and bicycle trips who had not made that travel choice. Due to this difference in the type of data collected, the transit mode has not been included in this dissertation. However, future studies may be designed to enhance the model and create a design that takes into account the transit mode.

An optimization model for transportation practitioners that will facilitate the optimal design of Complete Streets that achieves the highest level of traveler perceived service by mode within recognized design standards has been developed. This contribution is unique, opportune and is anticipated to be well received by engineers, planners, and decision makers. This chapter presents the models developed to estimate the traveler perceived pedestrian and bicycle LOS utilizing the cumulative logit modeling approach. In addition, this chapter includes a description of the approach taken to develop the Multi-objective Optimization Model for Complete Street Design.

4.1 Cumulative Logit Models

Cumulative Logit Models for ordinal responses are powerful models that provide cumulative probabilities reflecting the ordering of the response categories. A cumulative probability for a category indicates that the category will fall at or below a certain value and reflects ordering of the dependent variable (Agresti, 2007). To fit a binary logistic regression model, a set of regression coefficients must be estimated first. These coefficients will predict the probability of the dependent variable, in this case the probability of achieving a particular modal LOS (Norusis, 2009). The linear combination of parameters results from a function of the probabilities as shown in equation 4.1.1 (Norusis, 2009):

$$\ln(prob(event)/(1-prob(event))) = \beta_0 + \beta_1 x_1 + ... + \beta_k x_k \qquad \text{Equation 4.1.1}$$

The quantity situated to the left of the equal sign is the log of odds for an event to occur. The coefficients indicate how much the logit changes based on the values of the predictor variables. To incorporate the ordinal nature of a dependent variable the probability of the event and all events that are ordered before it should be considered. The ordinal logistic model for one variable is presented in equation 4.1.2 (Norusis, 2009):

$$\ln(\theta_j) = \alpha_j - \beta\ X\text{, j=1,…,n-1} \qquad \text{Equation 4.1.2}$$

For each logit there is a different α_j but all logits share the same β coefficient, indicating that the effect of the independent variables is the same for each logit function. The α_j values are similar to the intercepts in a linear regression model; however, there is one value for each logit. The expected values can be calculated for each case by using equation 4.1.3 (Norusis, 2009):

$$prob(event\_j) = 1/(1+e^{-(\alpha_j - \beta_x)}) \qquad \text{Equation 4.1.3}$$

This method of analyzing categorical data utilizes the entire data set of traveler perceived LOS to predict the probability of a particular LOS threshold and the entire distribution of LOS ratings (Norusis, 2009). The Cumulative Logit Model has been selected by the NCHRP 3-70 researchers for the auto mode and it has been used for the pedestrian and bicycle modes in this dissertation.

4.1.1 Pedestrian Mode

The cumulative logit model created by Ali et al. was developed by using four variables which were found to be significant for the LOS ratings by pedestrians. The results of the model were introduced in the Single-Objective Optimization Model and in the Multi-objective Optimization Model. The attempt to create the constraints for the Multi-Objective Model was not as successful as expected. The variables in the Ali et al. pedestrian model were continuous and it was determined that categorical variables were more appropriate with the generalized reduced gradient method used in the optimization process. Therefore, a new model was developed to include categorical variables.

The development of the Cumulative Logit Model for the pedestrian mode was preceded by the variable selection process. The selected variables were analyzed by creating box plots, presented in Chapter 3, that directed the process of categorizing the data to be better utilized by the optimization model. From the four variables previously selected only two were found to be statistically significant contributors to the model and were categorized as follows:

- *Number of Lanes (NL):* 1, 2, 3,
- *Sidewalk Width Category (SWC):,* < 4 ft, >4 ft,

The Maximum Likelihood Estimates for Ordinal Regression for the selected independent variables for the model are presented in Table 4.1.

Table 4. 1 Maximum Likelihood Estimate Parameters for Traveler Perceived Pedestrian LOS

Parameter	**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept LOS F, α1=	1	-2.934	0.221	175.919	<0.000
Intercept LOS E, α2=	1	-1.983	0.205	93.598	<0.000
Intercept LOS D, α3 =	1	-1.124	0.198	32.105	<0.000
Intercept LOS C, α4=	1	.100	0.195	.265	<0.607
Intercept LOS B, α5=	1	1.637	0.204	64.205	<0.000
Sidewalk Width , β =	1	.920	0.127	52.530	<0.000
Number of Through Lanes, β2 =	1	-.561	0.087	42.026	<0.000

The cumulative probabilities have been computed and presented in Figure 4.1. The model results were also aligned with the assumptions made, for example, the probability of traveler perceived pedestrian LOS rating of F increases as the number of vehicle through lanes increases as seen in Figure 4.1.

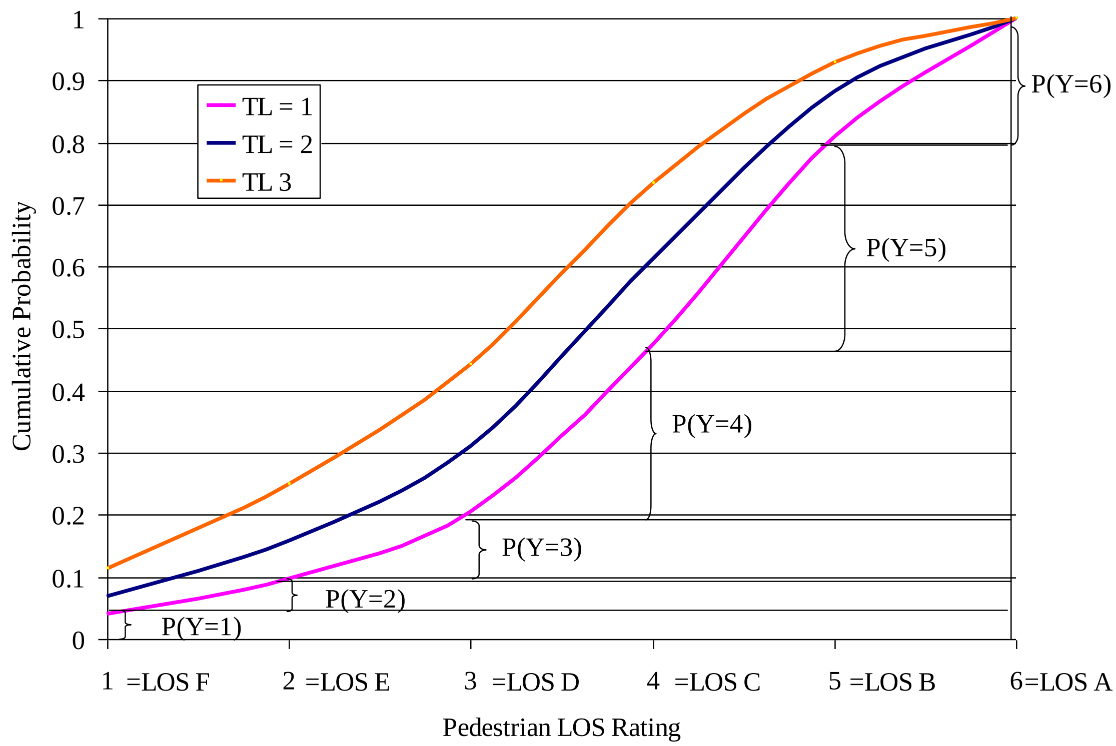

Figure 4. 1 Cumulative Probability Curves for Pedestrian LOS Rating

The two variables selected were found to be significant for this mode and the Chi Square coefficient (45.167) for the model indicated this was a strong model. Also it was noted that the alpha intercepts increase in value as the LOS increases. Therefore, this model was selected for the Multi-objective Optimization Model as presented further in this Chapter.

4.1.2 Bicycle Mode

Two cumulative logit models were developed for the bicycle mode, in order to find one model that would be suitable for the optimization model, as presented below. For the first model, the selected variables, as described in Chapter 3, are as follows:

- *Bike/Shoulder Width*: 0 ft, 4 ft, 5 ft, 8 ft,
- *Number of Through Lanes*: 1, 2, 3,
- *Speed Limit*: 20mph, 25mph, 30mph, 40mph, 45mph, 50mph, 55 mph.

The Maximum Likelihood Estimates for Ordinal Regression for the selected independent variables are presented in Table 4.2.

Table 4. 2 Maximum Likelihood Estimate Parameters for Traveler Perceived Bicycle LOS Model # 1

Parameter	**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept LOS F, α1=	1	-4.365	0.301	210.665	0.000
Intercept LOS E, α2=	1	-3.369	0.288	136.704	0.000
Intercept LOS D, α3=	1	-2.548	0.279	83.521	0.000
Intercept LOS C, α4=	1	-1.428	0.271	27.766	0.000
Intercept LOS B, α5=	1	.014	0.282	.003	0.960
Number of Through Lanes, β1 =	1	-.521	0.125	17.358	0.000
Bike/Shoulder Width, β3 =	1	-.062	0.007	69.880	0.000
Speed Limit (mph), β2=	1	.190	0.028	46.030	0.000

As can be seen in Table 4.2, the model had difficulty estimating the LOS B intercept; in addition, the positive and negative signs are not intuitive. One would expect that variables such as speed limit and number of through lanes would have the same sign. The cumulative probabilities were also computed to study the shape of the models and presented in Figure 4.2. The model results show that the probability of traveler perceived bicycle LOS rating of F increases as the number of vehicle travel lanes increases.

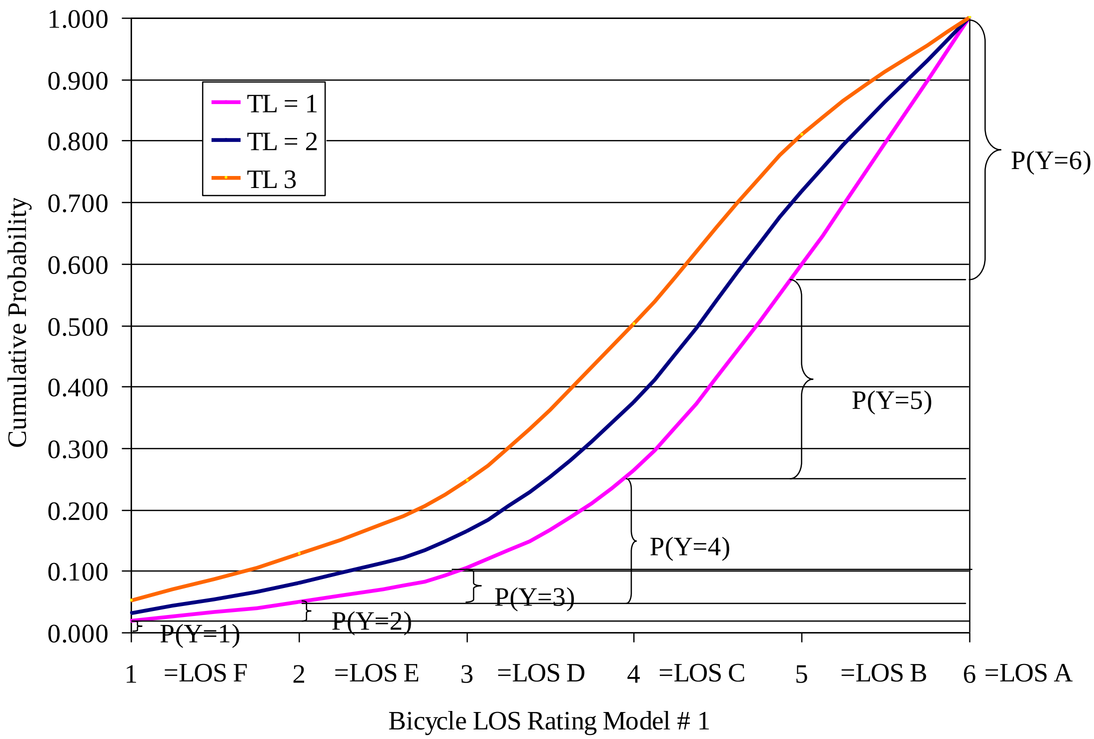

Figure 4. 2 Cumulative Probability Curves for Bicycle LOS Rating – Model # 1

The cumulative logit equation was introduced into the Optimization Model but it did not perform as expected, giving opposite results than anticipated. Further analysis of the data revealed that using the data in categorical form created a better performing model.

Model 2 was created using categorical data for the independent variables. For Model 2 the variables were categorized as:

- *Bike/Shoulder Width*: 0 ft = 0, 4-8 ft = 1
- *Number of Through Lanes*: 1, 2, 3,
- *Speed Limit*: 20-30 mph = 0, 40-55 mph = 1 (45mph was not present in the collected data).

The categorized independent variables were used to create a second Cumulative Logit Regression Model for Ordinal Responses as is shown in Table 4.3.

Table 4. 3 Maximum Likelihood Estimate Parameters for Bicycle LOS Rating –Model # 2

Parameter	**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept LOS F, α1=	1	-4.237	0.322	173.529	0.000
Intercept LOS E, α2=	1	-3.023	0.308	96.086	0.000
Intercept LOS D, α3 =	1	-2.004	0.299	44.881	0.000
Intercept LOS C, α4=	1	-0.512	0.294	3.044	0.081
Intercept LOS B, α5=	1	1.532	0.311	24.280	0.000
Number of Through Lanes, β1 =	1	-0.972	0.133	53.330	0.000
Bike/Shoulder Width , β3 =	1	1.695	0.175	187.087	0.000
Speed Limit (mph), β2=	1	-2.398	0.157	116.274	0.000

As seen in Table 4.3, the LOS intercept values increase with the LOS level, higher LOS levels corresponding to higher intercept parameter values. The goodness-of-fit Chi-Square coefficient (59.184) indicates that it is a strong model. The *Number of Through Lanes* and *Speed Limit* beta parameters have negative signs reflecting lower ranking of the LOS for bicyclists while the *Bike/Shoulder Width* beta parameter has a positive sign reflecting higher LOS rankings. In addition, all independent variables are statistically significant at the 0.10 level or less.

To better understand the performance of the model, the cumulative probabilities were computed and are presented in Figure 4.3. The model results show that the probability of traveler perceived bicycle LOS rating of F increases as the number of vehicle travel lanes increases as is expected when holding all other independent variables constant.

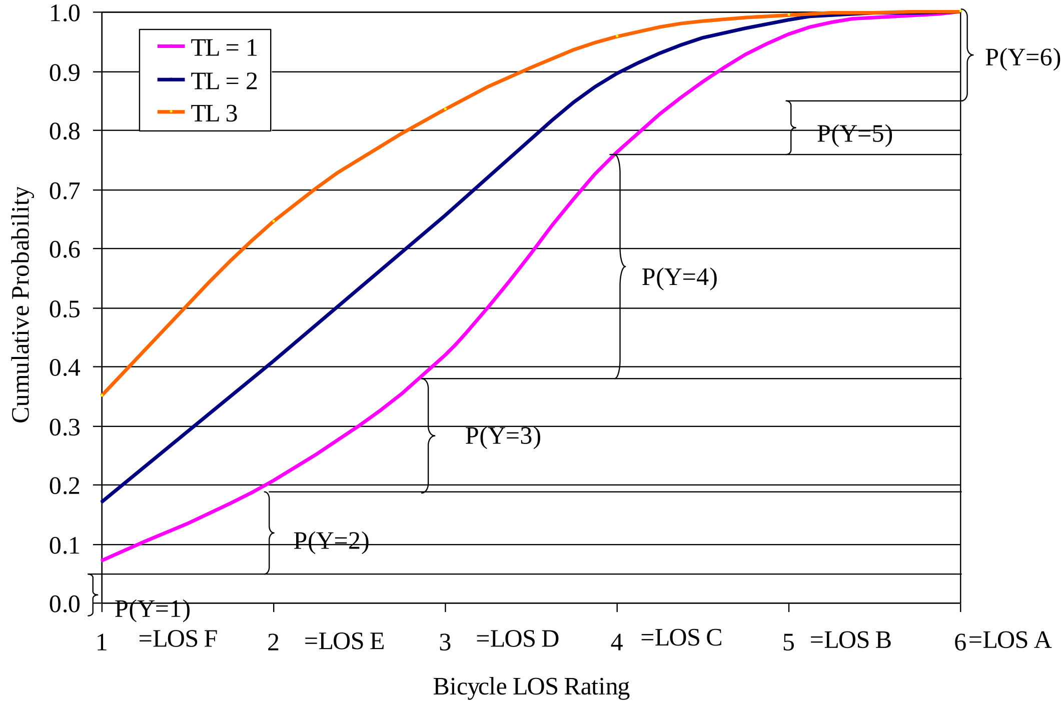

Figure 4. 3. Cumulative Probability Curves for Bicycle LOS Rating – Model # 2

Model # 2 was included in the Multi-objective Optimization Model as described in section 4.2.

4.2 Multi-objective Optimization Model

A Multi-objective Optimization Model has been developed to improve the design process for urban streets. The improvement consists of accommodating three modes simultaneously and including user perception of LOS in the modeling process, thus creating a new method of urban street design which accounts for perceived operational and safety performance by modal users. The three modes included in the modeling process are auto, pedestrian and bicycle modes. The level of satisfaction of the users of each of these modes can occasionally conflict with the other modes. For example, drivers tend to perceive a higher level of satisfaction on urban streets when the average travel speed is as high as or slightly higher than the posted speed limit and the road has multiple lanes. By contrast, pedestrians and bicyclist perceive a low level of satisfaction when their facilities adjoin streets with high posted speed limits and when traffic lanes exceed two or three through traffic lanes in the same direction of their movement. In Chapter 3, the data exploration process revealed statistically significant relationships between the independent variables and the participant ratings of LOS for the three modes. Constraints were also developed for each independent variable included in the modal models and optimization models were developed for each of the three travel modes to obtain the highest probability of LOS rating. The general flow of data in the modeling process is presented in Figure 4.4.

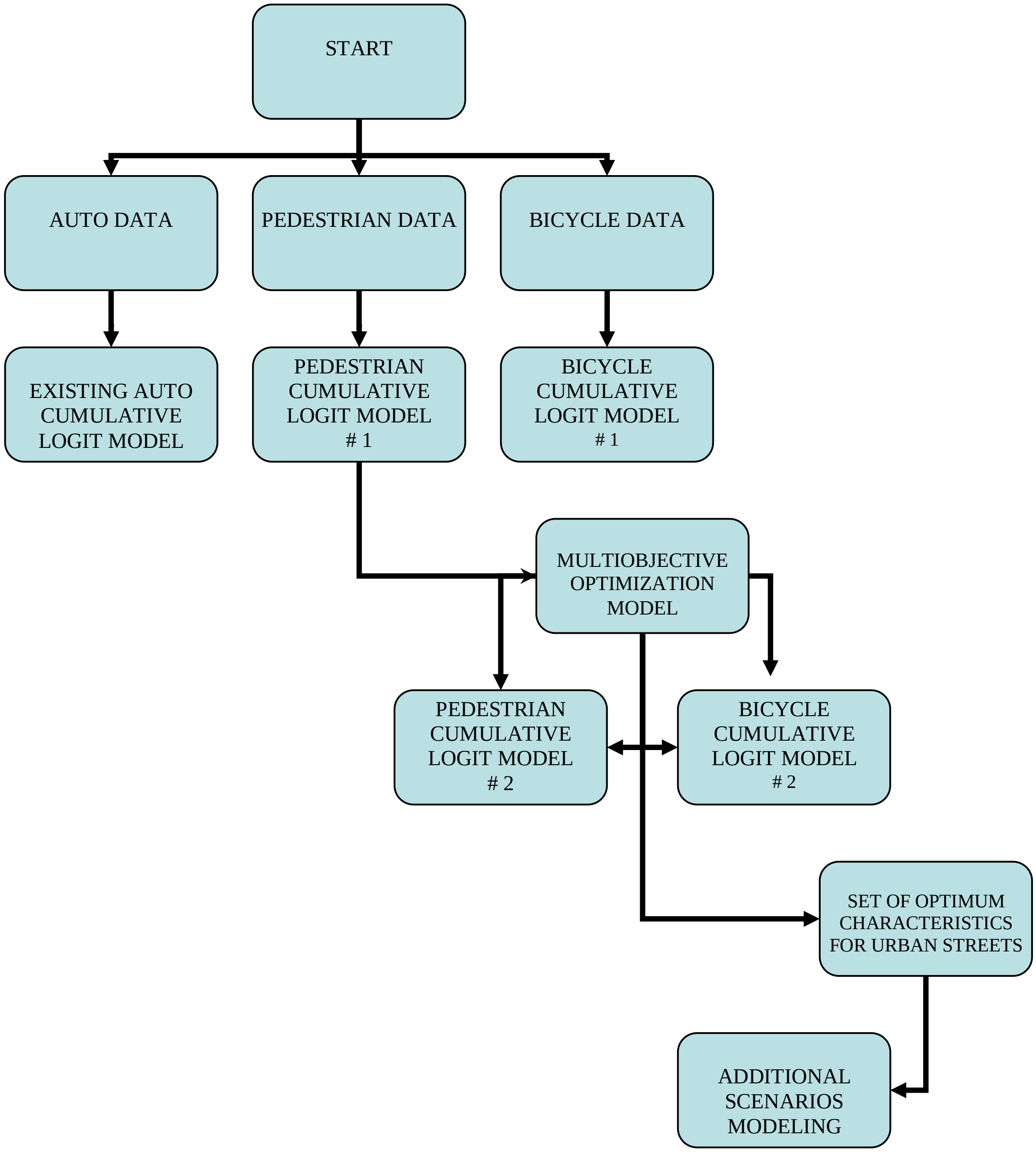

Figure 4. 4 General Flow of Modeling Process

Goal Definition

The developed Multi-objective Optimization Model has three objective functions:

- Auto modal users perception of LOS,
- Pedestrian modal users perception of LOS,
- Bicycle modal users perception of LOS.

Three goal statements were to optimize the three modal LOS (pedestrian, bicycle, auto) instead of a single goal. The objective functions are conflicting since increasing speed for automobiles impedes the bicycle and pedestrian perceived LOS. The Multi-objective Optimization Model will result in a compromise among these objectives, as encountered in real-life problems, and are often mathematical functions of contrasting forms.

The goal of the Multi-objective Optimization Model is to include three objectives which are further constrained by the available Right of Way (ROW) width. Ultimately the model will provide values for the characteristics of the urban street which will meet or exceed the required LOS for each mode.

Baseline, Balance and Goal Achievement

Following the definition of the goals, the three single-objective optimization models were created. The scope of each model was to minimize each of the three goals individually. For this step, no influence from the other modes has been included. The general form of the individual optimization model is as presented in Figure 4.5.

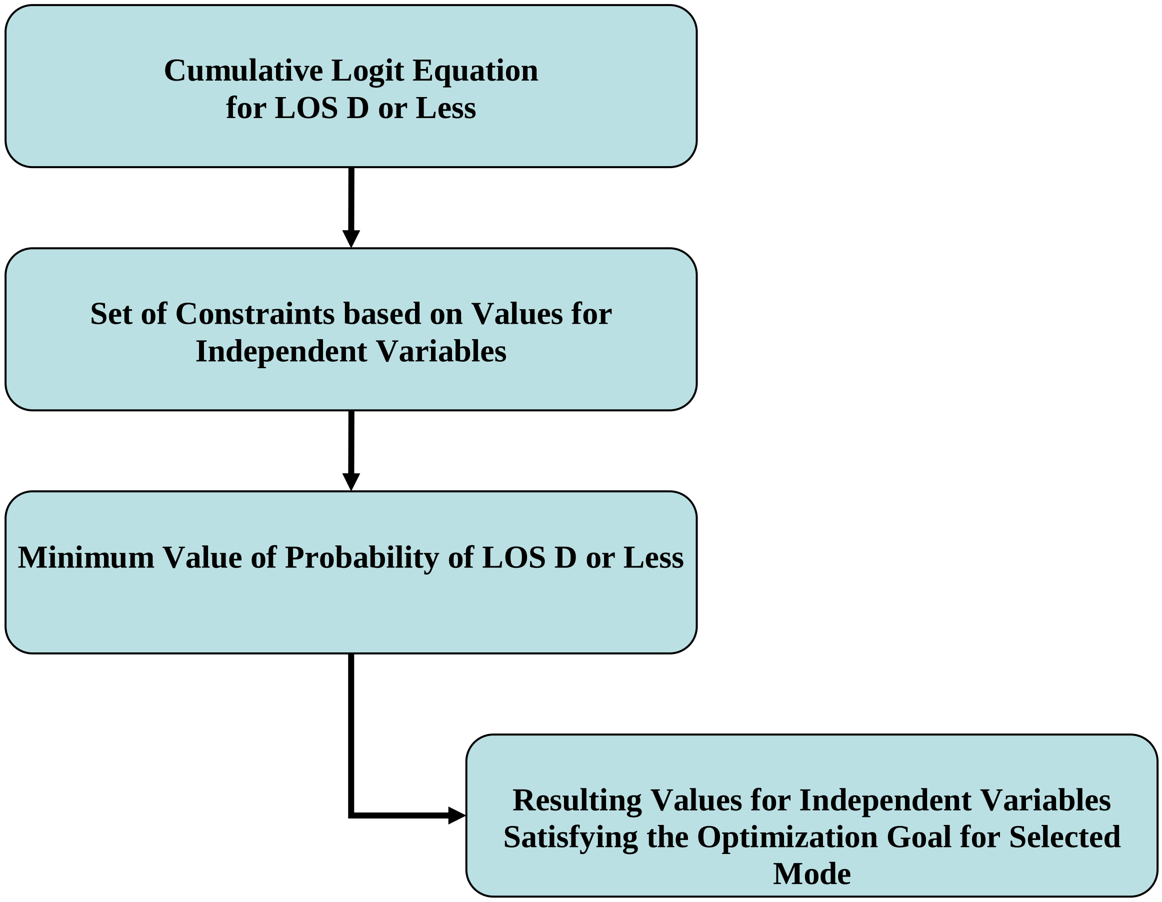

Figure 4. 5 Optimization Model-General Format

The modeling effort continued by creating the baseline for the Multi-objective Optimization Model, or Steps 1, 2 and 3, as shown in Figure 4.6.

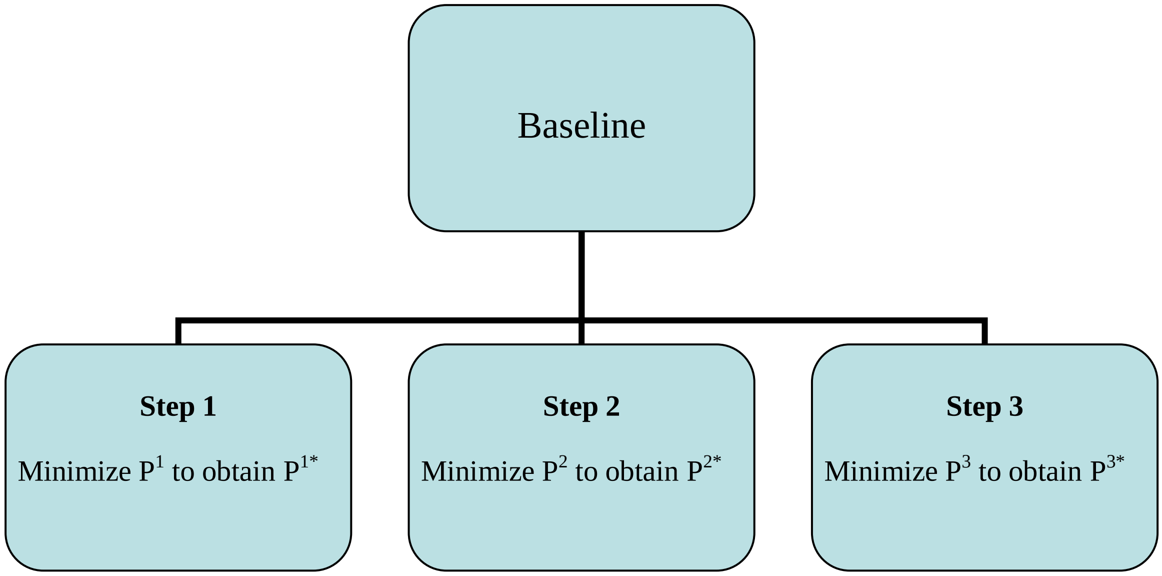

Figure 4. 6 Optimization Baseline

Where:

P1, P2 and P3 are the probabilities that the LOS ratings by the users of each mode will be less than or equal to LOS D (this is an arbitrary LOS which can be selected by the modeler).

The results from Steps 1, 2 and 3 constitute the lower threshold of the acceptable LOS for each of the three modes as shown in Figure 4.7.

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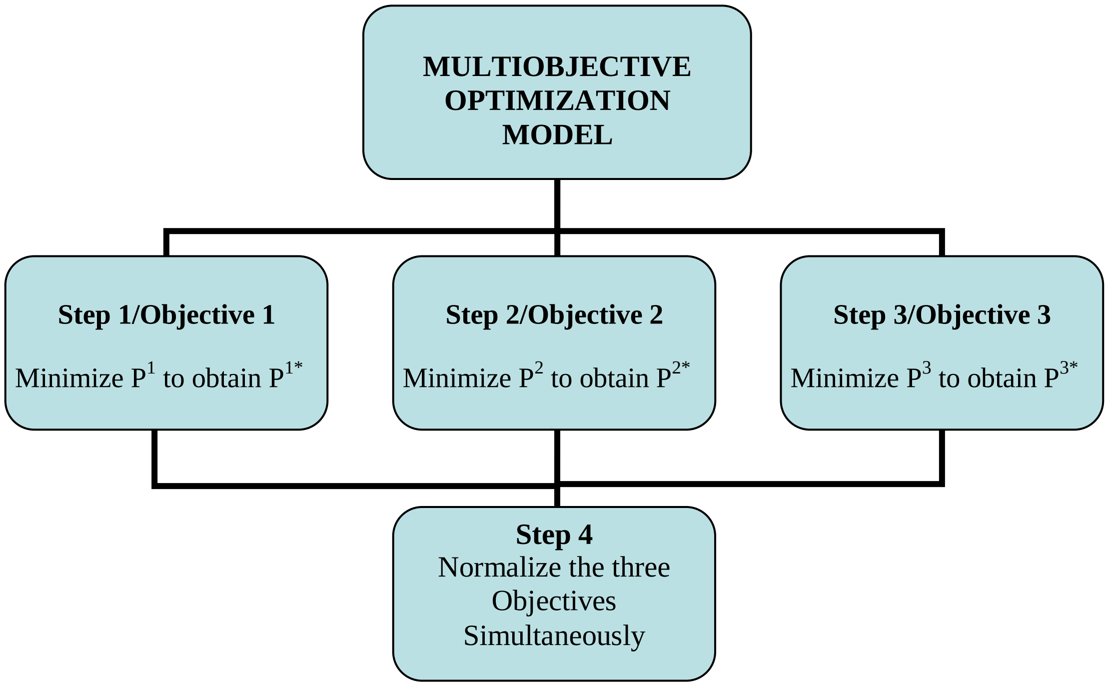

Figure 4. 7 Multi-objective Optimization Model

Step 4

Once the three modes have been optimized independently, the multi-objective goal achievement threshold was established. This threshold normalizes the three concomitant goals creating the optimization model.

The variables selected for the Multi-objective Optimization Model have a defined range that when changed in the optimization equation will provide a different outcome. The result of the optimization function is a combination of variables and ranges that provide the optimum LOS for the three modes concomitantly. The first three steps of the optimization process consisted of creating three Single Objective Optimization Models, one for each travel mode as described below.

The Target Cells, only one for each model, were defined by the Ordinal Logit model equation for cumulative predicted probability from the logistic model for LOS D.:

$$P(LOS \leq J) = 1/(1 + e^{-(\alpha_{(J)} - \sum \beta_k x_k)}) \qquad \text{Equation 4.2.1}$$

Where:

$P(LOS \leq J)$	=	Probability that an individual will rate the experience as LOS "J" or worse
e	=	Exponential function
$\alpha_{(J)}$	=	Intercept for LOS "J"
β_k	=	Calibration parameter beta for each attribute
x_k	=	Attribute "k" of the segment.

The LOS level selected was considered to be a level that will allow travelers to satisfactorily complete their trip. The goal of the model is to provide a facility that will provide at least LOS D for all three modes concomitantly. The estimated parameters used in the modal Ordinal Logit model were obtained from Maximum Likelihood Estimates for Ordinal Regression and have been discussed previously in this Chapter.

The numbers to be generated were the values that each independent variable would take when the optimum of the Target Cell was reached. The values these cells could take were constrained by the range of the data collected in NCHRP 3-70 study. These constraints were used to allow the probabilities of obtaining LOS ratings of D or less to be driven by the variables collected for the NCHRP 3-70 study and are presented below.

Multi-objective Optimization Model Step 1: Single Objective Optimization Model for Auto Mode

The objective for the auto mode is:

$$Minimize Z = P1 \qquad \text{Equation 4.2.2}$$

Subject to:

$$P1 = \Pr ob(LOS \leq D) = \frac{1}{1 + EXP(-(0.706*1 - 0.084*SMS - 0.224*MP))}$$

Equation 4.2.3

$$SMS \geq 4 \qquad \text{Equation 4.2.4}$$

$$SMS \leq 42 \qquad \text{Equation 4.2.5}$$

$$MP \in \{0,1,2,3\} \qquad \text{Equation 4.2.6}$$

These thresholds indicate:

- *Average Space Mean Speed (SMS)* was between 4 and 42 mph, as observed during the data collection process for NCHRP 3-70,

- *Median Presence (MP)* can take the values of 0, 1, 2 and 3

MP=0	means	no median present.
MP=1	means	the street was one way
MP=2	means	there was a two-way Left-Turn Lane
MP=3	means	a raised median was present.

Multi-objective Optimization Model - Auto Mode Step 1: Results

The Maximum Likelihood Estimate Parameters presented in Table 2.4 were introduced in Equation 4.2.2 resulting in minimum P1= 0.03 for values of the independent variables of SMS=42 mph and MP=3. The results of the optimization model indicate that auto drivers will be satisfied with their driving experience when the average space mean speed is closer to the upper observed *SMS* threshold and a raised median is present. The minimum value P1= P1* was introduced in the Step 4 of the Multi-objective Optimization Model.

Multi-objective Optimization Model Step 2: Single Objective Optimization Model for Pedestrian Mode

The objective for the pedestrian mode is:

$$Minimize Z = P2 \qquad \text{Equation 4.2.7}$$

Subject to:

$$P2 = \Pr ob(LOS \leq D) = \frac{1}{1 + EXP(-(-1.124*1 + 0.561*NL - 0.920*SWC))}$$

Equation 4.2.8

$$NL \geq 1 \qquad \text{Equation 4.2.9}$$

$$NL \leq 3 \qquad \text{Equation 4.2.10}$$

$$NL = INTEGER \qquad \text{Equation 4.2.11}$$

$$SWC = BINARY \qquad \text{Equation 4.2.12}$$

These thresholds indicate:

- *Number of Lanes (NL) can be 1, 2 or 3,*
- *Sidewalk Width Category (SWC) can be 0 or 1.*

The Maximum Likelihood Estimate Parameters presented in Table 4.2 were introduced in Equation 4.2.6 resulting in minimum $P2=P2^*$ for values of the independent variables of *NL*=1 and *SWC*=1. The results of the optimization model indicate that pedestrians will be satisfied with their walking experience when the number of lanes in the same direction as they are walking is at the lower threshold and the width of the sidewalk is at the upper threshold. The minimum value P2= 0.205 was introduced in the Step 4 of the Multi-objective Optimization Model.

Multi-objective Optimization Model Step 3: Single objective Optimization Model for Bike Mode

The objective function for the bicycle mode is:

$$Minimize Z = P3 \qquad \text{Equation 4.2.13}$$

Subject to:

$$P3 = \Pr ob(LOS \leq D) = \frac{1}{1 + EXP(-(-2.004*1 + 0.972*NL + 2.398*PSL - 1.695*BW))}$$

Equation 4.2.14

$NL \geq 1$ Equation 4.2.15

$NL \leq 3$ Equation 4.2.16

$NL = INTEGER$ Equation 4.2.17

$BWC = BINARY$ Equation 4.2.18

$PSL \geq 25mph$ Equation 4.2.19

$PSL \leq 55mph$ Equation 4.2.20

$PSL = INTEGER$ Equation 4.2.21

These thresholds indicate:

- *Through Lanes (NL) can be 1, 2 or 3,*
- *Bike Shoulder Width Category (BWC)can be 0 or 1,*
- *Posted Speed Limit (PSL) can vary between 25mph and 55 mph.*

Similarly with the pedestrian mode, these variables represent characteristics of the street facilities that are contributing to the multi-objective optimization model and represent the range of the data included in the study dataset.

The Maximum Likelihood Estimate Parameters presented in Table 4.4 were introduced in Equation 4.2.11 resulting in minimum P3= P3 * for values of the independent variables of *NL*=1, *PSL*=0 and *BWC*=1. The results of the optimization model indicate that the bicyclists will be satisfied with their bicycling experience when the number of lanes in the same direction as their travel is at the lower threshold, the posted speed limit is at the lower threshold and the width of the bike lane is at the upper threshold. The minimum value P3= 0.061 was introduced in the Step 4 of the Multi-objective Optimization Model.

Multi-objective Optimization Model Step 4

The objective function is:

$$Minimize Z = X \qquad \text{Equation 4.2.22}$$

Subject to

$$X \geq P1/P1^{*} \qquad \text{Equation 4.2.23}$$

$$X \geq P2/P2^{*} \qquad \text{Equation 4.2.24}$$

$$X \geq P3/P3^{*} \qquad \text{Equation 4.2.25}$$

$$ROWWA = ROWWO \qquad \text{Equation 4.2.26}$$

$$ROWO = MW + (NL * LW + SWW + GS + BLW) * 2 \qquad \text{Equation 4.2.27}$$

$$SMS \geq 4 \qquad \text{Equation 4.2.28}$$

$$SMS \leq 42 \qquad \text{Equation 4.2.29}$$

$$SMS > PSL * 5 + 20 \qquad \text{Equation 4.2.30}$$

$$SMS < PSL * 7 + 35 \qquad \text{Equation 4.2.31}$$

$$MP \leq 3 \qquad \text{Equation 4.2.32}$$

$$MP \geq 0 \qquad \text{Equation 4.2.33}$$

$$MP = INTEGER \qquad \text{Equation 4.2.34}$$

$$MP = 0 * MT0 + 1 * MT1 + 2 * MT2 + 3 * MT3 \qquad \text{Equation 4.2.35}$$

$$MT0 = BINARY \qquad \text{Equation 4.2.36}$$

$$MT1 = BINARY \qquad \text{Equation 4.2.37}$$

$$MT2 = BINARY \qquad \text{Equation 4.2.38}$$

$$MT3 = BINARY \qquad \text{Equation 4.2.39}$$

$$MW \geq 4 \qquad \text{Equation 4.2.40}$$

$$MW \le 80 \quad \text{Equation 4.2.41}$$

$$MW \le 0*MT0+0*MT1+14*MT2+80*MT3 \quad \text{Equation 4.2.42}$$

$$MW \ge 0*MT0+0*MT1+14*MT2+4*MT3 \quad \text{Equation 4.2.43}$$

$$NL \ge 1 \quad \text{Equation 4.2.44}$$

$$NL \le 3 \quad \text{Equation 4.2.45}$$

$$NL = INTEGER \quad \text{Equation 4.2.46}$$

$$NL \ge 1*MT0+1*MT1+1*MT2+1*MT3 \quad \text{Equation 4.2.47}$$

$$NL \le 3*MT0+3*MT1+3*MT2+3*MT3 \quad \text{Equation 4.2.48}$$

$$SWC = BINARY \quad \text{Equation 4.2.49}$$

$$SW \ge 4\,ft \quad \text{Equation 4.2.50}$$

$$SW \le 8\,ft \quad \text{Equation 4.2.51}$$

$$SW = INTEGER \quad \text{Equation 4.2.52}$$

$$PSL \ge 25mph \quad \text{Equation 4.2.53}$$

$$PSL \le 55mph \quad \text{Equation 4.2.54}$$

$$PSL = INTEGER \quad \text{Equation 4.2.55}$$

$$BW = BINARY \qquad \text{Equation 4.2.56}$$

$$BW \geq 4\,ft \qquad \text{Equation 4.2.57}$$

$$BW \leq 5\,ft \qquad \text{Equation 4.2.58}$$

$$BW = INTEGER \qquad \text{Equation 4.2.59}$$

The Multi-objective Optimization Model has been defined within a series of constraints that have been provided with this dissertation; however these constraints can be tailored as required for the environment planned to be used. The constraints have been developed to reflect the state of the practice and established standards by governing bodies such as the American Association of State Highway and Transportation Officials (AASHTO, 2004). In addition, a set of new decision variables as well as of a set of non-decision variables were added to aid the construction of the optimization model. An overview of the constraints contained in the optimization model is provided here.

Right of Way Width

The width of the Right of Way is a value that is available to the engineer or planner and represents the available width for the design of an urban arterial. This value is inserted into the assigned cell within the developed spreadsheet and governs the street characteristics optimization calculations. The decision and non-decision variables are manipulated and replaced in equation 4.2.60 which is the same with equation 4.2.26 to satisfy the equality:

$$ROWWA = ROWWO \qquad \text{Equation 4.2.60}$$

Where:

$ROWWA$ = Right of Way Width Available (given)

$ROWWO$ = Right of Way Width Optimum

The constraint for *ROWWO* is shown in equation 4.2.27 which is the same with equation 4.2.61:

$$ROWWO = MW + (NL * LW + SWW + GS + BLW) * 2 \qquad \text{Equation 4.2.61}$$

Where:

MW	=	Median Width (ft)
NL	=	Number of Lanes
LW	=	Lane Width (ft)
SWW	=	Sidewalk Width (ft)
GS	=	Grass Strip (fixed width)
BLW	=	Bike Lane Width (ft)

From the variables included in equation 4.2.61 the following variables have been created to allow the construction of the ROW width: *Median Width (MW), Lane Width (LW),* *Sidewalk Width (SWW)*, *Grass Strip (GS)* and *Bike Lane Width (BLW)*. The values these variables can take are defined as follows:

Median Width (MW)

A median is a portion of an urban street separating the opposing directions of traffic and it is highly desirable on arterials with four or more lanes. The width of a median can vary between 4 and 80 feet and it is selected based on ROW width available, type of street and location. For urban streets, narrower medians are desirable due to economic constraints (AASHTO, 2004); however widths less than 4 ft limit the ability to plant vegetation on the median. For the purpose of this dissertation, the median width has been set to vary between 4 feet and 80 feet.

Number of Lanes (NL)

The number of lanes for collector roads in urban areas may be established based on future development needs. When practical and economically feasible, two lanes in each direction should be provided; however one lane in each direction may be acceptable given that additional space for parking is provided based on AASHTO guidance. The correct assessment of the number of lanes needed for streets with high traffic volume would be determined from a capacity analysis (AASHTO, 2004). Due to the data collected, the optimization model has been designed to accommodate up to three traffic lanes in each direction.

Lane Width (LW)

AASHTO standards were consulted in order to select the adequate width for each facility. The desirable lane width for urban arterials is 12 feet; however 10 feet and 11 feet lanes are also considered acceptable. The increase in cost of 12-foot lanes is somewhat offset by the increased sense of safety for the drivers due to the desirable clearance from the opposing traffic, especially larger vehicles. The cost is also offset by the decrease in shoulder maintenance and the roadway surface maintenance due to less damage at the edge of the pavement from excessive wheel concentration. When there are multiple lanes in one direction of travel, the lane width can be uneven, with the wider lane on the outside allowing heavy vehicles and potentially bike travel. Narrower lane widths are acceptable where pedestrian crossings, ROW or existing development become strict controls. Lanes narrower than 11 feet are only recommended for low-speed facilities (AASHTO, 2004). For the purpose of this dissertation the lane width is set to vary between 10 feet and 12 feet.

Sidewalk Width (SW)

Sidewalks are facilities present in communities that have pedestrian concentrations along the streets. Shoulders may also accommodate pedestrian traffic if they encourage use in all weather conditions. When sidewalks are proposed there is desire for a border between the roadway and the sidewalk that serves the purpose of providing safety for pedestrians as well as accommodating street lights, fire hydrants, street hardware and aesthetic vegetation. This border has been called the grass strip throughout this dissertation. In residential areas the recommended sidewalk width may vary between 4 and 8 feet and a minimum width grass strip of 2 feet. A width of 4 feet is desirable where sidewalks are placed adjacent to the curb, allowing for street hardware and snow storage (AASHTO, 2004). For the purpose of this dissertation the sidewalk width has been set to vary between 4 and 8 feet. A grass strip of varying width has been added to different scenarios to provide the minimum required by existing standards.

A roadway cross section with bike lanes and sidewalks has been depicted in Figure 4.8.

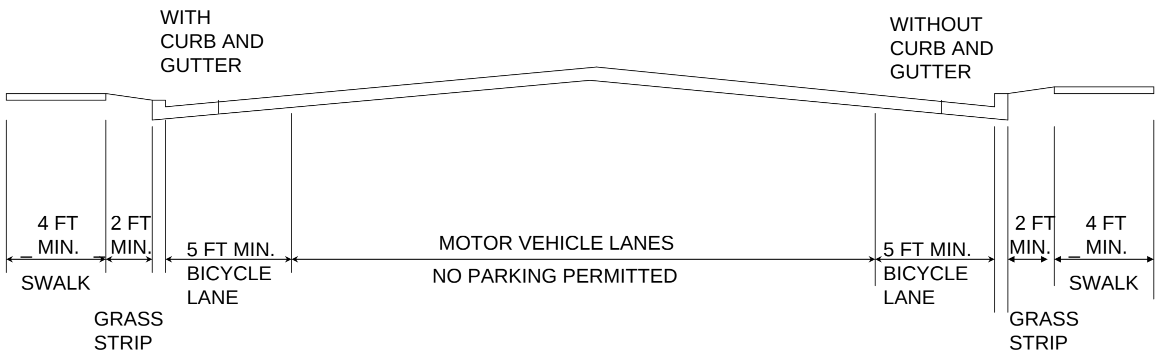

Figure 4. 8 Typical Sidewalk Cross Section

Sidewalk Width Category (SWC)

This variable has been generated by the data coding and it takes the values of 0 and 1. In combination with *SW* variable it contributes to the Multi-objective Optimization Model.

Bike Lane Width (BW)

Bicycle lanes are one way facilities, placed on the right side of travel lanes, carrying traffic in the same direction as the adjacent auto traffic. The width of the bicycle lanes, for roadways without curb and gutter should be no less than four feet (AASHTO, 2004). When on-street parking is permitted, the bicycle lane should be placed between the travel lane and the parking area. This dissertation will not include this scenario; however it may be included in future research.

The width of a bicycle lane varies based on the type of roadway. For urban streets with curb and gutter or with guardrail the recommended width is five feet from face of curb or guardrail to the bicycle lane stripe. A width greater than five feet is recommended for bicycle lanes adjacent to roadways that carry substantial heavy vehicle traffic or when traffic speed is in excess of 50 mph (AASHTO, 1999). The width of the bicycle lane has been set to vary between four feet and five feet for this dissertation.

A roadway cross section with bicycle lanes has been depicted in Figure 4.9.

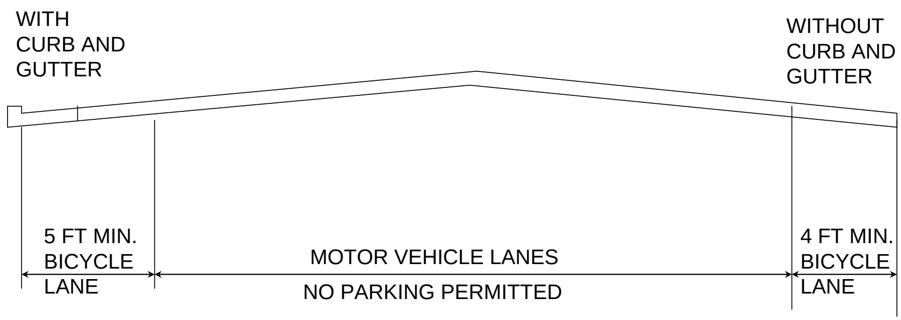

Figure 4. 9 Typical Bicycle Lane Cross Section

Bicycle Shoulder Width Category (BWC)

This variable has been generated by the data coding and it takes the values of 0 and 1. In combination with *BW* variable it contributes to the model.

Posted Speed Limit

The *Posted Speed Limit* variable was not included in the ROW equation; however this variable influences the perceived pedestrian and bicyclist LOS through the respective cumulative logit equations. Similarly, the Average Space Mean Speed variable was not included in the ROW equation but it has influence on the perceived LOS by drivers.

Five conditions that influence the *Posted Speed Limit* were identified in addition to driver capabilities and type of vehicle being operated, as follows:

- Physical characteristics of the roadway
- The amount of roadside interference
- Weather conditions
- Presence of other vehicles
- Speed limitations.

For the purpose of this dissertation two of the identified characteristics have been taken in to account: physical characteristics of the roadway and speed limitations.

The design speed is established based on topography, anticipated operating speed, the adjacent land use and functional classification of the roadway. For local streets speed control measures are often implemented therefore the design speed will be controlled differently (AASHTO, 2004). Measures including lane width, presence and width of shoulders and clearance to obstacles including walls and rails indirectly affect vehicle speeds. For this reason it is recommended to increase lane and shoulder width for roadways with higher design speeds (AASHTO, 2004).

For collector streets a design speed of 30 mph is customary, and it varies based on site controls (AASHTO, 2004). The *Posted Speed Limit (PSL)* for this dissertation has been set to vary between 25 mph and 55 mph, as included in the NCHRP 3-70 study.

The constraints for *SMS* provide the thresholds in relation with the *PSL*. For *PSL* value of 0 the *SMS* can vary between 20 and 35 mph and for *PSL* value of 1 the *SMS* can vary between 35 and 42 mph.

Equations 4.2.62 and 4.2.63 represent the constraints set for the *Median Presence (MP)* variable.

$$MT0 + MT1 + MT2 + MT3 = 1 \qquad \text{Equation 4.2.62}$$

$$MP = 0*MT0 + 1*MT1 + 2*MT2 + 3*MT3 \qquad \text{Equation 4.2.63}$$

The constraint for *Median Presence (MP)* involves the non-decision variables *MT0* to *MT3* and directs the model to select precisely the values of zero, one, two or three for the presence of median. These constraints have also been introduced to provide a relationship between the type or presence of median and the width of the median and the number of traffic lanes.

As mentioned before, the median width has been set to vary between four and 80 feet; however the *MP* variable dictates the width of the median. For *MP* type 0 or 1, the width of the median has been set to 0. For *MP* type 2, the width of the median has been set to 14 ft to represent a two-way center left turn lane. For *MP* type 3, the width of the median can vary between 4 and 80 feet. Equations 4.2.64 and 4.2.65 depict the constraints that establish the relationship between the type of median and the median width.

$$MW \leq 0*MT0 + 0*MT1 + 14*MT2 + 80*MT3 \qquad \text{Equation 4.2.64}$$

$$MW \geq 0*MT0 + 0*MT1 + 14*MT2 + 4*MT3 \qquad \text{Equation 4.2.65}$$

The type of median is restricted by the number of lanes. In the scenario for which the constraints are presented the median type is not restricted by the number of lanes. However, Equations 4.2.66 and 4.2.67 present the constraints that would allow a different scenario to be set where the type of median is dictated by the number of lanes.

For example, when only two lanes are present the median type should be restricted to 0 which means no median is present.

$$NL \leq 2*MT0 + 4*MT1 + 4*MT2 + 4*MT3 \qquad \text{Equation 4.2.66}$$

$$NL \geq 2*MT0 + 2*MT1 + 2*MT2 + 2*MT3 \qquad \text{Equation 4.2.67}$$

The Multi-objective Optimization Model for urban streets has been described and presented in detail above. As designed, the model involves three objective functions, each assigned to one transportation mode. The simplicity of the model makes it accessible and user friendly. Several scenarios have been created to further analyze the Multi-objective Optimization Model and are presented in Chapter 5.

CHAPTER 5 MODEL VALIDATION

Auto, Pedestrian and Bicycle Models

The foundation of the Multi-objective Optimization Model was the Cumulative Logit Model. The three conflicting objective of the model were developed using this method; the auto model developed by the NCHRP 3-70 study and the pedestrian and bicycle traveler perceived LOS models developed in this dissertation.

5.1 Auto Model Validation – Review of NCHRP 3-70 Findings

The auto model was tested for ability to accurately predict the distribution of ratings by comparison with the HCM ratings and the observed LOS ratings. The results of the testing were presented in Table 2.6. The cumulative logit model was able to predict approximately 32 percent more of the LOS ratings as compared to the *HCM* 2000. This comparison explains the preference of the researchers for this model.

5.2 Cumulative Logit Pedestrian LOS Model Validation

The Cumulative Logit pedestrian LOS Model, created with this dissertation was also tested for its ability to predict the LOS ratings. The validation data which was initially separated from the modeling data were used for this process. The comparison has been represented in Figures 5.1 through 5.4. The clips selected for the evaluation are the four clips shown at each of the four study sites in the NCHRP study. These four clips had the largest number of observations to develop a robust distribution of data. The data predicted by the model are following the trend of the video clip ratings distribution which suggests a good fit of the model to the data. In Clip 208, the validation data does not have any LOS A ratings. After watching this video clip again it was concluded that this can be due to the fact that the first portion of the selected path did not have a paved sidewalk only a wide grass strip. LOS F is also under predicted by the model. This difference can be attributed to the large traffic volume and to the long distance that the pedestrian had to travel to cross the street. Table 4.6 presents the evaluation of the pedestrian model in comparison with the validation data and the NCHRP 3-70 pedestrian model.

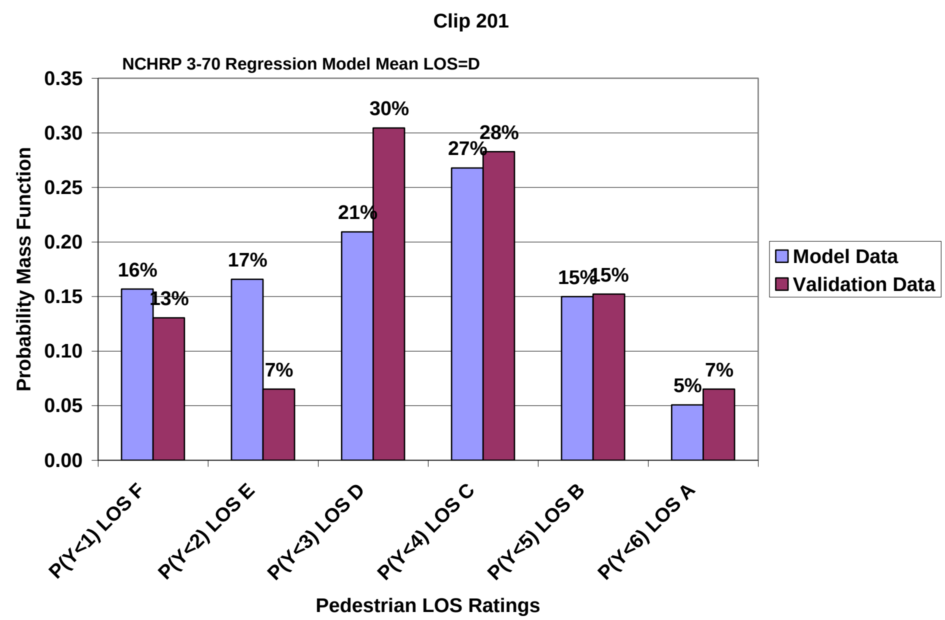

Figure 5.1 Comparison of LOS Distribution - Clip 201 and Estimated Pedestrian LOS Rating

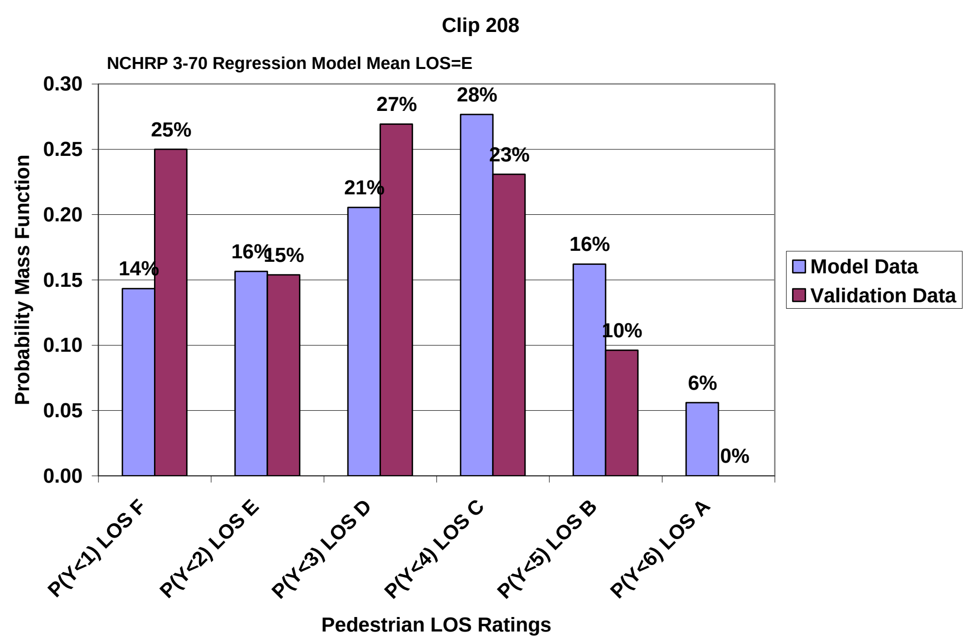

Figure 5.2 Comparison of LOS Distribution - Clip 208 and Estimated Pedestrian LOS Rating

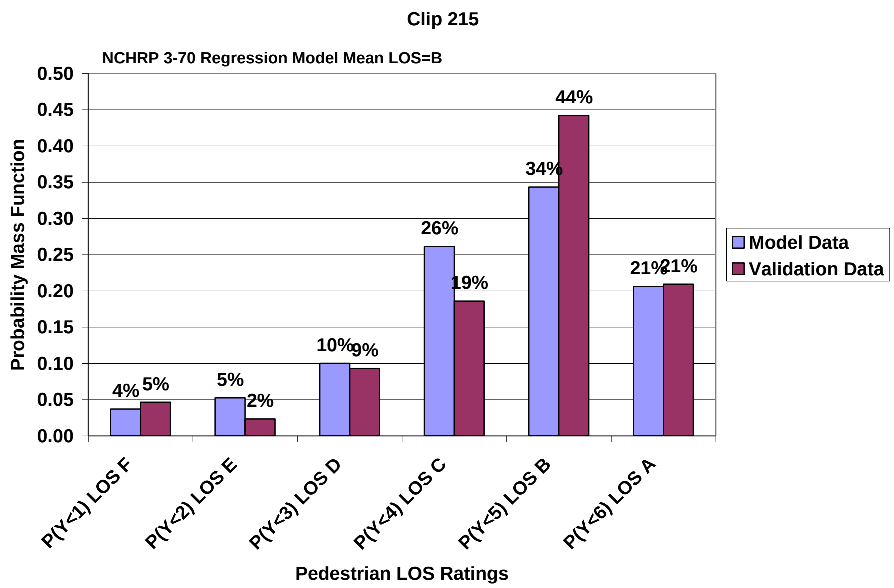

Figure 5.3 Comparison of LOS Distribution - Clip 215 and Estimated Pedestrian LOS Rating

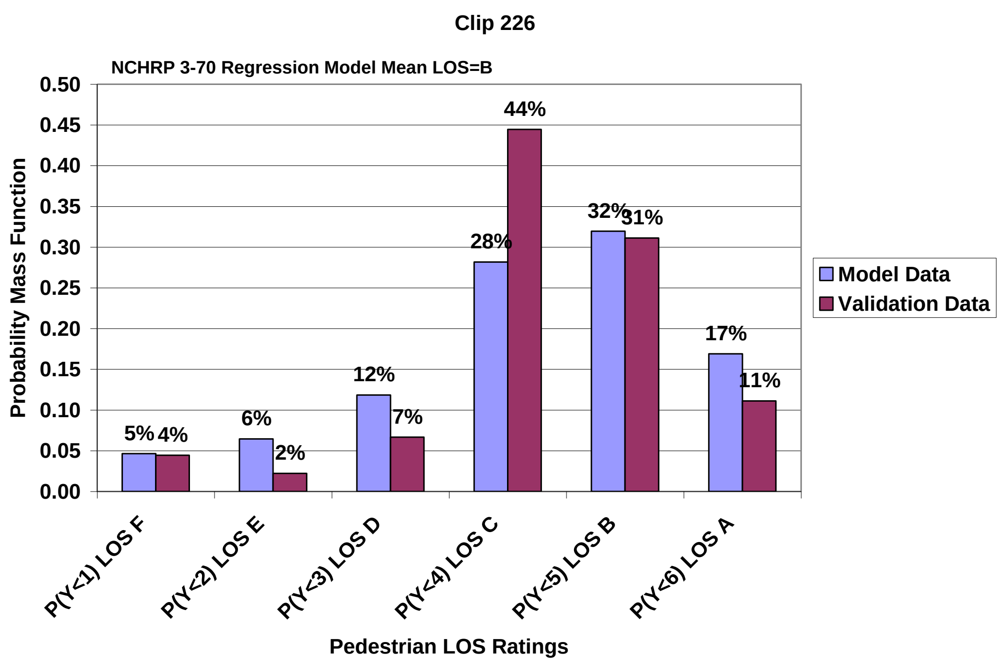

Figure 5.4 Comparison of LOS Distribution - Clip 208 and Estimated Pedestrian LOS Rating

The Cumulative Logit Model and the regression model developed by the NCHRP 3-70 study predict the participant rated LOS similarly, as shown in Table 5.1. Further validation of the Cumulative Logit Model was provided by performing a Pearson Correlation analysis for the validation LOS and the cumulative logit LOS and for the validation LOS and the NCHRP 3-70 regression model. The results of the test have been presented in Table 5.2.

The newly created pedestrian model has been considered to be more suitable for the scope of this dissertation and will be used for an optimization model and ultimately used in the Multi-objective Optimization Model. The decision of adopting the new model was based on the fact that pedestrian LOS can be estimated accurately using three variables as compared to twenty eight variables used in the NCHRP 3-70 model. In addition the Cumulative Logit Model can estimate the distribution of LOS rating as compared to a mean rating of LOS as estimated by the NCHRP 3-70 model.

Table 5. 1 Evaluation of Pedestrian Cumulative Logit Model

Clip No.	**Validation LOS**	**NCHRP Model 1 LOS**	**Cum. Logit Model**
215	C	D	D
227	D	C	B
230	E	B	B
221	E	D	C
224	D	E	D
228	D	E	E
226	C	C	D
232	C	B	D
229	C	D	C
205	B	B	B
211	C	C	D
214	C	B	D
225	B	B	B
218	C	B	B
222	C	B	B
219	B	B	C
220	B	C	B
223	C	A	B
210	B	B	C
216	C	D	C
217	B	C	B
203	C	C	B
204	D	D	D
231	C		D
201	D	D	B
209	E	C	B
206	E	B	C
208	D	D	D
Percentage Exact Match to Validation Data	100%	35%	35%
Percentage Within 1 LOS of Validation Data	100%	87%	83%

Table 5. 2 Pearson Correlation Coefficients of Pedestrian LOS Models

Models Compared	Pearson Correlation Coefficient
HCM LOS to Mean Observed LOS	0.059
NCHRP LOS to Mean Observed LOS	0.468
Model LOS to Mean Observed LOS	0.326

By using the cumulative logit model approximately 15 percent of the estimation ability has been lost. However, the NCHRP pedestrian model was created using twenty eight variables that are often difficult to collect, such as pedestrian delay, right turning vehicles on red and pedestrian volumes. Such a model would involve considerable efforts and resources which may not be attractive for practitioners potentially resulting in a lack of proper use of the model or lack of use at all. The Cumulative Logit Model developed in this study used only three variables that are easy to collect in the field or are in many cases readily available to practitioners.

5.3 Cumulative Logit Bicycle LOS Model Validation

The Cumulative Logit Bicycle LOS Model created with this dissertation was tested for its ability to estimate the LOS ratings. The validation data reserved for this process was used. The comparison is shown in Figures 5.5 through 5.8. These four clips, similarly with the pedestrian data, had the largest number of data points to develop a robust distribution of data. The LOS ratings estimated by the model follow the same trend of the video clip ratings distribution which suggests a good fit of the model to the data. In Clips 309 and 321, the validation data does not have any LOS A ratings. This fact can be due to the fact that the facilities in these clips did not have a bicycle lane and the traffic volume was high. LOS F is also under predicted by the model slightly. This fact can be attributed to the large traffic volume.

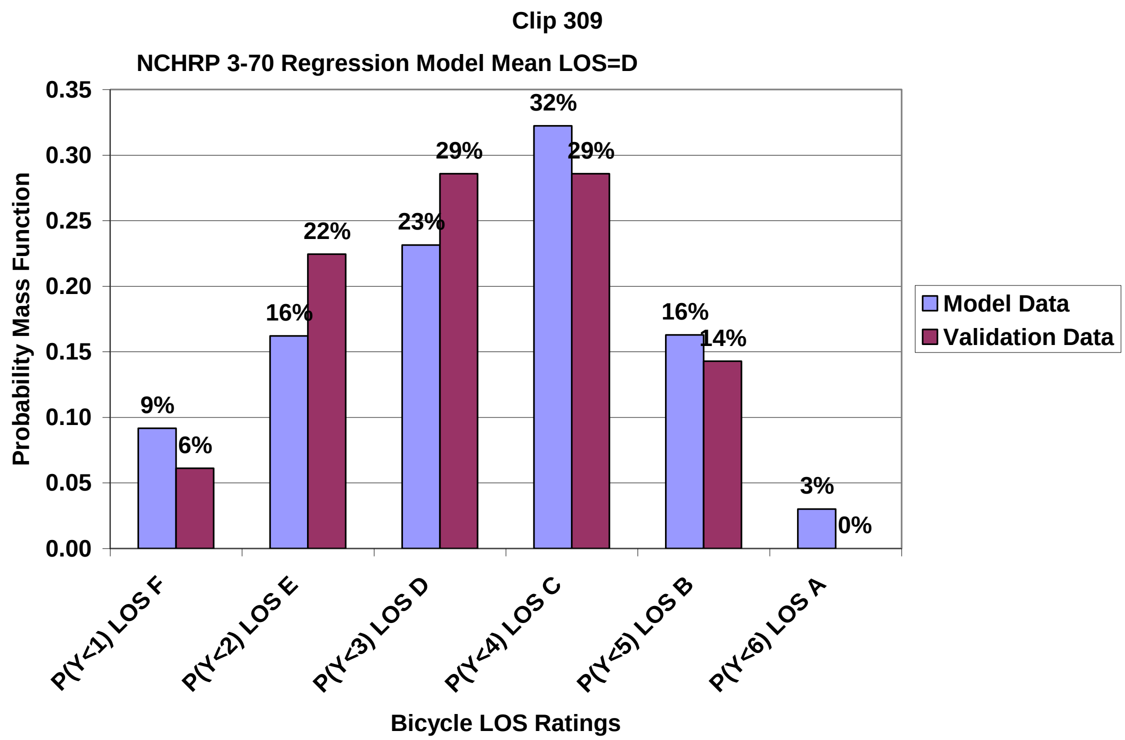

Figure 5. 5 Comparison of LOS Distribution - Clip 309 and Estimated Bicycle LOS Rating

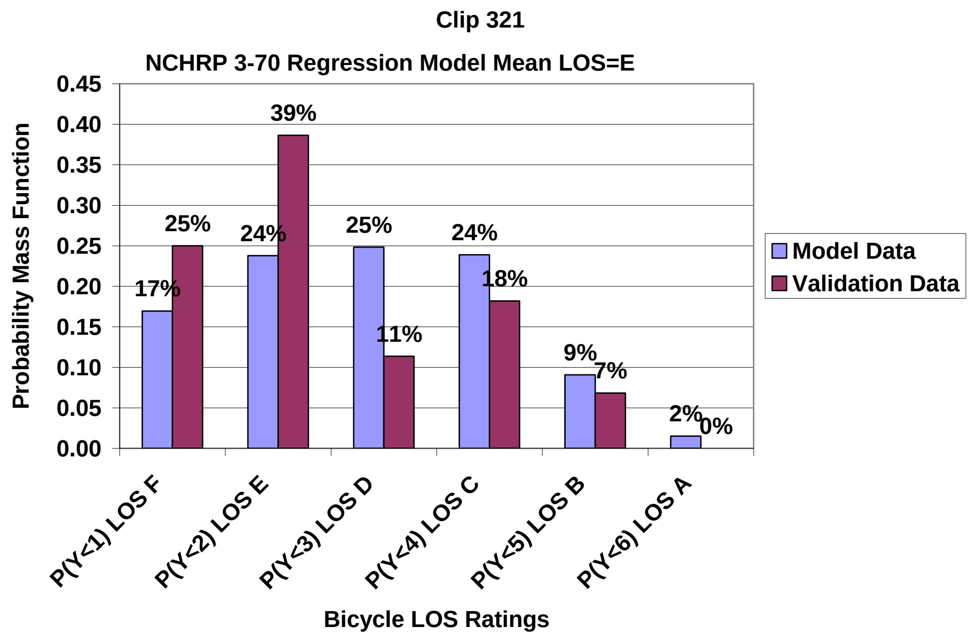

Figure 5.6 Comparison of LOS Distribution - Clip 321 and Estimated Bicycle LOS Rating

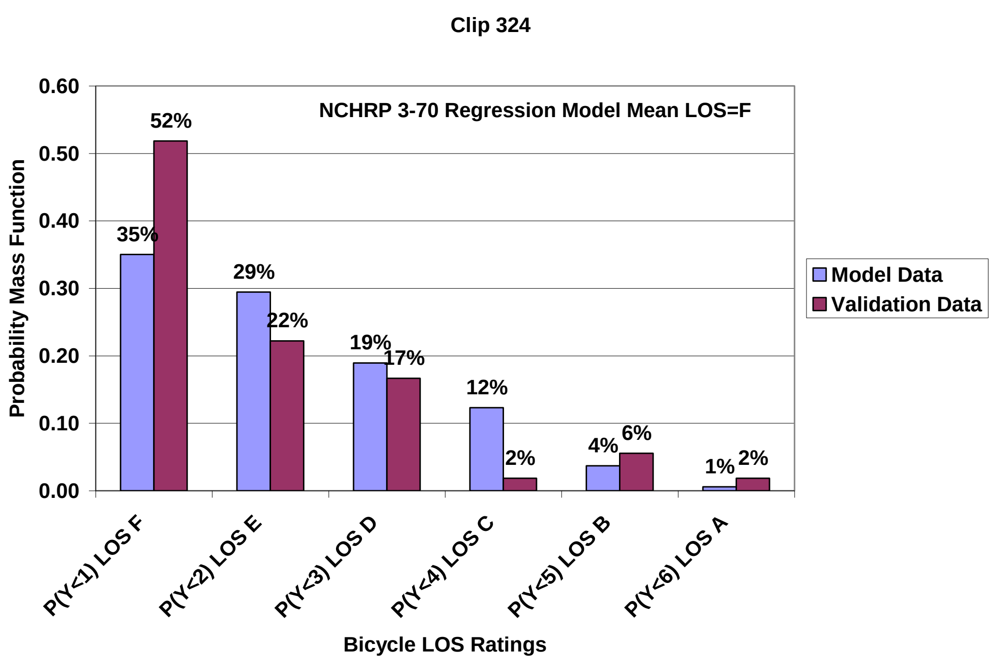

Figure 5.7 Comparison of LOS Distribution - Clip 324 and Estimated Bicycle LOS Rating

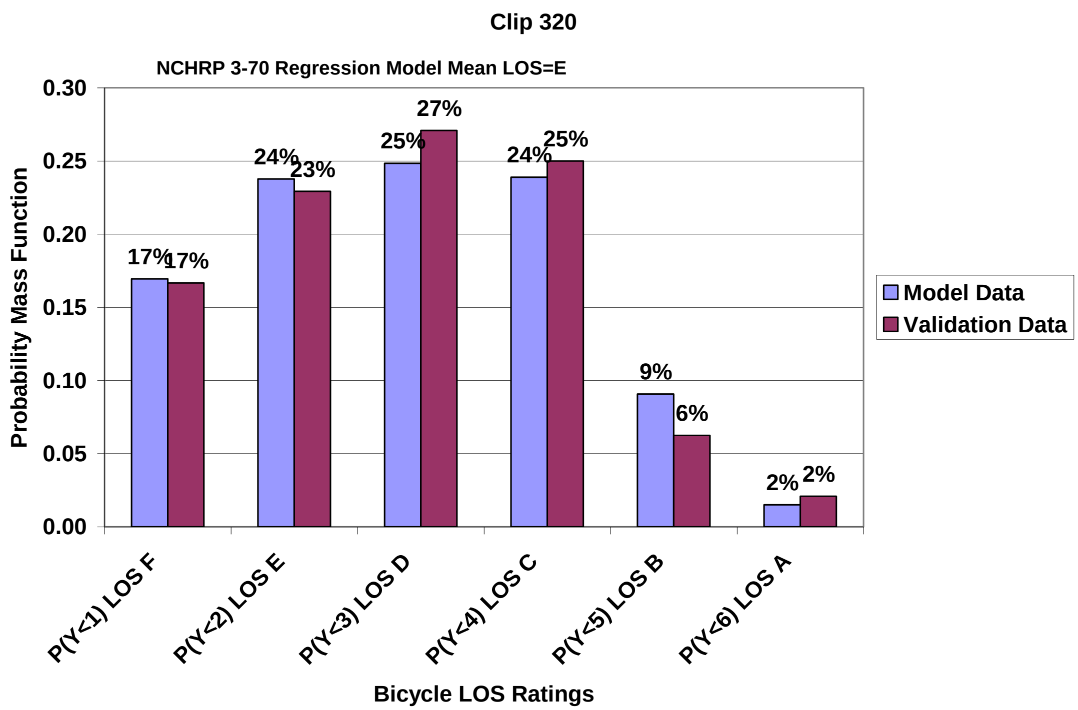

Figure 5. 8 Comparison of LOS Distribution - Clip 320 and Estimated Bicycle LOS Rating

Table 5.3 presents the evaluation of the bicycle model in comparison with the validation data and the NCHRP 3-70 bicycle model. The Cumulative Logit Model for the bicycle mode has been created to provide a better analysis of the existing data set than the one provided by the NCHRP 3-70 study as it utilizes all of the available data points, provides all the response categories and provides a complete distribution of LOS ratings based on participant ratings of LOS.

An evaluation of the Cumulative Logit model has been presented in Table 5.3. The Cumulative Logit Model matches the ratings of the validation data 38 percent of the time while the regression model developed by the NCHRP 3-70 matched only 27 percent of the time.

Table 5. 3 Evaluation of Bicycle Cumulative Logit Model

Clip #	**Validation LOS**	**NCHRP Model 1 LOS**	**Cum. Logit Model**
328	B	C	C
330	A	C	C
306	B	C	C
305	C	D	C
307	C	C	C
304	B	C	C
303	B	D	E
319	C	D	D
311	C	D	A
329	A	D	E
302	C	D	E
327	C	D	B
309	C	C	C
313	C	E	D
308	C	D	C
320	D	D	D
321	E	D	D
318	E	F	F
322	E	E	F
310	E	F	E
301	E	E	E
312	E	D	C
317	E	E	E
314	E	F	E
323	E	E	F
324	E	D	E
Percentage Exact Match to Validation Data	100%	27%	38%
Percentage Within 1 LOS of Validation Data	100%	85%	77%

The Cumulative Logit Model provides values that are closer to the video clip LOS, indicating a stronger model. The Cumulative Logit Bicycle Model was further tested by performing the Pearson Correlation analysis between the validation dataset and the Cumulative Logit Model estimated LOS and for the validation LOS and the NCHRP 3-70 regression model. The results of the test are presented in Table 5.4.

Table 5.4 Pearson Correlation Coefficients of Bicycle LOS Models

Models Compared	Pearson Correlation Coefficient
HCM LOS to Mean Observed LOS	0.016
NCHRP LOS to Mean Observed LOS	0.709
Model LOS to Mean Observed LOS	0.618

This model was developed using significantly fewer variables than the existing regression model developed in NCHRP 3-70. Also, the new model gives the distribution of ratings as compared to the mean of the ratings given by the existing model. The newly created bicycle model was selected for use in the optimization model for bicycle mode and ultimately in the Multi-objective Optimization Model.

5.4 Multi-objective Optimization Model – Sensitivity Analysis

The Multi-objective Optimization Model provides a method of distributing a given Right of Way (ROW) width between three modes. As designed, the model provides now equal weights for the three modes giving equal importance to all mode users. To test the model five different scenarios were created and presented here.

Scenario A – 100 ft ROW Width

This scenario represents a cross section design where the number of lanes has been set to three in each direction. Equation 5.1 presents the design elements included which are constraints defined in Chapter 4: *Median Width, Number of Lanes, Lane Width, Sidewalk Width, Bike Lane Width* and a fixed value for a grass strip, as required by AASHTO. The schematic in Figure 5.9 presents the results of the Multi-objective Optimization Model. The *Number of Lanes* result is for the lanes in one direction of traffic. The urban street features selected through the Optimization Model resulted in the lowest level of satisfaction for all three modes. The three modes have been accommodated at a less than desirable level of service. For drivers it appears that the level of satisfaction given by a large (upper threshold) number of lanes is counterbalanced by the dissatisfaction with a lower average space mean speed and the absence of a median. For practitioners this may mean that providing a median perhaps at the expense of having fewer lanes may provide a higher level of satisfaction with the facility. The results of the model are presented in Table 5.5.

$$OptimizedROWWidth = MedianWidth + (NoLanes * LaneWidth + SidewalkWidth + 2'GrassStrip + BikeLaneWidth) * 2$$

Equation 5.1

Auto Probability of LOS D or less = 0.154	Pedestrian Probability of LOS D or less= 0.411	Bicycle Probability of LOS D or less= 0.314

MW=0 ft; NL=3; LW=12 ft; SWW=8 ft; GS=2 ft; BLW=4 ft;
SMS=29 mph; PSL=20-30 mph

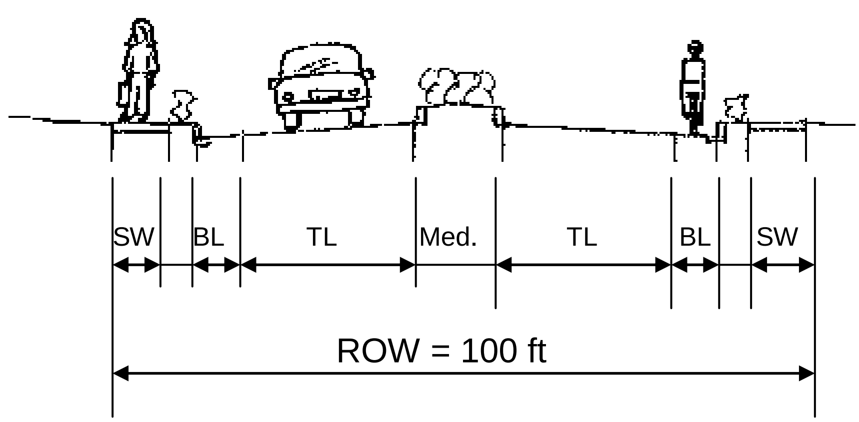

Figure 5. 9 Scenario A – Schematic of Multi-objective Optimization Model Results

Table 5.5 Multi-objective Optimization Model Results for Scenario A

Minimize Z		Z=5.14			
Auto Mode		**Pedestrian Mode**		**Bicycle Mode**	
Variable	Optimized Value	Variable	Optimized Value	Variable	Optimized Value
$P1/P1^*$	$\frac{0.154}{0.030}=5.14$	$P2/P2^*$	$\frac{0.411}{0.185}=2.22$	$P3/P3^*$	$\frac{0.314}{0.061}=5.14$
SMS	29	*NL*	3	*NL*	3
MP	0	*SWC*	1	*PSL*	0
MW	0	*LW*	12	*BWC*	1
MT0	1	*SW*	8	*BW*	4
MT1	0				
MT2	0				
MT3	0				
$ROWWA = ROWWO$ $ROWWA = 100FT$	$ROWWO = MW + (NL * LW + SWW + GS + BLW) * 2$ $ROWWO = 100FT$				

- For the auto mode, approximately 85 percent (1-0.154) of the users are most likely to rate this facility above LOS D. The urban street cross section allows for six through lanes in both directions at 12 feet wide. The absence of a median provides the least desirable scenario for automobiles.

- For the pedestrian mode, approximately 60 percent (1-0.411) of the users are most likely to rate the facility above LOS D. This finding can be explained by the sidewalk width of 8 feet and the presence of a grass strip providing separation between the pedestrians and automobile traffic. The *Average Space Mean Speed* and the *Posted Speed Limit* are both at the low threshold resulting in an acceptable level of satisfaction for the pedestrians.

- For the bicyclists 69 percent (1-0.314), are most likely to rate the facility above LOS D.

Scenario A represents a less desirable cross section design for urban streets where the three modes are at the lowest level of satisfaction compared to the scenarios that follow.

Scenario A1, with results presented in Table 5.6 was built by using Scenario A and forcing the number of lanes to remain two or fewer in each direction.

Table 5. 6 Optimization Model Results for Scenario A1

Minimize Z		Z=2.42			
Auto Mode		**Pedestrian Mode**		**Bicycle Mode**	
Variable	Optimized Value	Variable	Optimized Value	Variable	Optimized Value
$P1/P1^*$	$\frac{0.073}{0.030}=2.42$	$P2/P2^*$	$\frac{0.285}{0.185}=1.54$	$P3/P3^*$	$\frac{0.147}{0.061}=2.42$
SMS	31	*NL*	2	*NL*	2
MP	3	*SWC*	1	*PSL*	0
MW	22	*LW*	12	*BWC*	1
MT0	0	*SW*	8	*BW*	5
MT1	0				
MT2	0				
MT3	1				
$ROWWA = ROWWO$ $ROWWA = 100FT$	$ROWWO = MW + (NL * LW + SWW + GS + BLW) * 2$ $ROWWO = 100FT$				

Scenario A2, with results presented in Table 5.7, was built by using Scenario A and forcing the number of lanes to remain one in each direction.

Table 5. 7 Multi-objective Optimization Model Results for Scenario A2

Minimize Z		Z=1.75			
Auto Mode		**Pedestrian Mode**		**Bicycle Mode**	
Variable	Optimized Value	Variable	Optimized Value	Variable	Optimized Value
$P1/P1^*$	$\frac{0.053}{0.030}=1.75$	$P2/P2^*$	$\frac{0.185}{0.185}=1.00$	$P3/P3^*$	$\frac{0.061}{0.061}=1.00$
SMS	35	*NL*	1	*NL*	1
MP	3	*SWC*	1	*PSL*	0
MW	48	*LW*	12	*BWC*	1
MT0	0	*SW*	8	*BW*	4
MT1	0				
MT2	0				
MT3	1				
$ROWWA = ROWWO$ $ROWWA = 100FT$	$ROWWO = MW + (NL * LW + SWW + GS + BLW) * 2$ $ROWWO = 100FT$				

When comparing Scenarios A, A1 and A2 which have been built to force the number of lanes to be three or fewer, two or fewer, and one respectively, the perceived LOS has increased as the number of lanes decreased for all three modes. It should be noted that the auto LOS was found to increase due to the increase in required *Space Mean Speed* which may or may not be achievable but can be estimated by engineers and planners using simulation tools. Also, the LOS for drivers decreased as the median type decreased to 0 indicating that a raised median is the most desirable scenario for drivers.

For pedestrians and bicyclists, as the number of lanes increased the perceived LOS decreased, despite the fact that the bicycle lane and sidewalk widths remained relatively the same. In conclusion, the three modes appear to be satisfied at a higher LOS when the number of lanes is one or two and there is a raised median present. Figure 5.10 was created to graphically depict the results for scenarios A, A1 and A2.

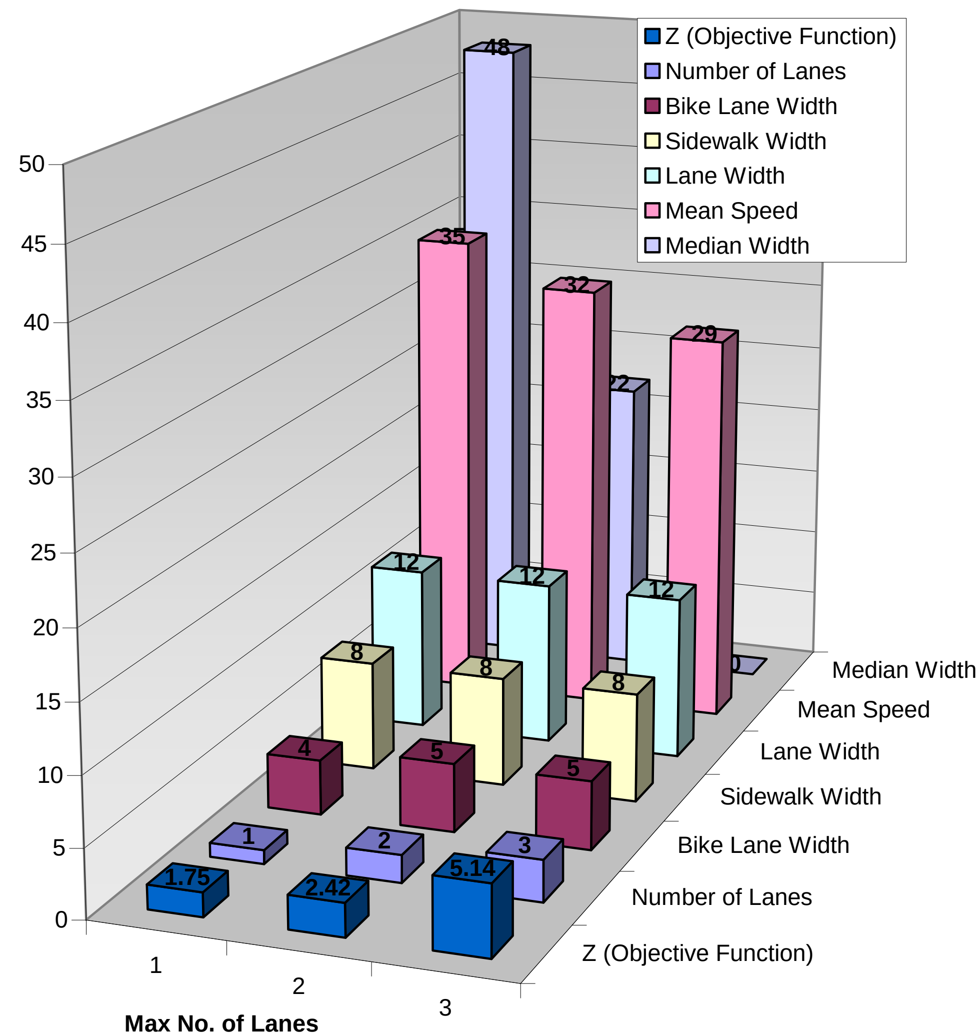

Figure 5.10 Sensitivity Analysis of Multi-objective Optimization Model

Scenario B - "Green Streets"

Under this scenario the ROW width includes a 15 foot grass strip and a wider median width as presented in Equation 5.2. The following design parameters need to be considered:

$$OptimizedROWWidth = MedianWidth + (NoLanes * LaneWidth + SidewalkWidth + 15' GrassStrip + BikeLaneWidth) * 2$$

Equation 5.2

Generously sized grass strips allow for consideration of Low Impact Development (LID) measures briefly presented below. LID measures enable the designer to mimic the pre-development hydrology of the soil by allowing rain water to infiltrate without traveling to an end point treatment facility. Several conditions have to be met, for this type of development, which have been presented below. The median and the grass strip can be graded to provide infiltration swales. To allow the rain water runoff from the streets to be collected in the swales it is preferred to have no curb and gutter along the streets. Eliminating this feature is not acceptable practice in some jurisdictions thus making this scenario not feasible in those jurisdictions (NRDC, 2009).

The probabilities for LOS D or less have decreased from Scenario A despite the fact that both sidewalk width and bicycle lane width did not change. This fact could represent a decline in model sensitivity as variables values are maximized. The upper threshold for the number of lanes for this scenario has been set at three in one direction; however, this constraint of the model can be changed to allow for more or for fewer lanes. It has to be noted that by increasing the number of through lanes the LOS for bicyclists and pedestrians will most likely decrease.

Scenario B represents an environmentally friendly sustainable option for Complete Street design and it should be considered where favorable conditions exist. The scenario can be further tailored to the needs of the community where will ultimately be implemented. The optimization model that generated this scenario is presented in Figure 5.11 below. The results of the model have been presented in Table 5.8.

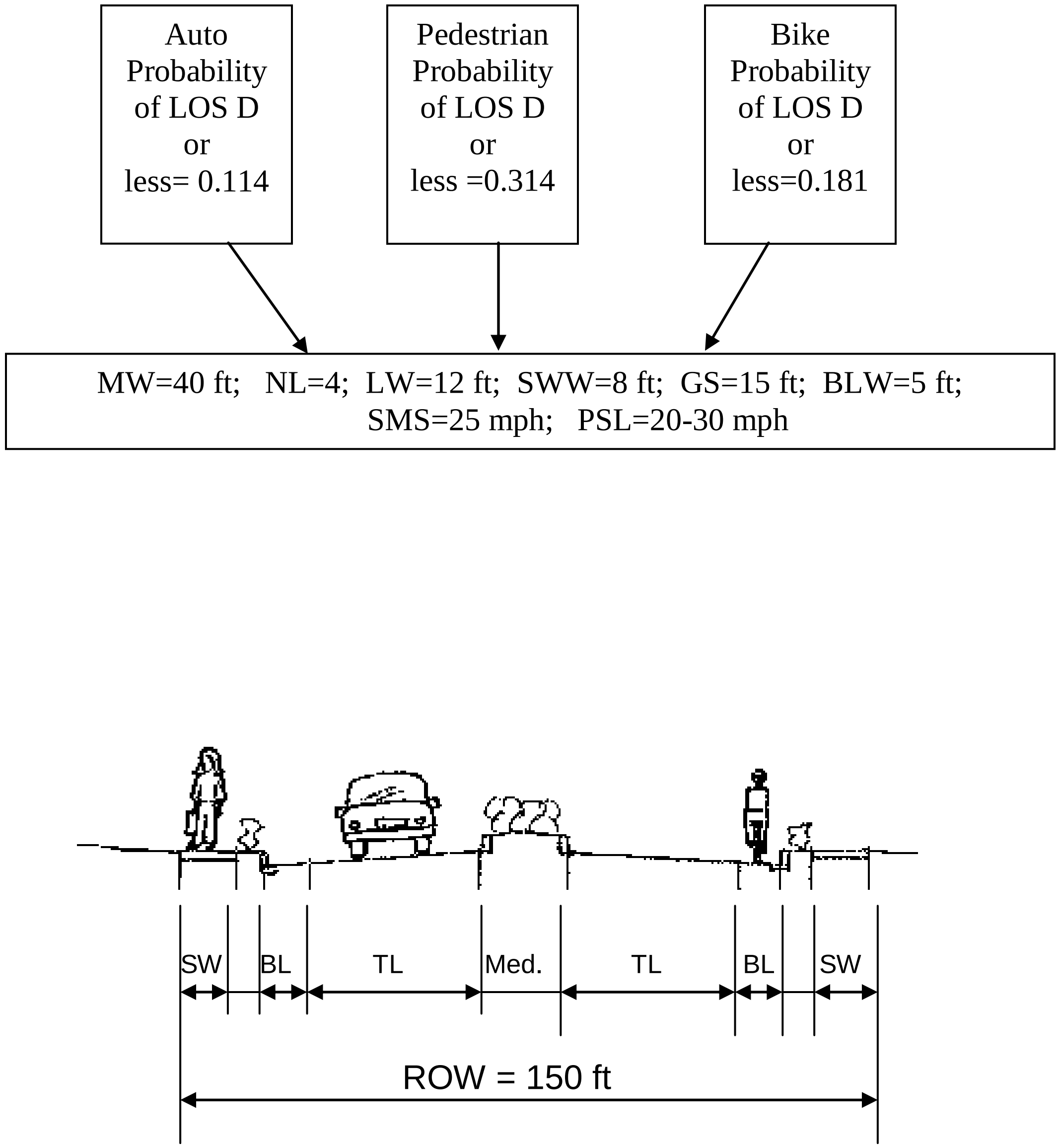

Figure 5. 11 Scenario B "Green Streets" – Schematic of Multi-objective Optimization Model Results

Table 5.8 Multi-objective Optimization Model Results for Scenario B "Green Streets"

Minimize Z		Z=3.80			
Auto Mode		**Pedestrian Mode**		**Bicycle Mode**	
Variable	Optimized Value	Variable	Optimized Value	Variable	Optimized Value
$P1/P1^*$	$\frac{0.114}{0.030}=3.80$	$P2/P2^*$	$\frac{0.314}{0.185}=1.70$	$P3/P3^*$	$\frac{0.181}{0.061}=2.9$
SMS	25	*NL*	2	*NL*	2
MP	3	*SWC*	1	*PSL*	0
MW	40	*LW*	12	*BWC*	1
MT0	0	*SW*	8	*BW*	5
MT1	0				
MT2	0				
MT3	1				
$ROWWA = ROWW$ $ROWWA = 150FT$	$ROWWO = MW + (NL * LW + SWW + GS + BLW) * 2$ $ROWWO = 150FT$				

Scenario C – 80 ft ROW Width

The perceived level of satisfaction for drivers, pedestrians and bicycles increased, when compared with Scenario B for the cross section provided with this scenario. Equation 5.3 presents the street characteristics included.

$$OptimizedROWWidth = MedianWidth + (NoLanes * LaneWidth + SidewalkWidth + BikeLaneWidth) * 2$$

Equation 5.3

The urban street features selected through the Optimization Model for this scenario generated similar levels of satisfaction for all three modes: auto mode ($P1/P1^{*}$=2.16), pedestrian mode ($P2/P2^{*}$=1.54) and bicycle mode ($P3/P3^{*}$=2.42). The balancing of the three objectives resulted in different values for each mode reflecting the fact that the independent variables take only integer values. The variables were set in this manner in order to obtain realistic results. Where the independent variables can take any value, the levels of satisfaction for the three modes would be equal. This scenario provided the values for the urban street characteristics that accommodated the three modes simultaneously at similar modal LOS.

- For the auto mode, approximately 90 percent (1-0.065) of the users are most likely to rate this facility at LOS C and above. The urban street cross section allows for two, 12-foot through lanes. The median type was changed to 2 which represents a 14-foot central two way left turn lane. Because the probability of being rated as LOS C and above increased from Scenarios A and B it leads to the conclusion that drivers do not see an impediment in having a marked median in place of a raised median. Because the *Traffic Volume* variable was not highly correlated with the LOS rating, and it was not included among the decision variables for the optimization model, it can be concluded that this scenario lacks strong proof that drivers will be more satisfied with two through lanes rather than three through lanes in one direction. This conclusion leads to recommendations for future research.

- For the pedestrian mode, approximately 82 percent (1-0.285) of the users are most likely to rate the facility at LOS C or above. In this Scenario the grass strip has also been eliminated, and the sidewalk width is 4 feet. The number of lanes decreased to one in each direction providing additional sense of safety resulting in an increase in the perceived level of satisfaction.

- For the bicyclists, this scenario provides the optimum LOS. The bicycle lane width is at the upper threshold and the number of through lanes is at the lower threshold resulting in a lower number of automobiles on the road thus influencing positively the perceived bicycle LOS. The fact that the posted speed limit and the average mean speed are also at the low thresholds are perceived positively by the bicyclists also contributing to the high LOS.

Figure 5.12 represents the optimization model that generated this Scenario.

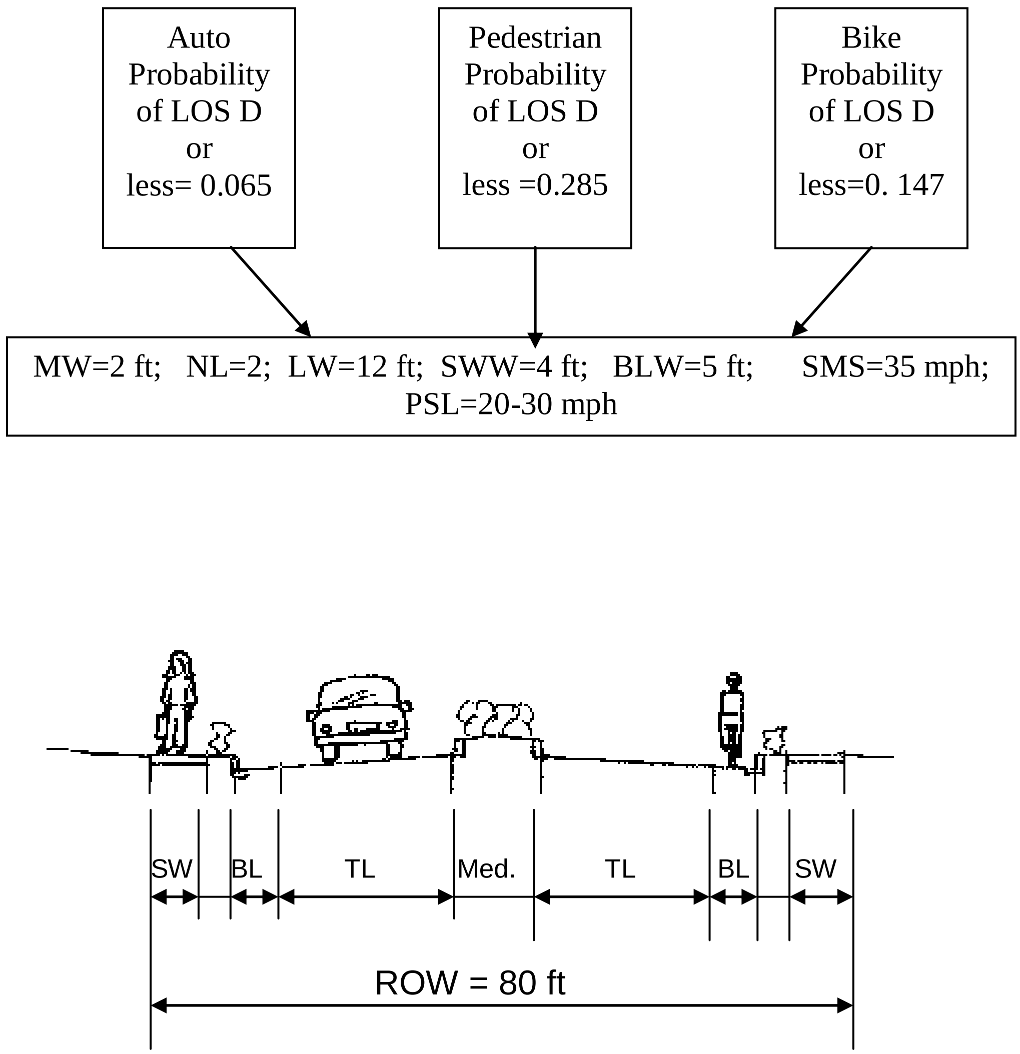

Figure 5. 12 Scenario C– Schematic of Multi-objective Optimization Model Results

Table 5.9 Multi-objective Optimization Model Results for Scenario C

Minimize Z		Z=5.14			
Auto Mode		**Pedestrian Mode**		**Bicycle Mode**	
Variable	Optimized Value	Variable	Optimized Value	Variable	Optimized Value
$P1/P1^*$	$\frac{0.098}{0.030}=3.27$	$P2/P2^*$	$\frac{0.411}{0.185}=2.22$ 0.	$P3/P3^*$	$\frac{0.314}{0.061}=5.14$
SMS	35	*NL*	3	*NL*	3
MP	0	*SWC*	1	*PSL*	0
MW	0	*LW*	12	*BWC*	1
MT0	1	*SW*	8	*BW*	4
MT1	0				
MT2	0				
MT3	0				
$ROWWA = ROWWO$ $ROWWA = 80FT$		$ROWWO = MW + (NL*LW + SWW + GS + BLW)*2$ $ROWWO = 80FT$			

The five scenarios presented provide insight in the Multi-objective Optimization Model by analyzing how the perception of LOS is influenced when characteristics of the streets vary.

5.5 Model Validation and Sensitivity Conclusions

This chapter presented the findings of the model validation for the pedestrian and bicycle Cumulative Logit LOS Models as well as a sensitivity analysis for the Multi-objective Optimization Model. As was noted, the new Cumulative Logit Models for the pedestrian and bicycle modes provide the analyst with methods to determine the entire distribution of traveler perceptions of service on urban streets. In addition, the models performed well as compared to the validation data set. One of the most important contributions through this effort lies in the ability to simplify the requirements on engineers and planners to estimate traveler perceived LOS for the pedestrian and bicycle modes on urban streets. The data requirements have been greatly reduced to only a few variables as compared to the large data requirements of the previously developed NCHRP 3-70 linear regression models that can estimate the mean traveler perceived LOS. The use of the Cumulative Logit Models for all three modes was included in the Multi-objective Optimization Model which was demonstrated through various examples of its application also in this chapter.

The Multi-objective Optimization Model has the ability to provide engineers and planners with alternative methods to analyze their choices in the design of urban street ROWs to best accommodate the bicycle, pedestrian, and auto modes on urban streets. Figure 5.13 has been provided to review the steps taken through this modeling effort.

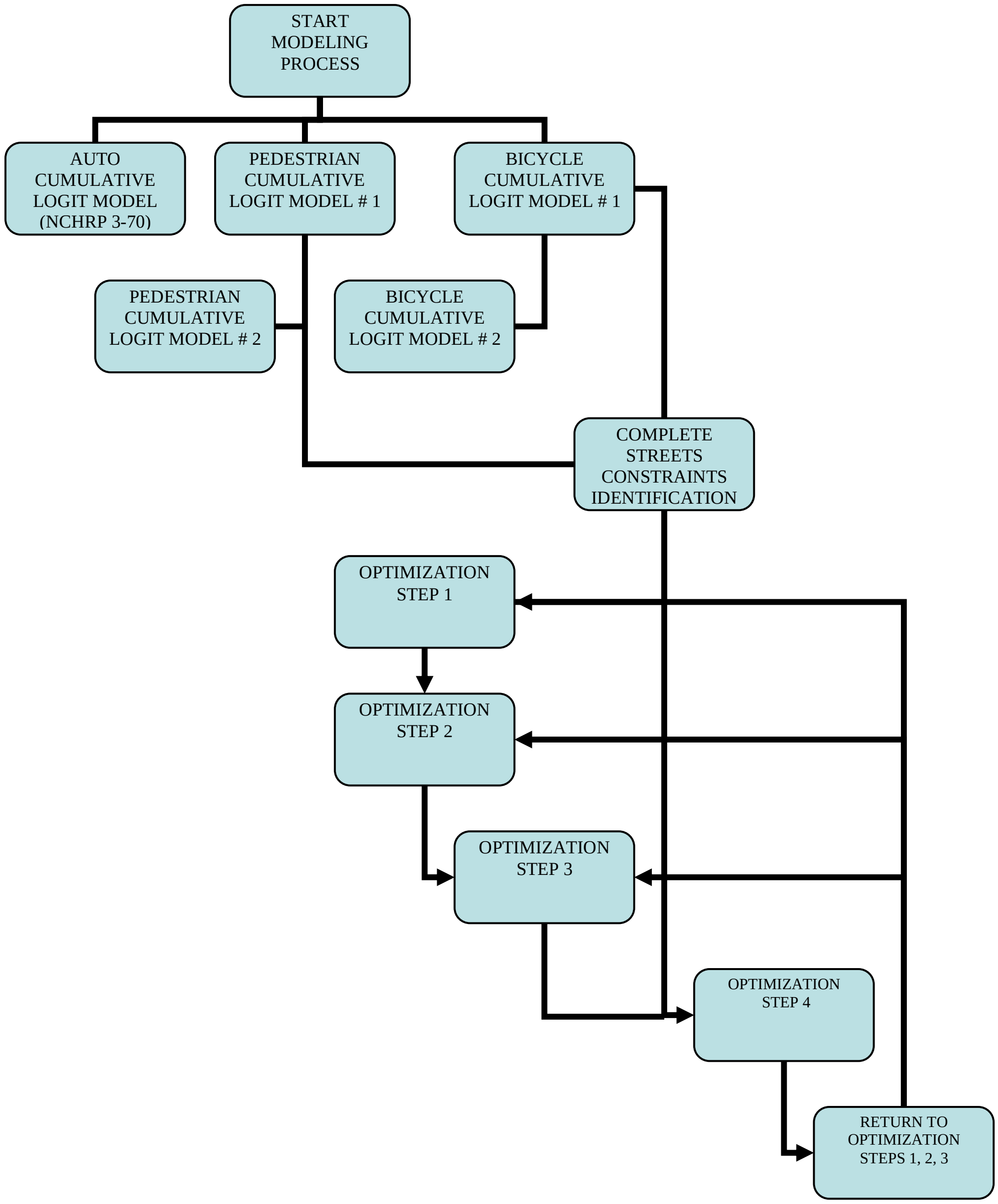

Figure 5.13 Multi-objective Optimization Modeling Path

CHAPTER 6: CONCLUSIONS

This dissertation analyzed an existing data set to determine the street characteristics that affect travelers' perceptions of LOS and combined the results of the selected method into a Multi-objective Optimization Model for street design.

Cumulative Logit Models to estimate travelers' perceptions of LOS on urban streets were developed in the pursuit of a Complete Streets design tool. The Cumulative Logit Models developed for the pedestrian and bicycle mode showed that the number of through lanes, the posted speed limit and the width of the sidewalk and bike lane, respectively, are among the most highly correlated street characteristic to pedestrian and bicycle LOS. When compared to the existing regression analysis models, the cumulative logit modeling technique was determined to be a more powerful and accessible model to determine the probabilities of travelers perceived LOS. This technique provides practitioners with the distribution of LOS ratings and these models require fewer number of variables that are easily accessible.

The probabilities of LOS ratings obtained with the cumulative logit models were incorporated into the proposed CRISTEI Multi-objective Optimization Model. The first three steps of the model were accomplished by creating three Single-objective Optimization Models, one for each of the three modes. The probabilities of obtaining ratings for LOS D or less were estimated for the auto mode from an existing cumulative logit model, and for the pedestrian and bicycle modes from newly created cumulative logit models. The street characteristics selected for these models were translated into constraints for three single-objective optimization models, one for each of the three modes. The results of these models were the minimum probabilities that travelers would rate a facility at LOS D or less.

The fourth step of the CRISTEI Multi-objective Optimization Model consisted of incorporating the three single-objective models into one multi-objective model.
The objective function of this model was to balance the probabilities of LOS ratings, constrained by a series of factors, and to prevent them from falling below the minimum probability calculated. The objective function was subject to decision variables and constraints selected from the data used and from standards. The constraint that brought the street characteristics for the three modes together was the ROW width. This constraint compared a given ROW width value with an equation for ROW width containing the values for street characteristics. Several scenarios that were created by varying the ROW width were created to show the sensitivity of the model to variation in street characteristics. The scenarios showed that the CRISTEI model provides information about travelers' satisfaction with different street designs.

The CRISTEI Multi-objective Optimization Model surpassed the previously created models by including three travel modes simultaneously into one optimization model.

It has been designed using readily available software thus creating a scholastic interface that allows easy manipulation of the components. However, the model can be further designed into a user-friendly interface that, when given to a designer, would allow the simple operation of inserting the given ROW width in a cell and a function button would be clicked for the model to start the iteration process. The final result would be the values for the street characteristics included in the design of a street segment. The Complete Street design will accommodate automobiles, pedestrians and bicycles within the same ROW while achieving an LOS level determined by the designer. The objectives of this dissertation were to design Cumulative Logit LOS Models for the pedestrian and bicycle modes and a Multi-objective Optimization Model to design Complete Streets which has been accomplished and demonstrated in this document.

CHAPTER 7: RECOMMENDATIONS

The CRISTEI Multi-objective Optimization Model proposed with this dissertation was an approach selected that was determined appropriate due to the structure of the data and the goal of the model. It is certain that different approaches can be explored in future studies, such as evolutionary computations. In addition, future models could incorporate cost calculations and a construction budget that the Optimization Model is indirectly including when restricting the ROW width.

Further, the CRISTEI Multi-objective Optimization Model does not include the transit mode due to the limits of the data collected through the NCHRP 3-70 study. Additional data collection could be conducted to allow for the inclusion of the transit mode in future studies.

Also, the perception of travel modes by the occupants of the adjacent facilities i.e. residents of private homes and people working in buildings adjacent to streets has not been considered and could be a deciding factor in adding or excluding sidewalks and bicycle lanes to urban street facilities.

The model can be further perfected where a bullet-proof interface would be presented to the user. An empty cell would allow the user to enter the available ROW width and a command button would allow the user to start the calculation process. Several conditional cells would be created to provide the user with error messages.

Several different options of the model can also be created where the user would have the ability to enter certain preferences, including the weight of a certain mode in comparison with the other modes. For example, where the bicycle traffic is very low, the contribution of the level of satisfaction of bicycle riders could be proportionally smaller then the level of satisfaction of the other modes in the overall optimization. Also, a single model can be created to combine several different scenarios where the user could select the constraints and the weights for each mode.

Overall the model performed well and provides a unique approach to the design of urban streets which can be termed Complete Streets. The methods provided within this document provide insight into the perceptions of level of service by bicycle and pedestrian modal users on urban streets, as well as providing a method for engineers and planners to design urban Complete Streets to reflect traveler's perceptions of service and relevant design standards.

APPENDIX 1

The data used for developing this dissertation has been collected through the NCHRP 3-70 effort. This Appendix includes a more detailed review of the data collection process in NCHRP 3-70, including:

- Development of testing stimuli
- Data collection methods (field and survey)
- Modeling efforts for the auto, pedestrian, bicycle, and transit modes
- Use of NCHRP 3-70 data for this dissertation

NCHRP 3-70 Development of Testing Stimuli

For auto mode, the data collection took place in two phases. During phase I of the study the street characteristics that proved to be the most important to participants were identified and used in the selection of the arterials for the second phase of the study for auto mode. The videotaping took place on pre-selected arterials. All videos were created in daylight conditions on days without precipitation. The materials used for filming the video clips were:

- Standard rented vehicles;
- Two video cameras (one for driver's perspective and one for the speedometer) and one GPS unit;
- Two camera tripods.

After the videotaping was complete, video clips were created using a series of software and video devices. The team of researchers identified the segments of the roadway that had consistent cross sections, lane positions and speed limit. Video clips were created that depicted various scenarios on urban streets. The video clips were shown to a total of 145 participants at four different locations in the US with four video clips shown to all participants in all locations and a unique additional six clips shown in each location. This resulted in a total of 1400 observations of auto traveler perceived LOS.

The data collection for the bicycle mode differed from the auto mode due to the different type of environmental factors that bicycle riders encounter. Field studies are the most desirable for this mode; however, this type of study imposes great risks on the participants. The research team selected the video simulation method with a "moving camera" approach. The collection of video clips used for the study included clips created by Sprinkle Consulting of Florida. A total of 30 bicycle video clips were created and showed to participants at four different locations within the US. Table 5 shows the video clip distribution by study location.

Pedestrian data collection was also performed using video simulation at four locations in the US. The locations were selected using a matrix of geometric and operational criteria representing typical ranges of urban streets in the US. To perform the video taping the following materials were used:

- Steady-cam unit;
- Stereo microphone.

For the data collection process video clips were selected for each mode. Four of the video clips were showed to all participants, and a total of ten were shown to each participant, as depicted in Tables A.1.1, A.1.2 and A.1.3.

Table A.1.1: Auto Clip Sequence in Each of the Study Locations

Presentation Order	**Location of Video Laboratory –Auto Clips Shown**			
	New Haven, CT	Chicago, IL	Oakland, CA	College Station, TX
Pilot Clip	25	25	25	25
1	21	20	12	15
2	55	56	56	7
3	52	10	8	52
4	60	51	65	13
5	53	14	59	58
6	56	2	29	56
7	54	62	6	2
8	2	63	15	1
9	15	52	2	61
10	57	15	52	64

Table A.1.2: Bicycle Clip Sequence in Each of the Study Locations

Presentation Order	**Location of Video Laboratory –Bicycle Clips Shown**			
	New Haven, CT	Chicago, IL	Oakland, CA	College Station, TX
Pilot Clip	326	326	326	326
1	301	319	302	311
2	323	308	310	328
3	321	306	305	324
4	320	309	324	315
5	317	320	327	309
6	312	318	321	313
7	309	304	309	303
8	307	324	322	319
9	314	321	330	320
10	324	329	320	321
Total Clip Time	13 min	13 min	13 min	13 min

Table A.1.3: Pedestrian Clip Sequence in Each of the Study Locations

Presentation Order	**Location of Video Laboratory –Pedestrian Clips Shown**			
	New Haven, CT	Chicago, IL	Oakland, CA	College Station, TX
Pilot Clip	212	212	212	212
1	223	201	215	208
2	208	226	220	217
3	226	225	206	215
4	204	208	201	214
5	205	219	227	201
6	203	228	226	230
7	201	211	209	218
8	231	215	216	232
9	215	229	224	226
10	210	222	208	221
Total Clip Time	16 min	18 min	16 min	19 min

Table A.1.4: Pedestrian Video Clip Characteristics

Clip No.	Sidewalk Width (ft)	Pedestrian Flow Rate (pph)	Outside Lane (ft)	Shoulder width (ft)	On-street Parking (%)	Barier (Y/N)	Buffer Width (ft)	Dir. Vol. (vph	Traffic Lanes (lanes)	Traffic Speed (mph)
215	8	60	12	0	50%	Y	7	170	1	25
227	6	200	16	0	0%	Y	4	630	2	30
230	6	220	12	0	0%	N	5	220	2	30
221	4	640	16	0	0%	Y	3	0	1	30
224	4	1320	12	0	100%	Y	2	80	1	30
228	6	180	10	0	40%	Y	1	370	1	30
226	9	190	20	0	50%	Y	5	1180	2	40
232	6	0	16	4	0%	N	0	540	1	45
229	6	280	10	0	40%	Y	0	310	1	30
205	10	0	12	4	0%	N	10	200	2	30
211	4	0	12	0	0%	N	5	570	1	45
214	9.5	0	12	5	0%	N	35	2030	3	45
225	9	280	20	0	50%	Y	5	1050	2	40
218	15	340	12	0	0%	N	12	60	1	30
222	6	610	16	0	50%	Y	3	220	2	30
219	7	640	16	0	100%	Y	4	150	1	30
220	7	820	16	0	100%	Y	4	150	1	30
223	6	1600	16	0	50%	N	3	0	2	30
210	0	0	12	0	0%	N	0	160	2	30
216	6	0	12	0	0%	N	0	360	1	30
217	6	0	12	0	0%	N	0	300	1	30
203	10	0	12	4	0%	N	15	270	2	30
204	10	0	12	4	0%	N	15	160	2	30
231	5	0	12	0	0%	N	6	570	1	35
201	0	0	10	0	0%	N	0	270	2	20
209	0	0	12	4	0%	N	0	2170	4	45
206	5	0	12	5	0%	N	23	1690	4	50
208	0	30	12	4	0%	N	0	1750	4	45

Table A.1.5: Pedestrian Variables

Pedestrian		
No.	**Variable**	**Range**
	Clip No.	#
1	Sidewalk Width	0 TO 15
2	Pedestrian Flow Rate (pph)	0 TO 1600
3	On-street Parking (%)	0,40,50,10
4	Number of Traffic Lanes (lanes)	1,2,3,4
5	Outside Lane (ft)	10 TO 20
6	Barier (Y/N)	Y/N
7	Posted Speed Limit (mph)	20 to 45
8	Shoulder width	0,4,5
9	Buffer Width (ft)	0 to 35
10	Dir. Vol.	0 to 2170

Table A.1.6: Auto Video Clip Characteristics - Part 1

Clip No.	1	2	5	6	7	8	10	12	13	14	15	16
Clip Distance (miles)	0.50	0.46	0.50	0.43	0.48	0.49	0.53	0.47	0.50	0.50	0.50	0.55
Street Name	Rt 234	Gallows Road	Wilson Blvd	Clarendon	Wilson Blvd	Wilson Blvd	Washington Blvd	Wilson Blvd	Washington Blvd	Glebe Rd	Glebe Rd	Fairfax Drive
HCM Class	1	3	3	3	3	3	3	3	3	2	2	3
LOS per HCM	1	6	5	3	4	2	3	3	5	1	1	1
No of Through Lanes	3	2	2	2	2	2	1	2	1	3	3	2
Presence of median	3	3	3	1	1	1	0	0	0	3	3	3
Total Travel Time (sec)	119	48	60	87	86	130	113	118	71	161	229	136
Space Mean Speed	15.1	34.5	30.0	18.3	20.1	13.6	16.9	14.3	25.4	11.2	7.9	12.1
Ped on sidewalk	0	0	2	2	2	2	2	0	1	2	2	2
# of stops (below 5 mph)	1	0	0	1	0	2	2	2	0	3	3	4
Total # of Signals	2	3	3	2	3	5	3	2	1	3	3	4
Pres of Excl LT L Signals	1	1	1	1	1	1	0	0	0	1	1	1
Presence of RTL Signals	1	1	1	0	0	1	0	0	0	1	1	1
Tree Presence	2	2	1	1	1	1	3	1	3	1	1	1
Average Lane Width (ft)	12	13	14	14	14	12	12	11	12	11	11	11
Width of Median (ft)	54	4	0	0	0	0	0	0	0	4	4	10
Right Shoulder Width (ft)	0	0	0	0	0	0	0	0	0	0	0	0
Left Shoulder Width (ft)	3	0	0	0	0	0	0	0	0	0	0	0
Width of Parking Lane (ft)	0	0	7	7	7	8	8	8	8	0	0	8
Width of sidewalk (ft)	4	4	10	4	10	14	6	11	6	8	8	16
Sep ROW to Sidewalk	3	3	0	0	0	0	0	5	0	0	0	0
Width of Bike Lane (ft)	0	0	5	0	5	6	0	0	0	0	0	5

Table A.1.7: Auto Video Clip Characteristics - Part 2

Clip No.	19	20	21	23	25	29	30	31	51	52	53	54
Clip Distance (miles)	0.52	0.55	0.50	0.54	0.54	0.50	0.55	0.50	0.44	0.41	0.60	0.60
Street Name	23rd St	Rt 50	Rt 50	M St	M St	Rt 234	M St	M St	M St	M St	Prosperity	Lee Hwy
HCM Class	4	1	1	4	4	2	4	4	4	4	2	2
LOS per HCM	4	2	2	2	3	4	1	1	1	2	3	4
No of Through Lanes	2	2	2	2	2	3	2	2	2	2	2	2
Presence of median	0	3	3	0	0	3	0	0	0	0	3	2
Total Travel Time (sec)	116	122	89	243	179	79	2998	471	240	186	121	93
Space Mean Speed	16.1	16.2	20.2	8.0	10.9	22.8	6.6	3.8	6.5	7.9	18.5	24.5
Ped on sidewalk	2	2	2	2	2	0	2	2	2	2	0	0
# of stops (below 5 mph)	3	1	2	3	2	1	8	9	4	3	1	2
Total # of Signals	8	2	3	8	8	3	8	8	9	7	2	4
Pres of Excl LT L Signals	0	1	1	0	0	1	0	0	0	0	1	1
Presence of RTL Signals	0	0	1	0	0	1	0	0	0	0	1	1
Tree Presence	2	1	2	1	1	2	1	1	1	1	2	3
Average Lane Width (ft)	10	11	11	10	10	12	10	10	10	10	12	12
Width of Median (ft)	0	17	17	0	0	54	0	0	0	0	15	14
Right Shoulder Width (ft)	0	8	8	0	0	0	0	0	0	0	0	4
Left Shoulder Width (ft)	0	2	2	0	0	3	0	0	0	0	0	4
Width of Parking Lane (ft)	7	0	0	10	10	0	10	10	10	10	0	0
Width of sidewalk (ft)	6	0	0	10	10	0	10	10	10	10	4	4
Sep ROW to Sidewalk	5	0	0	0	0	0	0	0	0	0	4	10
Width of Bike Lane (ft)	0	0	0	0	0	0	0	0	0	0	0	0

Table A.1.8: Auto Video Clip Characteristics - Part 3

Clip No.	55	56	57	58	59	60	61	62	63	64	65
Clip Distance (miles)	0.45	0.50	0.61	0.60	0.61	0.50	0.70	0.50	0.50	0.50	0.50
Street Name	Braddock Rd	Sunset Hills Rd	Lee Hwy	Rt 50	Rt 50	Rt 50	Rt 50	Rt 50	Rt 50	Rt 50	Lee Hwy
HCM Class	2	2	2	2	2	2	1	1	1	1	2
LOS per HCM	1	4	3	1	1	2	4	5	6	2	6
No of Through Lanes	2	2	2	2	2	2	3	3	2	2	2
Presence of median	3	3	0	3	0	2	0	0	3	3	2
Total Travel Time (sec)	128	77	129	144	182	120	91	49	53	92	50
Space Mean Speed	12.7	23.1	17.4	11.2	12.1	15.0	27.7	36.7	41.9	19.6	36.0
Ped on sidewalk	0	0	0	0	0	0	0	0	0	0	0
# of stops (below 5 mph)	1	1	2	1	3	1	1	0	0	1	0
Total # of Signals	1	1	2	3	2	3	3	2	2	3	3
Pres of Excl LT L Signals	1	1	0	1	0	1	1	1	1	1	1
Presence of RTL Signals	1	0	0	0	0	0	0	0	1	0	0
Tree Presence	3	3	3	3	3	1	3	3	3	3	2
Average Lane Width (ft)	12	12	12	12	12	12	12	12	12	12	12
Width of Median (ft)	15	8	0	10	0	14	0	0	6	6	14
Right Shoulder Width (ft)	0	0	0	0	0	0	0	0	4	0	0
Left Shoulder Width (ft)	0	0	0	0	0	0	0	0	4	0	0
Width of Parking Lane (ft)	0	0	0	0	0	0	0	0	0	0	0
Width of sidewalk (ft)	6	0	4	3	4	4	0	0	0	0	0
Sep ROW to Sidewalk	0	0	2	4	4	4	0	0	0	0	0
Width of Bike Lane (ft)	0	0	0	0	0	0	0	0	0	0	0

Table A.1.9 Street Characteristics Collected

Auto		
No.	**Variable**	**Range**
1	Clip Distance (miles)	0.4-0.6
2	Number of Through Lanes	1 to 3
3	Presence/Type of Median	0 to 3
4	Total Travel Time (seconds)	50 to 471
5	Space Mean Speed	3.8 to 41.9
6	Ped on Sidewalk	0 to 2
7	Avg Spot Mean Speed MPH	3.61 to 38.57
8	Variance of Speed	26.30 to 394.89
9	Lane Position	0 to 3
10	PED on Sidewalk	0 to 2
11	Pavement Quality (New, Typ, Cracked/worn, Poor)	0 to 3
12	# Stops (below 5 mph)	0 to 9
13	Total # of Signals	0 to 9
14	Stops/Signal (Yes, No)	0,1
15	Pres. Of Ex. LT Lane – Signals (Yes, No)	0,1
16	Pres. Of Rt Turn Lane- Signals (Yes, No)	0,1
17	Quality of Lane Markings (New, Typical, Worn, Poor)	0 to 3
18	Sign Quality	1 to 3
19	Landscaping	0 to 3
20	Tree Presence (Few or None, Some, Many)	1 to 3
21	Vehicle	0,1
22	Vehicle Driver	0,1
23	Position in Queue at Red Lights Sig 1-9	0-40
24	Estimated Control Delay By Signal Sig 1-9	0-125
25	Average Lane Width (ft)	10 to 14
26	Width of Median (ft)	0-54
27	Rigth Shoulder Width (ft)	0-8
28	Left Shoulder Width (ft)	0-4
29	Width of Parking Lane (ft)	0 to 10
30	Width of Sidewalk (ft)	0-16
31	Separation from Right-of-Way to Sidewalk (ft)	0-10
32	Width of Bike Lane (ft)	0-5.5

Table A.1.10: Bicycle Video Clip Characteristics

Clip #	Outside Lane (ft)	Bike/ Shoulder width (ft)	Through Lanes	Divided (D/UD)	Pk Hr Vol (vph)	Heavy Vehicle (%)	Spd Lim (mph)	Pavement Rate (1-5)	% OSP	Sig. Int X-Dist (ft)
328	12.0	4.0	1	U	79	0	30	4	0	0
330	12.0	4.0	1	U	136	0	30	4	0	0
306	11.0	4.0	2	U	717	0	30	4	0	72
305	12.0	3.5	2	D	813	8	30	3.5	0	65
307	11.0	4.0	2	U	757	0	30	4	0	72
304	12.0	3.5	2	D	428	0	30	3.5	0	65
303	12.0	5.0	3	D	1211	0	50	4	0	0
319	12.0	5.0	2	D	2961	0	45	4	70	53
311	12.0	8.0	1	U	631	0	25	3.5	0	33
329	12.0	4.0	2	D	1261	0	45	3.5	0	61
302	12.0	5.0	3	D	2119	0	50	4	40	0
327	12.0	8.0	2	U	165	0	30	3	0	40
309	10.0	0.0	2	U	134	0	20	4	0	52
313	10.0	0.0	3	OW	536	0	30	3.5	0	33
308	10.0	0.0	2	U	407	0	20	4	0	86
320	12.0	5.0	2	D	1898	0	45	4	0	64
321	12.0	5.0	2	D	2146	0	45	4	0	0
318	12.0	0.0	3	D	182	100	55	3.5	0	335
322	12.0	0.0	3	D	1544	0	45	3.5	0	0
310	11.5	0.0	2	D	1589	0	40	4	0	0
301	12.0	5.0	3	D	2549	0	50	4	0	0
312	12.0	0.0	1	U	631	0	25	3.5	0	49
317	12.0	0.0	2	D	495	17	55	3	0	0
314	12.0	0.0	2	D	638	0	45	3.5	0	142
323	12.0	0.0	3	D	357	0	45	3.5	0	142
324	12.0	4.0	3	D	636	0	45	4	0	887

Table A.1.11: Bicycle Variables

Bicycle		
No.	**Variable**	**Range**
1	Outside Lane (ft)	10 to 12
2	Bike Lane/ Shoulder width (ft)	0 to 8
3	Number of Through Lanes	1,2,3
4	Divided DUD	U,D,One Way
5	Peak Hour Volume (vph)	79-2961
6	Heavy Vehicles	0-100
7	Posted Speed Limit (mph)	20-55
8	Pavement Rate15	3,4
9	On-street Parking	0,40,70
10	Signalized Intersection Dist (ft)	0-887
11	Unsignalized Conflicts Per Mile	0-40

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